Proceedings of the Second ELECON Workshop

Consumer control in Smart Grids

October 28-29, 2014
Institute of Electrical Energy Systems - Otto-von-Guericke-University
Magdeburg, Germany

ELECTRICITY CONSUMPTION ANALYSIS & ENERGY EFFICIENCY

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Demand Side Management of Electricity aiming to Minimize Cost of Residential Consumers

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Abstract

The main objective of this study is to analyse the photovoltaic generation of electric energy by the consumer and to show possible energy management of his consumption. Different kinds of tariffs depending on the hour of use and system capacity are analysed. In addition, it is intended to show the benefits of the renewable energy of micro photovoltaic plants in residences, combined with practices of a better energy use through equipment/materials more intelligent/efficient, in other words, the possibility of a demand side management. In this way, initially it was listed the chances to promote the energy-efficiency by the analyses of the technology availability and a more efficient use of equipment. This study aims the development of residential projects that contemplate energetic optimization since its creation and enable the consumer to manage his consumption according with his priority in energy use. It is also taken into consideration the possibility to attend part of the consume using photovoltaic solar generation and the different values of energy tariff. For this, it was conducted a comparative study that verified the photovoltaic solar microgeneration technical-economic viability in residential dwellings considering the option of "Time-of-use Tariffs", that can provide to the residential consumer a better management on the use of electric energy and implies changes in consumption habits.

Keywords: microgeneration; conventional tariff; time-of-use tariff

1. Introduction

Better energy use and alternatives that reduce its usage are extremely important. The energy consumption grows worldwide, as well as the environment and sustainability concerns, so combine new technologies, change habits, and techniques that enable a more efficient use of energy are current needs.

In 2006, the International Energy Agency (IEA), on the World Energy Outlook 2006 (WEA), released an estimative of the World's energy consumption. They proposed two world scenarios, one as a reference, where efficiency policies already proposed are not considered but only that already in use. In a second scenario, it was considered the policies, actions and new technologies of efficiency expected to be implemented until 2030. As result, the estimative showed that the demand of the reference scenario in 2030 would be 12% bigger than the other scenario, which represents a 3421 TWh difference [1].

One of the challenges to the adoption of initiatives that promote energy efficiency is its costs.

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Conventional technologies are cheaper and easy to access. Awareness in relation to the change of habits and the idea of the return of investment could be of a hard understanding inside society.

The adoption of efficient practices is possible in all sectors of the electric system, but the current work has its focus on the residential sector, where the consumer, through possible habit changes affects the system and contributes for its efficiency (demand side management). Different actions, as new appliances and changing habits can promote a residential efficiency, with benefits for both the consumer and the electric system in general.

In residences, appliances can represent a great change on energy consumption, through the use of more efficient technologies. Within the possible changes, the highlights are: illumination, air conditioning, electric shower, refrigeration, computers, and stand-by lights (present in many devices). However, incentives and more information are necessary to promote these changes and raise awareness about the financial benefits.

Besides the consumption reduction through more efficient technologies, to control the time of use is also interesting, taking into account the peak-load present in Brazilian load curve as an example. Having a mostly hydraulic generation, the use of thermal sources, more expensive and pollutant, is only made during the peak hours, from 6 PM to 9PM. During this time period, people arrive at home from work; and public and commercial illumination are turned on simultaneously. So, reducing residential consumption during this time, could avoid the use of thermal sources. Measures that stimulate this reduction have been already taken, and there are some more that will be taken in the future.

With the advance of technology and the reduction of costs of the new sources of energy, as an example, the energy generated from photovoltaic solar panels, today is possible to generate electric energy from small generator units with low installed power. In the world, the use of generator units in residences is normal and is getting established gradually. The Distributed Generation has become an option for countries that are in need of resources for generating energy. In Brazil, this model of generation of energy is still in its initial stage, being introduced as a way of cutting costs for the residential consumption and for a better security of energy supply.

During the last years, it has been searched more and more the use of distributed generation, reducing the costs of transport from the source to the load. Also new proposes of energy tariffs with the objective of finding the better use of energy from a consumer point of view are being discussed.

The search for this alternatives are found in the Normative Resolution nº 482, 17/04/2012 [2] and in the Technical Note º 311/2010 [3] that establish the rules for use of distributed micro and mini generation for the electric energy distribution systems and the proposal of tariffs with different prices for low voltage consumers according the period of use, based on the load of the system (time-of-use tariff).

In this context, this paper has the goal of analyze the payback for a consumer supplied in low voltage, using a new tariff for the residential consumer established by ANEEL (Brazilian energy regulatory agency) together with photovoltaic solar energy microgeneration for residential consumer units.

2. Methodology

In the current paper, it was taken as reference the current Brazilian regulatory framework referent to microgeneration and tariffs types. Measured data provided by the company SMA Solar Technology [4] is used to simulate the performance of the solar generator. These data was collected by the Federal University of Santa Catarina – UFSC in a solar generator unit with installed capacity of 2kWp during a ten years period. Details can be obtained in [5].

In the beginning, it was made a wide literature review concerning the rules, resolutions, decrees, laws, and other documents related to: Time-Of-Use Tariff (called “Tarifa Branca” in Brazil); Microgeneration; Regulatory policies; and other important themes for the understanding of everything that covers the addressed issue. Then, a collection of data referent to: a) load curves of residential consumers class B1; b) costs of energy generation from the photovoltaic panel; c) tariff values applied by CELESC (utility of Santa Catarina state) according to Aneel Resolution nº 1322 31/07/2012; and d) to the technical and economic values related to the installation of a microgeneration systems. All these information were used together with a mathematical model to estimate some economic figures and an analysis of the results was made.

3. Case Study

3.1. Residential consumption demand

Based on the information given in [7] a graphic of load curves of two typical energy consumers in the

range of 300 to 500 kWh per month (range of the time-of-use tariff) were plotted (See Table 1 and Fig. 1).

Table 1. Demand data for two typical consumers

Hour	Consumption (kWh)					
	Consumer 1			Consumer 2		
	workdays	saturday	sunday	workdays	saturday	sunday
1	0.42	0.35	0.4	0.42	0.42	0.37
2	0.4	0.33	0.37	0.4	0.45	0.31
3	0.33	0.3	0.37	0.38	0.41	0.32
4	0.28	0.3	0.3	0.39	0.41	0.33
5	0.33	0.29	0.35	0.4	0.39	0.33
6	0.38	0.29	0.36	0.4	0.39	0.33
7	0.45	0.31	0.37	0.41	0.33	0.25
8	0.49	0.4	0.33	0.64	0.55	0.29
9	0.4	0.55	0.36	0.85	0.62	0.36
10	0.45	0.42	0.4	0.88	0.68	0.35
11	0.44	0.45	0.42	0.9	0.66	0.35
12	0.47	0.38	0.42	0.72	0.55	0.35
13	0.45	0.41	0.4	0.78	0.51	0.32
14	0.47	0.5	0.41	0.85	0.5	0.32
15	0.49	0.51	0.42	0.85	0.49	0.33
16	0.49	0.52	0.4	0.84	0.48	0.34
17	0.48	0.6	0.42	0.82	0.42	0.34
18	1.1	1	0.55	0.6	0.38	0.28
19	1.17	1.02	1	0.42	0.35	0.29
20	0.9	1.02	0.95	0.42	0.37	0.31
21	1.55	1.18	1.18	0.4	0.38	0.32
22	0.85	0.75	0.8	0.48	0.39	0.33
23	0.6	0.65	0.6	0.5	0.39	0.31
24	0.45	0.55	0.42	0.48	0.37	0.29

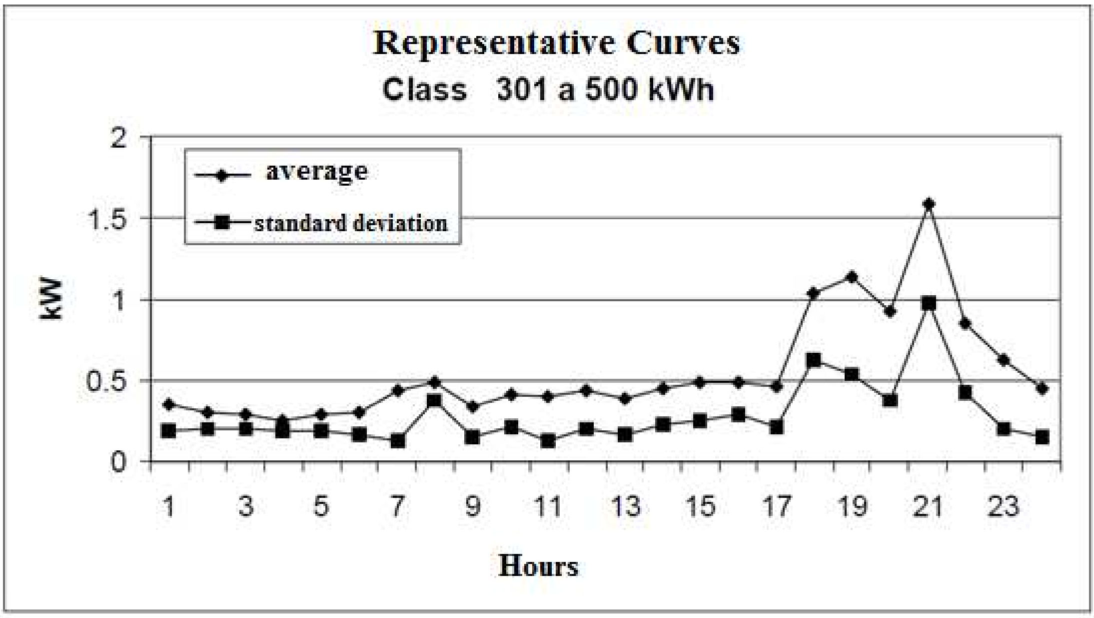

Fig. 1Typical load curve of the residential consumers in workdays. source: [7].

3.2. Energy Tariff for Residential Consumer

After obtaining the load curves, it was necessary to find data about the energy tariff for the B1 Group (Residential Consumer). For this objective, were used data from CELESC - Distributor of Santa Catarina, Brazil [6].

3.3. Microgeneration System

As source of microgeneration, it was used as reference data from a photovoltaic system with capacity of 2kWp, installed at UFSC. This was the first system in Brazil connected to the public electric grid, with 68 photovoltaic amorphous silicon modules, being 55 opaque modules (32Wp) and 13 semi-transparent modules (27 Wp) [5].

The values used are averages obtained from SMA SOLARES TECHNOLOGY AG (2014) available in their website. Fig. 2 shows the average generation of photovoltaic energy of the 2kWp module. It is necessary to highlight that the output of this system was used as a reference for the present study, and the values can be different considering the particularities of each residence. The goal here is to promote a base of evaluation of the payback of a working system in low voltage with conventional tariff and time-of-use tariff.

4. Results

4.1. Graphic Analysis

It is possible to notice, as showed in figures 2 and 3, that the photovoltaic generation has its larger scale production during 9AM and 3PM. It is important to emphasize that these data are an average of generation of the modules during 2012/2013, therefore, the peak of generation in some periods of the year are bigger than the showed in this study, and can be equal or higher to the maximum production of 2kWp or to the energy demand peak.

Figures 2 and 3 present the energy demand of consumer 1 and consumer 2 respectively, together with the average photovoltaic generation for 2 kWp system.

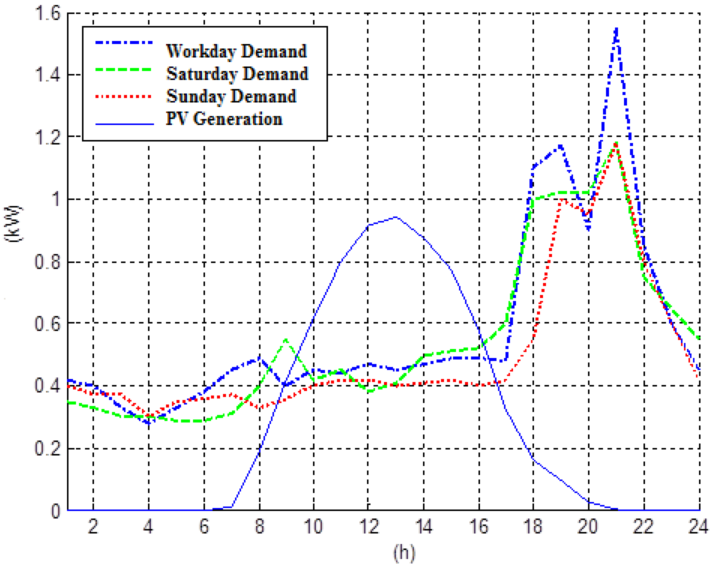

Fig. 2 – Demand of Consumer 1 and photovoltaic generation

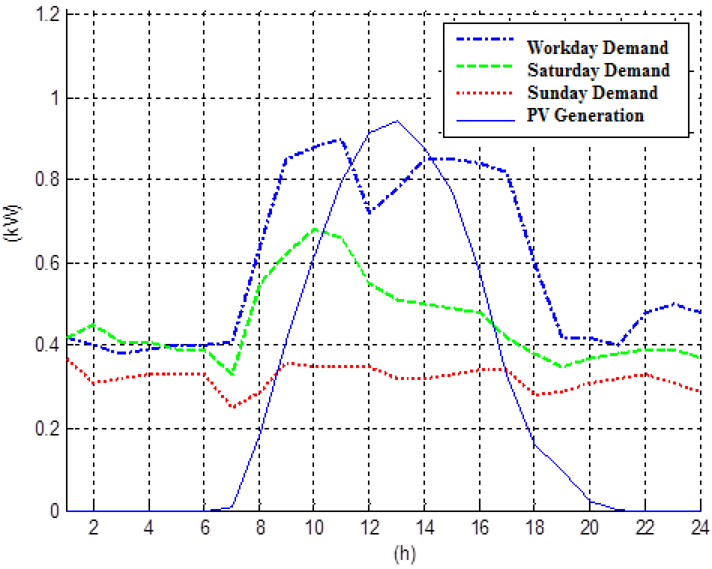

Fig. 3 – Demand of Consumer 2 and photovoltaic generation

Doing the balance between demand and generation for both consumers, the net energy imported from or exported to the grid is given in figures 4 and 5.

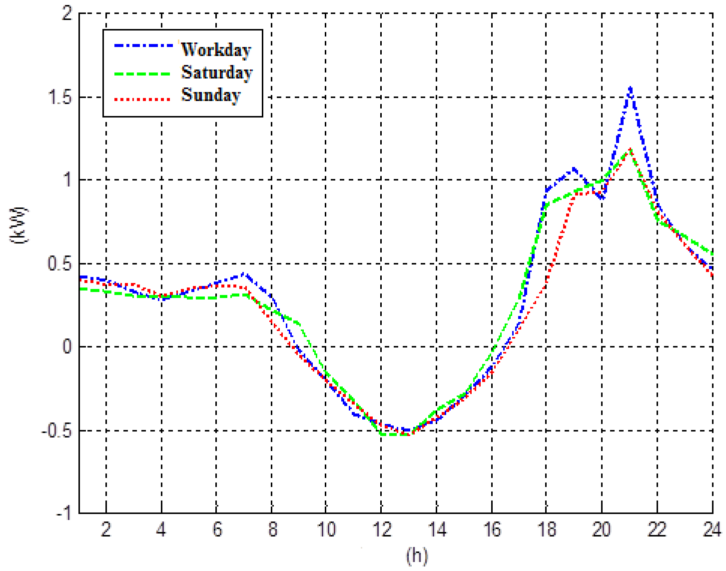

Fig. 4 – Difference between demand and photovoltaic generation for Consumer 1

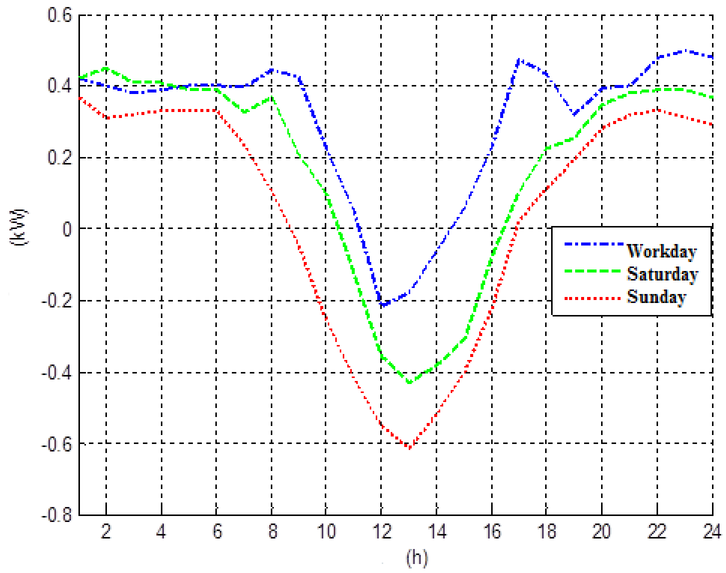

Fig. 5 – Difference between demand and photovoltaic generation for Consumer 2

It can be noticed that for these two cases the peak exported power to the distribution system is not greater than the peak imported because an average value of production and consumption of solar energy was used. However, as module solar power generation is 2 kWp there will be times when the energy delivered to the grid will be close to this value. If the distribution system is not dimensioned to receive this value, an increase in system capacity will be needed.

4.2. Costs of PV Generation System

Considering that the total costs of installing a 2kWp system, using as reference value of 5 euro/Wp, costs decrease of 5% per year, and interest rate of 8% per year, it results in value of euro €7500.00. Adding the maintenance it results in €8300.00.

With consumption demand and generation established, the evaluation impact resulting in the price of energy in that month using or not solar energy was estimated. Table 2 presents the result for consumers 1 and 2, with and without photovoltaic generation for both conventional and time-of-use tariffs.

Table 2 Monthly Tariff - Simulation

Monthly electricity bill (€)		
	with photovoltaics	**without photovoltaics**
Consumer 1 - Conventional Tariff	21.11	43.22
Consumer 1 – time-of-use Tariff	28.46	48.34
Consumer 2 - Conventional Tariff	19.14	41.15
Consumer 2 – time-of-use Tariff	20.23	40.11

The net-metering model (compensation energy system) used in Brazil, is a mechanism in which the energy is absorbed or transported to the grid instantly. The energy peak of the residential consumer 1 is within 6PM and 9PM, and it is in these hours that the time-of-use tariff has its higher price. Once the photovoltaic generation has its peak during the afternoon, the price paid by the time-of-use tariff is the lowest possible, it is more profitable the use of conventional tariff for both consumers when they have a photovoltaic system. An alternative would be the change of habits related to energy use, so de reduction on the energy bill with time-of-use tariff would be higher in comparison to conventional tariff. This observation also leads to the need of a more intelligent control of generation/consumption and a more detailed analysis of the consumption since depending on the consumption habits different alternatives for a demand side management can be implemented.

5. Conclusions

The objective of this work was to do some considerations about the way that a consumer could manage his energetic consumption, with a potential application of intelligent/efficient equipment together with the possibility of photovoltaic microgeneration considering the actual tariff policies

The usage of photovoltaic generators in combination with a good system design can bring good economic results, but with these new tariff policies this time could be drastically reduced, making this technology economically feasible. With the time-of-use tariff and the possibility of “selling” energy in watts, it is possible to export energy to the system during the day, and getting it back during the night, with price adjustment already made, but still bringing economy.

However, finishing this work, it was possible to check that the investment in the installation of a photovoltaic microgeneration system is not attractive yet with the actual costs and regulation, because the payback time was calculated in more than 30 years, and that the life cycle of the panels is around 25 years.

The distributed generation is an important alternative for cleaner energy production. It also could assure a stronger and with lower risks of interruption and faults energy production, promoting a robust system in all senses. Therefore, the incentives for the scope of microgeneration through regulatory policies or new tariffs, as the time-of-use tariff, should remain to promote a more correct and sustainable energy use by the consumers.

Following the conclusion of this work, it is suggested that a deeper analysis to check what would be the change on the bill if the consumer choose to change his consumption profile using energy out of the peak time.

Acknowledgements

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Using Typical Consumption Profiles to Stablish the Consumption Level for Short Time Periods

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Abstract

The current practices in the consumption metering by electricity utilities is currently largely based on monthly consumption reading. The consumption metering device is always calculating the cumulative consumption. Then, it is possible to calculate the difference between the actual and the previous consumption evaluation in order to estimate the monthly consumption. The power systems planning needs in many aspects to handle consumption data obtained for shorter periods, namely in the Demand Response programs planning. The work presented in this paper is based on the application of typical consumption profiles that are previously defined for a certain power system area. Such profiles are then used in order to estimate the 15 minutes consumption for a certain consumer or consumer type.

Keywords: Consumption estimation, Demand response, Typical consumption profiles.

1. Definition of Consumption Profiles

The definition of consumption profiles has been largely studied in the literature [1]. Several methods and approaches can be identified, namely: the Profile Administrator (PrA) [1]; the modified follow the leader [2-4], the self-organizing map (SOM) [3, 4, 5], the k-means [4, 5], the average e Ward hierarchical methods [5, 6] and the fuzzy k-means [6–8]. The work here presented is based on the typical consumption profiles definition currently in use in Portugal, as implemented by the regulatory authority ERSE [9].

ERSE publish annually consumption profiles concerning regular low voltage consumers (BTN), special low voltage consumers (BTE), and medium voltage consumers (MT) in order to be possible to once having the monthly consumption being possible to estimate the consumption for each 15 minutes period in consumers without metering capabilities able to measure this period detail. For the BTN consumers, three distinct profiles (Class A, Class B, and Class C) according to the rated power and to the total annual consumption of the consumer.

I order to obtain the consumption for each 15 minutes period, one must depart from the estimated monthly consumption. The estimated month consumption for client (consumer) *c*, in the month *m* and in the tariff period *p* ($\mathrm{C}^{\mathrm{c}}_{\mathrm{estimated}_{\mathrm{m,p}}}$) is estimated according to the consumption historic data. When the historic

data concerns a period longer than one year, the following equation should be used.

$$C^{c}_{Estimated_{m,p}} = \frac{cel^{c}_{P} * N_m}{N_d} \quad (1)$$

Where:
cel^{c}_{P} – Consumption between measurements (L2 – L1);
N_m – Number of days in the specific month;
N_d –Number of days between real measures.

The 15 minutes consumption for client “c”, calculated for the 15 minutes period “h” of the day “d” in the month “m”, belonging to the tariff period “p” ($CH^{c}_{m,d.h.p}$) is calculated as follows:

$$CH^{c}_{m,d.h.p} = \frac{P^{0}_{m,d,h}}{\sum_m P^{0}_{m,d,h}} * C^{c}_{Estimated_{m,p}} \quad (2)$$

Where:
$P^{0}_{m,d,h}$ – Initial profile, for month “m”, day “d”, and 15 minutes period “h”.

Using these equations, it becomes possible to the consumption diagram for each 15 minutes.

2. Methodology for the Definition of the Available DR

The proposed methodology, which aims at identifying the opportunities of using the typical consumption profiles in order to define the available amount of DR in each 15 minutes period has been implemented in MATLAB. The procedure is presented in Figure 1.

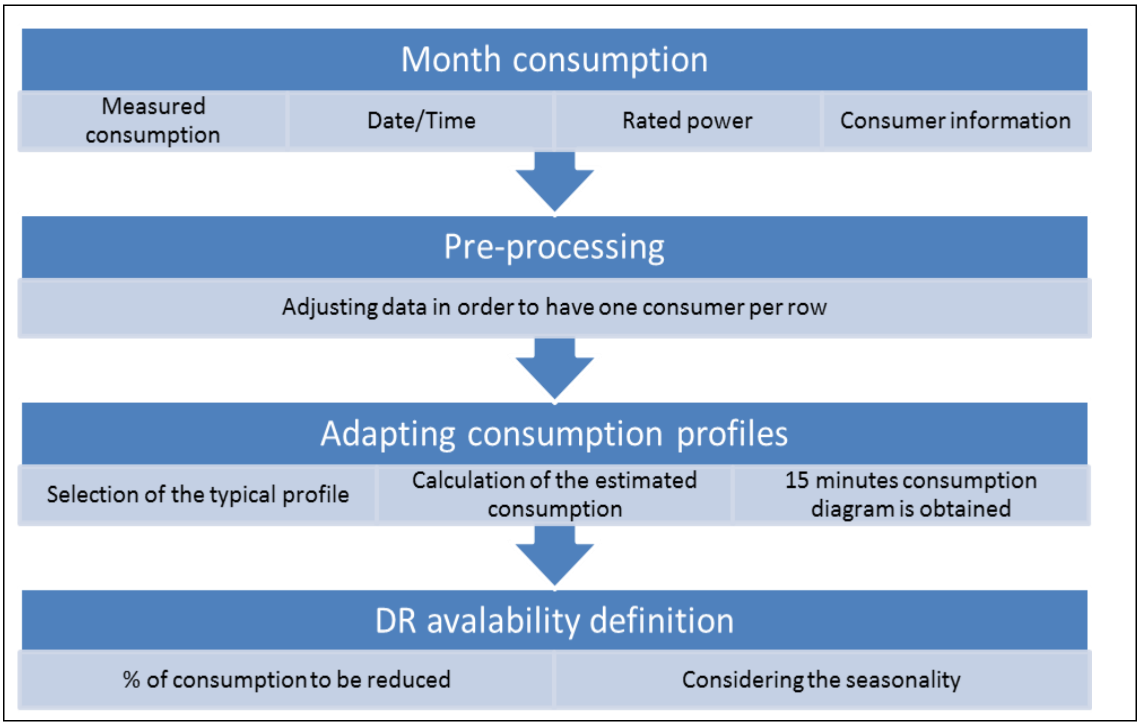

Figure 1 – Proposed methodology diagram.

Once we get the 15 minutes consumption diagram for a certain consumer and knowing the estimated percentage of consumption reduction, it is possible to, using the ERSE methodology estimate the available DR capacity. This is very important in the cases that the consumption data is only known for periods higher than 15 minutes.

3. Case study

Here is presented the application of the proposed methodology to a case study concerning to distinct clients, focusing on the definition of the 15 minutes consumption for each consumer and the respective error estimation error.

The Client 1 is characterized as follows:

⇒ Medium voltage consumer

⇒ Industrial type;

⇒ Measured peak power – 360 kW;

⇒ Rated power – 750 kW;

By applying the proposed methodology, it was possible to achieve the following results for client 1 and for client 2.

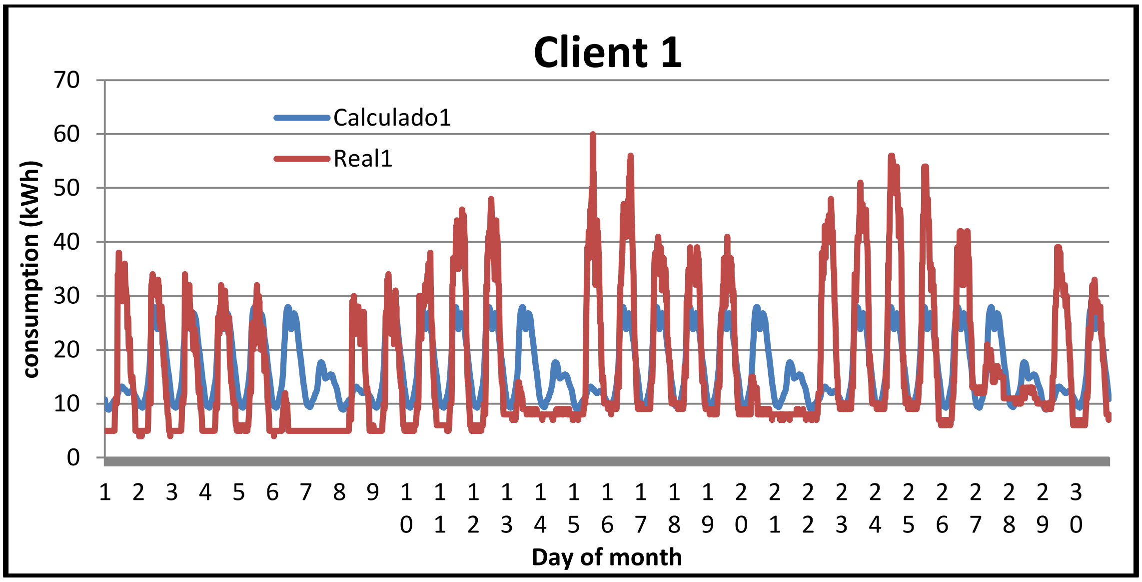

Figure 2 – Consumption of Client 1 in September.

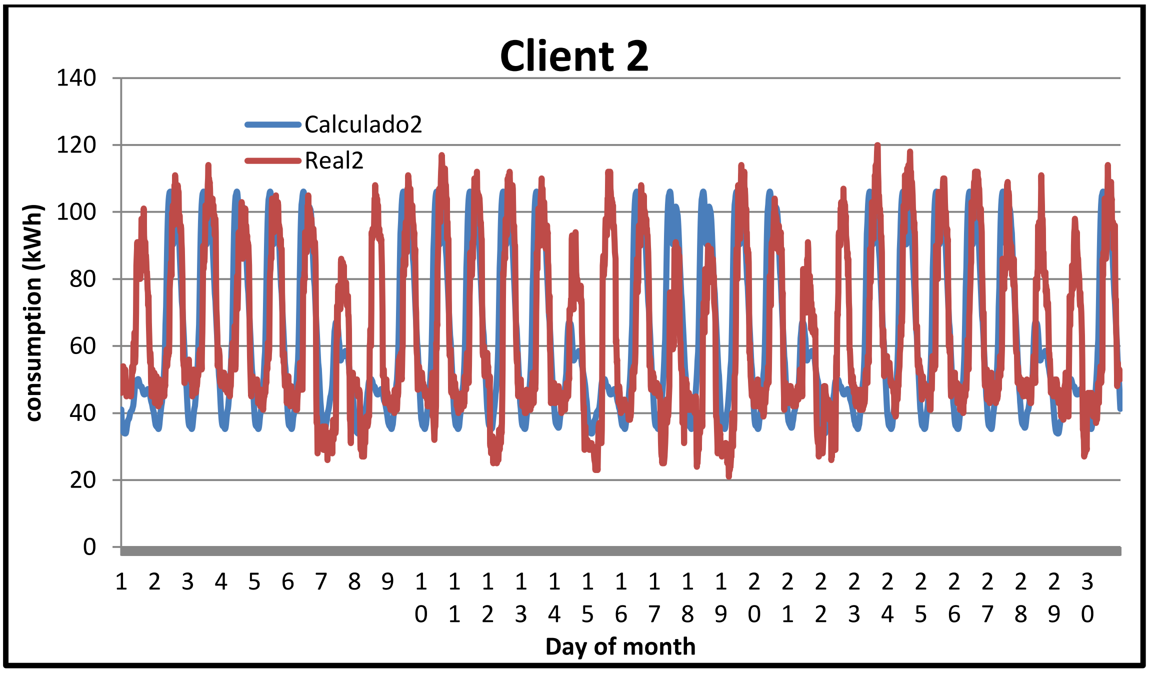

Figure 3 – Consumption of Client 2 in September.

Table 1 – Average and standard deviation of the estimation error.

Client:	**1**	**2**
Average Error	59,68%	26,21%
Error standard deviation	0,625	0,279

It can be seen that the estimation error is lower in the case of Client 2. In fact, these two clients are very different in what concerns its typical consumption profile so the proposed methodology obtains distinct performances in each one.

The authors have also made studies in order to compare the performance of the proposed methodology when applied to these 2 clients, in distinct tariff periods as actually implemented in Portugal, where the consumers are able to pay distinct prices for electricity, along the day. The maximum number of distinct tariffs is 4, for large consumers.

4. Conclusions

The present paper has bring a methodology for the determination of the consumption in each 15 minutes period, for consumers that have electricity consumption measurements monthly. Here it has been used the typical consumption profiles actually used by ERSE, the regulatory Portuguese entity for the energy sector.

The focus and motivation of the work relied on the fact that the implementation of demand response programs should be handled for consumption periods of reduced duration and the most of consumers are actually having only monthly measurements. The effectiveness and accuracy of the methodology has been done for 2 real consumers.

Acknowledgements

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Analysis of the Impact of the FIFA World Cup Brazil 2014 Games on Overall Consumer Behaviors

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Abstract

This paper presents the analysis of the impact of the 2014 soccer FIFA World Cup held in Brazil. This paper focuses on analysis of load curves provide for transmission systems in 4 countries: Brazil, Germany, France and Portugal. The paper shows the behavior of energy consumption before, during and after each game involving these 4 countries, which take part of the ELECON project (Electricity Consumption Analysis to Promote Energy Efficiency Considering Demand Response and Non-technical Losses), comparing at the same time the load profile in each country. This topic was chosen due to the high influence that soccer on many countries, specially in Brazil were the impact in the energy consumption was very strong when compared with the other countries.

Keywords: Energy consumption, Load profile, Soccer.

1. Introduction

Nowadays the energy consumption is increasing with the growing of cities around the world. Recent numbers indicate that the worldwide demand will reach 33,300 TWh by 2030, which is a 60% increase from the 21,000 TWh in 2010 [1]. For this reason, this topic is not only analyzed for the government energy program but also for investors, utilities, service marketers, consumers and academics, specially due to the tendency of demand peaks which put in risk the reliability and cost of the service with shutdowns.

For this and other reasons, it is necessary to know the behavior of the consumption of energy in each season of the year, for individual and collective customers. In some cases some events can change the behavior of the consumed energy, as for example during the FIFA World Cup. This is the most important event in the soccer area. It involves several national teams around the world. Other works about power system analysis during the world cup around the world have been published as described in [2] when the impact of the world cup games in the harmonic distortion is analyzed. In this paper an analysis on the energy consumption behavior during some of the World Cup Brazil 2014 matches is presented. As ELECON project involves universities from Brazil and Europe, the involved countries were taken into account to compare the energy consumption in the transmission network during the games. The matches occurred during the period from 12 June 2014 up to 13 July 2014. The countries involved are Brazil, Germany, France and Portugal. In the next chapter each transmission company involved in the study is

described. The analysis of the load curves is carried out according to the available information from the transmissions companies. The consumption during the days of the world cup is compared on the same weekly day and one or more weeks before and/or after, and sometimes through the operator´s forecast.

2. The Transmission System Operators

In this chapter are presented the main characteristics of the transmission operator companies of the 4 countries used in this paper: ONS (Brazil), 50Hertz (Germany), RTE (France), REN (Portugal).

2.1. ONS - Brazil

Currently, in Brazil, the *Operador Nacional do Sistema Elétrico ONS* (Electric System National Operator) is an entity of private right, non-profitable, created on 26 August 1998, responsible for coordinating and controlling the operation of generation and transmission facilities in the Sistema Interligado Nacional SIN (National interconnected Power System) under supervision and regulation of the Electric Energy National Agency (ANEEL). The Operator is composed of associate members and participating members.

The activities performed by the Electric System National Operator produce benefits for all the sector agents. It also has effects on consumers and, more generally, on society as a whole.

About 80% of energy generation in Brazil is from hydroelectric and there are more than 100,000 km of AC transmission lines from 230 to 750 kV and DC transmission lines in 600 - 800 kV. There are 108 transmission companies in Brazil around its 5 regions: South, South-East, Center-West, North-East and part of the North. All information used in this paper about Brazil is obtained at the ONS web site [3].

2.2. 50 Hz – Germany

In Germany there are 4 transmission companies: EnBW Transportnetze, Tennet TSO, Amprion and 50Hertz Transmission. In this paper 50Hertz was selected for the analysis which is responsible for the operation, maintenance, planning, and expansion of the 380/220 kV transmission grid throughout the northern and eastern part of Germany. The 50Hertz grid covers an area larger than 109,360 km² and runs a length of approximately 10,000 km (the distance from Berlin to Rio de Janeiro). This system supplies power to around 18 million customers and already takes up 40% of the wind power installed in Germany. The total energy production in 2013 was 629 TWh. All information related with the 50Hertz Transmission was obtained from its web site [4].

2.3. RTE – France

The French Transmission System Operator is RTE – Réseau de Transport d'Electricité (Network of Transmission of Electricity). It is a public company responsible for the entire transmission system of France. The system is constituted of 100,000 km of lines from 63 to 400 kV and 45 cross-border lines. In 2008, RTE posted turnover of €4,221m and currently employs around 8,500 staff. The aim of RTE is to ensure the operating and developing of the transmission network and ensure its stability and reliability.

The transmission network remains a monopoly despite of the opening of the electricity market. RTE has a mission of public service whose rules are defined by French law and the French energy regulator (CRE – Commission de Régulation de l'Energie). Every user of the electricity transmission system has to be treated in a non-discriminatory manner with public access charges that do not depend on the distance between the supply and the consumer. The CRE is responsible for fixing the tariff of electricity for using the transmission system – otherwise known as the TURPE charge. RTE also has to ensure compliance to the rules of interconnections between the different European TSO. Those rules are managed by the ETSOE (European Transmission System Operators for Electricity).

Then RTE has to guarantee – at the costs fixed by the authorities – the continuity and quality of supply of electricity. The guarantee of the continuity of supply is obtained by ensuring the balance of electricity flows on the network at all times. This balance is possible thanks to an accurate forecast of the consumption [5].

2.4. REN – Portugal

REN – Redes Energéticas Nacionais – is the transmission system operator of Portugal. It operates the transmission electrical system but also the natural gas system of Portugal (reception, storage and regasification). It also has activities in generation (Enondas – Energia das Ondas, electricity generated from sea waves) and telecommunication via RENTELECOM. Furthermore the company capital has international partners like State Grid and Oman Oil.

The objectives of REN are to ensure an uninterrupted supply of electricity and natural gas at the lowest cost with quality and safety. Furthermore all consumers have to have an equal access to infrastructures. In order to ensure an uninterrupted supply REN has to maintain the balance between those who require and those who supply energy.

REN has 8,733 km lines all over the country. The 400 kV grid lines mainly run north to south near the coast from the Alto Lindoso power station in the north to the Algarve, and west to east, where they interconnect with the Spanish grid. The 220 kV lines basically run between Lisbon and Oporto, diagonally between Miranda do Douro and Coimbra, along the River Douro and in Beira Interior. The extra high voltage grid is complemented by 150 kV lines, the first ever voltage in the RNT (since 1951). Operation is responsible for keeping all equipment and systems up and running efficiently [6].

3. Impact of the FIFA World Cup 2014 on the consumer behavior

In this section an analysis of the impact of some important matches during the FIFA World Cup 2014 in the consumer behavior of countries such as Brazil, France, Germany and Portugal is presented. The analysis is focused on the main four points of the game: the first half, the half time, the second half and the end of the game. All time intervals presented are in local time. For each country in the ELECON project, 4 or 5 matches are presented. The first and last matches are also studied. Some times 2 or 3 curves are analyzed at the same time depending on the available information from the TSO websites.

3.1. Brazil

- <u>Thursday 12th June:Brazil vs Croatia 17h (3-1)</u>

The opening ceremony of the World Cup occurred at 15h15. In Fig.1 it is possible to see the reduction of load with a decrease slope in the curve (red) of 12,400 MW approximately when compared with a typical day at Thursday 5th of June in the SIN.

The first game also influenced the load curve behaviour in the first time, half-time and second-time of the game in comparison with a typical day. Fig. 1 shows that 30 minutes before the start of the match the reduction was of 5,500 MW and 1,050 MW during the next 13 minutes.

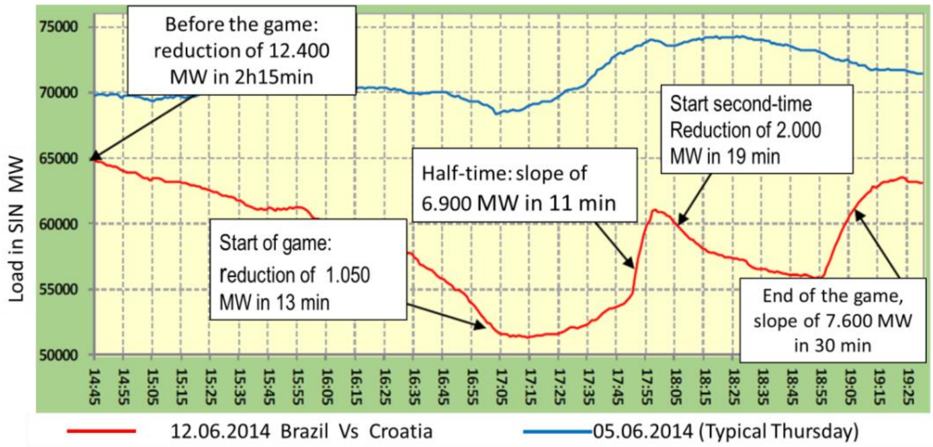

Fig. 1. Behavior of SIN energy consumption during the game Brazil vs Croatia

During the half-time a natural increasing of load of 6,900 MW in 11 minutes is observed. During the second-time the mean difference was 16,600 MW in comparison with a typical Thursday. After the end of the match, an increase slope of load of 7,600 in 30 minutes is observed.

- Monday 16th June Germany vs Portugal 13h (4-0)

During this match there are no relevant events or significant changes in the load profile in the SIN. The curve in Fig. 1 shows the behaviour of consumption during the day compared with equivalent typical day at Monday 2nd of June.

During game and at the end of the game the load behaviour does not present a significant difference with an equivalent typical day. The mean difference was up to 968 MW from the typical day but not related directly with the game.

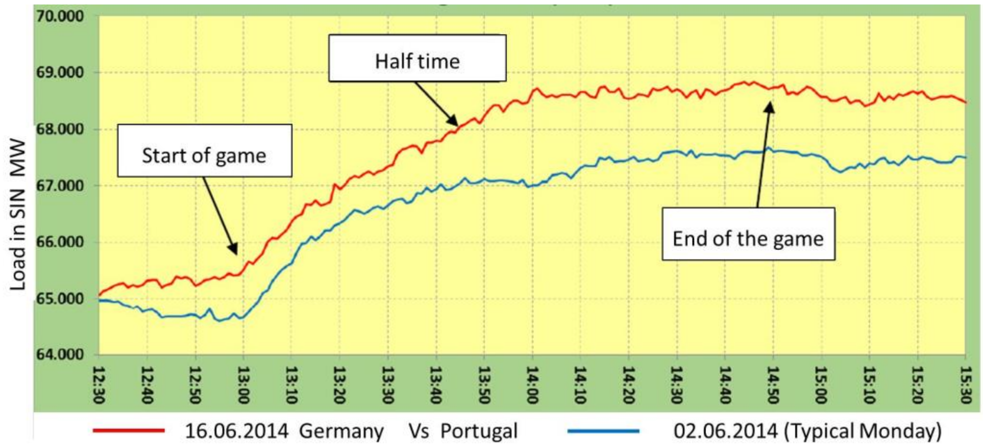

Fig. 2. Behavior of SIN energy consumption during the game Germany Vs Portugal

- Friday 4th June France vs Germany 13h (0-1)

This game does not present significant change in the shape of energy consumption in the SIN. The curve in Fig. 3 shows the behaviour of energy consumption during the day compared with the equivalent typical day of Friday 4th of June.

From the start of the first time to the start of the second time the curves are very similar, about the end of the second time is observed a small decrease in the energy consumption because of next game, Brazil Vs Colombia, would be at 17h in the same day.

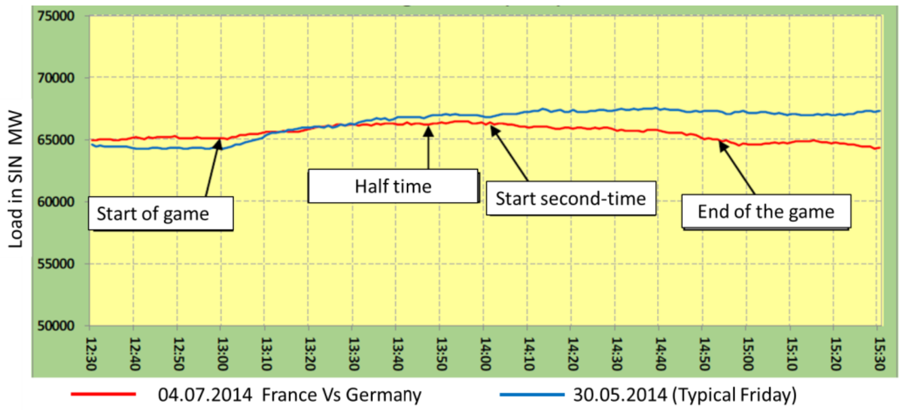

Fig. 3. Behavior of SIN energy consumption during the game France vs Germany

- Tuesday 8th July Brazil vs Germany 13h (1-7)

In this match the energy consumption suffered a change in its curve shape related with the game, as shows Fig. 4. Before the game, from 14h00 up to 15 minutes before the game it was observed a reduction on the load in SIN of 12,400 MW in comparison with a typical Tuesday curve (blue).

The next 30 minutes, that include the start of game, a decrease slope of 6,800 MW is observed. Thus the difference of load between the day of the game and the typical day before the game is nearly 17,000 MW in the first half-time.

In the half-time a 4500 MW load increase in minutes is observed because of the evening peak. At the beginning of the second half-time a reduction of load of 1,000 MW that is out of normal behaviour of a typical day, probably for the score of the game at this time. At the end of the game a slope of 4,200 MW in 15 minutes is noticed.

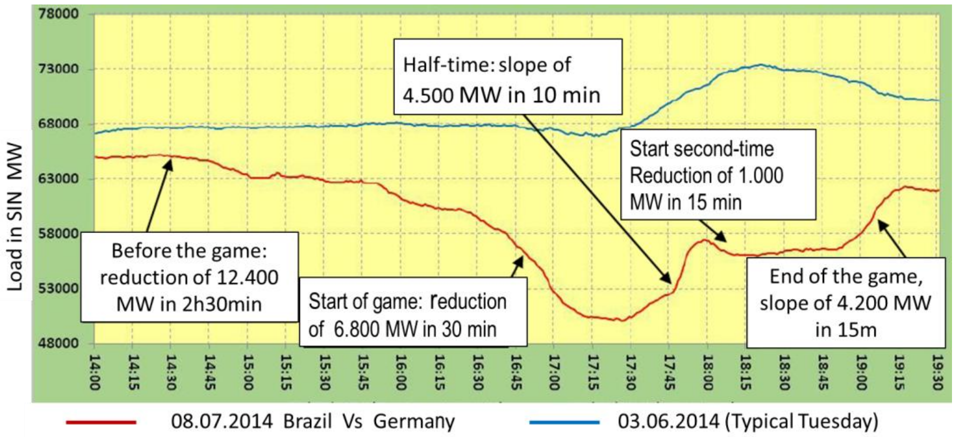

Fig. 4. Behavior of SIN energy consumption during the game Brazil vs Germany

- <u>Sunday 13th July Germany vs Argentina 16h (1-0)</u>

For the final match of the World Cup Brazil 2014 the behavior of the load curve (red) is very similar when compared with a typical day (Sunday - Blue) up to the start of game. At this time, it is noticed a smooth reduction and some changes in the half-time and end of the match when starts an increasing slope of the consumption, as shows Fig. 5. One can state that this game had an impact on the consumption behaviour in the Brazilian territory. However it was not as strong when compared with the first game Brazil vs Croatia or Brazil vs Germany.

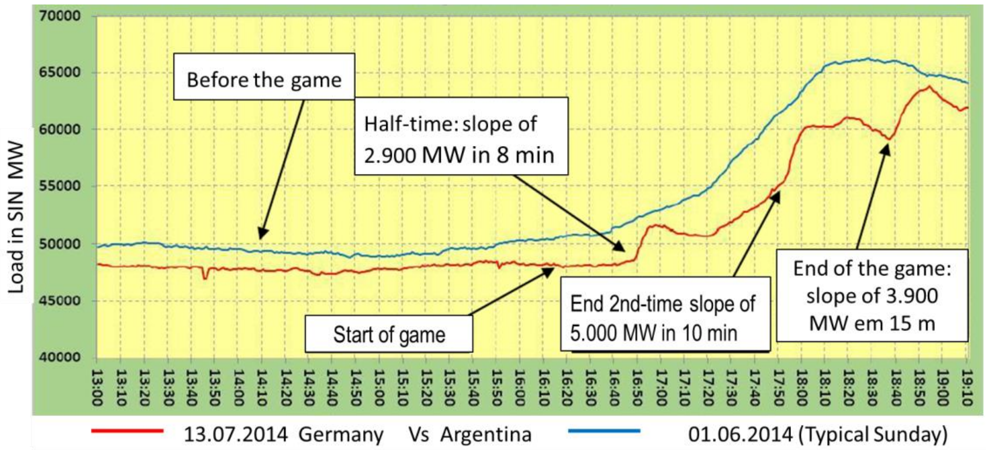

Fig. 5. Behavior of SIN energy consumption during the game Germany vsArgentina

3.2. Germany

- <u>Thursday 12th June Brazil vs Croatia 22h (3-1)</u>

From Fig.6 it is possible to see a similar shape of load curve in 50Hertz system in comparison with a typical day. The reduction of load occurs after the opening ceremony and continues almost constantly during the start of the game (354 MW) and the end of the game (529 MW). The reduction could be associated with the world cup but the impact is very low in the consumption profile. The curve does not show representative changes, probably because the time of the match.

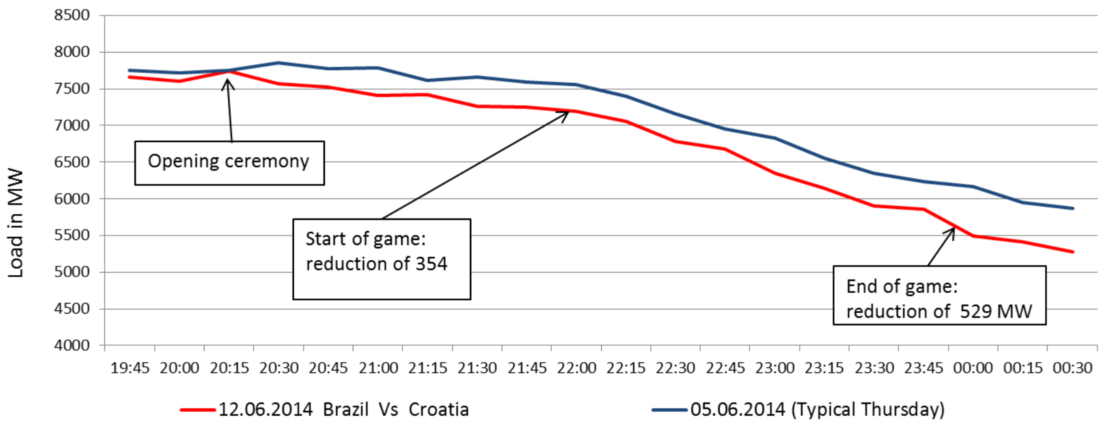

Fig. 6. Behavior of 50Hertz energy consumption during the Brazil vs Croatia

- <u>Monday 16th June Germany vs Portugal 18h (4-0)</u>

The behavior showed in Fig. 7 is quite similar to the match analysed before. This match had a low impact on the energy consumption.

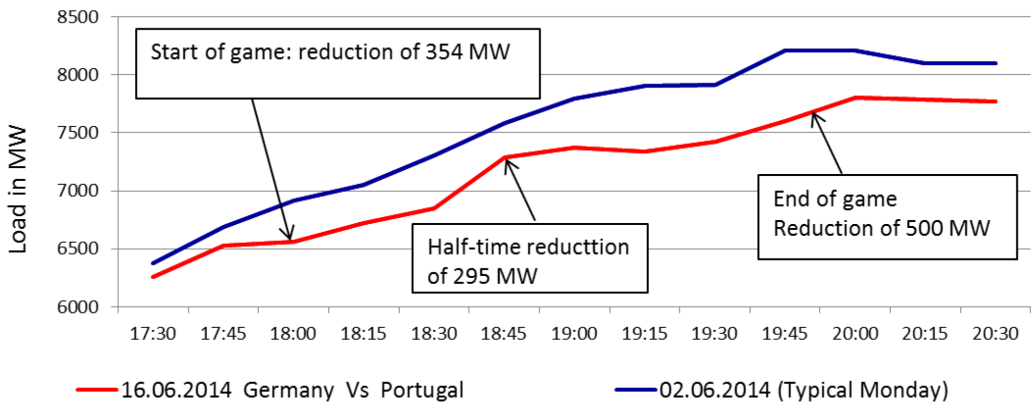

Fig. 7. Behavior of 50Hertz energy consumption during the game Germany - Portugal

- Friday 4th July France vs Germany 18h (0-1)

This match seems to not affect the behavior of energy consumption in Germany, because the reduction of load is very low in the start of the match and during half-time. The only remarkable variation is in the middle of second time with 807 MW of difference when compared with a typical day (06 June 2014).

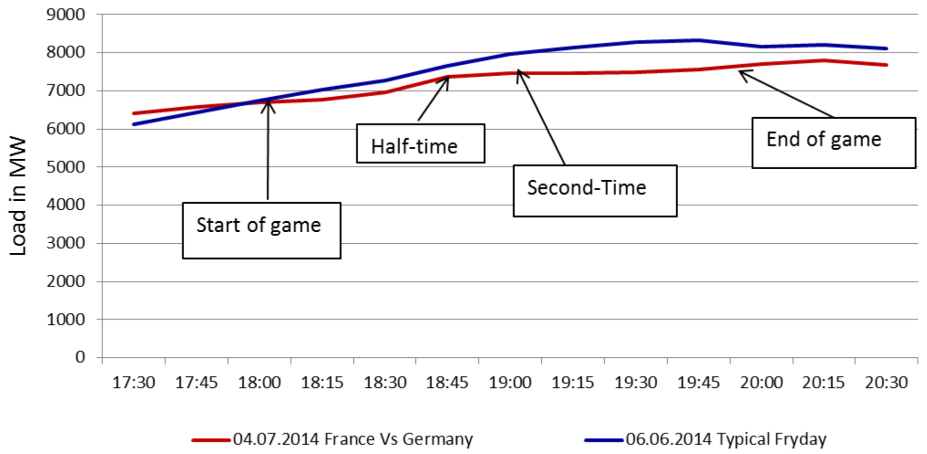

Fig. 8. Behavior of 50Hertz energy consumption during the game France vs Germany

- Tuesday 8th July Brazil vs Germany 18h (1-7)

In this day the game does not affect the behaviour of energy consumption, because the difference of load with a typical Tuesday is quite constant. In the end and the end of second half-time the difference is minimal as shown in Fig. 9. The main reason of that is probably that the game started at 22h when many people were resting.

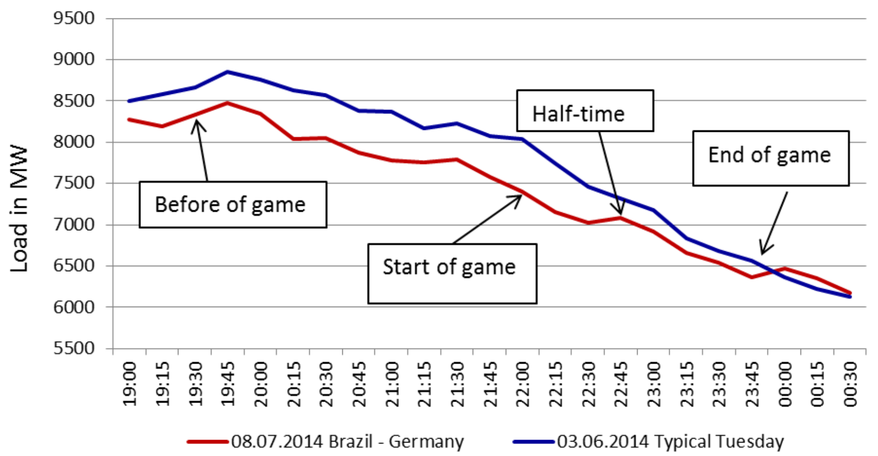

Fig. 9. Behavior of 50Hertz energy consumption during the game Brazil vs Germany

- Sunday 13th July Germany vs Argentina 21h (1-0)

For the final of World Cup Brazil 2014 the behaviour of the load curve (red) presents a reduction without fast changes if compared with a typical Sunday 1 (more than 1 month before, in blue) and an increase consumption when compared with the typical Sunday 2 (1 week after, in green) . This match does not present a high impact on the energy consumption in East Germany, perhaps due to the time of the match.

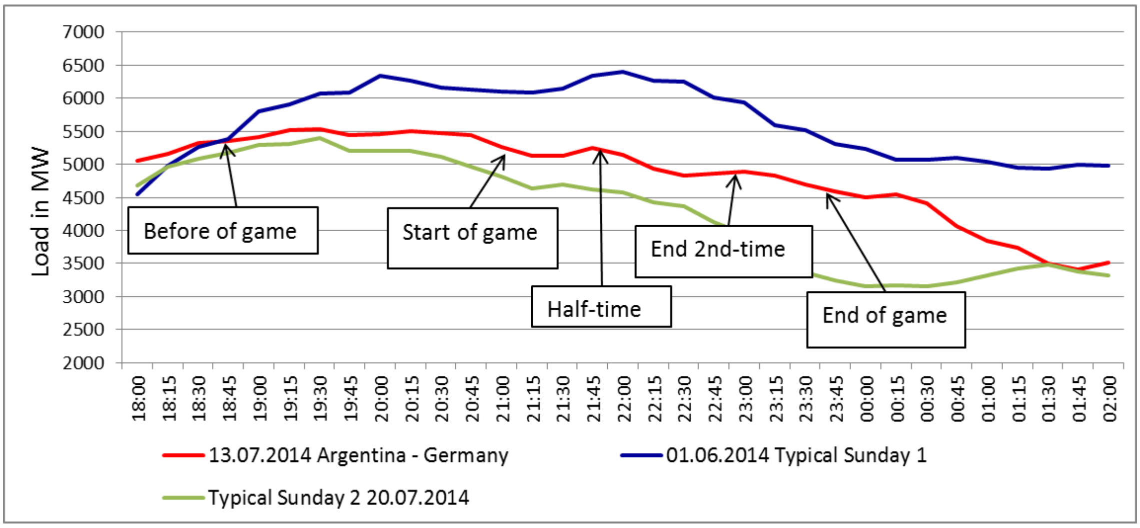

Fig. 10. Behavior of 50Hertz energy consumption during the game Argentina - Germany

3.3. France

- Sunday 15th June: France vs Honduras (3-0)

At the beginning of the game the consumption is higher that the forecast: 702 MW for the forecast a day before and 502 MW for the daily forecast. The consumption remains higher than the forecasts during the first half of the game. The trend is inverted after the half-time and the consumption begins to be lower than the forecast during the second half. At the end of the game the load curve fits again to the forecasts. By looking at the consumption of the Sundays a week before and a week after, it appears that the load curve is not similar to a normal consumption of a Sunday of June during the first half. From the moment of half-time the load curve fit with the curve of the day a week before. Nevertheless the average gaps observed between the real consumption and the forecasts during the game (340 MW for the forecast D-1 and 292 MW for the forecast D) are not big enough to represent a significant event.

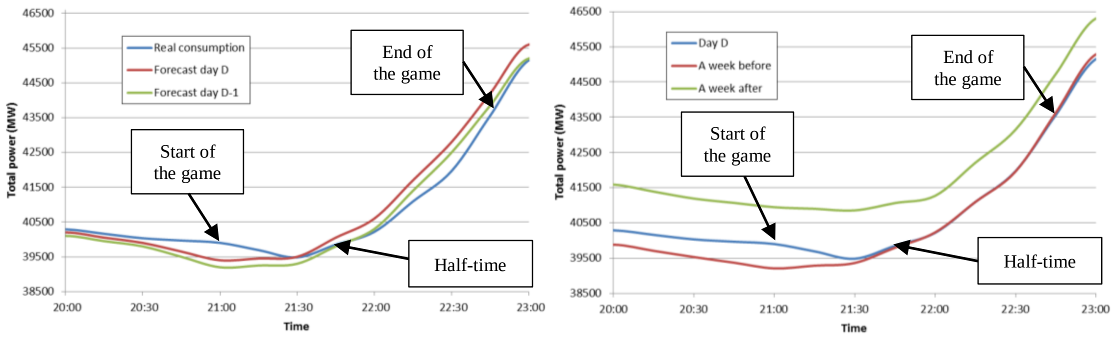

Fig. 11. Behaviour of RTE energy consumption during the game France Vs Honduras

- Friday 4th July: France vs Germany (0 – 1)

One hour before the match the forecasts are pretty good and the gap between the daily forecast and the real consumption is only 79 MW. The load curve seems also to fit well with the curve of the Friday a week after. But whereas the forecasts remain stable during the game, the consumption decreases by 507 MW during the first half-hour of the match. Then the gap between the forecasts is equal to 789 MW for the day D and 889 MW for the day D-1. During the end of the first half and the half-time the consumption increases by 528 MW. After that the load curve follows the trend of the forecast and the consumption a week before and after but stay low compared to them. Nevertheless the average gaps observed between the real consumption and the forecasts during the game (573 MW for the forecast D-1 and 440 MW for the forecast D) are not big enough to represent a significant event.

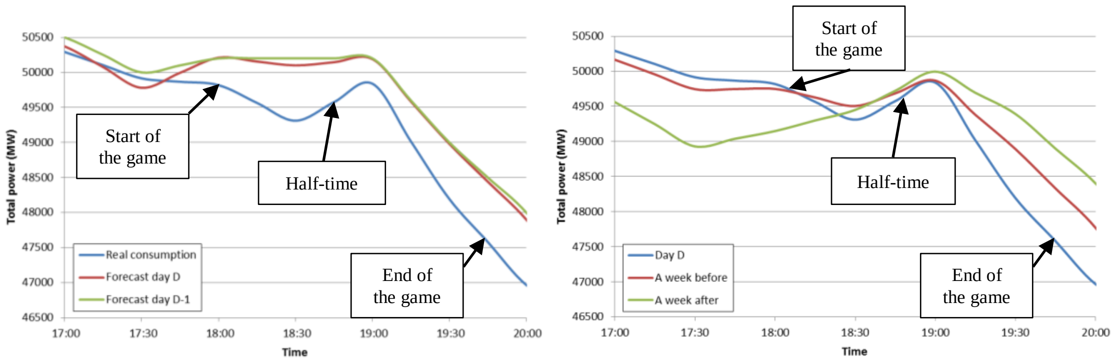

Fig. 12. Behavior of RTE energy consumption during the game France Vs Honduras

- Tuesday 8th July: Brazil vs Germany (1 – 7)

At the beginning of the match there is a gap of 993 MW with the forecast D-1 and 693 with the forecast D. During the second part of the first half the load curve fits with the forecast. After the half time the consumption is once again higher than the forecast and is 1242 MW higher than the forecast D and 1342 higher than the forecast D-1 at the end of the match. Nevertheless the average gaps observed between the real consumption and the forecasts during the match (727 MW for the forecast D-1 and 525 MW for the forecast D) are not big enough to represent a significant event. Furthermore the load curve is pretty similar to the profiles of the day a week before and after.

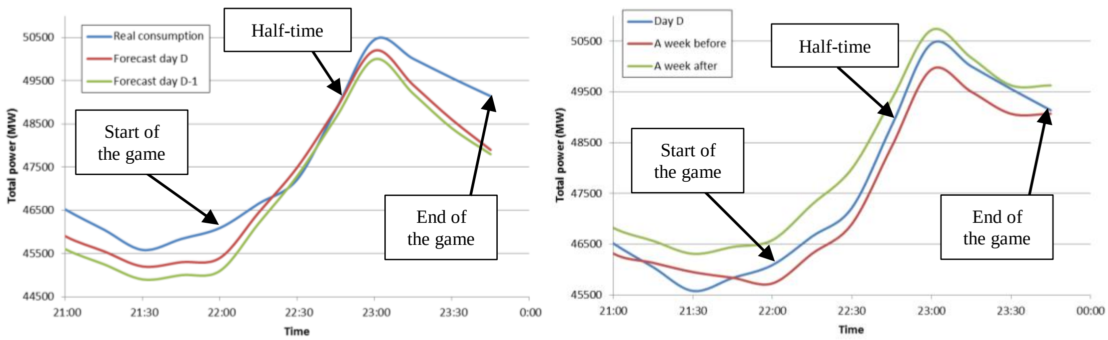

Fig. 13. Behavior of RTE energy consumption during the game France Vs Honduras

- Sunday 13th July: Germany vs Argentina (1 – 0)

During the entire match the consumption stays higher than the forecasts: up to 1068 MW for the forecast D and 859 MW for the forecast D-1. Nevertheless the average gaps observed between the real consumption and the forecasts during the match (800 MW for the forecast D-1 and 567 MW for the forecast D) are not big enough to represent a significant event. Furthermore the load curve is pretty similar to the profiles of the day a week before and after.

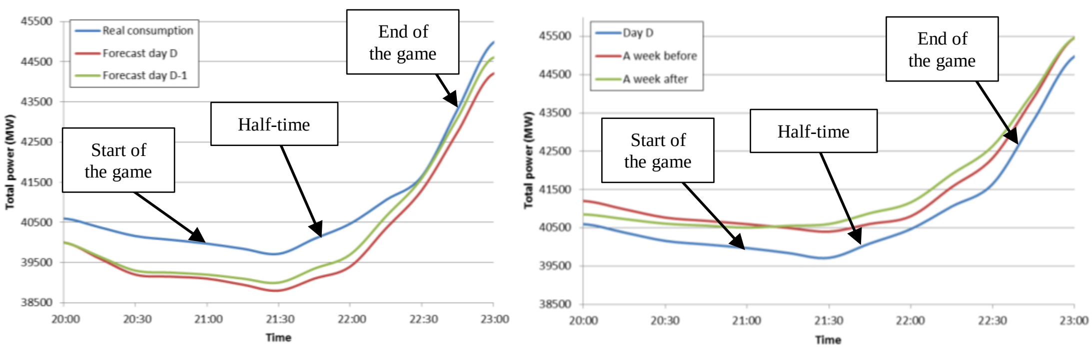

Fig. 14. Behavior of RTE energy consumption during the game Germany – Argentina

3.4. Portugal

- <u>Thursday 12th June Brazil vs Croatia 22h (3-1)</u>

During the opening of the world cup the behaviour of REN energy consumption in Portugal is very closed to a normal day, compared to the consumption a week before and a week after. The noticed differences are that the consumption remains higher than the for other normal days (up to 200 MW higher) and that the peak of consumption is emphasised.

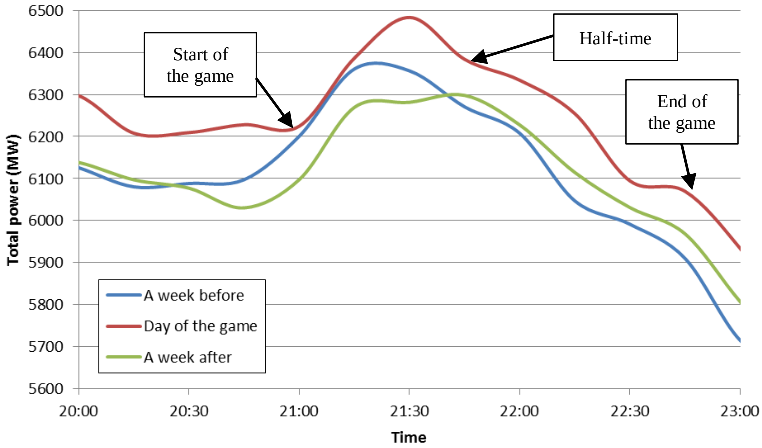

Fig. 15. Behavior of REN energy consumption during the game Brazil vs Croatia

- <u>Monday 16th June Germany vs Portugal 18h (4-0)</u>

For this particular day where the Portugal is playing it can be noticed firstly that the consumption remains higher that the other normal days, up to 800 MW higher. This is the biggest difference that is recorded among the days of matches in the world cup. Nethertheless the behavior of the energy consumed is quite the same as for normal days.

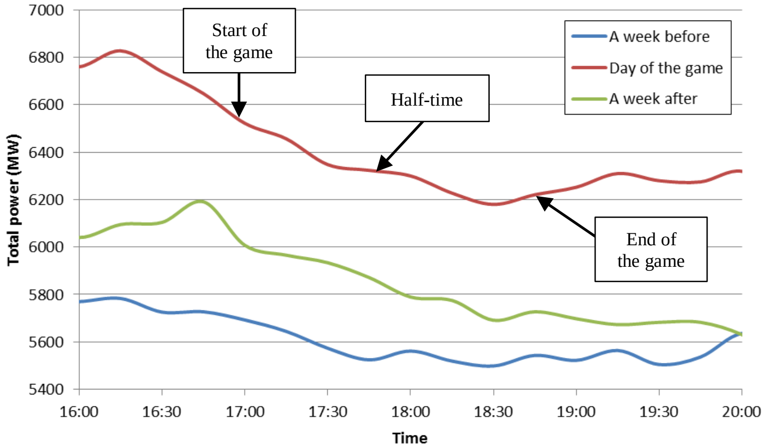

Fig. 16. Behavior of REN energy consumption during the game Germany – Portugal

- Friday 4th July France vs Germany 18h (0-1)

There is no impact of the world cup on the consumption on this day: the consumption level is comparable to other normal days, i.e.the behavior is similar. There is a progressive decreasing of the consumption during the match.

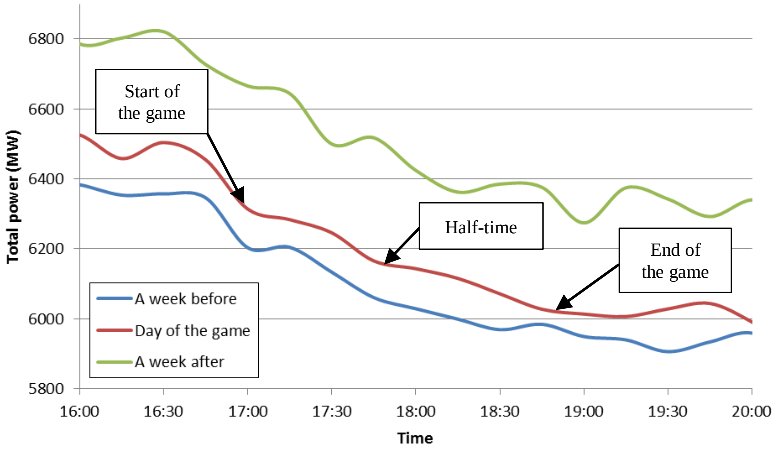

Fig. 17. Behavior of REN energy consumption during the game France vs Germany

- Tuesday 8th July Brazil vs Germany 18h (1-7)

There is no impact of the world cup on the consumption on this day: the consumption level is comparable to other normal days, i.e. the behavior is similar. There is a slight peak of consumption at 21h30 and then a slow decreasing of the consumption during the end of the match.

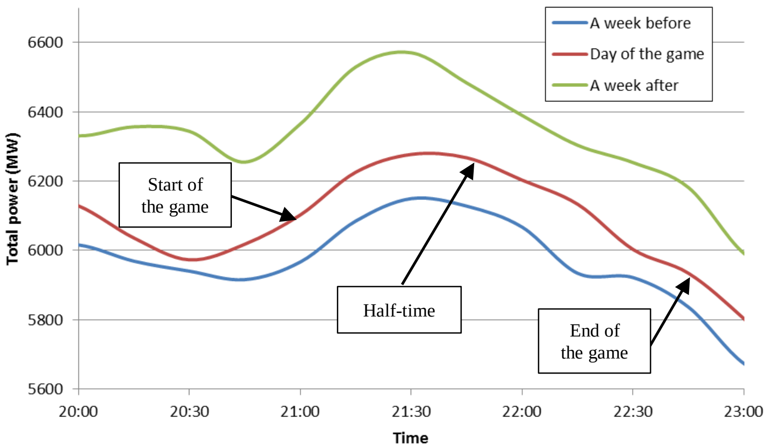

Fig. 18. Behavior of REN energy consumption during the game Brazil vs Germany

- Sunday 13th July Germany vs Argentina 21h (1-0)

During the final day of the world cup the consumption level in Portugal is higher than in other normal days. Comparing to a week before and a week after, up to 400 MW higher. Nevertheless the behavior is quite similar to the normal days. There is slow increasing of the consumption during all the match.

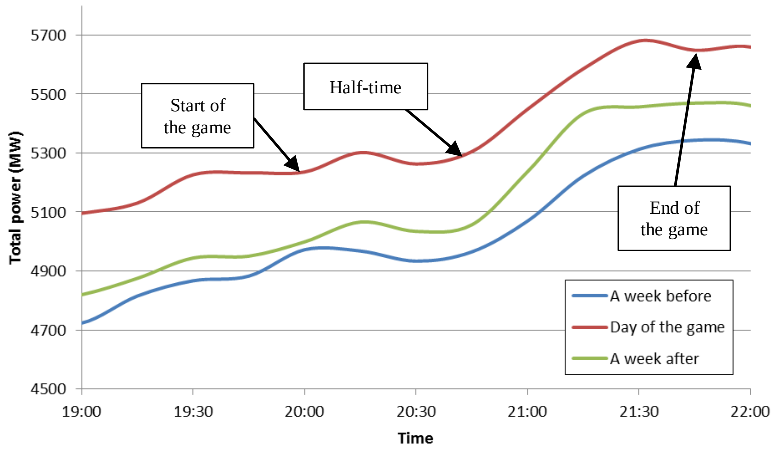

Fig. 19. Behavior of REN energy consumption during the game Argentina vs Germany

4. Conclusion

After analyzing 4 or 5 matches of the FIFA World Cup Brazil 2014 for the countries involved with the ELECON project, it is possible to conclude that:

- A high impact on the behavior of energy consumption in Brazil, especially first day (12 June 2014) due to the opening ceremony and the game Brazil vs Croatia, as shown in Fig.1. On other countries (Germany, France and Portugal) the impact was very small, due to local times in Portugal (4h ahead) and in France and Germany (5h ahead). Most of the matches occurred in the afternoon in Brazil, which means night time in Europe.
- Other matches involving Brazil showed high impact too in Brazilian territory especially when compared with the impacts in European countries. Another reason for that is that in the city where the game occurred, it was declared holyday and in the other cities in Brazil there was flexibility in industrial, commercial and education areas. Some days the banks were closed and the holiday period in the schools were moved because of the world cup.
- Matches involving European teams did not show an impact in the energy consumption in Brazil, except for the world cup final that shows some changes in the load profile. For the other countries the final match (Argentina vs Germany) did not show impact, probably because it started at 21h (Germany and France local time) ending at 23h40 approximately. It means that most of the match occurred in resting time in European territory.

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Acknowledgements

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Impact of Distributed Generation in the Transmission System Expansion Planning

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Abstract

In this work, the impact of distributed generation in the transmission expansion planning will be simulated through the performance of an optimization process for three different scenarios: the first without distributed generation, the second with distributed generation equivalent to 1% of the load, and the third with 5% of distributed generation. For modeling the expanding problem the load flow linearized method using genetic algorithms for optimization has been chosen. The test circuit used is a simplification of the south eastern Brazilian electricity system with 46 buses.

Keywords: Distributed Power Generation, Power Transmission Planning, Genetic algorithms

1. Introduction

Brazil is the largest country in Latin America, having a land area of 8,514,876.4 km2, endpoints of 4300 km of distance between themselves, and 190 million inhabitants [1]. The Brazilian generation park currently consists in 134 hydroelectric plants, 93 thermoelectric plants, 485 small hydro, 187 biomass plants, 56 wind farms and one solar plant, in addition to the excess production of Itaipu imported from Paraguay totalling 111,618 MW installed [2].

In 2012 the growth of electricity consumption in Brazil was of 3.5% according to the data from EPE (the Portuguese abbreviation for the Energy Research Company) released in [3], led by the growth in segments of trade and services (+7.9%) and of the residential sector (+5.0%), while the industrial remained stable. The increase of the system load was of 4.2%, - 0.7 percentage points above the increase in consumption, which is associated with the fact that commercial and residential sectors are mainly assisted in low voltage, causing a greater loss rate.

Due to the growth of the demand, transmission systems must follow that growth through improvements, which in Brazil is done based on the generation expansion [1]. Table I presents data for the estimation of the growth transmission lines (km) during the period 2012-2021 [4]. Figure 1 shows the planned investments for construction of transmission lines and facilities until 2021.

The expansion planning of the transmission system solves the problem of the system's improvement in order to transmit increasing amounts of energy, to connect new generators to the system, and to ensure that loads that are not interconnected can be met safely and reliably. In such planning, there are technical, economic, environmental and social studies to address all the possible approaches which involve large works related to the transmission system. However, recently the system of power transmission with traditional centralized generation, and long transmission lines transporting large amounts of energy and

unidirectional flow of electricity have been criticized because of its high costs, high rate of losses, environmental impact, and security vulnerabilities. That is the reason why distributed generation (DG) is now seen as the future of the electrical system [5].

Table 1: Estimation of the transmission line expansion (km) [4]

	Existent 2011	Planned 2011 - 2016	Planned 2017 - 2021	Planned 2021
800 kV	0	0	7.325	7.325
750 kV	2.683	0	0	2.683
600 kV	1.612	4.750	0	6.362
500 kV	34.851	21.547	5.342	61.740
440 kV	6.679	47	66	6.792
345 kV	10.063	337	0	10.400
230 kV	45.349	7.874	444	53.668
Total	101.237	34.555	13.177	148.969

As the penetration of distributed generation is still small or non-existent in most countries, some works analyze policies, prospects, challenges, and government incentives for the deployment of distributed generation [6], [7] and [8], or the performance of DGs in energy markets' environment [9] and [10]. Others analyze the impact of DG systems in distribution systems on factors such as reliability, control, power quality, and system security [11], [12] and [13].

In Brazil, DGs are still a projection where laws and regulations involving smart grids are still being developed. In this way, the presented paper aims to conduct an analysis of the impacts that distributed generation will bring to the expansion planning of transmission systems, especially the one held by the consumers and injected into the network, such as the solar generation.

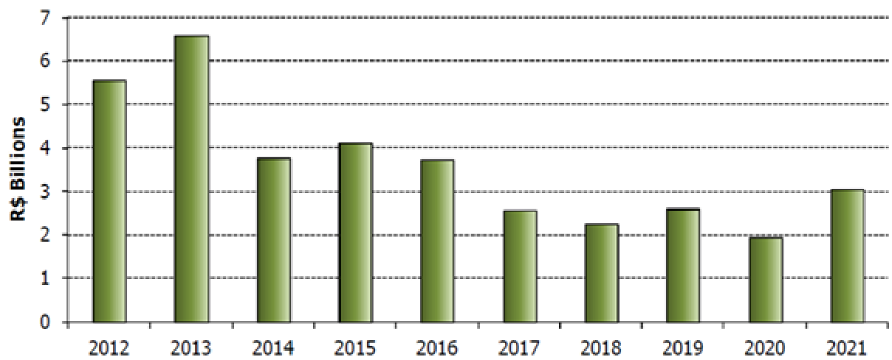

Figure 1: Planned investments in transmission lines [4]

This paper deals with the expansion optimization in a testing system for three different scenarios: 1) the anticipated load growth without taking into account the distributed generation; 2) considering a scenario in which distributed generation is equivalent only to 1% of the center power consumption loads; 3) a scenario in which DG is 5% of local consumption. In this way, the impact on the expansion cost of distributed generation will be obtained.

The optimization process will find the point of minimum cost for the expansion of the transmission system, respecting the problem constraints, such as flow limits in the power lines and the power balance in the buses. Although the optimization does not cover all the aspects that involve the transmission expansion, it is very useful to guide the planning, serving as a basis for further studies, such as social and environmental aspect. Its resolution is usually divided into two parts: the problem modeling and the optimization solution.

After this introductory section, section II presents a brief introduction to the concept of DC load flow used in this paper. Section III shows the expansion modelling, and section IV includes a brief review on the genetic algorithms concept – the method chosen for solving the optimization step of the solution. Section V presents the test circuit used, the scenarios and their results. Finally, section VI presents the main conclusions of the work.

2. DC Load Flow

The linearized model, or DC, is based on the fact that power flow is approximately proportional to the opening angle, moving from smaller towards larger angles.

It is mathematically defined as:

$$P_{km} = x_{km}^{-1} \times \theta_{km} = \frac{\theta_{km}}{x_{km}} = \frac{\theta_k - \theta_m}{x_{km}} \quad (1)$$

Where:

- P_{km} - flow of the bar *k* for bar *m*;
- x_{km} = line reactance;
- θ_{km} = opening angle between buses *k* and *m*;

It is important to note that in this case the presence of transformers was not considered. If it is necessary to include these components in the modeling, the following formulation matrix can be used:

$$P = B' \times \theta \quad (2)$$

Where:

- P = Vector of net injections of active power;
- B' = Nodal admittance matrix type;
- θ = Vector angles of the nodal voltages.

To solve the problem, one of the buses of the system was eliminated and its angle is set to 0 (slack bus). One of the reasons why the conventional load flow presents some convergence difficulties in planning studies is the lack of information on the system's reactive behavior (reactors, capacitors, taps, PV bus, etc.). The linearized model ignores the reactive part of the system, which will only be analyzed in later planning.

Further details on the deduction of DC load flow are available in [14].

3. Expansion modeling

In this study the DC model has been used for modelling the problem of expansion of the transmission system. This model involves the application of DC load flow equations for transmission systems, generating an optimization problem, which shows satisfactory results for planning and ease of convergence due to the fact that only the active powers are used. This model is interesting for the preliminary stages of planning. Disregarding transmission losses, the mathematical model is described as:

Minimize:

$$v = \sum c_{(ij)} n_{(ij)} \quad (3)$$

Subject to:

$$S \times f + g = d \quad (4)$$

$$f_{ij} - \gamma_{ij}\left(n_{ij}^0 + n_{ij}\right)\left(\theta_i - \theta_j\right) = 0 \quad (5)$$

$$\left|f_{ij}\right| \leq \left(n_{ij}^0 + n_{ij}\right)\bar{f}_{ij} \quad (6)$$

$$0 \leq g \leq \bar{g} \quad (7)$$

$$0 \leq n_{ij} \leq \bar{n}_{ij} \quad (8)$$

$(i,j) \in \Omega, k \in \Gamma$ *(9)*

Where:

- v = total cost of the transmission expansion
- c_{ij} = cost of building new circuits
- n_{ij} = number of new circuits
- S = matrix of connections between buses
- f = power flow
- g = active generations
- d = active demands
- γ = susceptance
- θ = phase angle
- Ω = set of possible paths
- k = generic bar circuit
- Γ = bus assembly of the circuit

Equation 3 is the objective function of the problem, in which the cost of system expansion v is calculated as the summation of the placement of each additional circuit c, multiplied by the number of circuits built into each line (n). Constraint 4 is the variation of the Kirchhoff's law of currents, adapted to the DC load flow context, while constraint 5 is a version of Ohm's law. However, the presence of a variable θ associated with the nodal matrix leads to a nonlinear equation. Constraints 6 and 7 represent the lines thermal limits and generation limits, respectively. Finally, constraint 8 ensures that the proposed number of circuits in each row is within the scope. A full subtraction of linear expansion modeling, including losses, can be found in [15].

4. Genetic algorithm

The Genetic Algorithm (GA) is a computational algorithm proposed by Holland in 1975 [16]. It provides a range of algorithms based on common optimization for a certain problem by analogy with the Darwinian principle of natural selection and genetic reproduction [17].

Basically, it creates an initial population of possible solutions to a problem. Using the criteria of selection, mutation and recombination applied to each generation, the population of solutions shows that the genetic material is transmitted to descendants, according to the probability of survival of individuals. Algorithm 1 shows the different phases of the optimization process.

INPUT: *Population, fitness function and stopping criterion.*
OUTPUT: *Individual with the largest chromosome fitness function.*
AUXILIARY: *Number of generations and chromosome (feature vector).*
1. Random generation of the initial population.
2. Evaluation of each chromosome through the fitness function.
3. **Stop** each generation, **make**
    4. Create a new population by following steps:
        5. Select the two chromosomes to be parents.
        6. Perform the crossover parents to a new generation.
        7. Apply mutation to change any position on chromosome.
        8. Place new offspring in the new population.
    9. Replace the old population by the new.
    10. Evaluate the new population.
    11. Stop when you reach the stop criterion
12. Return the individual with higher fitness function.

Figure 1: Genetic algorithm

5. Case Study and Results

In this case study three scenarios were presented: 1) considering a forecast growth in demand taking into account the distributed generation; 2) considering a distributed generation equivalent to 1% of the load; 3) considering a distributed generation equivalent to 5% of the load.

Figure 2 presents a diagram of the proposed methodology. An initial population of possible solutions generated by a random process is created. The objective function gives the expression cost, and if the problem is constrained, the evolutionary operator is applied to obtain the new generation. This cycle is repeated until the best solution in the population meets the requirements or until the maximum number of generation is reached. As can be seen the methodology follows the genetic algorithm idea.

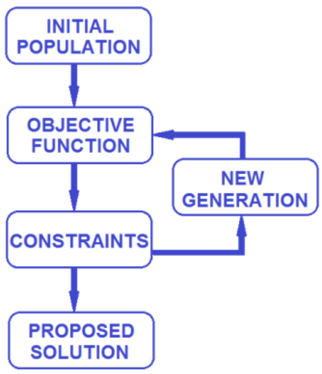

Figure 2: Diagram of the proposed methodology

For the simulation an algorithm using software MATLAB (MATrix LABoratory) has been created. A transmission network with 46 buses was used as a case study (Figure 3). This network represents a simplified version of the south eastern part of the Brazilian system chosen, and its data can be found in [18]. Altogether, there are 79 transmission lines; the expected total demand is of 6.800MW, and for this paper it was not considered the possibility of redispatch of generating plants.

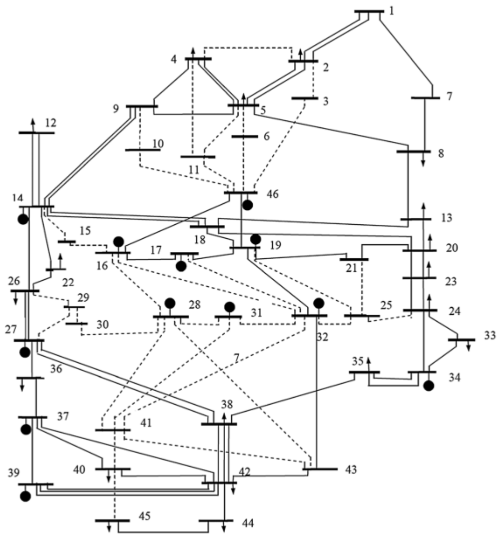

Figure 3: 46 buses circuit [18]

A. Scenario 1:

In the first scenario the presence of distributed generation was not considered, only the growth of the test system for the demand of 6.800MW. The solution found by the proposed method can be seen in Figure 4, in which the top graph shows the evolution of the best solution (the bottom line, in black), and the average of the solutions (the upper line, in blue) over the generations. It is important to note that a limit of 200 generations has been stipulated. However, the algorithm used 88 interactions to reach

solution.

The bottom graph depicts the amounts of transmission lines represented by 79 variables in the optimization problem. The solution proposes building two new circuits in lines 3, 4, 11, 46, 47, 73 and 74, and one new circuit in lines 23 and 52. The other lines remained with their initial circuits.

In Figure 4 one can see that the total cost of the best solution for the expansion of the system was of 115,009 monetary units (m.u.), while the average cost of the last generation stood at 123,589 m.u.. It was verified that all power flow in lines remained within the limits, making it a technically workable solution.

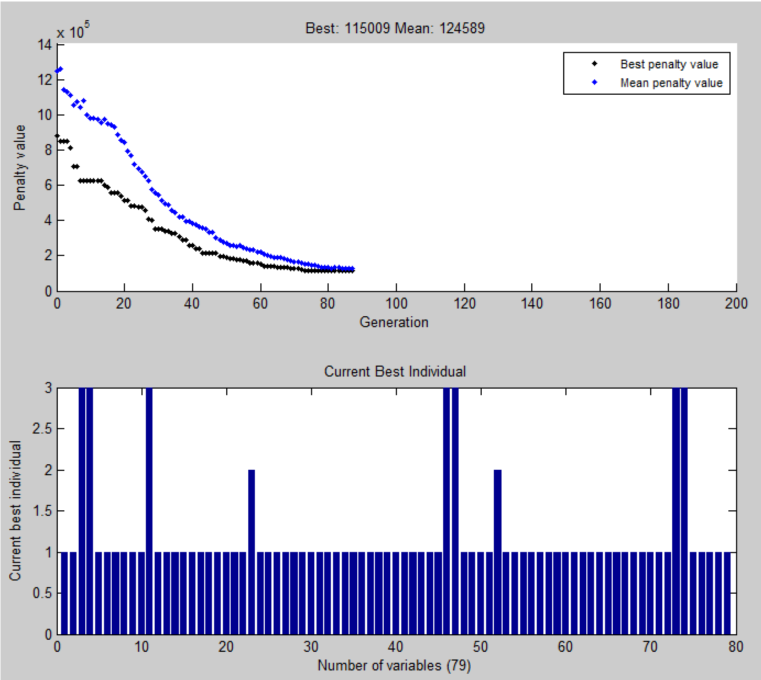

Figure 4: Proposed solution to the first scenario

B. Scenario 2:

The second scenario was conducted to determine what would be the impact of the distributed generation when it is equivalent to 1% of the total system load. For this scenario it was considered the gathering of distributed generation by consumers proportionally balanced.

The solution obtained can be seen in Figure 5. For this scenario it was necessary 130 generations to find the solution. However, genetic algorithms are a heuristic way of optimization, and there are no guarantees that the solution is always the same, or that would require the same number of interactions, since the initial population is generated by random process.

The total cost for the best solution found is of 101,024 monetary units. A reduction of 13,985 m.u. (12.16%) was obtained when compared with the base case (scenario 1).

This means that if the presence of distributed generation in consumer centers is considered, that can supply around 1% of the load, and it would lead to a reduction of 12.16% on the investment required for the construction of new transmission lines. It is important to note that this percentage depends on several factors, such as the circuit topology, plants (which have suffered a redispatch), the presence or absence of congestion lines, etc.

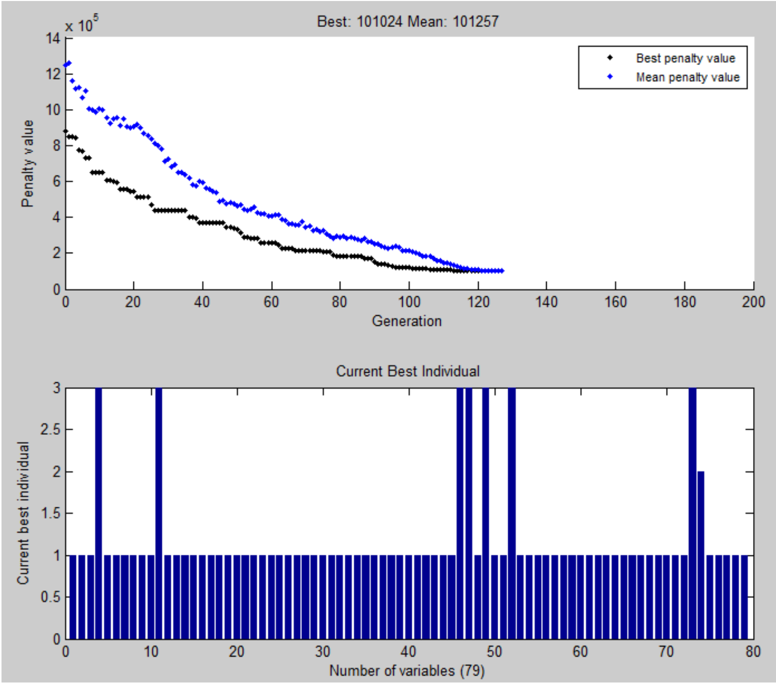

Figure 5: Proposed solution to the second scenario

C. Scenario 3:

The third scenario was conducted considering a distributed generation with 5% of the total load. This level of distributed generation in Brazil is above any realistic estimate for short or medium term, although it becomes much more coherent if scenarios like the European power system is considered. The solution obtained is shown in Figure 6. Taking into account the same number of generation limits (200) as the previous scenarios, one can see that the number of generations obtained is the same as scenario 1 (88).

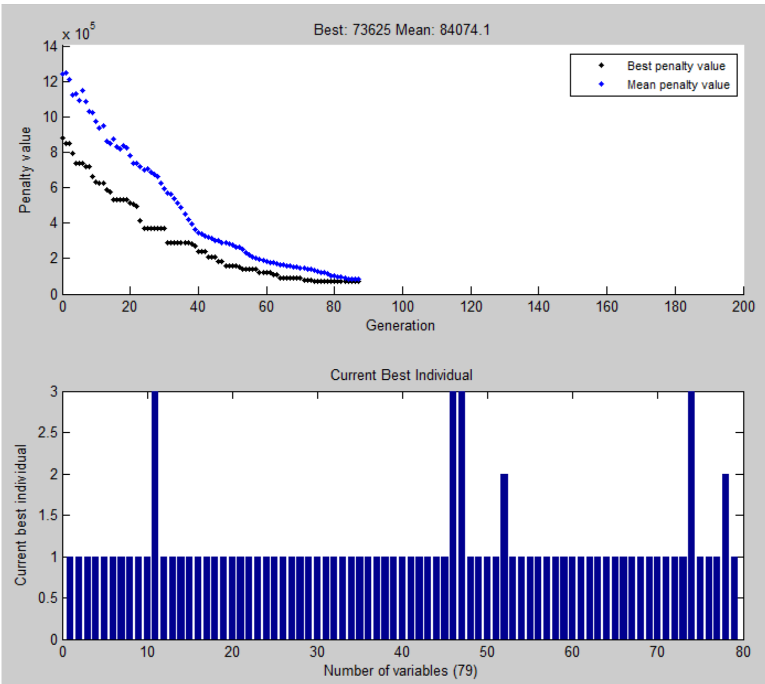

Figure 6: Proposed solution to the third scenario

In this scenario, the cost of the best solution was of 73,625 m.u., which corresponds to a reduction of

41,384 m.u. (35.98%) when compared with the base case. Once again, this percentage can vary sharply according to the circuit topology, redispatch plants, and the congestion in lines, among others. So, this result is a good indicator that distributed generation can contribute significantly to the reduction of the cost for building new transmission lines.

If it is considered the most basic type of distributed generation, for example photovoltaics, consumers themselves bear the costs of the equipment and its installation. The government's investment is relatively small, consisting primarily in tax incentives and opening lines of credit specialist. A part of the contribution necessary for these government initiatives may come precisely from the savings of the placement of new transmission lines.

It is noteworthy that reducing the number of transmission lines to be built has other benefits, besides the advantageous economic investment, such as lower environmental impact, both in the form of fewer areas that need to be occupied by the towers. This can be done by using a smaller amount of materials and consequent lower emissions of greenhouse gases related to manufacturing, transportation and installation of equipment, towers and cables. Relevant information about the environmental impact of transmission systems can be found in [19].

6. Conclusion

In this work the impact of distributed generation in the transmission expansion planning was analyzed. Three scenarios in the system with 46 buses were considered. The scenarios were conducted in order to optimize the expansion without the distributed generation; with distributed generation equivalent to 1% and 5% of the total system load, resulting in expansion costs of 115.009 monetary units, 101.024 monetary units and 73.625 monetary units respectively, representing economies of 12.16% and 35.98%, in comparison to the case without distributed generation. Considering the distributed generation, the government's investment is relatively small. Basically only tax incentives and specialized lines of credit, and a part of the necessary contribution may come from the savings of the placement of new transmission lines.

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Electricity consumers profiling- German Load Profiles

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Abstract

In this paper various standardized German Electricity consumer profiles for annual electricity consumption below 100’000 kWh or a connected capacity below 50 kW are summarized. First, this document introduces a brief methodology of the standardized load profiles and a presentation of the characteristic profiles itself, including appropriate explanations and curves. The necessity of these profiles as a result of the market opening concept is pointed out and is supplemented by a basic explanation of the load profile calculation and some allocation rules for mixed consumers. Furthermore, this paper shows the used standardized load profiles for households, business, agriculture, public lightning and night storage heating depending on the two important factors day of the week and period of the year.
Keywords: electricity consumer profiling; load profile

1. Electricity consumers profiling methodology

Distribution system operator use a simplified method to handle the electricity supply to small end customers and to calculate the balancing energy demand. Additionally, a use of a measurement system requires a non-profitable high technical, organizational and cost effort. According to this, load profiles have to be compiled for consumers with an annual consumption below 100’000 kWh or connected capacity below 50 kW. With respect to existing acts the following pages present a short overview of the necessity and the methodology how electricity consumer load profiles were created in Germany and why they are used for small costumers. The second part of this paper provides a description of the most important standardized load profiles as well as some explicit load diagrams.

1.1. Necessity of consumer load profiles in Germany

Based on some further regulatory statues in Germany, since 1998 any consumer can freely choose between every electricity company. Therefore every system operator has to guarantee a consistent availability of the grid for every electricity provider, while receiving a financial compensation (network-use fees) for grid use (energy transmission) and services like measurements, system services and furthermore. Because the system operator publish annual statistics of the network-use fees every consumer is enabled to choose each electricity provider by its costs or any other criteria.

This market opening concept was and is still easy to apply on key account consumers with contract based payments of electricity consumption and a high amount of energy demand. Their energy consumption can be planned by scheduled supply and by same time measurements of supply and consumption. In this first case the system operator can realize a reliable and secure network management based on the information by scheduled demand and real time measurement. In contrast this case of key

account consumers there is no existing energy measurement-system for most small costumers. But to ensure a balanced energy transfer, actual consumption values are required. Due to the technical and organizational complexity and considerable costs associated with installing a load profile meter, this was avoided. Nevertheless, the market opening required a reliable energy scheduled forecast for small costumers.

Accordingly, there was a need of simple network access, uniform and traceable supply relationship, a simple way of measuring and accounting as well as an applicable delimitation of delivery at the various stages of supply for small customers. By publishing network-use fees the network usage was regulated but not supply and "energy transit" through various stages of the supply chain. The supply company (producer/trader) is responsible to supply its customer and has to fulfill the entire electricity demand on time, at any time. Additionally, transmission operators have to be able to configure their network management for the expected load flows based on expected consumer demand forecast to prevent for example grid bottlenecks especially in the HV-network. This results in a need of a pre defined schedule, based on the expected system load (e.g. of the next day). [1]

1.2. Load profiles calculation

The methodology of creating load profiles is based on specific measurements. In order to minimize the failure between supply and demand, profiles were differentiated regarding specific time parameters such as hourly, daily (i.e. weekdays, Saturday, Sunday) and seasonal (i.e. winter, transition time, summer) time intervals. In addition to this first differentiation characteristics of various customer groups were taken into consideration that allow a more effective and realistic load forecast. The resulting profiles are called representative load profiles. The empirical load profiles for specific customer groups were based on existing measurements and profiles of different groups of customers. Using representative load profiles allows the use of simple and clear criteria to assign an appropriate load profile to each customer who is willing to change his energy supplier.

Under the assumption of annual electrical work of all customers of the specific group, the total resulting load curve is calculated and in correct time relation subtracted from the measured transfer power to pre-suppliers. The pre-suppliers calculate their aggregated load curve in the same way, at every stage of the supply chain. Hence, it is possible to calculate all supply relationships on every stage of the supply chain which allows to conduct a scheduled load forecast. To apply representative load profiles correctly assumptions have to be made: (1) a distinction by time parameters for every customer group (see above) and (2) deviations have to be corrected by network operator management. [1]

1.3. Normalization of annual curves

After the load profiles were defined based on given data, all profiles were normalized on a specific annual consumption of 1000 kWh/year. The reason to use the normalization is to quantify the individual customer schedules and load profiles based on the annual customer consumption.

The normalization was applied on the annual consumer curves of the load profiles household, business and agriculture. The profile data of each profile are given in ¼ h values for one year (365 days) and each day (96 ¼ h-load values). The annual load profile data were registered in a 365 x 96 matrix ("365 days" times "96 ¼ h-values a day"). Subsequently, the single ¼ h-values of the matrix have to be multiplied by a constant factor, to achieve in summarization, of all values of the 365 x 96 matrix, 1'000'000 units (1000 kWh). As a result the single values of the matrix present ¼ h –consumption in Wh (watt hour; = 1/1000 kWh). [1]

2. Characterized Electricity Consumer Load Profiles

This following section introduces the characteristic load profiles for the tariff costumer group, differentiated by household and several costumer groups as well as some additional profiles. The profiles include household (H0), seven business load profiles (G0-G6), three different agriculture load profiles (L0-L2), night storage heating (ULE) and public lighting (B1). The load profiles comprise ¼ h power values for one day, which are normalized to an annual consumption of 1'000 kWh. They are differentiated by working days ("*Werktag*"), Saturdays ("*Samstag*") and Sundays ("*Sonntag*") in the three periods of the year winter ("*Wi*" 11/1 – 03/20), transition time ("*Üz*" 03/21 – 05/14 / 09/15 - 10/31) and summer ("*So*" 05/15-09/14) [2].

2.1. Load profile- H0 Household

This profile incorporates are all households and those with (electrical) minor business demand, without installed heat pump, storage heating etc.

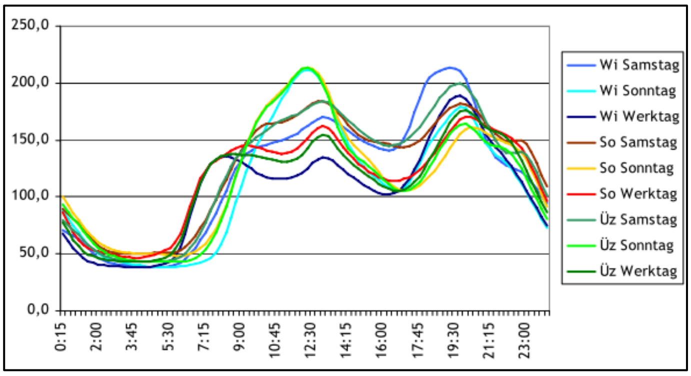

Fig. 1: Load profile - H0, households [2]

2.2. Load profile Business

2.2.1. Business general – G0

This profile can be applied if an assignment to one of the business profiles G1-G6 is not possible or not wanted. This profile is the weighted average of the total group G1-G6.

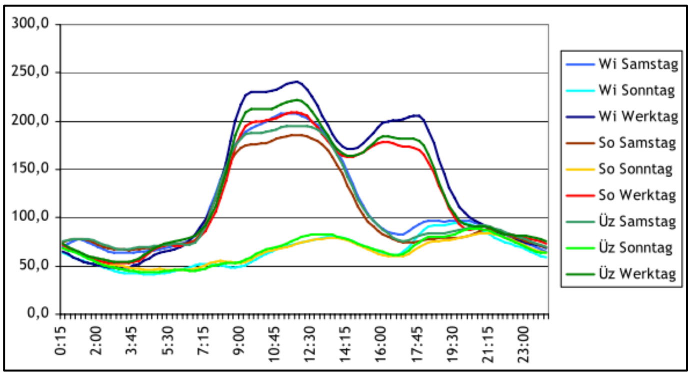

Fig. 2: Load profile - G0, business general [2]

2.2.2. Business on working days 8am – 6pm – G1

This profile applies to consumption points with typical consumption between 8am to 6pm on Working days and no or low consumption on weekends. That includes facilities such as for example offices, doctors and lawyer's offices, machine shops, print shops, schools, kindergartens and day care centers, government offices and banks.

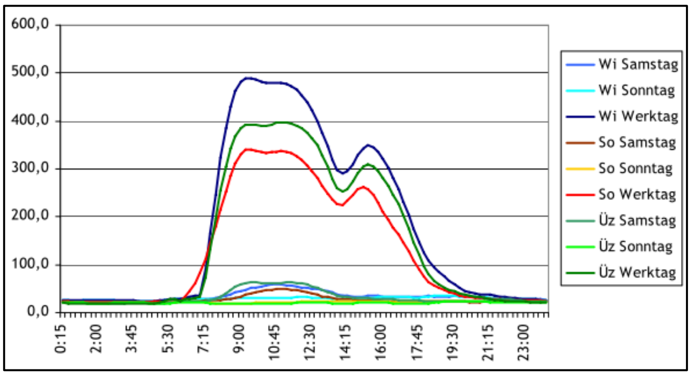

Fig. 3: Load profile - G1, business on working day 8am - 6 pm [2]

2.2.3. Business with high and predominantly consumption in evening hours – G2

This profile can be assigned to institutions with predominantly oriented lightning power consumption. These include for example petrol stations and shops with considerable window space. Furthermore, evening restaurants and leisure facilities are suited for this profile, unless they have their consumption focus on the weekend like fitness- and trainings- and youth centers.

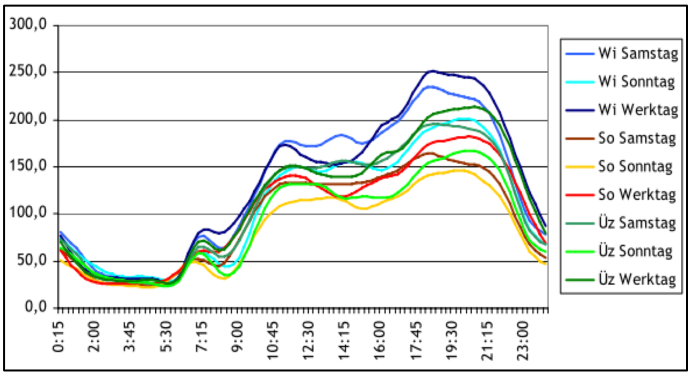

Fig. 4: Load profile - G2, business with high and predominantly consumption in evening hours [2]

2.2.4. Business continuously – G3

This is a classification of consumption points, which have a relatively uniform consumption with a noticeable continuous base throughout the year and also during the week. Examples are sewage plants, drinking water pumps, community facilities in residential complexes, cold stores, shops with significant demand for cooling and systems with forced ventilation.

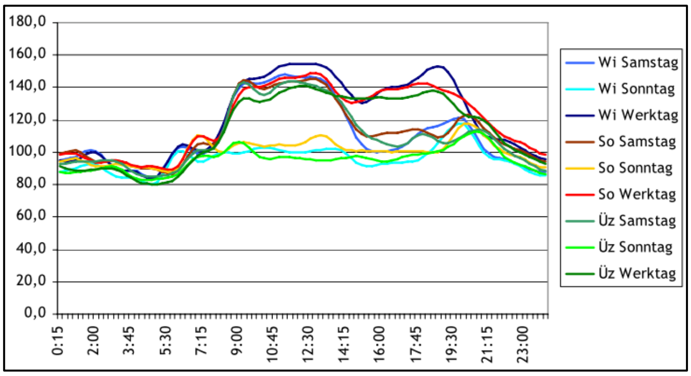

Fig. 5: Load profile - G3, business continuously [2]

2.2.5. Business shop/barbershop – G4

This is the typical profile for general shops of all kinds (opening times working days till night, Saturday until afternoon) and barbershops. Individual afternoons with no business operation or extended opening time to 8pm did not make any differences and have just little consequences in comparison to the base of the total group. Sales oriented bakeries, which prepare baked goods ("in-store baking"), are also included in this profile.

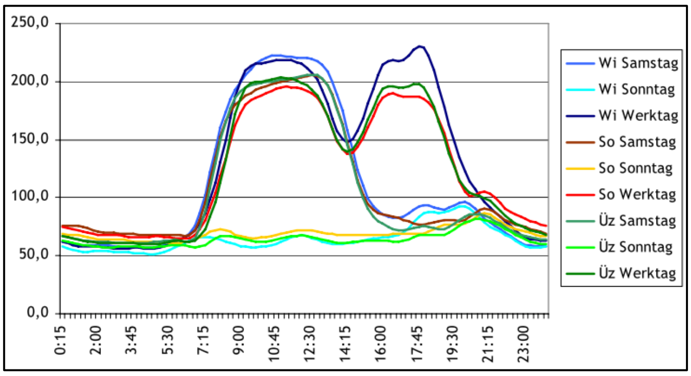

Fig. 6: Load profile – G4, business shop/barbershop [2]

2.2.6. Business bakery – G5

Bakeries have their main energy consumption on working days, early until 3am and until midnight in the night from Friday to Saturday. The daily consumption in comparison to the total demand is relatively low and is mainly determined by the selling activity. Sales oriented bakeries, which prepare baked goods ("in-store baking") behave like other stores and are included in the profile G4.

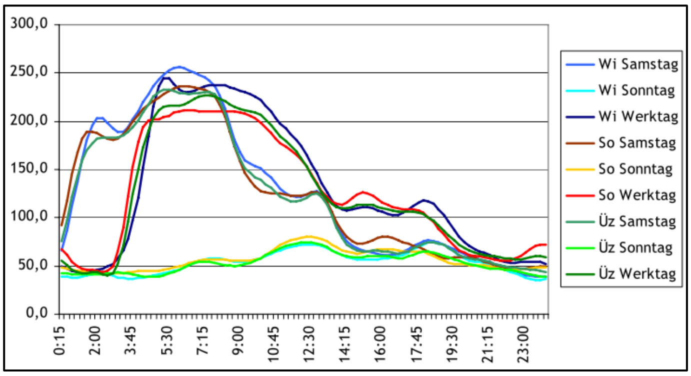

Fig. 7: Load profile - G5, business bakery [2]

2.2.7. Weekend business – G6

Certain companies have their main energy consumption on the weekends. These are mainly shops, which are characterized by leisure activities of the population such as youth clubs, tourist restaurants, petrol stations with car wash, movie theaters with diner, sports- and leisure facilities.

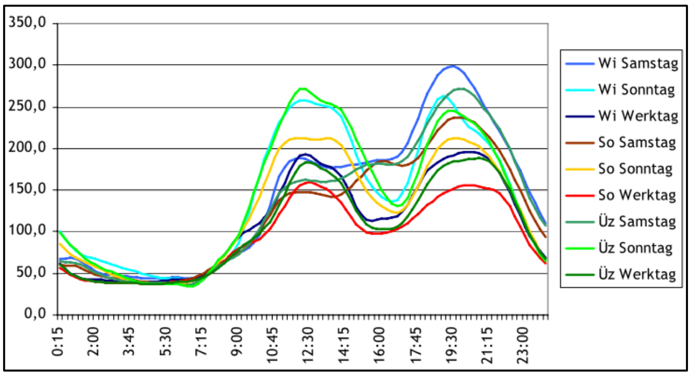

Fig. 8: Load profile - G6, weekend business [2]

2.3. Load profile Agriculture

2.3.1. Farm – L0

This load profile is used if an assignment to typical agriculture load profiles L1 and L2 or to a characteristic business profile is not possible.

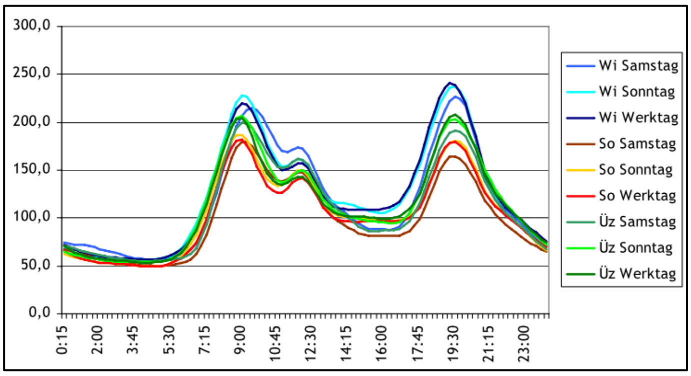

Fig. 9: Load profile - L0, farm [2]

2.3.2. Agriculture dairy farming / sideline animal breeding – L1

This profile is used for dairy farms, where the electricity consumption is dominated by the two periods of time milking and the subsequent cooling of the milk.

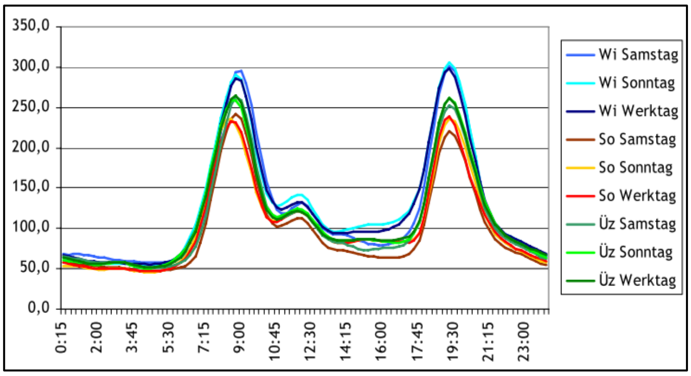

Fig. 10: Load profile - L1, agriculture dairy farming / sideline animal breeding [2]

2.3.3. Other agriculture – L2

In many cases, farms traditionally are characterized by a coexistence of household and production which is taken into consideration with this profile. This mean profile is applied for such business. The appropriate business profile has to be selected as far as on a farm is a largely daytime independent production.

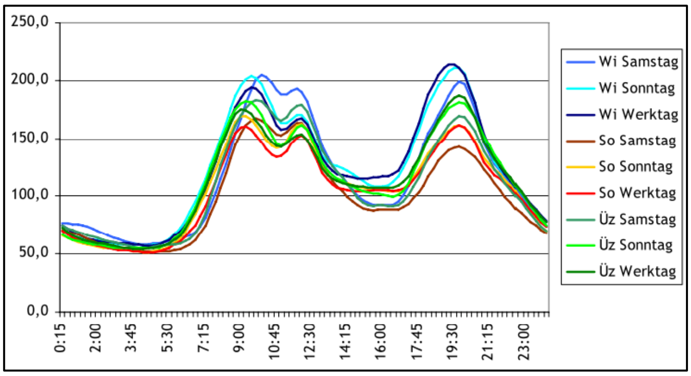

Fig. 11: Load profile - L2, other agriculture [2]

2.4. Further profiles

2.4.1. Night storage heating – ULE

This load profile is applied for night storage heaters without daily recharging. These systems show a distinct consumption focused in winter and a moderate consumption in the transitional period. For simplicity, no consumption is assumed in the summer.

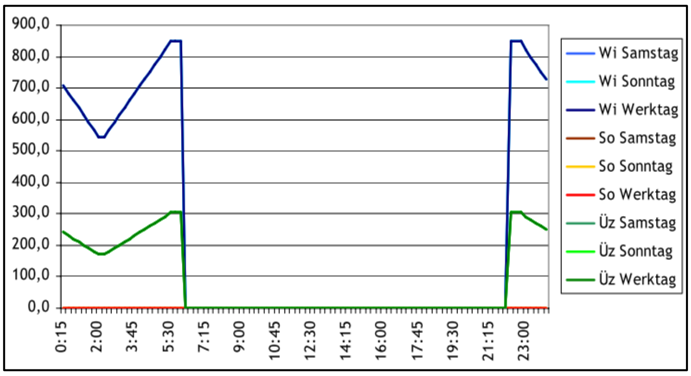

Fig. 12: Load profile - ULE, night storage heating without daily recharging [2]

2.4.2. Public lighting – B1

For the preparation of this load profile it was assumed that the lighting system is working constantly during the entire switch-on time. Any partial shutdowns during the night hours were not included.

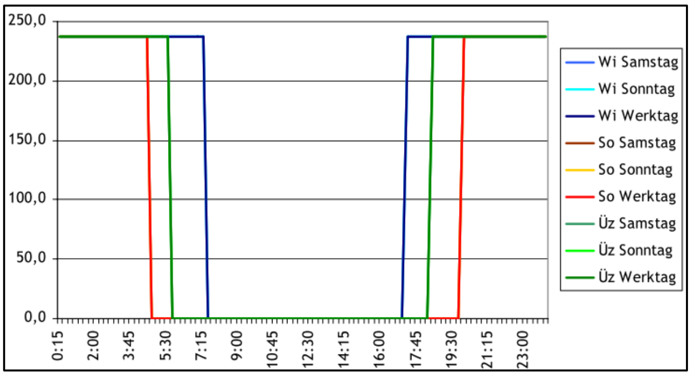

Fig. 13: Load profile - B1, public lighting [2]

2.5. Allocation rules for mixing consumers

Customer installations with one measuring point and mixed consumer characteristic (e.g. household and business) have to be allocated to this standardized VDEW[1] - load profile, which has the main consumption part. The values of allocation are given in Table 1.

Table 1: Values of allocation [2]

Consumption characteristic	**Annual energy consumption**	**VDEW-load profile**
Household / Business	< 8’000 kWh	Household H0
	≥ 8’000 kWh	Business (G0-G6)
Agriculture / Business	< 16’000 kWh	Agriculture (L0-L2)
	≥ 16’000 kWh	Business (G0-G6)
Household / Agriculture	< 8’000 kWh	Household H0
	≥ 8’000 kWh	Agriculture (L0-L2)
Household / Business / Agriculture (if just one measuring system is available)	< 8’000 kWh	Household H0
	≥ 8’000 kWh and < 16’000 kWh	Agriculture (L0-L2)
	≥ 16’000 kWh	Business (G0-G6)

3. Conclusion

This paper represent briefly a summarization of standardized load profiles in Germany which are applied on different groups of consumers with a consumption below 100’000 kWh or connected capacity below 50 kW. There are 11 different normalized load profiles which describe the demand behavior of households, business and agriculture consumers. Two additional profiles (public lighting and night storage heating) show the possibility to apply consumer load profiles on further characteristic consumers. This 11 profiles with their individual show different characteristics depending on daytime, weekday and season. This profiles applied to simplify accounting and the calculation of electricity demand for electricity provider and system operators without using price intensive measurement systems.

[1] German Electricity Association (VDEW)

Acknowledgements

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Electricity Consumption Characterization of the Different End-use Sectors of Brazil

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Abstract

Information about electrical consumption characteristics of the different economic sectors is crucial for any countries' electricity sector, and Brazil is not an exception. The country has experienced a continuous economic growth during the last years that has influenced the way electric energy is consumed. In this context, the present study aims to present the major findings of a literature review in order to characterize the Brazilian electricity sector. The characteristics of the residential, commercial and industrial subsectors that comprise the electricity sector are presented, as well as further information about their consumption profile. It is observed a higher amount of works devoted to study the residential sector, on the contrary there is a lack of newly researches focusing on the commercial and industrial sectors.

Keywords: brazil; commercial sector; electricity consumption; industrial sector; load profile; residential sector.

1. Introduction

The load to be supplied by a generation system can be represented by a load curve or load profile, which depicts the energy demand as a function of time *D(t)* for a given time interval *T*, in kWh [1]. A load profile represents the pattern of electricity usage of a segment of supply market customers. It gives an hourly pattern or 'shape' of usage across a day, and the pattern across the year, for the average customer of each of the profile classes. Typically, a load profile will vary according to customer type, temperature and holiday seasons [2].

The formulation of representative load curves for single consumers and groups of consumers is referred as load profiling. Based on a certain criteria, the consumers can be grouped together in a number of classes like residential, industrial, etc., but also in subcategories within these classes [3]. Load profiling has been identified as one suitable method of dealing with customers without time interval metering equipment [4]. Besides, knowing the characteristics of the loads to be supplied by a distribution system, the knowledge of the load profile of the consumer units entails advantages to the electric utilities [4], [5]. It enables the forecast of contracting power demand, especially at peak hour, thus improving the efficiency of the system and ensuring safe and reliable network supply. The distribution companies can improve their market strategies and offer new services, as well as develop new tariffs with this information. It permits the optimization of resources for planning the expansion of the distribution and transmission systems, as well as the generation plant. Allows a more detailed analysis for better elaborating a tariff framework for the consumers, as well as enables the identification of energy efficiency measures through demand management, thus contributing to energy consumption reduction. Finally, load

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profiling enables the consumers to play an active role in the competitive electricity markets. With accurate information of its demand pattern, the consumer is encouraged to alter its demand in periods where the generation cost is high.

The aforementioned reinforces the importance of knowing the electrical consumption characteristics of the different economic sectors. Since it constitutes strategic information for a good planning of the energy sector, a proper demand forecasting and assists in identifying rationalization measures.

In Brazil, scarce information can be founded in relation to the characterization of consumer load profile. Thus, the objective of this research was to gather the available information in the literature and present in the present article the most important findings derived from it, in order to give an overview of the Brazilian electricity sector in relation to consumer profiling.

The remainder of this work is organized as follows: Section 2 gives a brief description of the electrical system in Brazil, presenting the characteristics of the generation, transmission and distribution sectors in which it is divided. Section 3 introduces further information about the present situation of electricity consumption in Brazil displaying graphics on the historical development of this sector. The characteristics of the residential, commercial and industrial sectors are given in Section 4. Also in this Section the load profile of these sectors is characterized based on information obtained from a literature review. Finally, Section 5 summarizes the main conclusions of the present work.

2. Characteristics of the Brazilian Electrical Sector

The Brazilian electric system, which allows the exchange of energy between the various regions of the country, comprises three segments: generation, transmission and distribution of electricity. The geographical characteristics of Brazil determined the configuration the systems for generation, transmission and distribution have acquired over time and further determine the ease for access the grid for the local population.

With respect to the generation segment, Brazil has in 2014, 3,263 plants in operation, corresponding to an installed capacity of 135,870 MW (excluding the Paraguayan participation in the Itaipu binational hydroelectric power plant) [6]. Historically the country has relied heavily on hydroelectric generation, but the Energy Research Company (EPE), bureau in charge of energy planning in Brazil, intends to diversify the energy mix in order to reduce the dependency relationship between energy generation and hydrological conditions. As observed in Figure 1, two decades ago the hydroelectric generation accounted for nearly 90% of the installed capacity, in 2013 this share fell to 67.85%. Following the hydroelectric generation in order of importance is the thermal generation with 28.82% of the installed capacity, nuclear generation with 1.58% and the renewable sources (excluding hydroelectricity) comprise only 2.34% of the installed capacity. It is worth mentioning that nearly 35% of the electrical energy generated through thermal processes is due to biomass combustion, mainly sugar cane residues [7].

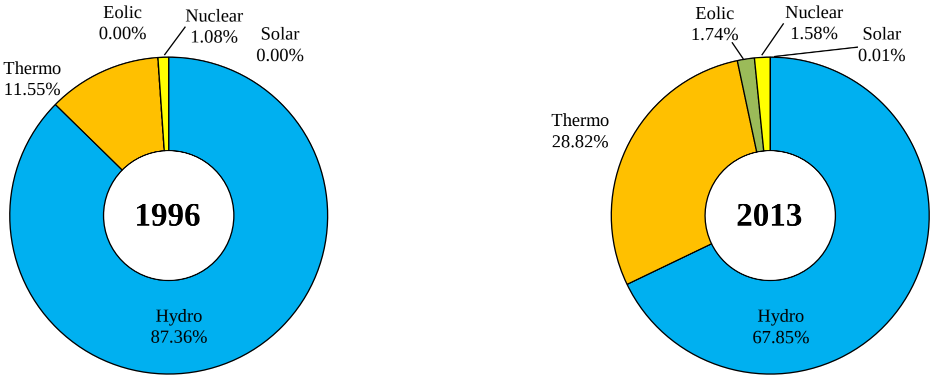

Figure 1. Evolution of the installed capacity for electricity generation from 1996 to 2013 [8].

The transmission sector in Brazil is composed of more than 100,000 km of electric lines and operated by 64 utilities. The vast extent of the transmission network is due to the nature of the generation sector, which is mainly composed by large hydroelectric power plants located distant from the regions where the energy is consumed. The transmission sector is divided into two subsystems: the National Interconnected System (SIN in Portuguese), which covers almost the entire Brazilian territory, and the Isolated Systems. Both systems provide power to more than 99% of the 58 million households in Brazil [9].

The SIN is extended through the South, Southeast, Central-west, Northeast and parts of the North regions. It is composed of approximately 900 transmission lines with voltages of 230, 345, 440, 500 and 750 kV, and is responsible for transporting 96.6% of the country's total electricity production [10] (see Figure 2a).

The Isolated Systems do not exchange energy with the other regions and are predominantly supplied by thermal power plants fueled by diesel and fuel oil, but also small hydro and biomass based power plants can be found (see Figure 2b). In 2008, the Isolated Systems accounted for 3.4% of the electricity produced in the country. However, since the inclusion of Manaus (the capital city of the state of Amazonas in northern Brazil) to the SIN, the share of these systems will be restricted to less than 1%.

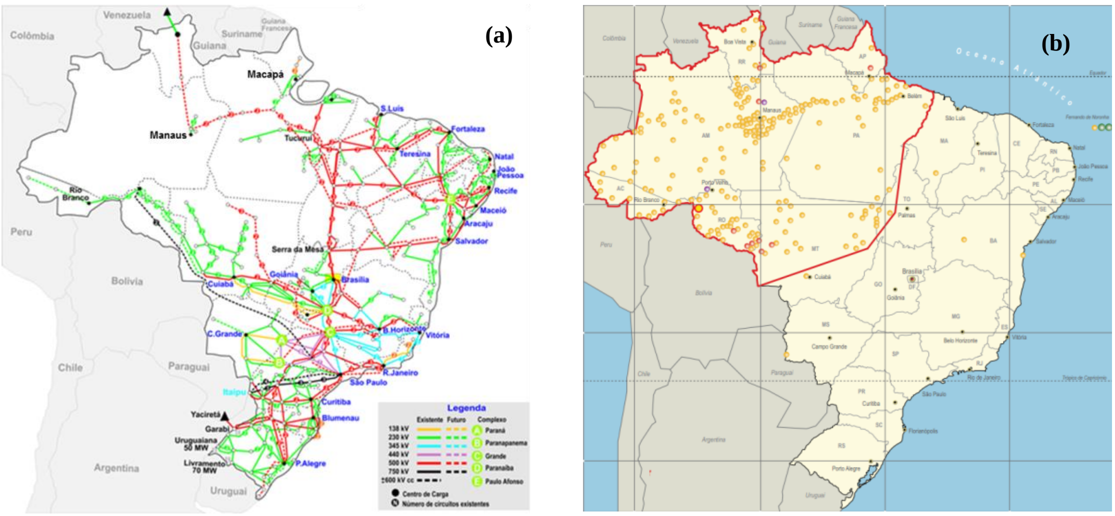

Figure 2. (a) Brazilian Interconnected System (SIN), the dotted lines represent the projected electric lines; (b) isolated systems, the yellow dots are the thermal power plants [10].

The electricity distribution network is a segment comprises the primary electrical networks (medium voltage distribution lines - 15 kV, 23 kV and 34.5 kV), and secondary networks (low voltage distributions lines - 230/115 V, 220/380 and 127V / 220V), whose construction, operation and maintenance is the responsibility of the electricity distribution utilities [10].

The standard voltage for residential consumers is usually 127 V or 220 V, depending on the region, with a frequency of 60 Hz. The common transportation constructions are overhead lines, especially in rural areas and small cities but there are also underground cable systems in big cities [11].

One big problem faced by the Brazilian electrical sector is the unusually high loss of energy. The total energy losses in the transmission and distribution system correspond to 14.4% of the total generated energy. This percentage is twice the world's average, and nearly three times the European average [12].

3. Electricity: Current Demand and Future Projections

In 2013, the electricity consumption in Brazil attained the amount of 516.4 TWh, with a per capita consumption of 2379.9 kWh/year [7]. The country is divided into five geopolitical regions according to geographic, social and economic factors. Each of these regions has a different level of participation in the overall electricity consumption. As it can be seen in Figure 3 the North region encloses 45% of the total land area, accounts for just 8% of the population and is responsible for 6.5% of the electricity consumption. In contrast, the Southeast region corresponds to 11% of the total land area, houses 42% of the population, and is responsible for about 52% of the electricity consumption. In the same Figure 3 the electricity consumption per capita is shown for all the regions. The Southeast and South regions present a per capita electricity consumption above the national average.

In order to monitor the evolution of electricity demand and projecting future scenarios, the EPE has a historical database in which the energy sector is divided into four sub-sectors: residential, commercial, industrial and other[2]. Figure 4 was build based in that information and it depicts the evolution of electricity demand from 1962 to 2008.

[2]Other = rural + public lighting + public service + public entities + self-consumption.

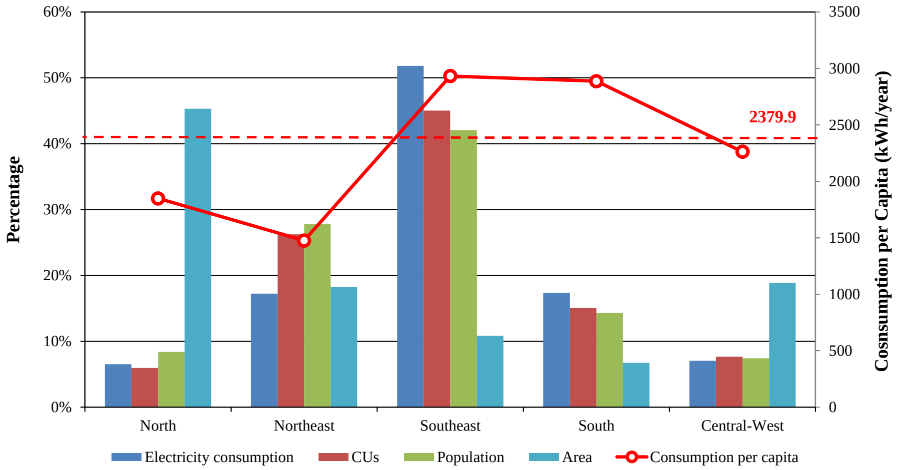

Figure 3. Percentage of electricity consumption, consumer units (CUs), population land area and electricity consumption per capita per geographic region of Brazil for the year 2012 [7], [13].

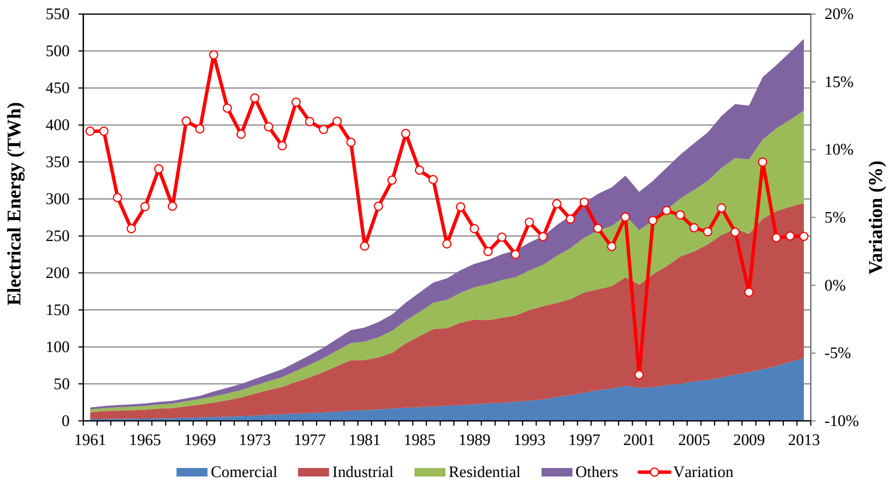

Figure 4. Evolution of the electrical energy consumption in Brazil in the period 1961-2013 [14].

It can be observed that, over the last 51 years, the total electricity consumption in the country has increased almost 30 times, which means an average annual rate of growth of approximately 6.8% year-to-year.

Although it was observed a net positive growth over the last decades, changes in consumption are usually not evenly distributed over time, as they depend on a number of factors such as the average income of the country, the price of energy, the stock of electric appliances, the installed capacity of the industry, the level of industrial activity, the price of substitutes (only in the industry), among others [15]. The aforementioned can be observed in the same Figure 4, which presents the variation in the annual growth rate of electricity consumption in Brazil.

The annual growth rate can be correlated with the economic situation of the country. During the years of the "Brazilian miracle" (70s) the growth rates were higher, exceeding an average of 11% year-to-year and reaching the historical peak of 17% between 1970 and 1971. After the second half of the 1980s decade, the historical averages remained at a much lower level, attaining the lowest value of -6.6% in 2001, year when the crisis that led to rationing in the electricity sector took place.

Historically, the industry represents the highest share due to the volume of energy consumption, but in recent years there has been a slight decrease in its participation. In the 70s its average contribution was 52.6%, however during the last ten years its share fell to 45%. The next sector in importance is the residential, which has increased its share from 19.5% to 22.8%. Likewise, the commercial sector and "others" had increased their share to 20% and 12% respectively, compared to 1970 [7].

Regarding future projections, the Electricity Demand Projection Plan 2014-2023, developed by the EPE, estimates an average growth rate of electricity consumption of 4% per year, reaching almost 689 GWh in 2023. The same study shows that the commercial sector will experiment the greatest expansion in relation to other market segments [16].

4. Load Profile for Commercial, Industrial and Residential Consumers in Brazil

From the literature review performed for the present study, it was evident that there is not much published information related to consumer profiling in Brazil. Some of the most salient works are mentioned following:

1) During the 1990s, Prof. Dr. J.A. Jardini and his research group from the São Paulo University performed a series of field measurements to determine consumers' daily load profile behavior, obtaining the representative curves of the most important consumers' classes, *i.e.* residential, commercial and industrial. The measurements were performed: in 1992 and 1993 for residential; in 1993 and 1994 for the commercial; and in 1994 and 1995 for the industrial segment. The results of this research were published in [17].
2) More recently, between the years 2005 and 2006, Eletrobras with the support of the United Nations Development Program (UNDP) and with funds donated by the Global Environment Facility (GEF) through the World Bank, conducted the research entitled "Assessment of Energy Efficiency Market in Brazil" [18]. This research project aimed obtaining information to adequately assess the market for energy efficiency in the country and the impact of rationing strategies, in search for a more efficient use of electricity. This study, that covered the commercial, industrial and residential consumption sectors, gathered information from 17 states provided by 21 electric utilities. The results of this research were published in the reports [19]–[21].

Based on the aforementioned references, in the following sections there are described the characteristics of the Brazilian Residential, Industrial and Commercial consumer sectors, providing further information about their electric load profile.

4.1. Commercial Sector

The commercial sector represented in 2013 approximately 16% of total electricity consumption in Brazil. This sector has experienced a continuous growth in the last decades, as seen in Figure 4.

In Figure 5a, the business type of installations with the largest representation in the commercial sector are depicted. It can be observed that hotels, supermarkets and banks together represent a share of over 57%; other salient facilities are hospitals and educational institutions.

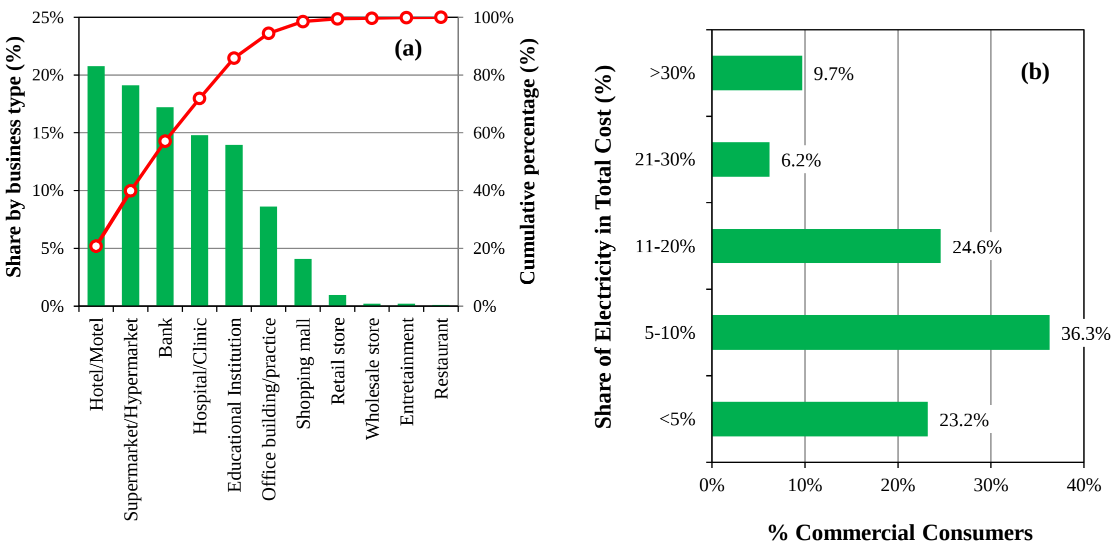

Figure 5. (a) Share of the most representative business types in the commercial sector; (b) relative weight of electricity in the total cost structure for Brazilian commercial sector [21].

The relative importance of the electricity in the cost structure of these consumers can be observed in Figure 5b. In 36.3% of the cases, the share of electricity in total costs lies between 5 and 10%, being the overall industry average 14.1% [21].

Air-conditioning, refrigeration and lighting, are the main electricity end-uses in this sector. The first one is responsible for about 47% share of the energy consumption in the whole commercial sector. But they can account for more than half of total electricity use in large office buildings, hotels, or shopping centers [22]. Refrigeration systems are mainly found in supermarkets and hospitals. On average, the cooling load represents 16% of peak demand in commercial installations [21]. Lighting systems also constitute a significant load in the commercial sector, representing, on average, 22% of peak demand. Entertainment and educational facilities present the highest share of demand due to lighting, with 41% and 34% respectively. Tubular fluorescent type of lamps are widely used in the commercial sector, they are used in 54% of the facilities.

4.1.1. Commercial Load Curves

The characterization of the load profile for the commercial sector is not a simple task given the wide range of activities that comprise it, which present dissimilar behaviors. As an example, Figure 6a and Figure 6b show the load curves for the two different commercial activities, observing how divergent can result the consumption profile depending on the type of commercial activity.

In 2000, Jardini *et al.* [17] presented the results of an extensive study of measurement and characterization of the commercial sector in which over a universe of nearly 200 commercial activities registered in the State of São Paulo.

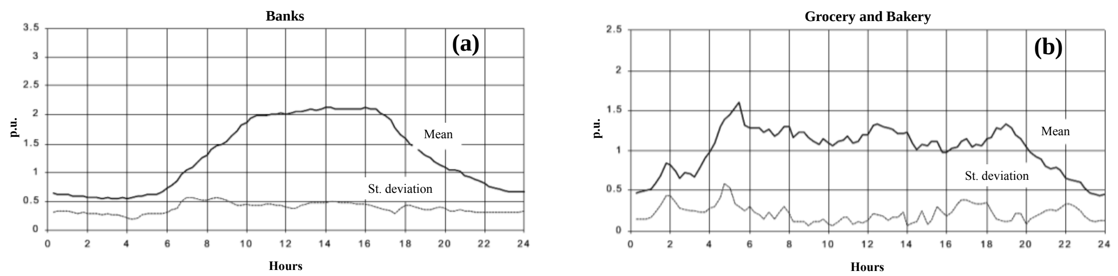

Figure 6. (a) Mean and standard deviation load curve for banks; (b) Mean and standard deviation load curve for grocery stores and bakeries [23].

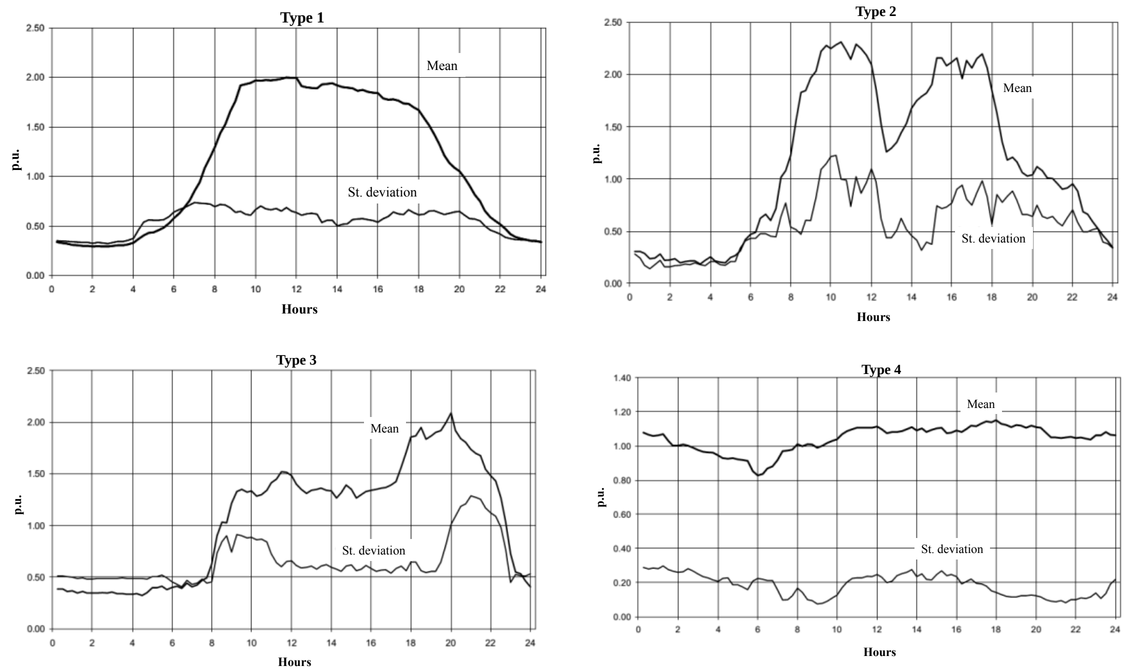

Figure 7. Groups of commercial consumer's curves [23].

In order to characterize the shape (typology) of the commercial load curve, the authors [17] performed a data clustering analysis. Firstly, the data was grouped according to the same activity and similar characteristics. As a result, one model for each activity was established. Afterwards the consumers with similar load curves where grouped independently of the activity they belonged to. This procedure resulted in a group of 4 simple curves shaped as Figure 7 shows. Any commercial activity may be represented by one of these four curves, which in turn can be used to obtain daily load curves in any point of the network by aggregation of the consumers' load, for example [17].

To give some examples, typical activities characterized by Type 1 curve are hotels and motels, banks, management service of real state and newspaper stands. Type 2 curve represents commercial activities like mechanical workshops and car dealers. Type 3 curve can be associated with restaurants, bars, coffee shops and petrol stations. And finally, Type 4 curve may represent radio stations, supermarkets and public transport services.

4.2. Industrial Sector

The industrial sector (excluding energy production) accounted for 40.7% of total electricity use in Brazil in 2013 (Figure 4).

In Figure 8a it can be seen the activities with highest presence in the industrial sector. The activities food and drinks, plastic and rubber and non-metallic minerals, account for almost 60% of the sector, being the former one the most significant industrial activities with a share of 27%.

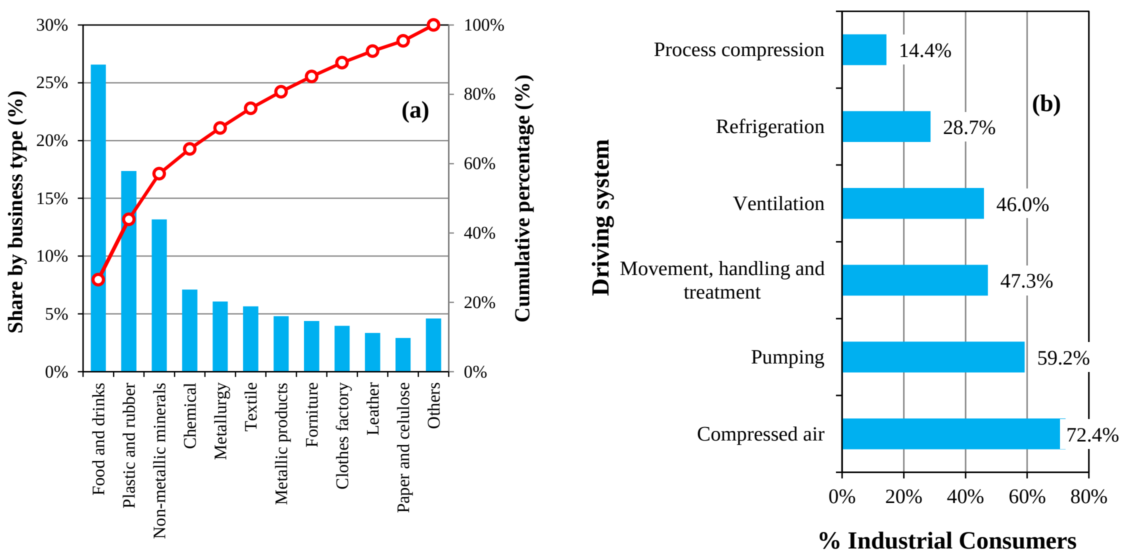

Figure 8. (a) Share of the most representative business types in the industrial sector; (b) Use of drive power in the most relevant industrial processes [20].

From the research conducted by the National Program for Electric Energy Conservation (PROCEL in Portuguese) it is estimated that electricity is used within the industrial sector mainly in motors (63%), electrothermal processes (22%), refrigeration (6%), lighting (6%) and electrolyze (2%) [20].

The main systems where electric motors are used in the Brazilian industrial plants are presented Figure 8b. It is noticed that compressed air systems are the most present in the industries with a share of 72.4%, followed by pumping systems with 59.2%.

About 39% of the industries make use of electricity to produce heat in its facilities using equipment such as ovens, stoves, heaters and boilers. The participation of electrothermal processes on the total maximum load is in average 13.8%, for the whole industrial sector. And the average installed power equals 570 kW.

Lighting represents close to 8% of the total maximum load for industrial facilities, being the assembler and metallurgic industries the ones who present the greatest requirement for illumination. The most common lamps used in the industries' facilities are the tubular fluorescent type, with a share of 51.6%. This model of lamp is mainly used in administrative areas, whereas mix and mercury-vapor type lamps are predominant in exterior areas.

4.2.1. Industrial Load Curve

The industrial load curve characterization was also performed in the work of Jardini *et al.* [17] in a similar way as with the commercial sector. In this case, 218 different types of industries were assessed in the study, and after the characterization and classification according to the quantity of consumers and the level of energy consumption, a final ranking of 26 more representative industrial activities resulted. Thus, 26 representative curves were establishment, one for each activity.

Due to the complexity and diversity in the load profiles that makes difficult to find a common pattern for grouping them, no attempt was made to derive a simple model for the industrial sector [17].

As an example, four load curves from different industrial activities are presented in Figure 9. It is observed that for some of the activities, the standard deviation values resulted high. This can be explained by the fact that in most industrial activities there are small size motors with an intermittent mode of operation during the day. Their loads are sometimes high if compared to industries average power, which may lead to quite high values of standard deviation, as seen in the shoe fabric industry depicted in Figure 9 [17].

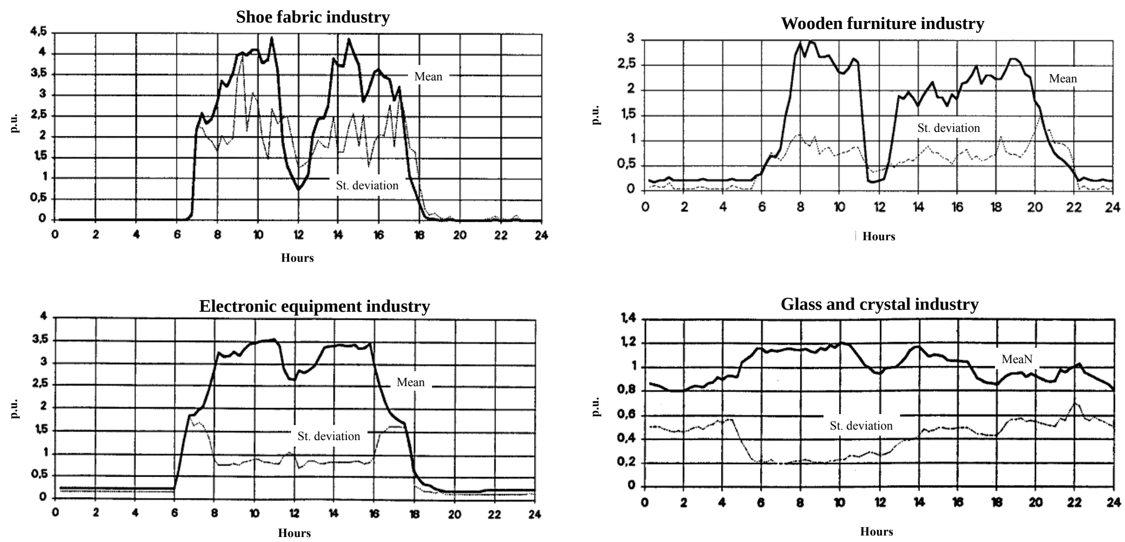

Figure 9. Industrial consumers' curves [23].

4.3. Residential Sector

The residential sector in Brazil represented 24.2% of the total electricity consumption in 2013, being the second sector in importance after the industrial.

This sector has received more attention from the researches as can be seen through the greater amount of publications concerning the residential sector compared with the other electrical sectors in Brazil. To mention some examples, [24]–[26] analyze the structure and evolution of the residential sector; [13], [27] assess the potential implementation of electricity conservation actions and energy-efficient household appliances; and [15] presents an economic approach in which the elasticity income-electricity cost is calculated.

In Figure 10 it can be observed that more than 68% of the households in Brazil consume less than 200 kWh/month, a relatively low level of consumption when compared with some developed countries such as USA (975 kWh/month) or Germany (300 kWh/month) [18]. The Brazilian regions with the highest share of households with consumption level less than 200 kWh/month are the Northeast and Central-west ones. The North region has the highest percentage of households that consume more than 300 kWh/month.

According to the results of the study conducted by [19], the share of household appliances in the Brazilian residential electricity consumption are as depicted in Figure 11. Despite some regional differences, the greater share corresponds to cooling (refrigerator and freezer), representing 27% of the total consumption, followed by water heating for bath (electric shower), with a percentage of 23.5%. Air-

conditioning, that represents 20% of the consumption in this sector, is provided by conventional cooling systems and by reverse cycle systems (cold/hot air).

Refrigeration system, electric showers and air-conditioning systems along with lighting systems account for 84.5% of the electricity consumption in Brazilian households [28].

It is also interesting to analyse the level of ownership of electric appliances in Brazil and over the country's geographical regions, which is depicted in Figure 12. As it can be seen, the refrigerator is present in all Brazilian homes since the national ownership average is 1.0 (Figure 12).

Other appliance that has a major impact in the Brazilian residential sector is the electric shower, which constitutes the most common method for heating water for bathing in the country. As observed in Figure 12 the national ownership level is almost 0.9, but due to different climatic conditions, this appliance is inhomogeneously used along the country.

The level of ownership of air conditioning and freezers is still low in Brazil, but this situation is expected to change in the subsequent years as the Brazilian economy is in continuous expansion, leading the population to acquire more electric appliances for their households. The highest percentages of air conditioning system ownership are in the South and North regions, pointing out that whereas in the North region this appliance is used only for cooling purpose, in the South region the reverse cycle air conditioners are commonly used for heating during the coldest months.

Lighting constitutes a significant share of consumption in the Brazilian residential sector. As the survey conducted by [19] demonstrates, in average, lighting represents 32.5 kWh/month per residence. The most common types of lamps utilized are incandescent and for the fluorescent, though in the latter case, the compact fluorescent lamps are more common than the tubular ones. It is worth noticing that the fluorescent lamp presents a higher level of ownership for regular use (extended periods of time), due to its better consumption/illumination efficiency.

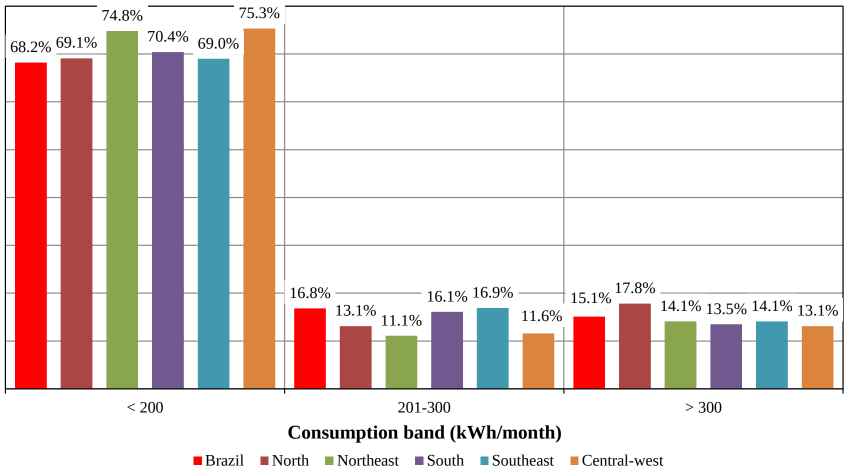

Figure 10. Distribution of residential consumers per consumption band [19].

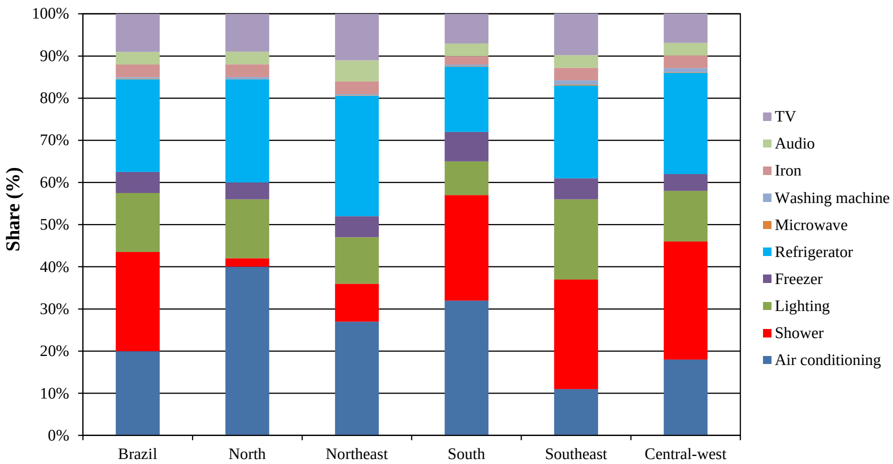

Figure 11. Participation of main household appliances in the electricity consumption of the residential sector [19].

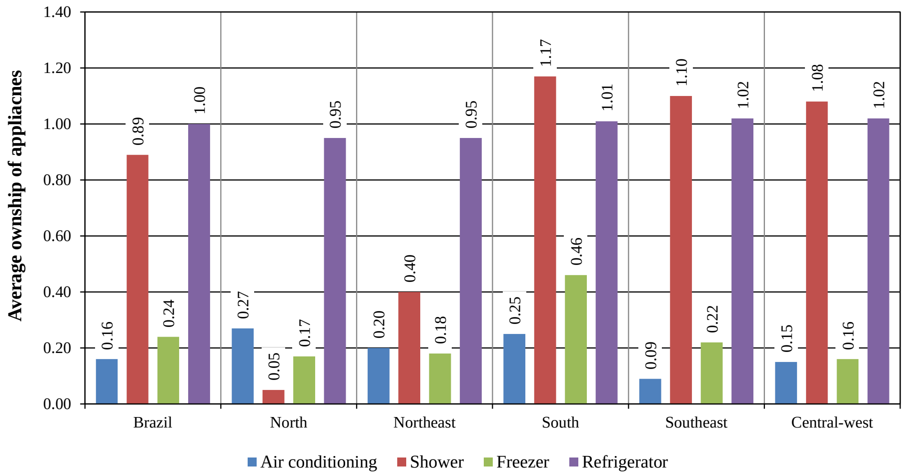

Figure 12. Average electric appliance ownership for Brazil and the different geographical regions [19].

4.3.1. Residential Load Curve

In Brazil, a series of surveys on electric appliance ownership and consumption habits PPHs (*Pesquisas de Posse e Hábitos de Consumo de Energia*) have been conducted in three occasions, 1988, 1997/98 and 2005/06. The results of these surveys give information on the participation of the different electrical appliances in the residential sector, and also after processing the information it is possible to obtain the profile of the consumers' load curve (or group of customers) [29]. This information is available for consultation in the Information System on Electrical Appliance Ownership and Consumer Habits (SINPHA) [30].

The load profiles for Brazil and their geographical regions are depicted in Figure 13. It is observed that the Brazilian load curve for the residential sector is characterized by two periods of peak consumption, one during the morning between 6 a.m. and 8 a.m., and the other during the early evening between 6 p.m. and 9 p.m., the latter contribute significantly to the overall system peak load [28]. These two peaks correspond with the moments when people wake up to go to work and the return to their residences after the working day. During the rest of the day the consumption is fairly constant.

With exception of the North and Northeast regions, the equipment that contributes more heavily to the overall peak load in Brazil is the electric shower. This appliance uses a resistance device that heats the water when coming out of it. Its power is about 3–5 kW, and the average shower period is 8 min [17], [28]. It is estimated that during the evening peak hour (6 p.m. to 9 p.m.), the residential consumption contributes with 22% to the overall consumption, from which 50% corresponds to the electric shower, thus this appliance contributes with roughly 10% of the global peak load [28], [31]–[33].

Other appliance that contributes extensively to the residential consumption is the air conditioning system, especially in the warmer regions such as the North and North-east. As can be seen in Figure 13 this appliance is used out of the working hours, when the people is present at their homes, and its use is extended all through the night. On the contrary, the electric shower is rarely used in the warmer regions of the country.

Lighting contributes clearly to the evening peak load demand all throughout the country and in the same proportion.

For a more detailed analysis of the residential load profile, data from a distribution utility of the State of São Paulo was obtained. This data corresponds to one week (27/03/14 – 03/04/14) of measurements performed in periods of 10 minutes in a 75 kVA transformer that supplies energy to 91 low-voltage residential consumers [34].

It is observed higher values of standard deviation in the early evening period between 5 p.m. to 10 p.m., see Figure 14. This period is characterized by the use of electric shower for bathing. The utilization of this appliance, is characterized by a short period of use (4 to 12 minutes) randomly distributed during the evening peak hour. This makes the loads of showers do not fully coincide at any given time in the distribution transformer. According to [23], [32] the coincidence or simultaneously factor of electric

showers in the transformers is 25%. The peculiar use of electric showers makes de residential load curve more difficult to characterize.

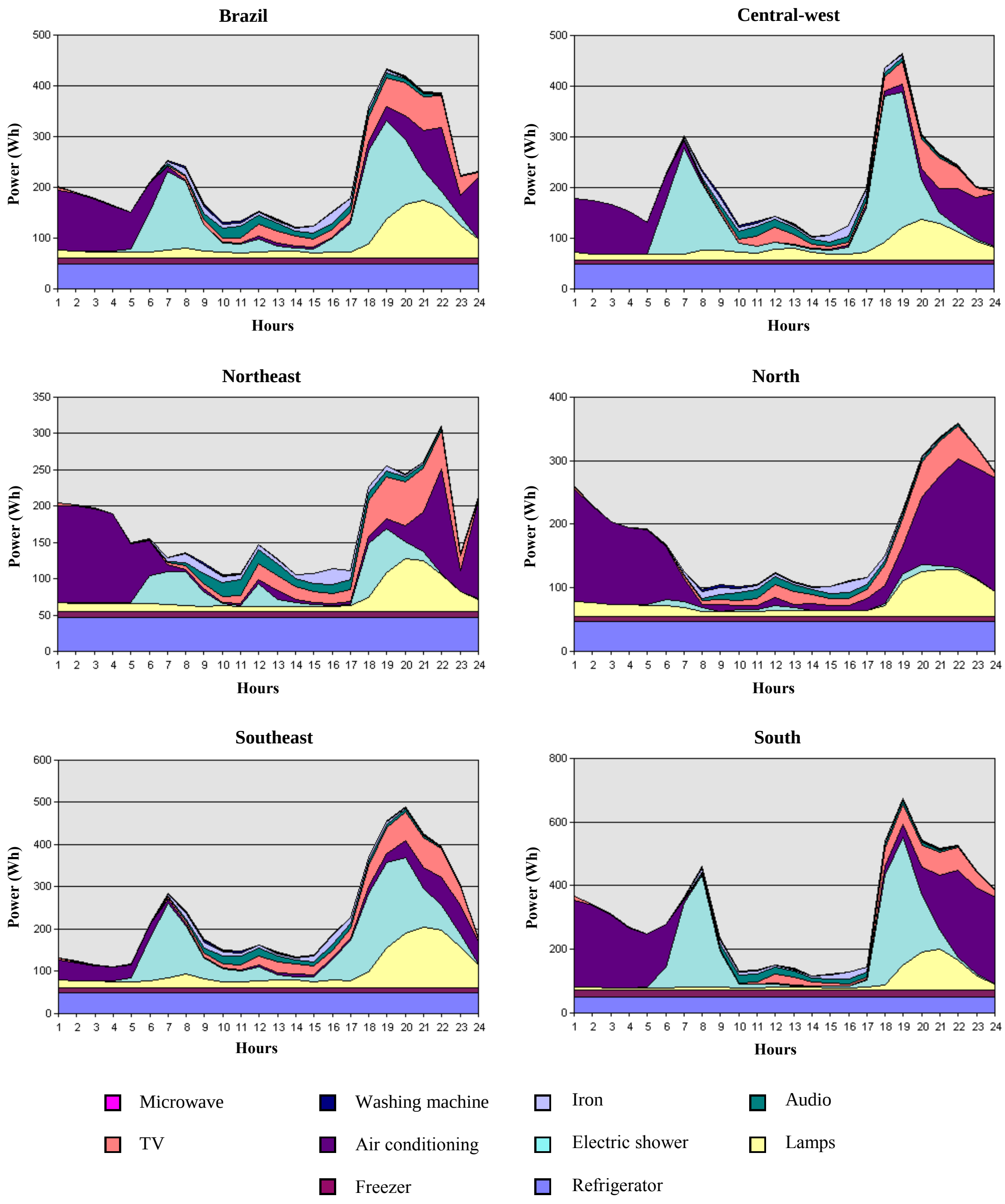

Figure 13. Average daily load curve for Brazil and its different geographical regions [30].

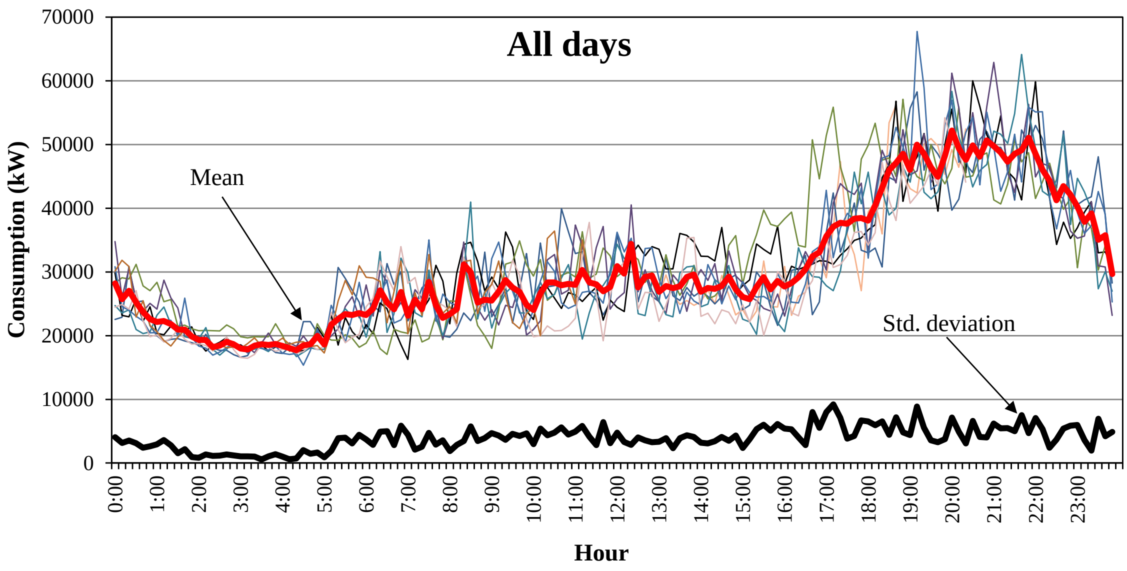

Figure 14. Load curves, mean and standard deviation for a group of residential consumers, considering only weekdays.

5. Conclusions

The present paper sought to present a general overview of the Brazilian electricity sector with focus on the characterization of the consumers' profile. The analysis was based on a literature review from which the available information was excerpted, analyzed and depicted in the form of tables and graphs for better understanding.

As it was perceived from the initial stage of the research, there is not much actual official information related to the electrical consumption of the different economic sectors in Brazil. With respect to the commercial and industrial sectors, the latest salient research was performed during the decade of 1990. On the other hand, more information related to the residential sector was found, where the bulk of the publications are focus on the study of energy efficiency measurements to be implemented in this sector.

The commercial sector accounts for nearly 16% of the total Brazilian electricity consumption and is characterized by a concentration of users in the group of less than 500 kW of peak demand. Air-conditioning, refrigeration and lighting are the main electricity end-uses in this sector, accounting for 85% of the consumption. It was found that any commercial activity may be represented by one of four typical profile curves which can be used to obtain daily load curves in any point of the network by aggregation of the consumers' load.

The industrial sector accounts for 40.7% of total electricity use in Brazil. In this sector, three-fifths of the electrical consumption is due to merely three industrial activities. The electricity is used mainly in motors, electrothermal processes, refrigeration and lighting, being that the motors account for more than 60% of the consumption. Due to the variability introduced by the high participation of small size motors, it results difficult to obtain a simple model to characterize the consumers' consumption profile.

The residential sector is the second in importance after the industrial, it currently accounts for nearly a quarter of the electrical consumption. As a developing country, the Brazilian residential electrical sector still presents a lower level of consumption when compared to developed countries; thereby it is expected a growth in the future as the country is in economic expansion. The appliances that most energy consume are refrigerator and freezer (27%), electric shower (23.5%) and air conditioning system (20%). The Brazilian load curve for the residential sector is characterized by one period of higher peak consumption, during the early evening between 5 p.m. and 10 p.m. It is estimated that the electric shower contributes with roughly 10% of the global evening peak load. Thus, the replacement of a low-efficiency heating system such as the electric shower represents a huge potential for electricity savings, implying the reduction of the investment level needed to meet the full demand during peak hours.

6. Acknowledgements

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Consumption Management of Air Conditioning Devices for the Participation in Demand Response Programs

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Abstract

Demand Response has been taking over the years an extreme importance. There's a lot of demand response programs, one of them proposed in this paper, using air conditioners that could increase the power quality and decrease the spent money in many ways like: infrastructures and customers energy bill reduction.

This paper proposes a method and a study on how air conditioners could integrate demand response programs. The proposed method has been modelled as an energy resources management optimization problem. This paper presents two case studies, the first one with all costumers participating and second one with some of costumers. The results obtained for both case studies have been analyzed.

Keywords: Air Conditioners; Demand Response; Direct Load Control; Energy Resource Management.

1. Introduction

With the spread of distributed energy, and the increase of energy consumption by different types of consumers, demand response (DR) takes higher importance. This paper suggests using a DR program to reduce consumption by the air conditioner for a short period of time. It is therefore necessary to lay down certain rules that define where it will be reduced the energy consumption by air conditioner. It has been implemented an optimization problem for this, based on several variables, including the cost of energy consumed and of the produced energy and to their respective powers.

The present section makes the introduction to demand response programs, air conditioning consumption trends, and to the opportunities for the air conditioning to participate in DR programs.

1.1. Electric Energy Consumption Trends

Since electric power systems exists, the value of the energy consumed worldwide is increasing, thanks to various reasons like: increase population, better quality of life, increase of electrical equipment

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and others. World electricity generation increases by 93%, from 20.2 trillion kilowatt-hours in 2010 to 39.0 trillion kilowatt-hours in 2040 [1].

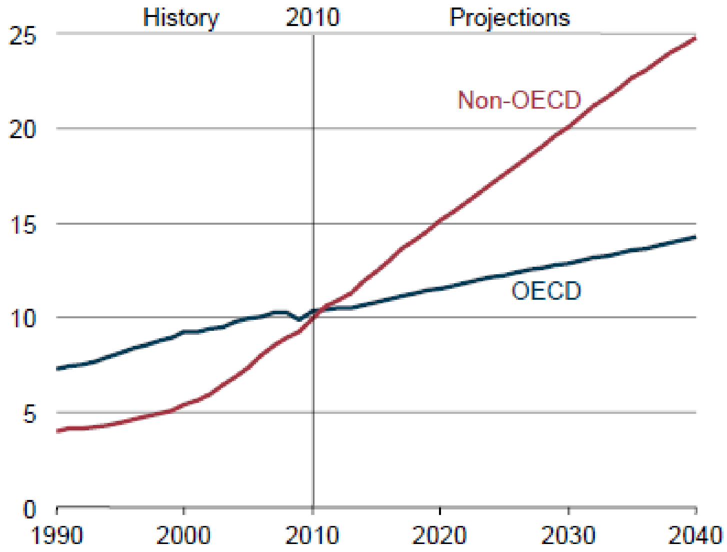

Fig. 1 Electricity generation by country in trillion kilowatt-hours (1990-2040) [1]

In fig. 2, one can see the electricity generation by sector, notice that the residential sector is the sector with the major increase of electricity consumption [2].

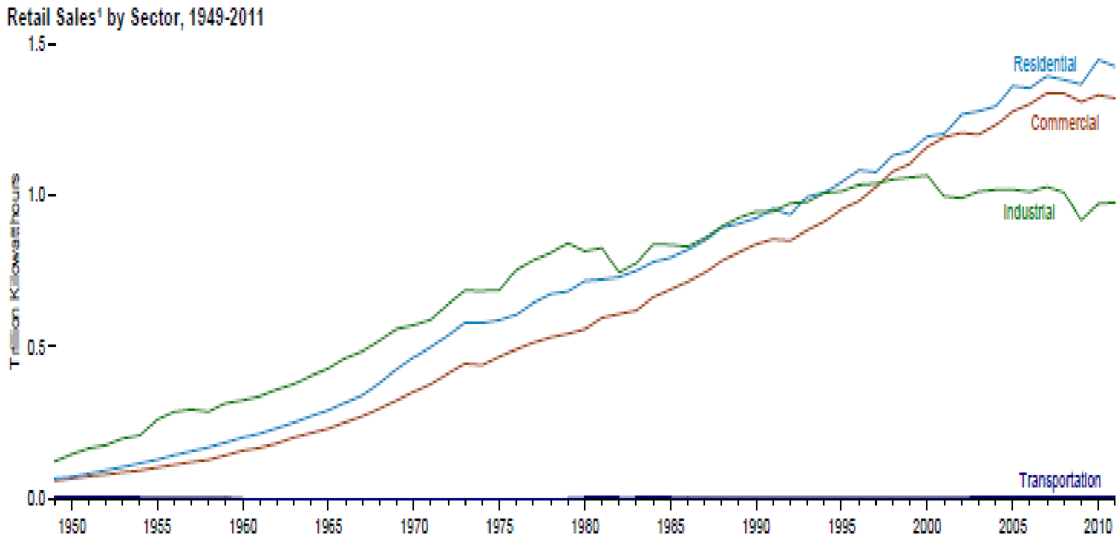

Fig. 2 Retail Sales by Sector (1949-2011) [2]

As for final, consumption by equipment, taking the example of housing, this has been changed over the years. Between 1993 and 2009, household appliances, lighting and heating are the equipment that has undergone major changes, having come to consume less and less energy, to the contrary, it has increased energy consumption are the handsets air conditioning [3].

The future trend in the residential sector between 2011 and 2040, is a continuation of what has been observed a reduction in lighting, water heating and appliances and a slight increase in air conditioning and ventilation [3]. The commercial sector will encounter a bit of what happens in the residential, except that here the air conditioning and ventilation, it is expected that tended to decrease in the period between 2011 and 2040, this decrease is the result of technological developments consequent increased energy efficiency of these devices, as seen in fig.3. [3].

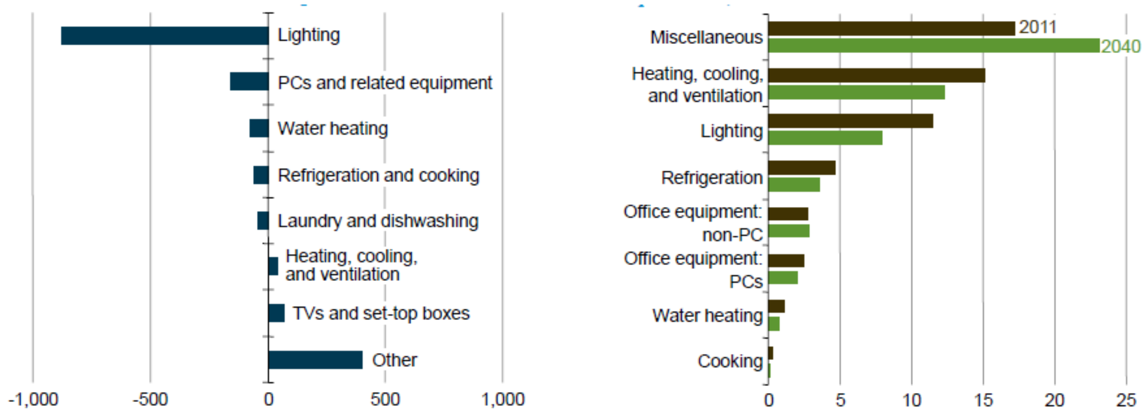

Fig. 3 . (a) Future trends in domestic houses, units kWh (2011-2040) [3] (b) Future trends in commercial houses, units btu (2011-2040) [3]

1.2. Demand Response programs

It's important for electric power systems, offering high reliability and lest there be power outages for consumers. When, for example, energy demand exceeds supply or when electricity costs are high energy provider asks and pays for the end customer help in reducing energy consumption. A good power management enables a lower cost and helps prevent service interruptions. [4 5]

There are several DR programs that have been developed over the years, as there are different environments from the production of energy by the type of customer, each DR program has better advantages when applied in the right [4] situation.

The DR programs can be divided into two distinct [4] categories: price-based or incentive-based. The programs are based on price-related changes in energy consumption by customers due to changes in its cost. These programs are [5,6]:

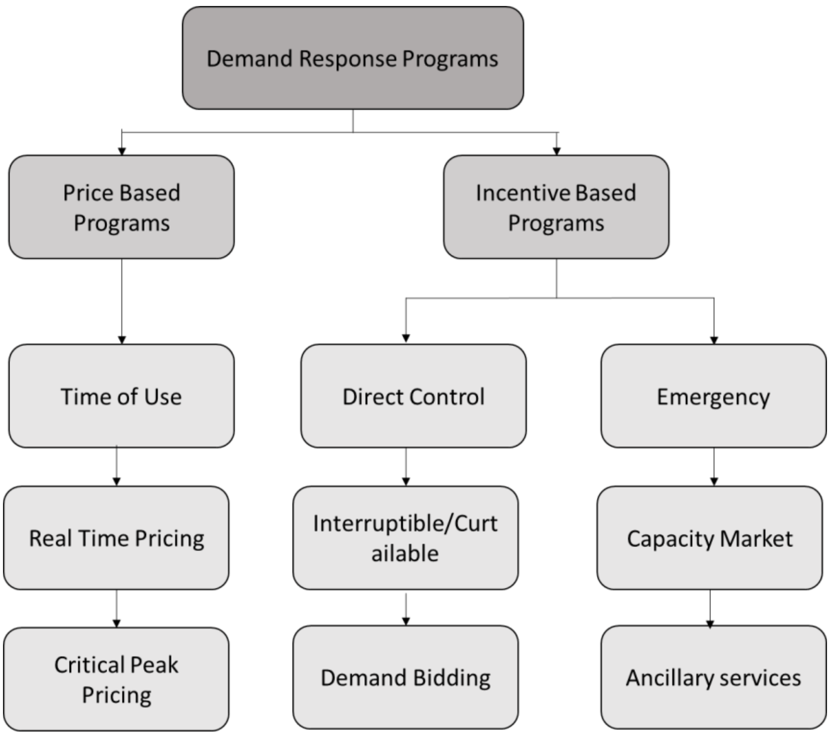

Fig. 4. DR programs classification [5, 6]

Price Based Programs

• Time Of Use (TOU): Different rates for each time period of the day.

• Real Time Pricing (RTP): The price is set for a given period of time, usually one hour.

• Critical Peak Pricing (CPP): It is a mixture of the two mentioned above, but with a price higher peak, which is used in specific situations.

Incentive Based Programs

• Direct Load Control (DLC): This is a program that remotely controls the electrical appliances, mainly used in homes or small trade.

• Interruptible / Curtailable Programs (ICS): It is based on the curtailment or interruption, reducing power consumption during periods of contingency. It is used in industries.

• Demand Bidding / Buyback (DBB): Customers who want to bid the cut. It is used in large power consumers.

• Emergency DR (EDR): On meeting with the programs and direct load control in Adjournment / Cutting Service, where the buffer becomes insufficient.

• Capacity Market (CM): load is cut to customers as the market for it is not necessary to power generation.

• Ancillary Service (AS): Similar to the bidding program, although only the market for auxiliary services.

1.3. Air conditioning and DR

With the increase of units of air conditioners, as can be seen in the graph of Fig 5 air conditioners becomes a possibility to integrate DR programs because there largest consumers of power they can be removed. Note that the application of a DR program of this kind could be more advantageous in some countries, especially where there are a greater number of AC unit and that they are used more frequently. In the fig. 5 only includes certain countries, for detailed consultation with all countries we suggests that you consult the reference [7].

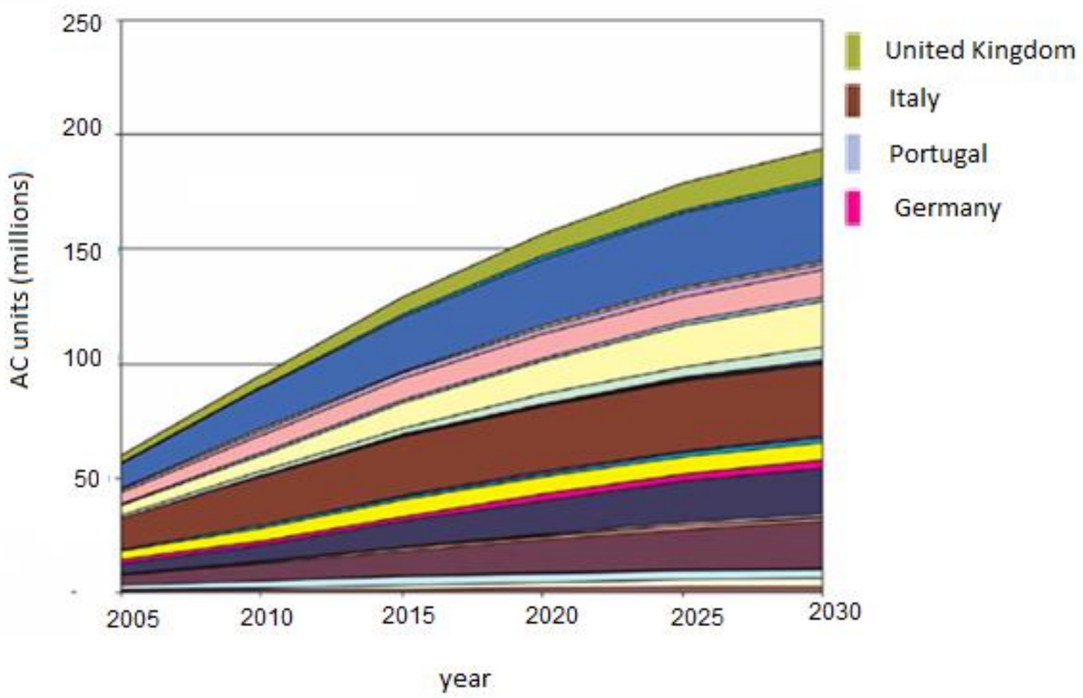

Fig. 5 AC future trends (2005 – 2030) [7]

The air-conditioned, offering good features to integrate in a DR program. Some of these features are the possibility of remote control to turn off or reduce the level of cooling can be turned off during periods eg 15 minutes without it materially affect the comfort of the people. Thus it is possible to control the air conditioners energy remotely, turning them off when necessary [8].

This time period may be increased or decreased according to some factors including the outside temperature or quality of isolation housing. Homes with good insulation can increase the period of time the air conditioner is switched off without affecting comfort, reducing energy consumption which turns into a decrease in the amount payable on the invoice to the distributor of energy. [9, 10]

For DR programs using the air conditioning, in general, do not yet exist in abundance. In Europe is still not present this type of programs related to air conditioning [11]. In the U.S.A. some distributor's mainly warmer zones are offering to the customers this type of DR programs.

2. Proposed resources management model

2.1. General Concepts

To do the management model, it took a few steps. Initially it was essential to obtain all data on the electric network. The data of the actual grid are: the price of energy per production technology, the type of consumer, the value of power consumption, the value of the power consumption of devices AC and the price of energy to the various types of consumers.

It is necessary to know the maximum possible power to be removed in AC per customer, as this is the maximum that can be reduced. Are also required to know the prices payable for each customer type for the optimization algorithm, minimizes costs to customers. The importance of power values generated their costs is also important for the production values are minimized and consequently the price is reduced by production technology. Known these values the next step was to apply them to an optimization problem, which in this case as aforesaid the software used was Matlab / Tomlab and Excel.

2.2. Optimization Problem

The strategy to use in solving the problem was with the optimization feature.

For the mathematical formulation first was necessary to understand and distinguish which are thr decision variables. Following the reasoning of the article studied [12] for the present study the variables that can be changed are the value of the power cut in AC and the power generated, these are the values obtained after the optimization problem solved, other costs and maximum possible powers to reduce initial and generated are fixed. With all the variables defined the next step was to identify the constraints and objective function of the problem.

The objective function and the constraints are:

Objective function:

$$\mathrm{Min}\,C = \sum_{b=1}^{nb}(P_{MaxCut(b)} \times c_{Customer(b)} + P_{Gen(b)} \times c_{Gen(b)}) \tag{1}$$

Constraints:

$$\sum_{b=1}^{nb}(P_{\mathrm{MinGen}(b)}) \le \sum_{b=1}^{nb}(P_{MaxCut(b)} + P_{Gen(b)}) \tag{2}$$

$$P_{totalLoad} = \sum_{b=1}^{nb}(P_{MaxCut(b)} + P_{Gen(b)}) \tag{3}$$

Where:

$MinC$	Minimum cost (€/kWh)
$c_{Customer(b)}$	Customer energy cost (€/kWh)
$c_{Gen(b)}$	Generated energy cost (€/kWh)

$P_{MaxCut(b)}$	Maximum power cut in AC (kW)
$P_{Gen(b)}$	Power generated by the generators (kW)
$P_{MinGen(b)}$	Minimum power generated (kW)
$P_{\text{totalLoad}(b)}$	Power consumed by the load (kW)

The objective function (1) is to minimize the operation costs of the grid for both the production side and consumers.

The first constraint (2) requires that for a given bus at maximum cutting power in the air conditioning plus the power generated will have to be higher than the minimum generated power.

The second constraint (3) requires that the load power subtracted from the maximum cutting power must be equal to the power consumed by the load.

2.3. Management Model Diagram

As shown in the diagram of Fig. the first step is to obtain data on the network that are important to the application of the model, these are: the price of energy by type of production technology, solar, wind, hydro, biomass, etc.; energy prices for consumers; the generated power and the maximum power possible to reduce the AC. The price values are needed because as seen earlier are included in the objective function whose goal is to minimize costs, affecting both the producers and consumers, thus model will choose a final set of values with lower costs than the original. The values of powers are given to the moment before starting the DR program. Known these values are applied in optimization.

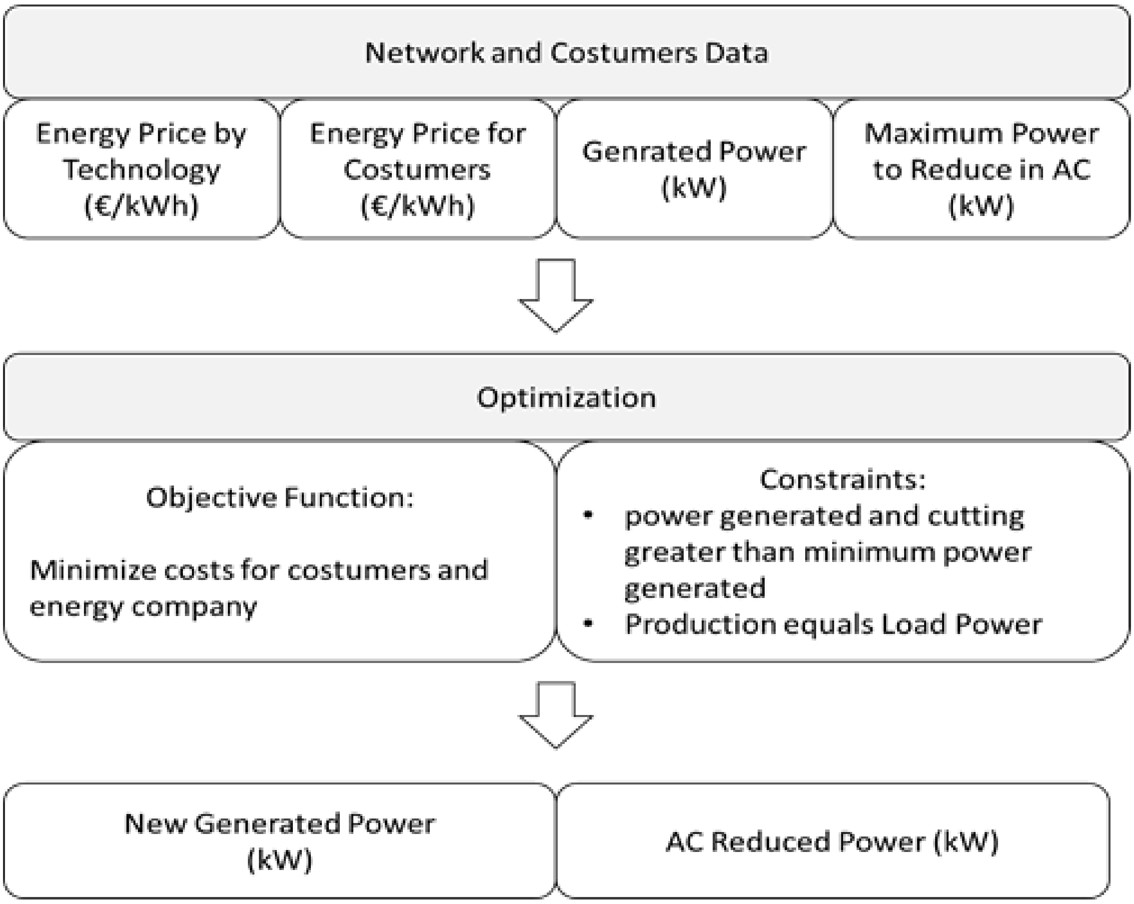

Fig. 6 – Implemented Model Diagram

In this paper we used *TomLab* to solve the optimization problem, the solver was cplex.

3. Case Study

3.1. Used Network

The presented scenario's is based on a distribution network used in [13], and showed in Fig.7.

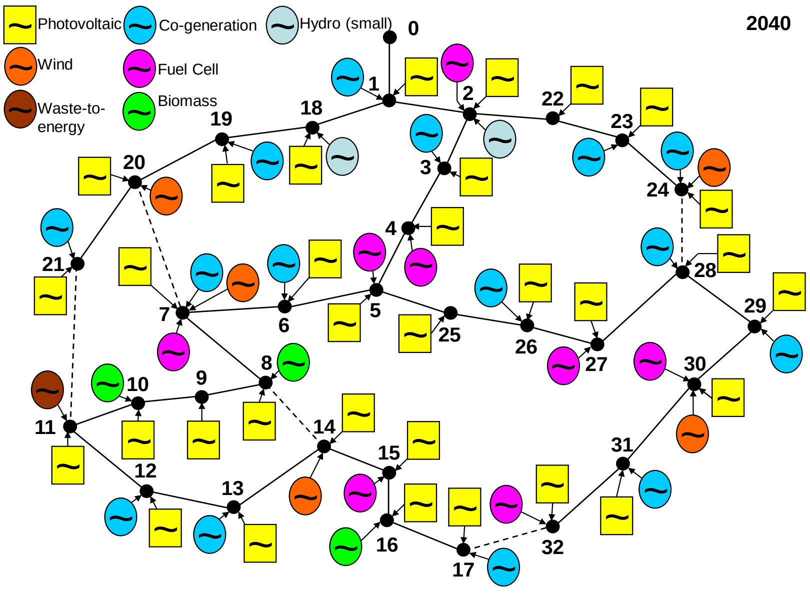

Fig. 7 – Distribution network [13].

There are 66 units of production. The total number of consumers is 218, and over the net present divided into the following classes: domestic (DM); small commerce (SC); medium commerce (MC); large commerce (LC); medium industries (MI) and large industries (LI).

As proposed in the model, we need to know electricity rates, energy costs (€ / kWh) for each type of consumer. These values are shown in Table 1. There are still more units power generation than those mentioned Fig.7, these are intended for special situations, such as a possible emergency, malfunction of any plant or even to consider the connection to the public distributor node 0 (Fig. 11). The value of production for these types of suppliers are followed by table 2-

Table 1 Price by consumer

Consumer type	**Price (€/kWh)**
DM	0,18
PC	0,19
MC	0,16
GC	0,20
MI	0,12
GI	0,14

Table 2 Additional suppliers

Source	Gen. Power (KW)	Price (€/kWh)
Supplier 1	1200	0,23
Supplier 2	800	0,24
Supplier 3	900	0,25
Supplier 4	1800	0,26
Supplier 5	800	0,26

Relying on these energy suppliers, the total energy when food was provided when the network was 8152.2 kW while consuming energy stood at 5827 kW.

To implement the management model is also necessary to get the AC portion of consumption on total consumption of a given installation. This value is the maximum value possible cut in AC. These percentages relating to the total consumption of AC consumption were obtained in accordance with the type of consumer, DM - Domestic consumers; SC - Small Commerce; MC - Medium Commerce, LC - Large Commerce, MI - Medium Industries and LI - Large Industries.

For the values of DM and SC had as the base document Annual Energy Outlook 2013 [3], where tables of energy consumption related to family dwellings and commercial buildings is described the amount and purpose of each type of consumption electric power, and the total consumption. These are values and annual btu units. Through these values we calculated the amount of energy consumed on the air conditioning using the values belonging to the cooling, these being 3.84btu and 1.77btu for DM and SC respectively.

$$DM = \frac{Space\ Cooling}{Total\ consumption} = \frac{3{,}84}{23{,}08} \cdot 100 \cong 16{,}6\%$$

$$SC = \frac{Space\ Cooling}{Total\ consumption} = \frac{1{,}77}{21{,}13} \cdot 100 \cong 8{,}37\%$$

Thus obtaining a value of 17% and 8% for DM for PC in 2040. The same process was followed for the remaining annual values 2010, 2020, 2030 and 2040.

Like the previous document did not contain the values for the remaining types of consumers, MC, LC MI and LI, these were extracted from a graph of this scientific article in the following bars: *A review on buildings energy consumption information* [14]. In the graph above listed consumptions hospitals, shopping centers and hotels, which are 30%, 42% and 41% respectively. Thus assigned them the values of the 30% MC and 42% of the LC and 41% for MI and LI.

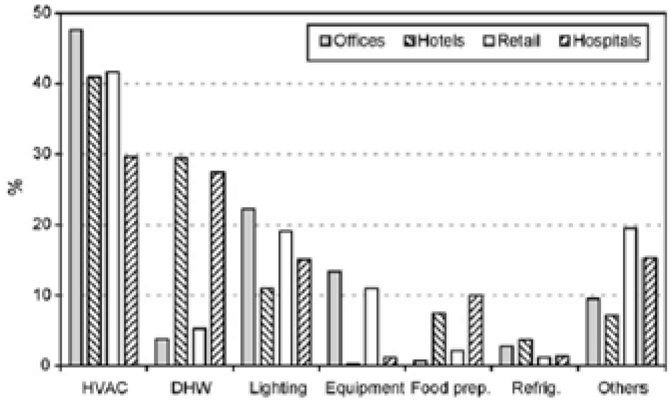

Fig. 8 Energy consumption by appliance

The values referred to in Article [14] correspond to the year 2003. Accordingly the values for the following years it was necessary from a criterion, this criterion was to make the extrapolation of values. As they were known for the 2003 MC LC MI and LI described above and removed from the graph of Figure 8, it was necessary to obtain the values of DM and SC in this year. These values were found in the *2003 Annual Energy Outlook 2005* document [15], these data from 2003 (MC and LC) is the extrapolation made by a simple rule of three for the remaining years, based on the trend of SC , example:

$$MC_{2010} = \frac{MC_{2003} \cdot SC_{2010}}{SC_{2003}} = \frac{30 \cdot 10}{8} = 37{,}5\%$$

$$LC_{2010} = \frac{LC_{2003} \cdot SC_{2010}}{SC_{2003}} = \frac{42 \cdot 10}{8} = 52{,}5\%$$

After these calculations for the necessary and consumers respective years made to Table 5, which summarizes the results of this small study on the consumption of AC in respect of all the appliances that installation of this type of consumer. In Table 5 are also marked as such values were obtained, directly or documents or by calculation.

Table 3 - Percentage of total consumption of AC equipment

Consumer type	2003	2010	2020	2030	2040
DM	10% a)	13% a)	14% a)	15% a)	17% a)
SC	8% a)	10% a)	8,8% a)	8,5% a)	8,4% a)
MC	30% a)	37,5% b)	33% b)	31,8% b)	31,4% b)
LC	42% a)	52,5% b)	46,2% b)	44,6% b)	44% b)
MI	41% a)	51,3% b)	45,1% b)	43,6% b)	43% b)
LI	41% a)	51,3% b)	45,1% b)	43,6% b)	43% b)

a) Obtained values from the document
b) Values obtained by extrapolation

3.2. Scenario 1

This first scenario under study concerns the application of the DR program referred to throughout this report. Briefly, it created a situation where the demand for energy by consumers was higher than supply, so as to maintain the operation of the power grid appealed to the DR.

For this case it was considered that all consumers actively participate in the DR program, ie all clients from small homes to large industries have subjected it to them to be removed from power air conditioners for a period of 15 minutes. Consumers to participate are as follows: DM, SC, MC, LC, MI and LI, where the percentage of maximum energy possible not to provide the apparatus is shown in table 3.

The network where the program was implemented is described in the previous section (3.1.). On the consumer side is not being made any changes to the maximum values that can be cut in AC. Overall consumption of the system at this time is 5827 kW. As part of the production was necessary to make a small change we changed the values in the designated power sources from different suppliers, keeping the same price, as shown in Table 4.

Table 4 – First scenario Supplier Values

Source	Gen. Power (KW)	Price (€/kWh)
Supplier 1	1200	0,23
Supplier 2	800	0,24
Supplier 3	200	0,25
Supplier 4	100	0,26
Supplier 5	0	0,26

This amendment was thus with a production value of 4952 kW, as consumption remained as originally found in the network, and its value 5827kW. With all the necessary values to the problem, namely: production values by generating unit and the appropriate price; maximum values of power cutting and respective consumer price tariff and total power consumed by the system, implemented in Matlab / Tomlab.

The graph in Figure 9 is intended to show the situation before application of the optimization problem, the bars are located production facilities by bus, and the two green lines the highest cutting power and other energy consumption.

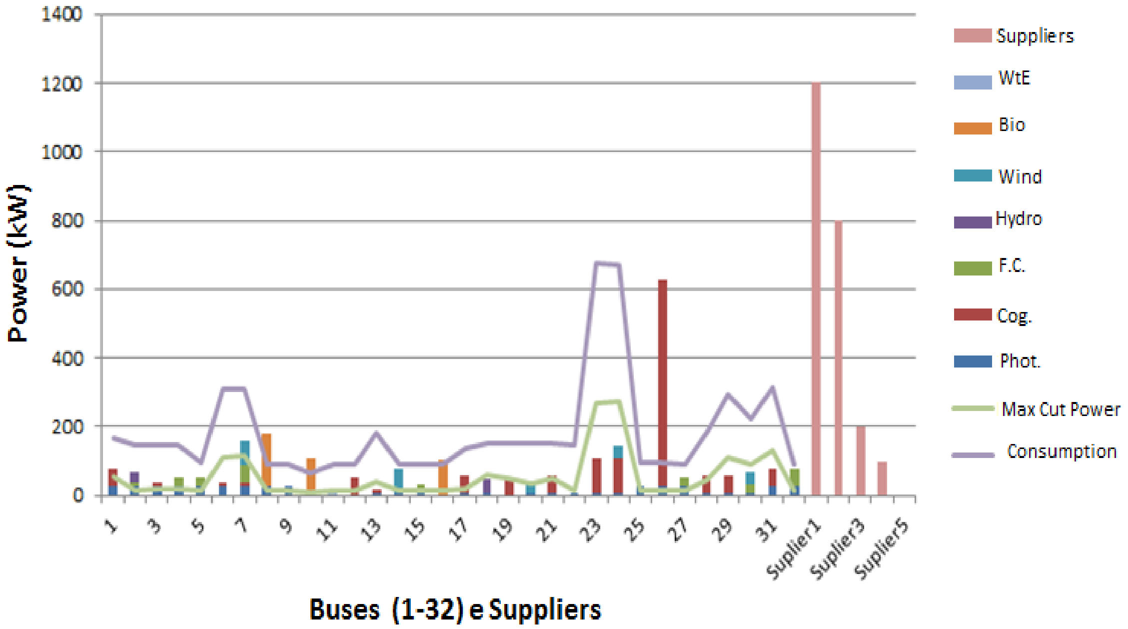

Fig. 9 - Graph summarizing the data input of the powers (scenario 1)

3.3. Scenario 2

This second scenario is around similar to the previous, the differences are that the value of output of suppliers have been increased, other changes were at the level of consumers to participate in the program, unlike the previous scenario, which all consumers actively participate in DR programs, now industrial consumers, MI and LI are not participating but domestic and commercial continue are actively participating.

All other output remained unchanged, with the total value of this production was 5252.2 kW, while consumption remained at 5827 kW just like scenario 1. For consumers the power that can be removed at the AC remained as in scenario 1 except consumer MI and LI as they do not allow them to be cut in AC power, ie they are out of the program.

Table 5 Second scenario Supplier Values

Source	Gen. Power (KW)	Price (€/kWh)
Supplier 1	1200	0,23
Supplier 2	800	0,24
Supplier 3	250	0,25
Supplier 4	200	0,26
Supplier 5	150	0,26

With this changes the total amount of power possible for them to be cut was 987.7 kW. This input data in the model, maximum cutting power and generated power are illustrated in Figure 10. Note that the line of green (maximum cutting power) gets lower values compared to the previous scenario in Figure 9.

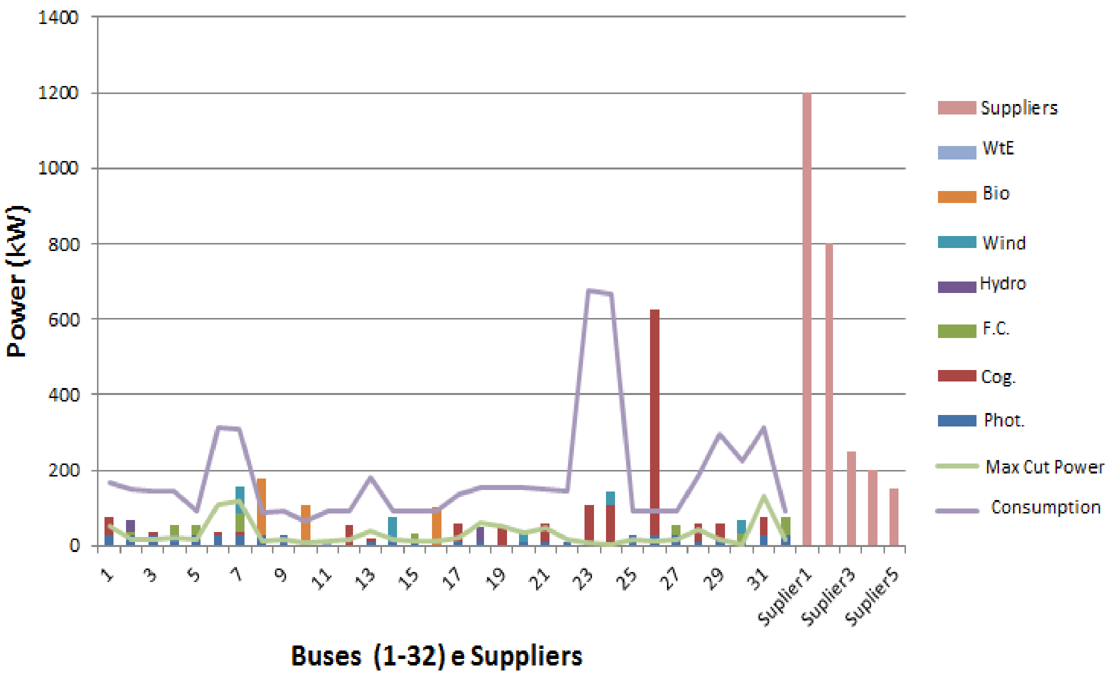

Fig. 10 - Graph summarizing the data input of the powers (scenario 2)

4. Results

4.1. Scenario 1 results

In the global consumer of each type, the amount reduced in power consumption can be seen in figure 11.

In Figure 12, here you can see the amount of energy that the AC was removed by client type and that would still be available for cutting.

It is noted that the cut occurs in the air conditioning for all consumers except those that have a higher value fare 0.20 €/kWh which are the LC, in all other consumers (DM SC MC MI and LI) see your AC to be turned off to them, it has energy value lower rate (tabela.1). This value cut, this is the maximum value ie the client is even without air conditioning for a short period of time. The total cutoff value was 1273.3 kW of a possible maximum of 1703.1 kW and calculating the difference obtains 429.8 kW value that could be cut if it were in a more extreme scenario.

Costs is also important for the distributor because with this model it is possible to be minimized. From the graph of Figure 12 you can see the difference between the costs of resorting to that DR program or not. The monetary value to pay for all plants was 702.7€ and the final value after optimization is 556.5€.

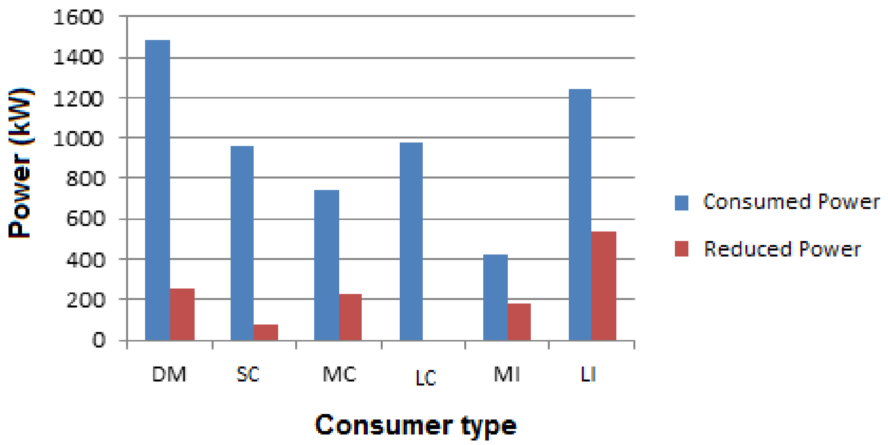

Fig. 11 - Power reduction by consumer type

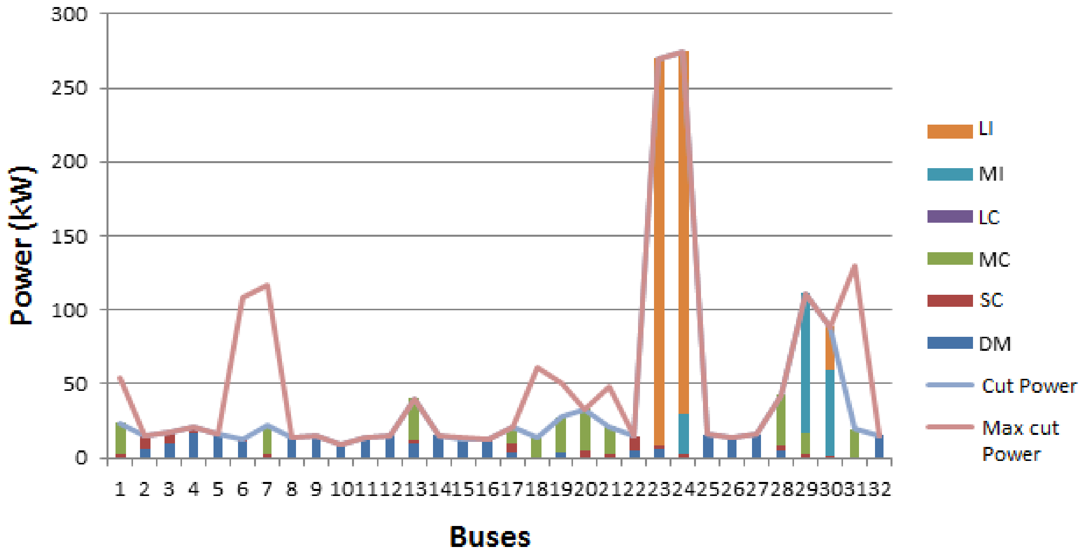

Fig. 12 - Values obtained from the consumer side

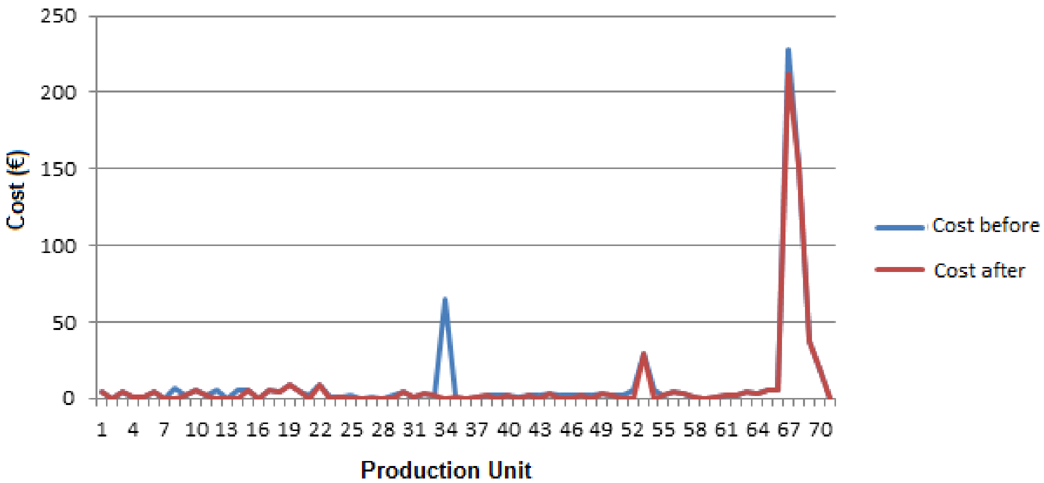

Fig. 13 – Production costs

Thus the initial scenario was that 4952.2 kW, that this power could not supply the load of 5827kW, with the DR program consumption is (5827kW minus 1273.3kW) equals 4553.7kW equalling output that has also become of 4553.7kW

The cutoff value in the AC was 1273.3 kW. The generator was producing 4553.7 kW and the costs of generating the total value was optimized before and after optimization € 702.7 € 577.8. On the customer side, before cutting the AC on full pay were going to pay 489.5€ with the AC cut will pay 96.5€.

4.2. Scenario 2 results

To this second scenario the amount reduced in power consumption can be seen in figure 14.

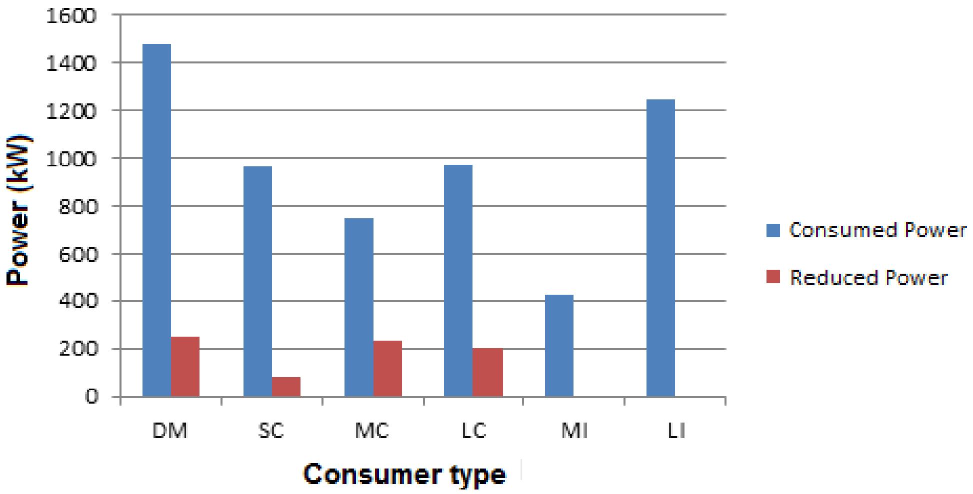

Fig. 14 - Power reduction by consumer type

In Figure 15, you can see the amount of energy that the AC was removed by client type and that would still be available for cutting.

In this scenario all clients, DM, SC and MC seen reduced the energy consumption of the plant, only cut the customers of type LC. This cut was 761.2 kW with a total of 987.7kW which was not necessary to use the total amount of power cut, the overall system cut in customers was 77.1%.

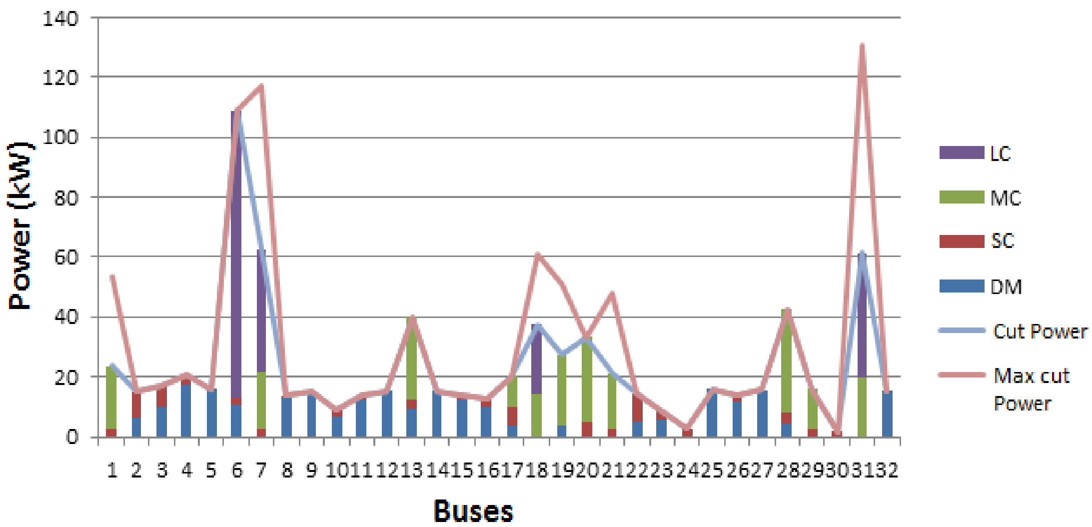

Fig. 15 - Values obtained from the consumer side

For the generating production from 5252.2kW to 5065.8kW which translates into a difference of 186.4 kW ie 96.5% compared to baseline. So with an initial load of 5827kW and a production of 5252.2kW insufficient to supply the load, 761.2 kW cut himself in charge getting equalling the value of production and consumption in 5065.8 kW.

The price paid for energy generated increased from € 759.7 to € 675.4, on the customer side in total had to pay 352€ instead of 489€. In this scenario the value of production was in 5065.8 kW against the

initial 5252.2 kW. For consumers the total amount withdrawn from AC was 761.2 kW. The price to pay for power generated was € 675.4, customers paid in full € 352 (See Fig. 16).

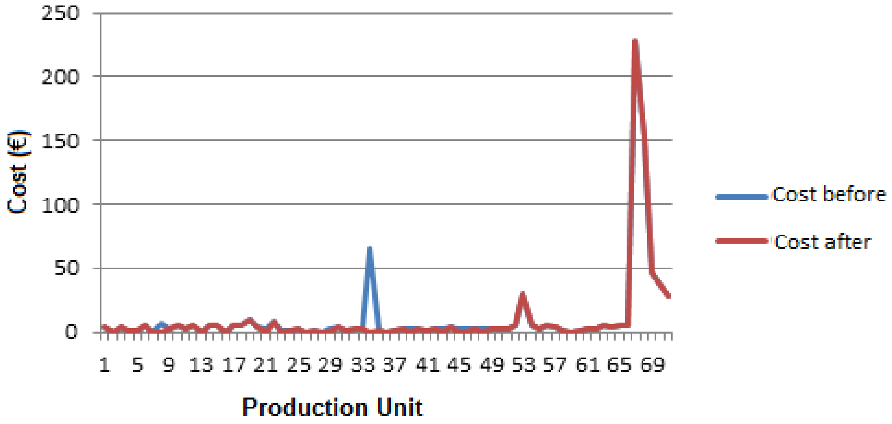

Fig. 16 - Production costs

4.3. Comparison of scenarios

Comparing the two scenarios in terms of the amount of cut, it is clear that in scenario 1 more power has been removed because it was no longer participating in the program and with great power available to cut. The Fig. 17 illustrates that even the difference between the two scenarios.

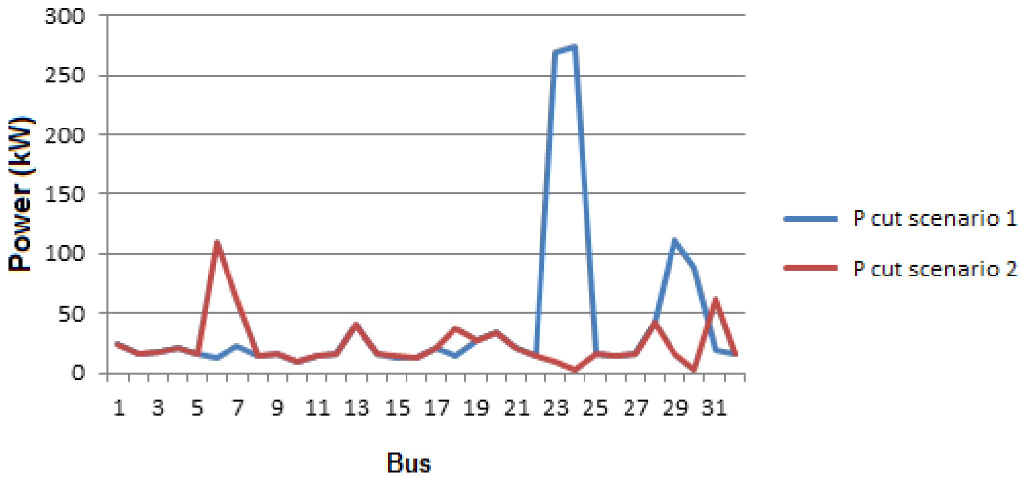

Fig. 17 – Cut power in both scenarios

As for generators, in the second scenario production from 5252.2kW to 5065.8 kW which was not such a marked reduction as in the first scenario, it should be that this second case broke a generated power exceeding and mainly because it was necessary to feed the air conditioning of the industries which has a significant consumption while in the previous case this had been curtailed (see Fig.18). In scenario 1, the generation level was 4553.7 kW while in scenario 2 it was 5065.8 kW.

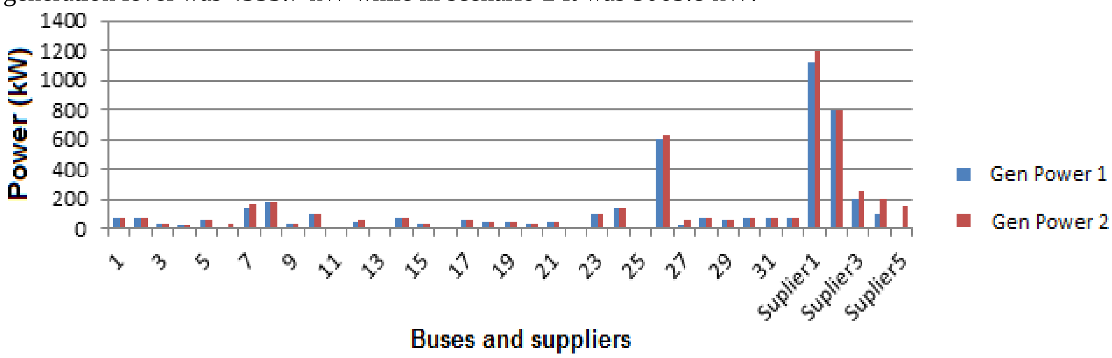

Fig. 18 Generated power comparison

5. Conclusions

The proposed methodology advantageous for both the consumer side and for energy utilities. The consumers has advantages in terms of price reduction and electric bill with a reduction in the air conditioning operation without a reduction in the comfort levels.

Analysing the presented scenarios, it is concluded that the ideal is that increasing the number of consumers participating in the DR program, makes possible to reduce the impact in the comfort levels. For networks with few customers, the implementation of this program will not only bring great benefits; possibly would succeed only in conjunction with other DR programs. It is very advantageous to use this type of program because customers can have savings while the network operator is able to increase the system reliability. This DR program is a good solution for the distribution companies to improve system reliability by increasing the quality of service and avoiding the need to invest in new infrastructure.

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Load Demand, Batteries, and Electric Vehicles Modelling to the Energy Management of Microgrids

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Abstract

This paper presents a mathematical model for load demand, batteries and the electrical vehicles to the Energy Management (EM) problem of a Microgrid (MG) by means of a deterministic Mixed Integer Linear Programming (MILP) approach. In the EM problem, the objective is to determine a generation and consumption policy that minimises, over a planning horizon, the operation cost subject to economic and technical constraints. We propose a detail modelling of critical, curtailable (also called shedable) and reschedulable (also called shiftable) load demands and Li-ion batteries, which could be also used to represent plug-in electrical vehicles (PHEV or V2G) and are important aspects in the MG concept. To analyse the proposed modelling, a didactic MG is used, connected to the main grid, although, the proposed models could also be used in the island operation. The results indicate that the models are adequate for the MG EM, analyses of the impacts and energies polices.

Keywords: load demand; batteries; electrical vehicles; energy management; microgrids; mixed linear integer programming

1. Glossary

Index / Sets

c	index related to CLDs (c=1,…, C);
d	index related to RLDs (d=1,…, D);
e	index related to batteries (e=1,…, E);
g	index related to DLDs (g=1,…, G);
t	notation for the time step (t=1,…, ND);

Variables

deb_{et}	battery e deviation of the energy from the set point in t (kWh);
dld_{gt}	DLD g shed or increased in stage t (kW);
eb_{et}	battery e energy in stage t (kWh);
pbc_{et}	battery e charge power in stage t (kW);
pbd_{et}	battery e discharge power in stage t (kW);
pdc_{ct}	power of CLD c (kW) in stage t;
pdc_{ct}	power of CLD c (kW) in stage t;
pdd_{d1t}	RLD $d1$ in stage t (kW);
pde_{t}	system deficit in stage t (kW);
pde_{t}	deficit during stage t (kW);

E^{D}	error associated with the demand forecasted (%);
EDD_{d2}^{total}	total amount of energy for the RLD $d2$ (kWh);
E^{PV}	forecasted photovoltaic generation error (%);
E^{PW}	error associated with the wind generation (%);
FDD_{d1}	final stage where the load RLD $d1$ is supplied;
H	planning horizon (h);
IDD_{d1}	initial stage where the RLD $d1$ could be turned on;
$IDLD_{g}$	minimum time between the DLD g shed (max ($FDLDg$, $SDL1_g$+ $SDL2_g$));
NC_{c}^{max}	maximum number of stages of load shedding for CLD c;
ND	horizon number of discretizations;
NDC_{c}^{st}	maximum number of load shedding for CLD c;
OFF_{c}	minimum down time for CLD c after turned off;
On_{c}	minimum up time for CLD c after be turned on.
PB_{e}^{L}	battery e power loss in stage t (kW);
PDD_{d2}^{max}	maximum power for the RLD $d2$ (kW);
PDD_{d2}^{min}	minimum power for the RLD $d2$ (kW);

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pex_t	excess generation during stage t (kW);
pgb_t	power purchase in stage t (kW);
pgs_t	power sell to the grid in stage t (kW);
rb_{et}	battery e power reserve in stage t (kW);
ub_{et}	binary variable for charging (ub_{et} = 1) in stage t;
$ub_{et}^{aux1/2}$	auxiliary binaries variables to set the status of current (1) or voltage (2) constant in charge mode at stage t;
uc_{ct}	binary variable that indicates whether CLD c is on (uc_{ct} = 1) or off (uc_{ct} = 0) in stage t;
ud_{d1t}	binary variable that indicates whether RLD $d1$ starts (ud_{d1t} = 1) in stage t;
udg_{gt}	binary variable that indicates whether DLD g starts (ud_{gt} = 1) in stage t;
ug_t	binary variable that indicates whether the MG is importing energy (ug_t = 1) in stage t;
yc_{ct}	auxiliary binary variable for indicating the end of the load shedding in stage t of CLD c;
zc_{ct}	auxiliary binary variable for indicating the start of the load shedding in stage t of CLD c;

Parameters

BP_t	energy purchase price in stage t (R$/kWh);
$CB1_e$	battery e constant power in constant voltage mode (kW);
CB_e	battery e maximum charge power in constant current mode (kW);
CC_c	incremental cost during one hour of load shedding (R$/kW) of CLD c;
CD	load deficit incremental cost (R$/kWh);
CDB_e	battery e cost due to the deviation of the energy from the set point in t (R$/kWh);
CE	system excess energy incremental cost (R$/kWh);
DB_e	battery e maximum discharge power (kW);
DC_{ct}	forecast CLD c in stage t (kW);
DLD_g^{max}	maximum numbers of sheds for the DLD g;
D_t	forecast critical load demand in stage t (kW);
D_t	forecast critical load demand power in step t;
EB_e^F	battery e final energy (kWh);
EB_e^I	battery e initial energy (kWh);
EB_e^{max}	maximum energy for battery e (kWh);
EB_e^{min}	minimum energy for battery e (kWh);
EB_e^{st}	battery e energy set point (kWh);
PDD_{id}	forecast RLD d in stage i (kW);
PGB_t^{max}	grid maximum power purchase in step t (kW);
PGB_t^{min}	grid minimum power purchase in step t (kW);
PGS_t^{max}	grid maximum power sell in step t (kW);
PGS_t^{min}	grid minimum power sell in step t (kW);
PV_t	forecast photovoltaic power in step t (kW);
PW_t	forecast wind electrical power in step t (kW);
RB	necessary number of stages for the reserve;
$SDL1_g$	number of stages in which DLD g is off;
$SDL2_g$	number of stages for recovers the DLD g shed;
SP_t	energy sell price in stage t (R$/kWh);
UDD_{d1}	number of stages in which RLD $d1$ is on;
$VDL1_g$	vector with [-1] times the number of stages in which DLD g is off;
$VDL2_g$	vector with [%] of the load shift sum in each time where DLD g need to recover;
α_e	$SDL1_g$
η_e^{bc}	battery e charge efficiency;
η_e^{bd}	battery e discharge efficiency.

Abreviations

CLD	Curtailable Load Demand
DER	Distribution Energy Resource
DLD	Diffuse Load Demand
EM	Energy Management
ESS	Energy Storage System
MG	Microgrids
PHEV	Plug in Electrical Vehicle
PLD	Pre-diffuse Load Demand
RLD	Reschedulable Load Demand
SOC	State of Charge
SOH	State of Heal
V2G	Vehicle to Grid

2. Introduction

The integration of controllable load demands, energy storage systems, small renewable generators, electrical vehicles in modern electrical energy grid is a trend that is currently in progress. The presence of these Distribution Energy Resources (DERs) and controllable loads can reduce fossil fuel consumption, load peak shaving, as well as postpone investments in new transmission and distribution lines [1,2]. In this new paradigm, it is important to highlight the Microgrids (MGs), which are emerging as an additional element to maintain the growth and sustainability of the modern electric energy industry. Roughly speaking, a MG consists of a group of DERs and controllable and uncontrollable loads that might operate in a controlled, coordinated way either while connected or in island operation.

A methodological challenge that supports the operations issues of MGs is the Energy Management (EM) problem [3,4]. In general, solving this problem requires determining a generation and a controllable load demand policy that minimizes, over a planning horizon, an objective function subject to economic and technical constraints. The generation policy is given by the on/off status, the respective output active power of each controllable DER, the on/off status of the Curtailable Load Demand (CLD, also called shedable) and the schedule of the Reschedulable Load Demand (RLD, also called shiftable). This policy is used as reference for the voltage and frequency control in MG real-time operation. Because it is necessary to minimize an objective function subject to constraints, the EM is usually performed based on the solution of an optimization problem [5].

Concerning load demand, it can be classified by priority and type as critical, CLD and RLD [6]. The RLD has a particular characteristic of being able to be allocated across a range of time. The CLD may

have the power supply cut, as a non-priority load, if necessary. The critical load demand has to be full supplied all the time, otherwise, it will cause deficit in the system. Regarding the batteries, the most ascending technology nowadays are the lithium-ion batteries, used in electric cars, mobile phones, notebooks, being the focus of this paper.

In this paper, the EM is obtained by solving a deterministic mixed-integer linear programming problem, where the planning horizon is 24 hours with one-minute time steps. This paper is organized as follows: in the next section, we detail the load demand, the lithium-ion battery and the electrical vehicles modelling; then, in Section 4, we present the didactical MG, the optimization model related to the EM problem and some computational experiments; finally, Section 5 provides the primary conclusions of this paper.

3. Load Demand, Batteries and Electrical Vehicle Modeling

3.1. Load Demand

As aforementioned, a MG may contain different load demands: critical, CLD and RLD. Naturally, the critical load is the most important, and the impossibility of supplying this type of demand is modelled as a deficit (expensive fictitious generator). We model the CLD using an on/off approach because these loads are usually controlled by a switch and the cost of shed a load is linked to the marginal cost. The CLD modelling is given by:

$$CC_{ct} \cdot pdc_{ct}\,, \tag{1}$$

$$-pdc_{ct} - uc_{ct} \cdot DC_{ct} \leq -DC_{ct}\,, \tag{2}$$

$$pde_t + uc_{ct} \cdot \left[D_t + \sum_{c=1}^{C} \left(DC_{ct} \right) + \sum_{d=1}^{D} \left(\max(PDD_{id}) \right) \right] \leq D_t + \sum_{c=1}^{C} DC_{ct} + \sum_{d=1}^{D} \left(\max(PDD_{id}) \right), \tag{3}$$

$$uc_{c,t-1} - uc_{ct} + zc_{ct} \leq 0\,, \tag{4}$$

$$-uc_{c,t-1} + uc_{ct} + yc_{ct} \leq 0, \tag{5}$$

$$\sum_{t=1}^{ND} zc_{ct} \leq NDC_c^{st}\,, \tag{6}$$

$$-\sum_{t=1}^{ND} uc_{ct} \leq -ND + NC_c^{\max}\,, \tag{7}$$

$$\sum_{i=1}^{OFF_c} zc_{c,t-1+i} \leq 1\,, \tag{8}$$

$$\sum_{i=1}^{ON_c} yc_{c,t-1+i} \leq 1 \tag{9}$$

$$0 \leq pdc_{ct} \leq DC_{ct}\,, \tag{10}$$

$$uc_{ct}, yc_{ct}, zc_{ct} \in \{0,1\}, \tag{11}$$

Equation (1) is the cost due to the discontinuity. This cost is related to the marginal cost of each step time and could also be used different values for different step time. Equation (2) is used to set DC_{ct} to pdc_{ct} when uc_{ct} is off (relate to the cost), while (3)[1] is used to prevent the deficit before any load demand shed in any situation. Equation (4) is the logical equation to the change of status of the load *c* (1-on to 0-off) while equation (5) is the logical equation to the change of status (0-off to 1-on). Equation (6) and (7) are the maximum frequency of discontinuity and the maximum time of discontinuity, respectively. Equations (9) and (10) are the limits of down and up time, respectively after the load be turned off or on. The maximum/minimum load demand cut and the associated binary variables are given by (10) and (11),

[1] The sum within the brackets, which is multiplied by uc_{ct}, and in the right side of the (3) is just to guarantee that it will a big number, although it could be used a bigger value.

respectively.

Note that if the respective CLD c do not have a minimum up time after the shedding the equations (5) and (9) do not need be used. The same is for the minimum down time with the equation (8), although the equation (4) needs to be used due to the maximum frequency.

If the approach for CLD model is with just continuous variables, allowing the control of the load power, just (1) is need, also including pdc_{ct} in (39) and removing $uc_{ct}.DC_{ct}$.

The RLD has a particular characteristic of being able to be allocated across a range of time. The economic benefit of this load could be measured with the normal load at time of use and the new schedule time of use. In the next equations, we present the modelling for each RLD d, non-interruptible, using binary variables approach:

$$\sum_{i=1}^{UDD_{d1}} PDD_{d1i} \cdot ud_{d1,t-i+1} - pdd_{d1t} = 0 \text{ for } IDD_{d1} \le t \le FDD_{d1}, \quad (12)$$

$$pdd_{d1t} = 0 \text{ for } FDD_d 1 < t < IDD_{d1}, \quad (13)$$

$$\sum_{t=IDD_{d1}}^{FDD_{d1}-UDD_{d1}} ud_{d1t} = 1, \quad (14)$$

$$ud_{d1t} \in \{0,1\}, \quad (15)$$

Equation (12) is the constraint to set the PDD_{di} to pdd_{dt} considering the binary variable ud_{dt} of the start. Equation (13) is to set zero to pdd_{dt} outside the range of RLD d. Meanwhile, (14) ensures that the load demand will be turned on only once, and (15) is the associated binary variable. Equations (13) and (14) are important due the excess of intermittent generation in some step times, not giving a correct answer to the system when there are more energy than necessary.

The equations above are used when the RLD is not interruptible, using binary variables and knowing the load behavior as presented in Figure 1 (a). If the RLD could be interruptible, keeping the same sequence of PDD_{di} the load could be divided in N intervals of not interruptible D RLD, as presented in Figure 1 (a). The sequence for these respective variables could be set as constraints.

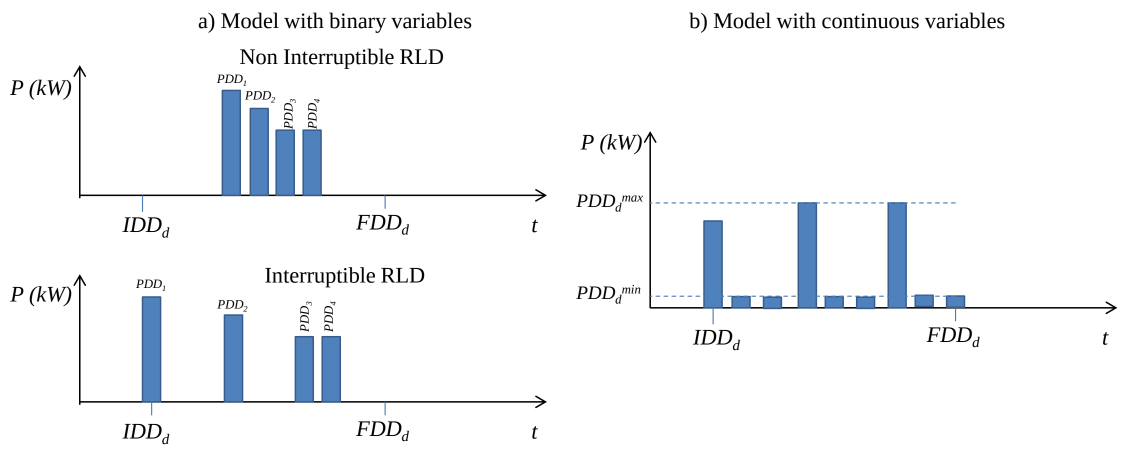

Figure 1: Example of RLD with the discrete and continuous modelling approach.

For some RLD models the use of just continuous variables is acceptable, controlling the power in each stage. The Figure 1 (b) presents an example for this load and the modelling is presented in the next equations:

$$\sum_{t=IDD_{d2}}^{FDD_{d2}} pdd_{d2t} \cdot H / ND = EDD_{d2}^{total} \quad (16)$$

$$pdd_{d2t} = 0 \text{ for } FDD_{d2} < t < IDD_{d2}, \quad (17)$$

$$PDD_{d2}^{\min} \le pdd_{d2t} \le PDD_{d2}^{\max} \text{ for } FDD_{d2} > t > IDD_{d2}, \quad (18)$$

Equation (16) is to guarantee that the total energy demand will be supplied, while (17) and (18) are to set the interval and the maximum and minimum power.

There are electrical loads demands which are used for thermals purposes (heating/cooling), following a specified comfort temperature. In some loads a control to track the temperature is performed. These control characteristic of follow a temperature range could not be interesting to the EM, mostly because it is not linked to the optimization modelling including the power/time of use. To deal with the problem some authors use these loads as controllable loads in the EM, including the power behavior and the limits of temperature in the problem, as presented in [7]. For each of these loads various peculiarities have to be considered, because the systems for heating or cooling a specific environment/equipment will have their particularly characteristics in the modelling.

For the modelling of an electrical load demand for thermal purpose, in this paper, we will use the diffuse approach [8] and assume: the electrical load demand is known for each step time; the load could be turned off for a specific number of step times if a previous/posterior known increment (%) of the load is performed without trespassing the temperature limits, as presented in Figure 2. The previous increment of the load demand we will call thermal Pre-diffuse Load Demand (PLD) and the thermal posterior Diffuse Load Demand (DLD).

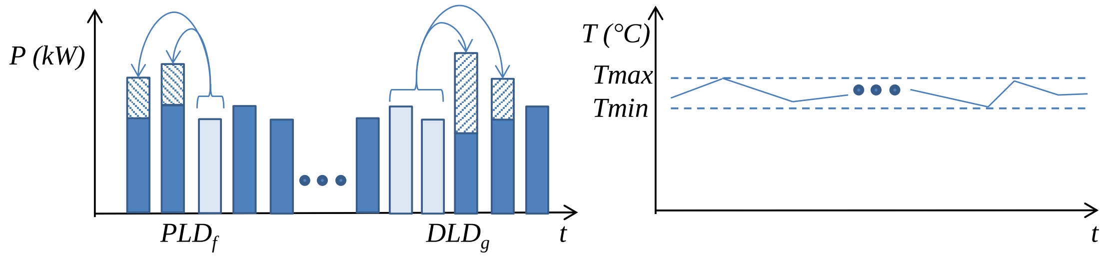

Figure 2: Example of PLD and DLD modelling.

The modelling for the DLD is given by:

$$\sum_{i=1}^{SDL1_g} VDL1_{gi} \cdot DLD_{gi} \cdot udg_{g,t-i+1} + \sum_{j=1+SDL1_g}^{SDL1_g+SDL2_g} VDL2_{gj} \cdot \sum_{i=1}^{SDL1_g} DLD_{gi} \cdot udg_{g,t-j+1} - dld_{gt} = 0, \quad (19)$$

$$\sum_{t=1}^{ND} udg_{gt} \le DLD_g^{\max}, \quad (20)$$

$$udg_{gt} \cdot 0.1 \le DLD_{g,t+SDL1_g+SDL2_g}, \quad (21)$$

$$\sum_{i=1}^{IDLD_g^{\max}} udg_{g,t+i-1} \le 1, \quad (22)$$

$$udg_{gt} \in \{0,1\} \quad (23)$$

Equation (19) is the constraint to set the $DLD_{g,i/j}$ to dld_{gt} considering the binary variable udg_{gt} of the start. Equation (20) is to set the maximum number of times that is possible the use of these load, while (21) is to prevent one load shed in the end of the load supply, before the possibility of recover. The equation (22) is to set a minimum amount of time between the sheds, while (23) is the binary constraint.

Note that the DLD and PLD have almost the same behavior in the modelling, just with slights adjusts in the previous equations (*t-i*+1 to *t*+*i*, *t-j*+1 to *t*+*i*, *t*+*SDL1*+*SDL2* to *t-SFL1-SFL2* in the indices and the parameters names), and due to this reason, it is not necessary to rewrite.

3.2. Batteries

The Energy Storage Systems (ESSs) are important for the MG, especially due to: intermittent

characteristics of the renewable generation and load demand; reserve of the system; and for the island operation of the MG. Consequently, the presence of ESSs in a MG might also increase significantly the quality and reliability of energy supply. The most common ESSs are electrical, mechanical, thermal, or chemical, as batteries, supercapacitors, flywheels, compressed air, superconducting magnetic energy storage and water pumping.

Regarding the general ESS modelling, for the costs and constraints on the problem of a MG EM, some basic information is needed such as:

- Cost of use: the life expectancy of ESSs could be linked to the number of cycles of the same, and depending on their technology, this consideration is necessary.
- Capacity: refers to the energy that can be accumulated in the ESS;
- Maximum power charge and discharge;
- Efficiency: this will represent a loss in power cycles of charging and discharging of the ESS;
- Self-discharge: ESS may have a decrease in the amount of energy storage over time, even without its use.

Even for the same type of ESS several characteristics in the modelling are different depending on the size and technology employed, as presented in [9] for the chemical batteries.

As we described before, we are interested in the modelling of the Li-ion batteries, which are increasing in presence in recent years. The classification types of Li-ion batteries there are: Lithium Cobalt Oxide; Lithium Manganese Oxide; Lithium Iron Phosphate; Lithium Nickel Manganese Cobalt Oxide; Lithium Nickel Cobalt Aluminium Oxide ; Lithium Titanate; and others [10]. Each of these Li-ion batteries have particularities for a specific use, although, we are modelling in a generic way. Some of the peculiarities are related with the charge and discharge operation.

In [11] is proposed a cost function for the battery use (due to the degradation of the State of Heal - SOH). It is proposed a quadratic cost function for the deviation of the State of Charge (SOC) from a set point and the energy charge in one time step time. The cost of discharging is considered null while the cost of charge is also quadratic. In the formulation proposed in this paper we will penalise the charge and the deviation of the SOC set point empirically with linear function. The deviation from the specific SOC was approximate by the following linear equations:

$$CDB_e \cdot deb_{et}\,, \tag{24}$$

$$eb_{et} - deb_{et} \leq EB_e^{st}\,, \tag{25}$$

$$-eb_{et} - deb_{et} \leq EB_e^{st}\,, \tag{26}$$

The quadratic depreciation cost due to the charge was approximate from [11] with a convex piecewise linear technique, with 4 linear functions, as described in [12].

The charges and discharges will influence the SOH and also are linked to the SOC of the batteries [10]. For discharge characteristics are highlighted: the performance decreases with cold temperature and increases with heat; heat shortens battery life; cannot over-discharging; deploy a larger battery if repetitive deep discharge cycles cause stress; moderate DC discharge is better for a battery than pulse and aggregated loads. As for charge: Li-ion cannot accept overcharge; the charge is between 0.5 and 1C in stage of constant current; Li-ion does not need to be fully charged and avoiding it prolongs battery life. Figure 3 presents an approximation of the charge characteristics in constant current and constant voltage, depending on the SOC [13].

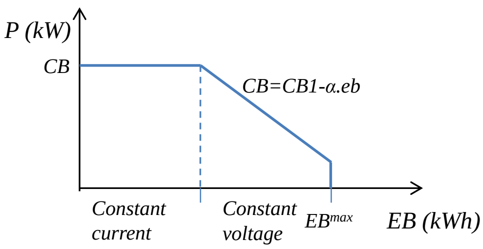

Figure 3: Li-ion charge characteristics.

The efficiency is very high for the charge and discharge and the self-discharge is very low for this battery technology. The temperature influence is negligible in this paper due to the constant temperature

assumption.

The others characteristics are modelling as constraints equations:

$$eb_{e,t+1} - eb_{et} + \left(\frac{pbd_{et}}{\eta_e^{bd}} - \eta_e^{bc} \cdot pbc_{et} \right) \cdot \frac{H}{ND} = -PB_e^L \cdot \frac{H}{ND}, \qquad \text{para } t=2,\ldots,ND\text{-}1, \tag{27}$$

$$eb_{e2} + \left(\frac{pbd_{e1}}{\eta_e^{bd}} - \eta_e^{bc} \cdot pbc_{e1} \right) \cdot \frac{H}{ND} = -PB_e^L \cdot \frac{H}{ND} + EB_e^I, \quad , \tag{28}$$

$$eb_{eND} - \left(\frac{pbd_{eND}}{N_e^{bd}} - N_e^{bc} \cdot pbc_{eND} \right) \cdot \frac{H}{ND} = PB_e^L \cdot \frac{H}{ND} + EB_e^F, \tag{29}$$

$$-eb_{et} + \sum_{i=1}^{RB} \frac{rb_{e,t+i}}{\eta_e^{bd}} \cdot \frac{H}{ND} \le -EB_e^{\min},\ eb_{et} \le EB_e^{\max}, \tag{30}$$

$$0 \le pbc_{et} \le CB_e,\ 0 \le pbc_{et} \le CB1_e - eb_{et} \cdot \alpha_e, \tag{31}$$

$$0 \le pbd_{et} \le DB_e,\ 0 \le rb_{et} \le DB_e, \tag{32}$$

$$pbc_{et} - ub_{et} \cdot CB_e \le 0, \tag{33}$$

$$ub_{et} \cdot DB_e + pbd_{et} \le DB_e, \tag{34}$$

$$ub_{et} \in \{0,1\}, \tag{35}$$

The constraint (27) is the energy balance of the battery throughout each stage. The initial and final energy for the battery *e* is defined by the constraints (28) and (29), respectively. The constraint of minimum and maximum battery energy is given by (30). Ramps for the battery charge are given by (31) and (32) for the discharge. We note that the reserve battery is the sum of the discharge for maximum power ramp, or in case you are not discharging during stage *t*, is the maximum power discharge itself. Constraints (33), (34) and (35) are used to prevent the battery charge and discharge on the same stage *t* (a situation that can occur when there is excess intermittent generation).

If is not possible control the charge power (i.e. when the control is not accessible and it is made by a switch on/off) the following equations are included:

$$\begin{aligned} &-pbc_{et} + ub_{et}^{aux1} \cdot CB_e + ub_{et} \cdot 10000 \le 10000, \text{[2]} \\ &-pbc_{et} - \alpha_e \cdot eb_{et} + ub_{et} \cdot 10000 + ub_{et}^{aux2} \cdot CB1_e \le 10000, \end{aligned} \tag{36}$$

$$\begin{aligned} &-ub_{et}^{aux1} \cdot 0.7 \cdot EB_e^{\max} + eb_{et} \le 0.7 \cdot EB_e^{\max},\ -ub_{et}^{aux2} \cdot 0.7 \cdot EB_e^{\max} - eb_{et} \le -0.7 \cdot EB_e^{\max}, \\ &ub_{et}^{aux1} + ub_{et}^{aux2} = 1 \end{aligned} \tag{37}$$

Equations (36) are to set the minimum and the maximum charge in the same level, while (37) are the logical auxiliaries binaries variables to verify the if the SOC is in the current or voltage constant charge (considering that the battery will be in the constant voltage charge in 70% of the SOC).

3.3. Plug in Electrical Vehicles (PHEV) and Vehicles to Grid (V2G)

The electrical vehicles that could be connected to the grid are increasing and its perspective is continuous this grow. These vehicles are usually classified by the technology used: the hybrid or the fuel cell technology which could be used as a conventional controllable microgeneration; the photovoltaic vehicles which could be connect to the grid and used as a renewable generation; and the plug-in hybrid (PHEV) or the battery-powered vehicles which could be used as an ESS. The advantages/disadvantages of the two first technologies are well known since the behavior is already well known in the literature, although the third one is currently in discussion [11].

The behavior of the battery-powered vehicles connected to the grid might be different depending on the local policy adopted. Most of this vehicles use Li-ion batteries and in this paper we will considered this technology. To quantify the impact expectation is necessary first modelling. In this paper we proposed the modelling as an electrical load demand or as a battery.

If the electrical vehicles will just be charged when connected to the system they could be modelled as

[2] The number 10000 is just a big number to guarantee the logical, although other big number could be used.

an electrical load demand. Since the SOC is known when the vehicle is connected the charge behavior could be forecasted, even for different speed charges with different charges stations. These loads could be considered as critical load demand or a RLD as modelled previously in item 3.1. If these vehicles could be connected to the main grid as an ESS they could provide essential support for the grid when connected, as described in the beginning of item 3.2. The model will differ from the previous sections due to the time when it is connect to the grid. If the owner of the electrical vehicle is different of the owner of the local electrical system different policies have to be established for the mutual interest be in accord, representing this on the model [14].

Since the modelling proposed for the electrical vehicles will follow the modelling for critical load demand, RLD or the Li-ion battery when connected, we will not model this explicitly, due to the modelling purpose of the paper.

4. Didactical Microgrid and Computational Results

4.1. Didactical Microgrid and Complete EM Modelling

To present the results of the models proposed in the previous chapter we formulate a problem for a microgrid composed by: a 4 kW photovoltaic panel; a 7 kW wind generator; possibility of buy/sell energy from/to the grid; critical load demand; a CLD; a RLD with Binary approach (RLDB); a RLD with the Continuous approach (RLDC); a DLD; and a 30kWh Li-ion battery. The Figure 4 illustrates the system.

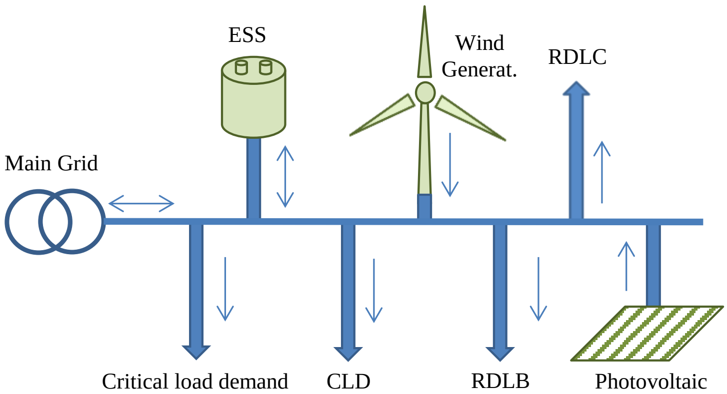

Figure 4: Didactic microgrid.

The complete model for the didactic microgrid is given by:

$$\min f = \sum_{t=1}^{ND}\left\{\left[\sum_{c=1}^{C} CC_c \cdot pdc_{ct} + \sum_{e=1}^{E} CDB_e \cdot deb_{et} + BP_t \cdot pgb_t - SP_t \cdot pgs_t + CD \cdot pde_t + CE \cdot pex_t\right] \cdot H/ND\right\} \quad (38)$$

s.t.:

$$\sum_{e=1}^{E}\left(pbd_{et} - pbc_{et}\right) + pgb_t - pgs_t + pde_t - pex_t - \sum_{d=1}^{D} pdd_{dt} - \sum_{c=1}^{C}\left(uc_{ct} \cdot DC_{ct}\right) - \sum_{g=1}^{G} dld_{gt} = D_t + \sum_{g=1}^{G} DLC_{gt} - PV_t - PW_t \quad (39)$$

$$-\sum_{e=1}^{E}\left(rb_{et}\right) - pde_t \le PV_t + PW_t - D_t - E^{D} \cdot D_t - E^{PV} \cdot PV_t - E^{PW} \cdot PW_t \quad (40)$$

$$PGB_t^{\min} \le pgb_t \le PGB_t^{\max}, \quad (41)$$

$$PGS_t^{\min} \le pgs_t \le PGS_t^{\max}, \quad (42)$$

$$pgb_t - ug_t \cdot PGB_t^{\max} \le 0, \quad (43)$$

$$ug_t \cdot PGS_t^{\max} + pgs_t \le PGS_t^{\max}, \quad (44)$$

$$ug_t \in \{0,1\}, \quad (45)$$

CLD (2)-(11),

RLDB (12)-(15),

RLDC (16)-(18),
DLD (19)-(23),
Li-ion Battery (25)-(35).

The objective function (38) is composed by CLD and batteries costs, as well as costs and profits associated with grid energy transactions and the artificial variables for deficit and excessive power generation[3]. Equation (39) is the energy balance constraints and (40) is the system reserve requirements. Notice in (40) the assumption that the system will prevent forecasts error and will supply at least the critical load demand, considering the for *RB* minutes (30). Equations (41)-(45) represent the limits of energy transactions with the grid and are used to prevent the import/export energy from/to the grid in the same step *t*. Note that the values for *C*, *D*, *E* and *G* are set to 1 (one) since we consider just one of these loads and batteries in the didactic microgrid.

Although the formulation consider a connected operation with the main grid, if the values of the $PGB(S)_t^{min(max)}$ are set to zero, the optimization problem then represent an island operation of the MG.

4.2. Input Data

The Figure 5a shows the forecast values for the critical load demand, CLD, RLDB and DLD and Figure 5b the energy price and the intermittent generation, where the planning horizon *H* is 24 hours, discretized in 1-minute time-steps (therefore, *ND* = 1440).

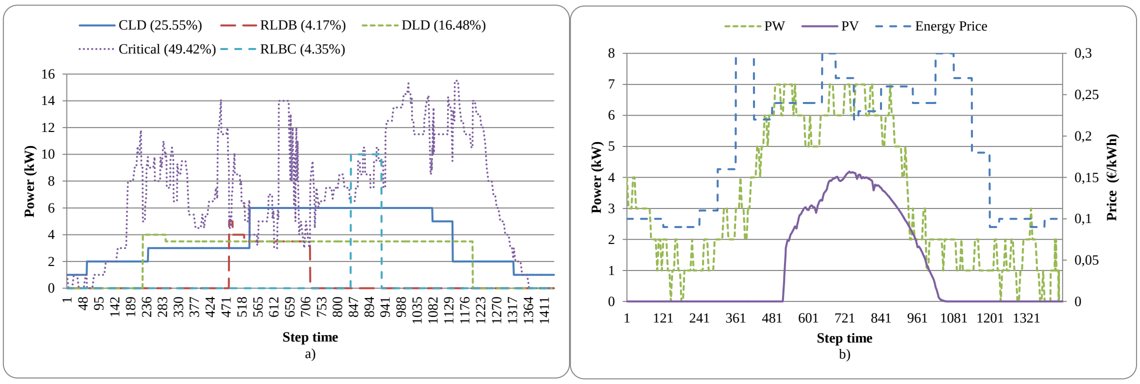

Figure 5: Loads demands, energy price and renewable generation forecasting

The maximum power grid interchange is 20 kW and the minimum is null, in all stages. The deficit incremental cost is 10 R$/kWh and the excess generation incremental cost is 2 R$/kWh. The forecast errors of the renewable generation are 10% and 5% for the demand. Others data are presents in Table 1.

Table 1. Battery, CLD, RLDB, RLDC and DLD data

Battery		RLDB/RLBC		CLD/DLD	
CB	18	RLDB		CLD	
CB1	60	*IDD*	1	*CC*	0.28
α	60	*FDD*	1440	NC^{max}	2
DB	30	*UDD*	240	NDC^{st}	240
RB	10			*OFF/ON*	60
EB^L	0			DLD	
EB^F	12			DLD^{max}	3
EB^I	12	RLDC		*IDLD*	60
EB^{max}	30	*IDD*	1	*SDLD1*	15
EB^{min}	6	*FDD*	420	*VDLD1*	[-1,…,-1][a]
EB^{st}	12	*EDD*	15	*SDLD2*	8
η_{bc}	0.9	PDD^{min}	0	*VDLD2*	[0.12,0.12,0.12,
η_{bd}	0.95	PDD^{max}	10		0.12,0.12,0.05,0.05,0.05]
CDB	5.04e-3				

[a] with the size = *SDL1*

[3] The artificial variables of deficit and excess generation exists to the model have a solution in any situation.

Then, considering the data presented in this section, the resulting EM problem is a MILP optimization problem with 21,795 variables (14,492 continuous and 7,303 binary ones).

4.3. Computational Results

The computational model is implemented in Matlab 2011b and the tests were executed in an Intel Quadcore i7 2.80 GHz. We use the Gurobi 5.5 as the MILP solver.

To exemplify the modelling we made several tests. The Case (*i*) is where all the loads demand are considered as critical, importing/exporting the energy from/to the main grid, without battery. Since the system does not have a battery, no reserve is considered and it is necessary contract 30 kW to supply the load demand. The Case (*ii*) is where the classical generic modelling[4] to the battery is considered [15]. The Case (*iii*) is where the Li-ion battery model is introduced. The Case (*iv*), (*v*), (*vi*) and (*vii*) include the different load demand modelling, now considering the loads as presented in Figure 5. The Case (*viii*) is to present the load modelling without the battery in the system. The cases and the results of the EM are summarized in the Table 2.

Table 2. Optimal costs and Computational time.

	Classic Battery	Li-ion Battery	DLD	RLDB	RLDC	CLC	Cost Function (€)	Comput, Time (s)	Comp Case (*i*)
Case (*i*)*	N	N	N	N	N	N	54,09	0,00	
Case (*ii*)	Y	N	N	N	N	N	48,68	59,06	-10,00%
Case (*iii*)	N	Y	N	N	N	N	50,17	19,80	-7,25%
Case (*iv*)	N	Y	Y	N	N	N	49,77	35,16	-7,99%
Case (*v*)	N	Y	Y	Y	N	N	47,49	60,08	-12,20%
Case (*vi*)	N	Y	Y	Y	Y	N	44,95	60,08	-16,89%
Case (*vii*)	N	Y	Y	Y	Y	Y	44,10	60,06	-18,47%
Case (*viii*)*	N	N	Y	Y	Y	Y	48,21	24,41	-10,87%

* These cases do not consider the 10min reserve due to the absence of battery

In Table 2, when the “N” appears in the table for the load demand, is that load is considered critical. The Case (*i*) presents the highest cost and the Case (*vii*) the lowest cost function, with a difference of 18,47% for these cases, although the difference could be bigger if the system reserve were not considered. Is important to notice that the Case (*viii*) and the Case (*ii*) together are correspondent to the Case (*vii*), although the benefit including both is higher than the benefit separately. Some cases reach the maximum time of one minute, although the error was less than 0.03% before the time convergence. In Figure 6 others results are presented.

The load DLD could provide an economy of 0.75% for the system in Case (*iv*) comparing to the Case (*iii*), although this impact could be amplified, depending on the system. The loads RLDB and RLBC, even representing just 4,17% and 4.35% of the total load, respectively, could provide an economy of 8.9% in the total cost (Case (*v*) and Case (*vi*)), been an important load for the system. The economy provide by the CLD is not always seen in the total cost because the model admits that these loads will be rewarded with the marginal cost of the shed. If the owner of the system would like to know the real economy is necessary multiply the $H*ND*CC_{ct}*pd_{ct}$ for all step time and sum them (in Case (*vii*) R$ 5.77), and it will be seen the real value of the economy (in Case (*vii*) 29.13%).

The difference in use for the modelling of the generic battery and the Li-ion battery could be observed also in the battery use, as presented in Figure 6a. It is possible to see that the new modelling do not have the same charge behaviour and the total amount of energy used is lower, preventing the rapid decrease of the battery SOH.

The detail of the DLD in Case (*iv*), showed in Figure 6b, presents exactly the formulation proposed for this load demand. It is possible to verify the behavior of the controllable loads demand in Figure 6c for the Cases (*iv*), (*v*), (*vi*) and (*vii*). Figure 6d presents the difference in the load exchange with the grid for the Case (*i*) and (*viii*) where the impact of the controllable load demand for the system could be evaluated.

[4] The differences are in (24), (25), (26) and (31).

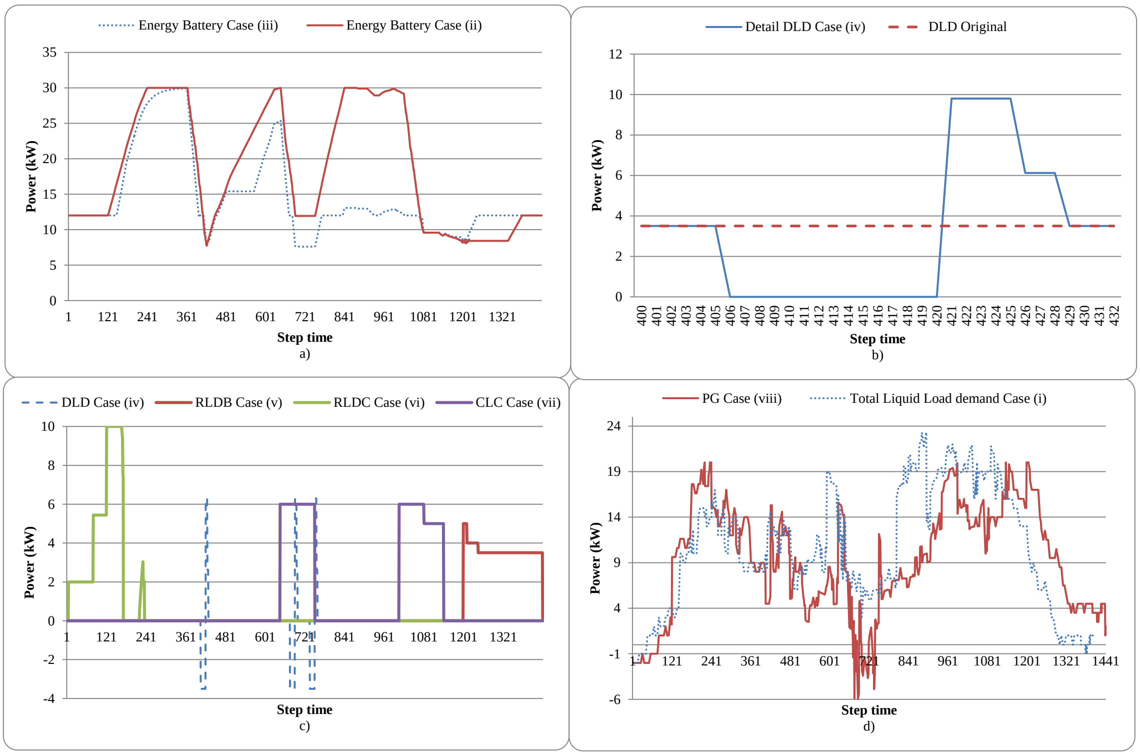

Figure 6: Cases results

5. Conclusions

The proposed modelling paper presents new models for controllable load demands and Li-ion batteries, also with a possibility of the models to be used for electrical vehicles for the microgrid EM, which proved feasible to implement. The models could be used to support the system operation, planning, policies and to quantify impacts. The results may not have demonstrated all the potential for EM economy, being necessary tests in other systems. Regarding the modelling of Li-ion batteries, this still needs more research on improving the modelling, especially due to the temperature, since they will be used in electric vehicles which are usually parked outdoors.

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Solar Intensity Forecasting using Artificial Neural Networks and Support Vector Machines

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Abstract

This paper presents several forecasting methodologies based on the application of Artificial Neural Networks (ANN) and Support Vector Machines (SVM), directed to the prediction of the solar radiance intensity. The methodologies differ from each other by using different information in the training of the methods, i.e, different environmental complementary fields such as the wind speed, temperature, and humidity. Additionally, different ways of considering the data series information have been considered. Sensitivity testing has been performed on all methodologies in order to achieve the best parameterizations for the proposed approaches. Results show that the SVM approach using the exponential Radial Basis Function (eRBF) is capable of achieving the best forecasting results, and in half execution time of the ANN based approaches.

Keywords: Artificial Neural Networks, Data Mining, Machine Learning, Solar forecasting, Support Vector Machines

1. Introduction

The use of renewable energy sources is having a significant increase in the last decades, encouraged by governmental policies and incentive programs whose concern is to avoid the exploitation of finite fossil fuel reserves and at the same time avoid environmental damages.

In Europe a set of legislation was defined having the known “20-20-20” as targets. The national targets will enable the EU as a whole to reach its 20% renewable energy target for 2020 - more than double the 2010 level of 9.8%. These targets, which reflect Member States' different starting points and potential for increasing renewables production, range from 10% in Malta to 49% in Sweden [1].

In this context alternative sources of renewable and clean energy, such as tidal, wind and solar have become of great importance. However the variable and intermittent nature of these resources poses a lot of challenges to several entities such as utility companies, power systems operators and market operators, especially when considering a significant market penetration rate as it expected and encouraged to

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achieve.

Solar energy is clearly the most abundant resource available to modern societies. Usually summer months, such as July and August in the northern hemisphere, have smaller variability. However, even during some sunshine months sudden changes might occur. The variability of the solar resource is mostly due to cloud cover variability and atmosphere conditions.

The contribution of this paper is the understanding and improvement of the solar irradiance forecasting, given its particular variability. For this, several forecasting methods, based on Artificial Neural Networks (ANN) and Support Vector Machines (SVM), are proposed and conclusions about the solar irradiance components and algorithms' parameters are taken. An hybrid approach, that combines ANN and SVM with a clustering algorithm that is used to filter the data that is most appropriate to be used in the training process of the forecasting methodologies is proposed and proved to be an interesting area of research, capable of improving ANN or SVM results. The usage of the specific historical data that most potentiates the optimization of the forecasting methods proves to have an equal or even higher importance than the optimization of the methodologies' parameters themselves.

Section 2 presents an overview of solar forecasting importance with particular emphasis to the smart grids and microgrids concepts. Section III highlights solar irradiance components and presents ANN and SVM techniques. In section IV experimental findings about the proposed methods and the obtained conclusions are presented and discussed. Real data from solar irradiance values of Florianópolis, in Santa Catarina, Brazil have been used in the experiences. Finally, section 5 presents the most relevant conclusions and contributions of this work.

2. Solar Forecasting

Despite its importance for the existence of life on earth, and human beings health, the sun is nowadays a source of clean energy and can contribute to reduce the difficulty in fulfilling the energy demand. Photovoltaic (PV) and solar thermal are the main sources of electricity generation from solar energy. In the case of solar thermal energy plants with storage energy system, its management and operation need reliable predictions of solar irradiance with the same temporal resolution as the temporal capacity of the back-up system [2]. The development in the power semiconductor technology has allowed higher efficiencies in the conversion of solar energy into electrical energy through photovoltaic cells [3] and PV systems have reached the end-user. The spread of PV technology took place initially in rural areas, but has nowadays been used to be integrated into roofs and facades of buildings to generate electricity.

The increase on the use of renewable energy sources (RES) affects the behavior of a considerable number of entities from the electricity sector and imposes economical and technical challenges. Forecasting renewable resources is important from the producers, retailers, aggregators, system operators and market operators point of view.

From the utility point of view, application of renewable sources can potentially reduce the demand for distribution and transmission facilities. Clearly, distributed generation located close to loads can reduce power flows in transmission and distribution circuits with two important effects: loss-reduction and the ability to potentially substitute for network assets. Furthermore, the presence of generation close to demand could increase service quality seen by end customers [4].

From the power system operators point of view, short-term forecasting is relevant for dispatching and regulatory purposes, to optimize the decision making by allowing corrections to unit commitment.

Concerning market operators, the prevision of the production is important for planning transactions in the electricity market in order to assure the balancing between supply and demand. From the economical point of view it is also important for electricity players to use this knowledge as competitive advantage in day-ahead electricity trading.

The balancing market is a complementary market to the day-ahead market, which allows agents to adjust their needs and renegotiate previously agreed energy by adjusting the quantities traded in the daily market. This enables players to overcome fluctuations of the production forecasts, which is particularly important for producers based on RES, such as wind and solar power, due to their variable and intermittent nature.

Solar, wind and load forecasting have become integral parts of the smart grid and microgrid concepts.

2.1. Smart grids and microgrids

According to the European Technology Platform of Smart Grids [5], a smart grid is an electricity network that can intelligently integrate the actions of all users connected to it – generators, consumers and

those that assume both roles – in order to efficiently deliver sustainable, economic and secure electricity supplies. A key goal of smart grids efforts is to substantially increase the penetration of environmental friendly energy sources, such as solar.

Microgrids, also characterized as the "building blocks of smart grids", comprise low voltage distribution systems with distributed energy resources (DER) (microturbines, fuel cells, PV, etc.) together with storage devices (flywheels, energy capacitors and batteries) and flexible loads [4]. Microgrids can be operated in a non-autonomous way, if interconnected to the grid, or in an autonomous way, if disconnected from the main grid.

The production sources within a microgrid can be dispatchable or intermittent for certain RES technologies, such as PVs and small wind turbines. Controllability of these intermittent units is limited by the physical nature of the primary energy source. Moreover, limiting RES production is clearly undesirable due to the high investment and low operating costs of these units and their environmental benefits over carbon emission. Consequently, it is generally not advisable to curtail intermittent RES units, unless they cause line overloads or overvoltage problems.

Solar irradiance forecasting is important for the integration of this source of renewable energy into these new concepts of electrical grid, to help grid operators to optimize RES production usage and/or reduce additional costs by preparing an appropriate strategy [6, 7].

3. Data and Methods

Here we review some fundamental concepts about solar irradiance components, related work on solar forecasting and the artificial intelligence techniques that we have used in this study and documented experiences.

3.1. Solar Irradiance Components

The solar irradiance fluctuates around an average value of approximately 1360Wm-2 [8]. The incident extraterrestrial beam radiation is divided in two distinct components: the Direct Normal Irradiance (DNI) and the Diffuse Horizontal Irradiance (DHI). The geometric sum of both results is the Global Horizontal Irradiance (GHI) that can be written as:

$$GHI = DHI + DNI*\cos\theta \quad (1)$$

where θ is the solar zenith angle. The extraterrestrial irradiation is measured above the Earth's atmosphere, so it is not influenced by clouds in the atmosphere and can easily be previewed throughout the year [9].

3.2. Solar Forecast

Usually, to predict renewable sources of energy two approaches may be used: an approach based on physical models [10], using mathematical equations to describe physics and dynamics of the atmosphere that influences solar radiation, and an approach based on time series analysis by means of statistical models [11]. Physical models work well for medium- and long-term solar forecasting, while statistical models have lower complexity and can perform well for short-term solar intensity forecasting.

In this work we focus on the second approach, thus on the analysis of an historical database by means of statistical analysis and learning methods, for short-term solar forecasting.

Several techniques have been applied to solar irradiation or solar power forecast such as regression techniques, Auto Regressive Moving Averages (ARMA), Auto Regressive Integrated Moving Averages (ARIMA), Artificial Neural Netwroks (ANN), Genetic Algorithms (GA) and Support Vector Machines (SVM).

References [9], [12] and [13] provide good overviews on the current state of the art in solar irradiance forecasting. In [14] a comparison on several forecasting techniques to predict solar power at a photovoltaic power plant in California is presented. In this work, ANN has proved to be a promising technique on this field, showing improved results while combined with GAs. The same conclusions about the use of ANNs were achieved by [15] and [16]. ANNs have also been successfully applied to the forecasting of other renewable sources based production types, such as the wind power, in [17]. The good results achieved by ANNs in the most varied fields [18, 19, 20, 21], provide an encouraging indication of ANNs' capability of coping with the problem approached in this work.

In [22], [23] and [24] the use of SVM proved to be a promising technique to solar forecasting research.

Based on these previous studies ANN and SVM are used as the basis for the present work on investigating the most relevant components of solar irradiance and other meteorological variables.

The accuracy of the forecast may be evaluated by several error indices, such as the mean absolute error (MAE), the mean absolute percentage error (MAPE), the symmetric mean absolute percentage error (SMAPE) and the standard deviation (SD) [25].

3.3. Artificial Neural Networks

Artificial Neural Networks (ANN) are inspired on the human brain and on how their neurons process information with high interconnectivity. ANNs are constituted by several nodes, or neurons, organized in different levels, and interconnected by numeric weights. They resemble to the human brain in two fundamental points: the knowledge being acquired from the surrounding environment, through a learning process; and the network's nodes being interconnected by weights (synaptic weights), used to store the knowledge. Each neuron executes a simple operation, the weighted sum of its input connections, which originates the exit signal that is sent to the other neurons. The network learns by adjusting the connection weights, in order to produce the desired output - the output layer values [26].

Based on a large number of correct examples ANN are able to change their connection weights until they generate outputs that are coincident with the correct values. By this way, ANN are able to extract basic rules from data [27].

3.4. Support Vector Machines

In 1936, R. A. Fisher [28] created the first algorithm for pattern recognition. The SVM algorithm is implemented by a generalization of the nonlinear algorithm Generalized Portrait that has been created by Vapnik and Lerner in the sequence of [29]. This was the first running kernel of SVM, only for classification and linear problems.

The SVM concept can be tracked to when statistical learning theory was developed further with Vapnik, in 1979. However, the SVM approach in the current form was first introduced with a paper at the COLT conference, in 1992 [30].

Some essential aspects to take into account when implementing a SVM based methodology are the feature space, the loss functions [31], and the kernel functions. The most applicable kernels for time series forecasting, as is the problem approached in this paper, of solar forecasting, are the Radial Basis Function (RBF) and the exponential Radial Basis Function (eRBF). These two kernels are specifically directed to regression in time series data.

4. Experimental Findings

This section shows the results of the tests that have been performed to assess the functioning of the methodologies and their parameters' tuning for better results achieving. All tests were performed for the same day and period, in order to conclude which is the most appropriate methodology for the day and period under analysis.

This section is divided into three parts, namely: (i) results of the ANN based methodologies; (ii) results of the SVM based methodologies; (iii) execution times comparison. This comparison allows reaching relevant conclusions about the best methodology to forecast solar intensity.

The used data are referent to Florianópolis, state of Santa Catarina, Brazil. These data correspond to the period from 1990 to 1999, including the values of Global, Direct, Diffuse and Extraterrestrial Irradiance, in W/m2; temperature in ºC; humidity in %; and wind speed in m/s. more details in the used data can be found in [32].

4.1. ANN Methodologies

Equally important to an adequate parameterization of the used forecasting methodology is the suitable interpretation of the used data. Time series data can be interpreted in many different ways, and data sequences can be looked at from different perspectives. For this reason various forecasting methodologies based on ANN have been developed. After exhaustive preliminary tests to choose the most suitable forecast input data, three promising solutions have been found. The authors have decided to implement these three solutions with the goal of studying and concluding which would achieve the best performance.

These three solutions, or topologies, use as input data:

- M1 - last 4 periods, i.e. use the 4 hours before the time that is intended to forecast;
- M2 - last 24 periods, i.e. use the 24 hours preceding the time of day that is intended to forecast;
- M3 - last 7 days, i.e., using data exclusively from the same hour that is intended to forecast, but corresponding the 7 previous days to the day intended to forecast.

Moreover, another issue concerning data types (fields) that influence the solar intensity has emerged. As already mentioned, the fields that are part of the historical records of solar data are: I_Glob_H (Global Horizontal Irradiance), I_Beam_N (Direct Normal Irradiance), I_Diff_H (Diffuse Horizontal Irradiance), I_Extr_H (Extraterrestrial Horizontal Irradiance), Temp (Temperature), Rel_Humidity (Humidity), Wind_Speed (Wind speed).

In order to implement, test and take conclusions, four different sets of fields have been used in the forecasting process. This way it is possible to realize which fields provide added value for the forecasting process. The four sets are:

- SM1 – only each of the four solar intensity fields independently (I_Global_H, I_Beam_N, I_Diff_H or I_Extr_H) ;
- SM2 – the four principal fields simultaneously (I_Global_H, I_Beam_N, I_Diff_H and I_Extr_H) ;
- SM3 – all fields (I_Global_H, I_Beam_N, I_Diff_H, I_Extr_H, Temp, Rel_Humidity and Wind_Speed);
- SM4 – The main field (I_Global_H) used with the three complementary fields (Temp, Rel_Humidity and Wind_Speed).

Thus, each of the three methodologies (last 4 periods, last 24 periods, and last 7 days), is subjected to four sub-methodologies (SM) based on the 4 datasets that were described before.

The sensitivity analysis consisted in a huge amount of tests, with the purpose of reaching the most advantageous combination of parameters. The parameters that have presented the higher influence on the results are: the number of nodes in the ANN's hidden layer, and the training limit, i.e. the amount of training data. Figure 1 presents the results of the variation of the number of intermediate layer nodes, when using each of the four fields of solar irradiance independently for the forecast, namely: I_Global_H, I_Beam_N, I_Diff_H and I_Extr_H. Figure 2 presents the SMAPE (%) error variation for different amounts of training data.

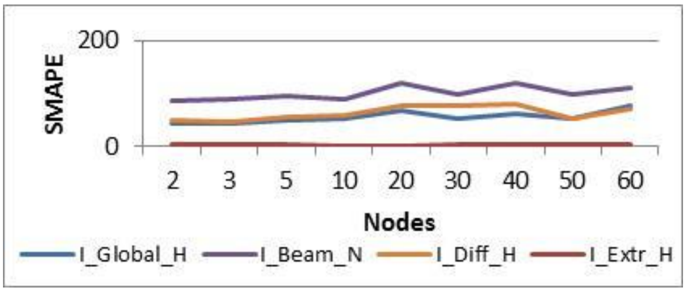

Figure 1 – Forecasting error for different numbers of intermediate nodes, for each solar field

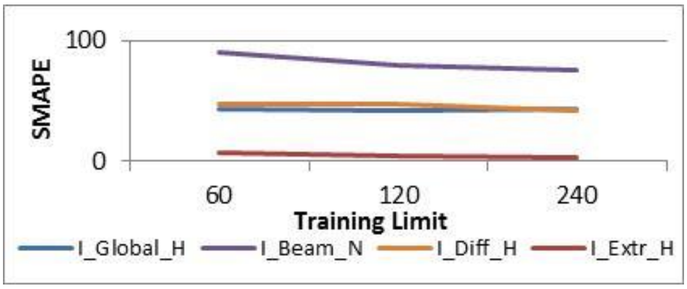

Figure 2 – Forecasting error for different amounts of training data, for each solar field

From Figure 1 and Figure 2 it is visible that the best combination would be to use 3 intermediate nodes with a training limit of 120. Figure 1 shows that the increase of the hidden layer nodes instigates an increase of the forecasting error values in three from the four solar intensity data types. Three nodes is the number that presents the best overall results for the four fields. Regarding the training limit, one can see from Figure 2 that the SMAPE values stabilize after the value of 120. This means that it is irrelevant to

include a larger amount of training data, as the increase in training execution time does not bring any added value for the quality of the forecasts.

Thus 3 intermediate layer nodes and a training limit of 120 are the values that are used for all ANN based methodologies. Table 1 shows the SMAPE (%) error values of the first topology (M1).

Table 1 – SMAPE error values obtained in the forecasts using M1 (with the last 4 periods), in %

	I_Glob_H	*I_Beam_N*	*I_Diff_H*	*I_Extr_H*
M1 - SM1	*39,81*	*81,49*	*38,24*	*1,16*
M1 - SM2	*37,22*	*76,19*	*47,68*	*7,00*
M1 - SM3	*43,67*	*81,82*	*34,6*	*8,16*
M1 - SM4	*40,14*	-	-	-

In SM4 only the I_Glob_H field is forecasted, therefore, Table 1 does not show the error value concerning the other solar intensity fields. For M1, one can see that the best results in forecasting the I_Glob_H field are achieved when using the four solar intensity fields at the same time, for the forecasting process (SM2). Table 2 shows the SMAPE (%) forecasting results, referring to the second topology (M2).

Table 2 – SMAPE error values of the M2 topology, in %

	I_Glob_H	*I_Beam_N*	*I_Diff_H*	*I_Extr_H*
M2 - SM1	*34,02*	*74,81*	*46,14*	*2,69*
M2 – SM2	*54,57*	*100,6*	*47,43*	*7,86*
M2 – SM3	*47,43*	*92,87*	*92,81*	*9,92*
M2 – SM4	*46,27*	-	-	-

From Table 2 it is visible that, concerning the forecast errors' analysis using the last 24 periods, using only one solar field (SM1) leads to obtaining better predictions. Table 3 presents the results of M3.

Table 3 – SMAPE error of the forecasts using the last 7 days – M3, in %

	I_Glob_H	*I_Beam_N*	*I_Diff_H*	*I_Extr_H*
M3 - SM1	*44,4*	*83,08*	*61,4*	*0,52*
M3 – SM2	*48,96*	*74,28*	*49,72*	*8,67*
M3 – SM3	*53,19*	*109,87*	*49,03*	*9,91*
M3 – SM4	*39,86*	-	-	-

From table 3, concerning the forecast error analysis with the last 7 days, we concluded that using one solar field (SM1) leads to obtaining better forecasts, precisely because it gets the best global solar intensity forecast.

Finally, to conclude the ANN tests analysis, in the first methodology, using the last 4 periods it was concluded that using the 4 solar fields obtain better forecasts, with and error of 37,22% for I_Glob_H parameter. In the second methodology, using the last 24 periods best forecasts are obtained using one solar field, with an error of 34,02% for the parameter I_Glob_H. Finally, the third methodology using the same period of last week, obtains better predictions using one solar field, with an error of 44,4% for the parameter I_Glob_H. The methodology which achieved better forecast, as can be seen by calculating the

error, was the second, using the last 24 periods, and the first sub-methodology, using only the I_Glob_H field as training data, while ignoring the other (M2 – SM1), with a SMAPE value of 34,02.

4.2. SVM Methodologies

Similarly to the ANN based methodologies, more than one approach has been considered, regarding the input data to train the SVM. Two solutions have been implemented, which use as input:

- SVM_M1 - the same period in the last days, i.e., using data from the same hour that is forecasted, but in the last days preceding the day to forecast;
- SVM_M2 - last hours, i.e. use the latest hours before the hour of the day that is being forecasted.

Considering the conclusion taken from the performance of the ANN based approach that the use of the I_Glob_H field by itself leads to better forecasting results, and given the intrinsic nature of SVM, which assumes a single data series prediction; only the historical data of the I_Glob_H field is used by the SVM based approaches.

Sensitivity tests have been performed in order to determine the best parameterizations for the SVM approach. The most influential parameters on the results are: the kernel function, the angle of the kernel function – σ, and the amount of training data – training limit. Regarding the kernel functions, as mentioned before, the most suitable kernel functions for time series prediction are the RBF and eRBF kernels; therefore, these two kernels have been used.

Figure 3 and Figure 4 present the evolution of the MAE and SMAPE error values for different training limits and σ respectively, when using the SVM approach with the RBF kernel.

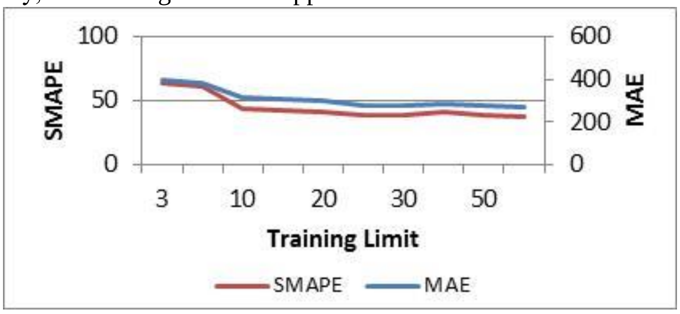

Figure 3 – Forecasting error for different training limits, when using the SVM approach with the RBF kernel

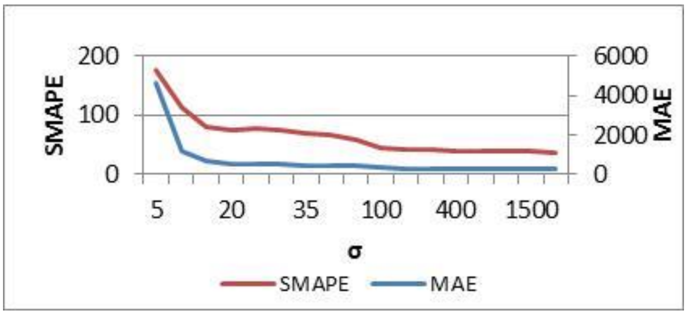

Figure 4 – Forecasting error for different kernel function angles, when using the SVM approach with the RBF kernel

From Figure 3 and Figure 4 it can be concluded that the use of the SVM methodology with the RBF kernel achieves the best results with a training limit of 25 and σ equal to 1000.

Figure 5 and Figure 6 present similar sensitivity analysis results for the SVM approach using the eRBF kernel.

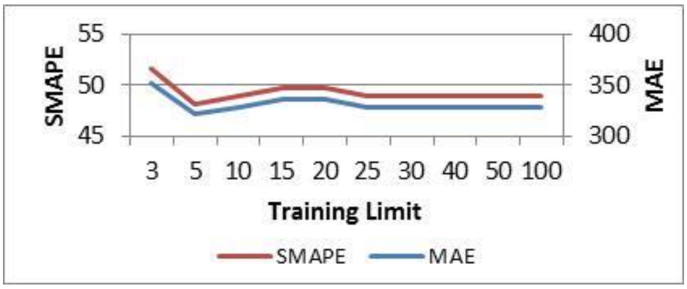

Figure 5 – Forecasting error for different training limits, when using the SVM approach with the eRBF kernel

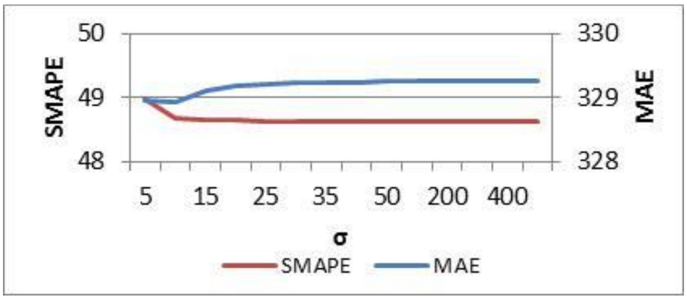

Figure 6 – Forecasting error for different kernel function angles, when using the SVM approach with the eRBF kernel

From Figure 5 and Figure 6 it can be concluded that the use of the SVM methodology using the eRBF kernel reaches its optimal performance with the training limit value of 25 and σ of 10.

Table 4 presents the Standard Deviation (SD), MAE and SMAPE (%) error values of the SVM methodology for the I_GLOB_H solar irradiance field.

Table 4 – SMAPE error of the forecasts using the last 7 days – M3

Methodology	*Kernel*	*SD*	*MAE*	*SMAPE*
SVM_M1	*RBF*	*229,5*	*270,77*	*38,37*
	eRBF	*301,56*	*328,97*	*48,99*
SVM_M2	*RBF*	*317,12*	*179,7*	*23,36*
	eRBF	*287,4*	*151,62*	*21,48*

From Table 4 it is visible that the second methodology (SVM_M2) achieves better forecasting results than SVM_M1, for both kernel functions. Additionally, despite the use of the RBF kernel being able to provide better results with the SVM_M1 methodology, the eRBF kernel was able to achieve better results with the SVM_M2 methodology, and also the global best ones of the SVM based methodologies. Therefore the conclusion is that using SVM_M2 with the eRBF kernel is the solution capable of reaching the best solar irradiance forecasts.

Finally, comparing the SVM approach with the ANN methodologies (which best result has been achieved by the M2 – SM1 methodology, with a SMAPE value of 34,02%), one can conclude that the SVM_M2 methodology with the eRBF kernel is the best overall approach, with a SMAPE of 21,48%.

4.3. Execution Times

The computational effort has been measured for both ANN and SVM methodologies. The parameter that, obviously, presents the higher influence over the execution time of both approaches is the training limit.

All tests have been executed on a machine with the following characteristics: Intel® Xenon® CPU X5450 3,00Ghz (2 processors), 4,00GB of RAM memory and a 32bits operating system.

Figure 7 presents the evolution of the average execution time after 1000 runs for the ANN M2-SM1 methodology.

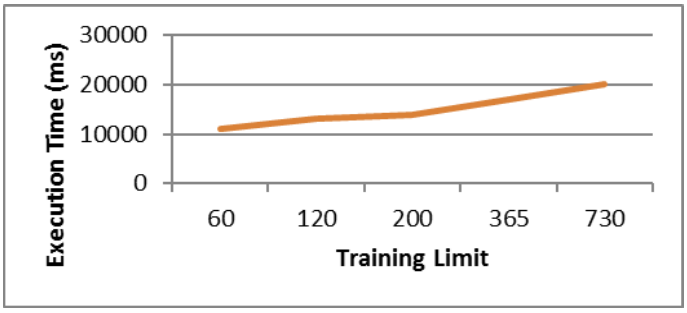

Figure 7 - Average execution time of the ANN M2-SM1 methodology

From Figure 7 is it visible that the execution time increases with the increase of the training limit. As presented in section 4.1, the ANN M2-SM1 methodology has been executed with a training limit of 120, which means an execution time of approximately 13500ms. The use of a higher training limit can produce a computational cost of 20000ms, while using a very low training limit takes nearly 10000ms to execute.

Figure 8 presents the average execution time after 1000 runs, for the SVM based methodologies.

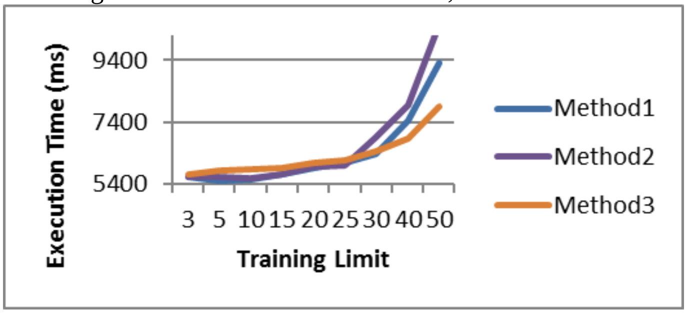

Figure 8 - Average execution time for methodologies based on SVM (Metodology1 that uses the same period of the last days, Metodology2 that uses the latest hours of day and Metodology3 where Clustering is applied), depending on the Training Limit

From Figure 8 it is visible that the SVM based approaches using the training limit of 25 (the optimal value for both kernels as presented in section 4.2) require nearly 6000ms to run. This value is less than half of the time of the ANN based approaches. Even with a very high training limit, the execution time of the SVM approaches is always lower than the faster ANN approaches.

5. Conclusions

This paper presented several forecasting methodologies based on the application of ANN and SVM, directed to the prediction of the solar radiance intensity. The methodologies differ from each other by using different information in the training of the methods, i.e, different environmental complementary fields such as the wind speed, temperature, and humidity. Additionally, different ways of considering the data series information has been considered. Sensitivity testing has been performed on all methodologies in order to achieve the best parameterizations for the proposed approaches.

From all the presented tests one can conclude that, for the approached problem of solar intensity forecasting, the use of additional data fields other than the I_Glob_H historic values, brings no added value to the forecasting process. In fact, the forecasting error increases when using additional information.

The ANN based methodology that achieved the best results uses the last 24 periods, and the first sub-methodology, using only the I_Glob_H field as training data, while ignoring the other (M2 – SM1), with a SMAPE value of 34,02%.

Regarding the SVM based methodologies, the eRBF kernel has shown to be the most suitable for this case. While the second methodology, using only the last hours before the hour of the day that is being forecasted, achieved the best results, with a SMAPE of 21,48%. SVM approaches achieved better forecast results than the ANN.

Regarding the execution time of the considered approaches, the SVM based methodologies present an execution time of about half the value of the ANNs.

As future work, the use of other forecasting methodologies, such as fuzzy inference systems can be mentioned. Additionally, the refinement of the ANN and SVM methodologies may lead to an improvement of the results.

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