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Data-driven energy resource planning for Smart Cities

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***Abstract*—Cities are growing and, therefore, the primary needs, such as the energy resources. Hence, managing them in the proper way becomes essential for a sustainable growth. This paper proposes a data-driven tool based on IoT data with the aim of reducing the gap between demand and consumption, minimizing the energy losses. Smart and efficient energy planning is the ultimate objective, where the final energy usage is fitted into the predicted demand. One day time horizon is used in order to provide energy managers, ESCOs or urban planners with an accurate forecast about the required energy. This service will be available on the urban platform of Vitoria under the context of the SmartEnCity project (GA # 691883). However, the training data has been captured from CITyFiED project (GA # 609129), which is energetically speaking similar. The city elements included in the training model have been characterized based on data from combined static and dynamic data to adapt the context through machine-learning techniques.**

***Index Terms*—Smart Cities, Energy efficiency, Energy Planning, Digital Services, Machine learning.**

I. Introduction

Nowadays, the growing of the population in cities is a fact. According to the United Nations [1], from the current 55% of world's population up to 68% of the people will live in cities by 2050. Then, it is clear that the movement from rural areas to cities will increase the population in urban zones by 2.5 billion people [1]. Therefore, local resources will be higher demanded. Among them, the energy will become one of the major challenges. For that purpose, cities must adapt to this new paradigm through the concept of Smart Cities to reduce environmental impact and develop sustainable growth in order to improve the quality of life of citizens.

However, there exist several definitions of the Smart City concept. According to the European Commission one [2], "a smart city is a place where traditional networks and services become more efficient with the use of digital and telecommunications technologies for the benefit of its inhabitants and business". The initial conclusion that might be extracted is the requirement of digitalization of the energy domain, i.e. IoT-based monitoring. Secondly, the use of the resources in a more efficient way, such as smarter urban transport networks, more efficient water supply facilities, waste management and/or more efficient ways of lighting and efficient heating / cooling systems for buildings [2][3]. Information and Communication Technologies (ICT) supports all these services and increases interactivity between systems.

As stated before, energy is one of the main pillars for cities and its management becomes crucial to ensure energy supply (avoid energy poverty). In this sense, the objective of this paper is to present an energy planning tool based on data with the aim of providing decision-makers, policy-makers or ECOSs (Energy Service Companies) with an instrument to predict the energy demand. Therefore, the planning of the energy resources might be determined in advance to assure both supply and comfort conditions.

The tool is framed within the SmartEnCity project [4], which "aims to develop a systemic approach for transforming European cities into sustainable, smart and resource-efficient urban environments in Europe". One of these cities is Vitoria (Spain), whose sustainable solution is based on the retrofitting of buildings, providing renewable-based district heating and penetration of renewables. Besides, among other actuations, Vitoria is developing its own urban platform, where verticals will allow the access to the different services. Nevertheless, energy conservation measures are still being implemented; therefore it still lacks historical data to validate the tool. To this purpose, CITyFiED project [5] data has served as training instead. The solution of CITyFiED in the city of Laguna de Duero (Spain) applies the same type of interventions, while the climate is also comparable to Vitoria, being the perfect side for training the energy model.

Energy is then a critical pillar in cities' management, being necessary to include it into the strategic plan. For this reason, section III explains how this tool fits within the SmartEnCity urban strategy. However, before, in section II, an overview of related work is conducted. Next, chapter IV provides the concept for the digital platform in Vitoria, while section V describes the energy planning service and section VI its main results. Finally, section VI gives some conclusions extracted, including the advantages and disadvantages.

II. Related Work

The importance of data is growing in order to analyze the boundary conditions and make better decisions in any context, especially energy. Thus, short- and long-term, as well as model-based energy planning processes are being integrated into the common procedures of cities and territories [6]. In these contexts, urban planners make use of tools to support the decision based on four main stages: contextualization, modelling, decision and monitoring [6]. Under this umbrella, cities seek to make decisions with greater precision and

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efficiency. For this purpose, the use of data (i.e. monitoring) is necessary and energy resources forecasting tools can provide accurate and valuable information.

In current practices, the most usual approach is the use of software, such as EnergyPLAN [7] or LEAP [8] as the case of the cities of Nantes, Hamburg and Helsinki [9]. Other cases, such as Valencia, based their decisions on real indicators [10] that are calculated on the basis of current data.

Decision support is one of the major topics in the scientific community thanks to new technologies like machine-learning, IoT or Big-Data. Some examples of the current state of the art are shown in [11] and [12]. In both cases, the authors review multi-criteria decision analysis algorithms for energy planning. One of the main drawbacks for these methods, according to the authors, is the time-consuming processing, as well as the conversion from conventional language to numeric modelling. Other approaches, such as [13] aim the optimal mix of energy resources to assure energy supply due to the scarcity of fossil fuels. Again, simulation and detailed modelling are required.

Other approaches like [14] apply deep neural networks to optimally manage the energy infrastructures. However, this type of solutions requires large data-sets, which is not common. Due to business privacy, many times, data are not shared with the rest of city agents. Other solutions aim for the combination of physical and virtual worlds such as the energy management system in [15], although they are still in the experimental stage. Finally, bottom-up approaches for regional energy planning are also under research, such as the one applied in Apulia region [16]. There, a relatively complex mathematical model is conducted, which requires a wide knowledge about the operational parameters for the different energy resources.

A. SmartEnCity approach

As observed from the previous references, energy planning to optimally manage the energy resources is a key topic. That is why, within SmartEnCity, the implementation of an energy planning tools is followed. In this case, it is proposed a data-driven methodology in contrast to the simulation-based approaches followed in the literature. One of the major issues of software like LEAP is the need to make assumptions in the long-term, which are susceptible to fail. Moreover, the SmartEnCity approach compared to other cities like Valencia envisages not only the use of indicators, but also energy resources forecasting based on historical information, without the need of large data-sets as was the case in [14].

Then, SmartEnCity proposes a combined clustering and regression method based on historical data to be able to predict energy requirements in the short- and medium-term period (from 24 hours horizon to one day) to dynamically determine the resources and continuously adapt to climate conditions. Besides, data are obtained at building level, which also takes into consideration human behavior (e.g. temperature set-points), which is neglected in the previous approaches and it is very important in energy models.

Finally, our approach uses clustering once (first time) and regression is run daily to update the 24h horizon (forecast) The adaptation of the regression model consumes limited time, reducing the time-consuming drawbacks.

III. ENERGY WITHIN THE URBAN STRATEGY

The SmartEnCity project [4] has as main objective the development of a highly adaptable and replicable approach for the urban transition towards sustainable, intelligent and efficient cities in the use of resources in Europe. This is at the same time based both on an integrated planning and on the implementation of measures aimed at improving energy efficiency in the main consumer sectors of cities, while increasing the supply of renewable energy. The project addresses three central pillars: energy, sustainable mobility and ICTs. ICT includes urban platforms and the digitalization of services for buildings, vehicles or infrastructures by means of sensor equipment.

Under this approach, SmartEnCity has generated a step-by-step methodology [17] (see Fig. 1) for a Smart Urban Decarbonisation transition, namely Cities4Zero [18], to help cities on their process of developing the most appropriate strategies, plans and projects for an effective transition having in mind the need for commitment of key local stakeholders. Cities4Zero consists of 16 steps, structured in three stages [18]. The Stage A (Strategic Stage) deals with the development of the City Strategy, while Stages B (Design Stage) and C (Intervention & Assessment Stage) address the design and deployment of the Key Projects identified in that City Strategy and the implementation and further evaluation of the envisaged interventions [17].

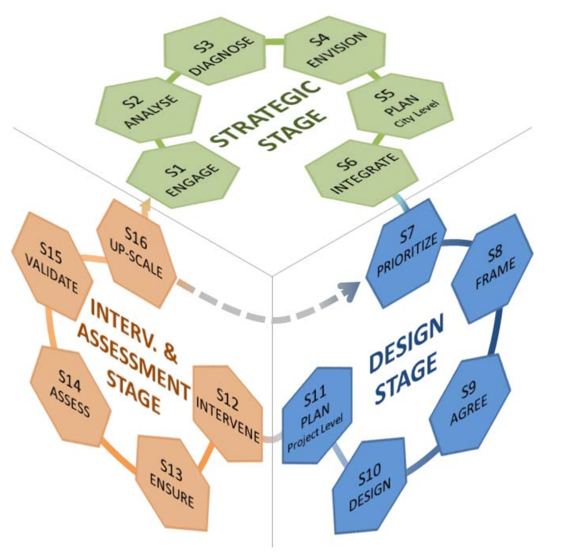

Fig. 1. SmartEnCity urban transformation strategy

Within this framework of urban decarbonisation transition, the energy planning tool described in this document has its place in different steps seeking different type of results depending on the moment of the process.

At the Strategic Stage, Step 3 (DIAGNOSE) related to the strategic city diagnosis and Step 4 (ENVISION) dedicated to the strategic planning with scenarios generation, this tool helps both on the buildings performance diagnosis phase to set the starting point, and on the simulation of scenarios turning to be a valuable decision-making supporting tool.

On the Design Stage, this energy planning tool provides significant information for the baseline definition to be used on further evaluation against the indicators system defined on Step 11 (PLAN Project Level) concerning the implementation plan and the indicators system.

Finally, on the Intervention & Assessment Stage is where this tool turns to show its better applicability, as a good demand estimation based on real data makes it possible to foresee in advance the needs of fuel purchase thus allowing to achieve a better profitability at Step 13 (ENSURE) Operation & in-use phase. Predicting the future demand can also give a tendency on the performance indicators in parallel to the evaluation performed on Step 14 (ASSESS) Project evaluation and impact assessment.

IV. SmartEnCity Urban Digital Platform

As it has been explained, digitalization is pivotal for the proper urban management. SmartEnCity and, in particular, the city of Vitoria, takes this digital shape in the form of an urban platform. The definition of urban platform is the digital realization of a logical architecture that exploits modern technologies like IoT, Big-Data, etc. in order to provide services. These are the so-called verticals (mobility, governance, energy) [19]. Having said that, the energy planning tool is one digital realization within the energy pillar.

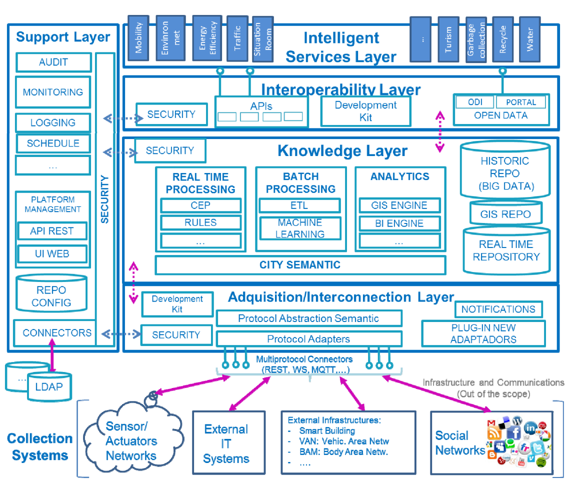

Fig. 2. SmartEnCity Urban Platform Architecture.

SmartEnCity project has selected the architecture defined by the standard UNE 17804:2015 [20][21] that defines it within its committee for Smart Cities CTN 178 [20]. This standard is also part of an international standard published by the ITU-T (International Telecommunication Union). The scheme is presented in Fig. 2 and is divided into different layers:

- Layer of data collection systems that are related to all the infrastructures that provide data, such as IoT sensors (SCADAs and PLCs), external information systems or social networks, among others.
- Interconnection and data collection layer that implements adapters with the protocols of the sensor network to acquire the necessary information.
- Knowledge layer: data models and their management (repositories) are deployed for analysis with ETL mechanisms (extraction, transformation and loading).
- Interoperability layer to facilitate the exchange of information between different parties through common models of representation.
- Smart services layer where value-added or "vertical" services are found, ranging from energy efficiency or mobility services to governance services. The energy planning tool is a digital service within the smart services layer, in particular, energy vertical.
- The last layer is the support layer (transversal to the previous layers) where logging, configuration and maintenance tasks take place.

V. Energy Resource Planning Service

A. Theoretical conceptualization

This section describes the theoretical concepts on which the energy planning service is developed. The objective of the service is the prediction of the energy demand at district level. To that end, building level data have been obtained. It is important to remark these data have been aggregated from dwelling level, which is subject to the GDPR (General Data Protection Regulation), as well as gathered from the district heating operation (business privacy).

The combination of district heating operation (substations) and aggregated dwelling energy use provides the overview of the real conditions under which the system is running. That is to say, comfort conditions due to difference between inlet and return temperatures, effects of the building statuses (i.e. insulation level, windows replacement) and impact of the climate conditions. In this specific case, the results guide the ESCO in the proper management of the generation system (boiler) and the distribution elements (substations). Energy demand and real consumption are nearly matched to minimize the energy losses, which is one of the major inefficiencies in energy management processes [22].

To that purpose, two machine-learning techniques are then integrated. On one hand, clustering to classify the buildings in multiple sets. On the other hand, regression methods to determine the energy usage in function of the consumer elements (set-points) and weather forecast.

Clustering is a static classification of the buildings as "consumer elements" based on different parameters. The intention is to group the buildings with similar constructive features, which deal with similar theoretical energy demand and, then, calculate the regression model for one sample of the cluster, reducing the time to execute the model, i.e. less computational needs. Finally, the result is extrapolated to the rest of the buildings of the district by applying proportionality (i.e. adjustment of the heated area). The clustering parameters are listed below.

- Orientation: It establishes the building orientation in order to "quantify" the solar gains. The possible values are 0-North, 0.5-East/West or 1-South.
- Status of intervention: Three levels as non-insulated (0), ongoing works (0.5) or insulated (1).
- Size of the building: Three typologies of buildings have been considered according to the dwelling sizes. Normalized according to the maximum value.
- Existence of adjoining block so as to determine the effects of the wind and thermal losses/gains. 0 means non-adjoining block and 1 if this exists.
- Shadowing by other buildings nearby, which limits the solar gains. 0 is shadowed building and 1 solar gains.
- Windows replacement percentage that also affects the tightness. Normalized according to the maximum rate.
- Heating schedule, which aims the timetable when the heating is on, considering a constant comfort set-point of 21ºC. Three levels are established, 0 heating is off, 0.5 stand-by (e.g. 16ºC) and 1 heating (21ºC).

The applied clustering technique is k-means, where k (number of clusters) could be 3-4-5 (results discussed later). Different indexes have been calculated in order to determine the optimal number of clusters (elbow method, silhouette coefficient and gap statistic method). As k values show some differences, a range has been selected to include all the options and compare different results.

The second technique used is machine-learning based on regression. The reason why regression is selected is because it is a common approach in building modelling. In common practices, linear regression between energy consumption and HDD (Heating Degree Days) is used in the energy field, being a valid method in statistically terms. Also, multi-linear regression is used to represent energy consumption in buildings with respect to occupancy patterns. In this case, the first approach is used following the IPMVP (International Performance Measurement and Verification Protocol) [23], where the energy usage is modeled against the HDD (this parameter represents the heating needs due to climate conditions), obtained from official weather services (AEMET [24] in the case of Spain), whereas other properties remain similar (same set-points, occupancy patters…).

Then, as stated above, the linear regression is applied in k buildings instead of n, where n is the total set of available buildings in the district. This reduces the computational load as data size is also decreased. Last, the k model results are extrapolated to the n buildings by applying ratio conversion (e.g. buildings in the same cluster with a difference in the heated area) [22].

VI. Results during the training process

Following the design principles from the previous section, the implementation of the clustering and regression methods provide the results explained in this chapter. However, it is important to explain the physical environment under which the model has been built. As explained in the introduction, the SmartEnCity project is ongoing and data are not yet fully completed. Data from the CITyFiED project [5] have been used to test our approach. Both projects are very similar in respect to interventions and conditions. First of all, the solution is the same, insulation of the façade (under the same regulation), replacement of windows and integration of a district heating (same ESCO in charge) [22]. Secondly, the climate conditions are comparable between Valladolid (location of the demonstrator for CITyFiED) and Vitoria. Indeed, Table I shows the difference between both cities with a temperature base of 18ºC.

TABLE I. HDD comparison between Valladolid and Vitoria

	Year 2017	Year 2018	Year 2019
Valladolid	1455	2784	2636
Vitoria	1558	2564	2611

CITyFiED project is located in the Torrelago district, residential area of Laguna de Duero (Valladolid). It consists of 31 buildings built around 1980 of three different topologies (A-B-C), which have 12 floors and gather 1,488 homes [25]. The blocks belong to two different administrative phases: blocks 1-12 are placed in the first one, and the other group, 13-31, in the second. The activities developed by this project affect more than 4,000 residents. In Fig. 3, the distribution of the blocks can be observed [26].

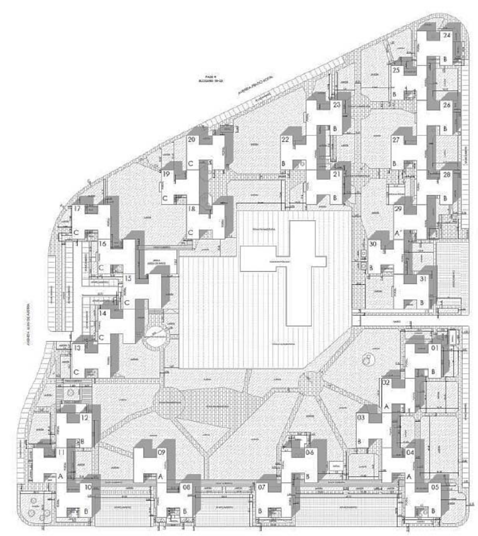

Fig. 3. Torrelago district buildings and classification by building topology

A. Classification and characterization of buildings

This task consists of three phases: variable selection (see building features selected), data normalization (also described above) and application of clustering techniques (k-means). Three different temporary moments have been considered: before starting the rehabilitation work (winter 2016-2017), during them (winter 2017-2018) and afterwards (winter 2018-2019). The buildings have been grouped differently in each scenario, as can be seen in Fig. 4 for winter 2017-2018 and Fig.5 for winter 2018-2019. The graph shows 4 clusters being the best committed model, whose numeric values for the accuracy are shown in Table II in cases of 3. 4 and 5 clusters. Although 5 clusters provide better results, increasing the number also increments the complexity.

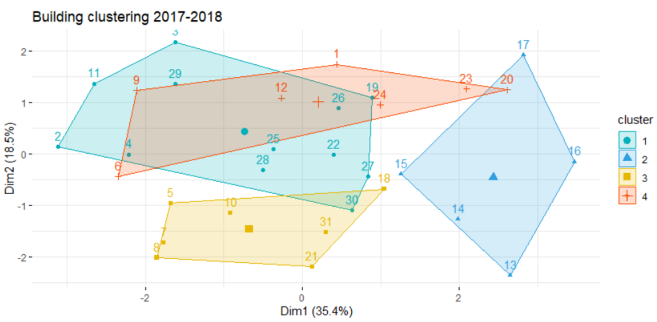

Fig. 4. Grouping of buildings for stages in winter 2017-2018

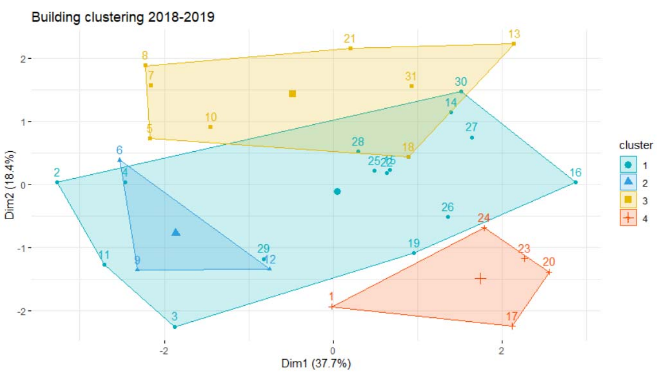

Fig. 5. Grouping of buildings for stages in winter 2018-2019.

TABLE II. PRECISION VALUES IN PERCENTAGE APPLYING K-MEANS

	Winter 2016-2017	Winter 2017-2018	Winter 2018-2019
3 clusters	75.7	48.49	59.02
4 clusters	82.6	62.36	66.5
5 clusters	88	69.55	73.51

B. Prediction of energy resources

As described before, the machine learning technique selected for this purpose is linear regression following the IPMVP approach [23]. This regression is carried out based on the HDD and the model fitting [27] the results obtained exceed the threshold of $R^2 > 0.75$ recommended by the IMPVP [23]. Likewise, the inclusion of new parameters related to weather conditions such as radiation, relative humidity and wind speed has been considered. After several tests, it has been proven that the results get worse when using all the variables at the same time. Only in the case of using radiation as an additional parameter, the result is satisfactory, but a small improvement, which is not significant for the increase that occurs in the complexity of the model. This has caused a multivariable regression model to be discarded. The results of the coefficient of determination (R^2), evaluated in the prediction data are shown in Table III for each of the scenarios considered and for two different time horizons: one week and 4 days.

TABLE III. MEAN R2 VALUES FOR EACH SCENARIO AND TIME HORIZON.

	Winter 2016-2017	Winter 2017-2018	Winter 2018-2019
Daily	0.82	0.93	0.8
	Winter 2016-2017	**Winter 2017-2018**	**Winter 2018-2019**
4 days	0.74	0.86	0.85

If an estimation is made of the consumption for 1 week horizon during a typical week of the month of October (with an average daily value for HDD of 10.71), the values shown in Table IV are obtained. Extrapolating the weekly results, a building belonging to cluster 1 with an area of 4,579.92 m^2, would consume a total of 1,252 kWh for one of the days included in that period, assuming the total district 38,190 KWh.

Note these data are calculated for the status after renovation, the reason why these low values. The validation has been performed against simulation results of the project [27]. The deviation obtained between simulation and regression model ranges 5-10%, which is an affordable calculation error.

TABLE IV. WEEKLY CONSUMPTION ESTIMATION BY CLUSTER

C1 ($13387.9\ m^2$)	C2 ($36989.3\ m^2$)	C3 ($23601.4\ m^2$)	C4 ($68343.1\ m^2$)
2.23 kWh/m^2	2.14 kWh/m^2	2.26 kWh/m^2	2.18 kWh/m^2
3662.22 kWh	9709.93 kWh	6542.92 kWh	18275.86 kWh

VII. DISCUSSION AND CONCLUSIONS

Within the new context of Smart Cities, the efficient and intelligent management of the energy resources, above all, the local ones, has become a key aspect within the new Smart City paradigm. In this sense, planning the energy resources would help to get more sustainable cities where energy would be better fitted into the real needs, highlighting that energy requirements will increase in the future due to population growth. Thanks to the processes of digitalization of cities and technology, new services are available so that smarter services support the decision-making process.

Under this scope, providing accurate energy planning tools avoid energy losses, contributing to a more sustainable world. The objective is to predict the demand that, in this case, has covered a set of buildings. With this demand, the city planner, energy manager or ESCO has the capacity to make a more sustainable energy purchase or to manage the generation and distribution systems more efficiently. Then, clustering and regression techniques have been applied, which demonstrate the possibility of improving the energy management process. The tool provides some advantages (A) and drawbacks (D), which are discussed below.

A - Matching energy demand and consumption, which reduces thermal losses when ESCOs or energy managers provide heating.

A - Anticipate climate conditions in the energy planning operation (e.g. solar gains).

A - Allow the optimal purchase of fuel, reducing the environmental impact, favoring local resources. As well, balancing the energy prices to better cost-efficient solutions.

A - Configurable to different districts. Static parameters are changeable in order to adapt them to the specific case by the energy experts, i.e. replicability.

D - Due to GDPR, energy demand is prepared for aggregated demand and consumption building-by-building. Hence, a single consumer is not a suitable user, being ESCOs or communities the focus groups.

D - Related to the previous one, data at building level are necessary, therefore, district heating networks should ensure data at substation level.

D - Graphical interface is mainly implemented for the SmartEnCity project, which requires some minor development changes to represent other districts, graphically speaking.

Finally, digital technologies help to better manage energy. Although preliminary results are promising, the future work will consist of the implementation of the same tool for the city of Vitoria and validate its performance with SmartEnCity data. In contrast to CITyFiED, the tool will be also used in the real environment where the ESCO and urban planner will make use of it for decision-support. More precise conclusion will be extracted once fully implemented and validated.

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