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enabling new Demand REsponse Advanced, Market oriented and secure technologies, solutions and business models

DELIVERABLE: D3.2 Recommendations for baseline load calculations in DR programs V1

Lead Authors: Edgar Jose Segovia Leon, Benjamin Hunter

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Author(s):	Giuseppe Rana, Luigi D'Oriano, Giuseppe Mastandrea, Angelo Cardellicchio (E@W) Francesco Bellesini (EMOT) Edgar Jose Segovia Leon, Benjamin Hunter (TU) Tudor Cioara, Marcel Antal (TUC)
Participant(s):	Lead Partner: Teesside University Contributing Partners: TUC, E@W, EMOT
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Executive Summary

The deliverable D3.2, within the Work Package 3, makes a comparison of the baseline load calculation methods involved in several key DR programs (resource adequacy/capacity, economic/energy tariff, balancing/ancillary services). These are vital to assess the success of the overall DR participation.

The studied methods will be based on moment of dispatch, average and weighted average over "X of Y" most recent days with the highest or medium load preceding an event (e.g. highest 5 of 10 previous admissible days). Consolidated Edison of New York and the NYISO (New York Independent System Operator) Emergency Demand Response Program Manual (12/02/2010 version 6.2 Section 5.2) will be taken into account together with the currently employed methodologies by the EU member states to calculate a Customer Baseline Load ("CBL") for Customers/Aggregators enrolled in DR programs.

In the eDREAM use cases, a data model will be applied and the prediction algorithm to predict the CBL will be taken from T3.1. In T3.2, an approach to produce the flexibility forecast will be chosen and applied to this particular part of the project. This task will result in recommendations for applying specific Consumer Baseline load (CBL) calculation methods across EU.

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List of Acronyms and Abbreviations

eDREAM	enabling new Demand Response Advanced, Market oriented and secure technologies, solutions and business models
ALFA	Automated Load Forecasting Assistants
CAISO	California Independent System Operator
CBL	Customer Baseline Load
CHP	Combined Heat and Power (Also known as cogeneration)
CRO	Common Reference Operator
DEMS	Distributed Energy Management System
DER	Distributed Energy Resources
DR	Demand Response
DR-BOB	Demand Response Block Building
DSO	Distributed System Operator
EC	European Commission
ERCOT	Electric Reliability Council of Texas
EV	Electric Vehicle
INEA	Innovation and Networks Executive Agency
ISO	Independent System operator
ISO-NE	Independent System operator New England
ISO-NY	Independent System operator New York
LEM	Local Energy Management
MAPE	Mean Absolute Percentage Error
MG	Micro-Grid
NN	Neural Networks
NYISO	New York Independent System

P2P	Peer to Peer
PJM	Pennsylvania-New Jersey-Maryland interconnection
RES	Renewable Energy Sources
RTO	Regional Transmission Organizations
SVM	Support Vector Machine
SVR	Support Vector Regression
UC	Use Cases
VPP	Virtual Power Plant

1 Introduction

1.1 Scope and objectives of the deliverable and relevance in the eDREAM framework

This report is produced within Task 3.2 of Work Package 3 with the aim identifying and analysing baseline load calculation methods for DR programs. The methods identified and recommendations made in this report will then feed directly into the second version of this deliverable, D3.6, where recommendations are made for applying these DR program baseline load calculations across the EU.

On a broader scale, the methods identified and evaluated by this report lay the groundwork for a key component of the eDREAM platform, baseline calculation, which will be an essential part of implementing an efficient and optimal DR strategy, as explored and implemented in Work package 4.

This document registers the combined knowledge produced through the cooperation of the different partners, and uses the collected information different scenarios and UCs.

1.2 Structure of the deliverable

Deliverable 3.2 "Recommendations for baseline load calculations in DR programs V1" is organised in five sections in which the first version of use cases and scenarios have been collected and described, as follows:

- General introduction and description of the scope and the structure of the deliverable
- Basic concepts and short description of the overall Framework Conceptual Architecture of the eDREAM
- Presentation of techniques and approaches used in different parts of the world; analysis of the technological context, in which the project is developed
- Definition of the methodologies for the description of the process that is approached for scenario identification and use case definition
- Analysis of results of the project
- Conclusions, recommendations, and references

1.3 Methodology

Production of this document was a result of a desktop research applied to collect and analyse evidence from various published information sources. Several mathematical procedures are identified and evaluated and then compared utilising historical energy data provided by members of the consortium.

2 Key Drivers for Demand Response

The future of demand response technology depends on the increase in speed and the efficiency with which we are able to communicate information, the advance of the technology to drastically improve the computing capacity and the speed with which we share information. One such development is Peer-to-Peer (P2P) technology, where rather than information being shared from a single point on a network, information is stored across many different interconnected nodes on a network and can be accessed using the most efficient route possible (Figure 1). With this technology we do not depend on the speed of a specific equipment but on a set of interconnected equipment, this concept has allowed the birth of Blockchain neural networks. Today, we can handle large amounts of information, process it and use it to predict the behaviour of the demand on an electrical grid. This allows more accurate load prediction, facilitating more accurate economic dispatch of generation resources and techniques to make energy load profiles more generation-friendly such as demand response. This report will present and evaluate which are the key drivers for p2p demand response. Of these, the most remarkable are: Stakeholders, Demand Response Programs, P2P Demand Response Flexibility assessment and data model for flexibility forecasting. These are the guidelines that mark any Demand Response Project.

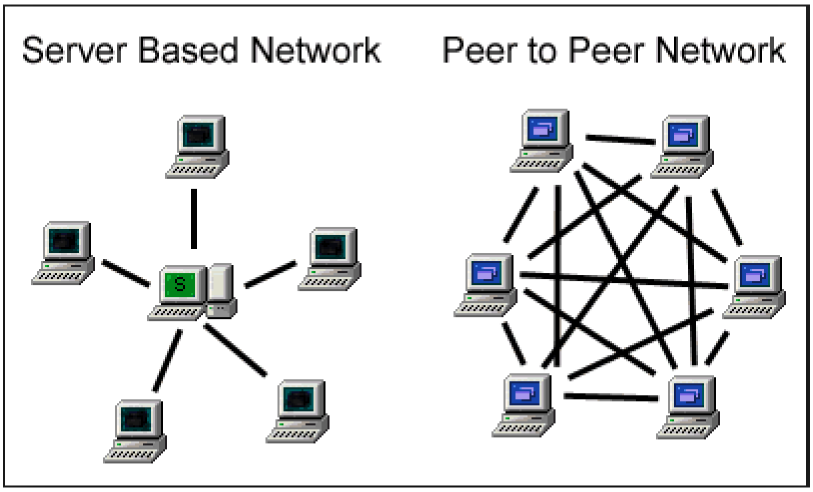

Figure 1 P2P network illustration

The Stakeholders are an important part of any project, they are the parties affected by the activities of a company or a project. These groups should always be kept in mind for the strategic planning of any business, and the two types of which are primary and secondary stakeholders. Primary stakeholders are those that are indispensable for the operation of the organization, that is all those who have some direct relationship, such as the employees, manager, owners. The secondary ones are those who do not participate directly in the activities, but who, nevertheless, are affected by it. For example, the customers, government and society. A project is not an entity that is isolated from the environment, it will always be disturbed to a greater or lesser extent by other organizations, or by its parts, the employees, the suppliers, the clients, they are groups, organized or not. They are indispensable for any company, therefore, the impact on the stakeholders must be taken into account in the planning, however, some impacts can be predicted before putting the Project into operation. New stakeholders may arise that were not foreseen, as parts of the society that were not taken into account in the initial planning. Projects always affect their environment in ways that were not expected for this reason is important to keep watch on all possible that will appear in the future. In the case of Demand Response, the primary stakeholders would be the employees of the Project. The persons in charge of carrying out the case studies, put ideas into practice, among the external stakeholders the most important would be the electricity production companies that receive the information of DR can plan their production depending on this and the final users of electricity, or customers, who receive more economical electricity.

We could also mention the environment, since the technology of renewable energies is favoured by the development of DR.

Typical dispatchable DR programs give incentives to DR customers based on the amount by which they reduce their energy/power consumption. To verify the amount, a customer baseline load (CBL) needs to be determined. CBL refers to the amount of electricity that would have been consumed by the customer if the DR event had not been occurred. The difference between actual load and CBL is considered as the amount of load reduction, i.e. the DR performance that the customer achieves. Hence, the accurate estimation of CBL is critical to the success of DR programs because it benefits all stakeholders by aligning the incentives, actions and interests of DR participants, utilities, and grid operators. Note that CBL plays a key role in implementing DR programs; if the baseline is determined relatively low, customers are less motivated to participate in the DR program because they might think their performance is not fully acknowledged. On the other hand, if the baseline is estimated relatively high, utility companies are less motivated to operate DR program because the amount of load reduction is over-estimated and thus more incentive should be paid to customers (Park, et al., 2015).

Currently Demand Response is a growing technology, and there are many different DR programs. These programs try to predict with the highest reliability the future electrical load profile, and almost all DR programs use the historical consumption as data principal, and as background, so that a model used in one specific site cannot be applied in another. Unless you have access to historical consumption data in this new site, or if a significant change in consumption characteristics occurs in the installations in a short time period, it would be possible that the model becomes ineffective. Some programs use the external temperature in real time, and have managed to demonstrate that the electrical consumption of some buildings is proportional to the ambient temperature, many use the electrical load data of one week to predict the load the for following week, and some DR programs use fuzzy logic to have gain flexibility and quick answers. There are so many methods that it would be impossible to describe all those that are currently being tested, thanks to the speed of data processing and information transmission with which now have the possibility to analyse more data more quickly, that will allow us to have more flexible systems and an accurate assessment.

A process that is not measured cannot be controlled, in all processes it is important to have feedback, for which you can select different measuring instruments, which gives us information that we will then have to interpret, in order to improve the process and close the cycle. Demand response programs are not an exception, all DR programs need to be flexible to respond to unexpected stimuli, and to be able to receive assessment. Otherwise it would be like having a blind man driving a car, a potential disaster. Advances in P2P technology make it possible to transmit information quickly, some of the most promising programs in the field of DR use the technology of neural networks to quickly analyse the information they receive, in order to give a quick and effective response, Some DR programs analyse data provided in real time by different sensors to try to be as accurate as possible in the forecasting.

In literature, there are many types of forecasting models to predict the electricity demand based on different algorithms, techniques and theories. Each forecasting model gives new information and has different characteristics, from the horizon that so much in the future can predict the electric charge, up to the speed of response, it will be how fast it responds to unforeseen events, or how flexible the model is, there are many models with different forecasting times periods, from a number of hours, a number of days to several weeks, and knowing the time period is fundamental for DR project,

In some sense, short term load forecasting is similar to customer baseline load estimation since it investigates same time scales. Baseline estimation is however slightly different to short term load forecasting since it must satisfy both consumers and utility side. The purpose of load forecasting for generation side is to match the amount of electricity generation to the consumption while minimizing generation cost. In contrast, the establishment of baseline load is aimed at demand side to measure the DR performance. Accurate demand forecasting can motivate customers to participate in DR programs and to receive monetary rewards from the utility company (Park, et al., 2015).

All these concepts are fundamental to plan and execute a DR project, and it is important to have these parts clear before analysing any DR project. For this reason, in the previous paragraphs the basic concepts were explained. In the following parts this DR Project will discussed, and its characteristics, stakeholders, DR programs, flexibility assessment, data model for forecasting will be examined. The basic concepts of this project will be available and will allow the results to be much easier to interpret by third parties, people who do not work directly within the program.

2.1 Stakeholders

Energy markets are evolving in a new connected vision, in which, compared to the classical framework, different stakeholders are called to take part into the whole energy value chain, from Generation to services for transmission and distribution. Keeping in mind the new paradigm of the today's smart grid scenario, we can specify the following stakeholders for the eDREAM project:

- **System Operators** (Transmission System Operators, Independent System Operators, Distribution System Operators and other local network operation entities)
- **Market Operators** (Retailers, Large producers & Traders, Brokers, Aggregators, ESCo, etc)
- **Governance and Policy Bodies** (Regulation Authorities, Governmental Institutions, Public administrations, Policy Makers, no profit Agencies)
- **Final Users** (prosumers, producers, large consumers, user cooperatives)
- **External Services providers** (all those subjects that does not produce, dispatch, sell or use energy and participate to the market in a subsidiary way: services providers, third part service providers, Research & Innovation Entities, industrial or consultancy providers, like the P2P Blockchain Service provider mentioned)

The diagram below indicates the relationship between the stakeholders among such new vision. From the final users like active consumers (or prosumers), the value chain is connected to form a bi-directional flow, where market players like aggregators, brokers, ESCOs and traders, provide services to system operators and/or to final users on the energy markets.

In the eDREAM concept, another stakeholder that can take part to the logic of Energy markets and DR programs is the P2P Blockchain Service provider: it may address one of the most promising target markets. Blockchain platform could be considered as enabling technologies to allow aggregators to reduce their operational risk and lowering transaction costs. On the other side, the majority of the typical activities covered by an aggregator could be done thanks to the automated support of P2P DLT/Blockchain platform. This is comprehensively defined in eDREAM D2.1: User group definitions, end-user needs, requirement analysis and deployment guidelines, Chapter 2.

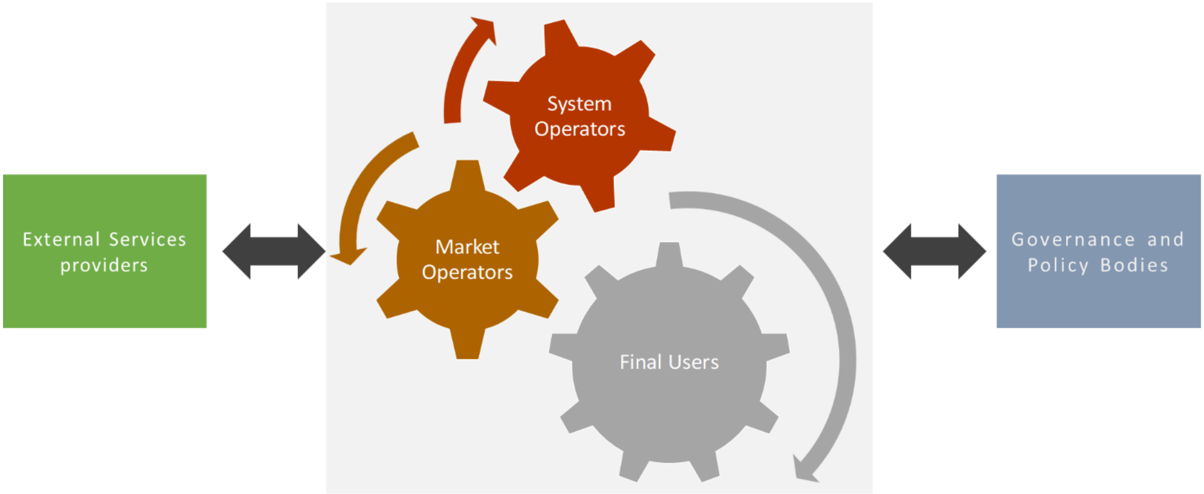

Figure 2 Stakeholders in a modern smart grid scenario

2.2 Demand Response Programs

Several definitions of Demand Response (DR) can be found in literature. One of the most popular and cited defines Demand Response as the changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time. Further, DR can be also defined as the incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardised ([i]).

Different DR programs exist and can be executed. They are mainly divided into two categories: Incentive Based Programs (IBPs) and Price Based Programs (PBP, sometimes referred as Time-Based Rate Programs). In IBP, the customer response is triggered by a form of explicit economic incentive that can be generated enabling the DR, while in PBP, the customer is induced to react to a change of price signals to have economical advantage and for this reason can be considered as an implicit form of DR.

Classification of Demand Response Programs

According to the classification done by Albadi et al.[ii],**Incentive Based Programs** can be **Classical** or **Market based**:

(i) **Classical IBPs** include

- **Direct Control Programs**, where a utility provider can directly control a customer equipment (i.e. shut down a renewable plant, or charge/discharge a storage, etc…), after an agreement usually made by a direct contract.
- **Interruptible-Curtailable Programs**. In this category the customer can interrupt-curtail their load in accordance with contractual arrangements, after a direct request from the system operator. This category usually involves large industrial or commercial customers.

(ii) **Market based Programs** include

- **Demand bidding** (or **buyback**), a program that encourages industrial large consumers to reschedule their energy consumption and decline their load in peak hours in return for financial rewards.[iii] Usually a customer can bid for a load reduction in the wholesale market. If the bid is accepted, the customer must reduce the load as specified in the bid otherwise penalties will apply.

- **Emergency DR Programs (EDRP)**, is activated in response to an emergency from grid operator such as shortage or congestion. For the EDRP program, the system operator typically sends notifications a day before the event and on the day of the event (in some cases up to 30 minutes prior to the event).[iv,v].
- **Capacity Market Programs**, designed mainly for security reason by central operators (i.e. TSO, like the Italian TERNA), to avoid blackout or other grid service issues. The main purpose is to ensure an adequate and reliable capacity available when needed. For that, customers or capacity providers are paid to make a disposition energy reserve for the whole duration of the contract.
- **Ancillary services market programmes**, services designed by system operators to securely manage the grid while ensuring a good quality of service. The **frequency response** is one of the ancillary service market programs.

Price Based Programs include:

(i) **Time of Use** (TOU), in which there are a set of blocks, each one with a specific price. Usually we can find 2-3 price blocks per day.

(ii) **Critical Peak Pricing** (CPP), consists in creating blocks with high prices in proximity of expected peak hours, and low prices for the remaining hours. Similarly, to CPP, there are other specific programs, namely **Extreme Day Pricing** (EDP) and **Extreme Day CPP** (ED-CPP).

(iii) **Real Time Pricing (RTP)**, where price changes on hourly basis, as function of supply and demand conditions.

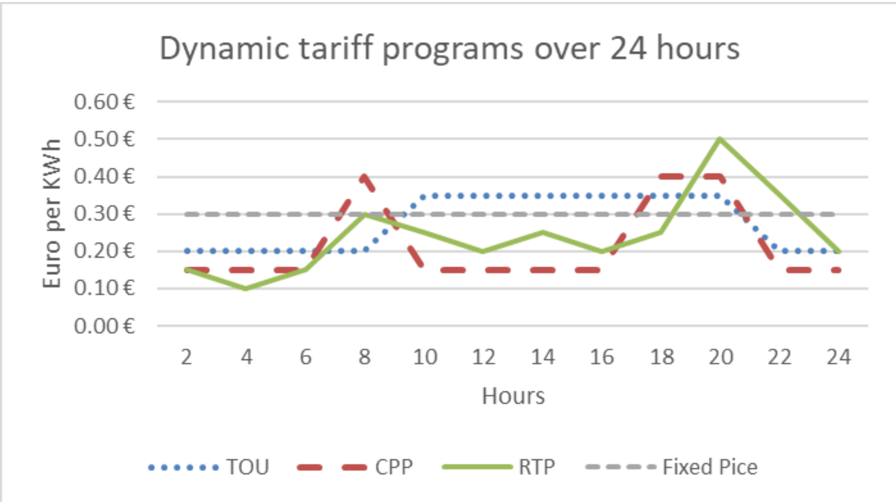

Figure 3 TOU, CPP, RTP and FP programs comparison over 24 hours

2.3 Flexibility Assessment and Demand Response

According to EURELECTRIC[vi], the flexibility of a power system refers to "The modification of generation injection and/or consumption patterns in reaction to an external signal (price signal or activation) in order to provide a service within the energy system".

Then, with the flexibility, we can refer to the ability of a system to change power supply/demand to any type of scale, from the single device to the entire building up to the electricity power plant.

The electricity distribution sector needs to increase the flexibility margins of users in order to exploit and manage the growth in variable RES which represent a growing share of electricity production. Indeed, the lack of flexibility results in a significant reduction in RES and/or an increase in the costs of generation and network.

Demand response is the most immediately available way to increase flexibility, allowing customers to take advantage of significantly lower energy prices than those established in the classic mode. To this end, it is important to tackle some issues that still stand between the application of demand response and market programs, such as the necessity to improve consumer's ability to react (meters, tariff structure and knowledge) and issues related to market design and regulation (access rules and incentives). Nevertheless, the demand response may encompass non-trivial uncertainty, especially for price-based DR programs or when non-compliance is not penalized and that all of this can lead to situations where more resources are activated for ensuring the required flexibility, which results in the increment of the overall cost of the service.

For these reasons, the implementation of Demand Response programs is fully dependent by the right assessment of the customer’s flexibility and for this reason, there are many methods to assess the flexibility.

All of these adapt to a spectrum, analysing exclusively the physical characteristics of all system resources in order to estimate the amount of flexibility available on the basis of historical data analysis or a detailed simulation of future years.

There are different flexibility assessment methods that could be grouped on the base of the level of detail of the data used into three categories (screening, intermediate and detailed), all of this must be used to quantify the flexibility at different time scales (<5 minutes, 5 minutes, 10 minutes, 1 hour, 3 hours). The simplest approaches evaluate the flexibility of the system by analysing the characteristics of physical resources on the system without considering their operation. More complicated approaches are based on the detailed simulation of system operation. Recently, these simulations also include a complete transmission representation, if transmission is an important scare resource of the system. The different categories can also be used in combination with each other, some examples are reported below[vii]:

- **Screening of available flexibility:** Evaluation of resources based exclusively on physical characteristics, without any evaluation of their status in operation. The aim of this type of analysis is to evaluate the capabilities to ramp of a given set of resources. The risk is to overestimate the availability of resources to provide flexibility. For this reason, this type of evaluation is considered as a screening activity. The screening analyses include the assumption of specific system conditions, such as peak and minimum load, and estimation of flexibility from these starting points or selection of a particular state of the system in which flexibility is expected is bound. Some well-known tools and methods for the screening of available flexibility are reported below:
    - **Flexibility Assessment Tool (FAST)[viii],** developed from the International Energy Agency, is based on a Microsoft Excel spreadsheet to analyse the flexibility of resources available. Dispatchability at peak and minimum load are estimated based on generator characteristics and user knowledge. The flexibility available from the resources is then quantified on different

time horizons of interest (from a few minutes up to a few hours) for up and down ramps. This is then extrapolated to determine the maximum variability that could be satisfied by the system resources.

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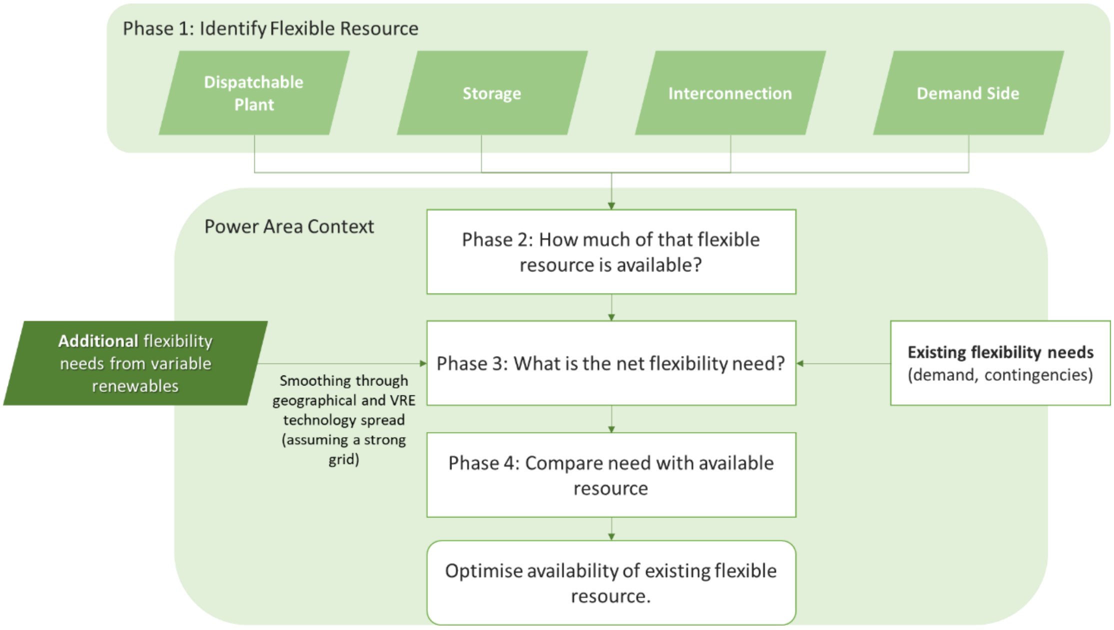

Figure 4 FAST screening Method

- **Portland General Electric's (PGE's) Integrated Resource Plan**[ix] aims to provide the answers to the following questions: (1) how many MW of dispatchable resources are needed to (a) meet load, and (b) meet flexibility requirements, (2) What is the optimal mix of new resources, given the characteristics of the existing fleet of conventional and renewable resources. This method tries to quantify the required flexibility and therefore the available flexible resource, for each of the relevant time scales for up to one hour. The available resource is quantified by activating all resources and moving them to the maximum capacity as soon as possible. By using this approach, the toll compares the amount of available capacity estimated with the required variability and determines whether sufficient flexibility exists.
- **Kirschen/Ma**[x]**:** In this method the flexibility of conventional generation resources is dependent on start time, ramp rate and operating range. This Method defines a flexibility index presented for units and system as a means to measure and compare flexibility across resources.

- **Intermediate Assessment:** in this case a more detailed approach than those in the previous subsection are used, but do not yet examine a comprehensive study of the dispatchment, with all the implications and challenges associated with modelling. Some methods known in the literature are reported below:
  - **Schillmoeller**[xi]**:** It makes use of an approach that makes it possible to sort the available resources on different time scales so that the different response rates can be combined to provide the possibility of overall system ramps. This shows the total ramping that can be provided for a certain period of time, first describing a cumulative curve of the ramp duration, which does not take into account the recovery of capacity. The capacity to recover during a net distribution is therefore described considering the initial conditions, indicated as a path. The total requirements are then calculated as the minimum required resource that satisfies

all paths. Comparing the requirements with the available capacity shows if and how the system does not have sufficient flexibility;

- **FAST2**[xii] starting from an initial, high-level assessment of power system flexibility based on a chronological hourly matching of load and variable renewable energy supply, this algorithm is able to calculate flexibility requirements from hourly load and variable renewable energy generation data over a period and matches it against flexibility provisions from flexible plants, interconnections, demand-side response, while taking into account existing inflexibility due to the minimum generation requirements of dispatchable plants. Its output is the number of hours with insufficient flexibility for different hypothetical levels of variable renewable energy penetration. Such an assessment can be conducted, in the long-term planning context, as ex-post validation of model results for a single future year.
- **EPRI**[xiii], is based on the use of System Flexibility Screening and Assessment Tool (InFLEXion), now in its 3.0 version[xiv] (first three level of the EPRI Multi-Level Flexibility Assessment). The Tool allows for easier analysis of flexibility requirements and flexible resources for systems with high levels of variable generation. This method assesses the variability of the system net load based on time series data (at least one year at 5 minute intervals) performing a number of historical analysis, similar to other methods, over a range of time scales, allowing various metrics to be quantified and graphs produced for flexibility requirements. Essentially, the metrics are of three types: Periods of Flexibility Deficit, Expected Unserved Ramping, Insufficient Ramping Resource Expectation. The detailed flexibility metrics allow for consideration of the flexibility sufficiency of a system, including how transmission impacts on the system flexibility metrics, and how different resources can improve system flexibility.

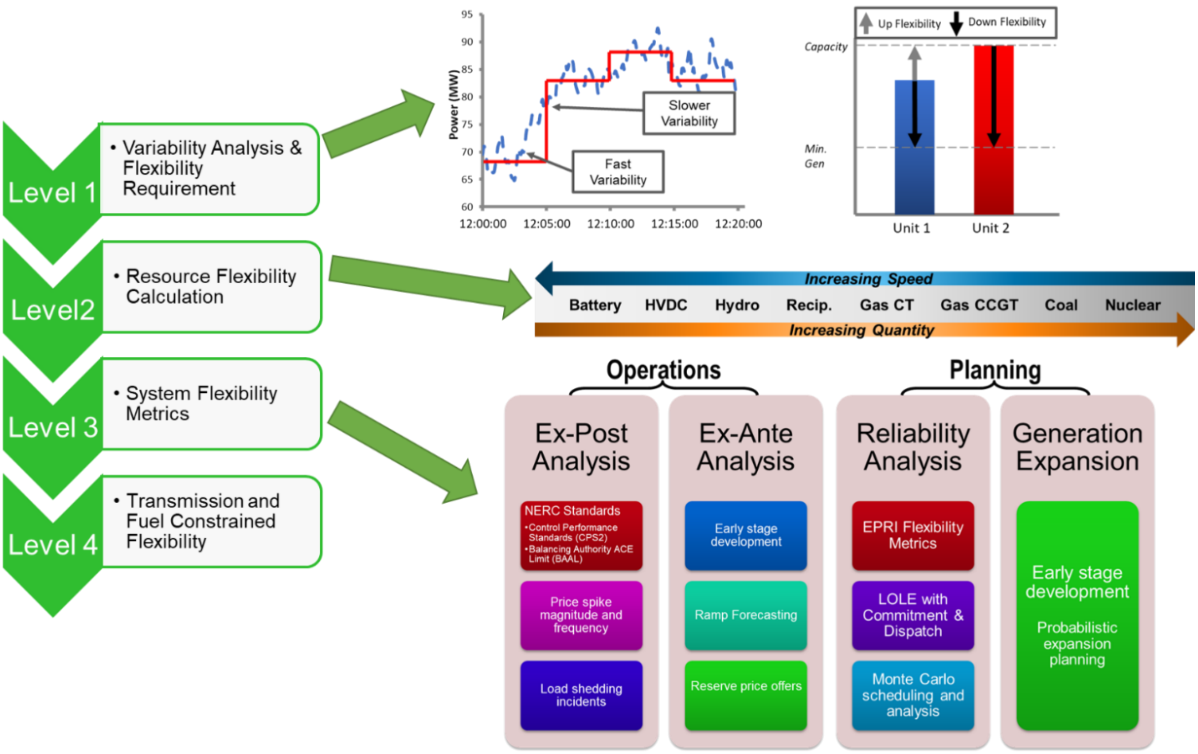

Figure 5 EPRI Multi-Level Flexibility Assessment

- **Detailed Assessment Methods:** The complete analysis to assess flexibility requires more details about system operations, which generally means complete information on how to occur the unit commitment and economic dispatch. To do this, new metrics and techniques have evolved from using existing or simulated production simulation tools to evaluate flexibility.
    - **E3 REFLEX**[xv], production simulation model designed to identify operational flexibility needs in the presence of a strong penetration of renewable energy by capturing the real-world constraints on operational flexibility to evaluate investments in flexible resources. The tool determines the availability of resources using conventional production simulation tools and present a large number of 3-day scenarios simulated, energy and reserve violations tracked. The shapes are determined to be used with tools based on flexibility required with penalties for not meeting energy or reserve;
    - **IRRE**[xvi], the insufficient ramping resource expectation (IRRE) is a probabilistic method of assessing the frequency of flexibility deficits. The metric defined by this method is dependent on the result of the production cost modelling that determines the dispatch level of each resource during a study period. Depending on the dispatch level, resource parameters and availability, a distribution of the flexibility available in the system can be determined. This can then be used to determine the probability of encountering ramp load events throughout the year. When these probabilities are aggregated into an expected value, the result is a metric for the overall flexibility of the system. This metric can be applied to ramping in the up and down directions and for a range of time horizons so that distinct flexibility issues can be identified.

The market for grid flexibility services is in a phase of constant growth in all of Europe thanks to the fact that renewables become an increasingly large proportion of the generation portfolio. A large generator can provide grid services and improve network flexibility by grouping storage with renewables. Isolation from the grid, aggregation of demand and local production to balance the supply and demand of a community, industrial park, city or any type of "island" result in reduced volatility and volume of demand that reaches the network. At the point of demand, storage behind the meter, demand management and managed charging can reduce the interaction and energy required by the grid, providing local small-scale back-up capabilities and provide then the opportunity to provide services network and arbitrage, recharge when prices are low and discharge when prices are high. Considering the continued growth in the spread of electric vehicles, the grid services will be provided increasingly also by vehicles.

In this context, peer-to-peer (P2P) energy trading represents the direct trade of energy between peers, where the energy from distributed energy resources (DER) in homes, offices, factories, etc. is exchanged between local energy prosumers and consumers. Strategic bidding behaviour of energy consumers and small-scale prosumers in P2P energy trading is mainly based on the planning of flexible demand and storage systems, if generation is considered by the uncontrollable renewable energy. The generations distributed by intermittent renewable energy can be managed through disconnection / reconnection or de-rating of the maximum powers for energy trading purposes. The flexible demand must be scheduled without sacrificing any satisfaction of end users, as compromising end-user satisfaction can also lead to greater flexibility for planning, but at the same time resulting in a higher social cost. This involves the need for an intermediary such as the aggregator of which the participation in the market is widely acknowledged as a key factor in initiating participation in demand in terms of flexibility. A P2P approach, respect to a traditional one, give the advantages in terms of consideration of flexibility optimization at the level of microgrid instead of the individual prosumers. Moreover, with P2P approach each microgrid optimizes its reserve supply, not only with its own resources but also with the rest of the microgrids in the cell, bringing out more energy resources in the wholesale market by lowering costs. P2P energy trading is a major identified use-case in the eDREAM project and is defined as a project use-case in Deliverable 2.2: Use case Analysis and application scenarios description V1, Chapter 3.3.2.

3 Techniques and Approaches for Energy Consumption Baseline Flexibility Estimation

The baseline forecasting are a central part in all DR program, is not possible control one variable if this variable is not measurable, there are numerous methodologies to make a forecasting baseline, anyone use different data, and different procedure, one of the most important characteristics is the horizon. Starting from the horizon, you can make pre-orders of a few hours, minutes or even weeks, and then use these preconditions so that the system and the grid are prepared, the predictions with a larger horizon give a longer response time, but they are more rigid, predictions with a shorter horizon give small response times but give great flexibility to the system, and a much more accurate prediction. The best for a DR project is to use more than one type of baseline, with different horizons taking the best qualities from both. In eDREAM the baseline forecasting models, follow the baseline forecasting pattern used in ENERCON (EnerNOC Utility Solutions, 2013):

- **Baseline type I**: use the historical load data and may also use weather to generate a profile baseline that usually forecasting any hour. This is the most typical baseline, and gives very good results in places where the demand is periodic, as in offices, or some types of factory, which maintain a load during the hours of operation or use of the facilities, and another pattern completely Different, when it is not working or used, a good example of this type of buildings are the office buildings, in their load they can see the beginning of the working day, the end and can be different the working days of the non-working days. An important factor that affects the load of a building is the weather, to make a more efficient prediction of the load, the best thing is to take into account the weather. For example, the summer consumption is not equal to the winter consumption and also the consumption may vary between colder and warmer ones.
- **Baseline meter Before-After**: baseline is generated using only actual load data from a time period directly preceding an event. This is one of the most flexible, because not only uses the historical data also uses the current load to predict the next, in these cases, the horizon, in this case, will be set by the System, and the response speed of the grid, in function of these parameters, is estimated the demand in the next instant and the grid responds in function of this prediction, for the eDREAM Project this type of baseline is the most important. Since it allows to make the contracts intact, at a given moment it is calculated the demand and next moment and in turn a contract is made with the producers that will supply that energy, in the case that the prediction is erroneous, the contract will be unfulfilled, increasing the size of the electric bill.
- **Baseline type II**: statistical sampling generates a baseline for a portfolio of customers, this type of baseline is one of the most unpredictable, because it does not work with the historical data of the building, instead of this work with the data of other buildings with similar characteristics and seen function of this predicts the electrical load. For example, if have the data of an offices building, it could be said that the consumption of another office building of the same dimensions with the same amount of workers, located in places with similar climatic characteristics, will have similar baselines, this is a very useful tool the case of not having access to historical data
- **Baseline generation**: baseline is set as zero and measured against usage readings, this type of baseline is only applicable for facilities with on-site generation (EnerNOC Utility Solutions, 2013)
- **Baseline baseload**: (also known PJM baseline) This model was developed and implemented in the PJM grid for that reason it is known by that name, and is based on maintaining a flat baseline level, and always keeping the client below this level.

3.1 Existing ISO Demand Response Products

There are numerous approaches to energy consumption baselines flexibility estimation, many groups in recent years have studied electric charge prediction models, each with different theories with different motifs, some have worked better others worse, all with features, data, algorithms, theories, some have been improved, and with the development of Computers are becoming easier to transmit information. This article presents some case studies that show different techniques and approaches, the cases that will show are, California Independent System operator, PJM, ISO New England, New York ISO, ERCOT, the review of all these case studies gives a better focus of the objectives that are pursued with this Project.

3.1.1 CAISO

The California Independent System Operator (CAISO) (Alaywan, 2000) started operation on 3/31/1998, with the Key drive to control the Situation's electrical grid (Goodin, 2012)CAISO is responsible for ensuring the safety and reliability of the transportation of electrical power and ensuring that resources have the same access to the meshes. The California power grid made up of high voltage, 500 kV, 230 kV, 115 kV, 70kV, and 60 kV, the power lines delivers 263 terawatts/hour, has more than 27 million customers per year, in addition, the grid takes large amounts of routing from other grids, California is an importer of energy, 20% of its energy the importance of neighbouring states. The method that CAISO uses allows them to forecast, in such a way, they know with a day of anticipation what the electrical demand will be and then they control the production and the energy exchange with the neighbouring states to match it with the consumption. Performing this forecasting is not easy considering that the California ISO is the second largest ISO in the United States after PJM, nonetheless, PJM exists in several states, because you could say that the CAISO is the largest ISO in any state, of the United States. Thus, CAISO's wholesale energy market incorporates two types of markets, one that focuses on day-ahead processes and another one that focuses on real-time processes (CAISO, 2019). In the day-ahead market the following steps are performed sequentially (CAISO, 2019):

(1) Run a market power mitigation test,

(2) Establish the amount of power needed to satisfy the forecasted demand, and

(3) Determine supplementary plants that must be prepared to generate electricity for the next day. Bids establish the electricity prices and the market is capable of identifying the cheapest energy to be provided to the consumer, by making use of the full network model.

Also in this market, scheduling coordinators have a specific time interval in which they can transact, i.e. seven days before the trade date until the last day before the trade date. The real-time market, named Energy Imbalance Market ensures that the power is provided to its customers at the lowest cost when demanded through its real-time trading system, which involves running an automated auction every 5 minutes daily. Such an approach enables the market's participants, both consumers and electric power companies, to buy or sell power right before it is used. Besides providing power at lower costs, the market also supports the integration of renewable energy. The renewable energy is predicted daily and in case of predicting an excess, the energy is provided at a lower cost to other areas in which the energy would otherwise be provided at higher costs and from less cleaner sources. Moreover, the Energy Imbalance Market maintains the grid's reliability and stability through its ancillary services, which regulate energy up and down, or provide spinning and non-spinning reserves.

3.1.2 ISO New England

ISO New England manages the electric grid spanning Connecticut, Rhode Island, Massachusetts, Vermont, New Hampshire, and Maine, and that administrates the associated wholesale electricity markets (i.e. Day-Ahead Energy Market, Real-Time Energy Market, Forward Capacity Market). In the Day-Ahead Energy Market wholesale electricity is sold or bought one day before it is used, while in the Real-Time Energy Market electricity is sold or bought right in the day it is used such that the differences that might appear in the day-ahead demand-response are balanced by the real-time demand-response (ISO New England, 2019). The participants in the Day-Ahead Energy Market can be either paid or penalized with a sum established in the Real-Time Energy Market in case of real-time demand or generation that is not according to the one established in the day-ahead (ISO New England, 2019). The aim of the Forward Capacity Market is to ensure the long-term reliability of the system by identifying the market's participants that commit to respond to the demand forecasted on the next three years. ISO New England also provides the following ancillary services to ensure the short-term reliability of the system (ISO New England, 2019):

(1) Regulation Market – selects and compensates the participants that respond to ISO's requests for output increase/decrease such that the grid's frequency is kept at around 60 hertz

(2) Forward Reserve Market – compensates the participants that can respond with electricity in case of an unexpected event,

(3) Real-Time Reserve Pricing – compensates the participants that can respond in real-time to ISO's requests for electricity supplying or electricity demand reducing,

(4) Voltage Support – compensates the participants that can maintain the voltage control,

(5) BlackStart Capability – compensates power plants, which can immediately take action in case of a blackout by restarting the transmission system.

One of the main consequences of the growing complexity of electrical grids and associated markets, is the growing uncertainty and variability in the demand, the ISO New England Project is designed to forecast the electrical demand, using a programming in the parallel computer cluster, (Ma, 2016) but nevertheless each time the systems are bigger and more complex. This makes the IT resources insufficient, additionally there are more and more users using the platform, which leads to a longer waiting time, this leads to the postponement of studies or the interruption of minor priority, the existing computer resources cannot meet the internal needs of profitable. For this reason the ISO-NE project has decided to adopt the technology of programming in the cloud for electrical systems, The concept of "Smart Grid Cloud" was discussed in detail in (Liu, 2017), and is designed to make cloud computing adjust to aspects of energy system The use of cloud computing for power Off-line planning studies system is an example of the analytical modules of the "Smart Grid Cloud" proposal.

3.1.3 New York ISO

New York ISO is the independent system operator that manages the electric grid of New York and associated wholesale electricity market since 1999. The aim of New York ISO is to (New York ISO, 2018): (1) balance the available power every six seconds over the 11173 miles of managed transmission lines, while adhering to 1000 reliability standards, (2) balance consumers' power demand with the energy producers' offers in a cost-effective manner by constantly reviewing the energy producers' bids, (3) supervise 24/7 how the power is delivered from generators to the utility companies that provide electricity to the 19.8 million population of New York, and (4) integrate renewable energy sources into the managed market which compete along with traditional energy sources. New York ISO implements two types of demand response programs within its market (New York ISO, 2018): (1) reliability-based programs – the Installed Capacity - Special Case Resource program and the Emergency Demand Response program, and (2) economic-based programs - Day-ahead Demand Response program and Demand-Side Ancillary Services. These models favour the reduction of the load (Lawrence, 2002) The reliability-based programs allow the demand to be reduced or reservation generators to be ignited when the generation is insufficient, for example when an emergency takes place. In such situations, through the Emergency Demand Response Program, the New York ISO will notify the Curtailment Service Providers that load must be reduced, with an amount computed according to the customer's baseline consumption determined by the last five days within a timeframe of ten days in which the energy consumption level was the highest (Lawrence, 2002). The notification is given both a day and two hours before the reduction must be enforced. To encourage the market's participants to reduce the energy consumption in this situation, the market pays Curtailment Service Providers according to the achieved load reduction. In the case of the Installed Capacity - Special Case Resource program, the participants are obliged to reduce load every time the New York ISO signals a reliability event for at least four hours, and receive monthly a capacity payment (New York ISO, 2018). A condition that must be fulfilled by a participant to be accepted in the reliability-based programs is to commit to reduce the load with at least 100kW. The economic-based demand response programs enable participants to offer load reduction even in non-emergency situations, when the electric grid is not stressed (New York ISO, 2018). For example, within the day-ahead demand response program, load reduction is auctioned and evaluated in the day-ahead market together with the energy supply bids (Lawrence, 2002). Thus, the energy demand is compared with the baseline forecasting, and incentives are given for those who decrease their daily demand in real time, while penalties are given in case the demand is not decreased in real time according to the scheduled load reduction. Once a load reduction is accepted and scheduled, the participant must respect the schedule. The participants in the Demand-Side Ancillary Services Program must respond with load reduction any time the New York ISO requests it in real time. A condition that must be fulfilled by a participant to be accepted in the economic-based programs is to commit to be able to reduce the load with at least 1MW.

3.1.4 ERCOT

DR programs can be used to make clients aware and to encourage them to reduce their electric consumption, through incentives, The Electric Reliability Council of Texas (ERCOT) started a DR program in 2010 to benefit customers, this program includes residential and industrial clients, and foresees the effective incorporation of renewable sources and batteries to the grid the proposed scenario presents the implementation of a solar panel system with batteries, in urban areas the price of renewable energy is decreasing, especially for solar panels, which are easy to install on the roofs of buildings, do not produce sonic pollution or CO_2. For these reasons the solar energy is the reference for the renewable energies in urban areas. On 2010, ERCOT launched a comprehensive nodal market where electric grid congestion information with more than 4000 nodes (Liu, 2014)ERCOT manages 85% of the electric power load in Texas, where they serve 23 million customers, any node give information about the price, the cost at to provide the next megawatt of power, This project is very ambitious and demonstrates that to integrate renewable energy into a grid it is necessary to make DR programs and modernize the grid so that it can be converted into a smart grid. The main goal of ERCOT is to ensure the reliability and manage the operation of the grid.

This goal is achieved by encouraging customers to participate as volunteers in ERCOT demand response (DR) programs. To illustrate the financial benefit obtained by the residential customers involved in the ERCOT DR programs, (Liu, 2014) presents three different scenarios of implementing photovoltaic (PV) systems and Li-based batteries for household under the ERCOT's demand response. The first scenario considers that only PVs are installed in the household and that the electricity will be imported from the grid when the PVs cannot produce enough electricity. The second scenario considers that only batteries were installed in the household and that the electricity will be stored in batteries when the Locational Marginal Pricing (LMP) is low. The third scenario considers that both PVs and batteries are installed in the household and that the surplus of electricity generated by PVs is stored in the batteries. The surplus of electricity will be used when the consumption of electricity is higher than the electricity generation, before importing electricity from the grid. Based on the results of the simulation, it has been noticed that in the first scenario the cost of electricity has been reduced by 53%, while the second scenario obtained not much reduction of the cost, because of the high cost of the batteries. The third scenario provides the best results in terms of the reduction of electricity costs.

Also, according to an ERCOT report in 2018 (ERCOT, 2018), it was found that the consumption of coal and natural gas as energy sources has decreased from 82.9% in 2007 to 71.0% in 2018 in the ERCOT service territory. This decrease is due to the fact that in 2005, the Public Utility Commission of Texas (PUC) in collaboration with ERCOT have decided to design competitive renewable energy zones (CREZ) which integrate as renewable energy resources the solar energy and the wind turbines. Also, a transmission plan has been developed, by which the renewable power is delivered from CREZ to the customers. The design of such competitive renewable energy zones (CREZ) has been motivated by the fact that the ERCOT region has world-class wind resources. For example, the month of October 2017 recorded a production of wind energy representing 54.0% of the total electricity load of the main power grid of the state (of Texas), while in March 31, 2018 the generation of wind electricity in Texas was 16,141 MW. The adoption of this strategy had a positive impact on the average wholesale electricity market prices by reducing the market price of electricity on average towards a value between $1 and $2.50/MWh. The reduction of the market price of electricity allowed customers to save money. For instance, in 2017 the money saving of the customers due to using renewable energy was of $855.9 million.

3.1.5 PJM

The Pennsylvania – New Jersey – Maryland interconnection (PJM), part of the Eastern Interconnection, is a regional transmission organization from the United States, that coordinates the wholesale electricity in the following states from the US: Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia, and the District of Columbia. PJM has 1000 members which serve 65 million customers. In 2016, PJM reported a generating capacity of 176,569 MW, 82,546 miles of transmission lines, and 830 terawatt hours of delivered electricity (TWhs) (PJM, 2016). PJM provides a voluntary Demand Response program for its customers, by which the customers that decide to reduce their electricity load when the reliability of the PJM grid is threatened or the energy price is high are financially rewarded (PJM, 2017).

Pennsylvania-New Jersey-Maryland interconnection, (Barancewicz, 2010) in 2006 in US introduced to the concept of utilizing reductions in load. This was done with a financial benefit through participation in the real-time option of the Pennsylvania-New Jersey-Maryland Interconnection (PJM) economic load response program. PJM is the most important grid in the US, The DR project in this grid has a significant impact on the US electricity market. according to Walawalkar, R, et al (2008) (Walawalkar, 2008) the benefits of the DR program in the grid PJM, are significant, because this is a large grid and if in the peak hours you can reduce a bit the consumption somewhere in the grid this represents a drop in prices and an increase In reliability throughout the grid, the RTO (Regional Transmission Organizations) merchants are very interconnected, this makes the System sensible to any disturbance. By load reduction programs, the customers have the opportunity to manage the way in which they use the electricity, based on the modifications recorded in the wholesale market (e.g. they can decide to reduce the electricity consumption when the wholesale prices are high or when the reliability of the grid is threatened). PJM integrates different energy resource types such as coal, natural gas steam, natural gas combustion turbine, oil steam, oil combustion turbine, nuclear, solar, wind, hydro, and battery/storage. Whereas in 2005, the coal, natural gases and nuclear resources generated 91%

of the electricity on the PJM system, in 2016 the percent decreases to 84% due to renewables energy resources that were integrated into PJM (PJM, 2017). The future strategy of PJM is to extensively grow the integration of the renewable energy resources, so as until 2020 to serve approximately 20% of the load (PJM, 2017). For integrating the heterogeneous renewable energy resources, PJM takes into consideration the possibility of using HVDC as electric transmission infrastructure. To measure the impact of the integration of HVDC systems into the Regional transmission organization (RTO) (J. TONG, 2015). PJM performed several market simulations that were conducted for annual periods using an hourly unit and a commitment software tool. These simulations assumed that the renewable energy resources were integrated into the PJM system from remote areas, which are not part of the RTO by using an HVDC system. The evaluation was performed by considering three metrics (production costs, demand costs, and emissions tons), and it demonstrates that HVDC is a viable option in contrast to using an AC system, that is not able to integrate large amounts of renewable resources over long distances into PJM.

3.2 Existing Baseline Methodologies

The electricity network operators face daily problems due to the lack or excess of energy and the great difference between peak consumption and basic consumption, even more after the advent of distributed generation by renewable energy sources, whose generation is intermittent and often occurs in the hours when users do not consume; in this scenario, Demand Response (DR) has been widely recognized as an important tool for balancing energy supply and demand. DR invites customers to reduce, move or temporarily lose their demand in response to price signals or other market incentives during the event period. To this end, quantification of demand reduction is becoming a major problem for both electric units and customers, so the baseline calculation is necessary to increase the performance of a DR program. A baseline is an estimate of the electricity that would have been consumed by a user in the absence of a DR event; the baseline calculation can be done through different methods, the following are shown below: "X of Y", weighted average, regression, comparable day and baseline adjustment.

3.2.1 “X of Y”

The most widely used baseline methods are the averaging methods, which create baselines by averaging recent historical load data to build estimates of load for specific time intervals. Averaging methods are often called “X of Y” methods; more precisely, there are two types of “X of Y” methods: the “High X of Y” and the “Middle X of Y”

X of Y methodology is, is the most basic to generate a good CBL, This method is used in grids as PJM or CAISO (EnerNOC Utility Solutions, 2013)is based on a baseline forecasting, using them as information Y days before the event and in turn of those days are selected the most significant X days, the selection depends on the method you want to use. There are two main ways, in this method, (Mohajeryami, 2017) simple average model-high X of Y and simple average model-middle X of Y, one or the other is chosen depending on the results sought.

Simple average model-high X of Y use the X days with the highest load, this way the most likely will be that the load is below the baseline, the mathematical model that corresponds with the procedure described above is as follows.

$$b_{(d,t)} = \frac{1}{X} \sum_{d \in High(X,Y,d)}^{d=X} l_{(d,t)}$$

Equation 1

Simple average model-middle X of Y uses the X days with the average load, excluding both the highest and the lowest loads, assuming that they are isolated events. In this way the baseline is much more stable, and the error with respect to the load is reduced, but in this case it is possible that the load exceeds the baseline in some moments weighted average. The mathematical model that corresponds with the procedure described above is as follows.

$$b_{(d,t)} = \frac{1}{X} \sum_{d \in Mid(X,Y,d)}^{d=X} l_{(d,t)}$$

Equation 2

In the previous paragraphs explain what the criteria should be to select the X days, but what is the best ratio of X and Y to do correct forecasting. The bigger it is Y the more the sample will be, this usually increases the effectiveness of the forecasting, but if Y is too big it could cause some problems, such as being affected by the change of station or a change in the characteristics of the load. The old information could be harmful to the accuracy of the forecasting. It is advisable not to take more than a few weeks, as deviations, caused by changes in climate. If use information from previous years, ensure that the facilities and teams have not undergone significant changes in the aftermath of the year, these things can be corrected by choosing correctly the X and Y values or making use of other methods, for example, some of these methods take into consideration the temperature, the mathematical model more accurate depends on each particular case, in the literature are taken into consideration (EnerNOC Utility Solutions, 2013), look-back window, exclusion rules, relationship between X and Y and time intervals.

The look-back windows is the range of days used to estimate the demand, actually, in the DR programs not there is a maximum restriction to this parameter, the restriction can be estimated for external factors, as calculation capacity, or ability of the grid to change the characteristics of the load quickly. This may be due to the inclusion of new customers, and occurs mainly in grids that are growing. The minimum restriction to the look-back windows, according to a study made by the Subcommittee of PJM conducted a study of baselines, cited in (EnerNOC Utility Solutions, 2013), 30 days is a period of short time, and recommends that it be at least 60 days.

Exclusion rules are the rules that must be followed to exclude days of the Y days before the event, in general, all DR programs exclude weekends, and in many cases also the days of the event, it is said that the threshold, recommended by the PJM is 25%.

Time Intervals are the time period in which the baseline is projected, usually a few minutes, from 5 to 15, but in some cases where the currents are low and little variable. This can be done every hour to save calculation power.

3.2.2 Weighted Average

This baseline method is based on a weighted average of the previous day's baseline and the present-day's actual measured load. The baseline is not calculated on weekends or holidays and it is updated on every day of the week when no DR campaigns are carried out. During DR campaign days, the baseline is defined as the previous day's baseline. In cases where there is no preceding computed baseline, the baseline is the simple average hourly load calculated for each hour of the day from the five most recent preceding business days with complete meter data.

3.2.3 Regression

The regression baseline is built using a customer-specific regression analysis to estimate load based on prior load behaviour, weather conditions, calendar data, system demand and time of day, as there is a clear similarity between the daily energy consumption and the average daily temperature in some circumstances. Regression analysis may be the most accurate and the most complex of baseline methodologies because it takes into consideration more variables that influence load. In detail, regression baseline is calculated using a regression model consisting of a daily energy equation, which has the customer's total daily kWh as the dependent variable, and 24 hourly energy fraction equations, in each of which is the dependent variable is the fraction of the daily load occurring in each hour of the day. The explanatory variables in the model include calendar variables (e.g., day of the week, holiday indicators, season), weather variables (dry-bulb temperature and various functions thereof), and daylight variables (e.g., daylight saving time, times of sunrise and sunset), to calculate the correction factor the maximum load of the X days is also used, the following formulas represent the described mathematic model.

$$\rho_{(d)} = \frac{X \sum_{x=1}^{d-1} l_{(x)} T_{(x)} - \sum_{x=1}^{d-1} l_{(x)} \sum_{x=1}^{d-1} T_{(x)}}{X \sum_{x=1}^{d-1} T_{(x)}^2 - \left(\sum_{x=1}^{d-1} T_{(x)}\right)^2}$$

Equation 3

$$l_{2(N)} = \rho_{(d)}\left(T_{(n)} - T_{(d)}\right) + l_{1(N)}$$

Equation 4

$$T_{(d)} = \frac{\sum_{n=1}^{N} T_{(n)}}{N}$$

Equation 5

In the preceding equations preceded, ρ is the correction parametron for the load, it must be calculated every day (d). T is the average temperature of the day, T* is the temperature at a certain time. l1 is the first calculated baseline, and l2 is the corrected baseline.

3.2.4 Comparable day

Comparable day is another method of forecasting, which uses historical data, to generate a baseline. In this case the baseline is not calculated, like the average values of the preceding days, for this case it only takes one day, it is selected for a day with similar conditions, and for example, if on a weekday a week end day or a holiday, this method can be used depending on the type of load.

To generate the baseline in this method, it is necessary to select the day most similar to the day you want to predict, for this we could go on things like the weather forecast, in that context, choose the climate day that is more similar to the climate we want predict, additionally we could go on data such as the day of the week, or the holidays, if the sufficient factors are not taken into account, the prediction could be erroneous.

In the case of climate, an algorithm of this type could be applied to select a comparable day

$$D_{(d)} = \frac{\sum_{t=1}^{N}\left|T_{f(t)} - T_{(d,t)}\right|}{N}$$

Equation 6

The factor D is calculated for each day, and then it will be necessary to take the day that corresponds to the lowest value of D. When the factor D * is close to 1, the baseline should be more accurate.

$$D_{(d)} = \frac{\sum_{t=1}^{N}\left|\frac{T_{f(t)}}{T_{(d,t)}}\right|}{N}$$

Equation 7

The challenges with this methodology are two: it is not possible to know the baseline during the event which could impede meeting curtailment goals and there are no objective criteria for selection of the day which makes it difficult to assess the appropriateness of a comparable day.

3.2.5 Baseline adjustment

Several factors affect a customer's load profile prior to DR event. The conditions on the event day are often different from prior day conditions, especially for customers with weather-sensitive loads that increase during extremely hot and/or extremely cold conditions. Programs that are triggered by peak demand conditions or emergencies caused by generation outages often coincide with days of extreme weather temperatures. For this reason, an appropriate adjustment mechanism is necessary to more accurately reflect the actual circumstances and avoid penalizing customers who are consuming more power than a 'like' day alone. Current DR programs usually use readily verifiable data, such as temperature or load in the period prior to an event as the basis for adjustment. The adjustment algorithm is to calculate the impact of special circumstances. Generally, the initial baseline is adjusted upward/downward according to the load for several hours before the accident, which means that the adjustment is used to compensate for the average hourly temperature differences between the baseline basis days and the temperature of the event hour. The following are two methods of baseline adjustment: multiplication adjustment and addition adjustment.

The multiplication adjustment is a parameter, a, is calculated for each day at each moment to adjust the baseline. The equation is adjusted as follows:

$$l_{2(t)} = a_{(d)} l_{1(t)}$$

Equation 8

$$a_{(d)} = \frac{\sum_{n=1}^{t-1} l_{r(n,d)}}{\sum_{n=1}^{t-1} l_{1(n,d)}}$$

Equation 9

In the present equations above, *a* is the adjustment multiplier, *a* is calculated for each day (*d*) as a function of the moment of the day (*t*), *lr* is the real baseline measured, *l1* is the first calculated baseline, *l2* is the baseline corrected. It can be seen that if *lr* is equals *l1*, then *a* = 1, therefore there would be no adjustment.

The addition adjustment, Δ*l,* modify the equation to calculate the baseline, with a linear adjustment, at the moment an adjustment is calculated that is added algebraically, and the measurements that describe this adjustment are the following:

$$\Delta l_{(d,t)} = \frac{1}{N-1}\sum_{n=1}^{t-1} l_{r(n)} - l_{1(n)}$$

Equation 10

$$l_{2(t)} = \Delta l_{(d,t)} + l_{1(t)}$$

Equation 11

There is another method of linear approximation, for this other method the Δl is calculated in a different way, It is important to mention that this method is not a correction like the previous methods, the mathematical model that describes this other approach is the following:

$$\Delta l_{(d,N)} = \frac{1}{X}\sum_{d=1}^{X} l_{1(d,N)} - l_{1(d,N-1)}$$

Equation 12

$$l_{(N)} = \Delta l_{(d,N)} + l_{r(N-1)}$$

Equation 13

There are more types of adjustments that can be made to generate a more presumed weather, one of the most used is weather adjust, which takes into consideration the air temperature to correct the baseline, it would be interesting to see the effects of using forecasting weather to correct the baseline, and compare it with the results obtained. The equation that is used to correct the baseline in this year would be the following.

$$l_{2(t,T)=l_{1(t)}\frac{T_{(t)}}{T_{m(t,x)}}}$$

Equation 14

$$T_{m(t,x)} = \frac{1}{X}\sum_{x=1}^{X} T_{(t,x)}$$

Equation 15

3.2.6 Short term load forecasting for Baseline Assessment

Short-term electrical load forecasting can be performed using the Support Vector Regression (SVR), Triple seasonal methods for short-term electricity demand forecasting, Automated load forecasting assistant, Neural Networks for Short-Term Load Forecasting and extended Recursive Least Squares Algorithm. These methods may be applied to the demand response strategy to allow it to make predictions in discrete spaces of time, from a period of a couple of minutes to a number of days.

Support Vector Regression (SVR) or support vector machine (SVM), is a mathematical tool uses algorithms and a database to predict the future behaviour of a variable. (Chen, 2017) Used a support vector regression model to estimate the DR, applying this model to 4 office buildings, however it does not prove that the model will not be able to apply other types of buildings, as the frequency of data was every 15 minutes and the historical data was about 13 days. The use of SVR requires real-time weather data, however the available forecast period is 8 hours for working days, and the forecast accuracy it typically 1.57 % to 20.08%, depending on the method used for calculating the forecast.

When a prediction is made, it is important to analyse the associated error, so that when the method is put into operation, it is known that magnitude of error is possible reach. (Taylor, 2010) Study the testing of the British and French national grids and apply some prediction methods for how effective the prediction is. The investigation suggests a forecast time period for half-hourly electrical loads, the forecast accuracy is of great importance it is not the only criterion to consider when select a forecast method. The report results states that, with mean absolute percentage error (MAPE) levels between 1.5% and 6%, in the exponential smoothing method, there is currently no clear approach to choose upon the number of cycles and the decision between unrestricted and restricted versions. MAPE is calculated using the following formula, Equation 16.

$$M = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right|$$

Equation 16

Where A_t is the actual error and F_t is the forecasted error.

Neural networks allow the decentralization of information, thanks to this a system with height organization level can give answers more quickly and be much more flexible. Additionally in this case we will add the fuzzy algorithms, a concept that is flexible logic, and allows you to give complex answers, not only binary answers of 1 and 0. (Hippert, 2001)he made a study in which he combined the technology of neural networks with the fuzzy logic, in his paper he made a collection of other papers published between 1991 and 1999, in which either of two ways: The first way by repeatedly forecasting one hourly load at a time. The second way by using a system with 24 NNs in parallel, one for each hour of the day. Considered the load stationary process with level changes and outlier, according to this study in the future, more studies with more complex NNs should be done to have results that are solid masters on which to base the possible role of the NNs in load forecasting.

The automated load forecasting assistants (ALFA) is a technique used to make baseline forecasting, the baseline is generated according to the temperature and the historical data. (Jabbour, 1988)Did an investigation using 10-years of electrical data, ALFA forecast load for the following day or 2 days in advance) and showing for each hour, ALFA uses this information and information about the weather, to predict the opportune moment at which moment the cargo will be, the information about the weather in the submissive the national climate Service, this study also sea. To the dependence of the electric charge with the weather, and compare the normal electricity demand of winter and summer. After analysing the data of both the weather and the historical data and the operator query, ALFA automatically generates the load forecast.

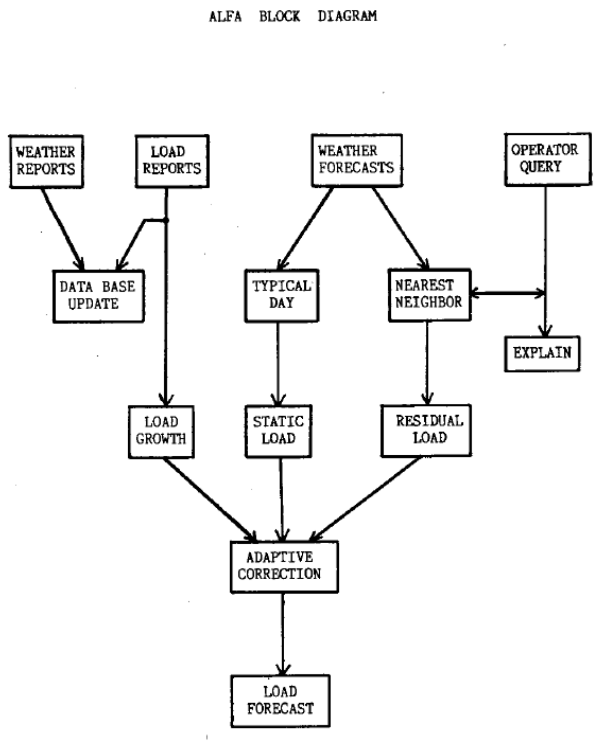

Figure 6 ALFA blocks diagram

A technique used to increase the reliability of renewable objects is to apply VPP (virtual power plant) in a grid. A VPP is to unite virtually prosumers with different baselines, that possibly complement each other, so that when one cannot generate another this general, and in the case of the consumers when one does not consume, consume the others. In a study Huang, J, et Boland, J, (2018) (Huang, 2018)determined that with a hybrid of solar and wind sources, the forecasting error was reduced between 13 and 35%, compared to the forecasting of independent sources

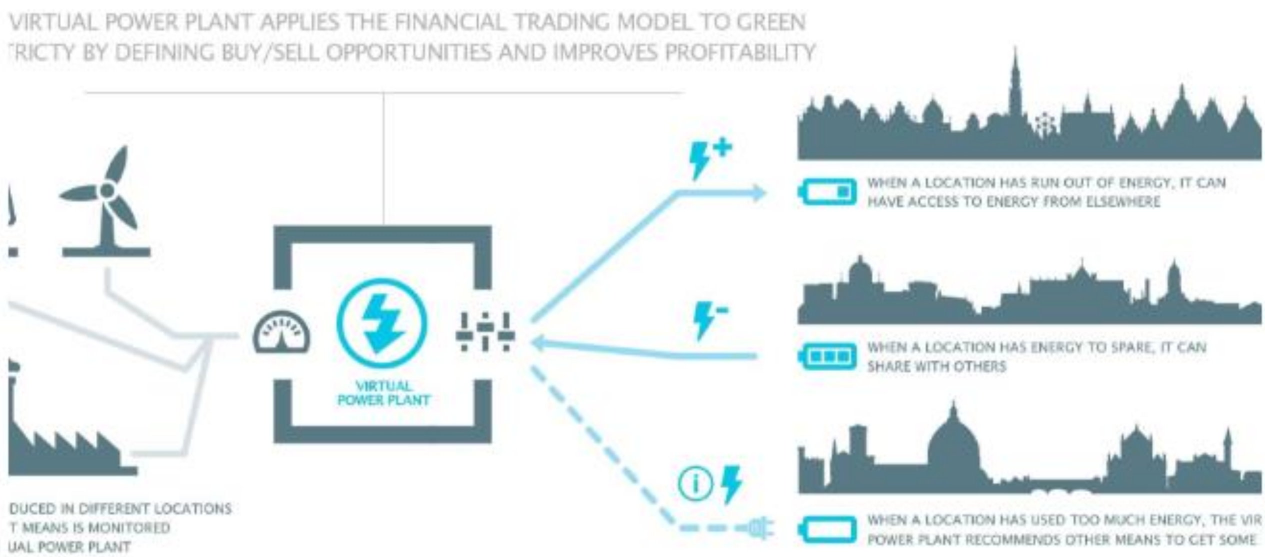

Figure 7 VPP design model

4 Customer Baseline Load (CBL) definition for eDREAM use cases

4.1 Methodology

Part of the aim of this project is to develop a system that can generate an optimal DR strategy for prosumers as part of an automated flexible contracting process. To do this, customer baselines must be calculated to understand how much energy a consumer/prosumer is likely to need at any given time. The process of calculating this baseline is examined in this chapter. These calculation methods are then verified using real-world data from a demonstration site, as specified in UC-HL01 and summarised below.

UC-HL01 takes advantage of a prosumer site in Terni, Italy, which is managed by the aggregator ASM Terni, one of the eDREAM consortium members. This site will utilised to test Prosumer DR flexibility aggregation via smart contract, providing a validation platform to test the calculation methods explored in this deliverable as well as serving as a platform to demonstrate the technology. The aggregator will adjust the supply and demand allowing a decentralized control, the DSO should look for and be able to evaluate in a flexible way the available services and act in response, allowing to optimize the provision of services.

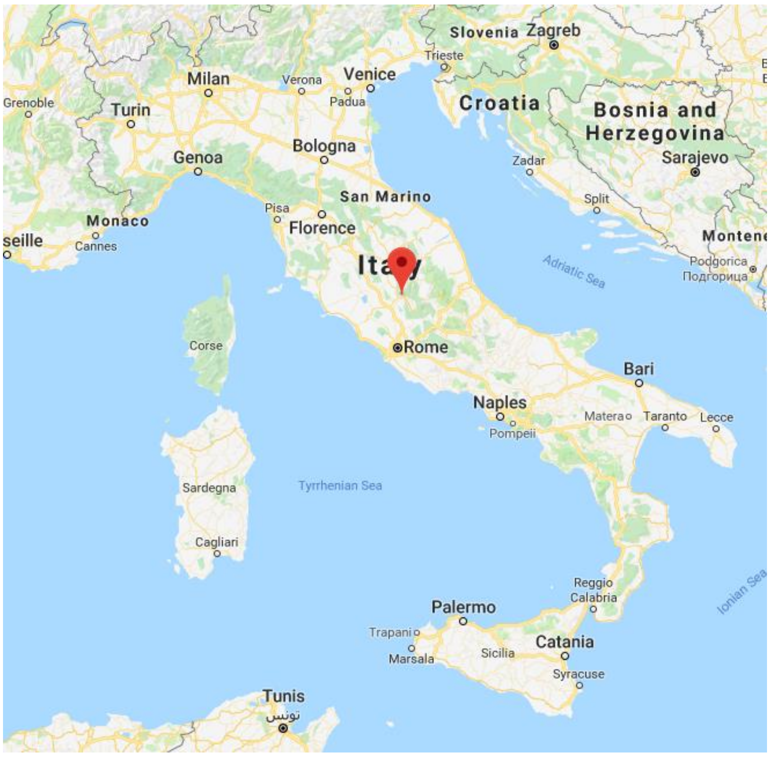

Figure 8 Geographical location of Terni site

The objectives of the case study at Terni are:

1) Maintaining the stability of source and demand in a decentralized system,

2) Achieving of reducing the overloading and

3) Attainment electrical grid stability by means of the flexibility provided by active micro-grids.

The operator for the micro-grids is prepared to work connected to the national grid or not in the case that it is not connected it works as an isolated grid. In both cases the prosumers and the consumers subscribed to the DR program make their capacity and energy flexibility available, and then they can accept smart contracts, the contracts are based on the consumption and the demand that in turn is estimated by the DSO. A DSO is able to find the points of Common Reference Operator (CRO) and send a flexible request, and then the DSO can accept the contracts and the aggregators control the load of the prosumers to keep the system flexible. Once the contract is accepted, this contract works as an unrolled control tool, allowing the parties to know what their role is in the production grid. Each party signs a contract in real time, and the prosumer has to use this information to balance the baseline on their own. The calculation to estimate how much you should modify your profile is based on the study of the CBL profile.

A good forecasting baseline needs an analysis of historical data. In this project we have data from 7 different buildings, in Italy these data are used to predict the behaviour of the baseline. In this study the types of baseline forecasting utilized are: "Baseline I" and "Baseline meter before meter after", and to see how the size of the historical sample affects wing prediction, if they made two approximations, one with the data of a week and another with the data of 3 weeks, all the Data used were measured during the month of September of the year 2018:

The mathematical model used to make the CBL was:

- For the Baseline meter before-after

$$l_{(t,n)} = l_{(t-1,n)} \frac{\sum_{d=1}^{n-1} l_{(t,d)} - l_{(t-1,d)}}{n-1}$$

Equation 17

- For the Baseline I

$$l_{(t,n)} = \frac{\sum_{d=1}^{n-1} l_{(t,d)}}{n-1}$$

Equation 18

L is the load, and it is a function of the time of day and day, being n the moment we try to predict, and n-1 the amount of historical data we use to make the prediction.

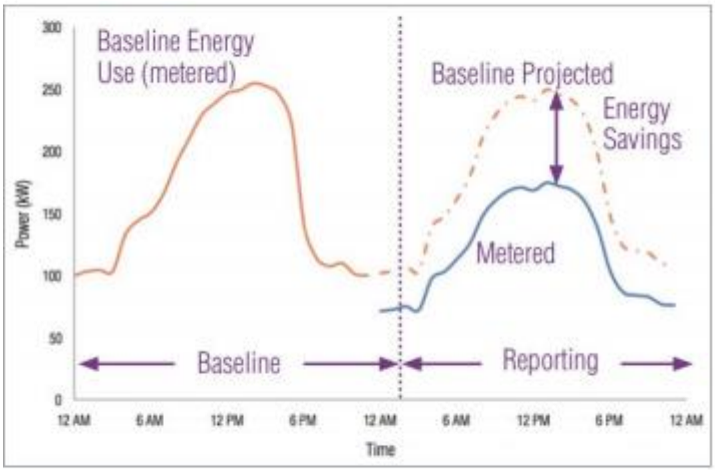

Figure 9 Baseline example

The predictions were made with the data of a previous week and with the data of 3 weeks previous, a significant improvement is seen when using 3 weeks and a reduction of the error of around 12% to an error of less than 5% in the case of baseline I and in the case of baseline BA the error goes down from 6% to less than 3%, it is important to note that in the case of the building the error with one week was very much higher than the others buildings, but by taking 3 weeks both the error and the percentage error decrease to equal the error of the other buildings.

4.1.1 VPP in energy community model

This scenario considers the inclusion of the local generation as a fundamental part of the future of electrical grids necessary, at the same time it considers necessary to optimize the output of the local generation, in this scenario it is combined output of the generation assets. Combining different sources of generation increases the reliability of the grid. For example, it may be that at one time it finds only but if wind and vice versa, making use of a VPP can virtually combine the production of a solar power station with a wind power, giving a parametron reliability higher than if you study separately. The objective to be achieved is an VPP that works to maximize the benefits and brined a flexible service, making use of a TSO / DNO, to achieve this is necessary:

1) The VPP generation modelling and forecasting, based on historical data, technical information, weather input.

2) Generate baseline micro-grids precise and VPPs in order to estimate the supply potential to the market.

3) VPP customer segmentation, segmentation is a crucial step to achieve greater reliability in the baseline, it is necessary to segment both production and consumption, segmented consumption maximizes economic benefits for consumers, and segmented production gives greater stability and reliability to the grid.

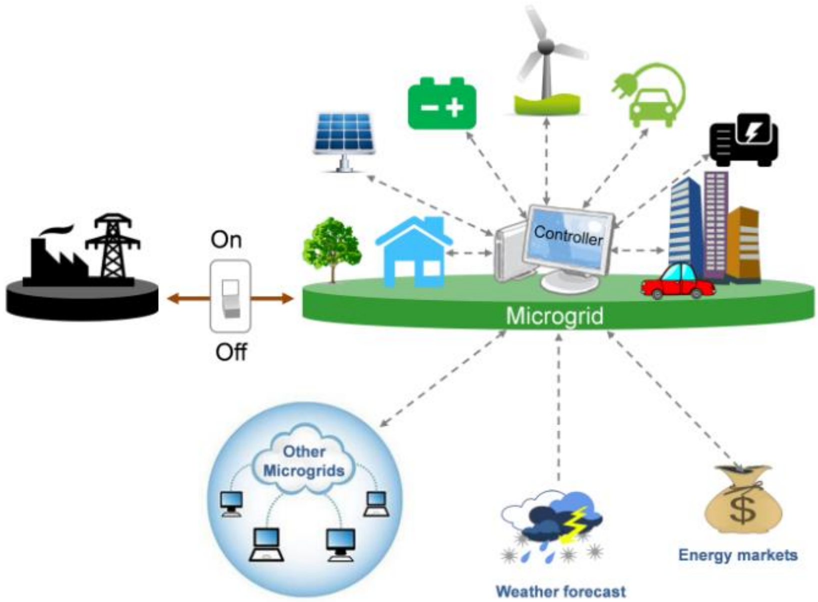

Figure 10 Microgrid Structure

4.1.2 Use Cases template

This part of the document aims to clearly present the case studies of the project eDREAM of the new community-driven energy ecosystem envisaged by eDREAM, categorised in two, Micro-Grids (MG) and Virtual Power plants (VPP) identifying three specific scenarios. Namely

(1) Prosumer DR flexibility aggregation via smart contracts,

(2) Peer-to-peer local energy trading market and

(3) VPP in energy community and the corresponding use cases (UCs).

The material is presented following a scheme, dividing the information into projects, all the data are extracted from the eDREAM report D2.2: Use Case Analysis and application scenarios description V1, in which case studies are explained in more detail. The presentation of all this information will allow a detailed and exhaustive analysis of the energetic, technological context, at the same time, this analysis will contribute advances with the objectives of eDREAM, of developing closed-loop DR management framework including innovative tools, thus allowing an operation of secure electrical grids based entirely on decentralization, and with the efficient application of Blockchain technology, intelligent contracts and validation algorithms and CBL. The use case that refers directly to customer baseline load (CBL) are in following table (Table 1).

eDREAM USE CASES INVENTORY
HL-UC01: Prosumers DR flexibility aggregation via smart contract
• HL-UC01_LL-UC01: Prosumers enrolment with the aggregator
• HL-UC01_LL-UC02: Prosumer flexibility availability
• HL-UC01_LL-UC03: Prosumer electricity production/consumption forecasting
• HL-UC01_LL-UC05: Congestion point detection by DSO
• HL-UC01_LL-UC08: Stationary and EV fleets load for local balancing services
HL-UC02: Peer-to-peer local energy trading
• HL-UC02_LL-UC02: Prosumers' bids/offers submission
HL-UC03: VPP in Energy Community
• HL-UC03_LL-UC01: Prosumers Profiling
• HL-UC03_LL-UC03: VPP for reserve services

Table 1- eDREAM use cases inventory

4.2 CBL for use cases and DR market programs

Several use cases explored in this project have use for CBL calculation. Those requiring CBL are listed below:

HL-UC01: Prosumers DR flexibility aggregation via smart contract

In this Project, prosumers enrol with aggregators and offer their baseline data to the aggregators, baseline data is used to give flexibility to the grid by activating the intelligent contracts, then, the intelligent contracts are made of the flexibility of the network, in turn, the flexibility of the network is determined depending on the data baseline of the prosumers, if failure to estimate baseline will result in a result of a breach in the contract, for that reason it is important to do a good job in this first part. In this case, the baseline is LEM

(Local Energy Management) because the aggregator works locally, each prosumer makes a prediction of the baseline itself and all the baseline as a whole are those that give flexibility to the system, This information is used by the DSO to predict the grid's congestion points, and to act accordingly, at this level the baseline type is DEMS (Distributed Energy Management System) because it generates a baseline depending on a group of consumers all with different energetic characteristics. Finally, the disposition of the batteries and the EVs is given so that in function of the baseline and of the forecasting they give a degree more flexibility to the System giving one more degree of freedom to the System.

This case is subdivided into several sub-cases, in the next subsections we will see in detail how in each of them they make use of the baseline data.

- HL-UC01_LL-UC01: Prosumers enrolment with the aggregator

  In this first step the prosumers install the aggregators, in turn, they supply their baseline data.

- HL-UC01_LL-UC02: Prosumer flexibility availability

  In this step, the aggregators periodically calculate, evaluate and correct the flexibility of the prosumers based on their baseline LEM

- HL-UC01_LL-UC03: Prosumer electricity production/consumption forecasting

  In this part of the Project, the aggregators predict what the daily load will be, making use of the data supplied

- HL-UC01_LL-UC05: Congestion point detection by DSO

  In this phase, the DSO estimate the baseline DEMS and determine which will be the congestion points of the grids

- HL-UC01_LL-UC08: Stationary and EV fleets load for local balancing services

  In the latter case, the generated load is greater than the demand and the DSO request flexibility to the aggregators to use the batteries and the EVs, taking the load surplus, this is possible thanks to the previous study of the baseline type, and if it does wrong, the batteries could be empty when necessary, or simply would not be used at the optimal moment and the venues would not be maximized.

HL-UC02: Peer-to-peer local energy trading.

  In this case a strong approach is made between the communication between prosumers and consumers, peer-to-peer, the objective is to establish a decentralized mechanism for the sale and purchase of electric energy, the technology was chosen for this was the smart contracts, you attract of Blockchain, with predefined contracts that producers generate and consumers can accept or not, or even accept a combination of several contracts to satisfy their energy demand, the contract is generated according to the baseline data supplied by the prosumer, The type of baseline used in this case is from LEM, and then validates that the energy trading market session rules are not violated.

- HL-UC02_LL-UC02: Prosumers' bids/offers submission

  In this step the prosumers supply the information of the available energy, for this they are based on a previous study of their baseline.

HL-UC03: VPP in Energy Community

  This case will be consisted in the application of VPP, in the existing electric market, allowing to join prosumers based on the previous study of their baseline, the objective of doing this is to have a better perspective of the large-scale energy market, to control more easily the balance between the supply and the demand of electrical energy and finally give a greater reliability to the system, this program foresees a study of the baseline of the LEM prosumer and its later grouping DEMS. From their group they will be treated as if they were a single baseline. When joining different suppliers, the reliability of the submersion increases, that solves one of the main problems of the renewable energies, its lack of reliability and allowing its incorporation to the electric market

- HL-UC03_LL-UC01: Prosumers Profiling

  In this first step the Aggregator receives data of short-term production forecasting, the aggregator run analysis to identify setpoints of dispatchable generators and new load profiles of users, and depending on the baseline, flexibility is generated, which the aggregator will communicate to the market.

- HL-UC03_LL-UC03: VPP for reserve services

  In this phase a (CHP) is created, combining generating plants of different (RES), they are combined in a single profile that will then be used for the energetic System.

5 Analysis of results

With the data from HL-UC01 in Italy, about electric consumption in buildings, this project applies the baseline prediction methods, to estimate what the load will be. The data of the Italian buildings has very marked characteristics, such as the clear differentiation between the consumption during the day and the consumption at night, the marked difference between weekdays and weekends, and the decrease in the average consumption in the last week. For these reasons we chose 4 different methodologies to general the baseline. The methodologies will be discussed below.

- The first approach is the comparable day, this methodology uses the data of a week of sample to do the forecasting of the next, having 4 weeks of data, it is possible to make a forecasting of 3 weeks.
- The second approach "X of Y medium" uses the data of 3 weeks to make a forecasting of the next, this allowed us to obtain the forecasting of a single week. According to the estimates of PJM (Barancewicz, 2010), the recommended number of sample days is 60 days, this would be impossible in this case because there is only one month of data.
- Addition adjustment. In this method a correction is made to the previous method to make a more flexible and accurate prediction. The correction is represented mathematically by a value added to the existing baseline. This was generated using Equation 12 and Equation 13.
- The fourth approach consists in making a correction using the temperature, and the historic temperature data.

The following Table 2 shows the input and output of each of the methods used:

Method	Input	Output
Comparable day	Historical data of consumption or generation	Generates a baseline with a time in advance that varies from one week to one day
X of Y medium	Historical data of consumption or generation	Generates a baseline with a time in advance that varies from one week to one day

Addition adjust	Takes a previously generated baseline and adjusts it Using the characteristics of the load at a moment.	Generates a baseline, with an advance hour.
Weather adjust	Take a baseline previously generated and adjusted Using the ambient temperature at the time The historical climate data	Generates a baseline, with an advance hour.
Recursive least square	Take a baseline previously generated and adjusted Using the ambient temperature at the time The historical climate data	Generates a baseline, with an advance hour.

Table 2 input and output, methods

There is flexibility with regard to the formats that are handled, the inputs are expected to be format .txt .xlrs, and the outputs will be given in some of the same formats. The algorithms are implemented in Matlab, Matlab is used to open the data and also to generate the results. Then all the graphs exposed in this part of the work are generated with Excel. The consumption data should be recorded in periods of 15 or 10 minutes, and the temperatures every hour, the temperature should be in Celsius degrees , however all the equations, transform the data before working directly with them because they should use Celsius degrees, or kelvin.

For the calculation of the error there are many procedures, and there are a great variety of different errors, used in science. The two types of errors that will be made in this project will be MAPE, Mean absolute percentage error and CVRMSE, CV Root Mean Square Error. The study of the types of error described in (Hong, 2016) and (Chai, 2014) the equations that allow us to calculate these errors will be described below.

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$

Equation 19

$$CVRMSE = \frac{100}{b_{medium}} (\sum \frac{(l_{(t)} - b_{(t)})^2}{n})^0.5$$

Equation 20

The graph in Figure 11 shows the real load measured in the days of September, and graphs the load in Watts every 10 minutes. There is a pattern that allows to recognize the working days (Monday, Tuesday, Wednesday, Thursday and Friday) and differentiate them from the weekend days (Saturday and Sunday).

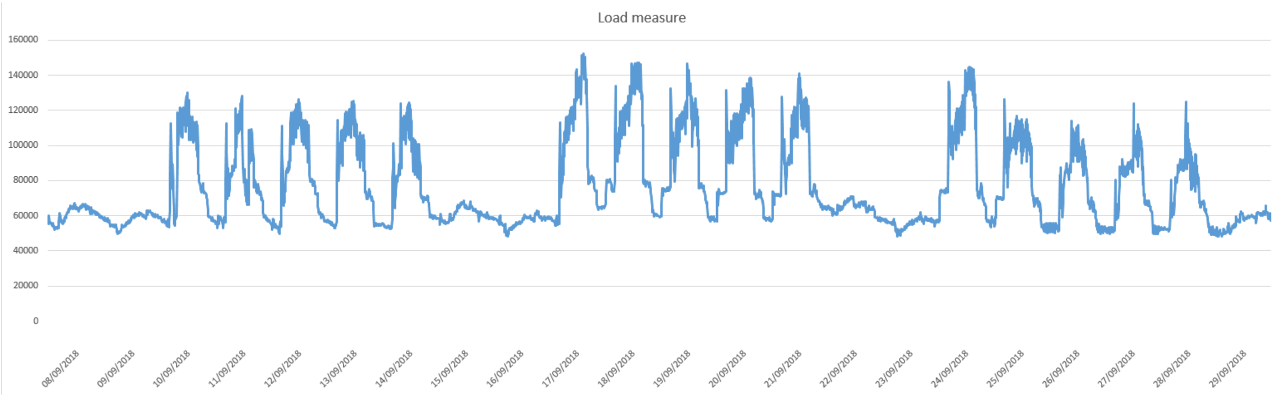

Figure 11 load measurement- HL-UC01

The next graph, Figure 12 **Error! Reference source not found.**shows, the forecasting load, the type of baseline is "Baseline I" that means that it is generated with the data of the previous days and allows to know with a week in advance which will be the next week load approach used was the comparable day, this methodology use one previous day to generate the baseline, the previous day was selected to be the most similar to the day that try to forecasting. At first glance you can see that the graphs (Figure 11 and Figure 12) are similar.

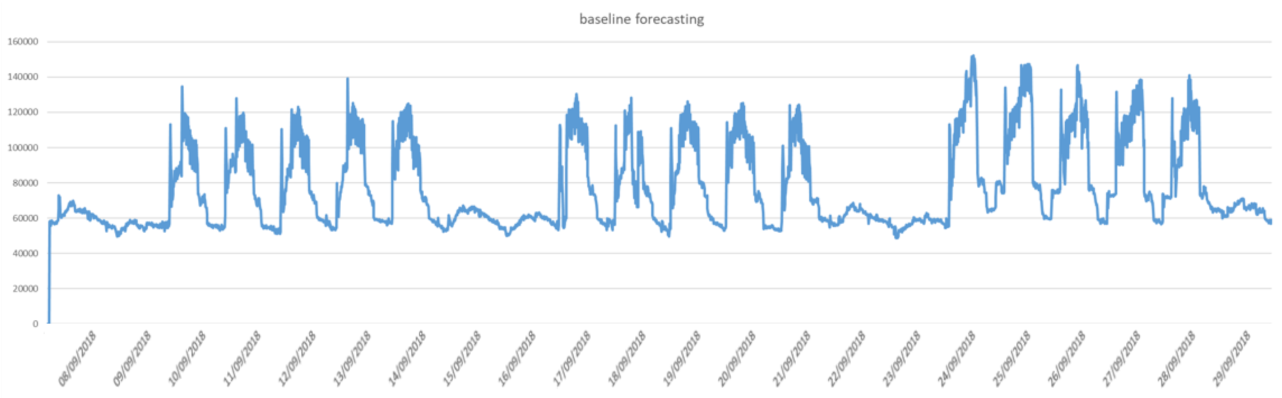

Figure 12 baseline I (comparable day)

The following graph (Figure 13) shows the percentage error of baseline forecasting. The method used to calculate the error is the MAPE method. The last week the error was somewhat high in some moments but in general you could say that it was quite low, the average percentage error is 11%. In the last week the average percentage error increases to 18%. The Graph in Figure 13 shows how the percentage error increases in this last week, this can be deviated from an external factor, the origin of which is unknown. It is important in this case the study of the last week to be able to compare it with the other procedures since in some procedures it will only be possible to forecast this last week, due to the need of a greater historical data.

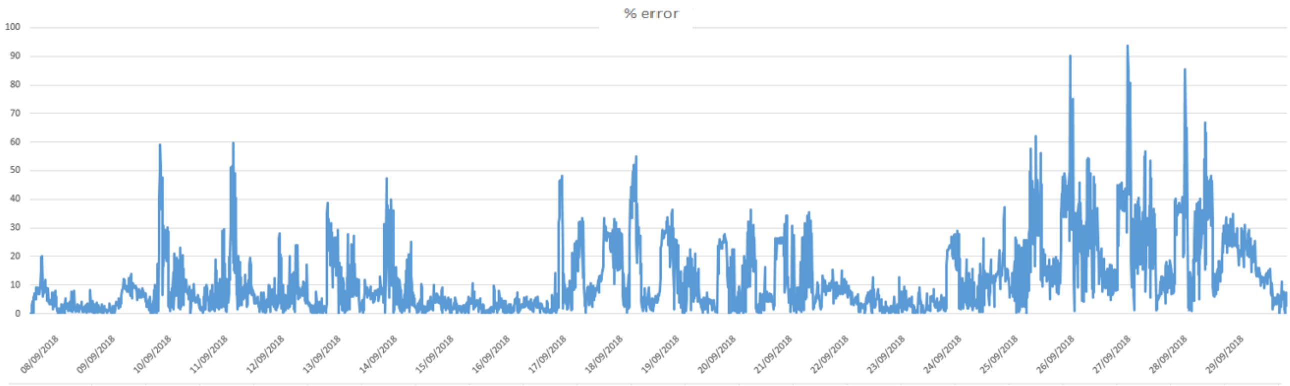

Figure 13 percentage error comparable day, HL-UC01

The Graph in Figure 14 shows a baseline of the type "Baseline Meter before- Meter after". This baseline is based on the Equation 12, Equation 13 and Equation 14. It makes a one-week forecasting using data from the previous week. By doing this type of Baseline, it is only possible to generate the baseline one instantaneously before the event, in this case the time window is one hour, and a more accurate baseline is obtained.

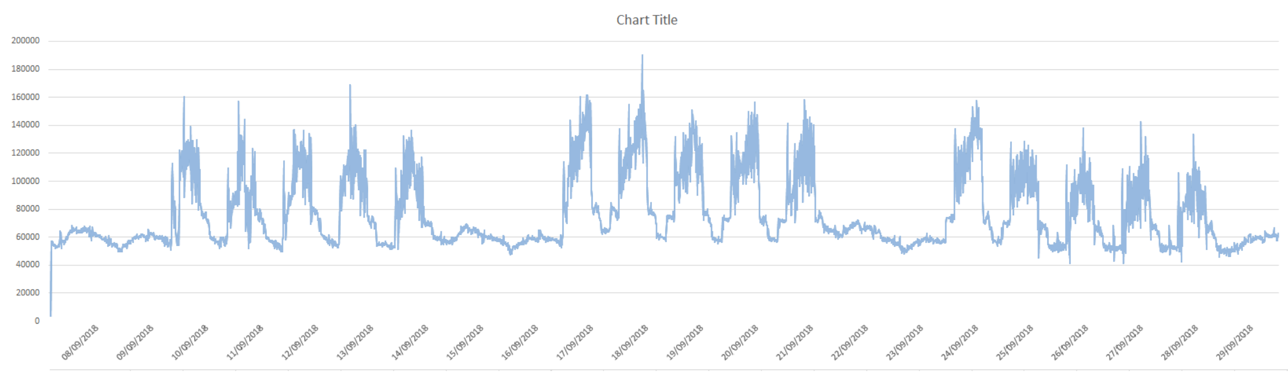

Figure 14 baseline I (addition adjust)

The error associated with this baselines is calculated in the same way as the previous case, using MAPE is represented in the Graph in Figure 15. In this case the average error is 5.8%, this graph shows the error in time, the average error corresponding to the last week is 6.8%

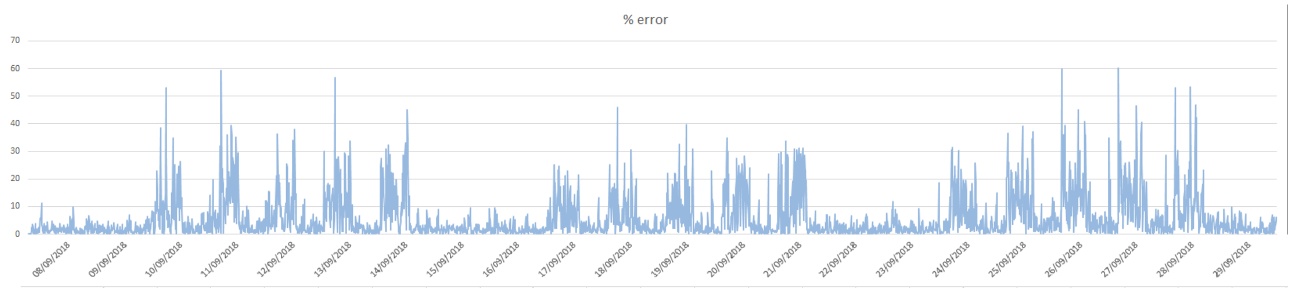

Figure 15 percent error, addition adjust, HL-UC01

The following graphs show the results of all of Baseline forecasting, using the data of the previous 3 weeks. The following Graph (Figure 16) shows the load measured in the last September of 2018.

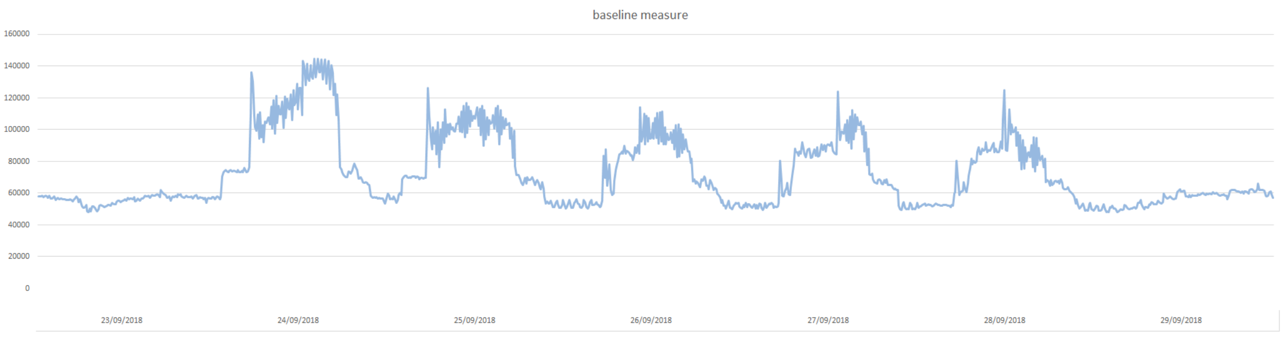

Figure 16 load measurement HL-UC01

The following graph (Figure 17) shows the baseline of type "Baseline I" made with the data of the three previous weeks and the Equation 2. To generate this baseline, the "x of Y medium" procedure and Equation 2 are used.

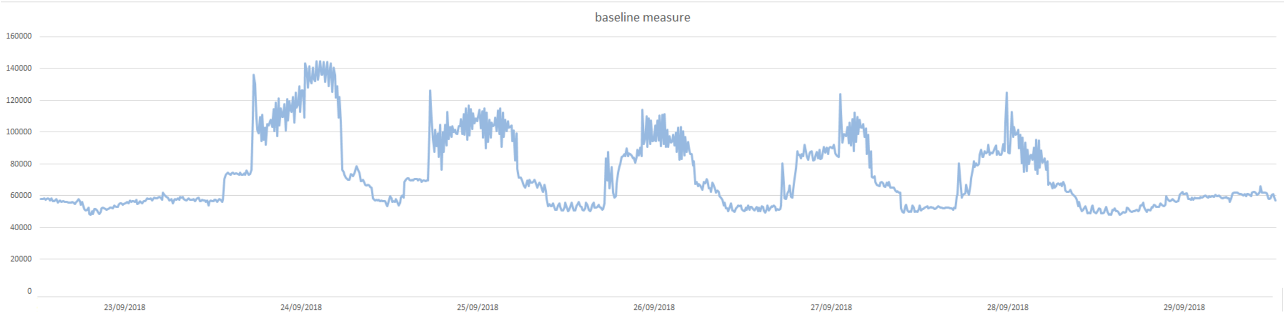

Figure 17 baseline I, X of Y medium, HL-UC01

In this case (Figure 18) the error is lower than in the case in which only one week was used as a sample, the error medium in this case is 12%. In the previous graph (Figure 17) corresponding to the same method we could see that in the last week the error was higher in the previous weeks, this could be derailed to an irregularity in the load that cannot be predicted only using historiographic data, however, now only the forecasting of that week was made and resulted in a medium error in the previous case.

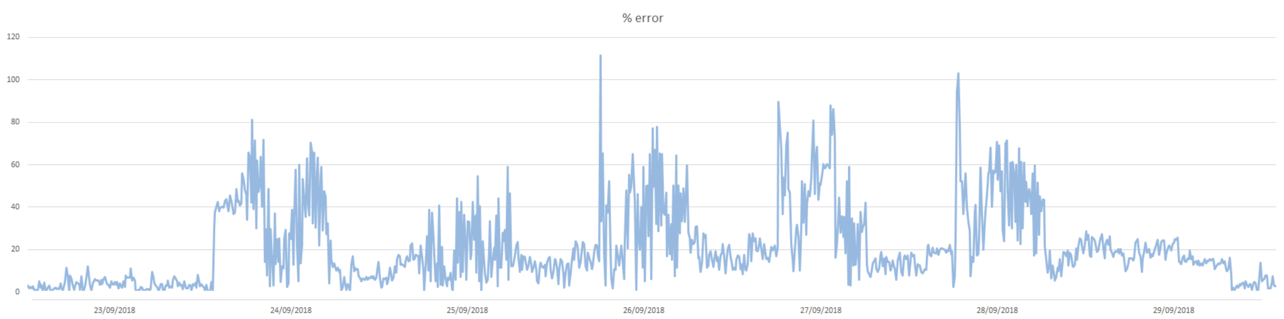

Figure 18 percent error, X of Y medium, HL-UC01

The Graph in Figure 19 represents a baseline of type "Baseline Meter before- Meter after". Generated this baseline using the approach of "x of Y medium" with addition adjust. The equations implemented were Equation 14 and Equation 15**Error! Reference source not found.**. To generate this baseline, the data of the first 3 weeks of the month of September were used and the last one was forecast.

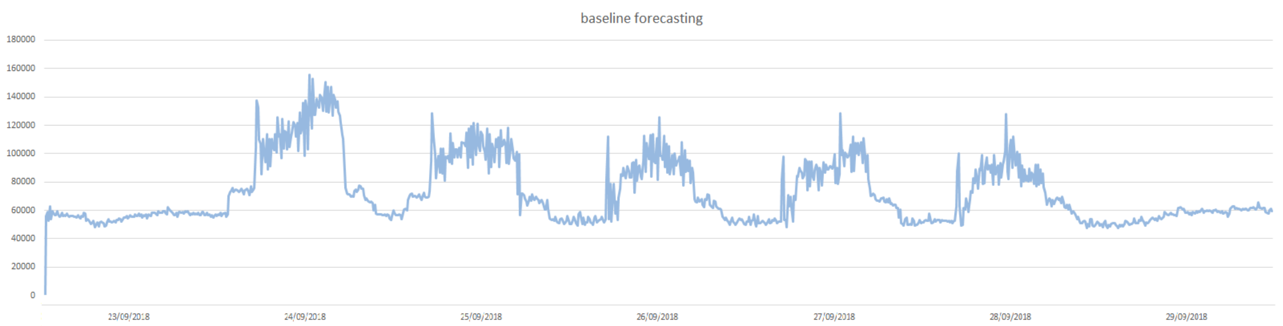

Figure 19 baseline, addition adjust, HL-UC01

Undoubtedly this baseline due the lowest average error of all the models studied, the graph in Figure 20 giving an average error of 5.4%, whereas the last week of the month of September is that it presents a demand with major differences from the rest of the month

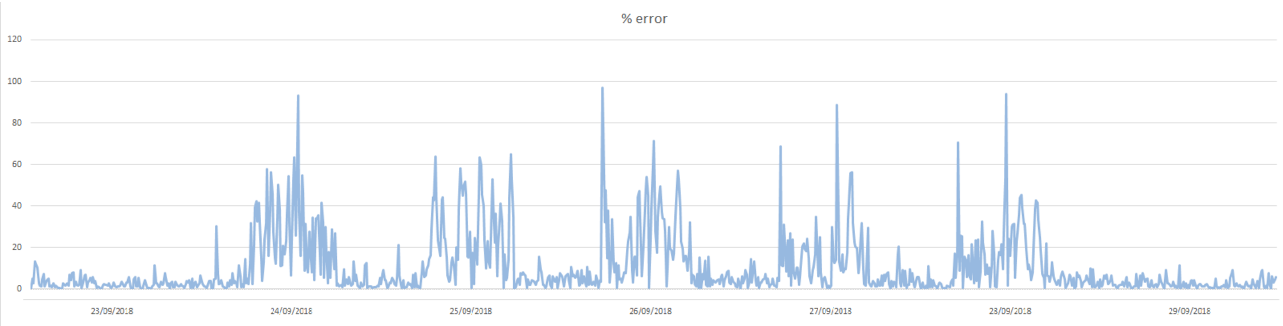

Figure 20 percent error, addition adjust, HL-UC01

In the following Graph, Figure 21, an adjustment of baselines "X of Y medium" was made using the environmental temperature data. Equation 14 and Equation 15 were used to analyse this data, in this case giving an average percentage error of 9.9%

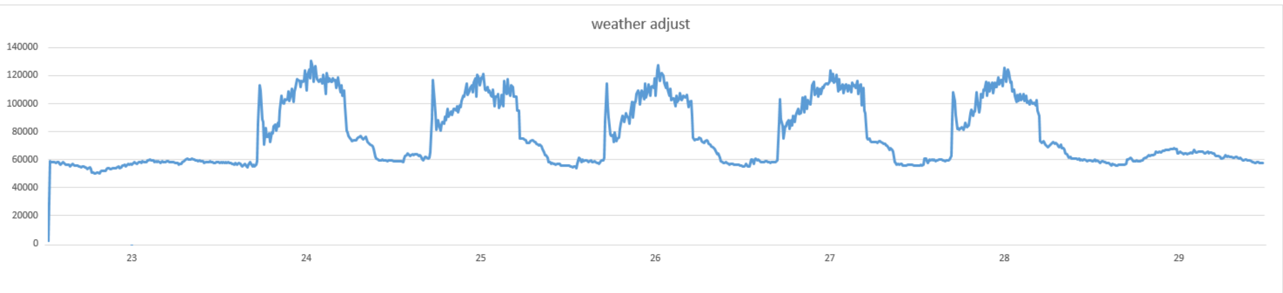

Figure 21 weather adjust, HL-UC01

The last methodology implemented in this scenario was RLS, making a correction to the baseline with the outside temperature, through a mathematical model that uses minimum squares. In this case the equations used were Equation 3, Equation 4 and Equation 5. This arrangement will decrease the error, the RLS models are based in making the error of each point of the dispersion be as small as possible, resulting in a low error. However, in this case the error is high, reaching an average error of 16%. This error is only exceeded by the method of comparable day.

Table 3 shows the methodologies used in HL-UC01 and the associated variables, the table is included with the intention of facilitating the comparison of the results obtained.

Method	Error- 3 weeks	Error- 1 week
Comparable day	11.86%	18.43%
Comparable day with addition adjust	5.88%	6.89%
X of Y medium Days	-	12.23%
X of Y medium Days with addition adjust	-	5.40%
X of Y medium Days with weather adjust	-	9.96%
Recursive least square	-	16.36%

Table 3 results, MAPE, HL-UC01

Method	CVRMSE, 3 weeks	CVRMSE, 1 week
Comparable day	19.34%	23.18%
Comparable day with addition adjust	12.67%	18.85%
X of Y medium Days	-	16.75%
X of Y medium Days with addition adjust	-	10.83%
X of Y medium Days with weather adjust	-	15.46%
Recursive least square	-	24.25%

Table 4 Results, CVRMSE, HL-UC01

The following graph in Figure 22 shows a comparison between the different baselines generated by the different methods of baseline forecasting. It is interesting to note that they all look alike, in that the weekends are lower and that the weekdays have an important growth, during the work hours. The graph shows that RLS on Thursday night and early morning on Friday has a somewhat different behaviour, or, maybe you could have some arrangement in this part to minimize the total error, but that in turn would modify the equations with some conditions. It is difficult to say for sure how baseline is best based only on the data from a case study and for a period of time as short as one month. However, working with these data gives the project the possibility of practically generating the baselines and analysing the results, we can give us an idea of the results that we will have in future deliverables where we work with a historical database that is much larger than all the case studies

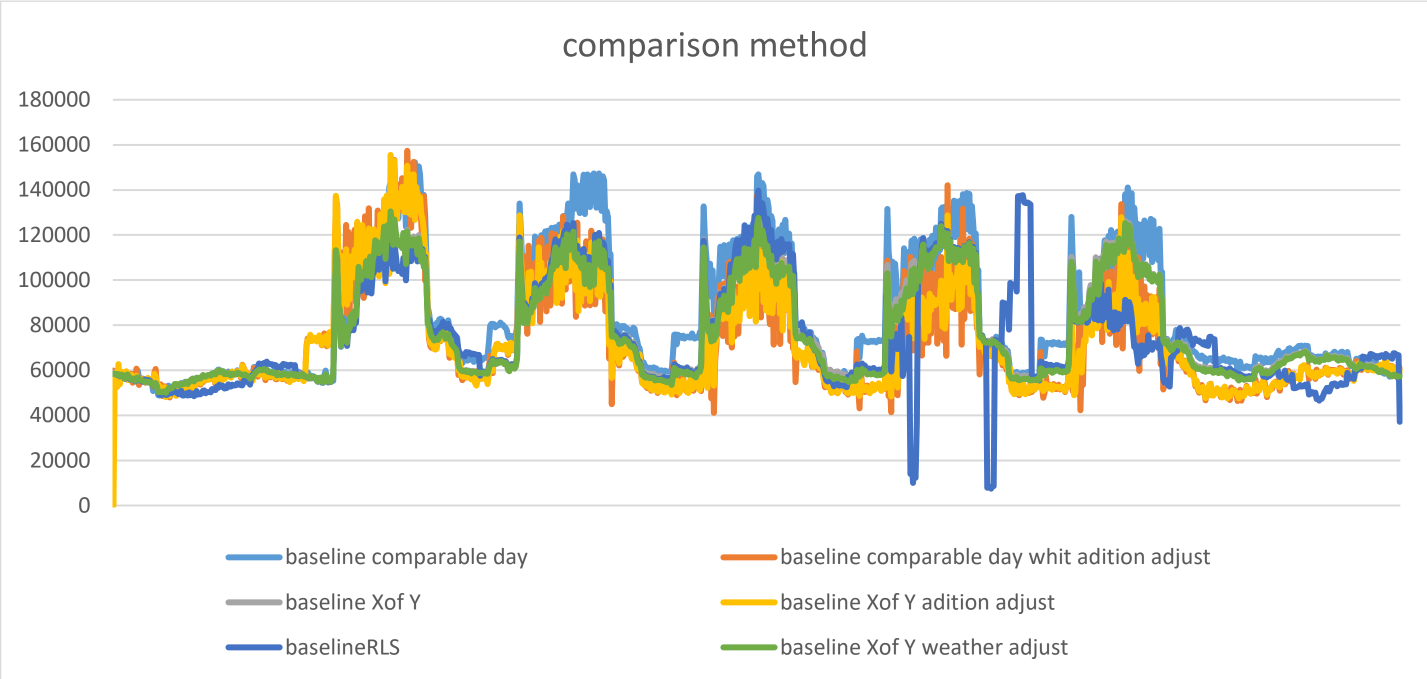

Figure 22 comparison method, HL-UC01

When talking about electrical grids, it is necessary not only to study consumers, it is also necessary to study the producers, in this case HL-UC01 consists of photovoltaic panels, capable of generating electrical energy every day. The approach used in this case will be slightly different, since the production does not depend on any human factor, such as the existence of weekly weekends or working hours, it only depends on the weather, priority was given to the immediately preceding days for selection of comparisons day, in other aspects the procedure used was the same as for consumption.

In the following graph you can see the approximation by X of Y medium days and by comparable day respectively

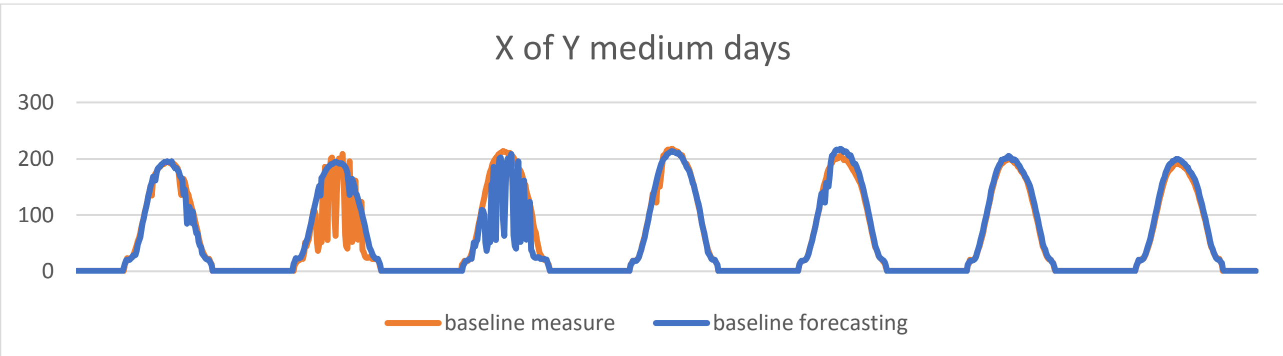

Figure 23 X of Y medium days, HL-UC01, PV

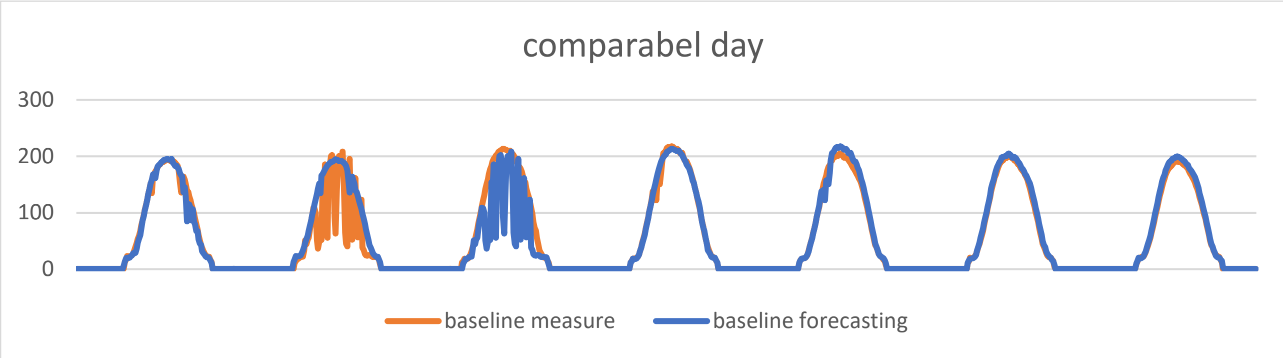

Figure 24 comparable day HL-UC01, PV

The graphs in Figure 22 and Figure 23 are similar, this is because the methods used, give similar results, for the forecasting of the generation of electrical energy using solar panels. The following Table 5 shows, the errors associated to the methods are of 12.65% and 12.96%, for that reason at first sight the graphs seem the same. It is advisable to apply the method of X of Y medium Days, with a large database, and compare the results.

As you can see in the previous graphs the baselines are similar, this is because during those days the climate and therefore the solar irradiation did not suffer great variations. It would be interesting for the project to have a larger data in which you can see the variations in the generation of electrical energy throughout the months or years. The following table compares the results obtained, the error of each of the forecasting methods used in the first scenario, specifically in the solar panels.

Method	MAPE	CVRLSE
Comparable day	12.65%	38.90%
Comparable day with addition adjust	11.24%	28.65%
X of Y medium Days	12.96%	34.10%
X of Y medium Days with addition adjust	10.30%	25.22%
X of Y medium Days with weather adjust	13.61%	34.85%

Table 5 results, HL-UC01, PV

in the previous graphs of this section, this document showed the results of HL-UC01 in Italy, and in the following ones this document will show the results of the study of the data supplied by HL-UC03 in the UK, these data correspond to the electric consumption of chillers, and the load that they can represent for the grid, specifically they are 6 chillers each one known with an id (IQGA0187, IQGA0189, IQGA0160, IQGA0170, IQGA0195, IQGA0017).

In HL-UC03 the historical data is much longer than in the HL-UC01, there are a year of measurements in the Graph in Figure 25 stand out being the best months for your study the month of December, January and

February, the rest of the month your consumption is low and unpredictable. It is important to note that the maximum consumption is given on a day of July or August, this may be because at that time the chillers are tested, after this date the load is minimal until reaching December, in the following graph you can see this trend.

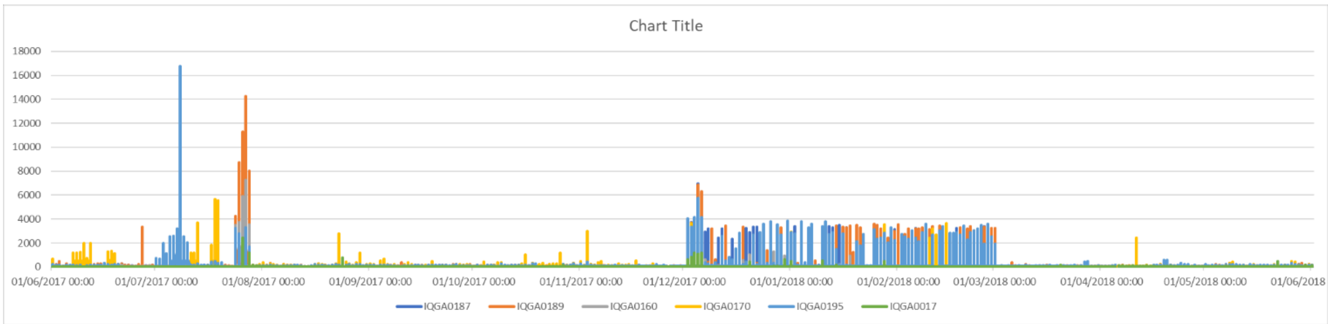

Figure 25 load measurement HL-UC03

The graphs in Figure 26 and Figure 27, refer to the load of the chillers IQGA0187 and IQGA0195 respectively, these graphs serve to have more detail the load characteristic for chiller.

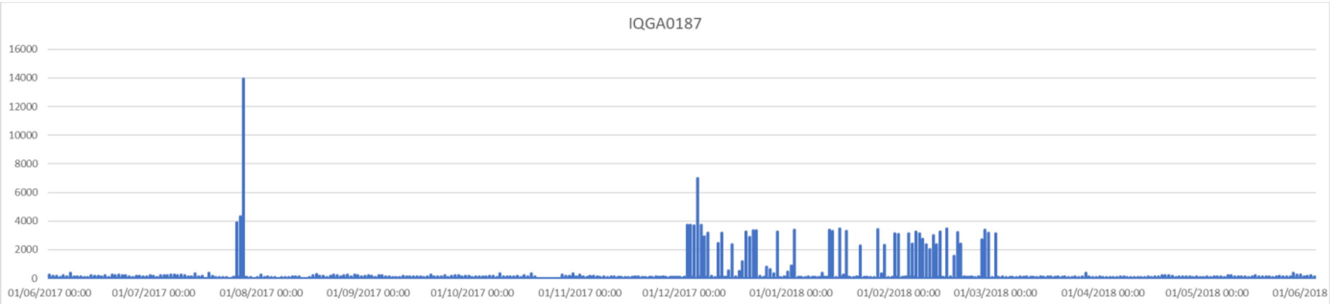

Figure 26 Chiller IQGA0187

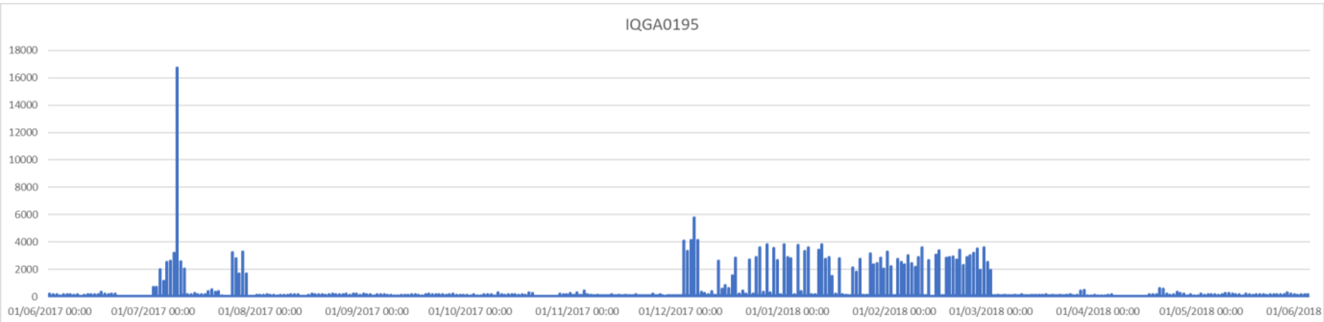

Figure 27 Chiller IQGA0195

It is not advisable to try to generate an annual baseline for this type of load, because its biggest concentration of work is a few months. In this work we concentrate on the corresponding data during the months of greatest intensity, December, January and February. These types of charges are usually constant in the hours of operation, the chiller is turned on, and has a constant consumption, or is paid and does not consume. In the following graphs, Figure 28, Figure 29, Figure 30, Figure 31, Figure 32 and Figure 33, a working model week for each of the chillers can be observed. It can also be seen how in many cases the load during the day is constant and almost nil during the hours at night and weekends. The most particular case would be that of the IQGA0017 chiller that does not behave like others, this may be due to external factors beyond our control.

The following graph shows the consumption of the chiller IQGA0187. This chiller has a regular consumption with the only exception of Monday, and the first hours of work on Tuesday. The regularity of use of this chiller gives us the possibility of predicting with ease the ease and efficiency of the consumption of this chiller using the method of forecasting detours previously.

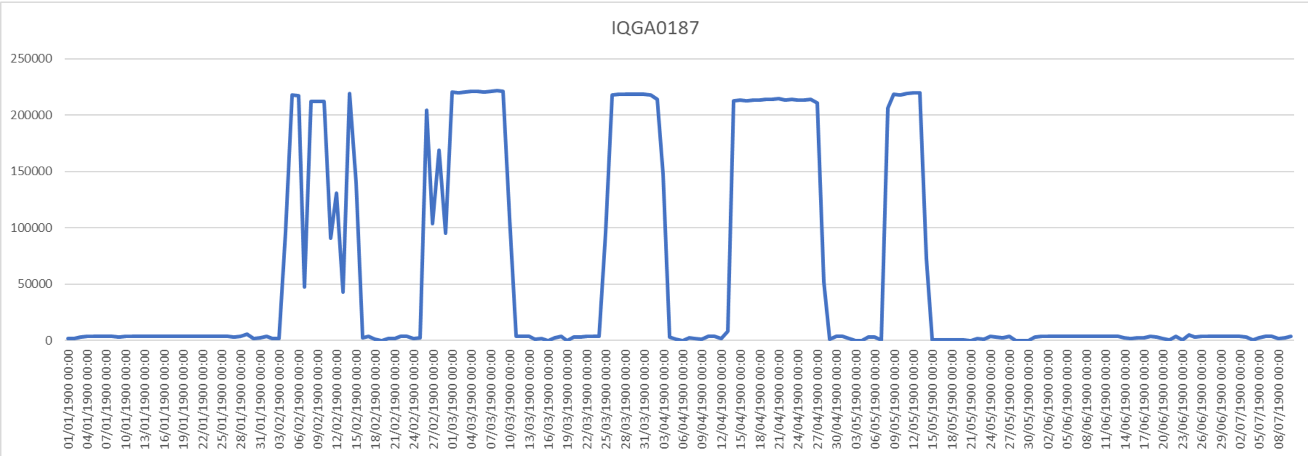

Figure 28 Chiller IQGA0187

The chiller IQGGA0189 is one of those that have better qualities to generate a baseline, this is due to the periodicity of the consumption cycles. This is the one that gives the best response to forecasting giving the lowest errors, between 6% and 7%.

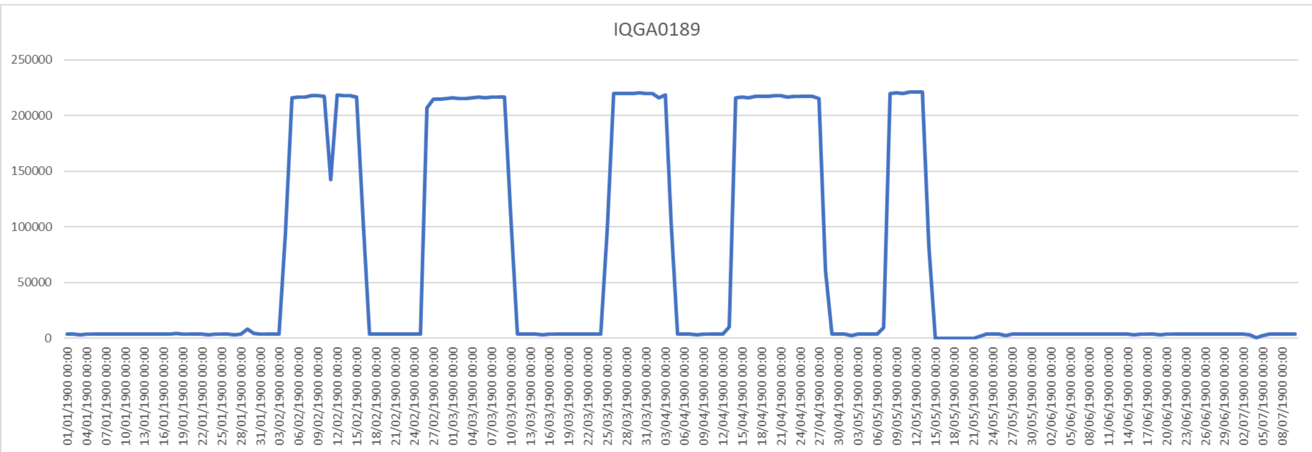

Figure 29 Chiller IQGA0189

The following graph in Figure 30 shows the consumption of the chiller IQGA0160, which is a very particular consumption, it is seen that the chiller is used on working days, but inconsistently, to be able to correctly forecast the consumption of this chiller, it would be necessary to analyse the particular case and know what variables depend on the consumption of the chiller. The low capacity to predict the consumption of this chiller is seen in the error that the forecasting procedures gave, when comparing the baseline generated with the consumption of the same between 20% and 38%.

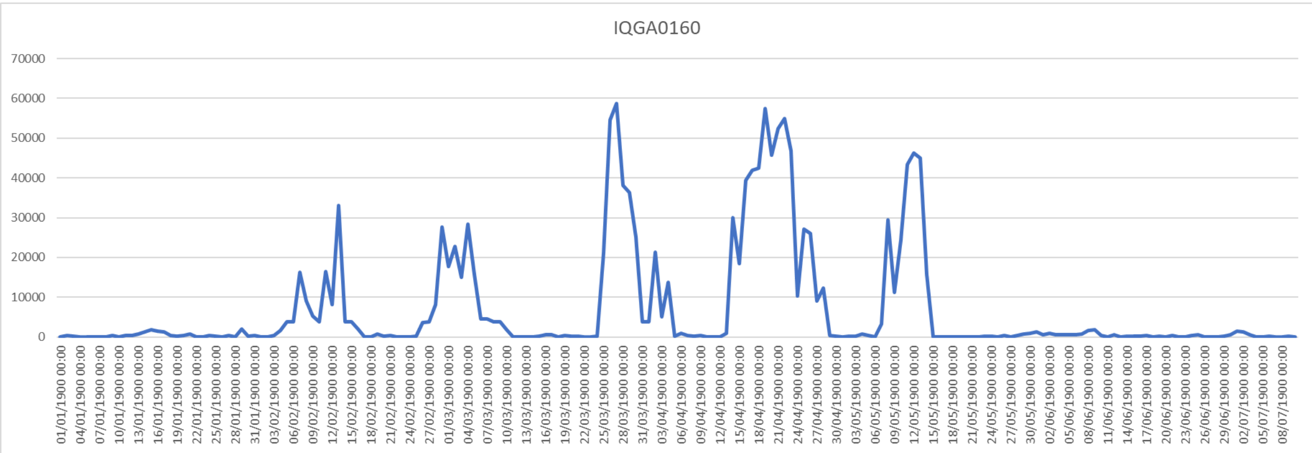

Figure 30 Chiller IQGA0160

The chiller IQGA0170 has some characteristics of particular consumption, that responds particularly well to the method of X of Y days, but not of the same method to the comparable days, this can be explained by the fact that we cannot exactly it is not possible to know which days the consumption will vary, because there is no definite pattern, but, the great the majority of the days have a stable pattern, which responds well to the average of the X of Y days.

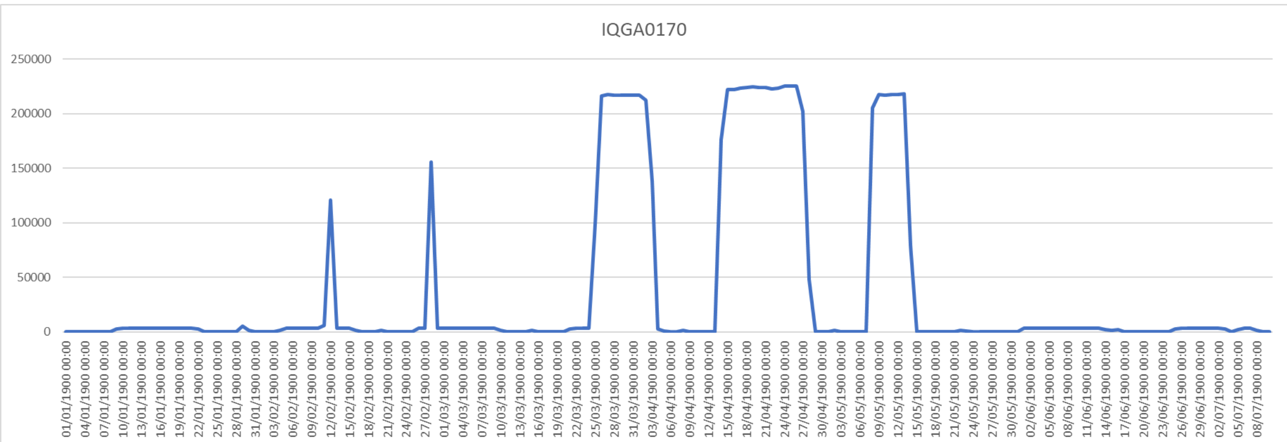

Figure 31 Chiller IQGA0170

The next graph, Figure 32 shows the consumption of the chiller IQGA0195, this chiller has a consumption not entirely constant, but it can be predicted with the baseline forecasting methods previously studied. It would be interesting to study the context in which this chiller is in order to be able to predict why some days consumes is lower than others. The results of this chiller are not the best, but they are decent is between 11% and 9% using MAPE to calculate the error.

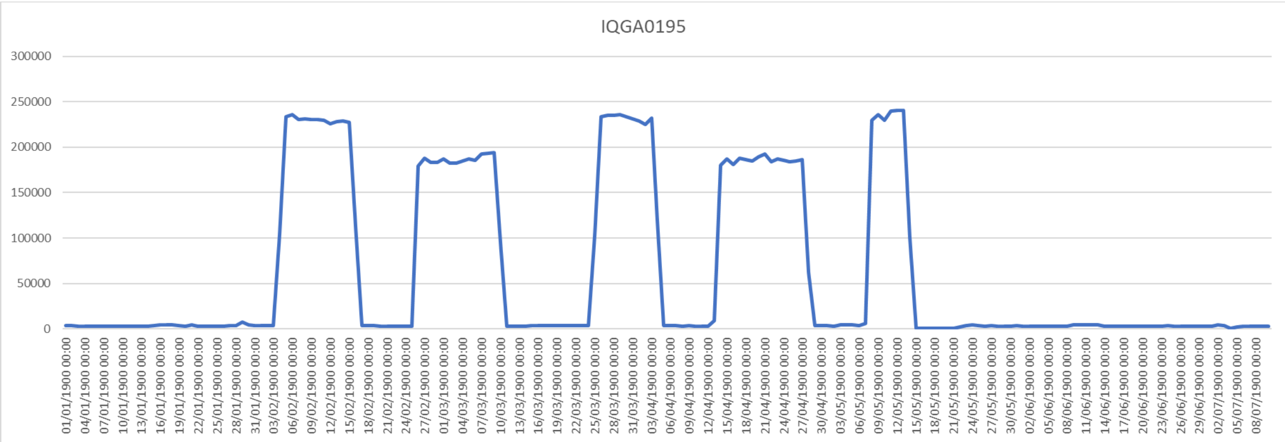

Figure 32 Chiller IQGA0195

The following graph, Figure 33, shows the consumption of a week type for the IQGA0017 chiller. The graph teaches that of all the chillers this is the one with the most erratic consumption, and the hardest to predict, you could only be sure that during the nights I consume it is low, but the day we cannot conclude anything, the Metrics of analysis and forecasting used in the other possessions are inefficient to generate a baseline in this case. It would be necessary an analysis of the case in specific to know that external factor directly affects the consumption of this chiller in particular.

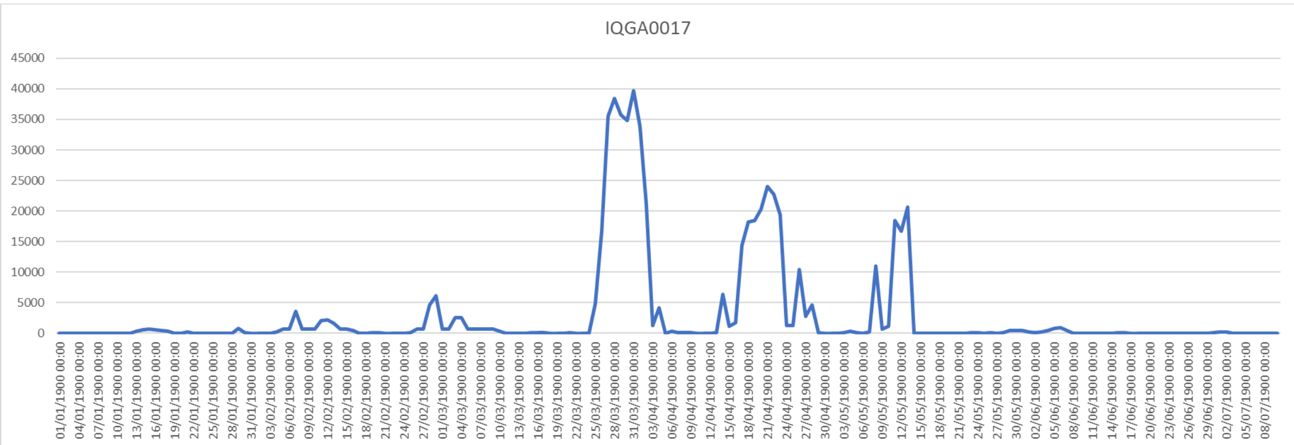

Figure 33 Chiller IQGA0017

The following Graph (Figure 34) shows the baseline for the Chiller "IQGA0187" corresponding to the first week of December. To do the forecasting the method of "X of Y medium” is used using only a week of data, before the event and then the error is plotted in Figure 35.

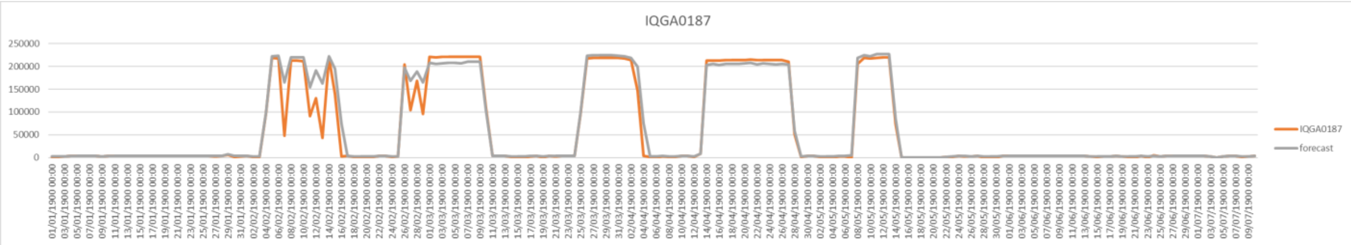

Figure 34 baseline "X of Y medium" IQGA0187, HL-UC03

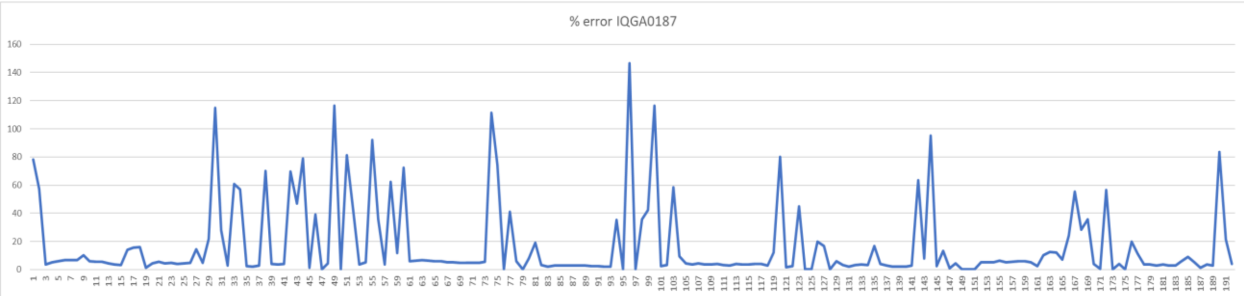

Figure 35 percent error, "X of Y medium, HL-UC03 , IQGA0187

At some points the error is considerably high, but the average error of the prediction for the Chiller case "IQGA0187" is 16% and for the cases "IQGA0189" "IQGA0195" is 8% and 11% respectively, showing that the "X of Y medium" method could be a valid method for doing chillers forcing, however, better results would be obtained if some kind of correction were made, for example with the climatic data, for the other chillers the error is high, because your load does not follow a fixed pattern, in this case surely better results are achieved by using the climatic data to adjust the baseline.

The following tables summarize the results, from HL-UC03, with the MAPE methodology as with the CVRMSE methodology

Method/(MAPE)	IQGA0187	IQGA0189	IQGA0160	IQGA0170	IQGA0195	IQGA0017
Comparable day	26.18%	6.90%	38.70%	29.51%	11.26%	36.05%
X of Y medium	23.91%	6.59%	27.97%	17.64%	18.61%	29.87%
Comparable day with Addition Adjust	17.23%	7.11%	20.10%	13.04%	9.35%	20.26%

Table 6 Results, MAPE, HL-UC03

Method/(CVRMSE)	IQGA0187	IQGA0189	IQGA0160	IQGA0170	IQGA0195	IQGA0017
Comparable day	59.54%	22.11%	173.17%	74.44%	28.12%	193.01%

X of Y medium	49.64%	18.91%	115.59%	53.41%	23.59%	151.16%
Comparable day with Addition Adjust	63.69%	21.23%	111.50%	42.65%	20.78%	101.03%

Table 7 Results, CVRMSE, HL-UC03

Method/MAPE	Lowest % error instances	Highest % error instances
Comparable day	0	4
X of Y medium	1	1
Comparable day with Addition Adjust	5	1

Table 8 UC-HL03 MAPE result analysis

Method/CVRMSE	Lowest % deviation instances	Highest % deviation instances
Comparable day	0	5
X of Y medium	2	0
Comparable day with Addition Adjust	4	1

Table 9 UC-HL03 CVRMSE result analysis

Table 3 and Table 4 show the MAPE and CVRMSE comparisons between the different baseline calculation methods for HL-UC01 respectively at 1 week and 3 week intervals. It can be seen that in this scenario, at the 1 week interval the X of Y medium Days with addition adjust has both the lowest MAPE error percentage, of 5.4% and the lowest deviation, CVRMSE of 10.83%. This is followed closely by the comparable day with addition adjust method, which has a MAPE of 6.89% and a higher CVRMSE of 18.85%. The worst method at a 1 week interval appears to be the Comparable day method, which has an average error of 18.43% and high deviation of 23.18%. At a 3 week interval many of the methods are not applicable, only the comparable day and comparable day with addition adjust method are calculated. Similarly to the 1 week interval, it can be seen that the comparable day with addition adjust method has a significantly lower error than the comparable day method, at 5.88% and a lower deviation of 19.34%. Based on these results the recommendation for the calculation to use for HL-UC01 would be the X of Y medium Days with addition adjust method for a 1 week estimation. If a 3 week time period is required, the comparable day with addition adjust method would be the most accurate.

Table 5 shows both MAPE and CVRMSE results for the calculations of the forecasted PV production in HL-UC01. The method with the lowest error (MAPE) is the X of Y medium Days with addition adjust method, with an error of 10.3% and the most consistent results with a CVRMSE of 25.22%. This method is therefore the clear recommendation for estimating the PV baseline metric in HL-UC01. Curiously, the worst method is X of Y medium Days with weather adjust, with a MAPE of 13.61% and a high CVMRSE of 34.85%

Finally, Table 6 and Table 7 show the MAPE and CVRMSE comparisons between the different baseline calculation methods for HL-UC03 respectively. Table 8 and Table 9 show a basic comparison of how many instances each method had the highest and lowest MAPE and CVRMSE. Table 8 shows that for 5 of the 6 chillers, the Comparable day with Addition Adjust method had the lowest MAPE, suggesting that this is the most accurate of the methods. Table 9 shows that this method was also the most consistent, with it having the lowest CVRMSE for 4 of the 6 chillers. Table 8 and Table 9 show that the comparable day method has both the highest error, and the most inconsistent results, as it has the highest MAPE in 4 instances and the highest CVRMSE in 5 instances. The recommendation for HL-UC03 is therefore the Comparable day with Addition Adjust method.

6 Conclusions

The main objective of this document was to collect information on the technology to do baseline forecasting, to present the status of different projects in the world that are currently based on baseline forecasting. In this document the case studies of this Project were presented and information on the current status of each one was given. Finally, the baseline forecasting technology was applied to the case studies, and the results obtained were presented. In future deliveries the database for each scenario will be applied and more complex models will be implemented to try to obtain a more accurate forecasting, which is essential for the Project. To be able to control a grid, you need to know its behaviour and be able to predict it. The final conclusion for the analysis of results revealed that for HL-UC01: Prosumers DR flexibility aggregation via smart contract, the recommendation for the calculation to use for the baseline would be the X of Y medium Days with addition adjust method for a 1 week estimation. If a 3 week time period is required, the comparable day with addition adjust method would be the most accurate. For the PV estimation aspect, the recommendation would also be to use the X of Y medium Days with addition adjust method, as this method has the lowest error and deviation compared to the other methods investigated. As for HL-UC03: VPP in Energy Community, the comparable day with Addition Adjust method appears to have the lowest error and most consistent results, and would therefore be the recommended method for this scenario.

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