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Probabilistic Determination of Consumers Response and Consumption Managing Strategies in Demand Side Management

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Alla mia famiglia.

Sommario

In seguito alla forte penetrazione degli impianti di produzione di energia elettrica da fonte rinnovabile ed alla diffusione ed incremento dell'utilizzo di apparecchiature elettriche, inclusi nuovi ambiti quali ad esempio la cucina, il riscaldamento ed i trasporti, i flussi di potenza nelle linee elettriche sono diventati molto elevati e variabili, si vede pertanto necessaria l'implementazione di adeguate strategie di controllo e gestione per garantire il corretto funzionamento della rete.

Uno dei meccanismi attraverso cui si cerca di regolare i flussi di potenza è il Demand Side Management (DSM), il gestore di rete cerca di effettuare un controllo del consumo di elettricità attraverso la richiesta agli utenti di modificare il proprio assorbimento elettrico o agendo direttamente sui carichi degli stessi.

La disponibilità dei consumatori a variare l'elettricità in uso e la quantità di energia elettrica che hanno a disposizione per queste variazioni non è costante a causa delle differenti condizioni in cui possono venire richieste queste azioni; gli elementi che condizionano la risposta possono essere ad esempio la stagione, il giorno o l'ora. Chi gestisce la rete si trova quindi a dover operare in una condizione di forte incertezza poiché non conosce con precisione quali utenti saranno disponibili ed in quale misura. Il metodo proposto vuole quindi, attraverso una analisi dei dati storici, caratterizzare gli utenti definendo la disponibilità di elettricità media per la variazione del carico in determinati contesti e stabilire la probabilità che ciascun utente soddisfi la richiesta del gestore con un predefinito taglio dei consumi. Una volta caratterizzati gli utenti, il gestore può selezionare quali sono i consumatori che più soddisfano le proprie necessità attuando così una strategia che punta ad un miglior e più certo risultato ed a benefici dal punto di vista economico.

Il metodo è stato implementato tramite il software RStudio e testato attraverso l'utilizzo di un database con dati reali, riguardanti i consumi elettrici di quattro edifici: due centri di studio, un centro di svago ed un ufficio.

Parole chiave

Demand Response (DR), Performance Evaluation, Smart Grids, Statistical Methods, Uncertainty

Abstract

This work aims to explore the uncertainty that affects the response of the consumers to the request to reduce electricity consumption during an electricity system's peak or when the electricity price is high. Due to the increasing presence of renewable sources connected to the grid and the diffusion of electric equipment, also in new sectors as cooking, heating or transportation, the power flows on the lines become very strong and variable, so a good managing strategy is required.

To solve the congestion in a line it could be necessary to ask to the consumers the reduction of the load; the response of the users to the request depends on several factors. In this work, a method that examines the response of the consumers to a load reduction request, defining the context in which the demand response event is carrying on and studying how the consumers react, using statistical methods, is proposed.

Then are proposed several strategies to optimize the consumers' participation in the load reduction basing the optimization on the previous characterization.

Using a database with real demand response events, the operation of the method was tested implementing it in RStudio. The data concern the consumption of four buildings, two educational centres, a leisure centre and a local office.

Keywords

Demand Response (DR), Performance Evaluation, Smart Grids, Statistical Methods, Uncertainty

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Acronyms

ADR	–	Automated Demand Response
COP	–	Conference of Parties
CPP	–	Critical Peak Pricing
DG	–	Distributed generation
DLC	–	Direct Load Control
DR	–	Demand Response
DRAS	–	Demand Response Automation Server
DSM	–	Demand Side Management
EE	–	Energy Efficiency
EMP	–	Energy Management Panels
EMS	–	Energy Management System
EV	–	Electrical Vehicle
GHGs	–	Greenhouse Gasses
RTP	–	Real-time Pricing
SG	–	Smart Grid
SR	–	Spinning Reserve
TOU	–	Time of Use

1. INTRODUCTION

The following sections have the objective to introduce the work, giving information about the issues which have been investigated and which are the goals of the study. After a quick contextualization, which has been more discussing in 2nd chapter, there is a description of the report's structure.

1.1. CONTEXT

The electrical consumptions are increasing exponentially during the last years and all the forecasting studies agreed that this trend will continue and intensify due to higher penetration of electrical equipment in the buildings like as electric cookers, heating and cooling systems, water heating systems or electric vehicles [1].

The power system needs to be expanded and strengthened but many investments could be saved with a good managing of the electric grid. The electric lines are used at the maximum capacity only a few hours or, sometimes, minutes a day and not every day; if it could be possible to reduce or delete the unnecessary electric consumptions during these periods it would indicate to reduce investments in new lines and equipment and reduce the soil consumption and the environmental impact of these structures [2].

Smart equipment is installed in all the electricity chain, from the transmission system to the private houses, so the managing of the grid is easier and real-time control of the power flows could be done through new mechanisms like the Demand Side Management (DSM) [3].

1.2. OBJECTIVES

This work aims to find a method that allows studying the response of the consumers to the request of a reduction in electricity consumption, during a peak of the system, and the forecasting of the load reduction in future events.

To achieve these goals, attention has been paid to several issues:

- Studies of the electricity grid structure;
- Studies of the implementation of Demand Side Management in the electricity chain;
- Studies in statistic's field;
- Studies in finance's field;
- Implementation of the defined method in R software.

This topic doesn't find much support in the literature; most of the papers report results from surveys or investigate the reasons that influence the response of the consumers but only a few try to obtain a characterisation of the consumers. This approach seems to be kind of innovative and would be useful to have a verification and optimization of the method proposed with big data to confirm the validity of the method itself. The hope of the author is that this work could serve as a starting point for future investigations.

1.3. CALENDARIZATION

This work, developed in GECAD[1], required 6 months, from February 2019 to July 2019. The first three months have been necessary to get general information, define the topic and look for the best way to solve it. A month was necessary to analyse the data from a trial and implement the first approaches in Excel, then the next month was dedicated to

[1] GECAD - Research Group on Intelligent Engineering and Computing for Advanced Innovation and Development - http://www.gecad.isep.ipp.pt

implementing the method on RStudio. The last month was used to write the report and to analyse the results.

1.4. WORK ORGANIZATION

After the 1^{st} chapter that gives general information about the work, other five chapters and the conclusions are presented. In the 2^{nd} chapter all the basic information, that are necessary to understand completely the background in which the topic has been developed, are presented. Details about the electric grid, the structure of the demand response programs and many notions that are useful to understand how it works are given in this chapter.

The 3^{rd} chapter introduces the topic which has been investigated. The focus has been placed on the reasons that could influence the failure of a demand response event and how it could be possible to avoid them, then a mechanism to implement the demand response is illustrated and a possibility of how to evaluate the results of an event is shown.

The 4^{th},5^{th} and 6^{th} chapters illustrate the method that has been developed, the data utilised to test it and the obtained results.

2. RELATED LITERATURE

In this chapter an overview of the Demand Response (DR) and how it is structured in order to contextualize it is presented. In the next pages, the reader can find information about smart grids that show how the demand response is organised and which programs are involved.

2.1. BACKGROUND

Climate change is one of the most debated and discussed topics in the last twenty years and it has primary importance in a lot of political, economic and energetic strategies of almost every country in the world.

In 2015 there was the XXI United Nations Climate Change Conference in Paris, a yearly conference also known as Conference of Parties (COP), aimed to obtain a worldwide agreement to reduce the greenhouse gasses emissions (GHGs). The Paris Agreement was signed by more than 190 countries and it was the first multilateral agreement on the climate change covering almost all of the world's emissions [4].

The Paris Agreement sets out a global plan, in order to avoid dangerous climate changes, requiring a global reduction of GHGs emissions to achieve climate neutrality in the second half of this century. Some of the key features of the agreement are:

- Limit global warming to well below 2°C above pre-industrial levels.

- A global transition to clean energy shifting away resources from fossil fuels.
- Obligation to pursue domestic mitigation measures for the parties [4].

Move away from fossil fuels involves a major utilization of renewable resources such as hydro, solar, wind and others in order to produce electricity in a way as clean as possible for the planet. In the last decade, the construction of new renewable power plants is grown exponentially; in an IEA (International Energy Agency) report, installed renewable-based generation capacity of 1 985 GW in 2015 was mentioned, exceeding for the first time the coal plants capacity (1 950 GW). Wind capacity was 35% higher than the previous year and solar photovoltaic increased by almost 25% [1]. In Figure 1 the amount of power capacity installed every year in the world and the percentage of the total capacity covered by renewables resources is shown.

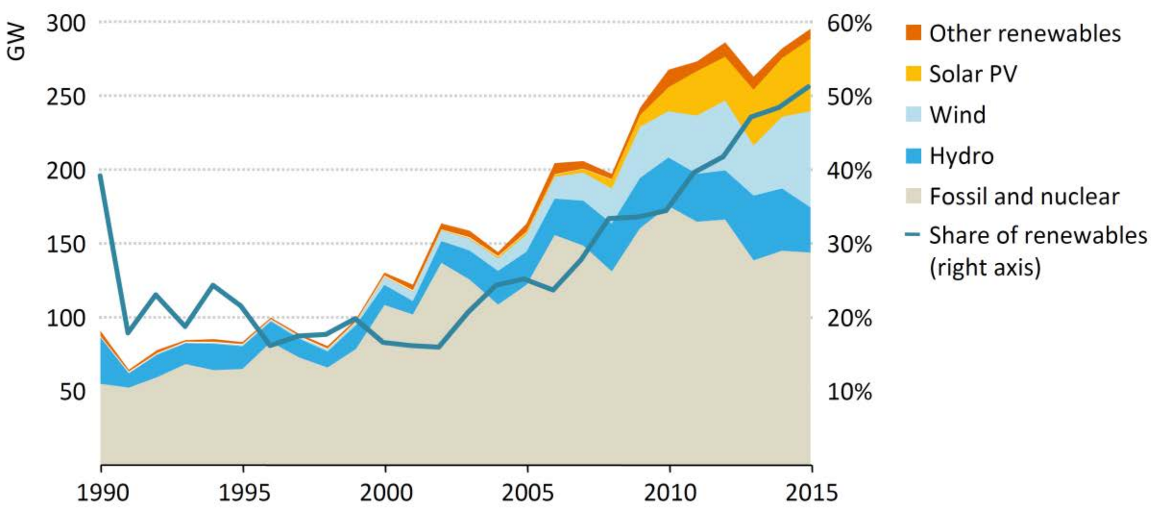

Figure 1 **World renewables-based power capacity additions by type and share of total additions** [1]

IEA, to achieve the COP21 goals, estimates the installation of 4 000 GW of new renewable capacity until 2040. A massive presence of these types of sources lead the power systems to change their classical modus operandi in the direction to a more active participation in order to guarantee the grid stability; power flows are no more unidirectional and power balance could be more critical due to the volatility of energy production of these plants, a good energy management system is required. Moreover, electrical consumption will grow up to 34 000 TWh, about 70% more than now, due to the higher presence of heat pumps, cooking induction systems and electric vehicle [1]. Electrical grids get updated with sensors and data collector appliance to become intelligent systems, defined as Smart Grids (SGs), able to reply to the significant challenges to the secure operation and planning of power systems [3].

2.2. SMART GRIDS

A smart grid is an electric grid that can deliver electricity in a controlled and smart way from point of generations to consumers, who are considered as an integral part of the SG [5]. End-use customers become also an active part of the grid because they can modify their consumption patterns and behaviours according to the information, incentives or disincentives communicated by the grid operator.

In the past, the electricity ran on the grid in only one way, from the generation plants to the users and the electrical system could be easily divided in four parts represented into Figure 2: generation, transmission, distribution, utilization.

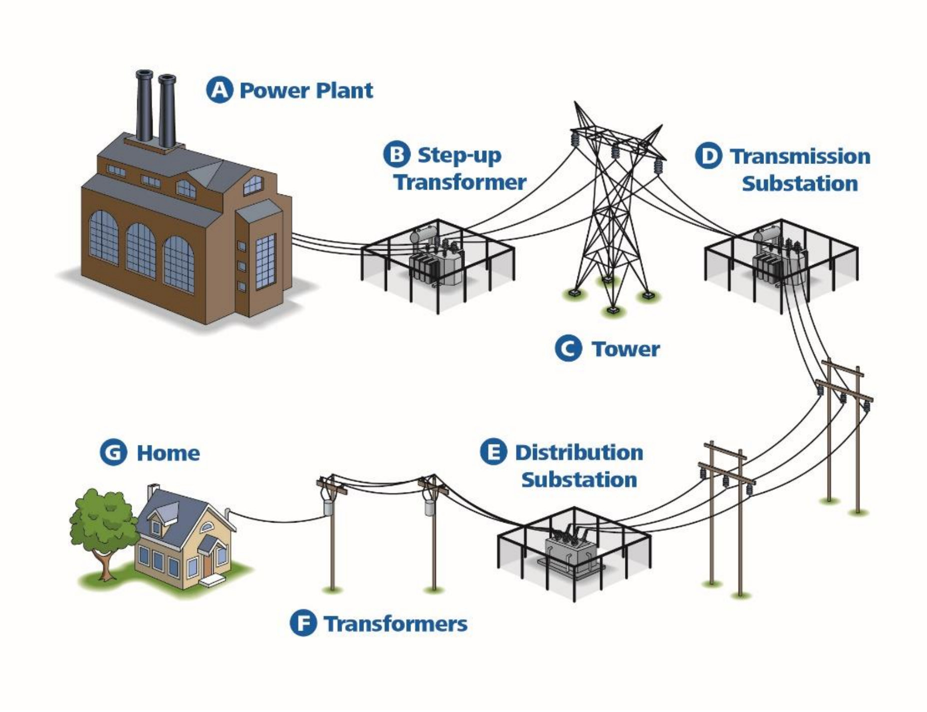

Figure 2 Traditional electric system [6]

The grid operator had complete control in the first three parts of the system and the operation of the grid could be done in an integrated way. The generation was supplied by big power plants, mainly operating with fossil fuels, nuclear or water, and the critical points of the lines were well known. Moreover, the transmission network has always provided a balancing and management role in the electric power supply chain and the distribution network has been designed to be passive in the operation [2].

By the end of the 20th century, this structure began to be inadequate to guarantee good reliability of the grid and to supply the desired energy at the desired time; moreover, the emerging of environmental issues concurred to the development of a new type of electric system, more complex but more efficient.

Distributed generation (DG) began to appear as support to the traditional centralized units. The DG is a key factor of the smart grid implementation, its integration in an electric grid that brings many benefits for customers, energy efficiency and network operation [7]. The distributed generation involved usually small and medium power generation units, connected to the low or medium voltage grid, that it uses as a resource mainly renewable sources as water, wind, sun or biomass. These power plants could not only be built to sell energy and inject electricity in the electric system but also an as integral part of an industry or a house to adsorb less electricity from the grid. Users became then an active part of the grid. The two major driving forces of the diffusion of the DG are the liberalisation of the electricity market, that allow to small customers to participate to it and to have a remuneration of their electricity, and the environmental goals that need to be achieved [8].

The potential benefits of the distributed generation are [9]:

- Increased electric system reliability;
- An emergency supply of power;
- Reduction of peak power requirements;
- Offsets to investments in generation, transmission, or distribution facilities that would otherwise be recovered through rates;
- Provision of ancillary services, including reactive power;
- Improvements in power quality;
- Reductions in land-use effects and rights-of-way acquisition costs;
- Improvements in infrastructure resilience.

The distribution networks became then an active part of the power supply chain, the power flows are now bi-directional and a new management system has to be implemented. This is not only necessary for the increasing development of the distributed generation but also the emerging intelligent building services, in both residential and commercial buildings. The distribution grid needs to be able to respond and adapt in real-time at all the complex and different interactions of all these factors and to guarantee a fast and accurate transmission of all the information of the network to the grid operator [2].

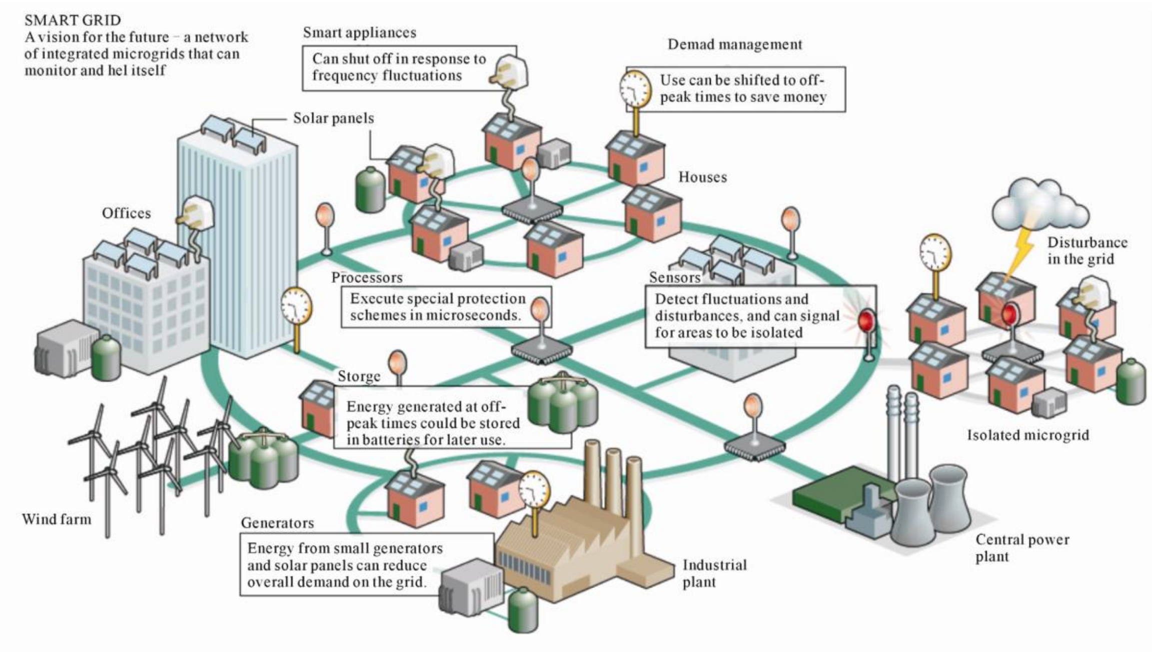

Figure 3 **A model set up of smart grid network** [2]

Figure 3 shows the main structure of an SG as a network of integrated microgrids that can monitor and manage itself. It's possible to observe:

1) Central power plant: represent the traditional power units that give stability to the grid and provide the main amount of electricity;
2) Wind farm: represent the medium generation units that provide electricity from a renewable source;
3) Photovoltaic panels and small generators: integrated with houses, commercial buildings or industrial plants. They can reduce the overall demand on the grid concurring to the reduction of power losses in transmission and distribution, of investments in new transmission infrastructures and take advantages in the bills;

4) Storage: the extra energy generated in off-peak could be stored and used during a peak when the price of the electricity becomes higher, this is useful for the owner of the storage system because he can use electricity at a lower price or he can sell it with a higher earning, moreover it's useful for the grid because the storage could be used to solve the congestion of a line or as a power supply to guarantee the stability of the grid;
5) Sensors and processors: the networks have to be full of sensors that can define the power flows, the electricity consumption and generation, the voltage and frequency fluctuations in order to guarantee the stability of the grid; all these data have to be elaborated and the information needs to be sent to all the actors of the networks management;
6) Smart appliances: to maintain a correct frequency and voltage are necessary equipment that can be turned off if it's required;
7) Demand management: the use of appliances can be shifted from on-peak times to off-peak times to save money, the user needs to know which the price of the electricity at the special time point is to reschedule the usage time.

Microgrids

As mentioned at the beginning of the last section we can define a smart grid also as an integration of more microgrids. Thanks to the distributed generation and the huge number of sensors it is possible to create small independent grids, called microgrids, which can operate without the presence of the main network. A microgrid is then a smaller, independent and decentralized system which uses a lot of modern technologies, it puts all together gas turbines, wind power, solar power and storage devices; moreover, it is directly connected to the user side.

Some characteristics of a microgrid are:

- Uniqueness: a microgrid is a small network consisting of micro-sources and load;
- Diversity: the composition of a microgrid is diverse, there are both traditional and renewable energies, storage and many types of loads;
- Controllability: according to operating conditions, a microgrid can choose different operation modes to guarantee reliability and security;

- Interactivity: as an independent generation equipment a microgrid can give strong support to the main grid;
- Independence: under certain conditions, a microgrid can operate independently [10].

Having more independent networks, than one big all linked grid, it improves the security of the system against blackouts and it's easier to reactivate if a strong issue incurs.

2.3. DEMAND SIDE MANAGEMENT CONCEPTS

In the smart grid structure the demand management was mentioned; the Demand Side Management (DSM) includes everything that is done in the demand side of an energy system, from an improvement in energy efficiency, as replacing old lamps with more efficient new ones, to invest in a load management system which helps consumers to reduce their bills by shifting electricity use in less expensive hours or turn off unnecessary appliances during the most expensive electricity price hours. Usually, in DSM context terms as "load management", "demand response" and "energy efficiency" are used to indicate the same purposes, however a difference between these terms exists, therefore it's good to clarify them.

Load management refers to the traditional way of DSM that implies a reducing in power consumption during the peak demand, or in an emergency condition, acting on elected loads.

Demand response (DR) programs refer to recent applications for DSM, like improving grid reliability or reducing wholesale energy prices and require an active participation of consumers; as defined in [11] DR refers to "changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized".

Energy efficiency, instead, refers to a permanent reduction in energy consumptions of a device or a system by employing high-efficiency equipment [3].

DSM can be also categorized by the timing and the impact of the programs on the customers' process; in Figure 4 we can see how DSM programs could be categorized:

a) Energy Efficiency (EE)

b) Time of Use (TOU)
c) Demand Response (DR)
d) Spinning Reserve (SR)

TOU is the easiest type of the DR programs. In this program, a day is split into two or more periods distinguished in On-peak, Off-Peak and Mid-Peak to penalize the use of electricity in certain periods thanks to a higher price. Prices are usually defined by a contract and they are based on the time of the day, the day of the week or the season; so they don't reflect the actual state of the grid or the electricity market but they are based through historical analysis of electricity availability, consumption and prices in the past years.

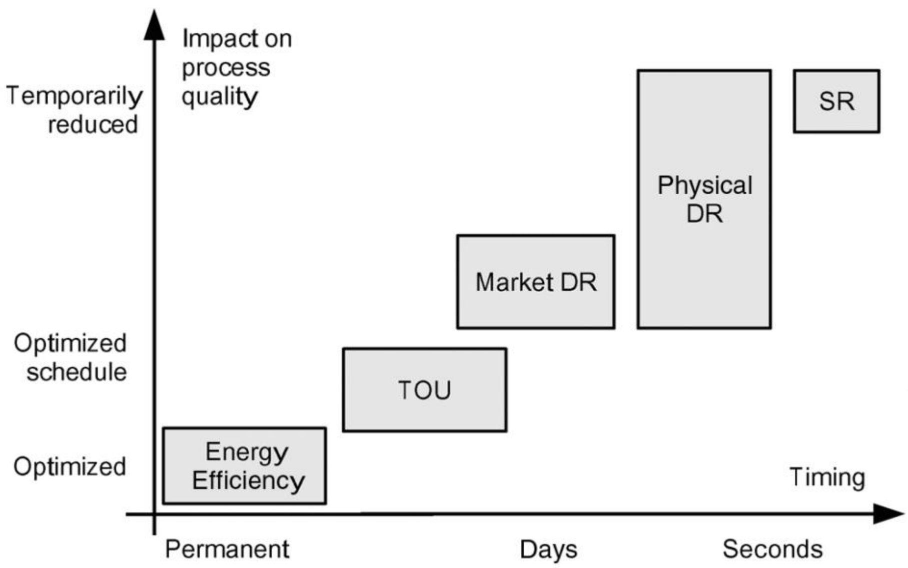

Figure 4 Categories of DSM [12]

DR programs can be split into two categories: Price-based DR and Incentive-based DR. Each category has a certain number of variants and the customers can choose the category that better fit their economic interests.

In Price-based programs, there is a change in electrical consumption related to a price change. There are different types of Price-based programs:

1. Time-of-Use rates: as previously explained different electricity prices are depending on the day-time: peak, off-peak or mid-peak hours are determined by a contract and they don't represent a real-time condition of the grid.

2. Real-time Pricing (RTP): in contrast with ToU, RTP prices are related to the wholesale electricity prices on hour-to-hour basis and costumers are usually notified of upcoming tariffs on a day-ahead or hour-ahead basis.
3. Critical Peak Pricing (CPP): similar to ToU, higher rates are applied when the grid is in a critical condition or when electricity prices are very high.

In Incentive-based programs, the costumers allow the grid operators, aggregators or utilities to control their loads in exchange of incentive payments which are separated from costumer's retail electricity rate. Usually, it is specifying a method to define a baseline for energy consumption, the success of a DR event and the amount of the load reduction is determined by a comparison between such baselines and the measured consumption.

Incentive-based programs can be divided in:

1. Direct Load Control (DLC) programs: customer's loads are directly controlled by the utility or the aggregator; in a DR event loads are shut down, cycled on and off or shifted in a lower demand period with very short notice. Usually, these customers receive a fixed monthly payment and an extra payment related to each DR event.
2. Interruptible/curtailable programs: similar to DLC but usually applicated to large commercial and industrial loads.
3. Emergency DR programs: costumers can voluntary reply to an emergency signal during reliability-triggered events receiving payment for the service.
4. Capacity market programs: customers receive capacity credits commensurate their load reduction capacity and extra credit if they cut their load in an emergency condition or peak demand [11], [12].

DSM can bring a wide range of benefits, from economic benefits to the power industry and the customers to environmental benefits.

In the list of the economic benefits it can be quoted:

- The reduction of the peak demand that reduces the investment in generation, transmission and distribution in systems which will be used only a few hours a year;
- The providing of ancillary service;

- A potentially decreasing in the volatility of the demand and the reduction of transmission and distribution losses.

Environmental benefits derive also from peak demand reducing and ancillary services providing because usually the power plants which provide these services give a significant contribution to GHGs emissions, moreover with these conditions, there isn't the necessity to build new power plants or electricity lines [13].

2.4. BASELINE CALCULATION

Any DSM program that requires a reduction of the "business as usual" load needs a baseline to measure the change in consumption. The baseline is an estimation of what the consume load profile of a customer should have been during a day in absence of a DR signal; reasonably the baseline should match the real consumption before the curtailment and the difference between the baseline and the power measurements during a DR event define the amount of the load reduction.

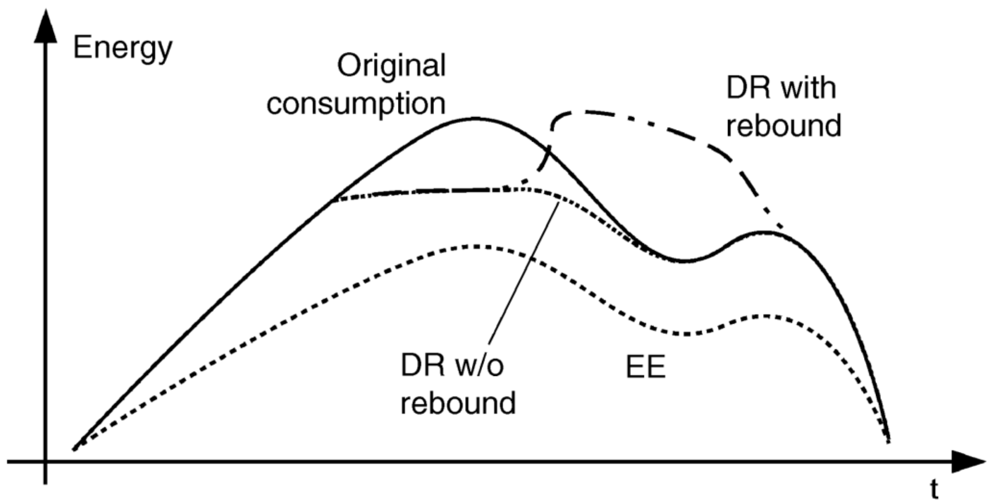

Figure 5 Baseline importance in DSM events [12]

Figure 5 shows that a good baseline determination is necessary to define the amount of energy saved; in the figure three events are reported: the comparison between an Energy Efficiency event and the baseline help to determine the amount of energy saving in all the day through the use of appliance with better performance, also the comparison between a

DR curtailment (w/o rebound) or shifting event (with rebound) and the baseline helps to determine the amount of energy saved or shifted and, depending on the incentive programs, the gain of the customers for the participation at the event.
The determination of the baseline it's more important in incentive-based programs than in price-based programs; in the last one the gain of the consumers is related to the price of the electricity during the usage and the possibility to reduce the load, in incentive-based programs the gain depends on the amount of the load reduction during the curtailment period and a contract is stipulated between the customers and a grid operator in which the baseline and adjustment calculation method is agreed.

Defining an accurate customer baseline is not so easy because usually a single customer has high volatility in energy consumption and every day and every hour it is a bit different from the others due to different necessities, moreover the local weather causes variations in the load. There are two main methods to estimate a baseline: average based and regression-based.

Average estimation methods are the most common because they are simple to implement and promoting transparency in the process; usually to calculate a baseline with these methods a ten weekdays window prior an event is considered, composed by non-event days and then an hourly average of some of these days could be done. There are several options to choose a proper number of days: *Pjm Economic Baseline* suggests an average of the 4 or 5 days with the highest consumption, *Casio Standard Baseline* utilizes all the ten days, *ERCOT Middle 8 of 10* discards the highest and the lowest consumption days in the window and then calculates the average of the remaining eight [14].

Regression-based estimation methods are better than average-based methods because they can take into account of some factors into account that cannot be considered in an averaging, in simple words a regression model determines a relationship between some observable factors and load which usually include day type, the hour of the day and weather. However using a regression estimation is more complicated to implement compared to a simple averaging and also requires more data that involves an higher risk to include days or factors which are different from the conditions of the curtailed day, moreover if in the regression model factors which don't influence the consumer's load are included, the model can be noisier than one with an average estimation. For example, using a weather model in a non-weather sensitive customer could give a worse baseline than other models do [15].

The calculated baseline is just a provisional one, many baseline calculation methods include also an adjustment method to fit better the forecast load profile with the real consumption measures.

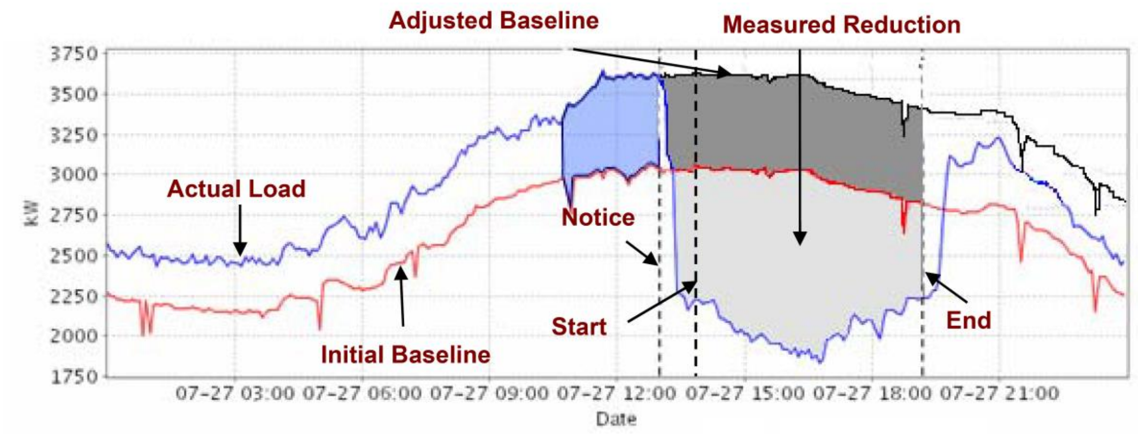

Figure 6 Example of baseline, adjustment and performance measurement [16]

In Figure 6 the calculated baseline (red line) and the actual load (blue line) are reported, calculated baseline needs to be translated of an adjustment factor to be used as a reference for a good determination of the load reduction. Without this correction the amount of energy saved would be higher than the expectations of the grid operator but, on the other hand, the customer's gain would be inferior because it's based on the difference between the baseline and the real load profile. There are two possibilities to calculate the adjustment factor to add to the initial baseline to obtain the adjusted baseline (black line): additive adjustment and scalar adjustment.

To operate an additive adjustment it is necessary to calculate a constant which will be added to the initial baseline for each hour of the curtailment period, in the simplest way the constant is calculated as the difference between the actual load and the provisional baseline for some period prior the curtailment.

In the scalar adjustment, the initial baseline is multiplied by the constant for each hour of the curtailment period; in this case, the constant is equal to the ratio of the actual load to the provisional baseline for some period prior the curtailment.

Usually the period prior to the curtailment that is taken into account involves the two hours before the DR event notification; in this way there is less opportunity for the consumers to manipulate the baseline by boosting load before the curtailment in order to have higher gains and there is less probability that the baseline can be underestimated due to an anticipated load reduction. Moreover, considering the hours next to an event the adjustment has a more accurate basis to be calculated [15].

In [17] it is investigated how to determine the characterization of the baseline approach that better fits the consumer historic consumption, in order to define the expected consumption in absent of participation in DR event and then determine the actual consumption reduction.
Normally the approaches to define the baseline are defined and they are applied to all the customers without a characterization of the users' behaviour, however every consumer has a different consumption pattern so, during the enrolment phase in a DR program, it would be advisable to determine the baseline approach that better characterizes it by analysing the historical consumption data.

A commonly used baseline method, proposed by EnerNOC [16], provides that, for a given time interval [t], initial baseline [b] is calculated as the average interval demand among the five highest energy usage days out of the prior ten non-event days, calculated in each interval during the DR event:

$$b_t = (C_{td1} + C_{td2} + C_{td3} + C_{td4} + C_{td5})/5 \qquad (1)$$

Then an adjustment factor is calculated, for each time interval t, as the difference in the observed demand and the estimated baseline, for a calibration period starting two hours before the event notification, with a minimum adjustment of 0:

$$a_t = max\left\{\frac{[(C_{t-1} - b_{t-1}) + (C_{t-2} - b_{t-2})]}{2}, 0\right\} \qquad (2)$$

The consumer participation or total performance [p] is measured as the integrated difference between the sum of the baseline [b] and the adjustment factor [a] less the consumption [c] for each interval [t] over an event period beginning at time [0] and ending at time [e]:

$$p = \sum_{i=0}^{e} (b_i + a) - c_i \qquad (3)$$

The methodology proposed in [17] considers a baseline window, defined as "w", that indicates the non-event days before the event that are considered and the number of highest consumption days "m" in order to define the best combination that better characterize the historic consumption data of that consumer comparing the results obtained with the adjustment window "a" composed by the two periods before the event. In this case, the adjustment factor is additive.

The baseline window considers from 6 to 14 days and the number of highest days considered is between 3 and 6. For each value of "m", an analysis with different values of "w" is done and the best result is the one in which the adjustment value is the lowest.

Defining a good baseline it's very important for this study because with a good baseline we can determine the performance of the user very precisely and then define the quality of his responsiveness.

2.5. AGGREGATORS

In the emerging power market structures, there are opportunities for third-party aggregators to provide demand-side services to multiple consumers. An aggregator is an energy service provider between the utility and the consumers. The aggregator has as objective to shave the peak demand as well as support the utility in supplying uninterrupted and high quality power to commercial, industrial and domestic as well as electric vehicles during peak hours with ancillary services [18]. The number of aggregators operating in energy markets has been on the rise since the end of the last decade [19].

DR programs, mainly in the residential sector, involve a large number of medium and small producers and consumers or, moreover, prosumers (consumers that produce, use and sell their electricity). To design an efficient demand response mechanism the system operator can't control all of them and, if every small user takes part in the electricity market the managing of the market itself would become very chaotic and complex, but the full implementation of DR also requires the participation of small size resources in electricity markets' DR programs, usually oriented to large size resources [20]. The need for an aggregator entity arises as a solution for the participation of small-size consumers when considering that it can create a virtual energy amount that enables enough energy to be negotiated in the market by the aggregators [19]. The aggregators play a role as Virtual Power Players (VPPs), they aggregate small energy resources, including DG and DR, making the participation in electricity market products intended for the participation of large players possible.

Aggregators act as mediators/brokers between users and the utility, so the aggregator is like a retailer which buys electrical energy in the day-ahead energy market and the utility also makes an ex-ant validation regarding the price bid by the aggregator. On the other hand, the utility provides information in advance to the aggregator about expected demand curve or particular peak period. Then, utility directs the aggregator that it has to curtail a certain bulk of power whenever it requires [18].

The aggregators, after an analysis of the consumer's load profile, conciliate the energy reduction of the consumer with its participation in the energy market. In this way, a cooperative relationship between the aggregators and the resources is achieved. Thanks to the presence of smart power meters the aggregators can easily know the consumption and the production of each user and the interaction between them can be practised. The aggregator has also to control the load of the costumers and develop a systematic strategy control that it achieves an earn for both of the parties. The aggregator has to:

- Maximize its revenue;
- Minimize the utility's operational cost;
- Provide DR services to the operator;
- Provide incentives to the consumers;
- Guarantee a reduced electricity bill to the end-users.

Each aggregator tries to shape the load pattern of its users and receives compensations for the cost savings incurred to the operator due to this shaping.

The objective of the aggregator "j" is to maximize the net profit by solving the following optimization problem:

$$\max \lambda_j \Delta c(p_j, P_{-j}) - \sum_{t \in T} p_{jt} d_{jt}(P_j) \tag{4}$$

The first term corresponds to the reward received from the utility and the second term is the compensation provided to the customers [18], [21].

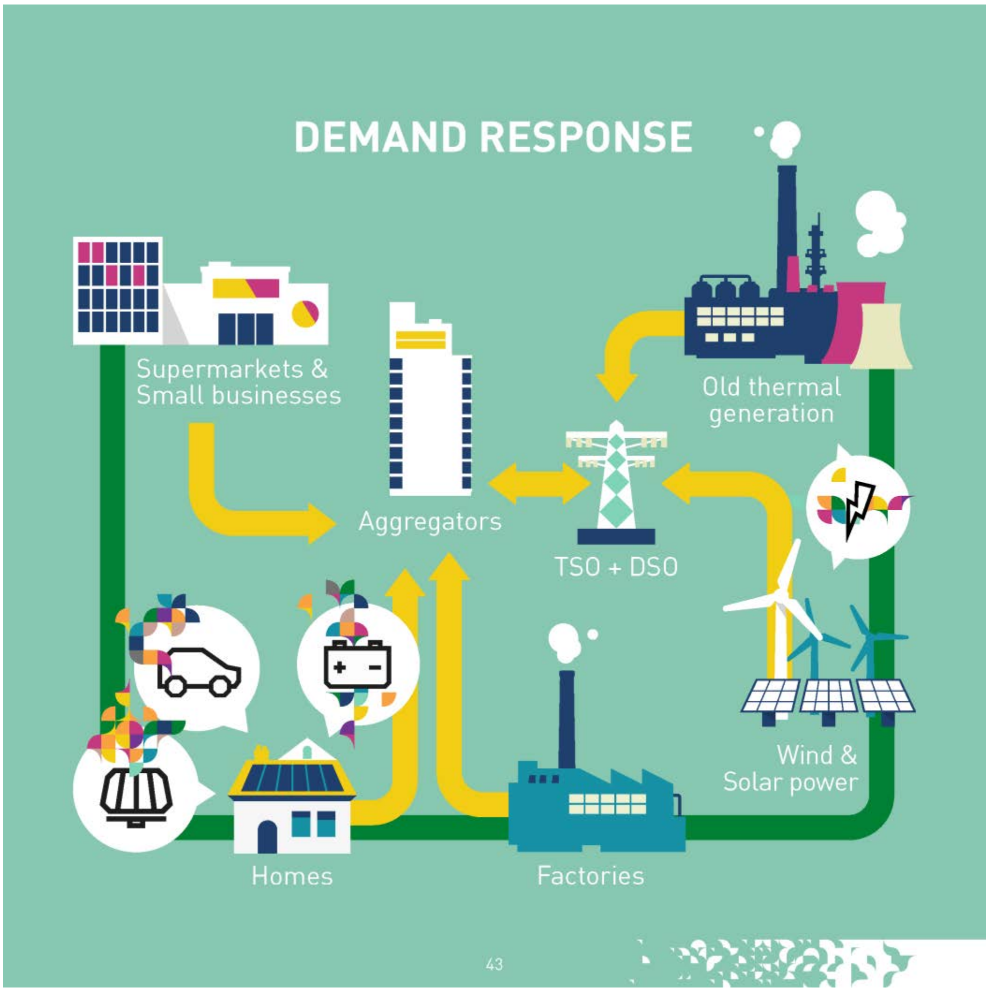

Figure 7 Communication role of aggregators [22]

There are several ways in which the interaction between aggregator and consumers is possible and they reflect the different types of DR programs [18]:

1) Direct load control (DLC): conventional DSM technique according to which the load is controlled by the aggregator at any time but in exchange, the consumer is not rewarded at all;
2) Price based control: it's the main strategy. By this strategy the consumer may be rewarded in many different ways, the most common is that the consumer would

gain fixed price against the load reduction otherwise, most of the aggregators, are offering dynamic pricing mechanism and thus the consumer would be rewarded with the price based on real-time electricity market;

3) Incentive based control: this method represents an opportunity for developing nations that are planning or implementing a smart network, incentive-based pricing mechanism effectively caters the social issues like the consumer satisfaction and the privacy than price-based methods and it also enables the customer to directly interact with energy market by bidding against its power curtailment.

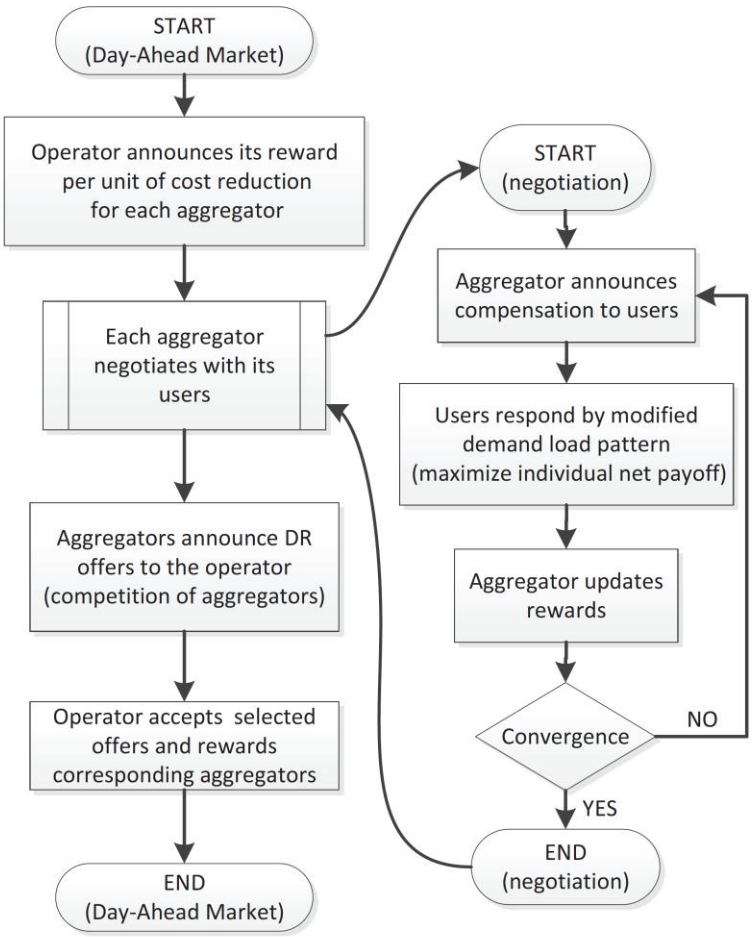

Figure 8 **Operation scheme of aggregators** [21]

Figure 7 shows how the aggregators are linked to other parts of the network, between utility and aggregators there is a bi-directional flow of information because the utility gives to the operator the demand profile and set the amount of energy that should be moved to minimize the operational costs and the aggregators inform the utility about the power schedule of the customers and how they can reply to the electricity consumption change request.

Figure 8 gives a summary of how an aggregator works to manage the request of the utility and how it is linked to the electricity market. The aggregators, once defined a schedule, compete in the main market and the ones with the best offers have the reward.

2.6. CLUSTERING

The aggregators provide to aggregate all the resources that they have to control in groups with similar characteristics using a clustering process; this allows them to work with a lower number of different users and simplify the management.
A categorisation based on the type of activity and commercial codes are generally not efficient for representing the specific aspects of the electricity consumption so, the core of the categorisation process is the use of appropriate clustering techniques to perform customers grouping [23].

The two main clustering techniques are known as *hierarchical clustering* and *partitional clustering*.

Hierarchical clustering

The hierarchical techniques use algorithms that generate a cluster tree by using heuristic splitting or merging techniques. A cluster tree is defined as "a tree showing a sequence of clustering with each clustering being a partition of the data set". Hierarchical algorithms can be of two different typologies: divisive or agglomerative. In the divisive hierarchical algorithms, all the patterns are assigned to a single cluster, then splitting is applied to a cluster in each stage until each cluster consists of one pattern. In the agglomerative algorithms, instead, each pattern is assigned to one cluster and the two most similar clusters are merged; the process is repeated until all the patterns are assigned to a single cluster [24].

Figure 9 shows how the hierarchical method split the amount of data in clusters.

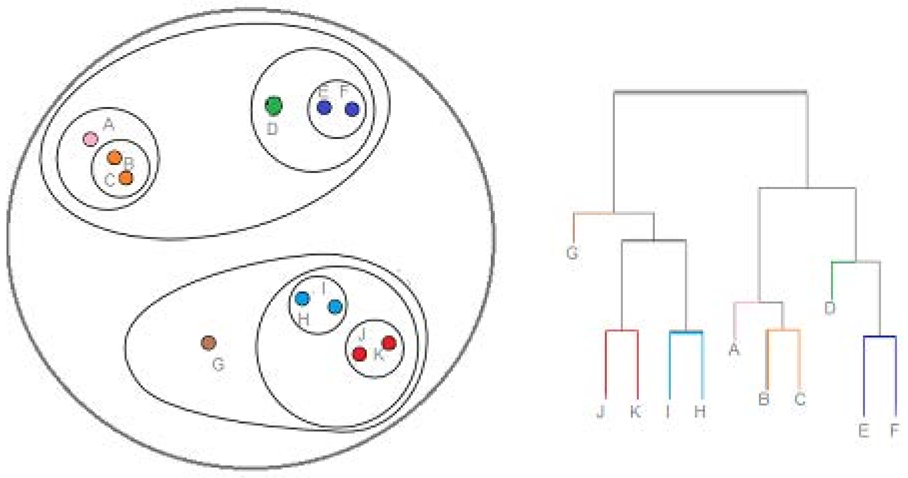

Figure 9 **Hierarchical clustering diagram** [25]

Partitional clustering

The partitional technique divides the data set into a specified number of clusters trying to minimize certain criteria (e.g. a square error function) and can, therefore, be treated as optimization problems. Partitional techniques are more popular than hierarchical techniques in pattern recognition because they are not so much computationally expensive and they aren't static, i.e. patterns assigned to a cluster can move to another cluster. The main disadvantage is that the number of clusters is defined before the calculation, so a preliminary analysis of the fair number of clusters that are required should be done.

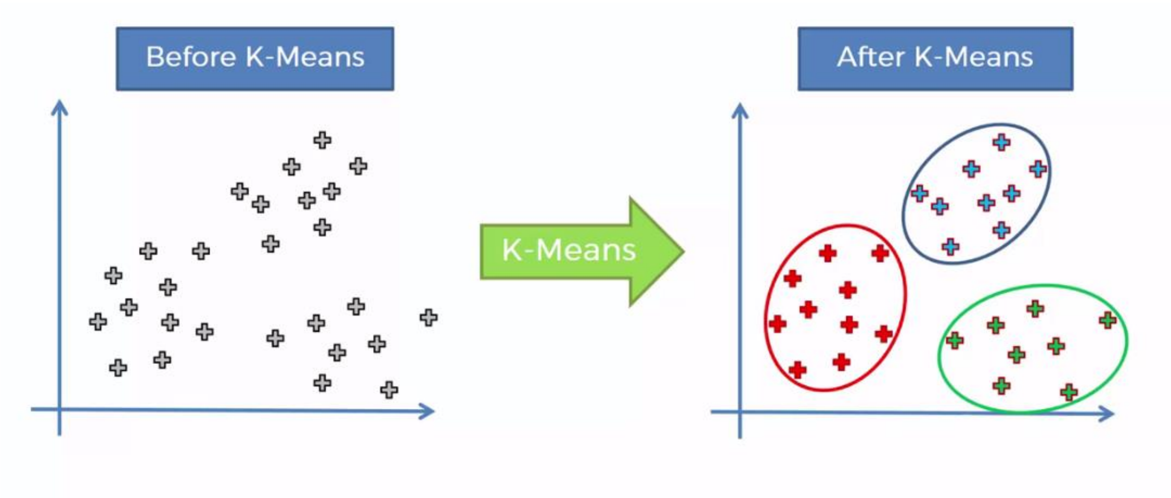

Figure 10 **K-means clustering process** [26]

The K-means iterative approach is the most widely used partitional algorithm. The algorithm aims to minimize the intra-cluster distance, it starts with K centroids (initial values for the centroids are randomly selected or derived from previous information) and then each pattern in the data set is assigned to the closets cluster (i.e. closest centroid). The centroids are recalculated according to the associated patterns and the process is repeated until the convergence is achieved [24].

Figure 10 shows how k-means clustering works: after defining the centre value of the clusters, all the data points are added in the cluster that they are closer.

3. Consumers' response to DR Events

This chapter wants to focus on the response of the consumers to the request of the aggregator to join to a demand response event. The reasons that could cause an unsuccess are investigated. Further, the questions "how the response of the user could be" and " how to evaluate it" are analysed.

3.1. DR events' failure

Assuming that the answer to a demand response call is not mandatory and it is a customers' decision if participating or not, and in which quantity, to a DR event, the prediction of the consumers' participation is not so easy, and the participation cannot follow the operator's expectations. Usually, consumers don't know very well the potential DR benefits, and this conducts them to not take up DR opportunities. As reported in [27] every DR program has its level of response that can vary from over 80% to 0% reduction compared to the reference load. Figure 11 shows that the program with the highest level of response is the DLC program probably because it has a high level of automatization and it is the grid operator that controls the load reduction. Consumers who use more dynamic programs, like price-based programs, show a very wide range of response with a high level of uncertainty and they are affected by factors such as automation, price, appliances types and climate.

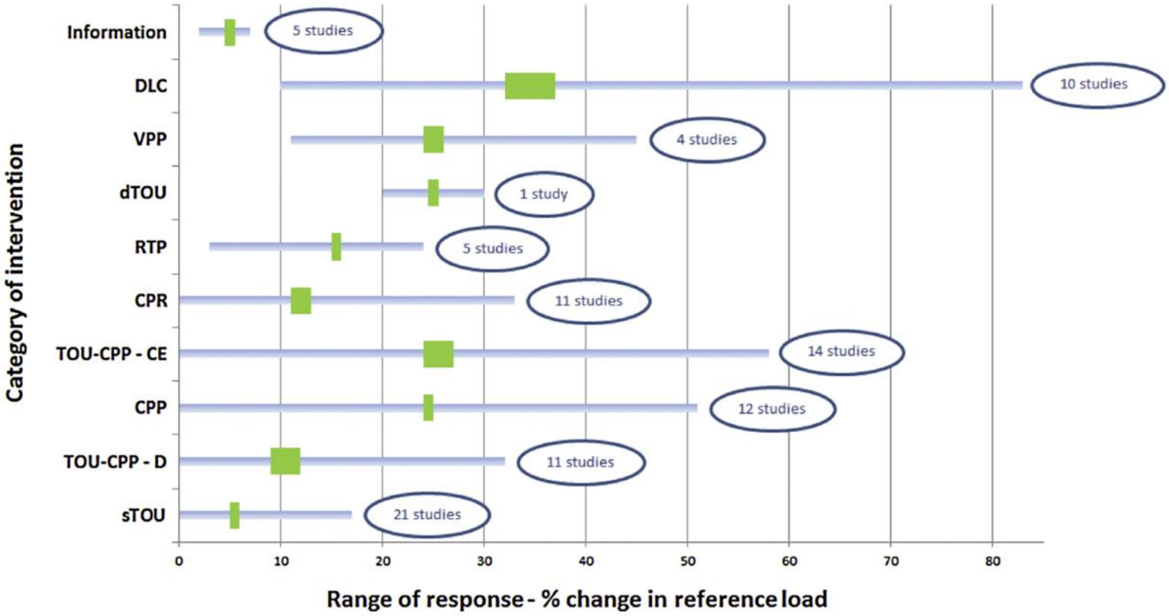

Figure 11 Range of response in different DR programs [27]

These programs involve the consumers in processes which were usually managed by electricity producers, so many users barriers must be overcome. Some consumers barriers concern [28]:

a) Consumer knowledge: many people have a very little knowledge about how the electricity market works and about the relation between appliances usage and electricity consumption, moreover utility companies usually don't invest enough in advertising about existence and benefits of DR programs. Out of these conditions, small participation in voluntary programs results and the response in mandatory programs is usually lower than the desired. A solution to increase the participation and the response could be combining education with mandatory participation in a dynamic price system;
b) Availability of technology: as electricity users need to know the price of the electricity, so utility providers need to be able to precisely know the real-time consumption of their customers to guarantee the right incentives and apply correct

tariffs. Smart meters must be large implemented but the high costs and the uncertainty about the real advantages often slow down the spread;

c) Information feeds: to obtain information about prices and consumption could be very hard for the customers, then they aren't encouraged to save energy even in the presence of money savings because the cost to have this information and understand them is higher than the economic benefits. If pieces of information are streamed directly to customers with a live feed and they can watch them in a simple home-display, we may expect a higher response and better energy-saving behaviour. Even without dynamic prices or DR programs, we could expect that seeing the amount of energy used improve energy usage;
d) Response fatigue: on a dynamic tariffs program, customers must actively respond at price changes rescheduling the use of their electrical appliances or shifting the use in off-peak period. As electricity is supplied continuously and without changes in quality, consumers use it when they need it, in a multiple price program this habit should change in order to utilize the electricity in a more convenient period. However, if more tariffs are in use, or if the price varies frequently, the users have more times to reschedule their consumption and this could cause stress and a refusal to adapt to this type of price schemes. The transition to a dynamic prices program must happen slowly and gradually to allow the customers to adapt and consolidate new habits.

In general, if the costumers have access to additional information, as in-home display indicating the current price level or the amount that could be saved, or automation systems, average responses are greater than those for pricing alone [27] .

An interesting study was conducted by Paetz & Co. on the user acceptance of DR programs [29]. In this study four test-residents moved into a smart home for several weeks and different solutions were tested in three phases: first an extensive feedback on the resident's electricity consumption and the power generated by the photovoltaic system, the second part tested the user's reaction to different electricity tariffs in load shifting instead in the third part an automated energy system was introduced. The smart home was equipped with intelligent and non-intelligent appliances integrated each other with an Energy Management System (EMS), smart meters to measure the electricity consumptions and several screens, called Energy Management Panels (EMPs), where information about consumption, power production, electricity price or other useful data can be shown. The EMS or Home Management System (HMS) should be able to manage effectively the total consumption, distributed generation, EV and the participation in demand response events; moreover, it should consider the consumption efficiency, the minimization of the energy bill and the required comfort levels in the operation context. To achieve these results the EMS has to include the ability to autonomously acquire knowledge on the user's behaviour adjusting the consumer's preferences during the management process, improving the global system performance and the consumers' satisfaction [30].

The first phase was focused on the familiarization of the users with the smart home, all of them were interested about their electricity consumption and they had fun to turn on different appliances, checked their consumption and cross-checked the appliances during the day. After the first period, they had better knowledge about the consumption of each appliance and they used to consult the EMP only if a new device was in use. Over time the interest in single appliances was outweighed by the interest in the total household consumption and its history. It is common opinion that the feedback doesn't change their daily habits but it induced changes in their perception and their attitudes towards electrical demand.

In the second phase, a dynamic price system was introduced. The first tariff in use was a day-and-night with fixed time zones between 8:00 and 20:00 hours; over 40% of the test-users consumption was in the low-price zone. Now the EMP is mainly used to know the electricity price for the upcoming 24 hours. Also, price systems with three and five different price zones were implemented; as a result, the users started to be more interested in the general price level (high, medium, low) instead of the specific price. Most of them, in fact, don't get the value of the saved money using an electricity price instead of another but they try to concentrate the main consumptions in the low-price zones. Some appliances as stove, coffee maker, television, that are theoretically shiftable, weren't shifted by the test-residents due to their comfort and entertaining services; also the using of appliances as the dishwasher, washing machine o dryer was not shifted into night times because they were perceived as too noise-disturbing. Users liked the test period with five price-levels because they felt to have more opportunities to consume electricity in low-medium price periods, as the time length of each price-level is shorter than the other price systems, but this involves a more complex managing of the use of all the appliances. In this context, most of the testers required the presence of an automated managing system. At last, emerged how the best results in terms of low-price electricity usage were obtained during the weekend when the users are more flexible and they can better manage the energy consumption.

In the third phase, an automated EMS was activated. The automated EMS helps the users to schedule the use of the appliances according to the price of the electricity. During the test phase, no remarkable increase in load-shifting can be reported due to the use of this system as the appliances with smart functionalities were the same as already shifted before.

This means that a good education of the consumers on the optimization of the use of the electricity and the presence of a properly EMS can be enough to achieve good results in demand response.

3.2. AUTOMATED DEMAND RESPONSE

Commonly the DR activities are manual and require people to first receive the DR signal through emails, messages or calls and secondly people to act on these signals to execute DR strategies.

The different levels of automation in DR can be defined in these three approaches [31]:

- *Manual Demand Response*: involves a labour-intensive approach such as manually turning off or changing comfort set points at each appliance switch or controller;
- *Semi-Automated Demand Response*: involves a pre-programmed demand response strategy initiated by a person via a centralized control system;
- *Fully-Automate Demand Response*: doesn't involve human intervention but it is initiated at a home, building or facility through receipt of an external communications signal, the receipt of the signal initiates pre-programmed demand response strategies.

Now the Fully-Automate Demand Response approach also defined as Auto-DR (ADR) is investigated.

ADR is being applied in all consumer sectors, including residential and industrial; however, the greatest potential is in commercial buildings, both individually and collectively as campuses or hospitals [32].

Most of the fully automated strategies can be split into these categories [32]:

- Heating, ventilation and air conditioning (HVAC): global temperature adjustment, variable fan speed, chilled water temperature increase and others;
- Lighting: common area or office area light dimming, turning off lights;
- Other actions are antisweat heater shed, fountain pump turnoff and noncritical process shed.

Is important to underline that, when an Auto-DR strategy incurs, the homeowner or the facility manager should be able to override the DR event if the event comes at a time when the reduction of the end-use services is not desirable; moreover it’s also important to point out that if the appliances normally involved in the Auto-DR strategy are already off before the beginning of the event the power reduction won’t follow the expectations and the load shed could fail for that user.

Once installed in the customer’s site, the ADR system communicates with the customer’s energy management system EMS to implement the appliance curtailment strategies that the user pre-selects based on his priority. The energy savings and the demand reduction depend by many factors such as the chosen curtailment strategies and the amount of customer load that is under ADR control. The ADR components include hardware and software from obtaining price signals and notifications from utility trough an ADR gateway [33]. The core of ADR it’s a component called Demand Response Automation Server (DRAS); it plays a crucial role in automating the interactions between the Utility/ISO and the DR program participants, in fact, the DRAS is designed to generate, manage and track DR signals between Utilities/ISO’s to aggregators and end-use customers and their control system that perform various shed strategies in response to the DR signals [34].

Utilities start scheduling a DR event and then a notification signal is sent for the upcoming event, the signal is received and processed by the DRAS. Now the signal is sent to a controller, located in the customer property, which premises the connection with the EMS of the facility. Once the signal is received, the EMS uses the priority list of pre-selected curtailment strategies according to the preferences of the users.

The implementation of ADR brings new challenges to utility companies because they are responsible for the supply-demand balancing of the distribution network then they need to make appropriate decisions on optimal managing of a DR event. To guarantee the efficient implementation of ADR there are many technical challenges which have to be considered [32]:

- *Different types of consumers*: ADR involve different consumers from different segments with different consumption profiles. Every facility has a characteristic load profile that has to be individuated; as for industrial or commercial utilities could be easier to define a load profile, more difficult could be determining it for the residential users due to the extreme variability of the consumption during the week, could be easy, for this kind of consumers, refer to a larger area such as the one served by one substation;
- *Prediction of baseline*: the estimation of the load that can be shed required a good baseline forecast, as described in 2.4 several methods to do that are available;
- *Modelling of lead and rebound effects*: if the DR event is planned a day, or more, in advance it’s important to accurately predict the lead and rebound effects due, for example, to a pre-cooling process occurring several hours before the event starting time or a higher electricity consumption after the event to lead the building in the usual comfort conditions. Figure 12 shows these effects.

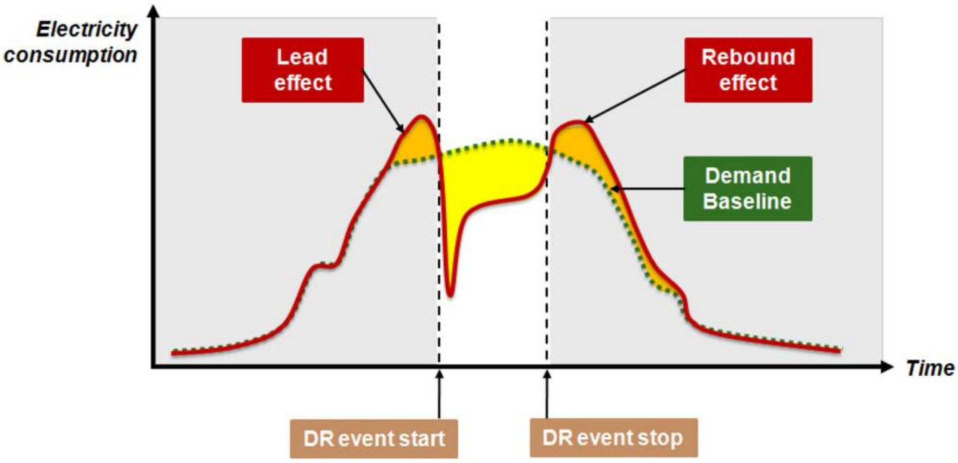

Figure 12 Lead and Rebound effects [32]

3.3. EVALUATION OF DEMAND RESPONSE EVENTS

To understand if a DR event had a positive result and to quantify the level of success or unsuccess of that event it is reasonable to define several parameters that can be useful to make an evaluation, a comparison or a rank of different events.

In 2.4 a first evaluation parameter has already been defined. In equation (3) the performance "p" as the difference between the adjusted baseline and the electricity consumption during the event was defined.

$$p = \sum_{i=0}^{e} (b_i + a) - c_i \tag{5}$$

The performance as defined previously is useful only to compare the electricity saved in events with the same duration. If we want to compare, through a performance index like that, events with different durations the capacity-setting performance "p_{avg}", given by the average performance during all intervals of the DR event, is defined [16] .

$$p_{avg} = \frac{\sum_{i=0}^{e} (b_i + a) - c_i}{e} \tag{6}$$

In [35] several Key Performance Indicators (KPIs) for measuring electricity consumption and peak reduction or KPIs for measuring the demand variation and reshaping after DR and others are defined.

Primitive KPIs

As primitive KPIs the energy consumption "e" can be defined by measuring power consumption over time:

$$e = \int_{t_i}^{t_f} p(t)\, \partial t \tag{7}$$

The average power over the period is then:

$$\bar{p} = \frac{e}{t_f - t_i} \tag{8}$$

The power variance over that period is:

$$\sigma_p = \frac{1}{t_f - t_i} \sqrt{\int (p(t) - \bar{p})^2 \partial t} \tag{9}$$

The power variance indicates how much the power consumption is differing from the average; if the load is distributed smoothly over time, the difference between the peaks of the power consumption $p(t)$ and the average is small, leading to smaller variance.

A KPI for the prediction can be the variance σ_Δ of the Δ_{PA} where Δ_{PA} is the difference between the predicted power consumption p_P and the real one p_A; the greater the variance, the worse the prediction.

$$\sigma_\Delta = \frac{1}{t_f - t_i} \sqrt{\int (\Delta_{PA}(t) - \overline{\Delta_{PA}})^2 \partial t} \tag{10}$$

KPIs for Peak Reduction Quantification

Generally, the purpose of a DR program is to reduce the peak demand. The peak reduction can be measured via these ratios:

- Change in the total electricity consumption per day: the original consumption is measured before starting the DR program and the new consumption is measured after the DR event.

$$\frac{orig.consumption - new.consumption}{orig.consumption} \tag{11}$$

- Change in total electricity consumption during the peak hours.

$$\frac{orig.peak.consumption - new.peak.consumption}{orig.peak.consumption} \tag{12}$$

- Change in total electricity consumption during the off-peak hours.

$$\frac{orig.offPeak.consumption - new.offPeak.consumption}{orig.offPeak.consumption} \tag{13}$$

KPIs for Demand Variation Analysis and Demand Reshaping

The demand variation is defined as the subtraction of the real demand to the baseline. A typical way to define how a DR event's performance leads to the reshaping of demand profile is the RMS (Root Mean Square) of the difference between baseline and real demand; this value is then compared to the RMS associated to the baseline, to assess the performance of the DR event.

To determine the quality of the response from the costumers several KPIs related to demand dispatch such as uncertainty or variation became important. To analyse the uncertainty of demand shed the time series that records the performance of a customer can be considered indicated as $\{X_1, X_2, \ldots, X_n\}$ and evaluate the demand reduction using:

- Variance: Var(X). The greater the variance, the greater the uncertainty;
- Entropy: Discretizing X in k bins with different thresholds $b_0, b_1, \ldots, b_k$ and let $p_k=\Pr(X_i \in [b_{k-1}, b_k])$. Then $H(X) = -\sum_{i=1}^{k} p_k \log(p_k)$ is an estimation of uncertainty in reduction; the greater the entropy, the greater the uncertainty;
- Risk: let $r_k = \Pr(X \geq b_k)$ i.e. the probability that the customer's reduction is at least b_k. r_k is an indicator of the uncertainty or risk associated with demand reduction of a customer; lower probability implies higher risk.

4. PROPOSED METHOD

Now, that all the notions necessary to understand the issues which have been investigated were furnished, it is possible to focus on the main topic of this work.

The participation of the consumers to a DR event is not mandatory and also the amount of electricity that they can shed isn't always the same and it depends from several factors such as temperature, day, hour, season, occupation of the building, availability of the user and many others.

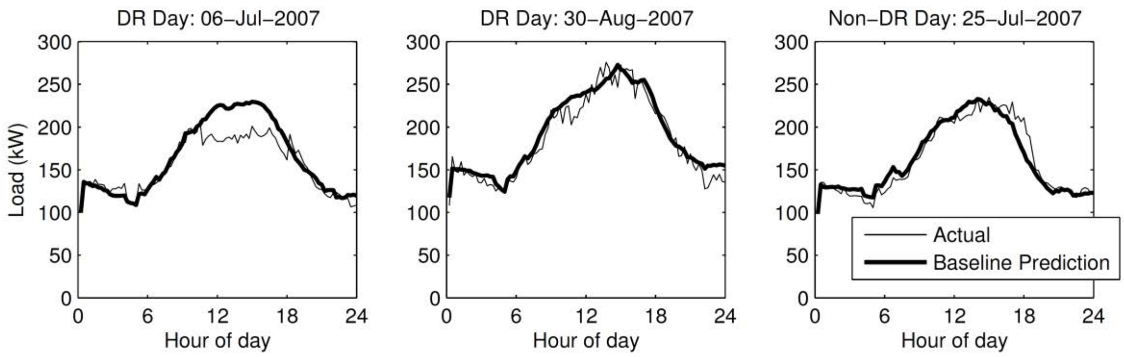

Figure 13 Actual and baseline-predicted demand for an office building on three different days [36]

The same user in the same building can reply in different ways to a DR event due to a different context as shown in Figure 13. The proposed method wants to analyse and classify the response of every single user to have a description of its response which could help the aggregators in the managing of the demand response. The method is focused on an ADR program, but it can also be extended to other programs.

4.1. METHOD'S OVERVIEW

The method aims to define the behaviour of the users in a demand side managing program, in different contexts, in order to identify when each customer is more useful to the electric system and how much it can influence the objective of a demand response event.

The first step is to obtain data about electricity consumption through a smart power meter. A smart power meter collects the information about the electricity consumption of a user and sends these data to the grid operator who can calculate the load profile, manage the bill or conduct useful analysis about the behaviour of the user or a group of consumers [37].

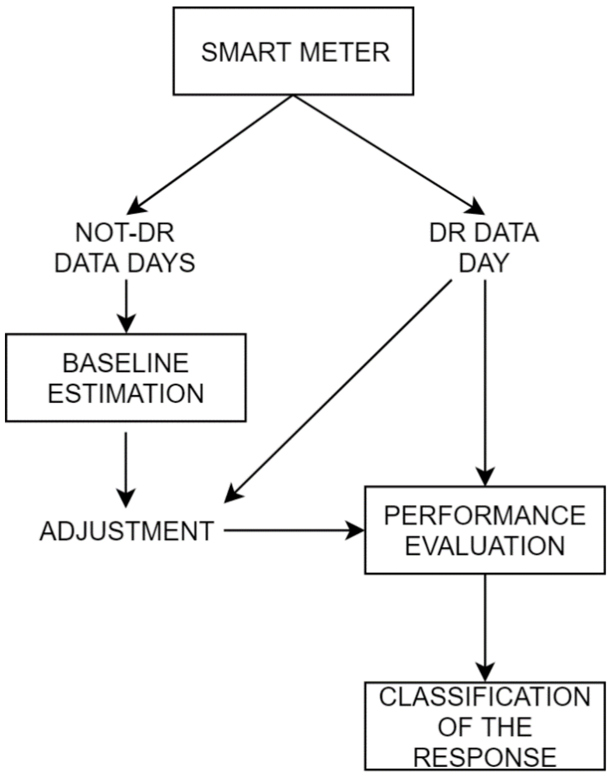

Figure 14 Structure of the method

Figure 14 gives a basic view of the structure of the method which is presented.

After the data collection, it's necessary to define the load profile of the user; to do that the technique described in 2.4. can be used for the baseline calculation. The forecasting of a baseline that is very similar to the real load profile is fundamental to have a good evaluation of the performance that the customer is able to achieve and then it is also very important for the characterization of the consumer's response. The data of the not-DR days are used to calculate the baseline, using the consumption's data of the DR day an ex-post analysis is done: the baseline is corrected, if necessary, to fit better the consumption measured in the day of the event and then many performance parameters can be calculated. To conduct this analysis only the baseline, the electricity consumption in the day of the event and some information useful to describe the context in which the DR event was performed are necessary.
After that, the response of the user can be characterized and it's possible to determine an optimal level of load shedding for the single user and the aggregators combining many consumers.

4.2. CONSUMERS' CHARACTERIZATION

In this section, the method is analysed in detail. To make the structure of the consumers characterization's method clearer are presented two schemes: Figure 15 and Figure 16.

In Figure 15 the first part of the method is represented, from the input data to the density distribution of the parameter considered.

In this section, a file must be given as input and it must contain information about:

- The date of the DR event;
- The time in which the DR event occurred;
- The duration of the event;
- The baseline;
- The electricity consumption during the day of the event.

Based on the date it is possible to identify the season in which the event occurred, the day of the week and the type of the day: it could be a midweek day, a day of the week-end or a special day in which there is a holiday or a particular event.

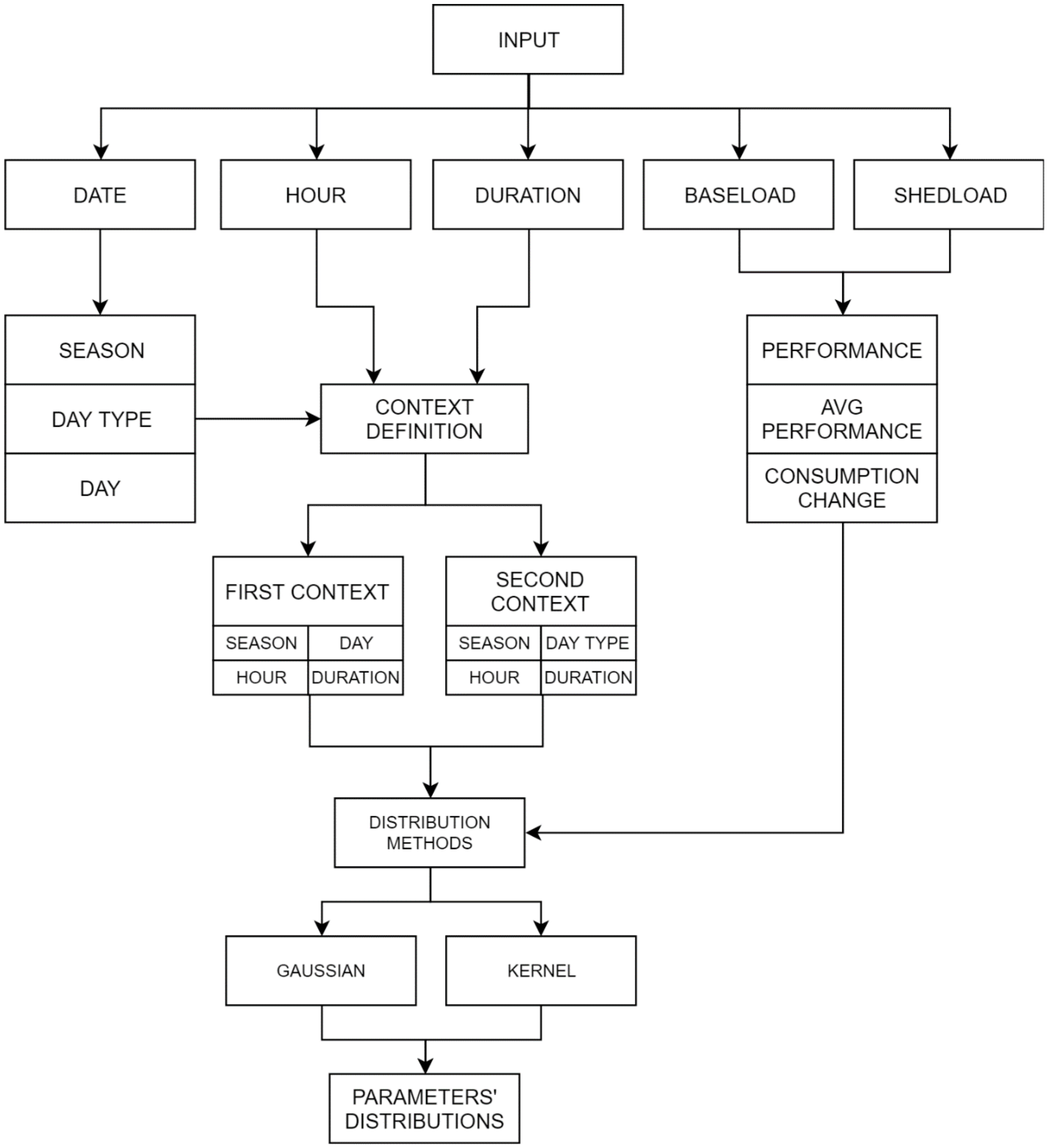

Figure 15 Definition's scheme of the parameters' distribution

Season, day or day type, time of the day and duration concur to define a context. These elements, in fact, have a high influence on the amount of electricity that the user is using and that could be available for the consumption reduction; the parameters of the events that happen in the same context are put all together in the way to have a database of events with the same proprieties that it is possible to analyse. There are two main contexts that differ only for the classification's day; this distinction is useful during the first phase of this kind of study because without the availability of many events in the same day it wouldn't be possible to calculate a quite accurate distribution; in this way all the events that occur in the same season, time of the day, with the same duration and during the midweek, for example, can be analysed together as, usually, the load profile during the midweek is similar in each day.

With the baseline and the consumption data of the event's day, which constitute the shedline as they represent a load profile in the day of the shedding, it is possible to obtain the parameters illustrated in 3.3; in particular the performance (5), the average performance (6) and the consumption's change (12) are considered. To obtain an accurate evaluation of the performance the presence of a quite high density of measures is also necessary, for example, a sample every 15 minutes can be rated as acceptable [38]. The baseline is supposed already known and its calculation isn't held as part of this method.

In the way that the method is structured the index that have more sense to be considered is the performance index, so now the focus is placed on the performance parameter.

Once that parameters and contexts have been linked, two distribution methods are applied to these data to understand how all the events with the same context are distributed and then a probabilistic value of the answer of the consumer can be obtained. Probabilistic modelling is commonly applied to fields as electric load or price forecasting but not many studies are conducted on load curtailment. A probabilistic characterization of the flexibility represents an interesting instrument to handle the risk that consumers are not always reacting to these DR signals as desired [38]. This approach aims to have a full picture of uncertainty and variability of each consumer's flexibility profile, i.e. the amount of electricity that can be reduced, by modelling the considered variables on the distribution functions. A common approach to do this is to assume a form of the conditional distribution and estimate its corresponding parameters from data.

The two distributions approaches that have been chosen are the Gaussian distribution and the Kernel distribution.
The Gaussian distribution is the easiest method that can be applied and usually, it describes well most of the events linked to the probability. Using the equation:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{14}$$

It is possible to obtain the density distribution of the parameter considered: μ is the mean of all the values of that parameter in a context, σ is the standard deviation of those values and *x* is a values' series composed of 61 values from μ-3σ to μ+3σ. This range was chosen to have a complete view of the distribution.
However, it may be not realistic in the field of demand responsiveness assuming normality in the distribution flexibility so, as the first approach, waiting for enough data for verification of the distribution shape, it is proposed to use also the Kernel method. This method is interesting because no distribution scheme is supposed and the curve is shaped depending on the data and the frequency that the values appear in different ranges.
The Kernel density estimator's formula, for any real values of x, is given by:

$$\widehat{f_h}(x) = \frac{1}{nh}\sum_{i=1}^{n} \boldsymbol{K}\left(\frac{x - x_i}{h}\right) \qquad (15)$$

Where x_1, x_2,..,x_n are random samples from an unknown distribution, n is the sample size, K (·) is the Kernel smoothing function and h the bandwidth [39].

Once the parameters' distributions are calculated, it's possible to define which is the optimal amount of electricity that is possible to obtain from each consumer.

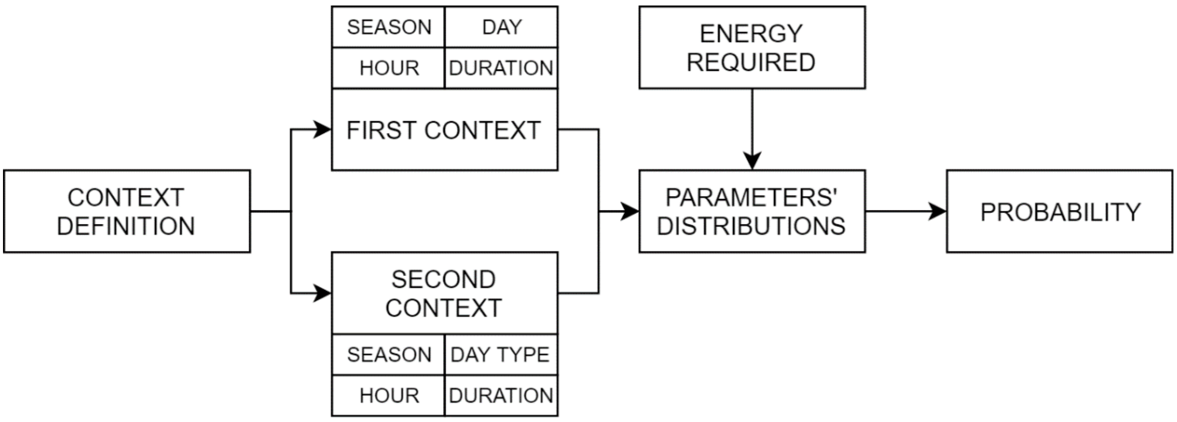

Figure 16 Probability's shed definition

In Figure 16 the second part of the customers' characterization is reported.

The objective is to know the amount of electricity that each user can reduce with a high probability. As the first step, it is necessary to define the context in which we are interested to investigate and then define the amount of electricity that we would like to obtain from that specific user.

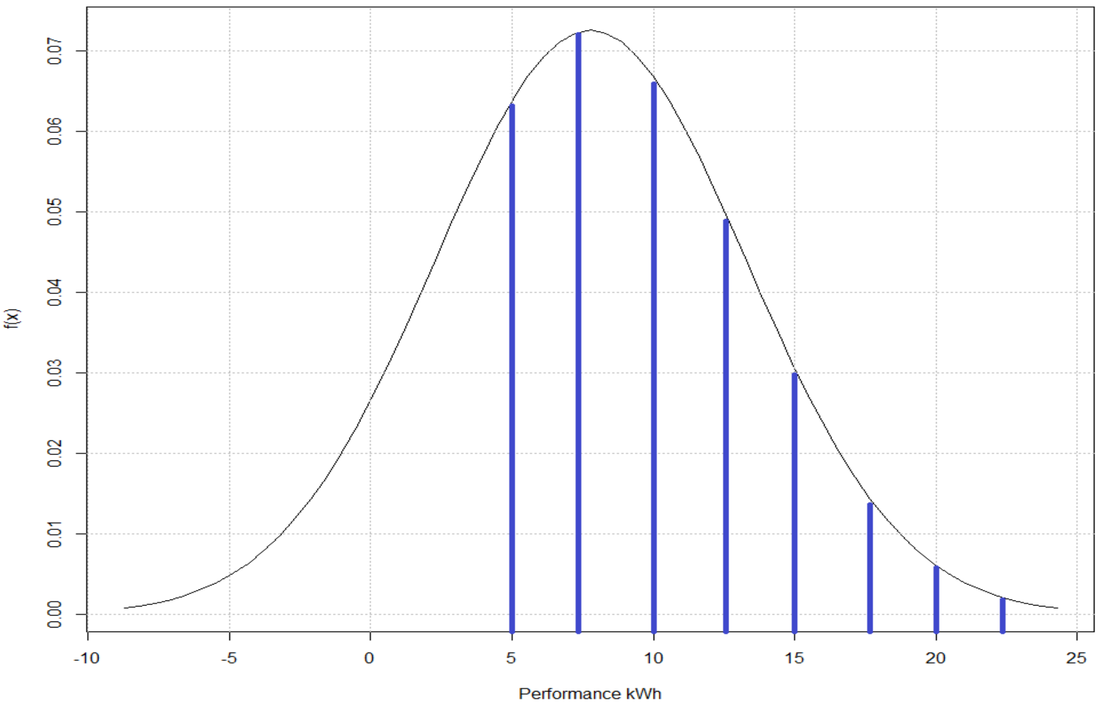

Figure 17 Probability's definition in a normal distribution

To define the probability to have a certain quantity of electricity that will be saved during a DR event from that user, it's necessary to calculate the area bounded from the distribution curve.

In a normal distribution, the probability is defined as:

$$Pr_{\%norm} = \int_a^b f(x)\,\partial x \quad \times 100 \tag{16}$$

Instead in presence of a Kernel distribution, the probability is defined as:

$$Pr_{\%kern} = \int_a^b \frac{1}{nh}\sum_{i=1}^{n} \boldsymbol{K}\left(\frac{x-x_i}{h}\right)\,\partial x \quad \times 100 \tag{17}$$

As an example, in Figure 17 the Gaussian density distribution of the performance of a user is shown: to know the probability to have a load shed of at least 5 kWh it is necessary to integrate the distribution from +5 kWh to +∞.

4.3. CONSUMERS' MANAGING STRATEGIES

Using the method described in the last section it is possible to obtain the characterization of the users involved in DR programs and to define, for each one of these users, the amount of electricity that is available for a DR event in a defined context. As in an ADR program the aggregators are the ones who sent a signal to activate the DR strategies, these pieces of information should be used by them to determine who are the consumers that better can perform the load shed request. In this way, the signal could not be sent to all the customers but only to a defined number and it's possible to have a quite good hypothesis of the real load reduction and to know which are the users to involve. Two methods were developed to obtain this objective.

Convolution method

The aim is to find the best combination of users that better fit the requests of the aggregators; to do that the sum of the probability density parameters that have been calculated in the previous step is required. In the probabilistic field it is well known that the probability distribution of the sum of two or more independent variables is the convolution of their distribution [40]. This method can be used with both of the probability density function previously illustrated.

Let f and g the density functions of two variables, the convolution is:

$$h(z) = (f * g)(z) = \int_{-\infty}^{+\infty} f(z-t)g(t)\,\partial t \qquad (18)$$

The convolution has the commutative propriety so it doesn't matter if the convolution between two or more users is done before or after the convolution with another user but, it's important to notice that, the users' order in which the convolutions are done influence the number and which user is involved.

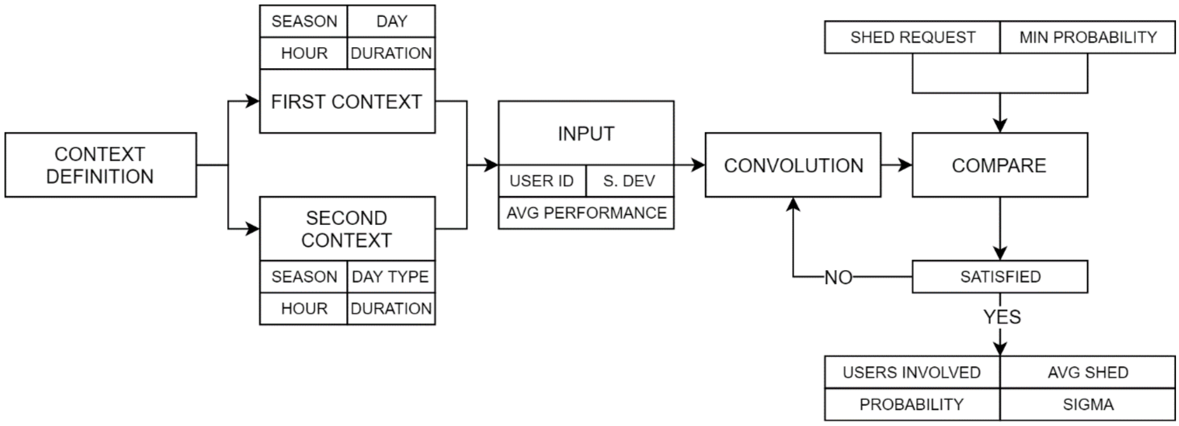

Figure 18 Convolution strategy for consumers' managing in DR events

Figure 18 presents the scheme of the convolution method: after defining the context in which the analysis has to be conducted, an input file, obtained from the previous steps, is going to be in use in the method chain.

The input file contains information about the users involved and for each user the value of the relative average performance and standard deviation. With this data, it is possible to calculate the distribution's values that can be used in the convolution. The users' order in the input file is the same with which the convolution occurs.

As it is possible to see from the scheme and as previously said, the users' order, with which the convolution occurs, influences the number and which user is involved in the event because when the aggregators' requests are satisfied the convolution stops. There are several ways in which the users can be ordered, here the ones that have been tested are reported:

- Standard deviation in increasing order: the standard deviation is an index of how the parameter's values are far from the average, the smaller the standard deviation, the higher the probability to have a new value not so different from the average. Doing a convolution with small standard deviation values leads to a convolution with a small standard deviation;

- Ratio between average performance and standard deviation value: in this case, there is a compromise between a good performance and a good standard deviation;

- Random: the aggregator can also decide to call the users randomly to give everyone the possibility to participate in an event.

After every convolution, the power that has to be cut and the probability to have this amount of power is compared with the request of the aggregators. If the requests are satisfied, the convolution process stops and is obtained a file with information about the users that have to be involved, the forecast average shade, the probability of the required shed and the standard deviation of the convolution, that is an index of the uncertainty of the shed level.

Markowitz method

The purpose of the Markowitz method is to apply an economic model to an engineering problem. Harry Markowitz received the 1990 Nobel Prize in Economics for the classical mean-variance approach, this method offered the first systematic treatment of a dilemma that afflicts each investor: the conflicting objectives of high profit versus low risk [41]. To link this model to the topic of this work the high profit has been associated to the total performance of the users and the risk has been associated to the uncertainty of the forecasted performance, i.e. the standard deviation. In the first part of this section the model from an economic point of view is presented, in the second part the correlations with the customers' managing problem and the structure of the applied method are explained.

The theory proposed by Markowitz aims to generate an optimal portfolio composed of assets intended to maximize the total revenue and minimize the risk. The assumptions on which the portfolio theory is based are:

1) Investors are rational and behave in a manner as to maximise their utility with a given level of income or money;
2) Investors have free access to fair and correct information on the returns and risk;
3) The markets are efficient and absorb the information quickly and perfectly;
4) Investors are risk averse and they try to minimise the risk and maximise the return;

5) Investors base decisions on expected returns and variance or standard deviation of these returns from the mean;

6) Investors choose higher returns to lower returns for a given level of risk.

The return of on investment is defined as the ratio between the profit and the initial invested capital.

$$R_T = \frac{P(t+T) - P(t)}{P(t)} \tag{19}$$

Where *P(t+T)* and *P(t)* are the prices of the asset in two different moments, this return can be calculated ex-post with already known information.

The classic approach requires a forecast to quantify an expected return ex-ante. The forecast of the expected return is based on an average value (μ), assumed by measuring the expected return of an asset, and the variance (σ^2), assumed as the level of uncertainty of the expected return.

The expected return is defined as:

$$\mu = E[R_r] = \sum_{i=1}^{n} R_i * p(R_i) \tag{20}$$

Where $p(R_i)$ is the probability that the expected return, for the "*i*" asset, will be R_i and n is the number of assets of the portfolio. Directly it is possible to assume the probability:

$$p(R_i) = \lim_{n \to \infty} \frac{N_i}{N} \tag{21}$$

Where N is the total number of observations. So, the expected return for each asset is:

$$\mu_i = E[R_T] = \frac{1}{N} \sum_{j=1}^{N} R_i(j) \tag{22}$$

The variance indicates how far the real return could be from the expected return, the higher the variance, the higher the probability that the future return can be far from the calculated average return.

$$\sigma^2 = Var\,[R] = \sum_{i=1}^{n} (R_i - \mu)^2 * p(R_i) \tag{23}$$

It's also possible to write the last equation as:

$$\sigma^2 = Var\,[R] = \frac{1}{N-1} \sum_{j=1}^{N} [R_i(j) - \mu]^2 \tag{24}$$

The model of Markowitz is based on the Gaussian probability distribution of the returns, this hypothesis simplifies the calculation of the expected return and the variance.

To calculate the risk and the return of a portfolio it's necessary to define the correlation between the assets and the percentage of the total capital invested in each asset, so the coefficient $w_j = {W_j}/{W}$ with the constrain $\sum_{i=1}^{n} w_i = 1$ is introduced.

The expected return of the portfolio is:

$$\mu_p = \sum_{i=1}^{n} w_i * \mu_i \tag{25}$$

And the variance is:

$$\sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i * w_j * C_{ij} \tag{26}$$

Where C_{ij} is the covariance between the assets.

Now it's necessary to solve an optimization problem to find the best combination of investment coefficients and then of return and risk maximizing the sharpe: $\max {\mu_p}/{\sigma_p^2}$ [41]–[43].

To move from a portfolio optimization to the optimization of the consumers to involve in a DR event it's only necessary to change the parameter that this method considers. Now the performance takes the place of the return and, rewriting the equation (20,22,24) we obtain:

$$\mu = E[P_r] = \sum_{i=1}^{n} P_i * p(P_i) \tag{27}$$

$$\mu_i = E[P_T] = \frac{1}{N} \sum_{j=1}^{N} P_i(j) \tag{28}$$

$$\sigma^2 = Var\ [P] = \frac{1}{N-1} \sum_{j=1}^{N} [P_i(j) - \mu]^2 \tag{29}$$

Now the coefficient w_j expresses the percentage of energy reduction required from the j user concerning the whole amount of energy reduction required for the DR event.

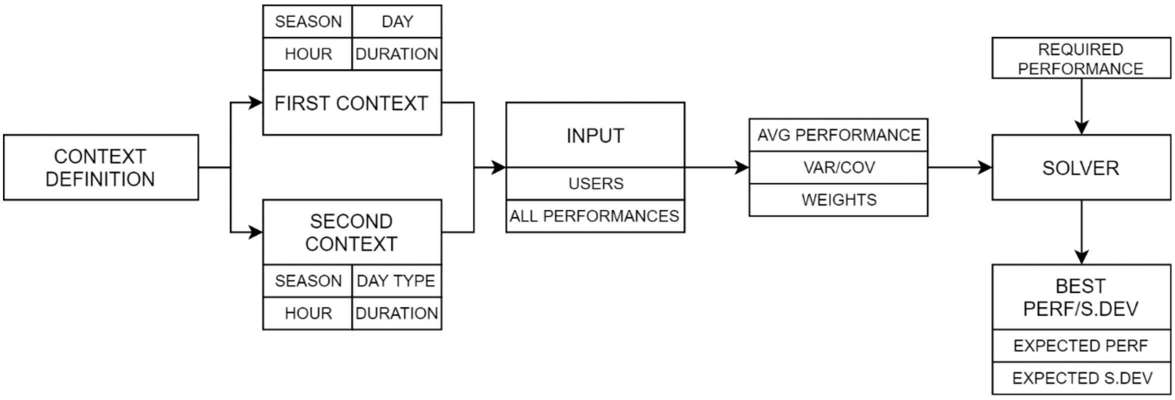

Figure 19 Markowitz strategy for consumers' managing in DR events

In Figure 19 the scheme of the Markowitz method is reported: after defining the context in which the analysis has to be conducted, an input file obtained from the consumers' characterisation is used.

The input file contains information about the users involved and for each user the value of all the performances. With this data it is possible to calculate the average performance of each user and the variance and the covariance of the consumers' performances. Concerning the covariance, it would be interesting to evaluate if the responses of the users are correlating or not each other in any way. If not, the covariance would be null and the computational time would decrease.

Then, different weights' combinations are given to the users and it is individuated the best combination of weights, performance and standard deviation that meets the aggregator's request.

5. USED DATA

The data used to test this method is the property of the New Thames Valley Vision (NTVV).[2]

The NTVV is a Low Carbon Network Fund Tier 2 project selected by Ofgem during the 2011 competitive selection process. Focussed on the low voltage network, the NTVV aims to demonstrate how electricity distribution networks can better serve their customers by understanding, anticipating and supporting their energy use as they move towards low carbon technologies [44].

Led by the Scottish & Southern Electricity Network, the goals of NTVV are:

- Understanding the consumption behaviour to determine potential network performance issues installing new monitoring equipment on the network;
- Anticipating future changes to identify new network management requirements;

[2] www.thamesvalleyvision.co.uk

- Supporting the necessary changes to network management through new technology and commercial solutions.

NTVV operates in the Bracknell Area, a region in the south of England and it conducted there many projects to maximize the reliability of the Bracknell network installing smart power meters and monitoring the network.

One of the projects involved the Automated Demand Response, through this trial they wanted to understand if it's possible to avoid the congestion of the network due to the increase of electricity demand and to defer costly investment in new capacity. To put in practice this project, 30 different types of buildings were enrolled, such as commercial, hospitality, leisure, healthcare, data centres, educational or public sector buildings with an aggregated load reduction of more than 1,1 MW. In each building involved in the program an ADR gateway was installed, this device accesses to an external software to initiate an "Electricity Load Shedding Strategy" programmed into each building's Energy Management System. Each building had its strategy, studied ad hoc, to have a minimal impact on the building's occupants and guarantee no alternation in the comfort.

The load shed strategies usually involved are [45]:

- Turn down supply and reduce fans speed;
- Switch off the Ari Handling Unit (AHU) serving the Atrium;
- Switch off the AHU serving the Reception Area;
- Adjust set points by 30 C chillers;
- Switch off one of the lifts in operation;
- Decrease or increase all zone temperature set points by 2ºC;
- Duty cycling of fan coil units;
- Pre-cool chilled water loop.

Acting on these devices it is typically possible to achieve up to 20% of peak reduction without any or high impact on building operation or comfort conditions.

The strategies start automatically when the signal is received, but the users can override them.

The considered trial went on from November 2015 to November 2016, one-year test in order to have data in every season. The events had different a duration, since half an hour to 4 hours and different types of load sheds were planned:

- 16:00 System Peak: this kind of events were performed at 4 pm when, usually, incurring a peak in the network;
- Local System Peak: the time of the load shed is chosen through analysis carried out on the feeder of the buildings to determine the best time for a load shed event for that area of the network;
- No notice events: there were also scheduled events without a notice at different times.

The buildings that have been tested included:

- Data Centre
- Educational Centre
- Leisure Centre
- Local Office
- MNC (Multi-National Corporation)

For each event a file with information about the power consumption on the day of the DR event and the baseline is available. The power samples are expressed in kW and they were taken with an interval of 15 minutes. The baseline was calculated as the average of the electricity consumption samples of ten days before the event excluding weekend, special days and days with DR events.

Unfortunately, the days with the same context aren't enough to have a good analysis of a building or more buildings so, as input test in order to verify that the method works, it has been decided to use real baseline and consumption data and to set dates which were useful for the purpose. The data refer to three events, for each building, carried out during the autumn at 16:00 System Peak with a duration of two hours; the buildings involved are two educational centres, a local office and a leisure centre.

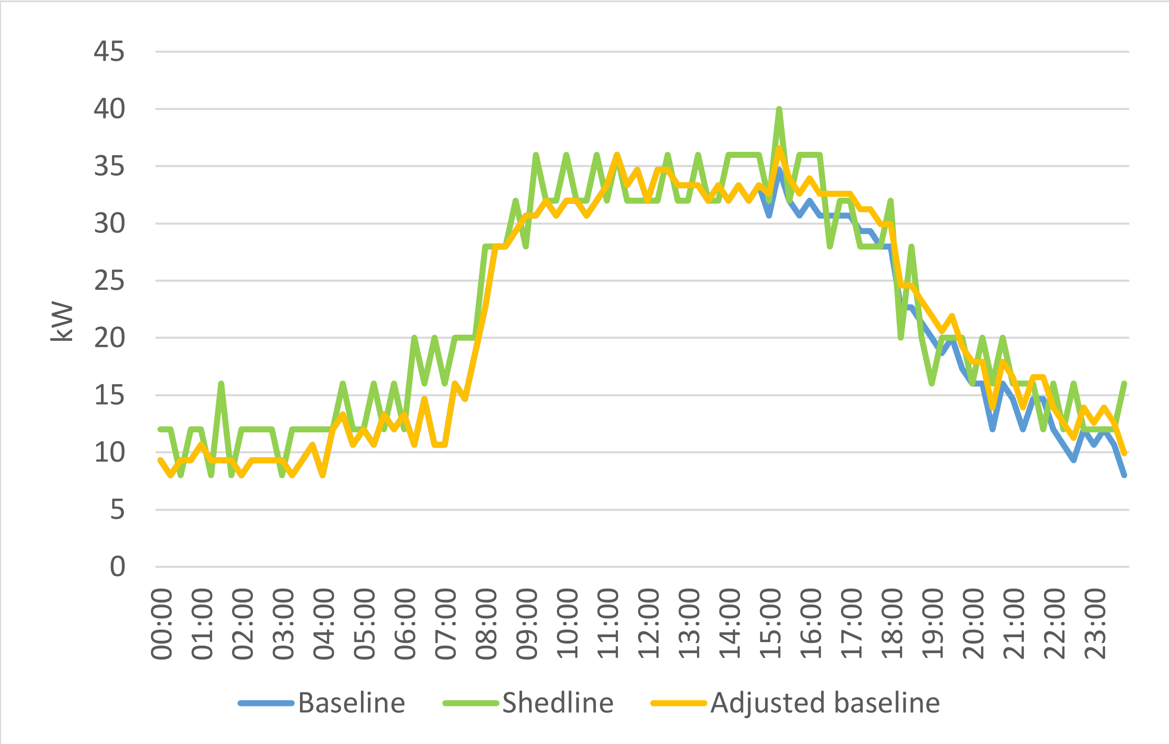

Figure 20 Educational centre load profiles

Figure 20 and Table 1 report an example of the data that have been used, referred to an event of one of the educational centres. The figure shows the baseline, blue line, the shedline, green line and the adjusted baseline, yellow line. Is possible to see the baseline colour only since the 14:00 because is the time as the adjusting was made, until that moment baseline and adjusted baseline are overlying. In the Table 1 there is an example of the data used in the method.

Time	Baseline [kW]	Adjusted Baseline [kW]	Shedline [kW]
00:00	9,33	9,33	12
00:15	8	8	12
00:30	9,33	9,33	8
00:45	9,33	9,33	12
01:00	10,67	10,67	12
01:15	9,33	9,33	8
01:30	9,33	9,33	16
01:45	9,33	9,33	8
02:00	8	8	12
02:15	9,33	9,33	12
02:30	9,33	9,33	12
02:45	9,33	9,33	12
03:00	9,33	9,33	8
03:15	8	8	12
03:30	9,33	9,33	12
03:45	10,67	10,67	12
04:00	8	8	12
04:15	12	12	12
04:30	13,33	13,33	16
04:45	10,67	10,67	12
05:00	12	12	12
05:15	10,67	10,67	16
05:30	13,33	13,33	12
05:45	12	12	16
06:00	13,33	13,33	12
06:15	10,67	10,67	20
06:30	14,67	14,67	16
06:45	10,67	10,67	20
07:00	10,67	10,67	16
07:15	16	16	20
07:30	14,67	14,67	20
07:45	18,67	18,67	20
08:00	22,67	22,67	28
08:15	28	28	28
08:30	28	28	28
08:45	29,33	29,33	32
09:00	30,67	30,67	28
09:15	30,67	30,67	36
09:30	32	32	32
09:45	30,67	30,67	32
10:00	32	32	36
10:15	32	32	32
10:30	30,67	30,67	32
10:45	32	32	36
11:00	33,33	33,33	32
11:15	36	36	36
11:30	33,33	33,33	32
11:45	34,67	34,67	32

Time	Baseline [kW]	Adjusted Baseline [kW]	Shedline [kW]
12:00	32	32	32
12:15	34,67	34,67	32
12:30	34,67	34,67	36
12:45	33,33	33,33	32
13:00	33,33	33,33	32
13:15	33,33	33,33	36
13:30	32	32	32
13:45	33,33	33,33	32
14:00	32	32	36
14:15	33,33	33,33	36
14:30	32	32	36
14:45	33,33	33,33	36
15:00	30,67	32,58813	32
15:15	34,67	36,58813	40
15:30	32	33,91813	32
15:45	30,67	32,58813	36
16:00	32	33,91813	36
16:15	30,67	32,58813	36
16:30	30,67	32,58813	28
16:45	30,67	32,58813	32
17:00	30,67	32,58813	32
17:15	29,33	31,24813	28
17:30	29,33	31,24813	28
17:45	28	29,91813	28
18:00	28	29,91813	32
18:15	22,67	24,58813	20
18:30	22,67	24,58813	28
18:45	21,33	23,24813	20
19:00	20	21,91813	16
19:15	18,67	20,58813	20
19:30	20	21,91813	20
19:45	17,33	19,24813	20
20:00	16	17,91813	16
20:15	16	17,91813	20
20:30	12	13,91813	16
20:45	16	17,91813	20
21:00	14,67	16,58813	16
21:15	12	13,91813	16
21:30	14,67	16,58813	16
21:45	14,67	16,58813	12
22:00	12	13,91813	16
22:15	10,67	12,58813	12
22:30	9,33	11,24813	16
22:45	12	13,91813	12
23:00	10,67	12,58813	12
23:15	12	13,91813	12
23:30	10,67	12,58813	12
23:45	8	9,918125	16

Table 1 Educational centre power data

6. RESULTS

The method was implemented in RStudio, an integrated development environment for R.
R is a high-level language and an environment for data analysis and graphics; it provides a wide variety of statistical (linear and non-linear modelling, classical statistical tests, time-series analysis classification, clustering,…) and graphical techniques [46], [47].
The implementation of the method in R allows strong automation of the analysis process and an easy way to upgrade the code with new features and better optimization process.

The purpose of the results reported in the next sections is to show that the method works, how it works and the results that are possible to obtain; the data available aren't enough to determine a real characterization of the buildings involved in the trial.

6.1. DISTRIBUTIONS' RESULTS

In this section, the distributions of the educational building, of which one-day consumption data were presented in the previous chapter, are reported.

The context of the data considered is:

Season	Day	Day Type	Event Time	Duration
Autumn	Tuesday	Weekday	16:00	2 h

Table 2 Context of analysed data

This context is the same for all the four buildings analysed.

About the events considered for the educational centre the parameter obtained are:

Date	Performance [kWh]	Avg Performance [kWh]	Consumption change %
04/10/2016	8	4	12,7
25/10/2016	13,16	13,16	21,52
08/11/2016	2,17	1,08	3,38

Table 3 Summary of the events in the educational building

Figure 21 and Figure 22 show the shape obtained applying the normal distribution function and the Kernel distribution function to the data reported in Table 3. In the normal distribution we obtained a performance curve with:

- Average performance: 7,78 kWh
- Standard deviation: 5,50 kWh

The standard deviation seems to be very high, mainly compared with the average performance and this is due to the great variability of the performance measured. To reduce the uncertainty in the distribution a quite high number of events on the same context is required to have a bigger set of performance values, moreover, a good quality of the baseline prediction is necessary. The baseline is essential for the determination of the performance, then, very high variability in the performance values could be also due to a not good baseline prediction. However, though the values analysed show a big uncertainty, the shape of the curve with a Kernel distribution is comparable with the curve using the Gaussian distribution. The smoothness of the curve depends on the bandwidth h in the equation (15), a bigger value of h leads to a smoother curve instead a lower value of h leads to a curve in which the single contributes are more visible; in this method an optimal value of h is chosen by the optimization algorithm implemented in the R’s kernel distribution method.

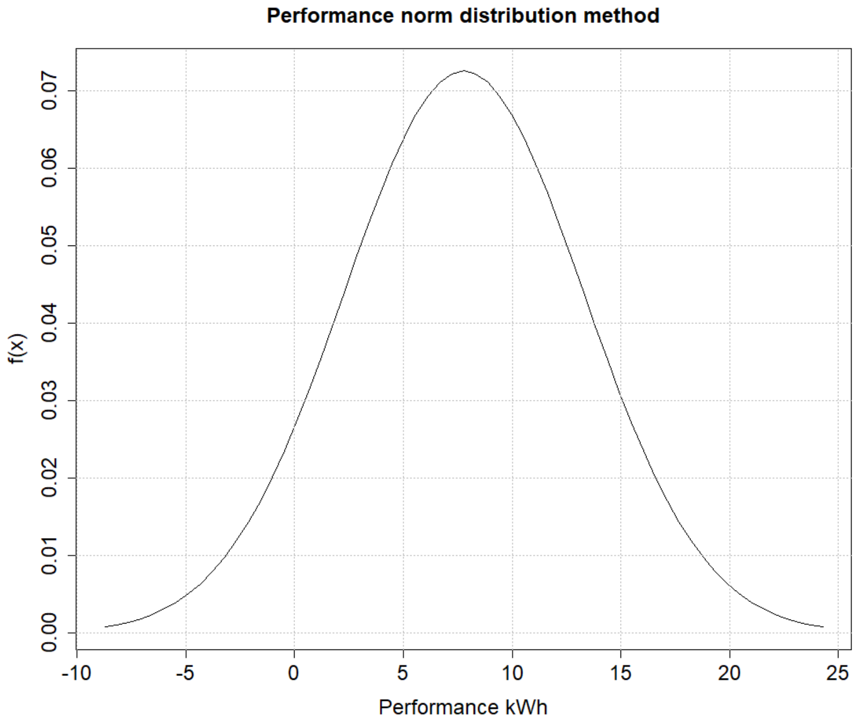

Figure 21 Performance's normal distribution educational building

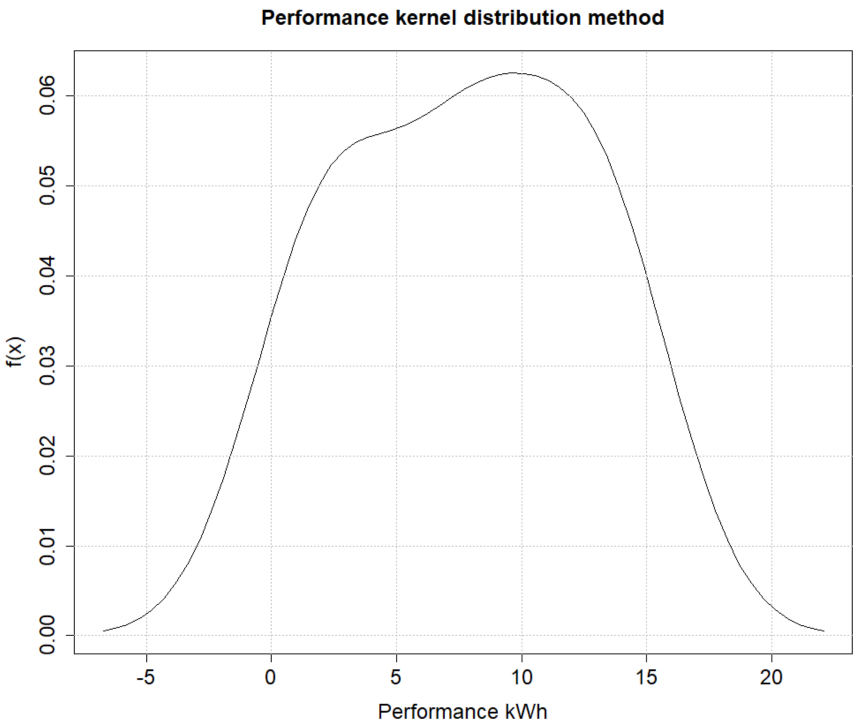

Figure 22 Performance's kernel distribution educational building

Table 4 shows the comparison between the probabilities calculated with the two different distribution functions, considering several values of saved power:

Probability %	Min Performance [kWh]				
	0	5	10	15	20
Normal	92,54	70,78	36,2	10,44	1,46
Kernel	93	69,59	38,12	10,78	0,35

Table 4 Summary of different performance probabilities

6.2. CONSUMERS' MANAGING RESULTS

In this section the results of the different strategies to manage the consumers during a DR event which have been illustrated in the previous chapters are presented. To test the methods four different users have been considered as participants to the DR program, these consumers had these characteristics:

User ID	Building	Performance [kWh]	Standard deviation [kWh]
1	Educational 1	7,78	5,5
2	Educational 2	17,55	11,81
3	Office	4,08	3,42
4	Leisure Centre	7,19	1,58

Table 5 List of the users involved in the methods' tests

The performances reported in the table are the mean of the performances considered for each building and the relative standard deviations. The context of the analysis is the same that has been reported in Table 2.

Two managing strategies have been illustrated in a previous chapter, one with the convolution and one using the Markowitz theory; as written the convolution strategy can bring to different results depending by the order in which the users are convoluted.

The tests performed are:

- Convolution test with consumers ranked by the standard deviation in increasing order;
- Convolution test with consumers ranked by the ratio between performance and standard deviation in decreasing order;
- Convolution test involving all the consumers;
- Markowitz test.

The tests refer to a required performance of 10 kWh with a probability at least equal to 70%.

Convolution with classification based on the standard deviation

Classifying users on the standard deviation in increasing order the convolution of a new consumer follows this list:

User ID	Building	Performance [kWh]	Standard deviation [kWh]
4	Leisure Centre	7,19	1,58
3	Office	4,08	3,42
1	Educational 1	7,78	5,5
2	Educational 2	17,55	11,81

Table 6 Convolution's order based on standard deviation classification

To achieve the result of a load shedding with, at least, 10 kWh of energy saved and a probability of 70%, it is required to involve the first three customers of Table 6.

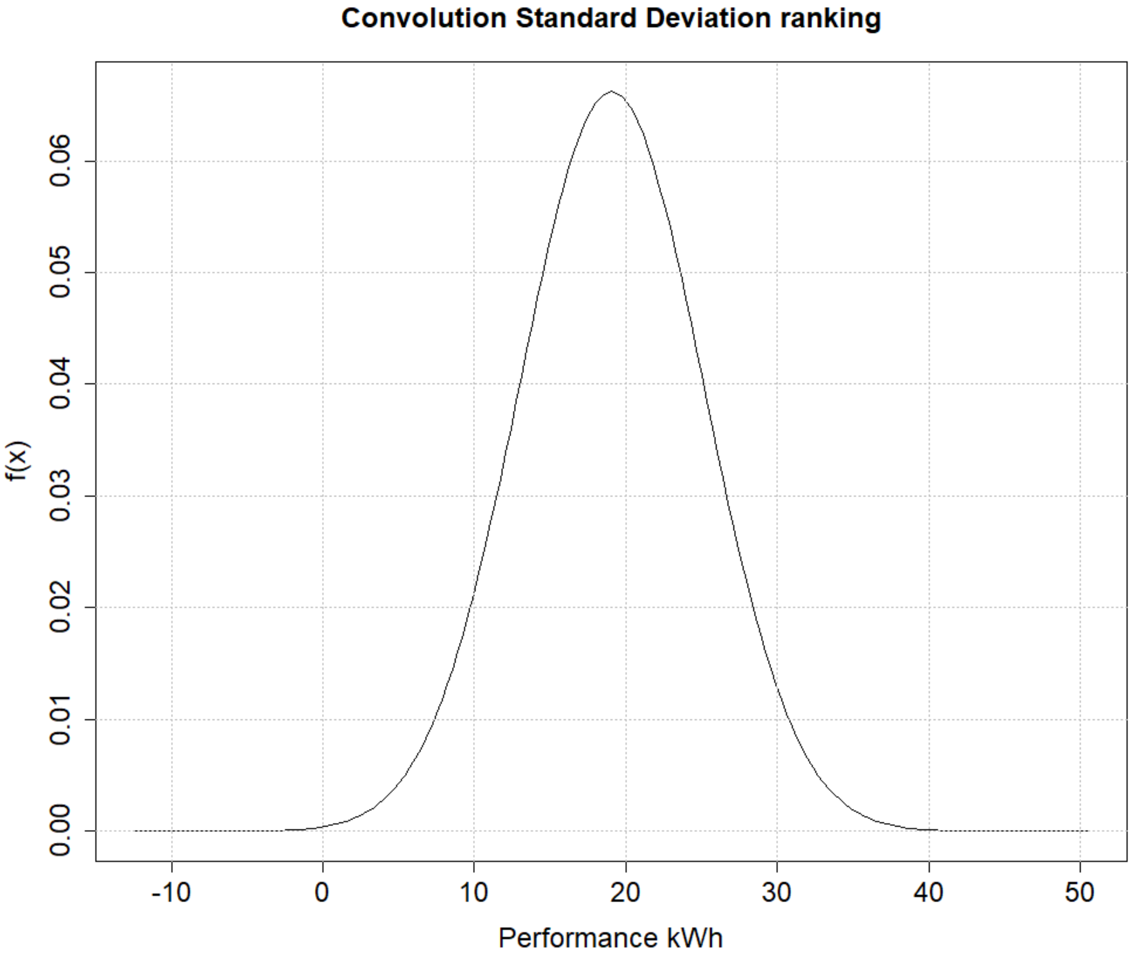

Figure 23 Distribution of the convolution based on standard deviation classification

With these three users involved in the DR event it is possible to obtain a load shed of 10 kWh with a 93,9% probability of success. The average performance, i.e. the performance with the 50% of probability that can be reached or exceeded, is equal to 19 kWh with a standard deviation of 6 kWh.

Users involved	Request [kWh]	Probablity %	Avg Shedding [kWh]	Std. Deviation [kWh]
3	10	93,89	19	6

Table 7 Summary convolution based on standard deviation classification

Convolution with classification based on performance/standard deviation

Classifying the consumers on the ratio between performance and the standard deviation in decreasing order, the convolution of a new consumer follows this list:

User ID	Building	Performance [kWh]	Standard deviation [kWh]
4	Leisure Centre	7,19	1,58
2	Educational 2	17,55	11,81
1	Educational 1	7,78	5,5
3	Office	4,08	3,42

Table 8 Convolution's order based on performance/standard deviation classification

Achieving the results of a load reduction of, at least, 10 kWh with a minimum probability equal to 70% requires the involvement of the first three users of Table 8. In this case, Educational Centre 1 joins the event because the relation between the energy that it can reduce, and the uncertainty is better than of other consumers.

With these three users involved in the DR event it is possible to obtain a load shed of 10 kWh with a 98,4% probability of success. The average performance is equal to 32,53 kWh with a standard deviation of 10,84 kWh. Even though the standard deviation is higher in this approach, the ratio between performance and that parameter is almost in both cases around 3.

Users involved	Request [kWh]	Probablity %	Avg Shedding [kWh]	Std. Deviation [kWh]
3	10	98,97	32,53	10,84

Table 9 Summary convolution based on performance/standard deviation classification

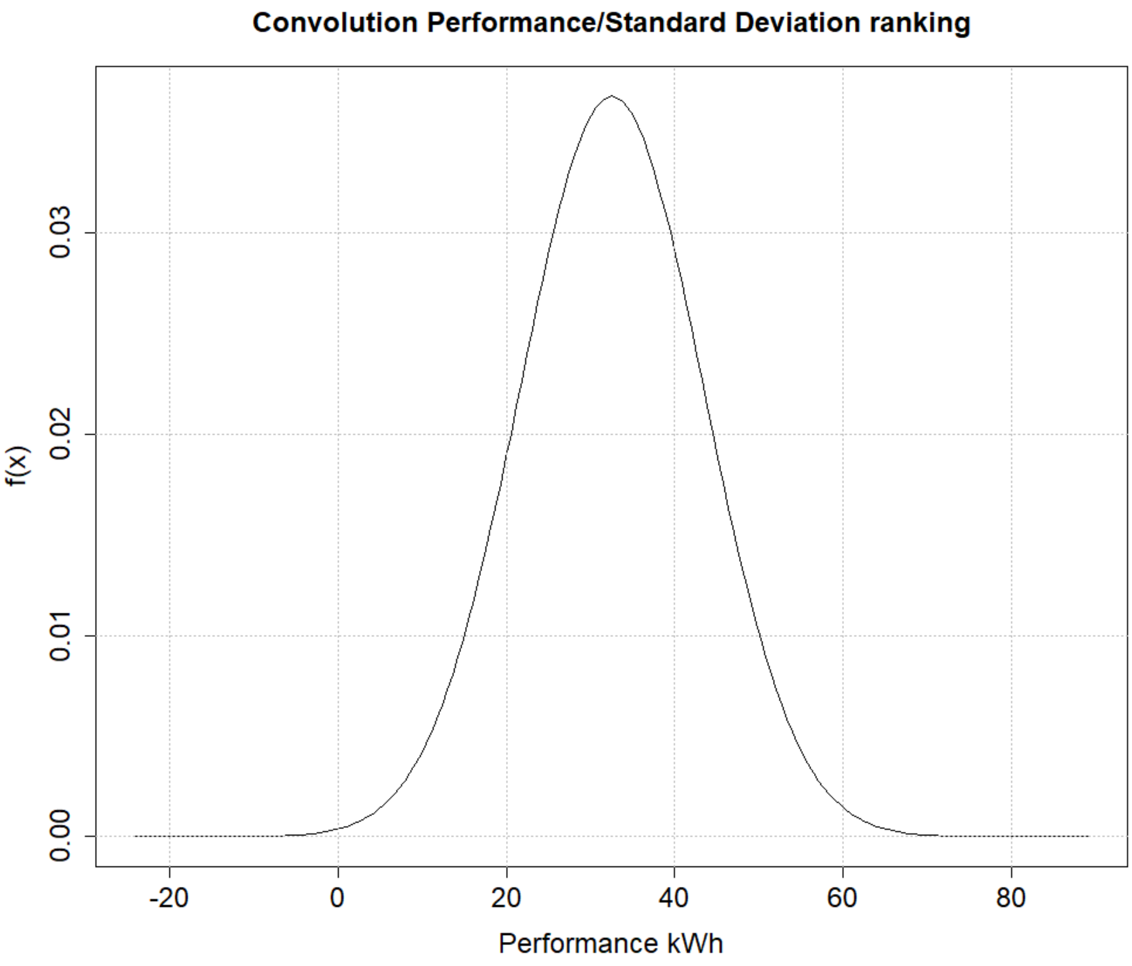

Figure 24 Distribution of the convolution based on performance/standard deviation classification

Convolution with all consumers

It can also be interesting to observe what happens if the signal to participate in a DR event is sent to all the users that take part to a DR program. This strategy could be chosen by the aggregator to give everyone the chance to participate in an event and have remuneration for participation.

In this case, all four users' performance distributions are convoluted. The result is an average performance of 36,60 kWh with a standard deviation of 11 kWh. Despite the involving of consumers which have been considered worse in the previous strategies, this strategy has the highest ratio performance / standard deviation. Looking at the required performance of 10 kWh, the probability that it happens is equal to 99,31%. In the case of a contribution in power reduction that is coming from a larger consumers group than the necessary, it could be enough asking for a lower load shed than the one plan in the strategy implemented in the ADR, with a higher chance of success.

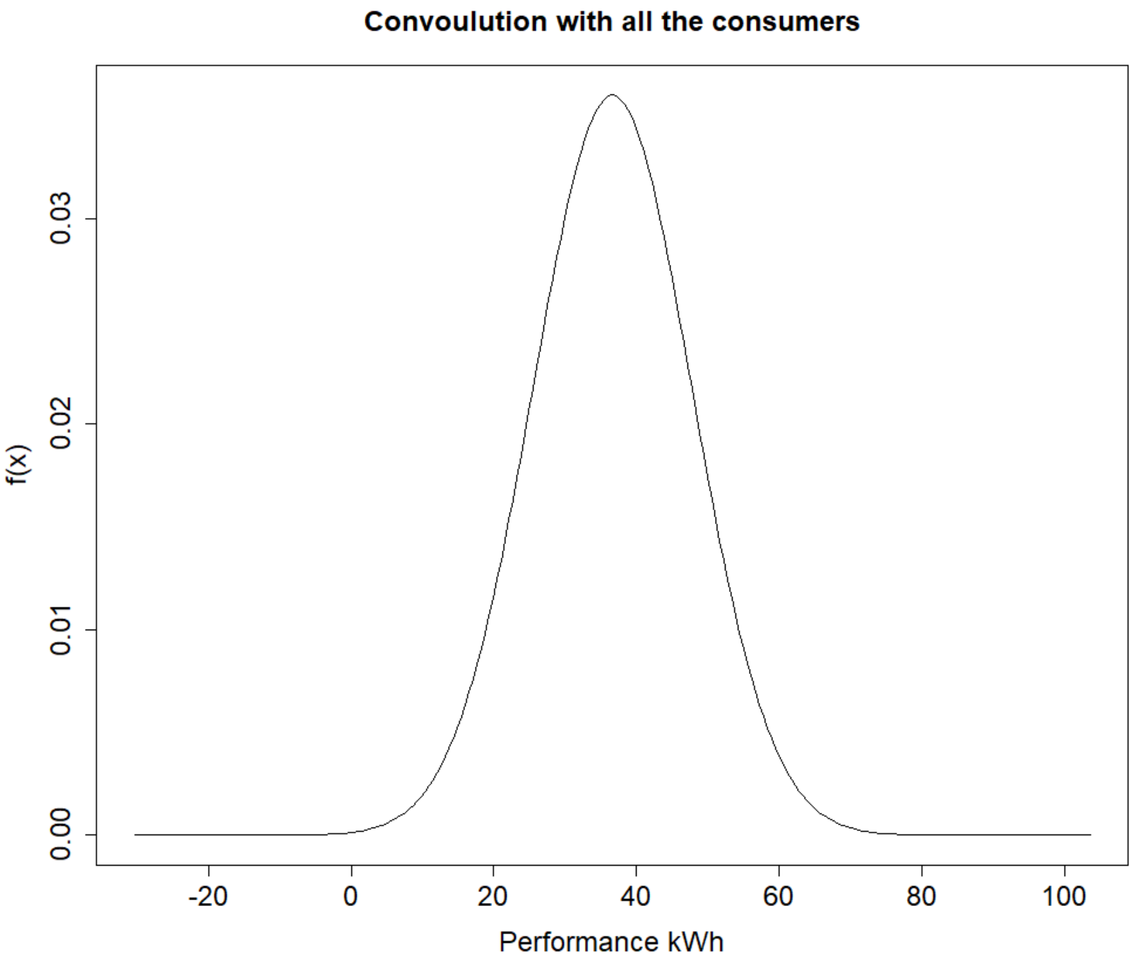

Figure 25 Distribution of the convolution involving all the consumers

Users involved	Request [kWh]	Probablity %	Avg Shedding [kWh]	Std. Deviation [kWh]
4	10	99,32	36,61	11,07

Table 10 Summary of the convolution with all the consumers

Markowitz test

To identify the best combination of consumers to involve in the DR event many combinations of the weight coefficient "w_j", introduced in 4.3., have been produced, and then the expected performance and the expected standard deviation have been calculated using the equations (25-26). The highest ratio value between the expected performance and the standard deviation, in the performance range that is required, was chosen as the best combination. A high value of that ratio means high performance and low uncertainty.

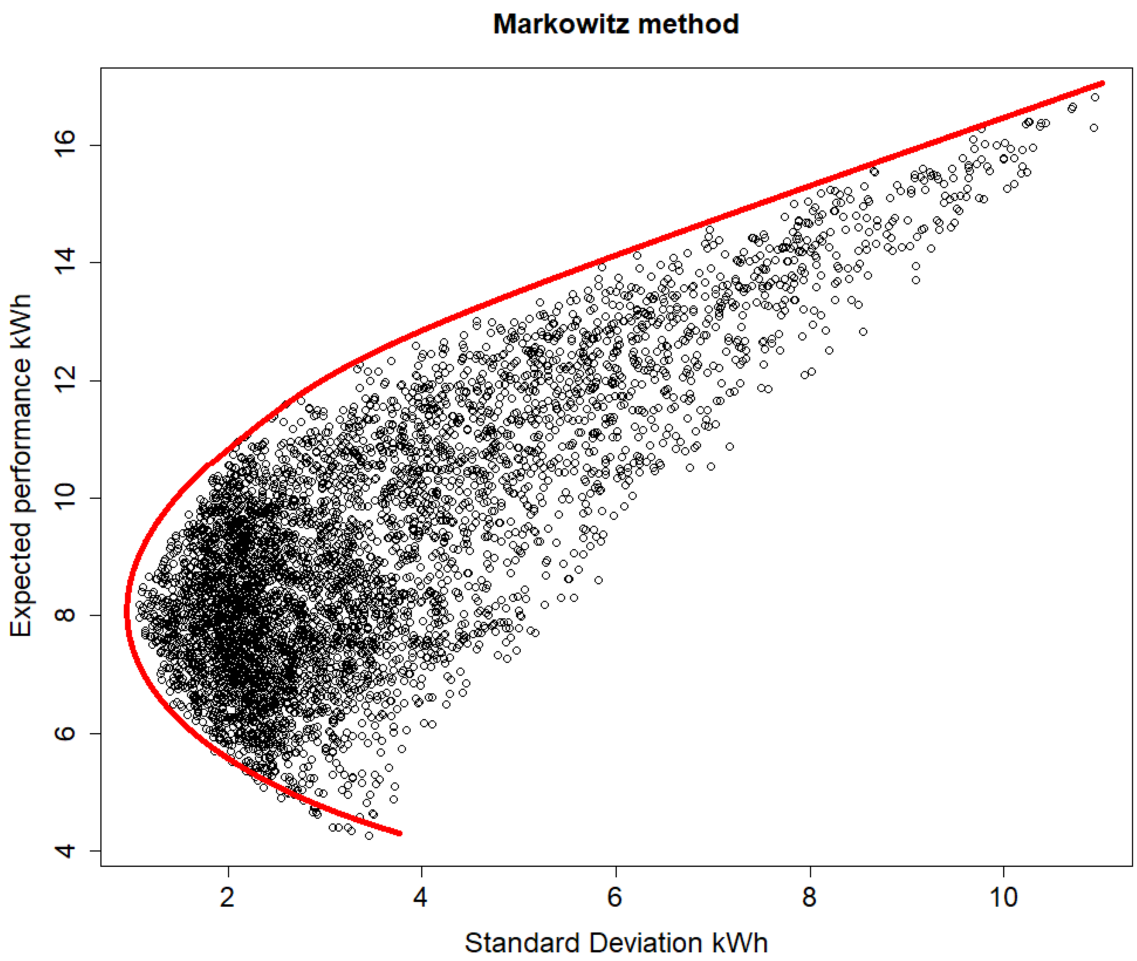

Figure 26 Expected performances and standard deviations with different weight combination

Figure 26 shows all the expected performances and the relative standard deviations calculated with different weight combinations. In that picture there are 5000 different points and the red line represent the efficient frontier; all the points on the efficient frontier have the lowest standard deviation for any expected performance value.

To compare the results of this method with the results of the previous ones it has been chosen to search for the best combination of performance/standard deviation in an expected performance range that can vary from 9,5 kWh to 10,5 kWh. Several tests have been processed with an increasing number of weight combinations:

Combinations	2000	5000	10000	15000	20000
Expected performance kWh	9,6	9,58	9,59	9,59	9,63
Standard deviation kWh	1,55	1,53	1,56	1,58	1,55

Table 11 List of expected performances and standard deviation with the Markowitz method

It is possible to see that a higher number of combinations doesn't involve a significative difference in the result. In that range of expected power, the best result is achieved with an expected performance of 9,6 kWh; to obtain this performance the users involved are three, as seen in Table 12, the user 3 doesn't give a contribution to the performance due to a low ratio between the performance and the standard deviation compared to the other consumer.

User ID	Participation	Performance required [kWh]	Probability
1	32%	3,1	82,79%
2	22%	2,1	91%
3	0	0	-
4	46%	4,4	96,67%

Table 12 Users' participation according to Markowitz's strategy

With this method it is possible to obtain more information than the convolution method because this strategy allows to know which is the expected performance of each consumer. The probability is referred to the probability to have a load shed of that level, or higher, considering the buildings separately.

6.3. CONCLUSIONS

The aggregator can choose which approach is better to use; in the strategies that use the convolution, the lowest uncertainty, i.e. the lowest standard deviation, belongs to the method in which the users have been ordered following an increase in standard deviation. The method in which the users have been ordered following a decrease ratio between performance and standard deviation has a higher uncertainty but the request should be satisfied with a higher probability; this method and the method that uses the Markowitz's theory lead to the same results about the users involved but, the last one, presents a very low uncertainty. This is due to the different method with which the standard deviation has been calculated and also the hypothesis of the existence of a correlation between the events; without a correlation the standard deviation would be higher but still lower than the method with the convolution. Taking the computational times into account it is possible to see that the methods with the convolution are faster than the method with the Markowitz approach. Moreover, the time that this approach needs grows up exponentially using a higher number of weight combinations, but as shown, with a low number of consumers it is not necessary to use a high number of combinations as the result is more or less the same.

Convoulution order:	S. Deviation	Perf/S. Dev	All
Time (sec)	0,10	0,08	0,09

Table 13 Computational time convolution methods

Markowitz weight points	2000	5000	10000	15000	20000
Time (sec)	0,4248	1,135925	2,2038	4,694775	7,414975

Table 14 Computational time Markowitz method

7. CONCLUSIONS

In the next years, our life will depend on electricity more than now. Important challenges await all the people involved in the energy sector because significant changes are being on. The electricity chain will change deeply, from the production to the utilization, and now, more than years ago, these two blocks need to collaborate synergistically to bring the highest benefits that are possible to everyone, including the environment.

The production, with the introduction of the renewable resources, will create a generation profile more unstable, sensitive to atmospheric phenomena and strictly dependent by the time and the seasons. The consumers need to adapt to this change and they become an active part in the chain of the electric energy, through their behaviour they can manage the security and the reliability of the electric grid; to do this, however, they need to be educated in order to understand their importance and how to act to be useful for the system.

However, with a high penetration of smart appliance it could be difficult, also for a well-educated consumer, managing the use of all the appliances in the best way. The automated managing systems, or ADR, can constitute a very good way to obtain good results; once set the preferences of the user, the system will manage automatically all the equipment with the information given by the aggregator and the aggregator has a higher control capacity on the grid.

The proposed method can be a useful support element for the aggregator's decisions. Classify the response of the consumers and forecast the load reduction are two key elements in the future grid managing because the implementation of good strategies brings to better results and money savings. The method also constitutes a good starting point for further improvement, additions and studies. With a good database more tests can be conducted with validation in reality.

Some improvements can be:

- Look for a relation between the performance and other external factors, such as the temperature, or the behaviour of the users;
- Improve the clustering to the method and verify if consumers with a comparable load profile have the comparable performances or if the users need to be clustered by the response.

The author hopes that the method illustrated in this report can have practical applications of success.

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