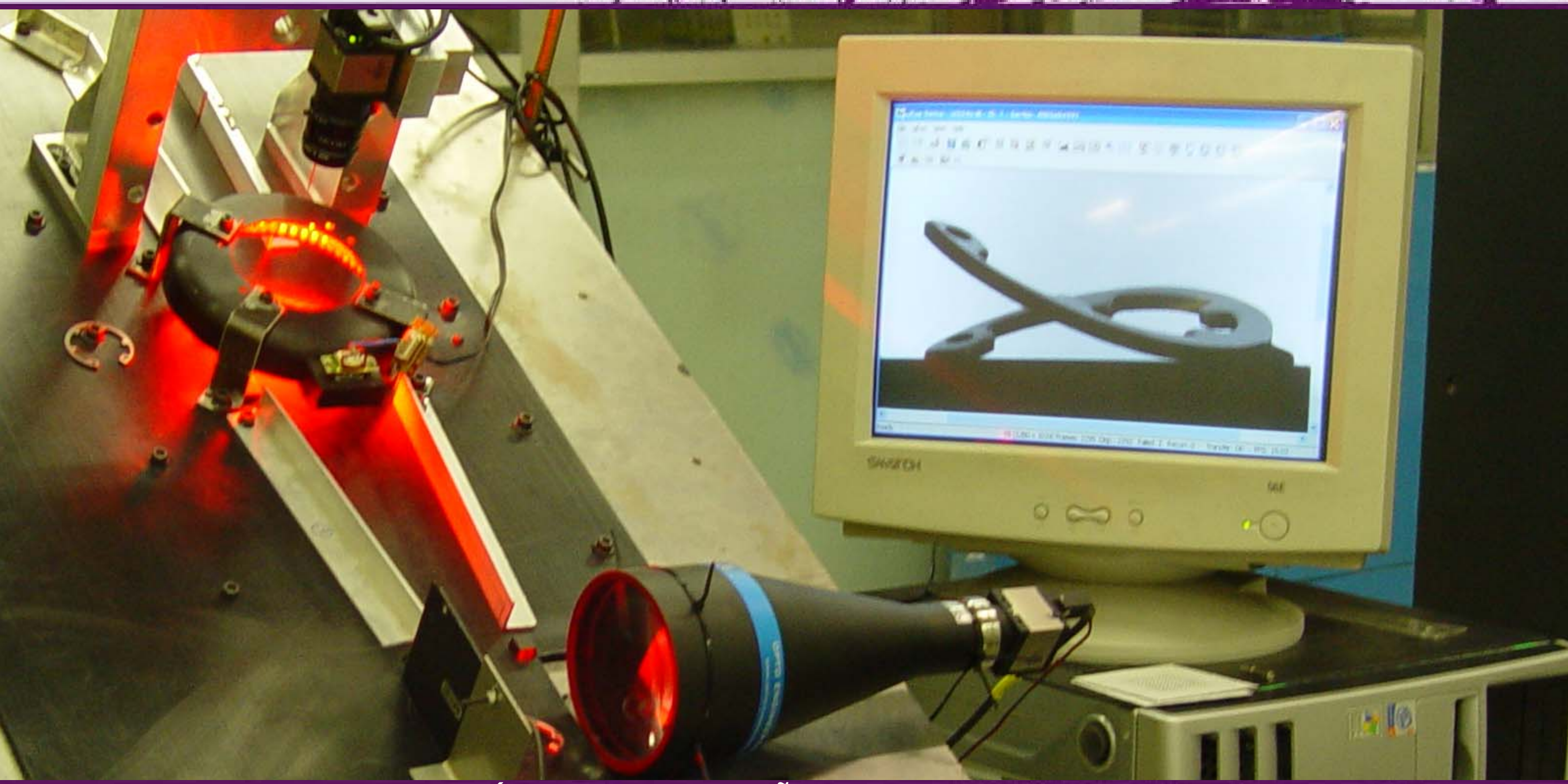
MONDRAGON UNIBERTSITATEA

TESIS DOCTORAL

APPLICATION OF ARTIFICIAL INTELLIGENCE TECHNIQUES TO THE SMART CONTROL OF SHEET METAL FORMING PROCESSES



ENEKO SÁENZ DE ARGANDOÑA // Arrasate-Mondragón, 2009

APPLICATION OF ARTIFICIAL INTELLIGENCE TECHNIQUES TO THE SMART CONTROL OF SHEET METAL FORMING PROCESSES

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A thesis submitted for the degree of

Doctor por Mondragón Unibertsitatea

Department of Mechanical and Industrial Production

Mondragón Unibertsitatea

February 2009

AGRADECIMIENTOS

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Como es sabido por todos los que me conocéis bien, soy una persona bastante parca en palabras, así que siguiendo con la tradición voy a intentar expresar mi gratitud a todas las personas que entiendo me han apoyado durante esta ardua fase de mi vida de manera breve y concisa. En primer lugar matizar que, aunque en ocasiones el tirar de este carro, con todo lo que ello acarrea, se ha hecho duro, no cambiaría todo lo que he tenido ocasión de experimentar y disfrutar a lo largo de estos años por nada del mundo. Lo haré por orden cronológico, y de esta manera espero no olvidarme de nadie.

En primer lugar al antiguo departamento de fabricación (hoy en día departamento de Mecánica y Producción Industrial) y más en concreto a su área de conformado por haberme dado la oportunidad, hace ya la friolera de 9 años, de poder compaginar mis estudios de ingeniería con tareas en proyectos de investigación. Ese fue el germen de mi vocación como ingeniero. Quiero agradecer a todos sus miembros de por aquel entonces, Aitor, Zigor, Wilson, Iñaki, (y seguro que me dejo alguno más) lo bien que me acogieron en su seno y especialmente a Rafa, Carlos y Ángel pues con ellos colaboré más estrechamente.

Posteriormente agradecer de nuevo tanto a Carlos García como a Ángel Oruna el que se acordasen de mí después de mi periplo por tierras escocesas y contasen conmigo para incorporarme al departamento de fabricación. Fueron dos años duros pero gratificantes al mismo tiempo. Durante este periodo agradecer todos los buenos momentos pasados junto con Joseba Pujana, Natxo Marquinez, Haritz Barrutia, Peio Jimbert o Unai Iraeta entre otras muchas personas que seguro se me olvidan.

Y después de todo esto me embarque en el tema que aquí nos concierne: la tesis doctoral. En primer lugar agradecer a Carlos García el darme la oportunidad de trabajar en el presente proyecto de investigación. Han sido cuatro años en los que he tenido la oportunidad de conocer a mucha gente de la que guardo muy buenos recuerdos. Como no, agradecer también a todos mis compañeros de fatigas en Fabri2 por toda la paciencia que en ocasiones han tenido conmigo. Han sido un gran apoyo para mí durante este tiempo. Eskerrik asko Amaiari, Andreari, Jon Anderri (compañero de fatigas desde mis inicios como becario) eta Landerri, a los últimos que se han incorporado Haritzi, Jokini eta Javierri eta bereziki Ibairi, Edurneri (compañera de piso también junto con Natxete) eta Gurutzeri. Bihotz bihotz mila esker.

I would also like to thank all the marvellous people whom I have met all over Europe during this time within the frame of the project Pro2Control (European project under the Sixth Framework Programme that has supported the present research work). Among others especially Michael Galle, Thomas Terzyk and Tom Wittbrodt from Brankamp, Guy Canova and Philippe Fillatreau from Delta Technologies, Iban Etxaniz, Belen Alzuaran y Mikel Gorostidi de Industrias Alzuaran, Antonio Arana de Industrias Garita, and Stefan Wagner, Tushar Khandeparkar and Robert Pop from the Institute for Metal Forming Technology in Stuttgart. I would like to specially thank Robert Pop for becoming one of my best friends and for all the adventures that we have spent together. Thank you very much to all you because this would not have worked without your help.

Y también aquí, dentro de la universidad, me gustaría agradecer a todos los compañeros que han trabajado junto a mí en el desarrollo de la presente tesis. Entre otros destacar a Idoia Romero, Ibai Guridi, Haritz Madinabeitia, Hariz Legarda, Alberto Milla, Iker Perez y especialmente a Alberto Izaguirre, Asier Aztiria, Rafael Ortubay (compañero de fatigas incluso antes de la realización de la tesis y excepcional persona) y Nestor Arana por todo lo que me han enseñado y por estar a mi lado cuando los he necesitado (muy especialmente a Nestor ya que en los últimos tiempos hemos colaborado estrechamente y me ha enseñado muchas y muy valiosas cosas). También quiero agradecer a todos nuestros técnicos de laboratorio especialmente a Arkaitz Garate, Gotzon Arrizabalaga e Iñaki Urrutia por sacarme de tantos apuros cuando la teoría bajaba a los talleres y necesitábamos el desarrollo de sistema tangibles.

Y por último y para mí lo más importante, agradecer infinitamente a toda mi familia el apoyo que me han demostrado durante todos estos años. A mi padre José Maria y a mi madre Maria Blanca, porque desde muy pequeñitos han sabido transmitirnos tanto a mi hermana Zuriñe como a mí todos los valores necesarios para conseguir formarnos como personas. Para ellos dos un Cum Laude porque lo han hecho *chapeau*. A mi hermana Zuriñe porque desde que no levantábamos más de un palmo del suelo siempre hemos estado muy unidos y porque ha sido, es y será un gran apoyo para mí. A mi cuñado Patxi, que desde hace mucho es uno más de la familia, agradecerle también todos los buenos momentos que hemos pasado juntos. I would also like to thank Lena, whom I have known in the last part of this research work (thanks to the destiny although helped by my friend Robert and her wife Galina) for supporting me; you are one of the best things that this thesis has given to me and I really hope that we will have greater chances in the future to spend more time together. A todos vosotros deciros que, especialmente gracias a vosotros, he llegado hasta aquí y que junto a vosotros espero avanzar mucho mas en el futuro.

Y seguro que me dejo a alguien, por lo que a todos vosotros que habéis remado conmigo para hacer llegar esta trainera a buen puerto

MILA ESKER DENOI

ABSTRACT

ABSTRACT

The present research work aims at evaluating the economical feasibility and the technological viability of implementing intelligent control systems in complex industrial manufacturing processes; in this case forming processes. Forming processes are manufacturing processes that use force and pressure in order to modify the shape of a material part until getting the final product. The wide range of non-linear factors (material properties, tool geometry, machine parameters and lubrication variables) that determine the final quality of the parts manufactured by these processes makes them to be inherently quite unstable. Thus, the control made by human operators is still essential nowadays. On the other hand, although human operators have demonstrated to be a very successful strategy when controlling this type of processes, the actual market evolution towards the fabrication of more complex parts, made of lower formability materials at higher production rates is decreasing their capacity of reaction when solving the daily problems.

Therefore, the development of new automatic and global control systems based, not on traditional control techniques and mathematical models but on the control strategy that has been successfully used for many years, the control through the experience and knowledge, is now even more necessary. In the present research work, two intelligent control systems based on AI techniques have been developed and evaluated. The main purpose of these intelligent control systems is to identify the process failures at forming processes and to propose the right solutions that should lead to their solution, all this in a quick and reliable way. Following this strategy, the solution of the process failures is considerably simplified because, after any process failure of defective part detection, human operators find a report where an explanation of the incidence, as well as its causes and the way to solve it, are displayed. This has the inherent advantage of decreasing the length of the downtimes at the manufacturing facilities and thus increasing the number of parts produced.

Together with the previously described core of the global control systems, two monitoring systems have been developed and implemented in a forming facility too. The purpose of these monitoring systems is to work as the senses of the intelligent control systems. The first one, an artificial vision system, is aimed at evaluating the quality of the produced parts by carrying out a 100% quality control at the end of the forming process. This will assure the right quality of all the products shipped to the customer. The second one, a sensors based process monitoring system, is aimed at detecting any process failure at the forming facility by means of force and acoustic emissions measurements. This will reduce the internal defective and will assure the security of the forming facility. Both systems are in charge of detecting any process failure and defective part and of reporting about them to the intelligent control system.

Since the aim of the research work was to evaluate the feasibility of implementing global intelligent control systems in the industry, all the developments and results achieved through the present research work have been carried out in an industrial environment. The research work is principally divided into three main parts; 1) the development and implementation of the sensors based process monitoring system, 2) the development and implementation of the AV monitoring system and 3) the development of the intelligent control systems. At the end, a summary of all the results and conclusions achieved through the development of the previous mentioned systems is given too.

RESUMEN

El presente trabajo de investigación tiene como objetivo evaluar en qué condiciones es económicamente viable y tecnológicamente factible la implementación de sistemas inteligentes de control en procesos de fabricación complejos; en este caso procesos de conformado. Los procesos de conformado son procesos de fabricación basados en la aplicación de esfuerzos o presiones sobre componentes con el objetivo de modificar su forma geométrica hasta conseguir un producto final. El gran abanico de variables no lineales (propiedades de materiales, geometría de herramientas, parámetros de máquinas y/o lubricación) que determinan la calidad final de las piezas conformadas hacen que estos procesos sean inherentemente inestables. Por ello, aun hoy en día, el control de estos procesos se realiza mediante operarios humanos. Por otro lado, aunque la experiencia ha demostrado que los operarios son capaces de controlar estos procesos de manera eficiente, la actual tendencia hacia la fabricación de piezas más complejas, fabricadas en materiales menos deformables y todo ello a cadencias de fabricación mayores, ha hecho que la capacidad de los operarios para reaccionar ante imprevistos se haya visto mermada.

Por lo tanto, el desarrollo de nuevos sistemas automáticos e inteligentes de supervisión y control basados, no en técnicas tradicionales de control o en modelos matemáticos, sino en la estrategia de control que ha dado buenos resultados a lo largo de los años, el control basado en la experiencia y el conocimiento, es cada vez más necesario. En el presente trabajo de investigación, se han desarrollado y evaluado dos sistemas inteligentes de control basados en técnicas de inteligencia artificial. El principal objetivo de estos sistemas es ser capaces de identificar los fallos de proceso en procesos de conformado así como de plantear, automáticamente, las instrucciones para su resolución, todo ello de una manera rápida y robusta. Siguiendo esta estrategia, la resolución de los fallos de proceso se simplifica ya que, tras una parada de máquina o la detección de piezas defectuosas, el sistema proporciona al operario un informe donde se detallan las acciones a llevar a cabo. Esto tiene como ventaja una reducción en los tiempos de parada de máquina (y por lo tanto aumento en la cantidad de piezas producidas) ya que la identificación de los fallos es inmediata.

Junto con el núcleo del sistema global de control, se han desarrollado e implementando en una instalación de corte progresivo dos sistemas de monitorización. El objetivo de estos dos sistemas de monitorización es recoger información sobre el proceso y enviársela al sistema de control. El primero, un sistema de visión artificial, tiene como objetivo analizar la calidad del 100% de las piezas fabricadas. Esto asegura la correcta calidad de todas las piezas enviadas a los clientes. El segundo, un sistema de monitorización de procesos basado en sensores, tiene como objetivo la detección de cualquier fallo de proceso. Esto reduce el defectivo interno y protege a las instalaciones frente a anomalías de proceso. Por lo tanto, ambos sistemas tienen como misión la detección de cualquier anomalía de proceso o pieza defectiva así como informar al sistema de control sobre las mismas.

Puesto que el objetivo de este trabajo es evaluar la capacidad de los sistemas anteriormente citados en el entorno industrial, todos los desarrollos y resultados obtenidos a lo largo del mismo se han llevado a cabo en una empresa. El trabajo se puede dividir en tres partes: 1) el desarrollo e implementación del sistema de monitorización basado en sensores, 2) el desarrollo e implementación del sistema de visión artificial y 3) el desarrollo de los sistemas de control inteligentes.

LABURPENA

Ikerkuntza lan honen helburua sistema adimendunak fabrikazio prozesu konplexuak kontrolatzeko erabiltzearen bideragarritasuna aztertzea da, bai ekonomikoki eta teknologikoki. Kasu honetan, konformazio prozesuetan inplementatutako sistema adimenduak ikertu dira. Konformazio prozesuak, amaierako produktua lortzeko, hasierako materialari esfortzu edo presioen bidez forma geometrikoa aldatzean datzate. Konformaturiko piezen amaierako kalitatea finkatzen duten aldagai ez-linealen ugaritasun zabalak (materialen propietateak, lanabesen geometriak, makinen parametroak eta/edo lubrifikazioa) prozesu hauek ezegonkorrak izatea ondorioztatzen du. Hori dela medio, gaur egun ere, prozesu hauen kontrola giza-langile bidez egiten da. Langileak prozesu hauek modu eraginkorrean kontrolatzeko gai direla erakutsi du esperientziak. Dena den, deformagarritasun txikiagoko materialez eginiko pieza konplexuagoak kadentzia altuagoetan fabrikatzeko gaur egungo joerak, langileek ezustekoen aurrean erantzuteko duten gaitasuna gutxitu du.

Ondorioz, prozesua gainbegiratu eta kontrolatzen duten sistema automatiko eta adimendu berrien garapena beharrezkoa bihurtu da. Sistema hauek ez daude kontrol teknika tradizional edo eredu matematikoetan oinarrituak. Sistema hauen kontrola ezagutza eta esperientzian oinarriturik dago, zeinak azken urteetan emaitza onak eman dituen. Ikerkuntza lan honetan adimen artifizial tekniketan oinarrituriko bi kontrol sistema adimendun garatu eta baloratu dira. Sistema hauen helburu nagusia konformazio prozesuetan emaniko akatsak identifikatu eta automatikoki ebazpen-proposamenak aurkeztea da, modu azkar eta sendoan. Estrategia hau jarraituz, prozesuko akatsen ebazpena errazten da, pieza akastunak atzematean edo makinaren geldialdi baten aurrean, sistemak langilea eman beharreko pausuak azaltzen dizkion txosten batez hornituko baitu. Makinaren geldialdiaren murriztea eta ondorioz, produktibitatea igotzea da honen abantaila nagusia, akatsen identifikazioa berehalakoa baita.

Kontrol sistema garatzeaz gain, puntzonaketa instalakuntza batean bi monitorizazio sistema martxan jarri dira. Bi monitorizazio sistema hauen helburua prozesuaren informazioa jaso eta kontrol sistemari bidaltzea da. Lehenengoa ikuspen artifizialeko sistema bat da, zeinaren helburua ekoiztutako piezen %100aren kalitatea aztertzea den. Honenbestez, bezeroei bidalitako piezen kalitate egokia bermatzen da. Bigarrena sentsoreetan oinarrituriko prozesuen monitorizazio sistema bat da. Bere helburua prozesuan emaniko edozein akats antzematea da. Honek akastun piezen kantitatea gutxitzen du eta instalakuntzak prozesuen ezegonkortasunetatik babesten ditu. Ondorioz, bi sistemen helburua prozesuan izandako arazo edo pieza akastunak antzematea eta kontrol sistemari hauen berri ematea da.

Lan honen helburua aurrez aipaturiko sistemen gaitasuna industri ingurunean ebaluatzea denez, aurkezturiko garapen eta emaitzak enpresa batean burutu dira. Hiru atal nagusi bereiz daitezke lan honetan: 1) sentsoreetan oinarrituriko monitorizazio sistema baten garapen eta inplementazioa; 2) ikuskapen artifizialeko sistemaren garapen eta inplementazioa; eta 3) adimendun kontrolean oinarrituriko sistemen garapena.

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SYMBOLS AND ABBREVIATIONS

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GNP	Gross National Product
GDP	Gross Domestic Product
PID	Proportional Integral Derivative Control
PC	Personal Computer
FPGA	Field Programmable Get Array
MF	Metal Forming
SMF	Sheet Metal Forming
AE	Acoustic Emissions
RMS	Root Mean Squared
KHz	KiloHertz
GHz	GigaHertz
CCD	Charge Coupled Device
LED	Light-emitting Diode
PCI	Peripheral Component Interconnect
RAM	Random-access memory
Dll	Dynamic Link Library
DSP	Digital Signal Processor
ASICS	Application Specific Integrated Circuits
IP	Intellectual Property
3D	Three Dimensional
SMES	Small and Medium-sized enterprises
AV	Artificial Vision
AI	Artificial Intelligence
KB	Knowledge Base
KBS	Knowledge Base Systems

KE	Knowledge Engineering
ANN	Artificial Neural Networks
CBR	Case-Based Reasoning
ES	Expert System
RBES	Rule-based expert systems
F problems	Formalized problems
NF problems	NonFormalized problems
GUI	Graphical User Interface
CLIPS	C Language Integrated Production System
MEMS	Micro Electromechanical Systems
PVC	Polyvinyl chloride
TCM	Tool Condition Monitoring
LF	Low Frequency
WED	Wire Electro Discharge Machine
USB	Universal Serial Bus
CMOS	Complementary Metal-oxide Semiconductor
EEPROM	Electrically Erasable Programmable Read Only Memory
PDA	Personal Digital Assistant

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Chapter 1

INTRODUCTION

1.- INTRODUCTION

The present thesis, entitled “Application of Artificial Intelligence techniques to the smart control of sheet metal forming processes”, has been carried out within the research area “Ciencía, Tecnología y Procesos de Transformación de Materiales” at the department of “Mecánica y Producción Industrial” in Mondragón Goi Eskola Politeknikoa (Mondragón University).

1.1. The Motivation and Concerns of the Research

Industry, and more specifically manufacturing industry, plays a vital economic role all over the world. As an example, manufacturing activity in Europe represents approximately 22 % of the EU GNP [EUR03] and manufacturing-related activities account for around 75% of the EU GDP [EUR08]. Although manufacturing industry plays a vital role in the economy of most of the developed countries, it is being increasingly challenged by the global competitive environment – and in particular by the ever more significant role of Asian manufacturers. In order to face this challenge, the manufacturing industries located at the developed countries have evolved towards the production of higher complexity parts, manufactured with less formable materials, using fewer steps production processes and all this at higher production rates and with stricter quality requisites.

Among manufacturing processes, forming processes, and more specifically forming processes, are especially sensitive to the aforementioned changes. Forming processes can be defined as manufacturing processes that use force and pressure in order to modify the shape of raw materials until getting final products. The wide range of non-linear factors that drive this sort of manufacturing processes makes them to be very complex and inherently quite unstable. On one hand, slight changes in the production parameters or in the material quality are usually enough to get the process out of its stability condition and to produce bad quality parts. On the other hand, when a tooling breakage or excessive wear occurs, the resulting parts are also defective. This situation is especially difficult to detect when producing small size parts, often manufactured in large quantities using high speed and production rate equipment. As a result, production of defective parts goes on until a statistical control is able to detect it and to stop the machine.

To avoid the aforementioned situation and guarantee a high reliability of manufacturing processes in general, a field of investigation named “robust processes” has evolved during the last years. This field of investigation tries to increase the stability of manufacturing processes by reducing or eliminating their sensitivity to the input variables. At forming processes, although traditional control techniques, mostly PID controllers, based on mathematical models, were initially widely used for this purpose, their high complexity became a big handicap and the development of global controllers able to maintain stable those forming processes was not achieved. At the same time, it was observed that the figure of the operator, able to successfully supervise and control forming processes based on his/her experience, was, and still is nowadays, an appropriate way to guarantee the right performance of these manufacturing processes. Then, and taking into account these past experiences, it was concluded that future attempts to improve the robustness of forming processes should be based, not on the use of traditional control techniques based on mathematical models, but on the control strategy that has been successfully used for many years: the human control based on the experience and on the knowledge.

At the same time, it must also be recognised that during the last few years, and due to the increasingly complexity of manufacturing processes, specific techniques able to help human operators to supervise and control them have also been developed. Among all these techniques, sensors based process and tool condition monitoring systems on the one hand, and artificial vision (AV) systems on the other hand, have been used in some types of industries. Both techniques try to complement the senses of human operators because they are able to capture more and richer information regarding the efficiency of the manufacturing processes than human beings are. For example, sensors based process and tool condition monitoring systems are used to evaluate specific process signals and to detect the presence of anomalous working procedures at the manufacturing facilities. From a different perspective, AV systems are used in manufacturing processes to evaluate the final quality of the products and to detect the presence of products which quality do not match with the predefined quality requisites. Thus, it is concluded that the combined application of both techniques into manufacturing processes should generate profitable synergies towards the detection of a wider range of malfunctions.

In fact, it seems that the combination of the previous mentioned monitoring techniques with artificial intelligence (AI) based control techniques will lead to an scenario where intelligent control systems will support human operators to survey and control manufacturing processes by, first, detecting the malfunctions at the processes and by, second, identifying those process malfunctions. This opens the gate towards the development of autonomous systems, able to reason the necessary solving actions to be carried out, in case of process malfunctions.

At the present research work, an industrial sheet metal forming facility consecrated to the manufacturing of small size retaining rings by means of blanking operations has been used as a demonstrator in order to verify all these assumptions. In this experimental case, and limited nowadays by the available actuators, all the developed systems are conceived as a support to the human operator but in future developments, if adequate actuators able to carry out the necessary actions to correct the manufacturing processes are developed, more autonomous manufacturing processes could be achieved.

1.2. The goal

The main objective of the present research work is **to analyse the feasibility and the technological viability of automatic control systems, where sensors based process monitoring systems, artificial vision systems and artificial intelligence techniques work together, in industrial manufacturing environments consecrated to the mass production of small size mechanical components at high rates** with the aim of:

1. Achieving the zero defect manufacturing at the client’s facilitates.
2. Reducing the downtime of the production facilities.
3. Reducing the internal defective.
4. Reducing the time (and therefore the cost) associated to inspection tasks.

Understanding feasibility as:

1. The economic cost of the complete system.
2. The set up cost in terms of the time necessary to tune the system up.
3. The achievable results, concerning the zero defects production, the reduction of downtimes, the reduction of internal defective and the reduction of time associated to inspection tasks.

4. The universality of the system in terms of its capacity to work with different processes or references.
5. The usability denoting the ease with which operators employ it.
6. The capacity to cope with or even to increase the production rate of the facilities.
7. The maintainability denoting the ease with which operators and/or maintenance personnel update it.

The attainment of the previous global objective is linked to the achievement of the next specific ones:

1. Development and implementation of sensors based process monitoring strategies into progressive blanking processes in order to detect the onset of process malfunctions.
2. Development and implementation of high performance AV strategies into progressive blanking processes in order to evaluate the quality of small size parts at high production rates.
3. Development and implementation of intelligent control strategies into progressive blanking processes consecrated to the manufacturing of small size parts in order to identify and promptly correct the process malfunctions.

The consecution of these partial objectives will bring to the manufacturing industry the next advantages:

1. **Elimination of the external defective**: since a 100% quality control is pursued by means of the implementation of an AV system, all the products will be analysed before shipping to customer and thus no defective products will be sent to the clients.
2. **Reduction of the internal defective**: complementing the previous advantage, through the implementation of an online sensors based process monitoring system, besides the surveillance of the integrity of the manufacturing goods, a big percentage of the defective parts produced will be immediately detected in process (earlier than with the visual evaluation). Therefore, and due to the immediateness of the detection, the internal percentage of defective parts will decrease.
3. **Increment of the man machine ratio**: and finally, and once that the external defective has been eliminated and that the internal defective has been reduced, another very important factor is the man machine ratio. In order to increase this factor, it is necessary to decrease the length of the downtimes at the production facilities. For this purpose, the developed intelligent control system will identify the malfunctions at the facilities and will suggest the operator the right actions to be carried out to solve them. This way, the necessary time to restart the production will be reduced and the productivity of the facilities increased.

1.3. Outline of the thesis

Since one of the key aspects at the present thesis is the fact that it has been carried out in an industrial environment, several determining factors were taken into account from the early beginning. Among others, the most remarkable ones are the high production rate of the facilities (and the impossibility to modify it), the presence of many different process failures and part defects, the variability of the production schedule at the forming facilities, the lay-out of the facilities within the company (what influences on the implementation of the systems), the loading of the raw material and the unloading of the produced parts (what influences on the development of the developed systems), the possible incidences during the production like for example, sudden tooling breakages or operators illnesses, the quality requisites of the parts, the ever present dirtiness in the industrial field or the lightening problems due to the environment.

Therefore, and taking into consideration all the previous factors, a logical task schedule able to achieve successful results has driven the present research work. An outline of the tasks (subsequent chapters) of this thesis is given below:

Chapter 2. The literature review provides the background material for this thesis. A brief overview on sheet metal forming processes and a deeper overview on sensors based process monitoring systems, AV systems and AI techniques is given. Among AI techniques, rule-based expert systems and case based reasoning techniques have been identified as the most suitable ones for the purposes of the research work. An explanation of the fundamentals, possibilities and advantages of each technique is given.

Chapter 3. The industrial environment where the entire intelligent system developed at the present research work has been evaluated is explained in detail. A description of the parts produced, the necessary tools and the forming facility where they are produced are briefly explained to help the reader to understand the working procedure and environment and its limitations.

Chapter 4. The implementation of a sensors based process monitoring system into the blanking facility used at the present research work and the results achieved are explained in chapter 4. The chapter comprises an explanation of the procedure to install the sensors at the tooling and at the blanking facility, a brief explanation of the work carried out with the sensors based process monitoring system and both, the process malfunctions that could be detected and the process malfunctions that could not be detected during the running of the process.

Chapter 5. The development and implementation of a high performance AV system into the blanking facility used at the present research work and the results achieved are explained in chapter 5. The chapter comprises an explanation of the hardware and the software developed to evaluate the parts as well as the results achieved through the part quality evaluation carried out. A summary of the defects that could be detected and the defects that could not be detected by the AV system is given too.

Chapter 6. Two intelligent control systems based on AI techniques and the results achieved through their implementation into the progressive blanking process are explained in chapter 6. The first intelligent system is based on rule based expert systems and the second one is based on case based reasoning techniques. The chapter details the results achieved by each technique, compares them and provides guidance about when is more suitable the application of each one of the evaluated techniques.

Chapter 7. General conclusions, discussion and suggestions for future work are presented in chapter 7. This chapter summarizes the performance of the intelligent systems developed and the results of the research work. It also discusses several important issues concerned, draws general conclusions and suggests the way forward.

Chapter 8. The dissemination at both, scientific and industrial level, carried out during the present dissertation is gathered in present 8. The chapter details the papers presented at international conferences and published in scientific journals where the knowledge created along the present research work has been spread over the scientific and industrial world.

1.4. Original contributions

Among all the works carried out during the present research work, next ones are the most remarkable ones in terms of novelty and originality:

1. Integration of a sensors based process monitoring system and an AV system into an industrial progressive blanking process in order to generate synergies and to

create a global control system focused on both, the process stability and the part quality.
2. Development and integration into an industrial progressive blanking process of a vision system based on a hardware / software co-design architecture able to improve the efficiency of actual vision systems and therefore able to work at high production rates not becoming a bottleneck in the process.
3. Development and integration of an intelligent control system in an industrial progressive blanking process able to identify the failures of the process and the defects at the produced parts and able to suggest the operator the right actions to solve them and to promptly restart the production.

1.5. Bibliography

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Chapter 2

SCIENTIFIC AND TECHNOLOGICAL BACKGROUND

2.- SCIENTIFIC AND TECHNOLOGICAL BACKGROUND

The contents of this chapter cover four different parts. The first part is a very brief introduction to the most important processes included in the family of sheet metal forming processes. The main aim of this initial part is to quickly explain the reader the basis of the manufacturing processes where the global intelligent control system developed at the present research work has been implemented.

The second part examines the monitoring strategies applied in sheet metal forming processes and briefly explains their evolution, their advantages and disadvantages, and the improvements that their implementation introduces into the forming industry. The aim is to briefly explain the reader about the techniques used at the present research work in order to evaluate the stability of forming facilities.

The third part briefly describes artificial vision systems and their role in the actual industry regarding inspection tasks. Some examples of previous works where artificial vision systems were applied in order to check the quality of manufactured products are given and a comparison between PC-based solutions and FPGA-based solutions is given too. The aim is to briefly explain the reader about the techniques used at the present research work to evaluate the quality of the parts produced at forming facilities.

And fourth part of this chapter gives an overview of knowledge-based systems and their role in the development of intelligent systems. At this point two different approaches towards the development of intelligent systems are given: rule-based expert systems and case-based reasoning. The advantages and disadvantages of each approach are summarised and systems developed in previous research works are described too. The aim is to briefly explain the reader the basis of the techniques used at the present research work to develop the intelligent control system that will help operators to face the daily problems at forming facilities.

Finally, a critical review of the explained techniques is given and the future challenges necessary to apply them into the forming processes are given too. At the same time, the advantages that the combined application of the previous mentioned techniques would bring to the forming industry are explained.

2.1. Production processes used in the field of forming technology

As described in DIN 8580, manufacturing processes are classified into six main groups: primary shaping, material forming, dividing, joining, modifying material property and coating (see Figure 2.1a) [SCH98]. Forming is defined by DIN 8580 as manufacturing through the three-dimensional or plastic modification of a shape while retaining its mass and material cohesion. In contrast to deformation, forming is the modification of a shape with controlled geometry. Forming processes are categorized as chipless or non-material removal processes. In practice, the field of “forming technology” includes not only the main category of forming but also subtopics, the most important of which are dividing and joining through forming (see Figure 2.1b).

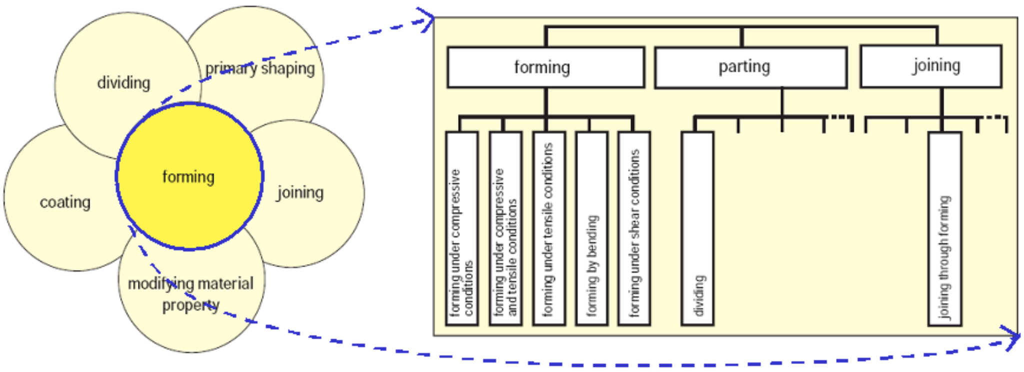

Figure 2.1: a) Classification made by DIN8580 of manufacturing processes, b) Production processes used in the field of forming technology [SCH98].

Since the present research work pursues the application of intelligent control techniques in forming processes, next the branches of forming and parting at Figure 2.1b will be briefly explained, not being covered at the present research work the branch joining.

2.1.1. Forming

Forming techniques are classified in accordance with DIN8582 depending on the main direction of the applied stress (see Figure 2.1b):

1. Forming under compressive conditions.
2. Forming under combined tensile and compressive conditions.
3. Forming under tensile conditions.
4. Forming by bending.
5. Forming under shear conditions.

At the same time, the DIN standard differentiates between 17 distinct forming processes according to the relative movement between die and workpiece, die geometry and workpiece geometry (see Figure 2.2).

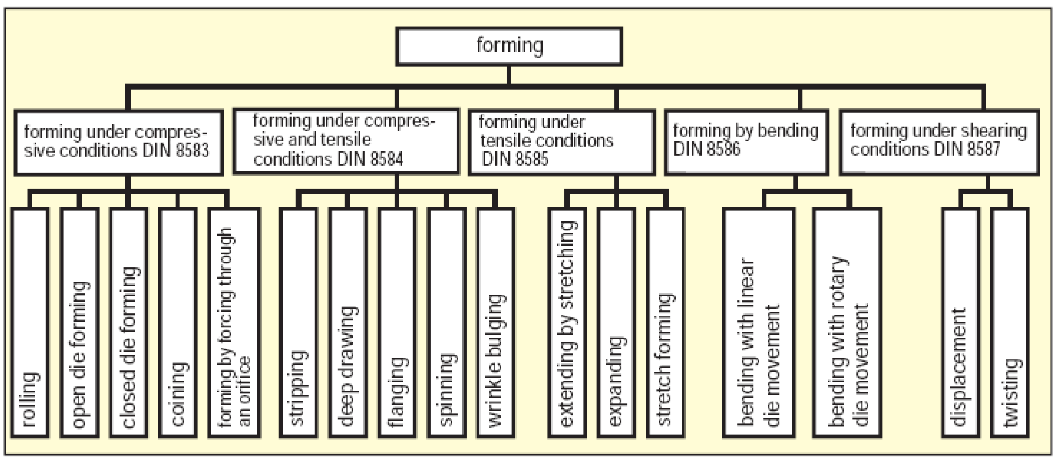

Figure 2.2: Classification of production processes used in forming in accordance with DIN 8582 [SCH98].

Among the 17 distinct forming processes, the deep drawing process, classified inside the group of processes “Forming under combined tensile and compressive conditions”, is one of the most widely used at the industry. A brief description of this forming process is given next.

2.1.1.1 Deep drawing

Deep drawing is a method of forming under compressive and tensile conditions whereby a sheet metal blank is transformed into a hollow cup, or a hollow cup is transformed into a similar part of smaller dimensions without any intention of altering the sheet thickness (see Figure 2.3). Using the single draw deep drawing technique, it is possible to produce a drawn part from a blank with a single working stroke of the press. In case of large deformations, the forming process is performed by means of redrawing, generally using a number of drawing operations. This can be performed in the same direction by means of a telescopic punch or by means of reverse drawing, which involves the second punch acting in opposite direction to the punch motion of the previous deep drawing operation.

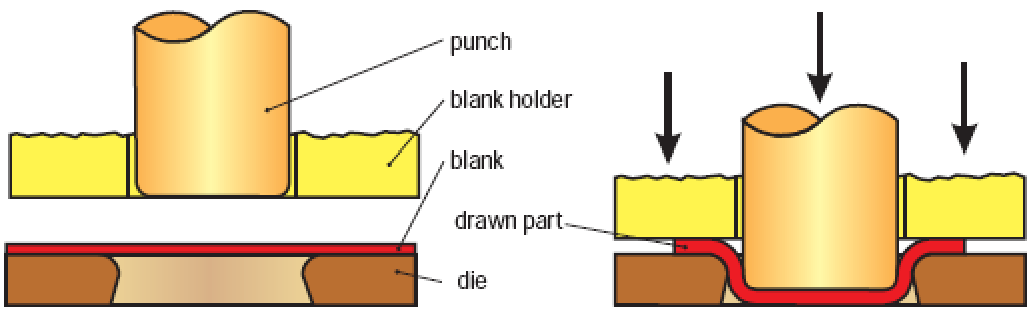

Figure 2.3: Deep drawing operation [SCH98].

The most significant case of deep drawing is done with a rigid tool. This comprises a punch, a bottom die and a blank holder, which is intended to prevent the formation of wrinkles as the metal is drawn into the die (when no feeding of material is allowed the process is named as stretch forming). In special cases, the punch or die can also be made of a soft material. There are deep drawing methods that make use of active media and active energy. Deep drawing using active media is the drawing of a blank or hollow body into a rigid die through the action of a medium. Active media includes formless solid substances such as sand or steel balls, fluids (oil, water) and gases, whereby the forming work is performed by a press using a method similar to that employed with the rigid tools. The greatest field of application of this technique is hydromechanical drawing, for example, for the manufacture of stainless steel components.

2.1.2. Parting

Figure 2.1a showed that parting is the second group of production processes used in the field of forming technology. Dividing (see Figure 2.4) is the first subgroup under the heading of parting, but is generally categorized as a “forming technique” since it is often used with other complementary production processes. According to the definition of the term, dividing is taken to mean the mechanical separation of workpieces without the creation of chips (non-cutting). The dividing category (according to DIN 8588) includes the subcategories shear cutting, wedge-action cutting, tearing and breaking. Among these, the shear cutting is the most applied in the industrial field.

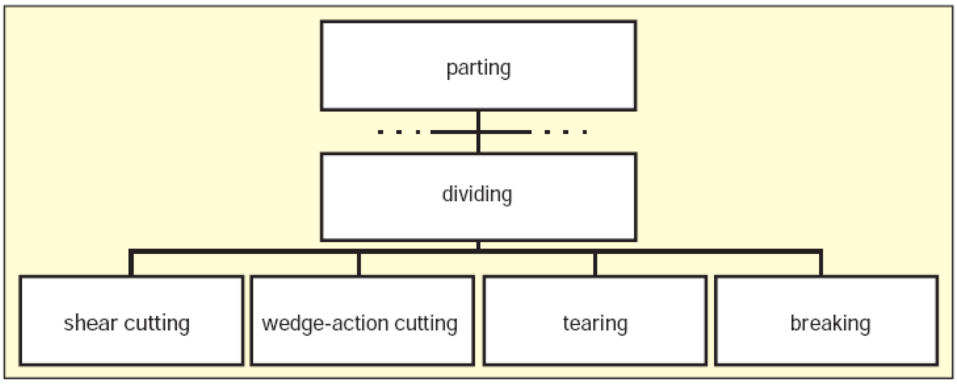

Figure 2.4: Parting techniques classified under forming [SCH98].

2.1.2.1 Shear cutting

Shear cutting, known in practice as shearing for short, is the separation of workpieces between two cutting edges moving each other. During single stroke shearing, the material separation is performed along the shearing line in a single stroke, in much the same way as using a compound cutting tool. Among shear cutting techniques, blanking processes are widely applied in the industry. Figure 2.5 shows schematically the blanking process for a closed contour, for example, when piercing. Here, the process is applied using blanking dies. The relative movement of the blanking punch to the female blanking die separates the metal (see Figure 2.5). The punch makes contact with the sheet metal, initially causing elastic deformation. The plastic deformation stage then follows, leaving the sheet metal with a permanent camber. The upper edge of the sheet metal then bends and draws in, followed by a shearing action that leaves a visible, smooth area on the cut surface. If the shearing strength is exceeded, cracks are formed. These generally run from the edges of the female blanking die and lead to complete breakthrough of the metal as the movement of the punch progresses.

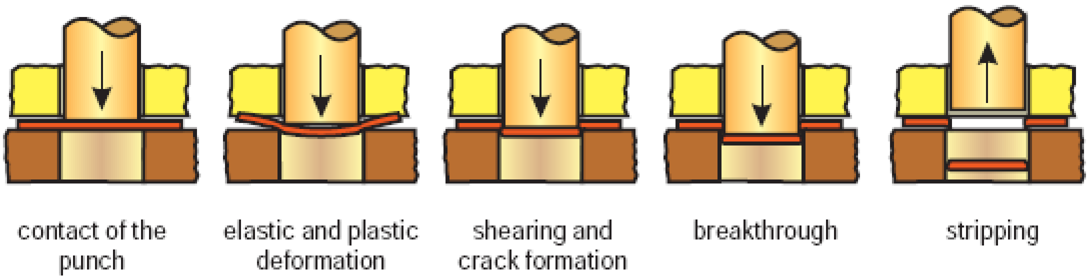

Figure 2.5: Phases of the blanking process [SCH98].

2.1.2.2 Fine blanking

A special process among blanking methods is fine blanking. Fine blanking (see Figure 2.6) is a single stroke shearing method that uses an annular serrated blank holder and a counter pressure pad. Thus, the generated blanked surface is free of any incipient burrs or flaws, which in frequently used as a functional surface.

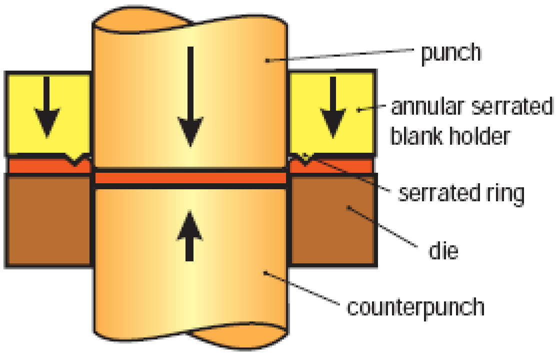

Figure 2.6: Fine blanking [SCH98].

2.1.3. The lack of stability of the process parameters

The factors that determine the final quality of the parts manufactured by sheet metal forming processes are divided into four main groups: material properties, tool geometry, machine parameters and lubrication variables. Thus, when the manufacturing process for a new reference must be designed, these are the main factors that must be determined. Material properties are implicit to the material used to produce the parts. There is no possibility to modify or adequate them and usually experience fluctuations that affect the final quality of the produced parts. Tool geometry, machine parameters and lubrication variables are defined at the beginning of the manufacturing process taking into account the material properties and the final characteristics of the part to be manufactured. Their values are usually calculated with the help of simulation tools at an initial step followed by a trial and error process (setting up of the process) that is very often based on the operator's experience. Having done all this, the quality of the produced parts is, in most of the cases, good at the beginning of the production.

Nevertheless, problems start when the number of produced parts increases and then some other factors, not considered during the setting up of the process, start to have great importance. The main factor to take into account is the wear of the tools. When the number of produced parts increases, the wear of the tools also increases. As the wear of the tools increases, some other variables must be readjusted to compensate this wear and to avoid the production of bad quality parts. For example, it is very common to modify the quantity or quality of lubrication applied when the wear of the tools increases. The problem is that this kind of factors, such as lubrication, are very difficult to calculate accurately during the simulation stage and are also difficult to control during the production set-up, being the operator the responsible of realizing about them and adopting the accordingly actions.

Therefore, control systems able to continuously monitor the processes and able to take the right decisions that compensate the fluctuations in the process parameters should be available. For example, in the case of tool wearing in blanking processes, there are two ways of realizing about it. The first and most commonly used is checking the quality of the produced parts. Mainly in blanking processes, when the wear increases, the burr in the cutting edge also increases and this is how the operator knows that he/she must modify the lubrication. When the burr is too big, the operator takes the decision of resharpening the tool. Another way is by using sensors based process monitoring systems that graphics the force or the acoustic emission (AE from now on) curves of the process. These systems are based on the fact that these curves increase when the wear of the tool increases and when the curves go beyond a predefined threshold, the system stops the facility for tool resharpening.

And finally, and as aforementioned, process parameters also depend on the properties of the material. During the simulation and set-up of the process, the operator is working with predefined properties of the material (achieved from supplier information or tensile tests). Problems may appear when the properties of the material vary within the same coil or in a new coil. Then, again the operator must take new decisions about what process parameters modify in order to get the right quality of the parts based on their quality or on the information from the sensors based process monitoring system.

What is clear in this kind of processes is that, even if the right set-up of the production is achieved at the beginning, there are some factors that modify the quality of the produced parts during the production. It is clear too that these variations cannot be a priori modelled and the operator must change on line the process parameters to compensate them. The capacity of the operator to continuously readjust the process parameters is based on his/her knowledge that has been gained through his/her experience.

2.2. Process and tool condition monitoring in SMF processes

The increasing complexity that the facilities consecrated to sheet metal forming processes have experienced during the last few years (manufacturing of more complex parts in fewer operations), has led to a situation where in-die monitoring equipments have become a necessity within the stamping industry. Historically, die monitoring meant adding a spring ground probe to act as a short-feed sensor, with possibly an optical sensor monitoring part ejection from the tool. The operator typically located the sensor as an additional step when loading a new tool. Die monitoring requirements were modest and simple systems monitored just a few sensors in the past.

On the other hand, the new manufacturing scenario in sheet metal forming processes with smaller lot sizes and lead times, reduction of direct labour and increment of the part quality has also as a consequence that more complex tooling are used. The increment of the steps within the tools also increases the likelihood and severity of die crashes and the necessity of on line part inspections inside the tools for quality assurance. To solve all the above mentioned drawbacks due to the new manufacturing strategies, new monitoring systems have emerged in the market with some main features: more sophisticated with higher electronics and automation requirements, larger number of sensors and combination of digital and analogical sensors [WEN05].

First monitoring systems in sheet metal forming processes were based on force measurement. The main purpose of those basic force-monitoring systems was to plot the total force that the press needed to form the parts, avoiding this way overloads in the facilities. Therefore, from a security point of view those basic force-monitoring systems gave very good results, but from a process monitoring point of view they did not give much information to the operators. Anyway, process control using force signals has for many years proven to be reliable and relatively low cost. Force signals have provided the following benefits: machine and tool protection, increased productivity and improved product quality. On the other hand, in the cold forming industry there has been and still there is a trend to boost machine output by increasing the running speed with additionally growing demands upon product quality. At the same time, the cold-formed parts are also increasing in their complexity and hence the probability of a higher failure rate is also increased. Thus, there is a need for monitoring devices with improved control accuracy.

Experience has shown that force-monitoring systems can be either too late in recognising, or unable to recognise, cracks in punches, dies, ejectors and spring elements. Experience has also shown that this problem can be overcome with the introduction of AE monitoring. The cracks, tears and breakages produce a short-term acoustic pulse that can be immediately recognised (see Figure 2.7) [TER96].

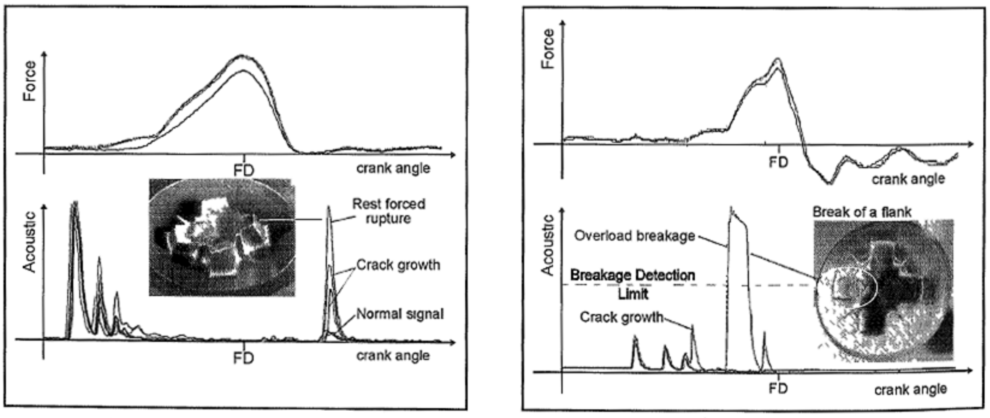

Figure 2.7: Comparison between force and AE signals during a crack growth and a punch breakage [TER96].

Therefore, the AE signals generated by the material during the deformation stage have become a promising technique to monitor and control sheet metal forming processes. It has been well known for centuries that wood and rocks emitted noises when they started cracking or breaking. Later, similar noise was identified during bending of tin bars, which is often known as “tin cry”. Joseph Kaiser, at the Technical University of Munich, made the first pioneering work on AE in 1950. Joseph Kaiser was able to examine the noise emitted by the deformation of materials by means of electronic equipment capable of detecting non-audible signals. One of the observations made was that irreversible processes were involved with this phenomenon, an effect later named the Kaiser effect [LIC79].

AE monitoring techniques, combined with force monitoring techniques, have been and still are nowadays the most successful sensors based process monitoring techniques in metal forming processes. The higher sensitivity of AE allows this technique to detect future failures before producing catastrophic consequences [BRA94]. Therefore, nowadays, sensors based process monitoring systems applied to sheet metal forming processes are based mainly on the measurement of two variables: forces and AE [COW00]. For example, Figure 2.8 shows the representation of two curves; one measuring the load of a press during a combined blanking-stamping operation and another one measuring the AE signals during a blanking operation.

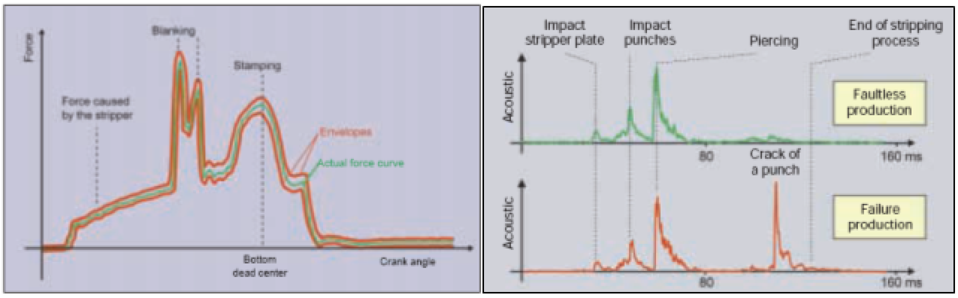

Figure 2.8: Force and AE curves [COW00].

2.2.1. Strategies to monitor blanking processes with AE signals

Among the forming processes, AE was first applied to the monitoring of blanking processes. Blanking processes are the most suitable process for AE monitoring among all sheet metal forming processes because of the high frequencies of the emitted AE signals. Several studies have been focused on finding the signature of these processes and the effect of the different variables into this signature. The signature of a process could be defined as the typical AE curve (signal) during the process. This curve (with the force curve) is shown in Figure 2.9 and is divided into three stages which are [KIM83, KIM83/2]:

1. The initial low amplitude part is due to the punch impact on the stock and the subsequent elastic deformation in the stock. During this period, the punch and ram do not experience any appreciable resistive force and are still in harmonic motion.
2. After this elastic period, plastic deformation takes place on both sides of the stock and an extrusion-type shearing fracture begins to occur. While this process continues, a strong resistive force is being built in the peripheral area of the stock between the punch and the die. Then, as the ram motion slows down (departing from the harmonic motion), the medium amplitude second portion of the AE signal is emitted.
3. When enough force has been built up in the punch and the ram to overcome the resistive force of the stock the final separation occurs. This type of fracture is instantaneous. Therefore the ram moves down rapidly after the snap-through and tries to recover the steady harmonic motion. The highest amplitude portion of the AE signal is emitted during this period and a ring down process follows.

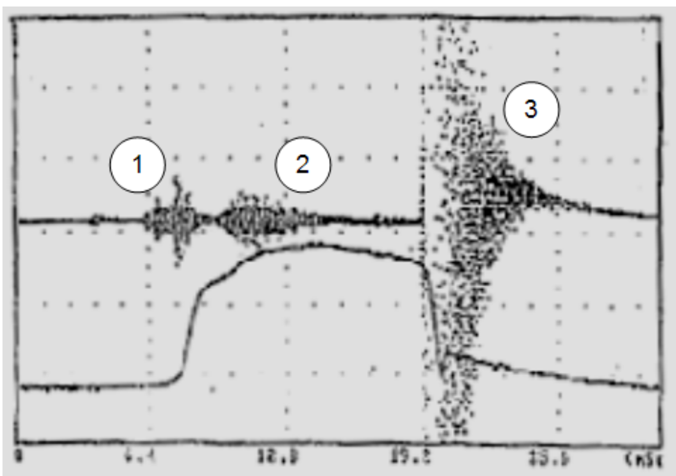

Figure 2.9: AE and force signals during a blanking process [MAR87].

A very important conclusion of the previous mentioned works is that real time analysis of stress waves using AE techniques is a very reliable method for detecting abnormal operation conditions that can lead to catastrophic failures in blanking processes [KIM83].

2.2.2. Strategies to monitor drawing processes with AE signals

Due mainly to the very good results obtained when monitoring blanking processes, the same strategies have been tried to be applied to the monitoring of drawing processes.

2.2.2.1 AE sources identification in stretching and drawing processes

First attempts were focused on the stretching process because of its larger simplicity. Stretching process is a drawing process where a very high blank holder force is applied and therefore the sliding between the die and the blank is prevented, guarantying pure stretching conditions [LIA86, LIA87]. The results of these first studies showed that the AE curve generated during this process can be divided into different stages as shown in Figure 2.10:

1. Initial contact and workpiece deformation (r=0-0.32) where r is the ratio between the displacement of the punch tip at any instance and the displacement of the punch tip when the material fractures an RMS voltage spike is seen at the beginning of operation due to the impact on the workpiece by the punch. Following the impact, the RMS voltage increases rather rapidly until a deformation ratio of 0.08. Then, the RMS voltage increases at a much lower rate to a ratio of 0.32.
2. Subsequent deformation and fracture (r= 0.32-1): over this period of stretching, the RMS voltage decreases almost linearly with increasing strain until the specimen fractures.
3. Post-fracture (r>1): the RMS voltage maintains a constant level through the remainder of the experiment.

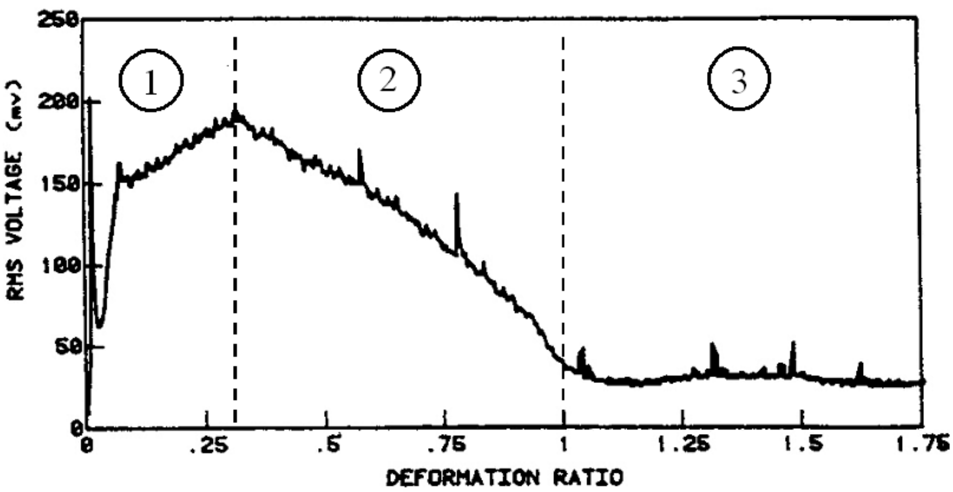

Figure 2.10: RMS voltage of AE during punch stretching process [LIA86].

Conclusions are that the AE signals come mainly from three sources: **plastic deformation** of the material, **friction between the blank and the tools** and the final **rupture of the material**. It was also concluded that although the third source is very easy to differentiate from the other two because of its high frequency signals, the first two sources have very similar frequencies and are almost impossible to differentiate.

This is shown in Figure 2.11, where an AE curve of a test similar to the previous one but with lubrication is shown.

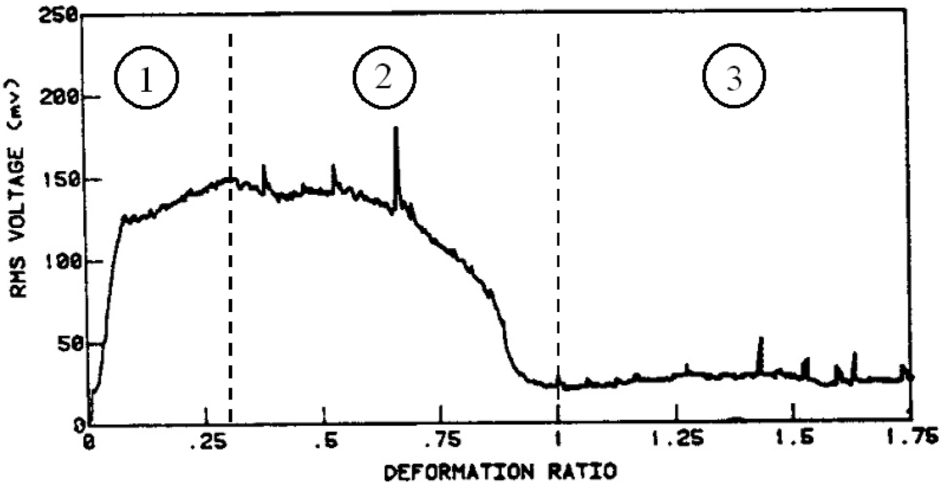

Figure 2.11: RMS voltage of AE during lubricated punch stretching process [LIA86].

The main differences between Figure 2.10 and Figure 2.11 are:

1. The initial RMS voltage spike at r=0.02 is not observed when the interface is lubricated. This can be easily explained by the fact that the interfaced lubrication layer absorbs the impact of the punch and the workpiece.
2. When the interface is lubricated, the overall RMS voltage level is lower than that in the non-lubricated case. This is primarily a result of the elimination of the resistive friction, which generates AE. This effect is more notorious over the plastic deformation range and the RMS peak at r=0,32 is less pronounced due to reduced punch/workpiece friction.
3. When interface lubrication is applied, RMS voltage is reduced by 10-20% before workpiece fractures. No significant different in the RMS reduction after workpiece fractures is noticed.

Therefore the AE from the plastic deformation of the material and from the friction between the blank and the tools are almost identical and are very difficult to differentiate. This is the main reason why AE signals do not offer as good results in stretching or drawing operations as they do in blanking operations. What is more, in drawing operations the results are more complex because the material is not stick and the friction between the blank and the blank holder introduces new AE signals. A curve of the AE signals generated during a deep drawing process (deep drawing of an aluminium 1100 blank with a thickness of 1.27mm and a diameter of 156.21mm, deep drawn by means of a hemispherical punch with a diameter of 76.2mm) is shown in Figure 2.12 [LIA90].

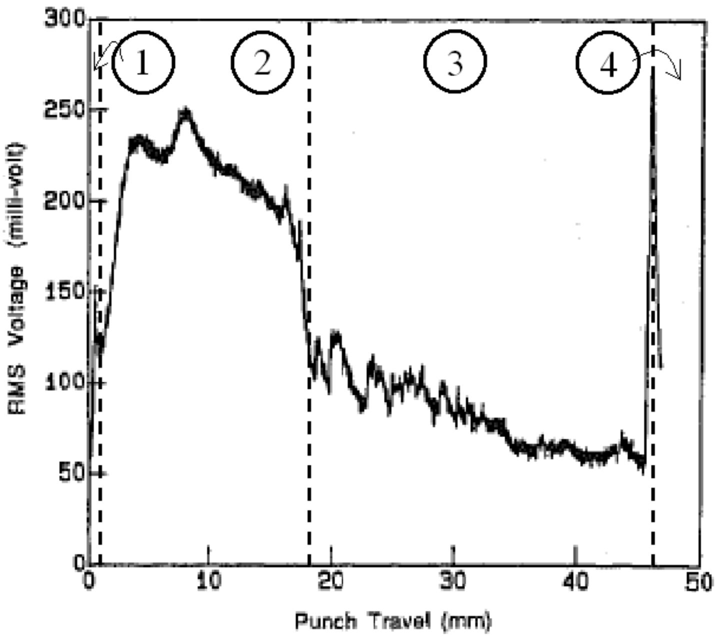

Figure 2.12: AE signal during a deep drawing process [LIA90].

From the curve shown in Figure 2.12 four different stages can be observed:

1. An RMS peak appears at the beginning of the operation as a result of punch/blank contact.
2. During the early stage of punch penetration (2mm-18mm), the AE energy rate shows a global maximum at a punch travel distance of 9 mm. There are 3 major sources of AE over this period: I) the stretching of the unsupported region. The specimen experiences mainly stretching action over this period since blank reduction ratio is quite small. Therefore the dislocation avalanche associated with initial yielding causes the RMS voltage to increase and subsequent strain hardening of the material causes the RMS voltage to decrease, as would be expected in a pure stretch forming operation. II) formation of wrinkles on the flange. Flange wrinkles are observed to form continuously starting from the beginning of the operation. Energy is consumed to plastically bend the flange into wrinkles and to continuously generate AE. III) small amount of sliding between flange and die. The friction between sliding flange and die generates AE.
3. During 18-47 mm of punch travel, the AE energy rate reduced drastically from the previous stage due to the transition of the dominant mechanism from axial stretching to deep drawing, where the associated AE activity is seen to be less intensive.
4. The final fracture of the workpiece is characterised by a high RMS level at a punch travel distance of 47 mm.

So deep drawing curve is a bit more complex than stretching curve and still has the same problem: AE from the plastic deformation of the material and from the friction between blank and tools are mixed. In order to separate AE from friction and plastic deformation there have been different studies to measure the AE from friction in drawing operations (for example [YAN03]).

<u>2.2.2.2 Friction identification in drawing processes by means of AE measurement</u>

In the case of the friction between a tool and a workpiece, the AE is due to adhesion and debonding or ploughing at the contact interface, which is a kind of fracture of material. While the holding pressure exceeds the yield stress of the workpiece, the contact point of the asperities yield and new surfaces appear at the contact surface, which cause a strong adhesion. During sliding the shearing force overcomes the adhesion so that the sticking points debond and emit AE due to the elastic release of the asperities under contact. In order to find the location of the friction sources in deep drawing processes, Yang et al. attached several AE transducers to a drawing tool and taking into account their position and the arrival time of the AE signals due to friction, the location of the AE sources was achieved. Figure 2.13 shows the apparatus used to measure the AE signals from the friction.

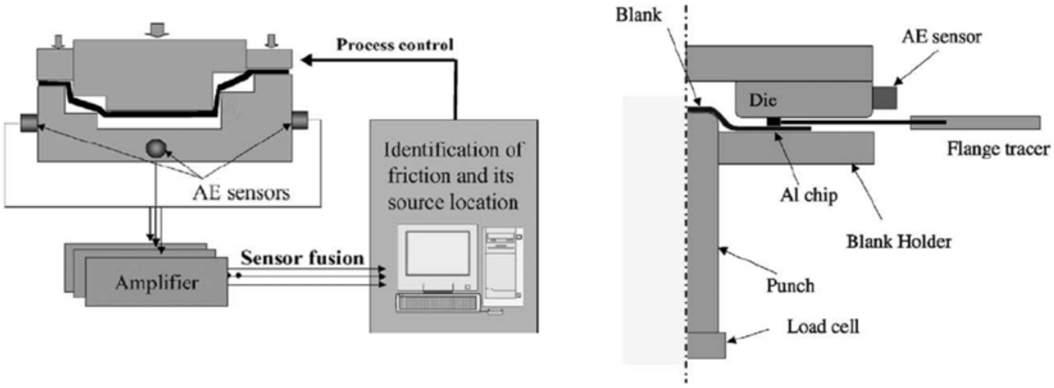

Figure 2.13: Apparatus developed to measure the AE signals from friction [YAN03].

In Figure 2.14, the results measured with the transducer are shown. It is well known that the signals from friction have low frequency. Therefore, as shown in Figure 2.14, the frequencies higher than 625 KHz were filtered from the original signals. The conclusion is that it is very difficult to distinguish AE signals generated by friction phenomena and AE signals generated by the plastic deformation of the material because both kinds of AE signals have the same frequency range.

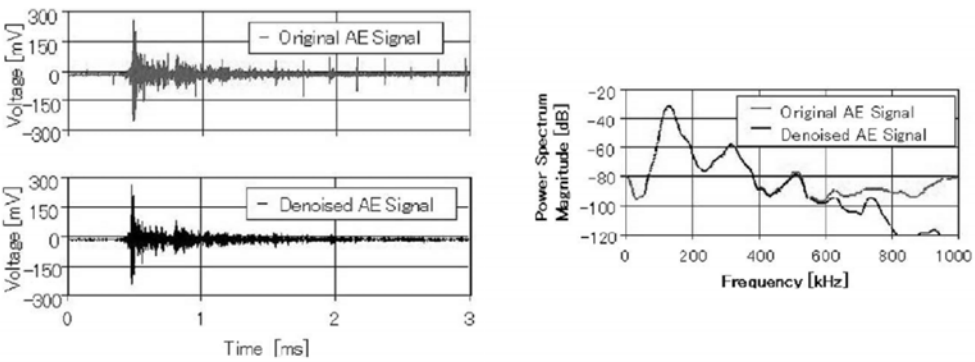

Figure 2.14: AE signals and their spectrum as measured and after reduction of noise [YAN03].

<u>2.2.2.3 Wrinkles detection in drawing processes by means of AE measurement</u>

Another process defect that must be taken into consideration in drawing processes is the formation of wrinkles in the flange of the parts. Wrinkles are generated by the tangential compression stresses that occur within the flange area when the material is fed towards the centre of the part. Although no research work has been found where attempts to detect wrinkles by means of AE measurements have been carried out, some other research works have proven the suitability of some other techniques to measure wrinkles in drawing processes. For example, Figure 2.15 shows the suitability of force signals to detect the formation of wrinkles in drawn parts (some other research works prove the same conclusion [GAR05, MAR02, ALM00]).

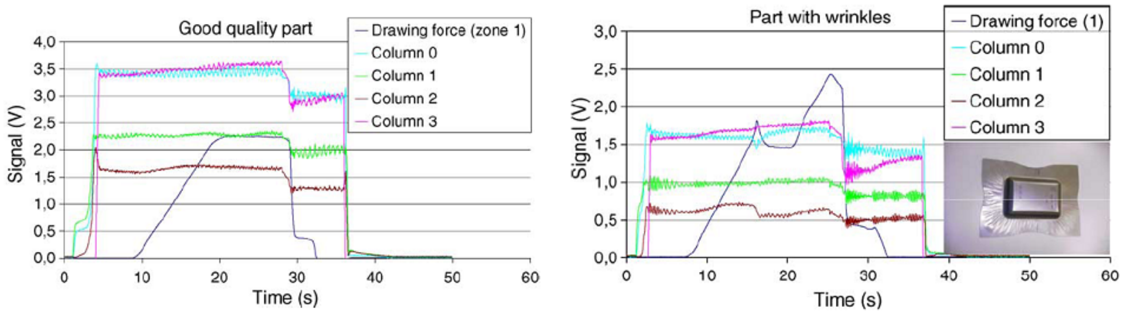

Figure 2.15: Force signals in a drawing process; a) good quality part, b) part with wrinkles [GAR05].

At the same time the formation of wrinkles leads to a gap increment between the tool sections blank holder and die. For measuring the height of wrinkles, Yoshihara et al. [YOS99] used inductive displacement transducers, which were attached either at the outer edge of the tools or directly in the corner area of the flange.

Therefore, and from the conclusions drawn in some of the works previously mentioned [LIA86, LIA87] at the present review, it can be deduced that since wrinkles are formed by means of a plastic deformation, the AE signals generated by this phenomena should be very identical (low frequency signals) to the signals generated by the plastic deformation of the material in the forming area and the signals generated by the friction generated during the sliding of the material inside the tool. Then, the application of the two techniques above mentioned for the measurement of wrinkles (force measurement and gap between die and blank holder measurement) seems to be much more suitable.

2.2.2.4 Tears detection in drawing processes by means of AE measurement

The other main defect in drawing operations is tearing. As it was previously said ("Chapter 2.2. Process and tool condition monitoring system"), tears are easier to detect with the use of AE techniques because the emitted signals have very high frequencies, which are very easy to separate from the signals coming from friction or plastic deformation. Therefore, as Figure 2.12 showed, there is a clearly differentiable peak in the AE curves of drawing operations that marks the appearance of tears. Figure 2.16 also shows AE curves and how the appearance of peaks when necking of cracking of the parts occurs [KIR95].

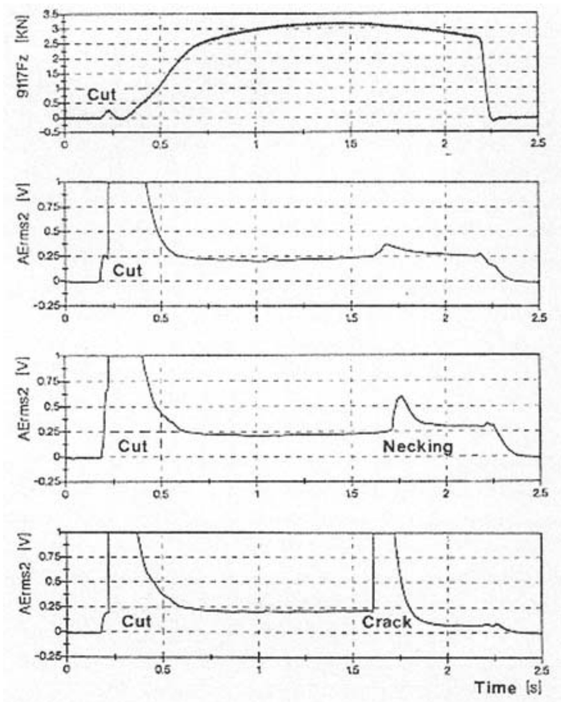

Figure 2.16: Force and AE signals in deep drawing operations [KIR95].

It must also be taken into account that tears are also very easy to detect with the use of force sensors (see Figure 2.17). As it was previously said ("Chapter 2.2. Process and tool condition monitoring system"), the use of force sensors is better because these sensors are much cheaper and the treatment of the signals is much simpler. Therefore, tear detection in sheet metal forming processes is more prompt to be done by force than by AE techniques. As it is shown in Figure 2.17, when a tear happens in the part the force curve falls instantaneously denoting the crack in the part (valley at the top of the drawing force curve in Figure 2.17b). More research works have been found in the literature with the same conclusion [GAR05, MAR02, ALM00].

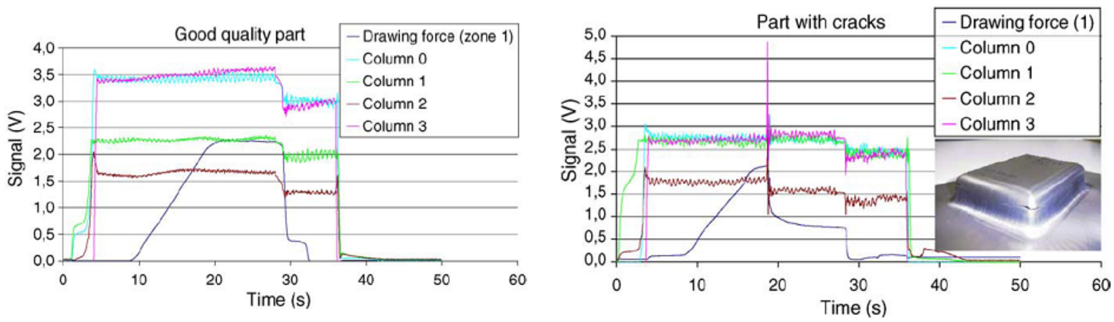

Figure 2.17: Force signals in a drawing process; a) good quality part, b) part with tears [GAR05].

2.2.3. Conclusions regarding monitoring of blanking and drawing processes

Two manufacturing processes, sheet metal blanking and sheet metal drawing processes have been briefly explained from a process failure detection point of view. For this analysis, the two variables most used in the industry nowadays have been taken into account: force measurement and AE measurement.

Sheet metal blanking processes are very prompt to be surveyed by sensor nets that combine force and AE measurement. The reason for this is that, besides the high efficiency of force sensors that are able to gathered a great amount of information at low cost, the principal phenomena at these processes (the blanking of the material) generates high frequency AE signals that can be very easily identified. This way, the combined acquisition of force and AE signals generates very clear process signatures where the initial contact between punch and metal strip, the initial deformation of the material and its final blanking are clearly identified (see Figure 2.9).

On the other hand, when analysing drawing processes, it is stated that the principal phenomena that drives these processes, the plastic deformation of the material, generates lower frequency AE signals. Besides this, the friction phenomena, also very important in drawing processes, also generate low frequency AE signals. Therefore in drawing processes, AE signals generated by plastic deformation and AE signals generated by the friction phenomena can not be distinguished being AE signals not able to produce reliable process signatures. Table 2.I summarises the most important process failures to be identified in drawing processes and the most suitable measurement techniques for all them.

Table 2.I: Process failures and techniques for their detection in drawing processes.

Process failure	AE frequency range	Variable to be measured	Type of sensor	Paper
Necking	High	AE	Piezoelectric	[KIR95]
Cracks/tears	High	AE/Force *	Piezoelectric	[KIR95]/ [GAR05, MAR02, ALM00]
Wrinkles	Low	Displacement/Force	Inductive/Piezoelectric	[YOS99] / [GAR05, MAR02, ALM00]

* Force measurement is more widely used because it is cheaper and more robust than AE measurement.

Therefore and analysing Table 2.I, it can be stated that force measurement is a suitable technique for the monitoring of drawing processes, being this technique the most widely used nowadays to monitor these processes in the industry.

Finally, and as a summary, taking into account the data gathered at the present subchapter and since it was decided that the present research work will deal with blanking processes, it was decided that the most advantageous sensors based process monitoring system for the present research work should be integrated by force measurement and AE signals measurement (shown in “Chapter 4. Sensors based process monitoring”). “Chapter 4. Sensors based process monitoring” shows the reliability of the developed monitoring system, which follows this architecture regarding the detection of process malfunctions in blanking processes.

2.3. Artificial vision systems for part quality assurance in SMF processes

Artificial vision (AV from now on) is a branch of the engineering field that uses video cameras and computers to replace human vision in evaluation and inspection tasks that are precise, repetitive or carried out at high speed rates. One of the most important advantages of AV is the possibility of improving the quality of the products while lowering their costs. AV systems have been increasingly introduced in the industry during the last few years and among their most successful applications visual inspection, robot position or robot visual servoing can be found [VIL83]. At the present research work and since the developed work was aimed at evaluating the quality of parts produced by forming processes, next subchapter is focused on the application of vision systems to visual inspection tasks.

2.3.1 Machine vision for visual inspection tasks

Machine vision is suitable at inspection when the task to be carried out is fast, well defined (the systems knows exactly what to do, how to do it and what is expected), precise and repetitive. On the other hand, human inspectors are better in low-speed and low-precision inspection or in inspection tasks that changes often [DAL07]. In machine visual inspection tasks, a camera or a set of cameras are used to take images of a part and to, after an image processing that could be patter matching or edge detection, find if the quality of the part is within the predefined tolerances. Figure 2.18 shows a vision system for automotive parts inspection. The purpose is to verify the presence of the holes within the stamped part.

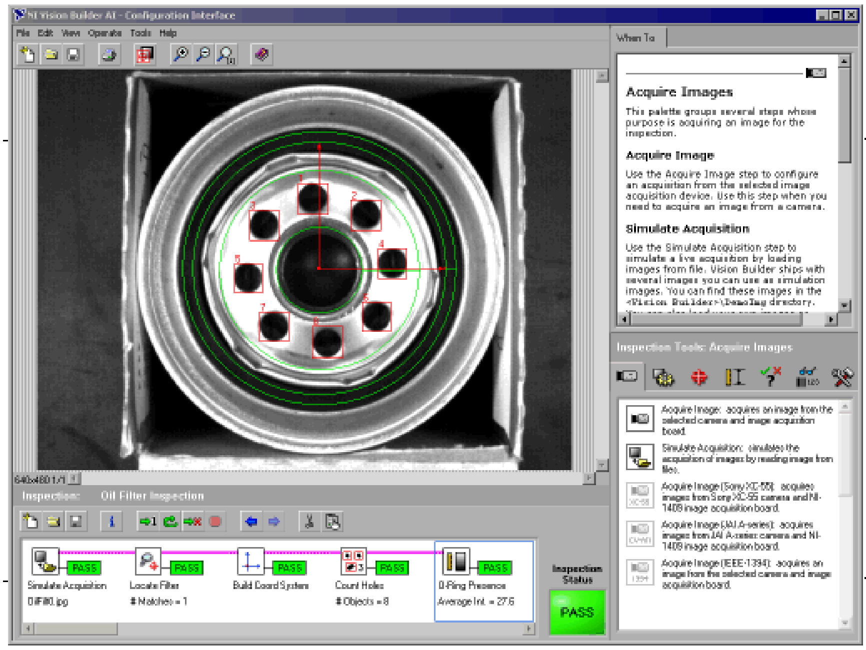

Figure 2.18:National Instrument AV system interface [NI07].

The reason for the progressive and continuous introduction of AV based quality controls in the industry is that video camera technology has been considerably developed over the recent past years, mainly by the invention of the Charge Coupled Device (from now on CCD). CCD uses light sensitive materials to convert light photons to electrical charge. Until approximately twenty years ago, Vidicon tubes were used as camera sensors, which meant that cameras were large in size and strictly limited to standard video timing defined by the designers of television. This technology was not well suited to industrial or scientific applications for a number of reasons (such as size or robustness) but mainly because it was very often necessary to control/reset the camera timing to coincide with products passing through the field of view [DAL07].

On the other hand, in CCD technology, and also in its latest variant CMOS (Complementary Metal Oxide Semiconductor), thousands of light sensitive diodes are positioned very accurately in a matrix array and shift registers transfer the charge from each pixel to form a video signal. Therefore, modern machine vision cameras are sophisticated, offering complete control of timing, high speed shuttering, sensitivity and many other important features. Cameras are now very compact (for example, the size of one of the cameras (MicroEye) used at the present research work is 34*32*34,4 mm and its weight is 75 grams) and machine vision is used in an ever-increasing number of sectors of the industrial and scientific market, replacing contact measurement systems and offering a method for complete quality assurance checking and automation [DAL07].

Nowadays, there are two main types of machine vision cameras in use: area-scan and linescan. The term area-scan refers to the camera sensor covering an area rather than a single line, as is the case with linescan cameras. An area-scan camera produces an image of an area, normally with an aspect ratio of approximately 4 to 3 and only needs one shooting to get the final image of the part. On the other hand, in applications where full vertical resolution is required with fast moving objects, a progressive scan camera is used. The concept of line scanning involves building up an image, one line at a time, using a line sensor (linear array), which passes in a linear motion over an object, or where the object passes in a linear motion under the sensor [DAL07].

In parallel to the development of most efficient and robust AV cameras, the lightening in AV systems has also been drastically improved. Nowadays, several light sources can be found in the markets that boost the results in hostile environments like industry. Among them, the most important ones are optical fibre illumination, fluorescent illumination, laser illumination or LEDs illumination. At the same time, during the last years, different illumination strategies have been developed for facing different problems. Among others, the most important illumination strategies are front illumination, back illumination, diffuse illumination, radial illumination or bright field [DCM07, INF07].

Another reason for the rapid introduction of AV systems in the industry has been the vast reduction of the image processing time and the increment in the results accuracy when treating the images. Some years ago, the main problem for the development of AV systems was the poor capacities of the processors that offered image processing times much longer than the cycle time of the manufacturing processes. This fact forced the AV developers to place the system in parallel to the manufacturing line instead of placing it in serial. Parallel AV systems were used to check some of the produced parts and to get statistical results of the production but never got to check the 100% of the produced parts. On the other hand, and thanks to the developments in this field, the final objective of actual AV systems (placed within the manufacturing line) is to check the 100% of the manufactured parts. This way, traditionally, image-processing algorithms have been implemented in high-level languages (C, C++, etc.) using personal computers (PC) and digitalisation boards (usually PCI bus based) to read the video signal delivered by CCD cameras into the RAM memory of the PC. Nowadays with the improvement of the computer capacities, several are the companies (Xcaliper [XCA03], Halcon [HAL03], CVB [CVB03], National Instruments [NI07] etc.) that sell vision systems containing optimised image processing algorithms for PCs and other workstations. In most cases, they allow fast testing and developing of vision solutions (e.g. by allowing one to integrate their system into visual programming tools as Visual Basic, Visual C++, creation of DLLs, ActiveX components, etc.). The drawbacks of this type of systems are their relatively high price (on the order of between 1,000€ and 5,000€), the lack of the source code of their algorithms, and the fact that the system is tied to one particular computer architecture (e.g. a PC), and operating systems (e.g. Windows XP, Linux, etc.).

At the same time, in the last few years a variety of solutions aimed at developing smart cameras have been attempted. Smart cameras are vision devices able to process vision algorithms what has as a consequence two main advantages. First is that since an important part of the processing can be made at the camera the need for powerful central stations is avoided and second since the cameras must only transmit the information obtained from the images the quantity of data transmitted is considerably reduced. The most important solutions applied to the development of smart cameras are summarised next:

1. The integration of a microprocessor within the camera is the most intuitive way of developing a smart camera. In fact, there are already in the market cameras that follow this design [BRM04]. However, most common microprocessors have very limited parallelization capacities, being mainly sequential and therefore do not take advantage of the parallelization possibilities of most of the low level image processing algorithms.

2. A variation of the previous solution are the SIMDs (Single Instruction Multiple Data) processors which are basically an array of simple processors. This solution allows to execute the same operation in multiple pixels in parallel what makes them very suitable for low level image processing algorithms [HEY05, KLE04, ZIV08].

3. Another possibility is the application of DSP (Digital Signal Processor) which are specialised microprocessors designed specifically for digital signal processing, generally in real time processing. Although this solution offers high speed performances, the DSP are better suited for the sequential processing, what makes them not suitable for the processing of the low level image processing algorithms [FLE07].

4. And finally, the last possibility is based on reconfigurable hardware such as FPGA (Field Programmable Get Array). The application of FPGA enables a great amount of flexibility and online reconfigurable possibilities. FPGAs are best used in processing parallel algorithms and thus are very well suited for processing low level image processing algorithms [LEE04, SHI06].

The solutions based on FPGAs (Field Programmable Get Arrays) have emerged in the market oriented to high speed processes or big products control quality guarantee. FPGA is a semiconductor device containing programmable logic components called "logic blocks", and programmable interconnects. Among others, the main advantages provided by the implementation of data, signal or image processing algorithms on FPGA (when such an implementation is possible), instead of implementing them on DSP or standard microprocessors are that [IZA07, RUS95, FIL01, FIL02]:

1. The processing times are reduced by 10 if compared to an implementation on DSP, and by 100 if compared to an implementation on a standard microprocessor.
2. High miniaturization possibilities are offered (sometimes no PC is needed).
3. The design of compact systems is allowed (the so called intelligent cameras) easier to harden that offer important advantages for use in applications where the environment is difficult or hostile (difficult industrial environments where vibrations or dirtiness are present; outdoor and space applications; etc).
4. Better guaranties for processing algorithms implementation perpetuity are offered, through a better control of the development chain (less dependency on proprietary tools).

Then, FPGAs based solutions allow the users to create quality inspection systems that check more than 2000 parts per minute, placing the inspection system in serial and allowing the system to check the 100% of the produced parts (Figure 2.19 shows an intelligent camera based on FPGA) [SAW88, COU89].

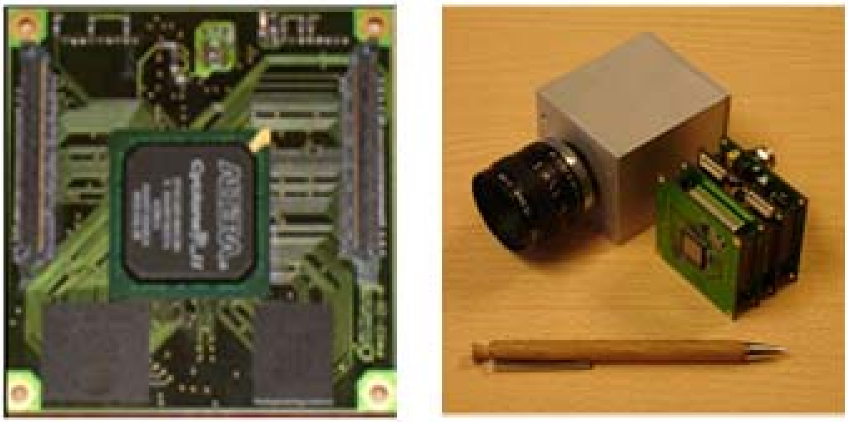

Figure 2.19: Altera FPGA board and DTSO intelligent camera [IZA07].

Furthermore, hardware programmable systems (FPGAs, ASICS, etc.) are becoming faster and cheaper. Main vendors, Xilinx [XIL03] and Altera [ATE03/1], not only develop the chip and environment to program these FPGAs, but they also provide IP-cores [ATE03/2], i.e. building blocks for FPGA design (e.g. one can buy an IP-core with the functionality of an 8051 microprocessor, thus having this microprocessor inside the FPGA). More and more web sites are related to free IP-cores [IP03], where one can download the cores that may be helpful to the development of his solution (even Xilinx and Altera have free-cores).

However, although the development of FPGAs has been considerably powerful during the last few years, smart cameras based on FPGAs or IPs in VHDL (Very High Speed Hardware Description Language) for advanced image processing are very difficult to find in the market and nowadays only smart cameras based on standard embedded microprocessors (e.g. PowerPC) or DSPs are commercially available [WIL07]. This way, standard in-camera processing functions, for commercially available FPGA-based cameras, are sensor configuration (e.g. gain, offset), region of interest programming, image subsampling, thresholding or image convolution. Many research teams are facing the problem of implementing advanced image processing algorithms on FPGA or developing FPGA-based smart cameras [CHA07, JEO07] defining direct co-design tools for the rapid prototyping and the implementation of distributed real time applications on mono or multicomponent architectures [KAO03, ELO04] or defining direct generic VHDL synthesis tools [ARA02/2].

Anyway, some research teams have already developed proprietary vision system in FPGAs (e.g. [ARR01]). As an example, the project TRIDICAM [ARA02/1] carried out the implementation over a FPGA of the image digitalization, image algorithms and control system of a laser 3D measurement camera based system. Some other references dealing with the use of FPGAs for image and AV applications are [ARA01, ZUE01, ARA02/2, MUK02, STO04, WEC04, WIN04].

Focusing on metallic forming processes, several are the AV systems developed to check the quality of the final products or the performance of the facilities. One example was the application of AV systems to the control quality of steel strip manufactured by rolling processes carried out by Garcia et al. The objective of this system was to calculate flatness indexes in the rolling industry for every strip, by comparing the length of its lateral profiles with the central length. The flatness inspection problem was largely based on the measurement of the height of the strip in each sample period. The optical triangulation method was applied to measure this height. In this method, a laser sends a monochromatic light beam over the strip surface. This light beam is reflected towards the lens of a linear camera. Thus, a relationship between the position where the laser beam strikes the camera photodiode line and the strip height can be established [GAD99].

The previous mentioned application can be achieved with the so-called 3D cameras (see Figure 2.20). Those are linear cameras able to measure 3D shapes with acquisition rates up to 30 thousands lines per second. The complete system is based on a linear laser lighting that is focused on the part to be measured and a linear CCD sensor with a resolution of up to 2048 points. The CCD linear sensor captures the reflexion of the laser light in the part surface and based on triangulation software reconstruct the surface of the part. The characteristics of the object to be measured are captured when this moves in front of the camera, working this last as a linear camera and communicating the data to the PC via the protocol CameraLink which allows a high speed transfer of data [INF07].

More recently and in the same manufacturing field, Olmedo et al developed an automatic visual inspection system for the detection of superficial defects in cold rolled carbon steel coils. The system was composed of five lineal CCD cameras and special illumination to filter the shines due to the lubrication coat of the metal coils. The system was able to deal with coils, which width was up to 2000mm and the maximum surveillance speed was up to 250 meters per minute. The improvements achieved were a reduction in the annual waste, a reduction in the external defective sent to the clients, what improves the image of the company and the identification of the defects provoked during the transportation of the raw materials from the customers [OLM08].

Figure 2.20: 3D laser scanning camera [INF07].

Another application of AV systems within the forming processes was the detection of surface anomalies on continuously moving long metal tubes manufactured by rolling and longitudinally welding carried out by Truchetet et al. The AV solution was based on a set of ten CCD linear cameras that continuously recorded images of the tube that was illuminated with special diffuse lights. After an image processing, the control system rejected the tubes that had superficial defects [TRU94, TRU97].

AV systems have also been applied to the visual inspection of three-dimensional metallic surfaces such as body parts or skin parts of the automobiles. In this case, the results achieved have not been very successful due to the big size of these components and to the small dimensions of the defects to be identified. For example, Gayubo et al. developed an AV system oriented to the detection of defects in car body parts where only the most problematic areas of the parts where controlled. This way, a camera was mounted into a 6 degrees of freedom robot arm and the movements of the robot were predefined depending on the reference to be controlled. Then, the 2D camera was placed in front of the most problematic areas of the parts and, by illuminating them with special lights, good quality images were captured [GAY04].

AV systems have also been applied to blanking processes in high speed presses, although this application has not been widely spread. Main factors that have inhibited the introduction of AV systems in SMEs (blanking or drawing companies are in most of the case SMEs), are the lack of time, staff and capital, and perhaps most poignantly the lack of specialist skills that are widely available in larger organizations. The main application of AV system in this type of companies is the detection of holes within a sheet using back illumination and matricidal CCD cameras. Some examples are the detection of holes within a field of view of 5 millimetres, with accuracies of 0.02 millimetres and production rates up to 1500 parts per minute [ASB85, PET99].

2.3.2 Conclusions regarding artificial vision inspection tasks in the industry

In conclusion, the development of AV systems for the quality evaluation of the produced parts in the manufacturing industry has reached such a high level of development that some PC based commercial solutions have appeared in the market during the last 10 years. These commercial solutions are, of course, very well suited for the industry because they are easy to implement and there is no need of high skills technicians within the companies (mainly in SME companies) although their processing times are too high for most of the SMF processes. On the other hand, FPGAs based solutions offer several advantages over PC based solutions in terms of higher throughputs, more stable performances and more robust solutions for industrial environments but they are not widely available in the market yet. The only disadvantage of FPGAs based solution over PC based solutions is its higher development time, its higher development difficulty and its lower flexibility. This is the reason why a mixed architecture, where the high time consuming algorithms (distortion correction, noise filtering, binarization, contour extraction…) are implemented in smart cameras based on FPGAs and the low time consuming algorithms (dimensions extraction, defects detection, part validity assessment…) are implemented in PC, seems to be a reasonable good solution [IZA07]. At the present research work, an AV system following such architecture will be developed to check the quality of the parts produced in a high production rate blanking facility. The development of the mentioned system and the improvements achieved after its application in the blanking facility are explained in “Chapter 5. Parts quality control”.

2.4. Computing techniques for intelligent control systems development

Artificial Intelligence (AI) is the part of computer science concerned with designing intelligent computer systems, that is, systems that exhibit the characteristics associated with intelligence in human behaviour: understanding, language, learning, reasoning, solving problems and so on [BAR81]. In other words, AI is concerned with programming computers to perform tasks that are presently done better by humans, because they involve such higher mental processes such as perceptual learning, memory organization and judgemental reasoning [MIN68]. In the end, AI is about the emulation of human behaviour: the discovery of techniques that will allow human beings to design and program machines that simulate or extend their mental capabilities [JAC90]. Since the work developed at the present research work is aimed at intelligently surveying and controlling forming processes, next subchapter is focused on the application of AI techniques to these purposes in forming processes.

2.4.1 Metal forming processes traditional control techniques

Human operators helped by local controllers have traditionally controlled industrial processes. The function of these local controllers in the industrial field has been to maintain the main process parameters close to the target values estimated by the operators. Therefore, human operators have represented, and still nowadays represent, the real global “control” of the industrial processes, and local controllers just guarantee that the control decisions taken by the operators are fulfilled. This control strategy still remains in most of the manufacturing environments being the presence of the human operator crucial.

The reason why successful automatic and non-human dependant global controllers have not been developed and applied yet to industrial processes is that, although traditional control techniques, such as optimal control, adaptive control or predictive control are suitable for the development of the previous aforementioned local controllers, they are not suitable for the development of global controllers except in a few specific cases. In this scenario, the most widely applied traditional control strategy has been the process control with feedback (for example PID controllers). Although feedback control has been applied to many fields, experience has shown that this traditional control strategy only yields satisfactory results when the next specific conditions are fulfilled:

1. The process to be controlled is linear, or at least the behaviour of the process in a small range close to the optimal values of the main variables, is linear.
2. The process response is quick; otherwise the control system is saturated.
3. There are not any external disturbances (noises) that could affect the behaviour of the system.

If the previous conditions are not fulfilled, the solution goes through the application of some other traditional control techniques that work based on mathematical models of the processes. These techniques are feedforward control techniques, like predictive control, adaptive control, model base control, optimal control or modal control. The biggest limitation when applying these techniques is that the development of a detailed model of virtually any real industrial process, even a relatively simple one, is likely to be very complicated. Therefore, the control engineer usually faces a solution in which a control system must be designed on the basis of a simplified description (model) of a complex process and consequently, the final results are quite poor.

Among others, the fields where traditional controllers have reached good performance are level control, pressure control, control of volume flow and volume mass, control of energy or control of temperature and enthalpy. Direct applications can be found in the control of mechanical separation processes, the control of heat exchangers, the control of evaporators or the control of drying processes. And the final industrial users, among others, are the pulp and paper industry, the oil extraction and refining industry or the petrochemical industry [BAL88].

On the other hand, there exist some other processes that show a high non-linear behaviour and that are almost impossible to be defined with mathematical models (described as non-formalised problems in [RYB05]). A clear example is sheet metal forming processes. These processes are inherently quite unstable processes which main variables, like the material behaviour under deformation, the lubrication and the friction at the material/tool interface or the wear of the tools are highly non linear.

Therefore, the application of traditional controllers to these processes has not offered good results yet.

Due to the presence of so many different process behaviours within the industry, there has been a tendency towards two schools of thought in the choice of a model structure for use in a control system. One school believes that the model should be based on known physical phenomena that characterise the process (**model based control**); that is, a first principle model (traditional control techniques). The other school tends towards a "**black box**" approach, which uses observed relations between the inputs and the outputs of the processes to characterise a general, usually non-linear transformation (transfer function), which internal parameters are sometimes unknown [BAL88].

2.4.2. Artificial Intelligence Techniques: Knowledge Based Systems

Among the different techniques based on the observed relations between the inputs and the outputs, AI has shown very successful results. AI is a science which main purpose is the replication of both the human reasoning processes and behaviour, with the aid of computers and other artificial devices, as well as the construction of machines able to simulate the decision making made by humans in imprecise and uncertain environments [ALI01]. Therefore, AI, as previously mentioned, is defined as the branch of the computer science that takes care of the automation of the intelligent behaviour, gathering a group of techniques and tools which main purpose is to simulate the human behaviour and to apply it to different life fields [HER85].

In order to understand this better, some of the capabilities normally associated with machines and with humans are described next. Machines, for example, are good at performing repetitive tasks, responding quickly to stimuli and controlling great forces with precision. They can also process, store and retrieve vast amounts of numerical data. Humans, on the other hand, perceive patterns well and can generalize by applying originality to conclusions and profiting from experience. Humans can also improvise, exercise good judgement, selectively recall past experiences, and adapt to the unanticipated. In this context, AI tries to bridge the gap between humans and machines by giving the machines some aspects of human capabilities [HER85].

One of the most successful applications of AI techniques has been the development of intelligent systems able to, by emulating human expertise, replace or support human beings during the decision making phase (for example, when surveying or controlling industrial processes). These intelligent systems, widely named as Knowledge Base Systems (from now on KBSs) have been developed for a variety of reasons, including: the archiving of rare skills, preserving the knowledge of retiring personnel and to aggregate all of the available knowledge in a specific domain from several experts and/or machines. The implementation of KBSs into different fields and domains, formerly managed by human beings, has given as a result several advantages to the industry like the achievement of more consistent answers for repetitive tasks, decisions and processes, in a more efficient and fast way and without any lack of performance because of pressure or tiredness [NOR05].

Research works carried out in the field during the last decades have shown how KBSs have achieved high success due to the implicit advantages that they offer over human expert beings. Lu et al summarised all these advantages as follow [LUS02]:

1. Provide consistent answers for repetitive decisions, processes and tasks.
2. Reduce the amount of human errors.
3. Sometimes can explain their reasoning and the proposed solutions.

4. Deal with incomplete information.
5. Create efficiencies and reduce the time needed to solve problems.
6. Combine multiple human expert intelligences.
7. Can be applied to a broad range of domains.
8. Centralize the decision making process.
9. Reduce employee-training costs.
10. Avoid repeating mistakes made in the past.
11. Review transactions that human experts may overlook.

Although KBSs offer all the previously mentioned advantages, they also have some limitations when compared to the reasoning of human beings. Lu et al also summarised the disadvantages as follow:

1. Lack of human common sense needed in some decision-making processes.
2. Not able to give the creative responses that human experts can give in unusual circumstances.
3. Some domain experts cannot clearly explain their logic and reasoning (drawback for rules generation).
4. Lack of flexibility and ability to adapt to changing environments.
5. Complex knowledge requires many rules

Anyway, all the previous mentioned advantages (even considering the limitations) represent, as the primary economic benefit of KBSs, an increment of the productivity by speeding professional and semi-professional work by factors of tens to hundreds [FEI90].

Although KBSs give response to a wide variety of applications, a general problem-solving category of them was summarised by Ching-Yu Tyan *et al.* in [TYA93]:

1. Interpretation: forming high-level conclusions or descriptions from collections of raw data.
2. Decision making: devising a series of actions and analysing consequences of given situations of human decision support.
3. Diagnosis: detecting the cause of malfunctions in complex systems based on observable symptoms.
4. Design: determining a configuration of system components that meets certain performance goal while satisfying a set of constraints.
5. Monitoring: comparing the observed behaviour of a system to its expected behaviour.
6. Control: governing the behaviour of a complex environment.

At the present research work, the developed KBS is focused on the third category, named diagnosis, that aims to find the causes of the malfunctions in complex systems (in this case sheet metal forming processes) based on observable symptoms (force and AE signals and part quality).

The process of developing KBSs is called Knowledge Engineering (from now on KE). The KE process is composed of the next six steps which final purpose is the building and maintenance of KBSs [LUS02]:

1. Problem selection: the first step in KE is selecting the "right problem", which is the goal of the project.
2. Knowledge acquisition: the objective of knowledge acquisition step is to acquire the knowledge of the problem, which is the foundation of expert system development.

3. Knowledge representation: this step involves representing the knowledge in the knowledge base as rules, frame scripts, semantic networks, or some combination of them.
4. Knowledge encoding: this step entails using the expert system shell/programming language to encode the knowledge.
5. Knowledge testing and evaluation: the major task of this step is to validate the overall structure of the system and its knowledge.
6. Implementation and maintenance: to periodically refine or update the knowledge to meet current needs after the system has been implemented.

From all the previous mentioned steps, knowledge acquisition and its further representation are the most important ones because the final success of KBSs relies very much on the richness of the acquired knowledge and the way it is represented. At this point a very important factor must be considered; whether the knowledge about the domain to be studied is deep enough to develop a rich knowledge base or not. In real life, domains vary in the degree to which they are understood, ranging from those that can be codified completely and correctly in terms of a set of rules of behaviour, to those for which no such rules are known. For each of the previous mentioned scenarios there are different techniques available that allow the user to develop the most suitable final system.

For example, in domains where a deep understanding is available, rule-based expert systems are the most suitable technique [GUI05, VAS96]. This way, it can be stated that rule-based expert systems are suitable in domains where a priori knowledge of the domain is very well known and thus the knowledge is easily implemented in the form of IF-THEN rules to develop a suitable knowledge base. At the present research work and since the human operator has all the knowledge regarding the blanking process to be controlled, rule-based expert system is a very suitable technique to develop the intelligent control system pursued.

On the other hand, in domains where a priori knowledge is not achievable and therefore no such rules are feasible, or when a simplification of the knowledge acquisition phase is pursued, there exist some other techniques that allow the system to automatically acquire the knowledge of the domain and to create a suitable knowledge base. Among others techniques, Aztiria et al identified four different learning techniques that are able to learn at domains where a priori knowledge is difficult to be identified or does not exist [AZT09]:

1. Artificial Neural Networks: ANN can be defined as extreme simplifications of the human brain functions which main objective is to develop representative models of unknown domains by using data gathered from those domains. In order to get this, a set of input-output data is fed into the ANN that internally generates a model able to match the input-output pairs. [UGA94]. This learning technique is not suitable at the present research work due to two principal facts: first fact is that a set of initial data (input-output pairs) is necessary to develop the model or the rules of the knowledge base and, as it will be explained later, the aim of the present research work is to use a learning technique able to learn without any set of initial data. And second fact is that ANN work like a “black box” approach where the final knowledge cannot be extracted in the form of IF-THEN rules.
2. Rule induction: rule induction, often referred as “learning sets of rules”, is a learning technique which represents the target function by means of if-then rules that jointly define the function. The limitation of this technique at the present research work is that a set of initial data must also be available to develop the IF-THEN rules. Therefore, this technique is not feasible at the present research work either.

3. Reinforcement learning: reinforcement learning algorithms is a learning strategy that tries to improve the performance of an initial model taking into account the reward or penalty that a trainer provides. This way, their performance is dynamically changed in order to get more optimised solutions. This technique is more focused on the improvement of an already initial developed model and therefore is not feasible at the present research work either.
4. Case-based reasoning (CBR): in contrast to the rest of the learning methods mentioned before, instance-based learning methods, often referred as “lazy” learning methods, (being CBR its most successful application) instead of constructing an explicit target function or IF-THEN rules knowledge base using training examples, they simply store the training examples to find the right solution for future examples. This learning technique perfectly matches the necessities of the present research work because it is able to start learning from the beginning and there is no need for any set of initial data. This can help during the knowledge acquisition phase making this phase much simpler that in the case of using rule-based expert systems. Therefore, CBR systems are very suitable for domains where the knowledge understating is not enough for its codification [GUI05, VAS96] and where no set of initial data is available for the constructing of the model or the knowledge base.

Summarising, depending on the initial available knowledge at the domain and, therefore, depending on the necessity of a learning phase, two different techniques can be implemented: rule-based expert system (for very well known domains) and case-based reasoning (for domains where the knowledge is not identified or even when a simpler knowledge acquisition phase is pursued). Next, an example found in the literature where a common domain is solved by these two approaches, is given. In the legal domain, when legal expert systems use rule-based formalisms to represent statutes (knowledge is known), the legal decision-making process is mechanically reproduced by an inference procedure that searches among the implemented rules [SER86]. On the other hand, legal CBR systems accomplish the decision-making process by establishing relations with judicial decision precedents by means of a matching process [RIS87, GUI05]. Next both knowledge representation methodologies, rule-based expert systems and case-based reasoning are briefly explained.

2.4.3.Rule-based Expert Systems

The first methodology able to deal with the acquisition of the knowledge and its further implementation into knowledge-based systems is rule-based expert systems (or simply named Expert Systems). This subchapter briefly explains the most important features of this methodology in addition to some of the successful applications found in the literature.

2.4.3.1. Definition

First some of the many Expert System (from now on ES) definitions found in the literature are given:

1. ES are sophisticated computer programs that manipulate knowledge to solve problems efficiently and effectively in a narrow problem area [WAT86].
2. ES are a class of computer programs that can advise, analyse, categorize, communicate, consult, design, diagnose, explain, explore, forecast, form concepts, identify, interpret, justify, learn, manage, monitor, plan, present, retrieve, schedule, test and tutor. They address problems normally thought to require human specialists for their solution [FIR89].

3. An ES is a computer program that uses knowledge and reasoning techniques to solve problems that normally require the services of a human expert [ALL93].
4. An ES is a system that provides for solving problems in a particular application area by drawing inferences from a knowledge base acquired by human expertise [MCD94].
5. ES are automated systems that incorporate the knowledge of top human experts and use it to respond to the emerging problems in a similar way, as the top experts would do [NGU97].
6. An ES is a program which mimics human problem-solvers in several senses: for example it contains an explicit representation of the knowledge which is used by humans who are experts at solving tasks in some problem domain, or it can explain its answers to its users in the same way as a human expert can explain his conclusions to his clients [JAC99].
7. An ES is a computer program that reasons in a narrow but deep field of expertise emulating the decision-making ability of a human expert and performing as well as, if not better than, humans operating in the same field [LUS02].

It can be concluded from the previous definitions, that rule-based ES are computer programs that codify specific domain knowledge, as a set of IF-THEN rules in knowledge bases, and further use the codified rules to solve problems related to the specific domain. Rule-based ES use the codified rules along with information contained in the working memory (definition of the actual problem) to solve problems in the next way: when the "IF" portion of the rule matches the information contained in the working memory, the system performs the action specified in the "THEN" part of the rule [LUS02]. Figure 2.21 shows schematically how rule-based ES work.

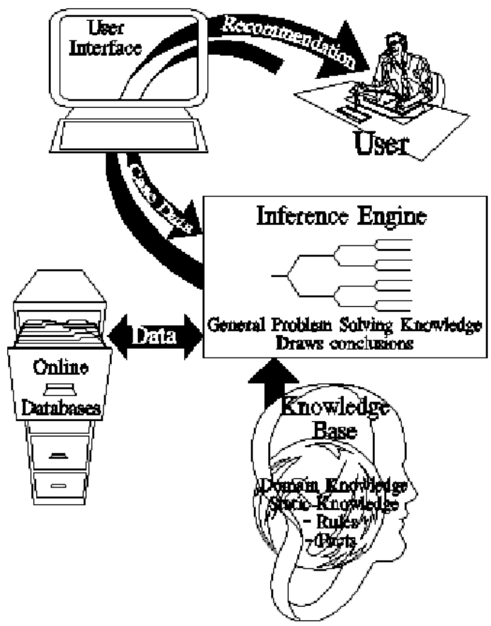

Figure 2.21: Schematic representation of rule-based expert systems [FAC08].

Therefore, while an ES is a computer program, it does not follow the traditional approach where the programmer specifies each step in solving the problem. Rather, the programmer (a knowledge engineer) codifies a large number of facts about the problem domain as rules. Rules specify one or more facts that may be inferred with some degree of certainty when some other facts are known to be true. A relatively simple control program called an inference engine can then be used to examine the rules in light of known facts. The ES methodology allows a system to draw useful conclusions even with incomplete or uncertain data. It is especially useful for solving problems where an algorithmic approach is either difficult or impossible to implement (traditional control strategies based on PID controllers) [MIL85, HAR90]. Following this reasoning, it is found that ES differ from the conventional application programs in that [JAC90]:

1. The main function of conventional programs is to store and to retrieve data, to carry out calculations and to do graphics. A conventional program cannot reason with the knowledge. On the other hand, an ES stores and retrieves knowledge and reasons with it.
2. ES simulate human reasoning about a problem in a narrow domain. They focus on emulating an expert's problem solving abilities.
3. ES solve problems by heuristic or approximate methods, which unlike algorithmic solutions, are not guaranteed to succeed. Such methods do not require perfect data and the solutions derived by the system may be proposed with varying degrees of certainty.
4. ES are capable of explaining and justifying solutions or recommendations, which helps the user to judge if the reasoning is in fact correct.

These properties are remarkably different from properties of a conventional program. Conventional programs basically depend upon the accuracy and integrity of the models. Thus, if any of the input data is missing or inaccurate, the conventional system will respond with error messages or it may output incomprehensible results. Whereas an ES can operate in the face of adversity, it does not need all the data to be accurate; it can use its reasoning facility to fill in or circumvent the gaps and it will return with results that include an estimation of reliability [LUS02].

2.4.3.2. When is profitable to use rule-based ES

In many application areas (e.g., in medicine, geology, economy, engineering), human beings often need to make decisions when they do not have the exact knowledge of the situation, and therefore, they cannot even formulate (not to say solve) the decision problems in precise mathematical terms. There are also some other cases when although human beings can formulate the problem precisely, this formulation leads to a complicated mathematical optimisation problem of the type that cannot yet be solved

In the middle 1980s and early 1990s, the scientific and commercial success of ES showed that, in actual practice, there is a sufficiently large class of problems that cannot be solved by the aforementioned methods of conventional programming (for example, when it is impossible to formulate the solution of the problem in mathematical terms in the form of a system of equations). This short of problems (named as nonformalized problems (NF-problems) in contrast to formalized problems (F-problems) in [RYB05]), have one or several of the following characteristics: they cannot be given in a numerical form; the goals cannot be expressed in terms of a strictly defined goal function; and an algorithmic solution exists, but cannot be used due to the limited resources (time and/or memory).

In all these cases, expertise is in charge of making decisions and human experts are who make reasonably good decisions: expert doctors successfully cure diseases, expert geologist find oil, expert astronauts know how to dock and land the Space Shuttle or expert operators know how to operate a chemical plant. In this scenario, where the problems to be solved are such complicated that can not be modelled by means of mathematical equations and where human experience and expertise is the only way to solve them successfully, is where it is desirable the availability of automated systems that, by incorporating the knowledge of human experts, will help people in making decisions. These systems are called ES [NGU97].

2.4.3.3 Components of an ES

One of the main characteristics of ES is the separation between the knowledge to be used in a specific domain and the procedures that manipulate that knowledge. The main advantage of this characteristic is that the knowledge is used in a more effectively and efficiently way. Following this criterion, ES are divided into three major components that are the knowledge base, the working memory and the inference mechanism. The linkage between the aforementioned components and the user is achieved by the graphical user interface (or just interface) as shown in Figure 2.22 [LUS85, KOW00, LUS02].

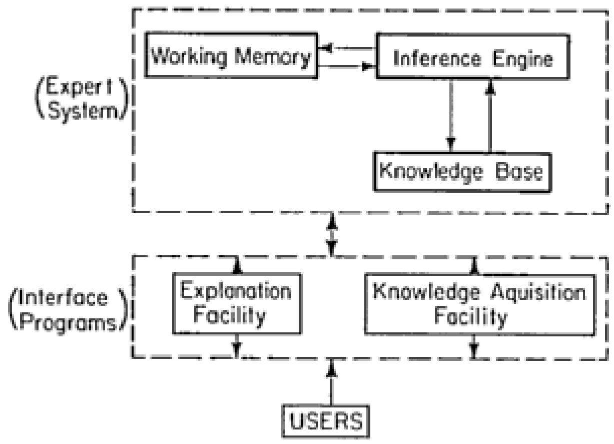

Figure 2.22: Structure of a complete Expert System [LUS85].

2.4.3.3.1 Knowledge base

The knowledge base of an ES is the component that stores, by means of rules, all the knowledge regarding the domain where the ES will be applied. A rule is a knowledge structure that relates some known information to other information that can be concluded from the known one. Therefore, a rule is a form of procedural knowledge that associates given information to some action. Rules represent reasoning knowledge and handle the complex relationship between facts. Rules can embody vague concepts, simple heuristics, mathematical expressions, data expressions, time expressions, character string expressions or functions. In rule-base ES, rules are written in an IF-THEN-ELSE format. Whereas the IF-AND-OR part of the rule is called the "premise or antecedent", the THEN-ELSE part is called the "conclusion or consequence" [LUS02].

The knowledge stored in the knowledge base can be classified in many different ways depending on what it represents (e.g, knowledge based on experience and heuristics, knowledge based on first principles and general theories, meta-knowledge). Generally, knowledge bases are composed of factual and heuristic knowledge [KOW00]:

1. Factual knowledge is that knowledge of the task domain that is widely shared, typically found in textbooks or journals, and commonly agreed upon by those knowledgeable in the particular field.

2. Heuristic knowledge is the less rigorous, more experimental, more judgmental knowledge of performance. In contrast to factual knowledge, heuristic knowledge is largely based upon past experiences and knowledge gained. For instance the knowledge that, if the same pattern of events take place then the same conclusion could be expected. It is the knowledge built from 'thumb rules'.

At the same time and from a representation point of view, the knowledge can roughly be divided into two main categories principally: declarative and procedural knowledge [RAJ91]:

1. Declarative knowledge is represented as a static collection of facts that will require a set of general procedures to manipulate them. Advantages of declarative representation are the convenience of adding new facts to the knowledge base and that facts only need to be stored once.
2. Procedural knowledge represents knowledge as procedures. Procedural representation is convenient to heuristic knowledge, for describing how to do things and for representing complex logic such as probabilistic reasoning

Therefore and summarising, the knowledge base is the part of the ES where all the knowledge that later will be used to solve the given problems is stored; in rule-based ES the knowledge is stored by means of IF-THEN rules.

2.4.3.3.2 The working memory

The working memory is the component of the ES in charge of storing all the information related to the process to be solved. Thus, the working memory initially contains the facts (or symptoms) of the problem that are used to infer the right conclusions, and at the end of the solving procedure, contains the problem conclusions inferred by the system. In order to get this, the working memory communicates with the inference mechanism that matches the symptoms (or initial information about the problem) stored in the working memory with the knowledge (IF-THEN rules) contained in the knowledge base. Whenever any of the initial symptoms matches with any of the IF-THEN rules antecedents, the consequences of that rule are transmitted to the working memory as the final conclusions [LUS02].

The working memory can load the initial information (symptoms of the problem) from different sources like external storage such as databases, spreadsheets, or sensors at the beginning of the consultation process. Sometimes, the system may obtain the information supplied by the user too. In the manufacturing field, the sensors that monitor the process usually supply the information to the working memory although the user can also provide valuable information. In the same way, at the end of the solving procedure, the final conclusions can be stored in the previous mentioned sources or can be directly transmitted to the user. When the user supplies the initial information or when the final conclusions want to be transmitted to the user, a Graphical User Interface (GUI), explained later, is necessary.

2.4.3.3.3 The inference mechanism

The inference engine (or mechanism) in an ES is a processor that matches the facts contained in the working memory with the domain knowledge contained in the knowledge base in order to draw conclusions about the problem. When an ES starts to examine the problem, it searches the rules for a match between the premises (or antecedents of the rule) and the information contained in the working memory (facts of the problem to be solved). When the inference engine finds a match, it adds the rule's conclusion (or consequence of the rule) to the working memory and continues to scan the rules looking for new matches. Either of the following two types of searching strategies can be used in an inference engine [LUS02]:

1. Forward reasoning (also named as modus ponens) starts with assertions about the problem, makes inferences looking for "matching" with the antecedents of the rules and draws conclusions (the consequences of the rules that are "fired"). This strategy is used when all the knowledge to make a decision is available before session begins.
2. Backward reasoning (also named as modus tollens) starts with the answer and works backwards to the problem description. The rule selection is guided by the conclusions rather than the conditions. This strategy is used in situations where the user can make a good guess about a possible solution and when more goals than combinations of initial assertions exist.

Summarising, forward reasoning is a search procedure or reasoning process using known facts to produce new facts and to reach a final conclusion. On the other hand, backward reasoning is a reasoning process, which starts with a desired goal and works backward, looking for facts and rules that support the desired result. In problem solving, since the reasoning procedure usually begins with the collection of facts (for example process variables in an industrial facility) and then the information is reasoned with the purpose of inferring the logical conclusions, forward reasoning is the most applied searching method. This way, the inference strategy of forward reasoning starts with a set of known facts, derives new facts using rules whose premises match the known facts, and continues this process until a goal is reached (for example right action to restart the production in the manufacturing field) or until no further rules have premises that match the known or derived facts (see Figure 2.23 for schematic explanation).

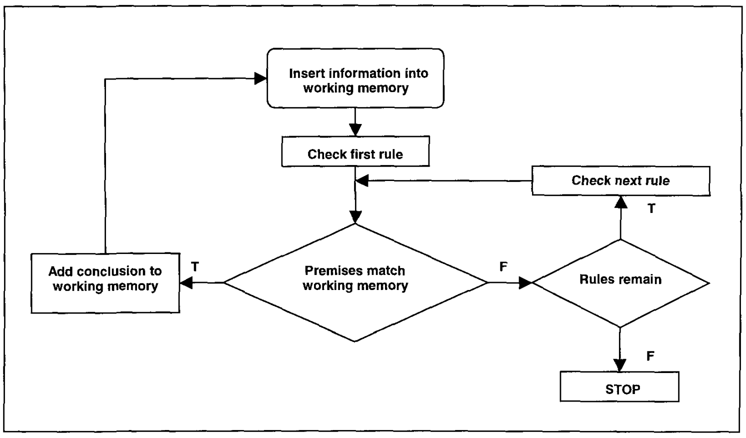

Figure 2.23: Forward reasoning process [LUS02].

Therefore, when ES are applied to problem solving procedures, what basically performs the inference mechanism is the activation of the consequents (solutions to the problem) of the rules which antecedents (problem symptoms) are fulfilled. A clear example is the application of rule-based ES to medical diagnosis. In these cases, the rule-based ES is fed with the symptoms of the patient to be treated and it searches for an illness, which symptoms match with the symptoms of the patient.

2.4.3.3.4. Graphical User Interface (GUI)

Although not directly integrated into the core of the ES, the communication with the users is also a very important factor to be taken into account when developing ES. Even if the ES has been developed correctly, with a knowledge base that describes perfectly the process and an inference mechanism that executes always the best possible action to be taken, if the user does not understand this information, the ES can be described as an “island of intelligence” within the factory. Therefore another very important component of ES is the interface with the users. The interface must allow all users, from the mechanical department head to the operator of the process, to understand and communicate with the system easily [RAJ91]. It is generally said that the interface of the ES must fulfil the next requirements:

1. To be very easy to learn by the user.
2. To avoid the entrance to the system of wrong data.
3. To show the results and actions in a very transparent way to the user.

2.4.3.4. Some previous successful applications of rule-based ES methodology in the literature

ES has been used in most processing applications, even very large ones needed for major chemical processes, metallurgical processes, quality control in pulp and paper and oil industries, cost control in power plants and other applications. Among other applications, operators and engineers have used ES for fault diagnosis. In such processes, ES can find the most probable cause and suggest corrective actions, being for example very useful in alarm management because, by communicating the critical alarms immediately, operators can react fast and correct the problem. This saves process downtime, operator time in locating the problem, and in the long run, saves money and reduces off-specification products [LUS02].

Since the first ES named DENDRAL, created by Lederberg and Feigenbaum in 1965 at Stanford University, this AI methodology has been broadly applied both in the academic and in the industrial field. Next some previous research works focused on the identification of failures, the topic that the present research work covers, are briefly explained:

1. Chun Cheung Siu *et al*. developed a rule-based ES able to deal with fuzzy knowledge, and applied it to the identification of vibration causes in rotating machines. The system was able to generate ranked fault hypothesis within an incrementally consultation and allowed for the revision of diagnosis results with respect to the revision of symptoms presented by the user [SIU97].
2. R. Amyot *et al*. developed an operational ES prototype to help mill operators and engineers to troubleshoot and optimise the steam and condensate portion of paper machine dryer sections. A major output of the prototype was to quantify the thermodynamic performance of the machine in order to inform the user when the steam and condensate system was wasting energy. This way, when the machine was operating outside of specified thresholds, the ES entered into a diagnostic dialog with the user to obtain more information aimed at determining the possible cause(s) of the deteriorated performance. A three-month validation phase conducted simultaneously in two mills led to the overall conclusion that, despite some room for improvement in the system's usability and functionality, it is a fundamentally sound and useful tool for monitoring and recording the performance of a S&C system, and for helping to diagnose the causes of poor performance [GOW01].
3. Warren R. Becraft *et al*. developed an operator advisory (INNATE/QUALMS) composed of a rule-based ES combined with artificial neural networks able to help operators at large-scale chemical process plants to diagnosis process failures. The developed diagnostic system exhibited good diagnostic performance under a

variety of conditions including novel faults, and the presence of sensor noise [BEC91].
4. D. Chester *et al*. developed FALCON, a rule-based ES able to identify probable causes of disturbances in a chemical process plant by interpreting data consisting of numerical values from gauges and the status of alarms and switches. The system interpreted the data by using knowledge of the effects induced by a fault in a given component and how disturbances in the input of a component lead to disturbances in the output [CHE84].
5. William R. Nelson *et al*. developed REACTOR, an ES able to assist operators in the diagnosis and treatment of nuclear reactor accidents. The purpose of REACTOR was to monitor a nuclear reactor facility, detect deviations from normal operating conditions, determine the significance of the situation and recommend an appropriate response [NEL82].
6. Massimo Gallanti *et al*. developed PROP, an ES for malfunction diagnosis and process surveillance concerning on-line monitoring of water pollution in a thermal power plant [GAL85].
7. Peter Chan, during his PhD work, developed a prototype rule based ES for civil engineering applications in the knowledge domain of diagnosis of deterioration and other problems in reinforced concrete structures. The developed system performed satisfactorily with about a 70% rate of success in real cases. The confidence values provided were found to be reasonable and the system was shown to be adequate in providing diagnosis of common problems of reinforced concrete but it did not perform well in special cases outside its knowledge domain [CHA96].
8. Agre *et al*. developed a rule-based ES intended to help the maintenance staff in search of faults in the personal computers of the family PRAVETS-8 (Apple-2 compatible) [AGR85]. At the same time Sgurev *et al*. also developed another rule-based ES intended to help the maintenance staff in the search of faults in disk subsystems, consisting of a controller and a hard disk drive module with 300 or 600 MB capacity [SGU91].

2.4.4.Case-based reasoning methodology

The second methodology studied at the present research work, able to deal with the acquisition of the knowledge and its further implementation into knowledge-based systems, is Case-Based Reasoning (from now on CBR). This subchapter briefly explains the most important features of this methodology in addition to some of the successful applications found in the literature.

2.4.4.1. Definition

First some of the many CBR definitions found in the literature are given:

1. CBR (e.g., [KOL93, RIE89]) is a paradigm that models the role of experience in refining problem-solving ability [LEA95].
2. CBR is based on the fundamental principle that problem solving can benefit from solutions to past problems that have been attempted [VER99].
3. CBR is a methodology for solving problems by utilizing previous experiences. It involves retaining a memory of previous problems and their solutions and, by referencing them, solve new problems [MAI00].
4. CBR is a problem solving method that uses knowledge from a past situation to help with the complexities of solving a new design problem [COB07].

It can be concluded from the previous definitions that CBR is based on the idea of utilizing solutions to past problems to solve new problems (see Figure 2.24). Thus, the solutions to ‘similar’ problems are retrieved from a case memory of solutions, and applied to new problems. This way, when a CBR system is presented with a similar problem, it does not re-reason from an initial set of facts and rules. Instead, it uses the plan that embodies the reasoning already utilized in the retrieved solution [VER99].

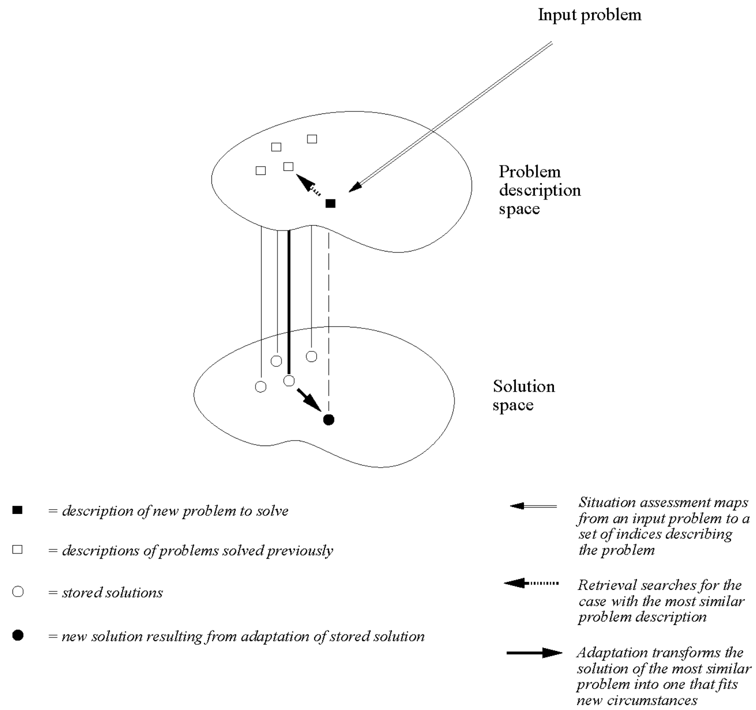

Figure 2.24:How CBR methodology generates a new solution [LEA96].

CBR can be traced back to the work of Schank's dynamic memory model [SCH82], but was Kolodner [KOL93] who developed the first case-based reasoner, known as CYRUS. CYRUS was based on the abovementioned Schank's memory model and was a question and answer system that contained the knowledge, as cases, of the travels and meetings of ex-US Secretary-of-State Cyrus Vance [COB07].

Generally, a case-based reasoner will receive a problem presented by either a user or another program or system. The case-based reasoner then searches its memory of past cases (the case base) and attempts to find a case that has the same problem specification as the current case. If the reasoner cannot find an identical case in its case base, it will attempt to find the case or cases in the case base that most closely match the current query case.

In the situation where a previous identical case is retrieved, presuming its solution was successful, it can be returned as the current problem's solution. In the more likely case that the retrieved case is not identical to the current case, an adaptation phase occurs. In adaptation, the differences between the current case and the retrieved case must first be identified and then the solution associated with the retrieved case must be modified taking into account these differences. The solution returned in response to the current problem specification may then be tried in the appropriate domain setting [MAI00]. As a final stage, the adapted case is then added to the case library for future use, making learning an integral part of the CBR process [LEA95].

As an example, consider a scenario of a doctor treating a patient. If the cure to a patient's illness involves the use of a combination of drugs, the doctor may refer to the patient's past medical record for prescription history. If, in the past, the patient responded to the drug in a positive way, the same prescription might be given, while if the response were negative or slower than anticipated, the doctor might try to improve the chances of recovery by introducing (adapting) a different combination of drugs. However, if there is no record of past illness and treatment, the doctor may use the experience induced from the treatment of other patients (or other well established sources) for treatment. Evidently, the doctor always keeps treatment cases categorizing and organizing them in an easy-to-retrieve manner, and reuses them to justify future treatment plans. In the same manner, CBR is configured to work on the basis of past experiences [VER99].

2.4.4.2. When is profitable to use CBR

The CBR methodology is known to be well suited to those domains where formalized and widely recognized background knowledge is not available [MAI00]. In these scenarios, the acquisition of cases becomes a natural mechanism for knowledge acquisition and avoids the need to extract the principles underlying a domain. Many works in the literature suggest that this significantly alleviates the knowledge acquisition problem, the main purpose of the use of this methodology at the present research work [LEA95].

This way, CBR actually allows one to build a knowledge base of past situations (cases), which represent an “implicit” (i.e. operative) form of knowledge that can be reused in present problems, possibly after an adaptation step. Representing a real-world situation as a case is often straightforward: given a set of meaningful features for the application domain, it is sufficient to identify the value that they assume in the situation at hand; typically, a case also stores information about the solution applied and the outcome obtained. Due to the simplicity of this process, and, as mentioned before, in many real world examples the knowledge acquisition bottleneck can be significantly reduced in comparison with the exploitation of other reasoning methodologies. Moreover, new knowledge is automatically stored in the case base during the normal working process and, as the case library grows, more and more representative examples are collected, what makes easier to find a proper solution to a new problem by means of this paradigm [MAI00].

2.4.4.3. Description of the CBR methodology

Although many authors have described the steps involved in the application of the CBR methodology [COB07, MAI00, VER99, WAT97], in general, CBR can be described in terms of five different tasks: mapping, retrieval, adaptation, revision, and storage [KOL93].

1. Mapping: recalling a case from the case memory is a pattern-matching problem that is based on the specification of a new problem. In order to map cases in case memory, the specification of a new problem is transformed into a pattern to be matched. The pattern may be taken directly as the user input specification or it may be modified, for example, to include an order of importance of the attributes.
2. Retrieval: the retrieval task in CBR searches in the case memory for matches between individual cases and the pattern that serves to index the cases. Each case in the case memory may be compared to the pattern, or the pattern may provide a set of indices to partition case memory, thus only a relevant subset of cases are compared with the pattern. Retrieval can be based on a perfect match, where the pattern is found exactly, or on partial matches. If partial matches are retrieved, a threshold may be set to determine when a partial match is close enough (always retrieve the best plan).

3. Adaptation or reuse: this function is responsible for applying the case solution from a retrieved problem to the problem at hand. In some problems, a selected case provides a solution to the new problem. In most problem solving, however, the selected case needs to be modified to be appropriate as a solution to the new problem. Adapting a case from case memory to solve a new problem requires additional knowledge. The form that this knowledge takes depends on how adaptation is done. The original case is called a base case, while the adapted case is called a derived case.
4. Revision: this is the actual running of the adapted plan against the problem. Application of the new plan needs to be evaluated in order to prepare it for storing. Zeid et al. suggested that a revision process can be modelled as a sequence of transitions from an initial or existing state to its final state [ZEI97]. Therefore, the revision process is necessary and useful in making sure that the final state of the plan is valid before storing it in the case memory for future use.
5. Storage or retain: this is concerned with adding and organizing the readjusted plan to the case memory. Once the plan is revised, it is introduced to the case memory to be stored. Whenever a new plan is introduced to the case memory, a storing procedure is activated. Indeed, if the plan deems satisfactory, the plan is stored, and if not, it may be discarded.

Figure 2.25 shows schematically the steps involved in the CBR methodology.

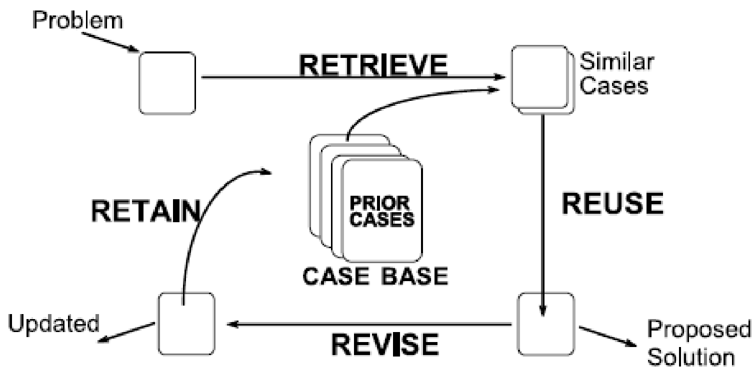

Figure 2.25: The Case-Based Reasoning cycle [LOP06].

Therefore, CBR is based on the storage of previous successful solved cases and its use for the solution of future problems. A case can be said to be the record of a previous experience or problem. The information recorded about this past experience will, by necessity, depend on the domain of the reasoner and the purpose to which the case will be used. In the instance of a problem solving CBR system, the cases will usually include the specification of the problem and the relevant attributes of the environment that are the circumstances of the problem. The other vital part of the cases is the solution that was applied in the previous situation. Depending on how the CBR system reasons with cases, this solution may include only the facts of the solution, or, additionally, the steps or processes involved in obtaining the solution. It is also important to include the achieved measure of success in the case description if the cases in the case base have achieved different degrees of success or failure [MAI00].

Since the solution to the actual problem is based on the previous solved cases, another very important point in CBR is the representation of the cases into the case base. The essential points for determining what is in case memory and how it is represented depends on the nature of the goals and constraints of each system. Initialization of case memory is needed to establish and represent the contents of each case. The representation of the contents of each case needs to be appropriately structured to operate effectively. The organization of the set of cases in case memory provides mechanisms for locating one case or a part of a case in case memory. The cases may be clustered or accessed by common attributes. As case memory becomes very large, the need for organizational structures becomes more important. The representation of a case is usually generalized for all cases in case memory, so that all cases are described by the same set of attributes or part-subpart relationships. This way, the organization of cases in case memory provides a template or model for defining the content of a case and for adding new cases to an existing case memory [VER99].

After analysing the cases and identifying their most fruitful representation, another very important decision is the election of the strategy to retrieve the most similar cases. Cases retrieval is based on the similarity index calculation between cases. Case indexing processes usually fall into one of these three kinds: nearest neighbour, inductive, and knowledge-guided or a combination of these [BAR91]. The following list briefly describes the main points of each of these techniques:

1. Indexing by nearest neighbour.
   - ✓ The technique compares a weighted sum of features in the input case against cases in memory.
   - ✓ The technique works well if the retrieval goal is not well defined or if only a few cases are available.
   - ✓ The main difficulty with this technique is that the feature weights are often context dependent.
2. Inductive indexing.
   - ✓ The technique is well adapted to situations where the retrieval goal or case outcome is well defined.
   - ✓ It can automatically, objectively, and rigorously analyse cases to determine the best features for distinguishing them.
   - ✓ The cases can be organized for retrieval into a hierarchical structure, a feature that speeds up appreciably the retrieval of cases.
   - ✓ This approach needs a reasonable quantity of cases to run smoothly.
   - ✓ The up front inductive analysis can be very time consuming.
3. Knowledge-based indexing.
   - ✓ The technique applies existing knowledge to each case.
   - ✓ Applicable only if explanatory knowledge is available and representable.
   - ✓ It is often difficult to codify enough explanatory information to complete knowledge-based indexing on a wide range of possible case inputs.

At the present research work, indexing by nearest neighbour has been selected to evaluate the actual case to be solved because the system will go though an initial learning period and because it is intended to achieve successful results as early as possible during this learning phase.

2.4.4.4. Some previous successful applications of CBR methodology in the literature

As mentioned before, first CBR system, CYRUS, was developed in 1982. Since then, CBR methodology has been broadly applied both in the academic and in the industrial field. Some previous research works focused on the identification of failures, the topic that the present research work covers, are briefly explained next:

1. Stefania Montani *et al*. applied CBR for failure diagnosis and remediation in software systems with the purpose of developing distributed software systems with self-healing capabilities. The suitability of the approach was demonstrated by some

tests conducted on the Moodle application, running on a distributed architecture. Moreover, it was also demonstrated the no necessity of structured knowledge, such as models of the system behaviour, thus easing its applicability to large-scale, complex software systems [MON06].
2. Erik Olsson *et al*. demonstrated the successful performance of CBR methodology to the identification and diagnosis of faults during the assembly of robots based on the recording of abnormal acoustic signals [OLS04].
3. Paal Skalle *et al*. also applied CBR in the oil extraction industry to the identification and solution of lost circulation during oil well drilling. The author demonstrated the capacity of CBR to provided useful knowledge such as cause factors and remedial actions when new problems arrived to the system [SKA00].
4. T. Warren Liao *et al*. implemented CBR methodology to the correct detection and identification of welding flaws in automated weld inspection systems. The system developed used radiographic weld images of the welding line and compared them to previous already classified welding flaws to perform a correct identification of the flaw at the part. The results obtained in the study indicated that better performance in terms of higher accuracy rate and lower false positive rate can be achieved than that of the fuzzy clustering methods employed before [LIA03].
5. Mark Devaney *et al*. developed a log identification system able to provide the data necessary to characterize operating cycles, maintenance schedules, periodic breakdowns, and most importantly, to identify and address abnormal failure rates in big industrial facilities before critical problems arise. All the knowledge was implemented into a database using a CBR methodology and the identification of new operating failures was provided to experienced maintenance engineers and managers who assessed the utility of the system [DEV05/1].
6. Mark Devaney et al. also developed a case-based reasoner for gas turbine diagnosis at the monitoring and diagnosis centre of General Electric in Atlanta. The main purpose of the developed system was to improve turbine and system reliability, reduced turbine operating/maintenance costs, and produce the greatest possible sustained availability from the power generation equipment. The case-based reasoner worked in next way: right after any gas turbine shut down, the monitoring and diagnosis centre of General Electric in Atlanta automatically received the operating data of the turbine. Then the data were analysed and the reasons and solutions to be apply were identified based on the data recorded from previous experiences. Finally the solutions to be applied were communicated to the maintenance personnel of the corresponding gas turbine [DEV05/2].

2.4.5 Conclusions regarding knowledge based systems in the industry

Since traditional control techniques do not have the abilities that autonomous control systems need to survey and govern very complex processes, some other techniques able to deal with them have emerged during the last few years. Among all these techniques, AI has shown a great performance in different complex fields ranging from, for example, engineering to medicine. Although AI has not been directly applied to the control of forming processes, the way that these industrial processes are controlled nowadays makes the application of AI techniques to become very suitable regarding their control. It has been stated over the time that human expert operators are the best solution to the control of forming processes and even, still nowadays, they are in charge of carrying out the control of forming processes helped by local control systems. Therefore, a suitable technique able to survey and control forming processes in the same way that human expert operators do, should be based not on mathematical equations that model the process, but on the knowledge and the experience.

KBSs are the branch of AI focused on the development of intelligent systems able to, by emulating human expertise, replace or support human beings during the decision making phase (for example, when surveying or controlling forming processes). The implementation of KBSs into different fields and domains, formerly managed by human beings, has already given as a result several advantages to the industry, like the achievement of more consistent answers for repetitive tasks, decisions and processes, in a more efficient and fast way and without any lack of performance because of pressure or tiredness. Therefore, it is concluded that the application of a KBS to the control of forming processes should bring a better performance and a higher efficiency.

Within the different available techniques used to create KBSs, rule-based ES is the most applied one and the one that more profitable results has offered over the time. Rule-based ES is a very suitable technique when a priori knowledge about the process to be controlled is available. At the present research work, and since a priori knowledge was available in the figure of the human expert operator, this technique has been chosen to implement all the knowledge that the operator has into a computerised system. This way, an intelligent process control system able to support the operator during the decision-making phase will be created.

Another important reason has been considered when choosing rule-based ES as the technique to be used for the development of the intelligent control system: its “transparency”. Since the implementation of the knowledge that the operator owns is in the form of IF-THEN rules, it is very easy to understand and visualize the control strategy being developed. This way, the application of this strategy allows to evaluate in a deeper way the suitability of AI techniques to create intelligent systems and to apply them to the control of forming processes.

Finally, and after determining the suitability of rule-based ES, CBR techniques have also been selected with the aim of making easier the knowledge acquisition phase and, thus, allowing the creation of more universal intelligent control systems able to evolve and to be applied in different forming processes and fields. At this point, it must be taken into account that the initial use of rule-based ES is considerably valuable because a deeper understanding of the processes to be controlled can be gained. This initial step will help the research team during the creation of the intelligent control system based on CBR techniques.

As a summary, taking into account the data gathered at the present subchapter and since the present research work deals with blanking processes, it was decided that the most advantageous AI techniques for the development of an intelligent control system should be Rule-Based ES and CBR techniques (shown in “Chapter 6. Intelligence Control System”). “Chapter 6. Intelligence Control Module” shows the systems created by the implementation of these both AI techniques, the results achieved by each one of them and a comparison between them.

2.5. Critical review of the current state of the art: work scope definition.

Sheet metal forming processes are inherently highly non-linear and complex processes where many different process parameters can affect the final quality of the manufactured products. In the last few years, and as a tool to help human operators to survey and control these processes, a wide range of sensors based process and tool condition monitoring systems has evolved within the market. Nowadays the most applied ones are based on force and acoustic emissions measurement and their main objectives are to protect the forming facilities avoiding catastrophic tool breakages and to identify instabilities at the forming processes. At the present research work, sheet metal blanking processes have been chosen to evaluate the capacities of sensors based process monitoring systems for the on-line detection of process malfunctions.

Following the directories of the state of the art, the sensors based process monitoring system used at the present research work will be composed of force and acoustic emission sensors installed in both, the tools and the blanking facility. The development of the mentioned system and the results achieved after its application in the blanking facility are explained in “Chapter 4. Sensors based process monitoring”.

On the other hand, and although the detection of some process instabilities can also lead to the detection of defective parts, the verification of the correct quality of the produced parts is not the main objective of sensors based process monitoring systems and therefore they are not able to assure that the 100% of the manufactured parts are good quality parts. Taking into account the limitations of these systems, another type of monitoring systems able to verify the right quality of all the manufactured parts is necessary. AV systems match perfectly with this market need (usually called as production under 0 ppm) because they are focused on checking the quality of the manufactured parts and thus, they can guarantee that all the parts sent to the client fulfil the quality requirements.

However, AV systems have not been widely used in the industrial field due to several reasons like the presence of dusty environments (what reduces the quality of the image acquisition), the expensive investment necessary to implement AV systems, the big size of the systems or the low efficiency of the computing techniques. In spite of this, during the last few years, due to the enormous improvement in the computing field and due to the new solutions developed, like for example intelligent cameras based on FPGAs, most of the drawbacks have been overcome and AV systems are more and more suitable for the manufacturing industry. This way, mixed architectures where the high time consuming algorithms (distortion correction, noise filtering, binarization, contour extraction…) are implemented in smart cameras based on FPGAs and the low time consuming algorithms (dimensions extraction, defects detection, part validity assessment…) are implemented in PC, seem to boost the capacities of AV systems although only laboratory attempts have been carried out. At the present research work, an AV system following such architecture will be developed to check the quality of the parts produced in a high production rate blanking facility. The development of the mentioned system and the results achieved after its implementation in the blanking facility are explained in “Chapter 5. Parts quality control”.

Following the previous reasoning and taking into account the capacities of each mentioned monitoring system, it can be stated that the combined application of both monitoring systems into forming facilities should profit from the advantages of both them, creating profitable synergies. Among all the advantages, remarkable ones are the next:

1. The AV system eliminates the faulty parts sent to the customer (external defective) what improves the image of the company towards its clients, avoids potential big economical losses due to rejection of complete sets of parts and reduce the chance of losing clients due to quality reasons. However, it must be considered that the control carried out by the AV system is off-line, after producing the parts.
2. Complementing the previous one, the sensors based process and tool condition monitoring system reduces the percentage of faulty parts produced within the company (internal defective) because it is an on-line monitoring system capable of instantaneously detecting some process failures that can lead to defective parts. At the same time, this system is able to protect the forming facilities and tooling, reducing economical losses and downtimes.
3. And finally, and since sensors based process and tool condition monitoring systems guarantees the security of the forming facilities and tooling and, at the same time, AV systems guarantees the right quality of the manufactured parts, their

combination opens a door towards a future manufacturing of parts without human presence, what should boost the productivity of the companies.

Although the previously mentioned improvements represents by itself an enormous advantage with respect to actual manufacturing procedures, they still have a limitation; production is stopped when any of the monitoring systems detects a malfunction in the manufacturing process. This condition leads to a scenario where luckily, if the process does not suffer any malfunction, it produces good quality parts for long periods of time without the presence of human operators. On the other hand, if any of the monitoring systems detects a process malfunction or defective parts are detected, the presence of the human operator to solve it and restart the production is required. Thus, next logical step towards autonomous facilities able to produce with a minimum presence of human operators is the creation of intelligent systems able to, besides detecting the process malfunctions or defective parts (achievable nowadays), find their causes and propose the right solutions to correctly restart the production.

The techniques of the AI used to create such an intelligent control system at the present research work will be rule-based ES and CBR techniques. Rule-based ES have been chosen because initially the knowledge of the human expert operator is available and because this technique offers a high understanding of the knowledge when is implemented into the control system. Therefore rule-based ES will be used to create an intelligent control system and to evaluate the capacity of AI techniques to deal with forming processes (in this case a blanking process). And finally, CBR techniques will also be used in order to make easier the knowledge acquisition phase during the development of such an intelligent control system. At the same time, the use of CBR techniques will allow the development of intelligent controllers able to learn and evolve over the time, what will spread the developed methodology to other blanking references, and even forming processes, without big efforts.

As a summary, the potential of this global methodology will be industrially evaluated at the present research work. First, a sensors based process and tool monitoring system and an AV system will be combined to verify the correct running of an industrial blanking facility. And second, a KBS able to, in case of any process failure or defective part detection, identify its reason and right solution will be developed too. The achieved system is not completely autonomous because human operators will carry out the solutions inferred by the KBS, but the main purpose is to validate the performance of such an intelligent system and, if valuable results are achieved, proper actuators should be developed in the future.

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Chapter 3

INDUSTRIAL PROCESS DESCRIPTION

3.- INDUSTRIAL PROCESS DESCRIPTION

With the purpose of facing the future challenges mentioned in “Chapter 2. Scientific and technological background”, an industrial manufacturing process has been selected. The selected industrial manufacturing process, briefly explained at the present chapter, is where the intelligent control system developed at the present research work has been implemented and evaluated. The selected process is the manufacturing of small retaining rings using progressive blanking tools and is carried out into a blanking facility consecrated to the production of small size parts at high production rates. The productive facility belongs to a SME (Small and Medium Size Enterprises) company located in the Basque Country, Industrias Alzuaran S.L. dedicated to the manufacturing of circlips, retaining rings, washers and special parts.

Before the implementation of the intelligent control system, the stability control of the process was based on a Brankamp PK550 unit and carried out by the operator. The Brankamp unit measured the force signal at the connection rod of the blanking facility and the acoustic signals generated during the process. Besides, the operator made a visual quality control of the produced parts following a predefined control procedure. The operator checked the quality of the parts by measuring their main dimensions and by detecting the presence of critical defects like excessive burrs. This quality control was made in predefined periods of time and the operator rejected the parts produced since the previous quality control if defective parts were found.

Although the Brankamp sensors based process monitoring system and the visual inspection made by the operator were able to detect some of the defects at the production, these methods did not assure the production in zero defects. For example, the Brankamp sensors based process monitoring system was able to detect some process instabilities like double parts inside the tool or punch breakages, but it was not able to detect the presence of local areas in the parts with big burrs due to punch micro cracks. On the other hand, although the operator was able to detect this last defect by visual inspection, it could happen that thousands of defective parts could have already been produced with the corresponding economical losses. Therefore, the main idea is to create a control system able to detect defective parts during their production leading to two consequences: the elimination of the external defective (defective parts sent to the customer) and the reduction as much as possible of the internal defective (defective parts detected during the manufacturing process).

At the present chapter, first, a very brief description of Industrias Alzuaran S.L., the company where the intelligent control system has been installed is given. And second, a deeper description of the blanking facility selected for the installation of the intelligent control system, the references to be controlled as well as the tools necessary for the manufacturing of the selected references is written down.

3.1. Industrias Alzuaran S.L.: a real industrial challenge

Since one of the aims of the present research work was to evaluate the developed intelligent control system in an industrial environment, with the advantages and constrains that it encompasses, a company consecrated to the manufacturing of small size parts by means of metal forming processes was initially selected (see Figure 3.1a). Industrias Alzuaran S.L. is a SME company founded in 1958 and dedicated to the manufacturing of circlips, retaining rings, washers and special parts for a wide variety of markets like locksmithing, trade distributors, household appliance white goods or the automotive industry (see Figure 3.1b). The factory is situated in Zaldibar with a usable surface of 5000 square meters and with a workforce composed of 35 people.

Figure 3.1: a) Outside view of Industrias Alzuaran S.L. located in Zaldibar (Spain) and b) Family of parts produced at Industrias Alzuaran S.L.

The factory is composed of four main productive areas (see Figure 3.2). The first area is consecrated to the production of special parts and is composed of 6 non-standard forming machines. In this area, raw materials (spring steel) displayed in coils are converted into special formed parts by means of progressive forming tools. The second area is consecrated to the manufacturing of standard and non-standard circlips, retaining rings and washers and is composed of 12 mechanical presses ranging from 50 to 200 tons. In this second area the raw materials are again spring steel in coils that are transformed into standard and non-standard parts by means of progressive blanking tools. The third area is composed of two furnaces where a heat treatment is applied to the parts to get the final hardness at the material. And finally, the fourth area is composed of tangential grinding machines where the burr produced during the blanking process is eliminated.

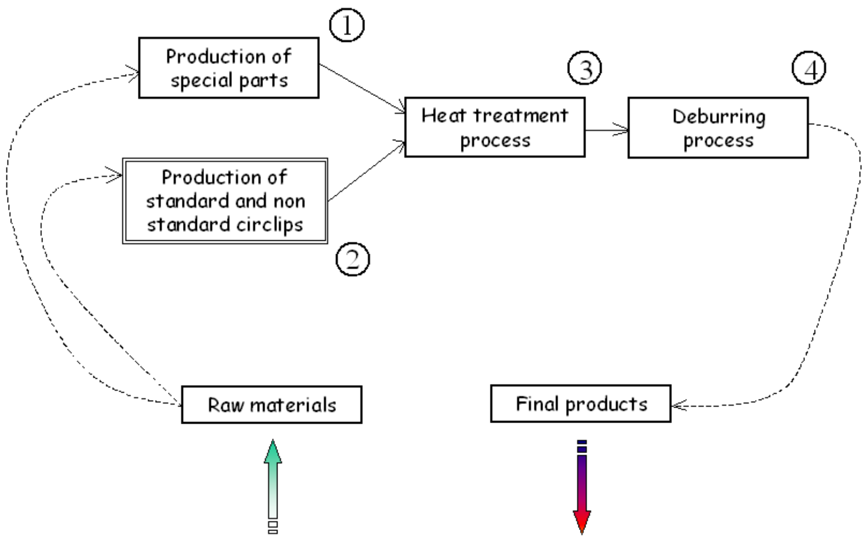


Figure 3.2: Schematic explanation of the manufacturing processes at Industrias Alzuaran S.L.

The manufacturing process of the references selected to be analysed at the present research work goes through the productive areas two, three and fourth described above. In the productive area two, as it will be explained more deeply later, spring steel in coils are transformed into the final parts by means of progressive blanking tools. At the end of this process, the parts get the final shape and dimensions but the hardness of the material is not high enough yet (following heat treatment in productive area three) and the burr created during the blanking process must be eliminated (following grinding process in productive area four). The heat treatment of productive area three and the deburring process of productive area four do not modify the quality of the final parts. This way, if the quality of the parts at the end of the process in productive area two matches with the predefined specifications, the final quality of the parts will be good. On the other hand, an excessive burr height in the parts at the end of the second productive area will not be eliminated in productive area four leading to the final production of defective parts with excessive burr.

Therefore a good quality, all dimensions within tolerances and not excessive burr, at the end of productive area two will lead to the production of good quality parts and this is the reason why the developed intelligent control system has been applied into one of the blanking facilities consecrated to the manufacturing of standard and non standard circlips, retaining rings and washers in productive area two.

3.2. The process: blanking of small retaining rings at high production rates

After evaluating several references produced at Industrias Alzuaran S.L., the most critical ones regarding defects were chosen. Finally, and as it will be explained later, three references that are manufactured in a common blanking facility were chosen. This way, three different cases could be studied by only applying the intelligent control system into one blanking facility. Next, the selected references, the blanking facility where they are produced and the tools for their production are briefly explained.

3.2.1. Description of the selected references

In the next lines, the references that have been studied during the present research work are described. As it was stated above, three references were chosen; reference IA-04, reference 0863-012 and reference 5828-001. The three references belong to the family of retaining rings. A retaining ring is a piece of hardware that holds on to a shaft in order to locate other items on the shaft, or to locate the shaft to a fixed item. There are external retaining rings, which go on the outside of the shaft and internal retaining rings, which go on the inside of the shaft [1]. Next, each of the references is briefly explained.

3.2.1.1. Reference IA-04

The reference described in the following lines is a washer clip that belongs to the family of retaining rings. This reference is used as a security ring to fix elements in axles in order to avoid relative linear movements of the elements with regard to the axles. This reference (IA-04) can be used as an exterior security ring or as an interior security ring. The reference IA-04 is applied in steering systems for the automotive industry and is used to fix some of the elements of these steering systems. Therefore, it can be considered to be a security part for the automobile industry.

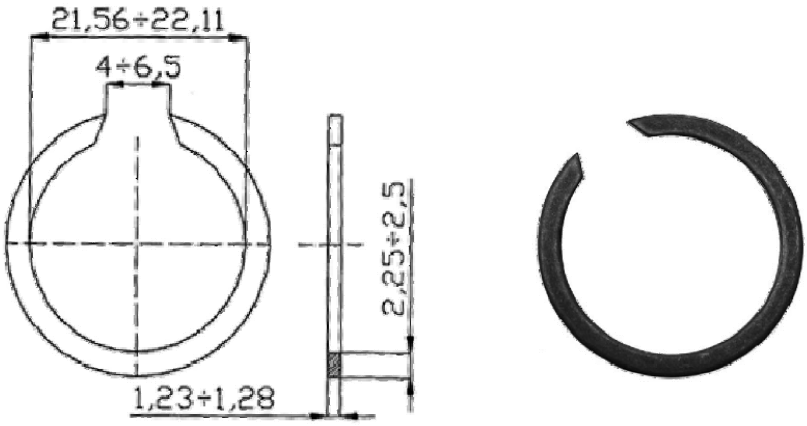


Figure 3.3: Main dimensions of the reference IA-04.

From a quality point of view, the principal characteristics to be fulfilled, in addition to the mechanical properties of the material, is that all the dimensions of the part must be within the tolerances that are presented in Figure 3.3:

- The diameter “A” must be between 21,56 and 22,11 mm.
- The dimension “B” must be between 4 and 6,5 mm.
- The dimension “H” must be between 2,25 and 2,5 mm.
- The thickness “E” must be between 1,23 and 1,28 mm.
- Burr height limited (under operator consideration).

3.2.1.2. Reference 0863-012

The second reference also belongs to the family of retaining rings and is an interior retaining ring. This reference works as a security ring and as it was explained for the first reference, is usually used to fix elements to axles, so these elements cannot move axially along it. This reference can only be used as an interior security ring. The reference 0863-012 is applied in steering systems for the automotive industry and is used to fix some of the elements of these steering systems. Therefore it can be considered to be a security part for the automobile industry.

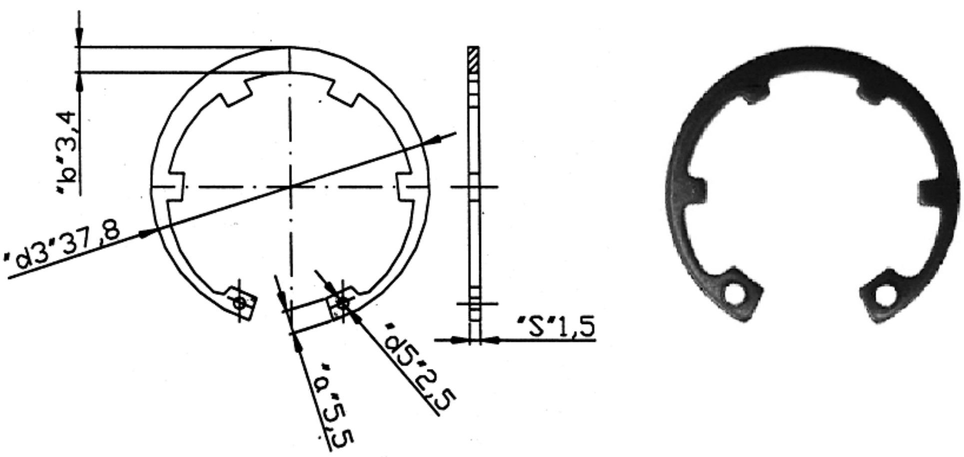


Figure 3.4: Main dimensions of the reference 0863-012.

As in the case of the first reference, the dimensions of the parts must be controlled very strictly and must be within the predefined tolerances. The dimensions that must be within the tolerances are described in Figure 3.4 and summarised next:

- The dimension “b” must be between 3,25 and 3,55 mm.
- The diameter “d3” must between 38,30 and 37,55 mm.
- The dimension “a” must be 5,5 mm as maximum.
- The diameter “d5” must be between 1,23 and 1,28 mm.
- The thickness “s” must be between 1,5 and 1,495 mm.
- Burr height limited (under operator consideration).

3.2.1.3. Reference 5828-001

And finally, the third reference also belongs to the family of retaining rings and as the second reference is an interior ring. This reference works as a security ring and as it was explained for the previous references, is usually used to fix elements to axles, so these elements cannot move axially along it. As mentioned with the second reference, this reference can only be used as an interior security ring. The reference 5828-001 is applied in air conditioning systems also for the automotive industry and used to fix some of the elements of these air conditioning systems.

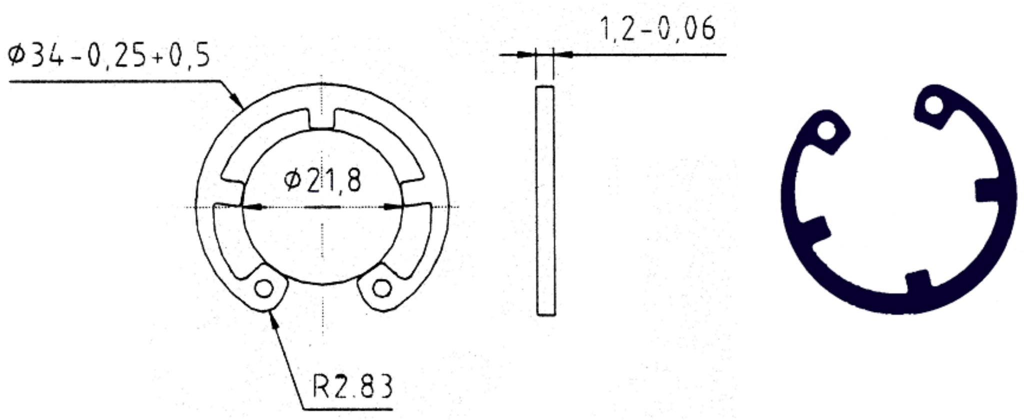


Figure 3.5: Main dimensions of the reference 5828-001.

As in the case of the previous references, the dimensions of the parts must be controlled very strictly and must be within the predefined tolerances. The dimensions that must be between the tolerances are described in Figure 3.5 and summarised next:

- The internal diameter “d3” must be between 21,60 and 22,00 mm.
- The external diameter must be between 33,75 and 34,50 mm.
- The diameter at the holes “d5” must be greater than 2,5 mm.
- The thickness must be between 1,14 and 1,2 mm.
- Burr height limited (under operator consideration).

Besides the above-described tolerances for each reference, a common and very problematic defect in the production of this kind of parts is the presence of local big burrs due to the appearance of micro cracks in the punches. The Brankamp sensors based process monitoring unit is not able to detect the punch micro cracks because they generate very small signals (see Figure 3.6). At the same time this is a repetitive defect and once the micro crack appears in the punch, all the parts that are produced until the operator realises and stops the machine are defective parts.

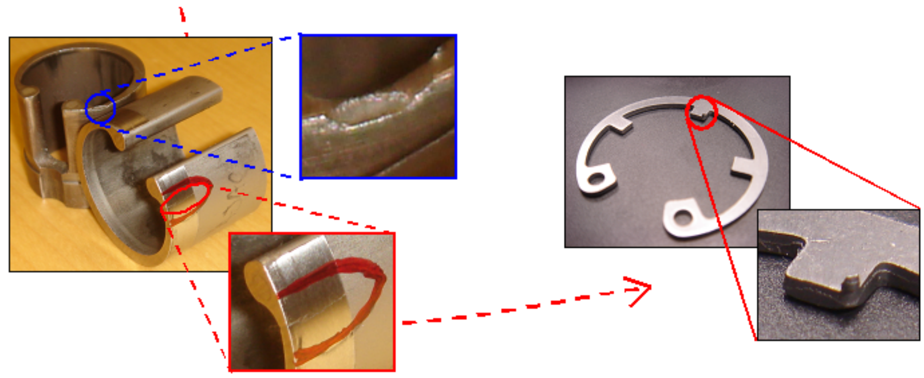


Figure 3.6: Micro cracks in blanking punches and their consequences regarding part quality.

The three references are produced with the same material, spring steel DIN 17222 CK67. Figure 3.7 shows the mechanical properties and chemical composition of the steel used for producing the references.

General data:

Aleación ....: CK-67
Calidad ....: K-70

Mechanical properties:

Resistencia (Nw/mm²) ....: 625,00
Lím. Elástico (Nw/mm²) ..: 590,00
Alargamiento (%) ....: 12,50
Dureza (HRb) ....: 92

Chemical composition:

Carbono ...(C): 0,684	Silicio ..(Si): 0,230	Manganeso (Mn): 0,670
Fósforo ...(P): 0,012	Azufre ....(S): 0,002	Aluminio .(Al): 0,006
Cromo ....(Cr): 0,176	Níquel ...(Ni): 0,000	Cobre ....(Cu): 0,000
Niobio ...(Nb): 0,000	Titanio ..(Ti): 0,000	Molibdeno.(Mo): 0,000
Vanadio ...(V): 0,000	Boro ......(B): 0,000	Nitrógeno (N) : 0,000
Plomo ....(Pb): 0,000		

Figure 3.7: Chemical composition and mechanical properties of CK67 spring steel.

3.2.2. Description of the production facility

All the selected references are manufactured in the same production facility. The production facility consists of a 125 tons Fagor mechanical press and a decoiler and straightener that supply the mechanical press with the raw material, steel sheet in coils (see Figure 3.8). The decoiler feeds the mechanical press and the straightener placed between the decoiler and the mechanical press straightens the material. At the entrance of the mechanical press there is a mechanically driven system connected to the press crankshaft that feeds the material into the tool. This way, the horizontal motion of the material through the tool is synchronized with the vertical motion of the ram. Once the material reaches the tool, the blanking operations take place and the manufactured parts are separated from the steel strip. The parts, depending on the tool's architecture, are pushed downwards through the die or are evacuated from the tool by means of pressurize air. In both cases, the manufactured parts reach the metallic box where the operator will perform the quality control. At the same time, the remaining strip of material is cut in portions of 300 millimetres and is stored in the red metallic box situated in the left of the forming facility.

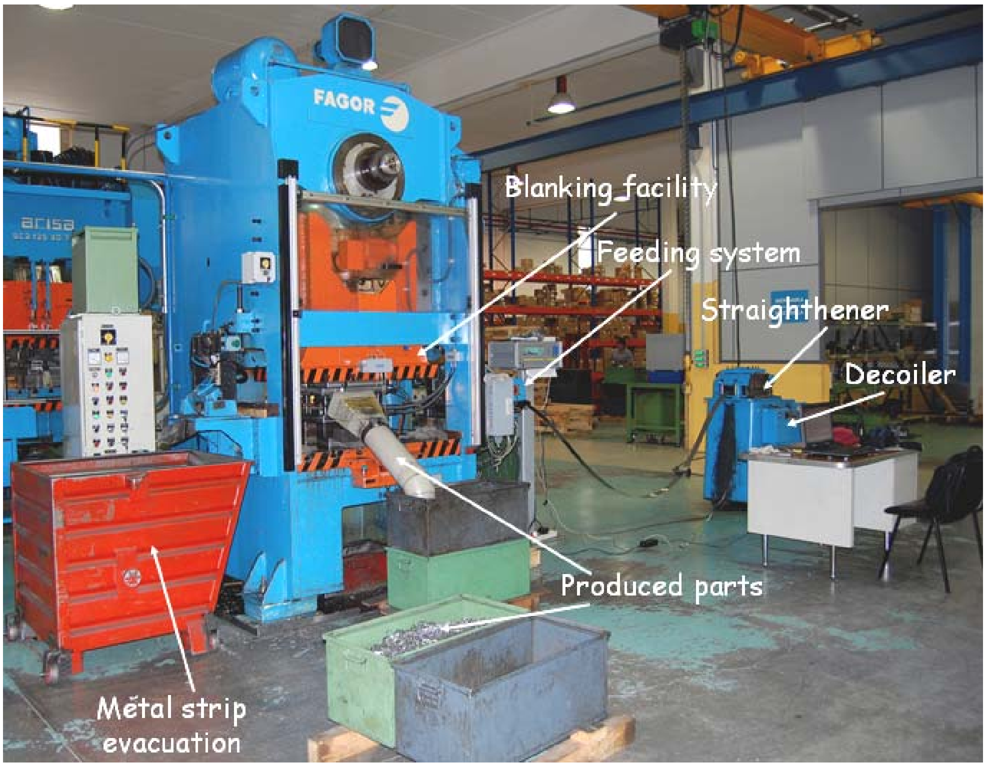


Figure 3.8: Blanking facility in Industrias Alzuaran S.L.

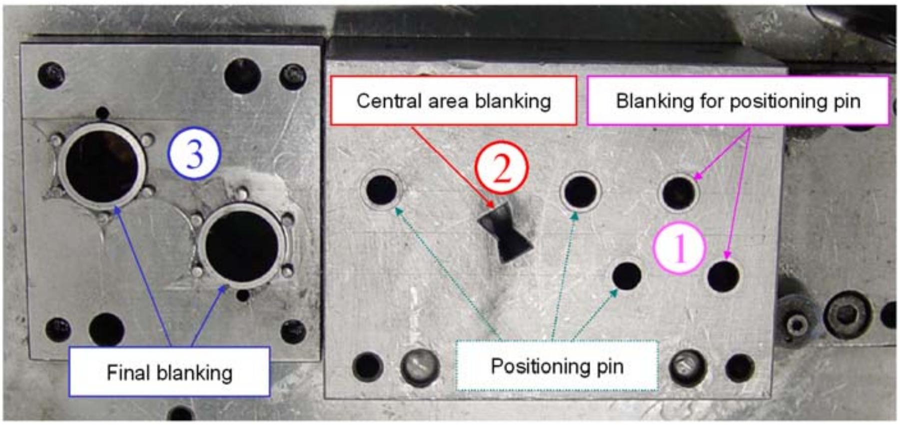
The production rate available at the forming facility ranges from 40 to 70 strokes per minute. The actual production rate selected by the operator is around 50 strokes per minute. The main reason for choosing this production rate is the fact that the operator is responsible of three more production facilities like the aforementioned described, and increments in the production rate could lead to a deficient supervision of the processes. Therefore, nowadays the production rate is 50 strokes per minute and since two parts per stroke are produced, 100 parts per minute are manufactured.

3.2.3. Description of the blanking tools

After describing the references and the manufacturing facility where they are produced, the necessary tools to produce the selected references are briefly described in the next lines. The description of the tools is very important to later understand (as it will be explained in “Chapter 4. Sensors based process monitoring”) the position of the force and acoustic Brankamp sensors. A common characteristic of the three tools is that they are progressive medium size tools that produce two parts per stroke (two lanes exist within each tool). Next, a brief explanation of each tool is given.

3.2.3.1. Reference IA-04

The manufacturing process of the reference IA04 is briefly explained in the following lines. As it was stated before, the part is produced in a progressive blanking tool (see Figure 3.9). The progressive blanking tool is composed of three stations. The forming steps are explained next:



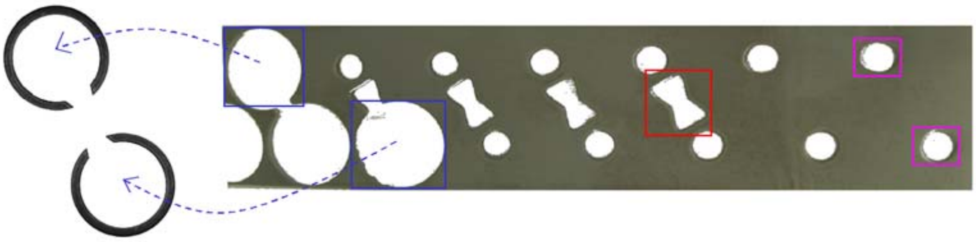


Figure 3.9: Tool and manufacturing process for the reference IA-04.

1. In the first station two cylindrical punches (see Figure 3.9, blanking for positioning pin) shear the metal sheet generating two circular holes. The geometry generated in this first station does not belong to the final parts, but it is used for positioning the strip within the progressive tool by means of the positioning pins.
2. In the second station, a sand clock shape punch (see Figure 3.9, central area blanking) shears a central area of the strip generating the opening of two consecutive parts.
3. And finally, in the third station, two punches (one per lane at the tool) (final blanking) shear the material in two diameters (external and internal final diameter of the parts) generating two parts per stroke that have a ring form as it can be seen in Figure 3.9 (final blanking). The parts are blown out by means of pressurize air and leave the blanking facility through two PVC tubes. The strip of material is cut in portions of 300 millimetres and is stored in a metallic box placed close to the forming facility.

3.2.3.2. Reference 0863-012

The manufacturing process of the reference 0863-012 is briefly explained in the following lines. As in the previous explained reference, the part is produced in a progressive blanking tool composed of three stations (see Figure 3.10). The forming steps are explained next:

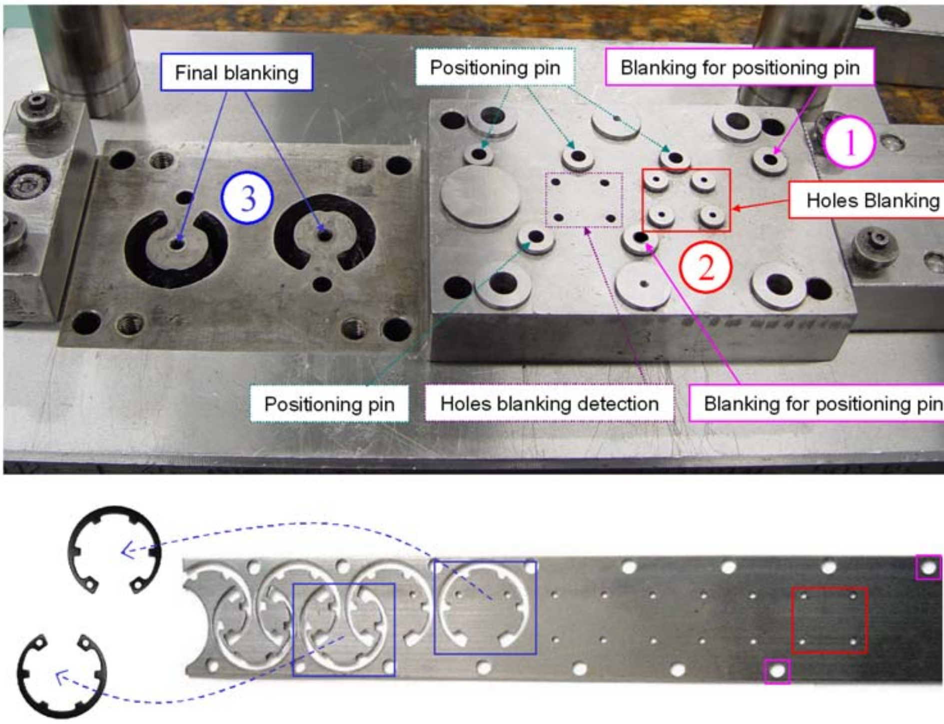


Figure 3.10: Tool and manufacturing process for the reference 0863-012.

1. As in the previous explained reference, and very common in this type of processes, the first station consists of two cylindrical punches (see Figure 3.10, blanking for positioning pin) that generate two circular holes. The geometry generated in this first station does not belong to the final parts, but it is used for positioning the strip within the progressive tool by means of the positioning pins.
2. The second station consists of four small cylindrical punches (see Figure 3.10, holes blanking) that create the corresponding small holes at the ears of the parts. After this second station, there is a checking station that verifies if the four holes were made. In order to make this verification, four pins goes through the previous sheared holes. If any of the pins is not able to go through the holes, the presence of a punch breakage is detected and a switch stops the blanking facility.
3. In the third and last station, two punches (one per lane at the tool) with the same shape as the final parts, shears the material and separate the final parts from the strip (final blanking). The final parts (see Figure 3.10) fall down through the cutting die and are stored in a metallic box under the blanking facility. The strip of material is cut in portions of 300 millimetres and is stored in a metallic box placed close to the forming facility.

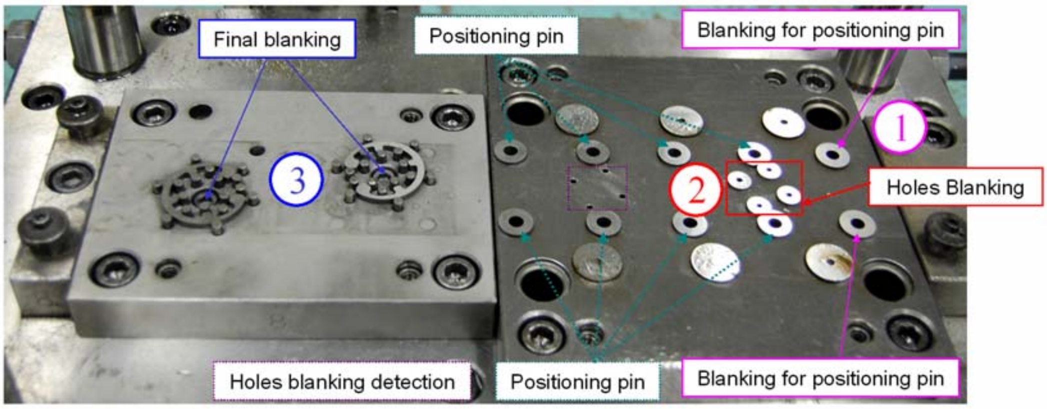
3.2.3.3. Reference 5828-001

The manufacturing process of the reference 5828-001 is very similar to the manufacturing process of the reference 0863-012. Actually, the only difference between these two references is the shape of the final parts. The forming steps of the reference 5828-001 are briefly explained next:

1. As in the previous explained references, the first station consists of two cylindrical punches (see Figure 3.11, blanking for positioning pin) that generate two circular holes. The geometry generated in this first station does not belong to the final parts,

but is used for positioning the strip within the progressive tool by means of the positioning pins.

2. As in the reference 0863-012, the second station consists of four small cylindrical punches (see Figure 3.11, holes blanking) that create the corresponding small holes at the ears of the parts. After this second station, there is a checking station that verifies if the four holes were made. In order to make this verification, four pins goes through the previous sheared holes. If any of the pins is not able to go through the holes, the presence of a punch breakage is detected and a switch stops the blanking facility.
3. In the third and last station, two punches (one per lane at the tool) with the same shape as the final parts, shears the material and separate the final parts from the strip (final blanking). Despite what happened with reference 0863-012, the final parts at this reference (see Figure 3.11) are blown out by means of pressurize air and leave the blanking facility through two PVC tubes (as happened with reference IA-04). On the other hand, as happened with reference IA-04 and reference 0863-012, the strip of material is cut in portions of 300 millimetres and is stored in a metallic box placed close to the forming facility.



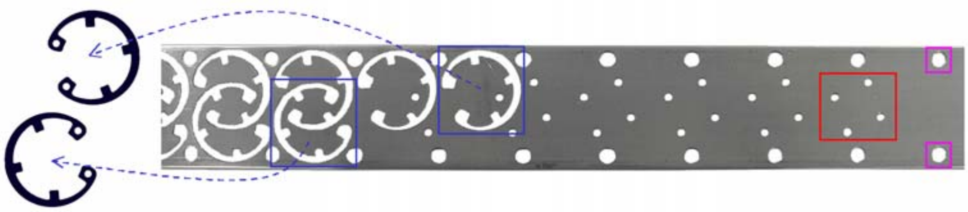


Figure 3.11: Tool and manufacturing process for the reference 5828.001.

3.3. Summary

The present chapter describes the industrial environment where the intelligent control system developed at the present research work has been implemented and tested. The industrial environment selected is a SME company consecrated to the manufacturing of circlips, retaining rings, washers and special parts. The manufacturing process selected within the mentioned company is the production of small retaining rings (external diameter around 50 millimetres) at high production rates (around 120 parts per minute). Since it was desired to carry out as many industrial tests as possible in Industrias Alzuaran S.L., three references, included in the retaining rings family, were selected; reference IA-04, reference 0863-012 and reference 5828-001. These three references were selected because they are very similar one each other and the process failures and defects are very similar for the three of them. Another reason for the election is that the three references are produced at the same production facility. The production facility is a 125 tons mechanical press and its correspondent decoiler and straightener that supply the mechanical press with the raw material, in the form of steel sheet coils. Finally the tools necessary to produce the selected references were also evaluated regarding the future introduction of the force and AE sensors that will survey the manufacturing process.

3.4. Bibliography

[WIK08] http://en.wikipedia.org/wiki/Retaining_ring

Chapter 4

SENSORS BASED PROCESS MONITORING

4.- SENSORS BASED PROCESS MONITORING

The present chapter describes the approach carried out to monitor an industrial blanking process. This approach uses a sensors based process monitoring system in order to detect the process failures in the production facility. The chapter explains the installation of the sensors based process monitoring system into the blanking facility described in “Chapter 3. Industrial process description” and summarizes all the achieved results during the experimental phase.

First of all, a brief worldwide benchmarking of the technology is given. The main purpose of the benchmarking is to select the industrial system that will be used during the research work. After this, a brief description of the sensors based process monitoring system selected for the present research work, the sensing techniques that this monitoring system uses and how the monitoring unit works is explained.

Next, the sensors architecture installed at each of the tools studied during the present research work is described. It is explained the different types of sensors and the different position of the sensors in both the facility and the blanking tools.

And finally, the results achieved with the sensors based process monitoring system during the experimental phase are written down. The results summarize the process failures that the sensors based process monitoring unit was able to detect during the experimental phase and the process failures that were not detected.

Since one of the process failures not detected by the sensors based process monitoring system during the experimental phase is the burr growth in the cutting edge of the parts, a study to find the relationship between this burr growth and the evolution of the blanking forces is presented next.

The chapter finishes with a brief summary of the results and conclusions achieved during the present research work regarding the monitoring of blanking processes by means of a sensors based process monitoring system.

4.1. Introduction.

Krzysztof Jemielniak, in his paper “Commercial Tool Condition Monitoring (TCM) Systems” [JEM99], presented a state of the art in commercially available TCM systems where summarised the leading suppliers of this technology in the market at the end of the last century. Almost 10 years have gone by since then, and the leader companies consecrated to the development of TCM systems are almost the same.

Each TCM system consists of one or more sensors, strategically installed in the production facility/tool, signal conditioners or amplifiers to treat the process signals and a monitor. The function of the monitor is, by means of a predefined strategy, to analyse the process signals coming from the sensors and to provide reliable detection of tool and process failures. It can be equipped with some signal visualisation system (interface with the operator) and is usually connected to the production facility control.

Although TCM systems have been applied to the surveillance of both cutting and forming processes, most of the TCM systems suppliers have been traditionally consecrated to the development of systems applied to cutting processes. This way, companies like Artis (Germany) [ART07], Kistler (Germany) [KIS07], Brankamp (Germany) [BRA07/1], Montronix (USA) [MON07], Nordman (Germany) [NOR07] and

Prometec (Germany) [PRO07] are nowadays the main market suppliers for TCM systems applied to cutting processes.

Regarding forming processes, the topic of the present research work, there are not so many companies consecrated to the development of TCM systems. Four companies are nowadays the leaders at this market.

1. Schwer and kopka (Germany) [SCH07] is also a company consecrated to the development and application of TCM to cold forming processes. Two people (Schwer and Kopka), who previously worked in Brankamp, founded this company in 1990. The TCM systems developed by this company are focused on both the structural integrity of the forming facilities and on the detection of the process failures. The TCM systems are equipped with a few sensing technologies ranging from piezoelectric sensors for force measurement, acoustic emission sensors, motor load sensors, inductive sensors for detection of metal parts to strain measurement sensors.
2. Unidor (Germany) [UNI09] is a company consecrated to the development of monitoring system for the forming industry. The TCM systems developed by this company are focused on both the structural integrity of the forming facilities and forming tools and also on the detection of the process failures. Unidor offers a wide variety of sensors like digital light barriers, analog inductive proximity sensors, force sensors, acoustic emission sensors, eddy current sensors or incremental and absolute path measurement sensors.
3. Siegfried (Czech Republic) [SIE09] is a company consecrated to the development of monitoring system for the forming industry. The TCM systems developed by this company are able to work with up to 8 channels.
4. Helm (US) [HELM09] is a company consecrated to the development of technology for many industrial applications like TCM system for both, the stamping and cutting industry. Helm offers a wide variety of products with TCM systems able to monitor up to 8 channels in real time. The sensors used for this company are principally strain gains and piezoelectric sensors in order to measure forces.
5. Imco (US) [IMC09] is a company consecrated to the development of precision load monitors and die overload detection systems. The systems developed by this company do not cover process monitoring but mainly care about the forces carried out by the facility to form the parts. These systems are very suitable for the detection of overloads that could lead to catastrophic breakages.
6. Brankamp (Germany) [BRA07/1] is considered to be one of the worldwide leaders in the development and application of TCM systems to stamping and presswork processes. Brankamp offers a wider variety of sensing techniques than its competitors and also offers several TCM systems that provide the users with many possibilities and opportunities to improve their processes. Brankamp is the TCM supplier chosen for the present research work. More information about the company and about its TCM systems is provided next.

4.2. Description of a sensors based process monitoring system.

Brankamp System Prozassautomation Gmbh is a German company founded in 1977 by Prof. Klaus Brankamp. The company's head office is in Erkrath, near Düsseldorf. The workforce of the company consists of 65 employees and the annual sales reach approximately € 10 million. Brankamp is considered to be one of the worldwide leaders in process monitoring with over 50.000 applications worldwide, around 30.000 applications located in Central Europe [BRA07/1].

Brankamp offers a wide variety of sensors based process monitoring systems [BRA07/2]. Up to 17 different sensors based process monitoring systems are offered depending on the process to be controlled and on the functions demanded by the user. The sensors based monitoring systems range from the simplest one, the Brankamp B100 [BRA07/3], able to measure up to two different channels to the most sophisticated one, the Brankamp PK6000 [BRA07/4], a windows embedded operating system able to measure up to 12 channels and equipped with a touch screen for an easier communication with the operator.

4.2.1. The monitoring unit.

The Brankamp system selected at the present research work is the PK550 unit [BRA07/5]. The PK550 unit is a sensors based process monitoring system specially designed for the monitoring of forming presses and thread rolling machines. It is able to measure up to 12 different channels, usually force and acoustic emission signals (see Figure 4.1).

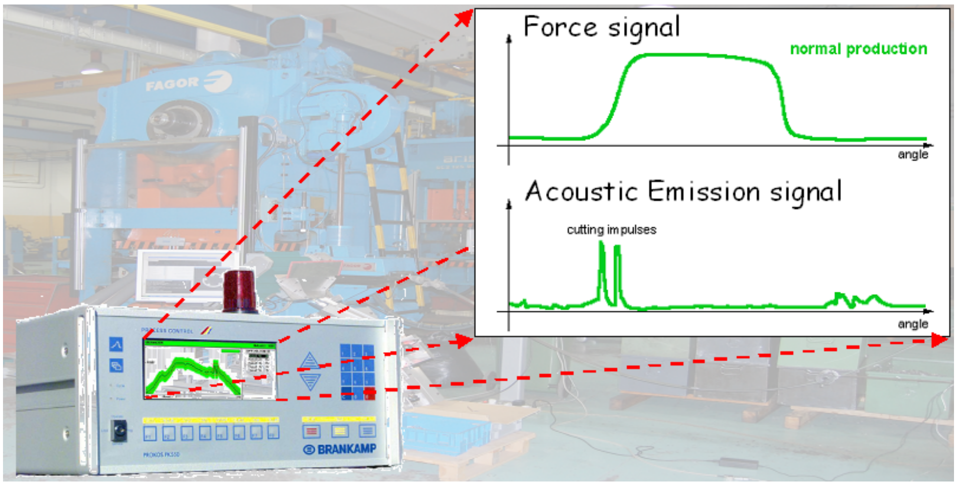


Figure 4.1: Process signal at Brankamp PK550 unit.

The Brankamp PK550 unit is a sensors based process monitoring system designed to monitor the tool and/or facility condition and the product quality during production by evaluating signals specific to the process [BRA07/6]. This Brankamp sensors based process monitoring system works in the following way: after getting a correct process set up at the beginning of the production, a learning phase, during which the signals coming from the process are recorded, is carried out. The recorded signals correspond to a process behaving correctly and producing good quality parts.

As a result, two envelope curves are created, an upper envelope curve and a lower envelope curve. These envelope curves represent the limits that distinguish a nominal production (green area in curves of Figure 4.2) from a faulty production (red areas in curves of Figure 4.9). The operator sets up the distance between the envelope curves. This distance, named sensitivity (see Figure 4.2), depends principally on how stable the process is. For very stable processes, the sensitivity and therefore distance between upper and lower envelope curves can be established around a value of 15 for force signals and 30 for acoustic signals [BRA07/4]. On the other hand, if the process is not very stable, the sensitivity must be set up at greater values, because otherwise, too many false machine stops would happen. The drawback of setting up big sensitivities is that some process failures could be hidden inside the envelope curves and not being detected. Therefore, the ideal situation is to get a very stable signal (sensor located close to the point where the signal is generated) in a very stable process. In this case the operator can choose a small sensitivity value and even small process disturbances will be detected by the system (right side at Figure 4.2).

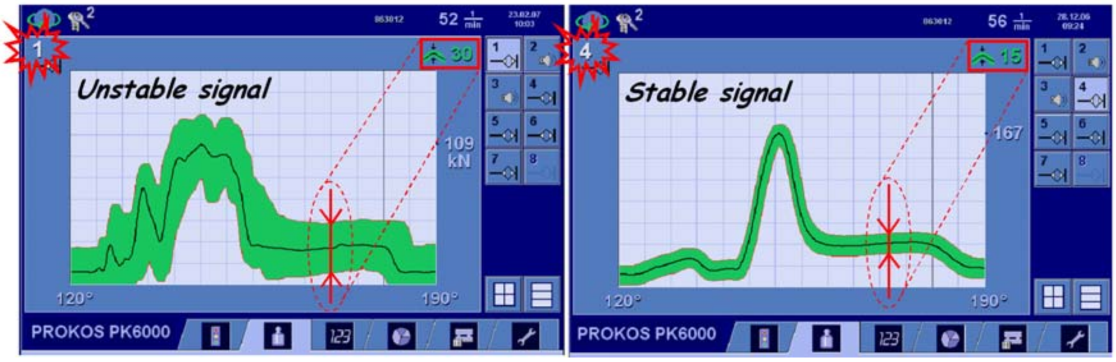


Figure 4.2: Sensitivity set up at Brankamp PK550 unit.

Once this is achieved, the monitoring system is turn into the Auto mode and compares stroke by stroke the signals coming from the process with the envelope curves. In the Auto mode, whenever at least one of the process signals (for example, Figure 4.2 shows the signal of the sensor/channel number 1 in the left side and the signal of the sensor/channel number 4 at the right side of a blanking process) goes beyond the envelope curves, it is interpreted as a disturbance of the process and a faulty production signal is immediately sent to the press control which can react by stopping the facility, issuing a warning or activating a sorter [BRA07/6].

An example of one process failure detection is shown in Figure 4.3. In this case, a slug of material inside the tool blocked the motion of the strip and made it not to move the right distance. As a result, in the next stroke the pilot pins of the tool crashed into the strip generating a faulty production. Figure 4.3 shows how the monitoring system detects a force peak at the beginning of the stroke and identifies that something unusual is happening inside the tool.

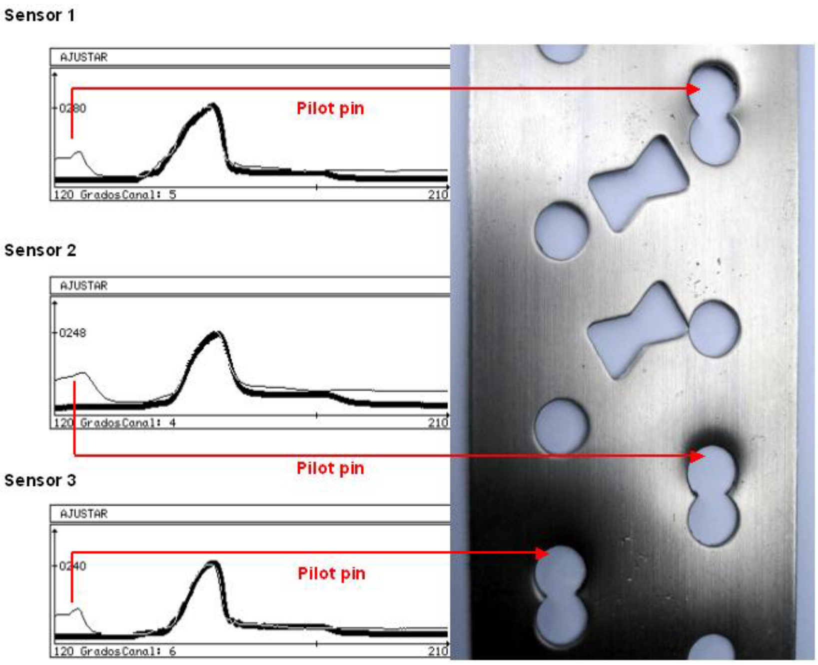


Figure 4.3: Machine feeder failure detection by force measurement.

4.2.2. Sensing techniques in metal forming (MF) process monitoring.

The very first variable used to monitor metal forming processes were the forces generated during the process. Force measurement offered a very good balance between the necessary investment and the achieved results. With the past of the time, and mainly due to the increasingly complexity of the dies and the higher production rates of the facilities, it was detected a lost in the efficiency of the systems that were only based on force measurement. Experience has shown that the monitoring systems that are only based on force measurement can be either too late in recognising or unable to recognise process failures, such as cracks in punches or dies that could lead to catastrophic failures. This is the reason why a newer variable, the measurement of the acoustic signals generated within the material during its deformation, has experienced a huge evolution and is nowadays the best complement to force measurement in sheet metal forming monitoring systems [TER96]. Consequently, sheet metal forming monitoring systems are mainly based on two variables nowadays: the forces generated during the process and the acoustic emission (AE) signals generated within the material during its deformation [COW00].

The aforementioned sensing techniques, force and acoustic emissions, are the ones used at the present research work. Three different types of sensors have been used, two of them for measuring force signals and the third one for measuring acoustic emission signals. All the sensors belong to the same family of transducers: the piezoelectric transducers. A piezoelectric sensor, or transducer, is a device that uses the piezoelectric effect to measure pressure, acceleration or force, by converting them to an electrical signal [WIK07]. Therefore when a force, pressure or acceleration is applied over the material the piezoelectric sensors will react by generating a proportional electrical signal. The applied load can be calculated by measuring the generated electrical signal. Next, the sensors used at the present research work are briefly explained.

4.2.2.1. The Vario Sensor.

The first type of sensor used at the present research work is the Vario Sensor. The Vario Sensor is a force acquisition piezoelectric sensor for indirect force measurement in machine structures. The sensors itself is able to work up to 500 KHz although for force measurements the amplifier only works up to 1 kHz. It is usually clamped in the connection rods of the machines and used to measure the tensile and compressive forces at the machine structure. The sensor is inserted in an 8 millimetres borehole (usually made at the connection rod of the press) and an integrated clamping device is used to preload the sensor (see Figure 4.4) [BRA07/2].

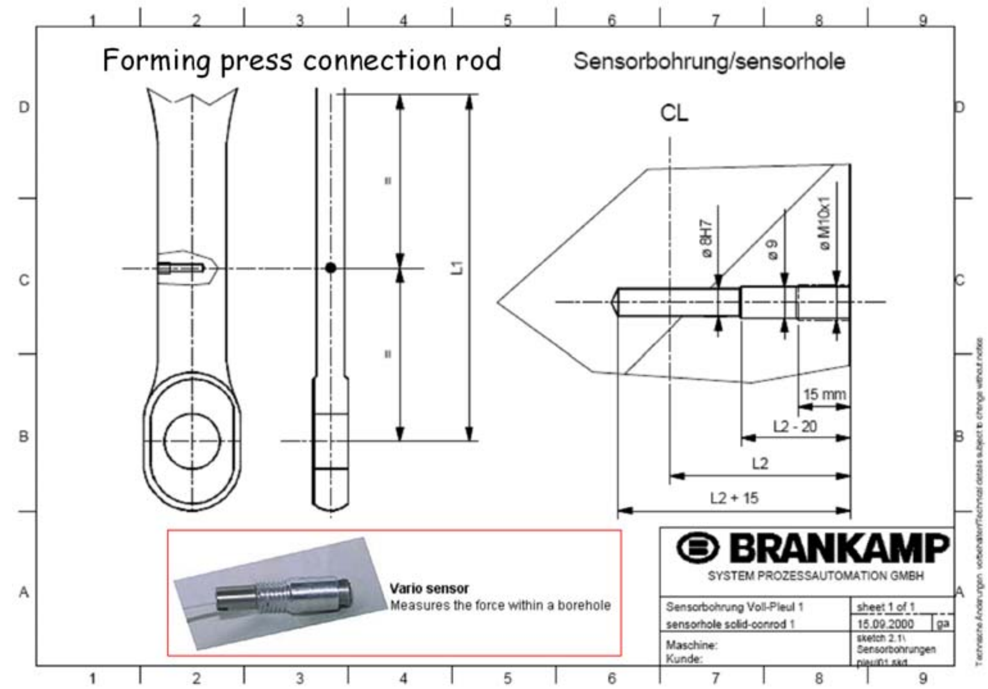


Figure 4.4: Schematic view of the Vario sensor and its installation.

4.2.2.2. The piezoelectric sensor (universal sensor).

The second type of sensor is the universal sensor which is used to measure the strains on the surface of the tools. This type of sensors offers much better responses than Vario Sensors because force measurement using Vario Sensors in the connection rod of the machine has three main limitations.

1. First limitation comes from the fact that there can be a long distance between the point where the force is generated and the point where the force is measured. The greater the distance is the more information that is lost in the way to the measurement point. In this case, since the force is generated within the tool and is measured in the connection rod, part of the force can be dissipated in the tool or even in the structure of the machine and not very accurate results are achieved.
2. Second is that the disadjustments in the bearings of the press or in some other dynamic elements can lead to noises and unstable measurements.
3. And third, when the force is measured in the connection rod of the machine, it is not possible to analyse separately the forces made at each station of the tool. On the

contrary, the sensor measures the complete force made by the machine at each stroke.

Summarising, when the purpose of the system is to work as an overload protection for the machine or for the tool, a Vario Sensor in the structure or in the connection rod of the machine is enough. On the other hand, when process monitoring wants to be achieved, the installation of universal sensors in the tools is much more efficient. The installation of universal sensors in the tools leads to more stable process signals and offers the chance to evaluate each station of the tool separately by installing several sensors in the tool.

Universal sensors are installed in the tools by inserting and sticking the sensor in a groove made at the base plate of the tools. This installation is very efficient because the sensor can be installed close to the punches and dies in the tool. This way a direct measurement is achieved leading to better results. For example, Figure 4.5 shows how for the reference IA-04 at the present research work, five grooves for the installation of five universal sensors were created in the tool. It can be seen how this way, the universal sensors can be installed very close to the punches and dies of the tools leading to very accurate measurements [BRA07/2].

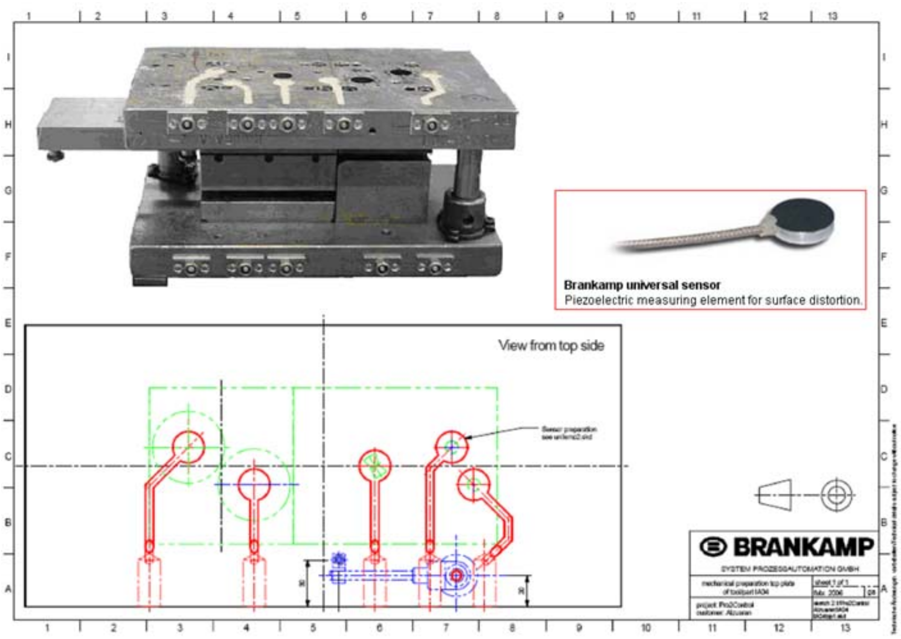


Figure 4.5: Schematic view of the universal sensor and its installation in the tool.

4.2.2.3. The Acoustic Emission (AE) sensor.

And finally, the third type of sensors is the Acoustic Emission (AE) sensor. As it was said above, AE sensors are nowadays the best complement to force measurement in forming processes. At the present research work, Brankamp provided AE sensors for detection of tool breakage in the low frequency (LF) range, from 1 kHz up to 30 kHz. These sensors are equipped with a partly free vibrating ceramic piezo element and are mounted with a M8 screw to the surface of the tool [BRA07/2]. AE sensors are usually installed in the upper tool. The reason is that the main purpose of these sensors is to detect the breakages of the punches at the tool. Figure 4.6 shows schematically how one of the AE sensors used at the present research work was mounted in the upper tool that produces the reference 0863-012.

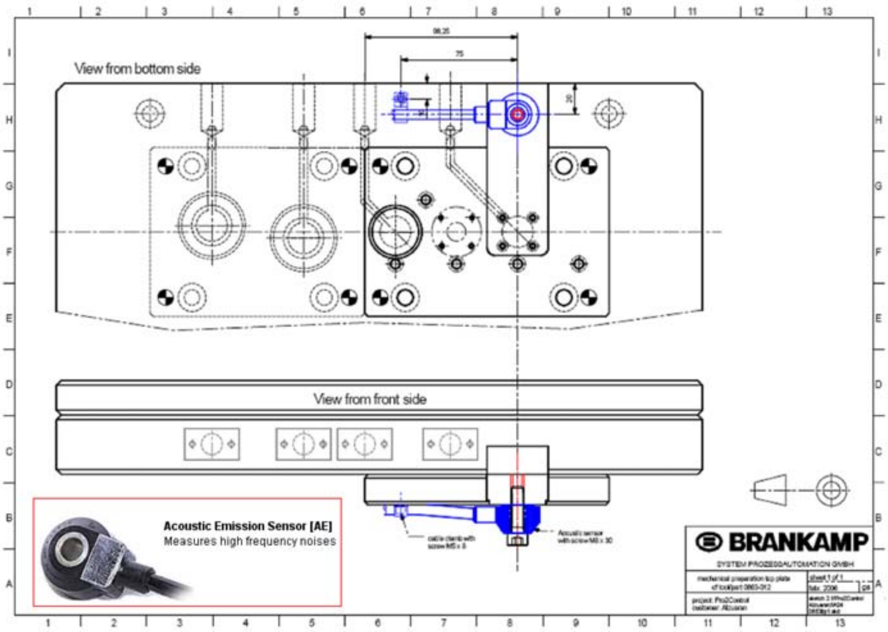


Figure 4.6: Schematic view of the AE sensor and its installation.

4.2.3. The measuring chain and the process signals.

After describing the PK unit and the sensors typology, next a brief description of the measuring chain at the process is given (see Figure 4.7).

1. The piezoelectric sensors, either force or acoustic emission sensors attached to both the tool and the machine, generate charge proportional to the forces or acoustic emissions signals generated during the process.
2. These electrical signals are driven to a connection box usually placed at the ram of the machine (for sensors attached to the top tool) or at the bed of the machine (for sensors attached to the bottom tool). The main function of the connection box is to make easier for the operator the connection of sensors from different tool references.
3. From this connection box the signals are driven to the amplifier box. In the amplifier box, specific electronic cards get voltage signals (0 to 10 volts). Each type of signal (force or acoustic emission signals) has specific cards and is filtered at specific frequencies. This amplification makes the signals more robust and therefore more accurate results are achieved.
4. After amplifying the signals, these are driven to the PK unit. In the PK unit, an analog to digital converter transforms the signals in order to compute them. Stroke by stroke, the process signals are compared and shown in the screen of the PK unit together with the envelope curves. Whenever the process curves are out of the envelopes, the PK unit sends a signal to the controller of the forming facility in order to activate a sorter and reject the part or to stop the production facility.

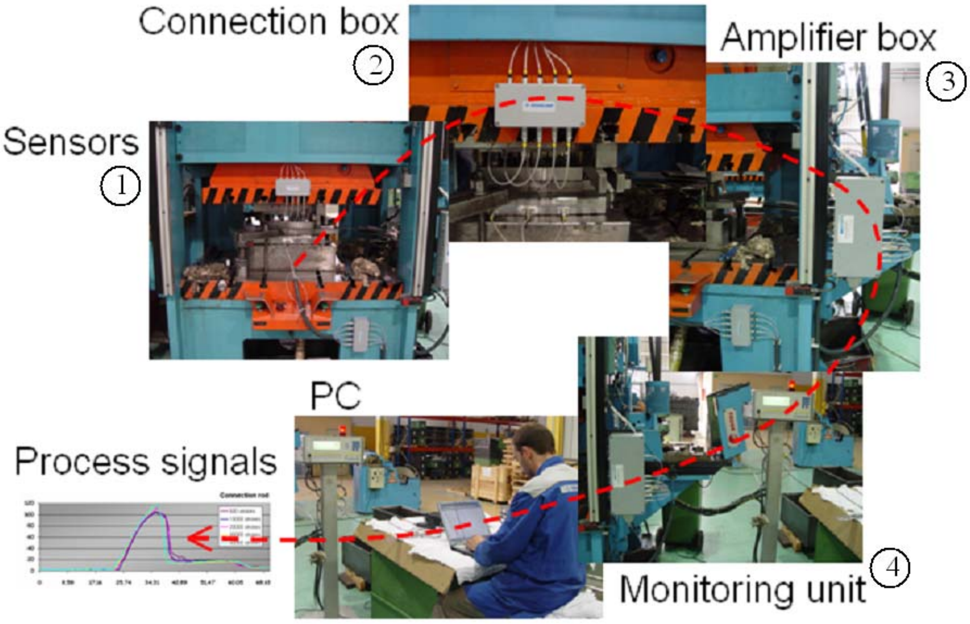


Figure 4.7: Measuring chain from the sensor to the PK unit.

The previous explained one is the working procedure of the Brankamp commercial systems. Besides this and for the actual research work, a computer was connected to the PK unit in order to download and record the process signals. The computer was connected to the PK unit through a serial line and text files containing the information of the process signals were downloaded into the hard disk of the computer (see Figure 4.8). In the PC, and as it will be explained in “Chapter 6. Intelligent Control System”, the signals coming from the process have been analysed with the purpose of identifying the process failure at the facility, its reason and the solution that should be applied to solve it. Figure 4.8 shows the representation of a process failure detected by the Brankamp PK unit. It shows how the text files downloaded from the Brankamp PK unit contain four rows of numerical values per sensor. First row is the time scale, second row is the lower envelope curve, third row is the actual process curve and fourth row is the upper envelope curve. Figure 4.8 also shows the representation of one text file made in Microsoft Excel where the process failure is clearly detected.

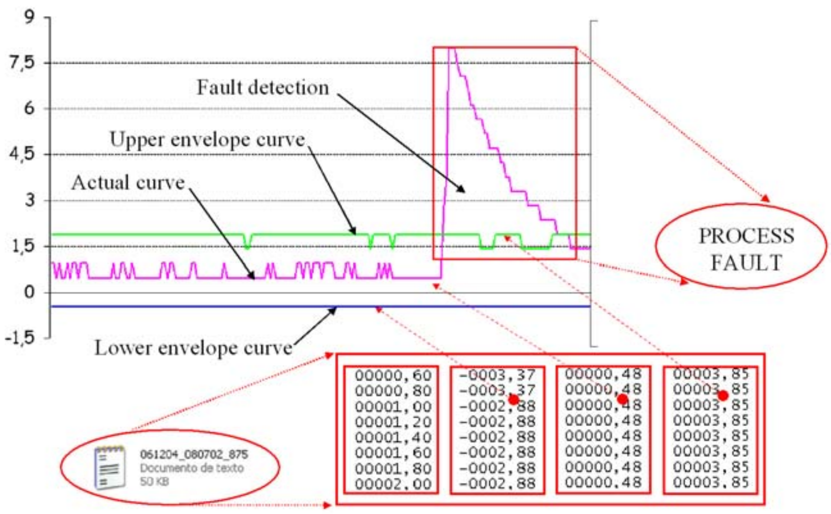


Figure 4.8: Text file containing the data of the process and its representation in Excel.

4.3. Implementation of the sensors based process monitoring system into the sheet metal blanking process.

Next, the sensor architecture proposed for each of the references studied at the present research work will be explained. At the beginning of the research work the blanking facility was already equipped with the Brankamp PK550 unit and three different process signals were recorded. The process signals captured were the force at the connection rod by a Vario Sensor and the acoustic emissions generated within the material during the cutting process and during the withdrawal of the ram by two AE sensors. With this architecture, the Brankamp PK 550 unit was able to detect some of the process failures at the blanking facility but was not able to detect all the possible process failures. The process failures detected with the previous sensor architecture are shown in Figure 4.9.

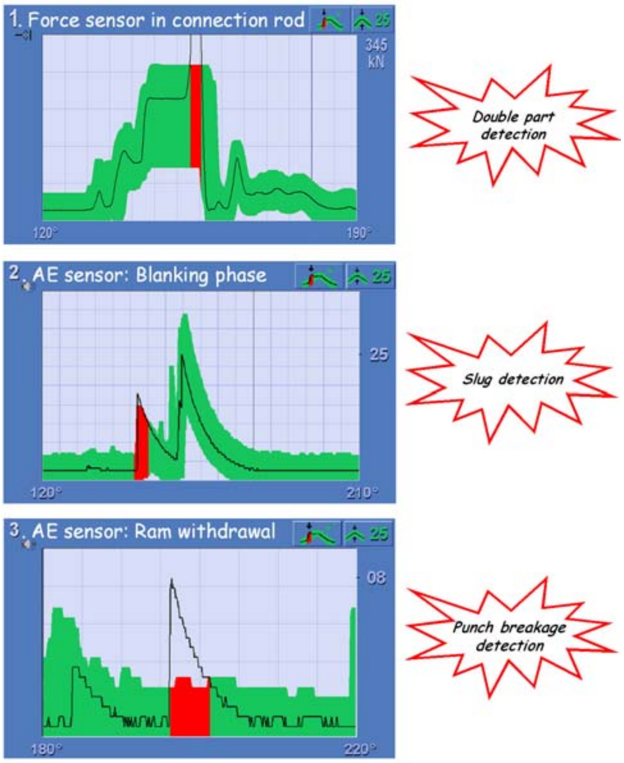


Figure 4.9: Process failures detected by the former sensor architecture.

As it is shown in Figure 4.9, with the former sensor architecture some of the process failures like double parts inside the tool due to malfunctions of the evacuation system, bad evacuated slugs of material due to misalignments in the punches / dies or punch breakages at the tool were able to be detected. It was also stated that the detection of these defects was not 100% assured due to the low reliability of the sensors (Vario Sensor in the connection rod). This former configuration had the advantage that no big modifications were needed when new references were produced at the blanking facility: only two screws at the new tool for the AE sensors. On the other hand, this former configuration based on a Vario Sensor in the connection rod and two AE sensors in the tool had a few drawbacks that are summarised next:

1. Not all the process failures were detected with the former sensor architecture. For example, as it will be shown later, the Vario Sensor at the connection rod of the machine was not able to detect the adhesion of the strip to the pilot pins or punches at the tool. This process failure leads to malfunctions of the feeding system.

2. The position of the Vario Sensor in the connection rod, far away from the blanking process, made this sensor not to get all the information from the process. Therefore, the reliability at the detection of the process failures was not very high, and happened that the same process failure was sometimes detected and some other times not detected.
3. Regarding the Vario Sensor in the connection rod, it was also found that the disadjustments in the bearings of the machine introduced noises into the captured signal. This made the Vario Sensor to behave very unstably, stopping the blanking facility many times. The consequence was that the operator always worked with a big sensitivity at this sensor and therefore some process failures were not detected due to this very permissible sensitivity.
4. In the cases when the sensors were able to detect a process failure, the position of the failure at the tool was not identified. Since the sensors were capturing the signals coming from all the stations at the tool, they were able to detect a process failure, but its position within the tool had to be found by the operator. It will be shown later how, with the sensor architecture proposed at the present research work, the position of the failure at the tool is also found by the sensors based process monitoring system.

After analysing all the previous mentioned drawbacks, it was decided to include universal sensors in the three tools that have been studied in the present research work. In order to achieve the best results, initial trials were carried out to evaluate the best position for the universal sensors within the tools. This way, sensors in the upper and lower side of the tools were placed ones in front of the others (as closer as possible to the blanking area). The conclusion, as shown in [SAE07], was that the sensitivity of the sensors placed in the upper side of the tools was bigger than the sensitivity of the sensors placed in the lower side of the tools. This fact is due to the place where the sensors can be positioned inside the tool; the sensors in the upper tool are completely centred with the cutting area whereas the sensors in the lower tool can not be centred because the parts, some of the references, are evacuated through the dies (in reference 0863-012 at the present research work).

This way, the three aforementioned sensors, the Vario Sensor at the connection rod and the two AE sensors in the tools were kept and the new universal sensors were installed in the upper blanking tools. A universal sensor was installed for each one of the stations at each tool in order to have the possibility of determining the station where the process failures happen. Next, a brief description of the sensors included for each reference is given.

4.3.1. Reference IA-04

As described in “Chapter 3.2.3. Description of the blanking tools”, the tool that produces the reference IA-04 can be divided into three stations. In the first station, two circular holes for guiding the strip through the tool are blanked. In the second station, a central area common to two consecutive parts is blanked. And in the third station, both parts are blanked and therefore released from the strip. It was decided to install universal sensors in all the blanking stations at the tool. As it is shown in Figure 4.10, five universal sensors were installed in the upper base plate of the tool.

1. Two sensors measure the force at the punches that blank the holes for the pilot pins.
2. One more sensor measures the force at the punch that creates the central area common to two consecutive parts in the strip.
3. And two more sensors measure the force at the main punches of the tool, the punches that blank the contour of the parts releasing them from the strip.

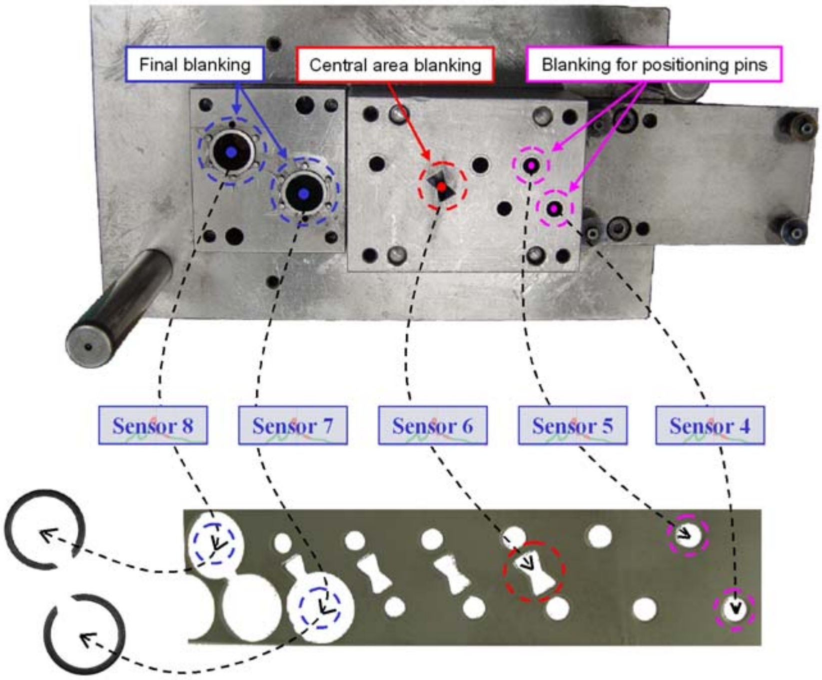


Figure 4.10: Universal sensors installation in reference IA-04 tool.

The installation procedure was the one explained in “Chapter 4.2.2. Sensing techniques in MF process monitoring”. This way, five grooves were machined in the base plate of the upper tool and the sensors were installed by means of specific glue.

The installation of all these sensors lead to a process monitored by eight different sensors. Next, the final sensor architecture applied to this reference is summarised (see also Figure 4.10 for force sensors attached to the tool).

- ✓ Sensor 1: Force sensor at the connection rod of the machine.
- ✓ Sensor 2: AE sensor capturing signal during the blanking phase.
- ✓ Sensor 3: AE sensor capturing signal during the withdrawal phase.
- ✓ Sensor 4: Force sensor at blanking for positioning pins (first) station in lane 1.
- ✓ Sensor 5: Force sensor at blanking for positioning pins (first) station in lane 2.
- ✓ Sensor 6: Force sensor at central area blanking (second) station.
- ✓ Sensor 7: Force sensor at final blanking (third) station in lane 1.
- ✓ Sensor 8: Force sensor at final blanking (third) station in lane 2.

After the installation, tests to check the performance of the sensors were made. The results are described in “Chapter 4.4. Results achieved with the sensors based process monitoring system”.

4.3.2. Reference 0863-012

As described in “Chapter 3.2.3. Description of the blanking tools”, the tool that produces the reference 0863-012 can be divided into three stations. In the first station, two circular holes for guiding the strip through the tool are blanked. In the second station, four small cylindrical punches blank four small circular holes in the central area of the strip. These small circular holes correspond to the holes at the ears of two consecutive parts. And in the third station, both parts are blanked and therefore released from the strip. At this tool, and since the station where the holes for the pilot pins are blanked was already monitored in the reference IA-04, it was decided to install sensors only in second and third stations. This way, four universal sensors were installed in the tool as it is shown in Figure 4.11.

1. One sensor measures the force that the four small cylindrical punches make when the small circular holes are created.
2. Another sensor is placed in the area where four pilot pins check if the small holes at the ears of the parts were correctly punched in the previous station.
3. And two more sensors measure the force at the main punches of the tool, the punches that blank the external contour of the parts releasing them from the strip.

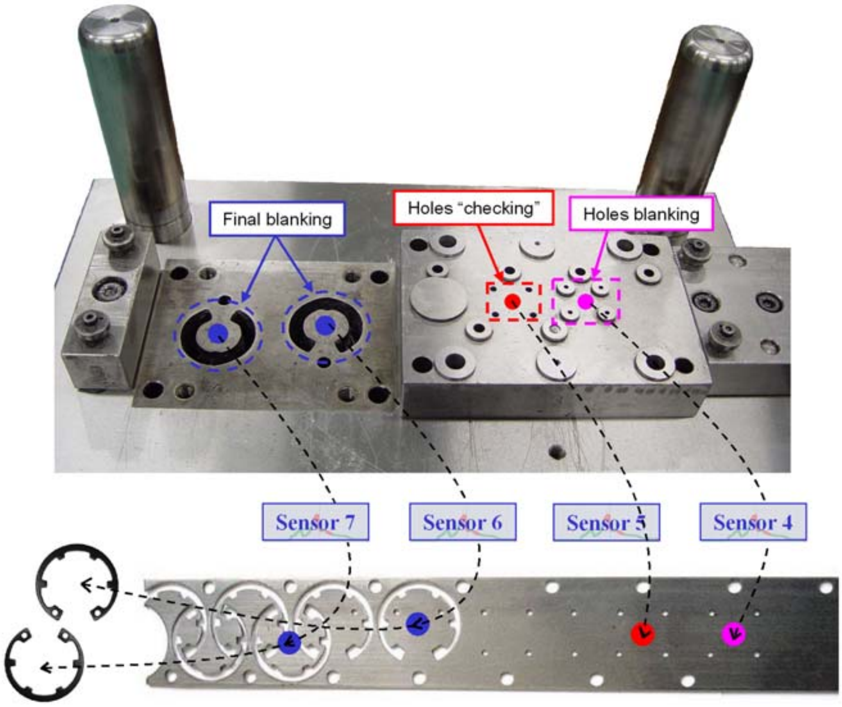


Figure 4.11: Universal sensors installation in reference 0863-012 tool.

Again, the installation procedure was the one explained in "Chapter 4.2.2. Sensing techniques in MF process monitoring". In this case, four grooves were machined in the base plate of the upper tool and the sensors were installed by means of specific glue.

The installation of all these sensors lead to a process monitored by seven different sensors. Next, the final sensor architecture applied to this reference is summarised (see also Figure 4.11 for force sensors attached to the tool).

- ✓ Sensor 1: Force sensor at the connection rod of the machine.
- ✓ Sensor 2: AE sensor capturing signal during the blanking phase.
- ✓ Sensor 3: AE sensor capturing signal during the withdrawal phase.
- ✓ Sensor 4: Force sensor at the holes blanking (second) station.
- ✓ Sensor 5: Force sensor at the holes "checking" (second) station.
- ✓ Sensor 6: Force sensor at final blanking (third) station in lane 1.
- ✓ Sensor 7: Force sensor at final blanking (third) station in lane 2.

After the installation, tests to check the performance of the sensors were made. The results are described in "Chapter 4.4. Results achieved with the sensors based process monitoring system".

4.3.3. Reference 5828-001

Finally, and as it was mentioned in “Chapter 3.2.3. Description of the blanking tools”, the manufacturing process and therefore the tool for producing the reference 5828-001 is very similar to the tool used for producing the reference 0863-012. Again, the tool can be divided into three main stations. In the first station, two circular holes for guiding the strip through the tool are blanked. In the second station, four small cylindrical punches blank four small circular holes in the central area of the strip. These small circular holes correspond to the holes at the ears of two consecutive parts. And in the third station, both parts are blanked and therefore released from the strip. In this case, three universal sensors were installed in the tool, as it is shown in Figure 4.12.

1. One sensor measures the force that the four small cylindrical punches make when the small circular holes are blanked.
2. Two more sensors measure the force at the main punches of the tool, the punches that blank the external contour of the parts releasing them from the strip.

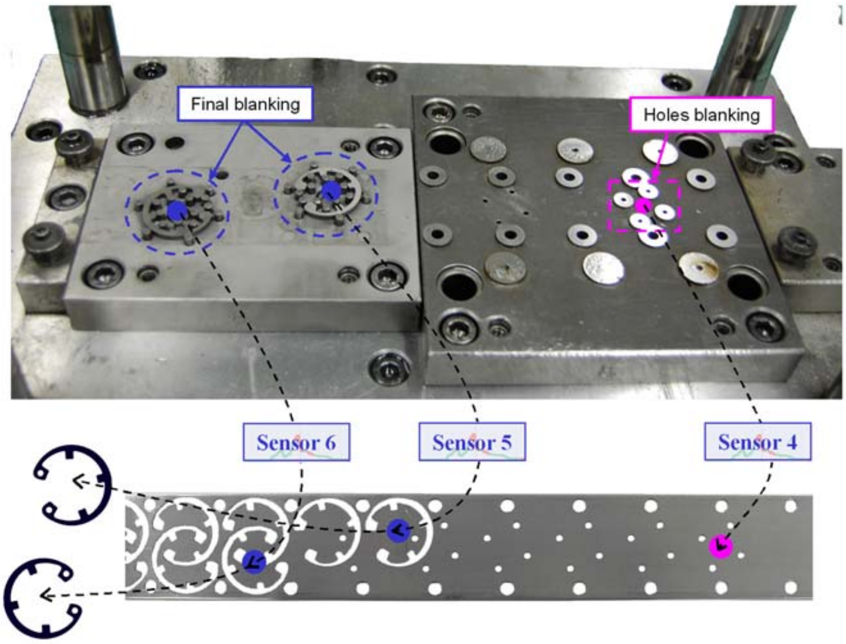


Figure 4.12: Universal sensors installation in reference 5828-001 tool.

And finally, the installation procedure was again the one explained in “Chapter 4.2.2. Sensing techniques in MF process monitoring”. In this case, three grooves were machined in the base plate of the upper tool and the sensors were installed by means of specific glue.

The installation of all these sensors lead to a process monitored by six different sensors. Next, the final sensor architecture applied to this reference is summarised (see also Figure 4.12 for force sensors attached to the tool).

- ✓ Sensor 1: Force sensor at the connection rod of the machine.
- ✓ Sensor 2: AE sensor capturing signal during the blanking phase.
- ✓ Sensor 3: AE sensor capturing signal during the withdrawal phase.
- ✓ Sensor 4: Force sensor at the holes blanking (second) station.
- ✓ Sensor 5: Force sensor at final blanking (third) station in lane 1.
- ✓ Sensor 6: Force sensor at final blanking (third) station in lane 2.

After the installation, tests to check the performance of the sensors were made. The results are described in “Chapter 4.4. Results achieve with the sensors based process monitoring system”.

4.4. Results achieved with the sensors based process monitoring system.

During the experimental phase, at the blanking facility in Industrias Alzuaran S.L., the aforementioned references as well as some other references produced at the same blanking facility were monitored. The reason for this is that the experimental phase was carried out in an industrial facility and the references to be produced were decided by the production manager in Industrias Alzuaran S.L. As mentioned before, this was also the reason for introducing sensors in more than one reference, to be able to produce as many parts as possible with sensorised tooling. Therefore, when the aforementioned references were monitored, the signals described in “Chapter 4.3” were recorded. On the other hand, when some other references were produced at the blanking facility, the experimental phase was carried out with the monitoring of the next described signals:

- ✓ Sensor 1: Force sensor at the connection rod of the machine.
- ✓ Sensor 2: AE sensor capturing signal during the blanking phase.
- ✓ Sensor 3: AE sensor capturing signal during the withdrawal phase.

Since most of the references produced at the blanking facility belong to the family of retaining rings and their manufacturing processes are very similar, it can be stated that the set of process failures detected at the blanking facility are common to all this family of parts. Next, a summary of all the process failures detected at the blanking facility for the produced references is described. At the same time, after describing the process failures that were detected, a small summary of the process failures that were not successfully detected using the Brankamp sensors based process monitoring system will be also described.

4.4.1. Process failures detected by the sensors based process monitoring system

Next, the process failures detected during the experimental phase with the help of the Brankamp sensors based process monitoring system are described. Up to nine different process failures were successfully detected with the Brankamp sensors based process monitoring system, what means approximately 95% of the possible process failures at the blanking facility. The other 5% of defective parts belongs principally to parts with local big burrs and parts out of tolerances (defects explained in “Chapter 5. Part quality control”) and parts with excessive burr (topic explained in “Chapter 4.5. Evolution of the process signals and part’s edge quality during the production”).

4.4.1.1. Feed failure I: Strip completely blocked

First process failure detected at the blanking facility happens when the metal strip is completely blocked and the feeding system cannot advance it between two consecutive strokes. When this happens, in the second stroke the punches go through the holes blanked in the previous stroke and the machine does not apply force at all over the strip.

Next, an example of this process failure during the production of the reference IA-04 is given. Figure 4.13 shows how the process failure is detected by the sensors based process monitoring system. The force and the acoustic signals in all the sensors are completely flat. This process failure happens when there is some metal slug inside the tool that has not been correctly evacuated. The metal slug blocks the movement of the strip and in consequence, the strip remains in the same position. This process failure does not represent an instant threat for the integrity of the tool or machine but at the same time stops the manufacturing process because no parts are produced. When this problem failure happens, the operator has to release the metal strip from the tool and find and evacuate the metal slug that avoids the advance of the strip.

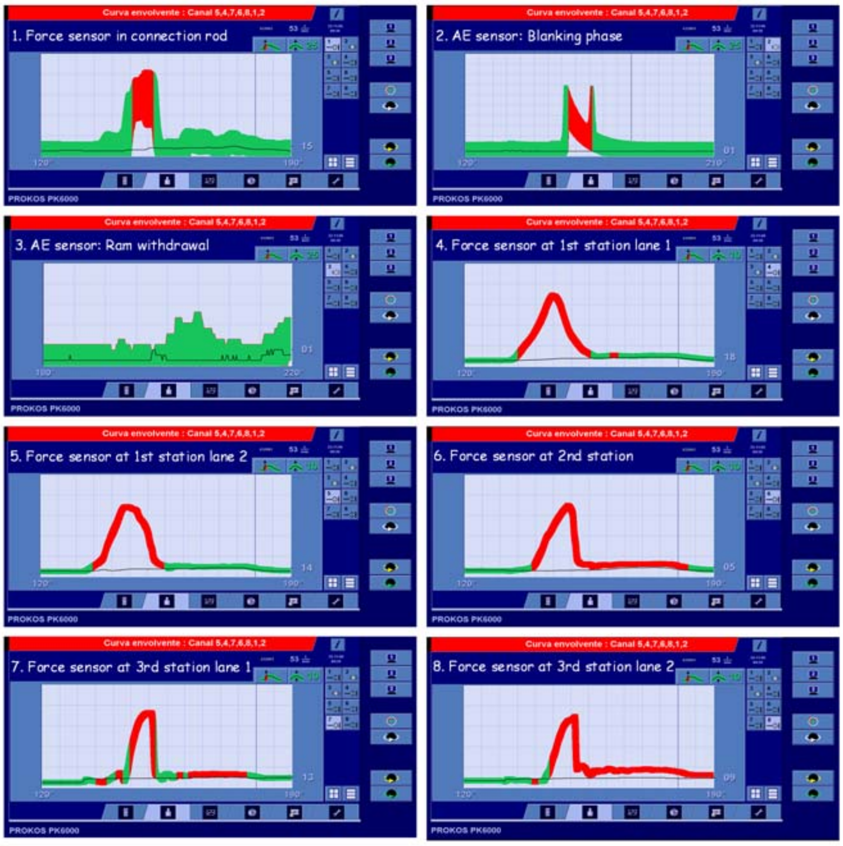


Figure 4.13: Process signals during feed failure I: Strip completely blocked (reference IA-04).

4.4.1.2. Feed failure II: Strip partially blocked

Second process failure detected at the blanking facility is very similar to the first one described above. In this case although the feeding system is able to advance the metal strip, this does not reach the right position because something is blocking its movement. When this happens and the metal strip does not get the right position inside the tool, the pilot pins, instead of crossing the centring holes, crash the metal strip generating faulty centring holes. These faulty holes and their consequences are shown in Figure 4.14 (during manufacturing of reference IA-04): the pilot pins blank the metal strip and therefore the right position of the strip inside the tool is lost. This could have two consequences: first consequence is that the quality of the produced part is lost because there is a misalignment between stations at the tool. And second and more problematic is that if this process failure is not detected on time, the dies and punches at future stations could suffer catastrophic failures due to the incorrect position of the strip inside the tool.

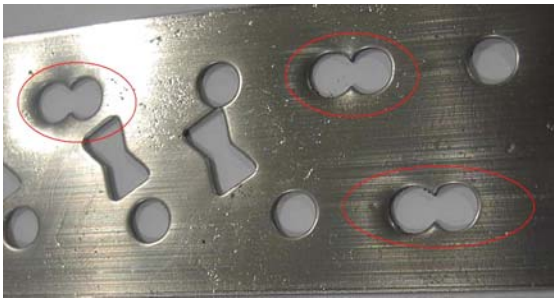


Figure 4.14: Consequences of the feed failure in the metal strip.

Since the pilot pins are longer than the blanking punches because they have to position the metal strip before the punches blank the new holes, the sensors based process monitoring system is able to find this defect due to the force increment detected at the beginning of the stroke. This force increment is due to the force that the pilot pins make for blanking the metal strip and is shown in Figure 4.15.

Since the pilot pins are located in the first and second station of the tool, is in this area of the tool where the forces are higher at the beginning of the stroke. It is shown in Figure 4.15 how the force signal at the beginning in sensor 4, sensor 5, sensor 6 and sensor 7 is bigger than the nominal. It also can be seen how the force signal is much bigger in sensor 4, sensor 5 and sensor 6 than in sensor 7. This is due to the proximity of the sensors to the area of the tool where the process failure happened. It can be concluded with this information that the process failure happened in the first and second station of the tool and not in the last station.

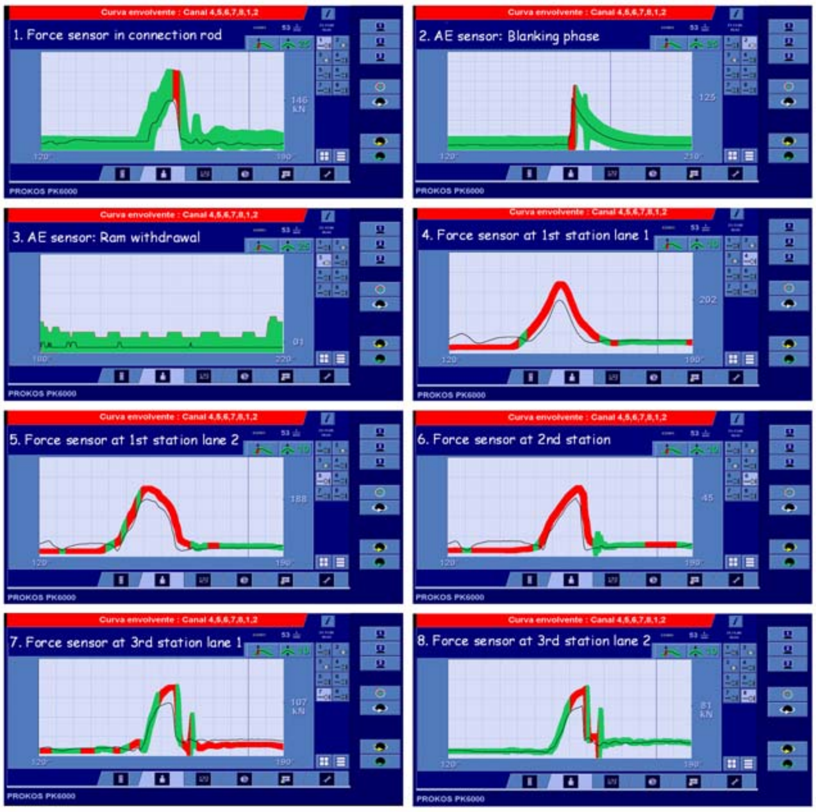


Figure 4.15: Process signals during feed failure II: Strip partially blocked.

At the same time, another fact must be taken into consideration. Although it is shown in Figure 4.15 that the signals coming from the machine are most of time out of the envelopes (represented as red area), it must be considered that only the first area where the signals are out of the envelopes represents the process failure. The reason for this is that once the sensors based process monitoring system detects this initial faulty area, the machine is stopped and therefore all the process signals are modified. Therefore, although it could be concluded that this process failure is also detected at references monitored only with the force sensor at the connection rod (first sensor), this is not so clear because the failure detected by this sensor (red area) in this case was due to the machine stop and not to the process failure itself. The force at the beginning of the stroke for sensor number one remains inside the envelopes (too big sensitivity due to an unstable signal).

The restarting procedure is the same as the one applied in the previous case: the operator has to release the metal strip from the tool and find and evacuate the metal slug that avoids the correct advance of the strip.

<u>4.4.1.3. Metal slug in pilot pins station</u>

Third process failure detected at the blanking facility is the presence of a badly evacuated metal slug inside the tool. An example of this process failure detected when the reference IA-04 was being produced is explained next. The tool for producing this reference evacuates the metal slugs through the dies in the first station. The punches, after blanking the initial holes for guiding the metal strip, push down the metal slugs through the dies. If the punches do not push the metal slugs down enough, these last remain in the area where the blanking process is carried out.

If the presence of the metal slugs does not avoid the correct advance of the strip, the punches will find them during their next downwards movement. This will have as a consequence that the metal slugs will be scratched against the metal strip generating “marks” in the metal strip that could lead to bad quality parts. These “marks” are shown in Figure 4.16. At the same time, and depending on the position of the metal slugs inside the tool, this process failure could lead to catastrophic tool failures.

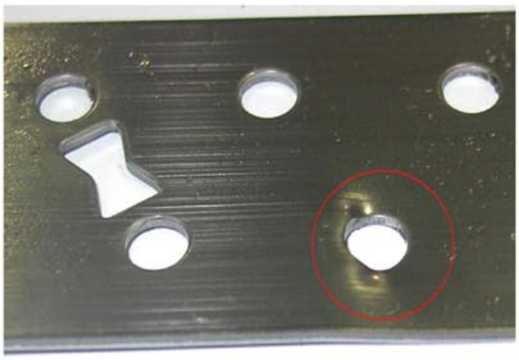


Figure 4.16: Marks in the metal strip due to bad evacuated metal slugs in first station.

Figure 4.17 shows how the sensors based process monitoring system detects this process failure. In this case, the position of the metal slug corresponds to the position where sensor number 5 was placed inside the tool. As it can be seen in Figure 4.17, the presence of metal slugs in the tool can represent two modifications in the process signals. First modification (most common one) is that the force rising begins earlier. The metal slugs make the strip to be a bit higher inside the tool and this is why the force increment starts a bit earlier than the nominal one. And second (not always detected), since the punches find, beside the metal strip, the metal slug, the necessary blanking force is bigger than the nominal. These two facts are shown in sensor number 5, where the force starts a bit earlier and is bigger than the nominal one. It can also be seen in Figure 4.17 how sensor number 1 in the connection rod was not able to detect the presence of the metal slug.

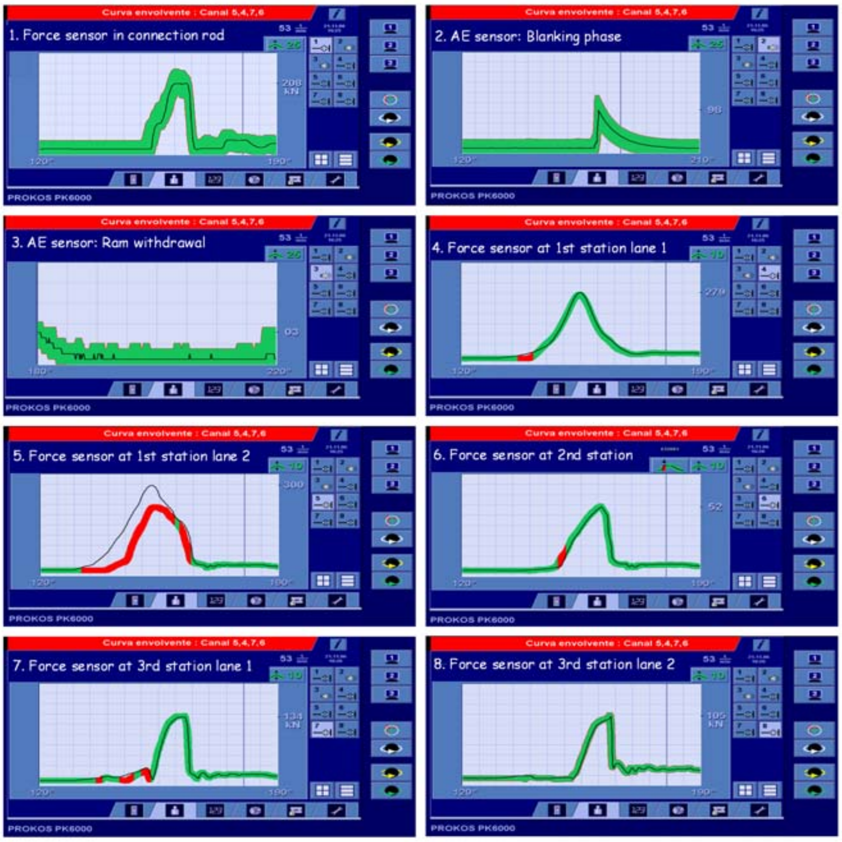


Figure 4.17: Process signals during "Metal slug in pilot pins station" failure.

The restarting procedure is the same as the one applied in the previous cases: the operator has to release the metal strip from the tool and find and evacuate the metal slug. In this case the operator finds the metal slug easier and faster because he/she knows the station of the tool where the process failure happened.

4.4.1.4. Metal slug in central area station

Fourth process failure is very similar to the previous one with only one difference: the position in the tool where it happens. Next, an example of this process failure detected during the production of the reference IA-04 is given. The previous process failure was due to the presence of a badly evacuated metal slug in the first station. In this case, the sensors based process monitoring system detects a badly evacuated metal slug in the second station of the tool. The consequences of this badly evacuated metal slug in the second station are shown in Figure 4.18 where the "marks" that the badly evacuated metal slug creates in the strip are shown. Again, this could have consequences regarding the quality of the produced parts and regarding catastrophic failures of the tool.

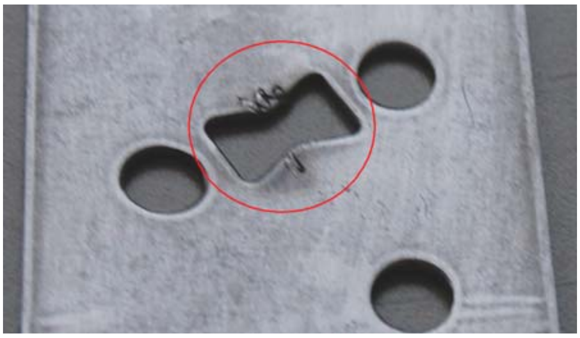


Figure 4.18: Marks in the metal strip due to bad evacuated metal slugs in second station.

Figure 4.19 shows the position of the process failure inside the tool. In previous failure, sensor number 5 was the faulty channel. At this time, sensor number 6, which detects the process failure, corresponds to the second station where the central area common to two consecutive parts is blanked. Therefore, the operator can identify from the sensors based process monitoring system the position of the process failure at the tool. At the same time, and regarding the typology of the process failure, it is shown in Figure 4.19 how the force rising starts a bit earlier in channel number 6.

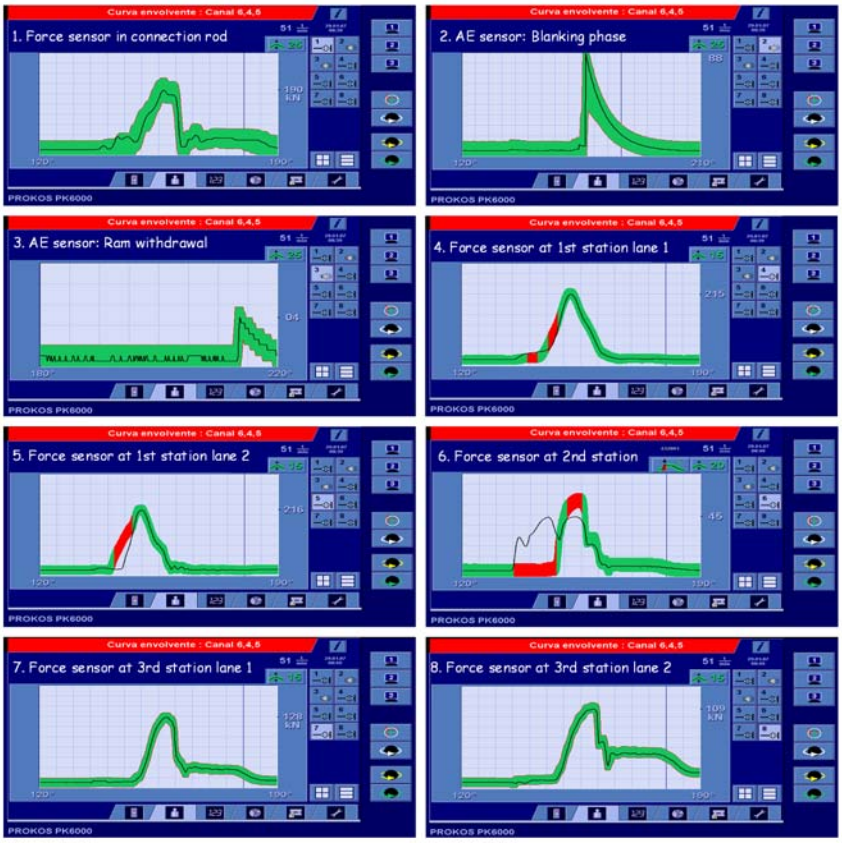


Figure 4.19: Process signals during “Metal slug in central area station” failure.

The restarting procedure is the same as the one applied in the previous case: the operator has to release the metal strip from the tool and find and evacuate the metal slug. In this case, as in the previous case, the operator finds the metal slug easier and faster because he/she knows the station of the tool where the process failure has happened.

4.4.1.5. Evacuation system failure I: “Double parts in pilot pins”

Fifth process failure detected during the experimental phase was the presence of badly evacuated parts inside the tool. At this point, it must be explained that regarding the final blanking station, the tools monitored at the present research work can be divided into two different groups. The final blanking station at the tool that produces the reference 0863-012 performs a simple action blanking process. This way, the punch, with the same external contour as the part and placed in the upper tool, blanks the part and pushes it downwards through the die.

On the other hand, the final stations at tools that produce the references IA-04 and 5828-001 perform a double action blanking process. These final stations are composed of two punches and two dies each. A first “couple”, punch and die, blanks the external contour of the part. After this, a second “couple” blanks the internal contour of the part releasing this from the metal strip. At this second blanking, the part is kept inside the die that is placed in the upper tool. After this, when the ram of the machine is in the upper position, one ejection system pushes the part out of the die. Then, when the part is falling down from the upper tool towards the lower tool, the air evacuation system blows the part out of the tool.

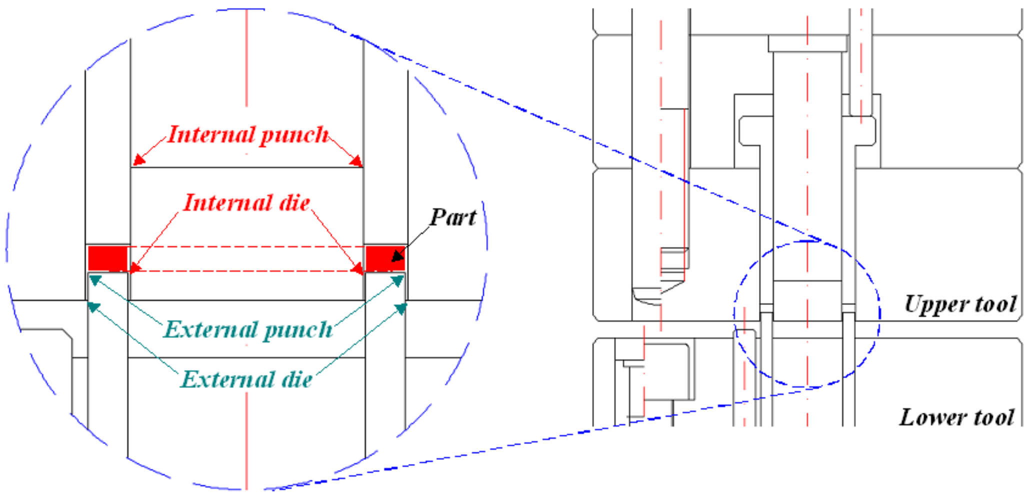


Figure 4.20: Double action final blanking station.

It was detected during the experimental phase that the air evacuation system does not always work properly and that sometimes the parts were not evacuated from the tool. The process failure described in the present lines was detected during the production of the reference IA-04. Figure 4.21 shows how two parts were not evacuated from the tool generating a process failure in the next stroke of the machine. This process failure could lead, depending on the position of the badly evacuated parts in the tool, to the production of bad quality parts and also to catastrophic failures of the tool.

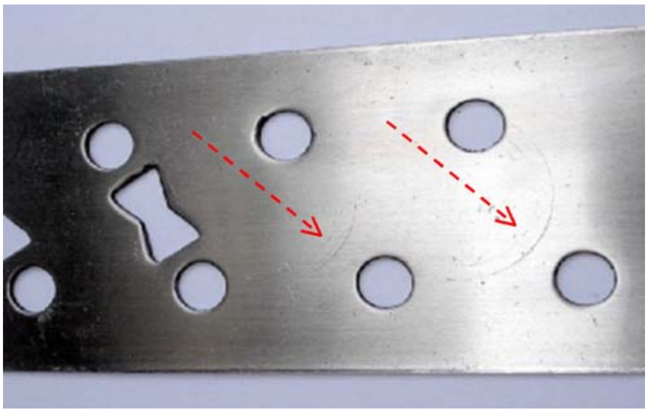


Figure 4.21: Marks in the metal strip due to bad evacuated parts in first station.

The detection of these badly evacuated parts inside the tool is very similar to the detection of badly evacuated metal slugs. Generally, the presence of the parts makes the punches to find the metal strip earlier, and therefore, there is a force rising right at the beginning of the force curve. This fact is shown in Figure 4.22 where sensor number 4, sensor number 5 and sensor number 6 suffer a force rising right at the beginning of the blanking curve.

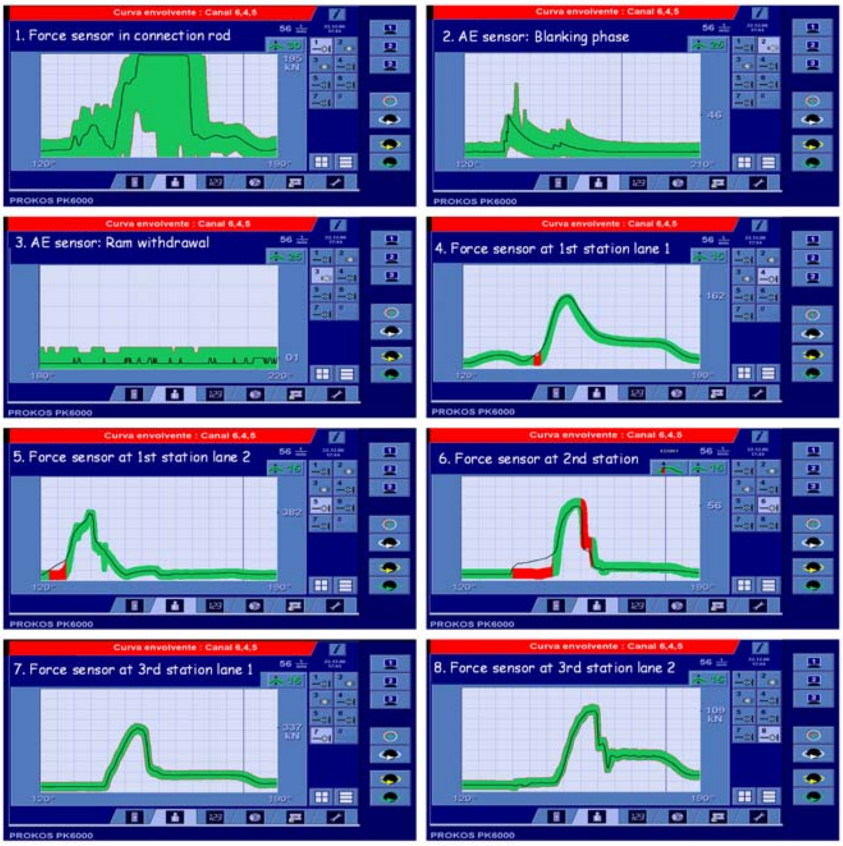


Figure 4.22: Process signals during "Double parts in pilot pins" failure.

The position of the parts inside the tool can also be determined with the sensors based process monitoring system. As explained in "Chapter 4.3.1. Reference IA-04", sensor number 4 and sensor number 5 are placed in the first station of the tool meanwhile sensor number 6 watches over the second station of the tool. Therefore it can be concluded from the process signals that the badly evacuated parts are in the first and second station of the tool. This diagnosis matches with Figure 4.21 where the presence of two badly evacuated parts in the first station and close to the second station of the tool is shown.

The restarting procedure consists on releasing the metal strip from the tool and find and evacuate the badly evacuated part. In this case, and as in the previous cases, the operator can find the badly evacuated part easy and fast, because he/she knows the station of the tool where the process failure has happened. At the same time, the operator has to check the right performance of the air evacuation system. Sometimes, and due to the vibration of the machine, this system suffers misalignments from its right position and this is the reason for its malfunction.

4.4.1.6. Evacuation system failure II: "Double parts in final blanking station"

Sixth process failure is very similar to the previous one with only one difference: the position in the tool where it happens. Next, an example of this process failure detected during the production of the reference 5828-001 is given. In the previous process failure, badly evacuated parts were detected in the first station of the tool. In this case, one badly evacuated part is detected at the final station of the tool.

When this process failure happens, the part that has not been evacuated in the previous stroke is compressed between the punch and the metal strip. Figure 4.23 shows the consequences of this process failure. First consequence is generation of "marks" in the metal strip. These "marks" can lead to the future production of parts with "marks" that will be defective. At the same time, and depending on the position of the badly evacuated part inside the tool, catastrophic failures in this last one could be generated. And finally, as shown in the right side at Figure 4.23, if the badly evacuated part is blanked and correctly evacuated from the tool in the next stroke, a defective part would be manufactured and sent to the customer with the associated problematic; rejection of the batch and economical losses.

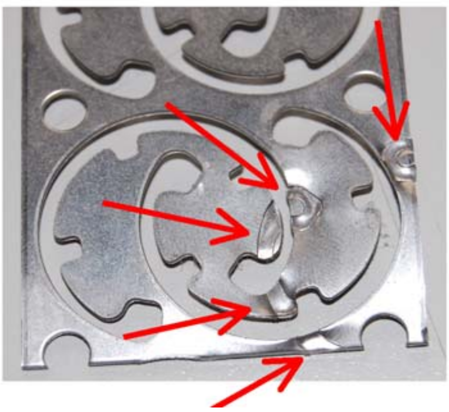


Figure 4.23: Marks in the strip and bad quality part due to bad evacuated parts in the final station.

The detection of this "double part" inside the tool is very similar to the previous explained process failure. The main difference is that instead of detecting the process failure in the sensors placed at the first station of the tool, the process failure is detected in the third station of the tool. Figure 4.24 shows how the process failure is detected in sensor number 5, placed in the final blanking station in lane 1.

Again, the presence of the bad evacuated part makes the punches to find the metal strip a bit earlier, and therefore, there is a force rising right at the beginning of the force curve. This fact is shown in Figure 4.24 where sensor number 5 suffers a force increment right at the beginning of the blanking curve.

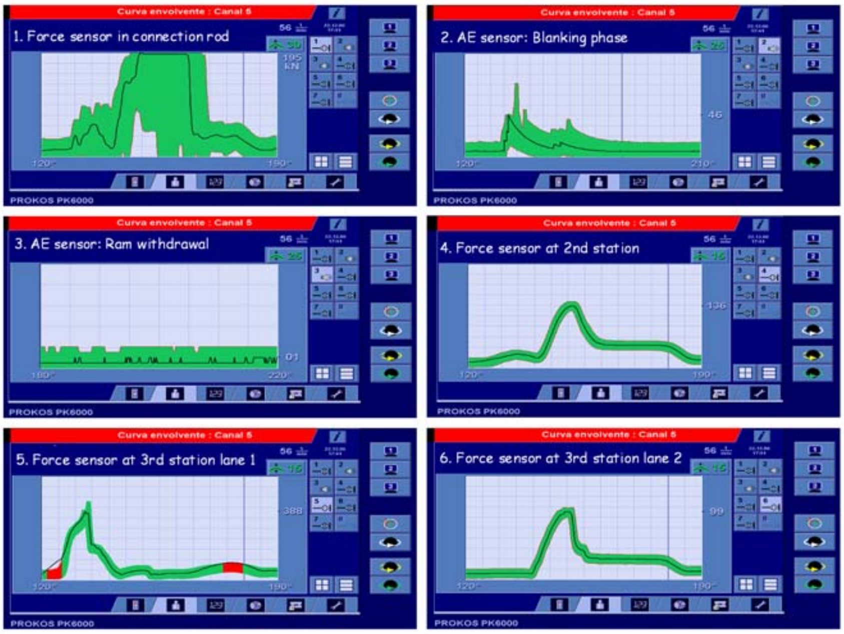


Figure 4.24: Process signals during "Bad evacuated parts in third station" failure.

The restarting procedure consists on releasing the metal strip from the tool and find and evacuate the badly evacuated part. In this case, and as in the previous cases, the operator can find the badly evacuated part easy and fast because he/she knows the station of the tool where the process failure happened. At the same time and as in the previous case, the operator has to check the right performance of the air evacuation system. Sometimes, and due to the vibration of the machine, this system suffers misalignments from its right position and this is the reason for its malfunction.

4.4.1.7. Ejector failure: "Double parts inside the blanking dies"

Seventh process failure happens when the ejection system that releases the parts from the dies in the double action blanking systems fails. Next, an example of this process failure detected when the reference IA-04 was being produced is given. The ejection system is composed of several pins that push the part down. When the ejection system fails, the part remains inside the die during the next stroke. When this process failure happens, the blanking of the parts in the next stroke is made correctly and no process failure is detected by the system. On the other hand, and right after blanking the parts and before arriving the ram to the lower dead point, the sensor placed in the final station detects a force rising.

Figure 4.25 shows this force increment at the end of the force curve in sensor number 8 that corresponds to the final blanking station in lane 2 of the tool. What happens in this process failure is that after blanking the part (with the previous part inside the die), this second part is also kept inside the blanking die. The presence of both parts inside the same die makes that when the ram of the machine reaches the lower dead point, both parts are compressed between the upper and lower tool generating a force rising. This force rising is monitored by the system that detects the process failure.

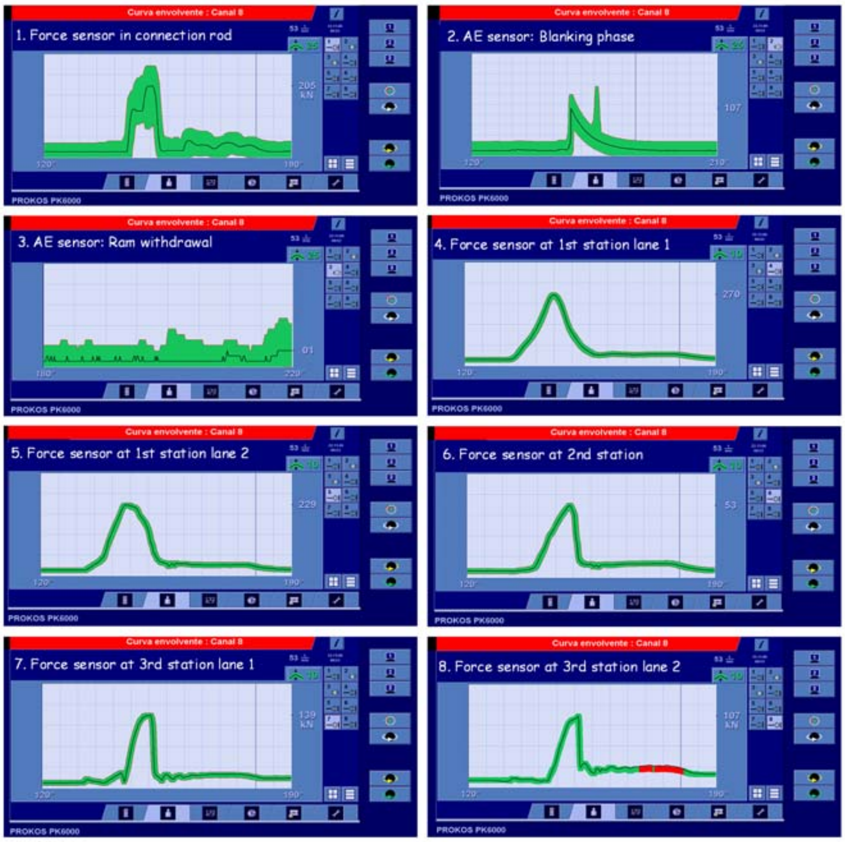


Figure 4.25: Process signals during “Double part inside the blanking die” failure for ref. IA-04.

The force variation experimented by the sensor during this process failure depends on several factors. In order to explain this better, the same process failure detected by sensor number 1 (placed at the connection rod) (see Figure 4.26) and detected by a universal sensor (placed at the tool) (see Figure 4.25 sensor 8) when producing the reference IA-04 are compared. Theory says that the detection of the process failure at the tool where the universal sensor was installed should be clearer. Reality, however, shows that the detection of the process failure in Figure 4.26 (sensor in connection rod) is clearer than the detection of the same process failure in Figure 4.25 (universal sensor inside the tool). The reason for this is that the sensor signal, besides the sensitivity of the sensor, also depends on the overload size. Channel 8 at Figure 4.25 shows how the overload generated is very small and only the universal sensor placed at the tool is able to detect it. In this case, the sensor placed at the connection rod does not detect this process failure. On the other hand, the overload generated in Figure 4.26 is so big that even the sensor placed at the connection rod is able to detect it. The value of the overload depends on the thickness of the produced parts and on the remaining distance between the upper and lower tool during the normal production (only one part inside the die). The restarting procedure consists on extracting the parts from the die and checking the reason why the ejection system is not working properly.

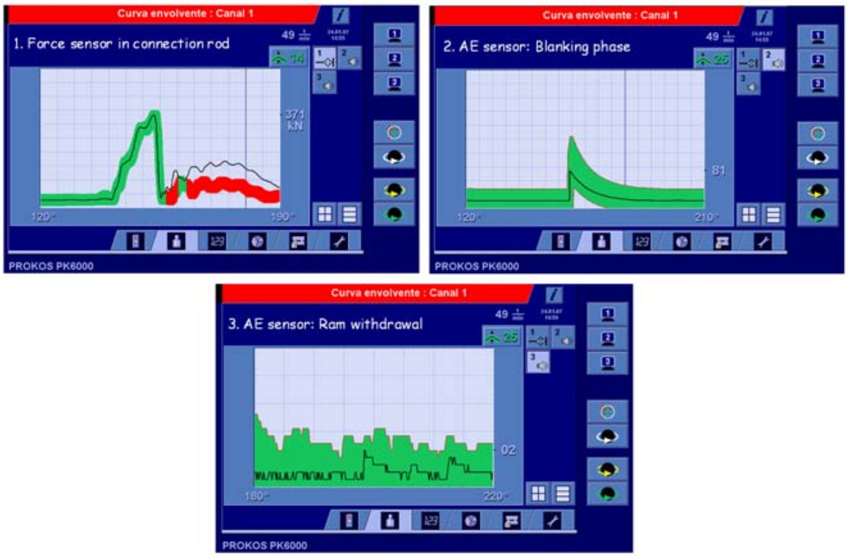


Figure 4.26: Process signals during "Double part inside the blanking die" failure (another ref).

4.4.1.8. Punch breakage

Eighth process failure corresponds to the detection of punch breakage. An example of this process failure that happened during the production of the reference 0863-012 is given next. This process failure usually happens when the wear at the blanking punches is considerably high. Contrary to popular belief, the breakage of the punches happens during the withdrawal of the ram. During the blanking phase the punches suffer compression stresses. On the other hand during the withdrawal of the tool, and due to the elastic recovery of the metal strip, the punches suffer tensile stresses and is during this phase when they are more prompt to be broken. For this reason, one AE sensor was installed in the tools and monitors the withdrawal of the ram.

Figure 4.27 shows the consequences regarding the quality of the produced parts. It is shown how one of the holes at the ears of the part was not completely blanked and therefore the quality of the produced part is not good. At the same time, if this process failure were not detected, the broken tip of the punch would be clamped in the metal strip leading to future process failures like defective advance of the strip through the tool that could have as a consequence catastrophic failures.

Figure 4.27: Part produced with a punch broken inside the tool.

Figure 4.28 shows how the sensors based process monitoring system detects the breakage of the punch during the withdrawal of the tool. It is clearly shown how the acoustic signal in sensor number 3 suddenly increases when the punch breaks. Another important conclusion is that this AE sensor is really important in this short of blanking facilities because it is able to stop the machine before the next stroke. Without this AE sensor the force sensor would detect this breakage only after next stroke, what could have already leaded to catastrophic consequences. This is the reason why AE sensors are the best complement to force sensors in forming processes monitoring.

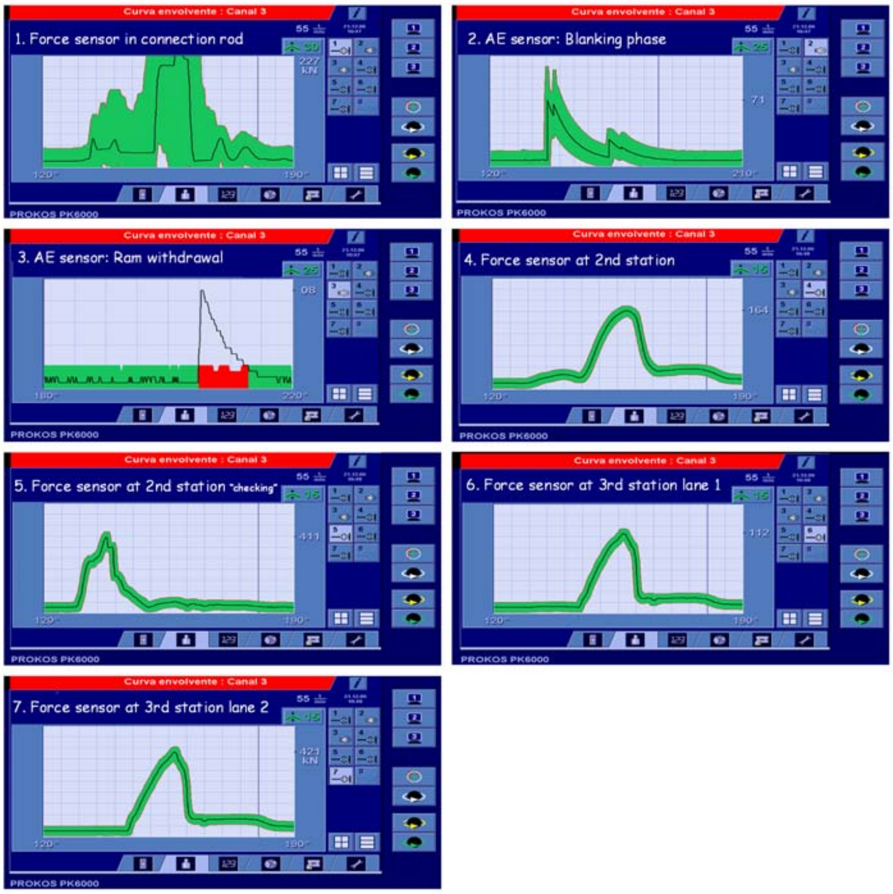


Figure 4.28: Process signals during “Punch breakage” failure.

The restarting procedure consists on extracting the metal strip from the tool, dismounting the broken punch and replacing it with a new punch. Depending on the length of the broken punch two different protocols could be used to replace it.

4.4.1.9. Metal strip adhesion to pilot pins

Ninth and last process failure detected during the experimental phase is the adhesion of the metal strip to the pilot pins due to an excessive burr at the guiding holes. An example of this process failure that happened during the production of the reference 0863-012 is given next. An excessive burr at the guiding holes makes these to have more adhesion to the pilot pins. Then the metal strip is vertically moved following the upper tool. This vertical movement leads to misalignments of the metal strip inside the tool and problems with the feeding system.

Figure 4.29 shows how the sensors based process monitoring system detects the adhesion of the strip to the pilot pins. Sensor number 5, sensor number 6 and sensor number 7, placed respectively in the second and third station (lane 1 and lane 2 in third station) of the tool detect a time gap in the signals coming from the process. This gap in the signals is directly linked to this process failure at the blanking tool.

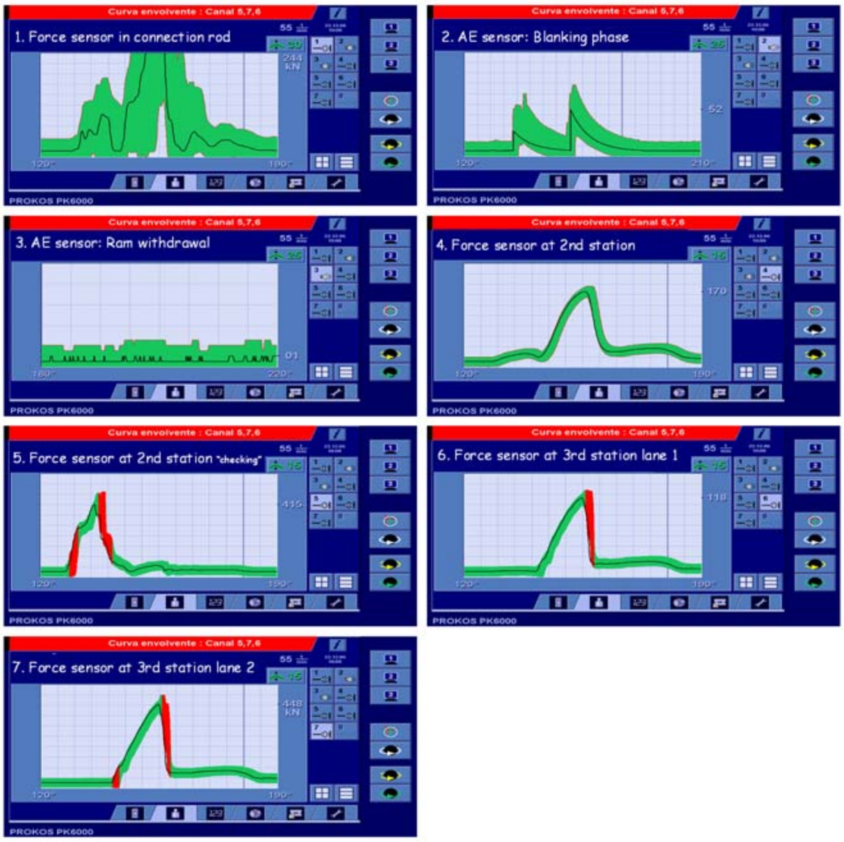


Figure 4.29: Process signals during "Metal strip adhesion to pilot pins" failure.

When this process failure happens, the operator has to find which one of the blanking punches at station one is wear and produces an excessive burr in the guiding holes and replace it with a new punch.

4.4.2. Process failures non detected by the sensors based process monitoring system

Although most of the process failures at the blanking facility were detected with the sensors based process monitoring system, there are also some other process failures that were not detected. The process failures that were not detected with the sensors based process monitoring system are mostly related to the quality of the manufactured parts and not related to process instabilities. Next, the process failures not detected during the experimental phase with the help of the Brankamp sensors based process monitoring system are described.

4.4.2.1. Local big burr due to punch micro-cracks

A very common process failure in blanking processes is the formation of small micro-cracks in the edge of the blanking punches. Micro-cracks in blanking tool structure may be originated from the onset of brittle fracture due to cyclic loading during blanking (fatigue damage) [KLA06]. Figure 4.30 shows micro-cracks detected in different blanking punches during the experimental phase.

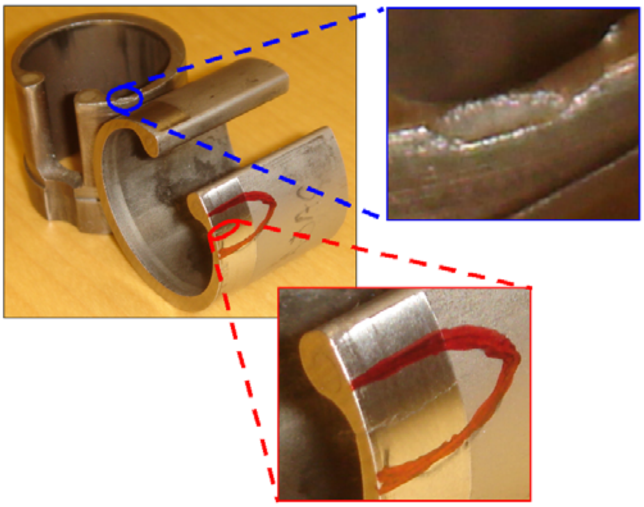


Figure 4.30: Micro cracks and cracks in the blanking punches.

The generation of these micro-cracks in the edge of the punches do not follow any predefined rule and cannot be predicted by any mathematical function. Micro-cracks can appear in the edge of the punch at the very beginning of the production, after a few thousand strokes or cannot appear during the entire production. Their growth depends on several factors like for example the roughness of the surface and the quality of the edge after the grinding process.

When these small micro-cracks appear in the edge of the tool, some quality defects appear also in the manufactured parts. When the parts are blanked in the final station of the tool, the material can flow through these micro-cracks in the punches and generates local big burrs in the manufactured parts. Although the parts go through a grinding process later, these local big burrs are not eliminated and bad quality parts are produced. This is a very important defect to take into consideration because once the micro-crack appears in the edge of one punch, all the following manufactured parts present these local big burrs and therefore are bad quality parts. Figure 4.31 shows an example of one part (5828-001 reference) with this defect.

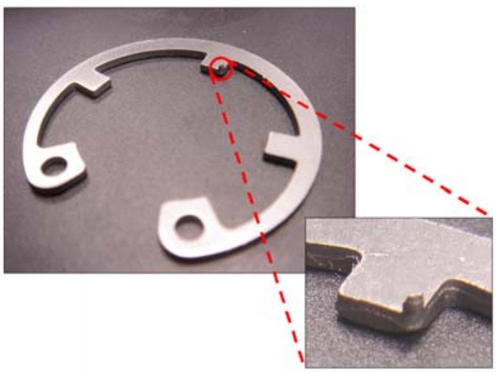


Figure 4.31: Local big burr in reference 5828-001 due to punch micro cracks.

Regarding the detection of this process failure, it has been stated during the experimental phase that the sensors based process monitoring system is not able to detect it. The growth of these micro-cracks represents a force variation in the blanking process, but this force variation is so small that even the universal sensors placed close to the punches in the tool are not sensible enough. At the same time the AE sensors do not experience any big changing when these micro-cracks growth in the punches.

Therefore, nowadays and since the sensors based process monitoring system is not able to detect this process failure, the operator of the blanking facility checks periodically the appearance of this defect in the parts. When parts with local big burrs are found in one periodical inspection, the operator stops the blanking facility and rejects the parts that have been produced since the previous inspection.

As it will be explained in “Chapter 5. Parts quality control”, an artificial vision (AV) system has been developed at the present research work to verify the quality and check for this short of defects in the 100% of manufactured parts. With this approach, an online control quality of the manufactured parts is achieved reducing the manufacturing of this short of defective parts and avoiding the shipment of these defective parts to the customer.

4.4.2.2. Excessive burr due to punch wearing

Second process failure regarding the quality of the manufactured parts that was not detected with the sensors based process monitoring system was the growth of the burr at the edges of the parts. Although the parts go through a deburring process at the end of their manufacturing process, there exists a limit burr height from which the deburring process is not effective any more (variable H in Figure 4.41). Therefore, the height of the burr at the parts must be controlled in order to re-sharpen the punches when these last ones present excessive wearing.

Nowadays the operator is in charge of checking the burr height periodically although he does not use any measuring device for it. The procedure is the next: the operator takes a few parts and “feels” with the fingers the height of the burr. Depending on his criteria, the operator decides to continue producing parts or to stop the production and re-sharpen the punches. This quality control is very subjective and depends principally in the experience of the operator.

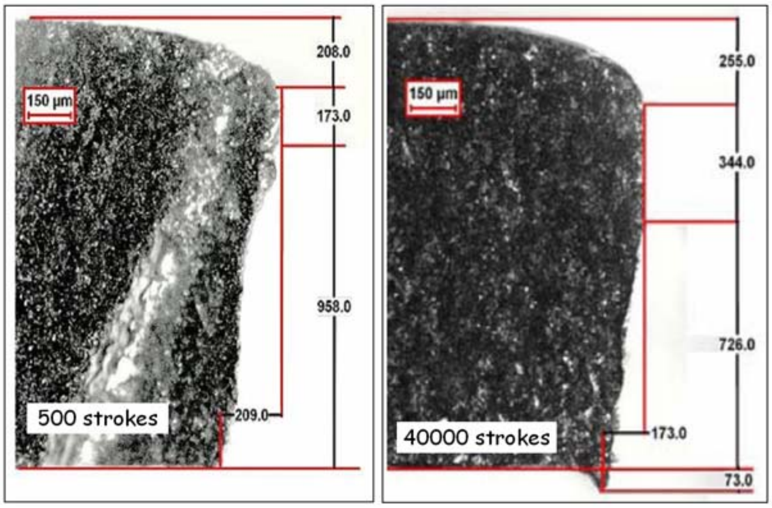


Figure 4.32: Burr growth at the edge of the parts.

Figure 4.32 shows how the edge of the parts suffers an evolution as the number of manufactured parts increases. The left side of the figure shows the edge of the parts at the beginning of the production. It is shown how at this point there is no burr at the edge of the parts. The right side of Figure 4.32 shows the edge of the parts after 40.000 strokes. It is shown how the height of the burr at this point has reached 73 microns. At this burr height the operator decided to re-sharpen the punches.

After the experimental phase, it was concluded that the sensors based process monitoring system by itself is not able to detect this increment in the wear of the punches, and therefore, the growth of the burr at the parts. On the other hand, it was also concluded that there exist a relationship between the variation of the blanking force and the wear of the punches and, therefore, the growth of the burr at the parts. A deeper study on this relationship was carried out in order to use the sensors based process monitoring system as a tool to predict the growth of the burr over the maximum allowable limit. This study is presented in the following chapter.

4.5. Evolution of the process signals and part's edge quality during the production

As mentioned in the previous subchapter, one of the conclusions during the experimental phase is that the sensors based process monitoring system is not able to detect when the burr height reaches its maximum allowable value. The reason for this is that the sensors based process monitoring system is more oriented to sudden changes at the signals coming from the process. On the other hand, the wear of the punches, besides generating the burr at the produced parts, has also as a consequence a smooth increment of the force necessary to blank the parts.

Therefore, although the sensors based process monitoring system is not able to detect by itself the maximum allowable burr height, a study has been carried out in order to find any possible relationship between the increment of the burr height and the variation of the process signals measured by the sensors based process monitoring system. This way, the operator will be able to use the sensors based process monitoring system to detect when the burr at the parts reaches the maximum allowable height and the decision to re-sharpen the punches will be taken in a more objective and robust way.

The present research was carried out during the production of the reference 0863-012. Figure 4.33 shows the two variables studied: the evolution of the process signals (examples given in different colours in the right graphic and further explained in Chapter 4.5.1) and the evolution of the edge quality (example given in the left graphic and further explained in Chapter 4.5.2) as the number of parts produced increments. Samples of the process signals and samples of the manufactured parts were taken at the blanking facility after 500, 10.000, 20.000, 30.000 and 40.000 strokes. After 40.000 strokes the operator decided to re-sharpen the punches because, following his criteria, the burr at the parts had reached its maximum allowable limit.

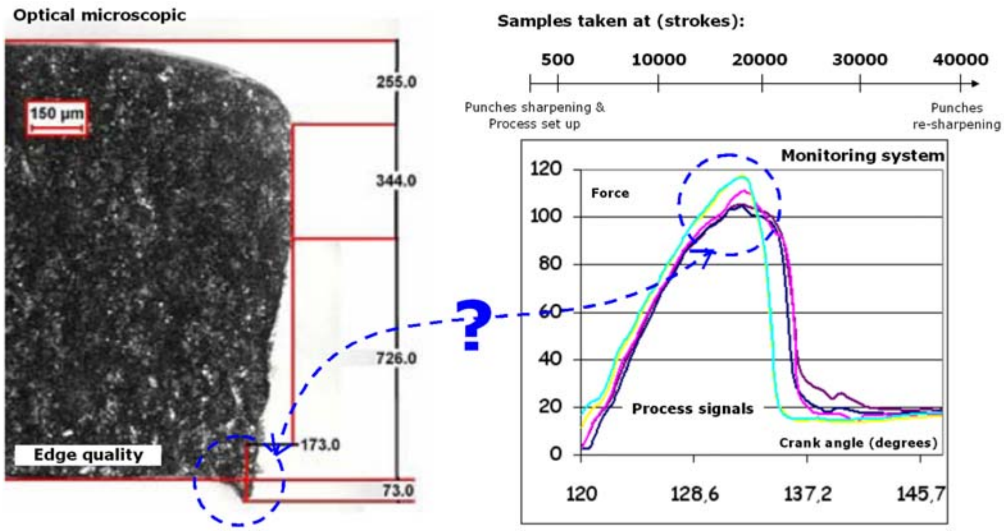


Figure 4.33: Process variables studied during the burr and force evolution study.

Next all the achieved results are shown. First, the process signals evolution for all the force and AE sensors used at the reference 0863-012 are shown. After this, the evolution of the edge quality, both internal and external, at the parts is shown. And finally, a comparison between these two factors is made and the consequent conclusions are written down.

4.5.1. Evolution of the process signals

First variable studied is the evolution of the process signal over the production of the reference 0863-012. In order to carry out this analysis, samples of the process signals were taken at some predefined intervals, after 500, 10.000, 20.000, 30.000 and 40.000 strokes. The samples collection was carried out in the next way: at each predefined interval, 20 consecutive process signals were downloaded from the Brankamp PK 550 unit to the hard disk of a computer. Since the process signals were recorded in an industrial environment and not all the variables were under control, it was decided to record 20 consecutive process signals in order to calculate their average and avoid the possibility of introducing noises in the measurements.

The analysis of the process signals was carried out using Microsoft Excel. After calculating the average value of the process signals, three different diagrams were developed to compare the process signals at the different manufacturing intervals (for example see Figure 4.34):

1. First diagram (force or AE signals depending on the sensor) represents the average value of the 20 recorded process signals. The vertical axis represents the value of the recorded signal. This vertical axis is measured in Volts, although it does not offer a real measurement of the blanking forces because the sensors are not calibrated. And the horizontal axis represents the crank angle of the machine. The unit is crank degrees.
2. Second diagram (upper area of the signals) is a zoom of the force signals at their maximum values area (this diagram was only developed for the force signals). The vertical axis represents the relation between the measured forces and the forces at the beginning of the production (500 strokes). The horizontal axis represents the crank angle of the machine. The unit is crank degrees.
3. And finally, third diagram (maximum force or maximum noise level) represents the maximum value of the curve for each process signal (both force and acoustic emission curves). The vertical axis represents again the signal variation with respect to the initial signal. This vertical axis is again measured in Volts and the values are relative to the maximum signal value at 500 strokes curve. The horizontal axis represents the number of strokes at which the samples were taken during the production.

The samples taken at the predefined intervals contain the information related to six sensors at the 0863-012 reference tool. Sensor number 5, installed in the station where the presence of the holes at the ears of the parts was checked, did not provide much information because this station does not perform any blanking process. A brief explanation of the sensors is given next, and the signals recorded at the present study are shown after.

- ✓ Sensor 1: Force signal captured by the Vario sensor in the connection rod of the forming facility.
- ✓ Sensor 2: AE signal captured during the blanking phase.
- ✓ Sensor 3: AE signal captured during the ram withdrawal.
- ✓ Sensor 4: Force signal captured by the universal sensor placed at the second station in the tool (blanking of small holes at the ears of the parts).
- ✓ Sensor 6: Force signal captured by the universal sensor placed at the third station (first lane) of the tool (final blanking of parts).
- ✓ Sensor 7: Force signal captured by the universal sensor placed at the third station (second lane) of the tool (final blanking of parts).

4.5.1.1. Sensor 1: Force signals at the connection rod

First process signal analysed at the present study is the force measured by the sensor placed at the connection rod of the machine that measures the total force that the machine needs to blank the metal strip.

The first diagram (top left in Figure 4.34) shows the force curves measured at the predefined manufacturing intervals. It can be distinguished how signals show a slight instability, with several waves at the beginning and at the end of the blanking phase, instead of being smooth curves. This is due to the distance between the signal source and the signal measurement point, and also due to the possible disadjustments due to wearing in the bearings of the blanking facility. This makes this sensor not to be a very reliable information source.

Regarding the maximum force, the second diagram (top right in Figure 4.34) shows the area where the machine applies the maximum load for blanking the metal strip. This zoom of the maximum force area shows how the maximum forces increases as the number of produced parts increases too. This tendency is clear although this diagram also shows how the force at 20.000 strokes suffers a big decrement being even smaller than the force at the beginning of the production. This fact does not match with the clear tendency of the forces at the connection rod and this is the reason why it was concluded that something unknown happened that made those samples not to be the correct ones. Again, and as a possible explanation, the distance of the sensor to the tool and the disadjustments in the moving elements of the blanking facility appears as the cause of this incorrect measurement.

And finally, third diagram (bottom centre in Figure 4.34) shows the tendency of the force only considering the greatest value at each force curve. For this diagram, the greatest value at 500 strokes curve was taken as the reference. It is shown how there is a clear tendency towards an increment in the maximum value of the force curves except for the force curves taken after 20.000 strokes. This value was not taken under consideration and it was concluded that the maximum force applied by the machine after 40.000 strokes is 33% bigger than the force applied at the beginning of the production.

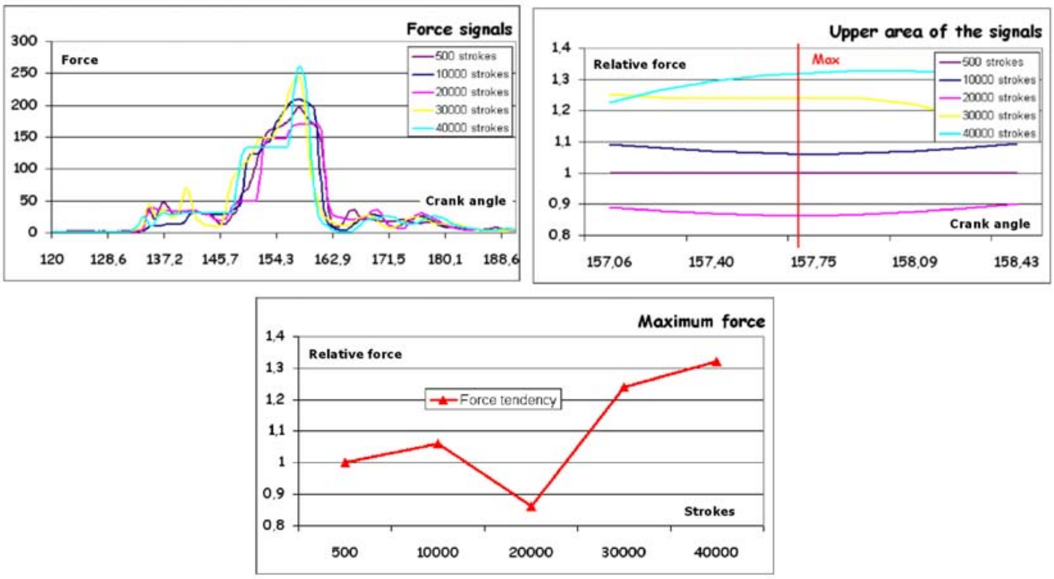


Figure 4.34: Process signals from force sensor at the connection rod.

<u>4.5.1.2. Sensor 2: AE signals during blanking phase</u>

Second process signal analysed at the present study is the AE measured during the blanking phase. The AE sensor is attached to the tool by means of one screw and in this case “listens” the process during the blanking phase, when the ram is moving down and the punches blanks the metal strip.

The first diagram (top left in Figure 4.35) shows the signals captured by the sensor. Each signal is composed of two peaks that represent the two phases during the blanking of the metal strip. First peak represents the sound emitted due to the impact of the punches with the metal strip. And second peak represents the ending of the material piercing.

Regarding the maximum noise level, the second diagram (top right in Figure 4.35) shows the tendency of the noise level only considering the greatest value at each acoustic curve. This second diagram shows the values for the first peak, the impact of the punches and the metal strip. For this diagram, the greatest value at 500 strokes curve was taken as the reference again. In this case the tendency of the maximum value is not very clear and does not contribute with much information about the process. At the beginning there is a clear increment up to 10.000 strokes but later the noise level decrements until the end of the production. No clear conclusions were drawn out.

On the other hand, the third diagram (bottom centre in Figure 4.35) shows the maximum values for the second peak, the piercing of the metal strip. For this diagram, the greatest value at 500 strokes curve was taken as the reference again. In this case it is shown how there is a tendency towards an increment in the maximum value although this increment is not very clear because there are two small decrements (at 20.000 and 40.000 strokes). Anyway, it can be concluded that the noise level increments with the number of produced parts. At the end of the production the noise level incremented around 28%.

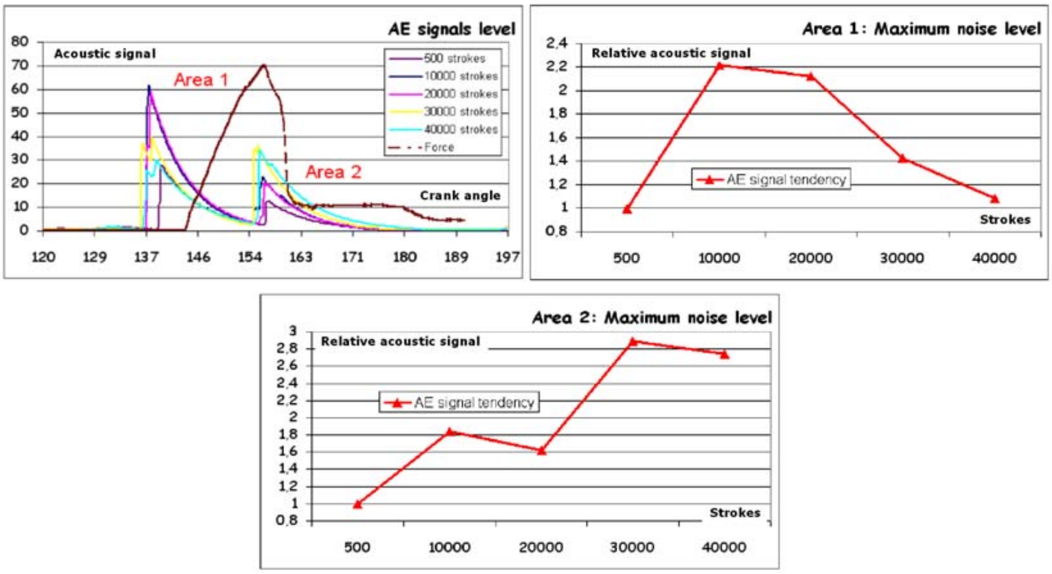


Figure 4.35: Process signals from AE sensor during blanking phase.

<u>4.5.1.3. Sensor 3: AE signals during ram withdrawal</u>

Third process signal analysed at the present study is the AE measured during the withdrawal of the upper tool. The AE sensor is attached to the tool by means of one screw and in this case “listens” the process during the withdrawal phase, when the ram is moving up. The main purpose of this sensor is to detect the breakage of the punches due to tensile stresses. These tensile stresses are generated when the material strip clamps the punches due to the elastic recovery of the material after being blanked. During this study no punch breakage took place, and therefore, not much information was extracted from this sensor.

The first diagram (top left in Figure 4.36) shows the signals captured by the AE sensor during the withdrawal of the upper tool. It shows how there is no clear information, the signals level is very low and they are very unstable. No major changes are shown in the signals during the manufacturing process.

Regarding the maximum noise level, the second diagram (bottom right in Figure 4.36) shows the tendency of the noise level only considering the greatest value at each acoustic curve. For this diagram, the greatest value at 500 strokes curve was taken as the reference again. In this case, the tendency of the maximum value does not contribute with much information about the process. It increments a bit at the beginning of the production but later remains constant until the end. No major conclusions can be drawn out from the information of these process signals.

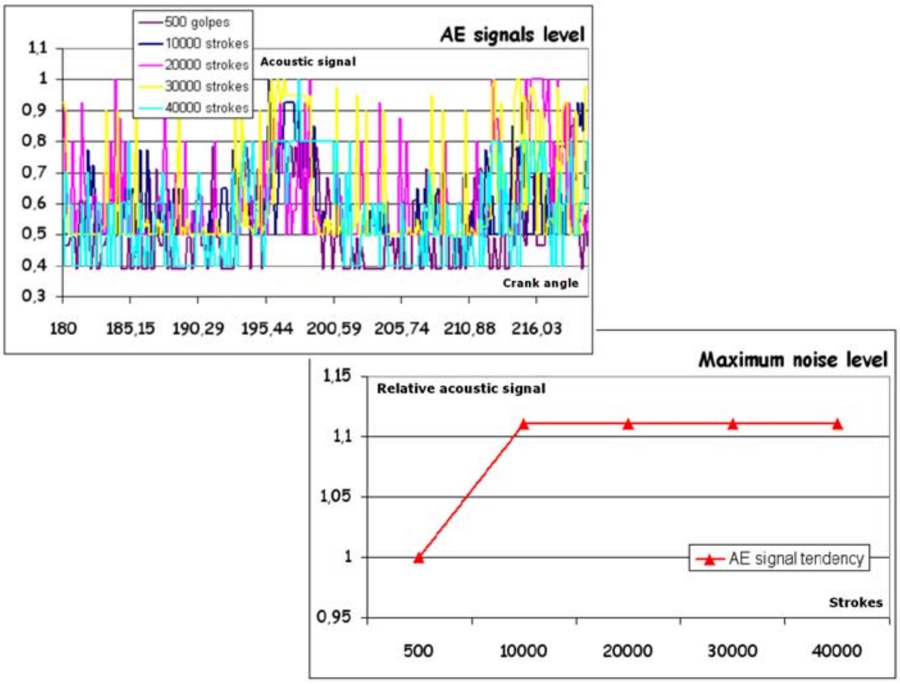


Figure 4.36: Process signals from AE sensor during ram withdrawal phase.

4.5.1.4. Sensor 4: Force signals at station 2 (small holes blanking station)

Fourth process signal analysed at the present study is the force measured by the universal sensor placed at the second station of the tool, which measures the force that the blanking punches at this station need to create the four small holes at the ears of the parts.

The first diagram (top left in Figure 4.37) shows the force curves measured at the predefined manufacturing intervals. It can be distinguished how, unlike the sensor placed at the connection rod, the stability of the captured signal is very good and no major instabilities are shown.

Regarding the maximum force, the second diagram (top right in Figure 4.37) shows the area where the small punches apply the maximum force for blanking the four small circular holes. This zoom of the maximum force area shows how the maximum force increases as the number of produced parts increases too. This tendency is clear although this diagram also shows how the force at 10.000 strokes is slightly smaller than the force at 500 strokes. One possible explanation is that since the tool needs to be opened every time that the punches are re-sharpened, once the tool is closed it needs a time to find the right position again and when this happens the force decreases a bit. Anyway, after this initial small decrement, it is shown how the forces increases progressively with the number of produced parts.

And finally, third diagram (bottom centre in Figure 4.37) shows the tendency of the force only considering the greatest value at each force curve. For this diagram, the greatest value at 500 strokes curve was taken as the reference again. It is shown how there is a clear tendency towards an increment in the maximum value of the force curves except for the initial slight decrement after 10.000 strokes. The diagram shows that the maximum force applied by the machine after 40.000 strokes is 8% bigger than the force applied at the beginning of the production.

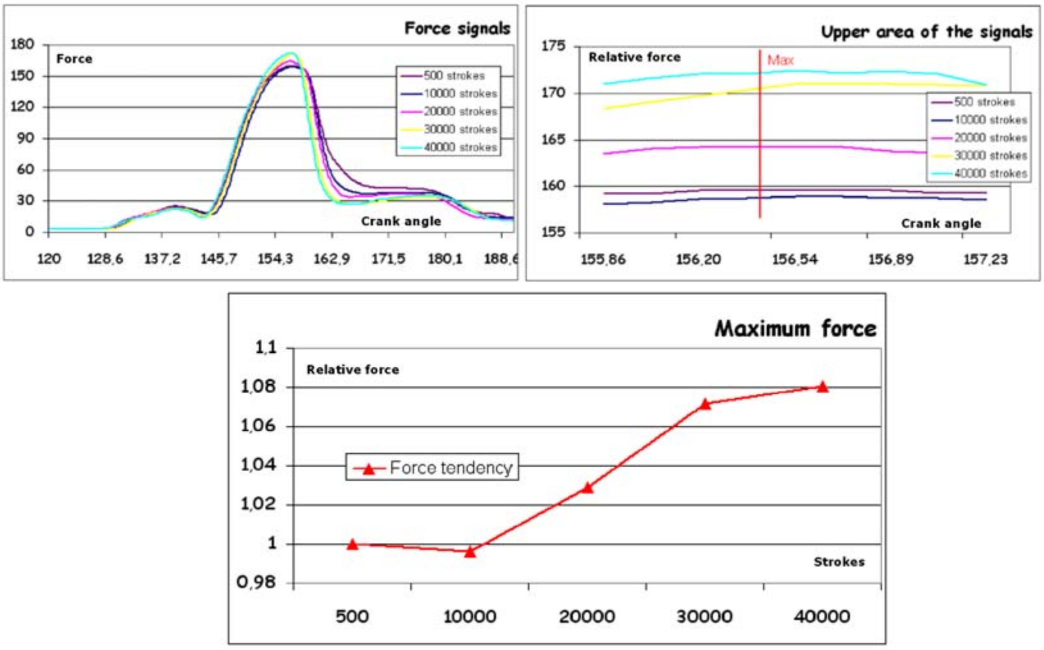


Figure 4.37: Process signals from force sensor at the second station in the tool.

<u>4.5.1.5. Sensor 6: Force signals at station 3 (final blanking) lane 1</u>

Fifth process signal analysed at the present study is the force measured by the universal sensor placed in the first lane at the third station of the tool. This sensor measures the necessary force to blank one part and separate it from the metal strip.

The first diagram (top left in Figure 4.38) shows the force curves measured at the predefined manufacturing intervals. It can be distinguished how the stability of this universal sensor is very good and no major instabilities are shown.

Regarding the maximum force, the second diagram (top right in Figure 4.38) shows the area where the punch at third station in the tool applies the maximum force for blanking the part of the first tool lane and separate it from the metal strip. This zoom of the maximum force area shows how the maximum forces increases as the number of produced parts increases too. This tendency is clear although this diagram shows again how the force at 10.000 strokes is slightly smaller than the force at 500 strokes. The possible explanation for this effect is the same as in the previous case; the tool must find its right position. Anyway after this initial small decrement, it is shown how the forces increase progressively with the number of produced parts.

And finally third diagram (bottom centre in Figure 4.38) shows the tendency of the force only considering the greatest value at each force curve. For this diagram, the greatest value at 500 strokes curve was taken as the reference again. It is shown how there is a clear tendency towards an increment in the maximum value of the force curves except for the initial slight decrement after 10.000 strokes. The diagram shows that the maximum force applied by the machine after 40.000 strokes is 11% bigger than the force applied at the beginning of the production.

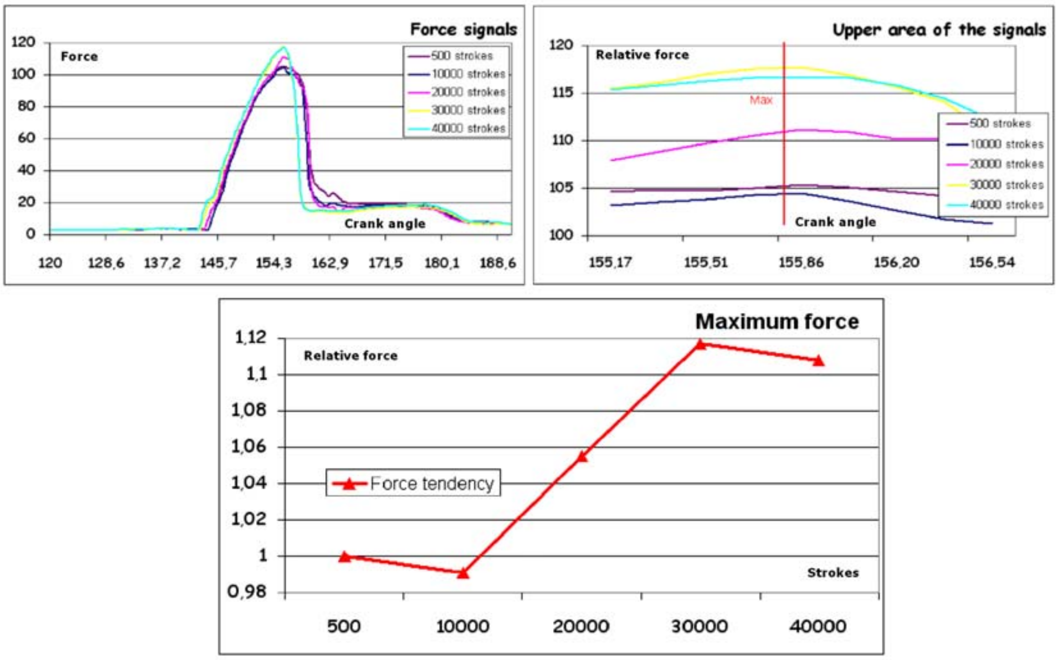


Figure 4.38: Process signals from force sensor at the third station in the tool (lane 1).

4.5.1.6. Sensor 7: Force signals at station 3 (final blanking) lane 2

And finally, the sixth process signal analysed at the present study is the force measured by the universal sensor placed in the second lane at the third station of the tool. This sensor measures the necessary force to blank one part and separate it from the metal strip.

The first diagram (top left in Figure 4.39) shows the force curves measured at the predefined manufacturing intervals. It can be distinguished how the stability of this universal sensor is very good and no major instabilities are shown. Therefore, the difference between the Vario Sensor (first process signal) and the universal sensors at the tool (fourth, fifth and sixth process signals) regarding the stability of the signals captured is very clear in this research. This is one of the reasons why universal sensors at the tool offer much better results than Vario Sensors at the connection rod of the facility.

Regarding the maximum force, the second diagram (top right in Figure 4.39) shows the area where the punch at third station in the tool applies the maximum force for blanking the part of the second tool lane separating it from the metal strip. This zoom of the maximum force area shows how the maximum forces increase as the number of produced parts increases too. This tendency is clear and in this case even the forces after 10.000 strokes are greater than the forces after 500 strokes. The aforementioned effect is not detected in this process signal. Therefore, it is shown how the forces increases progressively with the number of produced parts.

And finally, third diagram (bottom centre in Figure 4.39) shows the tendency of the force only considering the greatest value at each force curve. For this diagram, as in the previous cases, the greatest value at 500 strokes curve was taken as the reference too. It is shown how there is a clear tendency towards an increment in the maximum value of the force curves from the beginning until the end of the production. The diagram shows that the maximum force applied by the machine after 40.000 strokes is 22% bigger than the force applied at the beginning of the production.

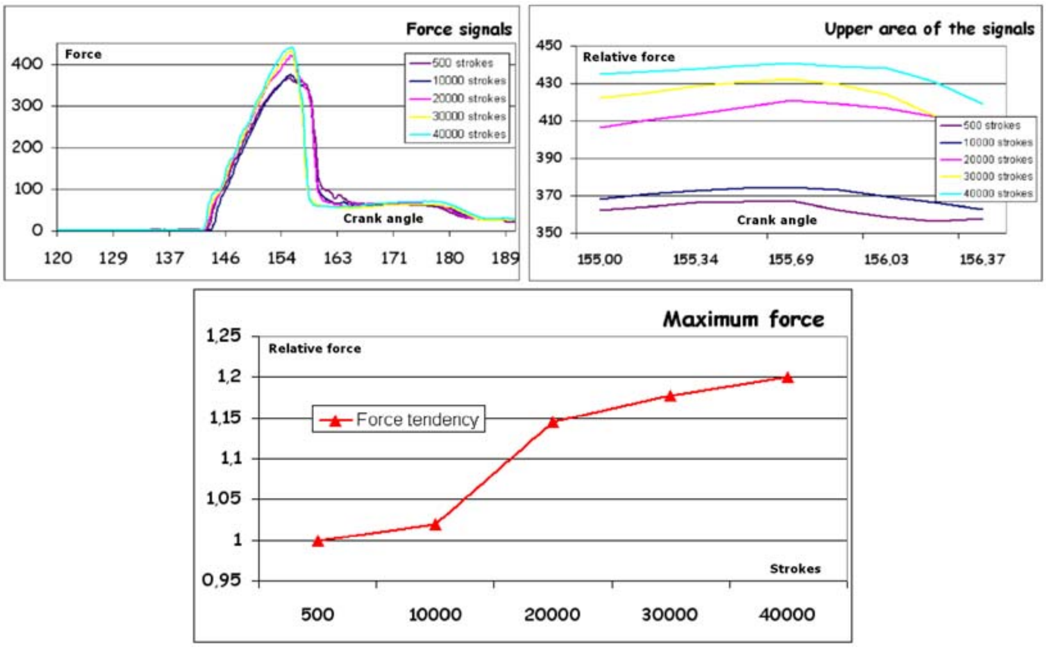


Figure 4.39: Process signals from force sensor at the third station in the tool (lane 2).

4.5.2. Evolution of the part's edge quality

The second branch of the present study consists on analysing the evolution of the edge quality at the manufactured parts. Again samples were taken after 500, 10.000, 20.000, 30.000 and 40.000 strokes. In this case, samples consist of several parts that were recollected after the predefined intervals.

After collecting and classifying all the parts, a (WED) wire electrodischarge machine (Charmilles Technologies Robofil 100) was used to cut the parts along the line A-A shown in Figure 4.40. It was decided to cut the parts using a wire electrodischarge machine because this is a contactless cutting method and therefore no loads are applied to the edge area during the cutting phase. The main purpose was not to modify the edge area and get accurate results.

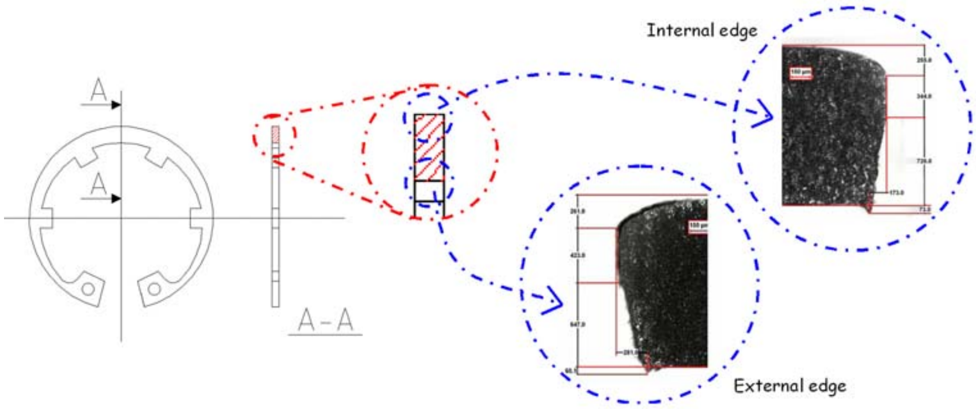


Figure 4.40: Internal and external edge measured at the optical microscope.

Figure 4.40 shows the procedure that was followed in order to prepare the specimens. Parts were cut following the cutting line A-A and after this both, the external and internal edges, were measured with an optical microscope Leica DM IRM. Next the evolution of both, the internal and the external edge, are described.

4.5.2.1. Evolution of the internal edge quality

Figure 4.41 shows the evolution of the internal edge quality during the entire production. Top side of Figure 4.41 shows the images acquired at the optical microscope for the specimens taken at 500, 10.000, 20.000, 30.000 and 40.000 machine strokes. And bottom side of Figure 4.41 shows the evolution of the different dimensions that determine the quality of the edge. The centre shows a schematic explanation [FAB07] of the sheared edge dimensions.

1. Dimension A represents the rollover depth. At the beginning of the blanking process, the punch engages the metal strip pulling the material downward. This initial contact draws the material into the clearance, which creates the rollover.
2. Dimension B represents the burnished depth. After the initial drawing, the punch continues to penetrate and shear the upper portion of the material, which creates a burnished area.
3. Dimension C represents the fractured depth. When the punch reaches a limit depth, the material becomes locked between the punch and the die and is fractured or separated completely due to the downward motion of the punch.
4. Dimension H represents the burr height. The burr is the protuberance that is formed at the bottom of the sheared edge due to the inclined fracture of the material.
5. And finally, dimension W represents the burr width.

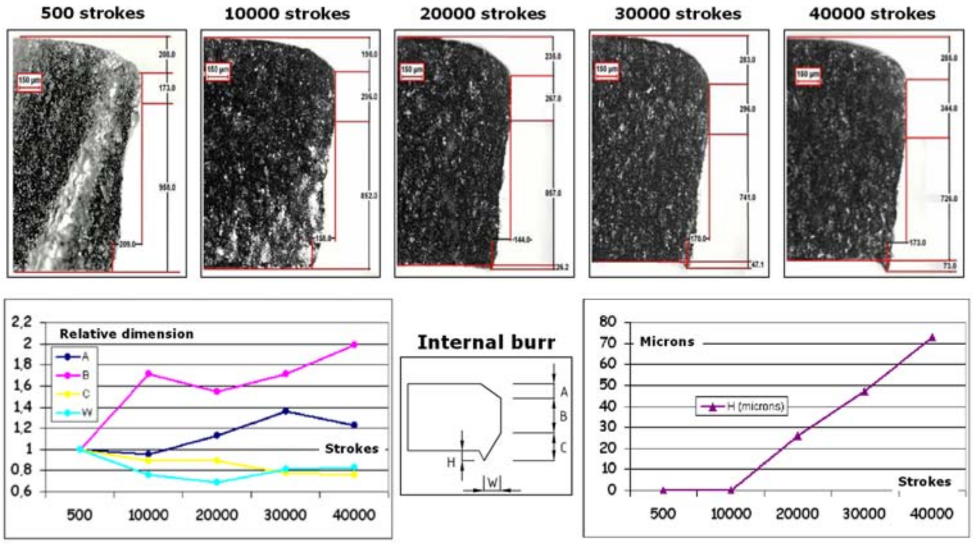


Figure 4.41: Evolution of the internal edge quality at the predefined intervals.

Since the most important variable regarding the quality of the part edge is the burr height, the present study will be focused on this variable. Anyway, and since the part edges were measured in the optical microscope, all the dimensions of the part edges are given in the Figure 4.41. In the bottom left side the evolution of the internal edge dimensions except the height of the burr are given. At the same time in the bottom right side the evolution of the burr height is given. The evolution of the burr height is very clear. At the beginning during the first 10.000 strokes the burr height is zero. After these 10.000 strokes the burr increments almost linearly up to 73 microns. At this burr height the operator sent the punches to be re-sharpened.

4.5.2.2. Evolution of the external edge quality

The same study was carried out for the external edge of the parts. Top side of Figure 4.42 shows the images acquired at the optical microscope for the specimens taken at 500, 10.000, 20.000, 30.000 and 40.000 machine strokes. And bottom side of the figure shows the evolution of the different dimensions that determine the quality of the edge. Again, all the dimensions that describe the edge (bottom centre) were extracted with the optical microscope. In the bottom left side, the evolution of the external edge dimensions except the height of the burr are given. At the same time, in the bottom right side, the evolution of the burr height is given. The evolution of the burr height is very clear. As happened in the internal edge, at the beginning during the first 10.000 strokes the burr height is zero. After these 10.000 strokes the burr increments almost linearly up to 60 microns. At this burr height the operator sent the punches to be re-sharpened.

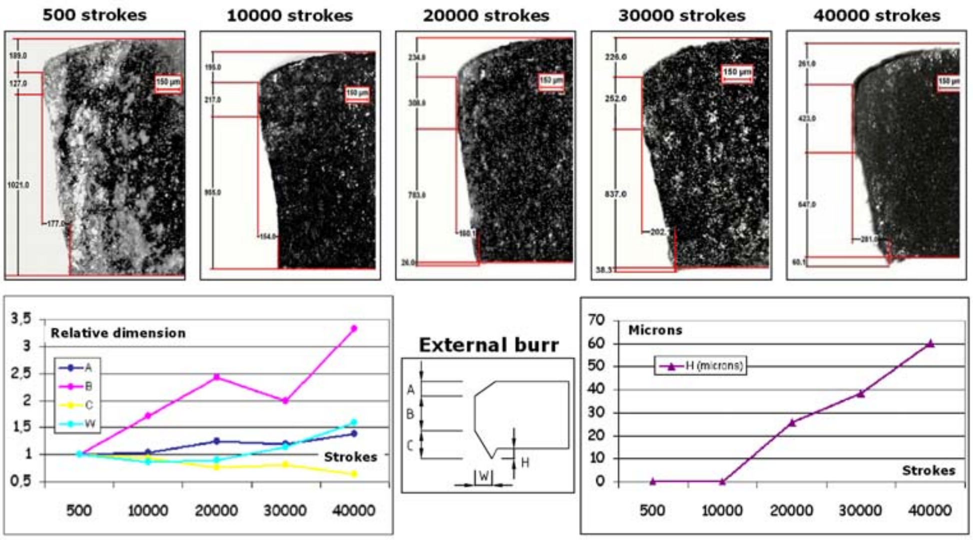


Figure 4.42: Evolution of the external edge quality at the predefined intervals.

4.5.3. Final comparison between process signals and part's edge quality

Finally, and since the main purpose of the study was to find the relationship between the variation of the edge quality and the variation of the process signals, a comparison between the aforementioned results has been done.

Figure 4.43 shows all the results achieved during the present study. The horizontal axis represents the number of strokes at which the samples were taken during the production. The vertical axis represents the signal variation for each variable with respect to the initial signal value (500 strokes) at each variable. Therefore, this vertical axis is dimensionless and the values are relative to the value at 500 strokes curve for each variable.

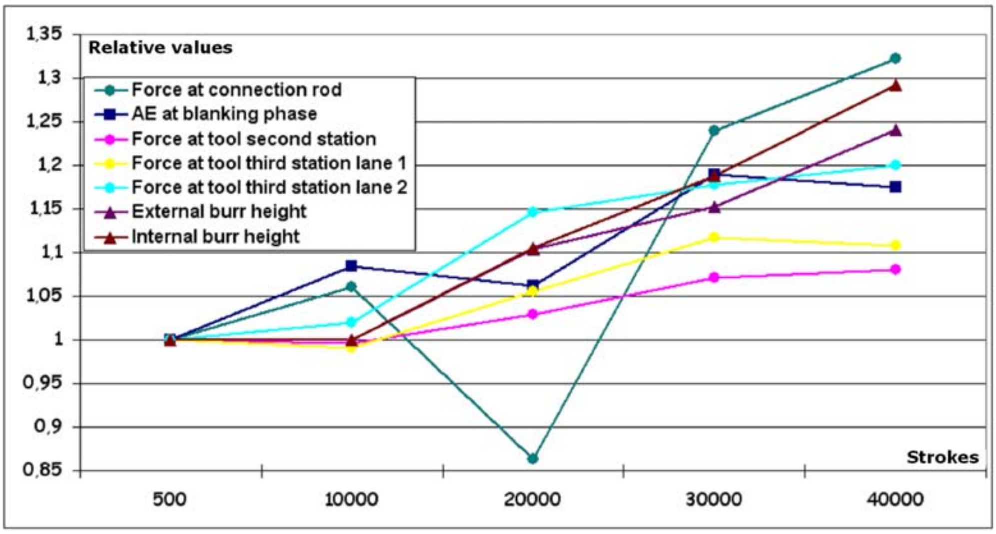


Figure 4.43: Comparison of the evolution in the edge quality and in the process signals.

All the analysed variables show an incremental tendency from the beginning until the end of the production. The only measurement that does not follow this tendency is the force measured after 20.000 strokes in the connection rod. As it has been previously explained, the reason for this “incorrect” measurement can be the low reliability of the Vario Sensor placed in the connection rod of the machine. Next, a brief description of the tendency of all the variables is given.

1. The force at the connection rod shows an incremental tendency being at the end of the production 32,22% bigger than the initial force. Although the force after 20.000 strokes does not match with this tendency, the rest of the measurements draw almost a linear incremental tendency.
2. The AE signals recorded during the blanking phase show also an incremental tendency although in this case the tendency is not so clear. As it is shown in Figure 4.43, AE signals after 20.000 strokes are slightly smaller that at 10.000 strokes, and the same happens when the signals after 40.000 strokes are compared with the signals after 30.000 strokes. Anyway, the AE signals at the end of production are 17,44% bigger than at the beginning of the production.
3. The force at second station of the tool, the station where four small circular holes corresponding to two consecutives parts are blanked, also experiences an incremental tendency during the entire production. It must be noticed that the force increment is almost zero during the first 10.000 strokes. On the other hand, after these initial 10.000 strokes the force increases almost linearly being after 40.000 strokes 8,07% bigger than at the beginning of the production.
4. The force at third station of the tool in first lane, where one of the parts is blanked out from the metal strip, also experiences an incremental tendency. In this case the tendency is not so clear again and the force after 10.000 strokes is slightly smaller that at the beginning, and the force after 40.000 strokes is slightly smaller than after 30,000 strokes. Anyway, the incremental tendency along the entire production is clear and the force at the end of the production is 10,77% bigger than at the beginning.
5. The force at third station of the tool in second lane, where the other part is blanked out from the metal strip, also experiences an incremental tendency. In this case the incremental tendency is clearer than in the previous case although this tendency is not completely linear. The force at the end of the production is 20,03% bigger than at the beginning.
6. And finally, both burrs, external and internal burr, also follow an incremental patter during the entire production. Figure 4.43 shows how the height of both burrs increases as the number of strokes increases too. Figure 4.43 shows relative values in order to have the chance to compare the increment of the burrs height and the increment of the forces and the AE captured by the sensors based process monitoring system. The final value of the burrs, as explained in previous subchapter, was 73 microns for the internal burr and 60 microns for the external burr.

Therefore, a direct relationship between the edge quality (increment of the burr height) and the process signals (increment of the blanking force) has been observed during the present study. After this initial observation, a deeper analysis of the results has been carried out using the software MatLab.

Table 4.I: Burr and blanking forces correlation factors for reference 0863-012.

Correlation factor	External Burr	Internal Burr
Blanking force at lane 1	0.9343	0.9350
Blanking force at lane 2	0.9549	0.9378

Table 4.I shows the correlation factors calculated that shows how the growth of the burr at the parts and the force increment are almost linearly related (factor of 1 means a perfect correlation). Figure 4.44 shows the evolution of both, the internal and the

external burr, compared to the evolution of the blanking forces (in this case for the second lane).

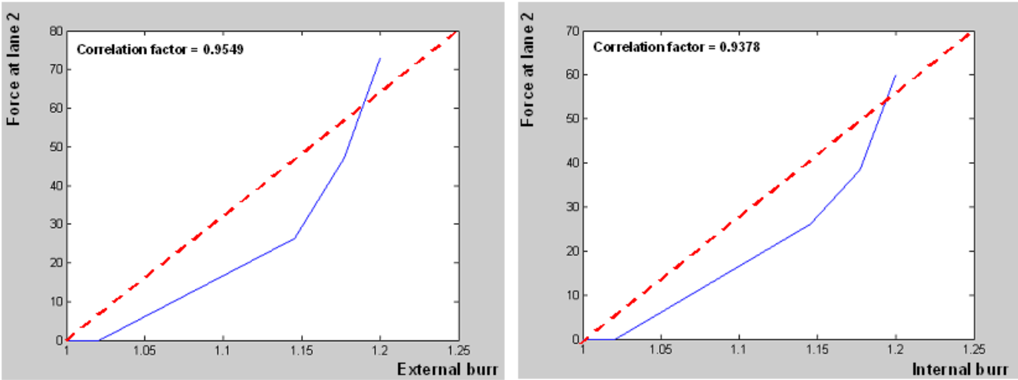


Figure 4.44: Correlation of both, the internal and external burr, with the blanking forces at lane 2.

This high correlation factor will help the operator to decide the right moment to re-sharpen the punches, and this way, this decision will be more objective than before starting the present research work (the operator used his fingers to “measure” the burr).

4.6. Summary of results and conclusions

A Brankamp sensors based process monitoring system has been implemented into a blanking facility and its performance has been evaluated. Three common sensors have been used for all the references produced at the blanking facility meanwhile three specific references have been also equipped with sensors inside the tools. First conclusion is that force and AE signals recorded directly at the tool offer much better reliability than signals recorded in the connection rod or in the machine structure.

From a process failure detection point of view, the sensors based process monitoring system has been able to detect up to nine different process failures at the blanking facility. Most of the process failures are related with the malfunction of the feeding system, the presence of metal slugs inside the tool and malfunctions of the air evacuation system used to extract the parts from the tool. At the same time, punch breakages, malfunctions of the ejection system in the double action tools and adhesions of the strip to the pilot pins of the tool were also detected. Figure 4.45 shows a summary of the process failures detected at the blanking facility during the experimental phase.

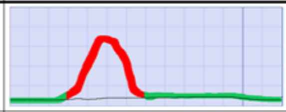
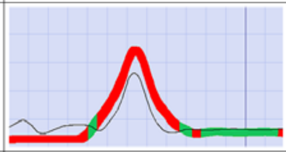
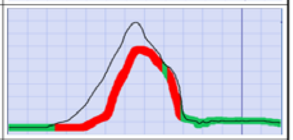
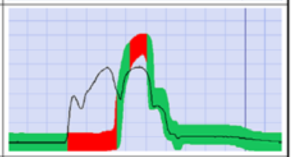
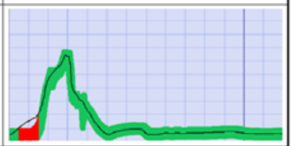
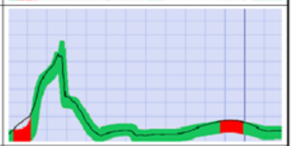
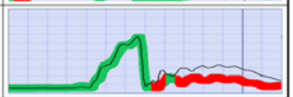
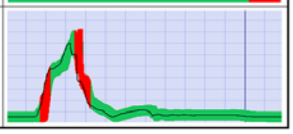
	Failure	Variation	Process signal
1	The metal strip is completely blocked inside the tool.	The signal is "flat" in all force and AE sensors.	
2	The metal strip did not advance the right distance between strokes.	There is a force peak at the beginning of the force sensors in first and second stations in the tool.	
3	A badly evacuated metal slug is blocking the first station.	There is a force peak right before the maximum force in sensors placed in the first station of the tool.	
4	A badly evacuated metal slug is blocking the second station.	There is a force peak right before the maximum force in sensors placed in the second station of the tool.	
5	A badly evacuated part is blocking the first station.	There is a force peak right before the maximum force in sensors placed in the first station of the tool.	
6	A badly evacuated part is blocking the third station.	There is a force peak right before the maximum force in sensors placed in the third station of the tool.	
7	There is a badly evacuated part inside the blanking die.	The force is too high at the end of the force curves.	
8	There has been a punch breakage.	There is a big vertical peak in AE sensor number 3.	
9	There is an strip adhesion to the pilot pins of the tool.	There is a time gap in the process signals in the force sensors placed inside the tool.	

Figure 4.45: Process failures detected during the experimental phase [SAE08].

Another important conclusion regarding the detection of these process failures is the ability of the sensors based process monitoring system to locate the position at the tool where the process failure takes place. Since several sensors were installed in the references studied during the research work, the sensors based process monitoring system is able to find the position where the process failure takes place. The analysis of this data in a suitable way can be converted into very useful information for the operator as it will be shown in "Chapter 6. Intelligent Control System" where the knowledge for the expert system is acquired and implemented. This ability to determine the position (and also the type as shown in Chapter 6) of the failure within the tool represents an improvement of the current monitoring systems implemented in the forming industry.

On the other hand, the sensors based process monitoring system was not able to detect some process failures at the blanking facility during the experimental phase. The most important process failure that the sensors based process monitoring system was not able to detect was the formation of micro cracks in the blanking punches. The formation of these micro-cracks represents a slight change of the force applied by the machine to blank the material but this change is so insignificant that the sensors based process monitoring system is not able to detect it. The consequence of these small micro cracks in the punches is the production of bad quality parts due to the presence of local big burrs. Next chapter explains how an artificial vision system has been developed in order to complement the sensors based process monitoring system and to detect this process failure not detected at this chapter.

And finally, another process variable that the sensors based process monitoring system was not able to detect directly is the growth of the burr over the predefined height limit. It is well stated in the literature that, as the blanking facility produces more parts, the edges of the punches get wear and change from a sharpen shape into a rounded shape. This effect has two direct consequences. First consequence is that the burr in the edges of the parts grows up. And second consequence is that the force to blank the material increases. At the present research work a study to evaluate how the wearing of the punches influences these two previous mentioned consequences at the industrial field has been carried out. The most important conclusion (complementing the current state of the art that mainly covers laboratory researches) is that a direct relationship between the height of the burr and the force necessary to blank the material was found. Following this direct relationship, the sensors based process monitoring system can be used to indirectly (by measuring the blanking forces) measure the burr height at the parts. The observed relationship at the present research work has been a blanking force increment of around 2,33% every 10 microns for the external edge and a blanking force increment of around 4% every 10 microns for the internal edge. More detailed conclusions are given in “Chapter 4.5.3. Final comparison between process signals and part’s edge quality”.

4.7. Bibliography

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Chapter 5

PARTS QUALITY CONTROL

5.- PARTS QUALITY CONTROL

The results achieved in the previous chapter showed that the sensors based process monitoring system is not able to detect some of the process failures at the blanking facility. The sensors based process monitoring system showed its capability to detect process failures like punch breakages, bad evacuated parts or feeding malfunctions in the blanking facility but, at the same time, it was not able to detect the presence of local big burrs in the parts due to punch micro cracks. Therefore, the present chapter explains the work that has been carried out in order to develop an artificial vision (AV) system, complementary to the previous sensors based process monitoring system, that will detect the process failures that were not detected by the sensors based process monitoring system. Furthermore, this AV system will measure the main dimensions of the manufactured parts controlling whether all the dimensions are within the predefined tolerances or not. The AV system is able to control the 100% of the produced parts at a high rate.

In this chapter, the handling system developed to manage the parts from the blanking facility to the final containers is described first. As shown later, this handling system was developed to fulfil the requisites directly linked to the geometry of the parts and the characteristics of the manufacturing process. After this, a brief explanation of the vision hardware elements that have been chosen to develop the vision system is given too. The hardware elements depend principally on the geometry of the evaluated parts and the features to be calculated from them. Next, the vision algorithms developed for the processing of the images acquired from the parts are briefly explained. These vision algorithms have been created with the aim of their further implementation on intelligent cameras in order to boost the processing rate of the vision system.

After evaluating that the implementation of the processing algorithms on a traditional architecture based on commercial cameras and image processing on PC was not fast enough for the purposes of the present research work, two FPGA based intelligent cameras have been implemented into the vision system speeding up the throughput of evaluated parts. This way, the production rate of the blanking facility was not limited by the vision system.

Finally, the results achieved by the AV system regarding the detection of local big burrs (not detected by the sensors based process monitoring system), the accuracy of the dimensions measured and the evaluation rate per part achieved are given. The chapter finishes with the main conclusions drawn during the development of the AV system and during the experimental phase.

5.1. Case studied: Retaining rings for the automobile industry

As mentioned before, the parts selected to carry out the present research work belong to the family of retaining rings. A retaining ring is a piece of hardware that holds on to a shaft in order to locate other items on the shaft, or to locate the shaft to a fixed item [WIK08]. In the present research work, the three selected retaining rings are very similar references used at the automotive industry, ranging their main diameter from 25 millimetres to 38 millimetres. All of them can be considered as small to medium size parts and are manufactured at medium to high production rates (approximately 100-120 parts per minute).

Regarding the quality control of the selected references during their production process, the results achieved in the previous chapter showed that a force and AE monitoring approach is very well suited to detect some process failures, like possible scratches in the surface of the parts due to bad evacuated parts or bad evacuated metal slugs from the tool, which at the same time are usually very difficult to detect using AV approaches. On the other hand, it was also stated that sensors based process monitoring systems are not well fitted to detect process failures like the presence of local big burrs due to punch micro cracks or parts out of tolerances, which can be detected accurately with AV systems. Therefore, the AV system developed at the present research work pursues to become a quality control tool complementary to the sensors based process monitoring system explained in the previous chapter. This way, both monitoring systems working together will create the necessary synergies to achieve a zero defect production.

The references and the dimensions to be controlled by the AV system during this research work are described in Figure 5.1. Although the three references belong to the same family of parts being very similar, the system necessary to handle them through an AV system should have different dimensions (to avoid blockages) and therefore it was decided to develop an industrial AV prototype for one of them. In this case the reference selected was reference 5828-001 because it was the mostly produced one at Industrias Alzuaran S.L.

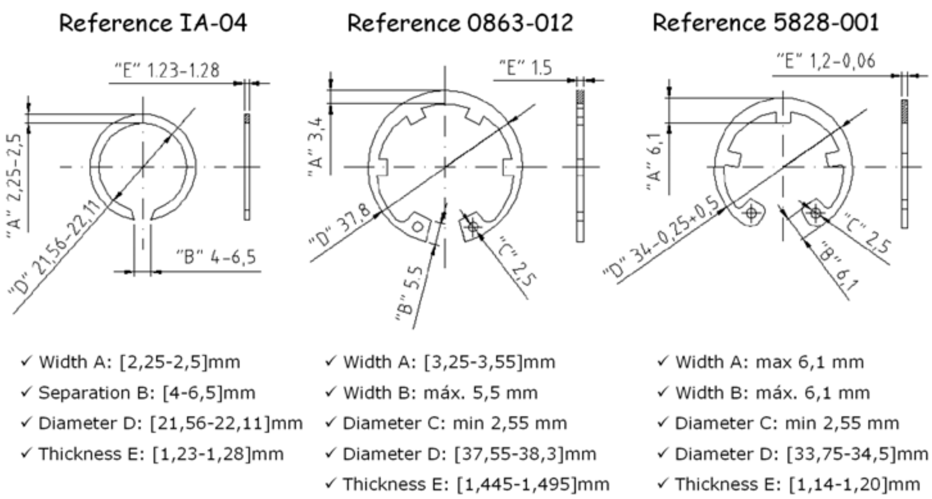


Figure 5.1:Dimensions to be controlled in the selected references.

Considering that the main objective of the AV system is to detect the process failures not detected by the sensors based process monitoring system (principally local big burrs due to punch micro cracks) and to evaluate the quality of the manufactured parts (verify that the aforementioned dimensions are within tolerances), it was decided to develop a vision system composed of two cameras. The first camera "looks" at the parts from above and evaluates their dimensions and the second camera "looks" at the parts from the side in order to detect local big burrs. Figure 5.2 shows a schematic concept of the developed vision system.

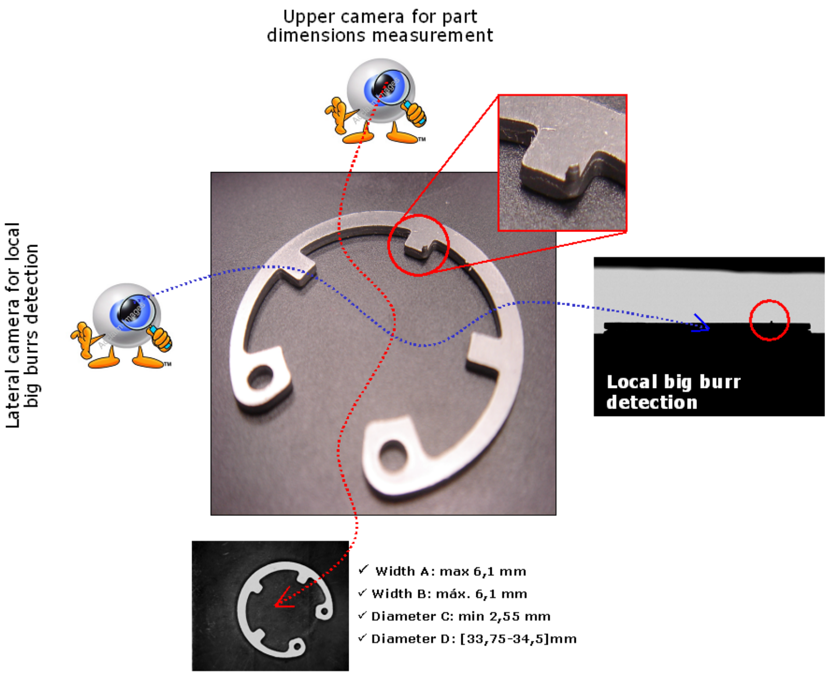


Figure 5.2: Schematic concept of the AV prototype developed.

After defining that the vision system should be composed of two cameras placed perpendicularly, next chapter explains the development of the entire AV system that will carry out the quality evaluation of the aforementioned references.

5.2. AV industrial prototype for retaining rings quality assurance

The AV system developed in the present research work is an automatic device able to capture two images per part and to evaluate around 100 to 120 parts per minute (although the image processing is much faster, approximately 500 parts per minute, the system is currently limited by the handling of the parts). Its development includes the integration of mechanical devices (for the handling of the parts), hardware automation (pneumatic elements for the process coordination), electronic devices (vision cameras and illuminations, triggers for shooting the cameras, etc.…) and computing software (vision algorithms for the parts quality evaluation). The handling strategy that allows to get high quality images of the parts, the image acquisition strategy, the vision hardware and the algorithms that process the aforementioned images are explained next.

5.2.1. Mechanical design: handling of the parts

The acquisition of good quality images of the parts to be evaluated is one of the most important factors in AV systems. Good quality images means that the vision algorithms will be able to find accurately the contours of the parts and, therefore, that the vision system will classify the quality of the inspected parts correctly. At this point the importance of a good handling system must be considered. A handling system can be defined as a mechanical device able to evacuate the parts from the blanking facility, position the parts in the area where the images are taken and finally direct the parts towards the right container (good or defective parts) depending on the AV system's decision. To carry out all these tasks at high production rates is usually quite complex, and this is the reason why it is very difficult to develop universal handling systems able to manage different kind of parts.

Initially, and since the three references are very similar, the development of a handling system able to work with the three references was proposed. Following this initial purpose, a flexible handling prototype specially developed for these references was built up and tests with the three references were carried out. After the initial trials, it was concluded that, for industrial purposes where the system must be able to handle high quantity of parts per minute, and no blockage of parts is allowed, more specific handling systems must be developed.

Then, it was decided that, in order to accomplish the objectives of the present research work, the handling prototype should be prepared only for one of the studied references. This way, the results of the handling prototype would be evaluated for one reference allowing at the same time its future adaptation to more references. Since the reference mostly produced in Industrias Alzuaran S.L. is the reference 5828-001, it was decided that the handling system and therefore the final AV prototype should be tuned up for the requisites of this reference.

The global handling prototype developed in the present research work is divided into two main blocks: the first block is in charge of transporting the parts from the blanking facility to the entrance of the AV system and the second block is in charge of handling the parts through the AV system. Next a brief description of each block is given.

5.2.1.1. Parts handling from the blanking facility to the AV system

After analysing the parts to be evaluated, the blanking process and the blanking facility where the parts are produced, the requirements for the evacuation of the parts from the blanking facility and its further transportation to the AV system were established:

1. A very important requirement is that due to the special geometry of the parts to be evaluated, the system must be able to separate them because they get tangled very easily and later is not possible to disentangle them.
2. Second requirement is linked to the way the parts are evacuated from the blanking facility. Since the final blanking station is a double action tool (explained in "Chapter 4.4.1.5. Evacuation system failure I: Double parts in pilot pins") and the throughput of parts is between 100 and 120 parts per minute, the current evacuation system at the blanking facility is based on the evacuation of the parts by blowing them out of the tool by means of air.
3. Third requirement is the necessity of positioning the parts at the entrance of the AV system. Since the throughput of parts ranges between 100 and 120 parts per minute, it is necessary to place the parts in a specific configuration at the entrance of the AV system; this way, the feeding of the parts into the AV system is carried out efficiently.
4. Fourth requirement is that, since the feeding area of the AV system is located in a higher position than the final position of the parts after being blown away from the blanking facility, a system to raise the parts is necessary. Therefore, a conveyor belt was implemented to transport and to raise the parts high enough to reach the entrance of the AV system.

Considering all the previous mentioned requisites, a specific handling system that links the blanking facility with the AV system was developed. The system is briefly explained next. As mentioned before, the final station of the tool used to produce the reference 5828-001 is a double action blanking station (see Figure 4.20). When the parts are blanked from the strip, the parts remain within the upper tool and when the ram of the machine is in the upper position, an ejector hits the parts pushing them down. When the parts are falling from the upper tool downwards to the lower tool, an air flow blows the parts out of the tool (image 1 in Figure 5.3). By means of the air flow, the parts leave the tool and go into two metallic funnels, especially designed to match with the tool. The metallic funnels and the PVC tubes where these metallic funnels end are shown in image 2 in Figure 5.3. Image 3 in Figure 5.3 shows the PVC tubes used to transport the parts to the conveyor belt.

After this, the parts arrive to the conveyor belt by means of a connection that links the PVC tubes and the conveyor belt (shown in image 4 in Figure 5.3). With this connection, the parts coming from the different lanes of the tool get a different position in the conveyor belt and the tangling of the parts is avoided. As mentioned before, this has been a main requisite in order to avoid blockages in the AV system. Finally, image 5 in Figure 5.3 shows how the parts go up through the conveyor belt and are thrown in the funnels that represent the beginning of the feeding area of the AV system (shown in image 6 in Figure 5.4).

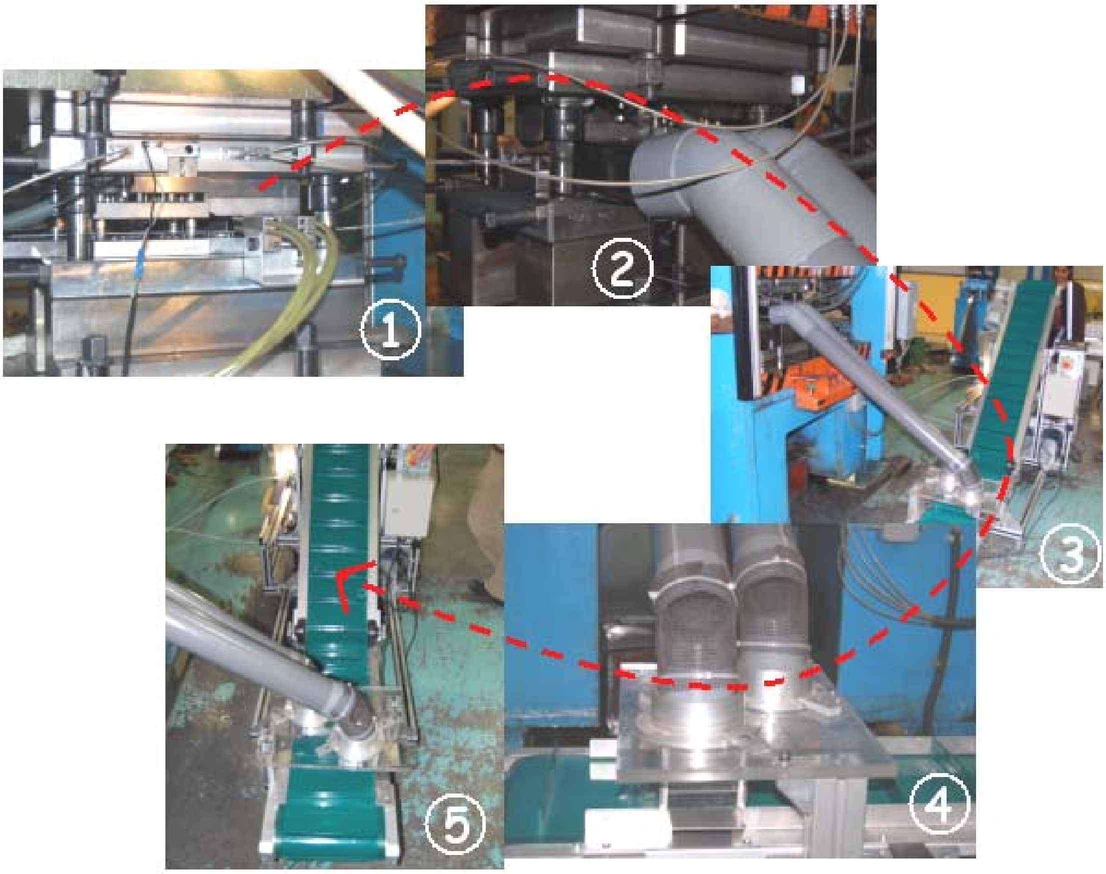


Figure 5.3: Handling of the parts from the blanking facility to the AV system.

5.2.1.2. Parts handling through the AV system

Once the parts arrive to the feeding area of the AV system, they go through the following way. First of all, the parts fall down into two different funnels, one funnel per lane in the tool (image 6 in Figure 5.4). These funnels lead the parts to their entrance into the “positioning boxes“ (developed together with the University of Suttgart) as shown in image 7 in Figure 5.4. The main purpose of the “positioning boxes” (graphically explained in Figure 5.5) is to position all the parts in the same configuration for their feeding into the AV system. Thus, at the end of the “positioning boxes” two vertical buffers gather the parts positioned one above the others. These vertical buffers allow the feeding system to reach a high feeding rate and to work independently from the blanking facility, compensating punctual variations in the arrival of the parts to the AV system. The concept of these “positioning boxes“ is explained in Figure 5.5. Basically the idea is to provoke the rotation of the parts making them to achieve the same orientation. This way, the opening of the parts finds the middle vertical wall and by gravity they are positioned brazing the vertical cylindrical buffer. From these vertical buffers, two lateral tongues feed alternatively parts to the area where the pictures are taken (shown in image 8 in Figure 5.4 and further described in “Chapter 5.2.1.3. Parts handling in the image acquisition station of the AV system”)

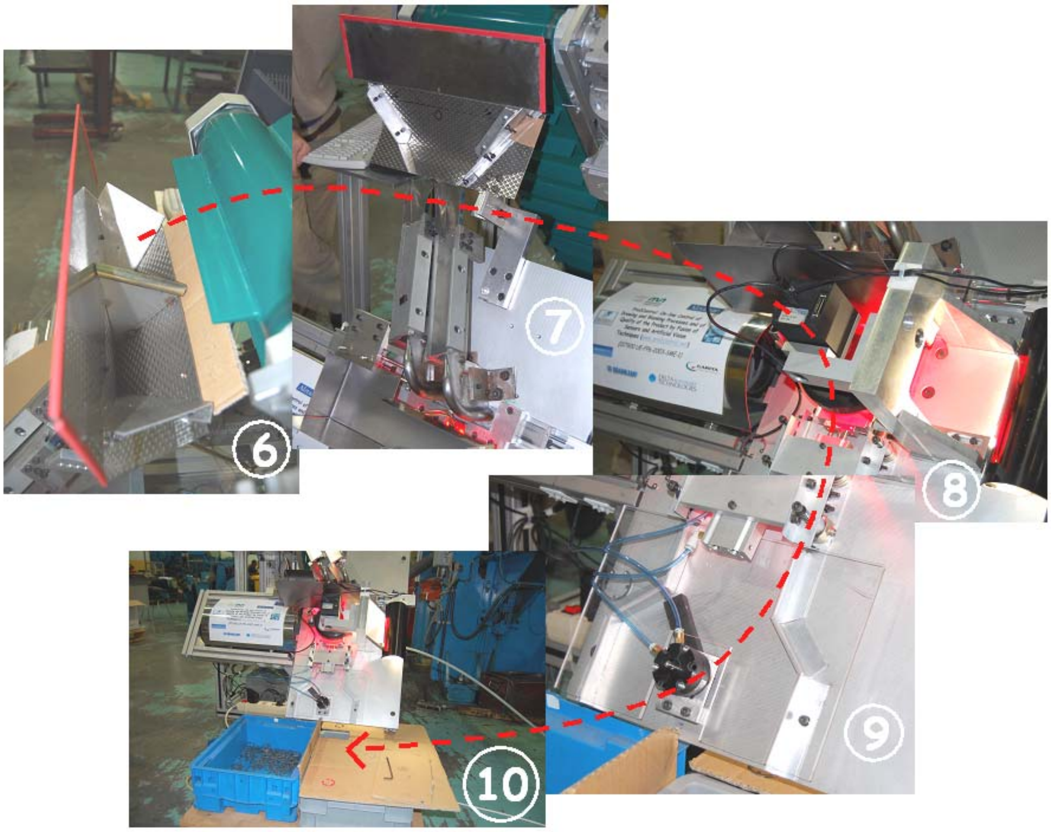


Figure 5.4: Handling of the parts through the AV system.

After acquiring and processing the images of the parts, an air flow pushes the parts down and a rotational cylinder sort out the parts depending on their quality (this is shown in position 9 of Figure 5.4). Finally, at the end of the AV system there are two containers, one for the good quality parts and another one for the parts that are defective (this is shown in position 10 of Figure 5.4).

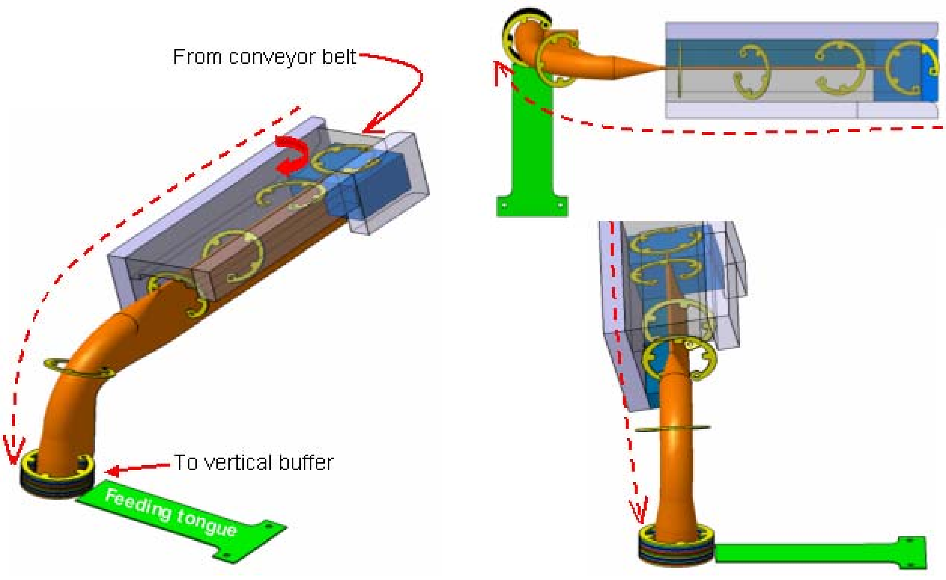


Figure 5.5: Positioning boxes for the AV system developed for Industrias Alzuaran S.L.

5.2.1.3. Parts handling in the image acquisition station of the AV system

In this chapter, a brief explanation of the parts handling in the station of the AV system where the images are taken (shown in image 8 in Figure 5.4) is given. Again, and this time after evaluating the parts to be controlled and the dimensions to be measured, the requirements that should be taken into account for the design of this station were established.

1. Since the production rate was between 100 to 120 parts per minute, the handling system must be able to feed one part, position it in the area where the images are taken and later direct it to the right container approximately every half a second.
2. From preliminary tests made with several references, it was concluded that the parts must be static when both, the upper view and the lateral view images, are taken (see Figure 5.6).

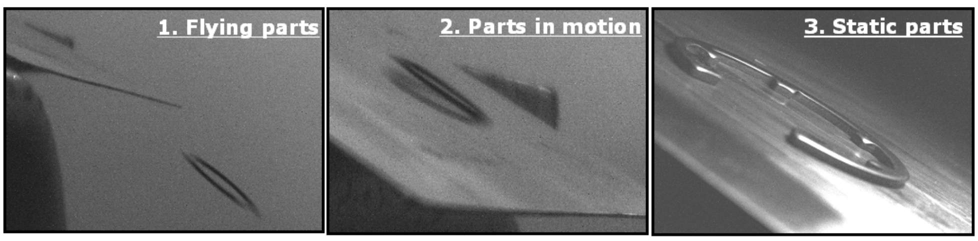


Figure 5.6: Image quality for parts flying, parts moving over a metallic ramp and static parts.

3. And finally, and as mentioned before, another requirement is the necessity of two vision cameras, one for taking the upper view image and another one for taking the lateral view image. Each camera has its own lens and illumination system and needs a suitable background able to provide a good contrast with the parts to be evaluated. All these requisites also influence the design of the area of the handling system where the parts will be stopped for the images acquisition.

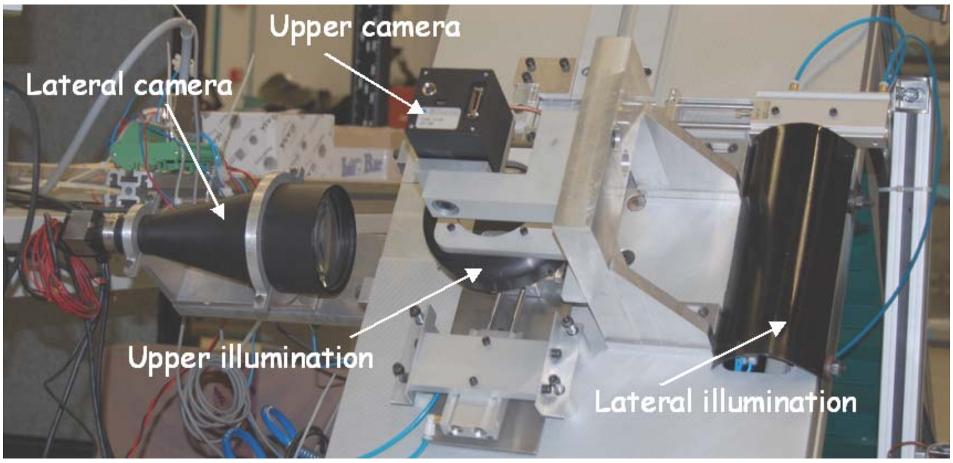


Figure 5.7: Upper view and lateral view cameras positioning inside the vision system.

Therefore, and aiming to fulfil the previous requirements, the station where the images are taken was designed for the introduction of both cameras. The position between both cameras forms a 90 degrees angle in order to capture an upper view image and a lateral view image (see Figure 5.7). This way, a third axis (perpendicular to the position of both cameras) is used to feed and withdraw the parts from the image acquisition area.

At the same time and fulfilling the necessity of capturing the images when the parts are static, Figure 5.8 explains the procedure developed to first stop and position the parts in front of the cameras and to later evacuate them from the image acquisition area.

1. In a first step, the parts coming from the feeding system (pushed by the tongues of the vertical buffers) fall over a slopping metallic ramp and “cut” a non-contact photoelectric trigger that initialises the image capturing sequence. At that time, the centring device (V-shaped part in Figure 5.8) is placed in the area where the images will be taken.
2. In a second step, the centring device stops the part and thanks to the V shape of this last one, the part gets the right position in the area where the images will be taken. A few milliseconds after cutting the trigger, an electromagnet placed under the ramp is activated. This electromagnet forces the part to keep the right position within the area where the images are taken.
3. In a third step and a few milliseconds after activating the electromagnet, the centring device is moved backwards. This way, the part remains in the right position and the centring device is not any more in the field of view of the cameras.
4. And finally, in a forth step, both cameras take the images consecutively, first the upper view camera and right after the lateral view camera. A few milliseconds later, the electromagnet is disconnected, the part falls down blown by air, and finally, the centring device is moved forward to receive the next part.

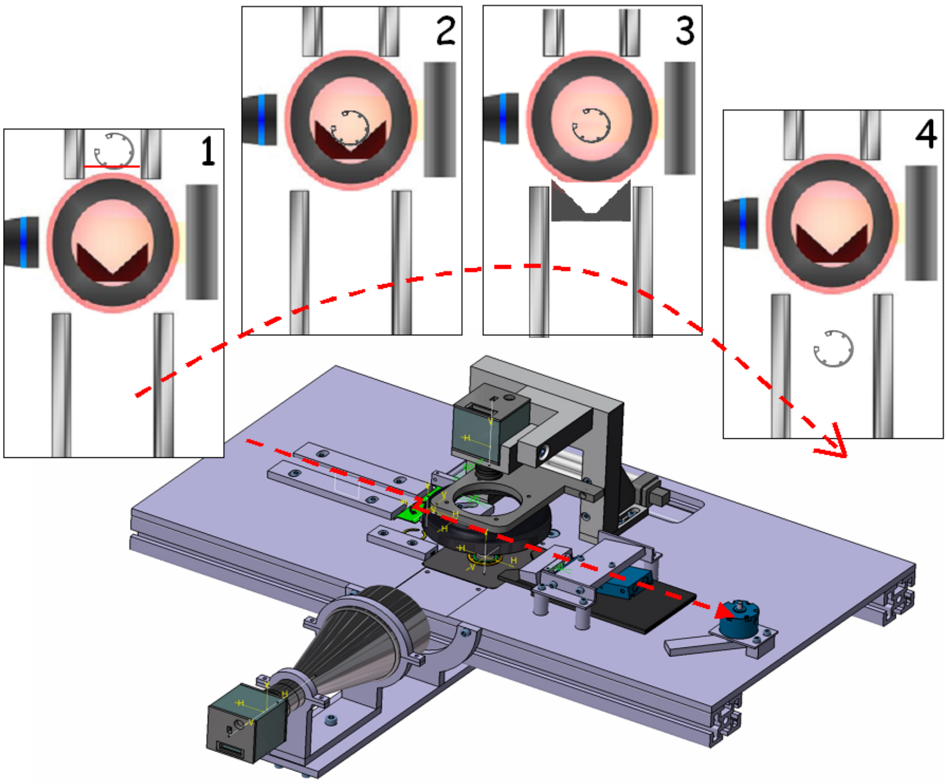


Figure 5.8: Strategy developed for stopping the parts for the images acquisition.

5.2.1.4. Results achieved by the handling system

Following the aforementioned steps, the quality of the images taken is very high what makes easier the extraction of the contours of the parts and therefore improves the quality of the evaluation. Figure 5.9 shows two examples of images taken following the aforementioned strategy. The images correspond to the reference 5828-001.

The left side of Figure 5.9 shows how the sharpness of the upper view image taken to the reference 5828-001 is very high. Among other factors, like the vision hardware chosen for this application that will be later explained, one of the most important ones is the fact that the part remains static when the images are acquired. This fact increases very much the sharpness of the images (what reduces the complexity of the algorithms and avoids the problems encountered with the parts in motion) and at the same time ensures the right position of the parts in front of the cameras (within the field of view and parallel to the cameras).

In the right side of Figure 5.9, a lateral view image of the reference 5828-001 is shown. Here again, the sharpness of the image is clearly shown. Figure 5.9 illustrates the detection of one process failure that was not detected with the sensors based process monitoring system: local big burrs due to punches micro cracks.

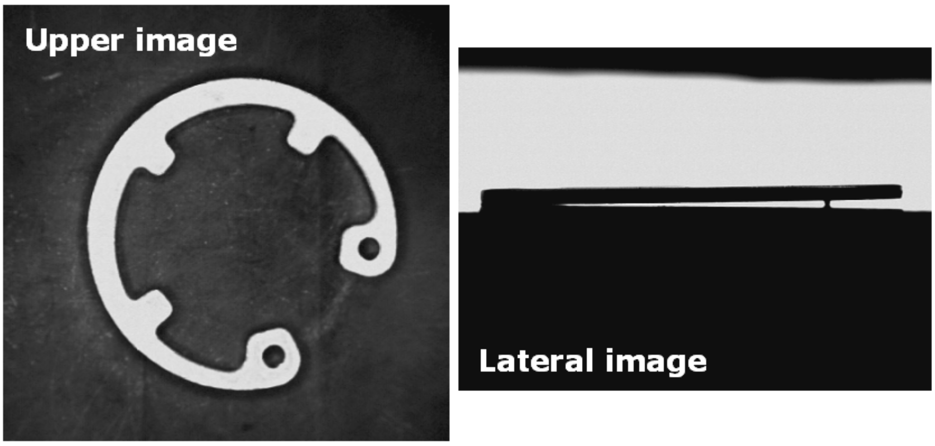


Figure 5.9: Upper view and lateral view images of reference 5828-001 taken with static parts.

5.2.2.Electronic design: selection of the vision hardware elements

The acquisition of good quality images in AV systems involves a few hardware devices. The minimum vision set to acquire images for part quality evaluation purposes includes an industrial camera with its correspondent lens and a suitable illumination system. The camera is in charge of digitalizing the image from a continuous (analog) signal into samples called pixels creating a digital image that later can be processed by algorithms. The function of the lens is to project the image to be acquired into the sensor of the camera. And the function of the illumination system is to enhance as much as possible the features of the parts to be evaluated.

These elements of the acquisition chain must be chosen to minimize noise in the images and optimise image quality. The parts to be evaluated have to be distinguished from the background as easily as possible, and the part features to be controlled have to be enhanced as much as possible. Since the AV system will be implemented into an industrial process, some environmental constrains have to be taken into consideration. The most influencing environmental constrains in this case are the vibrations generated by the blanking facilities in the company environment, the variability of the light level around the vision system and the dirtiness of the produced parts (e.g. presence of oil in the parts could lead to light reflections and therefore to false or difficult feature extractions).

A study was carried out in order to evaluate the consequences of these environmental constrains and to propose solutions for minimising their consequences. It was found that the vibrations in the environment do not generate fuzziness in the images, so this environmental constrain was discarded. Regarding the changeable light level in the environment and the dirtiness of the parts, special industrial illuminations like red Light Emitted Diodes (LED) were chosen. The main advantage of these special illuminations is their capacity to reduce or even eliminate brightness in metallic surfaces. The use of these special vision hardware increased the quality of the images taken by the cameras, reduced the complexity of the subsequent algorithmic processing step and produced good results regarding the evaluation of the produced parts.

Next, the vision hardware selected for both images, upper view and lateral view image, will be briefly described. At this point, it must be stated that the lenses and illumination systems described next have been used during the entire development of the system, from the initial setting up until the final prototype. On the other hand, two different kinds of cameras have been used during the development of the system. The initial cameras, commercial cameras purchased from the German company IDS, were used to set up and to evaluate the necessities of the vision system regarding the image acquisition process (distance of the cameras to the parts, acquisition timing of the cameras, selection of suitable lenses and illumination systems and further characteristics). After finishing these initial trials and once that the right setting up of the vision system was carried out, two proprietary iCam intelligent cameras, developed by Delta Technologies, were integrated within the AV system for speeding up the image processing.

5.2.2.1. Vision hardware elements for the upper view image acquisition

The first image acquired by the cameras is an upper view image of the parts to be evaluated (left image in Figure 5.9). The main aim of this image is to allow control of the main dimensions of the parts as explained in Figure 5.1.

Figure 5.10 gives an explanation of the architecture developed for the acquisition of the upper view image. For this image and since the purpose is to extract the contours of the part, the most suitable approach would have been a back illumination strategy. This strategy could not be applied because the part is in contact with the surface and even if a transparent material had been used, this surface would have scratched over the time making the quality of the illumination worse. Therefore, it was decided to apply a front illumination approach as shown in Figure 5.10.Furthermore, the material selected for the surface where the part is stopped for the image acquisition was black Teflon©, allowing to improve the contrast in the images between the part and the background (see Figure 5.10).

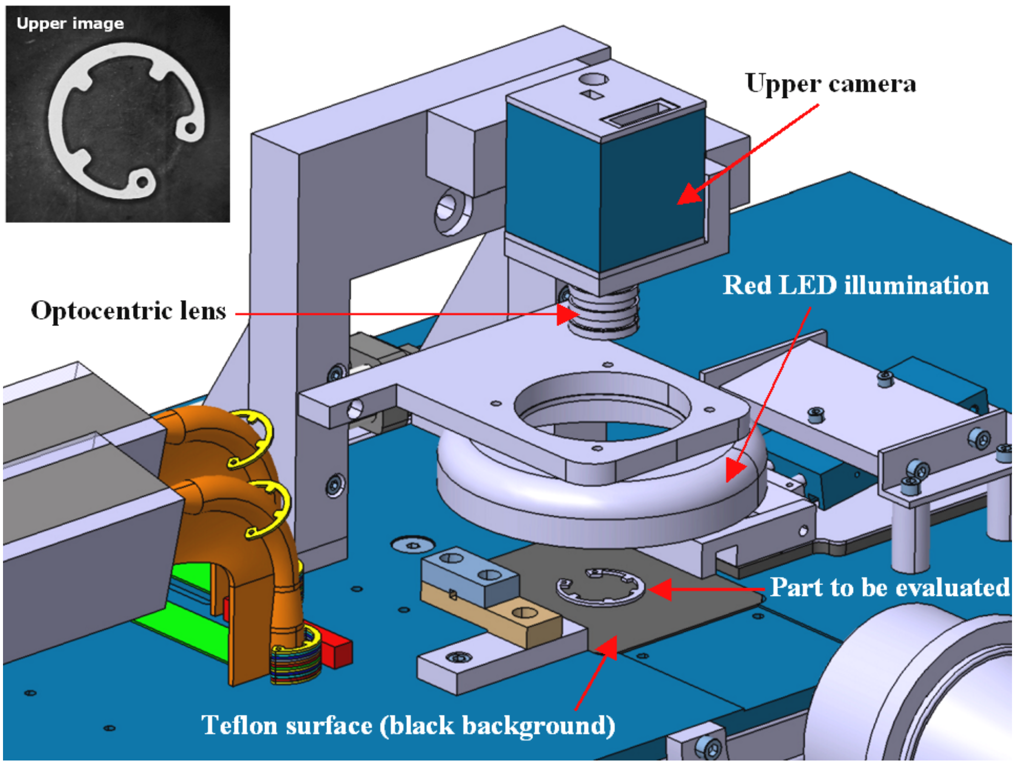


Figure 5.10: Hardware architecture for acquiring the upper view image.

For the upper view image, monochromic cameras (initially a commercial CCD camera for the set up and finally an intelligent CMOS camera for the final prototype) with a resolution of 1280*1024 pixels have been used at the present research work. It was calculated that sensors with this resolution, 1280*1024 pixels, allowed the system to achieve a spatial resolution of 50 microns per pixel, what is enough to evaluate the quality of the parts. At the same time, this sensor resolution is a standard size what made easier the acquisition of the components for the development of an intelligent camera with this resolution.

Regarding the optics, the camera was equipped with a standard (16mm F1.4 C 2/3”) optocentric lens from the German company Opto Engineering. Since the necessary depth of view for the image is approximately the thickness of the part, in this case 1,2 millimetres, no special lens are needed to capture the image. The optical distortion inherent to the optocentric lens (that could lead to errors in the measurements) was algorithmically compensated.

And finally the illumination used for the upper view image is a special red LED illumination ring which main purpose was to decrease the brightness due to the presence of dust or oil in the parts. At the same time, this kind of illumination supplies the light in an oblique angle, what stands out the part contours.

5.2.2.2. Vision hardware elements for the lateral view image acquisition

The second image acquired by the cameras is a lateral view image of the parts to be evaluated (right image in Figure 5.9 and also shown in Figure 5.11). The main aim of this image is to detect the presence of local big burrs that are not detected by the sensors based process monitoring system.

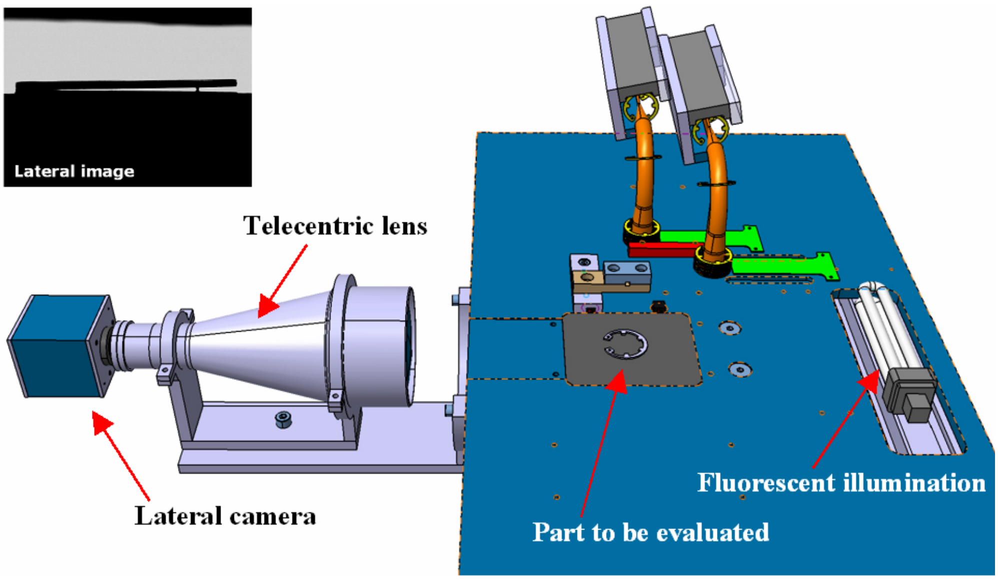


Figure 5.11: Hardware architecture for acquiring the lateral view image.

Figure 5.11 gives an explanation of the architecture used for the acquisition of the lateral view image. As happened in the previous case, since the purpose is to extract the contours of the part, the most suitable approach is a back illumination strategy. For the lateral view image, this back illumination approach has been used because there is no need for a surface between the camera and the illumination. Therefore, the image acquisition hardware for the lateral view image is composed of a camera, a telecentric lens and a fluorescent illumination. These elements are briefly explained next.

For the lateral view image the same reasoning as the one made for the upper view image was carried out. Monochromic cameras (initially a commercial CCD camera for the set up and finally an intelligent CMOS camera for the final prototype) with a resolution of 1280*1024 pixels were used. It was calculated again that sensors with this resolution, 1280*1024 pixels, allowed the system to achieve a spatial resolution of 50 microns per pixel, what is enough for the detection of local big burrs. At the same time, this is a standard sensor resolution, what made easier the acquisition of the components for the development of an intelligent camera with this resolution.

The lateral view camera was equipped with a telecentric lens from the German company Opto Engineering. The reason for choosing a telecentric lens instead of an optocentric lens is that a large depth of view (at least similar to the diameter of the parts in order to detect local big burrs at any position on the part) was needed.

Finally, and since the illumination strategy was back illumination, a powerful fluorescent illumination located behind the part was used. This powerful fluorescent illumination sticks out the contour of the parts, which allows to identify their silhouette correctly.

5.2.3.Computing design: vision algorithms development

After acquiring the images, the next step is their processing. Basically, the processing of the images consists on extracting the contour of the parts and verifying their right dimensions. At the present research work, two different vision algorithms have been created, one algorithm for the processing of the upper view image and another algorithm for the processing of the lateral view image. The processing of the upper view image, carried out by Delta Technologies and verified together with Mondragón University, evaluates whether all the dimensions of the part are within the tolerances specified in Figure 5.1 or not. And the processing of the lateral view image, carried out by Mondragón University, allows to detect the presence of local big burrs due to punch micro cracks (see Figure 5.2). In the next paragraphs, the algorithms developed for the processing of both, the upper view and the lateral view image, of the selected references are described.

5.2.3.1. Algorithms developed for the upper view image processing

Figure 5.12 shows the algorithmic approach developed for the evaluation of the upper view image. Figure 5.12 also shows an original image of the reference 0863-012 taken by the upper view camera. The algorithmic approach for processing the upper view image is divided into four main blocks that are briefly explained next. Since the final purpose has been to implement the vision algorithms in FPGA, the most suitable algorithms for their further implementation into FPGA were selected.

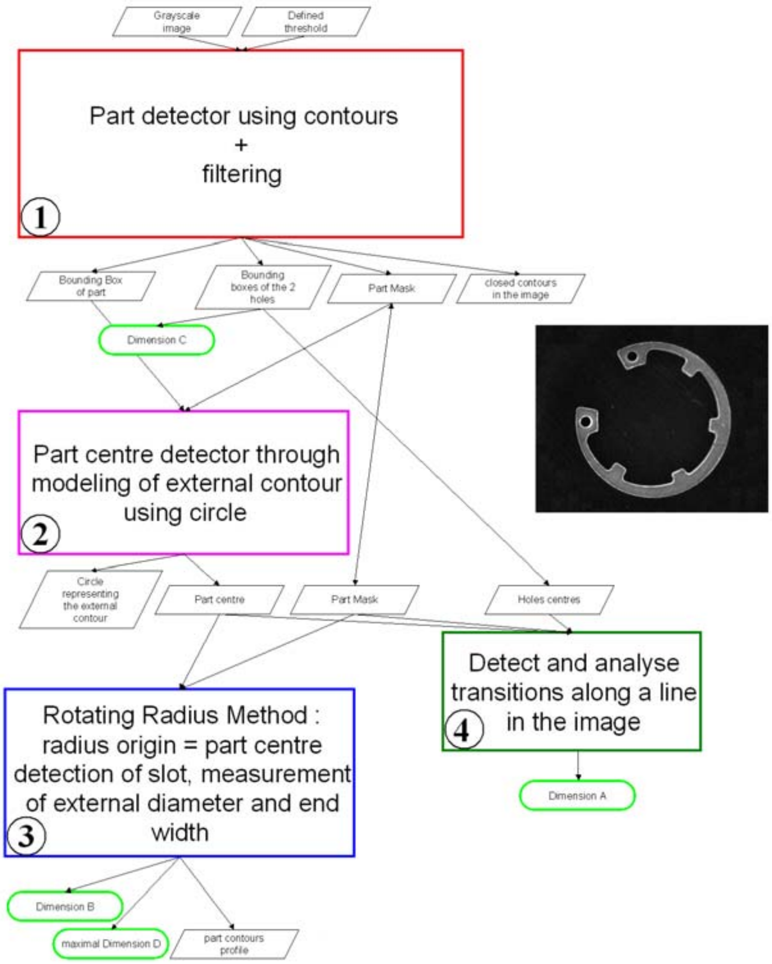


Figure 5.12: Algorithmic architecture for processing the upper view image (reference 0863-012).

5.2.3.1.1. Part detection and filtering

The first main block of the algorithm consists on generating a mask of the part. This mask of the part represents the part, once it has been separated from the background (the Teflon© background here) and the noise has been filtered. In order to obtain this mask, first an image thresholding is carried out and later all contours are detected and filtered depending on their size (see Figure 5.13).

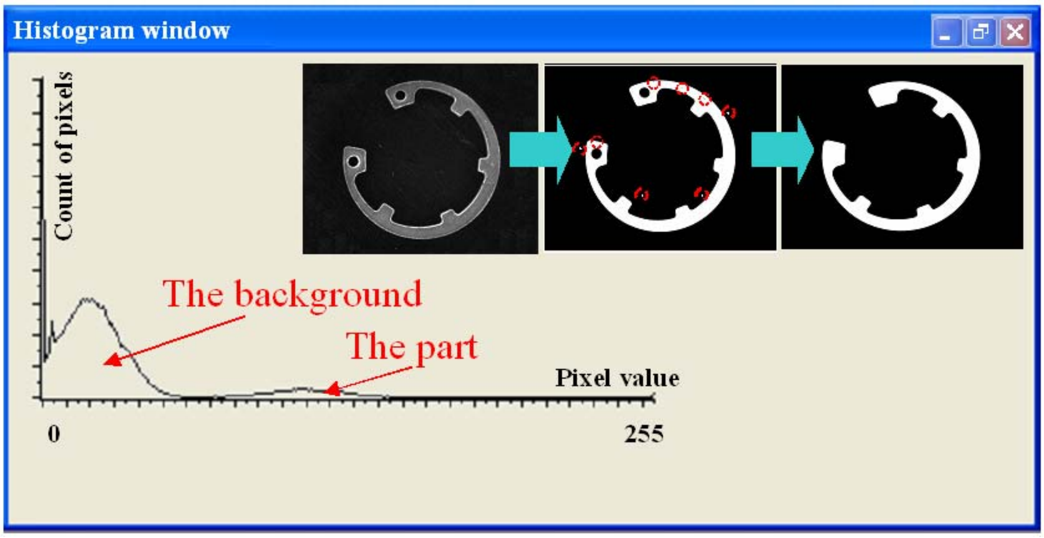


Figure 5.13: Thresholding and noise filtering for reference 0863-012.

5.2.3.1.2. Part centre detection

In the second block of the algorithm and taking as input the binarised image calculated in the previous block, the bounding box of the part is calculated and the part's external circular contour points are extracted (step 1 in Figure 5.14) in order to find the centre of the part. A least squares circle fitting of these contour points is performed in two steps. The first step computes an initial estimation of the centre (step 2 in Figure 5.14), and the second step deletes points that do not belong to the fitting circle (step 3 in Figure 5.14), allowing to refine the estimation of the circular contour and the part centre.

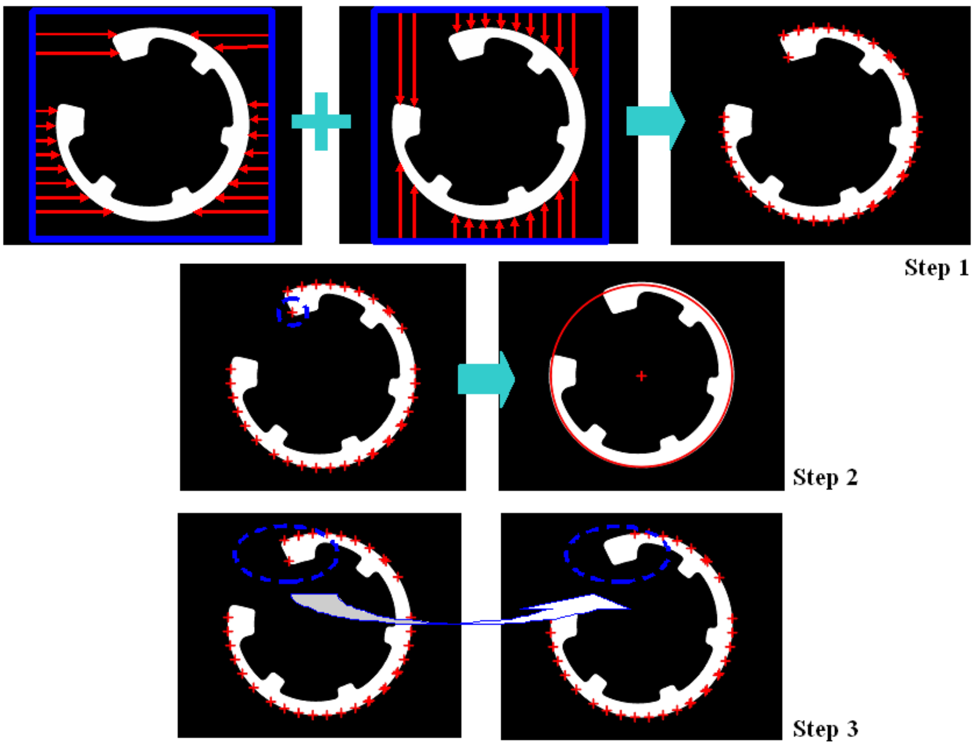


Figure 5.14: Detection of the external contour of the part.

5.2.3.1.3. Rotating radius method

In the third block, a procedure named rotating radius is carried out in order to calculate the main dimensions of the part. The rotating radius method uses a radius starting from the centre of the part that rotates over 360°, one degree per step. This radius looks for transitions of “black and white” pixels from the centre of the part towards its outside at each rotation (see Figure 5.15). This way, a first transition, from “black to white” pixels, corresponds to the internal contour of the part and a second transition, from “white to black” pixels, corresponds to the external contour of the part. Two profiles of distances, first profile representing the distance between the centre of the part and the internal contour and second profile representing the distance between the internal contour and the external contour, are built (red and blue contour in Figure 5.15)

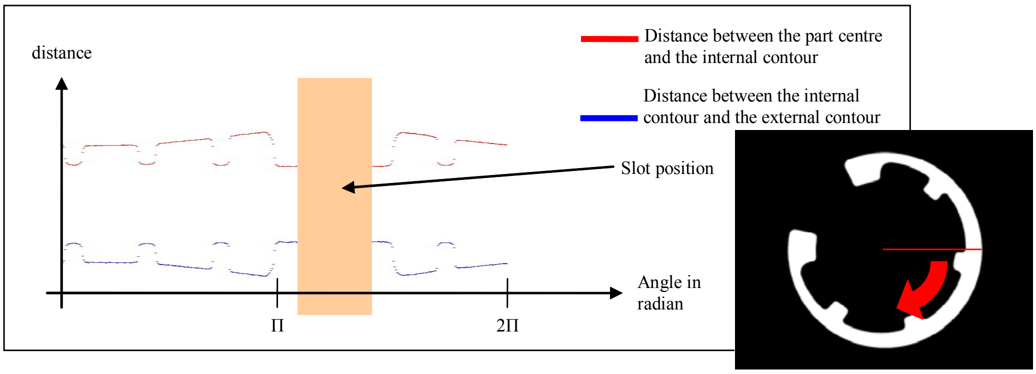


Figure 5.15: Rotating radius procedure to detect the internal and external contour of the part.

5.2.3.1.4. Final computation of the part dimensions

Through the implementation of the previously explained algorithmic approach, the calculation of the part dimensions is carried out. As explained in “Chapter 3.2.1.2. Reference 0863-012”, four main dimensions of the part must be controlled using the upper view image (also for reference 5828-001). The dimensions and the tolerances for reference 0863-012 and the approach for their calculation are summarised next:

- The dimension A must be between 3,25 and 3,55 mm.
- The dimension B must be 5,5 mm as maximum.
- The diameter C of the internal holes must be greater than 2,5.
- The diameter D must between 38,30 and 37,55 mm.

Dimension A:

Dimension A is the width of the part along its symmetry axis (left side in Figure 5.16). In order to calculate this width, three features have been derived from the previous calculations. The first feature is the mask of the part. The second feature is the centre of the two small holes at the ears of the part (being the ears of the part the thick areas of the part where the small holes are located). And the third feature is the centre of the part. Using the centre of the part and the centres of the two holes, the symmetry axis of the part is calculated (right side in Figure 5.16). Once the symmetry axis is calculated, transitions in the mask along this axis are detected. Two transitions are detected, first one from “black to white” pixels (internal contour of the part) and second one from “white to black” pixel (external contour of the part). After this, the distance between both transitions is calculated giving as the result the width “A” (left side in Figure 5.16).

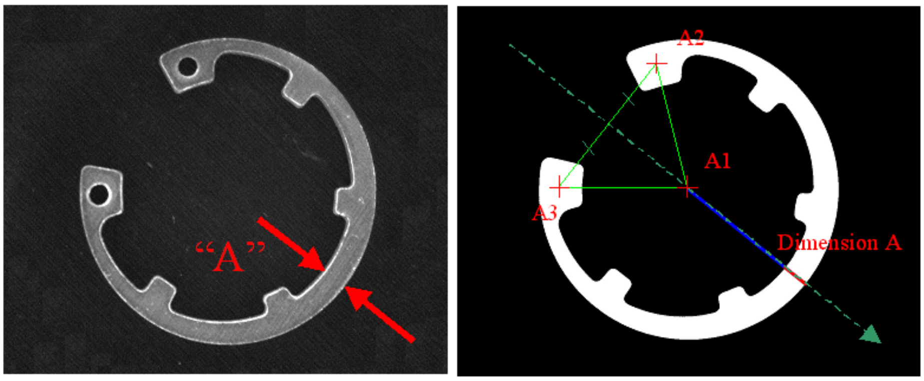


Figure 5.16: Width (A) of the part along the symmetry axis.

Dimension B:

Dimension B, the width at the ears of the part, was calculated too. In the information calculated in "Chapter 5.2.3.1.3. Rotating radius method", the blue distance profile represents the distance between the external and internal contour (see Figure 5.17). This information was used to measure the maximal distance between these two contours at the ears calculating this way dimension "B" (top left side at Figure 5.17).

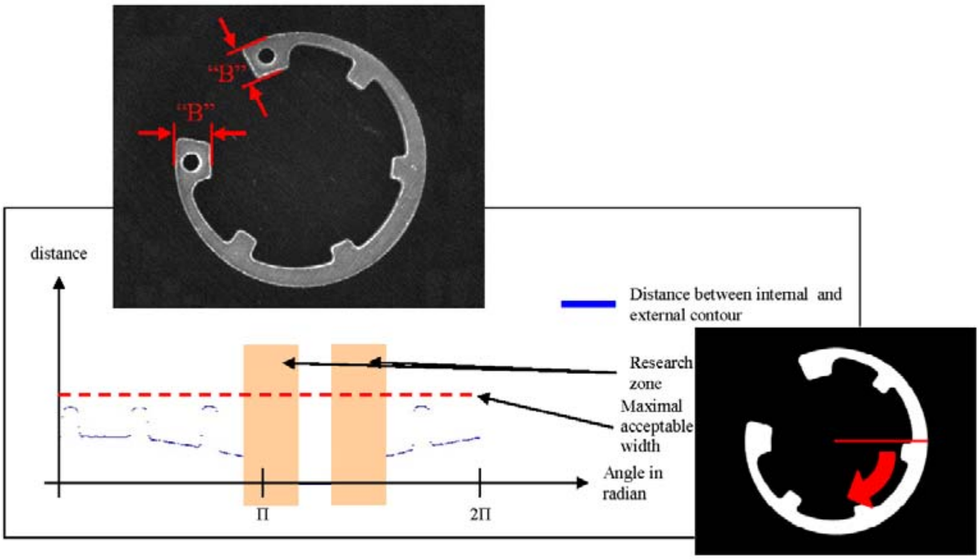


Figure 5.17: Width (B) at the ears of the part.

Diameter C:

To calculate diameter C, the diameter of the internal holes at the ears of the part, the bounding boxes, one per hole, created to localise these holes in the image were used (see Figure 5.18). A least squares circle fitting of the holes contours could have been made because each hole diameter is about 60 pixels but the targeting application does not require the accuracy of a circle fitting. Therefore, an approximation of the diameter of the holes was derived from the size of their bounding boxes.

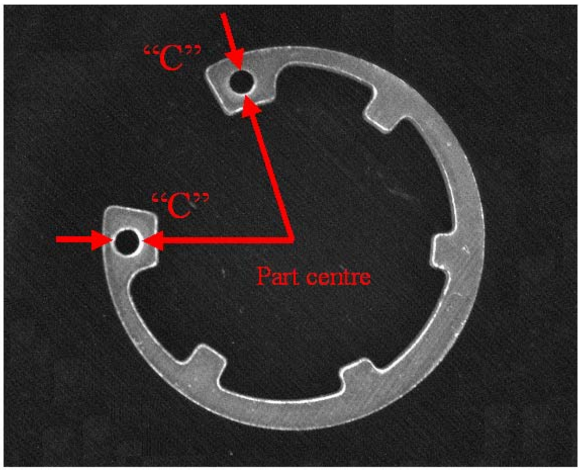


Figure 5.18: Diameter (C) of the holes at the ears of reference 0863-012.

Diameter D:

And finally, diameter D (shown in Figure 5.19), the external diameter of the part, was calculated using the external points of the contour of the part calculated in "Chapter 5.2.3.1.2. Part centre detection".

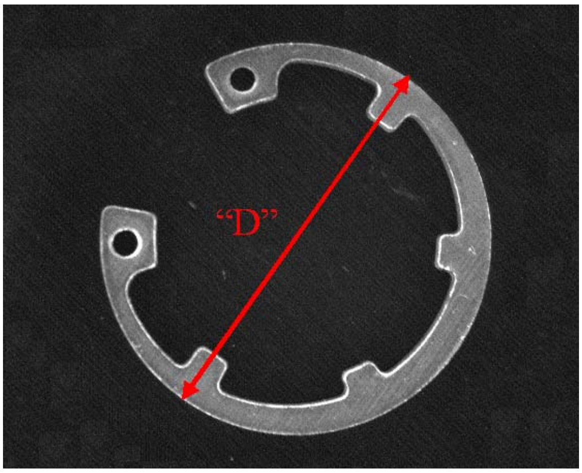


Figure 5.19: Main external diameter (D) for reference 0863-012.

5.2.3.2. Algorithms developed for the lateral view image processing

Regarding the lateral view image, an algorithm used for all the references has been created in order to detect the presence of local big burrs due to punch micro cracks. Figure 5.20 shows three lateral view images of the reference 5828-001. The image at the left side of Figure 5.20 corresponds to a part with a local big burr oriented upwards, the image at the centre corresponds to a correct part and the image on the right side corresponds to a part with a local big burr oriented downwards. The algorithm must be able to detect these process failures, which can not be detected with the sensors based process monitoring system.

Figure 5.20: Local big burr upwards, correct part and local big burr downwards.

Figure 5.21 shows the main skeleton of the algorithmic approach for the processing of the lateral view image that consists of three main blocks that will be briefly described next.

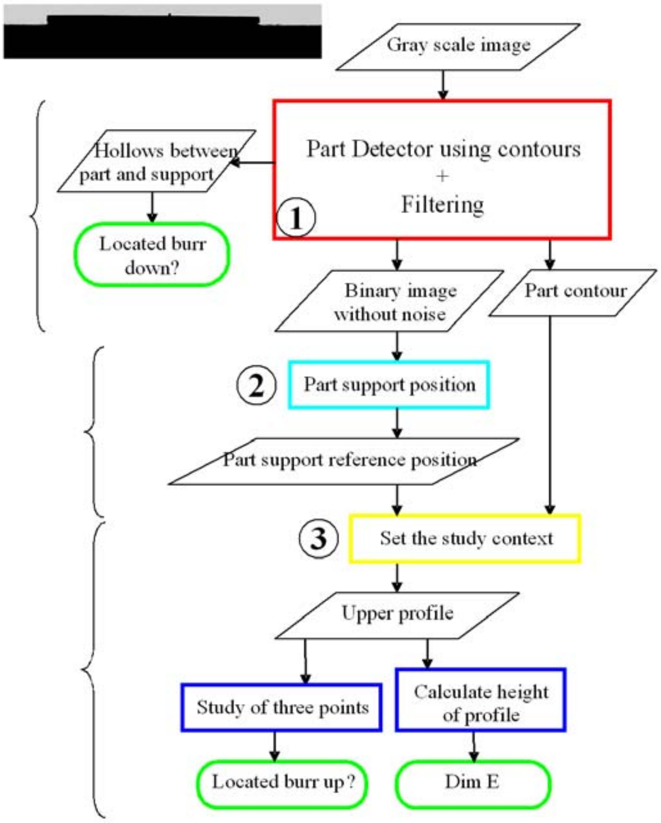


Figure 5.21: Algorithmic architecture for processing the lateral view image (all references).

5.2.3.2.1. Part detection and filtering

The algorithm used for the detection and noise filtering of the lateral view image is based on the algorithm applied for the upper view image in “Chapter 5.2.3.1.1. Part detection and filtering”. Therefore, after an image thresholding all contours are detected and filtered depending on their size (see Figure 5.22). The final output is the mask of the part.

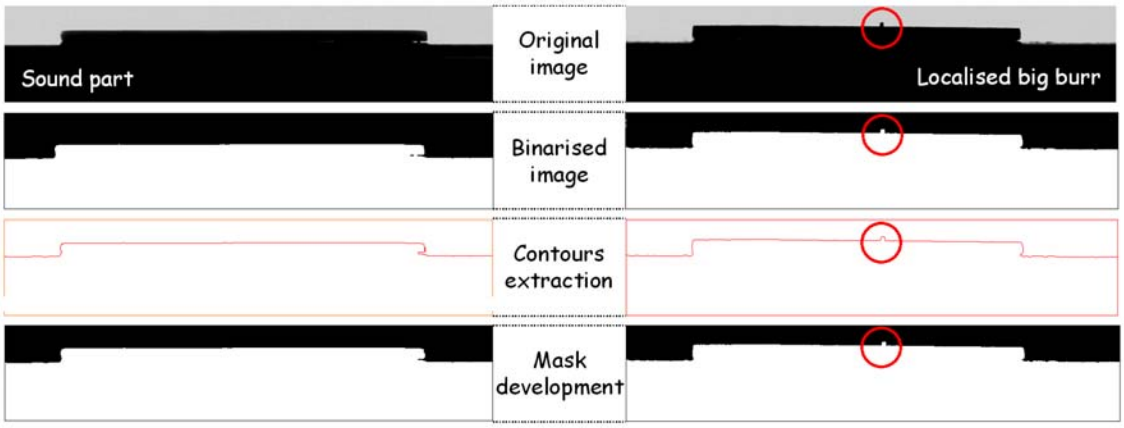


Figure 5.22: Steps at the processing of the lateral view image; from the original image to the mask.

During the contours extraction procedure, if any contour is found between the part and the Teflon© surface, as shown in right side at Figure 5. 23, it is interpreted as a part with a local big burr oriented downwards. This means that the parts with local big burrs oriented downwards are detected at this first block of the algorithmic approach.

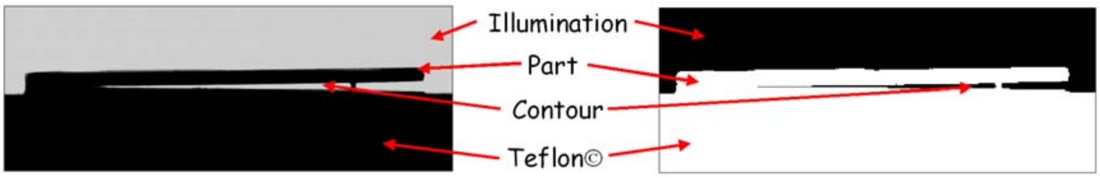


Figure 5. 23: Contour detection between the part and the Teflon© surface.

5.2.3.2.2. Part support position

The second block consists on determining the surface (base line in Figure 5.24) of the Teflon© where the part is located when the lateral view image is taken. The base line is computed doing a line fitting on a few points (grey points in Figure 5.24) extracted at the right and the left side of the mask image. These points are computed by detecting the transitions of the "black to white" pixels in the mask image (red lines in Figure 5.24).

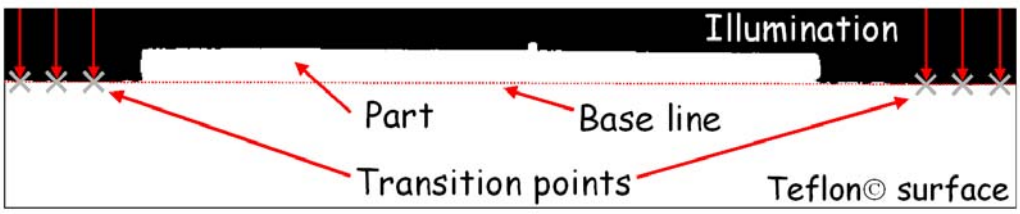


Figure 5.24: Base line of the Teflon© plate calculation.

5.2.3.2.3. Study of upper geometry

The final block consists on determining if there is any local big burr oriented upwards in the image. The first step consists on localising the transitions between the background (illumination) and the part in the mask image. In order to do it, vertical lines are used to find the nearest edges from the top of the image (see Figure 5.25).

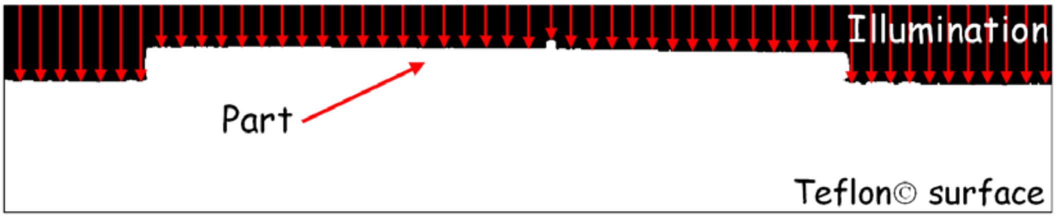


Figure 5.25: Detection of the upper contour of the part.

Through the searching strategy explained in Figure 5.25, the local big burr is the highest point of the part in the image whenever the top surface of the part remains horizontal. At the present case, a non-horizontal top surface could be provoked by two reasons. The first reason is the presence of a local big burr oriented downwards, which is previously detected by the second block of the algorithm. And the second reason is an erroneous positioning of the part on the Teflon© surface, which has not been critical in the present research work.

Assuming a horizontal top surface, when the highest point is localised, the height of the neighbour points in both directions, right and left direction, are calculated too. In case of any local big burr oriented upwards, the height of these points is lower (see Figure 5.26). At the present research work, and after evaluating the size of the local big burrs in the reference 5828-001, it was estimated that the local big burrs are correctly detected when a height difference of four or more pixels (corresponding each pixel to 50 microns) is found in the image. The distance in the horizontal axis between p2 and p1 and between p2 and p3 is five pixels.

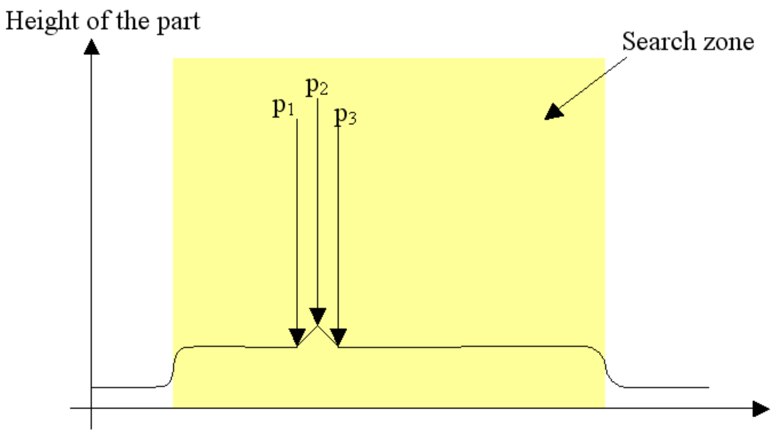


Figure 5.26: Schematic representation of a local big burr oriented upwards.

5.2.4. Vision system: a hardware / software co-design architecture approach

After developing the vision algorithms, a vision prototype working with two commercial cameras (uEye cameras of the German company IDS) connected via USB 2.0 to a PC (Pentium 4 at 3Ghz) where the image processing was carried out was developed. First trials showed that this vision architecture was not able to face the manufacturing rate at Industrias Alzuaran S.L. The main constrain of this initial vision architecture relies in the communication between the cameras and the PC. It was stated that when the cycle time was reduced to reach the aforementioned rate, the synchronization between the computer and the cameras represented a bottleneck for the system and some of the images received by the computer were corrupted.

The conclusion of these first trials was that another vision architecture able to speed up the cycle time of the images processing was necessary in order to face the current production rate in Industrias Alzuaran S.L. (120 parts per minute) and also to reach faster production rates of future applications (up to 1800 parts per minute). In order to do that, a hardware / software co-design image processing architecture approach was proposed. In this architecture some of the algorithms have been implemented in a standard microprocessor embedded in the main processing station of the system (a PC) and the rest of the algorithms have been implemented on FPGA (Field Programmable Get Array) embedded in the iCam smart cameras developed by Delta Technologies.

Among other reasons, this hardware / software co-design architecture has been chosen because the implementation of data, signal or image processing algorithms on FPGA (when such an implementation is possible) instead of implementing them on DSP (Digital Signal Processor) or standard microprocessors offers processing time reduction of 10 if compared to an implementation on DSP, and by 100 if compared to an implementation on a standard microprocessor [RUS95, FIL01, FIL07/2, FIL08]. Another important advantage of this hardware / software co-design architecture is the achievement of more compact and robust industrial solutions that in applications where the environment is difficult or hostile (difficult industrial environments where vibrations or dirt are present; outdoor and space applications; etc) offer good performances. At the same time, it offers high miniaturization possibilities [FIL07/2].

Since some kind of algorithms are suitable for implementation in FPGA while others are not, a study of the algorithms developed for the quality evaluation of the parts was carried out. Looking at them, two kinds of algorithms can be distinguished: low level algorithms and high level algorithms. Low level algorithms, which correspond to systematic processes applied to all the pixels of the image, like image thresholding or noise filtering are very suitable for being implemented on FPGAs. The reason for this is that such algorithms involve systematic non conditional processing and are easily parallelizable. On the other hand, high level algorithms process less data than the low level algorithms and present a conditional, non-parallel architecture that makes them not suitable for being implemented on FPGAs. Furthermore, low level algorithms process all pixels of an image (more than 1,3 million pixels per image), whereas high level algorithms process sparse data (e.g. image contours). In the present research work, the low level algorithms correspond to the first steps, i.e. thresholding, noise filtering, mask development and the high level algorithms correspond to the extraction and analysis of the part features.

In order to evaluate the difference between the low level and the high level algorithms developed at the present research work and to select the algorithms to be implemented on FPGAs, a study was carried out with the vision algorithms that process the upper view image. The vision algorithms for the upper view image have been selected because they are more complex, and therefore more time consuming, than the vision algorithms developed for the lateral view image. Therefore, the image processing algorithms developed for the upper view image of the reference IA-04 and the reference 0863-012 (also used for the reference 5828-001) were implemented and tested in a PC (Pentium 4 at 3Ghz) using free software libraries (OpenCv libraries for image), and Visual C++ using Gtk libraries for display. The algorithmic approach was divided into three steps and the computing time for each step was calculated. First step corresponds to the detection of the part, to the noise filtering and to the distortion correction. Second step corresponds to the centre calculation using the Least Square approach. And third step corresponds to the calculation of the dimensions of the part using the Rotating Radius approach. The processing times for both references are given in table 5.I.

Table 5.I: Processing time at a PC for the references IA-04 and 0863-012.

	Ref.- IA-04		Ref.-0863-012	
Part Detection + Image filtering + Distortion Correction **(Step 1)**	33 msec.	1818 analyses/min.	35 msec.	1740 analyses/min.
Center Calculation **(Step 2)**	0.64 msec.	93720 analyses/min.	0.58msec.	103440 analyses/min.
Dimension Calculation **(Step 3)**	4.4 msec.	13440 analyses/min.	3.8 msec.	15540 analyses/min.
Total time Calculation	**38 msec.**	**1580 analyses/min.**	**39 msec.**	**1538 analyses/min.**

First conclusion of the study is that the processing rate of a computer does not reach the optimal targeting one, 1800 parts per minute. Table 5.I shows that a PC is not able to reach the desired rate even when only the processing time (not including the acquisition time) of only one of the two images (the upper view image here) is considered. At the same time, these results have been used to decide which processing steps should be implemented in the intelligent cameras. The bottleneck corresponds to step 1 of the algorithm in Table 5.I. Step 1 of the algorithm takes 86,84% of the computation time for the reference IA-04 and 89,74% for the reference 0863-012. Step 1 of the algorithm is a low level algorithm that processes all the pixels at the image. Therefore, and since it is very easily parallelizable and adequate for its implementation in FPGAs, it has been decided to implement step 1 of the algorithm in FPGAs on board the smart cameras.

Step 2 of the algorithm, although also parallelizable, takes the smallest amount of time (takes 1,68% of the computation time for the reference IA-04 and 1,48% for the reference 0863-012); the implementation of this algorithm in FPGA would lead to a negligible decrement in the processing time. Furthermore, processing time of step 2 of the algorithm copes by far with the targeting throughputs for the image processing (1800 parts per minute). Thus and for the present research work, it has been decided to implement step 2 of the algorithm in PC and not on FPGAs. For future applications where higher production rates will be faced, step 2 of the algorithm could be implemented in FPGAs too.

Finally, step 3 of the algorithm takes much smaller time than step 1 (takes 11,57% of the computation time for the reference IA-04 and 9,74% for the reference 0863-012), and it is hard to implement in FPGA because it is a decisional algorithm. For this reason, step 3 of the algorithm has also been implemented in PC. Furthermore, it must be considered that a suitable approach goes through the implementation of the algorithm steps that are valid for several references in FPGA (step 1 and step 2 of the algorithm) and the algorithm steps that depend on each reference (step 3 of the algorithm) in PC, for being reprogrammed easily.

The final vision acquisition chain developed at the present research work is composed of two intelligent cameras and an industrial PC (double core Pentium 4 at 2.4Ghz with RAM 2048 Mb). Figure 5.27 shows the vision algorithms that are implemented in the intelligent cameras and the vision algorithms that are implemented in the PC. On the one hand, onboard the intelligent cameras, the parallelizable bottlenecked low level image processing algorithms are implemented. The distortion correction, a noise filtering by image convolution and a thresholding before sending data to the PC are carried out (left side at Figure 5.27). On the other hand, the post-processing part consists of proprietary non-bottlenecked image processing algorithms, implemented in a PC, using open source libraries that carries out the part contour detection and analysis, the part features extraction and the part validity assessment (right side at Figure 5.27). This new architecture reduces the computing time of the low level algorithms and, at the same time, reduces the time necessary to transmit the information from the cameras to the PC.

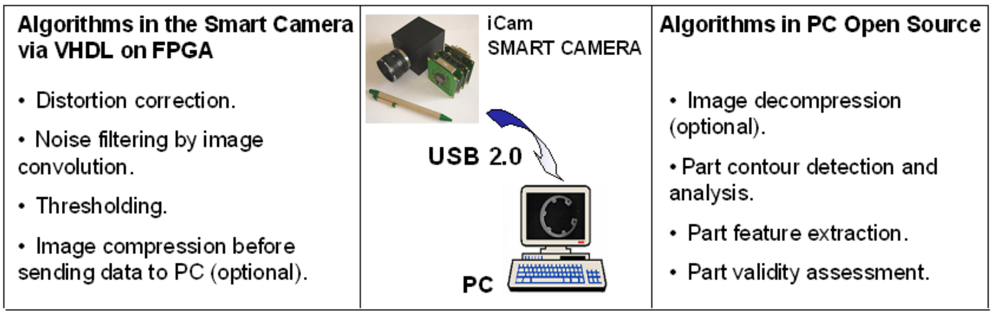
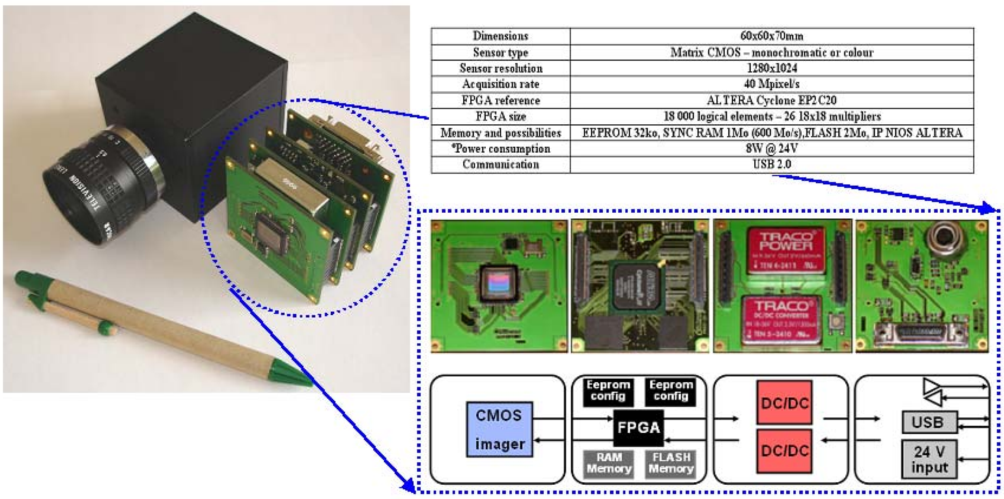


Figure 5.27: Hardware and software co-design and their corresponding algorithms.

Each intelligent camera contains a CMOS (Complementary Metal Oxide Semiconductor) sensor, FPGAs, RAMs (Random Access Memory) and a USB 2.0 (Universal Serial Bus) connection for the communication with the PC. Figure 5.28 shows the camera, its characteristics, the internal cards and the corresponding functional diagrams. The first card is the CMOS image sensor. The second card is the processing card, including one FPGA component and several memories: 2 EEPROM (Electrically-Erasable Programmable Read-Only Memory) memories are used to store the parameters for hardware/camera configuration and the processing parameters. This second card also includes RAM memory. The third card is the power supply card. And the last one is the input/output card, allowing power supply input and containing a USB 2.0 connection.



Dimensions	60x60x70mm
Sensor type	Matrix CMOS – monochromatic or colour
Sensor resolution	1280x1024
Acquisition rate	40 Mpixel/s
FPGA reference	ALTERA Cyclone EP2C20
FPGA size	18 000 logical elements – 26 18x18 multipliers
Memory and possibilities	EEPROM 32ko, SYNC RAM 1Mo (600 Mo/s),FLASH 2Mo, IP NIOS ALTERA
*Power consumption	8W @ 24V
Communication	USB 2.0

Figure 5.28: iCam intelligent camera and its internal cards.

The results achieved with the proposed hardware / software co-design regarding the processing time of the images are shown next. Figure 5.29 shows the time that the new vision architecture needs to acquire and to process both, the upper view and the lateral view image, per part. The horizontal axis is the time in milliseconds that measures the interval from the moment when the PC orders the cameras to start the images acquisition until the moment when the vision algorithms determine the quality of the evaluated part. This measure time interval includes the acquisition of the images, the pre processing made by the cameras, the transferring of the images from the cameras to the PC and the final image processing step in the PC. The vertical axis shows the percentage of parts (out of 3000 measurements made during the manufacturing of the reference 5828-001) that corresponds to each time interval. The global processing time ranges from 110 to 140 milliseconds (depending on the processes run by the computer at the moment that the images are taken) and the average time is around 120 milliseconds. At this point, it must be taken into account that the computer is in charge of managing all the pneumatic and electrical actuators necessary to handle the parts through the AV system and that the algorithms at the PC have not been completely parallelized. These results mean that the develop hardware / software co-design image processing architecture approach is able to acquire and process 8,33 parts per second (what means 500 parts or 1000 images per minute)

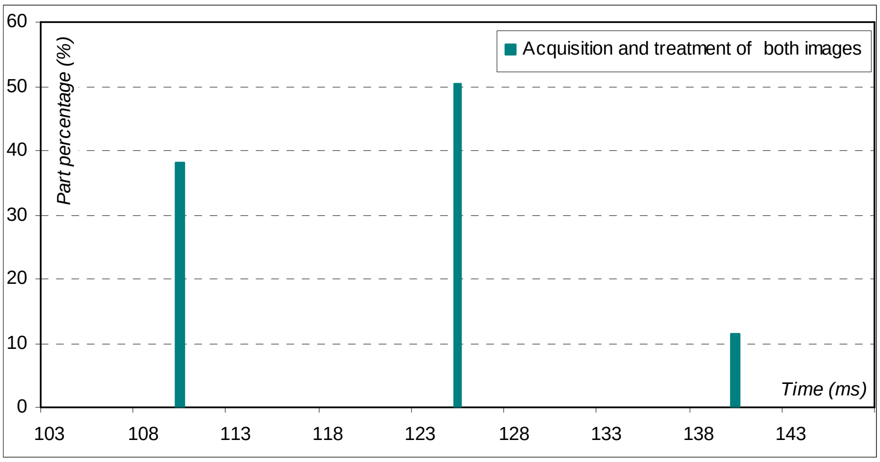


Figure 5.29: Time for the acquisition and processing of both images per part.

5.3. Results achieved with the developed artificial vision prototype

Figure 5.30 shows the final AV prototype where the two intelligent cameras and the PC for the final image processing have been integrated. The complete AV prototype, composed of the intelligent cameras, the PC for the final processing of the images and the pneumatic and electric actuators necessary for the handling of the parts were mounted in a conveyor belt in charge of carrying the parts from the blanking facility to the area where the images are taken.

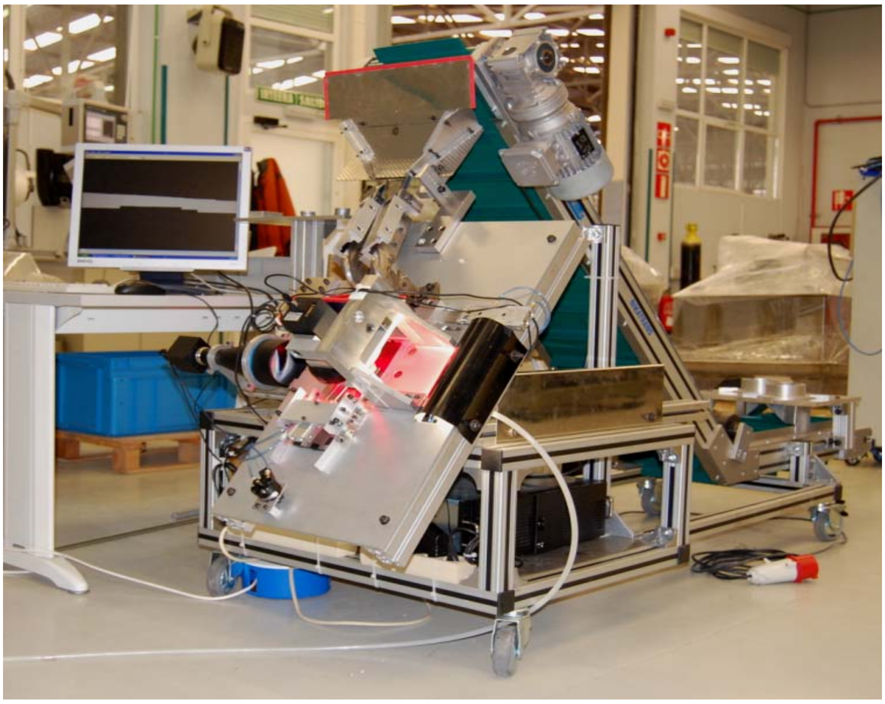
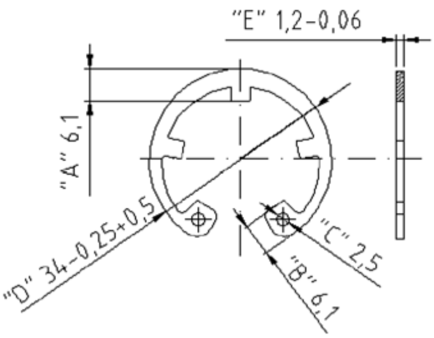


Figure 5.30: Final AV prototype.

The results regarding the evaluation rate achieved by the AV prototype and the results regarding the quality control achieved with the developed AV prototype are briefly explained next. The results regarding the quality control are divided into two main groups: the results achieved with the upper view intelligent camera and the results achieved with the lateral view intelligent camera. All the results were recorded during the tests campaigns carried out in Industrias Alzuaran S.L during the production period of the reference 5828-001. The manufacturing rate was around 100 parts per minute and the dimensions measured for the reference 5828-001 are presented again in Figure 5.31.



- ✓ Width A: max 6,1 mm
- ✓ Width B: máx. 6,1 mm
- ✓ Diameter C: min 2,55 mm
- ✓ Diameter D: [33,75-34,5]mm
- ✓ Thickness E: [1,14-1,20]mm

Figure 5.31: Control dimensions measured for reference 5828-001.

Width (A) of the part along the symmetry axis, width (B) at the ears of the part, diameter C, the diameter of the small holes at the ears of the parts and diameter D, the external diameter of the part are measured with the upper view camera. At the same time, the lateral view camera allows to check for the presence of local big burrs due to punch micro cracks.

5.3.1. Evaluation rate achieved by the AV prototype in Industrias Alzuaran S.L.

The cycle time of the AV prototype was measured during the experimental phase carried out in the blanking facility in Industrias Alzuaran S.L. The complete cycle time of the AV prototype includes the time necessary to feed one part from the vertical buffers in the AV system, position it in front of the cameras, acquire and process both images and evacuate the part from the image acquisition area directing it towards the right container. Figure 5.32 shows the evaluation rate results achieved by the AV prototype working in Industrias Alzuaran S.L.

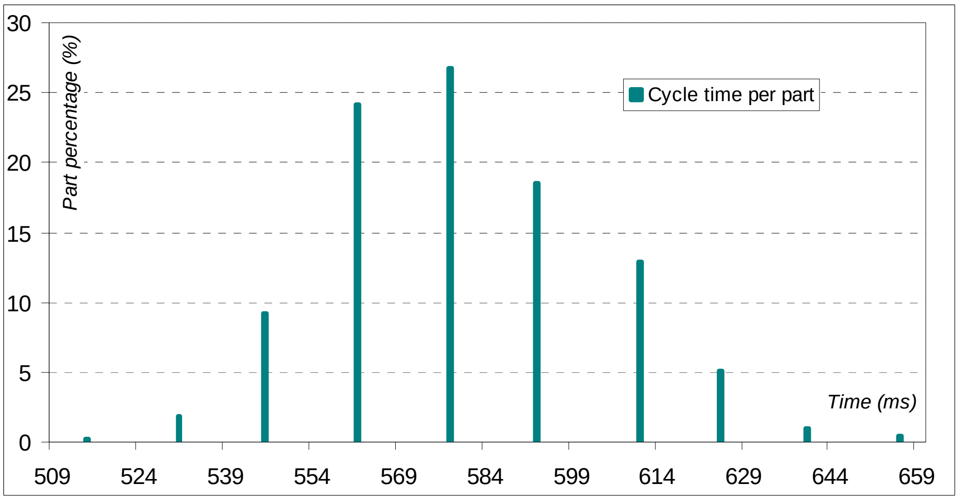


Figure 5.32: Cycle time per part at the developed AV system.

In Figure 5.32, the horizontal axis is time in milliseconds and measures the time interval from the moment when one part “cuts” the trigger that initialises the evaluation cycle until the moment when the next part cuts the trigger again. The vertical axis shows the percentage of parts (out of 3000 measurements made during the manufacturing of the reference 5828-001) that belongs to each time interval. The global cycle time ranges from 515 to 781 milliseconds and the average time is around 580 milliseconds. The cycle time variation is due to the fact that the parts are fed into the image acquisition area by means of the gravity and therefore the feeding is not completely controlled. These results mean that the vision system is able to evaluate 1,72 parts per second, which means an evaluation rate of approximately 103 parts per minute.

Therefore, it is concluded that the AV prototype is able to work at the production rate of the blanking facility in Industrias Alzuaran S.L. The current limitation of the AV prototype is the handling of the parts (103 parts per minute) that limits the processing rate of the AV prototype that is 1000 images (500 parts) per minute (as shown in Figure 5.29). Thus, through the implementation of a faster handling system, the evaluation rate of the AV system could be currently improved up to 500 parts per minute.

5.3.2. Results achieved for the upper view image in Industrias Alzuaran S.L..

The results achieved by the upper view camera of the AV prototype are described next. Regarding the spatial resolution of the upper view camera, although initially a resolution of 50 microns was achieved, the optical distortion correction methodology implemented on board in the camera for speeding up the processing of the images provided images with a spatial resolution of 100 microns (because of hardware constrains related to the memories onboard the smart cameras). The following results were recorded during the production of around three thousand consecutive parts of the reference 5828-001 in Industrias Alzuaran S.L. The results obtained for each one of the dimensions to be controlled at the part are briefly described next.

5.3.1.1. Width A: width of the part along the symmetry axis.

According to the part's specifications in Figure 5.31, dimension A must be smaller than 6.1 millimetres. Figure 5.33 shows the results of the measurements carried out for the dimension A where it is shown that around 80% of the measurements are within 5.78 and 5.95 millimetres, being the average value of the measurement 5.83 millimetres. On the other hand, 0,6% of the measured parts were out of tolerances (19 parts out of 3.120 measured parts) representing the percentage of false negatives (good quality parts classified as bad parts) of the system.

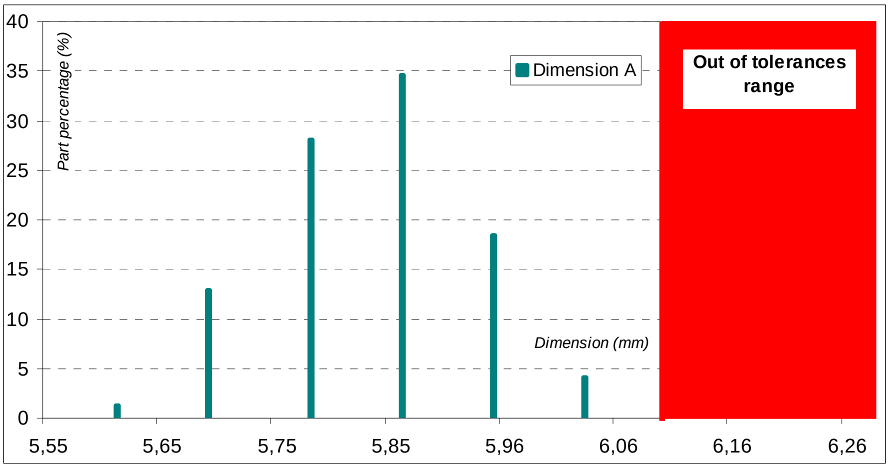


Figure 5.33: Dimension A of reference 5828-001 measured at 3000 consecutive parts.

It was observed during the experimental phase that a possible reason for these false negatives is the high evaluation rate (low cycle time) of the AV system (currently limited by the handling system). This high evaluation rate (working very close to the limits of the system) has as a consequence that some of the parts are not well located neither static in front of the cameras when these take the images. In order to evaluate this problematic, the production rate of the vision system was decreased down to 1 part per second and it was stated that the percentage of false negatives decreased from 0.6% down to 0.4%. Therefore, the handling strategy proposed for the AV system must be re-evaluated in order to reduce the false negatives.

At the same time, it was observed that the upper view camera needs a better spatial resolution in order to improve the measurement accuracy and decrease the false negatives. This way, if the spatial resolution of the camera was improved down to the initial proposed one, 50 microns per pixel (the CMOS sensor is compatible but the internal EEPROM memories of the smart camera need more capacity), the number of pixels covering the tolerance range (6 pixels nowadays) would be increased and the percentage of false negatives reduced.

5.3.1.2. Width B: width at the ears of the part.

According to the part's specifications in Figure 5.31, dimension B must be smaller than 6.1 millimetres. Figure 5.34 shows the results of the measurements carried out for the dimension B where it is shown that around 80% of the measurements are within 5.77 and 5.94 millimetres being the average value of the measurement of 5.87 millimetres. On the other hand, 2,4% of the measured parts were out of tolerances (74 parts out of 3.120 measured parts). In the same experiment carried out at an evaluation rate of 1 part per second, the percentage of false negatives decreased down to 1.2%, what means a reduction of around 50%. Therefore the effect of the evaluation rate (limited by the handling of the parts) is also important for this dimension. Again, and as happened for width A, an improvement of the upper view camera resolution would increase the number of pixels within the tolerance range too (5 pixels nowadays) and this would reduce the false negatives.

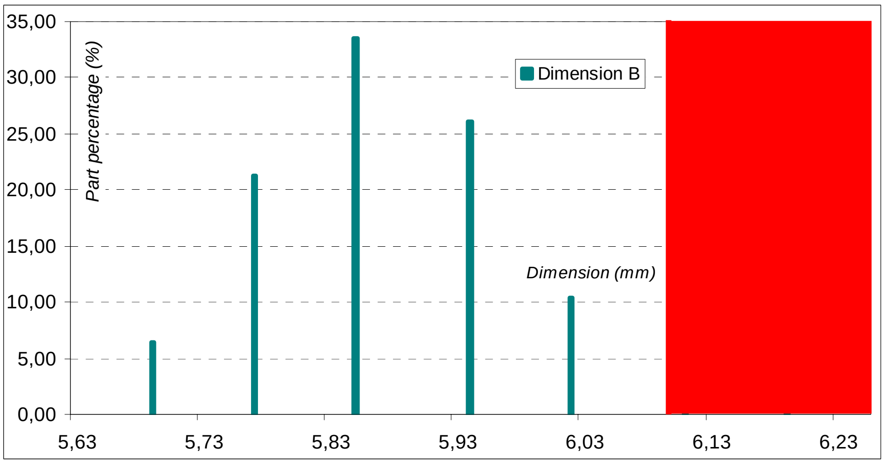


Figure 5.34: Dimension B of reference 5828-001 measured at 3000 consecutive parts.

5.3.1.3. Diameter C: diameter of the small holes at the ears of the part

According to the part's specifications in Figure 5.31, diameter C must be greater than 2.5 millimetres. Indeed diameter C is directly related with the diameter of the punches that shear the material. Since the diameter of the punches decreases along the production due to wearing, the dimension of this diameter decreases too. Figure 5.35 shows the results of the measurements carried out for the dimension C where it is shown that around 96% of the measurements are within 2.62 and 2.73 millimetres being the average value of the measurement of 2.69 millimetres. In this case no parts were found out of tolerances.

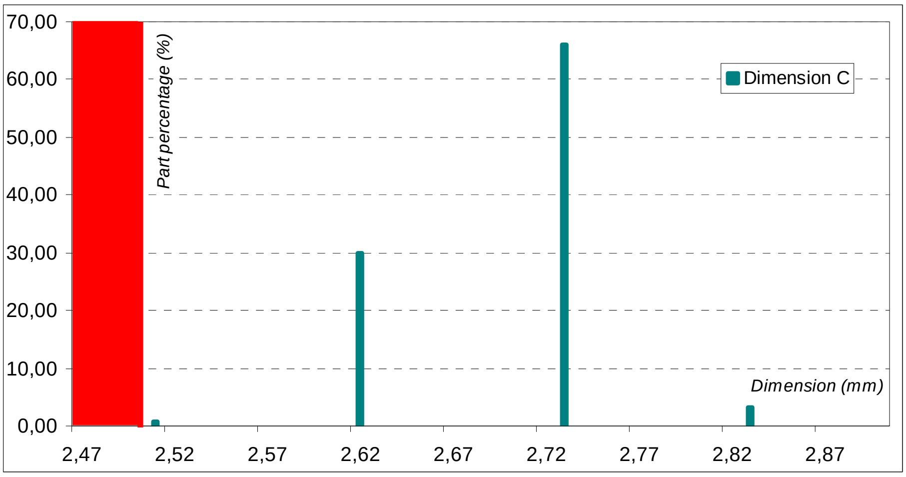


Figure 5.35: Dimension C of reference 5828-001 measured at 3000 consecutive parts.

5.3.1.4. Diameter D: external diameter of the part.

According to the part's specifications in Figure 5.31, diameter D must be within 33.75 and 34.5 millimetres. Figure 5.36 shows the results of the measurements carried out for the diameter D where it is shown that around 81% of the measurements are within 34.05 and 34.25 millimetres being the average value of the measurement of 34.08 millimetres. On the other hand, 3.96% of the measured parts were out of tolerances (123 parts out of 3.120 measured parts). For this dimension, in the experimental phase carried out at an evaluation rate of 1 part per second, the percentage of false negatives decreased down to 1.2%. Thus, it is necessary for this dimension too to re-evaluate the handling system if the percentage of false negatives wants to be reduced. Finally, an improvement of the upper view camera resolution would increase the number of pixels within the tolerance range too (6 pixels nowadays) and this would reduce the false negatives.

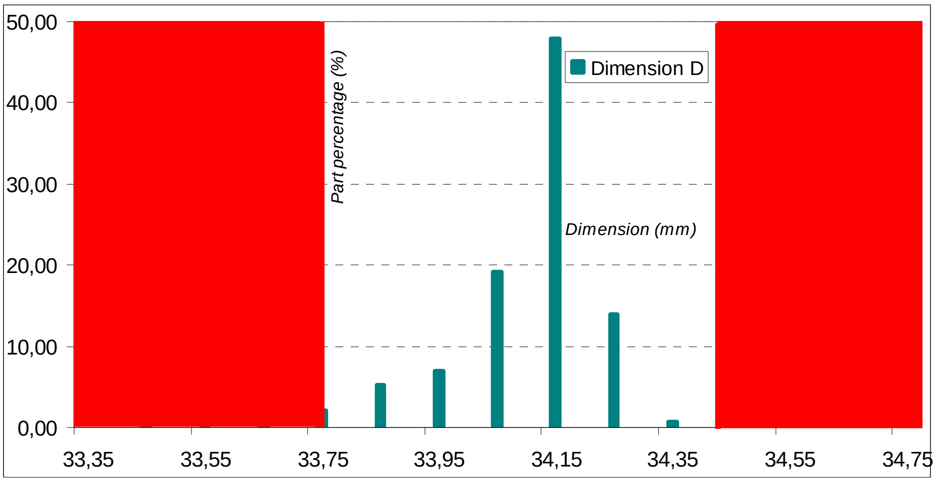


Figure 5.36: Dimension D of reference 5828-001 measured at 3000 consecutive parts.

As a final summary of the results achieved with the upper view camera, next table represents its overall performance during the experimental phase. The table specifies, out of 3.120 measurements, for each of the dimensions measured at the part, the lower and upper tolerances, the average value of the each dimension, the standard deviation of each dimension and the percentage of false negatives and false positives (bad quality parts that were classified as good parts) achieved for each dimension. The most important values at the table are the standard deviation that represents the variability of the measurements (around 150 microns the biggest one) and the false negatives (mentioned before) and false positives (cero because no defective parts were produced during the testing period). Finally, the last column represents the percentage of false negatives when the evaluation rate of the system was decreased down to 1 part per second.

Table 5.II: Results summary for measurements of the upper view camera (reference 5828-001).

	Lower tolerance (mm)	Upper tolerance (mm)	Average (mm)	Standard Deviation (mm)	False negatives (%)	False positives (%)	False negatives (%) at low rate
Dimension A	------	6,10	5,8392	0,0937	0,6089	0	0,3952
Dimension B	------	6,10	5,8706	0,0978	2,4046	0	1,1857
Dimension C	2,55	------	2,6987	0,0578	0	0	0
Dimension D	33,75	34,5	34,0849	0,1540	3,9600	0	1,1857

The main conclusion of this chapter is that, although the AV system is working properly (with a low standard deviation), the percentage of false negatives should be decreased. In order to achieve this, two solutions are proposed for the future. First one is to slightly decrease the evaluation rate of the AV system in order to have a better positioning of the parts in front of the cameras when these take the images. And second is to increase the internal EEPROM memories of the cameras in order to acquire higher resolution images of the parts. This will have as a consequence that a greater number of pixels will cover the tolerance ranges and therefore the accuracy of the system will be better (this could be easily evaluated by implementing the optical distortion correction on the PC when working at low production rates).

5.3.3. Results achieved for the lateral view image in Industrias Alzuaran S.L.

Regarding the lateral view image of the parts, the presence of local big burrs due to punch micro cracks is currently detected. In this case, the AV system does not qualitatively measure this defect and the detection is given through a binary signal, encoding the presence or absence of local big burr. Figure 5.37 shows an example of the detection of a local big burr in the preliminary tests carried out with the reference IA-04.

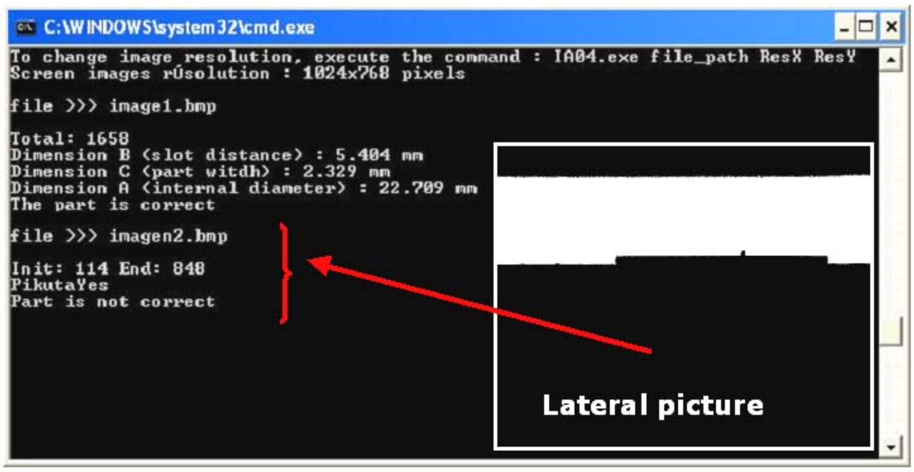


Figure 5.37: Local big burr detection through lateral view image processing.

The aim of the tests carried out at the laboratory was to determine the efficiency of the system and the percentage of false positives and false negatives of the system. In order to get it, two tests were carried out. In the first test, 100 parts with local big burrs were passed through the system. Out of the 100 parts, the vision system localised the big burr in 97 parts and 3 local big burrs were not detected. The conclusion of this first test is that the percentage of false positives is around 3%. The second test consisted on passing through the system 100 good quality parts mixed with one part with local big burr. After the test, it was shown that the system was able to detect the local big burr and to sort it out and, at the same time, it was shown that the system also classified two good quality parts as parts with local big burrs, what means a percentage of false negatives of around 2%.

5.4. Conclusions

An AV prototype for the quality evaluation of the reference 5828-001 has been developed. The AV prototype consists of two intelligent cameras that “look” at the parts to be evaluated from above (upper view image) and from the side (lateral view image) and a PC where the final processing of the images is carried out.

Figure 5.38 shows the final command window of the AV prototype. This command window was only used during the set up of the AV system. Currently the AV system is linked to the intelligent control system (explained in “Chapter 6. Intelligent Control System”) and the measurements are shown to the operator through its graphical user interface. Figure 5.38 shows all the information that the AV prototype gathers for each controlled part. The information related to the image 1.bmp in Figure 5.38 corresponds to the image taken by the upper view camera. The command window shows the four main dimensions of the part and also checks if each is within its predefined tolerances. And the information related to the image 2.bmp in Figure 5.38 corresponds to the image taken by the lateral view camera. First the coordinates of the part in the image are given and finally the presence or absence of local big burrs is detailed. In the example of Figure 5.38, a local big burr was found and therefore the part was sorted out as a defective part.

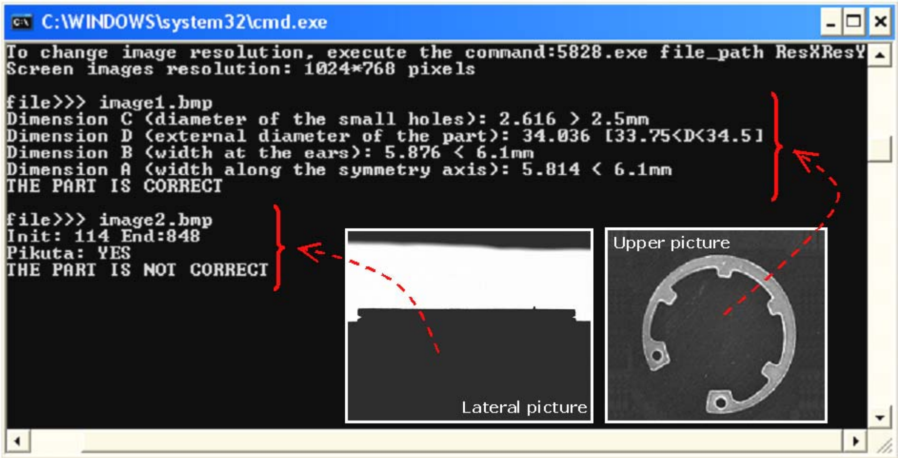


Figure 5.38: Command window of the AV system; big burr detection.

The developed AV prototype has fulfilled its main objective: to detect process failures that were not detected in the previous chapter with the sensors based process monitoring system. One critical example is the detection of local big burrs due to punch micro cracks. Figure 5.39 shows all the part defects that have been found during the setting up and during the experimental phase carried out with the AV prototype. Most of the defects are related with parts out of tolerances and with the localisation of local big burrs.

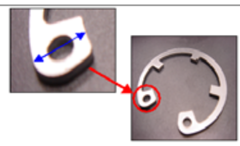
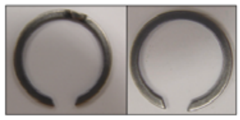
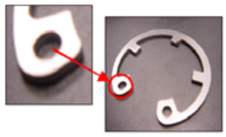
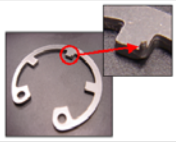
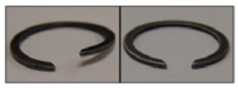
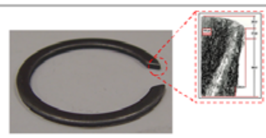
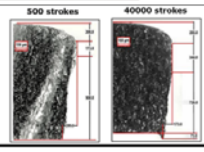
	Defect	Variation	Part image
1	Principal diameter of the part is out of tolerances.	Principal diameter of the part "Diameter D at the AV system" out of tolerances.	Defective part  Good part
2	Width at the ears of the part is out of tolerances.	Width of the ears "Thickness B at the AV system" is out of tolerances.	
3	Width of the part in front of the slot is out of tolerances.	Dimension in front of the slot "Width A at the AV system" is out of tolerances.	Defective part  Good part
4	Diameter of the small holes is out of tolerances.	Diameter of the small holes "Diameter C at the AV system" is out of tolerances.	
5	The opening of the slot is out of tolerances.	Width of the slot out of tolerances "Distance between corners in IA-04".	Defective part  Good part
6	There is a local big burr in the part.	Detection of local big burrs by the AV system.	
7	The part is not planar, it is bended.	Highest point of the part is out of tolerances.	Defective part  Good part
8	Thickness of the part is out of tolerances.	**NOT MEASURED** **LACK OF RESOLUTION** **MEASURED BY OPERATOR**	
9	The burr at the parts is too big.	**NOT MEASURED** **LACK OF RESOLUTION** **MEASURED BY OPERATOR**	

Figure 5.39: Part defects detected during the experimental phase.

Therefore, the AV system is a reliable complementary monitoring tool to the sensors based process monitoring system. In addition to this, the AV system is able to measure the control dimensions of the parts with a resolution of 100 microns (the intelligent camera can provide a resolution of 50 microns by improving the EEPROM memory onboard). Part by part, the AV system checks if the control dimensions are within the predefined tolerances being the maximal standard deviation around 150 microns. The AV system controls all the parts and allows the manufacturing facility to work under zero defects.

Regarding the image acquisition and processing rate, and since the evaluation time per part achieved with the commercial cameras at the beginning of the research work was not fast enough, an original hardware software co-design architecture has been developed and implemented into the blanking facility. The development and implementation of the architecture represent themselves an original contribution to the current state of the art in AV systems. The main purpose of this hardware software co-design architecture is to speed up the acquisition and the processing rate of the images. In the present research work, it has been pursued to optimise the throughput of parts beyond the possibilities of the manufacturing facility in Industrias Alzuaran S.L. with the aim of implementing this hardware software co-design architecture for the control of faster processes in the future. The time necessary for the acquisition and processing of both images per part was reduced down to 120 milliseconds, which means the possibility to control up to 8 parts per second (500 parts per minute).

Currently, the cycle time of the complete AV system (including parts handling) is very close to two parts per second what means that does not represent a bottleneck in the blanking facility. Anyway, it must also be said that from a mechanical point of view the AV system is very close to its limits regarding the handling of the parts. This fact has as a consequence that some of the images taken, mainly by the upper view camera, do not have sufficient quality and this is the reason why a low percentage of false negatives was detected during the testing period. In order to decrease the percentage of false negatives, the evaluation rate of the parts should be decreased. At the same time, the internal EEPROM memories of the cameras could be augmented in order to provide higher resolution images of the parts. This will have as a consequence that a greater number of pixels will cover the tolerance ranges and therefore the accuracy of the system will be better.

Finally, the developed "positioning boxes" represent also an original contribution to the handling of the retaining rings parts because they allow to reduce the manual operations needed to position the parts. This has been used at the present research for feeding the parts into the AV system but can also be used to position the parts in containers to be sent to customer or for the further steps in their manufacturing process (heat treatment of the parts for example). This fact can reduce the cost of manual operations what represents a big percentage of the cost of the parts.

5.5. Bibliography

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Chapter 6

INTELLIGENT CONTROL SYSTEM

6.- INTELLIGENT CONTROL SYSTEM

At the present chapter, the intelligent control system based on Artificial Intelligence (AI) techniques that has been developed and implemented into the demonstrator (blanking facility at Industrias Alzuaran S.L.) is presented. The main purpose is to create an autonomous control system able to, whenever a process failure or part defect is detected at the blanking facility, determine what the failure is, find the reason why it happened and suggest the operator solutions for an efficient and fast restarting of the production.

Figure 6.1 shows the main architecture of the intelligent control system developed at the present research work. The main core is a data processing unit that, taking as input the data gathered by the sensors based process monitoring system (explained in “Chapter 4.- Sensors based process monitoring”) and the AV system (explained in “Chapter 5.- Part quality control”), is able to analyse this data and to identify the process failure or part defect at the blanking facility.

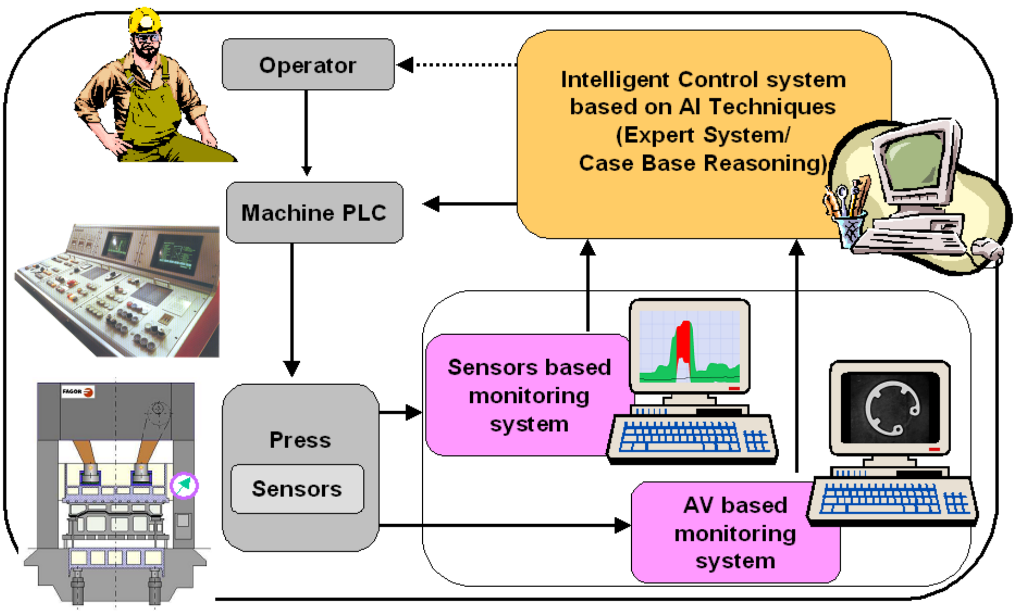


Figure 6.1: Intelligent control system architecture.

The present chapter explains the core of the intelligent control system. Two different techniques have been used to developed a system that is able to first, analyse the information coming from the sensors based process monitoring system and from the AV system and later, inform the operator about the incidence at the blanking facility, its causes and the actions that should be carried out in order to restart the production.

The techniques used at the present research work (selected according to the conclusions of the bibliographic review) are rule-based expert systems (ES) and case-based reasoning (CBR) techniques. The first technique, rule-based ES, has been used to verify the capacity of AI techniques to survey and control sheet metal forming processes (a blanking process at the present research work). And the second technique, the CBR approach, has been used to verify the capacity of AI techniques to, besides surveying the processes, learn automatically in such processes when a priori knowledge is not easily available. Next both techniques and their achieved results are briefly explained.

6.1. Intelligent control system development: rule-based ES based approach

The first approach to develop the intelligent control system is based on the application of rule based ES techniques. As mentioned in "Chapter 2.- Scientific and technological background", an ES can be defined as a problem-solving and decision-making system based on knowledge codified from the experience of human specialists in a field [MIL85]. The main advantages of ES compared with the traditional control strategy based on human operators is the achievement of more consistent answers for repetitive tasks, decisions and processes, efficiently and quickly and without any lack of performance because of pressure or tiredness. These advantages face an increasingly problem in the actual manufacturing processes: human operators are less and less able to react as quick and precise as the production rates and quality requirements demand. In the present research work, the human expert is the operator of the blanking facility at Industrias Alzuaran S. L. and the domain are the blanking processes carried out at Industrias Alzuaran S. L.

Several computer software appropriate for the development of ES can be found in the market nowadays. A brief study was carried out in order to choose the most suitable one for the necessities of the present research work. The specifications that have been analysed for the selection of the most suitable software in the market are the next:

- Kind of knowledge able to be implemented (Boolean and/or fuzzy).
- Facility to communicate with other systems (process monitoring and AV system).
- Facility to communicate with a Graphical User Interface (GUI).
- Operative system where can be installed (Windows or Linux).
- Existence of any commercial license (mainly for the industry).

Among the different software at the market, CLIPS software [CLI08] has been chosen for the development of the rule based ES. CLIPS is a public domain software tool for building ES. The name is an acronym for "C Language Integrated Production System". CLIPS was originally developed by the NASA in 1985 and nowadays is probably the most widely used ES tool because it is fast, efficient and free. CLIPS, as its own name details, is written down in C and like other expert languages deals with rules and facts; various facts can make a rule applicable and then the rule is asserted [CLI08]. The reasons why this software tool has been applied in the present research work are described next:

1. First reason is that this software tool (considering its extension FuzzyClips) is able to represent both Boolean and fuzzy knowledge. Although at the present research work only Boolean knowledge has been used, the research team pursued a software tool able to work with both kinds of knowledge for future possible implementations.
2. Second reason is that it is programmed and executed from C and this way it is moderately easy to develop a GUI (Graphical User Interface) using for example GTK libraries. At the same time, the communication with the AV prototype developed in C++ is easily achieved too.
3. And third reason is that it can be installed in both operative systems, Windows and Linux. Although at the present research work Windows operative system has been chosen, future developments could be implemented in Linux due to its higher robustness and the fact that is free.

The implementation of this kind of intelligent systems into industrial processes comprises a set of determined steps. Next, the steps carried out for the development and application of the rule-based ES into the blanking facility at Industrias Alzuaran S. L. are explained.

6.1.1. Identification of the expert

First step consists on finding where the knowledge about the process to be controlled resides in. In most of the cases, this knowledge belongs to the operator (or operators if more than one operator control the facility). At the present research work, only one operator controls the forming facility in Industrias Alzuaran S. L. and therefore, and as mentioned before, the operator of the blanking facility at Industrias Alzuaran S. L. is the human expert and the domain is the blanking process carried out in progressive tools.

Regarding the operator, two very important aspects must be taken under consideration. First aspect is that the operator must perceive the ES like a tool that will help him/her in the future, and not like something that will disturb him/her during his/her daily job. At this point, it is very important to explain the operator what the final purpose of the ES will be and how the ES will help him/her to solve the daily problems at the production facility. And another very important point is the ability of the expert human operator to specify all the knowledge about the manufacturing process that he/she has acquired through the experience. Sometimes happens that, although the expert human operator controls the process perfectly, he/she has difficulties when tries to specify all this knowledge. These two previous mentioned aspects are determinant for a successful implementation of the knowledge into the rule-based ES.

At the present research work, the operator of the blanking facility at Industrias Alzuaran S. L. understood perfectly the purpose of the ES implementation and was very helpful during its development. The research team organised meetings with him and spent several days working together with him at the blanking facility. This way most of his knowledge was written down for its future implementation into the ES. Although most of the knowledge was implemented into the knowledge base during this initial phase, it was also concluded during the experimental phase that not all the knowledge had initially been acquired. Therefore during the aforementioned experimental phase, new knowledge was implemented into the knowledge base improving the performance of the ES. In order to get this, the research team worked together with the operator during the experimental phase and new details and aspects that were not written down initially, were specified. This made the ES to achieve a higher efficiency and to improve its results.

6.1.2. Knowledge acquisition

Once the knowledge is acquired from the human expert operator, next step consists on writing down all that knowledge into the knowledge base. The knowledge base is a database for knowledge management. It contains a set of data, specified by means of IF-THEN rules, that mimics the knowledge of the operator. At the present research work, the knowledge taken from the operator has been structured into the knowledge database in a way that replies how the operator faces the daily problems at the blanking facility, asking the next three questions:

1. “What process failure(s) has happened at the blanking facility?”
2. “Which is the reason for that process failure(s)?”
3. “What should be done to solve the failure and restart the production?”

Two knowledge bases were created following the previous proposed structure. The first knowledge base comprises the process failures detected by the sensors based process monitoring system and the second knowledge base comprises the part defects detected by the AV system. At this point, it must be stated that although one unique knowledge base could have been created, two different knowledge bases were developed for a better understanding and distinction of the process failures detected by the sensors based process monitoring system and the part defects detected by the AV system. At the same time, the creation of two different knowledge bases allows an easier reusability in other processes.

The first knowledge base, (shown in Figure 6.2), describes the process failures detected by the sensors based process monitoring system in Chapter 4. The process failures, detected by the sensors based process monitoring system in “Chapter 4.- Sensors based process monitoring”, are now described from a detection point of view in the column named “process signal” at the Figure 6.2. At the same time, first three columns in Figure 6.2 describe the process failures from an operator’s knowledge point of view, that is, how the operator reacts after the detection of the process failure. First column, “**Failure**”, gives a description of the process failures at the blanking facility. Second column, “**Cause**”, describes the cause at the blanking facility that favours each process failure and third column, “**Solution**”, explains the actions to be carried out to solve the process failure and to restart the production at the blanking facility. Figure 6.2 shows how up to nine different process failures were found at the blanking facility and how each process failure is due to a specific cause and has a specific solving protocol to restart the production.

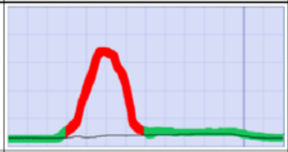
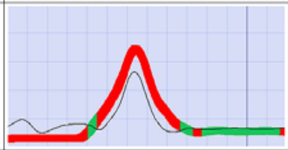
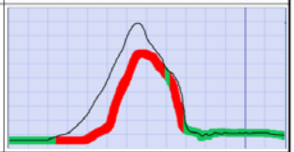
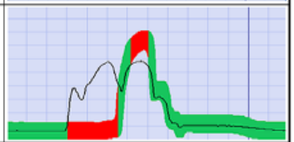
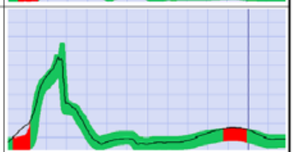
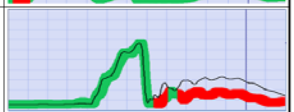
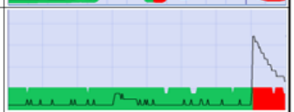
	Failure	Cause	Solution	Process signal
1	The metal strip is completely blocked inside the tool.	A badly evacuated metal slug is avoiding the movement of the strip.	Extract the metal slug and check the reason why it was not adequately evacuated.	
2	The metal strip did not advance the right distance between strokes.	A badly evacuated metal slug is avoiding the movement of the strip.	Extract the metal slug and check the reason why it was not adequately evacuated.	
3	A badly evacuated metal slug is blocking the first station.	The punches in first station are not evacuating the metal slugs properly.	Make the punches longer, move the ram down and check the dies´ wear.	
4	A badly evacuated metal slug is blocking the second station.	The punches in second station are not evacuating the metal slugs properly.	Make the punches longer, move the ram down and check the die's wear.	
5	A badly evacuated part is blocking the first station.	Misalignment of the air evacuation system due to the machine vibrations.	Extract the bad evacuated part and check the right position of the air evacuation system.	
6	A badly evacuated part is blocking the third station.	Misalignment of the air evacuation system due to the machine vibrations.	Extract the bad evacuated part and check the right position of the air evacuation system.	
7	There is a badly evacuated part inside the blanking die.	The ejection system is not working properly.	Extract the part and check the ejection system.	
8	There has been a punch breakage.	Excessive wearing of the punches.	Extract the broken punch and replace it with a new one.	
9	There is an strip adhesion to the pilot pins of the tool.	Excessive wearing of punches or pilot pins.	Replace the faulty punch or pilot pin.	

Figure 6.2: Knowledge base for process failures detected by the sensors based monitoring system.

The second knowledge base, (shown in Figure 6.3), describes the part defects detected by the AV system in "Chapter 5.- Parts quality control", and are now described from a detection point of view in the column named "part image" at the Figure 6.3. At the same time, first three columns in Figure 6.3 describe the part defects from an operator's knowledge point of view, that is, how the operator reacts after the detection of the defective part. First column, "**Defect**", gives a description of the defective part at the blanking facility. Second column, "**Cause**", describes the cause at the blanking facility that favours the production of each defective part and third column, "**Solution**", explains the actions to be carried out to restart the production at the blanking facility producing good quality parts. Figure 6.3 shows how up to nine different part defects were found at the blanking facility and how each part defect is due to a specific cause and has a specific solving protocol to restart the production.

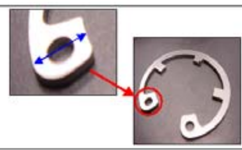
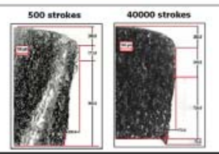
	Defect	Cause	Solution	Part image
1	Principal diameter of the part is out of tolerances.	Punches and/or dies lost the correct shape.	Check the shape of punches and dies and replace if necessary.	
2	Width at the ears of the part is out of tolerances.	Punches and/or dies lost the correct shape.	Check the shape of punches and dies and replace if necessary.	
3	Width of the part in front of the slot is out of tolerances.	Punches and/or dies lost the correct shape.	Check the shape of punches and dies and replace if necessary.	
4	Diameter of the small holes is out of tolerances.	Excessive wearing of the small punches.	Check the diameter of the punches and replace them if necessary.	
5	The opening of the slot is out of tolerances.	Punches and/or dies lost the correct shape.	Check the shape of punches and dies and replace if necessary.	
6	There is a local big burr in the part.	There is a micro crack in one of the final punches at the tool.	Refill the punches and dies to get sharpen surfaces.	
7	The part is not planar, it is bended.	The ejection system at the final dies is not work properly.	Check the ejection system and repair it if necessary.	
8	Thickness of the part is out of tolerances.	The thickness of the metal strip is out of tolerances.	Measure the thickness of the metal strip and change if necessary.	
9	The burr at the parts is too big.	The wearing of the punches is excessive.	Refill the punches and dies to get sharpen surfaces.	

Figure 6.3: Knowledge base for part defects detected by the AV system.

6.1.3. Feeding the expert system: facts

In previous subchapter (Figure 6.2 and Figure 6.3), the causes and solutions for all the possible process failures and part defects at the blanking facility have been described. Next step consists on creating the rules that will automatically identify the process failures and the part defects using the information acquired by the sensors based process monitoring system and the AV system. This action closes the loop and creates the necessary structure that allows the ES to first, identify the problem at the blanking facility, second, explain its causes and finally suggest, the right solution to restart the production.

Next, a brief description of the information supplied by both, the sensors based process monitoring system and the AV system, and used by the ES to identify the process failures and the part defects is given.

6.1.3.1. Process stability information from the Brankamp sensors based process monitoring system

Since in an ES the knowledge is implemented in the form of IF-THEN rules, the raw data, force and acoustic curves, acquired by the sensors based process monitoring system does not offer much information when is directly used by the ES (each process failure can be composed of up to 15.000 numerical values). More elaborated information is necessary and therefore a pre-treatment of the raw data acquired by the sensors based process monitoring system must be made in order to make it more intelligible to the ES. At the present research work, this pre-treatment consists on modelling the process failures by means of a set of numerical attributes that are later transferred as the antecedents to the knowledge base. After evaluating the appearance of the process failures at the studied blanking processes, and also based on the expertise of Brankamp GmbH, it was concluded that the set of attributes that most suitably define the process failures detected at the blanking facility during the experimental phase is the next one:

1. **Channel number**: Identify the sensor where the first fault (process signal going beyond the envelope curves) happens.
2. **Lower/upper**: Identify if the process signal has gone over the upper or under the lower envelope curve.
3. **Number of faults**: Counts how many times the process signal has gone beyond the envelope curves.
4. **Initial time**: Identifies the first time when the process signal has gone beyond the envelope curves.
5. **Real maximum value**: Represents the maximum value of the process signal.
6. **Real maximum value time**: Represents the time at which the process signal is highest.
7. **Hypothetical value**: Calculates, at the time when the first process fault reaches its maximum value, the intermediate value between the upper envelope curve and the lower envelope curve (approximate value that the process signal would have if no fault had happened, see Figure 6.4_a).
8. **Gradient**: Calculates the initial slope of the fault. In order to calculate it, the difference between the faulty process signal maximum value and its value when crosses the envelope curves is calculated (see Figure 6.4_b).
9. **Time percentage of the last fault**: Calculates the length (in time percentage) of the last fault compared to the total length of the curve (see Figure 6.4_c).
10. **Fault in the process signal slope up**: Identifies if the process signal goes beyond the envelope curves during the rising flank of the force curves.
11. **Fault in the process signal slope down**: Identifies if the process signal goes beyond the envelope curves during the falling flank of the force curves (see Figure 6.4_d).

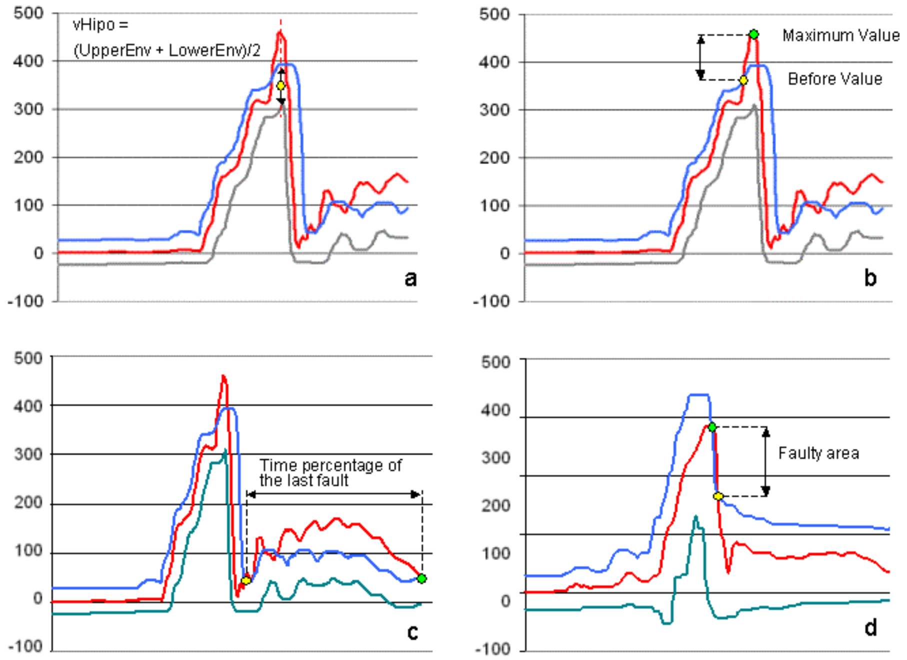


Figure 6.4: Explanation of attributes extraction from faulty process force/AE curves.

Following the previous explanation, each process failure coming from the sensors based process monitoring system is pre-treated (modelled) and converted into all the previous mentioned attributes. These attributes are later used in the rule base to carry out the identification of the process failures. As an example, a process failure and the attributes extracted from it are described in Figure 6.5.

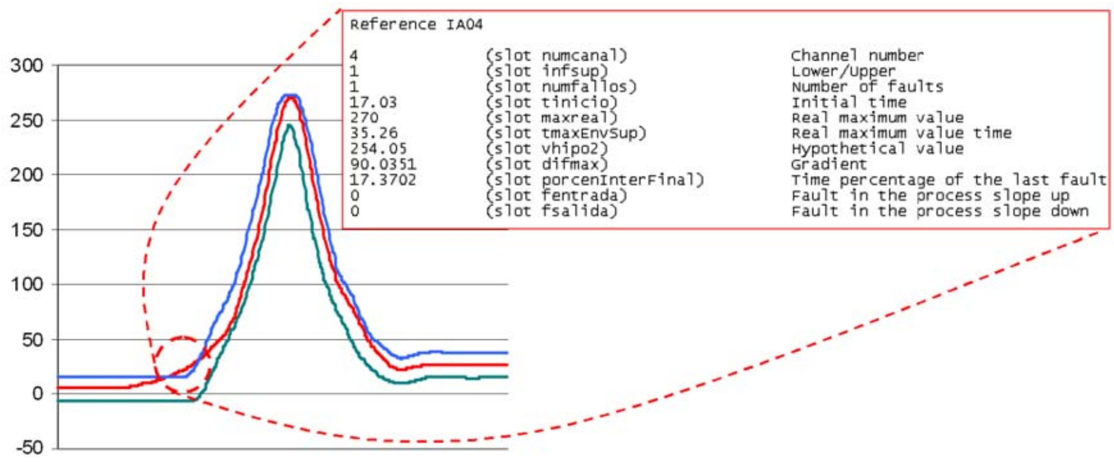


Figure 6.5: Attributes extraction example of a faulty force curve.

After this pre-treatment, the set of numerical values described in Figure 6.5 is transferred to the ES. This set of numerical values represents the antecedents at the ES and depending on them, and on the rules defined at the knowledge base (for example see Figure 6.7), the correct consequences (process failure, cause and solution) are then inferred.

6.1.3.2 Parts quality information from the Artificial Vision system

On the other hand, since the nature of the information supplied by the AV system is very different, no information pre-treatment is necessary and the information can be directly supplied to the ES. The reason for this is that this information consists of a set of numerical attributes (like the attributes extracted for the sensors based process monitoring system in the pre-treatment phase) that in this case represent the dimensions to be controlled in the parts. Then, with the appropriate rules defined at the knowledge base, and depending on the value of the numerical attributes supplied by the AV system (dimensions of the part that represent the antecedents), the correct consequences (part defects, cause and solution) are then inferred. Figure 6.6 shows the information (per part) that the AV system sends to the ES. This information contains the main dimension of the part and evaluates the presence or absence of local big burrs in the part.

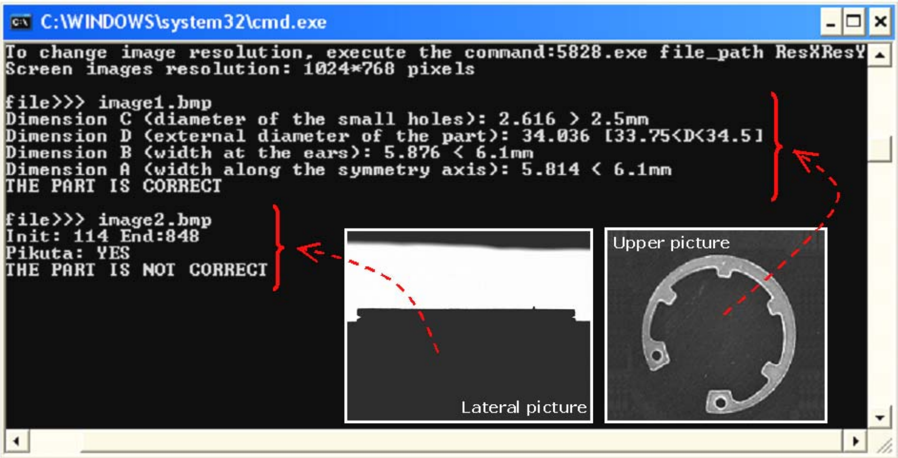


Figure 6.6: Information transferred per part from the AV system to the ES.

6.1.4. Knowledge specification into the rule database

Once the knowledge has been acquired from the expert operator and the necessary information supplied by the sensors based process monitoring system and by the AV system has been defined, next step consists on developing the rule base of the ES. The rule base of the ES is the codification of all the aforementioned knowledge in a suitable way such that the inference mechanism of the ES will be able to automatically assert the right consequences depending on the antecedents supplied by the sensors based process monitoring system and the AV system. Therefore, the rule base is the codification of the antecedents, the consequences and the rules used to describe the knowledge of the operator. Figure 6.7 shows an example of how a process failure is codified from its antecedents (attributes extracted from the signals supplied by the sensors based process monitoring system) to its consequences (actions that the operator should carry out to restart the production) using CLIPS. Specifically, the process failure codified in Figure 6.7 corresponds to the detection of a punch breakage in the tool.

Rule that detects the failure at the process:

```
(if (and (<= ?gradient 20) (= ?numchannel 3) (= ?infsup 1))
then (assert (defect (ident 4) (name process failure 4)
appreciation "A punch is broken in the tool")))
Bind ?*defect_list* (created $ ?*defect_list* 4)))
```

Process failure identification

Rule for determining the cause of the process failure:

```
(defrule cau_brokenpunch
?r1 <- (defect (ident 4)
)
=>
(assert (cause (ident 3) (name caubrokenpunch) (description
"Excessive wearing of the punches")))
(bind ?*cause_list* (create$ 3 ?*cause_list* ))
(bind ?*cause* 3)
```

Failure cause explanation

Rule for determining the solution to be applied:

```
(defrule sol_two_options
?c <- (cause (ident 3))
=>
(assert (solution (ident 3) (name soltwooptions) (description "If the punch is
broken close to the tip, change the punch and push with the new punch the
tip that is blocked in the die/If the punch breakage is longer, remove the tool
from the machine (with the metal strip inside) dismount it and extract the
broken punch from the tool. Before mounting the tool again replace the
broken punch with a new one")))
(bind ?*solution_list*(create$ 3 ?*solution_list* ))
(bind ?j (position_list solution3))
(if (> ?j 0) then
(bind ?temp (+ (- (length$ ?*defect_list*)(length$ ?*cause_list*)) 1))
(bind ?defect (nth$ (+ 1 ?temp) ?*defect_list*))
(bind ?cause (nth$ ?j ?*cause_list*))
;(show_screen ?defect ?cause solution3)
)
;(if (and (= (length$ ?*defect_list*) (length$ ?*cause_list*))(= ?*cause* 3))
;then (printout t ?*defect_list* " " ?*cause_list* " " ?*solution_list* crlf))
(printout t ?*defect_list* " " ?*caus_list* " " ?*solution_list* crlf)
)
```

Failure solution description

Figure 6.7: Example of rules codification for the detection of a punch breakage in the tool.

Figure 6.7 shows how the rules developed in the rule base of the ES have been divided into three main blocks. First block of the rule in Figure 6.7 states that IF the attribute "gradient", calculated in the pre-treatment phase, is smaller than 20 (what means a very sudden fault) AND the fault happens in sensor number three (acoustic emission sensor that supervises the withdrawal of the punches) AND it is an upper fault (process curve goes over upper envelope curve) THEN there has been a punch breakage in the tool. The second block of the rule states that IF there has been a punch breakage in the tool THEN the cause for the punch breakage in the tool is an excessive wearing of the punches. And finally, the third block of the rule states that the solution to solve the punch breakage at the tool is to replace the punch and provides two different solving protocols depending on the breakage length of the punch.

6.1.5. The core of the ES: the inference mechanism

And, finally, once the rule base has been developed, the inference mechanism of the ES is in charge of asserting the right consequences depending on the antecedents supplied by the sensors based process monitoring system and the AV system. The inference mechanism, or inference strategy, is a search method that performs the activation of the consequents (actions) of the rules which antecedents (conditions) are fulfilled [LUS85]. At the present research work, a data driven search method that emulates the operator has been used. This data driven search method works from known facts to the goal state like the operator does, from his/her perception of the process failure to the final action that successfully restart the production. Therefore, the ES receives information from both monitoring systems (sensors based and AV monitoring systems) and whenever a process failure or a part defect is detected, the ES is executed in the way described in Figure 6.8.

Figure 6.8 describes graphically the rule codified in Figure 6.7 and how the inference mechanism works. First step consists on finding the rule which antecedents match with the information supplied by the sensors based process monitoring system or the AV system. In this case, the antecedents which match are that the faulty channel (or faulty sensor) is number three (AE sensor that surveys the withdrawal of the punches), that the gradient value is smaller than 20 (very sudden fault) and that there is an upper fault. When these three antecedents are fulfilled, the rule for the punch breakage is "fired" and the identification of this process failure asserted. Next, the rule that links this process failure to their causes is activated asserting the reason of the problem. And finally, the ES determines the actions to solve the problem and restart the production at the facility.

Punch breakage

IF

Rule: **<u>Channel number</u> is 3 AND the value of the <u>gradient</u> is smaller than 20 and the fault is an <u>upper</u> fault.**

THEN

Consequence: **<u>Defect:</u> There is a broken punch inside the tool.**

<u>Cause:</u> Excessive wearing of the punches.

<u>Solution:</u> After extracting the metal strip there are two possibilities:

If the punch broken length is short, replace the broken punch

If the punch broken length is long, extract the coil and replace the broken punch

Figure 6.8: Steps in the inference mechanism during punch breakage detection in the tool.

Therefore, with the implementation of this ES into the blanking facility, whenever any of the process failures described in Figure 6.2 or any of the part defects described in Figure 6.3 happens in the blanking process, the ES will automatically identify it and inform the operator about its causes and the right actions to be carried out for restarting the production in a quick and correct way. "Annex I. Rule base of the ES" shows all the rules developed at the present research work.

<u>6.1.6. Results achieved by the rule-based ES approach</u>

The rule-based ES has been implemented in the blanking facility and works in connection to the sensors based process monitoring system and to the AV system (see Figure 6.9). Nine different process failures and nine different part defects have been identified and implemented into the ES. All the process failures and part defects identified are shown in Figure 6.2 and Figure 6.3. Among the process incidences, the most important ones are:

1. Strip feed failures due to bad extracted parts
2. Strip feed failures due to slugs of material inside the tool
3. Misalignment of the strip inside the tool
4. Clogging of the strip to the tool during withdrawal of the ram
5. Detection of broken punches
6. Detection of double parts inside the tool due to bad extracted parts
7. And detection of local big burrs due to punch micro cracks.

Besides this, the intelligent control system is able to detect the position within the tool where the incidence has happened. This way, the operator only has to consult in the graphical user interface of the ES in order to know the incidence, its position in the tool, its cause and the solution. At the same time, and regarding the part defects, the detection of local big burrs has been the most important incidence identified by the ES.

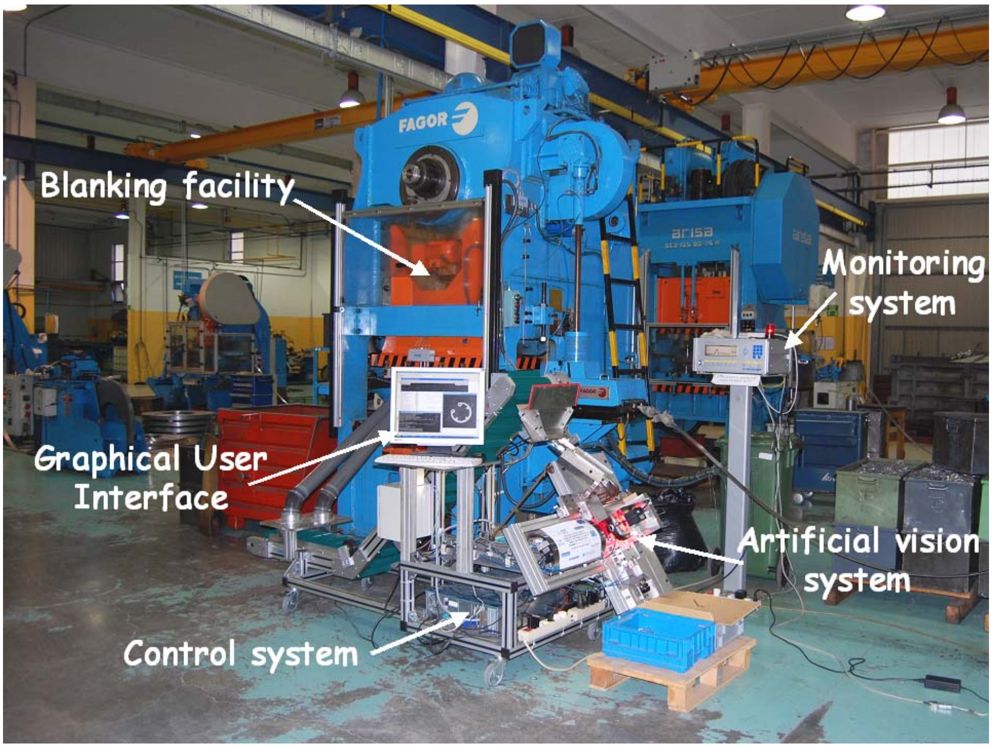


Figure 6.9: Complete intelligent control system installed in Industrias Alzuaran S. L.

At the end of the learning phase, which lasted during the production of more or less 200.000 parts, 95% of the failures at the blanking facility were detected. After this learning phase and during the next six months (experimental phase), new knowledge was implemented in the ES and nowadays the success rate is close to 100%.

Therefore, the implementation of the developed control system allows the elimination of the external defective because the AV system checks the quality of the 100% produced parts. This has three main advantages:

1. Since Industrias Alzuaran S.L. produces the reference 5828-001 for the automotive industry, they can not supply any defective part to their customers. This is currently achieved by means of a visual inspection task made by human operators after the process that increases the cost of the parts around 2.5% (what correspond to approximately 5000€ per year for the reference 5828-001).
2. If any defective part is shipped to the customer, Industrias Alzuaran S.L is responsible for the economic consequences that this originates (return of the complete batch, visual inspection of the complete batch and shipping of the batch to the customer again). Although this is not very frequent, it has sometimes happened originating economical losses (last year around 3000€ for the reference 5828-001).
3. And finally, the most important aspect but the most difficult to be quantifiable; since the companies working at the automotive industry are usually multinationals, the detection of any defective batch is known by all the companies (the reference 5828-001 is supplied to 8 different companies in three different continents). Therefore, any detection of defective parts made by the clients deteriorates the image of the company and can lead to big decrements of the quantity of parts demanded.

In parallel, one of the most important achievements of the ES is the reduction in time, and therefore in cost, when solving the facility stops (downtimes) due to process failures. With the introduction of the ES, the operator do not need to look for the failure in the blanking facility, but he directly finds in the interface of the ES a message with the instructions to solve the machine stop. Based on the experimental phase carried out in Industrias Alzuaran S.L., it is estimated a reduction of about 40% in the time that the operator needs to solve each machine stop in the blanking facility after the implementation of the ES. Considering an average of 5 machine stops per shift (8 hours of work), and estimating that each machine stop lasts for 10 minutes, it is concluded that the ES reduces the downtimes and therefore increases the productivity in about 4,16%. Finally, and due to the monitoring carried out at the blanking facility, the percentage of defective parts produced at the blanking facility is slightly decreased from a 0.1% down to a 0.08%, which means a 20%. Although this decrement in the production of defective parts has been mainly due to the implementation of the sensors based process monitoring system and of the AV system, the implementation of the ES results also in a better resolution of the process failures what leads to a reduction in trials and production of defective parts when solving the process failures.

6.1.7. Limitations of the rule-based ES approach

Although the results achieved by the intelligent control system implemented in the blanking facility in Industrias Alzuaran S. L. have been considerably good, it has also been concluded that the application of rule-based ES techniques to this kind of developments is not always the most suitable solution. This way, it has been verified how the development of the branch of the system that identifies the defective parts is much simpler than the development of the branch of the system that identifies the process failures. This dissimilarity resides on the existing initial knowledge regarding each monitoring system and the difference between the information supplied by the sensors based process monitoring system and the information supplied by the AV system. The reason why the rule-based ES approach is more suitable for the treatment of the information supplied by the AV system than for the treatment of the information supplied by the sensors based process monitoring system is briefly explained next.

The information supplied by the AV system to the intelligent control system is composed of a set of numerical values (attributes) that represent the dimensions to be controlled at the part. These attributes and their numerical ranges (tolerances of the part) are well known from the beginning and are very easily codified into the rule base of the ES. As an example, a rule codified in the rule base is given next: IF the dimension measured at the part is smaller than its lower tolerance limit THEN the punch that blanks that area must be replaced because its wearing is too high. Following this example, two rules per dimension to be measured should be created, one for the upper tolerance limit and another one for the lower tolerance limit, where the actions to be carried out in case of any dimension out of tolerances should be stated. Therefore, the development of an intelligent control system based on ES is very suitable when the defects to be identified are a priori well known and when these defects are also easily identifiable in the information supplied by the monitoring system, in this case the AV system.

On the other hand, all the process failures detected by the sensors based process monitoring system are not always a priori known and the information supplied to the ES, that represents the process signals during the blanking of the material, is composed of a vast amount of data (a time series composed of up to 15.000 numerical values per machine strokes at the present research work). The treatment of this information compared to the treatment of the information gathered by the AV system has two principal differences. First difference is that, as mentioned before and in contrast to the defects at the parts, the process failures at the blanking facility are not a priori known. And second difference is that, even when the process failures are a priori known, the process signals, time series, associated to each process failure are not known. Therefore, it is not possible to initially create an IF-THEN rule base because both the process failures and their representation in the process signals supplied by the monitoring system are unknown.

This way, the strategy applied for developing the branch of the ES able to identify the process failures at the present research work has been as follows. After the detection of each new process failure, a pre-treatment of the information supplied by the sensors based process monitoring system has been carried out. The main idea of this pre-treatment is to model the process signals associated to each process failure by means of a set of attributes (explained in Figure 6.5). This way, the 15.000 numerical values recorded by the sensors based process monitoring system are converted into 11 attributes (described in Figure 6.5) that represent the process failure and become the antecedents at the rule base. Next step consists on creating an IF-THEN rule that fulfil the previous calculated antecedents and that has as consequences the knowledge of the operator for that specific process failure (failure, cause and solution identification). This way, whenever the same process failure (very similar process signals although not exactly the same) arrives to the rule-based ES, very similar attributes are extracted in the pre-treatment, the same IF-THEN rule is fired and the same consequences are inferred.

Following this strategy, whenever a new process failure wants to be identified at the blanking facility, at least one new rule must be developed. Regarding the antecedents it could happen (depends on the appearance of the new process failure in the process signals) that the already defined antecedents are able to model the new process failure or that new antecedents should be added. If this situation is extrapolated to a new reference or to a new forming process, a new analysis of the appearance of the process failures on the new process signals should be carried out and new appropriate antecedents and rules developed (information pre-treatment and rules must be customised for each studied process). As verified during the present research work, this analysis takes quite a long time and big effort and besides, a person able to program in CLIPS must carry out the later implementation into the ES.

Previous limitations found at the intelligent control module based on rule-based ES when dealing with the identification of the process failures, encouraged the research team to develop a more universal strategy. This new strategy relies on the use of Case Based Reasoning (CBR) techniques for the identification of the process failures. The use of CBR techniques allows developers to create universal intelligent control systems able to be applied to different forming processes where no initial knowledge is available because these techniques are able to automatically learn without introducing any initial knowledge into the system. The intelligent control module based on CBR techniques is explained next.

6.2. Intelligent control system development: CBR approach

Second approach to develop the intelligent control system is based on the application of Case-based Reasoning (CBR) techniques. As mentioned in “Chapter 2.- Scientific and Technological background”, CBR is a methodology for solving problems by utilizing previous experiences. It involves retaining a memory of previous problems and their solutions and, by referencing these, solve new problems [MAI00].

This definition matches perfectly with the analysis necessary for the information gathered by the sensors based process monitoring system at the present research work because not all the knowledge about the process failures that will be found is initially available and because no initial knowledge about the representation of those process failures in the process signals acquired by the sensors based process monitoring system is available either. Therefore the purpose is to use CBR techniques to automatically learn from the process failures found in the forming process and, after a learning phase, generate a case base able to autonomously identify the process failures at the blanking facility.

CBR techniques have been chosen at the present research work because they comprise a set of techniques very suitable for certain kind of problems. Next, the specific factors or analysis conditions at the present research work that matches with the capacities of the CBR techniques are described:

1. First important factor is that **initially there is no data or knowledge available about the process**. This means that the CBR system must go through an initial learning phase. Furthermore, this initial learning phase must be carried out online during the blanking process because no training data is initially available either. Therefore, the requirements of the CBR system will be that even if no data or knowledge is initially available, it must offer good solutions as early as possible.
2. Second factor is the presence of the operator what converts the learning phase into a **supervised learning**. On the contrary to unsupervised learning, in supervised learning there is an expert who can continuously provide with the right solution to the CBR system. Therefore, the online learning phase can be interpreted as the training phase and will be carried out with the information provided by the expert operator, who does not need any programming skills.
3. Third factor is that, although the learning phase will be carried out in a supervised learning mode, **the CBR system will try to assert from the beginning the right solutions** by itself. This means that the operator will be a passive agent and only will tune up the CBR system when this takes wrong decisions. Therefore, the CBR system will try to identify each new process failure even during the learning phase.
4. Fourth factor is that after the initial learning phase, the CBR system must be able to **identify the process failures in an autonomous way** (although the operator will be able to correct and therefore teach it). The factor used to identify the nature of the process failures at the blanking process will be the similarity between the new (unknown) data gathered by the sensors based process monitoring system and the already existing data at the case base of the CBR system (explained in subchapter 6.2.2). It is expected that the operator will have a more active paper during the learning phase and less active (only when special conditions take place at the facility) during the running phase.

Since no CBR technique able to directly fulfil all the previous requisites was found in the literature, a special algorithm has been developed to carry out the identification of the process failures. The algorithm developed is based on the k-nearest neighbour classifier technique. The k-nearest neighbour classifier technique is a classification method, used to retrieve the most similar cases when CBR techniques are applied and is based on learning by analogy. The working methodology of this classification technique is as follows [HAN01]:

1. First, all the training samples (process failures in this case) are stored in an n-dimensional pattern space representing each sample a point. The n-dimensional space is based on the fact that each sample is described by n-dimensional numeric attributes.
2. Second, when given a new unknown sample, a k-nearest neighbour classifier searches the pattern space for the k training samples that are closest to the

unknown sample. These k training samples are the k "nearest neighbours" of the unknown sample. "Closeness" is defined in terms of Euclidean distance.

3. And finally, the unknown sample is assigned to the most common class among its k nearest neighbours.

The algorithm developed is based on the previous described k-nearest neighbour classifier but a few modifications have been made in order to customize it for the necessities of the present research work. Next, the main modifications are described:

1. The final purpose is to generate clusters composed of similar process signals, where each cluster will represent a process failure at the forming facility. Each cluster is modelled by its mean (centre) and by its deviation (distance between the mean and the farthest process signal at the cluster, what represents the size of the cluster). Therefore, the main big difference is that, contrary to the k-nearest approach where individual samples are used, clusters (grouping samples) will be created at the present research work.
2. When a new unknown sample arrives to the CBR system, the algorithm evaluates its similarity (distance) with the centre of all the already existing clusters. The similarity, contrary to the k-nearest approach, is evaluated attribute-by-attribute and not using the Euclidean distance. The reason for this modification is that initial tests carried out using the Euclidean Distance showed that different type of samples could be classified within the same cluster depending on the distances distribution between the clusters. Once the closest cluster is identified, if its distance to the new unknown sample is shorter than its deviation (evaluated attribute by attribute), the new unknown sample is assigned to that cluster. Otherwise the CBR system will identify the new sample as a new process failure.
3. The feedback of the operator is always used at the CBR system. During the first steps, the learning phase, the CBR system will propose the solutions to the operator but the operator can always give his/her feedback. When the CBR system is not correct and the operator introduces the right solution, appropriate actions to recalculate the clusters will then be carried out by the CBR system. After the learning phase, it is expected that the CBR system will have enough knowledge (previous cases) to identify all the new unknown process failures although the operator will have the chance to still tune it.

The CBR based algorithm developed to identify the process failures from the information captured by the sensors based process monitoring system is explained next. The algorithm has been programmed in C++ and is nowadays working in connection with the sensors based process monitoring system used at the present research work. The algorithm is divided into two main blocks. First block makes a pre-treatment of the information and, as happened in the rule-based ES, a set of attributes that modelled the faulty process signals is codified. In this case, the set is composed of 5 "more universal" attributes per process signal (sensor at the blanking facility) as explained later. Second block performs the clustering and identifies which one of the previous recorded process failures (cluster) matches with the new unknown process failure. The user can constantly correct the CBR system in case that wrong identifications are carried out and can also add information to the CBR system for improving the knowledge at the case base. Next, the first and the second block of the algorithm developed are explained and the results achieved when treating several sets of process signals from different forming facilities supplied by Brankamp GmbH are explained too.

6.2.1. Attributes extraction procedure from the process signals

The algorithm developed at the present solution is based on the calculation of the similarity between the faulty process signals. This way, very similar faulty process signals correspond to the same process failure and very dissimilar faulty process signals correspond to different process failures. If an efficient and fast methodology wants to be developed, a pre-treatment for modelling the faulty process signals must be initially carried out because, as mentioned before, the faulty process signals recorded by the sensors based process monitoring system at the present research work have been composed in average of 15.000 numerical values.

Therefore, an initial modelling of the faulty process signals by means of attributes is carried out. The election of the attributes is one of the most important steps during the entire process because if irrelevant attributes are chosen undesired results will be achieved. At the present study, when a process failure takes place at the blanking facility, the process signals recorded by the sensors based process monitoring system go out of the envelope curves defined at the monitoring system. This way, the area enclosed by the actual process signal and the envelope curve when the first one is out of the envelope curve is a very good characterization of the process failure. Figure 6.10 shows how the faulty area (actual curve out of the envelope curves) is calculated from the faulty process signals captured by the sensors based process monitoring system. This calculation is made for each process signal (sensor) at the sensors based process monitoring system. Once the areas of each process signal are calculated, they are modelled by means of a set of attributes that will be later used at the similarity calculation (second block of the algorithm).

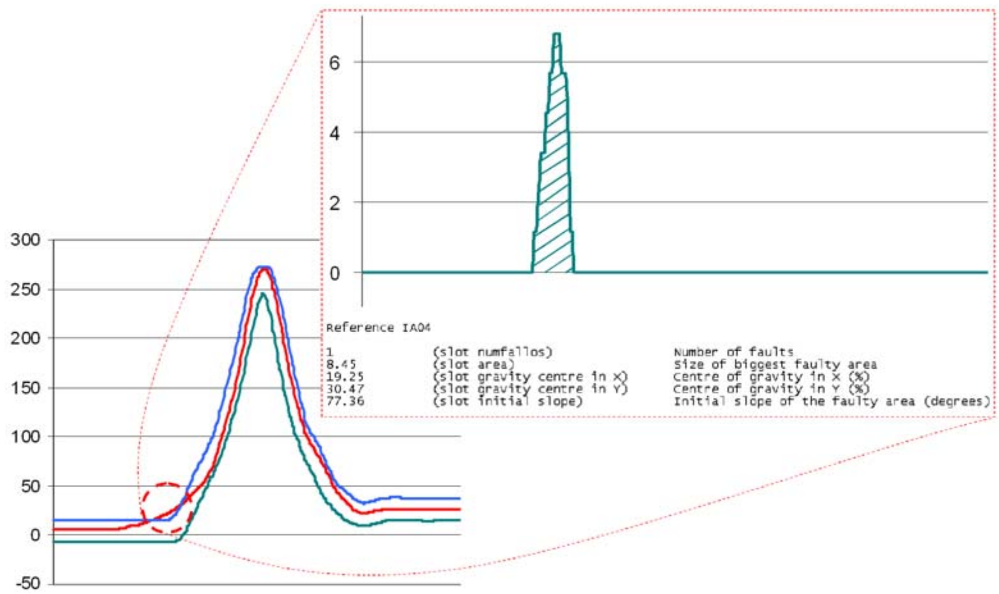


Figure 6.10: Faulty area calculation and its attributes extraction for a process failure.

So for each process signal (sensor at the blanking facility), the pre-treatment starts with the calculation of all the areas where the actual curve is out of the envelope curves (in Figure 6.10 there is only one faulty area but more than one could exist in the curves provided by the sensors based process monitoring system). Since the number of attributes per process signal (sensor) must remain constant if a similarity comparison wants to be performed, only the attributes of one area can be considered. After an initial try-out, it was decided that the greatest faulty area at each process signal is the one that best represents the process failure and that therefore smaller areas should be filtered.

Next step consist on identifying the most relevant attributes to model this greatest area. The next five relevant attributes were selected to model the area of each process signal (sensor):

1. Number of faulty areas: although following attributes model the greatest area, the number of faulty areas per process signal (including the greatest one) is also a very important attribute for the identification of some process failures.
2. Size of the biggest faulty area: represents how big the process failure has been. It is calculated by integrating the faulty area. It is calculated in percentage with respect to the area of the actual process curve in order to take into account matters like the sensitivity of the information acquired.
3. Centre of gravity in X-axis of the faulty area: locates the process failure within the blanking process cycle (approaching phase, blanking phase or withdrawal phase). It is calculated in percentage with respect to the cycle total length.
4. Centre of gravity in Y-axis of the faulty area: evaluates the shape of the process failure, sharpen (very strong and sudden) or flat (not so strong but longer in time). It is calculated in percentage with respect to the highest point of the faulty area in order to take into account matters like the sensitivity of the information acquired.
5. Initial slope of the faulty area: this final attribute represents how sudden the process failure starts. This final attribute is very important for the identification of some process failures like punch breakages. It is calculated in degrees.

Therefore at the end of this first block, an array of numbers that models the process failure is created. This array of numbers is composed of the previously calculated attributes repeated the number of process signals (sensors) at the blanking facility. For example, if the number of process signals (sensors) is ten, an array of fifty numbers will be created. This array of number is used at the second block of the algorithm to carry out the similarity calculation procedure. This procedure is explained next.

6.2.2. Customised supervised CBR algorithm

The second block at the algorithm performs the calculation of the similarity between the new unknown process failure (modelled as the array calculated at the previous block) and the already existing clusters at the case base. As mentioned before, each cluster is defined as its centre (arithmetic mean of the failures located in the cluster) and its deviation (distance between the centre and the furthest failure at the cluster), which represents the size of the cluster. Figure 6.11 shows all the possible decisions that can take place when a new unknown process failure arrives to the CBR system. Next, each branch of the decision making process is explained.

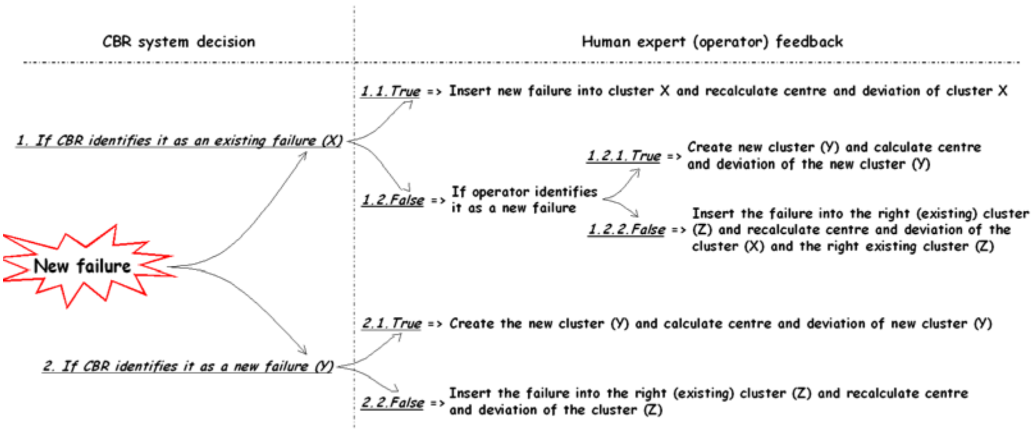


Figure 6.11: Supervised classification strategy architecture.

As shown in Figure 6.11, the first part of the decision making process is carried out by the CBR system. In this first part, the algorithm evaluates if the new unknown process failures belongs to any of the already existing clusters and therefore if it can be identified. Here two possibilities are given:

1. If CBR identifies the new unknown process failure as an existing failure (X): this happens whenever the distance between the new unknown process failure (to be classified and therefore identified) and the centre of one of the clusters is smaller than the deviation of that cluster. This way, attribute-by-attribute the algorithm evaluates this condition and when all the attributes fulfil this condition for one cluster, the new unknown process failure is located into that cluster.
2. If CBR identifies the new unknown process failure as a new failure (Y): if no one of the already existing clusters in the CBR system fulfils the previous condition, the CBR system identifies the new unknown process failure as a new process failure and a new cluster is then created.

The system could work alone based on the previous mentioned condition (unsupervised CBR system) and then the entire decision making procedure would be based on arithmetic (distances calculated between the existing clusters and the new unknown failures) but this initial unsupervised strategy has two limitations. First one is that, as mentioned previously, this short of manufacturing processes are highly non linear and therefore the unsupervised CBR system is not able to correctly identify all the process failures. The second and most important limitation is that the unsupervised CBR system is not able to learn because it does not know if the decisions taken are right or wrong. Therefore, and since the presence of the operator is necessary because he/she is in charge of implementing the description of the process failures, a supervised CBR system has been created and the operator can constantly improve the performance of the CBR system. This way, during the initial phase or learning phase, the operator will introduce knowledge into the system and will create the adequate clusters that correctly define the process failure at the CBR system. After this initial phase, and once that the right clusters have been created, the system will be able to autonomously identify the new unknown process failures based on the already existing clusters (that represent the process failures) at the CBR system. Anyway, even in the second phase, when special conditions take place at the blanking facility like, for example, the appearance of a new type of process failure that has not been detected during the learning phase, the operator will have the chance to introduce new knowledge and therefore identify the new process failure. Next the branches of the CBR system where the operator is involved are explained. The first branch, when the

CBR system identifies the process failure as one existing in the case base is explored next:

1.1. True: when the operator agrees with the solution given by the CBR system, the new unknown process failure is inserted into the cluster proposed by the CBR system and the centre and the deviation of the cluster are recalculated.

1.2. False: when the operator does not agree with the solution proposed by the CBR system, only two other possible solutions can be right: that the new unknown process failure is a process failure that had not previously been detected or that the new unknown process failure is different from the solution proposed by the CBR system.

   1.2.1. True: when the operator informs the CBR system that the new unknown process failure had not been previously detected, the CBR system creates a new cluster (associated to this new process failure) and calculates its centre and its deviation.

   1.2.2. False: when the operator informs the CBR system that the solution given is not the right one and that the new unknown process failure is another existing process failure at the CBR system, the new unknown process failure is introduced into the cluster specified by the operator and the centre and the deviation of both clusters (the one proposed by the CBR system and the one specified by the operator) are recalculated. In this case the deviation of the cluster proposed by the CBR system becomes smaller and the deviation of the cluster specified by the operator becomes bigger.

At the same time, when the CBR system identifies the new unknown process failure as a new one because it had not been previously detected, the operator can take the next decisions:

2.1. True: when the operator agrees with the CBR system that the new unknown process failure is a new type of process failure, the CBR system creates a new cluster (linked to the new process failure) and calculates its centre and its deviation.

2.2. False: on the other hand, if the operator does not agree with the CBR system and informs it that the new unknown process failure already existed in the case base, the CBR system will insert the new unknown process failure into the cluster specified by the operator being the centre and deviation of this cluster recalculated.

Following this strategy where the operator can constantly correct the CBR system and therefore this last one learns every time that a new process failure arrives, a very well structured case base is developed and after the arrival of several process failures during the learning phase, the CBR system is able to identify the process failures. Next subchapter explains the results achieved with the previous explained unsupervised and supervised CBR systems when dealing with different sets of process signals.

6.2.3. Results achieved by the CBR approach

In order to evaluate the efficiency of the developed CBR system, Brankamp GmbH provided several sets of process failures. Both the unsupervised and the supervised CBR strategies were used to classify the provided sets of process failures and the CBR strategy was evaluated. The results achieved through this analysis are given next. First, the results obtained by the unsupervised system are given. In this case, the system was provided with the files and the solution given by the system for all the files was considered to be right. After this first analysis, Brankamp GmbH also provided the right classification of the sets and the supervised clustering was executed following the right classification provided by Bankamp Gmbh; when the system gave a wrong solution, this was externally corrected.

6.2.3.1 Results achieved for Set 1

Set 1 is composed of 47 files, containing each of them a process failure detected in a forming facility during the production of one reference. In this case the forming process was monitored by means of nine force sensors (six sensors monitoring six stations at the tool and other three sensors placed in the frame of the press). Therefore, all the files studied at the present set are composed of nine channels. The group of clusters generated by the unsupervised system are given in Table 6.I:

Table 6.I: Results summary for the classification made by the unsupervised system for set 1.

Cluster (failure) number	File number
U1	362
U2.1	363
U2.2	375, 409
U3	364, 367
U4	365
U5	366
U6.1	369
U6.2	447, 452
U7	370
U8	372
U9	373
U10	374
U11	390
U12	391
U13	392
U14	393
U15	399
U16	400
U17	401
U18	402
U19.1	403
U19.2	407
U20	404
U21	405
U22.1	406
U22.2	475
U23	408
U24	410
U25	411
U26	412
U27	413
U28	415
U29	416
U30	417
U31	427
U32	429
U33	431
U34	432
U35	450
U36	472
U37	474
U (no fault detected)	414, 430, 473

Table 6.I shows how the unsupervised system found 37 different process failures in the forming process, what a priori, is an excessive number of different process failures. Besides this, the set also contained files with no process failure and the unsupervised system was able to find and cluster them (no fault detected). In order to evaluate these results deeper, the solution provided by Brankamp GmbH for this set is shown in Table 6.II.

Table 6.II: Solutions provided by Brankamp GmbH for set 1.

Cluster (failure) number	File number
S1	362, 364, 367, 400, 407, 411, 450
S2	365, 369, 405, 447, 452
S3	366, 390, 412, 415
S4	373, 399, 403, 404
S5	429, 431
S6	372, 416, 427, 432
S7	375, 409
S8	363
S9	370
S10	374
S11	391
S12	392
S13	393
S14	401
S15	402
S16	406
S17	408
S18	410
S19	413
S20	417
S21	472
S22	474
S23	475
S (no fault detected)	414, 430, 473

The relationship between the clusters calculated by the unsupervised system (Table 6.I) and the right cluster classification provided by Brankamp GmbH (Table 6.II) is given in Table 6.III.

Table 6.III: Relationship between the solution provided by Brankamp GmbH and the classification calculated by the unsupervised system for set 1.

Cluster (right solution)	Non supervised cluster number
S1	U1+U3+U16+U19.2+U25+U35
S2	U4+U6.1+U6.2+U21
S3	U5+U11+U26+U28
S4	U9+U15+U19.1+U20
S5	U32+U33
S6	U8+U29+U31+U34
S7	U2.2
S8	U2.1
S9	U7
S10	U10
S11	U12
S12	U13
S13	U14
S14	U17
S15	U18

S16	U22.1
S17	U23
S18	U24
S19	U27
S20	U30
S21	U36
S22	U37
S23	U22.2
S (no fault detected)	S (no fault detected)

When comparing the results at Table 6.I and at Table 6.II (shown in Table 6.III), two main conclusions are obtained:

1. The system is working properly regarding the distinction of the different process failures because not even one of the clusters at Table 6.I gathers process failures belonging to different clusters of Table 6.II. This means that the CBR system, even when working without supervision, is able to distinguish the different process failures.
2. The system is creating too many clusters (too many different process failures) because it is only based on arithmetical distances and it does not consider that files containing different faults could represent the same process failure (what actually happens). As an example, in Table 6.II, file 411 (with faults in channels 3 and 5) and the rest of the files in cluster number S1 (with faults in channel 3) represent the same process failure at the forming facility.

After obtaining the results achieved by the unsupervised clustering, next the supervised clustering system was also tested for the set 1. In order to test the supervised clustering, the solutions provided by Brankamp GmbH were used and whenever the system gave a wrong solution, this was externally corrected. This way, the final solution achieved by the supervised module matched with the right solution provided by Brankamp GmbH (emulation of the operator working with the supervised system when surveying the forming process) and at the same time, the corrections allow the system to learn about the process.

Following the structure of the supervised system, explained in “6.2.2. Customised supervised case based reasoning algorithm”, the solutions suggested by the supervised system could be:

1. Correct: the system automatically identifies the process failure correctly.
2. Wrong cluster: the system does not identify the process failure correctly because when trying to identify it, a mistake is made, and it is assigned to a wrong existing cluster.
3. New cluster wrong: the system identifies the process failure as a new one, but actually it is an already identified process failure.
4. Existing cluster wrong: the system identifies the process failure as one that already had been detected, but actually it is a new process failure not detected before.

Iteration	File number	Correct	Wrong cluster	New cluster wrong	Existing cluster wrong
1	362	☑	☐	☐	☐
2	363	☑	☐	☐	☐
3	364	☐	☐	☑	☐
4	365	☑	☐	☐	☐
5	366	☑	☐	☐	☐
6	367	☐	☐	☑	☐
7	369	☐	☐	☑	☐
8	370	☑	☐	☐	☐
9	372	☑	☐	☐	☐
10	373	☑	☐	☐	☐
11	374	☑	☐	☐	☐
12	375	☑	☐	☐	☐
13	390	☐	☐	☑	☐
14	391	☑	☐	☐	☐
15	392	☑	☐	☐	☐
16	393	☑	☐	☐	☐
17	399	☐	☐	☑	☐
18	400	☐	☐	☑	☐
19	401	☑	☐	☐	☐
20	402	☑	☐	☐	☐
21	403	☐	☐	☑	☐
22	404	☐	☐	☑	☐
23	405	☐	☐	☑	☐
24	406	☑	☐	☐	☐
25	407	☑	☐	☐	☐
26	408	☑	☐	☐	☐
27	409	☑	☐	☐	☐
28	410	☑	☐	☐	☐
29	411	☐	☐	☑	☐
30	412	☐	☐	☑	☐
31	413	☑	☐	☐	☐
32	414	☑	☐	☐	☐
33	415	☐	☐	☑	☐
34	416	☐	☐	☑	☐
35	417	☑	☐	☐	☐
36	427	☐	☐	☑	☐
37	429	☑	☐	☐	☐
38	430	☑	☐	☐	☐
39	431	☐	☐	☑	☐
40	432	☐	☐	☑	☐
41	447	☐	☐	☑	☐
42	450	☐	☐	☑	☐
43	452	☐	☐	☑	☐
44	472	☑	☐	☐	☐
45	473	☑	☐	☐	☐
46	474	☑	☐	☐	☐
47	475	☑	☐	☐	☐

Figure 6.12: Results achieved by the supervised module for the set 1.

Figure 6.12 shows the results obtained when treating the files of set 1 with the supervised system. The most important conclusion achieved after evaluating the results shown in Figure 6.12 is that 28 out of 47 files were classified correctly, what means a success rate of around 60%. At the same time, it must also be stated that the rest of the files (40%) were considered as “New cluster wrong” (considered by the system as a new process failures when actually is a process failure already detected) due to the fact that the system needs a learning phase to determine the size of the clusters. Finally, it is also concluded that sets with greater number of files would produce better results because a set with 24 different clusters (different process failures), when only 47 files are provided, still is in the learning phase.

<u>6.2.3.2 Results achieved for Set 2</u>

Set 2 is composed of 30 files, containing each of them a process failure detected in a forming facility during the production of different references. Process signals from different references were mixed in order to evaluate the universality of the CBR approach. The different forming processes were monitored by means of eight sensors and therefore, all the files studied at the present set are composed of eight channels. The group of clusters generated by the unsupervised system are given in Table 6.IV:

Table 6.IV: Results summary for the classification made by the unsupervised system for set 2.

Cluster (failure) number	File number
U1	648
U2	649
U3	659
U4	660
U5	670, 675, 683
U6	672
U7	679, 687, 703, 704, 705
U8	692
U9	694
U10	701
U11	706, 717
U12	707
U13	708, 712
U14	713
U15	714
U16	728
U17	729
U18	731
U19	735, 737
U20	736
U21	739

Table 6.IV shows how the unsupervised system found 21 different process failures in the process, what a priori, is again an excessive number of different process failures. In order to evaluate these results, the solution provided by Brankamp GmbH for this set is shown in Table 6.V.

Table 6.V: Solutions provided by Brankamp GmbH for set 2.

Cluster (failure) number	File number
S1	648, 659, 660, 670, 675, 679, 683, 687, 692, 694, 703, 704, 705
S2	649, 701, 708, 712, 713
S3	672, 707, 736, 739
S4	706, 717
S5	714
S6	728, 731
S7	729

The relationship between the clusters calculated by the unsupervised system (Table 6.IV) and the right cluster classification provided by Brankamp GmbH (Table 6.V) is given in Table 6.VI.

Table 6.VI: Relationship between the solution provided by Brankamp GmbH and the classification calculated by the unsupervised system for set 2.

Cluster (right solution)	Non supervised cluster number
S1	U1+U3+U4+U5+U7+U8+U9+U19
S2	U2+U10+U13+U14
S3	U6+U12+U20+U21

S4	U11
S5	U15
S6	U16+U18
S7	U17

When comparing the results at Table 6.IV and at Table 6.V (shown in Table 6.VI), two main conclusions are obtained again as happened in the case of Set1:

1. The system is working properly regarding the distinction of the different process failures because not even one of the clusters at Table 6.IV gathers process failures belonging to different clusters of Table 6.V. This means that the CBR system, even when working without supervision, is able to distinguish the different process failures.
2. The system is creating too many clusters (too many different process failures) because it is only based on arithmetical distances and it does not consider that files containing different faults could represent the same process failure (what actually happens). As an example, in Table 6.V, file 648 (with faults in channels 5 and 6), file 670 (with fault in channels 5) and file 735 (with fault in channel 6) represent the same process failure at the forming facility.

After obtaining the results regarding the unsupervised clustering, next the supervised clustering module was tested. In order to test the supervised clustering, the solutions provided by Brankamp GmbH were used and whenever the system gave a wrong solution, this was externally corrected. This way, the final solution achieved by the supervised module matched with the right solution provided by Brankamp GmbH (emulation of the operator working with the supervised system when surveying the forming process) and at the same time, the corrections allow the system to learn about the process.

Figure 6.13 shows the results obtained when treating the files of set 2 with the supervised system. The most important conclusion achieved after evaluating the results shown in Figure 6.13 is that 19 out of 30 files were classified correctly, what means a success rate of around 64%. At the same time, it must also be concluded that the rest of the files (36%) were considered as “New cluster wrong” (considered by the system as a new process failures when actually is a process failure already detected) due to the fact that system needs a learning phase to determine the size of the clusters. Therefore, the results of this new set are very similar to the results of Set 1. Finally, it is also concluded that sets with greater number of files would produce better results because only 30 files are provided. In this case, it must also be valuated that the process failures belong to different references.

Iteration	File number	Correct	Wrong cluster	New cluster wrong	Existing cluster wrong
1	648	☑	☐	☐	☐
2	649	☑	☐	☐	☐
3	659	☐	☐	☑	☐
4	660	☐	☐	☑	☐
5	670	☑	☐	☐	☐
6	672	☑	☐	☐	☐
7	675	☑	☐	☐	☐
8	679	☐	☐	☑	☐
9	683	☑	☐	☐	☐
10	687	☑	☐	☐	☐
11	692	☐	☐	☑	☐
12	694	☐	☐	☑	☐
13	701	☐	☐	☑	☐
14	703	☑	☐	☐	☐
15	704	☑	☐	☐	☐
16	705	☑	☐	☐	☐
17	706	☑	☐	☐	☐
18	707	☐	☐	☑	☐
19	708	☐	☐	☑	☐
20	712	☑	☐	☐	☐
21	713	☑	☐	☐	☐
22	714	☑	☐	☐	☐
23	717	☑	☐	☐	☐
24	728	☑	☐	☐	☐
25	729	☑	☐	☐	☐
26	730	☐	☐	☐	☐
27	731	☐	☐	☑	☐
28	735	☐	☐	☑	☐
29	736	☐	☐	☑	☐
30	737	☑	☐	☐	☐
31	739	☑	☐	☐	☐

Figure 6.13: Results achieved by the supervised module for the set 2.

6.3. Graphical User Interface: link between the operator and the intelligent control system

Although the core of the intelligent control system has been described in previous subchapters, another very important component of the system will be briefly explained next: the Graphical User Interface (named GUI from now on). A GUI is a type of user interface, which allows people to interact with electronic devices, like computers, hand-held devices, household appliances and office equipment [GUI08]. At the present research work a GUI has been created in order to establish the communication between the intelligent control system and the operator of the blanking facility. Through this communication the intelligent control system informs the operator about the process failures or part defects at the blanking facility, about the causes why the previous mentioned process failures happened and also suggests the operator about the protocols to restart the production. At the same time, the operator can interact with the intelligent control system in order to give his/her feedback about the condition of the process and of the part quality.

The main purpose during the development of the present GUI was to create a simple and an easy to use interface with the operator. The reason for this purpose was that the communication with the operator is vital for a good performance of the intelligent control system and that, at the same time, operators working in forming facilities are not very used to work with computers. Therefore, the simplest application should be developed if good results want to be achieved in the future.

The software used to develop the GUI at the present research work is GTK+. GTK+ is a library of object oriented graphical user interface elements for developing X Window applications in C/C++ and other languages. In this research work, GTK+ libraries were chosen because a friendly and value added GUI can be developed, because they are open source libraries and because can be implemented in C/C++, the programming language also used for the AV system and for the intelligent control system what makes the communication between them easier.

Figure 6.14 shows the appearance of the developed GUI during the detection of a punch breakage in the blanking facility at Industrias Alzuaran S.L. Next, the main zones of the GUI (see Figure 6.14), and the information that each one supply to the operator are briefly explained:

- ✓ Zone 1: GUI shows the operator that there is a malfunction in the blanking facility because a process failure or a defective part has been found by the sensors based process monitoring system or by the AV system.
- ✓ Zone 2: GUI shows the operator the process signal (in case of a process failure) or the defective part (in case of a defective part detection) that the sensors based process monitoring system or the AV system has detected. Figure 6.14 displays the faulty process signal detected by the sensors based process monitoring system during a punch breakage.
- ✓ Zone 3: after the analysis of the faulty process signal or the defective part, the GUI shows the operator the conclusions asserted by the intelligent control module. In this case, a punch breakage has been detected and its causes and solutions are displayed to the operator. This is the most important area of the GUI because displays the consequences asserted by the intelligent control system.
- ✓ Zone 4: the GUI allows the operator to give his/her feedback to the intelligent control system. In this area the operator can agree with the consequences asserted by the intelligent control system or can disagree. If the operator disagrees with the proposed solutions, he/she can introduce new knowledge that will be used for future process failures. This way the efficiency of the system can be improved.
- ✓ Zone 5: finally, the GUI also allows the user to check about the previous process failures and defective parts and also about the efficiency (statistics) of the intelligent control module. By checking the previous process failures and defective parts the operator can extract fruitful information about the running of the process and check which the most common process failures or defective parts at the facility are. At the same time, by clicking in the statistics, the operator, and also the control engineer, can check about the efficiency of the intelligent control module (success rate of the proposed solutions).

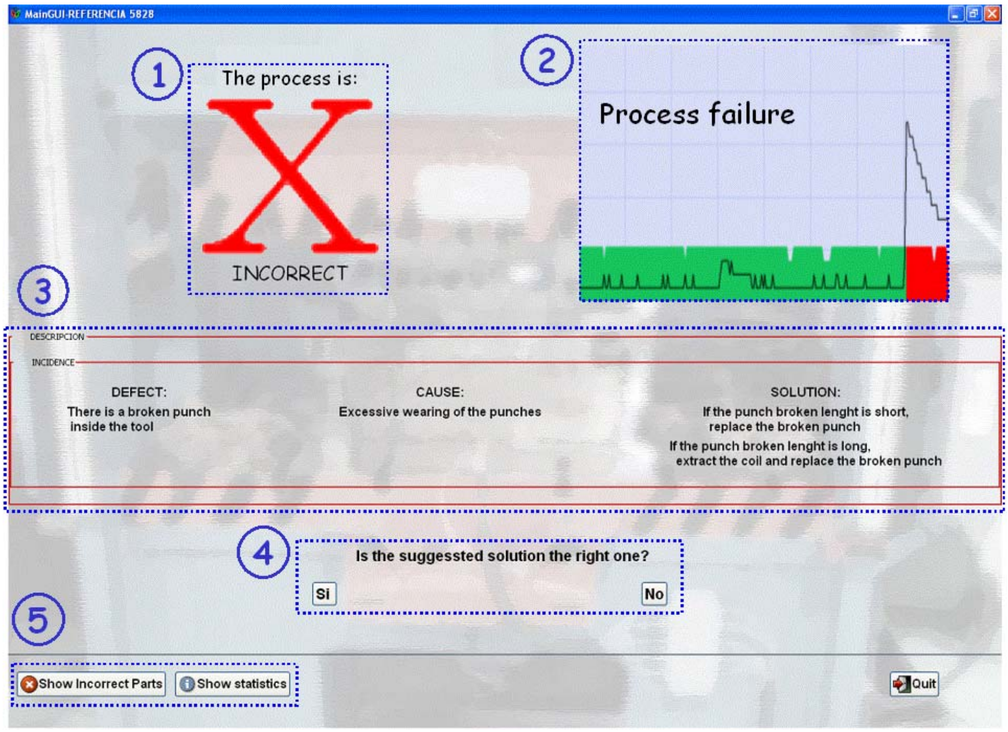


Figure 6.14: Graphical User Interface during punch breakage detection.

Therefore, the GUI developed at the present research work satisfies two main purposes; allows the operator to easily and friendly receive the suggestions asserted by the intelligent control system and, at the same time, allows the intelligent control system to gather new knowledge implemented by the operator. This flow of information, given in both directions, makes the operator to feel comfortable with the use of the intelligent control system and improves the performance of this last one because more and newer knowledge can be implemented into its knowledge base.

6.4. Conclusions

The main purpose of the intelligent control system has been fulfilled: to create a system able to identify the process failures and part defects at the blanking facility and therefore to help the operator to face the daily problems and to control the production facility efficiently. In comparison to state of the art monitoring systems, which are able to detect but not to identify the process failures, the developed intelligent control system analyses the information gathered by the sensors based process monitoring and the AV system at the blanking facility and informs the operator about the nature of the malfunction at the facility. The intelligent control system gives detailed descriptions to the operator about the process malfunction, its position within the blanking process, its causes and specific instructions to solve it and to correctly restart the production as soon as possible. Therefore, besides eliminating the delivery of defective parts to the clients through the implementation of the AV system and reducing the percentage of internal defective parts through the implementation of the sensors based process monitoring system, the implementation of the intelligent control system offers several advantages being the most important ones described next.

1. Reduction of downtimes after malfunctions. This is a very important improvement from an economic point of view. Before the implementation of the intelligent control system, and in answer to any machine stop, the operator had to first identify the malfunction and later solve it. This could last for a long time depending on the

operator experience and skills. This way, sometimes the production was restarted very soon but some other times the operator needed to open the tool, look inside and extract the strip of material before finding out the problem. After the implementation of the intelligent control system, the operator immediately finds an explanation for the facility stop and he/she only has to follow the instructions to restart the production. This fact could be even more important for operators who take care of more than one machine at the same time. For these operators, the information could be displayed in a universal where the operator will be informed about the malfunction at the machine. This way the operator will react immediately and by the time that he arrives to the forming facility he will know what he has to do to restart the production.

2. Standardization of the protocols to restart the production after process malfunctions. This is a very important factor and even more important at forming facilities where more than one operator work (forming facilities working in shifts). If standard protocols to restart the facility after process malfunctions are implemented into the intelligent control system, more consistent and robust operation procedures will be carried out. The advantages are the achievement of more reliable restarting procedures that lead to a decrement of the process failures and the fact that the knowledge of the operators can be written down and therefore shared between them, what leads to a better process control.

At the present research work, two AI techniques have been used to develop the intelligent control system: rule-based ES and CBR techniques. It has been stated that the suitability of each technique depends on the kind of information to be treated. This way, it has been found that the information gathered by the AV system is more prompt to be analysed by means of rule-based ES techniques whereas the information gathered by the sensors based process monitoring system is more prompt to be analysed by means of CBR techniques.

On the one hand, the information gathered by the AV system is composed of a set of numerical values that represent the dimensions of the reference to be controlled. By using rule-based ES techniques, rules to evaluate whether or not the dimensions are within the tolerances can be very easily defined. This way, the rules will assert the part defect, its cause and solution when any of the part dimensions goes out of tolerances. The factors that make rule-based ES techniques suitable for this kind of information is that all the defects at the parts are initially known and that, at the same time, the nature of these part defects does not change much between references. Therefore the application of rule-based ES to the identification of part defects is very suitable and does not represent a big challenge.

On the other hand, the information gathered by the sensors based process monitoring system is composed of a vast amount of numerical data (up to 15.000 numerical values per stroke) that represent the process signals during the blanking of the material. In this research work, the application of rule-based ES for the identification of the process failures implies that adequate antecedents (attributes extracted in the pre-treatment phase) and rules must be defined for each new process failure; at least one new rule per process failure and sometimes new antecedents too. Unfortunately, the way that the process signals represent the process failures at the blanking facility is initially unknown and, therefore, it is not easy to create the rules and the antecedents at the rule-based ES. Therefore, although a rule-based ES, able to identify the process failures detected by the sensors based process monitoring system has been developed, proving the big potential of this technique (up to nine process failures and nine part defects successfully identified), it has also been stated that the application of this technique to the identification of new process failures and to the identification of process failures in new references or processes needs big modifications at the rule-based ES, what is very costly and undesirable.

As a solution to the previous mentioned drawback, CBR techniques have been applied to analyse the information supplied by the sensors based process monitoring system. The most important advantage of CBR techniques at the present research work is their ability to develop systems able to learn from the experience (remembering previous cases). This way, a special algorithm able to identify the process failures from the information supplied by the sensors based process monitoring system has been developed. This algorithm extracts the most meaningful attributes of the process signals and evaluates their similarity with the attributes of previously recorded process failures (gathered as clusters). If the attributes of the new unknown process failure are very similar to the attributes of a previous process failure, the new one is classified and therefore identified as the same. Therefore, the algorithms searches for the most similar already identified process failure to identify the new arriving process failures. This algorithm works in an autonomous, but at the same time, supervised way because the operator has the chance to correct its decisions and thus improve the identification of the process failures. The developed algorithm can be applied directly to new references or processes without any modification what makes it more desirable than the solution based on rule-based ES. The results achieved with this new algorithm based on case-based reasoning techniques have been very good.

Finally, a Graphical User Interface (GUI) has also been created to allow the user to communicate with the developed intelligent control system. It has been stated that the communication between the operator and the intelligent control system is very important if a good performance of the intelligent control system wants to be achieved. This way, communication must be carried out in both ways, the operator reading the advices of the system and the intelligent control system acquiring new knowledge from the operator (for correcting it and making it to work better). At the same time, the operator must find the GUI friendly and easy to be used; otherwise he will not communicate with the system. At the present research work, a GUI has been developed and linked to the intelligent control system. The GUI offers several data to the operator, like the process failure or part defect detected, the reason why it happened at the process, advices to solve it and an image showing how the monitoring system found the defect at the system. Finally, the GUI also offers the operator the chance to introduce new knowledge or to correct the intelligent control system when this last one asserts wrong solutions.

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Chapter 7

MAIN RESULTS AND CONCLUSIONS

7.- MAIN RESULTS AND CONCLUSIONS

This chapter summarises the main results and conclusions achieved during the present research work. First, a summary of the results achieved through 1) the development of the sensors based process monitoring system, 2) the development of the AV system and 3) the development of the intelligent control system is given. After this, more conceptual conclusions regarding the advantages and limitations that the developed intelligent global control system offers to forming processes are given too. Finally, some tasks that have been identified as the future needs towards the industrialization of the present research work results will be explained too.

7.1. Summary of Results

As stated in "Chapter 1.2: The goal", the final objective of the present research work has been **to analyse the feasibility and the technological viability of automatic control systems, where sensors based process monitoring systems, artificial vision systems and artificial intelligence techniques work together, in industrial manufacturing environments consecrated to the mass production of small size mechanical components at high rates** with the aim of:

1. Achieving the zero defect manufacturing at the client's facilities.
2. Reducing the downtime of the production facilities.
3. Reducing the internal defective.
4. Reducing the time (and therefore the cost) associated to inspection tasks.

Understanding feasibility as:

1. The economic cost of the complete system.
2. The set up cost in terms of the time necessary to tune the system up.
3. The achievable results, concerning the zero defects production, the reduction of downtimes, the reduction of internal defective and the reduction of time associated to inspection tasks.
4. The universality of the system in terms of its capacity to work with different processes or references.
5. The usability denoting the ease with which operators employ it.
6. The capacity to cope with or even to increase the production rate of the facilities.
7. The maintainability denoting the ease with which operators and/or maintenance personnel update it.

In order to industrially evaluate the final objective above proposed, the present research work has been carried out in an industrial environment. The industrial demonstrator selected has been a blanking facility consecrated to the manufacturing of small size retaining rings at high production rates. The blanking facility consists of a 125 tons. mechanical press, and a decoiler and the straightener that supply the mechanical press with the raw material, spring steel DIN 17222 CK67 sheet in coils. Three different references, manufactured at 60 strokes and 120 parts per minute by means of progressive blanking tools, have been evaluated.

By going through the entire process, from the development of both monitoring systems and the controller, to their final integration in the industrial blanking facility, as shown in Chapters 4, 5 and 6, the evaluation of the intelligent control strategy has been carried out. Therefore, the research work can be divided into three principal tasks (development of the three subsystems), which working together as a global system, have evaluated the feasibility of globally controlling the industrial blanking facility. The main results achieved through the consecution of each subsystem are summarised below:

7.1.1. Application of a sensors based process-monitoring system into a blanking process.

In “Chapter 4. Sensors based process monitoring”, the complete sensors based process monitoring system installed in the blanking facility has been described. Chapter 4 explains how the installation of the force and acoustic emission sensors is more efficient when these are close to the forces and acoustic emission signals sources and therefore, an important result, is that achieving a good monitoring strategy goes through the installation of all the sensors inside the tool (preferably in the upper tool aligned with the blanking punches).

Thus, three different tools (that manufacture three different retaining rings references) have been monitored with force sensors in all the stations, in order to individually monitor the force at each blanking operation, and with two acoustic emission sensors in order to monitor the acoustics emissions produced during the blanking of the material and during the withdrawal of the punches.

After the experimental phase, carried out at the daily running of the industrial blanking facility, it was demonstrated that, for the references studied, the sensors based process monitoring system is able to detect up to nine different process failures. Among all them, the most remarkable ones are the detection of punch breakages, the detection of bad evacuated parts or material slugs and the detection of malfunctions of the feeding system. The efficiency of the sensors based process monitoring system is very high, the aforementioned process failures are always detected, due to the high sensitivity of the sensors installed inside the tool. Another result is that, by installing several sensors inside the tool, it is possible to even deduce the station inside the tool where the failure takes place. This ability to determine the position (and also the type as shown in Chapter 6) of the failure within the tool represents an improvement of the current monitoring systems implemented in the forming industry.

Regarding the sensors based monitoring of the process, another important result has been that the sensors based process monitoring system is not able to detect all the process failures and therefore to guarantee that the quality of the 100% produced parts is good. This way, during the experimental phase it has been observed how the sensors based process monitoring system has not been able to detect two failures; 1) the growth of the burr at the edge of the parts beyond the predefined limits and 2) the formation of micro cracks in the blanking punches that has as a consequence the generation of local big burrs in the parts. The reason why the sensors based process monitoring system is not able to detect these failures is that 1) in the case of the burr growth, the variation of the blanking forces as the burr grows up is so smooth that the sensors based process monitoring system modifies the envelope curves to adequate them to this variation, and 2) in the case of the formation of micro cracks in the blanking punches, the variation of the force is much smaller than the limits of the envelope curves and the sensors based process monitoring is not able to realise about this process failure.

In order to detect these two process failures, two studies have been carried out. First, in order to evaluate the possibility of detecting the maximum allowable burr growth limit, a study comparing the evolution of the forces (measured with the sensors based process monitoring system) and the evolution of the burr growth (measured in an optical microscope) was carried out. The main result regarding this study is that, as the current state of the art says at a research level, there is a direct relationship between the variation of the forces and the variation of the burr growth in the industrial field too. Deeper studies in this topic should create the necessary knowledge to implement into the sensors based process monitoring system the ability to predict the growth of the burr by measuring the variation of the blanking forces.

And about the second process failure not detected by the sensors based process monitoring system, the presence of local big burrs due to punch micro cracks, it was decided that since the force variation is much smaller than the limits established by the envelope curves, another monitoring system able to check the final quality of the parts should work in parallel with the sensors based process monitoring system: an AV system.

7.1.2. Development and implementation of a high efficiency artificial vision system into a blanking process.

In "Chapter 5. Parts quality control", the development of a high efficiency AV system and its further implementation into the blanking facility (the industrial demonstrator at the research work) has been described. The AV system is composed of two intelligent cameras that "look" at the parts to be evaluated from above (upper image) and from the side (lateral view image). This way, the main dimensions of the parts are evaluated by treating the image acquired by the upper camera and the local big burrs (not detected by the sensors based process monitoring system) are detected by treating the image acquired by the lateral view camera. The development and implementation of the architecture represent themselves an original contribution to the current state of the art in AV systems through the combination of low level processing steps made in FPGA with high level processing steps made in PC with the purpose of speeding the processing time. The results achieved by the AV system are explained next.

Regarding the upper camera, the system is able to measure the main dimensions of the parts (the four principal dimensions that must be within the predefined tolerances) with a spatial resolution of 100 microns. This way, if any of the dimensions is out of tolerances, the part is sorted out. And regarding the lateral view camera, the system is also able to detect the presence of local big burrs in the parts (and therefore, indirectly the formation of micro cracks in the blanking punches), what is valuable information to stop the production and resharpen the blanking punches. By means of both images, it has been identified that the system is able to detect up to nine different defects in the parts, what leads to a scenario where no defective parts are sent to the clients.

Regarding the effectiveness of the AV system, several tests were made and the results are that, concerning the upper camera, the AV system is able to work with a standard deviation lower than 0,150 millimetres, what in the practise means that the percentage of false negatives is smaller than 4% (no false positives were found during the experimental phase). Concerning the lateral view image, several tests were carried out too and the results are that the percentage of false positives is around 3% and that the percentage of false negatives is around 2%.

Regarding the capacity of the AV system, the production facility was not slowed down when the AV system was implemented in the industrial field so one of the main purposes of the research work, avoid a reduction in the production rate of the blanking facility, was achieved. This way, the AV system has been working at a nominal rate of 120 parts per minute (limited by the handling of the parts because the hardware software co-design architecture reached a processing rate of 1000 images per minute). Anyway, although the AV system has worked at the production rate, 120 parts per minute, it was observed that this rate was already the limit for the system because the handling of the parts was excessive fast and some of the images taken by the cameras did not have enough quality (percentage of false negatives). This way, it was demonstrated that when the tests were carried out at a nominal evaluation rate of 60 parts per minute, the percentage of false negatives was reduced down to 1%. At the same time, an improvement of the resolution of the upper camera, reduced during the research work due to a lack of memory in the internal EEPROM memories of the intelligent cameras, should offer better results by augmenting the number of pixels enclosed in the tolerance range.

So, another important result regarding the quality control of the parts is that, although a very efficient AV architecture has been created and the parallel application of intelligent cameras based on FPGAs and algorithms on PC has given as a result a processing time (sum of acquisition and treatment time) of 125 milliseconds (what means the possibility of checking 8 parts per second), the proposed approach for the handling of the parts has not answered with the initial proposed objective and therefore the handling has become the bottleneck of the AV system (hardly working at 2 parts per second).

Anyway the developed handling system represent an original contribution to the current state of the art handling systems focused on retaining rings. The developed system is able to position the parts in a row independently of the way the parts are extracted from the blanking facility. At the present research project the “positioning boxes” have been used to feed the parts into the AV system but they could also be used to reduce the manual operations needed to position the parts during their manufacturing process. This fact can reduce the cost of manual operations what represents a big percentage of the cost of the parts.

7.1.3. Development and implementation of an intelligent control system into a blanking process.

In “Chapter 6. Intelligent control System”, the development of an intelligent control system able to identify the process failures and the parts defects and to propose actions to solve them and to restart the production efficiently has been described. After analysing different AI techniques, it was concluded that the most suitable ones, for developing an intelligent system able to diagnostic any process failure or part defect, are rule based ES and CBR techniques.

Rule based ES were initially used to develop the intelligent control module because all the knowledge regarding the process control was available in the figure of the operator. This way, the knowledge was captured by interviewing the operator and by working together with him during long periods of time. After this time, the rule base that linked each process failure and part defect with the causes and the solutions applied to solve them was created. Next step consisted on linking each process failure and part defect with the information gathered by the sensors based process monitoring system (for process failure identification) and the AV system (for part defect identification).

Again, and by observing the blanking process, a set of rules (described in Annex I) able to link the information gathered by both monitoring systems with the knowledge acquired from the operator was built and the rule based intelligent control system was created. After the learning phase, which lasted approximately during the production of 200.000 parts, the system codified a set of 18 rules. After this learning phase and during the next six months (experimental phase), new knowledge was implemented in the rule based ES and, at the end of this period, the success rate has been close to the

100%. This means that the ES is able to define very accurately most of the process failures.

Although the achieved results have been considerably good, another very important result is that the rule based intelligent control module is very static and that is not able to learn automatically. Therefore, if another family of parts wants to be surveyed or if the intelligent control module wants to be installed in another forming facility, all the rules at the rule base should be learnt and implemented again. Consequently, each new implementation of the intelligent control system means a vast amount of work and makes it not feasible in the real industrial field.

As a solution to the previous drawback, another intelligent control system based on CBR techniques has been developed. This new CBR system is able to automatically link the knowledge of the operator and the information coming from the monitoring systems. This improvement avoids the initial phase of knowledge implementation and makes the system much more feasible. The learning capacity of the CBR based intelligent control system has been evaluated by feeding it with several sets of process failures supplied by Brankamp GmbH and it has demonstrated its own capacity to learn and to offer good results (approximately 65% of success rate during the learning phase even when mixing process failures coming from several references) without the necessity of initially teaching it off line.

7.2. Main Conclusions Drawn from this Research

From all the aforementioned results achieved through the development of the present research work, the following main conclusions can be drawn:

1. The main conclusion is that the implementation of automatic control systems, where sensors based process monitoring systems, AV systems that monitor the part quality and intelligent control systems work together, improves the efficiency of the manufacturing facilities by benefiting from the next advantages:
    - ✓ No defective parts are delivered to the clients because AV systems check the quality of all the manufactured products. This advantage has by itself several principal benefits like: a reduction of the manufacturing costs because no defective parts are scrap, a reduction of possible losses due to penalty clauses signed in the contracts (mainly when working for the automobile industry), a reduction in the time necessary to check the quality of rejected batches, a reduction in the cost in terms of parts transportation and very important, a better company image due to the clients satisfaction.
    - ✓ The man machine ratio is also increased (what means longer period of times producing parts) because the length of the downtimes after process failures at the production facilities is considerably reduced (30% approximately). The reason for this is that intelligent control systems are able to identify the malfunctions at the facilities and able to suggest the operator the right actions to solve them. This way, the necessary time to restart the production is reduced and the productivity of the facilities increased.
    - ✓ And finally, the percentage of internal defective parts (defective parts detected on line during the manufacturing process) is reduced too (20% approximately) because the sensors based process monitoring systems survey the manufacturing facilities detecting a great percentage of the defective parts much earlier than the visual evaluation. Besides this, the implementation of sensors based process monitoring systems permits the control of the integrity of the manufacturing goods what avoids catastrophic failures reducing the maintenance costs and the downtimes of the facilities.

2. Another important conclusion, and now regarding sensors based process monitoring systems is that, although currently available commercial systems offer great advantages, these systems (at least in the application checked at the present research work) are not able to detect 100% of the defective parts (assumable because they are not focused on part quality) and they are neither able to detect 100% of the process failures (able to detect the main process failures but not able to detect some small process failures like the formation of micro cracks in the blanking punches). For this reason, the complementary of these systems with AV systems is a very interesting solution to improve the performance of the manufacturing facilities.
3. Another important conclusion, and now regarding AV systems, is that the development of co-architectures, where intelligent cameras based on FPGAs and algorithms running in PCs work together, considerably speeds up the acquisition and the treatment of the images and, therefore, allows AV systems to work in serial with the process at the manufacturing rate.
4. And finally, the possibility of creating intelligent control systems able to give detailed descriptions to the operator about the process malfunctions or part defects, their causes and specific instructions to solve them and to correctly restart the production has been proven. Two different AI techniques have been used and good results have been achieved. The main advantages of this development are a reduction of the downtimes after process failures (because the operator directly find the description of the incidence and its solution and does not have to look for it) and the chance to create standard protocols to restart the production after process malfunctions (very useful for manufacturing facilities working in shifts).

7.3. Suggestions for the Way Forward

The present research work has demonstrated a useful, as well as interesting, modular approach in the development of intelligent control systems that can be quite powerful in tackling the huge and enormously wide subject of the identification and solution of process failures and part defects in forming processes and in general in manufacturing technologies. It is suggested that future work should aim at:

Concerning the intelligent control system developed at the present research work:

1. Regarding the sensors based monitoring system, more and deeper studies in order to find the relationship between the force increment and the burr height increment in industrial blanking processes should be made. This way, the necessary knowledge to implement into the sensors based process monitoring system a module to predict the growth of the burr by measuring the variation of the blanking forces in blanking processes would be created.
2. Regarding the AV system, faster handling systems for the parts should be designed in order to achieve faster production rates because nowadays, although the treatment of the images can be done at a rate of 8 parts per second, the handling device is only able to manage 2 parts per second. Works towards this purpose have already started to be carried out.
3. Regarding the intelligent control system, experiments with greater number of process failures should be made in order to evaluate the final capacity of the CBR system after its learning phase.

Concerning future works aimed at implementing the results achieved at the present research work into the manufacturing field:

1. After the final evaluation phase, the most remarkable one should go through the creation of a commercial intelligent control module, based on the CBR techniques studied at the present research work, and its further implementation into already

commercially available sensors based process monitoring systems. The achievement of this development will bring to the forming industry a great advantage because the already available monitoring systems will evolve into intelligent diagnostic systems, what means that, instead of just stopping the forming facility, they will provide the operators with a complete report about the process failures, their causes and the actions that they (operators) should carry out to restart the production.

2. Future works should also aim at implementing the global strategy developed at the present research work into other manufacturing processes, within the forming field like deep drawing processes or in other fields like machining, welding or injection moulding processes. Following this strategy, the research team have already started to carry out some tasks with the aim of developing a global control system in the field of rolling processes.
3. Aligned with the previous proposal, another work, already briefly covered during the present research work, would be the application of intelligent controllers to the online control of hydroforming processes. The main objective in this field should go through the development of intelligent controllers able to adjust online the main variables of hydroforming processes based on sensors based process monitoring systems and AI control systems. This development will bring an increment of the robustness of hydroforming processes, a reduction of their scrap and will minimize their dependence on the quality of the raw materials.
4. Another challenge is the creation of scalable solutions that learn and improve from collaborative experience. This way, several intelligent control systems, implemented in a set of common manufacturing processes or manufacturing facilities, will profit by creating a common knowledge base where all process failures will be gathered. Therefore, right solutions will be given for the first failure at one manufacturing facility if the same process failure has already happened in another one. The same could be applied to the maintenance of the manufacturing facilities (detection and identification of anomalous performances).
5. Regarding high efficiency AV systems, the potential of the AV hardware / software co-architecture evaluated at the present research work should also be evaluated in larger and higher added value parts. In this field, some movements towards the quality evaluation of body in white parts for the automotive industry have already been made. The big challenge in this field is that very small defects must be found in very large parts, what demands high capacity AV system and specific evaluation strategies.

Chapter 8

SCIENTIFIC CONTRIBUTION

8.- SCIENTIFIC CONTRIBUTION

8.1. Articles published in international scientific journals

[SAE08] Sáenz de Argandoña E., Aztiria A., García C., Arana N., Izaguirre A., Fillatreau P., Terzyk T. “Forming Processes Control by means of Artificial Intelligence Techniques”, Robotics and Computer-Integrated Manufacturing 24, 773-779, 2008. Impact factor: 0.804.

[FIL08] Fillatreau P., Sáenz de Argandoña E., Aztiria A., García C., Arana N., Izaguirre A., Bernard F.X., Terzyk T. “Sheet metal forming global control system based on artificial vision system and force-acoustic sensors”, Robotics and Computer-Integrated Manufacturing 24, 780-787, 2008. Impact factor: 0.804.

8.2. Papers presented in international conferences

[FIL09] Fillatreau P., Arana N., Saénz de Argandoña E., Izaguirre A., Zuriarrain. I., Pop. R. “An industrial validation of Artificial Intelligence Techniques in Forming Processes Control.” The 19th International Conference on Flexible Automation and Intelligent Manufacturing, FAIM 2009, Middlesbrough, UK, July 2009. Paper accepted.

[GAR07] García C., Sáenz de Argandoña E., Aztiria A., Arana N., Izaguirre A., Pop R., Galle M., Terzyk T., Fillatreau P. “Automatic detection of burrs in sheet metal cutting processes by a combination of a Sensor based Monitoring System, an Artificial Vision System and an Intelligent Control system”. 57th CIRP General Assembly, Dresden, Germany, August 2007. Presentation.

[AZT07/2] Aztiria A., Saénz de Argandoña E., García C., Arana N., Izaguirre A. “Aplicación de técnicas de Inteligencia Artificial para el control global de procesos de conformado”. The 2nd Manufacturing Engineering Society International Conference, MESIC 2007, Madrid, España, July 2007. Paper and presentation.

[FIL07/2] Fillatreau P., Saénz de Argandoña E., Aztiria A., García C., Arana N., Izaguirre A., Bernard F.X., Terzyk T. “Cooperation Strategies between Artificial Vision System and Force-Acoustic Sensors for Sheet Metal Forming Global Control”. The 17th International Conference on Flexible Automation and Intelligent Manufacturing, FAIM 2007, Philadelphia, USA, June 2007. Paper and presentation.

[SAE07] Saénz de Argandoña E., Aztiria A., García C., Arana N., Izaguirre A., Fillatreau P., Terzyk T. “Control of forming processes by means of artificial intelligent techniques”. The 17th International Conference on Flexible Automation and Intelligent Manufacturing, FAIM 2007, Philadelphia, USA, June 2007. Paper and presentation.

[AZT07/1] Aztiria A., Saénz de Argandoña E., García C., Arana N., Izaguirre A. “Application of Artificial Intelligent Technique for Sheet Metal Forming processes global control”. 40th CIRP International Seminar on Manufacturing Systems, 2007, Liverpool, England, May 2007. Paper and presentation.

[FIL07/1] Fillatreau P., Bernard Fx., Ardanza A., Arana N., Sáenz de Argandoña E., Izaguirre A., Garcia C., Mugarza J.C. "Calibrating Camera Position Parallel to a Surface for Dimension Calculation of Flat Parts", 8th International workshop on Electronics, Control, Modelling, Measurement and Signals 2007& Doctoral School (EDSYS, GEET), Liberec, Czech Republic, May 28-30, 2007. Paper and presentation.

[SAE06/1] Sáenz de Argandoña, E., García C., Arana N., Izaguirre A., Aztiria A. “Control de proceso en tiempo real y aseguramiento de la calidad en operaciones de embutición y corte mediante adquisición de datos y técnicas de visión artificial”. XVI Congreso de máquinas-herramienta y tecnologías de fabricación, Donostia, España, October 2006. Paper and presentation.

8.3. Articles published in industrial and academic journals

[SAE09] “Implementación de controladores inteligentes en procesos de conformado””, published in the Journal Adimendun (Intelligent Materials and Processes), nº22, February 2009, pages 1-4.

[POP07] Pop R., Saenz de Argandona E., Liewald M., Wagner S., Garcia C. ”Mit Prozesskontrolle zum Erfolg/ Künstliche Intelligenz zur Regelung von Stanzprozessen“ In: wt Werkstatttechnik online, 97th age-group (2007), 10th edition, SPRINGER-VDI-VERLAG.

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[SAE06/2] “Control de procesos de conformado en tiempo real”, published in the Journal Adimendun (Intelligent Materials and Processes), nº12, July 2006, pages 1-4.

Annex I

RULE BASE OF THE EXPERT SYSTEM

Annex I.- RULE BASE OF THE EXPERT SYSTEM

AI.1. Introduction

The present annex summarised all the rules that the research team has developed for identifying the process failures detected by the sensors based process monitoring system and for identifying the defective parts detected by the artificial vision system. The annex is structured as follows: first the list of rules codified for the identification of the process failures is written down. Right after that, the list of rules codified for the identification of the defective parts is written down too.

AI.2. Rules for the identification of process failure (sensors based process monitoring system)

AI.2.1 Feed failure I: Strip completely blocked

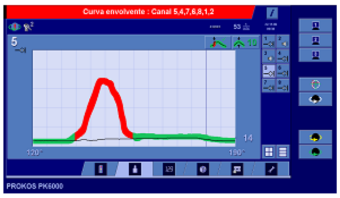
Feed failure I:Strip completely blocked

IF

Rule: **Real maximum value is much smaller than hypothetical value AND this happens in all the channel numbers.**

THEN

Consequence: **Defect: The metal strip is completely blocked inside the tool.**



Cause: Improperly evacuated metal slug is blocking the metal strip.

Solution: Extract the metal strip and remove any metal slugs inside the tool.

AI.2.2 Feed failure II: Strip partially blocked

Feed failure II:Strip partially blocked

IF

Rule: **Channel number is equal or bigger to 4 AND the initial time is lower than 20 AND the fault is an upper fault AND the number of faults is greater than 3.**

THEN

Consequence: **Defect: The metal strip did not advance the right distance between strokes.**

Cause: Improperly evacuated metal slug is blocking the metal strip.

Solution: Extract the metal strip and remove any metal slugs inside the tool.

AI.2.3 Metal slug in pilot pin station

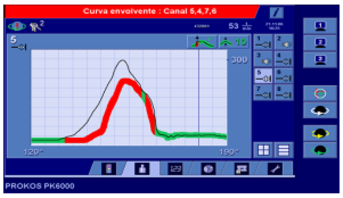
Metal slug in pilot pin station

IF

Rule: **Channel number is 4 or 5 (sensors in first station for reference IA-04) AND the initial time is smaller than the real maximum value time AND the fault is an upper fault.**

THEN

Consequence: **Defect: There is a metal slug in the first station of the tool.**



Cause: The punches did not evacuate the metal slug correctly from the tool.

Solution: After extracting the metal strip; replace the die, move the ram down or change punch for a longer one.

AI.2.4 Metal slug in central area station

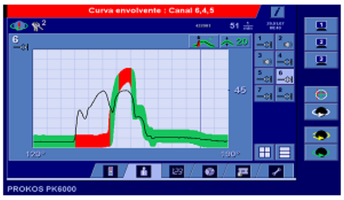
Metal slug in central area station

IF

Rule: **Channel number is 6 (sensor in second station for reference IA-04) AND the initial time is smaller than the real maximum value time AND the fault is an upper fault.**

THEN

Consequence: **Defect: There is a metal slug in the second station of the tool.**



Cause: The punches did not evacuate the metal slug correctly from the tool.

Solution: After extracting the metal strip; replace the die, move the ram down or change punch for a longer one.

AI.2.5 Evacuation system failure I: "Double parts in pilot pins"

Evacuation system failure I: "Double parts in pilot pins"

IF

Rule: **Channel number is 4 or 5 (sensors in first station for reference IA-04) AND the initial time is smaller than the real maximum value time AND the fault is an upper fault AND the real maximum value is 10% different than the hypothetical value.**

THEN

Consequence: **Defect: There is a part in the first station of the tool.**

Cause: The air evacuation system did not evacuate the part from the tool.

Solution: After extracting the metal strip check the position of the air evacuation system.

AI.2.6 Evacuation system failure II: “Double parts in final blanking station”

Evacuation system failure II: “Double parts in final blanking station”

IF

Rule: **Channel number is 5 or 6 (sensors in third station for reference 5828-001) AND the initial time is smaller than the real maximum value time AND the fault is an upper fault AND the real maximum value is 10% different than the hypothetical value.**

THEN

Consequence: **Defect: There is a part in the third station of the tool.**

Cause: The air evacuation system did not evacuate the part from the tool.

Solution: After extracting the metal strip check the position of the air evacuation system.

AI.2.7 Ejector failure: “Double parts inside the blanking dies”

Ejector failure: “Double parts inside the blanking dies”

IF

Rule: **Channel number is 1 or 7/8 (sensors in third station for reference IA-04) AND the time percentage of the last fault is greater than 20 AND the fault is an upper fault.**

THEN

Consequence: **Defect: There is a part inside the die in the third station of the tool.**

Cause: The ejection system did not work properly.

Solution: Extract the part from the die and check the correct operation of the ejection system.

AI.2.8 Punch breakage

Punch breakage

IF

Rule: **Channel number is 3 AND the value of the gradient is smaller than 20 and the fault is an upper fault.**

THEN

Consequence: **Defect: There is a broken punch inside the tool.**

Cause: Excessive wearing of the punches.

Solution: After extracting the metal strip there are two possibilities:

If the punch broken length is short, replace the broken punch

If the punch broken length is long, extract the coil and replace the broken punch

AI.2.9 Metal strip adhesion to pilot pins

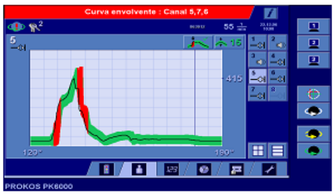
Metal strip adhesion to pilot pins

IF

Rule: **Channel number is greater than 4 AND fault in the process signal slope up OR fault in the process signal slope down is true.**

THEN

Consequence: **Defect:** **The metal strip is following the pilot pins upwards during the ram withdrawal.**



Cause: **Excessive wearing of punches or bad conditions of pilot pins.**

Solution: **Check conditions of punches for guiding the metal strip and pilot pins and change the faulty one.**

AI.3. Rules for the identification of defective parts (artificial vision system)

AI.3.1 Main diameter out of tolerances

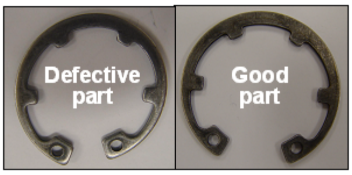
Main diameter out of tolerances

IF

Rule: **Main diameter of the part is out of the specified tolerances.**

THEN

Consequence: **Defect:** **Principal diameter of the part is out of tolerances.**



Cause: **Punches and/or dies lost the correct shape.**

Solution: **Check the shape of the punches and dies and replace if necessary.**

AI.3.2 Width at the ears out of tolerances

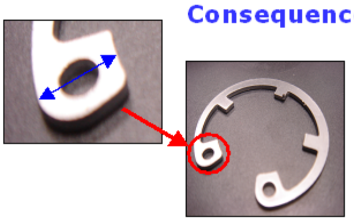
Width at the ears out of tolerances

IF

Rule: **The width at the ears of the part is out of the specified tolerances.**

THEN

Consequence: **Defect:** **Width at the ears of the part is out of tolerances.**



Cause: **Punches and/or dies lost the correct shape.**

Solution: **Check the shape of the punches and dies and replace if necessary.**

AI.3.3 Width in front of the slot out of tolerances

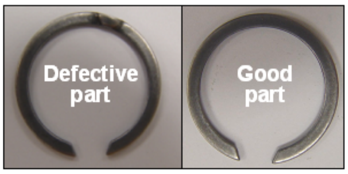
Width in front of the slot out of tolerances

IF

Rule: **The width of the part in front of the slot is out of the specified tolerances.**

THEN

Consequence: **Defect:** **Width of the part in front of the slot is out of tolerances.**



Cause: **Punches and/or dies lost the correct shape.**

Solution: **Check the shape of the punches and dies and replace if necessary.**

AI.3.4 Diameter of small holes out of tolerances

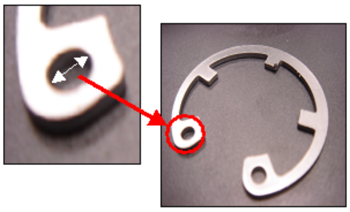
Diameter of small holes out of tolerances

IF

Rule: **The diameter of the small holes is out of the specified tolerances.**

THEN

Consequence: **Defect:** **Diameter of the small holes is out of tolerances.**



Cause: **Excessive wearing of the small punches.**

Solution: **Check the diameter of the punches and replace them if necessary.**

AI.3.5 Opening of the slot out of tolerances

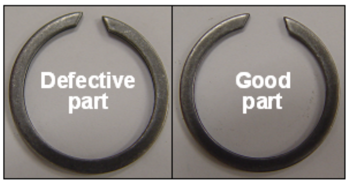
Opening of the slot out of tolerances

IF

Rule: **The opening of the slot is out of the specified tolerances.**

THEN

Consequence: **Defect:** **The opening of the slot is out of tolerances.**



Cause: **Punches and/or dies lost the correct shape.**

Solution: **Check the shape of the punches and dies and replace if necessary.**

AI.3.6 Local big burr detection

Local big burr detection

IF

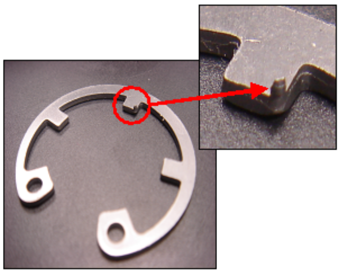
Rule: A <u>local big burr</u> is detected by the artificial vision system.

THEN

Consequence: <u>Defect:</u> There is a local big burr in the part.

<u>Cause:</u> There is a micro crack in one of the final punches at the tool.

<u>Solution:</u> Refill the punches and dies to get sharpen surfaces.



AI.3.7 Bended part detection

Bended part detection

IF

Rule: The <u>highest point of the part</u> is out of the specified tolerances.

THEN

Consequence: <u>Defect:</u> The part is not planar, it is bended.

<u>Cause:</u> The ejection system at the final dies is not working properly.

<u>Solution:</u> check the ejection system and repair it if necessary.

AI.3.8 Thickness of the part out of tolerances

Thickness of the part out of tolerances

IF

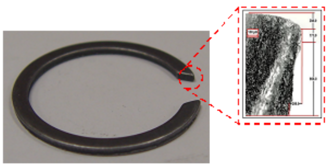
Rule: The <u>thickness of the part</u> is out of tolerances (MEASURED BY THE OPERATOR)

THEN

Consequence: <u>Defect:</u> The thickness of the part is out of tolerances.

<u>Cause:</u> the thickness of the metal strip is out of tolerances.

<u>Solution:</u> Measure the thickness of the metal strip and change it if necessary.



AI.3.9 Detection of excessive burr height

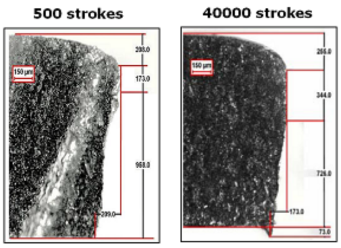
Detection of excessive burr height

IF

Rule: The height of the burr is excessive (MEASURED BY THE OPERATOR)

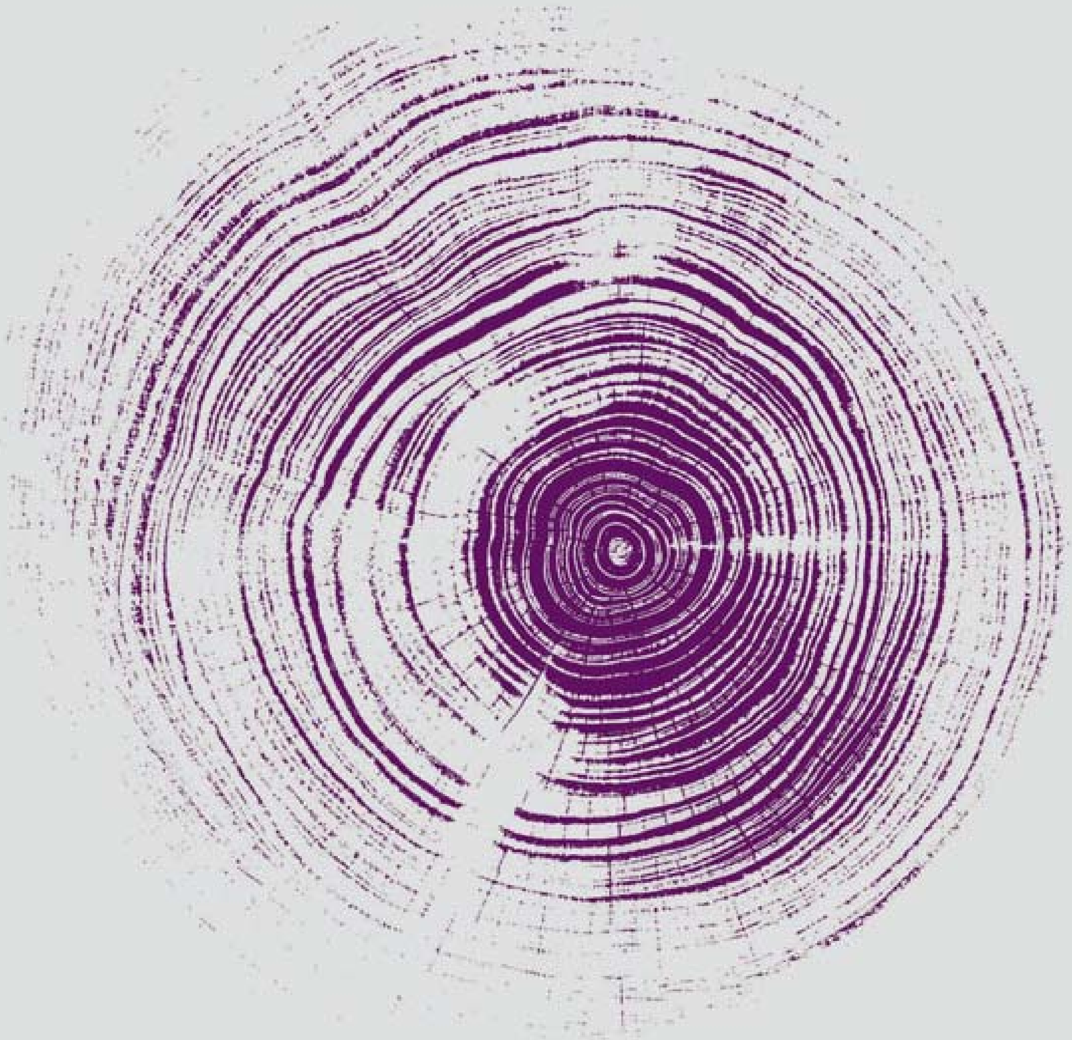
THEN

Consequence: **Defect:** The burr at the part is too big.



Cause: The wearing of the punches is excessive.

Solution: Refill the punches and dies to get sharpen surfaces.



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