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Demand response approaches for real-time renewable energy integration

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Institute of Engineering - Polytechnic of Porto, Porto, Portugal, January 16-17, 2019

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Indoor Real-Time Locating System comparison: Polaris vs FIND3

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Abstract

The use of real-time locating systems can be used in several fields, from security and health to building and energy management. However, there is no consensus in what the better solution or technology is to be used in an indoor location system. This paper presents a comparative study between a market real-time locating system and an open source real-time locating system. The systems that will be compared are Polaris and FIND3. The tests were performed in an office building.

Keywords: indoor location, real-time locating systems

1. Introduction

Real-Time Locating Systems (RTLS) are used to locate persons and objects inside an identified zone; usually indoors. They can be used in multiple fields, such as security [1, 2] and health [3-5]. However, the indoor location is not a trivial task and there are not, until now, a known technology that can, with efficiency and effectiveness, provide high-resolution location with minimal delay. Therefore, there are several solutions that use multiple techniques and technology to provide indoor locations.

In this paper, it will be deployed and compared two RTLS indoor solutions: Polaris [6], and FIND3 [7]. Polaris is a market solution that uses Zigbee protocol [8] and is able to identify the location of tags – physical devices that need to be coupled to the person/object that we want to monitor. FIND3 (Framework for Internal Navigation and Discovery 3) is an open source solution that combines Wi-Fi (IEEE 802.11) [9] and Bluetooth [10] and enables the location of persons using the smartphone signal. This paper will present the location results using these two systems.

After this introductory section, is presented in Section 2 the Polaris and FIND3 systems. Section 3 describes how these systems were deployed in an office building. Section 4 shows the results of the two systems in the same office. The main conclusions are presented in Section 5.

2. Real-Time Locating Systems

In this section, it will be presented the two RTLS used system: Polaris and FIND3. The two used systems differ from the technology that they use for indoor location but are similar in their operation and use. The biggest operation differentiation is that Polaris provides a geographical location (i.e., with two axes) while FIND3 only provides the identification of the zone where the user is.

2.1 Polaris

Polaris is an RTLS, developed by the Spanish company Nebusens. This RTLS solution uses the n-Core platform, provided by the same company, and it uses Zigbee standard in the communication between system devices. The system uses 3 types of devices that must be used: collector, reader, and tag. The collector device (e.g., n-Core Sirious A) is installed together with an RS-485 to Ethernet converted, it is responsible to collect all Zigbee data, provided by the reader, and sent it to the Polaris server. The reader devices (e.g., n-Core Sirious D) are responsible to read the tag signals and send the signal strength to the collectors. In readers can, it can be added a module for a relay control, this enables Polaris system to control physical resources, such as door lockers and lights. Collectors also provide the reader functionalities and can read tag signals. The tag devices (e.g., N-Core Sirious B or N-Core Sirious Quantum 2.0) are small devices that should be with the person or object that we want to monitor. These tags also have the ability to send custom signals to Polaris, each has two buttons that can be pressed by the user and their actions can be programmed in the Polaris system.

Polaris system provides a web interface for system configuration and location monitor. Fig. 1 shows the browser interface of Polaris. In the interface, an image is presented combining the satellite image of the building, the building's blueprint and the Polaris devices location; activated collectors, readers, and tags. The real-time interface provides the location as well as information regarding the tags (i.e., if a tag button was pressed). Polaris also provides an Application Programming Interface (API) using Simple Object Access Protocol (SOAP). The API enables the use of Polaris by third-parties, that can query Polaris system to check several parameters, such as tag positions.

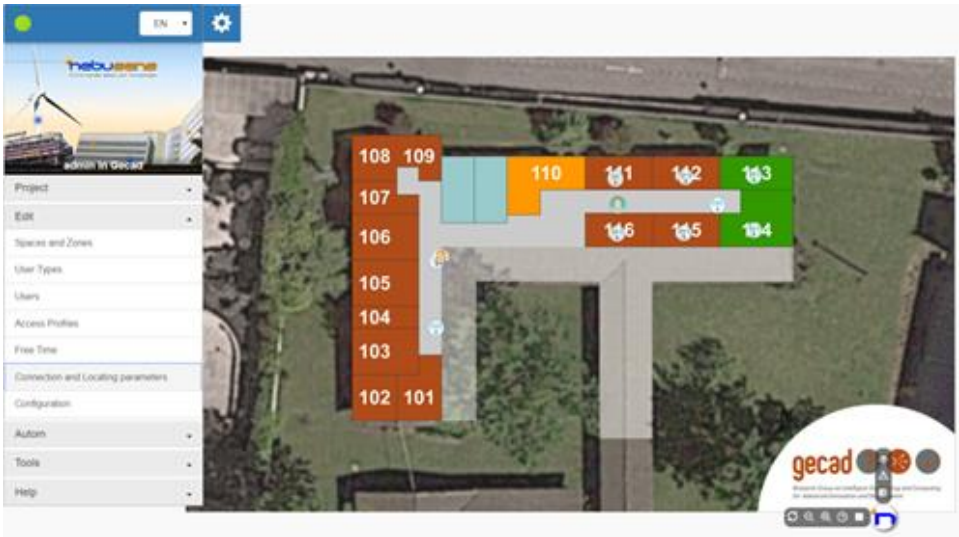

Fig. 1: Polaris web interface.

2.2 FIND3

Framework for Internal Navigation and Discovery 3 (FIND 3) is an open source solution wish allows locating people indoors based on Wi-Fi and Bluetooth technologies. In FIND3 there is no demand for hardware installation, the system is able to work using only one smartphone. However, to improve the location precision is recommended the installation of multiple devices. FIND3 uses the fingerprints of Wi-Fi and Bluetooth wireless networks to identify locations. For this to be possible, the user must create zones and train the system. The training is performed in a Wi-Fi and Bluetooth compatible device – can be a smartphone – where the user must go to each zone and stay there for a while. The mobile application will monitor Wi-Fi and Bluetooth networks signals and store this information in the server. By learning, the system will be able to identify, according to real-time Wi-Fi and Bluetooth readings, the user's location.

FIND3 provides a web interface where the real-time location values can be monitored. Moreover, the system is able to perform accuracy results for each zone. Fig. 2 shows the FIND3 web interface with the accuracy values for each zone created in the system: office N112, office N113, office N114, office N115, and office N116. The server can be installed locally or remotely. Also, FIND3 provides an API for third-parties to access the location data.

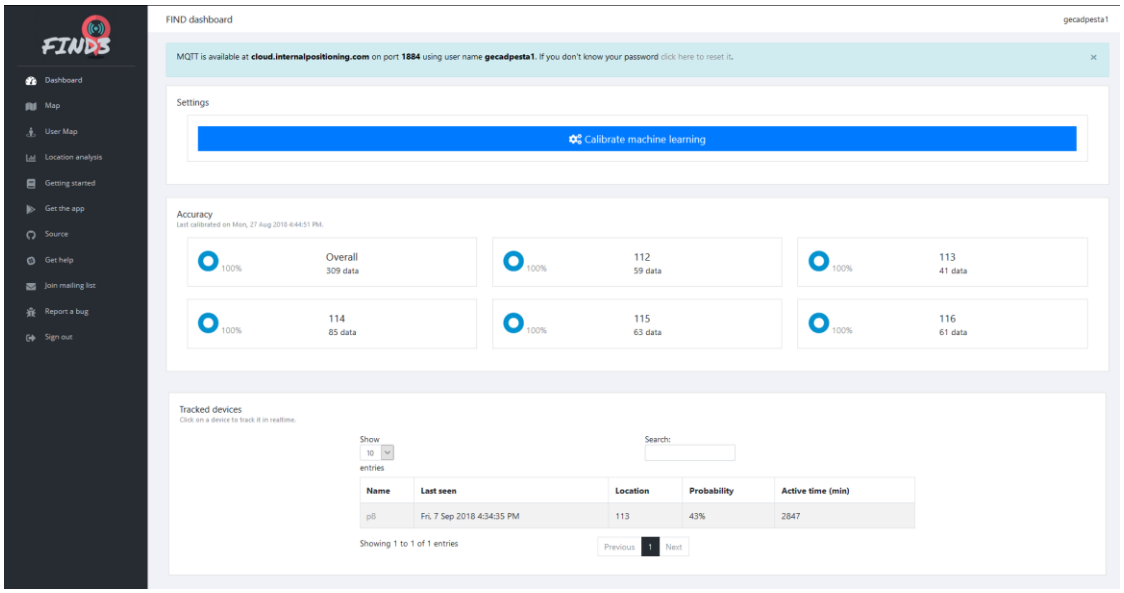

Fig. 2: FIND3 web interface.

3. RTLS deployment in an Office Building

Polaris and FIND3 were partially deployed in building N of Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development (GECAD), Polytechnic of Porto (P.PORTO). The offices used to deploy the system were N110, N111, N112, N113, N114, N115, N116 and the respective corridor, as shown in Fig. 3, where these offices are marked with colors. For FIND3, offices N110 and N111 were not considered.

Fig. 3: Offices where Polaris and FIND3 were deployed.

Fig. 4 shows the overall planning of Polaris deployment; where collectors are identified as pink pentagons and readers are identified as yellow stars. However, Polaris was not deployed in the entire building, as seen in Fig. 3. Each office has one reader and the corridor has two readers and one collector.

For FIND3 deployment, it was only used Wi-Fi networks. By default, the building has more than 20 Wi-Fi networks provided by indoor access points and from other building's access points. To decrease the FIND3 error, new low-range access points were added to each room. It was used the ESP8266 module to provide the new Wi-Fi signals.

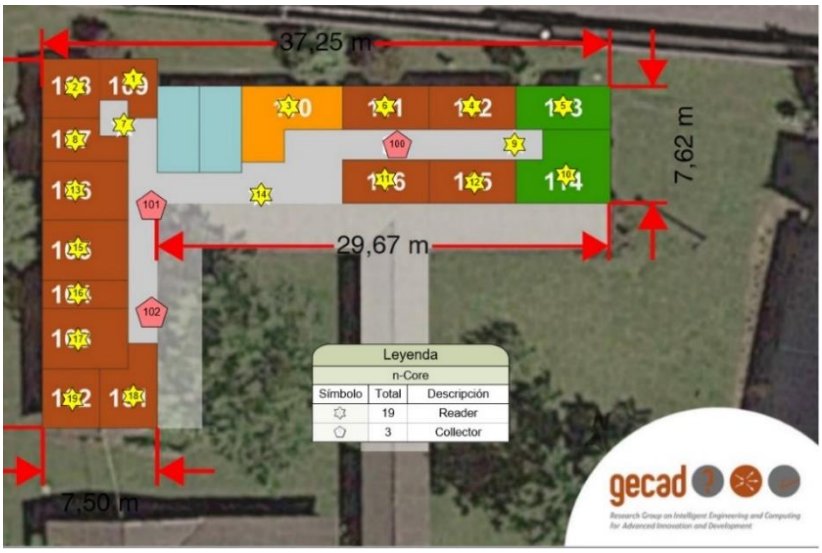

Fig. 4: Designated locations for the different types of Polaris devices.

The ESP8266 module has the ability to work as an access point. However, their wireless range was too expressive; reaching the entire building. To solve this issue, the antennas were cut to decrease the Wi-Fi signal; this enables the ESP8266 signal to stay only in the office and near the installation office. As seen in Fig. 5, some experimental cuts were done.

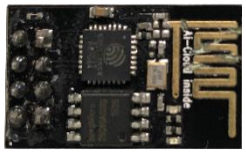

Fig. 5: ESP8266 with antenna cut off.

All the devices, to support Polaris and FIND3, were placed in the locations specified in Fig. 4. There was installed electrical boxes to accommodate each device, as can be seen in Fig. 6. In each installation, box was included a power supply of 5 V/DC and a step-down regulator from 5 V/DC to 3.3 V/DC.

Fig. 6: Installation.

4. Location Results of Office N112

Several test positions were specified in office N112 to perform the comparative tests; these positions are identified in Fig. **7**. The central position, B1, is also the location of the Polaris reader and the FIND3 ESP8266. The positions from A1 to A4 are placed near the office's corners. The A1-A2 wall (top of the image) is the division from offices N112 and N111, while the A3-A4 wall (bottom of the image) is the division from offices N112 and N113. All the measures were performed in the identified positions at a 95 centimeters height.

The 95 cm height was used to simulate a person; assuming that the Polaris tag and FIND3 smartphone will be in the user's pocket. The ordered of all the five positions were set clockwise and position A1 is always located in lower left corner; to identify the lower left corner the user must be inside the office facing its center and having his/her back pointing to office's door.

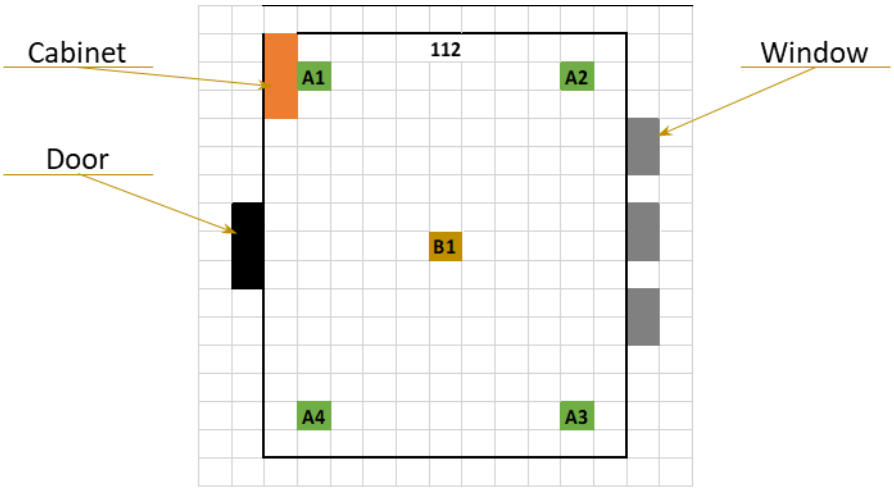

Fig. 7: Office N112 test positions.

The tests were made two times, one with the office's door open and one with the office's door closed. Because Polaris and FIND3 use wireless signals, the interference of a door can affect the results. Therefore, the tests were made with and without the door being open.

The tests were performed in each position during a 5-minute period where measures were taken each minute. The test, as stated before, were executed two times: with the door open, and with the door closed. The 5-minute window starts every time the Polaris tag and FIND3 smartphone are placed in a position. Therefore, is possible to see the reaction of both systems and the delay they have.

The bar chart of Fig. **8** shows the Polaris results for each position while the door stays open. The chart schematizes the distances, in meters, between a real and virtual position in the five samples made for five minutes, with the door open. Each position bar represents the minute measure; from darker blue to lighter blue. The virtual position is the position indicated by Polaris, while the real position is the physical position of the Polaris tag. In all the positions of this test, the distance error remained very similar during the five minutes measured. A1 position is the one that has the biggest error, reaching a 3.5 meters error, while B1 position has the smallest error. During the 5-minutes period, B1 position improved its accuracy, by decreasing its error, but in A2 position the results changed and the error increase alongside the time.

Fig. 8: Chart of Polaris results in room N112 with open door.

Fig. 9 shows the results of the tests using the Polaris system with the office's door closed. Unexpectedly, the errors increased in A3 position. However, all the other positions stayed with the same or lower error. In A1 and A2 positions, the error was constant for the 5-minute window, while the other points have slightly changed.

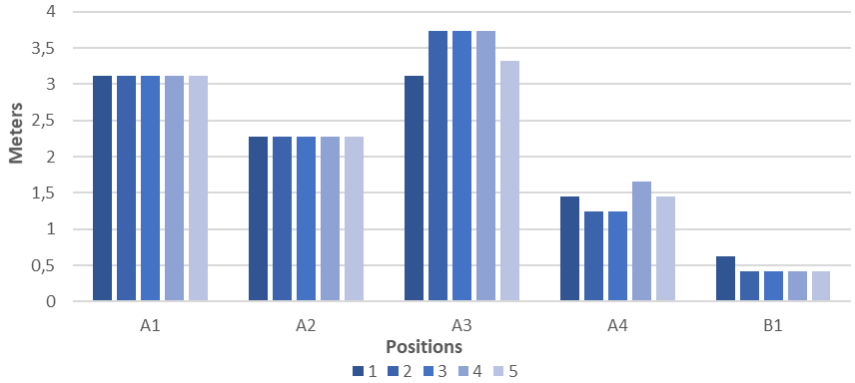

Fig. 9: Chart of Polaris results in room N112 with closed door.

FIND3 did not provide a precise location of the smartphone. Instead, the system identifies, by probability, the zone where the smartphone is. Fig. **10** shows the 5 samples measured for each position when the door was open. The colors identify the probability of the smartphone being in each of the offices/zones. With this representation, it is possible to see that in the 1st and 2nd minutes there is little density of darker colors aligned with 112 (middle of the chart). But from the 3rd minute on, the darker central color zone becomes more stable, even at position A2 (represented in Fig. **7**); which is the one that had the smallest accuracy. This means that initially, the office N112 is not well recognized in some of the positions tested with the door open. However, the accuracy of the system, in this room, began to improve significantly in the final minutes.

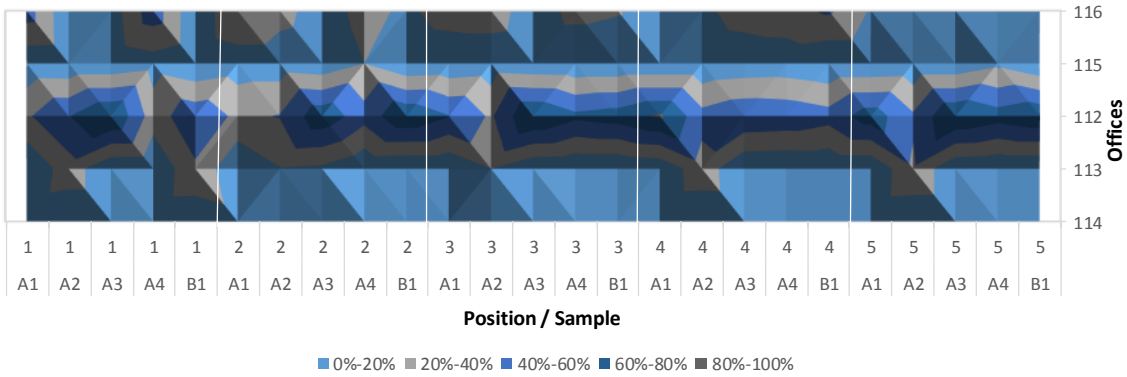

Fig. 10: Chart of FIND3 results in office N112 with open door.

In the closed-door scenario, the tests were also satisfactory as shown in Fig. **11**. With the door closed, the system reacted faster and even from the first minute is visible a darker central color indicating that the system knew the smartphone was in office N112. However, similar to the previous test, the A2 position presents the highest error.

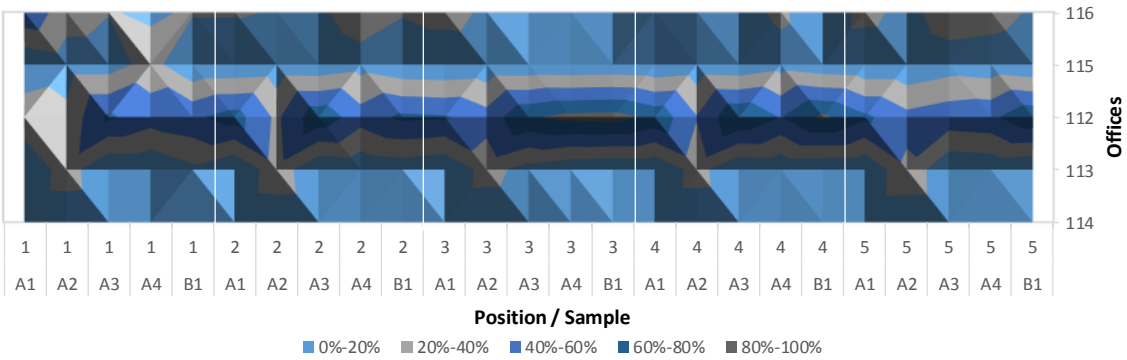

Fig. 11: Chart of FIND3 results in Office N112 with closed door.

5. Conclusions

This paper presents the analyses of two real-time locating systems: Polaris and FIND3. To provide indoor location, Polaris uses Zigbee wireless signals while FIN3 uses Wi-Fi and Bluetooth wireless signals. This paper describes the deployment of these two systems and their performance in the same scenario.

Polaris has the advantage ability to perform geographical locations, using two axes, while FIND3 is only able to identify the zone where the person/object is. However, the use of Polaris demands the installation of dedicated hardware and demands that the person/object carries one Polaris tag. Another advantage of FIND3 is the ability to continuously learn; enabling the user to teach the system about new zones or simply retrain existing zones to improve the system location accuracy.

Both systems have advantages and disadvantages, the decision of which one is better should depend on the need and goal of the user. To identify if and who is inside an office, FIND3 should be considered the best option because it does not demand the installation of hardware and uses the users' smartphones. However, if a precise location inside the building is needed, Polaris is the only option; between these two.

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Demand response approaches for real-time renewable energy integration
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Study of Price Elasticity's Predictability for Special Low Voltage Consumers

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Abstract

Demand Response programs have been assuming lot of importance in the simulations for electric systems in the last years. Their evolution brought to the need of new models able to consider the power consumption profile for every category of user; moreover, in order to better match energy consumptions and productions, highly precise forecasts of loads' profiles will be needed. This goal can be achieved also thanks to the definition of the elasticity factor. This paper proposes a way to obtain the elasticity price value for the BTE type of user together with an interpolation able to predict it. It will be discussed about the importance of having a real-time elasticity value able to vary according to specific factors, as for example user's habits during the weekends or weekdays and weather forecasts.

Keywords: demand response, price elasticy, elasticity forecasting, smart grid

1. Introduction

Demand Response represents a way both for final consumers and transmission system operator to optimize power fluxes during the all day by a technical and an economical point of view. It allows users to respond to electric market offers managing their power consumptions. Load shifting allows for the transfer of load from less to more attractive periods (e.g. lower energy tariffs when dynamic pricing is considered) [1], [2].

It may be interesting analysing demand response from a generation point of view, in fact load shifting represents a useful way to move load from periods where the generation availability is lacking to others when it is abundant (e.g. photovoltaic energy is only available during the day).

There are different categories of electric consumers according to their power consumption: domestic, commercial and industrial. For each one of these consumer's perspective, energy management systems can bring economic advantages: in order to get them several adaptive features are needed but they increase the consumer's comfort and reduce energy expenditure with an efficient strategy [3], [4].

According to [5] industrial and large commercial loads have generally been considered better candidates for DR programs as each individual customer can provide more response. Elasticity is a parameter that characterizes every user as it expresses how much is willing to change its power absorption in response to price changes. Two types of elasticities are defined, in order to better describe the behaviour of the final user in response to price variations: short-run elasticity and long-run elasticity. Short-run elasticity describes the consumer response during the first year since the variable of concern changed while the long-run one takes into account a larger amount of time. According to [6] this distinction allows to observe how

consumers' adaptation changes over time. In particular it shows that short-run elasticity describes the price-response from the system with its current infrastructure and equipment while long-run one considers investments that can be made in response to higher prices. In [7] it is also said that reduction in electricity consumptions in response to prices, particularly by residential consumers, is relatively inelastic in the short term. It means that even high price increases produce fairly small changes in electricity usage. Large consumers as industrial ones, on the other hand, are relatively price sensitive.

Elasticity parameter can be a characterization for every type of consumer because each costumer can have different consumption's profile. That brings to the need of define an elasticity value for each user, able to change in time according to factors as the day of the week or weather forecast. This could be helpful for the transmission system operator to better manage real time power fluxes.

In this paper the BTE user type will be analysed in order to demonstrate that is possible to predict elasticity value basing on historical data thanks to interpolating functions. This work intends to explain how the values are obtained and how good are the approximations, referring to MAPE method.

2. Analytical approach for elasticity's predictability

It is possible to predict users' elasticities from graphs of relative price variations in function of relative absorbed power's variations. Indeed, elasticity formula is given by equation (1):

$$\boldsymbol{e} = \frac{\boldsymbol{\Delta Q / Q}}{\boldsymbol{\Delta P / P}} \tag{1}$$

Where Q represents the absorbed power, ΔQ its variation (after and before Demand Response), P represents the price and ΔP its variation (after and before Demand Response).

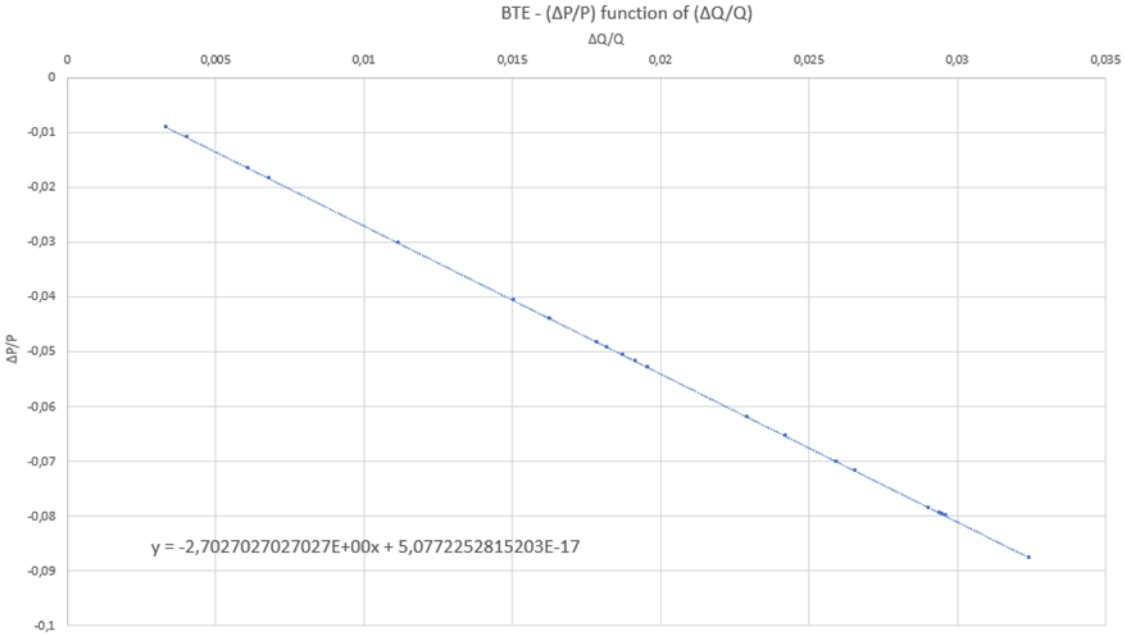

Fig. 1: Graph of ΔP/P in function of ΔQ/Q for BTE user type.

In Fig.1 it is shown how relative price variation is related to relative power absorption. The study was made using (DATA ORIGIN) as input data, assuming for the BTE consumer type the e=0,37 elasticity value. A linear interpolation line was adopted, whose equation is represented in the corner of Fig.1.

The angular coefficient represents the slope of the line, given by the equation (2).

$$\boldsymbol{slope} = \frac{\Delta \boldsymbol{P}}{\boldsymbol{P}} \Big/ \frac{\Delta \boldsymbol{Q}}{\boldsymbol{Q}} \tag{2}$$

Therefore, elasticity value is given by the reciprocal of the slope. Calculations brought a value of e=0,37 that perfectly matches the one given as input data. It means that linear interpolation can be a good method to predict elasticities' values.

Other types of interpolations are possible, such as polynomial (quadratic or cubic) and logarithmic. In order to see how much each interpolation is good the MAPE (3) was used. MAPE stands for "mean absolute percentage error" and according to [8] is one of the most widely used measure of forecast accuracy in businesses and organizations.

3. Results

$$\boldsymbol{MAPE} = \frac{\boldsymbol{100\%}}{\boldsymbol{n}} \sum_{\boldsymbol{t=1}}^{\boldsymbol{n}} \frac{|\boldsymbol{At} - \boldsymbol{Ft}|}{\boldsymbol{At}} \tag{3}$$

Equation (3) gives a value that express the accuracy of the interpolation referring to the input data. This value can be [9] less than 10, between 10 and 20, between 20 and 50 or over 50: it means that have been used a highly accurate forecasting, a good forecasting, a reasonable one and an inaccurate one respectively. That is because (3) equation considers the actual values (called "At") and the forecast values (called "Ft") both averaged on the total number n of elements. MAPE error has been computed for BTE user type for the case of linear, quadratic and cubic interpolation.

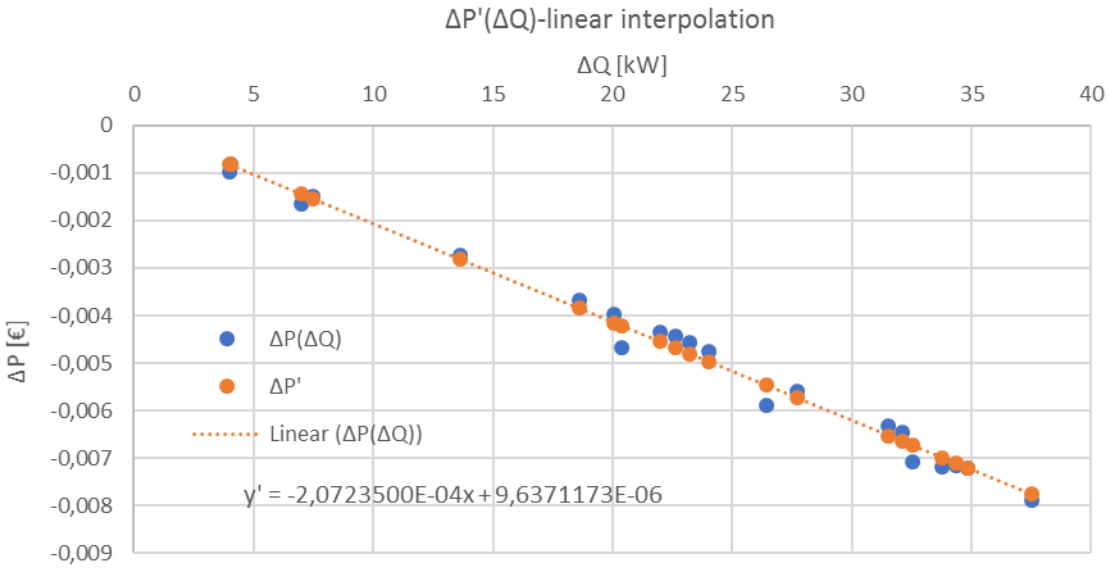

Fig. 2: Graph of ΔP in function of ΔQ (blue points) and forecast points (orange) based on interpolation line.

Fig. 2 shows new values of ΔP, called ΔP', based on interpolation line. Line's equation is written on the left corner of the graph and can be used to estimate ΔP forecast values in function of ΔQ points. MAPE has been calculated for this case: 21 elements were studied and put into equation (3) as n variable. The value is MAPE=4.884 meaning that a highly accurate forecasting has been made.

MAPE calculations have been made also with a quadratic interpolation, shown in Fig. 3. In this case MAPE=4.393, meaning that this interpolation is better than the linear one. Blue points represent measured values and orange ones the new values based on the interpolation function, written on the left corner.

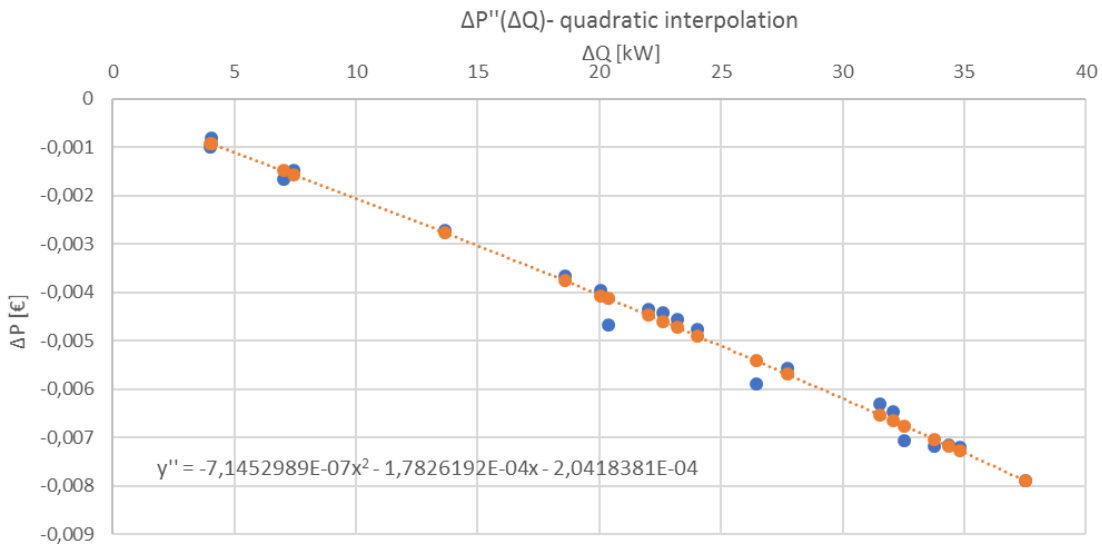

Fig. 3: Graph of ΔP in function of ΔQ (blue points) and forecast points (orange) based on quadratic interpolation.

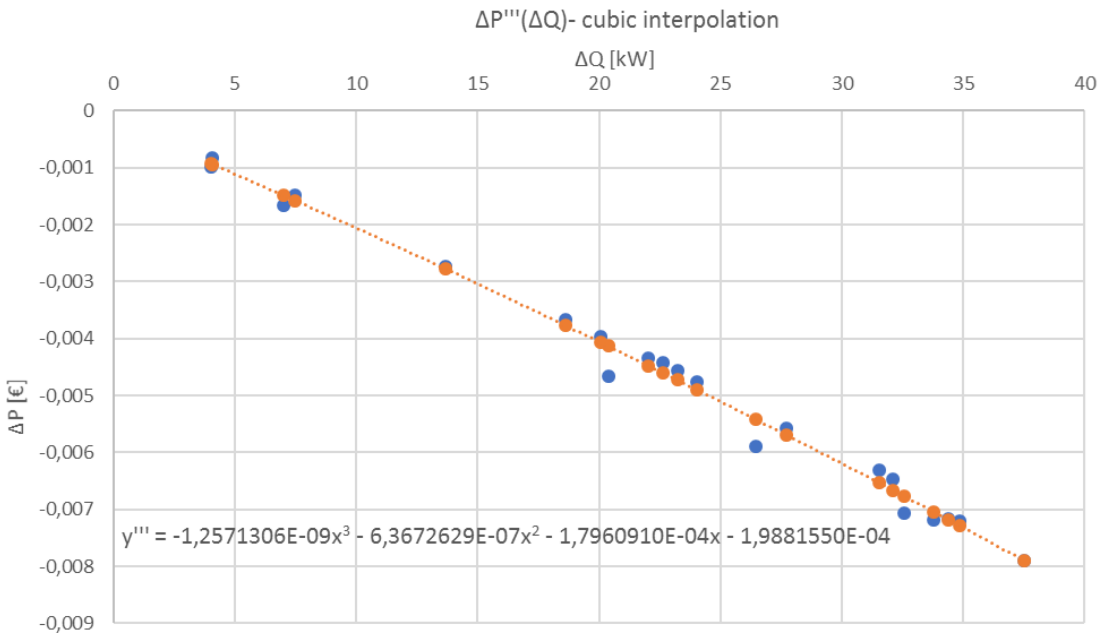

Fig. 4: Graph of ΔP in function of ΔQ (blue points) and forecast points (orange) based on cubic interpolation.

MAPE value in this case is 4.396. A comparison between quadratic and linear case shows that cubic interpolation is not better than the quadratic one.

Logarithmic interpolating function was taken into account, but it resulted to have a MAPE value worse than other methods, precisely 21.137. It is shown if Fig. 5. This means that the other interpolating methods presented (linear, quadratic and cubic) are more indicated. Moreover, if all values along the 24h of a day are collected, it may happen that some of them are related to moments without DR characterized by any ΔQ neither ΔP so logarithmic interpolation wouldn't be able to manage those points in the origin of the axes.

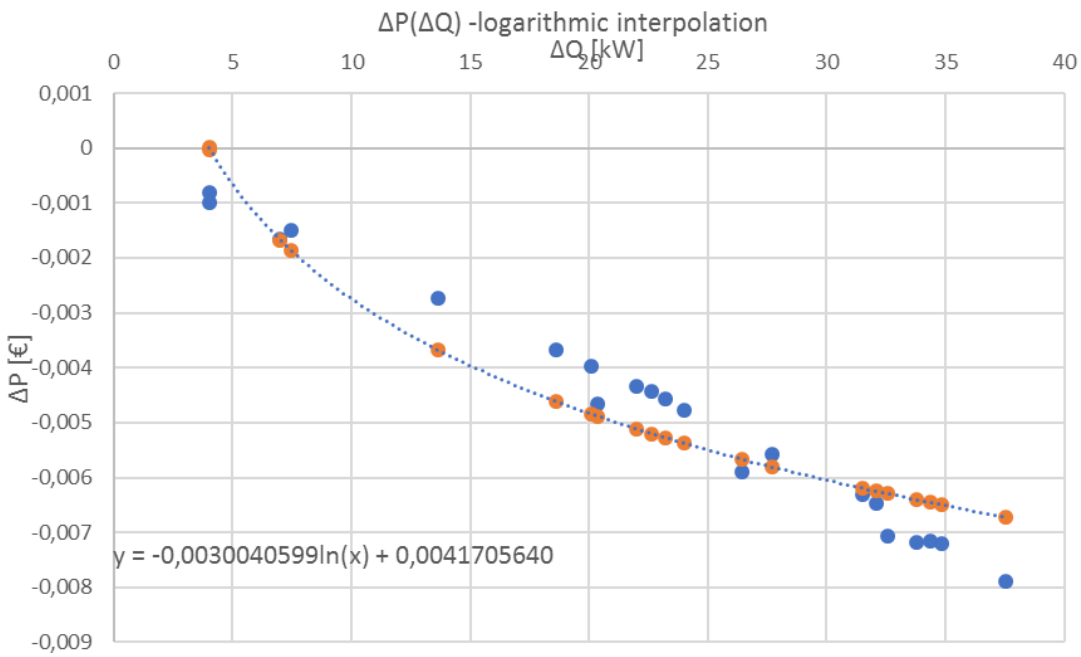

Fig. 5: Graph of ΔP in function of ΔQ (blue points) and forecast points (orange) based on logarithmic interpolation.

4. Conclusions

In this paper it was shown how to obtain the elasticity value of a user by analysing the graph of the relative price variation in function of the relative power absorption. By knowing that value, more accurate forecasts can be done resulting in a better balance between consumption and power offer. This will be handful for transmission system operator that is in charge to keep demand and offer always balanced. In the second part of the paper, a distinction between three types of interpolating functions has been made in order to see which way was more accurate by comparing the MAPE parameter. After excluding the logarithmic interpolation due to its high MAPE, it has been demonstrated that linear, quadratic and cubic functions are able to interpolate points with a good accuracy; in particular, there's not a sensitive difference between the quadratic and the cubic one.

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Demand response approaches for real-time renewable energy integration
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Review on the main flexible residential loads with potential to participate in Demand Response Programmes

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Abstract

Demand Response programmes represent an important component in the establishment of smart grids, since the management of load flexibility enables demand to be dynamically adjusted according to fluctuations in the price of electricity in the wholesale energy market, or according to the supply of distributed energy generation from renewable sources. Given the importance of load flexibility for the optimised management of smart grids, this paper argues that it is essential to carry out a technical characterisation of the main flexible residential loads with potential to participate in Demand Response programmes. For that, the scientific literature was reviewed. This review carried out in this study aimed to point out different approaches in the selection of flexible residential loads with potential to participate in DR programmers, as defined by 6 different authors. The main conclusion that can be drawn from the review of the studies selected in this paper is that there is a consensus on the main flexible residential loads with potential to participate in DR programmes. In conclusion, this study argues that there is the need to design and implement real case studies that examines the impact of the selected flexible residential loads under different scenarios and under real-market conditions to access the new market potential in this field. It is only through the successful implementation of innovative DR programme models (followed by the scaling up from pilots to commercial deployments) that the benefits of demand flexibility will be truly known.

Keywords: demand response, flexibility, load management, smart grid

1. Introduction

As evidenced by Yin et al. (2016) [1] and Tulabing et al. (2016) [2], the high penetration of renewable resources in the energy grid is increasingly driving the need to promote ancillary services as means to absorb potential interruptions of power supply caused by the intermittency of distributed energy generation, thus reducing critical peaks in energy demand. In view of this, the comprehensive management of load flexibility from the demand side through Demand Response (DR) programmes represents a low-cost alternative for the provision of ancillary services to the energy grid in comparison to the management of flexibility from the supply side through reserve generation units, which represent costly non-renewable sources of uninterrupted power to the grid that are activated during emergencies in power supply.

In view of this, DR programmes represent an important component in the establishment of smart grids, since the management of load flexibility (through mechanisms of load shedding or load shifting) enables demand to be dynamically adjusted according to fluctuations in the price of electricity in the wholesale energy market, or according to the supply of distributed energy generation from renewable sources [1] [2].

As pointed out by the abovementioned authors, the emergence of DR programmes was made possible in part by technological advances in Information & Communication systems, as it allows the optimal management and aggregation of distinct flexible loads in real-time, enabling in this way the transaction of these aggregated flexible loads in the wholesale energy market.

Dyson et al. (2015) [3] explains that DR programmes in liberalised energy markets could represent a major benefit for utilities, energy suppliers, aggregators, Distribution System Operators (DSOs) and Transmission System Operators (TSOs), since the balancing of supply and demand promoted by these programmes results in the reduction of the costs of maintenance of the energy grid infrastructure and in the reduction of the electricity price fluctuations in the energy market. In this sense, in order to remain competitive in the new paradigm brought forward by smart grids and distributed energy resources, these traditional big players need to develop new business models and learn from pilot programmes to design new services focused on the final customers that lead to behavioural changes related to the flexible consumption of energy, as means to encompass the new value proposition derived from DR programmes and create new revenue opportunities outside of traditional utility offerings.

In this sense, Dyson et al. (2015) [3] and Goldenberg et al. (2018) [4] suggest that policy makers should support the introduction of new incentives that facilitate public-private partnerships (PPPs), thereby fostering innovation in the energy sector. Furthermore, the authors also suggest that policy makers should support the creation of new regulatory frameworks that ensure investment recovery for those utilities that invest in the adoption of load flexibility management as a power grid balance asset. These developments may come in the form of new tariff models that reflect the marginal costs of utilities, ensuring that the reduction of the final customer's invoice (and hence the reduction of the utility's own revenue) also takes into account the significant cost reduction of network maintenance. Finally, the authors suggest that policy makers should support the creation of incentives (i.e., monetary incentives, such as rebates; and non-monetary incentives, such as automation and DR programmes) that facilitates the purchase of flexibility-enabling technologies to increase end-user involvement in DR programmes.

Given the importance of load flexibility for the optimised management of smart grids, this paper argues that it is essential to carry out a technical characterisation of the main flexible residential loads with potential to participate in DR programmes. For that, the scientific literature was reviewed.

2. Literature review

This review carried out in this study aims to point out different typologies of flexible residential loads with potential to participate in DR programmers, as defined by different authors. When loads were not clearly grouped and categorised, they were listed as individual loads.

2.1 Classification proposed by Tulabing et al. (2016)

Tulabing et al. (2016) [2] developed a load aggregation prioritisation algorithm based on the flexibility response characteristics of different typologies of residential loads. For this, the authors categorised different residential loads into 3 different typologies of flexible loads and 1 typology of non-flexible loads, as detailed in Table 1.

The study simulated 3 different scenarios to test out the proposed load aggregation prioritisation algorithm. For the simulations, battery-based energy storage technologies were left aside, and electric vehicles were taken solely as a load and not as a battery that supplies power to the grid. This was done to highlight the potential of the aggregation methodology to balance the grid without the need to rely on energy storage devices. In view of this, the 3 different scenarios are presented:

- Mitigation of system peak demand: the prioritised mechanism deployed in this scenario was load shifting capacity from electric vehicle charging, refrigeraton and non-urgent TCLs;
- Mitigation of distributed energy resources disruptions: the prioritised mechanism deployed in this scenario was load shedding capacity from HVAC systems, freezers and refrigerations;
- Mitigation of market price fluctuations: the prioritised mechanism deployed in this scenario was load shedding capacity from electric vehicle charging, non-urgent TCLs, fridges, and freezers.

Table 1: Definition of each typology of flexible residential loads with potential to participate in DR programmes proposed by Tulabing et al. (2016)[1].

Typology		Types of loads	Definition
Battery-based loads		Electric vehicles; stationary batteries	These loads are considered flexible since they can store chemical energy and can be recharged. They are also considered to be interruptive since they can be delayed as long as they meet the charging requirements set by the end-user. In this sense, the recharge can be interrupted when there is insufficient power in the network, which consequently approximates the "expected time to complete the recharge" to the "last available time to finish its recharge operation in time, as required by the end-user." Within these specifications, whenever there is a surplus electricity available in the network, recharging can resume automatically
Thermostatically Controlled Loads (TCLs)		HVAC systems; water heaters; refrigerators; freezers	These loads are considered flexible since they have the capacity to store thermal energy. These loads are prioritised according to the temperature deviations from their predefined setpoint – i.e., tolerance for temperature deviation (deadband). In this sense, loads with higher deadbands must be used first. The flexibility of TCLs is also achieved by maintaining the flexibility values below the established maximum temperature value (in the case of the cooling mode) or higher than the established minimum temperature value (in the case of the heating mode) even though it is still within the thermal zone of the deadband. In the case of HVAC systems, it is noted that load shifting mechanisms (i.e., precooling) are more efficient than load shedding, since the former can keep the thermal comfort of the interior of buildings for longer periods of time
Non-TCLs	Non-urgent	Dishwashers; clothes washers; Clothes dryers	This category includes non-urgent loads that are considered flexible since they can be started after some admissible time. Given that these loads can be delayed, they provide room for flexibility between "the expected end time based on the duration of its operation" and "the last time required to complete its operation on time, as required by the end-user." Unlike the batteries, the operations of these loads cannot be interrupted once they are started- Therefore, the prioritisation of the flexibility of this type of loads is to avoid exceeding the last time necessary to finish its operation in time, as required by the end-user
	Urgent	Entertainment (e.g., computers, televisions, video games, etc.); cleaning; cooking; lighting	These loads are not flexible since they need to respond instantly to the end-user's request as soon as the equipment's switch is turned on. Thus, they should have the highest priority and be addressed first among all types of flexibility, in order to allow end-users to have their daily routines affected as little as possible by DR programmes

2.2 Classification proposed by Hoogsteen et al. (2016)

Hoogsteen et al. (2016) [5] developed a mechanism for the creation of artificial residential load flexibility profiles, which allowed the evaluation of different approaches for DR programmes in smart grids. Specifically, the authors categorised the main flexible residential loads into 4 distinct classes: timeshiftables, buffer-timeshiftables, buffers and curtailable, as explained in Table 2.

On the other hand, non-flexible loads were divided into 6 different categories: stand-by loads, electronic equipment, lighting, induction equipment (ventilation), refrigerators and others.

[1] Source: Adapted from Tulabing et al. (2016).

Table 2: Definition of each typology of flexible residential loads with potential to participate in DR programmes proposed by Hoogsteen et al. (2016) [2].

Typology of flexible loads	Types of loads	Definition
Timeshiftable	Dishwashers; clothes washers; clothes dryers	Load flexibility is specified through operations with predefined start and end times. In this way, operations cannot be started before the start time nor finalised after the end time that were predefined
Buffer-timeshiftable	Electric vehicles	Load flexibility is specified by operations with a predefined start time, deadline and required energy demand. Electric vehicles have both their maximum power consumption capacity and buffer capacity fixed
Buffer	Stationary batteries; water heaters	These equipment have specified their maximum power consumption, production level and capacity
Curtailable	Photovoltaic panels	Load flexibility is defined through operations that establish a fixed profile of consumption and production, as well as the amount of energy that can be reduced

2.3 Analysis carried out by Yin et al. (2016)

Although the study conducted by Yin et al. (2016) [1] did not specifically focus on the categorisation of different categories of flexible residential loads, it presented promising results for DR estimation models targeting Thermostatically Controlled Loads - namely, heating, ventilation and air conditioning (in the case of commercial buildings) and multi-dwelling unit, single unit, water heaters and refrigerators (in the case of residential buildings).

Through the aggregation of the different flexible loads of these equipment, the proposed model quantified the DR potential (i.e., load shifting) for both commercial and residential sectors, as well as quantified the energy savings that could have been obtained through the creation of different scenarios of setpoint adjustment. The study concluded that HVAC systems represent a good asset for DR programmes for the following reasons:

- HVAC systems account for a substantial share of the electrical consumption of buildings;
- The “thermal flywheel” behaviour of indoor building environments allows HVAC systems to be temporarily switched off (i.e. load shedding) without immediate impact on the comfort of the building’s occupants;
- DR programmes targeting HVAC systems can be at least partially automated with smart management and control systems, thus reducing user responsibility for the implementation of the flexibility programmes.

2.4 Analysis carried out by Dyson et al. (2015)

The study conducted by Dyson et al. (2015) [3] performed an economic analysis of five main types of flexible residential loads, namely: air-conditioning; residential water heater; electric vehicle charging; clothes dryer; and battery energy storage. Specifically, this analysis designed different models for load shifting, taking into account the impact of distinct climates, tariff structures as well as PV production on load flexibility.

2.5 Analysis carried out by Goldenberg et al. (2018)

The study conducted by Goldenberg et al. (2018) [4] demonstrated that flexibility management of 8 different types of flexible loads through DR programmes (i.e., load shifting to periods of high availability of renewable energy in the grid) can level the load demand curve and reduce peak loads. The flexible loads selected for this study were: residential water heater; commercial water heater; residential air-conditioner;

[2] Source: Adapted from Hoogsteen et al. (2016) **.**

commercial air conditioner; residential heater; commercial heater; residential plug loads; and electric vehicles.

This study concluded that DR programmes of such magnitude can reduce the contingency (i.e., curtailment) of distributed generation by 40%; this increases the value of renewable energy by more than 30% when compared to a system with inflexible demand, thus transforming renewable energy into a more attractive asset for the deployment of smart grids. In addition, DR programmes can reduce energy demand during peak periods by 24%, as well as reduce the average magnitude of the multi-hour peaks (i.e., the "duck curve") by 56%.

2.6 Analysis carried out by Pipattanasomporn et al. (2014)

The study conducted by Pipattanasomporn et al. (2014) [6] trialled the potential of 11 different residential loads from two American households to participate in DR programmes. Specifically, the focus of this study was to elaborate an extensive dataset of the consumption profiles of these equipment.

The selected equipment is presented in Table 1, as well as their respective flexibility potential to participate in DR programmes.

Table 3: Potential of 11 different residential loads to participate in DR programmes[3].

Appliance type	Average peak power consumption in a cycle (W)	Average min power consumption if DR is performed (W)	Load reduction potential (W / %)	Possible interruption/ deferral period	DR potential	DR potential rank
House 1						
Clothes dryer	2,950	185	2760W-2950W / 94%–100%	Up to 30min/ Up to several hours	High	1
Air conditioner	1,150	0	1,150W / 100%	Vary	Medium	2
Clothes washer	580	0	580W / 100%	None/ Up to several hours	Low	3
Refrigerator	365/135	0	365W / 100%	Up to several hours (defrost cycle)	Low	4
House 2						
Clothes dryer	5,760	226	5,534W-5,760W / 96% - 100%	Up to 30min/ Up to several hours	High	1
Water heater	4,500	0	4,500W / 100%	Vary	High	2
Air conditioner	2,000	0	2,000W / 100%	Vary	Med	3
Dishwasher	1,180	0	1,180W / 100%	None/ Up to several hours	Med	4
Refrigerator	500 - 145	0	500W / 100%	Up to several hours (defrost cycle)	Low	5
Clothes washer	200	0	200W / 100%	None/ Up to several hours	Low	6
Oven	1,300 – 3,000	0	0	None	None	None

[3] Source: Adapted from Pipattanasomporn et al. (2014).

Table 3 compares the energy consumption of the different equipment, as well as their potential to reduce peak power, their load shedding/ shifting capacity (without affecting end-user comfort) and potential to participate in DR programmes.

As can be seen for House 1, the equipment that presented the highest potential for load reduction during peak hours through DR programmes was the clothes dryer, followed by the air conditioner, clothes washer and refrigerator.

In the case of House 2, the equipment that presented the highest potential for load reduction during peak hours through DR programmes was also the clothes dryer, followed by the water heater, the air conditioner, dishwasher, refrigerator and, finally, the clothes washer.

In view of these results, the authors reached the following conclusions:

- Clothes dryers represent the residential loads with the greatest flexibility potential to participate in DR programmes amongst all loads selected in this study. This is because the load shedding or shifting of this typology of flexible residential load has the potential to considerably reduce the total electric consumption of a household. Load shedding can be performed using hardware devices that disconnect the heating coils of the machines, thus allowing them to dry the clothes without heating. However, this interruption should not exceed 30 minutes to avoid excessive heat loss. Load shifting can also be performed using automated management and control systems that delay the start time of their drying cycles. The deadband to carry out the load shifting mechanisms can be of several hours, depending on the level of urgency of the end user in having the drying cycle completed;
- Water heaters can offer the second greatest flexibility potential to participate in DR programmes (namely load shifting performed through direct load control programmes – i.e., network operators have the right to directly change the load profiles and operating setpoints of electrical equipment according to the requirements of each end-user). To perform direct management and control of the water heating process without affecting end-user comfort, it is necessary to perform real-time monitoring of the water temperature inside the heating tank so that the interruption of the water heating operation takes place only within a predefined water temperature limit set by the end user. Thus, whenever the water temperature in the heating tank exceeds this limit, the heating operation of the water is resumed;
- Air conditioners offer a medium flexibility potential to participate in DR programmes, since their automated control can reduce approximately 1 kW of peak power consumption (in the case of splits) and 2 to 4 kW of peak power consumption (in the case of centralised HVAC systems). The simplest way to implement DR programmes with air conditioners is by adjusting their temperature setpoints. In this case, all DR programmes are carried out within the comfort limits set by end-users. Thus, while the indoor environment temperature is within the specified comfort range, the operation of the equipment may be interrupted;
- Dishwashers can reduce their load demand by up to 1 kW through load shifting mechanisms performed using automated management and control systems that delay the start time of their washing cycles. The deadband to carry out the load shifting mechanisms can be of several hours, depending on the level of urgency of the end user in having the washing cycle completed. However, these machines cannot have their washing cycles stopped once they are started, thus requiring a higher degree of rigor of DR programmes;
- Clothes washers and refrigerators have low potential to participate in DR programmes due to two reasons: firstly, both equipment do not have high consumption profiles; secondly, there are not many smart models available in the market that allow the automated shifting of the start of the washing, rinsing and spin cycles (in the case of clothes washers) or the defrost cycle (in the case of refrigerators);
- Ovens do not offer any load flexibility for DR programmes, since the shedding or shifting of their load significantly affects the comfort and convenience of end-users.

3. Conclusion

The main conclusion that can be drawn from the review of the studies selected in this paper is that there is a consensus on the main flexible residential loads with potential to participate in DR programmes. Specifically, the flexible loads that appear the most in the scientific literature under analysis were (by order

of magnitude): water heaters (6); HVAC systems (5); electric vehicles charging and clothes dryers (4); clothes washers, dishwashers, refrigerators and stationary batteries (3); and, finally, freezer and residential plug loads (1).

As for the impact of each type of flexible residential load in DR programmes, results vary greatly from study to study since it depends on a wide array of factors, such as: the purpose of the DR programme (e.g., mitigation of system peak demand, of distributed energy resources disruptions or of market price fluctuations); load aggregation (or not); use of algorithms for load prioritisation (or not); climate; available tariff structures; integration of distributed energy resources; overall demand profile; etc.

Finally, this study argues that there is the need to design and implement real case studies that examines the impact of the selected flexible residential loads under different scenarios and under real-market conditions to access the new market potential in this field. It is only through the successful implementation of innovative DR programme models (followed by the scaling up from pilots to commercial deployments) that the benefits of demand flexibility will be truly known.

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Demonstration of Electric Water Heater DR Possibility with Financial Benefit Analysis

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Abstract

The household small electrical appliances can participate in demand response events to support the local electrical infrastructures. Demand response (DR) plays a major role by reducing peak load consumption and controlling distributed generations. This paper presents a demonstration of DR participation of a water heater with financial benefit analysis by using a convenience tool. It also discusses a residential water heater DR possibility by analyzing the obtained data. The smart grid concept with building energy management system, DR flexibility and financial benefits are also discussed here. The main framework of the task consists of electric water heater modeling with several parameters and planning for the DR participation. The overall model is also demonstrated here with the execution of the planned tasks. The results obtained by using this tool is also represented graphically for the demonstration in the paper. It shows that the proposed methodological analysis is financially beneficial for both consumers and aggregators.

Keywords: consumption reduction, demand response, direct load control, financial benefit, modeling

1. Introduction

The idea of the smart grid (SG) concept is developed to support the vast possibilities of distributed energy resources and renewable energy generations with the latest information and communication technologies [1]. It also helps in developing advanced metering infrastructure for energy efficiency, both in demand side management and self-controlled electrical grid to maintain supply and demand reliability during peak consumption [2]. Use of building energy management system (BEMS) with the integration of SG technology can provide sufficient grid flexibility and energy efficiency. The main motivation of climate and energy targets for 2020 namely “20-20-20” is to provide an efficient energy system in every phase of the energy sector [3]. Electricity consumption in commercial and domestic buildings is increasing at a very high rate. The consumption by buildings is 70% in United States where consumption by commercial, industrial and residential buildings in Europe is about 40% [4].

Demand response (DR) provides flexibility in both the commercial and residential electricity management system [5]. The main objective of using DR is to make a balance between consumption and generation in the local electricity infrastructure. It can also provide emergency support to the grid, fill valleys and shave peak load for balancing electricity. Residential small appliances like Electric Water Heater (EWH), air conditioner, dish washer etc. have efficient DR potential. Among those appliances, EWH is considered one of the most suitable to participate in DR programs. It consumes a major amount (7.5% to 40%) of power in the traditional residences [6]. But it has a great potential in the field of power management

system as it has storage capability with large adjustment space and the automation control system can easily be adapted by it.

Incentive-based DR program offers incentives to consumers for controlling their usage pattern during peak hours. Direct load control (DLC) is one of the types of incentive-based DR programs. In this method, the activities in demand side can be controlled (shutdown or cycle change) by the aggregator and they can perform this remotely [7]. The main focus of our work is to show the DR program implementation possibility with the financial benefit analysis in the proposed EWH. Additionally, it is also shown the demonstration of the working methodology of the proposed system.

Designing of an EWH based on DLC program is analyzed in [8]. An automatic DLC program for an EWH with overall consumption reduction and cost-effectiveness is determined in [9]. An optimization algorithm based on DLC for thermostatically controlled devices is shown in [10]. It describes the optimal control schedule and the benefit of the reduced load in the electricity market. A novel real-time water flow control approach for EWH in DLC is efficiently presented in [11]. It also describes the demand reduction by using thermostat control.

Our paper describes and analyze the overall consumption for a certain period by using the DLC method, total incentives obtained from the aggregator for participation in this program. The comparison between the total cost and total cost by using this method is also shows significant financial benefit here.

The rest of the paper is organized as follow. Section 2 represents the main framework and modeling of the system. An overall representation of demonstration is described in Section 3. Section 4 discusses the case studies with consumption and financial analysis for different periods of the year. Results analysis is included in section 5. Finally, the main conclusions of the paper are discussed in Section 6.

2. Main Framework & Modeling

Home appliances modeling is essential to understand demand response control strategy. Physical load model can be considered for the case of EWH modeling purpose. An improved physical model of an EWH is analyzed here for demand response purpose. The EWH's parameters are also considered for the analysis purpose. The obtained temperature profile shows the significant variations in the different temperature scenarios. The heater's flow chart parameters model is represented in the Fig. 1 below.

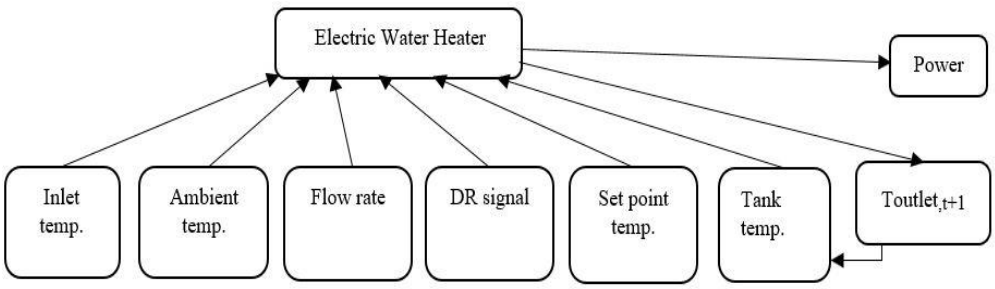


Fig. 6: Overview of Electric Water Heater parameters.

The effective control of the residential water heater depends on the accurate prediction of the heater's load and temperature. A previously established thermal model can be used to determine the real-time water tanks temperature [12]. This model can be found by using the solution of a differential equation:

$$T_H(t) = T_H(\tau) e^{-\left(\frac{1}{R'C}\right)(t-\tau)} + \left\{ GR'T_{out} + R'T_{in} + QR' \right\} \times \left[1 - e^{-\left(\frac{1}{R'C}\right)(t-\tau)} \right] \quad (1)$$

Here, $T_H(t)$ is tank water temperature at time t (ºF), $T_H(\tau)$ is initial temperature, $R' = 1/(B+G)(W/^{o}F)$,

$C =$ (tank volume).(water density). $C_P\,(W/^oF)$, $G = SA/R\,(W/^oF)$, R is tank thermal resistance ($m^2.^oF/W$), T_{out} is outside tank temperature, T_{in} is incoming water temperature, Q is the input energy as a time function (W), τ is initial time (hour). For all the known parameters and for any given time, the water tank inside temperature can be determined by using this thermal model. If for any case the value of water demand (W_D) or input energy (Q) changes then the initial time (τ) value should be reset to zero [13]. This model is used to control the resistor's ON/OFF status [14].

Two different types of node model can be used for the EWH heat transfer process are one-node model and two-node model [15]. A uniform temperature is usually considered in the one-node model. The model validity can be established by measuring all hot or all cold water of empty or full tank. The heat transfer process in here can be modelled by using the first order differential equation:

$$Q_{elec} - \dot{m}C_p\left(T_w - T_{inlet}\right) + UA_{wh}\left(T_{amb} - T_w\right) = C_w \frac{dT_w}{dt} \tag{2}$$

Here, Q_{elec} is the resistor heating capacity (BTU/hour), $\dot{m}$ is the water flow rate (lb/hour), C_p is the thermal capacitance (BTU/(lb °F)), T_w is the water temperature (°F), T_{inlet} is the inlet water temperature (°F), UA_{wh} is thermal conductance (BTU/°F/hour) where BTU is British Thermal Unit, T_{amb} is the room temperature (°F), C_w is thermal capacitance (BTU/°F). The switching action of the heater can be controlled by measuring the actual temperature by any given time which can be calculated by this model. The following conditions can be implemented to achieve the set temperature ($T_{w,set}$) [14]:

1) $If\ T_w >= T_{w,set} + T_{w,deadband}$; The heater turns off.
2) $If\ T_w <= T_{w,set} - T_{w,deadband}$; The heater turns on.

For the convenience of this work, the consumption data is considered as input while the obtained reduced consumption and financial gain by using the proposed DLC method is considered as output. The overall view and main framework of the method is shown in Fig. 2. It consists of five main parts which includes several sub parts also. The first part is about the EWH modeling and overall usage profile. The physical and thermodynamic model with parameters analysis is described in the modeling part. Usage profiling section considers and analyze user consumption pattern. The analysis of user consumption pattern is discussed in the usage profiling section.

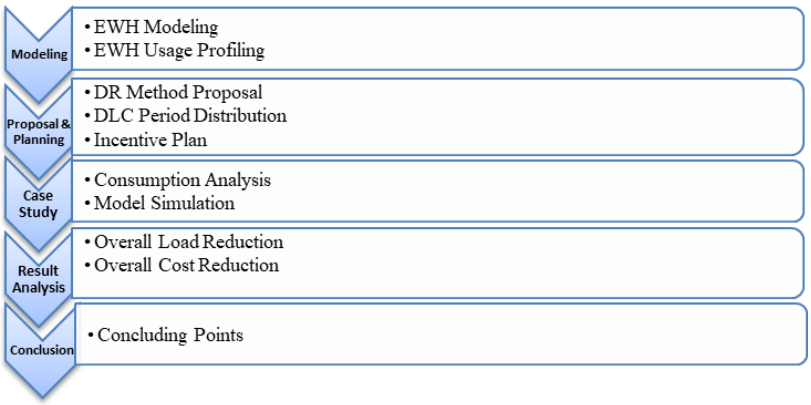


Fig. 7: The main framework of the DR DLC method.

DR method proposal, period distribution and incentive plan is explained in the next proposal and planning part. In where, DR method proposes the considered DR event program. The distribution period discusses the distributed months based on usage pattern for the considered period. In the yearly data, the months are distributed by high usage, medium usage and low usage months. Incentive plan can be made by the agreement between consumer and aggregator that discusses the total incentive for the consumers.

Overall consumption and the simulation model are discussed next in the case study part. The result part describes the total consumption reduction, total cost reduction and overall financial benefit gained by using

the proposed method. Conclusion part describes the concluding points, decision and summary of the outcomes of the used method.

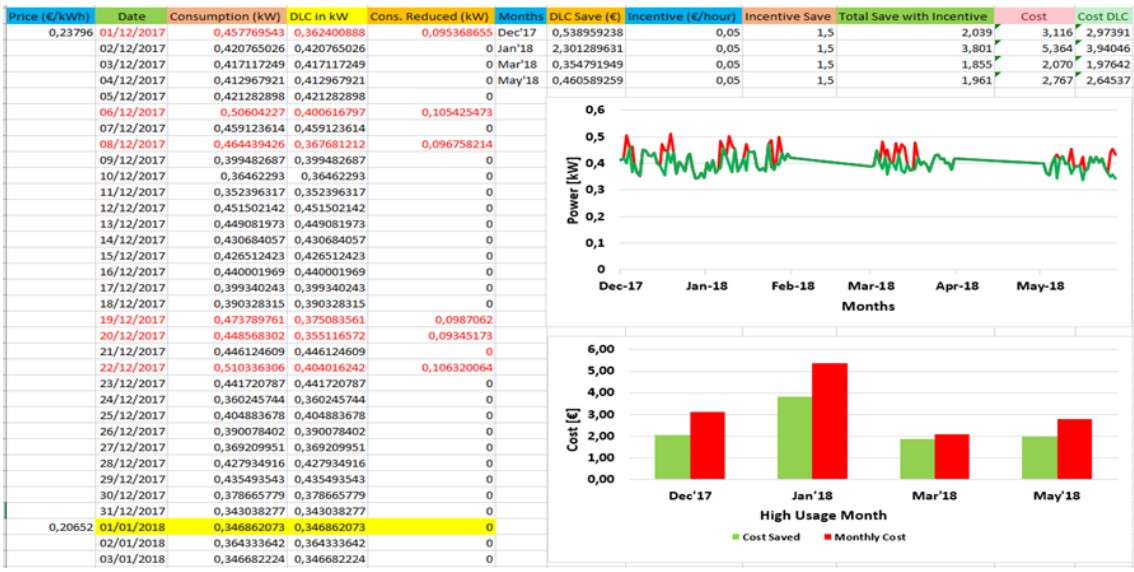
3. Demonstration

The demonstration of the proposed DR method with input data analysis and output result is discussed in this section. The proposed method is implemented and analyzed by using data integration Excel software. It is also used to illustrate the produced figures from the outputs.

The successful implementation of this method is illustrated in Fig. 3. Three main processes revealed by this proposed method are average consumption data (daily) calculation [16], overall average cost calculation and total reduced consumption calculation with the analysis of financial benefit. The heater's yearly consumption data is categorized based on the user consumption pattern.

The overall monthly, daily and hourly consumption profile is divided by using this convenient tool. For the data analysis convenience, the months are divided into three different periods are low usage months (LUM), medium usage months (MUM) and high usage months (HUM). Then the average daily consumption data for each month in each period is obtained by using Excel. The temperature profile of the heater is also discussed here. It is important to consider the DR participation of the heater. And it is the only parameter that can decide whether consumers can participate in direct load control (DLC) event or not. The residential EWH's monthly data [8] is calculated to obtain the desired output profile. From this data, the highest usage days from every month considered to be used in load control model. The model also gives the scope to the aggregator to control, change or modify data in order to obtain the desired result. In order to calculate the cost and overall financial benefit, real-time electricity price is included in this model.

Fig. 3 presents the cost calculation with financial analysis. The total cost for normal consumption is calculated by using the real time electricity price. The total cost for load-controlled method is also calculated then a comparison between both costs is also studied. The model also shows the total reduced consumption and the total cost saved by using this method. The proposed method proposes incentive-based tariff for the consumer here [17]. The described tool is used to calculate the overall financial benefit in this method. The normal power consumption profile and the consumption profile after using DLC method is also shown in the Fig. 3. The demonstration of the total cost and the total cost saved by using this program is also depicted in the Fig. 3. The result shows that the use of the proposed method is not only beneficial for the consumers but also for the aggregators. The cost difference, consumption difference, incentive achievement, power saved by the proposed method and all other related tasks can be obtained by this model too.



Price (€/kWh)	Date	Consumption (kW)	DLC in kW	Cons. Reduced (kW)	Months	DLC Save (€)	Incentive (€/hour)	Incentive Save	Total Save with Incentive	Cost	Cost DLC
0,23796	01/12/2017	0,457769543	0,362400888	0,095368655	Dec'17	0,538959238	0,05	1,5	2,039	3,116	2,97391
	02/12/2017	0,420765026	0,420765026	0	Jan'18	2,301289631	0,05	1,5	3,801	5,364	3,94046
	03/12/2017	0,417117249	0,417117249	0	Mar'18	0,354791949	0,05	1,5	1,855	2,070	1,97642
	04/12/2017	0,412967921	0,412967921	0	May'18	0,460589259	0,05	1,5	1,961	2,767	2,64537
	05/12/2017	0,421282898	0,421282898	0							
	06/12/2017	0,50604227	0,400616797	0,105425473							
	07/12/2017	0,459123614	0,459123614	0							
	08/12/2017	0,464439426	0,367681212	0,096758214							
	09/12/2017	0,399482687	0,399482687	0							
	10/12/2017	0,36462293	0,36462293	0							
	11/12/2017	0,352396317	0,352396317	0							
	12/12/2017	0,451502142	0,451502142	0							
	13/12/2017	0,449081973	0,449081973	0							
	14/12/2017	0,430684057	0,430684057	0							
	15/12/2017	0,426512423	0,426512423	0							
	16/12/2017	0,440001969	0,440001969	0							
	17/12/2017	0,399340243	0,399340243	0							
	18/12/2017	0,390328315	0,390328315	0							
	19/12/2017	0,473789761	0,375083561	0,0987062							
	20/12/2017	0,448568302	0,355116572	0,09345173							
	21/12/2017	0,446124609	0,446124609	0							
	22/12/2017	0,510336306	0,404016242	0,106320064							
	23/12/2017	0,441720787	0,441720787	0							
	24/12/2017	0,360245744	0,360245744	0							
	25/12/2017	0,404883678	0,404883678	0							
	26/12/2017	0,390078402	0,390078402	0							
	27/12/2017	0,369209951	0,369209951	0							
	28/12/2017	0,427934916	0,427934916	0							
	29/12/2017	0,435493543	0,435493543	0							
	30/12/2017	0,378665779	0,378665779	0							
	31/12/2017	0,343038277	0,343038277	0							
0,20652	01/01/2018	0,346862073	0,346862073	0							
	02/01/2018	0,364333642	0,364333642	0							
	03/01/2018	0,346682224	0,346682224	0							

Fig. 8: Used interface of the proposed method for DR.

In the end, the last part allows the user to discuss and analyze the obtained results from the executed method. It also gives the scope to the users to consider whether the proposed method with the considered incentive plan is suitable or not. The obtained figures, charts and, even the datasheet can be stored for future

use also. These figures can be used to elaborate the importance of the method and the selection of the period for DR scopes.

4. Case Study & Methodology

A single element electric water heater's one-year data is considered for the analysis purpose. The heater is taken from our research group (GECAD). It is used approximately by 15 people for daily washing purpose only not for taking a shower or other work. The outlet water temperature is measured by a sensor what is placed just outside of the water line. In our case, we consider the outlet water temperature as the heater's inlet water temperature. After analyzing the consumption data, it is classified into three different periods are High Usage Month (HUM), Medium Usage Month (MUM) and Low Usage Month (LUM). The considered months in HUM period are January, March and May; the months in MUM period are July, October, November, April and June; the months is LUM period are August, September and February.

The average daily consumption behavior of the HUM period is represented in the Fig. 4. As we can see in the figure that December has the highest consumption which is approximately 422 watts and January has the lowest consumption is approximately 418 watts. The calculated consumption cost for this period is depicted in the Fig. 5 below. It shows that the highest average daily cost of this period is in December and the lowest cost is in March.

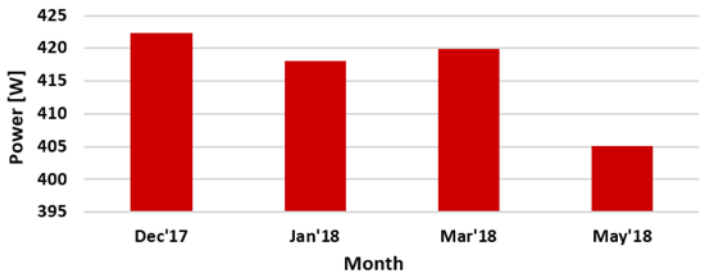


Fig. 9: Daily average consumption profile for HUM period.

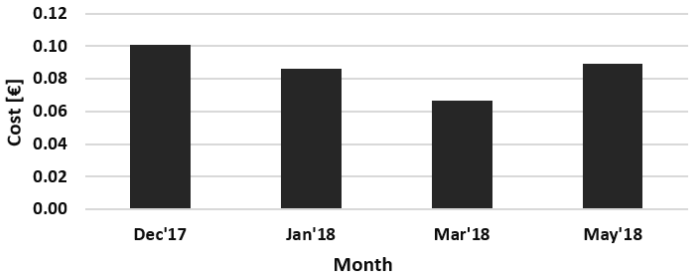


Fig. 10: Daily average cost for HUM period.

Fig. 6 shows the heater's daily average consumption profile for medium usage months. The highest daily average consumption for the MUM period is in November which is about 412 watts and lowest average consumption is in July is about 400 watts. And, Fig. 7 represents the daily average cost for the same period. The highest average daily cost of this period is in November and the lowest is in April.

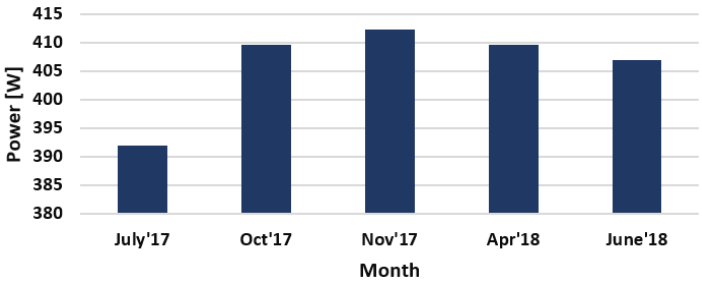


Fig. 11: Daily average consumption profile for MUM period.

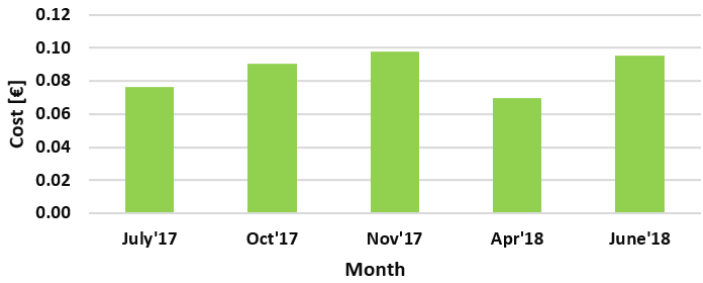


Fig. 12: Daily average cost for MUM period.

Finally, the average daily consumption profile and average cost profile for low usage month is shown in the Fig. 8 and Fig. 9 respectively. It has the smallest duration among the proposed periods. From the Fig. 8 it can be seen that February has the highest average daily consumption where August has the lowest daily average consumption in LUM period.

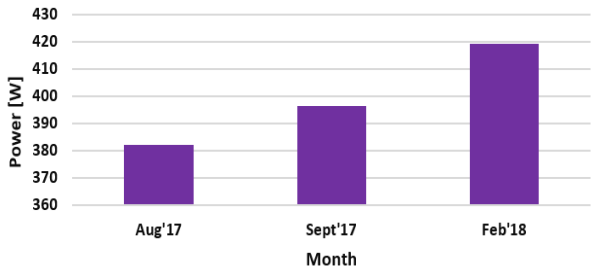


Fig. 13: Daily average consumption profile for LUM period.

According to the Fig.9, it is obtained that the daily average cost is highest in February but the lowest in August as it has the similar pattern in the consumption which is depcited in the previous figure.

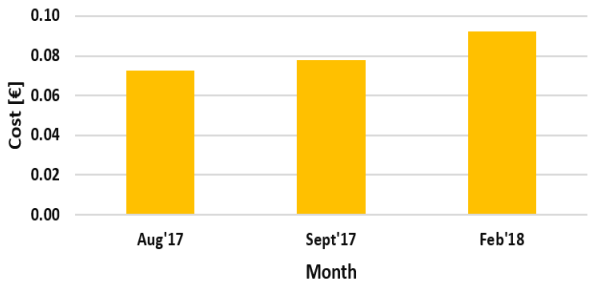


Fig. 14: Daily average cost for LUM period.

During the DR events, it is challenging to keep the temperature in a comfort [18] level. The daily temperature profile of the heater is represented in Fig. 10 below. It shows that the consumers temperature comfort level is approximately at 40ºC. It is also observed from the figure that the temperature is high during summer months. The limitation of the work is that, the measured data is the data of heater's outlet water data so the ambient temperature can be included in this profile too. As a result, it can have some faulty data though we are considering the data values are accurate if we ignore ambient temperature effect.

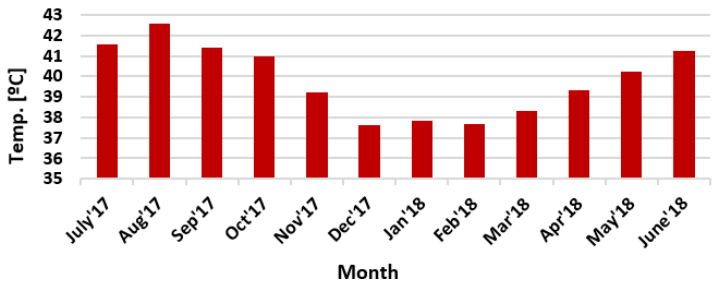


Fig. 15: Daily average temperature profile of the EWH for a year period.

In this part, it is discussed the proposed methodology for implementing the load control program to the heater. It is also discussed the overall cost calculation method using real-time market price. The initial market real-time price scheme is obtained from the Portuguese sector of Iberian Electricity Market (MIBEL) (www.omie.es).

Among different types of existing DR method, incentive-based DR program is considered here [19]. In this type of program, customer changes their consumption or stop their consumption for a certain period so that peak demand can be reduced. As a result, they can earn some extra financial benefits in their electricity bill. It is already mentioned before that direct load control DR program is considered in our work. As a part of the incentive program, the DLC method is proposed to apply in six high usage days the HUM period. In each of those days five highest consuming hours are selected to use. In MUM period, DLC is proposed to apply in five high usage days for four hours in each of those days. And, in LUM period, DLC is proposed in two high usage days for five hours in each of those days. The total hours considered to use in the DLC control is 250 hours.

For Incentive program, a daily flat plan is proposed in this work which varies from one period to another. For high usage months, the daily incentive is proposed to 5 cents per unit. For the medium usage months, the daily incentive is proposed to 3.5 cents per unit. And, for the low usage months, the daily incentive is proposed to 1.7 cents per unit. It is a contractual plan and the plan will only be executed if the consumer is agreed to control their load in the planned periods.

5. Results Analysis

This section describes the obtained results and outputs of the proposed analysis. A comparison between the average daily consumption and the average daily consumption after using the proposed DR DLC method is described here. The result indicates a significant decrease in the consumption. It is not only able to provide demand reduction fascility during peak load time, but also creates the scope to gain financially.

From the result, it is obtained that the average daily power reduction for every high usage month is 18.86 W. And, it is a significant amount for residential users. The value is obtained by subtracting to the daily average load controlled consumption from the daily average consumption. The daily reduced consumption for the medium usage months is approximately 12.20 W. Additionally, there is consumption reduction in low usage months though it is not very significant but in an acceptable range. The daily average reduction in low usage period is about 6.10 W.

The total financial gain is also discussed in this section. The daily average can be cost saved by using the proposed method for high usage months period is 5.20 cents. And, it makes a significants amount of money if consumers accumulate the incentives of all the days of the HUM period together. It is calculated by adding the obtained incentive value and the saved value for consumption reduction.

Fig.11 shows the cost difference between the daily average cost for normal period and daily average cost after using the DLC for HUM period. In the figure, the column in red is the daily average normal cost and column in green is the cost after DLC. The use of the proposed DR program reduces the electricity cost to 50% during HUM period. In some special cases, it can be even more.

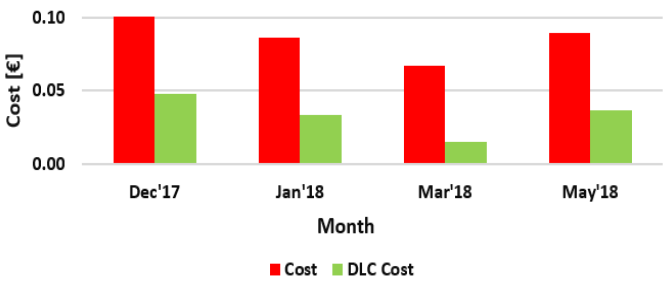


Fig. 16: Daily average cost difference for HUM period

The financial gain for medium usage months is described in this part. The daily average cost can be saved by using the DLC method for medium usage month is 3.70 cents. And, it is also a good amount of money that is considered for the MUM period. This gain includes the proposed obtained incentive value and the financial gain from consumption reduction.

Now, Fig.12 shows the cost difference between the normal daily average cost and daily average cost after DLC use for medium usage months. In this figure, the column in blue is the daily average normal cost and column in orange is the cost after using the DLC. The use of the proposed DR program reduces the electricity cost to 40% during this period.

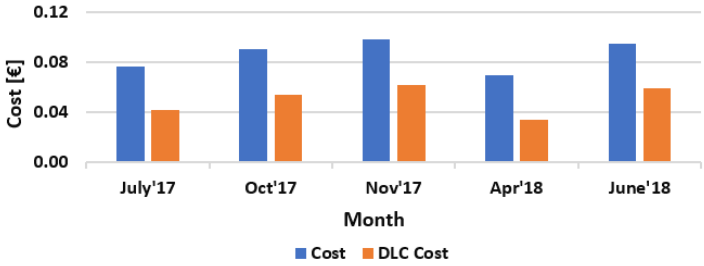


Fig. 17: Daily average cost difference for MUM period.

Next, the financial gain for lower usage months is discussed. The daily average cost saved by using the DLC method for lower usage months period is 1.80 cents. Fig.13 shows the cost difference between the daily average cost and daily average cost after DLC use for this period. In this figure the column in yellow is daily average normal cost and another column is the cost after DLC. The use of the proposed DR program reduces the electricity cost to 20% during this period.

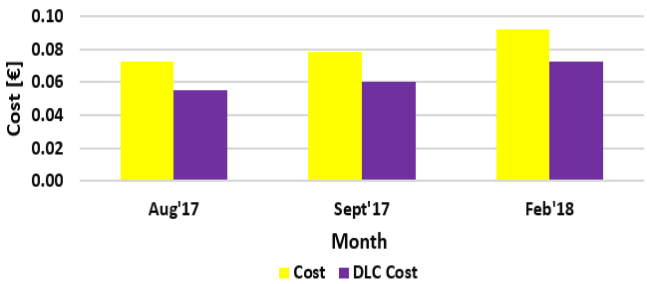


Fig. 18: Daily average cost difference for MUM period.

The results describe the changes in the consumer's consumption pattern due to the participation in the proposed method. But, these changes do not hamper user comfort level significantly which is on an acceptable level. It also analyses the overall reduction in consumption, the financial benefit by incentives in reducing electricity bill. This benefit will encourage people to participate in this type of DR program. Thus, the complexity in the traditional grid can be reduced too.

6. Conclusion

Traditional electrical infrastructure is facing more challenges to balance supply and demand due to the increasing penetration and uncertainties of renewable and distributed energy resources. Demand response with smart energy management system can help to solve these issues. It plays an important role to support the residential energy management system.

The experiences and findings regarding the considered demand response method are obtained here by using the Excel tool. The used tool allows users to analyze an optimized model of the EWH by using the consumption profile. It demonstrates the heater's different models and parameters for analysis purpose. The used tool is also capable of doing data analysis, data integration, and graphical analysis. The model and the tool are a part and parcel of the proposed work which turns into a successful implementation of the work. Additionally, it is a combination of different characteristics with a set of useful programs that helps to initiate the proposed model and end up with an event of successful results.

An aggregated direct load control system for the heater is possible to develop by using the proposed DR method. The real-time data of the heater are used for the analysis and DLC method is used for establishing the DR purpose. The load controlling method, the incentive benefits and other related task are discussed here. A single element water heater's consumption pattern is discussed here as it is the only existing heater of our building. This method can be implemented for dual element water heater or any other heater analysis purpose also.

The demonstrated model is an essential part of the DR analysis of residential electrical appliances. It will enable the users and the aggregators to calculate and understand the use of DR possibility with the financial benefit. In the end, the result of the analysis brings fruitful outcomes through the financial benefits. This work has a few shortcomings which will be improved in future work.

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Demand response approaches for real-time renewable energy integration
Fourth DREAM-GO Workshop

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Review of the state of the art of machine models for household consumption prediction.

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Abstract

Forecasting energy usage is a challenge that enables power suppliers to address particular behaviors. These activities that power suppliers may perform include finding out the customers' behavior in order to adapt their prices to their consumption or the intervals at which energy demand will be higher and have planned the adjustment of supply chains. To this end, an evaluation should be carried out of the methods that make it possible to predict the energy consumption of the future according to the consumption history and other parameters of the users themselves. In this paper we discuss the main machine-learning methods for the prediction of power consumption using a one-year data set of a shoe store. The revision made it possible to notice that for the data set applying Linear Regression and Support Vector Regression a success of 85.7% has been achieved with the best results provided.

Keywords: decision tree, energy forecasting, k-nearest neighbours, linear regression, machine learning, support vector regression, random forest

1. Introduction

Machine Learning is a scientific discipline in the field of Artificial Intelligence that produces systems that automatically learn. Learning in this context involves identifying sophisticated models in huge amounts of data. An algorithm that reviews data and is capable of accurately predicting future behaviour is actually the machine that learns. In this context, it implies that such systems are automatically improved over time without any human interaction. In the energy field, Machine Learning allows energy traders to predict when a consumer will use more power in order to adapt their bills or manage their energy provision. In other words, with Machine Learning you can go from being reactive to being proactive [1][2][3]. Historical data of all clients, properly structured and processed in blocks, create a database that can be used to predict upcoming power consumption, so that they can customize their marketing channels with new prices or adjust their supply routes to prevent high energy demand issues, etc.

This paper presents a survey of the most important learning models of machines used to predict electricity demand. In addition, this review will allow us to know which variables have a higher incidence in energy consumption [4][5][6]. Firstly, to predict energy consumption before the Smart Grids, to adjust the demand, and then to predict the energy consumption of smaller consumers so that it can be established whether the energy-saving recommendations made to users, which are based on their own behaviour patterns, are effective.

The developed system employs a system that implements the machine learning models, as well as the auxiliary tasks of data extraction. The main contributions of this paper are summarized as follows:

- A literature review of the main machine learning models focused on energy usage prediction.
- A case study in which it has been possible to compare the efficiency of the methods studied.

This article is organized as follows: section 2 describes the state of the art of machine learning models used in energy predictions, Section 3 describes the proposal, and Section 4 presents the results and conclusions.

2. Home Energy Management System Machine Learning Models for Predicting Electrical Energy Consumption

This section details the need to carry out an exhaustive review of the main models of prediction of energy consumption, as well as the variables with which these algorithms or models are used, as well as the type of systems that use them. In order to achieve the marked goal of showing which machine learning model produces the best energy prediction results in a house in this subsection, we will review the literature.

Linear Regression (LR) is a model that allows to know the relationship between the response variable (energy consumption) and the return variables (the other variables). The objective of regression analysis as a causal method is to forecast the demand for energy from one or more causes (independent variables), which may be, for example, the day of the week, price of energy, presence in housing or other variables. Linear regression is a method that is used when a trend in historical forecast data is evident. Due to this, and its simple application has been used in numerous works related to the prediction of electricity consumption.

In [7], Bianco et al. made a comparison with the consumption forecasts of other countries, based on complex econometric models, such as Markal-Time, demonstrating that the developed regressions are consistent with official projections. Other studies, such as the one developed by Mohamed and Bodger [8] studied a model for electricity forecasting in New Zealand. The model is based on multiple linear regression analysis, considering economic and demographic variables. Saab et al. [9], instead, investigated different univariate modelling methodologies to forecast monthly electric energy consumption in Lebanon. These studies have shown outstanding results using this statistical model.

Support Vector Regression (SVR) have been used regularly in the prediction of electrical consumption [10], [11]. The SVRs have also been used together with other techniques to obtain better results in terms of prediction such as ant colony optimization that serves to perform feature extraction and avoid training with a large data set, many of them redundant [12]. Kavaklioglu developed a method based on SVR that allowed to predict the consumption of energy in Turkey, for it he first made a model of each variable such as gross national product, imports and exports and these models were combined to produce consumption prediction values. The data set consisted of thirty-one-year data and the model was able to predict the next six years [13]. One of the reference algorithms in terms of making predictions is K-Nearest Neighbors (KNN). This algorithm has been widely used due in part to its simplicity and the ease to find similar instances in multivariate and large-dimensional feature spaces of arbitrary attribute scales. However, this method, insofar as it is limited to identifying past causes of the same dependent variable to coincide with future realizations, is not a causal approach to forecasting. Therefore, this method must be complemented with temporal information as variables that identify the day of the week, the day within the year or the week within the year in a way that facilitates the search in similar neighbors. [14]. This incorporation of temporary information will be incorporated in the process of preprocessing the data. This methodology has been used in several studies to make predictions of both photovoltaic plants and electricity Price forecasting [15], [16]. Random Forests (RF) is another machine learning model widely used to make predictions since parea a broad set of data produces a classifier with a great success rate [17]. As in KNN, variables that provide temporal value must be used to improve the prediction to be made. One of the studies that has used RF with a large percentage of success to make predictions of electricity consumption in the province of Tucumán, Argentina is carried out by Diego F. Lizondo et al. [18].

Gaussian Process Regression (GPR) to powerful machine learning model to perform Bayesian inference about functions. GPR is a model whose regression of the Gaussian process is generalized much better, being often much better than other regression methods, especially when the availability of sufficient training data is a problem [19]. Works such as the one made by Hu & Wang show how, with a set of data that is not excessively broad, they achieve more than satisfactory prediction results. These same authors in another research work make a comparison between different methods such as ARIMA (Autoregressive Integrated

Moving Average), ELM (Extreme Learning Machine), SVM (Support Vector Machine), Decision Tree (DT) and LSSVM (Least Square SVM) using a GPR [20][21][22][23]. In this comparison highlights the success rate of GPR.

From the present review of the state of the art, it is clear which are the machine learning models that show the best rate of success in varied data sets. From this review it is also extracted which variables are suitable to introduce to incorporate temporal information that is very suitable for certain algorithms such as KNN or RF. In the proposed system that will allow us to assess which of these models has a higher prediction rate for a shoe store data set, a system will be developed that will implement the following models LR, KNN, RF, SVR and DT.

3. Parameter Study for Dataset Training of Machine Learning Models

To meet the objective of checking which machine learning model has the best percentage of success, the system is specifically designed to preprocess the data in the data set and apply the selected models in the state of the art. The case study with which the evaluation of the system has been developed has made it possible to provide data on energy consumption and the value of other variables used for the evaluation of the system that implements the energy consumption prediction algorithms. For the evaluation of machine learning models, the system has used a set of data belonging to a shoe store located in Salamanca, Spain. The data in the data set belong to the range between 05/01/2016 and 11/12/2018. The data set consists of the date, day of week, day of year, week, weekend, Previous day electricity consumption (kWh), electricity consumption (kWh), as shown in **Error! Reference source not found.**

Table 1: Example of data from the dataset.

Date	Day of week	Day of year	Week	Weekend	Prev. day electricity consumption	Electricity consumption
2016-01-05	1	5	1	0	26.0950	20.374
2016-01-06	2	6	1	0	16.1960	12.018
2016-01-07	3	7	1	0	11.6495	11.281
2016-01-09	5	9	1	1	11.2080	11.102
2016-01-09	5	9	1	1	11.2080	11.314

The data set includes the electricity consumption of the previous day, since a training process was first performed without using the data set with this variable and the machine learning models did not yield good prediction values.Although there is a natural relationship between the day of the year and the energy consumption, the strong variations in the latter due to external causes make this an insufficient predictor, as evidenced by the low values of the Pearson correlation index. Pearson correlation that reveals the importance of including the variable Previous day, with r = 0.921. To complete this information, the consumption of the previous day has been used as an additional attribute, with which there is a clear correlation, as shown in the right part of the same figure. Weekends are also important to determine the energy consumption, as shown by the conditional distributions. To provide a better representation of the day of the year, it has been linearly scaled to the range [0,1], continuously mapping the summer solstice to 1 and winter solstice to 0.

The present section shows the results obtained in terms of scheduling of the appliances defined by the dependency vector and the energy bought from the network. Once prepared the set of data that better conditions presents to train the models is necessary to train them so that we can perform the prediction processes. Models are built with different methods, using the transformed day of theyear, the previous day energy consumption, and the business day or weekendcondition. Actual vs predicted values are shown in Fig. 1.

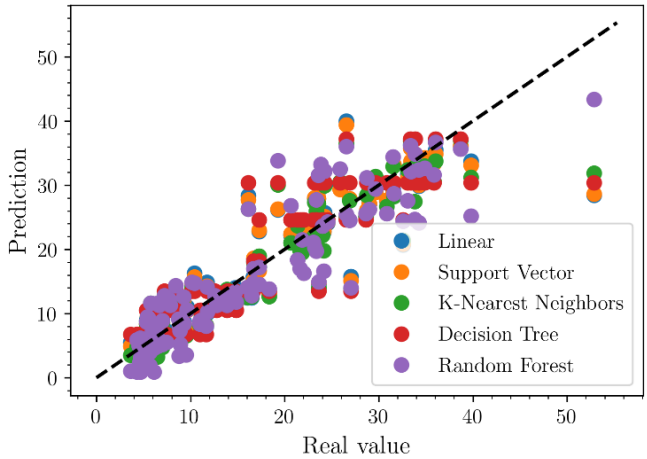

Fig. 1: Scatter plots of the actual values vs predicted values of every machine learning model used by the system.

Table 2 shows quite similar prediction results highlighting Support Vector Regression. However, these results can be improved by using a selection of paramenters that are used to enhance the training process.

Table 2: Machine learning methods score without parameters selection.

Machine learning method	Accuracy
Random Forest	0.798
Decision Tree	0.641
K-Nearest Neighbors	0.843
Support Vector Regression	0.844
Linear Regession	0.857

The individual results of each Machine Learning model are shown below using a selection of the parameters that produce the best prediction results. In **Error! Reference source not found.** we can see the results of Random Forest

Table 3 shows the precision results of the machine learning models used, using the method of selecting the parameters that produce the best results in the prediction process for each of the models. You can see how there is a slight improvement over the method that uses all the parameters in the prediction.

Table 3: Machine learning methods score with the selection of the best parameters to train.

Machine learning method	Accuracy
Random Forest	0.799
Decision Tree	0.830
K-Nearest Neighbors	0.854
Support Vector Regression	0.857
Linear Regession	0.857

4. Conclusions

This paper has presented a review of the main models of machine learning focused on the prediction of energy consumption. Specifically, the models of machine learning that the literature shows that better results produce (K-Nearest Neighbors, Linear Regression, Random Forests, Support Vector Regression and Decision Tree) have been evaluated.

In the case of the study that has allowed the evaluation of machine learning models, daily consumption data of a dwelling composed of two people have been used. These data have made it possible to know that the LR and SVR has obtained 85.7% accuracy, partly due to the inclusion of the previous day in the training process, with Random Forest being the model with the worst result, being 79.9%. However, this comparison does not mean that LR and SVR is better than the rest of the models, simply because it fits better the variables that make up the dataset (day, weekday, week, presence and so).

As future work is proposed the expansion of variables to be incorporated into the data set as the outdoor temperature, solar radiation on the facade of the building, relative humidity or precipitation measurement among others, as well as a comparison against other models of machine learning or statistical methods.

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Demand response approaches for real-time renewable energy integration
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Electric Water Heater Modeling, DR Approaches Analysis and Study of Consumer Comfort for Demand Response

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Abstract

With the smart energy management system household residential appliances is able to participate in the demand response events. To reduce peak load demand and complexities in the local infrastructure DR can play an important role now a days. This paper presents a study and analysis of several papers on residential EWH DR modeling and implementation. It shows an overview of analysis of the most used and recent DR models for EWH. It also shows the analysis of the used methods to model this and the used approach in several papers. Additionally, the discussed consumer comforts and obtainable benefits in several papers by participating in DR events is also shown here. The study and analysis in this paper will contribute to the future research and encourage the end users to participate in households DR events.

Keywords: comfort analysis, demand response; model analysis

1. Introduction

Smart grid (SG) technology is used to develop the modern energy management system. Now a days the focus has been shifted to demand side management (DSM) as the main focus of this is to manage the demand load curve by peak shaving, peak shifting and valley filling [1]. In SG, the efficiency and reliability can be improved also by delivering energy from the suppliers to the customers with the help of modern digital technology [2]. Sufficient grid flexibility and energy efficiency can be provided by the integration of SG technology in the building energy management system (BEMS). It is the main motivation to provide an efficient and reliable energy system of climate and energy targets 2020 namely “20-20-20” [3].

DSM is the potential most solution to solve the problems during peak load consumption. For the purpose of covering all concepts and methods for energy management system in demand side is covered by DSM [4]. There are different types of DSM strategies in controlling domestic EWH.

In the SG, demand response (DR) mechanism is an important feature for the electricity management. The capacity of DR is stated as “the potential for flexible response from end-use appliances across the commercial, industrial and residential sectors” [5]. To reduce both total energy consumption and peak demand, DR is used as a basic tool by the Independent System Operators (ISOs) in the recent modern electricity infrastructure. It has an important contribution by managing electricity demand in response to supply conditions in the smart grid technologies. Time-based rates and incentive-based programs are the important features of DR [6].

EWH is the largest single consumer of electricity so it is the most suitable appliance to be considered for DR events. In the modern grid a significant source of energy consumption is represented by the EWH. In the form of a water storage tank it has also built-in thermal storage system inside of it. It has also higher nominal power ratings combined with large thermal buffer capacitance that make it well suited for demand management. It does not need reactive power support from the grid because the heating element is actually a resistor. This special feature makes the heater very flexible and convenient to control the switching actions.

Additionally, the water heating in the heater is easily shiftable in time as it does not impact significantly on the user's comfort. The considerable temperature inside a heater range from very low to a very high value (e.g., 40 – 85 ºC). So, it does not interrupt the consumer's comfort level due to this higher range of temperature [7].

The rest of the paper is organized as follow. Section 2 represents the different model analysis from several papers. Modelling approach or DR approach is described in Section 3. Section 4 discusses the consumer comfort analysis from different papers. Finally, the main conclusions of the paper are discussed in Section 5.

2. Different Model Analysis

There are several models existing in the current electricity management system for demand response of EWH. Overall 100 papers were analyzed and studied for this purpose. An Excel work sheet was made to analyze the overall models. From the study it is found that Load Model [8], [9], [10] is the most used model in the EWH management system. This model discusses the electrical heater load characteristics and behaviour in according to the appliance elements. Then the second most used model found in the study is the Thermal Model [11], [12], [13]. Thermal model discusses the thermal behaviour of the heater.

After a brief analysis it is found that Mathematical Model [14], Simulation Model [15], Aggregate model [16] and so on comes sequentially after this in the most used model. An overview of the analysed and studied model from several papers is shown in the Table 1 below.

Table 2: An overview of the studied model with reference.

Reference Paper No.	Used Approach
2.	Black-Box Model
17.	Linear Model
18.	Dual Element Model
19.	Dynamic Model
20.	Predictive Model
21.	User Comfort Model
22.	Physical Model
23.	Transient Model
24.	Boiler Profiling Model
25.	Statistical Model

There are several other interesting models also analysed in our study. For example, Average Illumination model, Metrics Model, Stochastic model Non-invasive model and so on.

3. DR Approach/Modeling Approach Analysis

The studied models are analysed by using different DR approach to be implemented in the smart energy management system. In this section, it was discussed about the studied DR approaches for the DR implementation based on the several papers analysis.

A group of approaches were gathered from several papers and studied in order analyse. From the analysis it is found that the most used approach is to Follow Water Temperature [26], [27], [28] of the heater. In this approach, the solution is taken based on the water temperature of the heater as it is considered as the main

parameter to solve. Then, the second most used approach is Load Control [29], [13], [15]. This approach is used to solve for DR of the appliance by controlling the load during peak load or high demand time.

Then it comes sequentially Load Shifting [30], Load Curtailment [29], Direct Load Control [31] etc is in the list of used approach for DR in the studied papers. Load Shifting is used to shift the EWH load, Load Curtailment is used to curtail the EWH load and Direct Load Control is used to control the heater remotely during the peak demand period. An overview of the analysed and studied approaches from several papers is shown in the Table 2 below.

Table 2: An overview of the analyzed approaches with reference.

Reference Paper No.	Used Approach
10.	Cluster Analysis Method
32.	Linear Optimization
16.	Monte-Carlo
2.	Machine Learning Algorithm
33.	Smart Metering Solution
34.	Artificial Neural Network
35.	Load Scheduling
36.	Dynamic Pricing
37.	Peak Shaving
14.	Parameter Analysis

There are many other existing DR approaches also studied during this work. Among them the interesting approaches are Heuristic Algorithm, Water Temperature Assessment, Mixed-Integer Non Linear Programming.

4. Consumer Comfort Analysis

This section describes the analysis of consumer comforts based on the study of the used model and DR approach from the papers. It also discusses the consumers benefit or convenience for the proposed analysis. Water Temperature Profiling [8], [11], [38] is the most found user convenience situation in the studied paper. The term means that user can have a clear profile of the water inside the heater. This will help them to use the heater according to their needs.

The second most convenience found from the analysis is Peak Load Reduction [30], [39], [40]. This term means that by using the proposed method in the referenced paper, peak load can be reduced so that it can fulfill the DR conditions. The other comforts and user convenient terms are found like Low Computational Complexity [15], Performance Analysis [41] and Pricing Knowledge [30]. An overview of the analysed and studied user comfort from several papers is shown in the Table 3 below.

Table 3: An overview of the analyzed user comforts and benefits with reference.

Reference Paper No.	User Comforts/Benefits
13.	Usage Prediction
42.	Power Management
28.	Cost Minimization
30.	Financial Benefit
12.	Energy Consumption Reduction
18.	Thermal Comfort
43.	Optimal Control
21.	Payback Effect Decreasing
22.	Parameters Identification
24.	Efficient Energy

With the above mentioned user comforts and benefits there are other benefits and comforts for end users found during the analysis also. Among those the most important options are Load Extraction, Smart Interface, Energy calculation, Energy savings etc.

5. Conclusions

The main challenge in the traditional electrical infrastructure and management system is to balance demand and supply during peak demand time. The complexity is also growing because of the increasing penetration and uncertainties of the renewable and distributed energy resources. Residential household appliances have a great influence in the peak load increase among the local grid. To solve this issue smart energy management system and demand response can take part in the electricity management.

Among the several residential appliances, electrical water heater is considered to analysis in this paper. It includes the study of the used models in several papers, the approach to model this is for DR purpose and at the end the benefits or comforts analysis for the users.

This study reveals that there are several models are very convenient to use, implement and execute to perform DR for residential heater. This will show a pathway for the researchers to work on EWH in future and choose the right models for their work. Also, it discusses the used convenient approaches to solve this and model this. An overview of the user comfort and benefit analysis is also shown which will encourage the consumers to make participation in households demand response.

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Demand response approaches for real-time renewable energy integration
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An Optimization Algorithm for Cost Minimization in Residential Buildings

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Abstract

The increment of the electricity consumption around the world has led many efforts on the network operators to reduce the consumption in the demand side and encourage to increase the use of renewable energies. Since the buildings have a significant part in energy consumption, and lighting systems have an important role in the energy consumption of the buildings, the optimization of the lighting system should be effective. Hence, the focus of this paper is to minimize the lamps consumption of a residential house based on electricity price and try to take advantages from photovoltaic generation as much as possible. The methodology of this work is proposed as a linear optimization problem that manages the generation of a renewable energy resource, which supplies a part of the energy consumption of the house. For the case studies, the amount of the renewable energy generation, total consumption of building, consumption of the lights, and electricity price are considered.

Keywords: optimization, renewable energy photovoltaic

1. Introduction

Nowadays, the increment of electricity usage has become to a big global concern [1]. The environmental problems, such as global warming, and CO2 emissions have drawn the attention to the Renewable Energy Resources (RER) and optimization strategies [2]. A significant part of electricity consumption is dedicated to all type of buildings including commercial, residential, and industrial [3]. Currently the demand of RERs and Demand Response (DR) programs are increasing [4]. In the DR programs, consumers are emboldened to change their electricity consumption pattern based on the variation of electricity price, or technical commands from the network operators [5]. DR programs can be classified into two main incentive-based and price-based. Real-Time Pricing (RTP), Time-Of-Use (TOU), and Critical-Peak Pricing (CPP) are included in the price-based programs [6].

Due to environmental problems that have occurred aftermath of increasing electricity generation from fossil fuels, the attentions were drawn to the renewable energies [7]. Portugal also has investments on distributed generations and renewable energy. Recently in Portugal, the consumers are able to utilize the Renewable Energy Resources (RERs), consuming their own produced energy. In the past, they should inject all the generated power to the utility grid and pay for their consumption. However, with the new rules, the end-users are encouraged to consume their own produced energy [8].

In order to implement the DR programs in a building, the lighting system plays an important role. The lights are considered as dynamic and flexible loads somehow their consumption can be reduced or interrupted [9] [10].

However, the main purpose of this paper is to minimize the Electricity Bill (EB) of a residential house with optimizing the lamps consumption and interference of RERs, specially a Photovoltaic (PV) system that supplies part of power demand of the building. The lighting system of the building should be controllable for reducing the illumination. The system may consist several laboratorial and commercial equipment and instruments, such as several Programmable Logic Controllers (PLCs) and several energy meters that these technical issues are out of scope of this paper.

This paper is proposed in five sections. After this introductory section, the system description is presented in Section 2. Section 3 demonstrates the case study surveyed in this paper considering two different scenarios, and the obtained results are described in the Section 4. Finally, the conclusions of this work are presented in Section 5.

2. System Description

The proposed system regarding the optimization of lamps consumption in the residential house is based on the electricity price variation and PV generation during a day. In this way, the consumption reduction for each lamp is limited, and since any room should not lose its light completely, a minimum value of light for each lamp, have been considered. The residents of the house can define their preference for each lamp as numbers between 0 and 1 that show which lamp is more important or less.

The optimization algorithm that is used in this paper is started with definition of input data including generation of the PV, total consumption of the building, electricity price, and the detail of the total consumption of the lighting system. Algorithm needs a set point price to decide for optimizing. This set point can be defined by residences or can be calculated as the average price by algorithm. After checking the input data and conditions such as set point price and PV generation, if the desired condition is met, the optimization process is not required and should check the values again and again as long as the system is in the high consumption level or expensive price periods. Then, the program starts to optimize the consumption of the lamps to fulfill the system goal. Each lamp of the building has a priority based on its location and user preferences. After that, the required power reduction of whole lighting system, the maximum consumption reduction of each lamp, and the minimum required light intensity of each room are defined as several constraints for the proposed optimization problem.

This optimization algorithm is modeled as a linear problem which can be solved by software which has LP solver environment.

The objective function of the optimization problem is as in eq. (1):

$$\begin{aligned} &Minimize \sum_{t=1}^{T}\sum_{l=1}^{L} P_{(l,t)} \times C_{(t)} \times PR_{(l)} \\ &\forall\, t \in \{1,\dots,T\} \\ &\forall\, l \in \{1,\dots,L\} \end{aligned} \tag{1}$$

P is the power consumption of each lamp in each time period. C is the electricity cost in each time period. PR is the abbreviation of Priority of each lamp. L and T represent the total number of lamps and time periods, respectively. The model constraints are as in eq. (2)-(4):

$$\begin{aligned} &\sum_{l=1}^{L} P_{(l)} = RR \\ &\forall\, l \in \{1,\dots,L\} \end{aligned} \tag{2}$$

$$0 \leq P_{(l,t)} \leq MR$$
$$\forall\, l \in \{1, \dots, L\} \tag{3}$$
$$\forall\, t \in \{1, \dots, T\}$$

$$0 \leq PR_{(l)} \leq 1$$
$$\forall\, l \in \{1, \dots, L\} \tag{4}$$

RR stands for Required consumption Reduction, and MR is abbreviation of Maximum consumption Reduction that is considered for each lamp for avoiding turning off any lamp completely. As it can be seen in Eq. 4, corresponded PR for each lamp is a number between 0, and 1. The lamps with priority numbers close to 0 are the lower important lamps than lamp with priority number close to 1. It should be noted that the lamps that are considered for lighting system are able to be reduced.

3. Case Study

This section represents the case study used for verifying the proposed optimization methodology. As it was mentioned, the main purpose of this paper is to optimize the consumption of the lamps of a residential house, based on the electricity price variation. The considered house consists of three bed rooms, one living room, one kitchen, and two bathrooms, and the corridor. The overall map of the house can be seen in Fig.1. According to Fig.1, there are 10 reducible lamps in the house with 100 W maximum power consumption. Regarding the RERs, there is a PV system located at the top roof of the building, which supplies a part of the consumption of the building. The maximum capacity of PV generation is 4 KW.

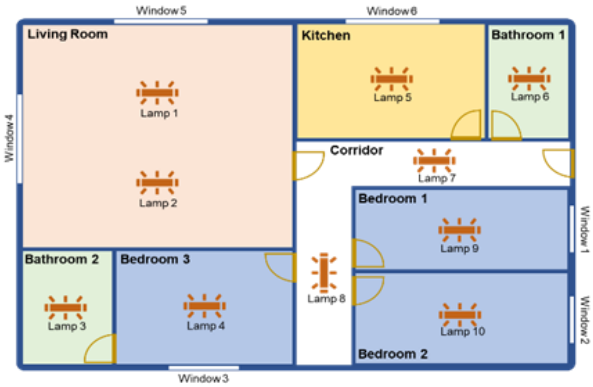

Fig. 1: Plan of the house and the lighting system.

If all the lights are turned on with the maximum intensity, the maximum consumption of lighting system in this house will be 1000 W. The total power consumption of the building, the power consumption of lighting system, and PV generation are shown in Fig. 2. This consumption profile refers to a daily profile in summer.

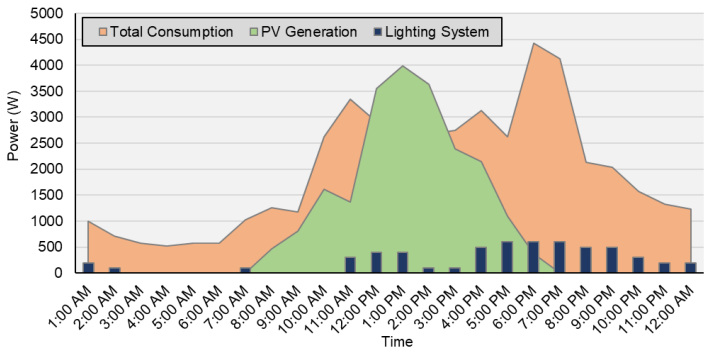

Fig. 2: Consumption and generation profile considered for case study.

As one can see in Fig. 2, the blue line indicates the part of the building consumption that belongs to the lighting system. As it is clear in Fig. 2, there are several moments that not only the PV generation (Green Columns) supplies the entire electricity demand of the building, but also the excess of the produced power can be injected to the utility grid, or store in energy storage if exist.

The electricity prices that are used for this study are the market prices for a summer day in 2018 and have been adapted from Portuguese sector of Iberian Electricity Markets [11]. The optimization algorithm checks the electricity price in each moment in order to calculate the set point price to make decision for running the optimization.

It is obvious that in the periods of day that PV generation can supply the electricity consumption completely, there is no need to reduce the lamps consumption despite the high electricity cost.

4. Results

This section represents the obtained results of proposed methodology. The consumption reduction of lighting system can be seen in Fig. 3. Also, the electricity prices are shown on Fig. 4.

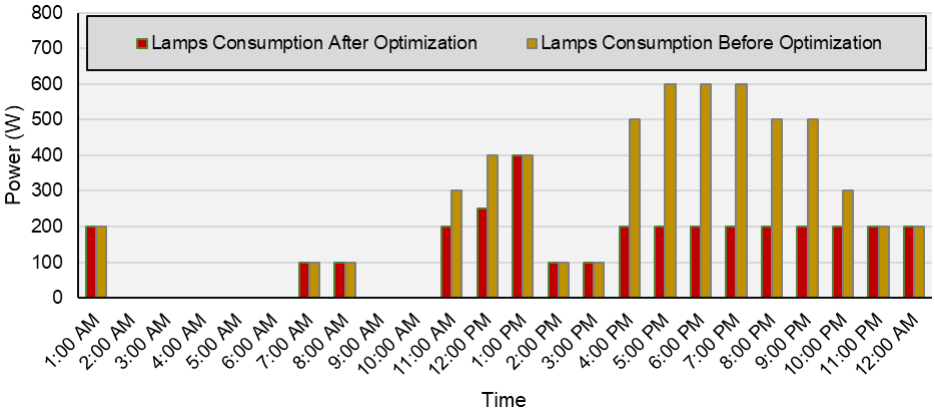

Fig. 3: Consumption and cost comparison between before and after optimization.

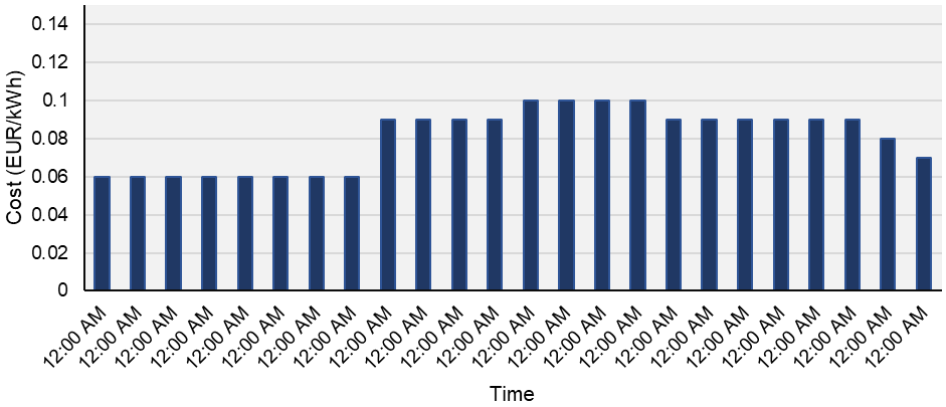

Fig. 4: The daily electricity price of a residential building.

As it can be seen in Fig.3, the lamps consumption is reduced in the expensive prices such as 11 am, and 12 am, or from 4 pm to 11 pm. There is no power reduction in some periods such as 1 pm to 3 pm which PV generation is enough for supporting the house consumption, despite the expensive electricity price. As a last result, Table 1 illustrates the effect of optimization in the energy bill of the building for one day.

As it can be seen in Table 1, the optimization process leads to reduce the energy cost of the house in one day from 0.506 EUR to 0.29 EUR, by respecting to the user's preferences.

Table 3: Accumulated costs comparison before and after the optimization (EUR).

Periods	Before Optimization	After Optimization	Periods	Before Optimization	After Optimization
1	0.012	0.012	13	0.127	0.127
2	0.012	0.012	14	0.137	0.132
3	0.012	0.012	15	0.147	0.137
4	0.012	0.012	16	0.197	0.157
5	0.012	0.012	17	0.251	0.175
6	0.012	0.012	18	0.305	0.193
7	0.018	0.018	19	0.359	0.211
8	0.024	0.024	20	0.404	0.229
9	0.024	0.024	21	0.449	0.247
10	0.024	0.024	22	0.476	0.265
11	0.051	0.051	23	0.492	0.281
12	0.087	0.087	24	**0.506**	**0.295**

5. Conclusions

In this paper, an optimization algorithm has been proposed for a residential house. This algorithm considered real-time pricing schemes and optimize the consumption of lighting system of a house in the periods that electricity price is greater than a specific value. The main purpose of the paper was to optimize the power consumption and reduce energy bill with take advantages of renewable energy resources. The presented model can be solved via several software with a linear programming solver environment.

Acknowledgements. The present work was done and funded in the scope of the following projects: H2020 DREAM-GO Project (Marie Sklodowska-Curie grant agreement No. 641794); and UID/EEA/00760/2019 funded by FEDER Funds through COMPETE program and by National Funds through FCT.

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Irrigation Scheduling in Crop Management System

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Abstract

Center pivor systems are widely used to suppress the irrigation needs of agricultural fields. In this article, we propose an autonomous to improve the low efficiency of this method of irrigation, developing a system based on the water requirement of the plantation, through field data (local temperature, local wind, soil moisture and precipitation forecast) and soil evapotranspiration calculation. The stored information will allow to calculate the real evapotranspiration, not being necessary to restrict to lysometric measures. Accordingly, it is possible to schedule the irrigation for the period in which it has the lowest cost, considering the energy produced locally and the price of energy bought in the main market. Irrigation must be carried out within the time interval in which the plantation does not reach the wilding point, so it will be carried out at the time of the lowest cost.

Keywords: agricultural irrigation, smart farming, water requirements, water resource scheduling

1. Introduction

The need for irrigation management has become relevant in many regions, specifically in Mediterranean, as result in the water resources are limited, changes in the climatic conditions and the negative effect of human behaviour on the environment.

The purpose of the irrigation is to give to plants the proper amount of water to guarantee their necessity. Requirement of water in irrigation system is very important, and the new irrigation methods should implement in such a manner that requires less water consumption when compare to old technologies. Smart irrigation means not only consuming less water it also provides water supply to optimize crop production.

For optimum yield, soil water in the crop root-zone must be maintained between desirable upper and lower limits of plant available water. Proper irrigation management will help prevent economic losses (yield quantity and quality) caused by over or underirrigation (plants should not pass the wilting point). The objective of irrigation management is to establish a proper timing and amount of irrigation for greatest effectiveness.

The measurements performed by the proposed system, in monitoring the soil moisture and the precise calculation of the evapotranspiration of the plantation have a significant advantage in terms of energy and water consumption. Real-time information on the current parameters of the system (soil moisture, evapotranspiration, precipitation) allows scheduling irrigation for the period in which it presents the lowest cost.

2. Literature Review

In this section, we first introduce central pivot irrigation systems, and then the related work is discussed.

2.1 Center-pivot systems

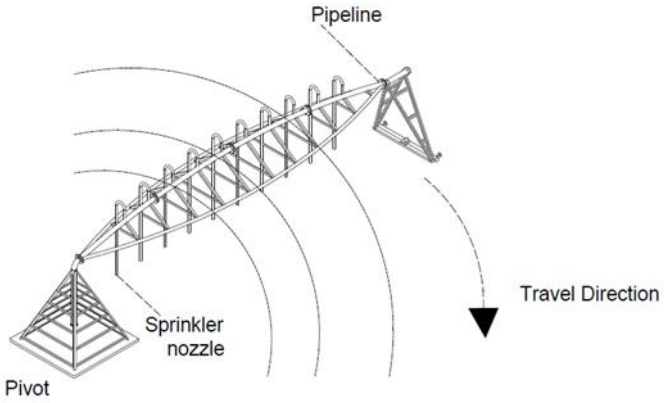

Fig. 19: Basic components of a center pivot (CP) system.

In agricultural fields, the intention to reach the maximum yield of the crop with the minimum operational costs has evolved consciously. One of the methods developed that improves the efficiency of the use of water, as well the use of energy is the irrigation by sprinkler with a system of center pivot (CP).

In Fig. 1, it is possible to visualize a CP in which equipment rotates around a pivot, in a circular path, and crops are watered with sprinklers as the machine moves [1].

2.2 Related Works

In [2], [3] a soil moisture sensor is used to water pumping the plantation when the minimum moisture level is verified, in addition [4] the system also incorporate solar photovoltaic is not only environmental friendly; it is also contribute to the improvement in power quality and enhance the reliability of the power systems [5], [6]. A Center pivot irrigation optimization to reduce the crop water necessity [7], [1] is proposed based on undergrounds sensors, and in [7] a multi depth sensors approach is tested to monitor soil. The evapotranspiration method to calculate the water requirements is proved in [8]. A approach for water irrigation scheduling is presented [9], which provides planning of the daily irrigation but not consider the minimum price of the energy bought from the main network.

The dynamic irrigation low limit method [10], which considers the parameters relates with crop growth and development time and water supply to settle the irrigation low limit. Four solutions of smart irrigation software are explained in [11], where is explored data obtained from different sensors.

3. Crop Water Necessity

To estimate the period and the adequate amount to irrigate the field, it is necessary to calculate accurately the evapotranspiration of the plantation.

The FAO Penman-Monteith method (1) is used to estimate the potential evapotranspiration (ET0) and the evapo-transpiration of the crop (ETc), which takes into account the stage of vegetative growth of the crop by weighting the potential evapotranspiration by the coefficient Kc. [8]

$$\boldsymbol{ET_0} = \frac{\mathbf{0.408}\Delta(\boldsymbol{R_n} - \boldsymbol{G}) + \boldsymbol{\gamma}\frac{\mathbf{900}}{\boldsymbol{T} + \mathbf{273}}\boldsymbol{U_2}(\boldsymbol{e_s} - \boldsymbol{e_a})}{\Delta + \boldsymbol{\gamma}(\mathbf{1} + \mathbf{0.34}\boldsymbol{U_2})} \tag{1}$$

ET_0 reference evapotransporation [mm.day^{-1}];
R_n net radiation at the crop surface [MJ.m^{-2}.day^{-1}];
G soil heat flux density [MJ.m^{-2}.day^{-1}];
T air temperature at 2m height [ºC];
U_2 wind speed at 2m height [m.s^{-1}];
e_s actual vapour pressure[kPa];
e_a actual vapour pressure [kPa];
e_s-e_a saturation vapour pressure deficit [kPa];
Δ slope vapour pressure curve [kPa.ºC^{-1}];
γ psychrometric constant [kPa ºC^{-1}].

The calculation of ETc (2) is the product of ET0 and Kc, where kc is determined from the type, growth length of the crop and selects the corresponding coefficients Kc.

$$\boldsymbol{ET_c = ET_0 * K_c} \tag{2}$$

ET_c crop evapotransporation [mm.day^{-1}];
ET_0 reference evapotransporation [mm.day^{-1}];
K_c single crop coefficient.

4. Proposed system

The circular irrigation infrastructure demonstrated in Fig. 2, introduces multiple zones of the agricultural field, in which we can have different plantations or plants of the same type but in different stages of growth. The system considers the irrigation need for each zone and acts on the speed of the infrastructure motor and valve motor of the water pumping, if it is necessary to irrigate the area in which the infrastructure is located.

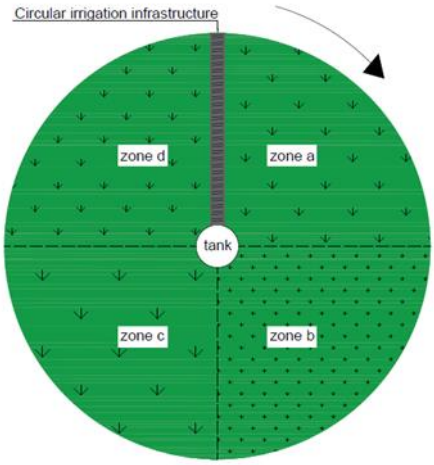

Fig. 20: The areas considered (a, b, c and d) may have distinct plantations.

It is calculated how many hours are left until the level of soil moisture is below the limit established for the plantation of the different zones, considering the evapotranspiration of each zone and the precipitation forecast.

In this way it is possible to obtain a daily schedule of irrigation for a given area considering the local energy production, the market price of energy and the restrictions of the logistic operation, in order to optimize the use of water and minimize the cost of energy purchased from the main market.

5. Conclusions

Real-time monitoring of agriculture has become indispensable and is a tool for obtaining data that are important for the development of energy efficiency systems. Therefore, the present methodology intends to take advantage of this information not only to minimize the use of water, but also to minimize the energy cost of the irrigation system's electrical installation.

Acknowledgements. The present work was done and funded in the scope of the following project: Eco Rural IoT project funded by TETRAMAX-VALUECHAIN-TTX-1, and UID/EEA/00760/2019 funded by FEDER Funds through COMPETE program and by National Funds through FCT.

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Aggregation of Consumers and Producers in a Community with different Clustering Methods

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Abstract

The consumer concept is shaping up as the grid is improving to a smart way. Moving from an actor with little information about what was happening in the energy market, to player with an active and important role in its management. The term prosumer will revolutionize the way the electrical system operates. The possibility of the participation of distributed small-scale energy resources in the network infrastructure changes the current management model. The authors propose a model that optimally associates all concepts. Scheduling, aggregation and compensation are the main phases that compose this model. In this paper, the author focusses only on the second, being the main goal compare between being a consumer, a producer or a prosumer in this method. In this way, two partitional clustering methods were used, testing different k clusters.

Keywords: aggregation, clustering, market, prosumers, smart grid

1. Introduction

The era of smart grids has revolutionized the energy market and opens the door to new players. In this context, one of the main objectives is to move from a formerly centralized model to a more decentralized paradigm, allowing the participation of Distributed Energy Resources, [1]. In this way, the consumer concept can be updated according to this new change. This introduced the prosumer – making a combo between the consumer, storage and local level generator capabilities. Through the Smart Grids, there is the possibility of participation in the small-scale production market, enabling this new consumer, which now may have the possibility to produce its own energy. With this ability, doesn‘t need to request anything from the network and may also, in some cases, sell the excess. Most of them rely on, for example, solar energy sources, through photovoltaic panels, [2].

There are several benefits associated with this change for a smarter grid: reliability increase, carbon footprint reduction, increase in revenue and decrease in consumer energy expenses. However, the current transportation and distribution system is not ready for a successful implementation and hence there is still a long way to go. Right now, the grid presents challenges in terms of design, operation, control, energy storage technologies integration and regulatory issues. It is necessary to update and apply new Information and Communication Technologies so that the system can flow correctly and reliably, [3]. Overcoming these difficulties, prosumers and small-scale production will be allowed to make electrical and economic transactions in so-called local electricity markets (also known to micro-markets by some authors). They can feed consumers belonging to the local community, reducing, for example, transport losses, [4].

In this paper, the authors suggest a way of integrating these local and small-scale markets into the energy market through aggregation with clustering methods. This is the development of previous work, [5]. Thus, one of the main objectives will be to compare the benefit of being prosumer in this type of model: consumers and producers will be separately aggregated and then as prosumers. Throughout this paper two types of clustering methods and various k cluster will be tested.

The first section presents a brief introduction to the main topic addressed throughout this paper: prosumers. Next, the approach by which the authors decided to invest and the proposed model is described. The third section presents the case study and the fourth section the results coming from it, as well as its analysis. Finally, it presents the conclusion of the studied subject.

2. Approach

As discussed in the previous section, this paper deals with the development of previous work. In this section, the proposed model is presented in order to situate the reader in the context in which this article is developed. Therefore, the Fig. 1 presents an overview of the model, highlighting the part in which this work focuses. The three main phases are presented and then a general description of what the purpose of each of them will be presented.

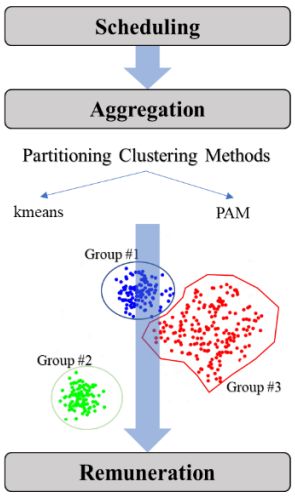

Fig. 21: Overview of the proposed methodology for this paper.

In the infrastructure of the electrical system, the aggregator may play a crucial role. This methodology presents the proposal of the authors of how it may be linked to the tasks belonging to the market of this sector.

First, the model proposes that an optimization should be made to schedule all the resources associated with a particular aggregator, in an optimal way - these resources may be small scale distributed production units, consumers that can be part of demand response programs and suppliers. Only if small-scale resources fail to supply the demand, the suppliers will be used. The input parameters for this optimization may, for example, consider the price elasticity of demand, the possibilities of direct control of the load or even the production of either heat or electricity. The objective function is to minimize operating costs from the Virtual Power Player (VPP) point of view and, in addition, to fairly remunerate all resources that are aggregated and actively participate in community management. In this way, price and operating restrictions are considered in this optimization as well as operational restrictions imposed by the VPP in order to achieve its objectives

Finishing the optimization, the second phase of the model imposes itself - aggregation of resources. The definition of groups is performed taking into account the results obtained previously. By grouping these small resources, the VPP will be able to enter the market with a considerable amount of energy. With this, it will also allow the entry, in a more direct way, of this type of consumers / producers in the transactions of the market.

In this paper, the authors chose to use a clustering method that is one of the most famous of unsupervised machine learning when it comes to partitioning – kmeans. The model created by Hartigan-Wong in 1979 defined one of the possible variations for this method. The total variation within a cluster is then taken to the sum of the squares of Euclidean distance between a point and the center of the cluster, and then assigns the point to the nearest cluster, [8]. This study was carried out using software R.

In the end of this paper, the authors propose to compare the results obtained for kmeans with another clustering method belonging to partitioning – Partitioning Around Medoids (PAM). PAM is a method that looks for objects to represent a cluster – medoid. At each iteration, it is considered the exchange of the current medoid by a non-medoid in the case of some improvement. The criteria of the objective function - the minimization of the sum of the dissimilarities of all objects relative to the nearest medoid, [6]. However, PAM has a disadvantage relative to larger datasets. The problem of finding relatively small clusters in the presence of large clusters in the data set is a difficulty for this method. In the case of databases being greater than thousands of observations, Clustering Large Applications (CLARA) is an extension of this method to deal with this type of problems, [7].

Regarding the last phase of the model, the remuneration step, after aggregation, resources will be rewarded by continued collaboration with the aggregator. This phase serves as a motivation and as a advertising for new potential candidates for the aggregation. Through the cooperation of all resources, the management of network operation flows optimally.

3. Case Study

In this section it is detailed the case study that will be studied throughout this paper. The objective is to apply the second phase of the presented model - aggregation, to a data base constituted by 100 consumers and 100 producers. With the introduction of the concept of prosumers, the authors include it in this study. In this way, and with the existing players in the database, the hypothesis of each of them was tested to form a prosumer. Thus, in the end, the aggregation of 100 prosumers will be tested.

This database was provided by the company Discovergy, which through its smart meters can obtain different types of information, important for this type of study, from its clients. In this paper, only the energy consumed and produced were used. For each of the elements of the database, there is data with intervals of 3 minutes. In this paper, the authors opted to use 175 210 values of those collected in order to provide the method with a high set of elements.

4. Results

This section presents the results obtained by applying the model proposed to the case study presented previously. In a first phase, the idea would be to compare different k clusters through the kmeans clustering method. At Fig. 22 the results for the aggregation of consumers are presented. To aggregate this type of player, the values of energy consumed (kWh) were used by each of the 100 consumers studied for a total of 175 201 periods (with intervals of 3 minutes).

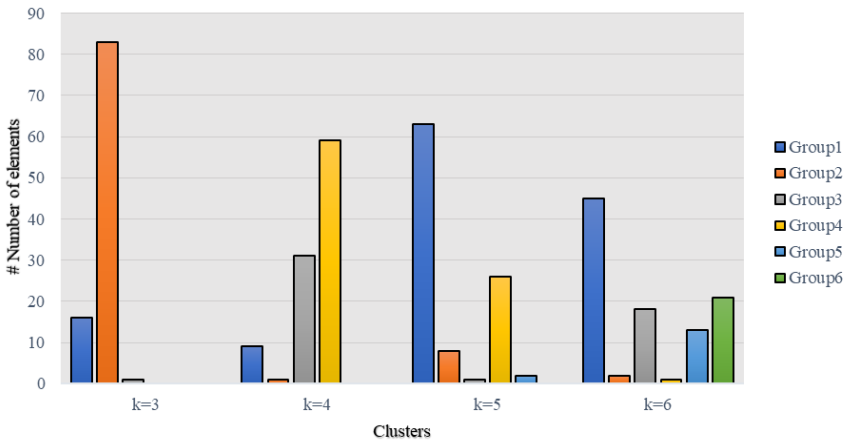

Fig. 22: Consumers – Results from clustering method kmeans for different k clusters.

Table 4: Consumers – Detailed results from clustering method kmeans for different k clusters

	k=3	**k=4**	**k=5**	**k=6**
Group1	16	9	63	45
Group2	83	1	8	2
Group3	1	31	1	18
Group4	0	59	26	1
Group5	0	0	2	13
Group6	0	0	0	21

Through the analysis of the Fig. 22 e da Table 1, for k = 3, the method agglomerated most of the consumers in Group 2. Regarding k = 4, the group that led the previous test was divided into Group 3 and Group 4, the latter group with most of the elements. Already in k = 5, the 63 elements that form Group 1 were also in the referred groups. Finally, at k = 6, the elements are more dispersed, emphasizing that the Consumer 25 has been kept in a separate group in all tests performed.

Turning to the analysis of the Producers, the logic was the same as that presented previously with the Consumers database. Together, the Fig. 23 e a Table 5 present the results from the aggregation of the elements from the database with 100 producers.

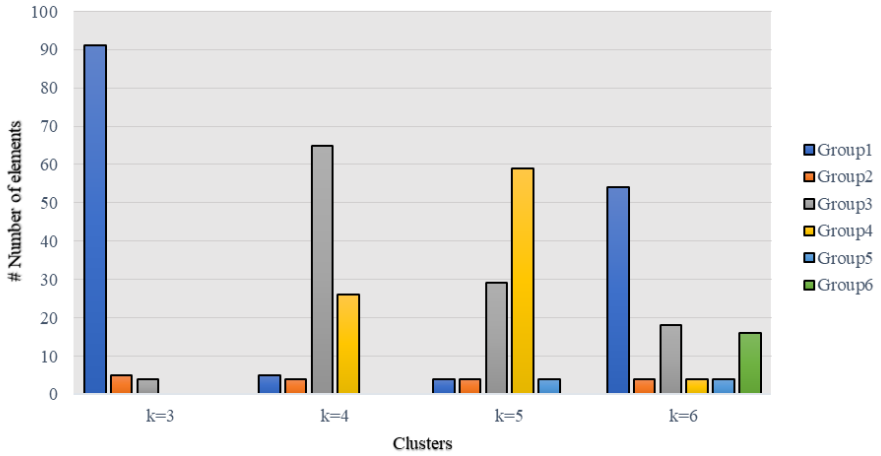

Fig. 23: Producers – Results from clustering method kmeans for different k clusters.

Table 5: Producers – Detailed results from clustering method kmeans for different k clusters.

	k=3	**k=4**	**k=5**	**k=6**
Group1	91	5	4	54
Group2	5	4	4	4
Group3	4	65	29	18
Group4	0	26	59	4
Group5	0	0	4	4
Group6	0	0	0	16

The information in Fig. 23 and Table 5, shows that for k = 3, this method chose to join most of the Producers, 91 elements in 100, in a group. Although in k = 4, these same elements form groups 3 and 4. Moving to k = 5, 3 of the 5 groups are formed by 4 elements. Finally, for k = 6, Group 3 and Group 6 are formed mostly by elements formerly belonging to Group 3 in k = 5.

Moving on to the analysis of the prosumers, this new player was formed through the junction of the Producers and consumers previously studied. Again, following the aforementioned logic, we tested the

kmeans clustering method for different k clusters. Like the figures and tables presented above, the Fig. 1 e a Table 6 show the results obtained for the aggregation carried out.

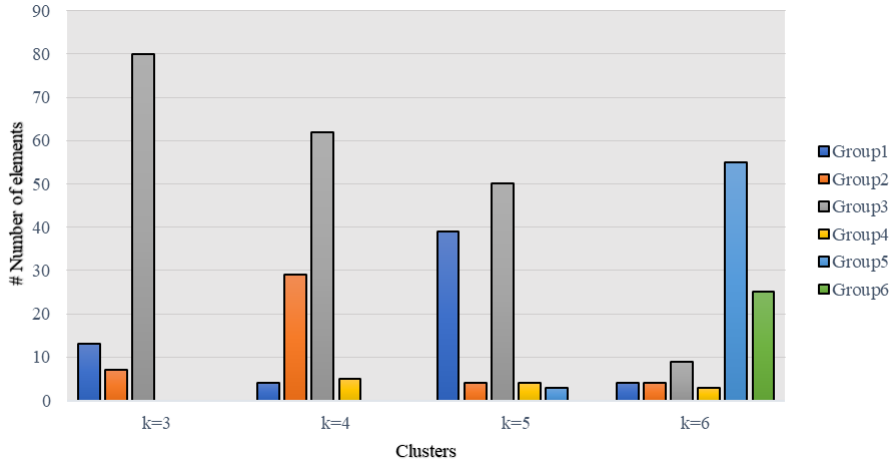

Fig. 24: Prosumers – Results from clustering method kmeans for different k clusters.

Table 6: Prosumers – Detailed results from clustering method kmeans for different k clusters.

	k=3	**k=4**	**k=5**	**k=6**
Group1	13	4	39	4
Group2	7	29	4	4
Group3	80	62	50	9
Group4	0	5	4	3
Group5	0	0	3	55
Group6	0	0	0	25

After examining and comparing with the previous results we can verify that, as in the case of the Consumers in k = 3, the group consisting of the majority of the elements has about 80. This groups are rather similar since 66 of the 80 elements are the same that belong to Group 1 of the Consumers. In k = 4, we can see similarities in the case of Producers. It should be noted that two of the groups have the same elements: Group 1 corresponds to Group 2 of Producers and Group 4 corresponds to Group 1 of Producers. At k = 5 and k = 6, the similarity continues between this Prosumers test and the Producers test.

It was also decided to test another method of clustering. In this paper, the selected method was CLARA, an extension of PAM, and it was compared for a k cluster - in this case we chose k = 6, with the method used before, kmeans. Considering the two methods belonging to Partitioning Clustering, the authors found this final comparison interesting.

Table 7: Comparison between two clustering methods.

	Consumer		**Producer**		**Prosumer**	
	CLARA	**kmeans**	**CLARA**	**kmeans**	**CLARA**	**kmeans**
Group1	43	45	32	54	25	4
Group2	22	2	55	4	39	4
Group3	10	18	5	18	1	9
Group4	18	1	1	4	28	3
Group5	6	13	3	4	3	55
Group6	1	21	4	16	4	25

According to the results presented in the Table 7, for Consumers the groups are similar, differing only in a very small number of elements. Concerning Producers and Prosumers, the differences are more noticeable.

5. Conclusions

The concept of smart grids revolutionized the electrical system and with the introduction of new concepts the level of complication of the management became higher. The possibility of distributed resources to actively participate allows the creation of the concept of prosumers – consumers with the possibility of producing and even selling their own energy. The authors suggest a methodology to manage these new players more efficiently - through aggregation methods. By associating them optimally, it will be easier to enter the market and then, according to the model proposed, remunerate the resources in accordance with their cooperation to better manage the operation of the network. This paper focuses on the aggregation phase, comparing different clusters and two different methods.

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Demand response approaches for real-time renewable energy integration
Fourth DREAM-GO Workshop

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Demand Response Approach for the Coordination Between Aggregators and Providers

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Abstract

Nowadays electricity system is looking for innovation in its role. New approaches are being able to discuss because of several issues as environmental, costs, quality and reliability of the electric energy production. In this paper one more aggregation's scheme for demand response will be proposed. Based on National Grid's programs that already exist in the market which will be shown on the current paper. This paper will be a support for a master thesis in electrical engineering based on the same topic.

Keywords: aggregation models, demand response, market.

1. Introduction

Market liberalization isn't a new approach in Europe anymore, even looking for a retailer or wholesale market. The meaning of this paper is an approach on demand response models regarding to UK's programs.

To improve system's reliability, quality and reduce price for the end consumer, according with, [1]–[9], renewables energies has been installed. Managing this production is not an easy task due to renewable production hasn't an accurate forecast during short term. In fact, within one timescale day solar and wind productions can quickly change, due to weather conditions.

The meaning of flexibility, according with [2], is how consumers can change their profile's consumptions without including or removing elements of the manufacturing process (in factories' cases), so flexibility means the ability of changing consumption regarding to outside system's inputs to adapt itself to a better profile.

In renewable production's cases is necessary a more accurate balancing system. To balance the system, loads most be more flexible to shift consumption for demand response instructions, according with [2] and [3]. Both describes how a consumer can be more flexible in a manufacturing enterprise and its importance for the system and factory's sustainability improvement.

In [7], it shows how a provider can be flexible in a microgrid regarding to renewables productions. Providers most adapt consumption or production according with energy price (electric and natural gas), renewable production, demand requirements and storage. Regarding for the optimum point between energy purchase, production and consumption during one year of analyses.

According with [10], there are three types of aggregators. First, production aggregator, responsible to group small generators to access the market; Demand Aggregator, intermediate retailers or distribution companies and consumers with production and/or storage capability; and Commercial Aggregator, response

to balance energy supply and buy locally generation electricity. Those aggregations types are important to handle with system's balance and economics issues.

In UK during 2001 the New Electricity Trading Arrangements (NETA) were installed. The big difference between old system and NETA is that while in first one the cost of system's balance was divided by everyone who were connected in electricity system, in NETA the cost of balancing is within the market, making providers get paid to improve system's balance. (Now the) system is not like an electricity pool anymore where market used to change energy and money ignoring technical requirements of balance and operations.

Demand response in this new system can improve, technically, quality, reducing costs and open a new market with providers, aggregators and retailers.

To provide demand response is necessary to be in a pretty regulated market because there are several technical details that system must obey and financial requirements that are important for system's operations reliability. Thus, many entities are studying models to improve demand response. Firstly, models were just for the biggest loads on grid, in order to provide large scale. As consequence, most consumers couldn't be able to provide demand response. In order to solve this problem of provider's constrains, aggregation models in all parts of the world were getting importance to be implemented in the electric system.

The most important thing in this aggregation approach is to improve response reliability and increase power response in different sites of the distribution grid (and not just transmission system). with an aggregator providing DR's management smaller consumer can start to enter in the market of balance and production of energy in distributed energy resources cases.

2. UK programs

Table 8 Shows four demand response programs found in UK [11]–[13]. Those programs have some differences between each other in terms of response time, quantity, reduction or increase load and main meaning for the system.

Fast Reserve provides rapid and reliable energy delivery when it's needed by the system, in this case it improves system's reliability for a short timescale.

Table 8: National Grid's DR programs.

Fast Reserve		**STOR**		**DTU**		**FFR**
Requirements:		**Requirements:**		**Requirements**		**Requirements**
Delivery in 2 minutes after ordering.		Deliver at least 3 MW over a period of 20 minutes.		Minimum power of 1 MW.		Operational meter that switches loads.
Delivery rate greater than 25 MW / minute.		Provide for 240 minutes (continuously 2h).		Aggregates equal to or greater than 0.1 MW each.		At least 1 MW of response.
At least 15 minutes of cutting or production.		Instruction recovery in 1200 min.		Energy counter with by minute-by-minute or half-hourly.		Aggregation, communicate by only one site with the OS.
Deliver at least 50 MW.		availability three times a week.		Only e-mail access for instruction.		Communication with an automatic control device.
Fees:		**Fees:**		**Fees:**		**Fees:**
Availability [Pounds / hour] Remuneration for being ready to provide the service.		**Availability [Pounds / hour]** Remuneration for being ready to provide the service.		**Availability [Pounds / hour]** Fixed drive demand.		**Availability [Pounds / hour]** Provision for delivery.
Nominal [Pounds / hour] Reserve utilization in the available window.		**Utilization [Pounds / hour]** By capped energy in the available window.		**Utilization [Pounds / hour]** Fixed and optional demand.		**Initialization of window [pounds / window]** Payment for the windows in which they are requested.
Utilization [Pounds / MWh] By capped energy in the available window.		**Optional [Pounds / hour]** By limiting power outside the available window.		-	-	**Utilization [Pounds / hour]** Use when requested.
-	-	**Services** Committed and flexible		-	-	**Window Review [Pounds / hour]** For calls outside the contracted window.
-	-	-	-	-	-	**Energy response [Pounds / MWh].** Energy provider delivered.

The meaning of STOR is to provide extra power to help manage actual demand on the system being greater than forecast or unforeseen generation unavailability.

Demand Turn Up (DTU) is used to manage renewables energy resources. When the renewable production's level is high, and the consumption is low is necessary to use this energy in a useful way to hold system's balance. Then DTU is used for this type of balance situations.

Firm Frequency Response (FFR) gives for the provider and SO (System Operator) an alternative route to the market, necessary for the price uncertainty. In this program providers can be in available in the same time in another kind of DR's program and system's frequency is improved.

A simple brief of those programs is presented on Table 8 with some technical requirements and types of payments to provide each program.

3. New proposed model

Is proposed a new model of remuneration and penalties regarding for an aggregation communication between provider and aggregator. This new model has been implemented in a computational simulation with twenty providers managed by one aggregator.

Firstly, is necessary to contract providers in a tender process. In this part, each provider agrees with an aggregator the response information, on which most contain all data of available response. Including: Contract Power (CM), normally in MW for large-scale providers; Response Time, is the time that each provider can maintain continuously the contracted power; availability and utilization's fee; maximum permissible error, it's maximum error in delivered power that the provider can fail. If provider deliver less than maximum error, it's considered as deliver failure and it won't be remunerated in the current settlement period. Else it's considered success but by this percentage will reduce availability and utilization payments.

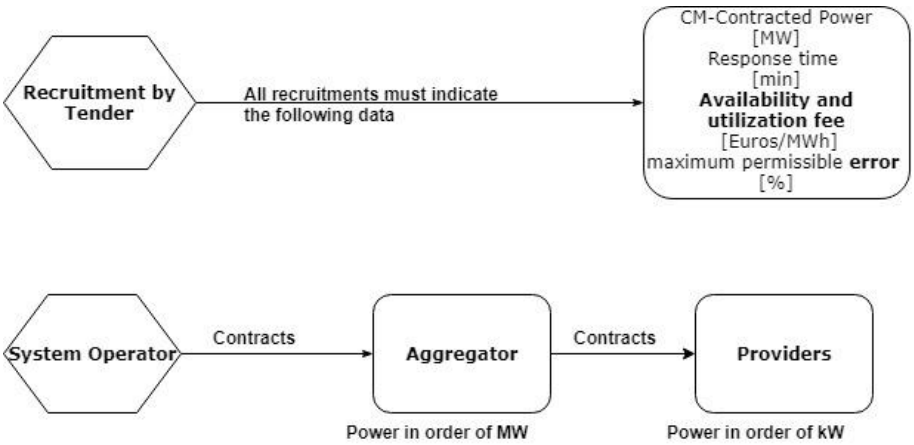

Fig. 25: Contract flowchart.

Fig. 26 presents how providers are dispatched. To provide is proposed a time before the event's beginning to do a communication between provider and aggregator to improve response's reliability and to bring more flexibility to providers in different event's situations.

Firstly, in Fig. 26**Error! Reference source not found.** the aggregator consults all providers about how much they can provide in the next event. "Treply" is the reply time to providers send an answer to aggregator about how much they accept to provider (provider's reply variance is set in the initial contract); "Tanalyze" is the aggregator's time to analyze all possibilities between providers to reduce load, in that time he calculates the optimum dispatch looking to utilization fee, power available and power needed to reduce; Notification is the moment that the aggregator sends a signal to each provider be dispatched, in that moment they will receive the information about how much power they have to provide, how long and the exactly time.

Ramp up and down can be done however providers prefer due to the only requirement is that after event time and before event end the delivered power most be the instructed power by aggregator.

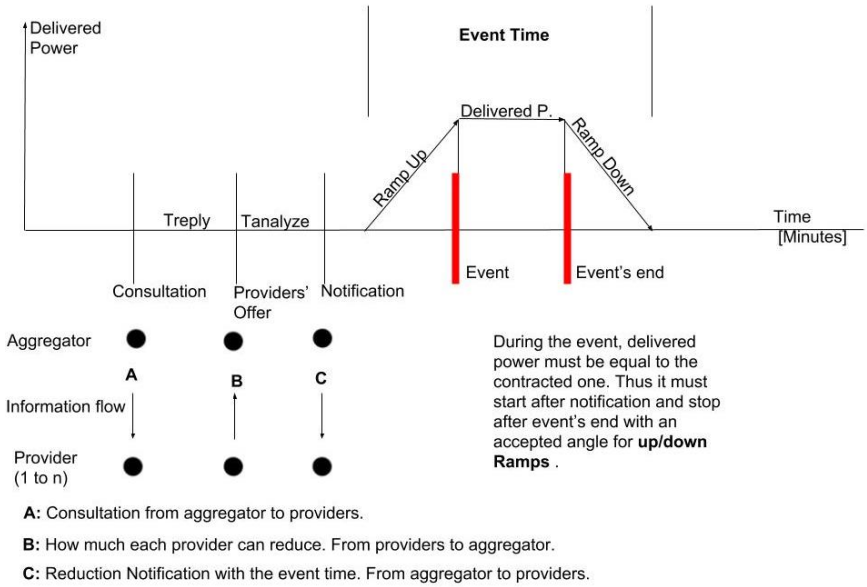

Fig. 26: Event Timeline.

Fig. 27 shows a flowchart describing how aggregator's communication works between all providers and acceptance conditions. In the first part aggregator send the first signal, which has response time data with reduction time, event date and power required. All providers have it as input and they analyze according with their respectively issues. After this period, fixed by contract within any settlement periods times, providers reply to aggregator an output with the valuer of power and time that they accept to provide.

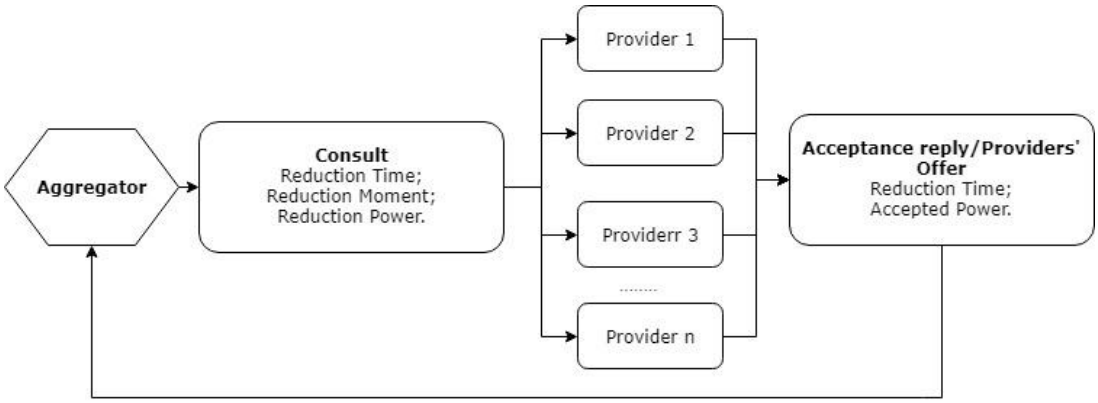

Fig. 27: Aggregation's consultation and providers' offer.

4. Payments

To calculate providers' remuneration this model presents two simple types, called: Availability and utilization payment. Both were inspired in STOR.

First payment scheme is shown in Fig. 28 as availability payment, this flowchart demonstrates all possible situations for each settlement period.

Where, in Fig. 4, the first stage is a failure ask, if in the current settlement period it have failed. If it has the current won't be remunerated. Weather not, it sums all previous failures and increase MP in 1% for each failure (the maximum MP can be negotiated between them). After calculate MP, Rb (Base remuneration, called availability) is done according with contracted data presented in Fig. 1.

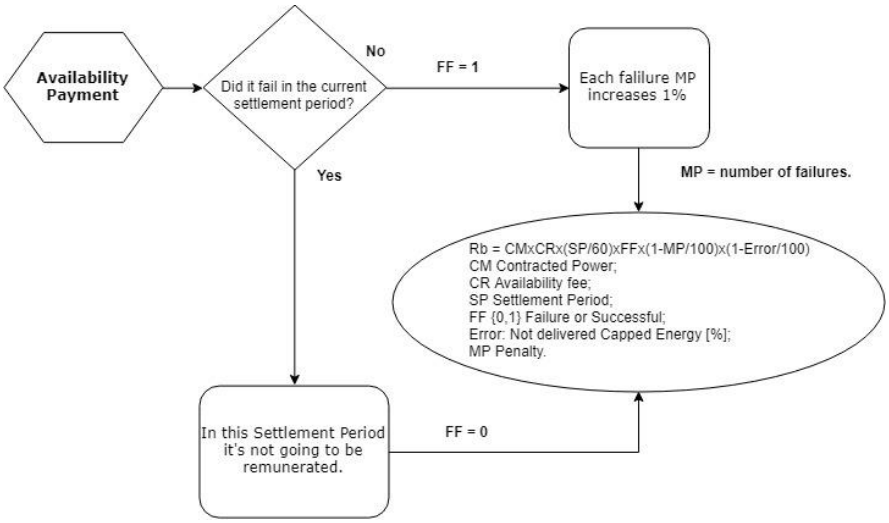

Fig. 28: Availability payment scheme.

Secondly, proper utilization remuneration is shown in the flowchart (Fig. 29).

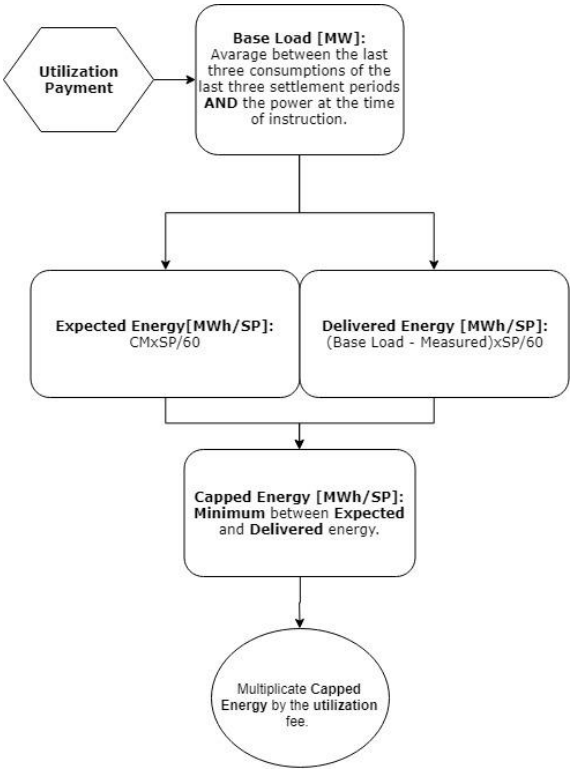

Fig. 29: Utilization payment scheme.

For Fig. 29 its calculations will be done in the event time (red colour in Fig. 26) and stops in the event ends (second red color).

Base load means how much power it was consuming moments before the event. The average between the current time of the notification (instruction) and three last consumptions values, one for each settlement period. Those four values are used as base load to the next steps.

Expected energy is how much it should be providing in the current event and delivered energy is how much it's really providing for the system. Calculated by base load less measured in the current SP. Showing how much it's reduction of power comparing with the previous load (Base Load).

Finally, capped energy is the minimum between expected and delivered energies. Weather it's providing more than expected it will be remunerated by the expected. Otherwise it will be remunerated by how much it is really providing.

According with capped energy is applied utilization fee to calculate how much money it will receive for the current SP.

Total remuneration is the sum of availability and utilization's payment.

5. Case Study

To validate the proposed model a simulation has been done. Using a university campus as one group of providers, where each building represents one provider with its own consumption's profile.

During one consumption year, all providers are considered able for demand response in the high load periods of the day, according with [14], it's shown in Table 9.

Table 9: Peak of electric system's load.

Winter (29/out – 26/mar)	**Summer (26/mar – 29/out)**	**Time (Peak/Not peak)**
9am – 10:30am	10:30am – 1pm	Peak
6pm – 8:30pm	7:30pm – 9pm	Peak

Those times are used to instruct providers along one year for demand response analyses. Is chosen these periods of event because they represent the biggest consumption period in Portugal, according with [14].

Table 10: Maximum interruptible power of each provider.

Provider	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Power [kW]	0.391	0.35	0.436	1.98	1.724	0.562	0.196	1.236	3.564	1.493
Provider	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Power [kW]	2.156	0.715	3.65	1.119	0.929	0.424	1.383	1.283	0.629	1.02E-02

Table 10 shows how much power providers can dispatch within a reduction event as related in Table 9. This level of power comes from each providers average between the higher hours of their consumption. Due to reliable measurement and uncertain about consumers reducible profile is taken as maximum reducible load 90% of the average between 12:30pm and 3pm consumption of each one.

Table 11: Aggregator's notification.

Provider	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Power [kW]	0,704	0,630	0,914	5,352	3,103	1,011	0,353	2,810	6,414	2,687
Provider	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Power [kW]	3,881	1,287	6,569	2,504	2,029	0,888	3,220	2,938	1,132	0,031
		Required by SO [KW]:		48,457						

Table 11 shows how much power each provider is dispatched after aggregator's optimization, regarding to minimizes costs and provide required power by SO. In this case the optimum is found using Dual-Simplex

as a deterministic exact optimization approach, which isn't useful for a bigger case study, due to its low converge velocity comparing with other optimizations approaches as found in [2], [5]–[7] and [9].

Simulated one year of demand response with those twenty providers, one aggregator and the System Operator to produce profit with demand response.

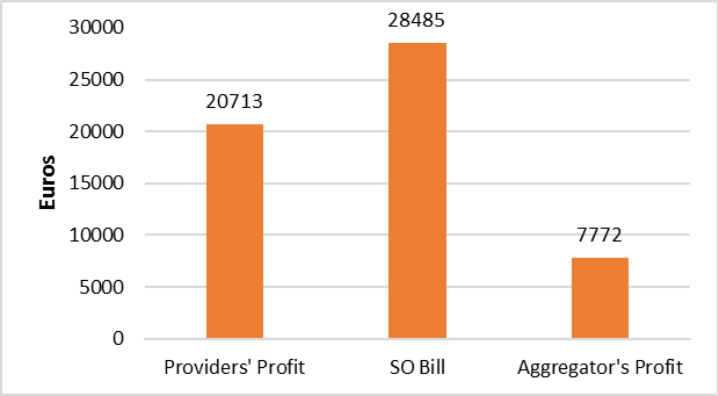

Fig. 30: Aggregation's result.

Fig. 30 shows how much SO most to pay for the system balancing after one year reducing loads in the high energy consumption's moments.

All providers will be remunerated by €20713.00 as showed before but in this valuer isn't includes costs of implementation of any device or other possible cost that can be made by adhering the program. Aggregator will be remunerated as the difference between SO's Bill and Providers' profit, due to SO pays to the aggregator and aggregator pays to providers.

6. Conclusion

This model is a new approach to manage demand response with aggregation. It's an important role to improve links between small providers of renewable energies and/or demand response with the electricity market, where is needed more purchase power to deal with that environment.

Its validation has been done in a simple way so the second step for future works is simulate with real time load to measure power reduction with real devices to control the system's response. Loads most have a real reducible power with a useful machine (for example, heating, cooling, elevators, light controlling, etc…) can be changeable examples for demand response applied in real terms.

Acknowledgments. The present work was done and funded in the scope of the following project: H2020 DREAM-GO Project (Marie Sklodowska-Curie grant agreement No. 641794).

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Demand response approaches for real-time renewable energy integration
Fourth DREAM-GO Workshop

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Applying real-time pricing for wind curtailment scenario using D2RD module of TOOCC

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Abstract

Multi-agent systems are widely used tools to simulate and study the energy sector because of their distributed architecture. There are several simulator tools available in literature, however, much of these prove to be very domain specific. The emergence of the Tools Control Center tool allows these simulators to cooperate in order to solve more comprehensive problems and more complex scenarios. This paper presents a module of this tool known as Demand Response Registration Digital, which allows the study of the model and programs of Demand Response. To understand the operation of this module, an example is given considering a wind curtailment scenario.

Keywords: demand response, energy resources management, multi-agent simulation, real-time simulation, semantic interoperability, smart gridIntroduction

1. Introduction

Achieving an increasingly clean and sustainable energy policy are the main objectives of the European Union for the coming years. To make this possible, the EU has set targets that will significantly change the behavior of electric power systems, as well as the role of participating entities. These targets are aimed at reducing greenhouse gas emissions, increasing the use of energy from renewable sources and increasing energy efficiency [1].

With the growth in the use of renewable energy sources, especially with Distributed Generation, network management has become a much more complex task due to its impact on the grid. Although it has great advantages such as reduced cost of on-peak operation, reduced losses, and increased quality of service, the unpredictable nature of this type of power source makes network balance and reliability a challenge. This way, it is necessary to find efficient mechanisms for the study of these systems that allow to detect failures, to plan the energy management and even to find more efficient models [2][3]. In this sense, the simulation tools have a great importance, since its versatility allows to support the diverse activities of the sector, from the operation of the network, to the final consumer [4]. In the literature can be found several simulators for the various areas of energy systems. Some examples are Eurostag [5], OMNeT ++ [6], MOCES [7], DRSim [8], GridLAB-D [9], among others. In addition to these, there are also several simulators that are based on multi-agent technology, which is particularly well adapted due to its distributed nature, such as EMCAS [10], MAN-REM [11], MASCEM [12], Power TAC [13], SGiC [14], AiD-EM [15], among others works.

Although there is a wide range of simulators in the area of energy systems, they have a major disadvantage: they are geared towards solving problems in specific areas of the industry, such as energy markets, network management, etc. To carry out studies closer to reality, where all areas are related, it is desirable that the different simulators from different areas are be able to talk in a way to simulate more

comprehensive and complex scenarios with all their dynamicity. Although there are already simulators that try to interconnect the different areas of energy systems, such as EPOCHS [16], GECO [17] and Mosaik [18], they do not have the ability to dynamically construct scenarios for simulation, i.e., the user can not set up a scenario that does not has been pre-established.

The Tools Control Center framework (TOOCC) has been designed with the aim of filling the gap and thus allows the interoperability between heterogeneous simulation systems, by combining the simulation capabilities of each tool to be linked, allowing to simulate and analyze more comprehensive and complex scenarios. TOOCC allows the creation of scenarios with information on electricity markets, SG operation, modeling of concepts such as consumer, aggregator, pricing, real-time pricing, demand response programs, among others.

This paper intends to present the D2RD module of TOOCC, developed to model and simulate DR scenarios, considering consumers, producers, tariffs, real-time pricing, supply energy and DR programs. For its demonstration, the simulation of a real-time pricing scenario for wind curtailment with 6 consumers is described.

After this first introductory section, the TOOCC framework and D2RD module will be presented in Section 2. Section 3 shows a practical example how to use these tools and their features. Finally, Section 4 will present the main conclusions of this work.

2. Tools Control Center

The TOOCC framework [19] is a stand-alone multi-agent system that allows to take advantage of the strategic integration of other simulation tools. To this end, TOOCC acts as a facilitator in the integration of heterogeneous systems, using them as subsystems in the simulation of scenarios that consider different areas of energy systems. In the integration between systems, ontologies are used which allow the mapping of concepts and their relations. In addition, it is also possible to define the models that consider the necessary parameters, and run them on different machines in the domain, taking advantage of their features and installed software. At the end of the simulation are presented the results of each execution, allowing the user to draw conclusions and make decisions.

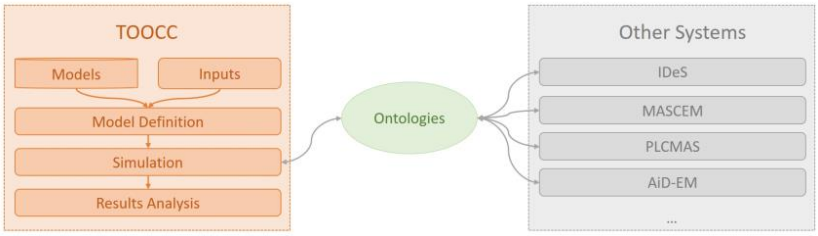

Fig. 31: Global perspective of TOOCC framework.

As can be seen in the Fig. 31, the tool is executed in three phases: model definition, simulation and results analysis. To fill the models can be considered simulated or real data, derived from a wide variety of sensors, consumers, production units and tariffs. The models are designed according to the tools that will be used in the simulation. For the simulation, more or less systems and/or algorithms may be included, depending on the complexity of the problem. The tools with which TOOCC connects for the purpose of executing the simulation are: the Intelligence and Decision Support Multi-agent System (IDeS) that allows the execution of different DR optimization, scheduling, forecasting, and decision support algorithms; Multi-Agent Simulator for Competitive Electricity Markets (MASCEM), which performs simulation of electricity markets; Adaptive Decision Support for Electricity Market Negotiation (AiD-EM), which provides decision support to participating players in electricity market negotiations; Network Manager (NM) is a system that allows to simulate the network manager, analyzing the satisfaction of consumer needs and network balance; Facility Manager (FM), which simulates energy management within a facility, managing current-connected devices such as home appliances; and Programmable Logic Controller Multi-Agent System (PLCMAS), which allows to simulate the results obtained in real environment, represented in a laboratory. These tools can communicate through the use of ontologies, which allow the mapping of the concepts between inputs and outputs, ensuring that different systems are able to understand the same concepts, and avoiding different interpretations of the same information. These ontologies are public and can be consulted in [20].

2.1 Demand Response Registration Digital

Demand Response Registration Digital (D2RD) is a TOOCC module designed to study and simulate DR programs and models. The models were developed according to the characteristics of the markets for electricity and smart grids and what is expected to be their evolution, by defining a set of characteristics. These are composed of information about participating entities (ISOs, curtailment service providers, and aggregators, including VPPs, and consumers of several types); the ways that can be used for their interaction in short and real-time DR events and the required technologic means; and DR contracts and consumer remuneration methodologies [21].

The graphical interface developed for this module allows consumers to register the expected consumption, flexibility and envisaged incentives prices for each moment, which later, together with the information of other consumers, allow to manage the DR using the available programs (Fig. 32). In the end, the network energy is optimized according to the needs of all consumers, avoiding waste and taking advantage of lower prices from the energy market.

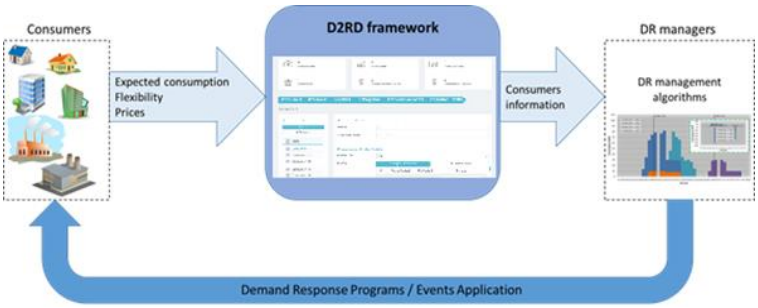

Fig. 32: D2RD module general perspective.

An architectural perspective of the module is represented in Fig. 33. The diagram shows the interaction of the several components for register the consumers information, such as the other entities, and simulate demand response models.

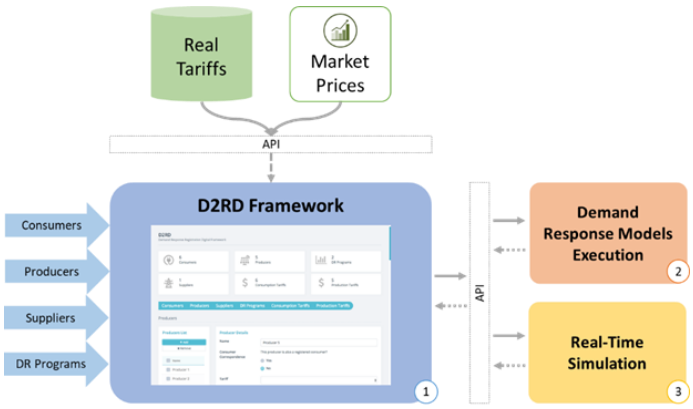

Fig. 33: Architecture model representation of D2RD module.

The framework takes advantage of the use of real tariffs and real-time pricing. When the model is prepared, the demand response manager can execute the demand response algorithm, and then proceed to the simulation in real-time in a laboratory which is able to simulate a house and its appliances. In this way, it is possible to analyze the impact of different entities and models in demand response management.

3. Real-Time Pricing for Wind Curtailment Example

In the present section, a case study will be presented for an real-time pricing for wind curtailment scenario, already used in [22]. To this end, 6 consumers will be registered. In their registration they should indicate to the manager of the DR their flexibility to increase or decrease power, at each instant of time. This information will be processed by a demand response manager who will distribute the energy in the appropriate way, considering the fluctuations in the energy price. Those results will be launched in OPAL-Simulink simulation, in a real environment [23].

Once all the constituent features of the scenario have been set up, the next step is the real-time simulation of the data. For this purpose, OP5600 real-time simulator has been used, which is a powerful Hardware-In-the-Loop (HIL) machine able to integrate the simulation environments with the real world. OP5600 can run MATLAB/Simulink models in real-time for controlling the real hardware resources and obtaining the actual results.

The TOOCC platform has been connected to the OP5600 via MODBUS TCP/IP protocol for exchanging the data, as figure illustrates. In fact, the main purpose of this integration is firstly to perform the optimization algorithm for TOOCC user data, and then execute the optimized results in the real hardware resources.

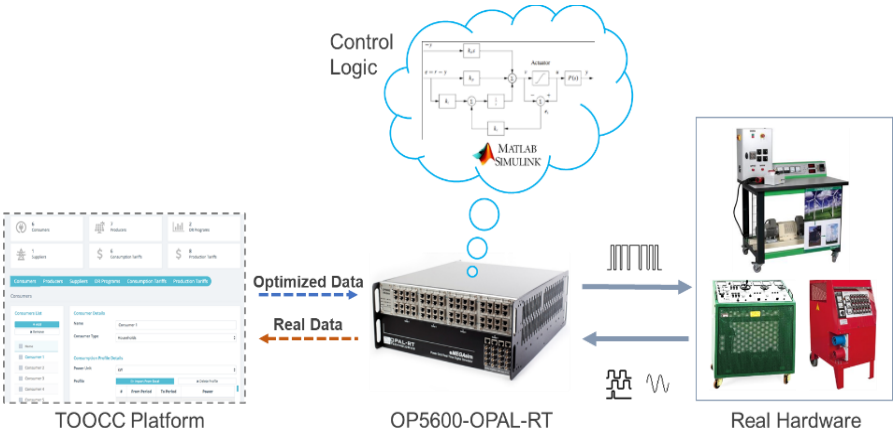

Fig. 34: TOOCC plataform integrated with real-time simulator.

As it can be seen in Fig. 34, the TOOCC platform starts the simulation by transmitting the input data to the DR Provider algorithm to perform the optimization, and the optimized consumption and generation data is sent to the OP5600. After that, the real-time simulator employs the MATLAB/Simulink model embedded in the machine and execute it in real-time. In other words, OP5600 sends controlling commands to the real hardware resources and receives the real-time consumption/generation of them. In the last stage, OP5600 transmits these real-time data to the TOOCC platform in order to be displayed as a chart to the user. In this process, the real-time market prices are also considered.

The used optimization algorithm is developed with the objective of operate distribution network and manage the available resources, by maximizing the social welfare. This considers the values of the demand forecast and of the demand increase and the respective prices (initial price and price reduction), for each consumer, of each type. The distributed generation resources (as the case of wind power generation), are divided into ordinary (ODG) and prioritary (PDG). The prioritary ones regard the resources that should be entirely used, as the case of non-dispatchable energy generation resources that are not storable. Otherwise, a cost (curtailment cost) is paid due to the generation curtailment. The energy acquired from the upstream network from one or several suppliers is divided into a quantity previously obtained (from Supplier Sp) at a given price, and an additional amount available at a distinct price. The objective function is presented in equation (1).

$$= \left[\begin{array}{l} \sum_{Type=1}^{NType} \sum_{C=1}^{NC} \left[\begin{array}{l} \left(E_{Demand(Type,C)}^{Forecast} + E_{Demand(Type,C)}^{Increase} \right) \\ \times \left(C_{Demand(Type,C)}^{Initial} - C_{Demand(Type,C)}^{Reduction} \right) \end{array} \right] \\ - \left(\begin{array}{l} \sum_{Sp=1}^{NSp} \left[E_{Supplier(Sp)} \times C_{Supplier(Sp)} \right] \\ + E_{Supplier(Sp)}^{Additional} \times C_{Supplier(Sp)}^{Additional} \\ + \sum_{PDG=1}^{NPDG} \left[\begin{array}{l} E_{DG(PDG)}^{Prioritary} \times C_{DG(PDG)}^{Prioritary} \\ + E_{DG(PDG)}^{Curtailment} \times C_{DG(PDG)}^{Curtailment} \end{array} \right] \\ + \sum_{ODG=1}^{NODG} \left[E_{DG(ODG)}^{Ordinary} \times C_{DG(ODG)}^{Ordinary} \right] \end{array} \right) \end{array} \right] \quad (1)$$

Fig. 35 shows the results of real-time simulation using TOOCC platform and several laboratory consumers and generators. These results are for 96 periods of 10 seconds (960 seconds in total), which means OP5600 transmits the desired rate of consumption/generation to the resources for each 10 seconds, and the resources send their real-time consumption/generation rates to the OP5600 with 1 second time interval.

The first chart in Fig. 35 is related to the consumption profile of a community of consumers (known as Consumer 2 in the TOOCC), and the second and last charts are related to the laboratory emulators that have been employed by OP5600 for emulating the consumption of generation profile of a customer.

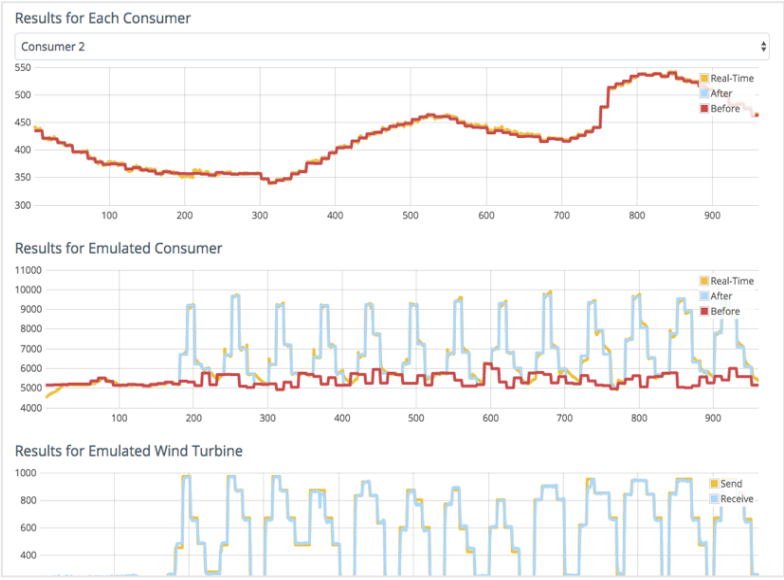

Fig. 35: Real-time simualtion results.

4. Conclusions

There are several advantages and challenges that the DG's implementation brings to the energy sector. To address some of these challenges, simulation tools, especially multi-agent architecture, are essential for its evolutionary process. However, much of the state-of-the-art tools are designed to solve problems in very specific domains, losing the essence of an industry where all areas are interconnected with a high level of complexity. In this context, the TOOCC tool emerges, which allows the interconnection of different systems in order to solve problems that cover the various domains of energy systems.

This paper presents the D2RD module of TOOCC. The D2RD module allows the study of DR models and programs through the consumers' registration of flexibility, expected consumption, and envisaged costs for using such flexibility. This is important information that can be managed by different entities, namely network managers, in order to manage the available energy and the needs of its consumers, avoiding waste and taking advantage of fluctuating market prices, reducing costs.

To better understand the operation of the module and its advantages is presented an example of a wind curtailment scenario, where are demonstrated some features; the steps necessary for the user to use the tool; and how to interpret the results.

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Demand response approaches for real-time renewable energy integration
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Economic Survey on a Community of Prosumers and Distributed Generations

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Abstract

The use of demand response programs and distributed renewable energy resources play an important role in nowadays electricity markets. Most of the demand response programs are performed for large-scale resources. This is a barrier for the small and medium scale consumers, producers, and prosumers in order to participate in the electricity market negotiations. To overcome this barrier, a third-party entity, such as community or an aggregator, should play a role an intermediate player between the end-users and network operators. However, before the implementation of the business models, they should be well surveyed in term of economic and financial profits in order to prevent future problems. This paper proposes an economic survey on a community of the consumers and distributed generations, considering different pricing schemes. The community consists of residential, commercial, and industrial consumers as well as photovoltaic and wind turbines. In this survey, the annual costs of this community are investigated considering the current pricing schemes in two countries of Portugal and Germany.

Keywords: aggregator, community, demand response, distributed generation

1. Introduction

The appearance of Demand Response (DR) programs in nowadays power system, create an opportunity for the research society to focus on this topic. DR programs can be defined as altering the consumption profiles of the end-users in order to react to the price variations due to the economic or technical issues [1]. Two main categories are considered for DR programs, which electricity customers can participate in the programs considered on those categories [2]: price-based and incentive based. In fact, DR programs bring flexibility to the electricity markets by controlling the consumption patterns [3].

Furthermore, the use of Distributed Renewable Energy Resources (DRERs), especially wind turbines and Photovoltaic (PV), enables power distribution network to reduce the congestion of network on the peak hours as well as full benefits from them while participating in the market negotiations [4].

The main issue in these new concepts is the minimum capacity rate that the resources should contain, in order to be able to participate in the market negotiations. Based on [5]–[7], the minimum reduction capacity of DR resources is 100 kW in different electricity markets. Therefore, the small and medium resources would not be capable to individually participate in those markets [8]. For solving such problems, a third-party entity, such as a community or an aggregator should be placed between the demand side and the grid side in order to aggregate the small and medium scale resources and participate them as one resource in the electricity market [9][10]. However, all the models and scenarios should be well investigated in term of economic and financial profits in order to prevent the future problem.

This paper presents an economic survey on a community of consumers, producers, and prosumers by considering different electricity pricing rates. The consumers participated in this community consist of residential buildings, commercial centers, and industrial units. Also, the DRERs of the community include PV pilots in two scale of small and large, PV arrays in the residential buildings considered as prosumers, and several wind turbines. The consumption and generation profiles utilized in this paper are real data provided by a smart metering company in Germany (www.discovergy.com). Several pricing schemes would be applied to this community in order to survey the annual costs considering DRERs.

After this first introductory section, the community model will be presented in Section 2. Section 3 will present the economic survey of the community and the annual costs will be provided. Finally, Section 4 will present the main conclusions of this work.

2. Community Model

A local community grid is related to a group of consumers, producers, and prosumers that some of them may have a contract with a central controller unit called Community Manager (CM), in order to be controlled and organized by this unit. The differences between a community and an aggregator are that a community has a smaller number of grid players, however, an aggregator has a significant number of players. Also, the community is interest based, however, the aggregator is profit based.

Fig. 1 illustrates an overall view of the proposed community grid. In this model, there are 100 consumers and 100 producers. The consumers of the community consist of 79 residential houses, 16 commercial shops, 3 commercial centers, and 2 industrial units. The producers include 22 small-scale PV pilots, 13 large-scale PV pilots, 18 wind turbines, and 47 PV arrays in residential houses considered as 47 prosumers. These classifications are performed based on the average daily consumption/generation rates of the resources.

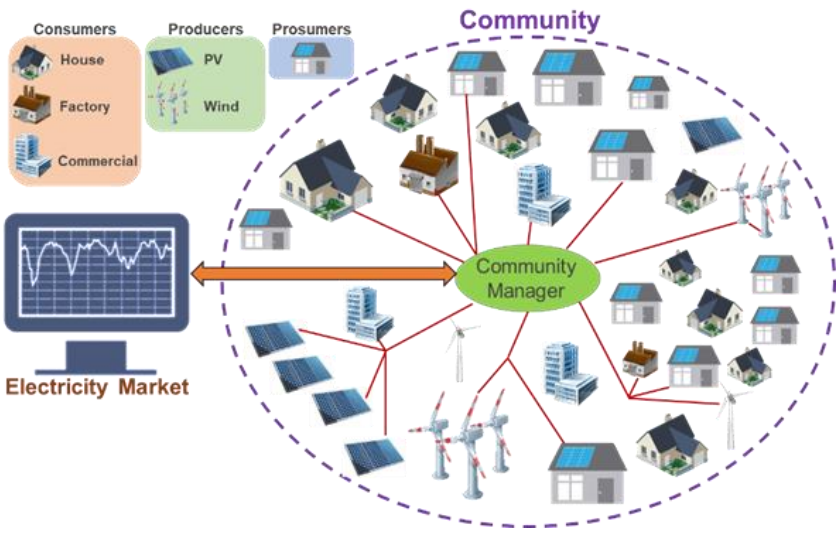

Fig. 36: Overall perspective of the community model.

In this network, the CM is not owning any resources of the grid and it is responsible to balance the rate of consumption and generation in the community members, by providing some strategic plans, namely DR programs or resource scheduling, to the players. The main interest of CM is firstly to feed the demand of the players by its local energy resources available in the community as well as the surplus of production of the prosumers. By this way, the CM would be able to stop purchasing energy from an external supplier. Also, if the generation rate of the community is less than the electricity consumption, it is affordable for the CM to pay incentives to its members to reduce their consumption instead of buying energy from the market. For this purpose, the CM is able to perform DR programs in order to be applied by the consumers and prosumers.

Fig. 2 shows the total consumption and generation profiles considered for the community network. The data shown on Fig. 2 are the real consumption and generation data for an entire year with three minutes time interval, which have been adapted from the smart metering company in Germany (Discovergy GmbH).

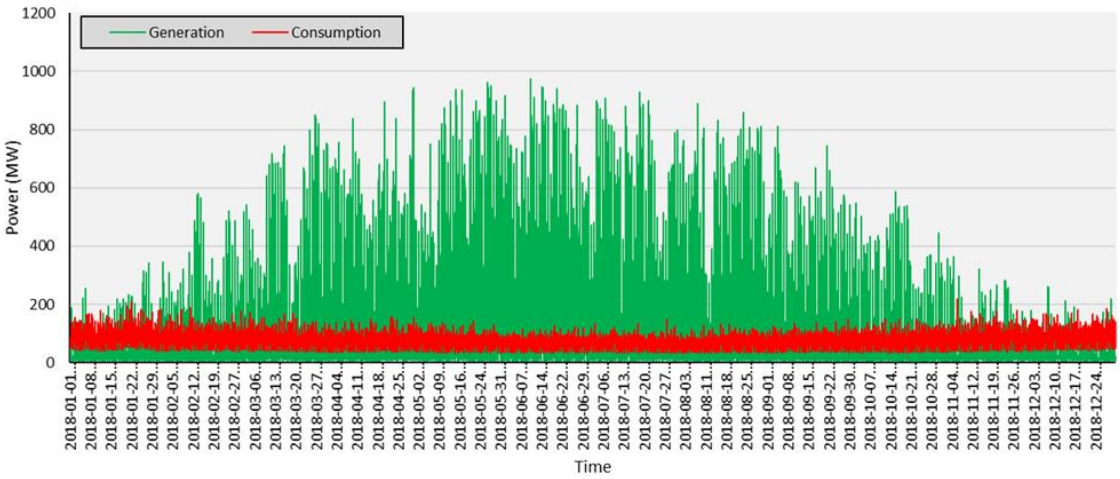

Fig. 2: Total consumption and generation profiles considered for the community.

As can be seen in Fig. 2, the generation rate in summer is much higher than in the winter, which is due to the high generation rate of PV pilots. Since the rate of consumption is almost equal during the year, the CM not only is able to supply the community demand via the local resources but also, it can export energy to the external supplier during the summer. Detailed consumption profiles of the community are shown by Fig. 3, which are related to residential houses, commercial shops. Commercial centers, and industrial units.

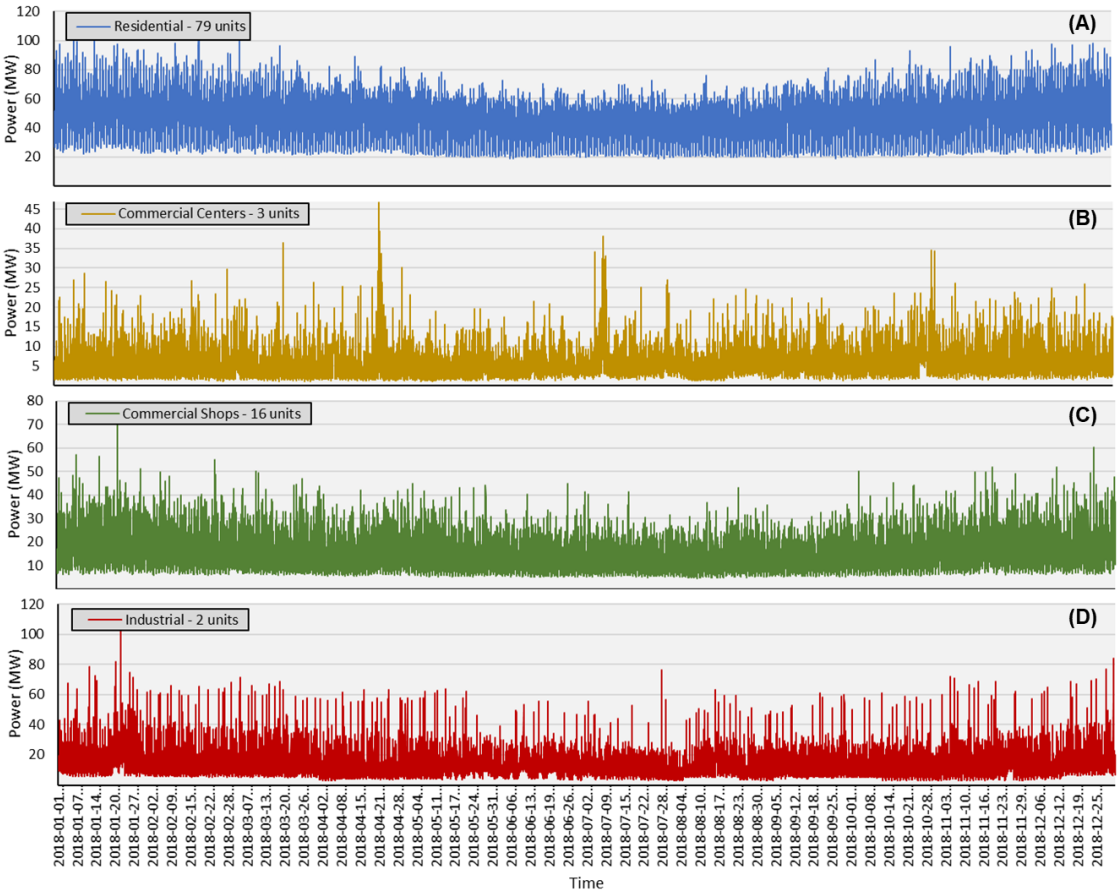

Fig. 3: Consumption profile of the community players: (A) 79 residential houses, (B) 3 commercial centers, (C) 16 commercial shops, (D) 2 industrial units.

As it is clear in Fig. 3, the consumption profile of residential houses is a bit lower in summer comparing to the winter. This is due to the geographical areas and weather conditions. Also, in the same figure, the profile of commercial buildings in the working hours is higher than the nights. These points would be useful for the CM in order to perform DR programs or loads scheduling. The profiles shown in Fig. 2 and 3, will be used in the next section in order to compare and analyze the annual costs of the community.

3. Economic Analysis

In this section, it is considered that the community is in two countries in Europe: Portugal and Germany. Therefore, the electricity prices and regulation of these two countries would be applied in the community and the results will be compared.

The first analysis is given to the annual costs of the community with the Portuguese electricity prices. Therefore, the electricity price for consumption has been adapted from [11], which is 0.15 EUR/kWh. Also, the price of electricity generation has been adapted from [12], which stands as 0.09 EUR/kWh. Fig. 4 shows the calculated annual costs for Portugal.

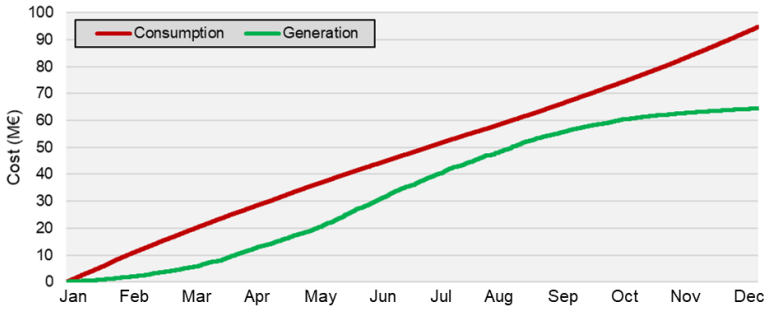

Fig. 4: Accumulated costs of the community for one year with Portuguese prices.

Furthermore, Table 1 demonstrates the detailed accumulated consumption costs for the different sectors of the community while it operates with Portuguese prices.

Table 12: Accumulated consumption costs of community with Portuguese electricity prices.

	Consumers				**Producers**
	Residential Houses	**Commercial Centres**	**Commercial Shops**	**Industrial Units**	**PV and wind turbines**
Cost (M€)	54.6	24.2	9.6	5.4	64.5
	Total: 93.8				**Total: 64.5**

Regarding the community costs with Germany electricity prices, Fig. 5 and Table 2 demonstrate the economic analysis. In those results, the electricity price for consumption has been adapted from [13], which stands for 0.25 EUR/kWh, and the generation costs adapted from [14] stands for 0.09 EUR/kWh.

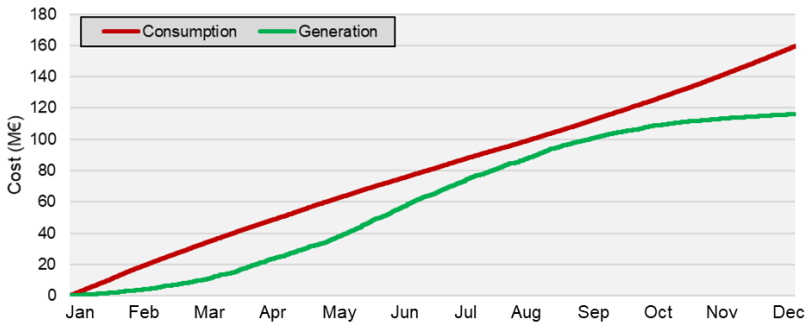

Fig. 5: Accumulated costs of the community for one year with prices in Germany.

Table 2: Accumulated consumption costs of community with German electricity prices.

	Consumers				**Producers**
	Residential Houses	**Commercial Centres**	**Commercial Shops**	**Industrial Units**	**PV and wind turbines**
Cost (M€)	97.7	10.1	28.1	23.5	116.1
	Total: 159.4				**Total: 116.1**

4. Conclusions

This paper provides a community model of the consumers and producers considering several players. The community players consist of residential houses, commercial buildings, and industrial units. Moreover, an economic survey on the annual costs of the community was performed. The consumption and generation data were the real data adapted from a smart metering company in Germany.

The results of the paper illustrate a comparison between the consumption and generation costs for an entire year while the pricing schemes of the two countries in Europe are applied. These kinds of analysis are very useful for network operators and community managers in order to identify the best and optimal situations for performing demand response programs and loads scheduling.

Acknowledgments. The present work was done and funded in the scope of the following projects: H2020 DREAM-GO Project (Marie Sklodowska-Curie grant agreement No. 641794); and UID/EEA/00760/2019 and funded by FEDER Funds through COMPETE program and by National Funds through FCT.

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Impact of drought periods on hydroelectric production in Portugal: A Study from 2015 to 2017

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Abstract

The production of hydroelectric power is strongly affected due to periods of drought. In Portugal there are about forty-nine hydroelectric plants with installed capacity of more than 10MW. In the year 2017 the generation of electricity in Portugal was 54.52 TWh, of which about 14% was hydroelectric production reflecting a year below normal in hydroelectric power production. This article discusses the impact of drought periods on hydroelectric power production in Portugal, which address the importance of hydroelectric production in Portugal. Among the factors influencing the production of hydroelectric power, a method is presented for analysis of a dry month through the monthly precipitation indicators, energy production by monthly technology and energy price. These indicators were presented and analyzed in three case studies presented in this article. A solution is also presented to reduce the impact of drought periods on Hydro production.

Keywords: importance of hydro power, hydroelectric generation, hydro power, power generation

1. Introduction

The hydroelectricity is a 100% renewable energy based on water energy and kinetic energy of water, taking advantage of an infinite resource obtained from nature. The main objective of this article is to focus on the impact of drought on the production of hydroelectric power in Portugal, so as to raise the awareness of the academic population and even the general population about the importance of renewable energies, especially the vital role of hydroelectricity in production of electricity [1]. Currently, although hydroelectric power has been increasing gradually, the national utilization potential is only around 50%.

Just because, compared to other European Community countries, Portugal is well below the European average, in some cases as France, Germany and Italy, around 90%. In order to be aware of the importance and impact that this type of energy has, Hydropower, which includes hydroelectricity, represents 28% of the installed electricity power in Portugal, more than Wind (22%), than Coal (11%) and then Natural Gas (18%) [2]. Hydroelectricity plays a key role in the electricity market because it has many advantages such as a rapid and efficient response to the variations of the demand and consequently an adjustment in production, in the price of electricity produced is constant and has a high reliability of service, enabling a supply of constant energy, among other advantages [3].

As mentioned previously, the main objective of this article is to focus on the impact of drought on hydroelectric production in Portugal in 2017, in an extremely dry year and to verify the impact of drought on energy production in general, to verify that was offset the lack of water production and lastly to analyze the variation of the electric energy price. The same analyzes were carried out for the years 2016 and 2015 in order to have a possible comparison. In section II we speech about factors that influence the production

of hydroelectric energy, in section III we explain the study methodology, in section IV we present the case study's in section V we do a conclusion of this paper.

2. Factors that Influence the Production of Hydroelectric Energy

The Hydroelectricity production has a great advantage when compared to the production of wind power, that is highly irregular and unpredictable. One of the major factors that influencing hydroelectricity are the periods of drought, due to lack of precipitation and inability to store water in dams that have reservoirs. In the year of 2017, Portugal recorded a fall in the production of hydroelectric energy, around 55%, due to the drought that the country was experiencing [4]. There are many factors that together have led to this dry period, such as high temperature, little rainfall and not enough water in the rivers to be able to produce energy and consequently the pumping barrages could not perform this process to not destroy the flora rivers and to protect all living things in rivers.

This set of factors led to an extreme drop in water production that Portugal tried to compensate with wind energy, but like this irregular and unpredictable was not enough and had to compensate the lack of hydropower through fossil fuel power stations such as coal and natural gas. In sum, in Portugal water production fell by 55% to 7,200 GWh in 2017 while natural gas production increased by 53% (8,029 GWh) and coal production increased by 27% (16,847 GWh).

3. Study Methodology

The method used in the cases studies is represented in Block Diagram in Fig. 1. The (1) will be the starting point, (2) will be the definition of the month that is the variable "M", and the variable "X" will take the values less than or equal to 6 before the variable "M ", and the (3) will make a relation between the precipitation occurred for that same month to verify if the month can be considered dry, in case the precipitation is less than 40% of the value said normal for that same month is considered dry and the program proceeds, otherwise a matrix with the data of the months analyzed with the indicators of energy produced by monthly energy and monthly energy price is printed in the step (5).

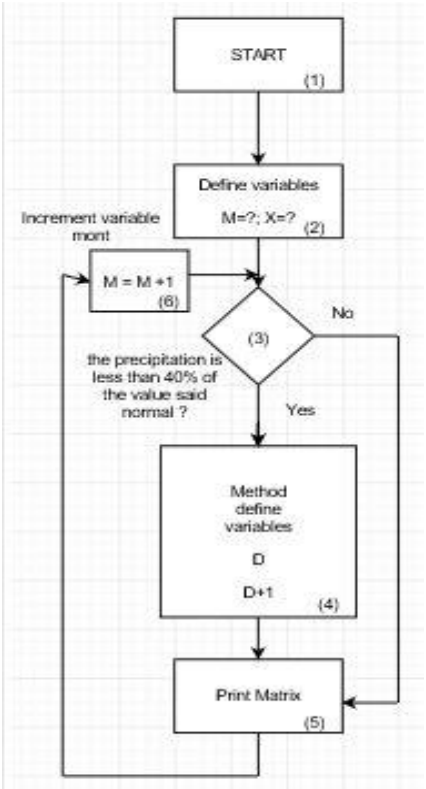

Fig. 37: Base of the applied method.

In the case of a valid relation, it follows the step (4) where the analysis of the driest month is performed, thus defining the variable "D" and the following month, thus defining the variable "D+1", analyzing the precipitation indicators monthly and will perform step (5) by extracting the matrix with the indicators data, monthly precipitation, energy production per monthly technology and monthly energy price and indicating the driest month and the following month, the method will proceed to the step (6) by incrementing the "M = M+1" function to analyze the months following the month defined in step (1) for the variable "M". Will proceed to step (3) and create a loop until to stop the method. It is recommended that variable "*X*" take value less than or equal to 6 to be correlated with month "*M*", because if month "*M*" is December 2000 and "*X*" take values greater than 6, in the month January 2000 may it has rained a lot and in the following months and only in August was it has become a dry height, this will influence the December analysis in relation to energy production data and market price. The analysis of the data of the months closest to the variable "M" will make the analysis more precise and concrete.

4. Case Study

Based on the method presented previously in Fig. 1, in the case studies we performed an analysis of monthly rainfall data, energy production per monthly technology and energy price to verify the impact that the dry periods have on the Portuguese market and how this behaves with little or no availability of hydroelectric production. Therefore, three case studies were performed:

- The first will be between December 2017 and October 2017, the latter being considered the driest month of the last six months, consequently the month of November 2017 will be considered the following month. Finally, a comparison will be made between these months and the month of March 2018, which is considered a rainy month.
- The second case study will be between the month of December 2016 and July 2016, the latter considered the driest month on the last nine months, consequently the month of August 2016 that is the following month. Finally, a comparison will be made between these months and the month of February 2017 that is considered a rainy month.
- The third case study will be between the month of December 2015 and July 2015, the latter considered the driest month on the last twelve months, consequently will be analyzed the month of August 2015 considered the following month. Finally, a comparison between these months and the month of January 2016 that is considered a rainy month.

The Table 1 shows the values assigned to the variables according to the basis of the applied method.

Table 1: Values assigned to variables.

Variables	Case A	Case B	Case C
M	December 2017	December 2016	December 2015
X	6 months	9 months	12 months
D	October 2017	July 2016	July 2015
D+1	November 2017	August 2016	August 2015

A. Dec 2017

- **Precipitation data:**

According to Table 1, our chosen month "*M*" is the month of December 2017. When we begin to execute our method, the month of October is the variable "*D*" since it is the month where the current amount of precipitation is the lowest as we shown in the Table above. Consequently, the variable "*D+1*" will be represented by the month of November 2017. Like we see in above in the Table 2, the month of October assumes the variable "*D*" (being less than 40% of the normal value for that month), according to the method implemented. On the other hand, and with the course of the method, and knowing that we increase the function "*M = M+1*" to analyze the months following the month defined by the variable "*M*", we verify that the month of March can also assume the variable "*D*", but in this case to take over as the month very rainy.

Table 2: Precipitation values of case A (Built with data from [5]).

Year 2017			
October	24,4	92,5	Lower
November	43,2	118	Lower
December	116,2	129,8	Near
October	24,4	92,5	Lower
Year 2018			
January	63,4	126,8	Lower
February	74,9	112,2	Lower
March	259,2	93,5	Higher
January	63,4	126,8	Lower

Looking at IPMA data, we observed that the month of October was the hottest of the last 87 years for October, when 2 heat waves ran occurred from 1 to 16 and from 23 to 30 October, which covered a large part of the territory continent, and the total rainfall in October was about 30% below of normal, being considered the driest of the last 20 years with an average value of precipitation of 26.9 mm, which correlates with the implementation of our method [6]. Consulting also the same data, but this time for the month of March 2018, in Continental Portugal was considered an extremely rainy and very cold month. The average value of the amount of precipitation in March was about 4 times the monthly average value and it was considered the second rainier month of March since 1931 which correlates with our method [7].

- **Production Mix Statistics:**

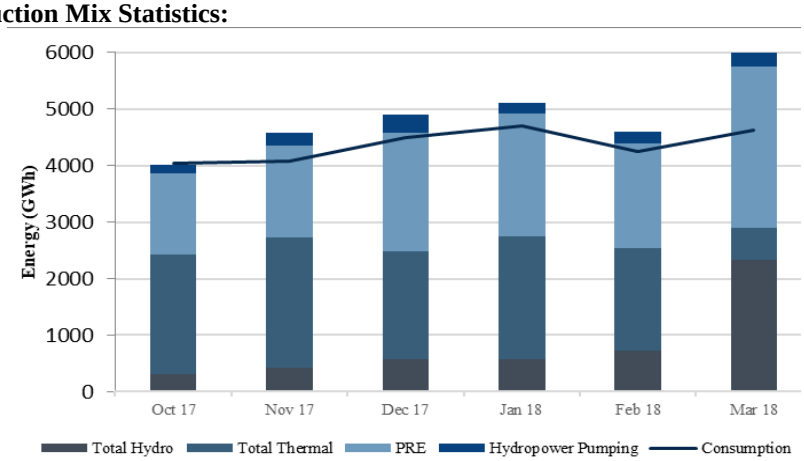

Fig. 38: Monthly Production Mix Statistics of Case Study A (Built with data from [10]).

According to Fig. 2, October presented a large deficit of hydroelectric energy used (about -58.5% in relation to the previous year), which correlates the data obtained for precipitation shown in Table 1, which we classified the month as extremely dry. Thus, thermal energy was needed to be used more than normal (10.5%) in order to compensate for the lack of hydroelectric production that would be expected for October. Regarding the energy of the Special Regime Production, there is not a large difference in relation to the previous year, but there is an increase in hydroelectric pumping (6.9%), which may be justified by the need to recover the average flow rates of rivers. In the case of the month of March, there is a substantial increase in water production (155%), which is justified by the fact that is a month where a above precipitation occurred that was expected (as shown in the first Table), with energy hydro together with the energy coming from the Special Regime were practically able to meet demand / supply demanded by the energetic market, so that thermal energy was not so necessary for this month, noting a variation of (-67.5%) compared to the previous year. For the energy sources of the Special Regimes, wind energy production contributed the most by (52.1%).

Energy price (€/MWh):

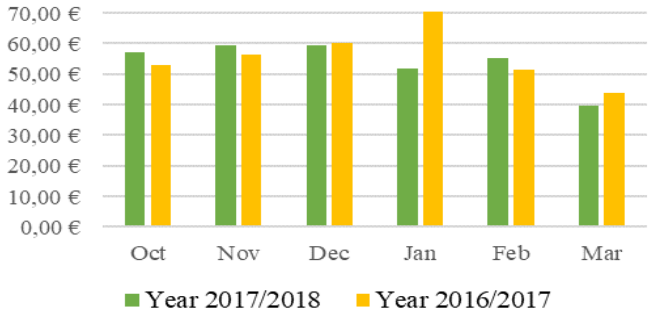

Fig. 39: Average monthly price (€ / MWh) of case study A (Built with data from[11]).

Regarding the average monthly prices of energy Fig. 3, our cases of studies, and comparing with the data obtained so far, we found that the month of March was the lowest month in the average monthly price (€/MWh), which could be explained by the fact that in these month the hydroelectric power has been the most used since there was enough abundance of this sector, as well as the production of these kind of energy are considered the cheaper in the production of electric energy. In turn, the months of October, November and December were the most expensive months in which justification will be since there was no available hydraulic energy and it was necessary to resort to thermal energy, which energy is more expensive to produce energy in order to meet the needs of the electricity market.

B. Dec 2016

- **Precipitation data:**

According to Table 3, our chosen "M" month will also be the month of December for the year 2016. When we start executing our method, the month of July will most likely become the "D" variable due to the fact of being the month in which the current amount of precipitation is the lowest as shown in Table 3. Therefore, the variable "D+1" will be represented by the month of August.

Table 3: Precipitation values of case B (Built with data [5]).

Year 2016			
Month	**Actual rainfall (mm)**	**Average precipitation (mm)**	**Relationship**
July	2,8	10,3	Lower
August	3,7	11,6	Lower
September	18,2	41,8	Lower
October	64,4	92,5	Lower
November	98,7	118	Lower
December	51,3	129,8	Lower
Year 2017			
January	47,8	126,8	Lower
February	87,9	112,2	Lower

It is shown that the month of July assumes the variable “D“ (being less than 40% of the normal value for that time of the month), going according to the implemented method. On the other hand, and with the course of the method, and knowing that we increased the "M = M+1" function (as we did for the first case) to analyze the months following the month defined by the variable "M" the month of February may also assume the variable “D”, but in this case to assume as a very rainy month. The month of July 2016, in mainland Portugal, was extremely hot and very dry. It should be noted that according to the IPMA data, in many regions of the North and Central coast and the Alentejo and Algarve there was no precipitation this July. [8] As for February 2017, it was classified as a normal month for the season of the year for precipitation and temperature[9].

- **Production Mix Statistics:**

In relation to energy production Fig. 4, we can see that in December 2016, it was verified that a great part of the energy was produced through the thermal, about 36.8%, as a result of the little precipitation that occurred in this month, even when compared to December 2015 there was an increase in water production, the same goes for the month of July 2016.

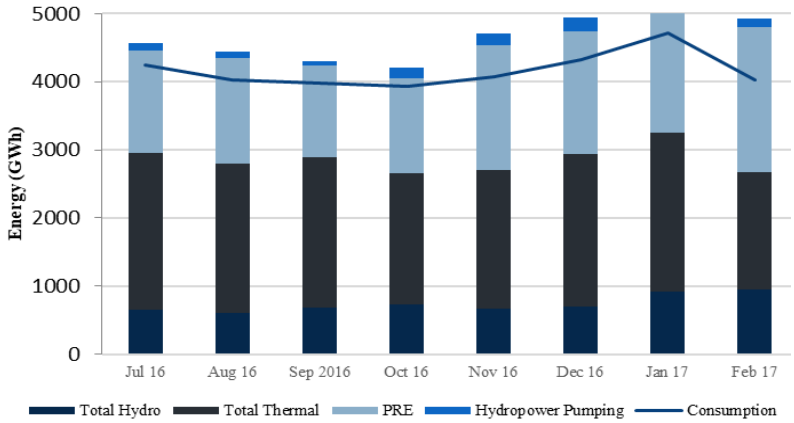

Fig. 40: Monthly Production Mix Statistics of Case Study B (Built with data [10]).

As for February 2017, it was verified that there was a 56.3% fall in the production of hydroelectric energy, given that in February 2016 it was the 2nd rainiest month of the year, and in counterpart to compensate these values there was an increase in more than 100 % in thermal power production in February 2017 compared to 2016, and a 29% increase in hydroelectric pumping.

- **Energy price (€/MWh):**

According to the data of average monthly prices for the years 2016/2017 and 2015/2016 Fig. 5, we can verify the highest price for the energy occurred in January 2017, approximately 71,52 €, where much of the energy produced was through the Thermal energy. In contrast, in January 2016 a large part of the energy produced was through hydropower.

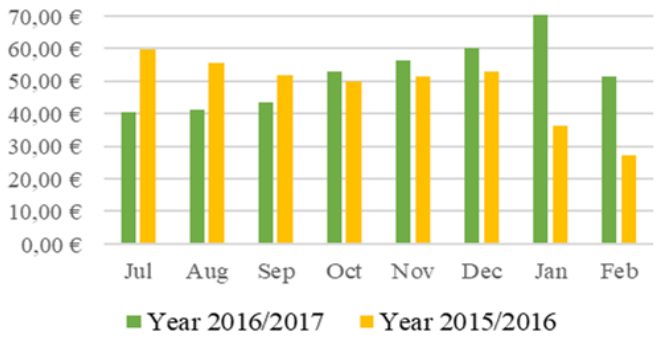

Fig. 41: Average monthly price (€ / MWh) of case study B (Built with data from [11]).

We can also verify that in the months of July, August and September 2015 the energy value is higher compared to the same months of 2016, since a great part of the energy production in the months of 2015 comes from thermal energy, whereas in the months 2016 already come from water production. We can then verify that the price of energy varies with the type of production, thermal or water, and when this same production comes from the water, that is when there is more water in the reservoirs also the energy price decreases.

C. Dec 2016

- **Precipitation data:**

In this case study our chosen month, "*M*", was the month of December 2015. During this month the average value of precipitation was about half of the normal value, as we can see in Table 4. It was verified that during the year of 2015, in only two months of the year, the volume of precipitation was higher than the monthly average, making this year, a year dry, and in about 6 months of this year the precipitation volume was lower by about 50% of the average value [12].

Table 4: Precipitation values of case C (Built with data from [5]).

Year 2015			
Month	**Actual rainfall (mm)**	**Average precipitation (mm)**	**Relationship**
July	4,1	10,3	Lower
August	7,1	11,6	Lower
September	45,4	41,8	Near
October	118,7	92,5	Higher
November	46,5	118	Lower
December	61,1	129,8	Lower
Year 2016			
January	166,9	126,8	Higher

When we performed the method considering the month “M” December, our month “D” is July, since it was the month with the least precipitation, at the amount of precipitation in July 2015 this value was 4.1 mm, lower than the average value of 10.3 mm, and month “D+1”, August. January 2016 was characterized as a very rainy month with enough wind. As for precipitation, the values in January 2016 were 166.9 mm, higher than the average value, being the highest value of the last 15 years. In some days of January, there were high values of precipitation in certain regions, mainly north, and strong wind [13].

- **Production Mix Statistics:**

About Production Fig. 6, we can verify that the values of water energy production in both July and December 2015 are low and in comparison to previous years, namely 2014, there was a reduction of this production in about 56% in December and 17% in the month of July, as we have seen, these months have been hot and dry due to the little precipitation we had. On the other hand, thermal energy increased in these months, probably to compensate for this reduction in water, and compared to 2014 there was an increase of about 40% in July and near 31% in December, as well as pumping, namely in December (48.4%).

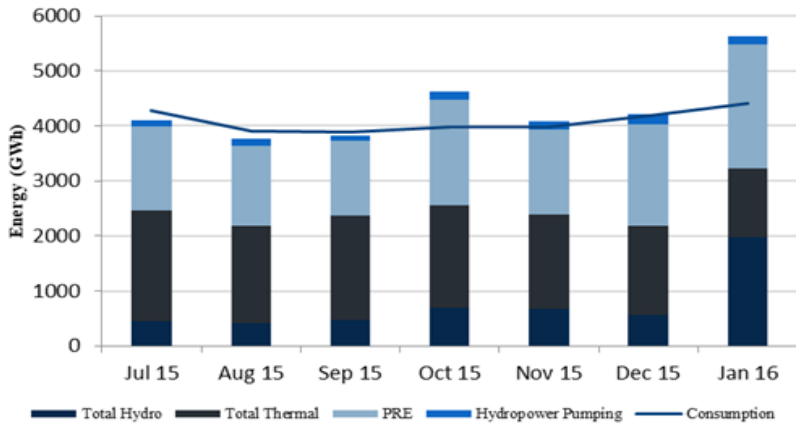

Fig. 42: Monthly Production Mix Statistics of Case Study C (Built with data from [10]).

As for January 2016, the opposite occurs: once it was a very rainy month there was an increase in water compared to 2015 by 98.5% and a reduction in thermal energy production by about 15%. This month there

was also a 23% increase in hydroelectric pumping. Also, in January there was an increase in energy production under a special regime, mainly 33.5% in wind energy production, given that it was considered a month with strong wind. [10]

- **Energy price (€/MWh):**

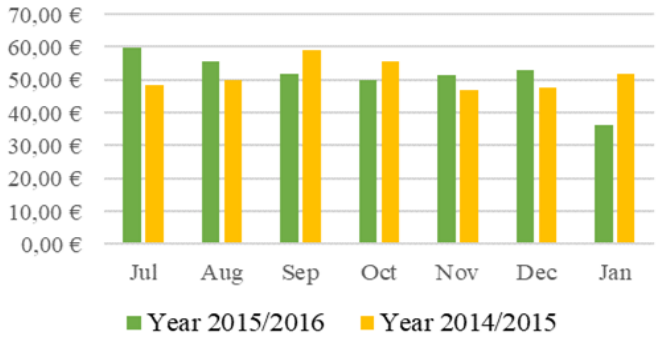

Fig. 43: Average monthly price (€ / MWh) of case study C (Built with data from [11]).

According to Fig. 7, we can verify what we have already considered, in which the price of energy will vary depending on its type of production, thermal or water, reaching higher prices when thermal energy production is higher, as in the case of July 2015, or reaching lower prices as production increases through hydropower, as we can verify in January 2016.

5. Conclusions

It is verified that in Portugal the hydro production has a very significant weight in the energy production, it is concluded through the cases of study that the lack of hydro energy production led to the necessity of the use of thermal production plants to compensate the lack of production as a consequence there was a high increase in energy prices in the months of the years studied. This variation in hydroelectric production is due to periods of drought. The implemented method of study became useful for the analysis of the case studies because through the inputs of the assigned variables there was a quick sampling of all the data necessary for analysis of the cases, either the precipitation data, the production data by monthly energy and monthly market prices. It is noteworthy that this method can be applied to any month of any year. Since most of the major rivers that exist in Portugal have their source in Spain, whenever droughts occur the water becomes scarce in order to produce enough hydro energy to maintain normal energy prices and not need to resort to energy production through fossil fuel power plants. A solution to this type of situation would be to use the smaller rivers that have their source in Portugal and which flow into these large rivers, is where it would be possible to use a reservoirs using the retention of water in these tributaries, taking into account the, so that during these periods of drought we can use this retained water in the tributary rivers to increase the main riverbed where the dams are installed for the production of hydroelectric energy.

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Demand response approaches for real-time renewable energy integration
Fourth DREAM-GO Workshop

Institute of Engineering - Polytechnic of Porto, Porto, Portugal, January 16-17, 2019

Modeling of a Low Voltage Power Distribution Network of a University Campus

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Abstract

The use of renewable generation and demand response programs become a reality in the nowadays electricity markets and distribution networks. An intelligent energy management system is required in all levels of electricity supply chain, in order to efficiently profit from the distributed energy sources. However, before the implementation of the business models, the mathematical and simulation models should be well surveyed and verified. This paper presents a model of low voltage distribution network of a university campus developed in MATLAB/Simulink tools. Several types of resource modelings have been used in order to develop a reliable distribution network model. In the case study of this paper, the real consumption profiles of the buildings located in the university campus are provided to the developed model and the behaviors of the network components are surveyed.

Keywords: demand response programs, low voltage network modeling, microgrids, simulink

1. Introduction

Nowadays, the network operators are forced to use efficient solutions for renewable energy sources due to the daily increment of energy demand [1]. Demand Response (DR) programs and Distributed Renewable Energy resources (DRERs) are two main concepts, which are appeared with the implementation of smart grids and microgrids. DR programs can be defined as altering the consumption profile of customers in response to the price variations or financial profits paid by the DR managing entity, namely aggregator [2]. This means the DR programs would aid the two sides of the network, including demand sides and network operators. There are two classifications for the DR programs: price-based and incentive-based [3][4].

The demand side customers utilize DR programs for reducing their electricity costs, and the network operator employs DR program to reduce the congestion of the grid and reduce the peak consumptions [5]. The integration of the DR programs with DRERs is the hot topic of research society since they can provide flexibility for the market negotiations [6]. However, the consumers should have enough capacity for consumption reduction in order to participate in the DR programs. This means the small and medium consumers should be aggregated and participated in the electricity markets as a unique resource [7][8]. Therefore, the role of this small and medium consumers should be well tested and validated through several models in order to identify future problems [9][10].

This paper presents a modeling of low voltage distribution network of a university campus considering DR programs and DRERs. The model is implemented in MATLAB/Simulink tools. Three types of loads

has been tested in this model: A Series RL load, a Parallel load, and Dynamic load. Through several studies, it is found out that dynamic load is the best choice for network modeling of a university campus, somehow each building of the university is simulated by a dynamic load block. The model developed in MATLAB/Simulink is based on the real architecture of the transmission lines implemented in the area of the university, and all power loses, and impedances are considered in the model. In the case study of this paper, at first, the behavior of one specific bus in the network is surveyed while several load modelings are implemented in order to validate and select the best approach, considering response time and accuracy of the simulation. In the second stage, several scenarios investigate the reaction of the entire network in various conditions. The real consumption profile of each building is presented to the load model associated with that building, and the simulation results regarding the entire network as well as each consumer will be surveyed.

After this section, Section 2 presents the real university network and the developed Simulink model. Section 3 focuses on the case study description, and its results are provided in Section 4. Finally, the main conclusions of the work are explained in Section 5.

2. University Campus Modelling

The low voltage distribution network considered in this paper is related to a university campus in Porto, Portugal. This network consists of 21 buses, one bus for each building, connected via underground electrical lines with a total length of 3.350 km. There is an MV/LV transformer in BUS 21, which connects the campus network to the external supplier with the following features: 15kV / 400V-230V, 2050 kVA. Fig. 1 illustrates the network architecture indicating the location of the buildings, buses, and transmission lines. Also, Table 1 provides the electrical characteristics of the distribution network.

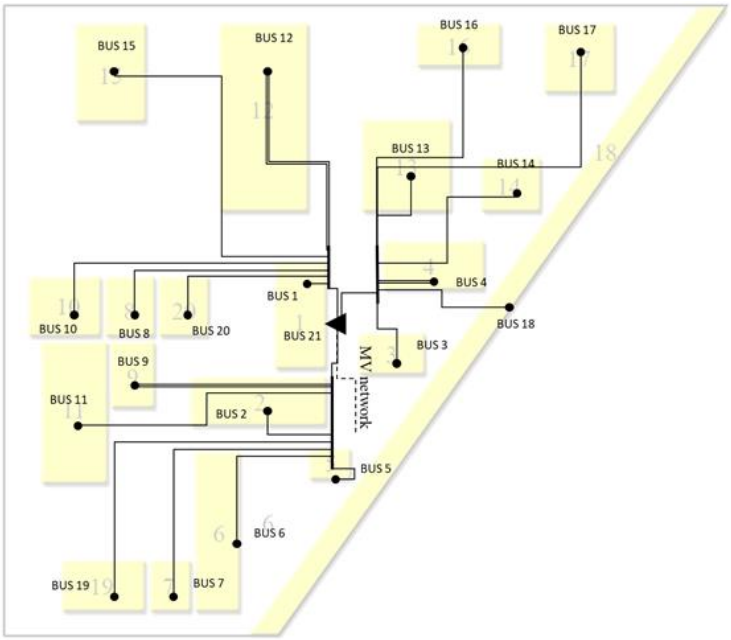

Fig. 44: Internal low voltage distribution network of the university campus.

Fig. 2 illustrates the setup of the network in the Simulink tool. As it was mentioned, the distribution network contains 21 buildings, which each building is modeled as a load. All the loads are connected through a branch that has resistance and an inductance value, as shown in Table 1. The three-phase loads provide the information regarding the voltages and currents, and therefore, the model would be able to calculate the number of power losses in the branches for different buildings of the university.

The network model is operated as 400 V and 1000 VA at a frequency of 50 Hz. Also, the source of the network is modeled as a three-phase source providing 400 V and 1000 VA at 50 Hz, which are based on the real data in the current form of the network. Moreover, as it can be seen in Fig. 2, the entire network buses are modeled with three-phase loads. BUS #18 that is the most distant bus from the supply, is surveyed with two different load models, including a series and a dynamic load. By this way, the most suitable load model is determined and used for the entire model.

Table 13: Electrical charactriscits of university campus distribution network.

Line	Bus	Distance (km)	R (p.u)	X (p.u)	Maximum Power Limit (kVA)
1	21 – 1	0.04	1.67×10^{-4}	2.00×10^{-5}	121
2	21 – 2	0.07	6.96×10^{-5}	3.50×10^{-5}	276
3	21 – 3	0.08	2.47×10^{-4}	3.50×10^{-5}	143
4	21 – 4	0.135	4.16×10^{-4}	5.90×10^{-5}	133
5	21 – 4	0.135	4.16×10^{-4}	5.90×10^{-5}	133
6	21 – 5	0.080	1.97×10^{-3}	4.00×10^{-5}	37
7	21 – 6	0.085	6.79×10^{-5}	3.71×10^{-5}	316
8	21 – 7	0.155	2.26×10^{-3}	7.75×10^{-5}	52
9	21 – 8	0.135	2.89×10^{-4}	5.90×10^{-5}	170
10	21 – 9	0.170	5.24×10^{-4}	7.44×10^{-5}	133
11	21 – 9	0.170	5.24×10^{-4}	7.44×10^{-5}	133
12	21 – 10	0.175	1.37×10^{-4}	8.75×10^{-5}	251
13	21 – 11	0.115	3.54×10^{-4}	5.03×10^{-5}	143
14	21 – 12	0.195	2.39×10^{-4}	9.75×10^{-5}	240
15	21 – 12	0.195	2.39×10^{-4}	9.75×10^{-5}	240
16	21 – 13	0.105	1.28×10^{-4}	5.25×10^{-5}	238
17	21 – 14	0.215	1.98×10^{-3}	1.08×10^{-4}	69
18	21 – 15	0.245	2.25×10^{-3}	1.23×10^{-4}	69
19	21 – 16	0.255	7.86×10^{-4}	1.12×10^{-4}	133
20	21 – 17	0.240	1.88×10^{-4}	1.20×10^{-4}	251
21	21 – 18	0.085	1.24×10^{-3}	4.25×10^{-5}	52
22	21 – 19	0.155	6.47×10^{-4}	7.75×10^{-5}	121
23	21 – 20	0.115	1.06×10^{-3}	5.75×10^{-5}	78

As can be seen in Fig. 2, each load of the network is modeled by a group of three blocks. The blocks are a three-phase series branch, a three-phase measurement block, and three-phase series load. Also, the three-phase source located in BUS #21 supplies the loads and a three-phase V-I measurement block measures the main power input of the whole network.

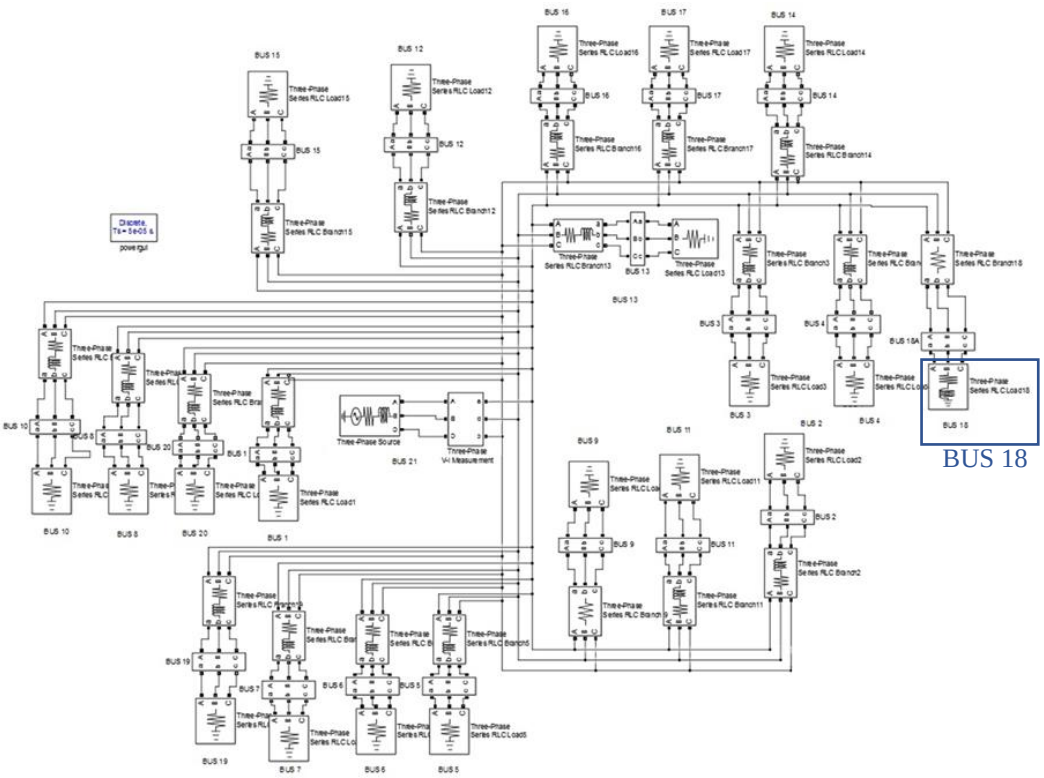

Fig. 2: Simulink model of the distribution network of the university campus.

3. Case Studies

In this section, several case studies are implemented in order to test and validate the proposed network modeling. For this purpose, the behavior of the network will be surveyed in different conditions considering various rates of consumption.

At the first stage, the focus is given to BUS #18, which is the most distant bus from the power source. Three types of load modelings are considered for BUS #18 in order to survey the behavior of this specific bus. In the first test, a dynamic load is considered for BUS #18 while the rest of the loads are modeled as series loads consuming 100 kW, and in the second and third tests, a series and a parallel load is associated respectively for BUS #18 while the conditions are as same as the first test. The results of these three experiments would be illustrated and surveyed in the next section.

The second part of the case study is related to validate the performance of the developed model, while all the loads are modeled by dynamic loads. Three scenarios are considered for this section:

1. **Winter profiles**: the real consumption profile of each building on a winter day is considered for the network model;
2. **Summer profiles**: the real consumption profile of university on a summer day is considered;
3. **Off-peak**: the profiles would be as same as scenario 1, however, it is considered that the three most consuming buildings are not participating in the consumption profiles, since it is a public holiday and there are no classes in the faculty.

Fig. 3 shows the real consumption profiles of each bus (each building) considered for three scenarios. All the charts are stacked lines, which means the last line presents the total consumption of the network.

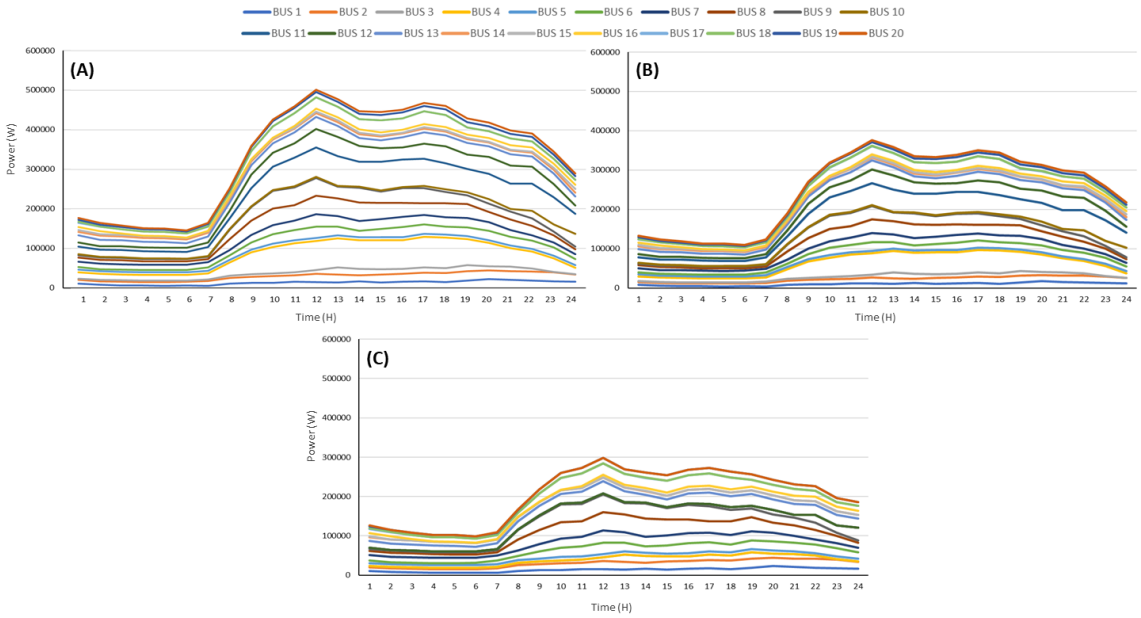

Fig. 3: The real consumption profiles of university considered for the case study in three scenarios: (A) winter profiles, (B) summer profiles, (C) off-peak.

As Fig. 3 shows, the profiles are for one day with a 1-hour time interval. The simulation is set to run each hour period values in a fixed-step size of 30 seconds. Therefore, the outcomes of simulations would be obtained in 12 minutes after it starts running.

4. Results

The present section shows the results obtained from the simulation described in the previous section. The first gained results are related to the performance of BUS #18 with three different load models. Fig. 4 shows the behavior of these load models in the first second of the simulation while there is 100 kW active power and 40 kVAR reactive power demand in BUS #18.

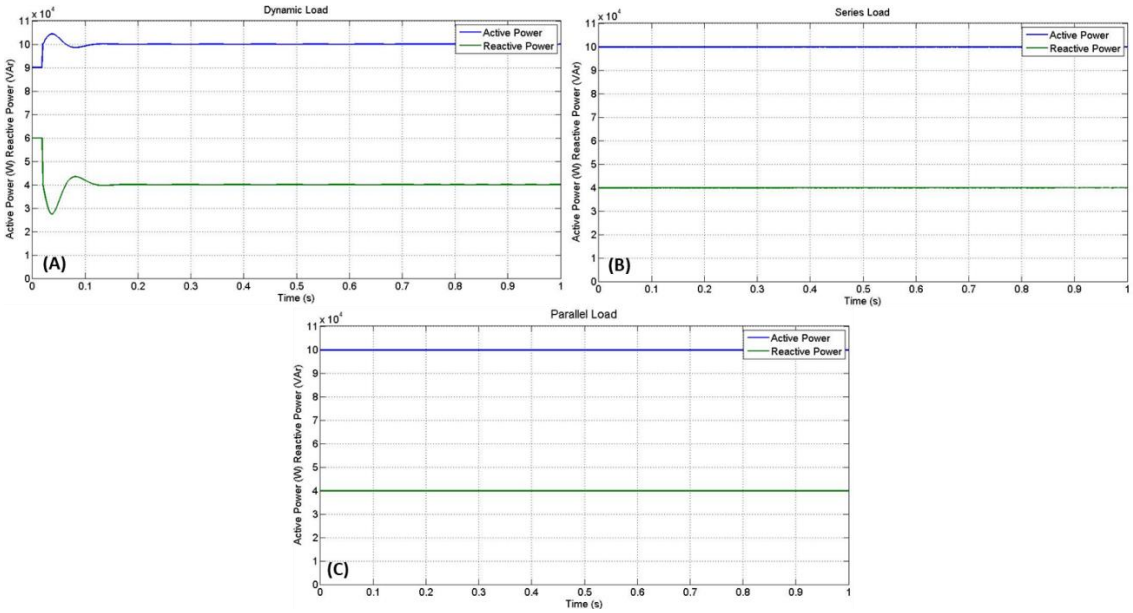

Fig. 45: Behaviour of BUS #18 in the first second of the simulation with three different loads modeling: (A) Dynamic load, (B) Series load, (C) Parallel load.

As Fig. 4 shows, the response of the dynamic load is slower to reach to its permanent state comparing to the other two load models that have similar behaviors. In the dynamic load, it takes 0.15 seconds for the reaching to the permanent state while the other two load models immediately reached the desired rate. Furthermore, Table 2 presents the power consumptions of loads and branches in BUS #18 at the end of the simulation. As it can be observed from Table 2, there are some internal losses in the series and parallel load model somehow, they do not allow the consumption rate to be as same as the desired rate. Also, the losses in the branch of the dynamic load are slightly higher than the rest of the loads.

Table 2: Power measurement regarding BUS #18.

	Measured Power		**Branch Power**		**Total Consumption**	
	P (W)	Q (VAR)	P (W)	Q (VAR)	P (W)	Q (VAR)
Dynamic Load	100000	40000	145,4	0	100145,4	40000
Series Load	99641,805	39857,541	144,5	0	99786,3	39857,54
Parallel Load	99642,372	39856,817	144,5	0	99786,87	39856,82

Another important difference between these models is to set the desired power rate. In Series and Parallel loads, the power consumption rate can only be set before starting the simulation, however, in the dynamic load model it can be changed throughout the simulation. These differences between the load modelings, especially the dynamic load, are due to the nature of the type of loads and blocks that are being used for the testing in the Simulink tool.

Regarding the results of the whole network, Fig. 5 shows the overall consumption of the network simulated by the developed model for the university campus distribution network in three scenarios mentioned before. In all three scenarios, the loads are modeled using dynamic load, since its outputs are closer to a realistic load and also it allows to change the power input while the simulation is running.

The results shown in Fig. 5, are for 12 minutes in total, which means each 30 seconds a new power consumption rate is transmitted to all loads and therefore, they react and try to reach the favorable consumption rate. Also, in the same figure, while the consumption rate is changed, there is a peak in active power, which is due to the nature of the dynamic load, as it was discussed in Fig. 4.

Based on the results shown on this section, it can be concluded that the developed Simulink model has adequate and acceptable performance in simulation, and the obtained results validated the functionalities of that in different conditions with the various rate of consumption.

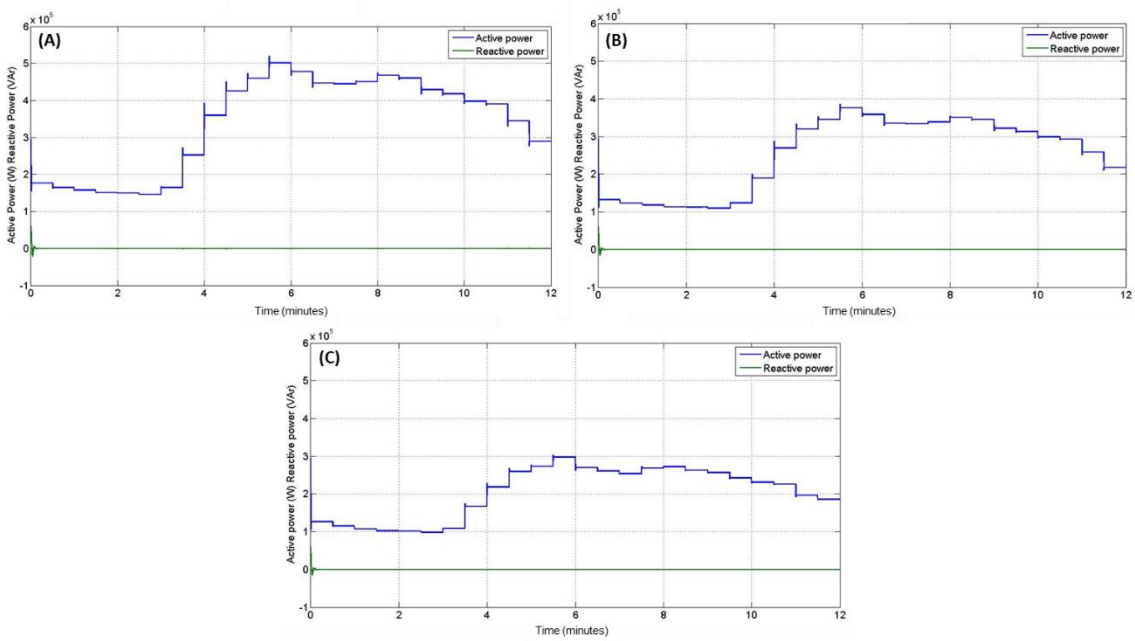

Fig. 5: Overall consumption of university campus network simulated by the developed Simulink model: (A) winter profiles, (B) summer profiles, (C) off-peak.

5. Conclusions

This paper presented a MATLAB/Simulink model of a low voltage distribution network of a university campus. Several load modelings have been surveyed and their performances in various conditions were demonstrated. The real consumption profiles of the university campus were used for the case studies through different scenarios. In the model, each building of the university was considered as a dynamic load for simulating the consumption rate. The results of the simulation show that three-phase dynamic load is the best approach for modeling the consumption of each building since it reacts closer to a realistic load. Moreover, the dynamic load model allows the user to modify and change the rate of consumption while the simulation is running, which this is not possible to implement using other types of load modelings.

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Demand response approaches for real-time renewable energy integration
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Real-Time Simulation of Hybrid Energy Solution for Microgeneration in Residential Buildings

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Abstract

The unplanned power outages have occurred for all of us, and we know that from the household inhabitant's standpoint, power outage even for a short period of time is not pleasant. This matter is also true for the residential buildings that are far from the main cities, namely in the countryside or in a small village, and they may have a power outage for a long-term even with a small problem in the power transmission lines. Therefore, an energy solution module is required in order to prevent power outage for household inhabitants. In this paper, an off-grid energy sustainability solution for residential buildings will be represented by considering several small-scale generators. The module consists of several microgeneration units and energy storage systems for maintaining the energy balance. Also, a software-based control unit is used for controlling the production. The main focus is given to survey the performance of the wind turbine utilized in this energy module. The behavior of an induction machine and a permanent magnet machine will be investigated in two levels of simulation and emulation in order to realize the best solution for the wind turbine of presented energy module.

Keywords: hybrid energy solution, power outages, real-time simulation, wind turbine

1. Introduction

The hierarchical structure of the power distribution networks is being updated and move towards the smart grids, and microgrid paradigms [1]. Smart grid concepts provide several flexibilities based on resource management somehow the network operator would be able to control the rate of consumption and generation [2]. On the other hand, the daily increment of electricity demand leads to reduce the method of generation using fossil fuels [3] and optimally utilize sustainable and renewable energy resources, especially Photovoltaic (PV) and wind turbines [4].

The use of the new concepts of the power system, such as Distributed Renewable Energy Resources (DRERs) and Demand Response (DR) programs, by the small and medium players, make the network management more difficult and unstable [5]. This fact could lead to having an unplanned power outage. The power outages have occurred for everyone all around the world, which is very unpleasant for all people, especially household inhabitants. Furthermore, the residential buildings out of the main cities, such as in countryside or in a small village, can suffer from this issue since they may have a power outage for a long-

term with a small technical problem in the distribution network. The Energy Storage System (ESS) can be considered as a solution to overcome this problem. However, all ESS has a limit capacity and it can only supply the electricity demand for a short period of time. Also, an ESS with adequate capacity for storing energy is not affordable for the residential buildings in the countryside and small villages. This means an energy solution module is essential to be developed and utilized in those areas in order to prevent the power outages, especially for household inhabitants.

This paper presents an off-grid energy sustainability solution for residential buildings, which employs several small scales generators. This energy module includes several microgeneration units, such as PV panels, a wind turbine, and an emergency generator. Moreover, two ESS are utilized in the module for keeping the energy balance, and a software-based control unit is used for controlling the rate of production. This module so-called HibridGER and a prototype has been implemented by the GPRI research group in Brazil (www.labteca.ecolabore.net). The main focus of this paper is given to study several simulation and emulation models for the wind turbine that can be utilized in the HibridGER. MATLAB/Simulink tools are used for the simulation of the models. Also, a real-time simulator (OP5600), and a 1.2 kW laboratory wind turbine emulator will be employed as Hardware-In-the-Loop (HIL) in order to compare the obtained results from the simulation and emulation.

After this introductory section, the HibridGER module is described in Section 2. Section 3 presents the simulation and emulation wind turbine models implemented by Simulink and OP5600, and their results are demonstrated in Section 4. Finally, Section 5 clarifies the main conclusions of the work.

2. HibridGER Module

As it was mentioned in the previous section, the HibridGER module is related to an off-grid energy solution, which employs several generation resources, including renewable sources, as well as ESS. The renewable sources consist of PV panels with 350 W generation capacity and a wind turbine with a 1000 W generation rate. Furthermore, two 12 V batteries with a total capacity of 85 A/h, are connected to the module. Besides these, a generator with 2000 W capacity supports the module in critical moments. Fig. 1 illustrates an overview of the presented module.

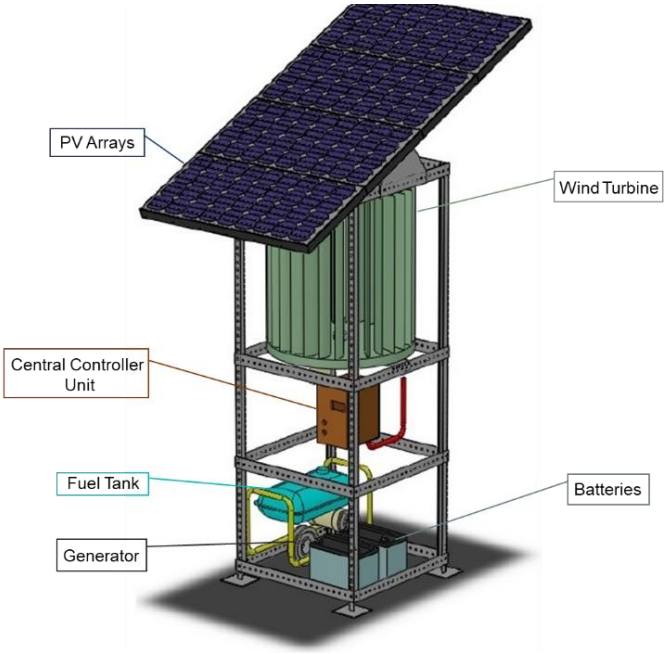

Fig. 46: Architecture of HibridGER Module.

The central control unit of this module is responsible for several functionalities. Several energy meters and relays are embedded in the module that are all connected to a software-based controller (Arduino® - www.arduino.cc) in the central control unit. Energy meters are responsible to monitor the energy generation and the output of the module, and the relay is accountable for connecting or disconnecting the sources of the module.

The software-based controller intelligently decides about the operation of the sources based on an internal algorithm. The priority of the system is to supply the demand from the renewable sources, and while there is no demand, the batteries would be charged from those sources. If the electricity demand is out of the capacity of renewable sources, the controller connects the batteries in the power circuit to feed the loads. In the last stage, if the renewable sources and batteries were not adequate for supplying the demand, the emergency generator would be connected to the power circuit in order to supply the loads.

3. Wind Turbine Models

This section surveys the functionalities of the wind turbine used in HibridGER by providing two types of machines in order to identify the most efficient solution. Therefore, this section is divided into two subsections, which the first one describes the performance of an induction generator, and the second subsection focuses on a permanent magnet generator.

3.1 Wind Turbine Models

The induction machine considered in this section is related to a laboratory 1.2 kW wind turbine emulator. In this emulator, an inductive three-phase generator has been coupled with a three-phase asynchronous motor with variable speed. In fact, the motor emulates the blades of the wind turbine. Therefore, the operator can simulate the wind speed by controlling the speed of the motor. While the emulator is turned ON, the generator is connected to the power network in order to inject the produced power. Consequently, the emulator should follow the frequency of the grid (normally 50 Hz). If the speed of the generator goes above the frequency of the grid, the generator injects the produced power to the grid. However, if the speed of the generator is not adequate, it would not be able to produce energy.

In order to control and manage this emulator by the real-time simulator (OP5600), the analog input terminal of the speed control unit has been integrated into the analog output board of OP5600. Then, the wind speed data have been converted from km/h to a value in the range of 0 to +10V in order to provide it to the speed control unit. The computations of this conversion have been implemented in Simulink. Also, for monitoring the real-time generation of the emulator, an energy meter has been embedded in the machine, which is connected to the OP5600 through Ethernet interface, with MODBUS TCP/IP protocol. More information about this process is available on [6][7]. Fig. 2 illustrates these configurations.

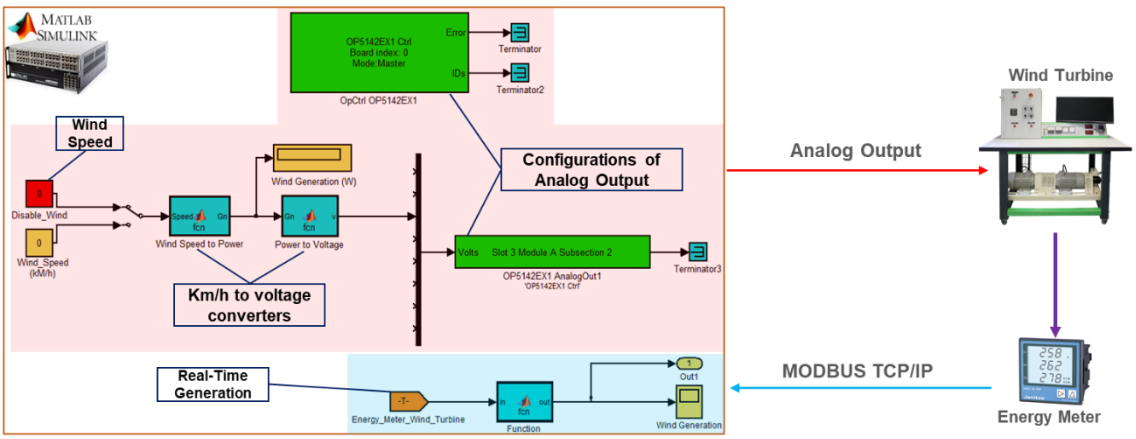

Fig. 2: Real-time simulation architecture for wind turbine emulator.

As can be seen in Fig. 2, the OP5600 would be able to control and monitor the emulator in real-time. In other words, OP5600 can send the desired wind speed data to the emulator and receives a real-time amount of generation. By this way, the performance of the induction generator could be surveyed, as it will be demonstrated in the next section.

3.2 Permanent Magnet Machine

The permanent magnet machine is another target of this paper in order to investigate its performance while it is used as a wind turbine. Since there was no available laboratory equipment for this machine, it is decided to develop a MATLAB/Simulink model, as Fig. 3 shows.

In this model, the permanent magnet machine is configured with a three-phase connection while the stator phase resistance is set as 0.0018 ohms and stator phase inductance is set to 8.5e-3. Also, the voltage rate is configured as 400V line to line, and the torque of the machine is controlled externally from the other blocks. The model is shown in Fig. 3 is embedded in OP5600 and the results and its performance will be shown in the next section.

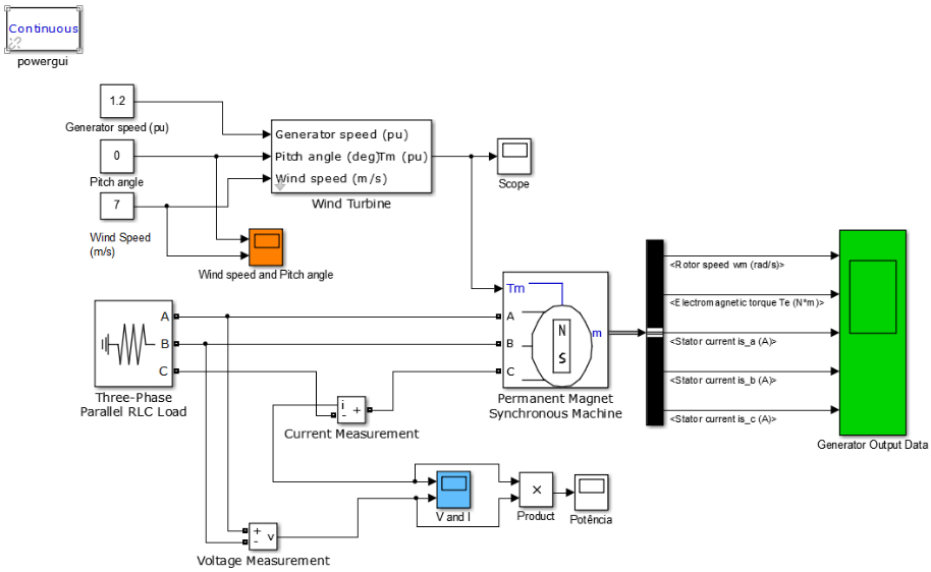

Fig. 3: Simulink model of a permanent magnet wind turbine.

4. Results

This section demonstrates the results obtained from the simulation and emulation models described in the previous section. At first, the results of wind turbine emulator controlled by OP5600 are proposed, and then the permanent magnet behaviors are discussed. Fig. 4 shows an experiment implemented by the 1.2 kW wind turbine emulator.

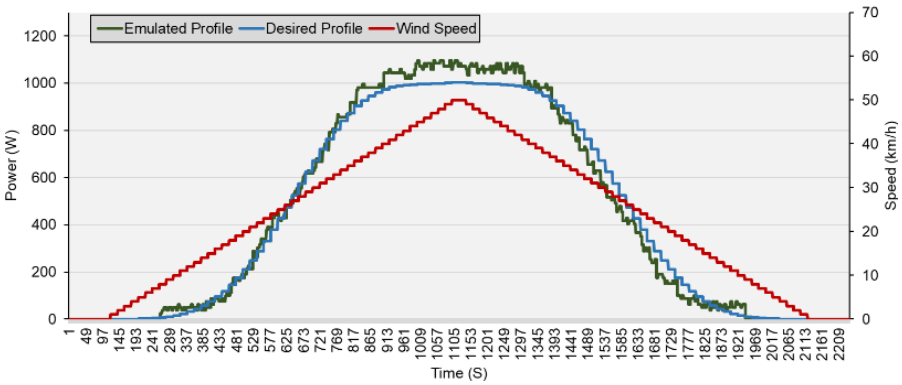

Fig. 4: Comparison of real and simulated wind generation profiles by wind turbine emulator.

The results shown in Fig. 4 are related to a test that has been performed by OP5600 and 1.2 kW wind turbine emulator. In this test, the wind speed has been increased from 0 to 50 km/h and vice versa. The blue line in Fig. 4 is the desired power rate and the green line is the output generation of wind turbine emulator. Moreover, Fig. 5 illustrates the results of another test implemented by the wind turbine emulator. In this second test, the wind speed data has been acquired from [8], which is the actual wind speed data provided to the emulator. As can be seen in Fig. 5, the set points are the favorable values that have been requested from the wind turbine to be emulated. Consequently, the emulator produces power and transmits the actual measurements of active power generation (green line in Fig. 5) to the OP5600. By this way, the system is able to emulate the wind generation profile based on the electrical grid conditions, such as voltage variations. Regarding the permanent magnet machine, Fig. 6 illustrates the obtained results from the Simulink model.

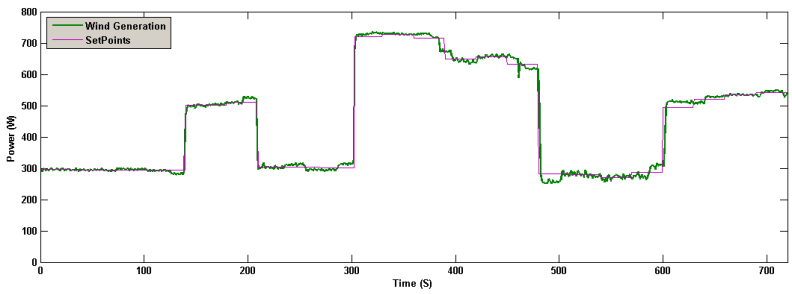

Fig. 5: Real-time results of wind turbine emulator.

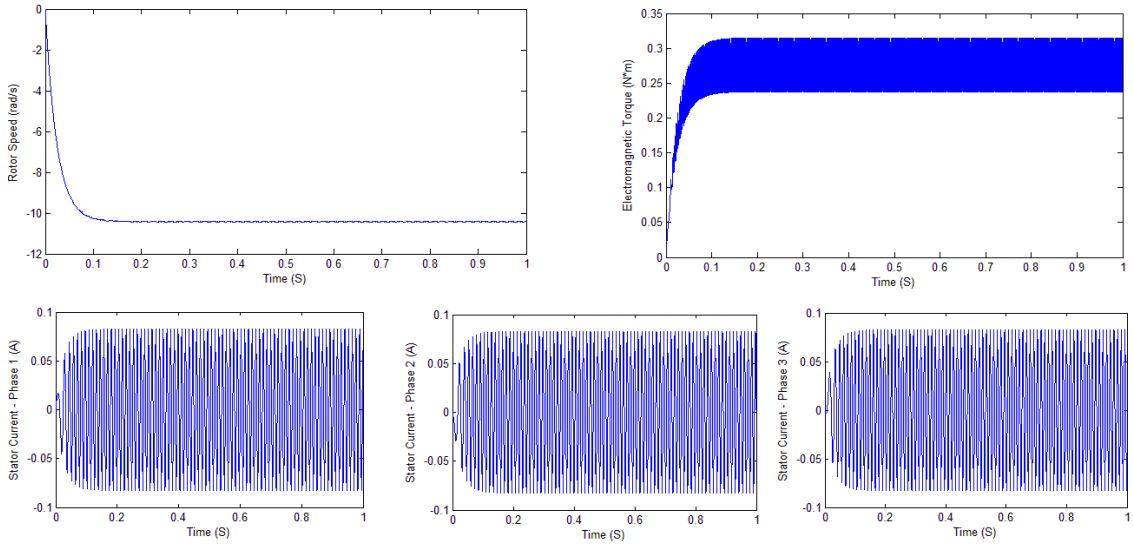

Fig. 6: The results of simulation for the permanent magnet generator.

The results shown in Fig. 6 are gained while the wind speed is set to 7 m/s, generator speed is 1.2 p.u, and 30 degrees in the pitch angle.

5. Conclusions

This paper proposed an off-grid energy solution for residential buildings in order to overcome the power outages. This energy module consists of renewable energy sources, energy storage systems, and an emergency generator. Two models, including an induction machine and a permanent magnet machine, were presented for the wind turbine employed in this energy module. All the models have been simulated and emulated by laboratory equipment and a real-time simulator, and the obtained results are presented. The outcomes of the paper show that the induction machine is more acceptable and suitable to be used as a wind turbine in the proposed hybrid energy solution.

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