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Practical training in industrial statistics and design of experiments in higher education

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Abstract The effective teaching of statistical concepts and experimental design is vital in engineering education, yet educators often face challenges in imparting these skills due to their abstract nature. This article proposes practical pedagogical approaches to address these challenges, focusing on teaching industrial statistics tools and design of experiments (DOE). We present an innovative hands-on learning system implemented in the Industrial Organization Engineering degree program at Mondragon Unibertsitatea, featuring a configurable car prototype and sensor-equipped ramp for data collection. Through experimentation with various car prototype configurations and statistical analysis using software tools such as R and Minitab, students engage in experiential learning that bridges the gap between theory and practice. The paper details the practical implementation of experiments, the flow of practices, and the statistical tools applied. By integrating practical methodologies into the curriculum, students develop a deep understanding of Industrial Statistics concepts and their real-world applications, preparing them for the challenges of the industrial landscape.

Keywords: Statistical thinking, Industrial statistics, higher education, practical learning, design of experiment (DOE)

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1 Introduction

In this paper, we explore practical pedagogical approaches aimed at enhancing the teaching of Industrial Statistical concepts and design of experiment (DOE) concepts in engineering education. In the realm of engineering education, the mastery of statistical concepts and experimental design stands as a cornerstone for advancing knowledge and enhancing industrial practices. However, educators often encounter significant hurdles in effectively imparting these crucial skills to students (Ben-Zvi, 2001; Unzueta and Eguren, 2023). Students in turn, frequently encounter difficulties in grasping foundational statistical principles due to their abstract nature and the requirement of mathematical proficiency (Ramirez et al., 2012). Moreover, designing experiments that provide meaningful insights and optimize resource allocation is essential to drive innovation and competitiveness in engineering industries (Antony, 2002; Unzueta et al., 2019). However, teaching students to conceptualize, plan and execute experiments within real-world constraints requires not only theoretical knowledge, but also practical experience. In addition, the dynamic nature of engineering environments requires the adaptation of experimental design methodologies to various scenarios, which further complicates the educational process. As a result, educators face the ongoing challenge of fostering a deep comprehension of statistical methodologies that are essential for informed decision-making and problem-solving in engineering practice (Lampert, 2010).

Bridging the gap between theory and practice while instilling these fundamental skills is essential for producing adept engineers capable of addressing real-world challenges. This article presents an innovative solution applied in the Industrial Organization Engineering degree at Mondragon Unibertsitatea, where these challenges are met by introducing a hands-on learning system that allows students to experiment, generate real experimental data and develop their analysis using statistical software (R and Minitab). The system consists of configurable prototype car that can be experimented with by comparing different configurations, and a sensorized ramp to automatically capture data that serves as a test bench.

2 Configurable prototype car and test bench

For experimentation, a configurable car prototype is employed, fabricated using a 3D printer utilizing PLA material. The ramp, serving as the testing bench, is equipped with two detection sensors for data collection. Sensory data acquisition is facilitated through Arduino, coupled with MS Excel employing the Data Streamer functionality (Fig. 1). Arduino facilitates real-time data acquisition from the sensors (Y_1), ensuring prompt and accurate data capture throughout the experimentation process. The utilization of a configurable car prototype enables the manipulation of various design parameters (Xi), providing a versatile platform for experimentation.

The experiment consists of launching the car down the ramp, and measuring the time required to go down the ramp (Y_1), and the distance travelled to stop (Y_2).

Overall, the combination of the configurable car prototype, sensor-equipped ramp, Arduino, and MS Excel's Data Streamer functionality provides a comprehensive and efficient framework for conducting experiments and facilitating data collection. This setup enhances the practical learning experience within a real-world engineering context.

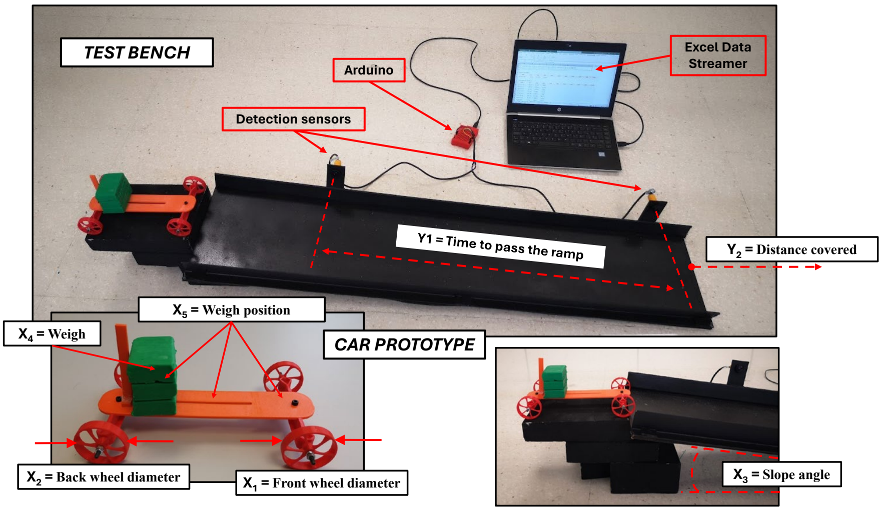

Fig. 1 Configurable car prototype and test bench

Table 1 lists the variables with which it is possible to experiment (Xi), and the responses (Yi) that are measured during experimentation.

Table 1 Variables used to experiment (Xi) and Response measured (Yi)

	Variables	Levels	Variable type	Unit
X_1	Front wheel diameter[1]	25 to 75	Continuous	mm.
X_2	Back wheel diameter[1]	25 to 75	Continuous	mm.
X_3	Slope angle	6,8,10	Discrete	degree
X_4	Weight[1]	50 to 300	Continuous	gr.
X_5	Weight position	front - middle - back	Discrete	

	Response	Unit
Y_1	Time to pass the ramp	milliseconds
Y_2	Distance covered	cm.

[1]Is possible to experiment on any value of the range indicated.

3 Development of practices

The flow chart of the progress of the practices (**Fig. *2***) shows which statistical tools can be applied, the number of variables and levels of each variable used to build each car configuration, and the expected outcome of each practice. In each practice, specific statistical concepts are worked on.

To obtain the results of each experiment (or run in the case of the DOE practice), the student must think about the configuration with which the car should be launched. With this action, the abstract thinking inherent to the statistical concept is converted into logical thinking (comparing two different wheel diameters, comparing three different slopes, etc.). The goal is for the student to develop statistical thinking.

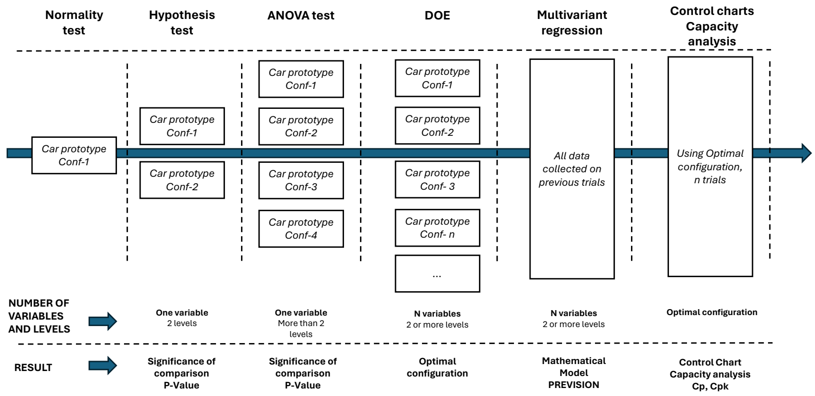

Fig. 2 Practice progress flowchart

Through practical experimentation, the student internalizes that the data obtained in each run is not for "free", therefore, to be efficient, the student needs to think before executing the experiments what and how he/she wants to answer. For this purpose, the instructor prepares a series of questions before each practice: Do the results of configuration X (Conf.1 for example) follow a normal distribution? do the results of cars with wheel diameter 20mm and 40mm differ? are there differences according to the angle of the launch ramp? Etc. Based on these questions, the student must propose hypotheses to be tested. To validate or deny the null hypothesis (H_0), the student must select the appropriate statistical tool, think about the number of runs to execute, execute the runs, and analyse the results. **Table 2** shows the statistical tools that can be used in practice.

The time required to perform each launch is 20-30 seconds, but building the car with the proper configuration requires more time (1-2 minutes). In the case of the development of an experimental design with randomized runs, considerable time is needed (1,5-2 hours to perform seventy-two runs), which makes it necessary to select the experimental design suitable to the time defined to complete the practice. In this way, the student understands the consequences of the number of variables selected, the number of levels at which to experiment with each variable, the number of replicates or the sample size.

Table 2 Possible statistical tools to be applied and proposed experiments.

Statistic Tool	Proposed experiments	Number of trials
Normality test	Launch the same car configuration (Conf.1) and measure the Yi.	More than 30
Correlation	Analyze the relationship between Y1 and Y2	More than 30
Hypothesis test	Comparing two levels of any input variable (Xi), wheel diameters, weight position, launch angles, etc. (Conf.1 vs. Conf.2)	More than 30 on each level
ANOVA	Comparing more than two levels of any input variable (Xi), wheel diameters, weight position, launch angles, etc. (Conf.1; Conf.2; Conf.n).	More than 30 on each level
DOE	Full factorial 2^k, Full factorial at various levels, Fractional factorial 2^{k-j}, central composite design (CCD), Box-Behnken, Taguchi orthogonal arrays, etc. (Conf.1; Conf.2; …, Conf.n).	Depending on the experiment design applied
Regression	Using all data collected (normality test, Hypothesis test, DOE, ANOVA, etc.), define the multivariant regression model.	All data collected on previous experiments.
Control Charts and Capacity test	After selecting the optimal design, test the repeatability of the system. XR plot, I-MR plot, capacity analysis (Cp, Cpk), etc.	Depending on the plot used

In addition to the tools shown on **Table 2**, students have been able to apply and understand other graphical tools and concepts such as: histograms, temporal series, residual analysis, regression model fitting, predictive ability of regression models, or sample size definition and its relation to experimental power.

4 Results

The pilot test was carried out (in two groups of 25 students each) in the 2nd year of the Industrial Organization Engineering degree at Mondragon Unibertsitatea during the period of the semester project, executed through the project based learning methodology (Unzueta and Eguren, 2023). In the project each team (composed of 5 students) has selected different variables and levels, completing a full factorial design. As a result, they have obtained a multivariate regression model that describes the product-process and based on this model the students have been able to respond to the hypotheses raised in the project. The results obtained in the individual defence of the project (Unzueta and Eguren, 2023) demonstrate how the students have acquired the required knowledge; mean = 6,9 out of 10 (6,33-7,44; α=0,05), 43 out of 50 passed the exam, 70% of the students obtained a mark above 6, 36% above 7, 24% above 8, and 14% above 9. Qualitative feedback from the satisfaction surveys shows that students feel that the experience has been enriching. In subsequent courses, the practice will be applied within the subject "Industrial Statistics".

5 Conclusions

The integration of practical learning methodologies has significantly enhanced the understanding of industrial statistical concepts and experimental generation of data. Hands-on experimentation allows students to grasp statistical concepts and their practical applications, translating theoretical knowledge into industrial contexts. This experiential learning fosters a statistical mindset, improves problem-solving skills, and deepens appreciation for statistical methodologies. Based on our experiences, we have observed in our students, the effectiveness of this approach in enhancing comprehension of statistical principles and improvement on their practical skills in data analytics and the application of DOE methodologies. The primary challenge for the teaching staff was aligning theoretical concept explanations with the time required for experiments. To address this, explanatory videos on using statistical techniques in Minitab and R software were created, utilizing flipped learning methodologies and techniques (Aldalur et al., 2024). In essence, the combination of experimental learning, statistical analysis, and real-world application creates a holistic learning experience that not only equips students with essential skills but also instils a sense of confidence and competence in their ability to navigate complex engineering problems.

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