POLITECNICO MILANO 1863

SCUOLA DI INGEGNERIA INDUSTRIALE E DELL'INFORMAZIONE

EXECUTIVE SUMMARY OF THE THESIS

Monitoring, data mining and demand side management strategies for a residential district in Milan

TESI MAGISTRALE IN ENERGY ENGINEERING – INGEGNERIA ENERGETICA

AUTHOR: Nicola Perrucci

ADVISOR: Prof. Rossano Scoccia

CO-ADVISOR: Filippo Bovera, PhD

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1 Introduction

1.1 Scope of the work

A smart grid is an electric grid designed to deliver electricity in a controlled, smart way from points of generation to consumers. Consumers are considered an integral part of the smart grid since they are able to modify their purchasing patterns and behaviors based on the information and incentives they receive. Smart meters, connected appliances, and in-home displays open up new opportunities for demand-side innovation. Empowered consumers can then play a bigger role by changing their consumption habits [1].
The presented work focuses on electrical consumption analysis of a residential district of 615 apartments in Merezzate, Milan. Data mining is necessary to manage all energy consumption data which is becoming always larger with the increase of smart applications.
Clustering techniques have been implemented in post-processing of data retrieved from smart meters, with the objective to create groups of customers based on their electricity consumption trends.
A chapter of the work in centered on energy communities in Merezzate and their feasibility in two scenarios: the real district heating case and a hypothetical heat pump heating case.
Residential demand side management strategies have been investigated in the last chapter of the thesis, taking into consideration Time of Use, Critical Peak Pricing and Incentive Based Pricing techniques.

1.2 Demand response

Demand response is defined as end-use consumers' variations in energy usage from their regular consumption patterns in response to changes in power prices over time. There are different types of demand-response programs, which can be classified into two main categories: Price-Based Programs (PBP) and Incentive-Based Programs (IBP). Incentive-Based Programs can be further divided into classical programs and market-based programs. Electricity suppliers offer time-varying pricing, which can range from simple

day and night rates to highly dynamic rates based on hourly wholesale rates.
These rates include the Time of Use rate, Critical Peak Pricing, Extreme Day Pricing, Extreme Day Critical Peak Pricing, and Real Time Pricing. Demand response programs implemented for residential customers have been analyzed in many studies like [2]–[4].

1.3 Monitoring systems

Smart technology, such as smart meters, are required to monitor energy use on a more regular basis for most DR programs. Italy was the first European country to introduce large-scale electricity smart meters for low-voltage end customers, and by 2021 it is considered to be the top country in the world for the number of electricity smart meters in service [5]. The accuracy of demand response studies is influenced by the home load profile and electric power usage. This can be achieved by installing smart plugs into our homes, devices that sit between a power outlet and a home appliance. A smart plug allows appliances connected to it to be operated remotely and provides feedback on the appliance's energy usage. Smart metering and smart plugs are examples of innovative enabling technologies that allow for improved consumer receptivity as well as greater utility confidence.

1.4 Clustering methods

Clustering is a term that encompasses a wide range of approaches for identifying subgroups, or "clusters," in a data collection. Load profiling, which refers to consumers' energy consumption patterns over a given period of time (for example, one day), can assist in determining how electricity is really utilized by different customers and obtaining their load profiles or load patterns.
The clustering techniques can be classified into two categories: direct clustering, the approach that uses data obtained directly from smart meters, and indirect clustering.
The two methods used in this thesis are time-series k-means clustering and hierarchical clustering, thanks to their simplicity.

2 Merezzate district

The Merezzate project [6] co-funded by EIT Climate-KIC (Knowledge and Innovation Community) consists in a residential district near Rogoredo Santa Giulia, in the eastern part of Milan. It is composed of 615 apartments partially dedicated to social housing. The project's goal is to boost the adoption of innovative solutions by incorporating them into an urban development model that promotes social inclusion, renewable energy and energy efficiency, sustainable mobility, and circular economy activities. A2A Smart City, alongside with A2A Calore e Servizi, Politecnico di Milano and Poliedra, is one of the Partners of Merezzate + project.
The monitoring systems used for power metering in Merezzate are Unreti’s second generation smart meter, Chain2Gate and Smart plugs.

a) b) c)

Figure 2-1: a) Smart meter, b) Chain2Gate, c) Smart plug

3 Data mining

3.1 Preliminary analysis and energy demand

Different aspects have been analyzed in the preliminary evaluations.
Power consumption data of Merezzate residents are measured with a 15 minute interval. By summing the quarterly power for a month period and reporting the power demand into a 24 hour range, it’s possible to find the mean daily total power. The maximum at dinner time is in the range of 160-170 kW, and the minimum during night hours around 30 kW.

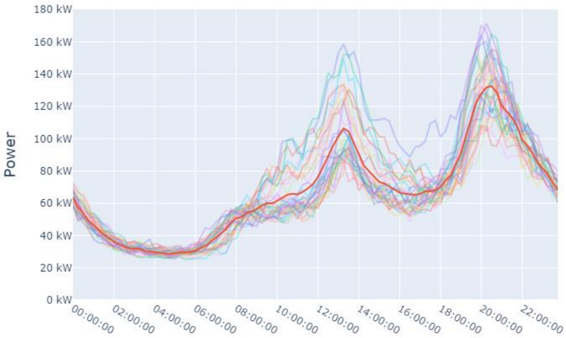

Figure 3-1: Daily total power trend, May 2021.

It has been noticed that moving by looking at the total power trend that the minimum power demand changed with the change of daily temperature. In particular, from the 4th of June to the 16th of June it was recorded an increase of 70% in the minimum power demand, which could be linked to a raise in HVAC systems during the night.

It was possible to compute the total energy demand of each month that has been considered in the analysis (May, June, July and August), by summing the energy of each apartment. It was found out that the most energy demanding months were June and August, with a total around 39'000 kWh for each month.

3.2 Load curves clustering

After some data cleaning steps, each resident would have two load curves, one representing the mean power for weekdays and one for weekends. Load curves of residents have been clustered with time-series k-means method. It has been decided to divide the load curves into three clusters, because the separation into three classes (low, medium and high consumption) looked the more natural and suitable.

Figure 3-2 and Figure 3-3 are a visual representation of the three clusters found.

During both workdays and weekends, the typical power demand presents two peaks, one around lunch time and one around dinner time. However, the magnitude of power demand is different. Weekdays typically present a larger peak in the late afternoon. Weekends have a power demand where the two peaks have about the same magnitude, due to the different lifestyle of each resident.

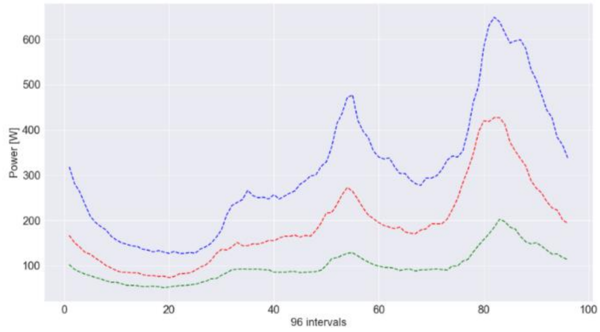

Figure 3-2: Mean curves of the three clusters (weekdays), May

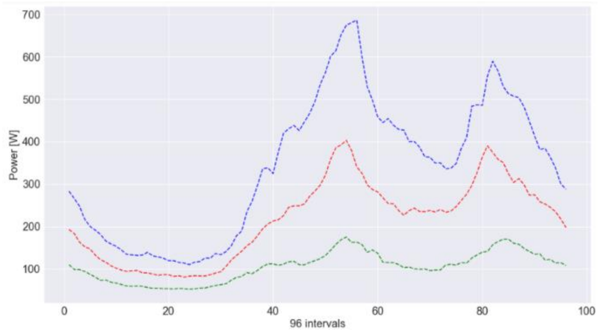

Figure 3-3: Mean curves of the three clusters (weekends), May

After the clustering process, it has been added the information of the apartment type, whether it was a one, two, three or four-rooms apartment.

Table 3-1: Cluster vs apartment type classification, workdays, May (load curves)

	One-room	Two-room	Three-room	Four-room
Low	73%	67%	22%	17%
Medium	13%	25%	54%	45%
High	13%	7%	23%	38%

Looking at the "low" cluster, we can notice a decreasing trend going from one-room to four-room apartment. Most of the one-room and two room apartments have been clustered in the "low" group, while just about 20% of three-room and four-room apartments have been grouped as "low" power demand. On the contrary, most of three-room and four-room apartments have been grouped as "medium" and "high" power consumers. The same trend can be seen in the case of the other months.

3.3 Energy consumption clustering

Next, it was performed the clustering of Merezzate neighborhood based on the energy consumed by each apartment during a month period. In this analysis the information about apartment typology has been added before the implementation of the clustering technique.

The clustering method chosen for this section is hierarchical clustering. This method is different from k-means clustering method because it doesn't depend on the number of clusters that must be specified at the beginning of the assignment.

The method can be visually represented by the typical dendrogram, where all the data are linked in clusters, depending on the measure of dissimilarity between the groups.

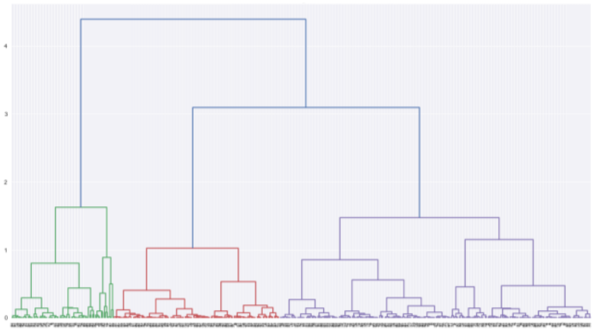

Figure 3-4: Dendrogram for hierarchical clustering

The results of clustering can be seen in different ways. The three mean values (centroids) of each cluster of Figure 3-5 are "low" = 54,8 kWh, "medium" = 126,9 kWh, "high" = 226,5 kWh, visible in the plot of apartments ordered in ascending energy consumption order.

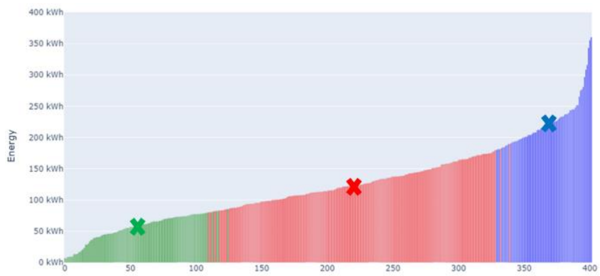

Figure 3-5: Monthly energy consumption of clusters, May

Another visual representation is the one of Figure 3-6, which is also possible to view analytically in Table 3-1. The results of these clusters are not very different from the one of workdays of the analysis based on power load curves. There is always a decreasing trend for the "low" cluster, and an increase in the percentages for the "high" cluster. Talking about the "medium" cluster, it keeps almost constant, with about 50% of the apartments that are clustered in this group, for all the apartment types.

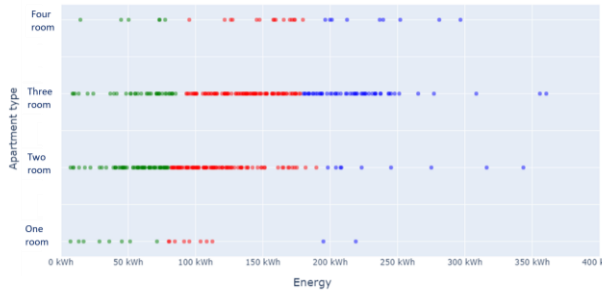

Figure 3-6: Monthly energy vs apartment type, clusters, May

Table 3-2: Cluster vs apartment type classification, May (energy)

	One-room	Two-room	Three-room	Four-room
Low	44,44%	38,82%	19,02%	20,00%
Medium	44,44%	55,88%	53,26%	50,00%
High	11,11%	5,29%	27,72%	30,00%

The same trend can be seen for other months of the analysis. By looking at the users that going from May to August have been clustered always in the same group, it becomes possible to define the mean monthly energy consumption of the clusters of this thesis: "low" = 42 kWh, "medium" = 110 kWh, "high" = 287,3 kWh, values in line with literature, especially for mean energy consumption which is estimated to be 1200 kWh/year.

3.4 Smart plugs data mining

Smart plugs have been installed in about 60 households as an efficient way to follow the consumes of home appliances. This gives another valuable information when combining this data with the global apartment consumption as it can be seen in Figure 3-7.

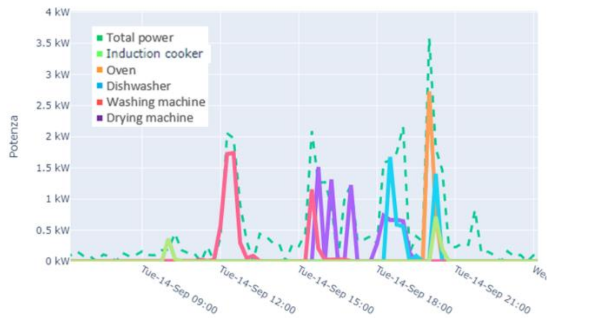

Figure 3-7: Single day power demand of one apartment with details of appliances (14th of September 2021)

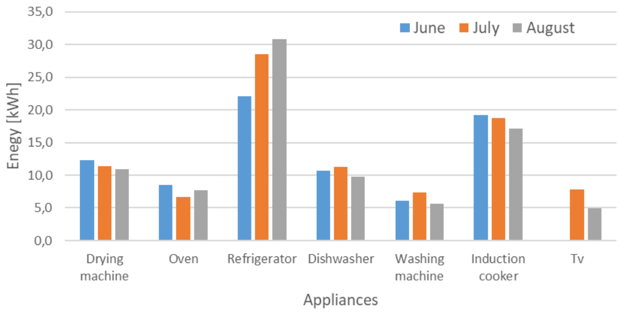

Figure 3-8: Monthly mean energy consumption per home appliance

From a mean point of view, Figure 3-8 shows that the refrigerator is the most energy consuming appliance, while the second is the electric induction cooking stove.
If we sum the mean monthly energy of each appliance we can find the value of energy consumption of a typical resident that possess those appliances, which is in line with what was found with clustering on energy consumption (110 kWh/month for "medium" consumer).

4 Energy community

4.1 REC definition

The clustering of residents into groups based on their power demand habits gives the possibility to simulate a scenario with the presence of a REC, Renewable Energy Community.
It is a configuration in which the energy produced with a renewable plant can be shared between residents of the same condominium of neighborhood, gaining advantages from the environmental and economic point of view.

4.2 District heating

In Merezzate there is a district heating plant dedicated to the heating of the neighborhood and on the roof of each building there is a photovoltaic plant (PV) that produced clean energy. The analysis in this chapter has been made of one building "Edificio 2", made of 30 apartments divided into three clusters. Three different cases have been considered: DH 1 is the case with district

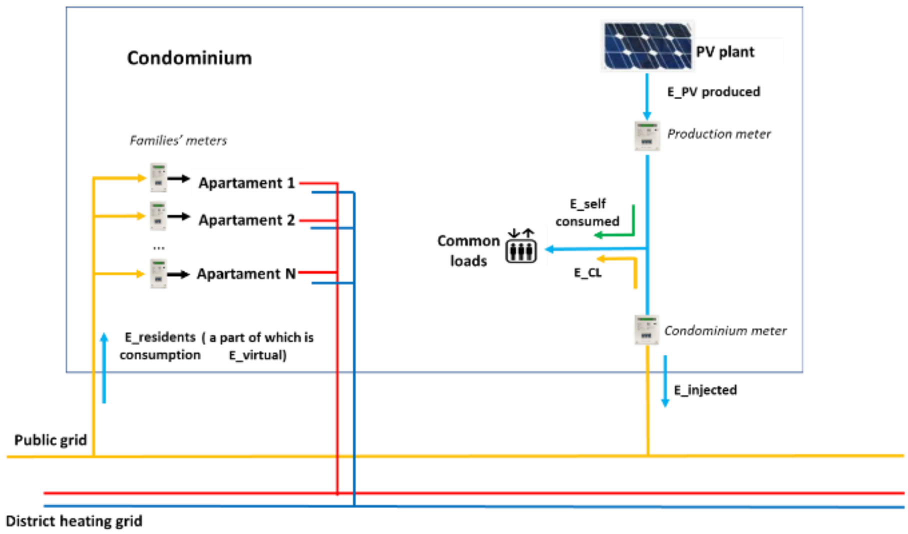

Figure 4-1: Building scheme District Heating and PV plant

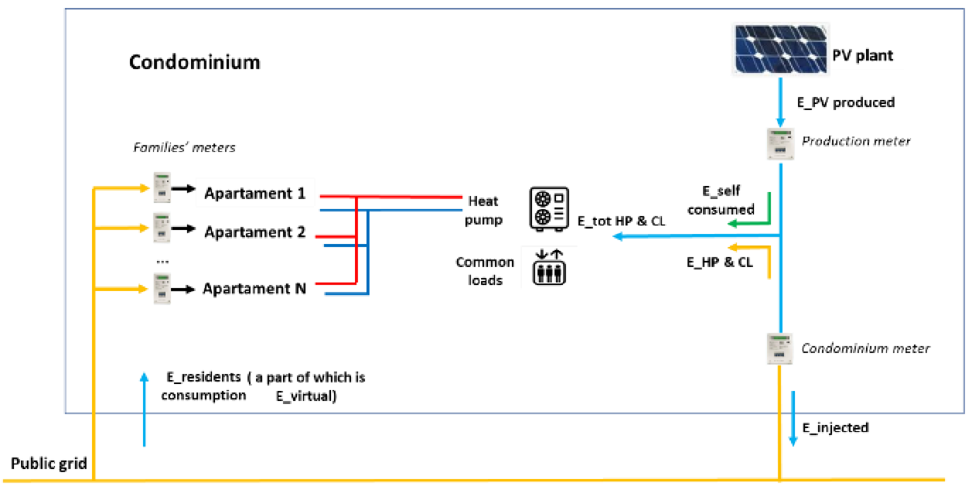

Figure 4-2: Building scheme Heat Pump and PV plant

Table 4-1: PUN for each time slot, May 2021

	F1 (€/kWh)	F2 (€/kWh)	F3 (€/kWh)	F23 (€/kWh)
May 2021	0,074270	0,077970	0,063020	0,069897

heating, a PV plant of 10 kW and no REC, DH 2 is the case equal to DH 1 but with the Renewable Energy Community and finally DH 3 is the case of district heating, with a bigger PV plant of 30 kW and with REC.
Energy consumption of the condominium has been evaluated with RECON, a REC simulator developed by ENEA [7].
By considering a price of electricity equal to 0,22 €/kWh, a selling price of electricity of 0,05 kWh and a MISE incentive on the shared energy equal to 0,1 €/kWh, it's possible to obtain the net cash flow of each scenario. The introduction of REC is clearly an advantage from the point of view of the cash flow since the MISE incentive are an additional revenue.

4.3 Heat pump

The same evaluations can be made for a case with a heat pump as heating system for the building, instead of district heating. The heat pump would then self-consume a portion of the energy produced with the PV plant.
The scenarios are the same as district heating, called HP 1, HP 2 and HP 3.
Net cash flow is estimated to be lower than DH cases, thanks to the possibility to self-consume energy produced with PV. In addition, as for the DH cases, REC is more convenient for both residents and environment.

Table 4-1: Economic analysis for District Heating

	DH 1	DH 2	DH 3
DH cost [€/y]	-7718,75	-7718,75	-7718,75
DH OPEX cost [€/y]	-617,5	-617,5	-617,5
Residents' bill [€/y]	-8360	-8360	-8360
Common areas bill [€/y]	-53,24	-53,24	-53,24
Revenues fed grid [€/y]	+512,65	+512,65	+1738,95
Revenues MISE [€/y]	+0	+849,2	+1501,5
Net cash flow [€/y]	-16237	-15388	-13509

Table 4-2: Economic analysis for Heat Pump

	HP 1	HP 2	HP 3
HP cost [€/y]	-3227,4	-3227,4	-2533,5
HP OPEX cost [€/y]	-379,07	-379,07	-379,07
Residents' bill [€/y]	-8360	-8360	-8360
Revenues fed grid [€/y]	+182,2	+182,2	+958,8
Revenues MISE [€/y]	+0	+348,3	+1200
Net cash flow [€/y]	-11784	-11436	-9114

For the DH 3 and HP 3 cases, there is the CAPEX cost of the additional 20 kW of the PV plant. Taking DH 1 and HP 1 as base cases, the Payback-time of the investment is respectively 9 years and 10 years.

5 Demand response analysis

The DR analysis consists of quantifying the economic advantages for end users that derive from the modification of their energy consumption habits. May is the month that has been considered in the chapter of DR, with the respective Price of Electricity (Prezzo Unitario Nazionale, PUN in Italian). Electricity contracts for residential users are typically made considering just two time slots, F1 (peak hours) and F23 (off-peak hours).
Three residents have been taken as typical consumers, one for each cluster found before.
All DR tests have been performed by making the hypothesis to "move" 20% of energy consumption from the high cost time slot to the low cost time slot.

Table 5-2: Savings of DR feasibility tests, 20% shift of energy

	F1 & F23	4TS	CPP	IBP
Low	0,41 %	0,76 %	3,40 %	6,2 %
Medium	0,46 %	0,65 %	2,79 %	5,5 %
High	0,36 %	0,76 %	2,95 %	6,7 %

The first test was performed using real PUN prices of peak hours and off-peak hours. The results were not promising, and reason could be linked to the small difference in cost between F1 and F23. Then, the next step was to create a new ToU scheme divided in 4 time steps (4TS), based on the real trend of May's PUN. With the cases of F1&F23 and 4TS just described, it becomes very difficult to implement a residential DR mechanism in which residents would change their energy habits to have a reduction in energy cost component of just around 0,4-0,8%.
The third DR strategy that has been tested is CPP, Critical Peak Pricing. 4TS scheme has been modified by raising the peak price to 3 times of the original value. In this way, a change in habits of 20% from peak to off-peak periods bring savings in the order of 3% of the sole energy component of the

electricity bill, equal to about 5 €/year for a medium consumer.
Another demand-response mechanism that has been evaluated is IBP, incentive based pricing. In particular, it has been considered a scheme where residents would receive a monetary compensation of 0,1 €/kWh for their active modification of energy consumption from peak to off-peak. Results of this case are the most promising, in the order of 6% of savings of energy cost for all "type" residents.

6 Conclusions

The proposed thesis work analyzes different aspects of residential energy demand.
Merezzate+ is the case study, a new generation residential district where state of the art measuring instruments such as 2G Meters and Smart Plugs are installed.
Power demand profile of the residents has been obtained, identified by two peaks around lunch and dinner time and one minimum at night. The trend is dependent on the day of the week, or also on users' habits.
Clustering has been performed of both power load curves and monthly energy consumption.
By adding the info of type of the apartment, some trends have been found: one-room apartments have been clustered for the major part in the "low" power demand group, while three-room and four-room apartments have a higher chance of being grouped in the "high" power demand cluster.
Clustering results have then been applied on the Renewables Energy Communities, both for district heating and heat pump heating scenarios.
The last chapter treated DR feasibility for residents of Merezzate. Of four rates described, the most promising is IBP, with savings of about 6% of the energy cost.
Next step would be to mine data for a longer period of time
Investigate different DR mechanisms like Real Time Pricing, thanks to the advanced measure instruments installed in the district.

7 Bibliography

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Author: **Nicola Perrucci**

Student ID:	928453
Advisor:	Prof. Rossano Scoccia
Co-advisor:	Filippo Bovera, PhD
Academic Year:	2020-21

Abstract in italiano

Il settore civile è oggi incentrato sul miglioramento dell'efficienza energetica degli edifici, con lo scopo di ottenere residenze dal consumo energetico estremamente basso per combattere i cambiamenti climatici. Siamo ancora in una fase di sperimentazione di soluzioni ampiamente studiate a livello teorico per quanto riguarda l'applicazione di tecniche di modifica del carico energetico residenziale. Questa tesi analizza la sperimentazione in corso su un intero distretto di edifici di un quartiere di Milano, attraverso il monitoraggio dei residenti tramite smart meters e smart plugs. Sono state adottate tecniche di clustering per effettuare la segmentazione dei residenti in tre gruppi in base alle caratteristiche di consumo energetico. Combinando le informazioni sul consumo di energia e il tipo di appartamento, la maggior parte dei monolocali e bilocali sono stati raggruppati nel gruppo "basso" e la maggior parte dei trilocali e quadrilocali in "medio" e "alto". Inoltre, il clustering dei residenti dà la possibilità di trovare chi tende ad essere un consumatore virtuoso o chi dovrebbe abbassare il suo uso di energia per essere più simile ai suoi vicini. I risultati del clustering sono stati implementati nella simulazione di una Comunità Energetica a Merezzate. È stato considerato un unico edificio composto da 30 appartamenti che condividono l'energia prodotta da un impianto fotovoltaico. Sono stati studiati due scenari, uno con il teleriscaldamento e uno in cui questo viene sostituito da una pompa di calore. L'introduzione della comunità energetica porta un notevole aumento dell'autoconsumo del campo fotovoltaico già presente, fino al 76% nel caso di teleriscaldamento e 96% per la pompa di calore. La parte finale della tesi consiste nell'analisi di fattibilità delle strategie di demand side management, facendo l'ipotesi di "spostare" il 20% dei consumi energetici dalla fascia oraria ad alto costo a quella a basso costo. Sia un primo test con i prezzi reali delle ore di punta e delle ore non di punta, sia un secondo schema Time of Use (ToU) non portano oggi a vantaggi significativi data la piccola differenza di costo delle fasce orarie. La terza strategia DR che è stata testata è il CPP, Critical Peak Pricing che porta un risparmio nell'ordine del 3% della sola componente energetica della bolletta elettrica. L'ultimo meccanismo DR che è stato valutato è l'IBP, Incentive Based Pricing, dove i residenti riceverebbero una compensazione monetaria di 0,1 €/kWh per la loro modifica attiva del consumo energetico. I risultati di questo caso sono i più significativi, nell'ordine del 6% di risparmio del costo energetico.

Parole chiave: monitoraggio, data mining, clustering, demand response, demand side management, efficienza energetica, comunità energetiche

Abstract

Nowadays the civil sector is focused on improving energy efficiency of the buildings, with the aim of obtaining residencies with extremely low energy consumption. We are still in a phase of experimentation of solutions widely studied at theoretical level regarding the application of techniques that modify the residential energy load. This thesis analyzes the experimentation in progress on an entire district if buildings in a neighborhood of Milan, through monitoring of residents using smart meters and smart plugs. Clustering techniques have been adopted to make residents segmentation into three groups based on energy consumption characteristics. Combining information of energy consumption and apartment type, most of one and two-room apartments have been clustered in “low” group and most of three and four-room into “medium” and “high”. Also, clustering of residents give the possibility to find who tend to be a virtuous consumer or who should lower their energy use to be more similar to their neighbors. Clustering results have been implemented in the simulation of a Renewable Energy Community (REC) in Merezzate. Here it was considered a single building made of 30 apartments that would share energy produced by a photovoltaic plant. Two scenarios are investigated, one with district heating and one where it is replaced with a heat pump. The introduction of the energy community brings a significant increase in the self-consumption of the PV plant already present, up to 76% in the case of district heating and 96% for the heat pump. The final part of the thesis consists of the feasibility analysis of demand side management strategies, making the hypothesis to “move” 20% of energy consumption from the high cost time slot to the low cost time slot. Both a first test with real PUN prices of peak hours and off-peak hours and a second Time of Use (ToU) scheme do not lead to significant benefits today given the small difference in cost of the time slots. The third DR strategy that has been tested is CPP, Critical Peak Pricing which brings savings in the order of 3% of the sole energy component of the electricity bill. The last DR mechanism that has been evaluated is IBP, incentive based pricing, where residents would receive a monetary compensation of 0,1 €/kWh for their active modification of energy consumption. Results of this case are the most promising, in the order of 6% of savings of energy cost.

Keywords: monitoring, data mining, clustering, demand side response, energy efficiency, energy community

Contents

List of Abbreviations

Abbreviation	Meaning
DR	Demand Response
DSM	Demand Side Management
PBP	Price-Based Programs
IBP	Incentive-Based Programs
DLC	Direct Load Control
ToU	Time of Use
CPP	Critical Peak Pricing
RTP	Real Time Pricing
TSO	Transmission System Operator
DSO	Distribution System Operators
BRP	Balance Responsible Parties
VPP	Virtual Power Plants
PLC	Power Line Communication
EIT	European Institute of Innovation and Technology
KIC	Knowledge and Innovation Cmmunity
IoT	Internet of Things
AC	Air Conditioning
C2G	Chain2Gate
CEC	Citizen Energy Community
REC	Renewable Energy Community
ENEA	Italian National Agency for New Technologies, energy and Sustainable Economic Development
RECON	Renewable Energy Community ecONomic simulator
DH	District Heating

HP	Heat Pump
SCOP	Seasonal Coefficient Of Performance
PV	Photovoltaic
CAPEX	CAPital EXpenditure
OPEX	OPerating EXpense
PBT	Payback-Time
NPV	Net Present Value
MISE	Italian Ministry of Economic Development
GME	Gestore dei Mercati Energetici,
PUN	Prezzo Unico Nazionale
ARERA	Autorità di Regolazione per Energia Reti e Ambiente
4TS	Four Time Slots

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1 Introduction

In this Chapter the scope of the work is presented as well as the state of the art of demand response strategies. The last introductory part is centered on the monitoring systems used in this thesis.

1.1 Scope of the work

The presented thesis work treats different aspects related to residential energy consumption of a residential district of Milan, REDO Milano, also called Merezzate. Thanks to the several monitoring devices installed it is possible to know the power consumption habits of the residents. Many techniques of data mining have been implemented in this study, in order to analyze different aspects linked to power consumption, from transformers, to apartments' energy consumption, to daily energy curves. Results of data mining have then been implemented in a simulator to evaluate the advantages that could derive from the establishment of a renewable energy community. The last part of this thesis is centered on the feasibility of different demand side management techniques for the residents of Merezzate.

1.2 Demand Response - State of the art

The following section will focus of demand response. It will be presented an introduction on smart grids and demand response, a definition of demand response, demand response programs, residential demand response and an overview on demand response in Europe.

1.2.1 Introduction on smart grids and demand response

A smart grid is an electric grid designed to deliver electricity in a controlled, smart way from points of generation to consumers. Consumers are considered an integral part of the smart grid since they are able to modify their purchasing patterns and behaviors based on the information and incentives they receive.

The demand side management process, which includes everything done on the demand side, is an integral part of the smart grid. Communication systems, sensors, automated meters, mobile devices, and specialized processors are all required for demand response to be fully integrated in the smart grid.

Programs implemented by utilities to manage energy consumption at the customer side of the meter are known as demand side management. Electricity markets can operate more efficiently with these programs that can help reduce peak demand and spot price volatility, benefiting both utilities and their customers.[1]

For years, demand response has been active in the electrical system; for example, suppliers offer time-of-use rates to their customers. Nonetheless, as the electricity system evolves, it is becoming more crucial.

With big, controllable power plants on one hand and relatively easy-to-predict demand on the other, matching electricity supply and demand has historically been quite simple. However, smaller, more variable, and less predictable renewable power has emerged in recent years. Furthermore, rather than being connected to the transmission grid, renewable energy generation is frequently connected to the distribution grid.

As a result of these developments, it is becoming more difficult to match supply and demand at all times, and the energy system requires more flexibility. Smart meters, connected appliances, and in-home displays, on the other hand, open up new opportunities for demand-side innovation. Empowered consumers can then play a bigger role by changing their consumption habits: another weapon in the flexibility toolbox is demand response. [2]

1.2.2 Demand response definition

Demand response is defined as end-use consumers' variations in energy usage from their regular consumption patterns in response to changes in power prices over time. Demand-response may alternatively be described as payments intended to incentivize the decrease of power use during periods of high wholesale market pricing or when the system reliability is endangered. Demand response refers to all changes in end-use consumers' energy consumption patterns that are designed to change the timing, level of instantaneous demand, or overall power consumption [1], [3], [4].

There are three main activities that may be implemented to get a consumer response. Each of these activities has a cost and a set of steps that the client must do. First, consumers can minimize their power use during high-priced peak periods without affecting their other consumption patterns. This approach entails a short-term loss of comfort. When the thermostat settings of heaters or air conditioners are temporarily altered, for example, this reaction is obtained. Second, consumers may respond to high power rates by moving part of their peak demand operations to off-peak hours, for example, dishwashers and pool pumps. In this situation, the residential customer will not suffer any losses or pay any costs. However, if an industrial client decides to reschedule some operations, he will likely incur into rescheduling fees to compensate for missed services. The third form of customer response is onsite generation. Customers that produce their own energy may see little or no change in their consumption patterns but, from utility perspective, usage patterns will vary a lot, and demand will appear to be lower [1], [3].

Demand response may be done both manually and automatically as a proactive strategy. The term "manual demand response" generally refers to the regulation of the usage of specific appliances at different times of the day. A pre-programmed demand response strategy is launched by a human via a centralized control system in semi-automated demand response. Demand response that is fully automated does not require human interaction and is launched at a house, building, or facility in response to an external communications signal [4].

1.2.3 Demand response programs

There are different types of demand-response programs, which can be classified into two main categories, like it can be seen in Figure 1-1:

- Price-Based Programs (PBP) and
- Incentive-Based Programs (IBP).

Incentive-Based Programs can be further divided into:

- classical programs and
- market-based programs.

Classical IBP include Direct Load Control programs and Interruptible/Curtailable Load programs. Market-based IBP include Emergency DR Programs, Demand Bidding, Capacity Market, and the Ancillary services market.

Customers who participate in Classical IBP programs are compensated for their involvement in the programs, generally in the form of a bill credit or a discount rate. Participants in market-based programs are compensated with a monetary sum for their efforts, based on the amount of load reduction achieved during critical situations.

Utilities participating in Direct Load Control schemes have the option to remotely shut down participant equipment at any time. Air conditioners and water heaters are common examples of remotely operated equipment. This type of offer is mostly targeted towards residential and small commercial users.

Customers who participate in Interruptible/Curtailable Programs get upfront incentive payments or rate savings, just as those who participate in Direct Load Control programs. Participants are instructed to lower their power load to predetermined levels. Participants who do not answer may be penalized, depending on the terms and circumstances of the program.

Demand Bidding (also known as Buyback) schemes allow users to bid on particular load reductions in the wholesale energy market. If a bid is less than the market price, it is accepted. If a bid is approved, the customer must reduce his load by the stipulated amount or suffer penalties.

Customers who participate in Emergency DR Programs, on the other hand, get compensated for calculated load reductions during emergency situations.

Customers who can agree to pre-specified load reductions when system emergencies arise are eligible for Capacity Market Programs. Participants are generally given a day-ahead notice and are punished if they do not comply with requests to reduce their load.

Through Ancillary services market programs, customers can bid for load curtailment in the spot market as an operational reserve. Participants are paid the spot market price for agreeing to be on standby, as well as the spot market price for energy if load reduction is necessary.

Price-Based Programs are based on pricing rates that change with time, so that electricity prices are not flat. The tariffs change in accordance with the real-time cost of electricity. The final goal of these initiatives is to flatten the demand curve by charging more during peak times and less during off-peak times.

With this knowledge, customers may choose (or have chosen for them) to move their power consumption away from periods of high costs, lowering their energy bill. Electricity suppliers offer time-varying pricing, which can range from simple day and night rates to highly dynamic rates based on hourly wholesale rates.

These rates include the

- Time of Use rate,
- Critical Peak Pricing,
- Extreme Day Pricing,
- Extreme Day Critical Peak Pricing, and
- Real Time Pricing.

Time of Use rates are the most fundamental form of price-based program, and they are the rates of electricity price per unit use that change in various time ranges. During peak periods, the rate is greater than during off-peak hours. The most basic Time of Use rate consists of two time blocks: peak and off-peak. The tariff structure aims to represent the average cost of power over time.

Rates for Critical Peak Pricing contain a pre-determined increased power use charge that is overlaid on Time of Use or standard flat rates. For a limited number of days or hours per year, Critical Peak Pricing rates are utilized during contingencies or high wholesale power costs.

Extreme Day Pricing, on the other hand, is similar to Critical Peak Pricing in that it has a higher electricity price, but it varies from Critical Peak Pricing because the price remains constant for the whole 24 hours of the extreme day, which is unknown until a day in advance.

Furthermore, during extreme days, Critical Peak Pricing prices for peak and off-peak hours are referred to as Extreme Day Critical Peak Pricing rates. On the other days a flat charge is utilized.

Customers are charged hourly changing prices reflecting the true cost of power in the wholesale market under Real Time Pricing systems. Customers that use Real Time Pricing are notified of pricing a day or hour in advance. Many economists believe that Real Time Pricing schemes are the most direct and efficient DR programs for competitive electricity markets, and that policymakers should focus on them. [1], [3]

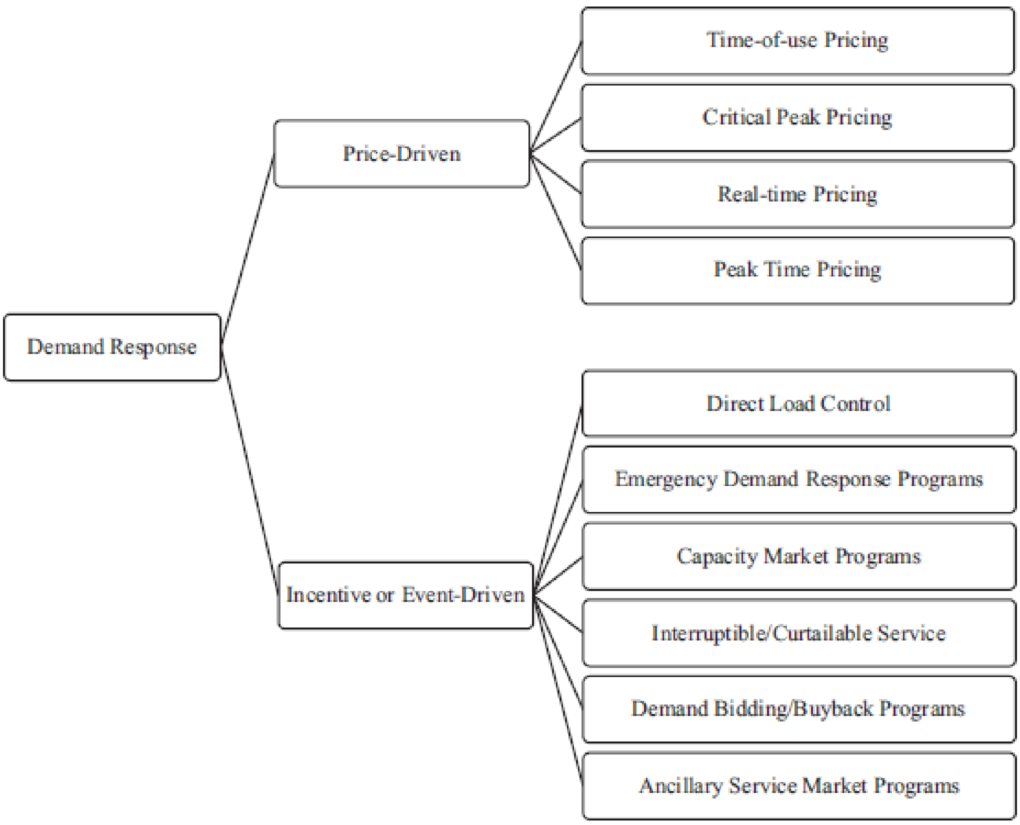

Figure 1-1 - Demand Response Programs

Differentiating between market DR (i.e., real-time pricing, price signals, and incentives) and physical DR (i.e., grid management and emergency signals) is another approach to look at the many DR initiatives. Market DR is triggered by economics, whereas physical DR is triggered by reliability needs.

Emergency-based, system-led, load-response, incentive-based, direct-load control programs are often used to increase system reliability. On the other hand, DR with the goal of lowering system costs is often achieved through price-based, market-led, price-response and passive load management programs. [1]

1.2.4 Residential demand response

In comparison to big commercial and industrial customers, residential customers have relatively modest and limited types of power loads and are not motivated to invest much in order to regulate their electrical use.

In the first decade of the 2000s, residential consumers exclusively participated in retail electricity markets and mostly in direct load control programs. This is already changing, owing to the adoption of new standards and technologies such as enhanced metering infrastructure, which allows for the sale of lower-cost equipment. Smart homes can now provide technical assistance to the smart grid thanks to new building automation standards and technology. [1]

Smart metering (advanced metering) is a metering system that collects a customer's usage and other characteristics on a regular basis (hourly or more often) and transmits the data to a data consolidation point hourly or even minutely through a communication network. Real-time electrical energy usage monitoring inside the smart grid has become widely available as a result of better infrastructure in residential sectors and greater penetration of smart meters.

Demand response programs implemented for residential customers have been analyzed in many studies. Papers from [5] and [4] review the residential demand response programs summarizing all the studies that have been performed during the years. In particular, the first paper analyzes 14 demand response programs, 9 demand response scheduling techniques and 8 IoT applications in demand response. The second paper focuses on price driven demand response program, analyzing 25 case studies divided based on the program type: Time of Use, Critical Peak Pricing and Real Time Pricing. The different types of DR programs are described in the table in the next page, with the respective advantages and disadvantages.

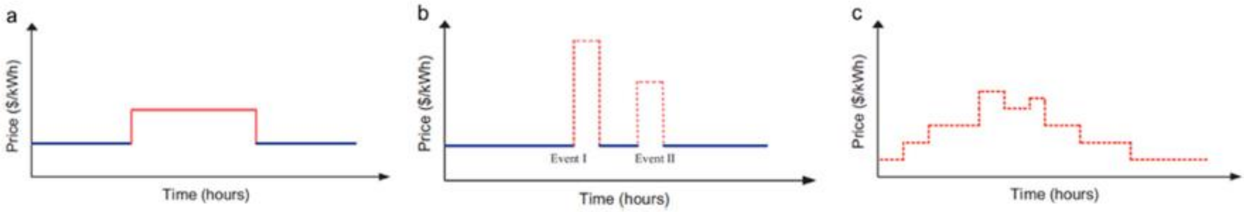

Figure 1-2 – Price-driven demand response programs
a: Time of use, b: Critical peak pricing, c: Real time pricing

Comparison for demand response programs.

DR program	Scheme type	Rule	Situation	Rate type	Activation period
Time of Use (ToU)	Price based	Non-dispatchable	Periodic	Variable	Vary hourly with a day-time and seasonally with a year
Critical Peak Pricing (CPP)	Price based	Both	Causative/periodic	Static	At any time
Real Time Pricing (RTP)	Price based	Non-dispatchable	Periodic	Variable	Variable within a day
Direct Load Control (DLC)	Incentive based	Dispatchable	Causative	Static	At any time
Interruptible	Incentive based	Dispatchable	Causative	Static	At any time
Bidding	Incentive based	Dispatchable	Causative	Variable	At any time
Emergency	Incentive based	Dispatchable	Causative	Static	At any time

DR program	Response type	Advantages	Disadvantages
Time of Use (ToU)	Customer side	Low price rate during off peak, user can shift load with min. cost	One price rate for all customers' consumption levels, user should follow the price change with respect to time.
Critical Peak Pricing (CPP)	Customer side	Customer response for a short time period to get discount offers	The customer should shift or curtail home resource for certain time.
Real Time Pricing (RTP)	Customer side	The customer can minimize the cost with respect to price change in a day, month, or season	Customer need to instantaneously respond to minimize bill cost
Direct Load Control (DLC)	Utility side	The utility offers good discount for limited load reduction or shifting.	The customer should give the utility company a level of authority to shift or curtail certain load in order to balance energy used.
Interruptible	Customer side	Customer respond for a short period to get discount rates	The customer should shift or curtail home resource for certain time.
Bidding	Customer side	The utility offers good discount for limited load reduction or shifting.	The customer should shift or curtail home resource for certain time.
Emergency	Utility side	Customer can get credit or discount rate for the short response	The customer should shift or curtail home resource for certain time.

1.2.5 Demand response in Europe

The Energy Union Strategy which was published in 2015 is one of the key elements of the European Energy Commission. The aim was to build an energy union the gives the consumers secure, sustainable, competitive and affordable energy. The energy union was built on five pillars:

- Security, solidarity and trust
- A fully integrated internal energy market
- Energy efficiency
- Climate action, decarbonizing the economy
- Research, innovation and competitiveness

The main instrument to put forward these objectives was the Clean Energy Package, in which Demand Response is clearly mentioned as one of the tools to achieve a competitive, consumer-centered, flexible and non-discriminatory electricity market. The European Green Deal of 2019 is relevant for DR, in order to better integrate renewable sources and reach decarbonization of the energy sector.

The customers of Demand response are Transmission system operators (TSO), Distribution System Operators (DSO) and Balance Responsible Parties (BRP). The services can be offered through DR Aggregators, the energy provider retailers or energy communities and individual active consumers.

Boundaries and labels between Virtual Power Plants (VPPs), demand response providers, and prosumers are becoming less relevant as demand-side flexibility platforms proliferate. Major utility providers are diversifying their offers even further by offering VPPs that combine DR with other types of demand-side flexibility and/or generation. DSOs are increasingly sourcing flexibility locally and attempting to postpone or prevent grid improvements and reinforcement by utilizing local demand-side flexibility, among other things. In the United Kingdom, Netherlands, Germany, and Norway, this is already done through third-party platforms or direct purchase by DSOs. [6]

The status of DR in the European Union is analyzed in [6] and an extract is reported below.

Belgium and France have both defined roles and responsibilities for independent aggregators. A number of other countries including the Nordics, Netherlands or Austria have implemented retailer-based DR programs, but not yet recognized aggregators. In Ireland 426 MW cleared in a 2019/20 capacity auction from demand response, out of 8266 MW total. In the United Kingdom DR aggregators participated in capacity auctions up until 2018 when the European Court of Justice suspended it due to violation of EU state aid rules. In Germany DR underway through VPPs qualified by TSOs. In Italy there are 350 MW of power dedicated to DR through

Virtual Power Plants. Also, the fully deployment of smart meters are a key component to the development of residential DR and with the integration of Chain 2 second generation of smart meters make it the best way to have efficient price signals.

The EU market monitor for demand side flexibility shows that UK, Ireland, France and Finland are the countries that have the best engagement for demand side flexibility, with Germany, Italy, Netherlands, Austria and the Nordics following behind [7]. It is worth noticing that industrial customers are the most engaged with demand response programs, but less than 2% of the global potential for demand-side flexibility is currently being utilized with a huge portion of energy set to residential market that can be efficiently managed [6].

Access to markets for DR providers in Europe continues to be a challenge for many reasons. There is lack of standardization across countries and lack of a framework for DR providers. The integration of implicit and explicit Demand Response is complex in a fragmented market [8].

Demand Response is seen as a crucial technology on the Strategy for the Energy Union, by allowing the full participation of consumers in the market. In terms of accelerating Demand Response in the residential sector, the promotion of household appliances that are able to modulate temporarily their energy use, smart metering systems and energy storage possibilities are seen as solutions for an effective adoption of Demand Response in the European market. [9].

1.3 Monitoring systems

This section is formed of four sub-sections: Introduction on monitoring systems, Power smart metering, Power smart metering and Chain2 in Italy, Smart plugs.

1.3.1 Introduction on monitoring systems

Smart metering and advanced information and communication technology solutions for building energy management look to be a real possibility for achieving energy savings, utilizing renewable energy resources, and encouraging consumer involvement in the energy market. Demand response faces new problems as new infrastructures facilitate more efficient network operation and allow for the delivery of rapid pricing adjustments. They provide a far more dynamic, reactive pricing system, which is necessary to account for real-time renewables availability and to track the evolution of the supply-demand balance in real time.

Smart technology, such as smart meters, are required to monitor energy use on a more regular basis for most DR programs, allowing for an increase in the amount of load that may be lowered. Smart metering and smart plugs are examples of innovative enabling technologies that allow for improved consumer receptivity as well as greater utility confidence. These smart technologies enable a variety of tasks, such as automated energy consumption reduction in response to high-energy processes or an emergency signal from the DSO [1].

1.3.2 Power smart metering

There are numerous requirements that must be met for the effective deployment and usage of smart appliances and home energy management systems in the smart home. Some of the most significant include the implementation of smart meters, the existence of smart grids, an unrestricted market for Demand Response, and the availability of a fast internet connection. This will allow for a gradual but continuous shift in paradigm, with energy consumers transitioning from a passive to an active role in the energy system.

The installation of a smart meter is the first step toward improved control of the household's energy usage patterns. The fact that end consumers may access near-real-time data on their consumption habits and act on it may provide leverage for energy system changes on both the supply and demand sides.

A set of standard minimum functional requirements for power smart metering systems was defined by the EU Commission. The meters should send readings to the customer immediately, as direct consumer input is considered essential for ensuring energy reductions on the demand side. There is also a reference for standardized interfaces that should allow real-time energy management systems such as home automation and demand response schemes to be implemented. Reading updates should be made every 15 minutes at the very least. Meters should allow remote reading, provide two-way communication between the smart meter and external networks, and allow frequent readings so that the information may be utilized for network planning on the metering operator's side [9].

1.3.3 Power smart metering and Chain2 in Italy

In the early 2000s, Italy was the first country to implement smart meters on a wide basis. Between 2001 and 2011, the country installed 36.7 million meters. Enel Distribuzione (now known as e-distribuzione), the largest DSO, which controls approximately 86 percent of the distribution points, began the rollout on its own initiative in 2001-2006, encompassing almost its whole network. Other DSOs, such as Unareti and Areti, followed when the regulator imposed an obligatory strategy [10].

Italy was the first European country to introduce large-scale electricity smart meters for low-voltage end customers, and by 2021 it is considered to be the top country in the world for the number of electricity smart meters in service. According to a recent report by the European Commission, Italy's smart metering system, with replacement of traditional meters since 2001, was the most efficient in Europe [11].

The first generation meter installed in the first roll-out phase in the early 2000s has the following characteristics. The bidirectional communication between the meter and the concentrator takes place by means of a Power Line Communication (PLC) signal that uses the same low voltage power line for data transmission. The data collected by the concentrator are then addressed and processed by the Central System [12].

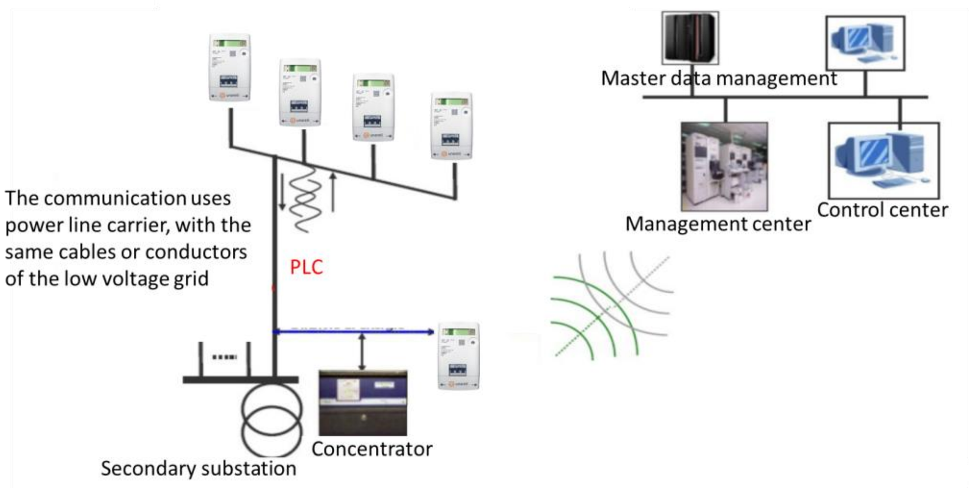

Figure 1-3 – PLC communication

Italy’s smart meters installed until 2011 were in line with the EU requirements, but after EC communication of 2012 the necessity of a new meter raised. Italy's smart meters were not capable of giving an updated reading at least every 15 minutes [10].

The natural consequence was the implementation of a second generation (2G) meter, which exploits the so-called Chain 2. At present, Unareti's active 1G meter fleet totals approximately 1.1 million meters. The installation plan will be focused over 6 years, with the goal of replacing 94% of the meters in the 2020/2025 phase.

The 2G meter has the possibility to communicate with the concentrator also through a second channel in addition to the primary one. The first channel exploits the low voltage electrical connection between the meter and the concentrator and uses PLC technology for communication. In fact, in the event that the meter is not reached by PLC, remote management takes place via radio frequency (160 MHz) from one of the nearest concentrators which is able to establish communication through this backup channel. Consequently, the new backup channel allows to overcome some problems typical of the first generation meter equipped with only PLC channel. For example, electromagnetic disturbances generated by equipment not belonging to the Distributor and therefore extremely difficult to detect and eliminate can be avoided [12].

The electricity market will inevitably change with the arrival of these new devices as it is believed that Sales Companies will be able to issue invoices more promptly and in line with real energy use and therefore more consistent with consumption actually incurred by the end customer. In addition, a wider range of new offers (prepaid, hourly, customizable bands) will create greater commercial opportunities [13].

1.3.4 Smart plugs

The accuracy of demand response studies is influenced by the home load profile and electric power usage [14]. This can be achieved by installing smart plugs into our homes. Smart plugs are devices that sit between a power outlet and a power-hungry gadget. Because of their intelligent characteristics, these devices have the ability to transform non-smart equipment into smart ones. A smart plug allows appliances connected to it to be operated remotely and provides feedback on the appliance's energy usage. [9]

To attain its full potential, a smart house must connect with a variety of agents, such as energy or internet suppliers. Smart appliances and smart home gadgets such as smart plugs and smart thermostats have been on the market for a few years now, and some of the benefits that may be reaped in terms of energy savings are already evident, even though their full potential has yet to be realized. [9]

1.4 Clustering methods

The present section is composed of three sub-sections. The first consists of the definition of clustering, the second is on Load profiling and the third focuses on Clustering techniques classifications.

1.4.1 Clustering definition

Clustering is a term that encompasses a wide range of approaches for identifying subgroups, or "clusters," in a data collection. Cluster analysis, often known as data segmentation, serves a number of purposes. One of them is generally to create a natural hierarchy out of the clusters.

When we cluster a data set's observations, we want to split data so that items within each cluster are more closely connected to one another than objects in other clusters.

Of course, we must define what it means for two or more observations to be similar or different in order to make this tangible. Indeed, this is frequently a domain-specific judgment that must be made based on prior knowledge of the material under investigation. [15] [16]

This chapter focuses on clustering of electricity consumption load curves and on total monthly energy consumption clustering.

1.4.2 Load profiling

Load profiling, which refers to consumers' energy consumption patterns over a given period of time (for example, one day), can assist in determining how electricity is really utilized by different customers and obtaining their load profiles or load patterns.

Time of Use tariff design, nodal or customer scale load forecasting, demand response and energy efficiency targeting, and non-technical loss detection are examples of some applications benefitting from load profiling. [17].

Usually, the load profiling process can be divided into five stages:

- Stage 1: Load data preparation.
  Individual customers' electricity usage trends collected by smart meters may contain inaccurate information. The first step should be to clear the data.
- Stage 2: Load curve clustering.
  Clustering is a technique for dividing large load curves into several clusters. A typical load curve is at the middle of each cluster. Load profiling relies heavily on clustering. Researchers have experimented with a number of clustering approaches.

- Stage 3: Clustering evaluation.
  The load curves in the same cluster should have similar patterns, but the curves in separate clusters should have substantial differences. By measuring these similarities and differences, several criteria may be used to evaluate clustering performance.
- Stage 4: Customer segmentation.
  Client categorization is a method of assigning a new customer to a certain customer group based on the customer's load profile pattern.
- Stage 5: Result application.
  Load profiling has many applications including demand response, load forecasting, and non-technical loss detecting.

Customers' active engagement in the smart grid is a critical component of the two-way power flow, and demand response is one approach to achieve this.[18]

1.4.3 Clustering techniques classification

The clustering techniques can be classified into two categories: direct clustering and indirect clustering. Direct clustering is a clustering approach that uses data obtained directly from smart meters. Instead, we talk about indirect clustering if the load data have been treated by dimension reduction techniques or another approach before clustering.

On the basis of load data collection and processing, various clustering techniques are used to detect the electricity consumption patterns. The most widely used methods for clustering to handle load profiling are K-means, Fuzzy k-means, Hierarchical clustering, and Self-Organizing Map, which have been provided and analyzed in different papers. These traditional clustering methods are often used as a benchmark to assess other new methods. [18]

As previously stated, indirect clustering refers to the clustering of characteristics derived from electricity consumption data rather than the data itself.

The technique of feature extraction is frequently used to decrease the size of input data. The indirect clustering approaches may be classified into two types depending on the feature extraction techniques used: dimension reduction based and time series based clustering. Dimension reduction based clustering consists of Principle Component Analysis, Sammon map, Deep learning, others. Time series based clustering techniques are Discrete Fourier Transform, Discrete Wavelet Transform, Symbolic Aggregate Approximation, Hidden Markov Model, others [18][17].

Every clustering method for load separation has pros and cons, widely treated in literature. Despite the fact that there are several current clustering algorithms, k-means has a significant advantage in that it is easily applicable, interpretable and performs well in a variety of problem-solving scenarios [19].

1.4.3.1 Number of clusters

Two choices in clustering analysis heavily influence the results of clustering: the number of clusters and the distance measure between each data.

The selection of clusters number necessitates a detailed analysis. On the one hand, clustering performance varies depending on how many clusters we're looking for. Clustering should be repeated several times to determine the number of clusters that produce the best performance metrics. However, having an additional information on the dataset that has to be clustered gives a hint on the number of clusters that are to be found.

1.4.3.2 Similarity distance

Another factor that has a direct influence on clustering performance is the similarity distance chosen. The three most commonly used metrics are Euclidean distance, Dynamic time warping and Shape-based distance [20].

Euclidean distance is the most widely used distance measurement in a wide range of applications. The equation below shows how to compute the Euclidean distance between two time series $T1 = (T1_1, T1_2, \dots, T1_n)$ and $T2 = (T2_1, T2_2, \dots, T2_n)$

$$d(T1, T2) = \sqrt{\sum_{i}^{n} (T1_i - T2_i)^2}$$

Dynamic time warping (DTW) is a mapping of points between a pair of time series, $T1$ and $T2$ designed to minimize the pairwise Euclidean distance.

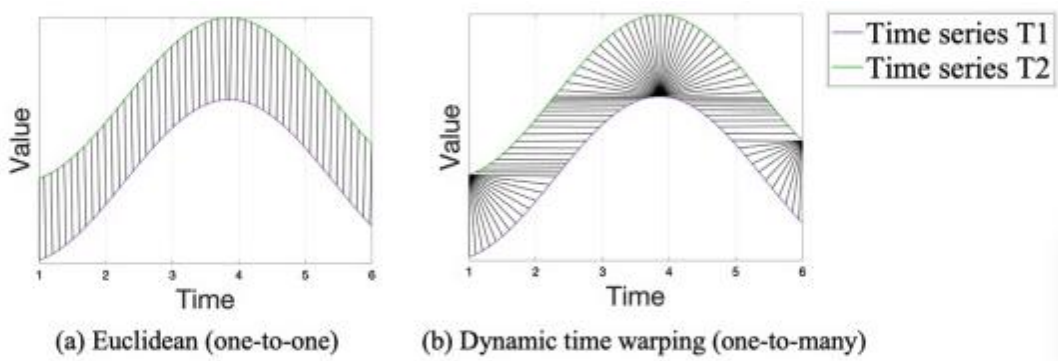

Figure 1-4 – Alignment between two time series for calculating distance [20]

The third distance metric is Shape-based distance which is both shift-invariant and scale-invariant, so that it is not affected by the shifting or scaling of the time series data. The metric evaluates the cross-correlation between two time series and returns a distance value ranging from 0 to 2, with 0 representing identical forms and 2 suggesting maximally dissimilar shapes. Each time series is normalized to guarantee that the distance metric is scale-invariant.

1.4.3.3 Evaluation criteria

Based on clustering results, various assessment criteria may be used to measure the performance of different clustering algorithms and lead us to pick an acceptable number of clusters [18].

External or internal metrics might be used to evaluate clustering output [20]. When class labels are provided for individual data points, external measures are utilized. Examples include the Rand Index (RI), Adjusted Rand Index (ARI), Adjusted Mutual Information (AMI), Fowlkes Mallows index (FMS), Homogeneity, and Completeness. Internal measures, which do not require class labels, quantify the quality of clusters based on an optimization target for the clustering output. Examples include Silhouette score, Davies–Bouldin index, Calinski–Harabasz index, the I-index and sum of square errors (SSE).

1.4.3.4 Time-series k-means clustering

The two methods used in this thesis are time-series k-means clustering and hierarchical clustering. The first one has been used for clustering of daily power load curves, while hierarchical clustering is dedicated for clustering of monthly energy consumption. For this reason, the two methods will be discussed in detail in the next pages.

One of the most common iterative descent clustering algorithms is the k-means algorithm. It's designed for scenarios when all of the variables are quantitative [16]. The k-means clustering method divides a data set into k separate, non-overlapping groups in a straightforward way. To use k-means clustering, first it is necessary to know the number of clusters k in advance; then the k-means algorithm will allocate each sample to one of the k clusters. The K-means clustering technique is the outcome of a simple mathematical problem. K-means clustering is based on the concept that a successful clustering has as little within-cluster variance as possible. There are several ways to define the metric distance, but the squared Euclidean distance is by far the most used.

The algorithm for K-Means Clustering is the following:

- Assign a number to each observation at random, ranging from 1 to K. These act as the observations' initial cluster allocations.
- Iterate the following two points until the cluster assignments stop changing:
    - Calculate the cluster centroid for each of the K clusters. The vector of the p feature means for the observations in the kth cluster is the kth cluster centroid.
    - Assign each observation to the cluster with the closest centroid, where closest is defined using Euclidean distance.

The results achieved will be dependent on the initial random cluster assignment of each observation in Step 1 of the Algorithm since the K-means algorithm finds a local rather than a global optimum [15].

K-means method has been implemented for time series clustering. The library scikit for Python provides this method. Three variants of the algorithm are available: standard Euclidean k-means, DBA-k-means (for DTW Barycenter Averaging) and Soft-DTW k-means, based on the DTW distance measure.

1.4.3.5 Hierarchical Clustering

The number of clusters to be found and the initial configuration assignment affect the outcomes of using K-means clustering methods. Hierarchical clustering approaches, on the other hand, do not require such inputs. Instead, they ask the user to provide a measure of dissimilarity across sets of data based on pairwise differences between the observations in the two groups [16].

Divisive and agglomerative techniques are the two primary types of hierarchical cluster analysis methodologies.

- Agglomerative is a "bottom-up" approach: each observation starts in its own cluster, and as one progresses up the hierarchy, pairs of clusters are combined.
- Divisive is a "top-down" method in which all observations begin in one cluster and are divided iteratively as one travels down the hierarchy.

Agglomerative techniques are more often used in practice. [21].

The merging strategy is determined by the linkage criteria [16]:

- Single linkage; minimizes the distance between the closest observations of pairs of clusters.
- Complete linkage; minimizes the maximum distance between observations of pairs of clusters.
- Average linkage; minimizes the average of the distances between all observations of pairs of clusters.
- Ward; minimizes the sum of squared differences within all clusters.

Hierarchical clustering, as the name implies, produces hierarchical representations in which clusters at each level of the hierarchy are produced by merging clusters from the previous level. Each cluster has a single observation at the most basic level. There is just one cluster that contains all of the data at the highest level.

Each level of the hierarchy reflects a distinct grouping of observations into separate groups. The whole hierarchy is made up of such groups in an orderly succession. It is up to the user to determine which level truly reflects a "natural" clustering in the sense that observations allocated to various groups at that level are sufficiently more similar to each other.

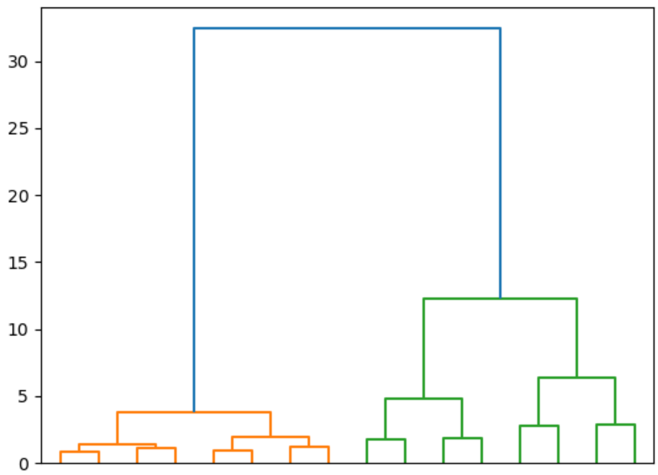

Figure 1-5 – Hierarchical clustering dendrogram [22]

A dendrogram (such as the one shown in Figure 1-5) is a graphical representation of a highly interpretable full description of hierarchical clustering. The length of the tree's branches along the vertical axis is proportional to the dissimilarity between two clusters. This is one of the primary reasons why hierarchical clustering methods are so popular [16].

2 Case study – REDO Milano

This thesis project has been written based on an internship in A2A Smart City from March 2021 to November 2021.

A2A Smart City is the largest Italian multi utility company and is part of the A2A Group. It develops and manages enabling technology infrastructure for integrated, networked digital services. The first step toward the smart city is the expansion of digital, innovative IoT technologies that enable the collection of recorded data from sensors. The competences of A2A Smart City, as well as its interaction with the territory, ensure the rapid implementation of new initiatives aimed at improving city quality of life.

The present Chapter presents two sections, the Merezzate+ project and the Monitoring systems used in the case study.

2.1 Merezzate+ project

A2A Smart City, alongside with A2A Calore e Servizi, Politecnico di Milano and Poliedra, is one of the Partners of Merezzate + project.

The Merezzate+ project intends to demonstrate an innovative approach in a new affordable housing district in the south-east of the city of Milan called REDO Milano, composed by 800 apartments 615 of which dedicated to social housing. It is near Rogoredo Santa Giulia, in the eastern part of Milan. It is a living lab for integration of clean energy, sustainable mobility and circular economy. A2A Smart City played the role of installing surveillance systems and IoT technologies for homes of Merezzate residents. In particular, the different types of devices installed consists of lampposts, thermostats, smart meters, smart plugs, smart water meters, for a total of more than 2200 instruments.

In this thesis only data retrieved with smart electricity meters and smart plugs have been analyzed.

EIT Climate-KIC is a Knowledge and Innovation Community (KIC) dedicated to speeding up the transition to a carbon-free, climate-resilient society.

Climate-KIC, which is funded by the European Institute of Innovation and Technology, identifies and supports innovation that aids society in mitigating and adapting to climate change. The main focus of the Community in on three key systems to deliver the outputs and impacts required by 2030. They are in the area of focus of Urban transitions, Sustainable land use, Sustainable production systems and Decision metrics and finance.

Climate-KIC focuses on transformational, systemic innovation, which entails multiple interconnected ideas occurring at the same time to cause a systemic shift. Its goal is to transfer products, good ideas, or services from niche to mainstream in order to achieve a tipping point and have the most influence possible.

The Knowledge and Innovation Community has identified cities, land use, and manufacturing as the three major systems that, if change were triggered wholesale and emissions reduced, would have the most potential in realizing a climate-resilient society and net-zero carbon economy, as guided by the Paris Agreement, advisors, and community.

Climate-KIC takes the strategy of piloting, testing, and scaling to create room for experimentation.

Milan Merezzate+ is one of numerous Climate- KIC's strategic initiatives taking place in Milan. Much of the information about the trials is still confidential, but they involve fundraising and leveraging a carbon fund, new contracting and procurement models, new policies and resilience, greening Milan through nature, and controlling the effects of the urban heat island [23].

The Merezzate+ project aims to demonstrate an innovative method in a new affordable housing district in Milan's south-east, with 615 apartments partially dedicated to social housing. The project's goal is to boost the adoption of innovative solutions by incorporating them into an urban development model that promotes social inclusion, renewable energy and energy efficiency, sustainable mobility, and circular economy activities.

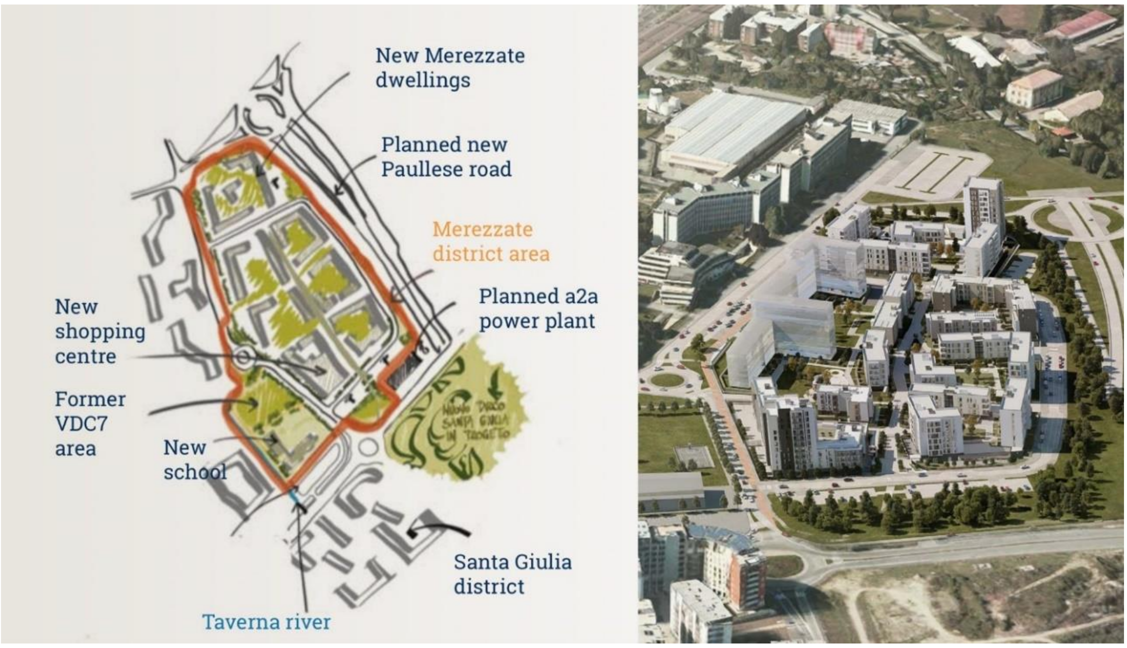

Figure 2-1 – Merezzate district area

The activities are fueled by the district's new residents, as well as the main local public actors and demand-side players like housing associations and utilities providers. This allows for a better reflection of user needs and, as a result, increased efficacy, the creation of a community, and the encouragement of social activities.

Merezzate+ results will be utilized to develop recommendations for the model's possible transferability and replication in other parts of Milan, as well as other Italian and European cities.

An integrated set of measures has been co-designed, executed, and monitored, based on the three pillars of the project:

- Clean energy and energy efficiency
- Sustainable mobility
- Circular economy

The testing of a new low-temperature district heating model in the Merezzate+ neighborhood has a unique feature: it is the first plant of its kind in Italy to also be utilized for summer cooling, making it an excellent alternative for efficient clean energy production in our cities. The air conditioning and ventilation of a few specific environments has been achieved using "Freescoo," an innovative technology that is mostly powered by the district heating network. Other apartments present split air conditioners.

ICT solutions for controlling individual residences' thermal and electrical consumption have been evaluated, allowing tenants to monitor their behaviors in real time, ensuring autonomy in the management of comfort in interior spaces, and establishing the conditions for sensible energy usage [24].

All appliances installed in Merezzate district are electric. The trend of newly constructed buildings is going in the direction of creating only electric neighborhoods to prevent the dangers linked to gas leaks explosions. The main difference with respect to “classical” Italian apartments is the absence of gas for the water boiler heaters and for the cooking stove.

2.2 Monitoring systems used in Merezzate

The monitoring systems used in this case study are mainly of three types. The most obvious instrument is Unareti’s smart meter installed in every apartment. The second is the so called Chain2Gate, a device that has been developed by Mac srl (a company based in Recanati, Italy) and produced by A2A Smart City. This device is installed in the electrical panel of every apartment in Merezzate and sends data monitored by the smart meter to the network server of A2A Smart City. The third device are the smart plugs, produced by enginko (an Italian company that designs and manufactures IoT devices, software applications and cloud systems).

2.2.1 Second generation smart meter

As stated before, smart meters installed in Italy have to be replaced due to the absence of possibility to retrieve data at least every 15 minutes. In the case of Merezzate, second generation smart meters have been installed during the construction of the buildings in every apartments.

The smart meter communicates with the concentrator through PLC channel, with the possibility to talk also via a second PCL channel.

Figure 2-2 – Second generation smart meter

2.2.2 Chain2Gate

Chain2Gate has been installed in 615 apartments in Merezzate and monitors the energy consumption of every residence. It’s the device that talks with the power meter via PLC channel, retrieving data every 15 minutes. Data is then sent via LoRaWan protocol to the gateways in Merezzate neighborhood, so that they arrive in A2A Smart City’s network servers.

The properties measured with Chain2Gate are Active Energy, Instantaneous Active Power and Mean Active Power.

Figure 2-3 – Chain2Gate

2.2.3 Smart plug

Smart plugs are installed to follow the energy consumptions of home appliances of residents in Merezzate. A first batch of smart plugs was delivered to the users in October of 2020, while a second distribution happened in June 2021. A total of 200 smart plugs have been given to Merezzate residents.

Smart plugs manufactured by mcf88 (a branch of engiko) have the possibility to remotely switch on/off the appliance, even if this feature was not applied in this study. The features for power metering include the measure of instantaneous active, reactive and apparent power, instantaneous active, reactive and apparent energy, current, tension and running time. All this data is sent via LoRaWan protocol, just like Chain2Gate devices.

Figure 2-4 – Smart plug

3 Data mining

The goal of this chapter is to show how raw data can be edited to obtain information on the single electricity consumer and on the whole Merezzate district.

In particular, the following sections of this Chapter will focus on the transformers, clustering of the customers (by clustering load curves and monthly energy consumption), analysis of smart plugs and the last step is about combining the information of electricity consumption of an apartment with information about the set of appliances checked with smart plugs.

3.1 Introduction on data mining

One of the main parts of this thesis is about the analysis of the collected data from smart plugs and chain2gate devices.

In order to work with the big mole of data it was necessary to use Python programming language and the most common libraries for data science. In particular, Pandas and scikit-learn are the libraries used for data mining in this thesis work. Plots have been produced with matplotlib and Plotly libraries.

Data analyzed in this thesis received a preliminary cleansing process, in order to have the best set of measurements possible. For instance, data retrieved from a Chain2Gate every 15 minutes showed one or more missing values for a single day. The method used for correcting this missing value was linear interpolation. Simply the vacant value was addressed as the mean value of the previous and the following measure. This reasoning is in line with the methods used is real measurements for billing electricity consumptions.

If the missing values for a day were greater than 20, on a total of 96 quarter-hour intervals, the data for that single day was considered non valid and discarded.

Many papers regarding clustering of load curves implemented the normalization of data between values ranging from 0 to 1 to find similar profiles between different types of users, like residential, offices, companies and factories. In this thesis normalization was not used. The main reason for this decision is that the group of residential customers tends to have a comparable load profile and the objective of clustering of load curves was to define who consumed more than others. This can be done if the data is “raw”, not normalized, otherwise there would be only the information on the time at which energy have been consumed, not the quantity.

3.2 Preliminary analysis

One of the possible things to analyze is how the transformers are working in a certain period. Thanks to the information of how each apartment is connected to the respective transformer, it is possible to identify the five transformers that are installed in Merezzate.

In total there are 412 apartments of the 615 total apartments that are connected to the grid because they have been sold or given in social housing. About 200 apartments haven’t been delivered yet at the time of this thesis.

The 412 apartments are respectively connected to the transformers as follows:

- Transformer 1: A01943_TR1 – 95 apartments
- Transformer 2: A01944_TR1 – 85 apartments
- Transformer 3: A01946_TR1 – 41 apartments
- Transformer 4: A01947_TR1 – 99 apartments
- Transformer 5: A01948_TR1 – 92 apartments

Every transformer is not completely dedicated to the apartments, so the info found in this paragraph is solely related to the information received by the chain2gate instruments. It’s important to point this out because it could be possible that some other services are connected to these five transformers like shops, electric cars’ charging stations and street lighting.

Summing the active power measured every quarter of an hour of all the apartments that are connected to the respective transformer, it is possible to obtain five different curves. Each curve is referred to one transformer.

The graphs related to the month of May 2021 for each transformer are reported in the Appendix. It’s also possible to obtain the total curve of the active power as a sum of the five power curves of the transformers.

The result is a line whose trend shows how the transformers are busy, due to the power demand of residences in Merezzate neighborhood. In Figure 3-1 it has been represented in black.

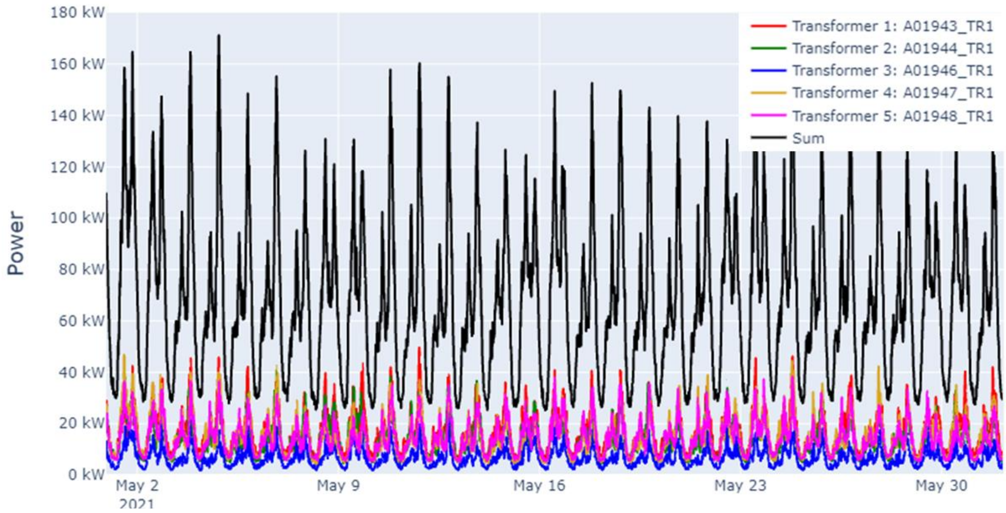

Figure 3-1 – Total power trend, May 2021

From a quick look at the graph, it’s possible to notice that the maximum requested power for this month is between 160-170 kW and it has been reached for about four times in the whole month. Meanwhile, the minimum power ranges around 30 kW, continuously asked each day.

The plot of Figure 3-1 can be difficult to visualize, so below is reported a week of May, in particular form Monday the 10th to Sunday the 16th.

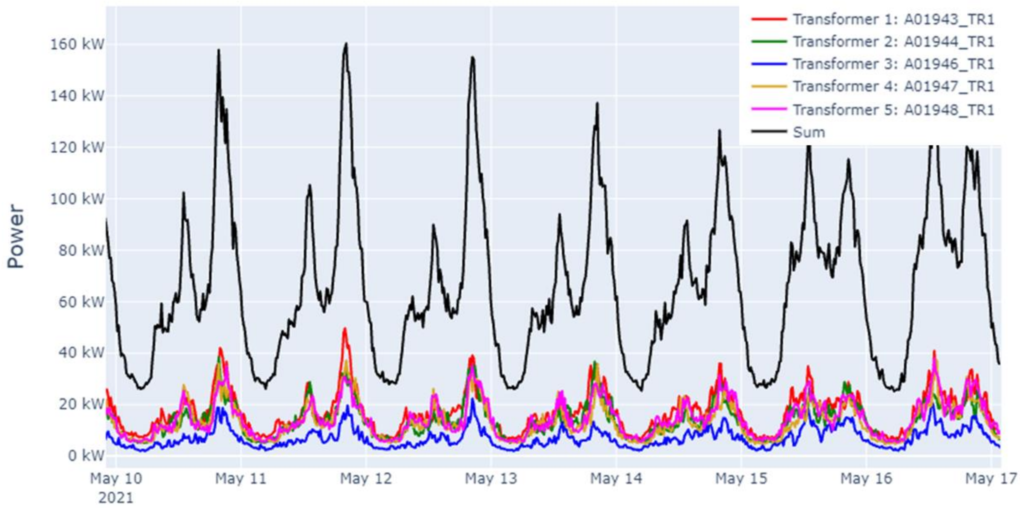

Figure 3-2 – Total power trend of one week, 10th to 16th of May 2021

From Figure 3-2 we can see that power consumption differs based on the day of the week. In particular, weekdays from Monday to Friday present a peak around dinner time. Energy consumption in weekends have a different trend, linked to the habits of residents to stay at home since early in the morning. This will be further examined in the section on clustering of the residents.

The power load curves can be seen in the same daily time range, from 00:00 to 24:00. It can be seen in the figure below with respect to the month of May 2021, with the addition of the mean trend colored in red. Every line is the power curve of one day.

The mean curve of Figure 3-3 clearly tells us that residential power demand has a minimum during night hours and two peaks around lunch and dinner time. This is a common trend for all months that has been analyzed in this study. The differences between months will be further analyzed in the next sections, from the power and energy point of view.

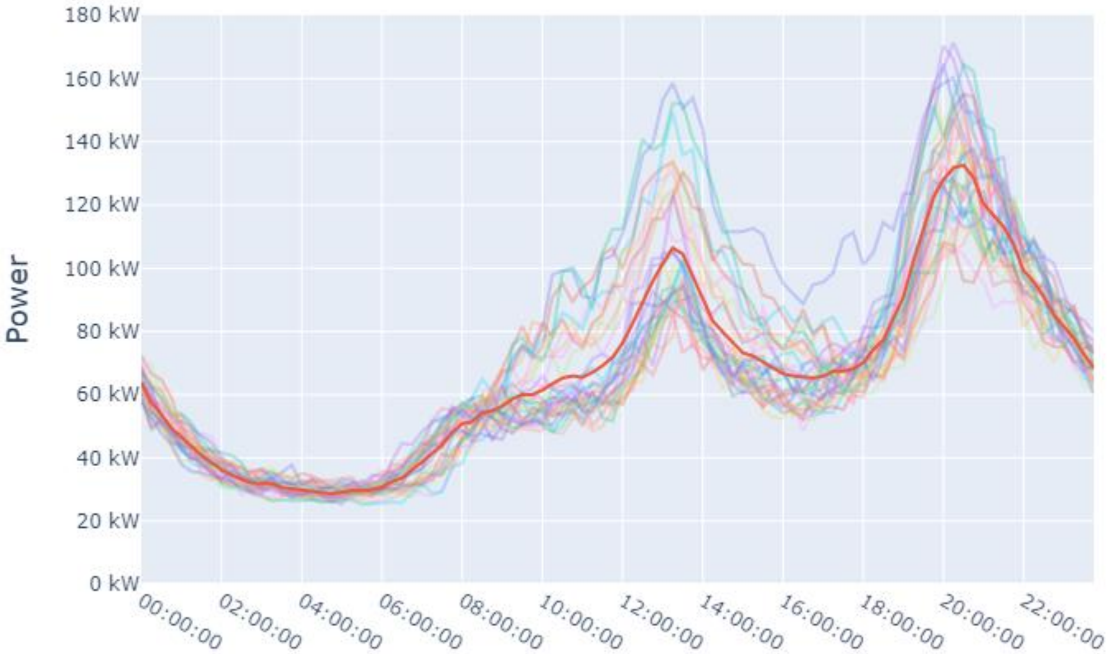

Figure 3-3 – Daily total power trend, May.

The same graph can be obtained for the following months, June, July and August 2021.

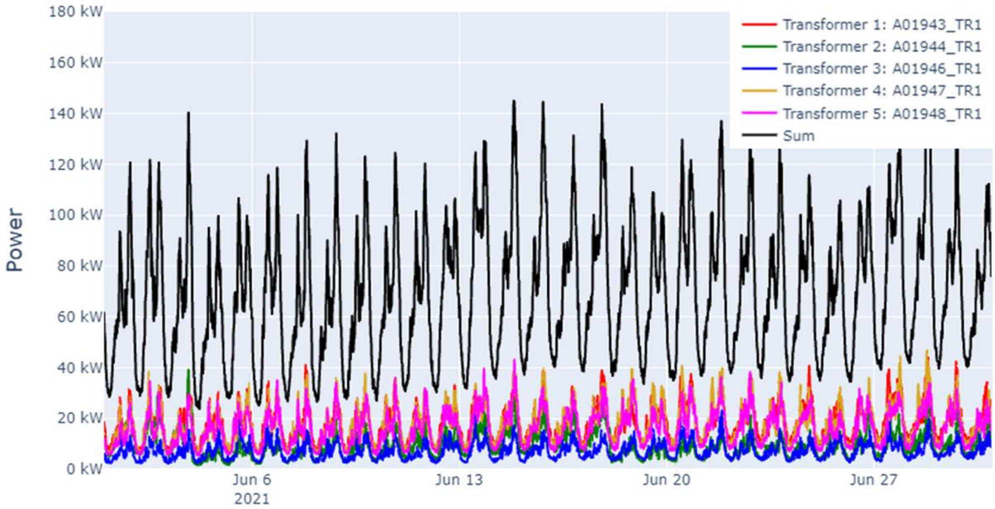

Figure 3-4 – Total power trend, June 2021

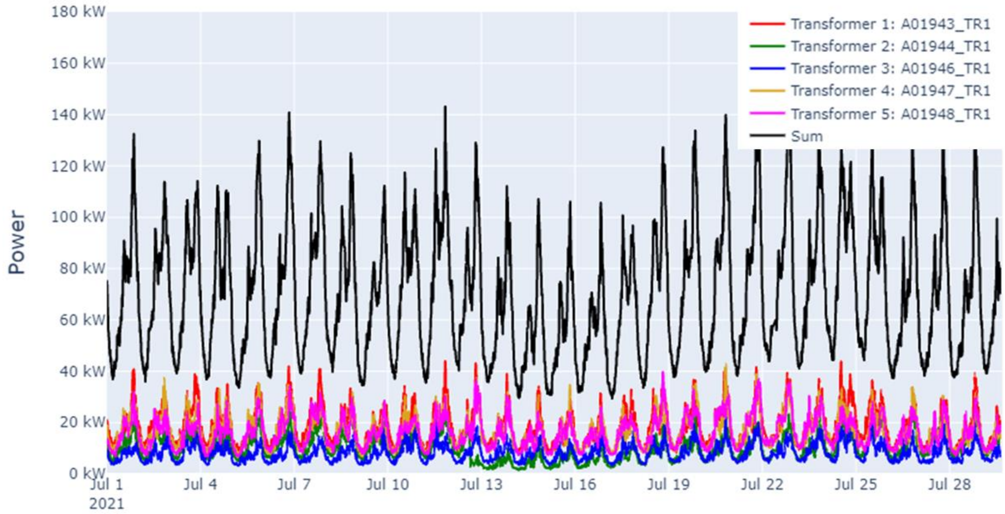

Figure 3-5 – Total power trend, July 2021

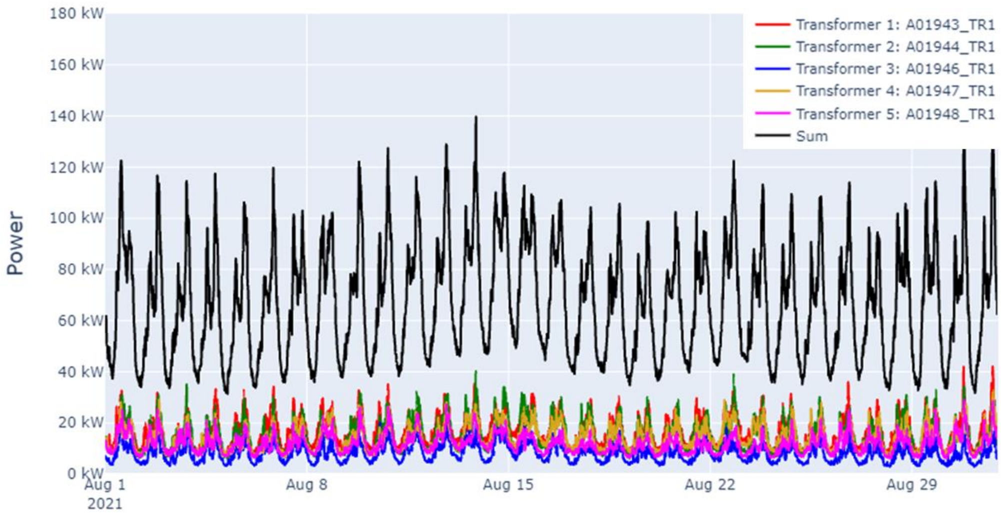

Figure 3-6 – Total power trend, August 2021

From these power consumption trends, it’s possible to make some remarks.

The maximum power demand is quite variable, ranging from 100 kW to 170 kW. It is reached every day around dinner time, from 19.00 to 21.00 depending on the day. This is an indication of the fact that the contemporaneity of power consumption is linked to cooking appliances. This aspect will be pointed out in the section about smart plugs measurements analysis.

Another aspect that can be observed is that the trend of the minimum power raises from May to July, as it can be seen in Figure 3-7. The red circle points out this trend.

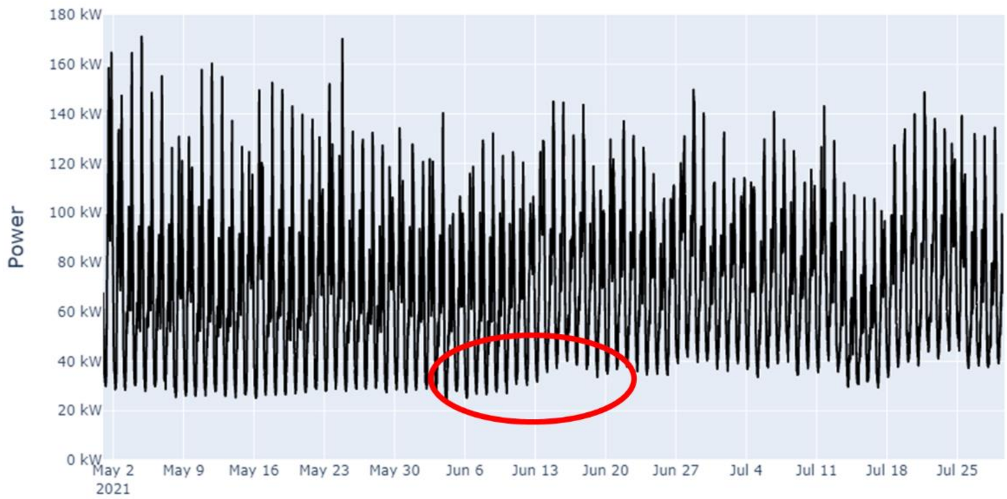

Figure 3-7 – Total power trend – May, June and July

An obvious link to the increase of power consumption can be found in the temperature increase, typical of summer months. In particular, the correlation can be seen considering the perceived temperature by humans, as a combination of temperature and humidity (heat index).

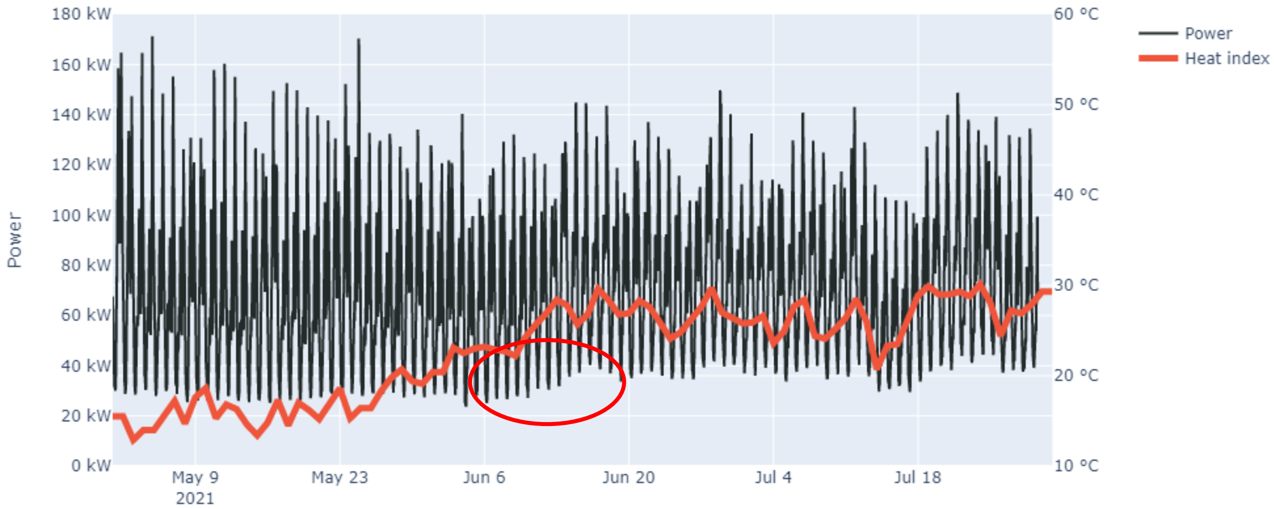

Figure 3-8 – Heat Index and Total power trend – May, June and July

The red line in Figure 3-8 shows the trend of apparent temperature perceived by people living in Milan during months from May to July.

Combining the information of power and heat index, it's possible to notice that when the heat index raises over a value of 25°C, the minimum power consumption in Merezzate district raises. In particular, the minimum power demand was equal to 23,7 kW on the 4th of June. The temperature and humidity increase of the following days brought an increase in minimum power up to 40,2 kW on the 16th of June. The increase is equal to 70% with respect to the value of 4th of June. This could be linked to a raise in HVAC usage during the night.

In the next section there will be some insights about this power increase trend from the point of view of active energy analysis.

3.3 Energy demand

Active energy is measured with Chain2Gates every 15 minutes for each apartment. From the sum of all apartments' active energy, it's possible to obtain the following graphs. On the x-axis there is the number of quarter-hours, while on the y-axis there are represented the values of average active energy for the respective quarter-hour.

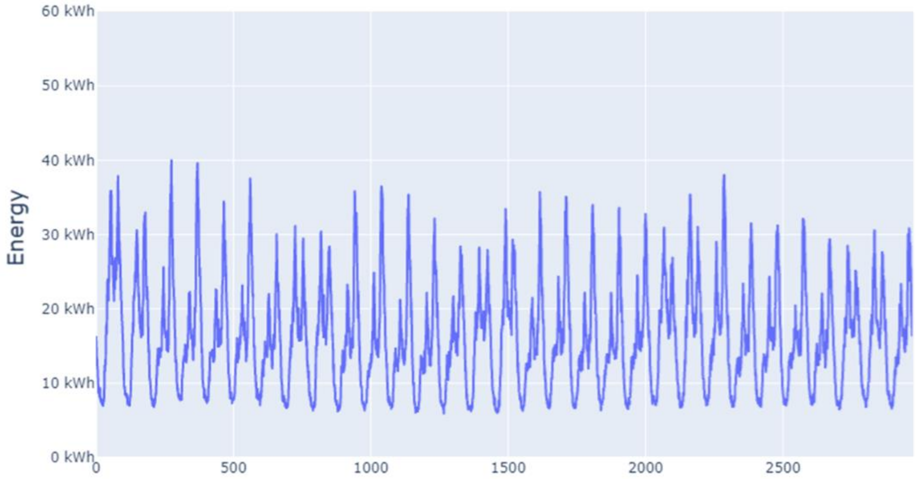

Figure 3-9 – Energy consumption - May

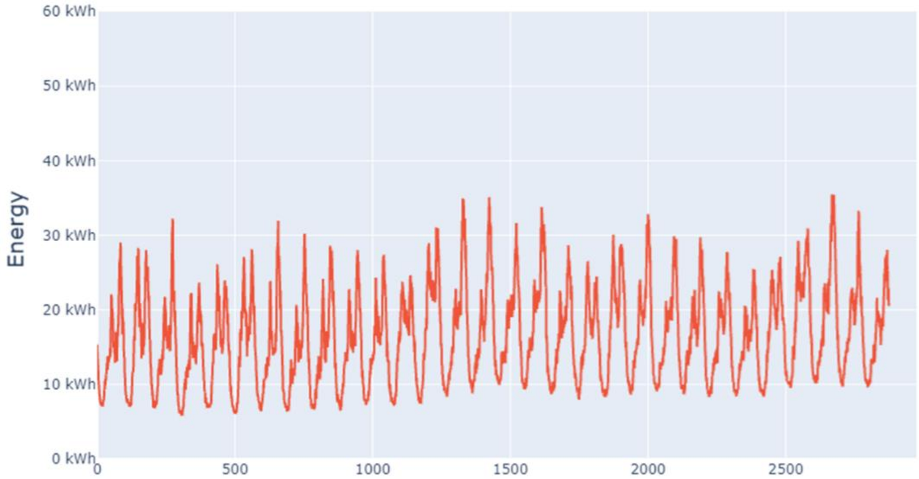

Figure 3-10 – Energy consumption – June

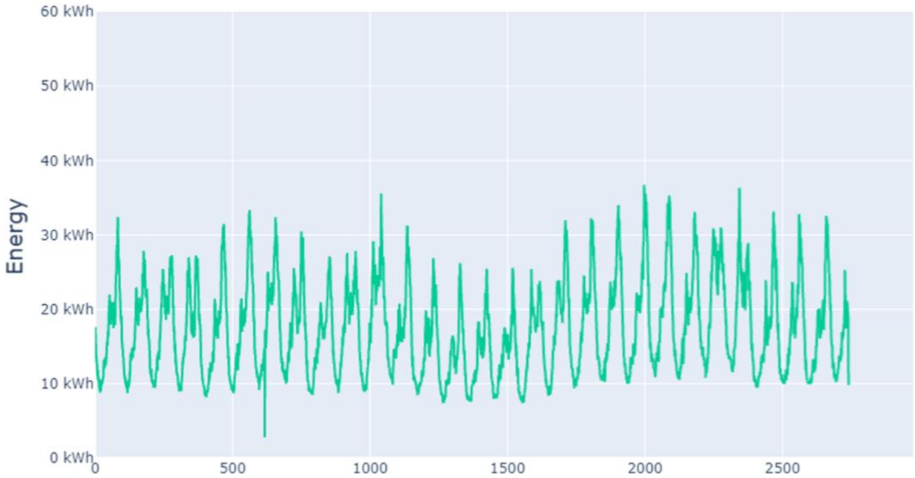

Figure 3-11 – Energy consumption – July

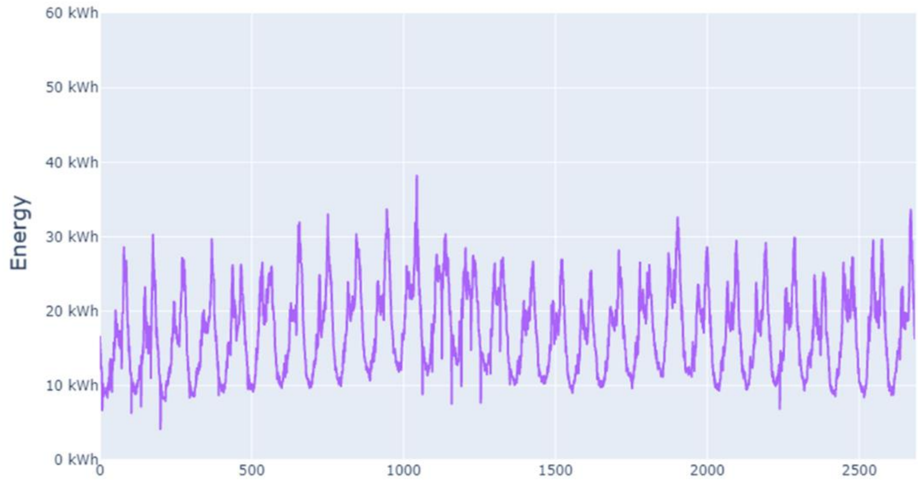

Figure 3-12 – Energy consumption – August

It is quite trivial to find some additional information by just looking at these graphs separately, so in the following plot it is represented a comparison of the different energy consumption trends. As an additional point, the plots have been shifted to match weekdays and weekends of different months so that they are comparable.

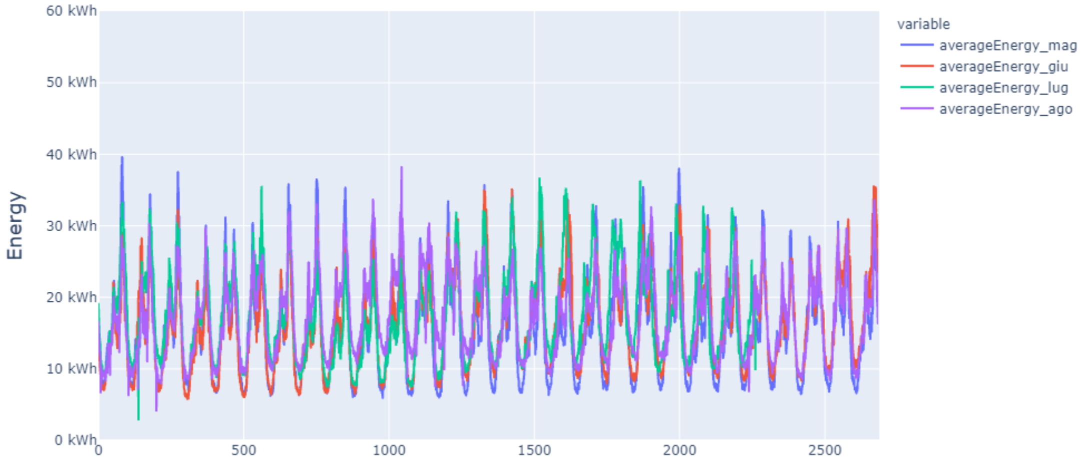

Figure 3-13 – Energy consumption trends overlapped

A thing that can be pointed out is that the maximum energy consumption for the whole apartment complex doesn't exceed 40 kWh for all the months taken into examination. An important thing to notice is that the maximum is not the only problem related to the stability of the distribution grid. In fact, as it is explained in the Unareti's 2021 development plan [13], another important factor is the surge of energy consumption in the night-time hours. One of the most recent examples is related to a heat wave that affected Milan from 24th of June to 30th of June 2019. In the 5-day range, the maximum power distributed my Unareti increased by 27%, while the minimum power of the night-time of the same 5-day range increased by

40%. This brought to thermal stresses extended in time, resulting in grid failures and power outages. In the case of this data mining, it can be seen in detail the increase of minimum energy consumption making a close-up of the graph above.

Considering only May and June, respectively in blue and red.

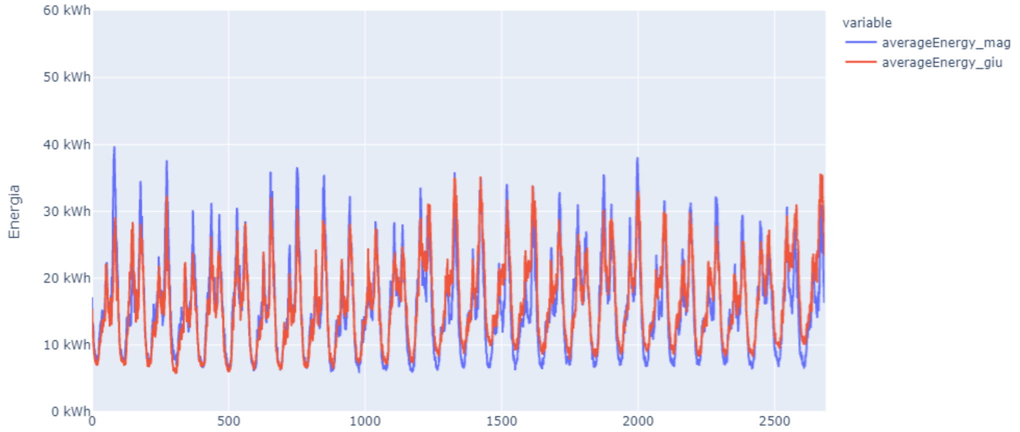

Figure 3-14 – Energy consumption of May and June

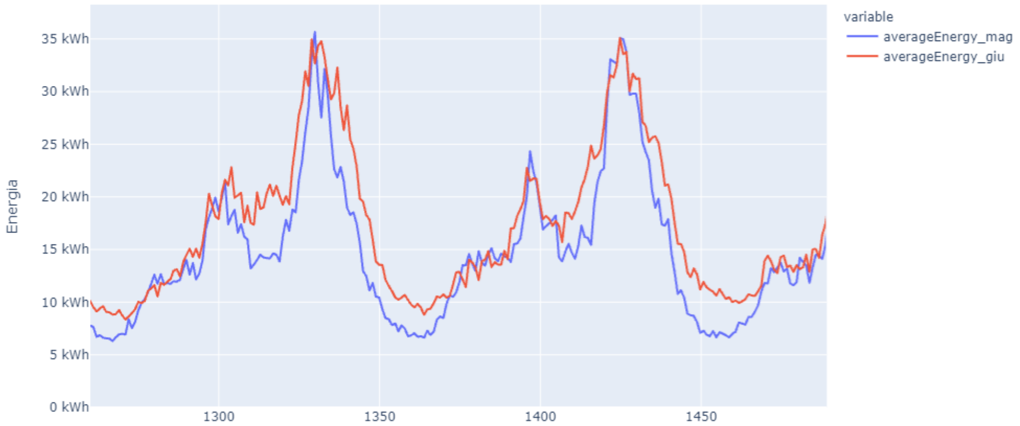

Figure 3-15 – Detail of energy consumption of 13th and 14th of May and June.

As stated in the previous section this increase in energy consumption in the night-time can be linked to the increase in ambient temperature. In particular, after the 12th of June the profile of Merezzate district changes due to the beginning of air-conditioning use.

As a next step it is interesting to understand if the energy usage is increasing or decreasing from May to August. Considering a specific set of days in order to have a good comparison, it has been defined a set of days for each month:

- From the 4th to the 25th of May
- From the 1st to the 22nd of June
- From the 6th to the 27th of July
- From the 3rd to the 24th of August

In this way there is the same number of weekdays (fifteen) and weekends (eight) for all months taken into consideration.

The results are the following:

May	35’748,3 kWh
June	36’324,3 kWh
July	39’331,2 kWh
August	39’023,7 kWh

In each month it has been measured an increase in energy consumption. From the percentages point of view, June increased by 1,6% with respect to May, July increased by 8,2% with respect to June and August decreased just by 300 kWh with respect to July.

As stated before, the minimum energy consumption increases in June and July during the night-hours, but it is interesting to know if this increase concerns also peak daily hours. For this purpose, we can obtain the graph of the mean power consumption of each daily measurement for each month.

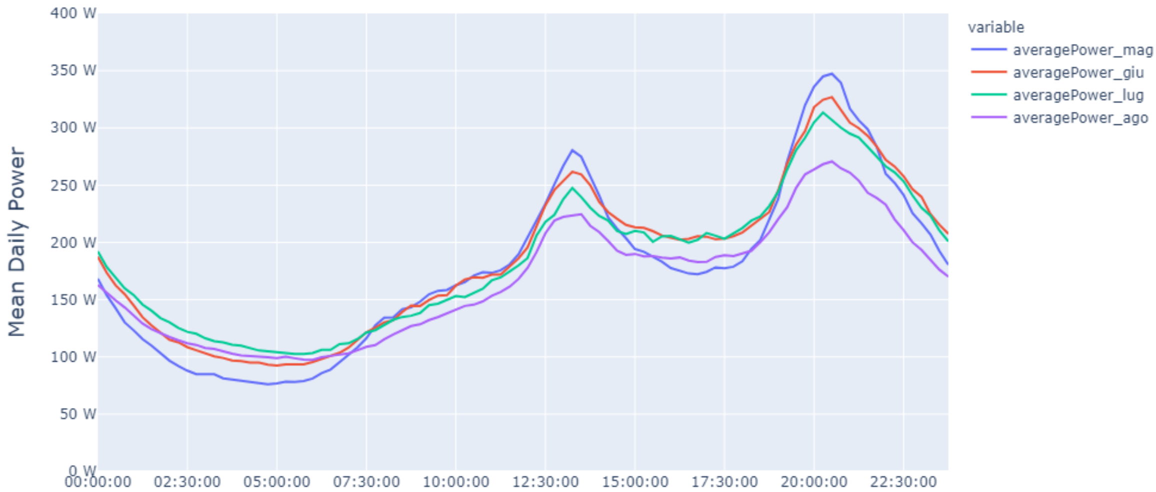

Figure 3-16 – Daily mean power consumption

From the graph above, it can be noticed that peak hour electricity demand was lower for June and July, while during off-peak hours (afternoon and night-time) the mean power increased. This off-peak power increase is the main component that led to an increase in global energy consumption in Merezzate neighborhood.

The purple curve is related to the mean power consumption of all apartments in Merezzate during August and it is clearly showing lower peaks, while during the night it is similar to June and July’s trends. The low peaks can be linked in an important number of people that went on holidays, leaving their dwellings for some days.

3.4 Load curves clustering

This section will focus on post-processing of data retrieved from Chain2Gate meters, with the objective to create clusters of customers. The idea is to split the users into groups based on their trends of electricity consumption. The result of clustering can be exploited into different types of analysis and evaluations, like demand-response and peak shaving mechanisms.

Into this section the separation of users will be based on daily power load curves, as the one represented in Figure 3-17.

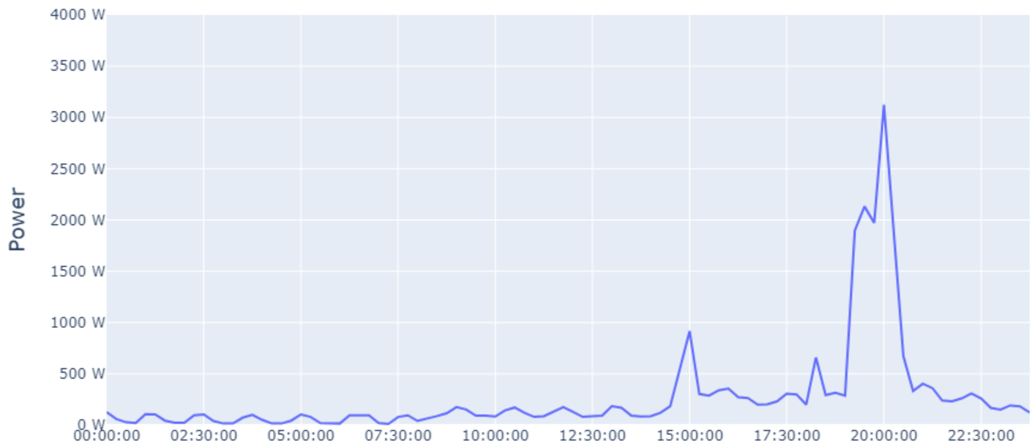

Figure 3-17 – Example of daily load power curve of one customer

The curve is referred to the active power requested by an apartment during the 18^{th} of May As we can see, it had a peak in the range of the 80^{th} quarter of hour, which is referred to about 20 pm, probably because the customer had dinner and cooked something with kitchen appliances.

Obviously, this curve is different for every day and for every apartment, based on the appliances that are in use in a specific period. The curves are influenced by the type of appliance in use and from the resident's habits. For a whole month there would be around 30 curves, one for each day.

In order to “normalize” the curves of every customer, it has been performed the mean of the load profiles, as it can be seen in the two graphs below.

Since it is known that the trend of electricity consumption differs from weekdays and weekends, it has been made a separation. Every user would have two mean load profiles, one for weekdays and one for weekends. In this way it is possible to understand who consumes more during the working days and less during the weekends of vice versa.

Figure 3-18 represents the weekdays daily power curves (with lower opacity) and the red line is the mean value of one single resident.

Figure 3-19 is the same but with respect to weekends.

The apartments that are inhabited are around 400, on a total of 615 apartments since some of the remaining 200 are still to be occupied. For this reason, the clustering method has been done on a total of about 400 curves, with each curve representing the mean power consumption of a single customer.

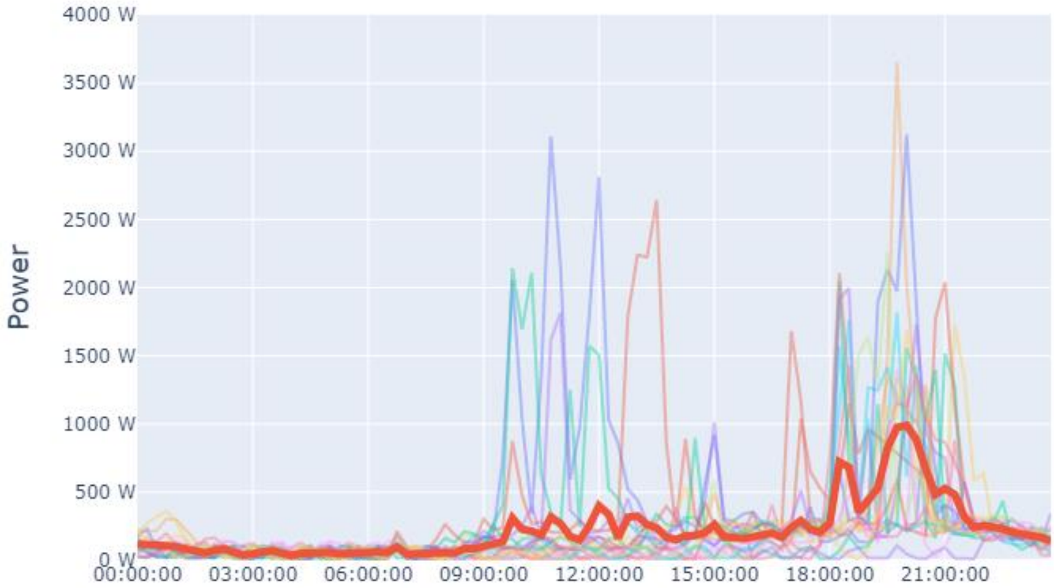

Figure 3-18 – Daily (weekdays) power curves of one customer, May.

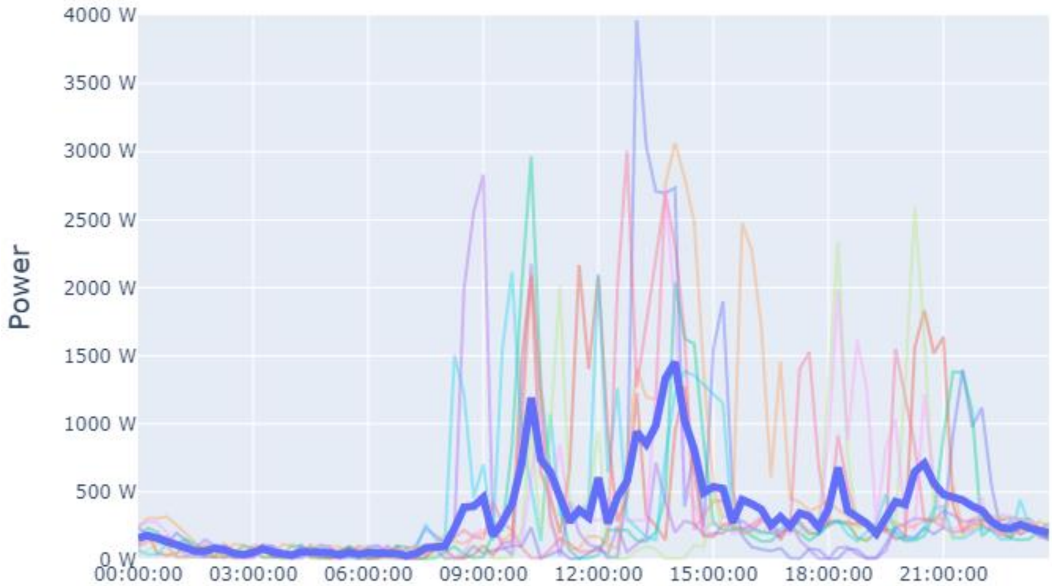

Figure 3-19 – Daily (weekends) power curves of one customer, May.

3.4.1 Clustering

To divide the mean load curves into clusters, it is necessary to define a clustering method. The method employed for this purpose is a k-means method built for time series clustering. This algorithm is present in scikit-learn, an open-source machine learning library for Python programming language.

The parameters that must be decided for the implementation of this clustering method are the number of clusters to be found, the metric used for cluster assignment and barycenter computation and the number of iterations of the k-means algorithm for a single run.

The number of clusters needs to be decided a priori. It has been decided to divide the load curves into three clusters, because the separation into three classes (low, medium and high consumption) looked the more natural and suitable, looking at other analysis performed in literature. This decision has been validated during the hierarchical clustering analysis of Section 3.5 (Energy consumption clustering), which finds the best customers separation into three clusters.

As for the metric it has been chosen a Euclidean metric, in line with what was described in Section 1.4.3.4 Time-series k-means clustering.

The number of iterations for a single run was set to 50, since k-means algorithm needs a lot of iteration to find the best solution.

The result of clustering of customers for the month of May is the following. Talking about weekdays' curves clustering, on a total of 389 mean load curves, 167 were clustered in one cluster, 155 into the second cluster and 67 into the third cluster.

A visual representation of this division in groups can be seen below, where there are drawn the mean curves of the 3 clusters.

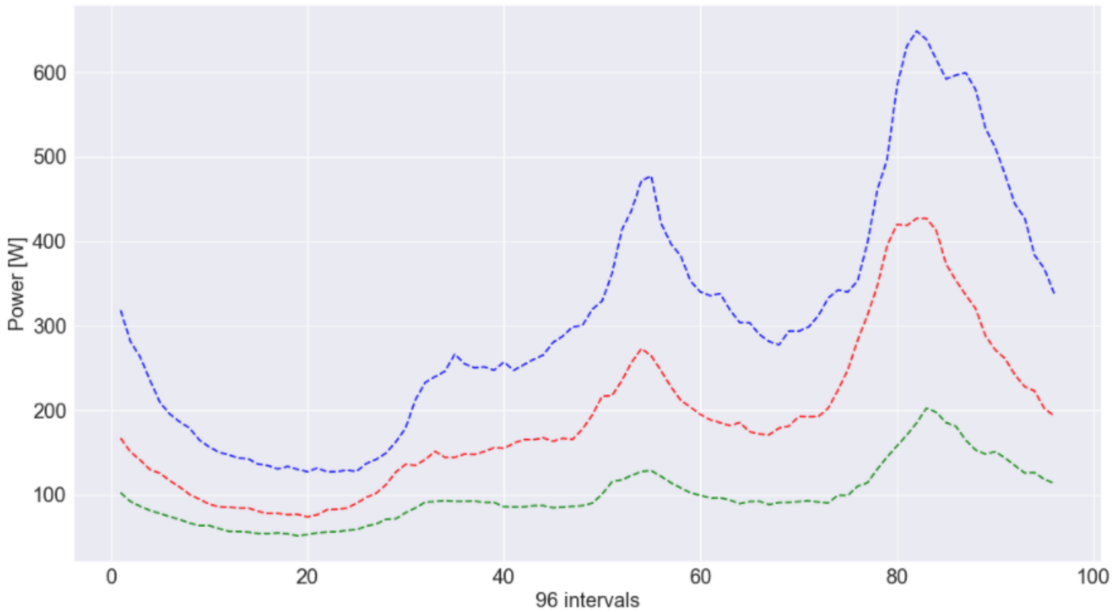

Figure 3-20– Mean curves of the three clusters (weekdays), May

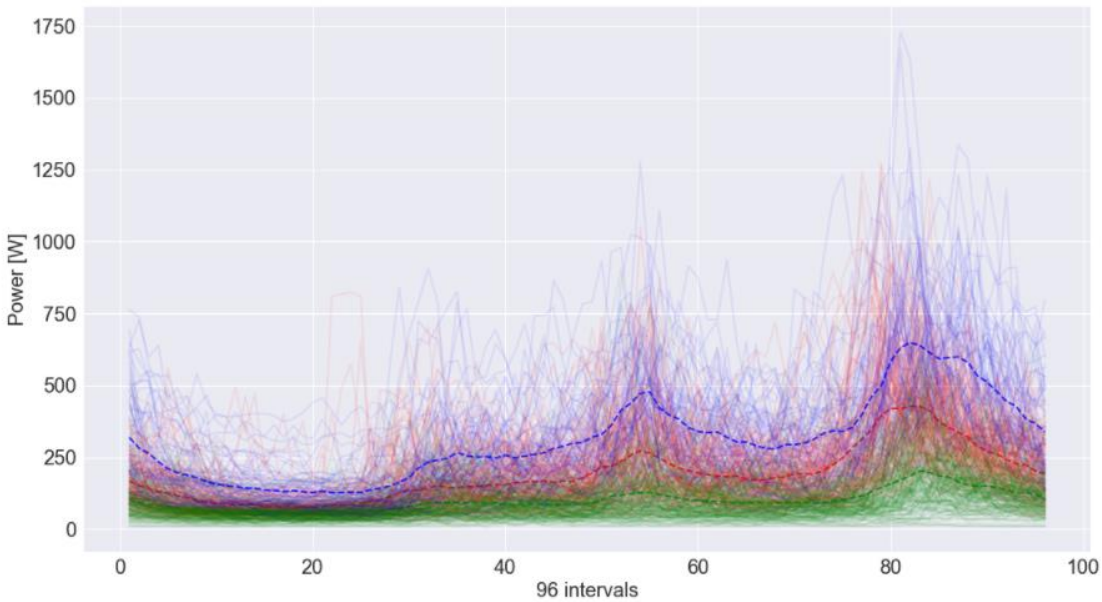

Figure 3-21- Mean curves of the three clusters and mean power curves of daily (weekdays) power curves of all customers, May.

It is possible to see that the clustering algorithm divided all the curves into three groups, that can be called as "low", "medium" and "high" consumption.

From Figure 3-20 it can be noticed a distinct color difference in the mean load curves, based on the group they belong to, which justifies for this classification.

As stated above, clustering has been made making the differentiation between weekdays and weekends. The result of weekends clustering referred to the month of May is the following.

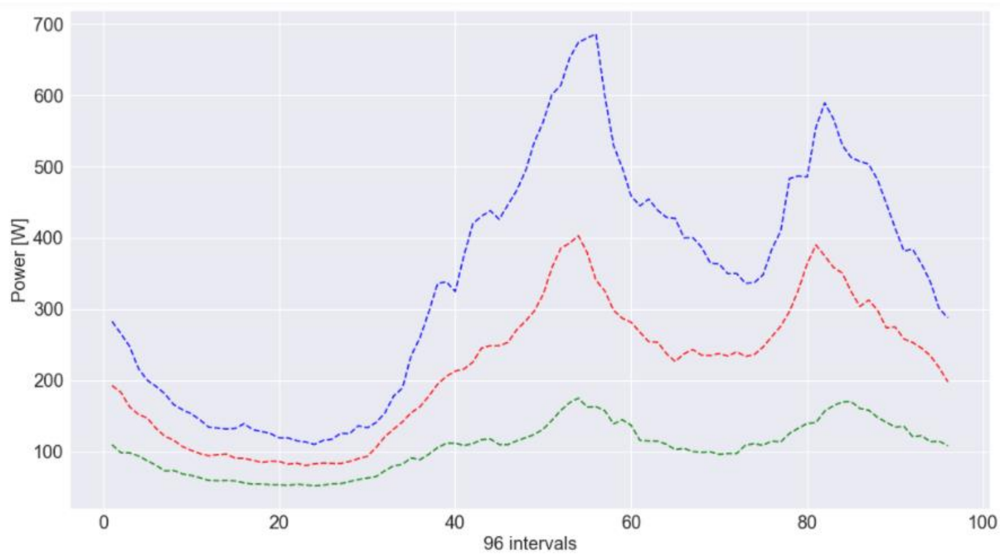

Figure 3-22– Mean curves of the three clusters (weekends), May

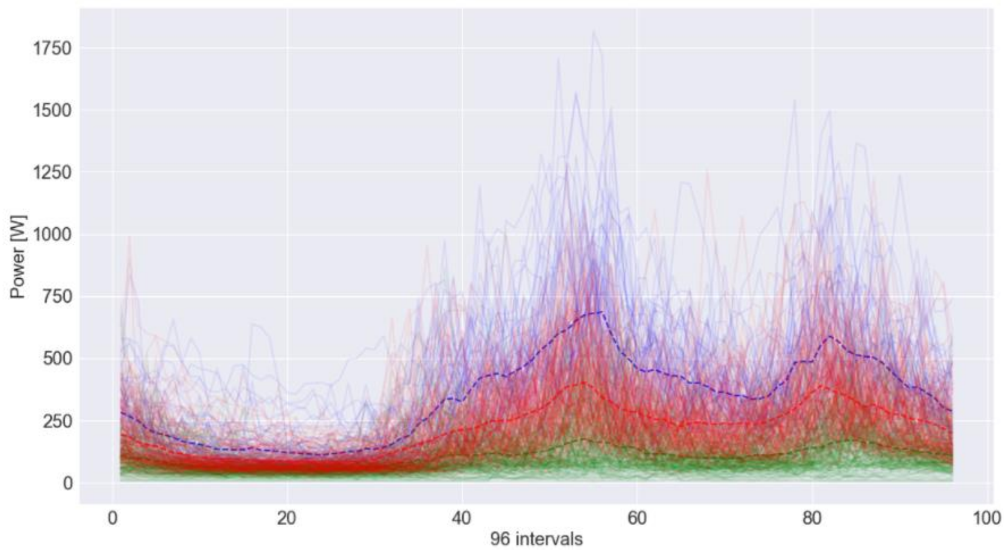

Figure 3-23- Mean curves of the three clusters and mean power curves of daily (weekends) power curves of all customers, May.

It is possible to notice a distinct difference in mean power consumption, by looking at Figure 3-20 and Figure 3-22. During both workdays and weekends, the typical power demand presents two peaks, one around lunch time and one around dinner time. However, the magnitude of power demand is different. Weekdays typically present a larger peak in the late afternoon, mostly because people tend to work during daytime. Weekends have a power demand where the two peaks have about the same magnitude, due to the presence of the tenants who tend to use home appliances earlier. The different lifestyle of each resident influences and considerably affects the electricity demand pattern [25]. This difference in power consumption trends justifies the separation between weekdays and weekends to notice the different tendencies of every customer.

The clustering of the data has been performed for the months during which electricity consumption was monitored with Chain2Gates. The graphical results of clustering for June, July and August are represented in the Annex, both for weekdays and weekends.

It's interesting to focus on the numbers of the clustering division. The total number of users for each clustering differs because of a pre-processing of the data. For instance, users that presented a mean power consumption curve with all the values lower than 30 W have been removed from this clustering, because they wouldn't be important for this analysis. The result is a dataset that varies, from 389 residents for May to 436 residents for August.

So, the numbers of people divided into the three clusters, low, medium, and high, for the four months of the analysis can be seen from a percentages point of view.

Table 3-1 – Percentages of division of mean power curves into clusters (workdays)

Clusters	**May**	**June**	**July**	**August**
Low	42,9%	48,7%	56,3%	61,7%
Medium	39,9%	36,4%	33%	27,5%
High	17,2%	14,9%	10,7%	10,8%
Total	100%	100%	100%	100%

It's possible to notice that the percentages of customers divided in clusters change with the months; in particular, going from May to July, a higher percentage of apartments are clustered into the "low" power consumption cluster, while the percentage of "medium" and "high" cluster decreases. This could be linked to the change in habits of people typical of summer months where it's usual to leave the habitation to go on holiday. In this way the electricity consumption decreases a lot because the only appliance that could be operating would be the fridge that has a low energy demand, almost constant in time. This observation can be done in the exact same way for clustering of weekends.

3.4.2 Clustering analysis vs Apartment type

Another information that has been added to this clustering analysis is the type of apartment that are present in Merezzate district. There are four types of dwelling indeed: one-room, two-room, three-room and four-room apartments.

Adding this information to the previous clusters found, it's possible to obtain a table of the three clusters (low, medium, high) versus the apartment type. The table below represents this classification for the clustering of workdays in the month of May for a total of 389 apartments.

Table 3-2 – Cluster vs apartment type classification, workdays, May

	One-room	Two-room	Three-room	Four-room
Low	11	111	40	5
Medium	2	42	98	13
High	2	12	42	11
Total	15	165	180	29

As for the previous case, the table above can be better understood from the percentages point of view, computing the percentages with respect to the total apartments number of each typology.

Table 3-3 – Cluster vs apartment type classification – percentages, workdays, May

	One-room	Two-room	Three-room	Four-room
Low	73%	67%	22%	17%
Medium	13%	25%	54%	45%
High	13%	7%	23%	38%

Highlighting with colors like in a density map, it becomes easy to notice a peculiar trend. Looking at the "low" cluster, we can notice a decreasing trend going from one-room to four-room apartment. Most of the one-room and two room apartments have been clustered in the "low" group, while just about 20% of three-room and four-room apartments have been grouped as "low" power demand. On the contrary, most of three-room and four-room apartments have been grouped as "medium" and "high" power consumers.

The same trend can be seen in the case of June and July.

Table 3-4 - Cluster vs apartment type classification – percentages, workdays, June

	One-room	Two-room	Three-room	Four-room
Low	80%	69%	33%	17%
Medium	7%	26%	46%	50%
High	13%	5%	21%	33%

Table 3-5 - Cluster vs apartment type classification – percentages, workdays, July

	One-room	Two-room	Three-room	Four-room
Low	77%	76%	41%	36%
Medium	23%	20%	43%	46%
High	0%	4%	16%	18%

For both June and July, the percentages decrease going from one-room to four room in the case of "low" cluster, while the percentages increase for both "medium" and "high" cluster going from one to four room apartment.

A thing that could be noticed by looking at the differences between May, June and July is the increase of the percentage of three-room and four-room apartments that are grouped in the "low" cluster. This is linked to the same observation made for Table 3-1.

It's important to notice that these trends have been found a posteriori of the clustering of mean power load curves, without using the information of the type of the apartment as an additional input in the clustering method.

3.5 Energy consumption clustering

The previous section focused on clustering of residential customers' power load curves, with a differentiation between workdays and weekends, to notice the different trend of power consumption in terms of magnitude. This type of analysis keeps into consideration the difference in habits between workdays and weekends, so that one residential customer could be grouped in a "low" cluster for workdays and in a "high" cluster for weekends.

This section is made to have a clustering of Merezzate neighborhood based on the energy consumed by each apartment during a defined month. Also, in the following analysis the information about apartment typology will be added to the clustering algorithm.

3.5.1 Monthly energy consumption

As said in a previous chapter, Chain2Gate retrieves data of mean active energy consumption every quarter-hour for each apartment, measured in Wh.

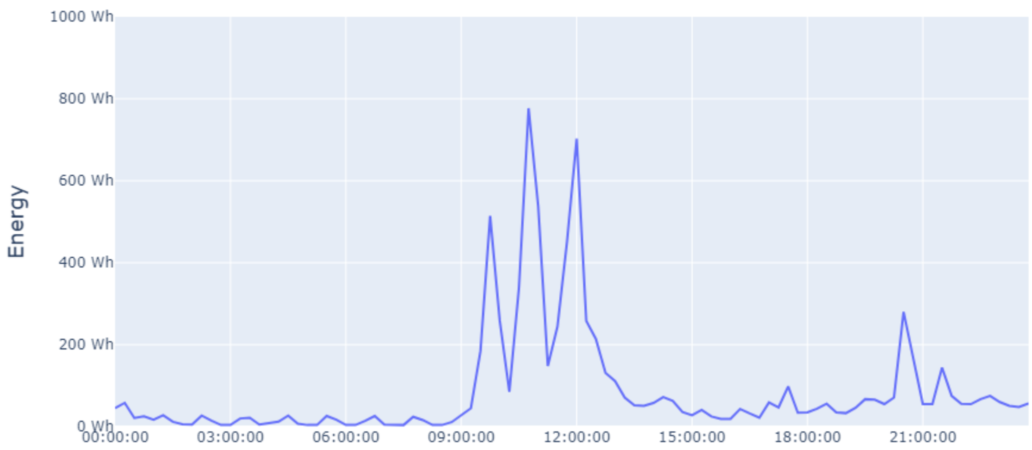

Figure 3-24 – Energy load curve of a single day for a user, example

The sum of active energy measured in the 96 intervals is equal to the active energy of the day. Summing the total energy for all the days of a month gives us the value of energy consumed by an apartment, measured in kWh.

In addition, for every user we will add the information of the apartment type. Like for the case of power curves clustering analysis, in Merezzate there are one, two, three or four-room apartments. The typology of apartment is inserted into the dataset for clustering via a ratio of monthly energy consumption over the apartment size. For instance, if one inhabitant of Merezzate consumed 120 kWh of energy for the month of May and his apartment size was 72 m^2, the ratio of energy consumed per square meter would be 1,66 kWh/m². The addition of this ratio is interesting in the visual representation of the clustering results.

The dataframe for clustering has the following appearance. For each device ID-code, there is the respective energy consumption of the analyzed month and its energy consumption over apartment size ratio.

deviceId	Energia_tot	kWh/m2
240ac41e6ffd	193.9065	2.693146
240ac41e700d	189.7265	4.412244
240ac41e7051	93.6180	2.177163
240ac41e7da5	137.7135	1.912688
240ac41fdd7d	187.0055	2.597299
...	...	...
840d8ee26509	167.5890	2.327625
840d8ee26515	252.0010	2.896563
840d8ee31675	265.3110	3.684875
c44f331cc91e	113.3455	2.635942
c44f331cc93a	119.8200	2.786512

Figure 3-25– Dataframe for clustering

3.5.2 Clustering and user behavior impact

The clustering method chosen for this section is hierarchical clustering. This method is different from k-means clustering method because it doesn't depend on the number of clusters that must be specified at the beginning of the assignment. Instead, hierarchical clustering needs the specification of a measure of dissimilarity between the groups. The result is a hierarchical representation of the dataset where every level of the hierarchy is created by merging clusters at the nearest lower level.

The method can be visually represented by the typical dendrogram, where all the data are linked in clusters, from the lowest level where the number of clusters is equal to the number of single data, to the higher level where all data are grouped in a single cluster.

The measure of dissimilarity in this data analysis is "ward linkage", which minimizes the variance of the cluster that must be merged from a lower level to a higher level.

Hierarchical clustering method is implemented in the scikit-learn library for Python, the same that was used for power load clustering.

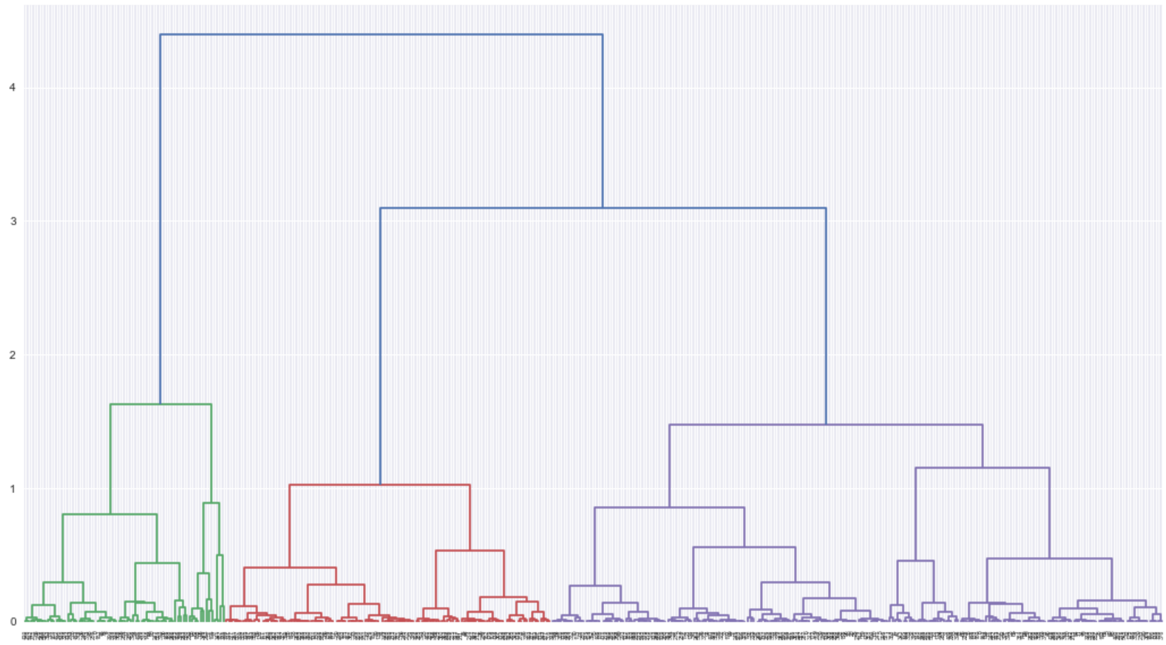

Figure 3-26– Dendrogram for hierarchical clustering with ward linkage

Above is represented the dendrogram of the dataset of May. By making a straight horizontal line it becomes possible to find the number of clusters that are wanted to be found. As a similarity with the previous clustering of power load curves, the number of clusters is set equal to three.

The results of hierarchical clustering of data of May show that 115 users have been clustered as "low" energy consumption, 216 as "medium" and 71 as "high". This classification is easily understandable by looking at the plot of monthly energy consumption in ascending order for all the apartments in Merezzate, represented with the respective color of the cluster they belong. On the x-axis there is the number of apartments. The centroid of the three clusters can be obtained by summing the active energy of every apartment that belongs to the same cluster and dividing the total by the number of apartments in that same cluster. In this way it's possible to obtain the three mean values of each cluster: "low"=54,87 kWh, "medium"=126,92 kWh, "high"=226,53 kWh.

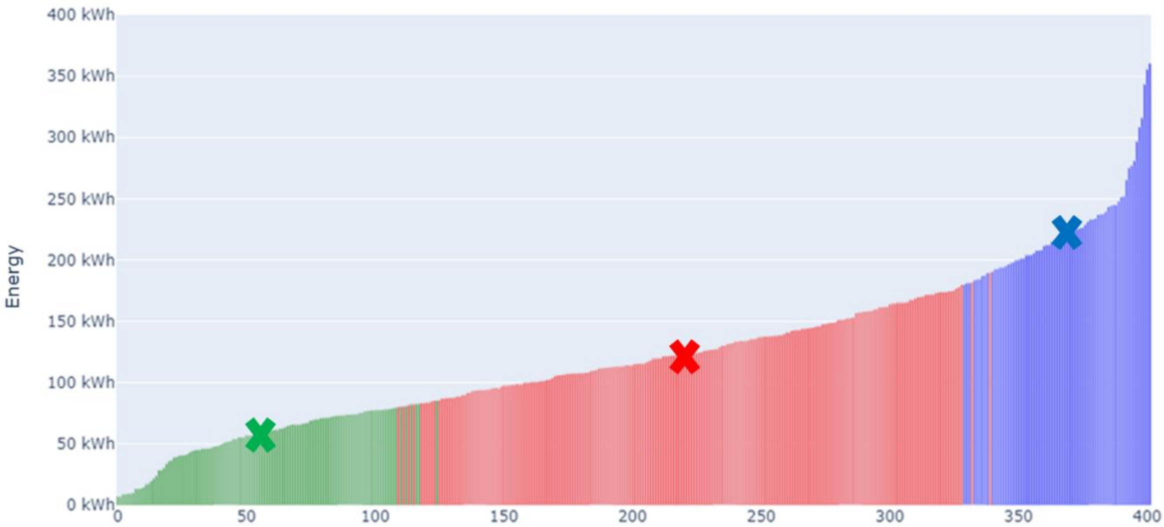

Figure 3-27– Clustering results (May), Monthly energy consumption

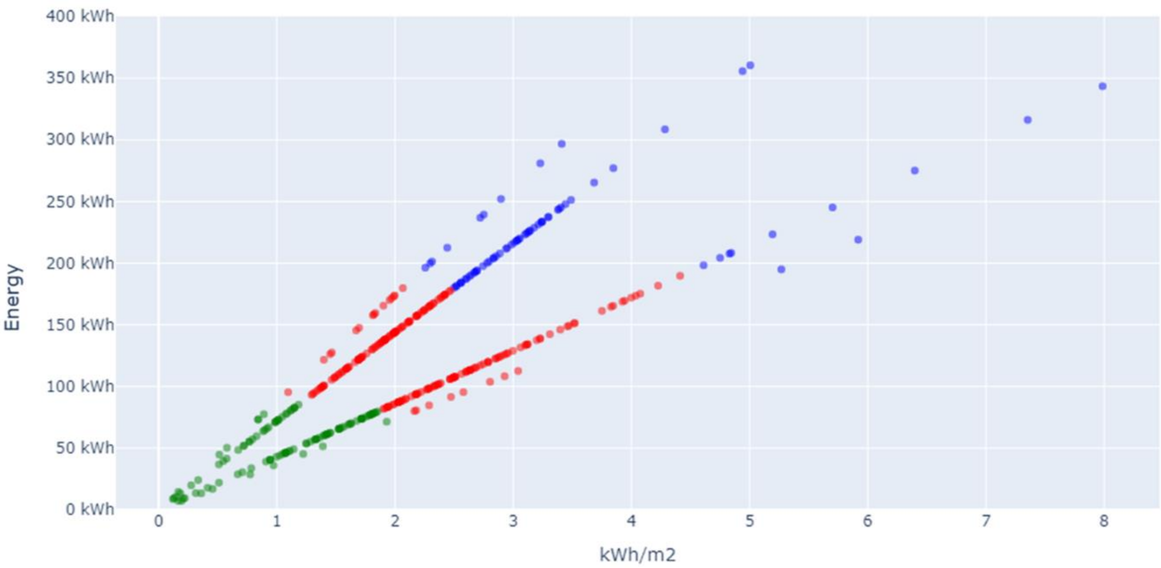

Figure 3-28 – Clustering results (May), Monthly energy vs energy consumption per square meter

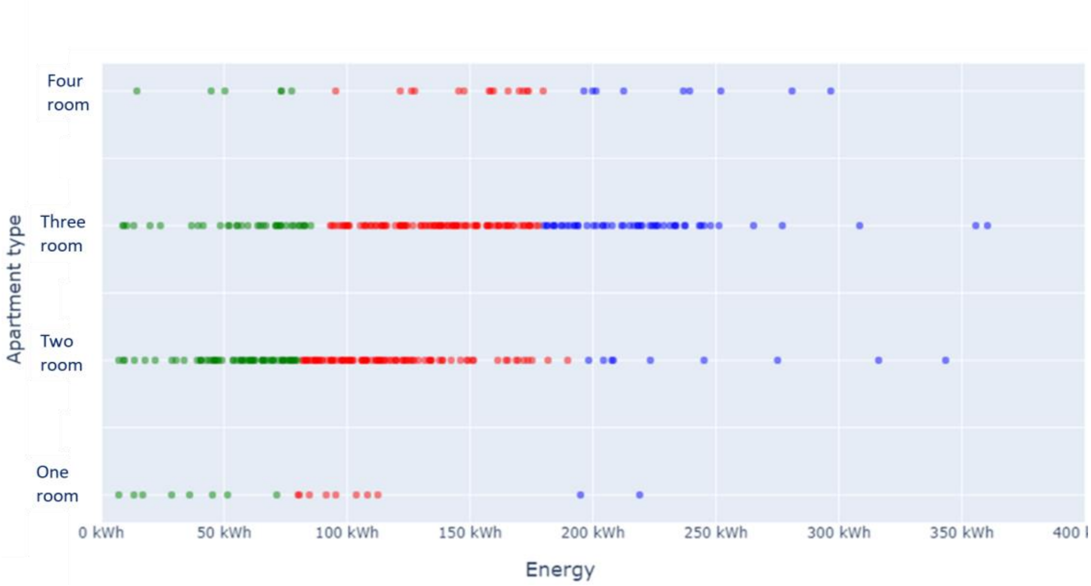

Figure 3-29– Clustering results (May), Monthly energy vs apartment type

From Figure 3-28 and Figure 3-29 we can see how clustering separated the apartments considering the information on the typology of apartment.

We can obtain a table of the users clustered by apartment typology like for the case of power load curves.

Table 3-6 – Cluster vs apartment type classification, May

	One-room	Two-room	Three-room	Four-room
Low	8	66	35	6
Medium	8	95	98	15
High	2	9	51	9
Total	18	170	184	30

And transforming it into percentages points:

Table 3-7 – Cluster vs apartment type classification – percentages, May

	One-room	Two-room	Three-room	Four-room
Low	44,44%	38,82%	19,02%	20,00%
Medium	44,44%	55,88%	53,26%	50,00%
High	11,11%	5,29%	27,72%	30,00%

The results of these clusters are not very different from the one of workdays of the analysis based on power load curves. There is always a decreasing trend for the "low" cluster, and an increase in the percentages for the "high" cluster. Talking about the "medium" cluster, it keeps almost constant, with about 50% of the apartments that are clustered in this group, for all the apartment types.

Clustering of data from June is different from the month of May for the following reason. By clustering into three groups like as before, the result is depicted by the image below.

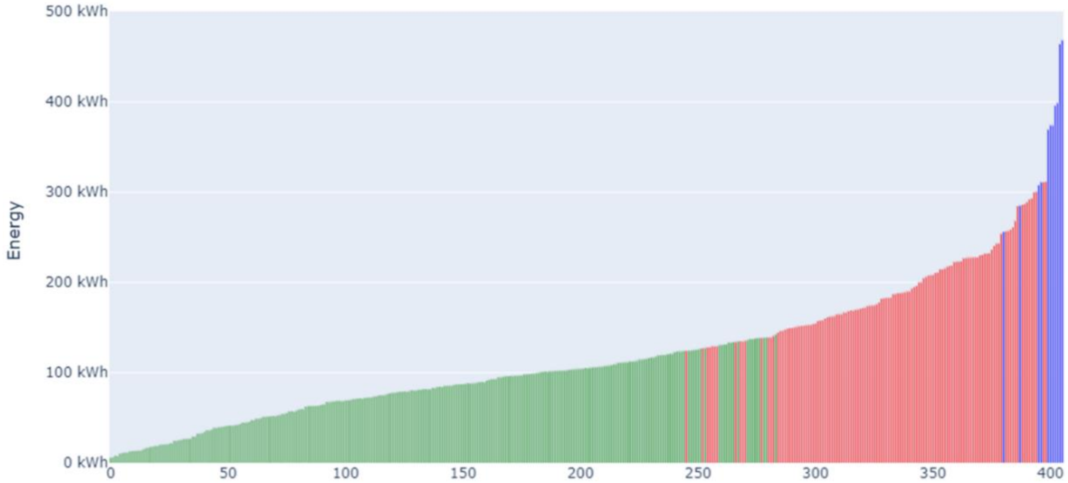

Figure 3-30– Clustering results (June), Monthly energy consumption

There are only 11 users that are clustered into the "high" energy consumption cluster simply because they consumed a lot more than the other inhabitants of Merezzate. This suggests that clustering for the month of June can be done by finding four clusters instead of three, by threating this "high" cluster as a sort of an outlier.

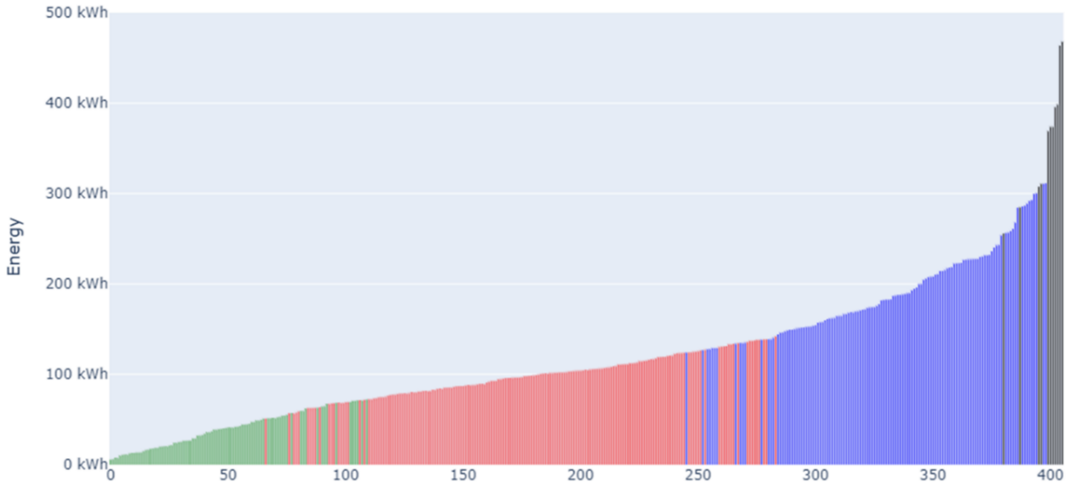

Figure 3-31 – Clustering results (June), Monthly energy consumption, 4 clusters

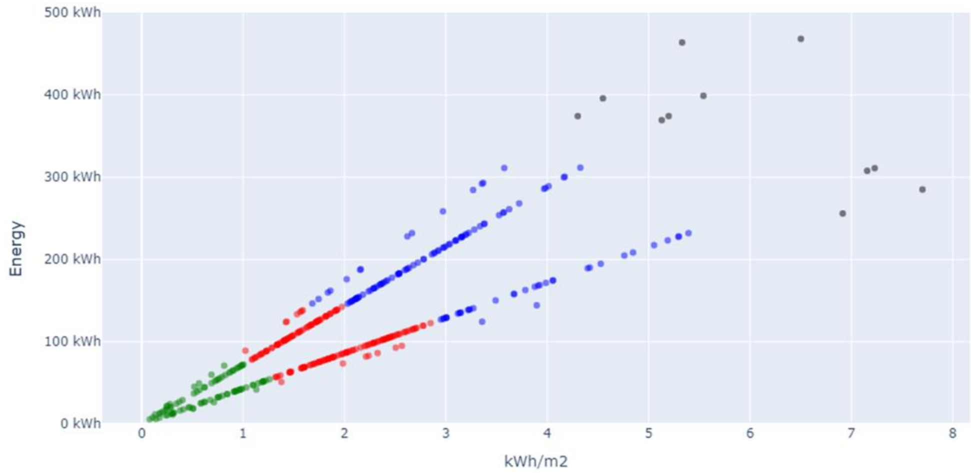

Figure 3-32– Clustering results (June), Monthly energy vs energy consumption per square meter

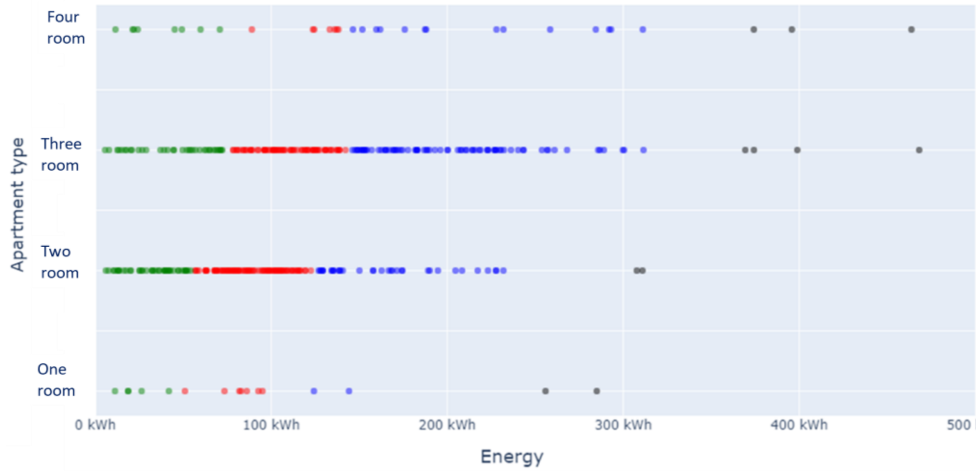

Figure 3-33– Clustering results (June), Monthly energy vs apartment type

Separation of user's electricity consumption in four clusters for June can be seen from percentages point of view like May, with the same considerations.

Table 3-8 – Cluster vs apartment type classification – percentages, June

	One-room	Two-room	Three-room	Four-room
Low	31,25%	24,42%	18,82%	18,75%
Medium	43,75%	54,65%	38,17%	28,13%
High	12,50%	19,77%	40,86%	43,75%
Very high	12,50%	1,16%	2,15%	9,38%

The analysis on clustering of data related to June, suggests that the number of clusters can be different than three, with the purpose of making different evaluations.

In the analysis of curve power load clustering, the information about type of apartment was added after clustering. For clustering of monthly energy consumption, the info of the apartment type has been used combined with the energy values. Now the next step is making the previous separation of Merezzate apartments based on the type of apartment before clustering. In this way one-room apartments will be clustered into three groups (low, medium, high). Then two-room apartments will be clustered and so on. In total, this reasoning leads to a total of 12 separated groups that can all be labeled as "low", "medium" or "high" energy consumption, bringing the clusters number back to three.

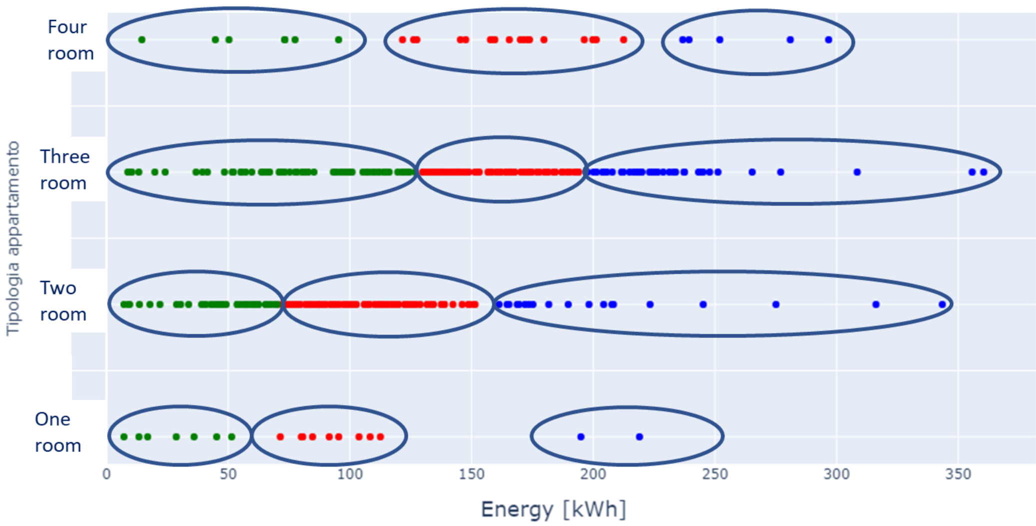

Figure 3-34– Clustering results based on apartment type, May

The separation into 12 clusters is easily seen from Figure 3-34, where each cluster is circled in blue, while the three "classic" clusters are indicated by the colored dots.

It's possible to notice the consequence of this analysis by having a comparison of the graph of monthly energy consumption in ascending order.

We can see that values in Figure 3-35 are more heterogeneous with respect to Figure 3-36. This is linked to the fact that by dividing the users beforehand by the typology of their apartment, the hierarchical clustering method have been implemented four separated different times, one for each apartment type. The result is a case where it becomes possible to define if a particular user consumed energy in a "good" way, in line with similar users, or in a "bad" way, by consuming more electricity with respect to the whole apartments in the neighborhood.

For instance, users that live in a two-room apartment that have been clustered in the "medium" group and have consumed less than 100 kWh are actually "low" energy consumption users, by the global clustering results. However, the two-room apartment users that consumed more than 150 kWh are asking too much energy when comparing them with the other two-room apartment users, so they should lower their energy use.

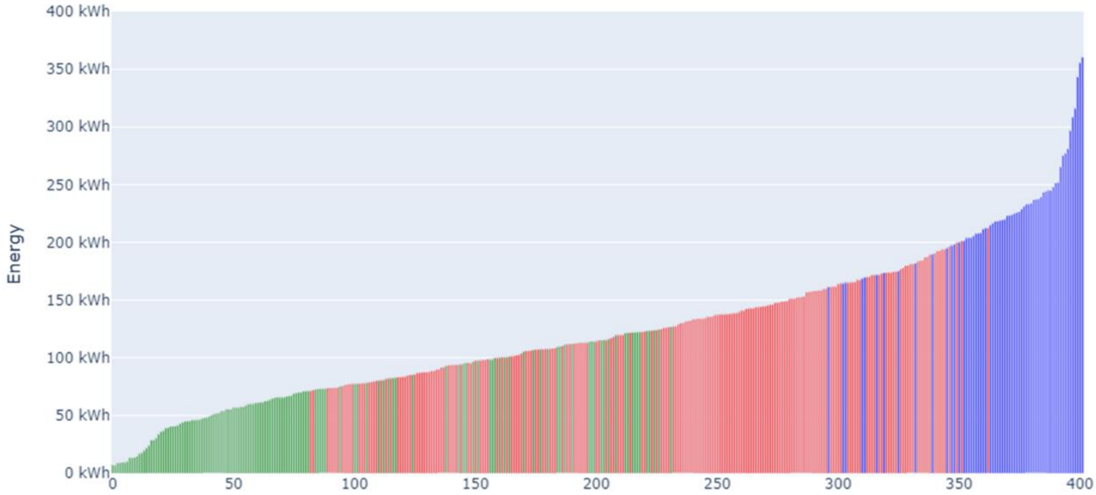

Figure 3-35– Clustering results by apartment type (May), Monthly energy consumption

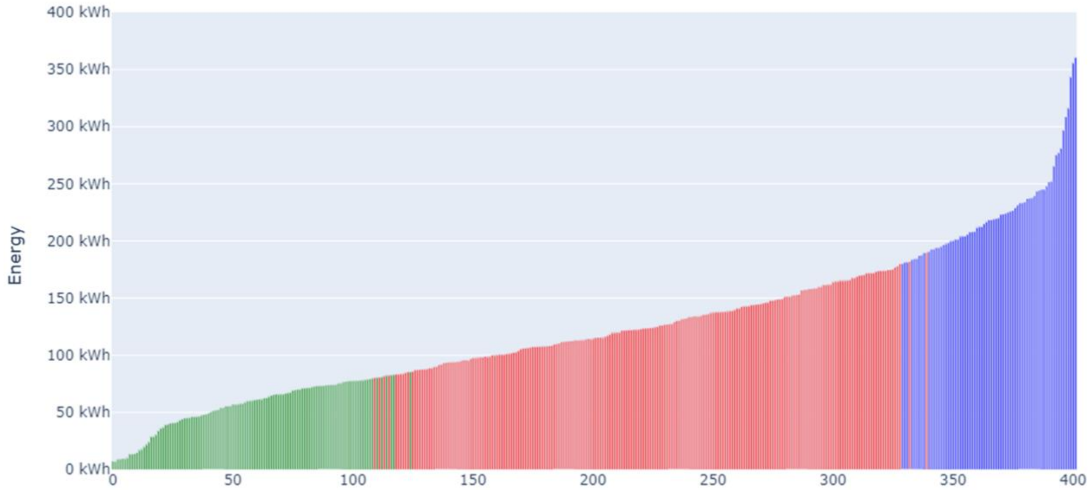

Figure 3-36– Clustering results (May), Monthly energy consumption

After performing the clustering on data related to all the months in exam, it becomes possible to notice who has been clustered always into the same category, or who moved from one cluster to another, based on their monthly energy consumption.

By combining data from May, June, July and August into a single dataframe with the information of the clusters for each apartment, it's easy to filter users. Now the goal is to find the apartments that have always been clustered into the "low" group, for May, June, July and August.

Table 3-9 – Number of residents clustered in the same group from May to August

	Cluster			
May	Low	Low	Low	Low
June		Low	Low	Low
July			Low	Low
August				Low
	111	56	52	46
	100%	50%	46%	42%

	Cluster			
May	Medium	Medium	Medium	Medium
June		Medium	Medium	Medium
July			Medium	Medium
August				Medium
	209	113	95	66
	100%	54%	46%	32%

	Cluster			
May	High	High	High	High
June		High & very high	High & very high	High & very high
July			High	High
August				High
	71	59	22	16
	100%	83%	31%	23%

The number of apartments on the fourth column of these tables are the apartments that never changed their habits of electricity consumption, being grouped always as the same type. For "low" and "medium" clusters, about the 42% and 32% of the users that were clustered into that group of May kept the same group in June, July and August. It's obvious that the remaining 58% consists of users that changed their energy consumption and have moved of cluster. In the same way, 23% of residents that were grouped in the "high" cluster of May, were still grouped in the "high" group. It's interesting to notice that the cluster changing rate has a different trend for each cluster. For instance, the decrease of "low" customers in less steep that "high" customers since "low" group goes from 100% to 42% from May to August, while "high" group drops from 100% to 23% in the same four months period.

We can use these "true" consumers to obtain the mean energy consumption values of the different months divided by cluster.

Table 3-10 – Mean energy consumption for "true" residents

	Low	**Medium**	**High**
May	46,6 kWh	118,4 kWh	234 kWh
June	38 kWh	104,3 kWh	265 kWh
July	40,6 kWh	105 kWh	315 kWh
August	42,4 kWh	112,8 kWh	335,1 kWh
Mean energy consumption	41,9 kWh	110,1 kWh	287,3 kWh

3.6 Smart plugs analysis

Smart plugs are tools used to control electricity consumption of home appliances installed in Merezzate district. After a first survey, 18 residents have accepted to install from one to five smart plugs in their dwelling. The second survey brought the total apartment number with installed smart plugs to 65 of the total 615 apartments of the whole neighborhood.

Smart plugs monitor incremental active energy, instantaneous power demand, current, voltage, inputs and outputs. Measure of these quantities are carried out every fifteen minutes.

In this study smart plugs have been implemented as an efficient way to follow the consumes of home appliances to have another valuable information when combining them with the global apartment consumption. In this section there will be analyzed data from June, July and August.

The following sub-sections treat different aspects of smart plugs analysis. First, it will be shown the mean energy consumption per each appliance typology followed with smart plugs in Merezzate. The next point will focus on how appliances have been used during the day in a 24-hours span, with some details on demand-response mechanism. As a last sub-section, it will be presented how information of Chain2Gate (power metering) and smart plugs (appliance metering) can be combined to educate the resident on his electric consumptions and for an overall better user experience

3.6.1 Mean energy consumption per appliance

As a first step, it was interesting to find what appliance was the most energy demanding. This has been performed by analyzing the monthly active energy demand of each smart plug, dividing them by type of appliance performing a weighted mean between all the same appliances.

In the following table it can be seen the number of appliances followed by smart plugs installed in Merezzate, with the respective mean energy consumption.

Table 3-11 – Mean energy consumption per home appliance

	June		**July**		**August**	
	n°	Energy [kWh/month]	n°	Energy [kWh/month]	n°	Energy [kWh/month]
Drying machine	2	12,3	3	11,4	3	10,9
Oven	9	8,5	12	6,7	13	7,7
Refrigerator	1	22,1	11	28,5	11	30,8
Dishwasher	7	10,7	10	11,3	10	9,8
Washing machine	17	6,1	33	7,4	33	5,6
Induction cooker	11	19,3	16	18,7	16	17,1
Tv	0	-	10	7,8	10	5,0

From Table 4-11 we can see that the number of appliances increased from June to July because A2A Smart City gave out more smart plugs for residents in Merezzate to have a higher number of devices to be followed.

In particular, the smart plugs distribution carried out in June (with the activation of the plugs in July) gave the possibility to have the trends of consumption of television, a new appliance that wasn't considered before. Additionally, refrigerators controlled with smart plugs became eleven and washing machines almost doubled, being seventeen in June and thirty-three in July and August.

This increment of appliances was necessary to have a better understanding of the situation. For instance, the only refrigerator that was paired to a smart plug in June consumed 22,1 kWh. By increasing the refrigerators inspected with smart plugs, it was possible to determine an increase in mean energy consumption. This let us define that the most energy consuming appliance between the ones analyzed into this study is the refrigerator. However, it is worth noticing that this increase in mean energy consumption could be linked to the increase of temperatures typical of summer months, so it would be necessary to have yearly data to better understand this effect.

The same table from above can be seen from the graphical point of view.

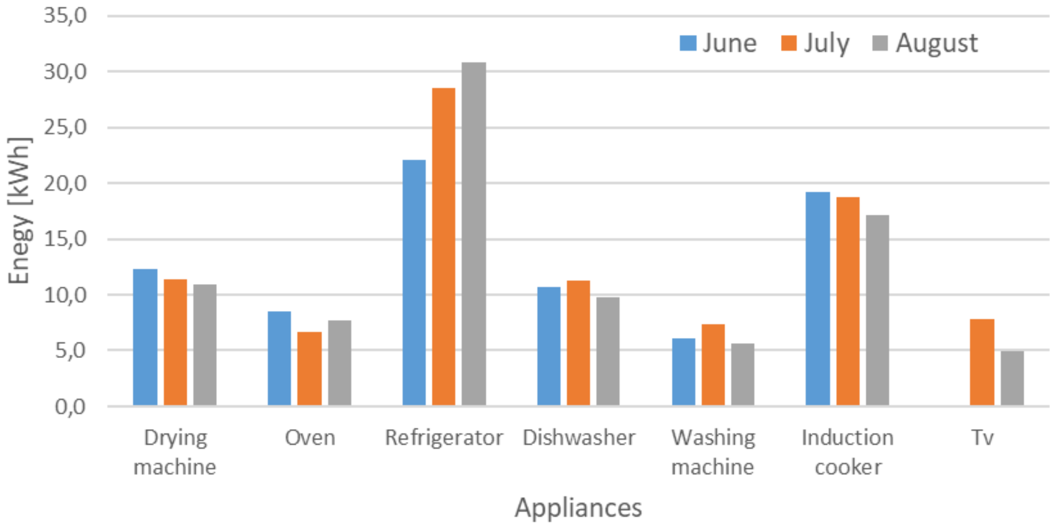

Figure 3-37 - Monthly mean energy consumption per home appliance

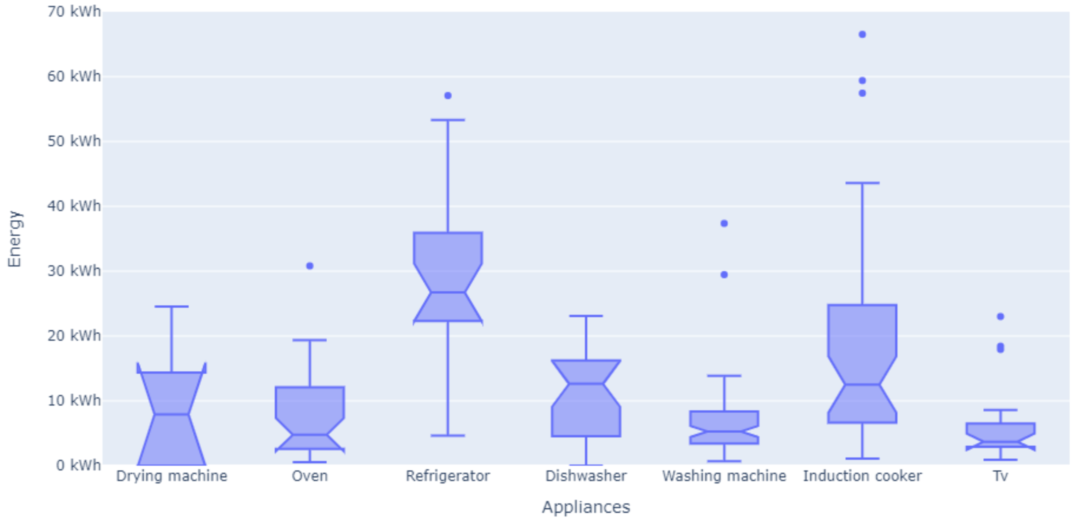

Figure 3-38 – Boxplot of monthly energy consumption per home appliance (June, July, August)

From Figure 3-37 it's easy to see that the refrigerator is the most energy consuming, while the second appliance is the electric induction cooking stove, from a mean point of view. This tells us that if the residents want to lower their energy consumption, the first appliance they should invest in is the refrigerator. Mostly because it is a home appliance that is always working 24/7, its efficiency affects greatly the annual energy consumption. The higher the efficiency class, the lower the energy consumption and therefore the energy costs decrease.

Obviously, this analysis should be refined by having access to a higher number of appliances to be checked. By raising the number of appliances, the values of mean energy consumption should stabilize to the most realistic value.

From the boxplot of monthly energy consumption values (Figure 3-38), it’s possible to notice the variance for each home appliance. Here it becomes clear that people with induction cookers that are followed with smart plugs have very different habits in appliance use. For instance, a person could use very little it’s induction cooker because he often goes out of his home to eat, while other families tend to cook a lot both at lunch and dinner. The big variance for the refrigerators is probably linked to the different class of the appliance or to the different model. For example, an A+ Refrigerator would consume a lot less than a 30 year old fridge. Also, a small refrigerator would consume less than a double door style refrigerator, hence the big difference in monthly energy use.

One of the factors that influence these results in the presence of people in their dwellings. This is a key data because it influences all appliances usage, from the induction cooker to the fridge. This information is not in our possession, so for a further study this could be taken into account as an additional point of view.

If we sum the mean energy of each appliance for each month, we should find a value of energy consumption of a typical resident that possess the appliances considered in this analysis. For example, a customer that has into his home a drying machine, an oven, a refrigerator, a dishwasher, a washing machine, an induction cooker and a tv, should consume around 90 kWh. This value doesn’t consider the energy consumption due to appliances that were not followed with smart plugs. For instance, lighting devices, electronics (like personal computers) and air-conditioning systems should add a value of energy consumption to the monthly estimate.

However, considering this lack of information, the value of mean energy consumption for the months of July is equal to 91,7 kWh, while for August is equal to 86,8 kWh. These two values are not so distant from the ones find with clustering analysis, where the result of medium “pure” cluster was around 105 kWh.

3.6.2 Number of uses during the day

Another aspect that can be analyzed from smart plugs' data is how appliances have been used during the day. This step was achieved by representing the smart plugs measurements of one month in a single 24-hour span. To notice the differences in appliance consumption trend, it has been implemented the difference between workdays and weekends.

The result is a graph where each color represents a home appliance type and on the y-axis there is the number of times that the appliances have been used, having done the mean value by dividing the total number of uses for the number of appliance of that type. This brings to a total bar-plot which indicates a contemporaneity information on Merezzate residents. In this plot data of refrigerators and tv are not reported because they tend to have a constant usage during the day, without showing particular trends.

The difference in plot shape is a confirmation of what was found from Chain2Gate data mining. From Figure 3-39 it's possible to see that weekdays present a peak in appliance usage in the evening around dinner time, from 19.00 to 21:00. On the contrary, weekends tend to have a different profile, with an increase in home appliance use from early in the morning, with a peak around lunch and dinner hours.

This implies that residents in Merezzate district that were followed with smart plugs have a tendency to use home appliances depending on the day of week based on their habits. If a person works an 8-hour job from Monday to Friday, he will probably use home appliances during late evening and during weekends. Many variables come into this thinking, like the number of people that live in the apartment, the age of the residents, the wealth of the family. Figure 3-39 Figure 3-40 are an indication of how lifestyle considerably affects home appliance use and therefore energy demand.

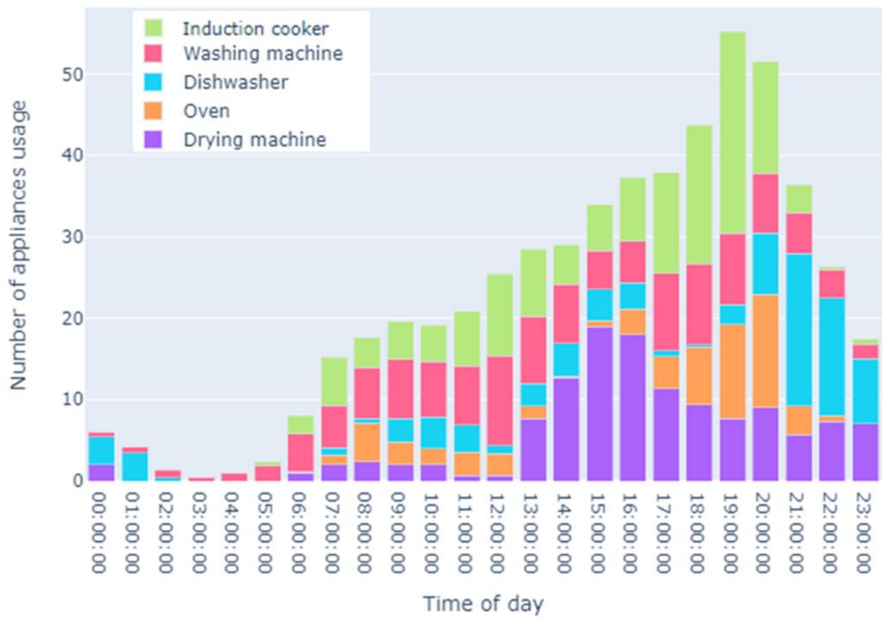

Figure 3-39 – Number of daily appliance usages for one month period. Weekdays

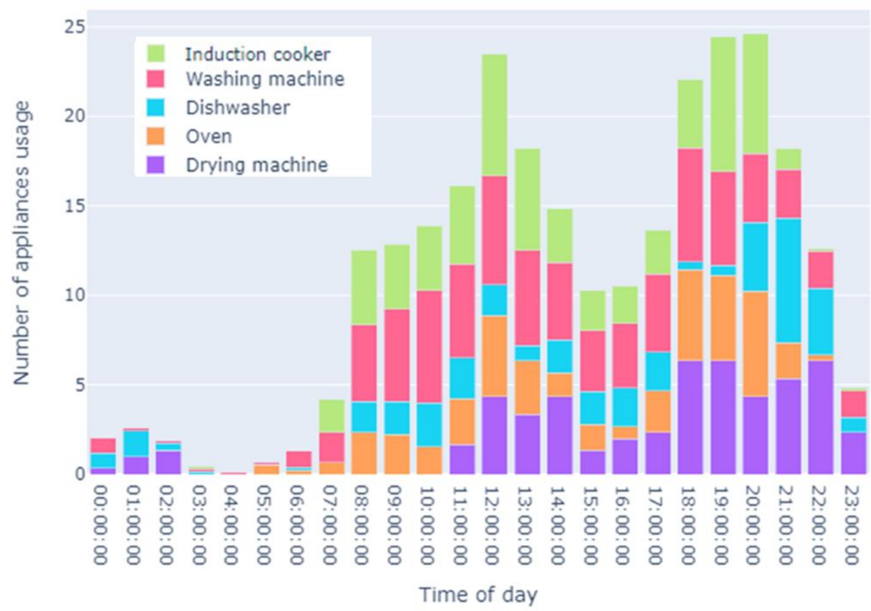

Figure 3-40 – Number of daily appliance usages for one month period. Weekends

The next step is to understand which appliance is the one that weighs more in the peak hour. As stated before, peak hour for workdays is from 19 to 21 in the evening, due to the presence in their homes of a higher portion of residents, with respect to daytime.

By representing the number of uses of home appliances from Figure 3-39 and Figure 3-40 in percentages, it's possible to obtain the values of Table 3-12.

Table 3-12 – Percentages of appliance use during peak hour (19.00 – 21.00)

	Weekdays	**Weekends**
Induction cooker	46%	32%
Oven	19%	18%
Washing machine	17%	25%
Dishwasher	8%	10%
Others	10%	15%

Here it's possible to notice that the most used appliances are electric cooking stove and oven. These two appliances combined sum up for 65% and 50% in workdays and weekends respectively. This is expected, as during dinner time from 19 to 21 pm people would tend to use those appliances to cook instead of others.

The point that was just exposed is interesting in a demand-response peak-shaving logic. In the peak hour induction cooker and oven can't be used for a direct load control demand-response program because it's very inconvenient to users to stop cooking for energy demand reasons. Using a price driven demand-response program could reduce the peak because users would tend to use just the necessary appliances for cooking in order to reduce the cost of energy consumed. Demand-response will be further analyzed in Chapter 6.

3.7 Smart plugs + Chain2Gate

One of the pros of installing smart plugs to follow electricity consumption of users is the possibility to implement information of single appliances on the total energy demanded by an apartment.

For example, we can consider an apartment in which electric cooking stove, oven, dishwasher, washing machine and drying machine are connected to their respective smart plug. Data is sent every 15 minutes by each smart plug to the A2A Smart City's network, like data related to the whole apartment electricity demand followed with the Chain2Gate instrument. The near-real time measurements give the possibility to create an interface for the resident of the apartment where he can follow his electric utilities consumptions.

Figure 3-41 shows the power demand of the apartment taken into consideration, with respect to the 1st of May 2021. Here it's possible to notice that he used four of the five appliances that are followed by smart plugs. The dark green line represents the total power demand for the apartment, data coming from Chain2Gate. We can see how the contemporaneity of appliance usage around 13 pm caused a peak in power demand of about 3,2 kW. Obviously, the Chain2Gate connected to the meter shows some electricity consumes that are not checked with smart plugs, like the last peak power demand on the right of Figure 3-41 around midnight.

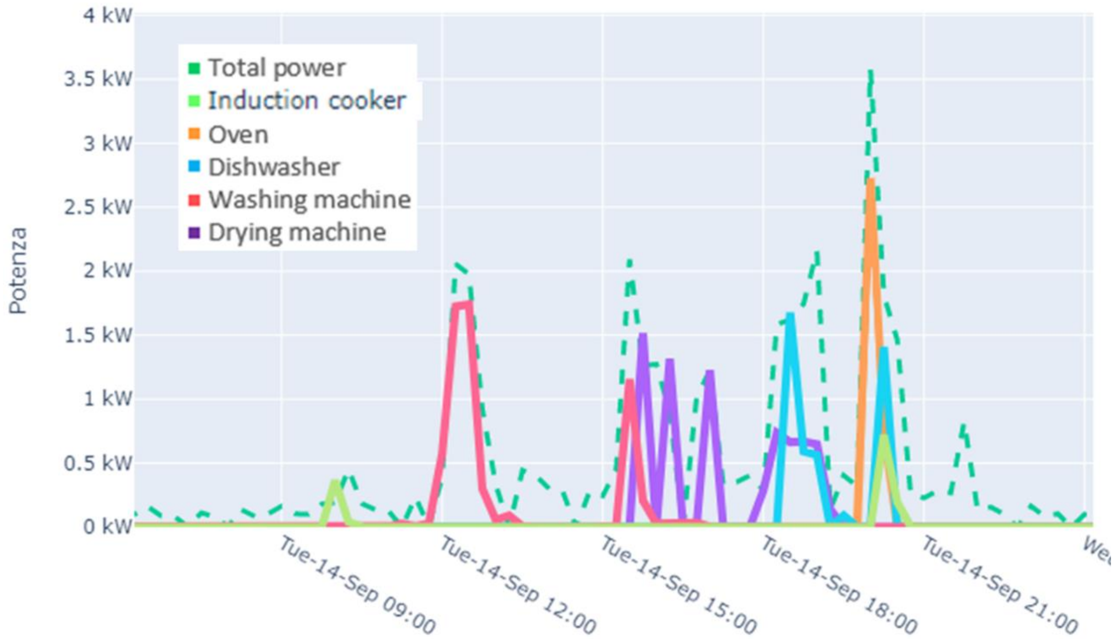

Figure 3-41 – Total apartment power demand with details of appliances

The same plot can be made for every apartment, to follow daily power consumptions of different home appliances. It's easy to understand that the higher the number of appliances connected to a smart plug, the higher the quality of the plot from a thoroughness point of view.

Another step that can be made with data retrieved from smart plugs consists in a monthly report for each user in Merezzate neighborhood. From Chain2Gate data, we have the monthly energy consumption for each apartment and from smart plugs we have the monthly energy consumption of each smart plug.

The values of energy consumption could be given raw, measured in kWh, on into a more graphical way thanks to a pie chart. Also, the information of monthly energy consumption can be given with respect to the mean of the cluster into which the customer has been grouped. With more months of analysis, it becomes possible to make a comparison with the previous month. Here the terms would be how much the energy consumption increased or decreased and therefore if the user has been grouped in a different cluster.

As a sample, it has been chosen an apartment followed with Chain2Gate and four smart plugs. The appliances connected to the plugs are cooking stove, oven, refrigerator and washing machine.

These reports like the ones of Figure 3-42 give the knowledge to the user so that he can better understand how his habits influence his energy bill. It becomes possible to auto-modify the appliances in use to reduce the monthly energy consumption. For instance, the resident of the apartment that has been analyzed in the following pages can modify the electric consumption of the fridge by buying a more efficient one, can decide to change his cooking habits. If he tends to cook for long periods of time, reducing the cooking stove usage by 30% also the cost of electricity related should reduce of 30%. This type of pie chart representation invites the user to adopt more smart plugs to have a better view of his energy consumption trend.

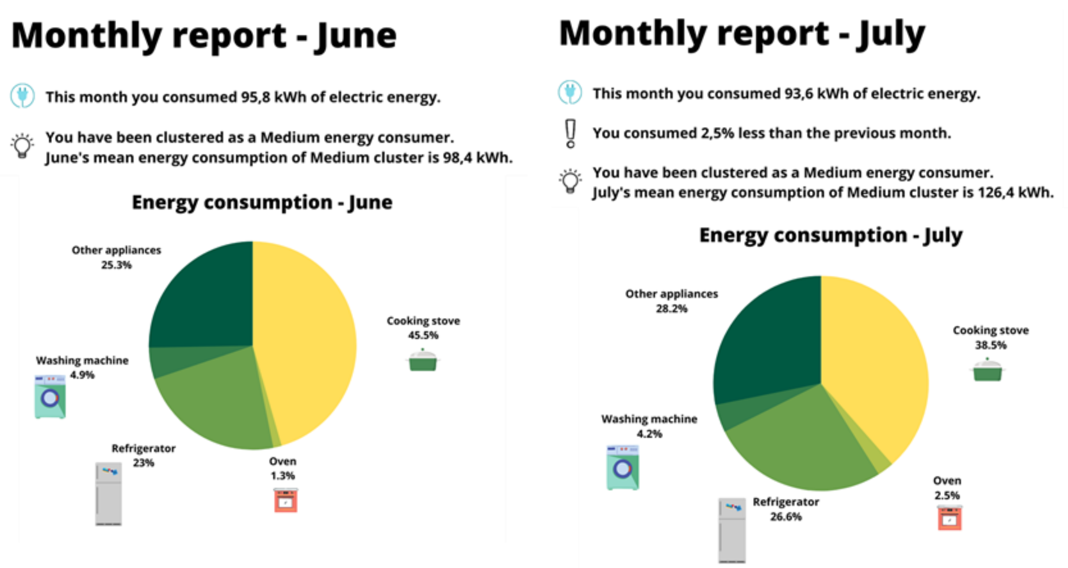

Figure 3-42 – Example of monthly reports of one apartment

3.8 Other appliances

Smart plugs give a huge help in following energy consumption trends of a resident's home appliances. The optimal solution would be installing a number of smart plugs equal to the number of appliances that a person owns. In this way the single user would have the best possible analysis of his energy habits.

One of the appliances that hasn't been analyzed with smart plugs in this thesis is the air conditioner. During the smart plug delivery campaign, it was confirmed that many residents of Merezzate neighborhood did not have an air conditioning system in their dwelling. Other residents have air conditioning but directly connected to the electrical panel, so it was impossible to implement a smart plug for their energy consumption.

Figure 3-43 – Split air conditioner

Having information on air conditioning would have been interesting to understand how each inhabitant tends to cool his home, whether by using AC all day or activating air conditioners only in small time slots to cool one room.

The global energy consumption related to air conditioners would be the difference in energy between summer months and the rest of the year, where usually AC is not turned on. It would be interesting to have some real time data to better understand the problems related to air conditioning linked summer blackouts.

On the other hand, heating hasn't been analyzed in this thesis. The main reason is because in Merezzate it has been implemented a district heating plant. Also, the analysis focuses on summer months, during which heating is typically shut off in northern Italy cities like Milano.

If we imagine that a study like this can be developed on the level of a whole city or region, the possibility to follow electric boiler consumptions arises. This would be a very interesting aspect to examine, especially to notice heating habits and boilers efficiency's influence.

For the installation of new water electricity boilers, there are some new technology boilers that work in combination with the second-generation meter, talking through the chain 2.

The example is Ariston's new boiler PRO 1 Powerflex T-flex 2.0, which implements the chain 2 technology for some user focused advantages. Advantages are the home blackout prevention, usually caused by exceeding the contract limits of an apartment, and the half time necessary to heat up the water. Blackout prevention is achieved by modulating the power demanded by the boiler if home utilities are asking too much electricity that would cause the power to go out.

Figure 3-44 – Ariston's PRO 1 water boiler

Just like the boiler can reduce its power, it can also increase the power demand up to 2,5 kW during periods low energy demand periods, with the goal of reducing the time of water heating.
As an added benefit, the user would have an application on his smartphone like the smart plugs app that gives him the possibility to follow his boiler power demand.

The combined use of appliances that are always smarter that can "talk" with the power meter and smart plugs that give the possibility to the user to modify appliances use bring people's homes to a higher level of technology and closer to the concept of home automation.

4 Renewable Energy Community scenarios

Clustering of residential energy demand can be used for different purposes. One of these is the evaluation of a renewable energy community establishment. The first section of this Chapter focus on the definition of energy community. Then, there is an energy analysis for the real case with district heating. The energy analysis in the hypothetical situation with a heat pump as heating technology is the third section. The last part of the chapter consists of the economic analysis of district heating and heat pump case, with and without the presence of renewable energy community.

4.1 Energy community

The EU has included the notion of renewable energy communities into its legislation through the Clean Energy for All Europeans package, notably as citizen energy communities and renewable energy communities.

More specifically, the Directive on common rules for the internal electricity market ((EU) 2019/944) includes new rules that enable active consumer participation in all markets, whether by generating, consuming, sharing, or selling electricity, or by providing flexibility services through demand-response and storage, either individually or through citizen energy communities. The order intends to increase the number of energy communities and make it simpler for residents to become active participants in the power system [26].

Table 4-1 – Energy community definitions

	Citizen Energy Community, CEC (IEM 944/2019)	**Renewable Energy Community, REC (RED II 2001/2018)**
Membership	Open to different legal forms, but decision making not to commercial shareholders	No-profit entities or small enterprises not operating in the energy sector
Spatial Limitation	No geographical limitation	All shareholders located near the renewable projects they own
Allowed Activities	Limited to electricity sector, but entailing all types of activities	Active in all energy sectors for production, consumption and supply
Technologies Involved	Technology neutral	Limited to renewable energy

Table 4-1 summarizes the two definitions of energy community stated by the EU and in this thesis, there will be considered the second one on REC, Renewable Energy Communities.

4.2 District heating and energy community

In Merezzate there is a district heating plant that delivers heating in all homes during winter period and hot sanitary water during the whole year.

On the roof of the buildings there are photovoltaic power plants dedicated to the production of renewable energy.

For the analysis presented in this chapter it will be considered a single REDO Milano building, Building 2 of UDC 1. It is made of 30 apartments, and the dwellings are divided in three clusters with the characteristics of the Table.

Figure 4-1 – Condominium 2, UDC 1, Merezzate district

Table 4-2 – Residents' consumption values

	Cluster 1	**Cluster 2**	**Cluster 3**
Cluster name	Low	Medium	High
Number of apartments	15	10	5
Number of occupants	2	3	4
Surface of apartment	40 m^2	65 m^2	90 m^2
Monthly consumption	41,9 kWh	110,1 kWh	287,3 kWh
Annual energy consumption	500 kWh	1400 kWh	3400 kWh
Annual energy consumption during peak hours	150 kWh	400 kWh	980 kWh

The electricity consumption of the condominium is equal to 38'000 kWh/year, result of the sum of all dwellings' consumption. The energy part dedicated to the elevator and illumination of common areas has been estimated to be around 500 kWh per year.

The total heated surface is equal to 1625 m^2, resulting in a thermal demand necessary for heating and hot sanitary water. Respectively, the thermal energy for heating of Merezzate apartments is equal to 30 kWh/m^2 and the thermal energy for the production of hot sanitary water is 17,5 kWh/m^2. The resulting value is 77'187,5 kWh/year of thermal energy produced by the district heating plant.

As it can be seen in the Figure 4-1, on the building's roof there are 33 photovoltaic mono-crystalline silicon panels of dimensions of 1,6x1 meters, for a total of 51 square meters. The photovoltaic plant has an installed power equal to 10 kW of peak power at standard test conditions.

The scheme of the condominium is the one below, with the district heating technology.

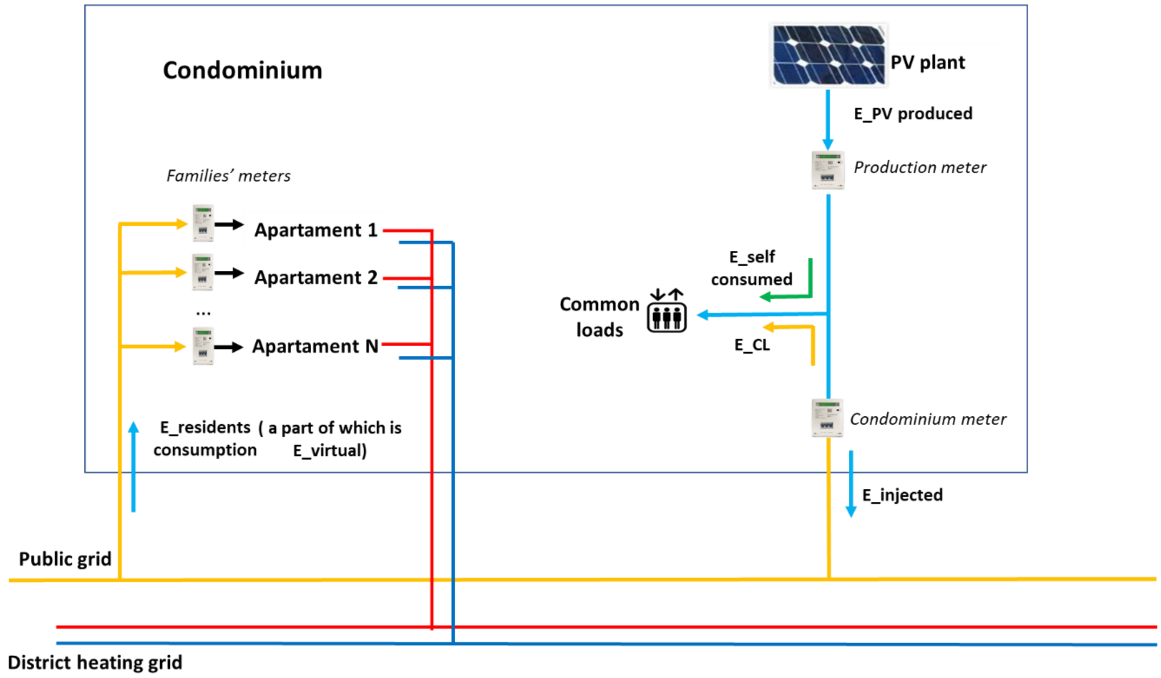

Figure 4-2 – District heating scheme

RECON [27] is a simulator developed by ENEA, Italian National Agency for New Technologies, Energy and Sustainable Economic Development. It is a tool designed to support preliminary energy, economic, and financial assessments for the establishment of renewable energy communities (RECs) or renewable energy self-consumers acting collectively.

The characteristics of the apartments, the energy consumption values and the information of the photovoltaic plant can be implemented into the simulator. The results of the simulation that are considered in this section are solely related to the energy point of view, and the economic evaluation will be made afterwards.

The table reports the results of the simulation in the case of Building 2 of Merezzate+ district, with district heating, a 10 kW PV power plant and no Renewable Energy Community.

Table 4-3 – Energy results DH 1

	District heating + PV 10 kW, no REC
E_tot, Total electrical consumption [kWh/y]	38.500
Daily electrical consumption [kWh/y]	17.735
E_PV, PV plant production [kWh/y]	10.511
E_self-consumed, Energy self-consumed [kWh/y]	258
E_injected, Energy fed into the grid [kWh/y]	10.253
E_virtual, Shared Energy [kWh/y]	0
E_excess, Energy in excess sold to the grid [kWh/y]	10.253
Physical self-consumption index	2,50%
Virtual self-consumption index (shared energy)	0,00%
Total self-consumption index	2,50%

It can be seen that a part of the energy produced by the PV plant has been self-consumed by common areas and the remaining energy has been injected into the grid. The virtual energy, also called shared energy, is equal to zero kWh since there is no energy community in this simulation.

The possible evolutions of this configuration are many, and here are reported two of them. The simplest evolution is the adoption of renewable energy community scheme, with the possibility to share energy produced with the renewable photovoltaic plant between residents of the condominium.

The second evolution is the choice of REC with the addition to install other 20 kW of photovoltaic panels on the surface of the roof of the building, reaching a total of 30 kW of installed nominal power.

The three scenarios identified in this section are related to the district heating, hence they are abbreviated as DH 1, DH 2 and DH 3. Respectively, DH 1 is the case with district heating, a PV plant of 10 kW and no REC, DH 2 is the case equal to DH 1 but with the Renewable Energy Community and finally DH 3 is the case of district heating, with a bigger PV plant of 30 kW and with REC.

The results of the RECON simulator are presented in the table below.

Figure 4-3– Condominium 2, UDC 1, Merezzate district, PV plant of 30 kW

Table 4-4 Energy results, DH 1, DH 2, DH 3

	DH 1	**DH 2**	**DH 3**
	District heating + PV 10 kW, no REC	District heating + PV 10 kW + REC	District heating + PV 30 kW + REC
E_tot, [kWh/y]	38.500	38.500	38.500
Daily energy consumption [kWh/y]	17.735	17.735	17.735
E_PV, [kWh/y]	10.511	10.511	35.038
E_self-consumed, [kWh/y]	258	258	258
E_injected, [kWh/y]	10.253	10.253	34.779
E_virtual, [kWh/y]	0	7.720	13.650
E_excess, [kWh/y]	10.253	2.533	21.129
Physical self-consumption index	2,50%	2,50%	0,70%
Virtual self-consumption index (shared energy)	0,00%	73,40%	39,00%
Total self-consumption index	2,50%	75,90%	39,70%

Some things can be observed from this table. The activation of REC raises the value of virtual energy (shared) from 0 to 7720 for the DH2 case, with the following increase of virtual self-consumption index.

For DH3 there is the obvious increase of PV energy production and shared energy by the residents. In this scenario the energy in excess sold to the grid increases a lot because the daily energy consumption of the building is almost saturated by the shared energy part. The consequence is that the self-consumption index decreases.

4.3 Heat pump and energy community

Now it will be analyzed a different base case. Instead of the district heating system, there is a centralized heat pump that provides heating for the whole condominium.

The electricity consumption data used for the heat pump has been derived from data of the district heating plant. In particular, taking into account the SCOP, seasonal coefficient of performance, of the district heating plant (equal to 4 for heating and 3,5 for hot sanitary water) it becomes possible to obtain the value of electric energy that would consume a vapor compression heat pump.

The resulting energy needed for heating of the building is 13'930 kWh for heating, 7'108 kWh for hot sanitary water, for a total of 21'038 kWh/year.

The electrical energy consumed by the condominium is now equal to the sum of electricity consumption of the residents, common areas and heat pump, resulting in 59'540 kWh/year.

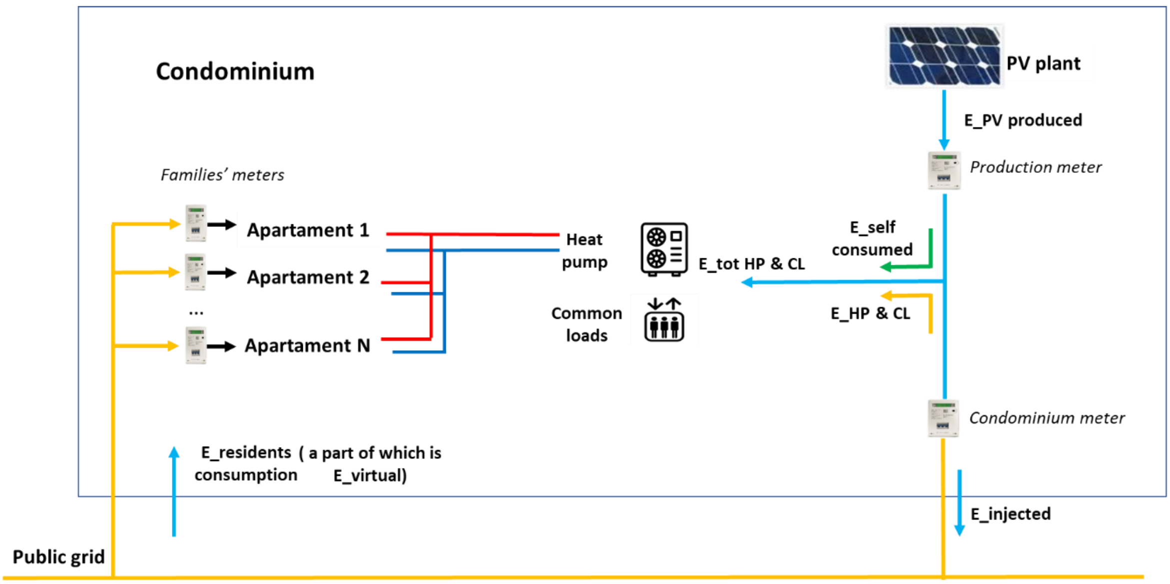

Figure 4-4 – Heat pump scheme

From the scheme of this case, there is no district heating grid, and the heat pump is connected to the condominium's power meter, together with common areas. In this way, the heat pump can utilize energy produced by the PV plant installed on the roof.

Just as the case of district heating, in this heat pump case three scenarios have been identified (HP 1, HP 2, HP 3) with the same logic as before and calculations for the energy consumptions have been performed with RECON simulator.

Table 4-5 - Energy results, HP 1, HP 2, HP 3

	HP 1	**HP 2**	**HP 3**
	Heat pump + PV 10 kW, no REC	Heat pump + PV 10 kW + REC	Heat pump + PV 30 kW + REC
E_tot, [kWh/y]	59.540	59.540	59.540
Daily energy consumption [kWh/y]	30.024	30.024	30.024
E_PV, [kWh/y]	10.511	10.511	29.198
E_self-consumed, [kWh/y]	6.868	6.868	10.022
E_injected, [kWh/y]	3.644	3.644	19.176
E_virtual, [kWh/y]	0	3.166	10.909
E_excess, [kWh/y]	3.644	478	8.267
Physical self-consumption index	65,30%	65,30%	34,30%
Virtual self-consumption index (shared energy)	0,00%	30,10%	37,40%
Total self-consumption index	65,30%	95,50%	71,70%

It's worth noticing that for the heat pump, the difference from between HP 1 and HP 2 consists in the presence of virtual energy for the case with energy community.

The energy self-consumed increases with the increase of installed power of PV plant, which suggests that the heat pump can still consume energy directly from the PV plant.

4.4 Economic analysis

Energy evaluations of the previous two sections can be associated with economic evaluations, taking into account different costs.

The following subsections will treat about the economic analysis of district heating scenario and heat pump scenario.

4.4.1 District heating economics

Annual cash flows can be identified in different voices: cost of district heating (DH) and DH OPEX operating costs, residents' electricity bill, common areas bill, Revenues from PV. If there is a Renewable Energy Community, there are the additional revenues linked to the MISE incentive.

The cost of electricity has been considered equal to 0,22 €/kWh.

The price of electricity at which energy is sold to the grid is equal to 0,05 €/kWh.

The electricity consumption of the condominium is equal to 38'000 kWh/year, and as stated before, they are divided between 30 apartments in 3 clusters. As a result of the product of the electricity consumption by the cost of 0.22 €/kWh, the electricity bill of the condominium amounts to 8360 €/year. This value is equivalent for all the cases of district heating and heat pump.

Common areas electricity bill is the value of energy dedicated to the common areas, paid at cost of electricity. For DH cases, it is always equal to 53,2 €/year.

Cost of district heating can be obtained by multiplying the annual thermal energy by the cost of district heating of 0,1 €/kWh_thermo.

$$C\_district\_heating = E\_DH * c\_thermo$$

Operating costs are assumed to be 10% of the annual cost of C_district_heating:

$$OPEX\_district\_heating = 0{,}1 * C\_district\_heating$$

Revenues from PV plant are computed by multiplying the energy fed into the grid by the price of electricity sold to the grid, p_z.

$$Revenues\_PV = Energy\ injected\ in\ the\ grid * p\_z$$

The energy that has been shared benefits an incentive of 100 €/GWh, issued by MISE (Ministero dello Sviluppo Economico, Ministry of Economic Development):

MISE incentives are computed on the quota of shared energy. Obviously it is equal to 0 for DH1 case since there is no energy community.

$$MISE\ incentive = Shared\ Energy * 0{,}1$$

The net result of district heating is:

$$Net\_DH = C\_district\_heating + OPEX\_district\_heating + Electricity\ bill + Common\ areas\ bill - Revenues\_PV - MISE\ incentive$$

Table 4-6 – Economic analysis DH 1, DH 2, DH 3

	DH 1	DH 2	DH 3
	District heating + PV 10 kW, no REC	District heating + PV 10 kW + REC	District heating + PV 30 kW + REC
District heating cost [€/y]	-7718,75	-7718,75	-7718,75
District heating OPEX cost [€/y]	-617,5	-617,5	-617,5
Residents' electricity bill [€/y]	-8360	-8360	-8360
Common areas electricity bill [€/y]	-53,24	-53,24	-53,24
Revenues from energy fed into grid [€/y]	+512,65	+512,65	+1738,95
Revenues MISE incentive [€/y]	+0	+849,2	+1501,5
Net cash flow (year 0) [€/y]	-16236,84	-15387,64	-13509,04

The observations that can be made on this table are that the last three rows are changing with the change of DH 1 into DH 2 and DH 3. With the activation of the energy community the MISE incentive appears, and with the increase of PV plant the revenues from energy injected in grid increase, with a net cash flow decreasing.

The last value of the table can be used to compare DH 3 with the cases DH 1 and DH 2 and compute the Payback-time (PBT) of the investment and the Net Present Value (NPV).

The PV plant is estimated to have a CAPEX of 1400 €/kW, so for an increase of nominal power of 20 kW, the resulting CAPEX is equal to 28'000 €.

The OPEX cost for the maintenance of the PV plant is estimated to be 690 €/year for a 20 kW PV plant.

The deduction on the CAPEX is equal to 50% of the total, delivered each year for a duration of ten years.

The actualization factor equal to 2% gives the possibility to find the actualized cash flow:

$$Cash\_flow = (Net\_DH\ 1 - Net\_DH\ 3) + Exemption - OPEX\ of\ PV$$

$$Actualized\ cash\ flow = \frac{Cash\_flow}{((1+f)^{year})}$$

Table 4-7 - PBT and NPV results, DH 1 vs DH 3, DH 2 vs DH 3

	DH 1 VS DH 3	**DH 2 VS DH 3**
CAPEX PV [€]	28000	28000
OPEX PV [€/y]	690	690
PBT [years]	9	16
NPV (20 years) [€]	17.896,57	4.010,93

It can be seen that for the scenario with district heating, the introduction of energy community and the enhancement of the PV plant to 30 kW (DH 1 vs DH 3) has a payback time of 9 years of the investment, which coincides with the CAPEX of the PV plant.

For the case of DH 2 vs DH 3, the presence of REC causes some revenues that were not present for DH 1, so the difference in net cash flow between DH 2 and DH 3 is lower. This brings to a PBT of 16 years and a NPV after 20 years which is around 4'000 €.

4.4.2 Heat pump economics

Economic analysis for the scenario in which there is the heat pump as heating technology is the same as the district heating case, with some differences.

The electricity that is consumed by the heat pump (and common areas) is the difference between the total demand of heat pump (and common areas) and the self-consumption.

$$E\_heat\ pump = E\_tot\ heat\ pump - E\_self\ consumed$$

The energy from the heat pump is paid for at the classic market price of electricity of 0.22 €/kWh.

$$C\_heat\ pump = E\_heat\ pump * price\_electricity$$

The operating cost of the heat pump is estimated to be 8% of the heat pump cost:

$$OPEX\_\ heat\ pump\ =\ 0{,}08 *\ C\_\ heat\ pump$$

The net result of heat pump is:

$$Net\_HP = C\_heat\_pump + OPEX\_heat\_pump + Electricity\ bill - Revenues\_PV - MISE\ incentive$$

Table 4-8 - Economic analysis HP 1, HP 2, HP 3

	HP 1	**HP 2**	**HP 3**
	Heat pump + PV 10 kW, no REC	Heat pump + PV 10 kW + REC	Heat pump + PV 30 kW + REC
Heat pump cost [€/y]	-3227,4	-3227,4	-2533,5
Heat pump OPEX cost [€/y]	-379,07	-379,07	-379,07
Residents' electricity bill [€/y]	-8360	-8360	-8360
Revenues from energy fed into grid [€/y]	+182,2	+182,2	+958,8
Revenues MISE incentive [€/y]	+0	+348,3	+1200
Net cash flow (year 0) [€/y]	-11784,3	-11436	-9113,8

The same comments of the previous sub-section can be made for this table, with the additional note that there is the additional change in cost of heat pump (and common areas). This value decreases for HP 3 case because of the increase of electricity production of the PV plant, with the increase in self-consumed energy by the heat pump.

Table 4-9 - PBT and NPV results, HP 1 vs HP 3, HP 2 vs HP 3

	HP 1 VS HP 3	**HP 2 VS HP 3**
CAPEX PV [€]	28000	28000
OPEX PV [€/y]	690	690
PBT [years]	10	11
NPV (20 years) [€]	16.959,14	11.264,59

Similar comments of the case of district heating can be made here, with the case HP 3 being the best solution from the economic point of view. The investment that has to be sustained for the increase in power of the PV plant comes back after 10 years when compared to HP 1 and after 11 years when compared with HP 2.

4.4.3 Conclusions on energy communities

The choice to make an energy community is always convenient form the environmental and economic point of view.

The implementation of a 10 kW PV plant brings to an avoided annual CO2 around 3,5 tons of CO2, while the choice of a 30 kW plant avoids 11,3 tons of CO2 every year.

The increase of the surface of the photovoltaic power plant is not always economically convenient since there is a maximum point at which the energy demand of the building is saturated. Still, the two sizes of PV plant considered in this chapter always bring savings.

MISE incentives are very convenient, both in the district heating and heat pump scenarios. They are the main economic reason to form an energy community. In addition, the possibility to share energy between the members of the energy community is a valid option to answer the residential demand of condominiums.

This intelligent way to consume energy produced by the PV is a very powerful tool necessary to move towards a more affordable and climate oriented world.

5 Demand response

One of the objectives of the project Merezzate+, funded by European Institute of Innovation & Technology's KIC, Knowledge and Innovation Community, was the feasibility and implementation of a demand-response program in a new generation neighborhood. The community of Merezzate is partially made up of social housing projects, whose residents have been selected based on their affinity for themes like environment sustainability, the best subject for the research project.

The analysis consists of quantifying the economic advantages for end users that derive from the modification of their energy consumption habits. For this purpose, data of electricity meters retrieved with Chain2Gate instruments were necessary to study the feasibility of demand-response mechanisms in Merezzate.

The following Chapter will focus on DR feasibility, with a first digression on electric energy price in Italy, necessary to quantify the savings for residents.

Next, there will be an evaluation of what would change by modifying the electricity price. The section after will consists in the demand-response tests implementing different DR techniques.

At last, the final section hints demand-response feasibility for the whole city of Milan, whether to change the investments of grid expansion of the distribution system operator.

5.1 Electricity price

The two core elements for the analysis of demand-response program feasibility are the price of electricity and the energy consumption of the residents. This section will focus on the Italian price of electricity.

The electricity wholesale market in Italy is divided in four steps and is based on a bidding mechanism. The first step consists of long terms markets where players buy or sell electricity with future delivery in a continuous trading mechanism that can range from 365 days before the day market to 2 days before the day market. The second step is the day ahead market where equilibrium price is set trough an auction mechanism. Intraday market is the third step where market player adjusts their net withdrawn of injected position. The last step is called balancing market where the Transmission System Operator acquires services to resolve grid constraints to maintain real time balancing. The most important session is the second one, Day Ahead market, where one day before the delivery of electricity bids are presented to buy and sell electricity for every hour of the following day.

The key element of Italian electricity market is PUN (Prezzo Unico Nazionale) national unitary price, measured in €/kWh. The PUN is defined by GME (Gestore dei Mercati Energetici), energy market operator. The value of PUN is defined as the mean of zonal prices of Day Ahead market weighted on the total purchases, after deduction of purchases of pumped storage and foreign zones. PUN changes every hour based on the balancing of supply and demand and can be monitored constantly on GME site [28].

Typically, the price of electricity varies based on the time of the day so that the price is higher in those time slots where it's more difficult the energy production and lower in the time slots where there is a surplus in energy production.

PUN varies every day, and with data from GME site it's possible to plot the daily trends for a whole month.

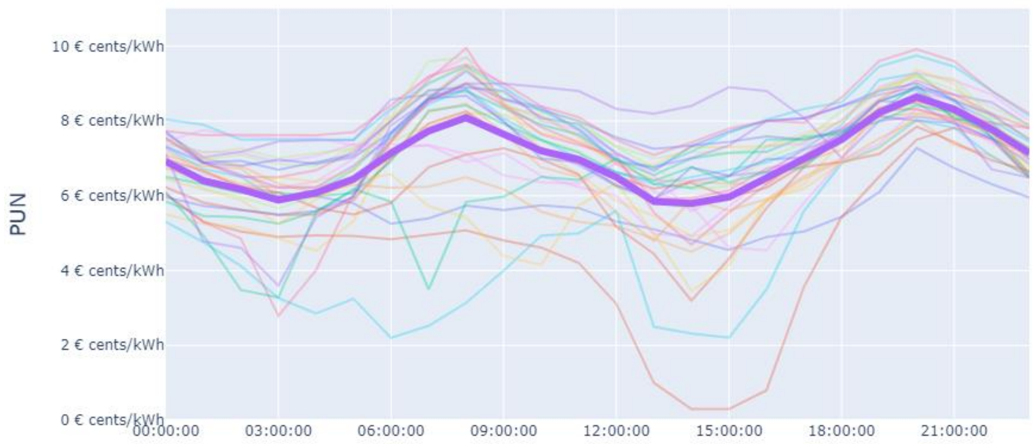

Figure 5-1 – Daily PUN, May 2021

The trends in Figure 5-1 represent the curves of electricity price for each day. These can be grouped into one single trend that is representative of the electricity price of the whole month of May, by making the mean value of PUN for every hour. This is highlighted in purple in Figure 5-1 and Figure 5-2. In particular, the mean hourly value of PUN for the month of May varies between 6 and 8,5 € cents/kWh, showing two peaks at 8 in the morning and 8 in the afternoon.

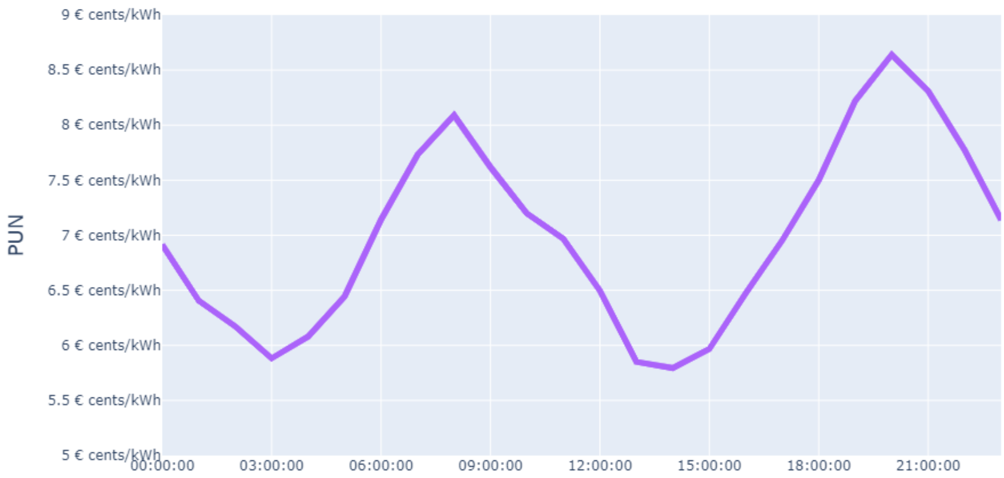

Figure 5-2 – Mean daily PUN, May 2021

PUN variations brought to the definition of time slots by ARERA (Autorità di Regolazione per Energia Reti e Ambiente) which is the organism that conducts regulation and control in sectors of electric energy, natural gas, hydro cycles and waste cycles.

For the electricity market there are three time slots: F1, F2 and F3. Each time slot has its electricity price.

Table 5-1 – Time slots

F1	**Monday to Friday**	**8:00-19:00**
F2	Monday to Friday Saturday	7:00-8:00, 19:00-23:00 7:00-23:00
F3	Monday to Saturday Sunday and Holidays	00:00-7:00, 23:00-24:00 00:00-24:00
F23	Monday to Friday Saturday, Sunday and Holidays	19:00-8:00 00:00-24:00

As it can be seen from Table 5-1, time slots are implemented considering the day of the week and holidays. There is the need to point out that the use of three time slots is typical of industrial electricity pricing.

For domestic customers, the price of electricity of time slots F2 and F3 coincide into time slot F23, whose time specifics are reported in Table 5-1.

The following analysis on demand-respond will focus on real PUN values for time slots of the month of May 2021, reported in Table 5-2 [28]. A thing that can be pointed out is the fact that for May 2021 the price of electricity in F2 is higher than F1. This is linked to the different trends of electricity price during the day in the different months of the year. The main reason for the lower price of F1 is due to the penetration of photovoltaic energy produced during the day. PV plants produce energy at marginal cost equal to zero, so they are present on the electricity market at cost equal to zero; the following effect is that the total energy demand is equal to the total energy demand minus the electricity produced with renewables. The result is a "net" demand that during the hours of the middle of the day and during the night tend to be equal, because in the first case there is a high demand and a high production from PV, while in the second case there is a low demand and no production from PV. The remaining hours of early morning and evening present a high demand, but with little PV energy production, with a result in a higher electricity cost for F2.

Even if it's not so unusual that F2 is greater than F1, in the end the low peak price of electricity for resident customers (F23) is always lower than F1.

Table 5-2 – PUN for each time slot, May 2021

	F1 (€/kWh)	F2 (€/kWh)	F3 (€/kWh)	F23 (€/kWh)
May 2021	0,074270	0,077970	0,063020	0,069897

5.2 Demand response test

As stated above, electricity contracts for resident users can be made considering just two time slots, F1 and F23. The proposals for electricity contracts of A2A Energia (the company of A2A Group which offers services and delivery of electric energy and gas) are based on a mono-hour or two time slots systems. For this reason, a first analysis will focus on just two time slots PUN, F1 and F23.

Data retrieved with Chain2Gates every 15 minutes from every active apartment in Merezzate gives us the possibility to make a division of energy consumption of each customer based on the time slots during which they consumed energy.

After writing a code that could address at each user his energy consumption in Peak and No-Peak time slots, it was possible to make a preliminary cost analysis.

As an example, it has been analyzed a first apartment that has been clustered as a high energy consumer. The total energy consumed in May is equal to 233,23 kWh, with a detail of 166 kWh during workdays, and 66,23 kWh in weekends. Workdays' energy can be divided between F1 and F23, while weekends energy consumption is always paid with the PUN price of F23. By multiplying the energy for the respective price of electricity, it's possible to find the cost that the resident has to pay for the only electricity part of the bill.

Table 5-3 shows what's been described before. It's important to notice that the price of electricity used is the respective PUN of F1 and F23 of Table 5-2.

Table 5-3 – Energy consumption and cost of a sample apartment, May 2021

	Weekdays		**Weekends**		
Energy	166,00		67,23		kWh
	F1	**F23**	**F1**	**F23**	
Energy	71,79	94,21	0	67,23	kWh
Energy cost	5,33	6,58	0	4,7	€
	11,92		4,7		€
	16,62				€

It's obvious to understand that the energy that could be moved from the peak F1 to the "low price" time slot F23 is equal to 71,79 kWh.

5.2.1 Energy shift from F1 to F23

The following step wants to focus on what happens if a portion of energy consumed in peak hours would move to F23. If the resident changed his habits and moved 20% of energy consumption from F1 to F23, it would result in a decrease in monthly energy cost of just 0,07 €. This can be seen in the Table 5-4, which consists of Table 5-3 with a 20% shift in energy consumption.

The same results are obtained if we consider another resident that have been clustered as low or medium energy consumption.

Table 5-4 – Energy consumption shifted and cost of a sample apartment, May 2021

	Weekdays		**Weekends**		
Energy	166,00		67,23		kWh
	F1-20%	**F23+20%**	**F1**	**F23**	
Energy	57,43	108,56	0	67,23	kWh
Energy cost	4,26	7,59	0	4,7	€
	11,85		4,7		€
	16,55				€

This mere change in energy cost is linked to the obvious fact that energy that is shifted from F1 to F23 has to be paid at PUN relative to F23.

The maximum savings in this case happens if the resident would have shifted all his energy consumption into F23, with a result of 1,02€ of saving (15,60 €/month paid as energy cost). This extreme and almost unreal case serves as the limit of the Time of use demand-response. With the case just described, it becomes very difficult to implement a demand-response mechanism for residents of a neighborhood in which they would change their energy habits to have a reduction in energy cost component of just around 0,5%.

If moving energy from peak hours to non-peak hours leads to these results, it becomes obvious that one problem of this analysis consists in PUN values. In particular, by looking at Figure below, it’s easy to notice that the delta of price between F1 and F23 is very small.

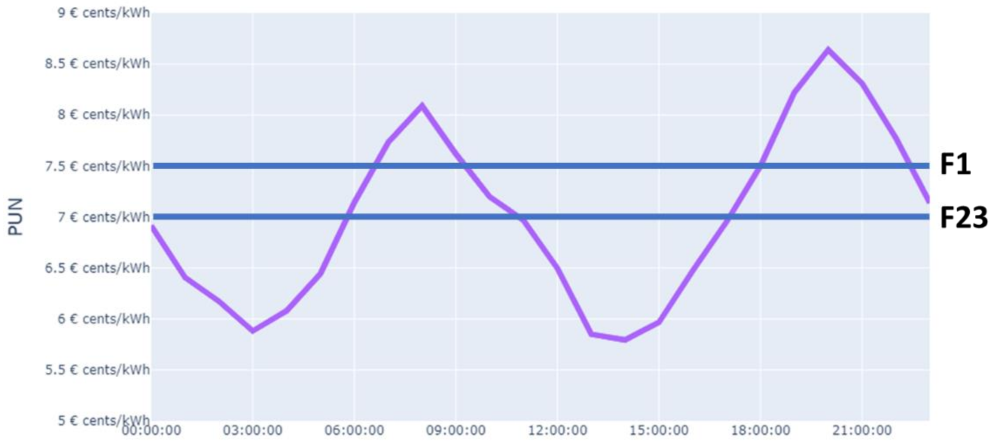

Figure 5-3 – Delta of price between real F1 and F23 prices

5.2.2 New 4 time slots, 4TS

For this reason, the next step focus on analyzing how it would have changed if the energy costs were defined in a different way, with higher differences between peak prices and off-peak prices. The test considers 4 time slots so that the delta of energy price is higher. PUN prices are defined as it can be seen in the graph below.

Figure 5-4 – Delta of price between 4 new time slots

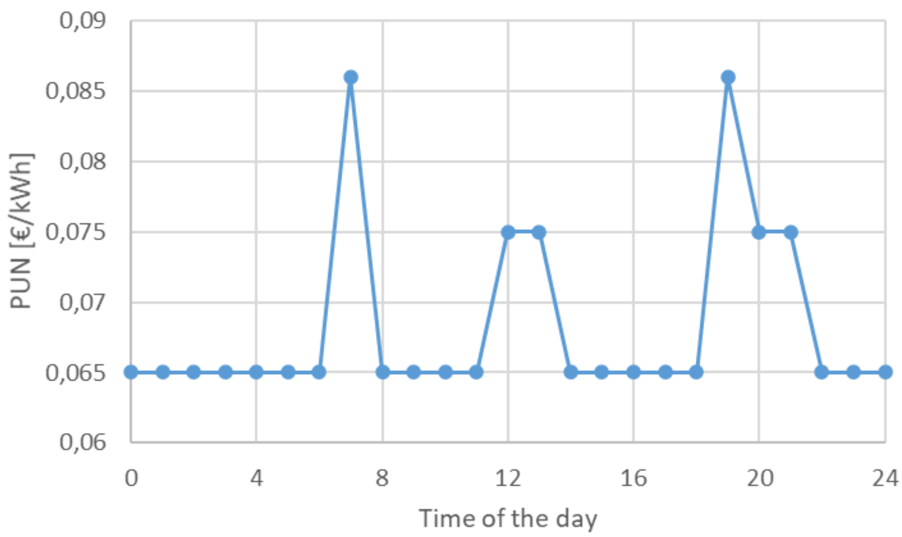

Figure 5-5 – 4TS, 4 time slots PUN trend from Monday to Friday, May

Table 5-5 – 4TS, 4 time slots PUN trend

	Day of week	Time range	PUN [€/kWh]
F1	Monday to Friday	7:00-8:00, 19:00-20:00	0,086
F2	Monday to Friday	12:00-14:00, 20:00-22:00	0,075
F3	Monday to Friday	00:00-7:00, 8:00-12-00, 14:00-19:00, 22:00-24:00	0,065
F4	Saturday, Sunday and Holidays	00:00-24:00	0,058

As stated before, the chain2gate data gives the possibility to determine the time slot in which energy has been consumed, so it's possible to write a code that divides the monthly energy consumption of a customer into these 4 new time slots. The reasoning that has been implemented for the demand-response feasibility is the same as the previous sub-section: what changes if 20% of peak energy consumption from F1 and F2 moves to off-peak F3.

Considering a high, medium and low energy consumption resident, results are very similar to the case with just 2 time slots. In the annex it's possible to view at the simulation made in Excel for three test residents for the month of May.

This Time of Use DR mechanism with four time slots performs slightly better than the two time slots mechanism. If the resident shifts 20% of his energy consumption from peak to off-peak, he can achieve savings ranging from 0,10€ to 0,06€ for the month of May.

Results of Time of Use DR are not promising for residential customers that would not tend to reduce their energy consumption for a very small return.

5.2.3 Critical peak pricing

As a following step, it has been analyzed the possibility to implement a critical peak pricing demand-response mechanism, modifying the DR scheme of the previous sub-section.

Table 5-5 has been modified into Table 5-6 so that the cost of sole electricity in peak hours, F1, would be more than double, fixing it at 0,25 €/kWh.

Table 5-6 – CPP pricing

	Day of week	Time range	PUN [€/kWh]
F1	Monday to Friday	7:00-8:00, 19:00-20:00	0,25
F2	Monday to Friday	12:00-14:00, 20:00-22:00	0,075
F3	Monday to Friday	00:00-7:00, 8:00-12-00, 14:00-19:00, 22:00-24:00	0,065
F4	Saturday, Sunday and Holidays	00:00-24:00	0,058

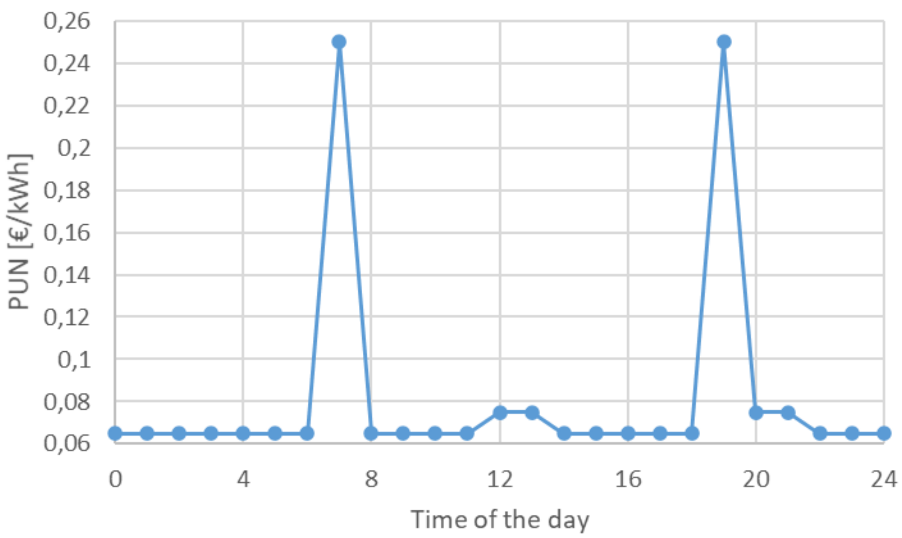

Figure 5-6 – CPP PUN trend from Monday to Friday, May

In this case, for all the resident clusters it becomes more realistic to modify one's electricity habits to obtain a monetary saving. Considering data of a resident of medium cluster, it can be seen that the energy in time slot F1 is equal to 8,14 kWh, with a respective cost of 2,03€ for the month of May. By reducing of 20% the energy consumed in F1 and F2, it's possible to reach a decrease in cost of sole electricity of 2,79%.

If we make the hypothesis to use May as the prototype month, we can multiply the cost of sole electricity by 12 to find the annual cost of electricity of a single resident of Merezzate. In this way it's possible to quantify in euros the annual savings linked to a demand-response method.

Table 5-7 – Energy savings for CPP demand-response test

	Energy cost [€/y]	Energy cost – CPP DR [€/y]	Savings [€/y]	Savings [%]
Low	84,49	81,62	2,88	3,40
Medium	145,16	141,12	4,05	2,79
High	233,19	226,31	6,88	2,95

Savings are linked to the quantity of energy consumed in peak hours. For instance, the low energy resident that has been taken as example had 6,3% of electricity demand during F1, 11,39% during F2, 45,4% during F3 and 36,9% during F4. The higher the share of energy in time slot F1, the higher the energy savings that a customer can reach.

It's important to point out that the energy cost of Table 5-7 is related to the sole energy component of the bill. Italian electricity price for a domestic user is essentially composed of four shares: energy expenses, expenses linked to transportation of energy and meter management, system charges and finally taxation. Typically, the most volatile voice is the energy expenses, linked to the cost of raw materials used for electricity production. The remaining voices cover a total of 0,128 €/kWh for the second trimester of 2021 [29]. Introducing this cost voice, the total energy annual bill is in line with real values.

By making this CPP demand-response test, it's possible to determine that the residents would obtain a reduction in electricity bill, but if we consider the whole bill, a 20% shift in energy consumption from peak hours to off-peak hours brings only to a 1% reduction on the annual bill cost.

5.2.4 Incentive based pricing

Another demand-response mechanism that has been evaluated is incentive based pricing. In particular, it has been considered a scheme where residents would receive a monetary compensation for their active modification of energy consumption.

The evaluation for this thesis has been done on data from May, following the same 3 sample residents of the previous sub-section and using energy prices defined in Table 5-5 (new 4 time slots PUN trend). Here the reasoning implemented for this step consists in shifting 20% of peak energy consumption to F3. As an incentive, the energy that have been shifted is paid to the resident at a hypothetical price, fixed at 0,1 €/kWh.

In this way, the cost of energy of time slot F3 is reduced, on the contrary of what happened for the CPP demand-response mechanism. The savings for the incentive-based DR come from this modification of voice cost.

Table 5-8 – Energy savings for IBP demand-response test

	Energy cost [€/y]	**Energy cost – CPP DR [€/y]**	**Savings [€/y]**	**Savings [%]**
Low	72,86	68,36	4,53	6,21
Medium	129,14	122,03	7,11	5,51
High	206,72	192,85	13,87	6,71

In the annex it's possible to see the excel sheets used for the IBP simulation for all three resident samples.

One thing that can be noticed by looking at Table 5-7 and Table 5-8, is the difference in the first energy cost, without a DR mechanism. It's clear that cost related to energy in a CPP scheme is higher with respect to an incentive DR program, because of the fact that the price of electricity in the peak hours is way higher than the other time slots. For this reason, a change of energy use brings a reduction in costs.

For an incentive-based program, the base energy cost is the same of a realistic 4 time slots energy contract. The savings here are linked to the incentive value. Obviously, the higher the incentive, the higher the savings for the client. One of the key elements for the success of an incentive-based DR program is the determination of the incentives. In this thesis analysis it has been decided to use a fixed value measured in €/kWh for simplicity of the calculations, but it is surely not the best possibility and needs further investigations.

For instance, an article published on Energy Policy by [30], focus on an experiment of incentive-based residential electricity demand response. Residents in the implementation area can participate in trials of demand response by receiving SMS messages from the platform about the plan. After, the platform can track changes in the electricity consumption levels of the residents and calculate energy savings, which can automatically provide rewards to eligible clients. The test has been performed on 20000 Chinese dwellings. Households who perform well in the trials will receive monetary subsidies, and the subsidies will be stored in an electronic account that is used to pay the houses' electricity bills. The conclusions of this study highlight the necessity to increase the monetary return as much as possible, to publicize the demand-response mechanism and policy to promote energy-saving behaviors.

This study suggests that a test like this can be implemented in a European city like Milan. It could focus on one the active modification of energy habits of a neighborhood like Merezzate, or on a greater scale for a whole side of the town.

5.2.5 Thoughts of feasibility of demand-response models

A preliminary analysis like the one performed in this thesis let us understand some aspects of demand response models and their feasibility in a real neighborhood like Merezzate. The three DR mechanism seen in the previous sub-sections lack all under some aspects. Time of Use DR with two or four time slots if greatly affected by the PUN value and in particular of the delta of price between peak-hours and off-peak hours. Here is highly necessary a greater difference in electricity price in order to have a valid monetary saving linked to the variation of energy consumption.

Critical Peak Pricing DR shares the same basic idea of Time of Use DR, but the price of peak hours is way higher, so that a reduction in energy use during those hours has a positive effect of money savings. However, this could be one of the problems for the policy makers because the resident user would have a high disadvantage if he or she couldn't make a modification of the energy habits. Incentive-Based Pricing has the highest potential between these three methods because users would have to actively modify their home appliances use and would see a real money subsidy for their home electricity bill.

For an in-depth understanding of the DR methods, it would be necessary to develop more detailed models where active residents play a key role changing energy consumption in a DR methodology way. Example would be models developed in studies like [19], [31], [30], [32].

The next step for residential demand response becomes possible with the implementation of devices like Chain2Gate that follow residents' energy consumption in a near-real time way. Thanks to the second-generation smart meter and Chain2Gate, it's realistic to warn residential users of the price of electricity in real time. The result would be to implement a model with active residents that modify their energy trends based on requests or based or real time prices of electricity. This can be possible because price of electricity is at clear view of everyone on GME site. The idea would be letting the resident know the price of electricity a quarter of hour in advance so that he can decide when to use his home appliances in a more intelligent way. This last Real Time Pricing DR would be similar to the telecommunications plans active in the nineties in Italy. The price of making a phone call during peak hours was way higher than low peak hours, due to the high demand of tertiary industry where telecommunications were essential for working. In a similar way, a real time pricing would lead to a high energy price linked to the high demand of industry, commercial and residential users and the higher difficulty in providing the electricity demanded. At low hours where there is an abundance of renewable energy and a lower demand from the user side, electricity prices would decrease. Implementing this scheme on a residential level, there would likely be a modification in peak demand because the user would have more knowledge and info at his disposal.

5.3 Demand-response for grid development

During the internship in A2A Smart City it has been brought up the possibility to have a brainstorming with Unareti, the company of the A2A group that deals with gas and electricity distribution. During this conversation it has been considered the possibility to implement a demand-response mechanism in large scale as an additional model for the handling of power peak demand in the city of Milan. In the development plan of Unareti issued in 2021, the solutions described for the peak power demand management are vehicle-to-grid, behind-the-meter generation with photovoltaic, hydrogen, energy storage and Power-to-Grid/Grid-to-Power mechanisms [13]. All these options are oriented to the reduction of congestions on the electricity grid, the main problem of high peak demand. An additional solution could be demand-response.

The idea of the rollout of a demand-response project on a city scale is that a portion of the annual investment destined to the upgrade and expansion of the grid could be allocated as an incentive of a DR program. For instance, from the development plan of Unareti, the investment made in 2020 for the Milan's grid expansion was equal to 91 M€/y [13], while the investment for 2021 was budgeted at more than 100 M€/y.

If we assume that for the year 2022 the grid expansion investment would be around 120 M€/y, it becomes possible to calculate that reducing the investment by 30% the investment for grid expansion would become 86 M€/y, while the budget for a demand-response program would be the remaining 36 M€/y. This last quantity is the monetary value that could be destined as incentives for an incentive-based DR program. By dividing the 36 M€/y for the total number of users served by Unareti in Milan (9 million people), it's possible to find an estimated monetary compensation that can be given to the users of 40 € each year for the participation in a demand response program. This number can help reduce a hypothetical electricity bill of 600 €/y of around 6%, which is considered to be not enough. A reduction of investment for the global expansion of the Milan electricity grid should bring a way higher result for the customer for thinking to be feasible. The critical issues for Unareti are linked to the congestion of the electricity grid. It's essential to make investments to enhance the grid in order to avoid blackouts and lack of service for Unareti clients. The exponential increase in energy demand for the city of Milan badly needs the increase of investments on the grid to sustain future energy scenarios.

Incentive based DR can become a solution if the Italian state of the European Commission decide to invest a very important amount of money in order to sustain the costs. The other solution could be a critical peak pricing of energy where peak hours energy costs way more than off-peak hours, so that the clients are obliged to modify their energy habits to avoid very high electricity bills.

6 Conclusions and remarks

The proposed thesis work analyzes different aspects of residential energy demand.

The first Chapter, divided in three sections focus on state of the art of Demand response, Power metering instruments and clustering techniques for residential customers.

The second Chapter is centered on the presentation of Merezzate+ case study. It is a new generation residential district which aims to be sustainable and to create a community of intelligent energy users, via the implementation of state of the art instruments such as smart meters, smart plugs and smart thermostats.

In the third Chapter the main goal was to analyze data retrieved with smart meters (chain2gate) and smart plugs. Firstly, data was analyzed from a global point of view, by looking at the connections of the households to the transformers. Form this it was firstly noted how the total power ranges between a maximum (160-170 kW) and a minimum (30 kW), following patterns dependent on the day of the week. For instance, workdays from Monday to Friday tend to have the higher peak at dinner time, while weekends and holidays tend to have a power trend with two peaks of around the same magnitude, due to the fact that people tend to stay home more and use home appliance early in the morning.

Then it was pointed out how the minimum power increases with the variation of perceived temperature. In particular, for the days of 12-15th of June, a high increase in ambient temperature and humidity in Milan led to the increase of minimum power demand (+70 %) that maintained for the summer months.

In the following section data was analyzed from the energy point of view and it was possible to notice this increase in the daily mean trend. Here, the difference between the months analyzed (May, June, July and August) is the increase in the minimum energy demand during night-time, which can be linked to the beginning of air conditioning systems.

The analysis then continued with the clustering of time series with k-means algorithm, doing the differentiation between workdays and weekends. Here, clustering of power load curves has been performed by making the mean of daily load curves for each resident. In this way, it was possible to find three clusters one for low, one for medium and one for high power demand. The difference of trends between workdays and weekends has been also found here, confirming the global power trends for the single residents' profiles.

By adding the information of type of the apartment in which residents live there have been found some trends of use. In particular, one-room apartments have been clustered for the major part in the "low" power demand group, while three-room and four-room apartments have a higher chance of being grouped in the "high" power demand cluster.

As a next step it was performed a different clustering analysis, based on the total energy consumption of the residents over a month period. The information of type of apartment have been inserted before the clustering as an additional parameter. The results of this clustering are very similar to the ones of time series clustering. The motivation of the differences between the two methods used is mainly the fact that clustering of monthly energy consumption keeps into consideration all energy use, without the difference between workdays and weekends.

Clustering of monthly energy has also been performed for single type of apartments, obtaining 12 separate clusters. Then the clusters were brought back to 3. With this reasoning it was possible to visually determine the residents that are consuming more or less than the residents in the same type of apartment.

The following section consists of smart plugs data mining. The home appliances considered in this thesis work are conduction stove, oven, dishwasher, washing machine, drying machine, tv, refrigerator. The mean monthly energy consumption shows that the refrigerator and the cooking stove are the two most energy demanding appliances, even if their power demand is different, being the refrigerator always turned on, while the cooking stove is used only when necessary.

From the daily trend of home appliance usage, it was possible to notice that during peak time from 19.00 to 21.00, the most used appliances are cooking stove and oven in the range of 50-60% of uses. The remaining home appliances are the ones that could be moved in a demand response mechanism (not considering refrigerator and tv).

Information of energy use from smart meter and smart plugs can be used together to give added value to the resident. It's possible to make a real time power demand graph with both info of power meter and smart plugs. Another visual output could be a monthly report with information of energy consumption, divided for home appliance followed by smart plugs. The optimal situation would be a resident with all of his appliance connected to smart plugs so that he could understand his energy habits at best.

Results of monthly energy consumption have been implemented in a renewable energy community simulator called Recon. Here the three cluster of residents have been characterized by the mean value of energy consumption for the respective clusters. Two different scenarios have been considered: the first one is the real configuration, based on a district heating, system and in the second one a centralized electric heat pump heating system is considered. A simulator like Recon gives the possibility to understand the feasibility of the creation of a photovoltaic power plant for a neighborhood, giving back information on energy consumptions and environmental impact. Then, a section was dedicated to the economic analysis of the two scenarios, taking into account the realization of an energy community and the enlargement of the PV plant.

The introduction of REC is clearly an advantage from the point of view of the cash flow since the MISE incentive are an additional revenue computed on the energy shared between residents of the same condominium.

For the cases of district heating the incentive is about 850 €/year for a renewable energy community of 30 apartments that share energy produced with a 10 kW PV plant, while it is 1500 €/year for the same case but with a bigger PV plant of 30 kW.

Similar results are obtained for a heat pump that would self-consume a portion of the energy produced by the PV plant. The revenues would be around 450 and 1200 €/year for the two cases of 10 kW PV and 30 kW PV, a bit lower that the district heating case, mostly because the heat pump would consume a higher portion of energy produced by the photovoltaic plant, so there would be less energy dedicated to being shared.

The last chapter of this thesis in centered on the feasibility of a demand response program for residents of Merezzate neighborhood. At first it was analyzed the price of electricity, PUN. With a real value of PUN, it has been performed a first test by moving 20% of energy consumption from the high price to the low price time slot, as in a Time of Use DR mechanism. This leads to very thin 0,5% of cost of energy decrease. A similar result has been obtained by implementing a ToU mechanism with 4 new time slots (F1, F2, F3, F4). Cost reduction in this case was just of 1%.

The next step was to understand the feasibility of a Critical Peak Pricing DR mechanism. The results are definitely better than ToU, leading to a cost reduction of around 3%, by moving 20% of energy use from peak hours to low peak hours.

The final DR analysis focused on Incentive-based DR mechanism, where the resident should be motivated by the incentive to move the energy use from peak hours to off-peak hours. Here the result brought to an energy cost reduction of around 5-6%.

Last subsections have been written to summarize DR mechanisms seen in this thesis and to understand if DR can be an alternative to grid expansion. For this last point, it was possible to come to the conclusion that DR can be powerful tool to lighten the system, but it has to be used with the conjunction of the increment of the grid, which is vital for big cities like Milan.

Some aspects of this thesis project need some further analysis that couldn't be analyzed for time or external reasons. For instance, the data collected with smart instruments are related to a 6 month period. Without any doubt, the possibility to have access to data ranging from January to December would give us the chance to make some remarkable considerations. Surely it would be possible to better analyze the seasonality of energy consumption of a whole district.

In the chapter regarding data mining, it was possible to determine the increase in minimum power demand passing from May to June, due to the increase in ambient temperature and humidity. A further step would be to identify this change in energy consumption linked to other season changes, for example moving from autumn to winter or from winter to spring.

A thing that could be pointed out is that the power demand curve could have a different profile. For instance, the peak power demand at dinner time could be also higher, or the whole power demand profile could be different from the one found in this data. The Covid-19 pandemic, for example, changed the residential profile of energy demand. It has been seen in many studies [33], [34], [35] how the trends of workdays became very similar to weekends, due to the compulsory presence of people in their dwellings.

Data for this thesis was related only to 2021, so it was not possible to identify the differences between Covid time, from March 2020, and post-Covid time.

For sure, the collection of data for the next years will give us the possibility to find different trends if there will be the complete return to normality or even if there will be a new external event like a pandemic.

The apartments that are occupied in Merezzate kept increasing during 2021 and, at the time of writing of this thesis, it reached 450 apartments inhabited on a total of 615 apartments. A following step would be to analyze data when all the apartments are occupied so that all results would be as realistic as possible. Another possible solution would be the data mining of an already living neighborhood. Here it would be interesting to find the differences in energy consumption patterns with respect to Merezzate residents. In fact, people of Merezzate have been preliminary selected based on their interests on environmental and sustainability matters. A different district with people of another mental approach could and should bring to different results.

Another aspect that could be found by analyzing other pre-existing districts is that the efficiency of the buildings and of the home appliances should impact on the energy consumption patterns.

Regarding the clustering of monthly energy consumption, it would be very interesting to introduce the information of the number of inhabitants in each apartment, like in the study of [36]. In this way it would be possible to have an additional level on analysis that can give further results for customer segmentation.

The results of clustering of monthly energy consumption would be definitely useful for the implementation of a simulator like Recon. Here, energy for the month would be used as an input for all single months, without the need to make a mean value that characterizes the yearly energy demand.

For the smart plugs point of view, it is obvious that having access to a higher number of home appliances can be crucial to better understand the power demand trends and habits of use. Also, if every resident will have the possibility to install many smart devices, he will have more control over his home and more knowledge over his energy use.

For what regards the feasibility of Demand Response mechanisms in the residential sector, it has been described in this thesis that the delta of price between peak slot and off-peak slot is too little to act on energy consumption to have important money savings for the resident. It becomes obvious that a PUN, price of electricity, with a higher variability and difference between maximum and minimum value could lead to the active implementation of DR programs.

It is worth noticing that a Direct Load Control DR program has not been analyzed in this thesis. The main reason for this choice is that the only appliances that could be feasible for this type of program are Dishwasher, Washing machine and Drying machine. Even if there have been made some studies in this direction, one of the common results is that this mechanism turns out to be uncomfortable for the final user. It has been decided to analyze energy use from a total point of view, with the concept of giving the user the possibility actively to modify his power trends and habits.

A next step for this thesis would be the realization of an experiment implementing a Real Time Pricing DR program with real residents. In fact, this method requires some effort to evaluate in an analytical environment, so it would be better to directly see the results on a real residential case.

In the near future, when most of the Italian population will have the second generation smart meter, one of the goals will be to have to analyze a large amount of data in an intelligent way. One of the results is that residents will be more informed about their consumption and will be able to react to responses from the outside such as a real-time change in the cost of energy.

An example of application could be a solution to the problem created in August, September and October 2021. In Europe, and in particular in Italy, there are increases of around 40% in electricity and gas costs linked to the increase in the cost of raw materials [37].

The case is becoming really important and is getting more and more political and media attention; it is estimated that rising energy prices will lead to the temporary closure of manufacturing companies [38].

The real-time response of the customer will be an excellent point of advantage of a DR technique, because it would bring immediate added value to the customer, who would have the possibility to avoid consuming energy in the most expensive time range.

The problem of the increase in the cost of energy in August, September, October is mainly related to the increase in the cost of raw materials, in particular natural gas, so partly detached from the dependence of daily demand. Energy costs more on average throughout the day.

Without a doubt, the implementation of energy production from renewable sources remains one of the possible solutions to the problem. This is one of the main reasons why it is necessary to encourage the emergence of energy communities that produce renewable energy bringing benefits to the residents of which they are an active member.

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Appendix

The appendix of this thesis consists of graphs and calculations that have been omitted for the sake of simplicity of the text.

In order, there have been reported:

- Transformers, May
- Clustering results, May, June, July and August
- Monthly reports examples, June, July and August
- DR calculations for:
    - 4 time slots
    - Critical peak pricing
    - Incentive based pricing

Transformers

May

Here are reported the power trends of apartments in Merezzate for the month of May, with their respective link to the transformers.

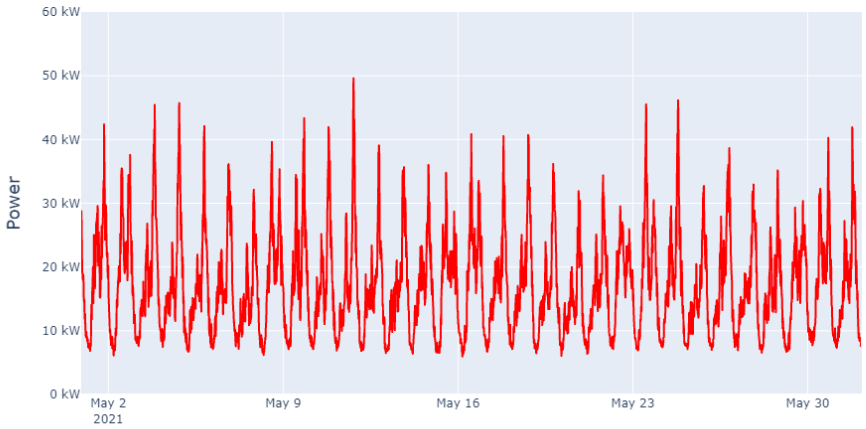


Figure 6-1 – Power trend of Transformer 1: A01943_TR1, May

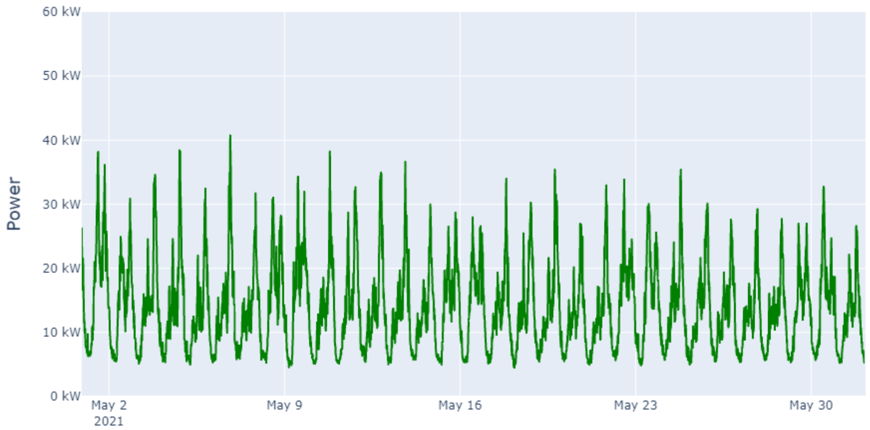


Figure 6-2 – Power trend of Transformer 2: A01944_TR1, May

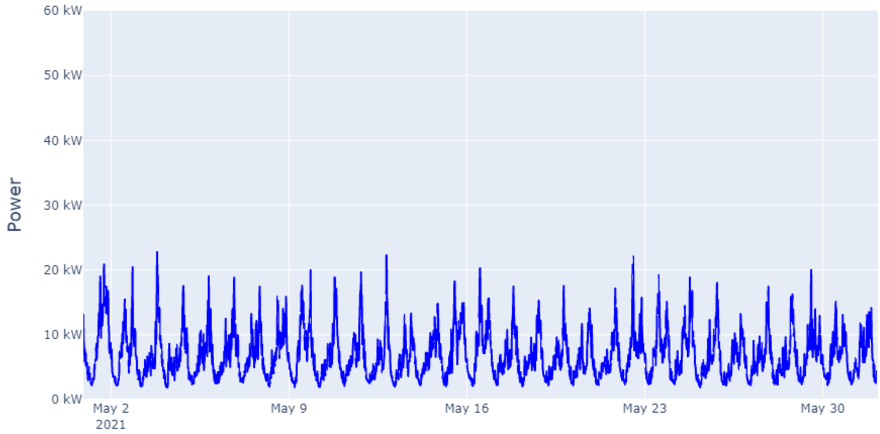


Figure 6-3 – Power trend of Transformer 3: A01946_TR1, May

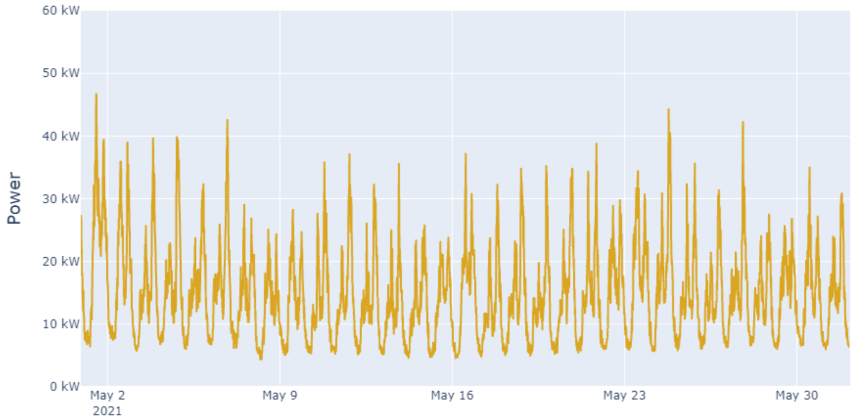


Figure 6-4 – Power trend of Transformer 4: A01947_TR1, May

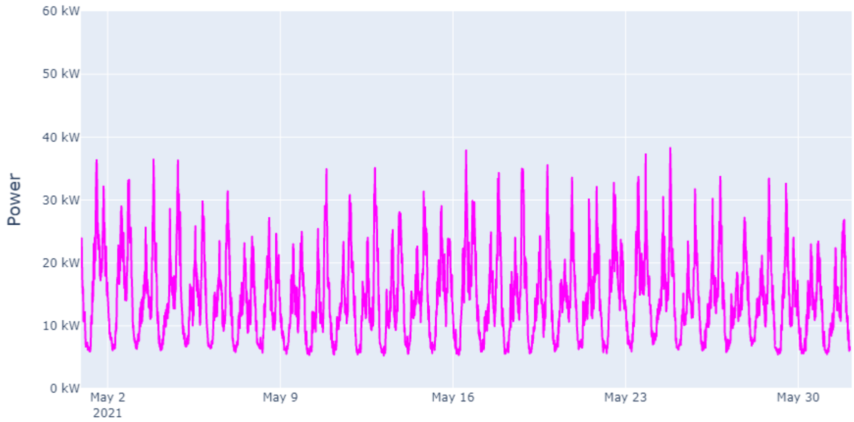


Figure 6-5 – Power trend of Transformer 5: A01948_TR1, May

Clustering results

JUNE

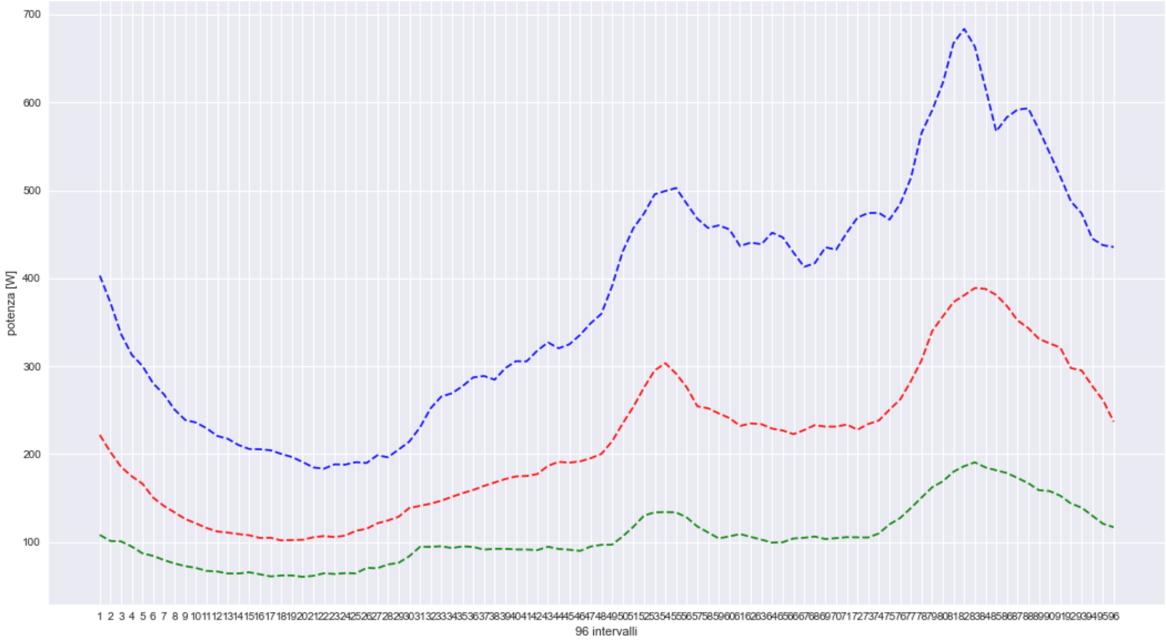


Figure 6-6 – Mean curves of the three clusters (weekdays), June

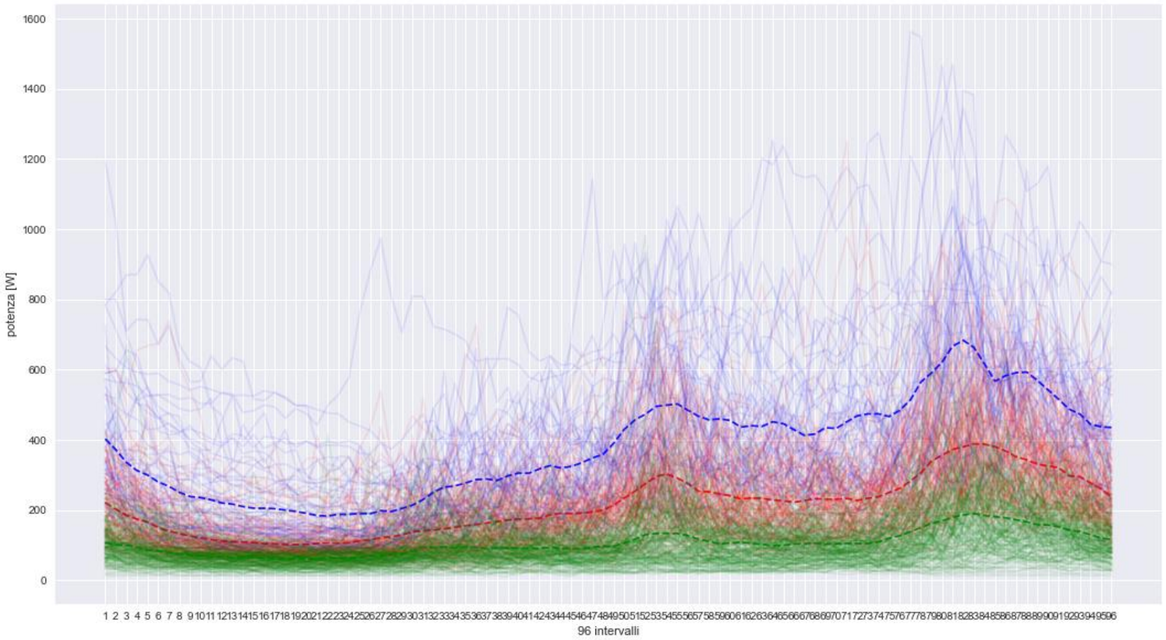


Figure 6-7 – Mean curves of the three clusters and mean power curves of daily (weekdays) power curves of all customers, June.

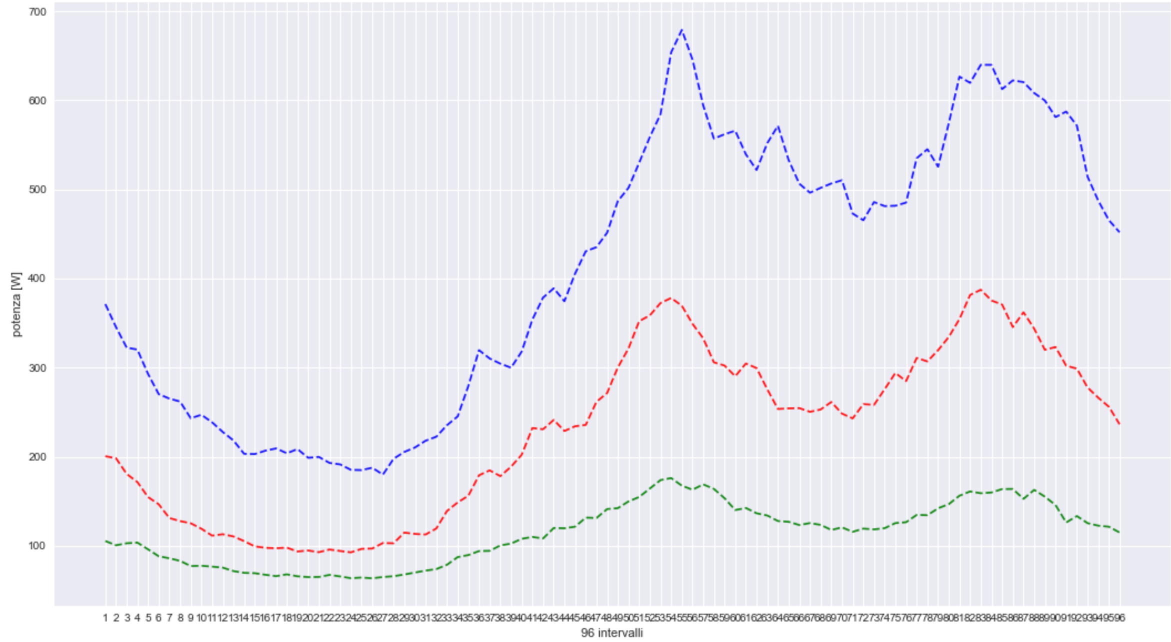


Figure 6-8 – Mean curves of the three clusters (weekends), June

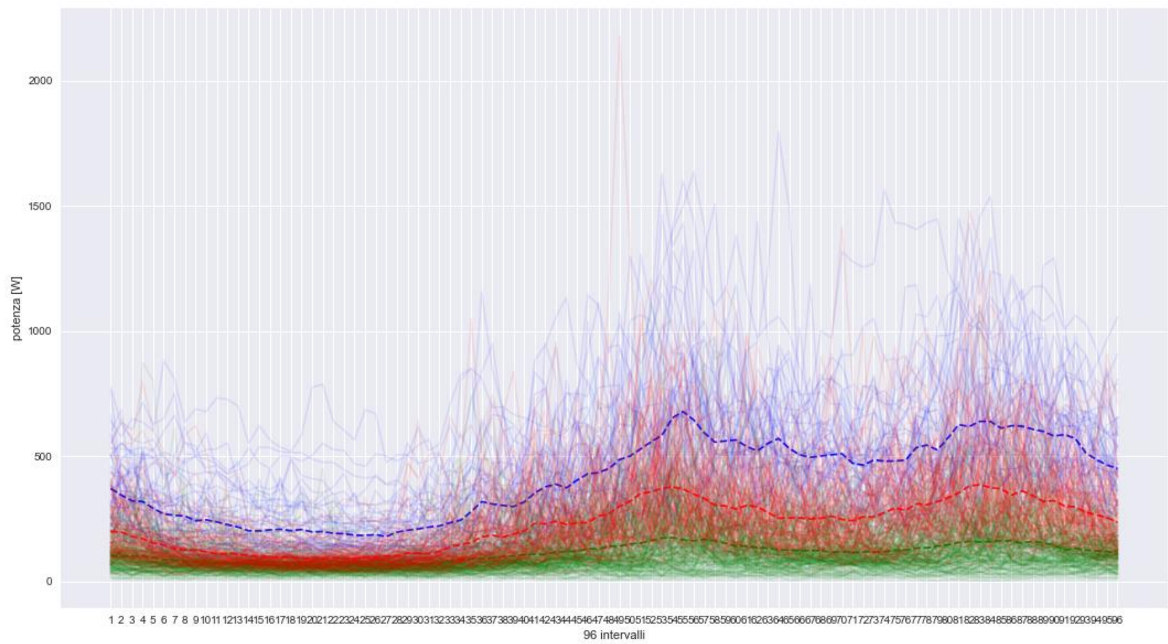


Figure 6-9 - Mean curves of the three clusters and mean power curves of daily (weekends) power curves of all customers, June.

JULY

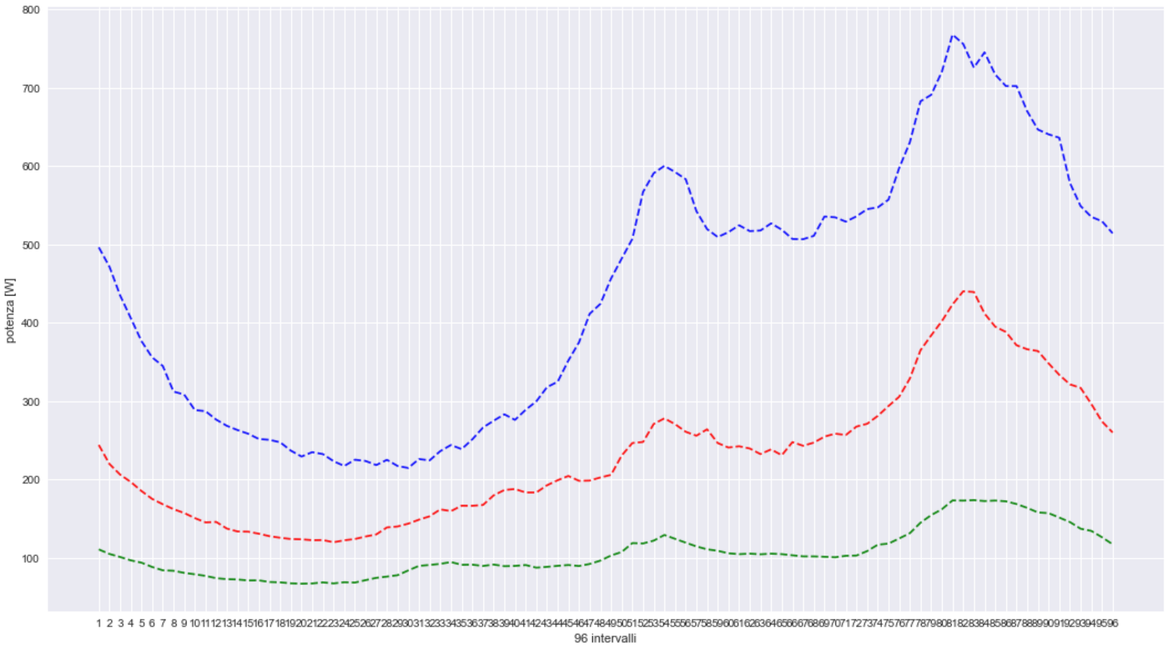


Figure 6-10 – Mean curves of the three clusters (weekdays), July

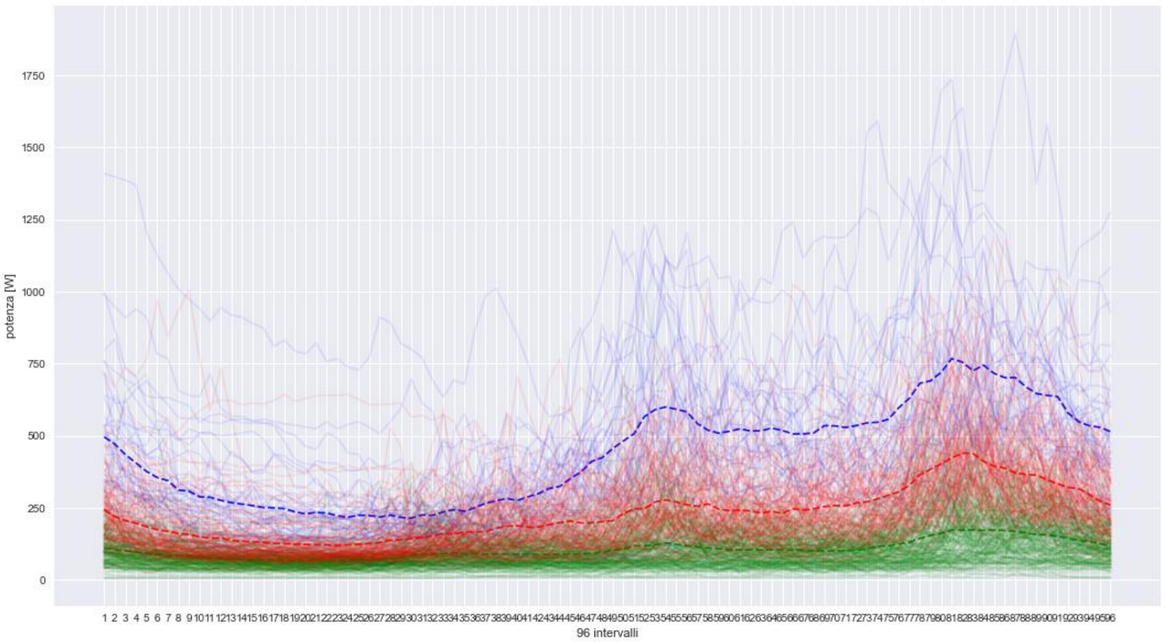


Figure 6-11 – Mean curves of the three clusters and mean power curves of daily (weekdays) power curves of all customers, July.

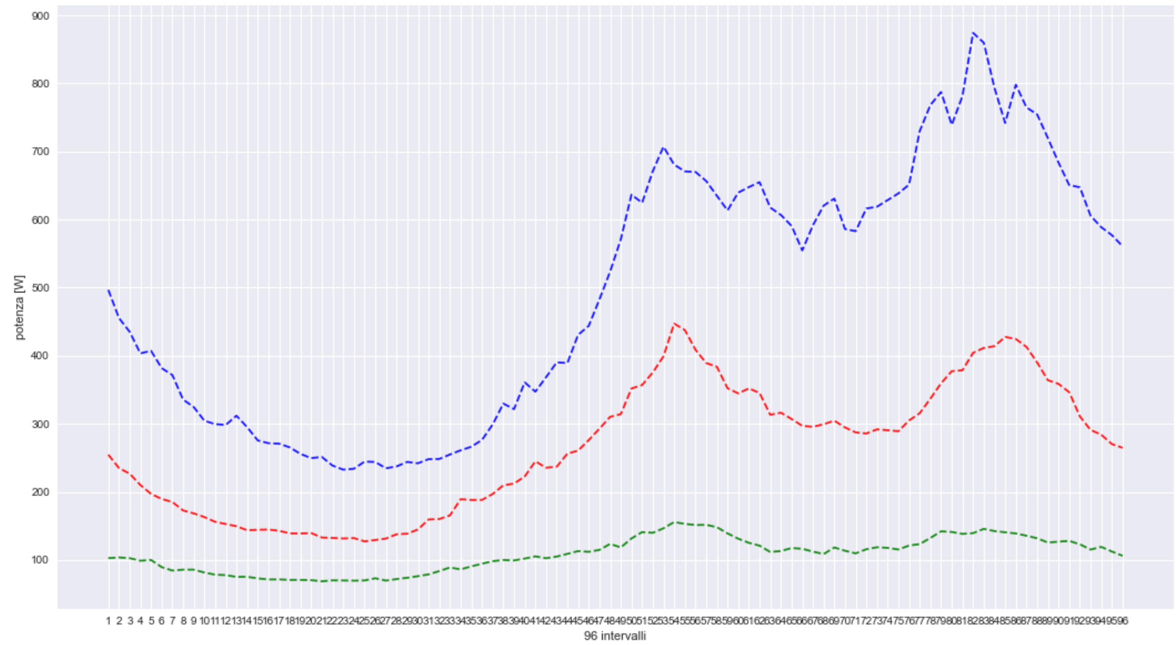


Figure 6-12 – Mean curves of the three clusters (weekends), July

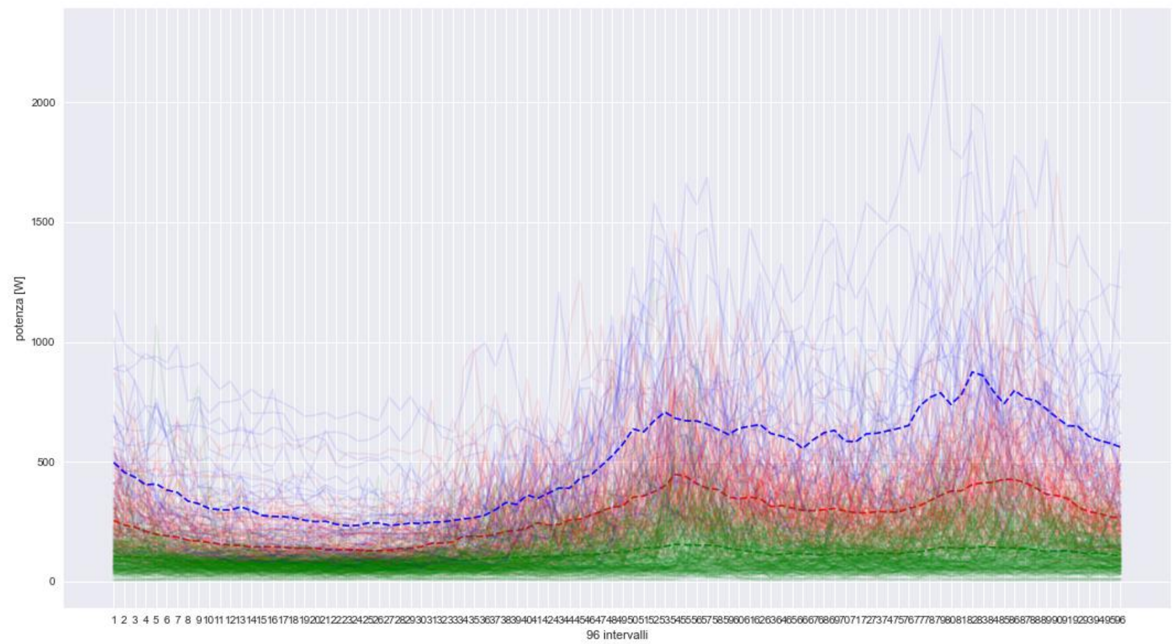


Figure 6-13 – Mean curves of the three clusters and mean power curves of daily (weekends) power curves of all customers, July.

AUGUST

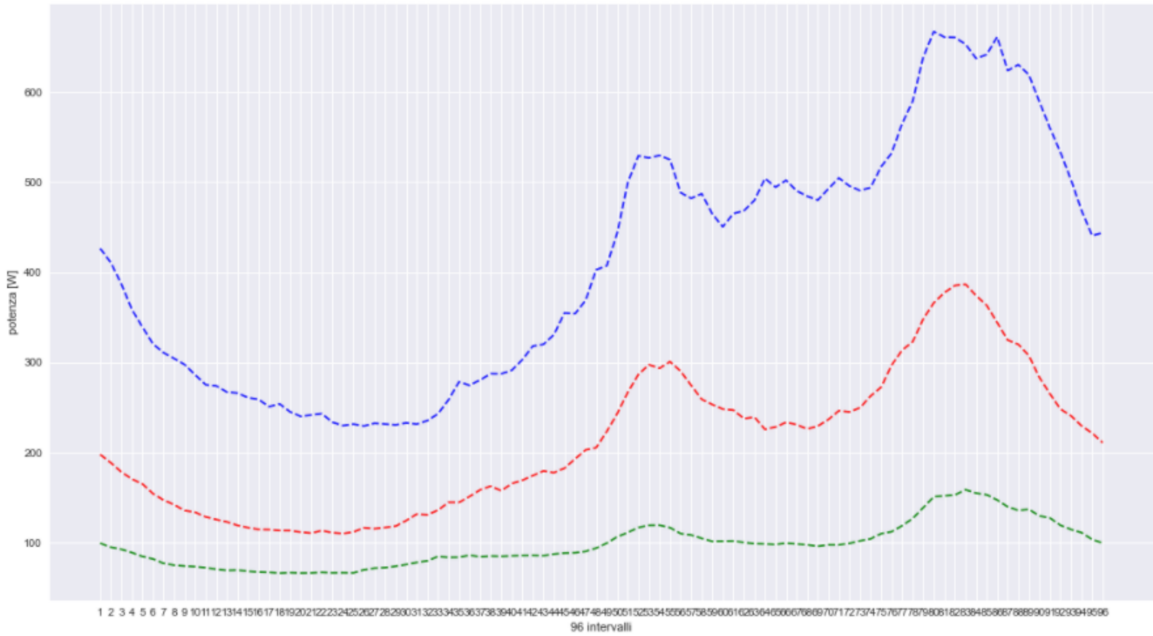


Figure 6-14 - Mean curves of the three clusters (weekdays), August

Figure 6-15 – Mean curves of the three clusters and mean power curves of daily (weekdays) power curves of all customers, August.

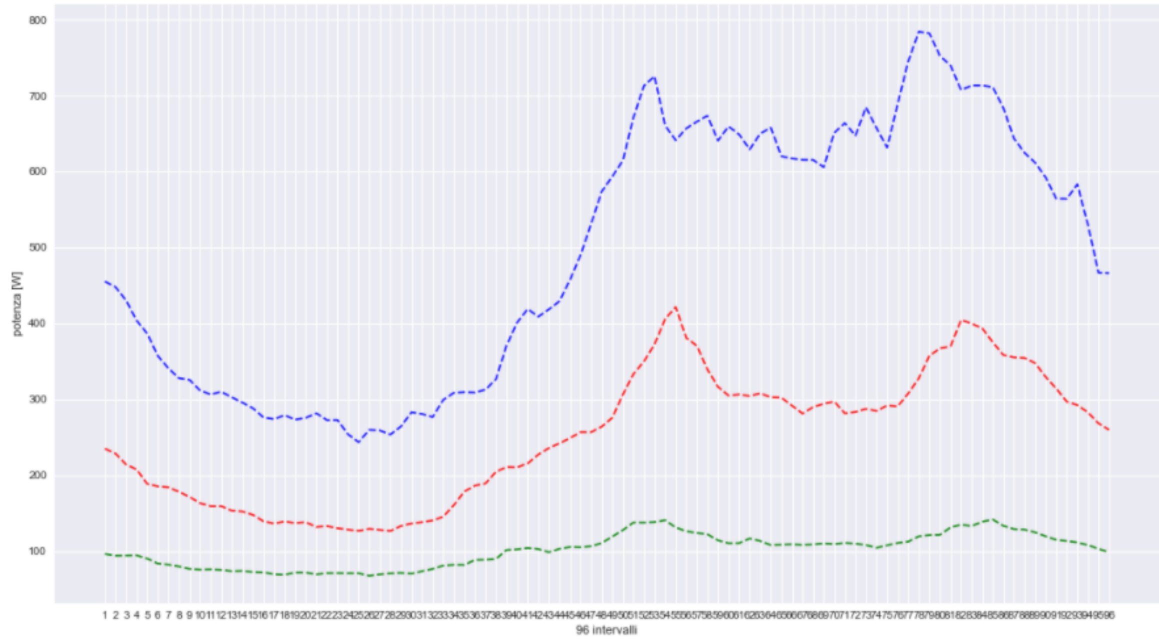


Figure 6-16 -– Mean curves of the three clusters (weekends), August

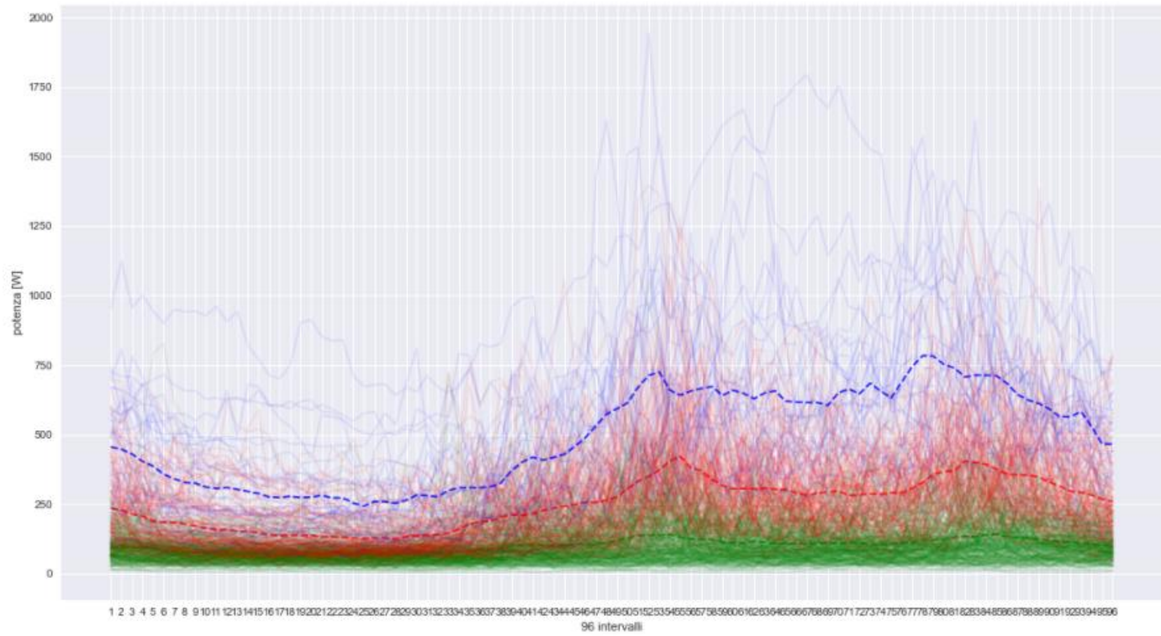


Figure 6-17 – Mean curves of the three clusters and mean power curves of daily (weekends) power curves of all customers, August.

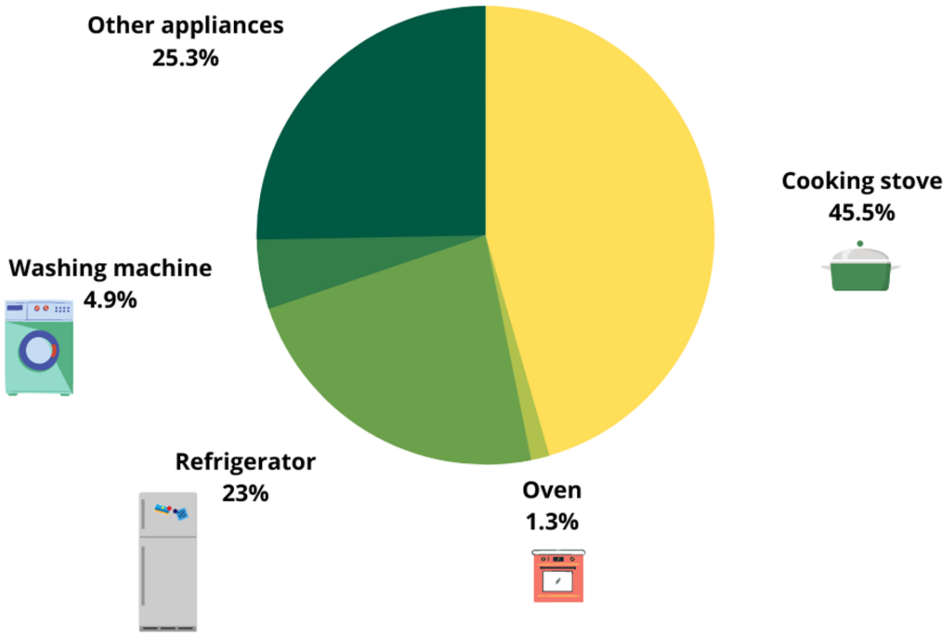
- Monthly reports examples, June, July and August

Monthly report - June

This month you consumed 95,8 kWh of electric energy.

You have been clustered as a Medium energy consumer.
June's mean energy consumption of Medium cluster is 98,4 kWh.

Energy consumption - June



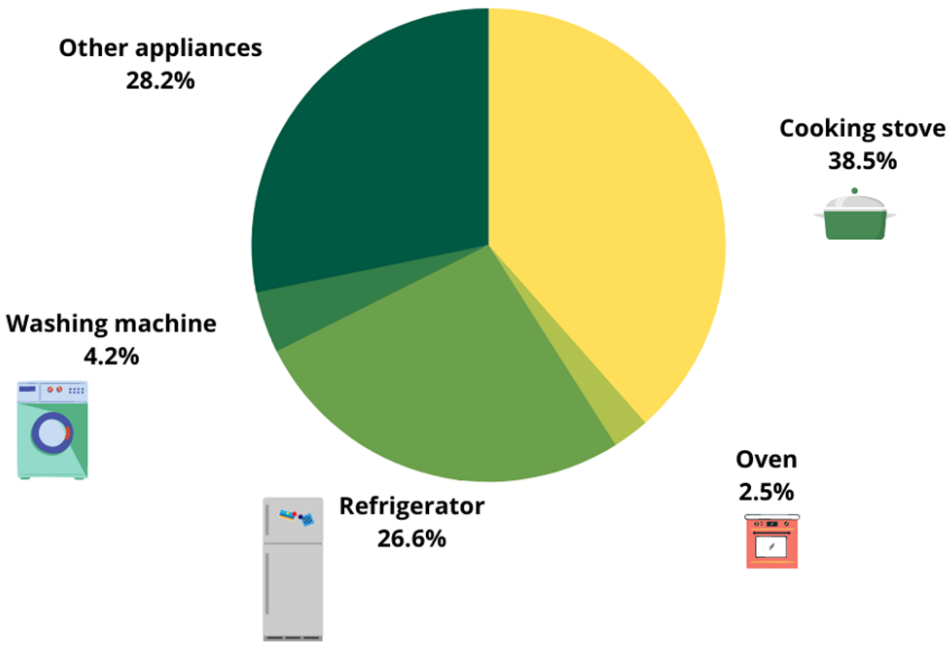
Monthly report - July

This month you consumed 93,6 kWh of electric energy.

You consumed 2,5% less than the previous month.

You have been clustered as a Medium energy consumer.
July's mean energy consumption of Medium cluster is 126,4 kWh.

Energy consumption - July



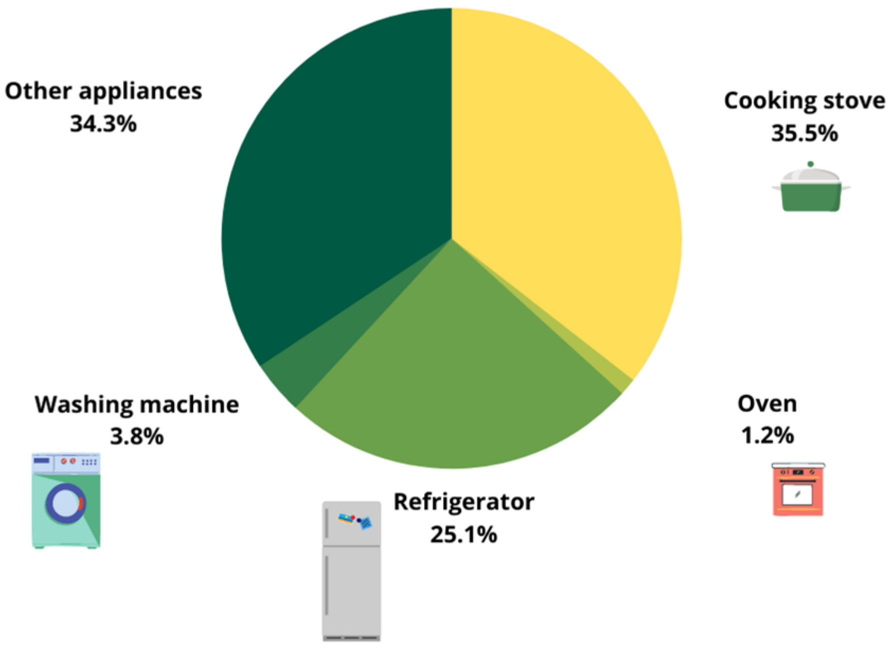
Monthly report - August

This month you consumed 107,2 kWh of electric energy.

You consumed 12,7% more than the previous month.

You have been clustered as a Medium energy consumer.
August's mean energy consumption of Medium cluster is 127,6 kWh.

Energy consumption - August



DR calculations

4 time slots – 20% energy shift

840d8ee31675 - ALTO

	FASCE	PUN		ENERGIA	COSTO	ENERGIA_NEW	COSTO NEW	
feriale	F1	0,086 €/kWh		13,45 kWh	1,1567 €	10,76 kWh	0,92536 €	20
	F2	0,075 €/kWh		37,743 kWh	2,830725 €	30,1944 kWh	2,26458 €	20
	F3	0,065 €/kWh		117,238 kWh	7,62047 €	127,4766 kWh	8,285979 €	8,031749
festivo	F4	0,058 €/kWh		96,8785 kWh	5,618953 €	96,8785 kWh	5,618953 €	0
			tot feriale	168,431 kWh	11,6079 €	168,431 kWh	11,47592 €	1,13695 %
			tot festivo	96,8785 kWh	5,618953 €	96,8785 kWh	5,618953 €	0
			tot	265,3095 kWh	17,22685 €	265,3095 kWh	17,09487 €	0,766106 %
					206,7222		205,1385	1,583712 €/anno

840d8ee26509 - MEDIO

	FASCE	PUN		ENERGIA	COSTO	ENERGIA_NEW	COSTO NEW	
feriale	F1	0,086 €/kWh		8,1395 kWh	0,699997 €	6,5116 kWh	0,559998 €	20
	F2	0,075 €/kWh		17,9915 kWh	1,349363 €	14,3932 kWh	1,07949 €	20
	F3	0,065 €/kWh		72,588 kWh	4,71822 €	77,8142 kWh	5,057923 €	6,716255
festivo	F4	0,058 €/kWh		68,87 kWh	3,99446 €	68,87 kWh	3,99446 €	0
			tot feriale	98,719 kWh	6,76758 €	98,719 kWh	6,697411 €	1,036839 %
			tot festivo	68,87 kWh	3,99446 €	68,87 kWh	3,99446 €	0
			tot	167,589 kWh	10,76204 €	167,589 kWh	10,69187 €	0,652004 %
					129,1445		128,3024	0,842027 €/anno

240ac41e7051 - BASSO

	FASCE	PUN		ENERGIA	COSTO	ENERGIA_NEW	COSTO NEW	
feriale	F1	0,086 €/kWh		5,8995 kWh	0,507357 €	4,7196 kWh	0,405886 €	20
	F2	0,075 €/kWh		10,6655 kWh	0,799913 €	8,5324 kWh	0,63993 €	20
	F3	0,065 €/kWh		42,493 kWh	2,762045 €	45,806 kWh	2,97739 €	7,232677
festivo	F4	0,058 €/kWh		34,56 kWh	2,00448 €	34,56 kWh	2,00448 €	0
			tot feriale	59,058 kWh	4,069315 €	59,058 kWh	4,023206 €	1,133088 %
			tot festivo	34,56 kWh	2,00448 €	34,56 kWh	2,00448 €	0
			tot	93,618 kWh	6,073795 €	93,618 kWh	6,027686 €	0,759145 %
					72,88553		72,33223	0,553307 €/anno

Critic peak pricing – 4 time slots – 20% energy shift

840d8ee31675 - ALTO																
	FASCE		PUN			ENERGIA		COSTO		ENERGIA_NEW		COSTO NEW				
feriale	F1	7-8, 19-20	0,25	€/kWh		13,45	kWh	3,3625	€	10,76	kWh	2,69	€		20	
	F2	12-14, 20-22	0,075	€/kWh		37,743	kWh	2,830725	€	30,1944	kWh	2,26458	€		20	
	F3	00-7, 8-12, 14-19, 22-24	0,065	€/kWh		117,238	kWh	7,62047	€	127,4766	kWh	8,285979	€		8,031749	
festivo	F4	sabato e domenica	0,058	€/kWh		96,8785	kWh	5,618953	€	96,8785	kWh	5,618953	€		0	
					tot feriale	168,431	kWh	13,8137	€	168,431	kWh	13,24056	€		4,149042	
					tot festivo	96,8785	kWh	5,618953	€	96,8785	kWh	5,618953	€		0	
					tot	265,3095	kWh	19,43265	€	265,3095	kWh	18,85951	€		2,949346	
								233,1918				226,3141	€	differenza	6,877632	€/anno

840d8ee26509 - MEDIO																
	FASCE		PUN			ENERGIA		COSTO		ENERGIA_NEW		COSTO NEW				
feriale	F1	7-8, 19-20	0,25	€/kWh		8,1395	kWh	2,034875	€	6,5116	kWh	1,6279	€		20	
	F2	12-14, 20-22	0,075	€/kWh		17,9915	kWh	1,349363	€	14,3932	kWh	1,07949	€		20	
	F3	00-7, 8-12, 14-19, 22-24	0,065	€/kWh		72,588	kWh	4,71822	€	77,8142	kWh	5,057923	€		6,716255	
festivo	F4	sabato e domenica	0,058	€/kWh		68,87	kWh	3,99446	€	68,87	kWh	3,99446	€		0	
					tot feriale	98,719	kWh	8,102458	€	98,719	kWh	7,765313	€		4,161015	%
					tot festivo	68,87	kWh	3,99446	€	68,87	kWh	3,99446	€		0	
					tot	167,589	kWh	12,09692	€	167,589	kWh	11,75977	€		2,787028	%
								145,163				141,1173			4,045734	€/anno

240ac41e7051 - BASSO																
	FASCE		PUN			ENERGIA		COSTO		ENERGIA_NEW		COSTO NEW				
feriale	F1	7-8, 19-20	0,25	€/kWh		5,8995	kWh	1,474875	€	4,7196	kWh	1,1799	€		20	
	F2	12-14, 20-22	0,075	€/kWh		10,6655	kWh	0,799913	€	8,5324	kWh	0,63993	€		20	
	F3	00-7, 8-12, 14-19, 22-24	0,065	€/kWh		42,493	kWh	2,762045	€	45,806	kWh	2,97739	€		7,232677	
festivo	F4	sabato e domenica	0,058	€/kWh		34,56	kWh	2,00448	€	34,56	kWh	2,00448	€		0	
					tot feriale	59,058	kWh	5,036833	€	59,058	kWh	4,79722	€		4,757206	
					tot festivo	34,56	kWh	2,00448	€	34,56	kWh	2,00448	€		0	
					tot	93,618	kWh	7,041313	€	93,618	kWh	6,8017	€		3,402952	
								84,49575				81,6204			2,87535	€/anno

Incentive base pricing – 4 time slots – 20% energy shift

840d8ee31675 - ALTO

	FASCE		PUN			ENERGIA		COSTO		ENERGIA_NEW		COSTO NEW			
feriale	F1	7-8, 19-20	0,086	€/kWh		13,45	kWh	1,1567	€	10,76	kWh	0,92536	€	20	
	F2	12-14, 20-22	0,075	€/kWh		37,743	kWh	2,830725	€	30,1944	kWh	2,26458	€	20	
	F3	00-7, 8-12, 14-19, 22-24	0,065	€/kWh		117,238	kWh	7,62047	€	127,4766	kWh	7,262119	€	-4,93452	
festivo	F4	sabato e domenica	0,058	€/kWh		96,8785	kWh	5,618953	€	96,8785	kWh	5,618953	€	0	
			incentivo		tot feriale	168,431	kWh	11,6079	€	168,431	kWh	10,45206	€	9,957326	
			0,1	€/kWh	tot festivo	96,8785	kWh	5,618953	€	96,8785	kWh	5,618953	€	0	
					tot	265,3095	kWh	17,22685	€	265,3095	kWh	16,07101	€	6,709504	
						18,57167		206,7222				192,8521		13,87003	€/anno

840d8ee26509 - MEDIO

	FASCE		PUN			ENERGIA		COSTO		ENERGIA_NEW		COSTO NEW			
feriale	F1	7-8, 19-20	0,086	€/kWh		8,1395	kWh	0,699997	€	6,5116	kWh	0,559998	€	20	
	F2	12-14, 20-22	0,075	€/kWh		17,9915	kWh	1,349363	€	14,3932	kWh	1,07949	€	20	
	F3	00-7, 8-12, 14-19, 22-24	0,065	€/kWh		72,588	kWh	4,71822	€	77,8142	kWh	4,535303	€	-4,03318	
festivo	F4	sabato e domenica	0,058	€/kWh		68,87	kWh	3,99446	€	68,87	kWh	3,99446	€	0	
			incentivo		tot feriale	98,719	kWh	6,76758	€	98,719	kWh	6,174791	€	8,759245	%
			0,1	€/kWh	tot festivo	68,87	kWh	3,99446	€	68,87	kWh	3,99446	€	0	
					tot	167,589	kWh	10,76204	€	167,589	kWh	10,16925	€	5,508146	%
								129,1445				122,031		7,113467	€/anno

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	FASCE		PUN			ENERGIA		COSTO		ENERGIA_NEW		COSTO NEW			
feriale	F1	7-8, 19-20	0,086	€/kWh		5,8995	kWh	0,507357	€	4,7196	kWh	0,405886	€	20	
	F2	12-14, 20-22	0,075	€/kWh		10,6655	kWh	0,799913	€	8,5324	kWh	0,63993	€	20	
	F3	00-7, 8-12, 14-19, 22-24	0,065	€/kWh		42,493	kWh	2,762045	€	45,806	kWh	2,64609	€	-4,38213	
festivo	F4	sabato e domenica	0,058	€/kWh		34,56	kWh	2,00448	€	34,56	kWh	2,00448	€	0	
			incentivo		tot feriale	59,058	kWh	4,069315	€	59,058	kWh	3,691906	€	9,274508	
			0,1	€/kWh	tot festivo	34,56	kWh	2,00448	€	34,56	kWh	2,00448	€	0	
					tot	93,618	kWh	6,073795	€	93,618	kWh	5,696386	€	6,213725	
								72,88553				68,35663		4,528907	€/anno