PREDICTION OF ELECTRICAL CONSUMPTION OF DOMESTIC HOT WATER BASED ON STATISTICAL MODEL

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Abstract

To complete at the end of the project.

Keywords: Electrical building prediction; solar panel energy consumption.

I- Introduction

In the European context, the building industry is responsible for approximately 40% of primary energy consumption. It is also a significant contributor to CO_2 emissions, around 30% according to ADEME. These emissions can be categorized as direct and indirect, with direct emissions encompassing aspects like furniture and their usage, and indirect emissions due to the production of electricity and heat required within a building. The main objective of this research is to mitigate CO_2 emissions and minimize the interaction with the grid, particularly those resulting from the consumption of fossil fuels which tends to release a higher volume of CO_2 into the atmosphere. To this end, there has been a massive shift towards Renewable Energy Sources over recent years. The decreasing availability of fossil fuels leaves no choice but to develop sustainable solutions, and reliance on Renewable Energy Sources serves as a viable response to this issue.

However, the utilization of renewable energy presents some challenges such as their intermittent availability and less efficient energy storage capabilities when compared to fossil fuel. For example, solar panels produce electricity exclusively when exposed to sunlight and are ineffective at night or under cloudy conditions. Consequently, solar panels find more application in regions with a lot of sunlight. Subsequently we need to gather the energy generated from the solar panel, store it, and make it accessible whenever wanted.

The main goal is to store renewable energy and manage renewable energy to precisely match the daily energy consumption of buildings. Nevertheless, it needs a comprehensive understanding of a building's energy consumption which can often be a difficult task. This highlights the importance of accurately predicting building energy consumption to align it with energy production. Correct predictions offer the opportunity to rely on renewable energy to produce the exact amount of energy required. It also enables to anticipate the way to produce electricity and to consume the energy locally available. It is then important to note that failing to utilize renewable energy when it is available can lead to missed opportunities for clean energy usage, showing the need to predict a framework.

In this research, the focus centers on predicting the electrical energy required for heating domestic hot water. According to the International Energy agency, heating domestic hot water consumes between 7.5 and 40% of energy. Reliable prediction in this domain provides the capacity to rely on renewable energy production and then, reduce the environmental impact. It is worth noting that the consumption of electrical energy for domestic hot water is directly correlated with the building's hot water demand. Consequently, the initial step involves several questions: How do we effectively store the energy generated by the solar panel, and what quantity should be stored to ensure access to hot water whenever required? For the purpose of storing energy for heating domestic hot water, a solution is to use a tank. This tank can receive the hot water produced by the solar panel, preserving it for use when necessary. However, a subsidiary question arises: How many tanks do we need? The consideration here is whether a single tank is sufficient for one apartment or if it should serve a group of apartments. In this paper, we will explore different approaches to address this question, recognizing that predicting the consumption of a group of apartments may be easier than for a single apartment.

Additionally, the question arises regarding the quantity of water that needs to be stored to ensure a consistent supply of hot water. To answer this question, we must work out the mean consumption of the apartments. This mean consumption serves as a reliable indicator of the accumulated amount required to obtain sufficient water when needed. Since the energy generated by solar panel is intermittent, only accessible when there is sunlight, it cannot provide energy on demand. Determining the required accumulation allows us to store enough water over a specific period when solar energy is available. The objective is to identify a timeframe when consumption patterns become consistent, enabling the sizing of tank associated with the required water volume.

Then, the next step involves predicting the domestic hot water consumption in a building, which then gives information about the required electrical energy production for water heating. In this paper, we consider energy consumption as a time series and use statistical methods for short-term load prediction. In general, short-term load prediction includes prediction window from one-hour to one-week time interval. In this research, we are focusing on a prediction window of one day with a one-hour time interval.

II- Literature

Ibrahim Ali Kachalla et al. [1] researching the prediction of domestic hot water (DHW) and its electrical consumption, highlights multiple factors influencing these consumptions. These factors encompass climate, environment, building characteristics, time of use, user behavior, technical factor and system design, control design and strategy, sources of data and measurement technique and intraday energy market.

Analyzing climate conditions and seasonal variations involves real-time and logistic projections, considering local meteorological conditions, seasonal fluctuations, habits, environmental concerns, working days or weekend and socio-economic level to predict consumption trends.

Illustrating the importance of these factors, the study conducted by Kaiser Ahmed et al. [2] focused on creating an hourly profile of individual DHW consumption, incorporating seasonal variations and occupant numbers. The study, based on 182 apartments with 379 inhabitants in Finland over a two-year period, revealed an annual average domestic water consumption of approximately 43L /day. Importantly, they observed maximum consumption in November and minimum in July, with variations of +15.3% in colder periods and -17.4% in warmer period. Furthermore, they described that the consumption was higher from November to February and lower from May to July. The study emphasized the importance of considering seasonality, prompting efforts to derive correction factors based on the month for an accurate consumption profile.

However, Kaiser Ahmed's research primarily focused on creating on hourly profile, while others aimed to predict DHW consumption, such as the research conducted by Lukas G. Swan et al. in 2011 [3]. Their analysis centered on a bottom-up approach for annual predictions in Canada. Although this differs from our current research, their findings are noteworthy. They employed an artificial neural network as a statistical method to estimate DHW consumption, suggesting that consumption is influenced by household demographics including dwelling type, the population density, system energy factor, soil temperature, heating and cooling degree day, storage tank, dishwasher use, clothes washer use… Notably, they identified a correlation between DHW consumption and average soil temperature, which tends to be greater in areas with colder soil temperatures.

Ibrahim Ali Kachalla et al. [1] also accentuates the significance of time to use in influencing consumption. Peak-hour needs are impacted by user activities, and understanding patterns can be highly complex. In their research Kaiser Ahmed et al. also attempted to explore these aspects. They showed the distinctions between weekdays and weekends, noting that the morning peak consumption is generally lower than the late evening peak as mentioned earlier.

Moreover, understanding people's behavior can provide valuable insights for predicting DHW consumption. The study conducted by Cao et al. [4] focuses on the influence of occupant behavior on consumption, considering the shower habits. Utilizing Support Vector Machine (SVM), they aimed to predict occupants' shower profiles, achieving results with an average accuracy and recall of 0.3 and 0.7 each. After predicting the shower profiles, they estimate the future hot water demand by summing individual predictions for each occupant. Impressively, the study demonstrated that predicting the shower habits of inhabitants could lead to accurate predictions. To prove it they worded out the root mean square error which is equal to 77.83% and the hot water supply assurance which is equal to 99.01%. This study proves that occupant's behavior can have a huge impact on the consumption as we thought.

Furthermore, Ibhrahim Ali Kachalla et al. [1] addressed the importance of technical factors in minimizing losses, emphasizing strategies like optimizing the pipe insulation and home-run plumbing designs to reduce energy losses. These measures aim to enhance consumption efficiency.

He also discussed the impact of control design and strategy on energy consumption, highlighting examples such as rescheduling control based on occupant consumption patterns to reduce wastage. Drawing on the findings of Kaiser Ahmed et al.'s [2] study which aimed to make consumption profile, it is obvious that such profile analysis can contribute significantly to controlling consumption over time.

Additionally, he compiled a list of methods for predicting consumption. Primarily, there are time series forecasting models designated to anticipate future water consumption by analyzing past trends and historical data. These models aim to identify patterns caused by daily routines or specific events. Among the most utilized models are Auto-Regressive Integrated Moving Average (ARIMA), Seasonal Auto-Regressive Integrated Moving Average (SARIMA), Exponential Smoothing Model, and machine learning methods such as Recurrent Neural Networks (RNN) and Long-Short Time Memory (LSTM) networks.

Mohammad Ebrahim Banihabib et al., [5] conducted research in Tehran, located in northern Iran, focusing on the forecasting methods of ARIMA and Non-Linear Auto-Regressive Exogenous (NARX). Their objective was to assess the accuracy of both methods with and without additional forecaster factors such as climatic variables. Their aim was to evaluate the impact of each factor on determining the most effective model. The evaluation of their methods involved criterions like Root Mean Square Error (RMSE), Mean Absolute Relative Error (MARE), Maximal Root Error (MAXRE), Mean Bias Error (MBE) and coefficient of determination (R^2). Their findings indicated that the ARIMA method yielded an improved forecast for DHW consumption, particularly when considering sunny hours. In the case of the NARX method, incorporating such factors such as sunny hours and population growth enhanced the prediction model for DHW consumption. The relevance is attributed to the notion that increased sunshine hours can lead to more evaporation, while population growth directly impacts water consumption.

Ibrahim Ali Kachalla et al. [1] didn't discuss another conventional method of time series research, the grey Markov model, as employed in the study conducted by Wang Zhaocai et al. [6] for the annual prediction of DHW. The researchers observed that this model provides a better fit of the original data series due to its lack of after-effects. The accuracy was further improved through Markov correction applied to the initial grey model. It's noteworthy that this method is not well-suited for long-term domestic water consumption prediction; it aligns more closely with our study's focus on short-term predictions.

For consumption prediction, data-driven, machine learning methods and Artificial Neural Networks can also be employed, considering data features such as outdoor weather, indoor environment conditions, time occupancy type, occupant energy usage behavior or historical energy consumption and degree of cloudiness. Lazzari Florencia et al., [7] employed this approach to predict hourly consumption one day-ahead of electrical consumption using smart meters and information on the local weather and the influence of the stochastic part of the user's behavior. The study was conducted in the southeastern region of Spain and fiscal smart meters were used to make the research applicable to real scenarios where personal data gathering is not feasible. To predict the overall electricity consumption, the researchers employed Gaussian mixture clustering to identify behavior clusters. Then they utilized the Extreme Gradient Boosting classification model, a tree method, to predict the day-ahead behavior pattern. This prediction was integrated into an Artificial Neural Network to enhance the analysis of user behavior and predict the electrical hourly consumption for the following day. Finally, the classification model was evaluated using the Euclidean Distance-based Accuracy.

Ibrahim Ali Kachalla et al. [1] also highlighted the Support Vector Machines (SVM) methods that are less prone to overfitting and can yield robust models. This methodology was applied in a study conducted by Jae Yong Lee et al., [8], where they aimed to forecast the demand for DHW using SVM. SVM, as a structural analysis method, considers the relationship between water consumption and various influencing factors. The study focused on 918 households over two months in both summer and winter in the Republic of Korea. Like Ahmed et al., they underline the importance of seasonal behavior, noting that winter flow demand was 4.7 times higher than in summer, with distinct morning and evening peak consumptions during weekdays from 7 to 8 in the morning and 18 to 19 in the late afternoon. The researchers also explored the demand predicting based on the preceding outdoor temperatures. They discovered that the consumption might depend on the outdoor temperatures several days before the prediction day. To forecast DHW demand, they employed SVM, utilizing outdoor temperature and DHW energy demand. The study included k-fold cross-validation and the Nash Sutcliffe model efficiency coefficient to identify the most effective model. Their results indicated that the predictions were most accurate in winter when considering a four-day ahead outdoor temperature, while a five-day ahead temperature was optimal for summer.

Finally, we can introduce another approach that depends on the specifics of the study's country. For instance, Wojciech Rzeznik et al., [9] conducted a study comparing actual and forecasted domestic consumption and heat power demand in buildings in Poland. Their research included a comparison of various methods to determine the most effective one. Data for this research were gotten from the annual monitoring of DHW and heat power demand in eight buildings situated in Central Poland during 2021. The compared prediction methods included Sander's, Recknagel's, the standard method and the method according to Polish regulation 2018 and 2015. Their evaluation focused on the relative forecasting error. It is noteworthy that the study revealed that the optimal method for predicting DHW consumption differed from that for forecasting heat power energy for DHW. Specifically, for DHW consumption, the best method was identified as the standard regulation of 2015 in Poland, whereas for heat power, the standard method proved to be the most accurate. The 2015 regulation method is grounded in factors such as apartment area, average heat power, average efficiency of the DHW system, usable energy demand for DHW and annual water consumption. On the other hand, the standard method relies on the average and maximum hourly DHW demand, utilizing the hourly coefficient of irregularity.

III- Methodology

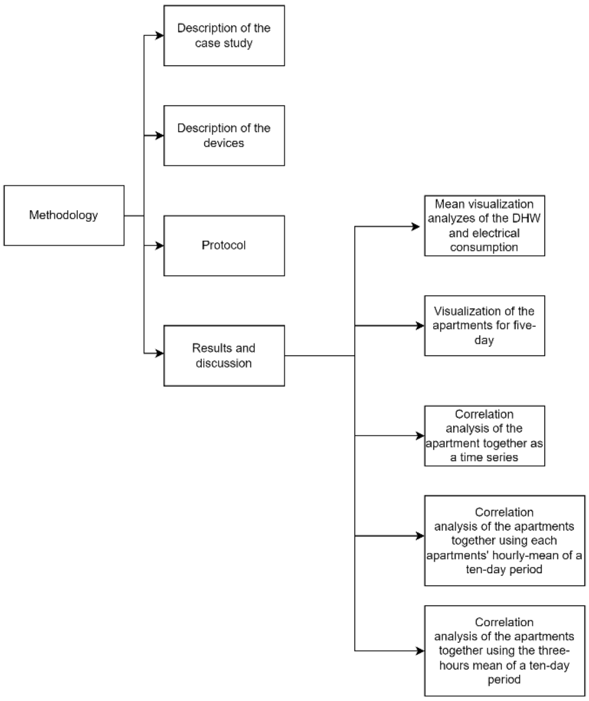

Figure 1: Framework

a. Description of the case study

The case study involves a two-years data collection period from 2020 to 2021 in the City of Villefontaine, situated near Lyon in France. Specifically, the data was gathered in the 'Les Roches' district which contains five sets of three buildings each. The measurements were conducted in building C, and specifically on the building C2 which is a R+5 building of the larger complex. The complex is made of two building with five stories (R+5) and one of three stories (R+3). This building C2 comprises four apartments located on the second floor and four apartments situated on the third floor. The apartments are respectively identified as 33, 34, 35, 36, 63, 64, 65, 67. It is noteworthy that apartment 33 remained unoccupied during the monitoring period. Therefore, its data was excluded from the analysis.

The measurements were made on the building called C which is composed of two buildings in R+5 and one building in R+3. The monitored values were taken in the building C2 in R+5, four apartments were on the second floor of the building and four other on the third floor. The apartments are respectively named 33, 34, 35, 36 and 63, 64, 65, 67. Noted that the apartment 33 is not occupied so we didn't take its data into account in the method.

The next table gives information about each apartment considering their apartment's type, population, daily average DHW consumption, DHW system, tank volume, yearly energy consumption and the use of the individual heater.

The case study also involves the city of Rive de Gier in the Loir department in central France. The district is called 'Maréchal Juin' and formed of two-building. One of the buildings is a R+8 building and the other is a R+6 building. The measurements were made on three apartments on the 7th floor of the R+8 building and two apartments of the R+6 buildings, they are identified as 25, 26 and 27 in the R+8 building and as 8 and 9 in the R+6 building. However, we won't take into consideration the apartment 8 because we don't have enough measurements about the electricity consumed by the DHW.

The Table 1 gives information about each apartment considering their apartment's type, population, daily average DHW consumption, DHW system, tank volume, yearly energy consumption and the use of the individual heater.

Table 1: Information about the apartments

Apartment n°	Apartment						ily average DHW consumption (l/day)	DHW system	Tank volume (L)	Yearly NRG consumption (kWhelec/year)	Use of the heater individual
33	T3	-	-	-	-	-	-	-		-	Not active
34	T3	1	-	2	-	-	95	off-peak hour	150	5600	Active
35	T4	2	1	1	1	-	105	off-peak hour	200	6100	Not active
36	T4	-	2	1	1	-	82	off-peak hour	150	11500	Not defined
63	T5	3	-	3	3	-	316	without off-peak hour	150	11500	Active
64	T2	-	-	1	-	-	28	off-peak hour	150	2000	Active
65	T2	2	-	2	2	-		without off-peak hour	150	10200	Active
67	T5	-	-	1	1	-	53	off-peak hour	200	3900	Not Active

b. Description of the devices

To collect all the necessary data, the main monitoring device utilized is the Eco-Touch device, supplied by the company OGGA, and serves as an energy supplier working with a 230V power source upstream of a circuit breaker. This instrument is able to measure electricity consumption directly and can facilitate other types of measurements such as indirect ones.

Direct measurements are those acquired by the Eco-Touch device itself, which is connected to the main electrical board of the house. It has four toroids, each one is monitoring a specific electrical consumption parameter. One toroid is dedicated to capturing the overall electrical meter reading, another focuses on the circuit breaker for outlets, a third is dedicated to the additional electrical DHW circuit, and the fourth is designated for the electrical radiator circuit and, when present, the air conditioning circuit.

Indirect measurements, on the other hand, are accomplished through a set of sensors and transmitters. These include an indoor temperature and humidity sensor that can be placed in various indoor spaces where monitoring is required. Temperature readings are taken every 100 seconds and sent to the Eco-Touch whenever a change of 0.5°C or a change of 2% of humidity is occurring.

Additionally, an outdoor temperature and humidity sensor is used, which sends data when there is a variation of 0.6°C in temperature and 2% in humidity. If the values remain stables, periodic status updates are sent every 100 to 3000 seconds.

There is also an illuminance sensor, provided by the company Eltako which is equipped with a small solar cell and a battery. This sensor communicates with the Eco-Touch when the illuminance level is above 300 Lux and whenever there is a notable change of brightness, typically above 500 lux within about 100 seconds.

Furthermore, the monitoring system includes a window opening detector and a volumetric meter for DHW consumption. The measurement of hot water is accomplished using three instruments working together: the volumetric meter Aquadis + mark ITRON, the Cyble Impluse Sensor mark ITRON and the OGGA Impulse Counter mark OGGA.

Overall, the case study has a huge monitoring approach, covering aspects such as window openings and closures, both internal and external temperature and humidity, external illuminance, volume of domestic hot water consumed, average electricity consumption for various systems including heating, DHW, household appliances, underground heating and the total average electricity usage.

On the figures below, there is the map of the sensor in the building C2 (Figure 3 and Figure 3: Plan of the third floor of the building C.) and the district of 'Maréchal Juin' (Figure 5 and Figure 5).

Figure 2: Plan of the second floor of the building C.

Figure 3: Plan of the third floor of the building C.

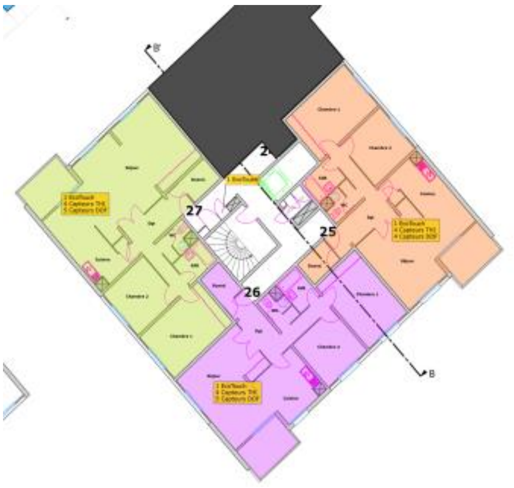

Figure 4: Plan of the seventh floor of Rive de Gier

Figure 5: Plan of the R+6 building of Rive de Gier

c. Protocol

The initial phase of our study involves visualizing the data. The first analysis focuses on mean values over the two-year period with hourly sampling. Our second hypothesis is to examine the data-patterns over a five-day period using hourly sampling to identify common trends. Subsequently, this visualization will serve as the basis for our correlation analysis.

Our initial hypothesis involves grouping apartments together with similar patterns before predicting consumption. Predicting consumption for a group of apartments seems more manageable than for individual ones. Therefore, we start our study by searching a method to group our apartments together. Our first assumption is that they show a time-series connection, meaning some apartments are correlated over the days, with a correlation coefficient above 0.5. To test this hypothesis, we initially observe a five-day week time series from 07/12/2020 to 12/12/2020 for all apartments. Subsequently, we work out correlations among all apartments to identify potential groups. However, the patterns may change if the period is not from 07/12/2020 to 12/12/2020 so we extend the analysis by adding one more day and examining if the correlation coefficients remain constant or change. As a comprehensive approach, we also examine another five-day week from

14/12/2020 to 19/12/2020 to ascertain whether the identified groups, if any, persist or undergo modifications. In the case of changes, we look at the coefficients to understand their variations.

If our first hypothesis to group the apartments together is unsuccessful, our second hypothesis to group the apartment together aims to identify correlation between apartments and patterns by smoothing the variations among apartments using mean values over a ten-day period, creating a more accurate and refined feature than a single day's observation. This involves calculating the mean values over ten days for each hour and apartment, along with observing the corresponding standard deviation. Then, we will analyze the correlation between the mean values of each apartment to identify potential correlations among them. To validate the consistency of these correlations, we will replicate the study using another set of ten days, determining whether the observed correlations remain unchanged or undergo modifications.

If unsuccessful, an alternative approach involves investigating whether an apartment exhibits temporal self-correlation and determining the appropriate timestep for such correlation. This study begins with three-minutes samples and progressively increases the timestep, moving to one-hour samples and further resampling for morning and afternoon periods. The underlying hypothesis suggests that a sole apartment may have a longer timestep for self-correlation. If this proves true, the next step is to examine the mean consumption of five apartments together, hypothesizing that it might reduce the timestep when combining multiple apartments. The rationale is that predicting consumption for a group of apartments may be more manageable than for an individual one. The objective is to minimize the timestep based on our findings, as this will guide the determination of the tank size needed to accommodate the consistent consumption. If the required storage timeframe is too extensive, it could lead to an impractically large tank.

If successful in establishing distinct groups, our further goal is to predict the time-series based on specific criterion. These factors are the amount of data, data quality, seasonality, trends and unexpected events. The amount of data is about the quantity of available data, where having a lot of data enhances the potential for constructing a more accurate model. Data quality involves the lack of duplicates, a standardized data format and a constant interval for the data. Seasonality refers to the distinct periods of time for the data when it contains consistent irregularities. The trends indicate whether a variable within the time series is expected to increase or decrease over a specified period. Finally, the unexpected events encompass unpredictable noise present in historical data. To predict the time series, we will use multiple linear regression, utilizing both the time series input and past consumption data.

d. Results and discussion

i. Mean visualization analyzes of the DHW and electrical consumption

The preliminary analysis is divided into two main sections. The first section examines the daily average consumption for domestic hot water and electrical usage of domestic hot water. While the second section explores the average consumption of domestic hot water and its electrical usage over several days.

Our initial step includes looking to the time intervals associated with each apartment's data since the data files have varying time step. The average time interval for electrical consumption data falls in the range of 2-3 minutes, while for domestic hot water consumption, it falls between 5-10 minutes. To standardize our analysis, we perform a resampling of all the data with an interval of 10 minutes.

We initiate our study by focusing on the average domestic hot water consumption. We obtain this data from the devices described earlier. We are first resampling our data to get the mean values per hour. Then we have the Figure 7 and Figure 7 that illustrates the mean hour consumption of hot water for one day.

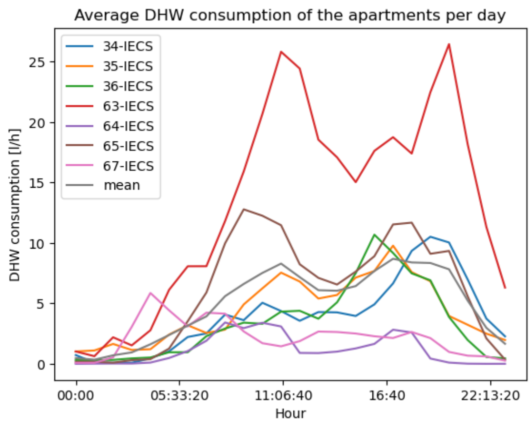

Figure 6: Graph presenting the average DHW consumption of each apartment per day of the city of Villefontaine

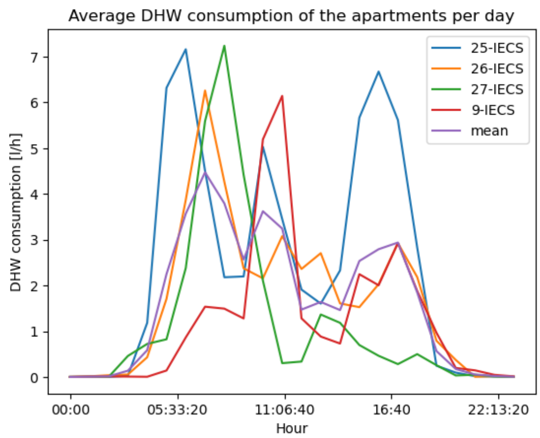

Figure 7: Graph presenting the average DHW consumption of each apartment per day of the city of Rive de Gier

To get these values, we worked out the mean across the two-year dataset at our disposal. A pattern emerges from the data, with a peak of hot water consumption occurring between 5 and 11 AM and again in the late afternoon, present until 10 PM. It is noteworthy that most apartments apartments have higher consumption levels in the late afternoon in the city of Villefontaine while the peak is in the morning in the district of 'Maréchal Juin'. This suggests a recurring pattern where inhabitants tend to use domestic hot water primarily in the morning or late afternoon.

Further examination reveals that four apartments of the city of Villefontaine seem to share a similar consumption pattern. Their major consumption preak is in the late evening, and they have lower consumption levels in the morning. Nevertheless, it's important to note that apartment 63 stands out with an extremely different consumption pattern. It has the highest daily consumption of domestic hot water over the day.

The examination of the apartment of the city Rive de Gier reveals that only one apartment shows a consumption pattern like the one observed in the Villefontaine apartments. Specifically, this apartment demonstrates a peak consumption in both the morning and late afternoon. In contrast, the remaining apartments display different patterns. Notably, a common trend among these apartments is the occurrence of higher consumption peaks in the morning, although the timing may vary. The apartments 26 and 27 appear to share a similar consumption pattern throughout the day, while the apartment 9 also shows a comparable pattern, even though with a peak in late morning as opposed to the early morning peaks observed in the Villefontaine apartments.

For further information, we can also examine the histogram presented in Figure 9 and Figure 9.

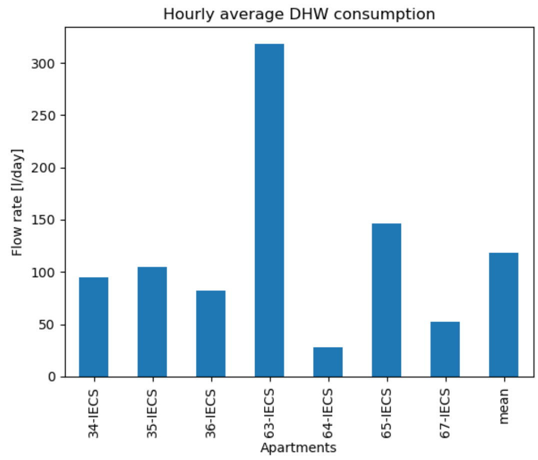

Figure 8: Histogram of the average DHW consumption per day of the city of Villefontaine

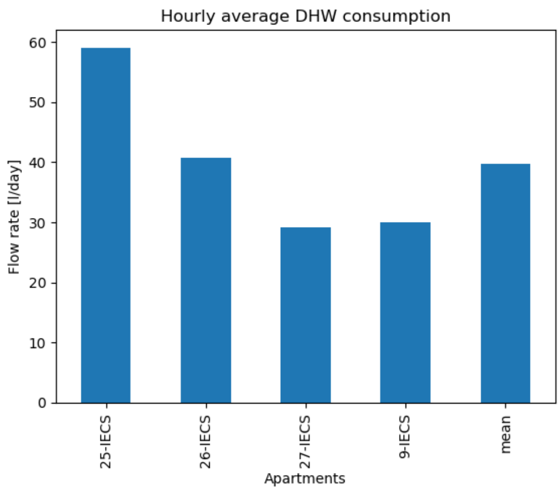

Figure 9: Histogram of the average DHW consumption per day of the city of Rive de Gier

As anticipated, the histogram of Villefontaine shows that the consumption patterns of apartments 34, 35, 36 and 65 are nearly identical. However, it is clear that the apartment 63 stands out with a significant higher consumption rate, almost three times that of the other apartments. This can be attributed to the fact that it accommodates more residents. On the other hand, the apartment 64 has notably lower consumption levels.

In contrast to the values observed in Villefontaine, it is evident that the apartment 25 shows a consumption pattern nearly identical to those observed in the group encompassing the apartment 34, 35, 36 and 65. On the other hand, the apartments 9, 26 and 27 demonstrate lower consumption levels like the apartment 64.

Then, we will examine the electrical consumption associated with the demand of domestic hot water over one single day. In the Figure 10 and Figure 11, we observe a peak in electrical consumption for seven apartments at 10 PM. This is due to the boiler's operation during off-peak hours when there is minimal consumption. It presents a challenge when attempting to predict the electrical demand for hot water throughout the day, as it is based on the overall demand for a day rather than real-time demand. This is one of our motivations behind our goal to predict domestic hot water consumption as a precursor to accessing electrical consumption. The electrical consumption in the four other apartments is distributed throughout the day, attributed to the fact that the system remains active all day.

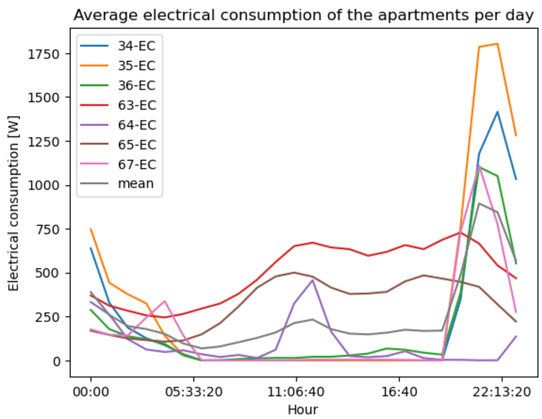

Figure 10 : Average electrical consumption of each apartment of the city of Villefontaine per day

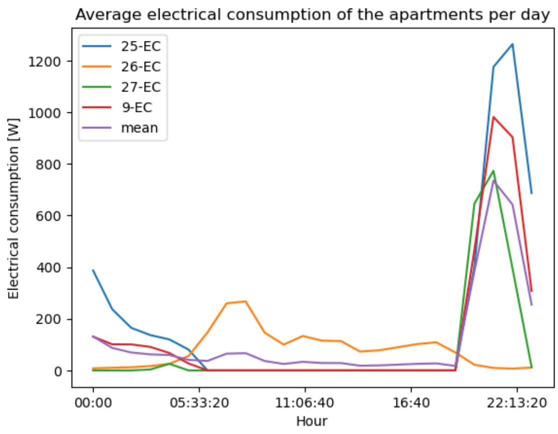

Figure 11 : Average electrical consumption of each apartment of Rive de Gier per day

Furthermore, examining the histogram in Figure 13 and Figure 13, we note that the apartment 63 still has higher consumption compared to the others, but the clear pattern observed earlier is not as pronounced. In this context, we can group the apartments 34, 35 and 65 together, while the consumption pattern of the apartment 36 is not as clear as previously.

In the case of Rive de Gier, it is notable that Apartment 25 shows a tendency to share similar values with the apartment 36. Similarly, the apartments 9, 26 and 27 appear to show values equal to those of the apartment 64, as observed previously for water consumption.

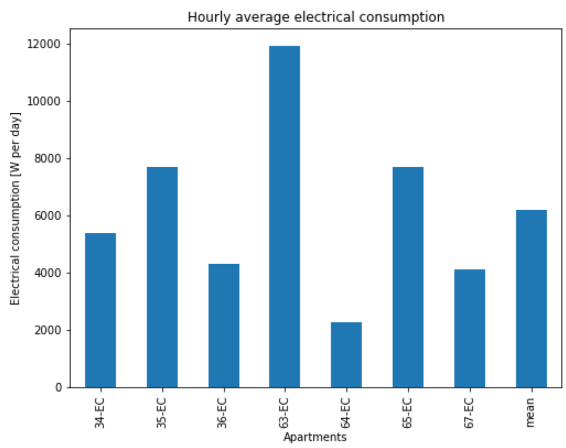

Figure 12 : Histogram of the electrical consumption per day of Villefontaine

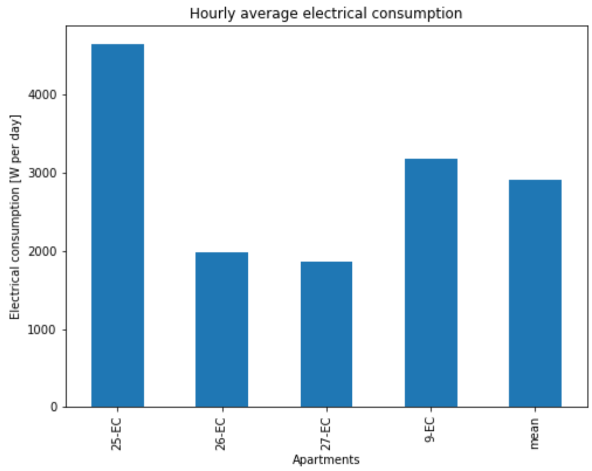

Figure 13 : Histogram of the average electrical consumption of the apartments per day of Rive de Gier

ii. Visualization of the apartments for five-day

As described in the protocol, we have organized our data into two distinct sets: one for training purposes and the other for testing. It involves the collection of data over a span of several day. Specifically, we follow the protocol's guidelines, which prescribe a data collection period of five weekdays, starting from December 7 to December 11, 2020.

As previously mentioned, our approach includes clustering the apartments into groups with similar consumption patterns. Firstly, we analyzed the average daily consumption, and now we are extending our analysis to a five-day consumption pattern.

Our study is based on hourly predictions, and for this phase of our study, we are evaluating the hourly means for each apartment over the course of the five days selected.

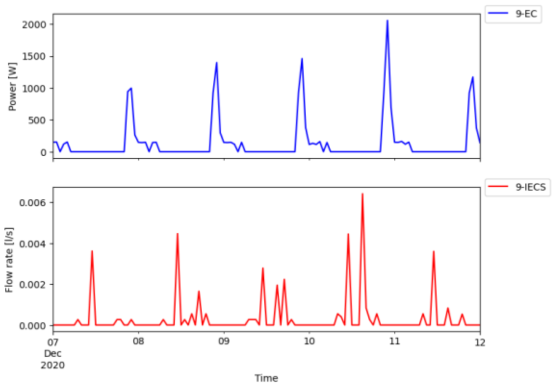

Figure 14 : DHW (red) and electrical (blue) consumption between December 7th to December 12th, 2020 of the apartment 9

Figure 14 provides information regarding the consumption of DHW and the associated electricity usage for heating water in the apartment 9. The electrical analysis exhibits a gap during the day, with a peak occurring towards the end of the day. This pattern is due to the system operating during off-hours. Notably, there is a peak flow rate in the middle of the 7th day, while from the 8th to the 11th, the consumption appears to be distributed more evenly throughout the day. On December 10th, both DHW and electrical consumption reach their highest points, with this day showing the maximum electricity usage over the five-day period. Furthermore, the lowest electrical peak corresponds to the lowest consumption observed on December 7th. Interestingly, on December 9th, the DHW consumption is spread across the day, whereas on the 8th, there is a peak with some lower consumption. Despite these differences both days result in an equal electrical peak at the day's end.

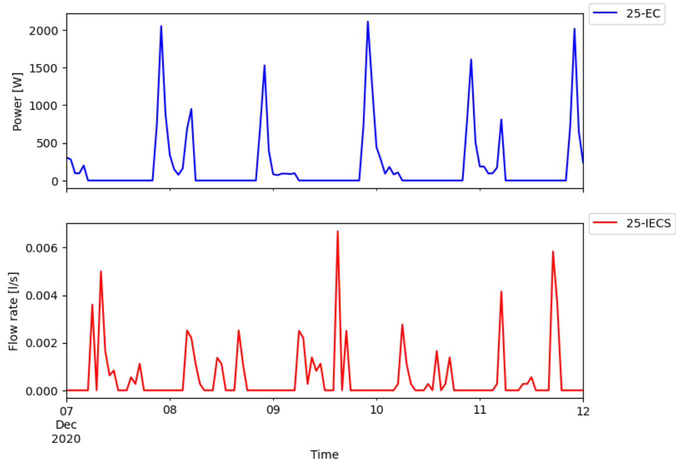

Figure 15 : DHW (red) and electrical (blue) consumption between December 7th to December 12th, 2020 of the apartment 25

Figure 15 provides insights into the DHW and electrical consumption of the apartment 25. The electrical analysis indicates a lack of usage during the day, with a peak occurring in the late evening and early morning, even though the early morning peak is lower than the nighttime peak. When comparing this apartment to the apartment 9, it is observed that the consumption is higher on December 9th instead of December 10th. However, the electrical peak on that day is not the singular highest one. Interestingly, there are three peaks in electrical consumption, both around 2000 W, occurring on December 7th, 9th, and 11th.

Further examination reveals that the consumption pattern on December 7th appears to resemble that of December 9th but is more dispersed, with a peak in the morning instead of the afternoon. On the contrary, the consumption on December 11th differs significantly, featuring two peaks, one in the morning and another in the afternoon. Notably, the consumption on December 8th and 10th follows a similar pattern with spread consumption and an electrical peak around 1500 W.

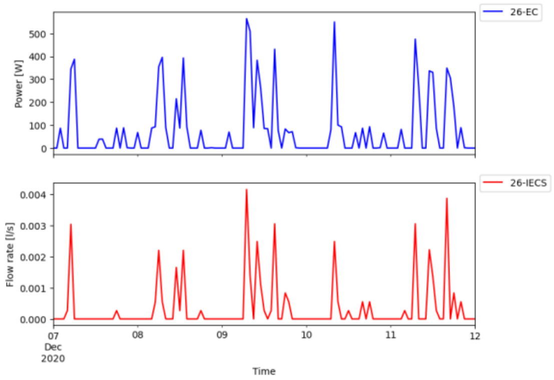

Figure 16 : DHW (red) and electrical (blue) consumption between December 7th to December 12th, 2020 of the apartment 26

Figure 16 illustrates the DHW and electrical consumption patterns in the apartment 26. The electrical analysis reveals a consistent consumption throughout the day, meaning that the system operates without off-hours. Notably, the electrical consumption peaks never exceed 500 W. Interestingly, the peaks in electrical consumption align with the DHW peaks observed throughout the day.

For example, the single peak on December 7th corresponds to an electrical peak of approximately 400 W. Similarly, both DHW peaks on December 8th are repeated in the electrical consumption, manifesting as two distinct peaks. Furthermore, December 9th is the day with the highest electrical, featuring a morning peak and additional dispersed peaks throughout the day. This high consumption corresponds with high demand for DHW. Interestingly, the minor peak on December 10th results in a notable morning peak in electrical consumption.

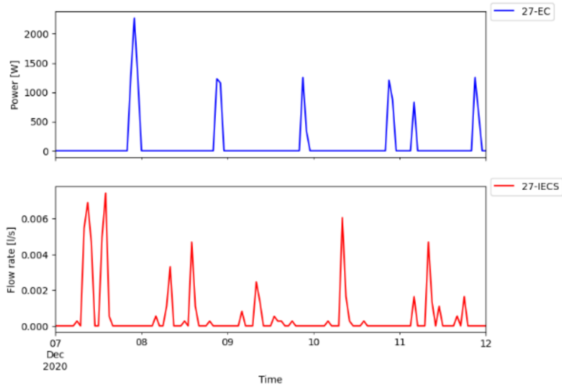

Figure 17: DHW (red) and electrical (blue) consumption between December 7th to December 12th, 2020 of the apartment 27

Figure 17 represents the consumption patterns of the apartment 27. The electrical analysis reveals that the system operates during off-hours, exhibiting peaks in the late evening. The highest peak in electrical consumption aligns with the DHW peak consumption on December 7th, characterized by two morning peaks. Interestingly, the four subsequent peaks in electrical consumption remain consistently the same, even though the associated DHW consumptions do not exhibit identical patterns. For instance, on December 8th, two mornings peaks are observed, while on both December 9th and 11th, the consumption is lower and dispersed throughout the day. Notably, December 10th stands out with a sole peak in the morning, contrasting with the preceding days, despite having the same level of electricity consumption.

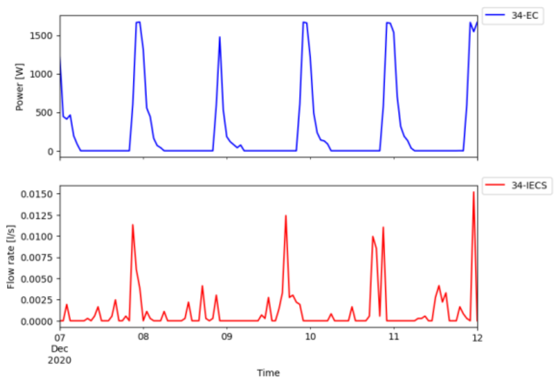

Figure 18: DHW (red) and electrical (blue) consumption between December 7th to December 12th, 2020 of the apartment 34

Figure 18 displays the DWH and electrical consumption trends in the apartment 34. The electrical system operates during off-hours, with peaks occurring in the late evening. It is noteworthy that these peaks are consistently around 1500 W. However, it's worth noting that the DHW consumption do not shared patterns across all days. Indeed, peak consumptions occur towards the end of the day, except for December 9th, when the consumption is spread throughout the entire day.

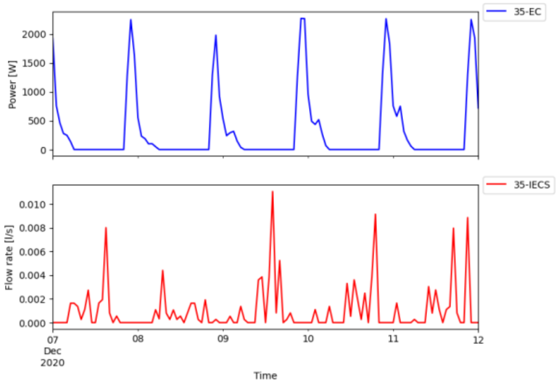

Figure 19: DHW (red) and electrical (blue) consumption between December 7th to December 12th, 2020 of the apartment 35

Figure 19 represents the DHW and electrical consumption patterns of the apartment 35. The electrical consumption patterns reveals that the system is operating during off-hours. Like the apartment 34, the apartment 35 also displays electrical peaks consistently around 2000 W even though variations in DHW peak consumption. For instance, December 9th, 10th and 11th appear to exhibit the highest DHW consumption peak, whereas on December 8th, the consumption is dispersed throughout the day. December 7th represents a mix of patterns observed in other days, featuring both spread consumption and a peak in the late afternoon.

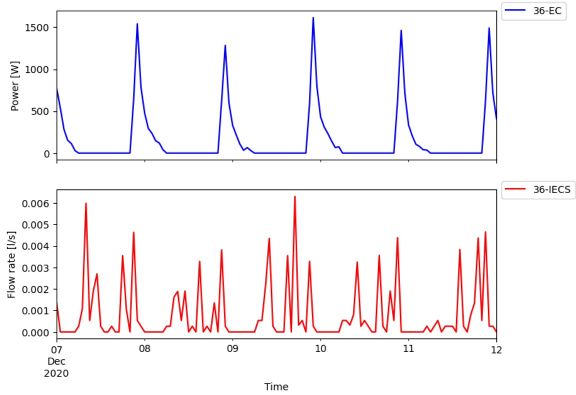

Figure 20: DHW (red) and electrical (blue) consumption between December 7th to December 12th, 2020 of the apartment 36

Figure 20 illustrates the DHW and electrical consumption of the apartment 36. The electrical consumption pattern exhibits some peaks at the day's end meaning that the system is operating during off-hours. The consumption pattern exhibits a consistent use of DHW throughout the day. Peaks are spread across various times, with the highest peaks not consistently occurring simultaneously and varying from day to day. Furthermore, the days with the highest DHW consumption, such as December 7th and 9th, corresponds to the peak in electrical consumption. Nevertheless, it is noteworthy that even on days with lower DHW consumption, the electrical usage remains above 1000 W.

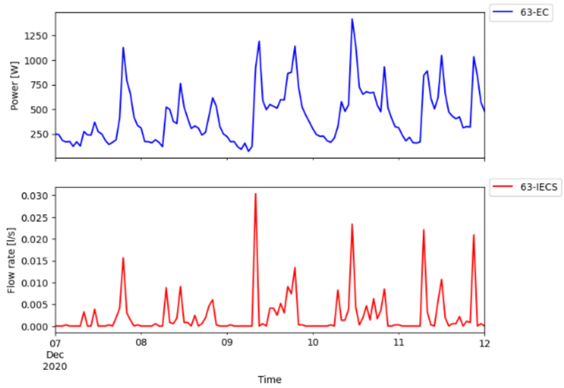

Figure 21: DHW (red) and electrical (blue) consumption between December 7th to December 12th, 2020 of the apartment 63

Figure 21 displays the DHW and electrical consumption of the apartment 63. The electrical consumption is consistent throughout the day, we assume that the system is operating without off-hours. The peak in electrical consumption during the day aligns with the highest demand for DHW. Interestingly, even when the DHW demand is low, electrical consumption maintains a level around 250W throughout the day. On the contrary, for systems operating during off-hours, the consumption drops to 0 during the day.

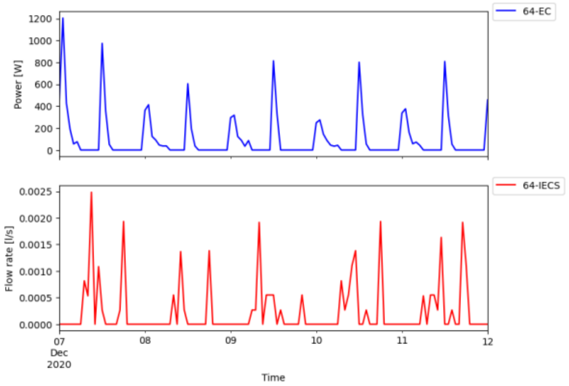

Figure 22: DHW (red) and electrical (blue) consumption between December 7th to December 12th, 2020 of the apartment 64

Figure 22 provides insights into the DHW and electrical consumption of the apartment 64. The electrical analysis reveals two main peaks in the day: one in the midday and the other in the late afternoon. This suggests a potential dual operating of the system during off-hours. Comparing the DHW and electrical pattern, it can be assumed that the morning electrical peak corresponds to the DHW demand in the morning. For example, on December 7th, there is a higher peak at 12 in the morning, aligning with the high demand for morning DHW, and a lower peak in the afternoon, corresponding to the sole DHW peak in the afternoon. Conversely, the lowest electrical peak is linked to the lowest DHW consumption peak in the morning, as seen on December 8th. Notably, the electrical pattern remains consistent on December 9th, 10th and 11th, while the water consumption differs. This suggests that the water consumption for these days is relatively similar in terms of electrical usage.

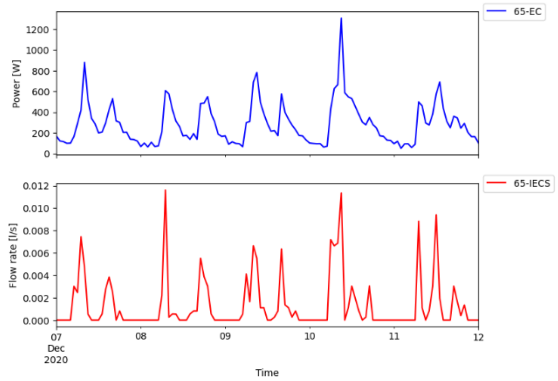

Figure 23: DHW (red) and electrical (blue) consumption between December 7th to December 12th, 2020 of the apartment 65

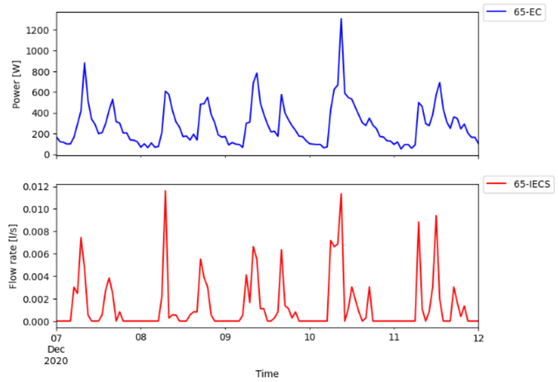

Figure 23 represents the DHW and electrical consumption of the apartment 65. The consistent electrical consumption pattern is a clue to deduce that the system is operating without off-hours. Once again, the electrical peak aligns with the demand for DHW. Interestingly, the highest peak on December 9th does not coincide with one of the highest electrical peaks. In fact, it corresponds to one of the lowest electricity consumptions over the five-days period. On December 12th, two main peaks are observed, yet the associated electrical consumption is around the weekly mean of approximately 600 W. On the contrary, the peak on December 10th results in the highest peak in the electrical analysis, highlighting it as the sole day with a discernible difference in electrical consumption compared to the other days.

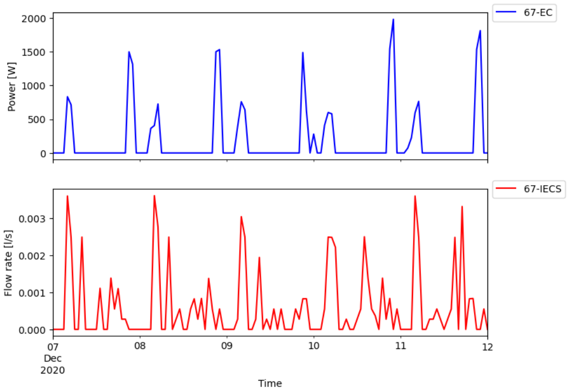

Figure 24: DHW (red) and electrical (blue) consumption between December 7th to December 12th, 2020 of the apartment 67

Figure 24 dwells the DHW and electrical consumption of the apartment 67. The electrical consumption, composed of peaks in the late afternoon, provides insights about the system used to get electricity, the system is operating during off-hours. Examining the DHW consumption patterns, there is a consistent spread of hot water usage throughout the day. Typically, one or two peaks are observed, followed by dispersed consumption through the day. Noting that the highest DHW consumption does not necessarily align with the highest electrical consumption. For example, the peak electrical consumption occurs on December 10th, while the DHW consumption on that day corresponds to one of the days with the most dispersed DHW demand. However, the overall DHW demand remains high throughout the day, distinguishing it from the other days with reduced demand.

The data presented in the figures above illustrates the hourly mean values over a five-day period for each apartment. Notably, the apartments 34, 35 and 36 show similar consumption profiles, with their higher peak occurring nearly simultaneously. However, the apartment 34 show a lower consumption outside of these peaks compared to the apartment 35 and 36, which have higher consumption levels throughout the day. As they use water during the day, their peak is lower than that of the apartment 34.

Then the apartments 64 and 65 also appear to share comparable consumption profiles over the five days, with consumption values varying within a range of 10^(-2) for each apartment and the same peak. It is noteworthy that, the apartment 64 shows a domestic hot water consumption higher than the apartment 65.

We can assume that the apartments 25, 26 and 27 share a similar pattern as well. Their peaks occur at nearly the same time, although some apartments have higher peak than others. Furthermore, their higher consumption is around 0.006 l/s for each apartment.

The observed patterns in this second visualization are clearly distinct from those in the initial one. This difference will influence our correlation analysis. Indeed, we will determine whether it is more advantageous to identify patterns based on mean values or time-series correlations, if feasible.

iii. Correlation analysis of the apartment together as a time series

Our initial time-series correlation analysis spans from December 7th to December 12th, 2020, covering a five-day period as described in the methodology. The correlation values were worked out for all apartments across these five days. The Figure 25 illustrates that the correlation values consistently remain below the 0.5 threshold, indicating a lack of correlation among the apartments. Consequently, our hypothesis of forming groups based on these specific days is not suitable. However, we aim to investigate whether this absence of correlation is exclusive to this particular time frame. To explore this, we will assess correlation between apartments on different days within December and then compare them with correlation on a different month, June. Our goal is to determine if correlation values persist for the same apartment within the same month and if they remain consistent across different months of the year.

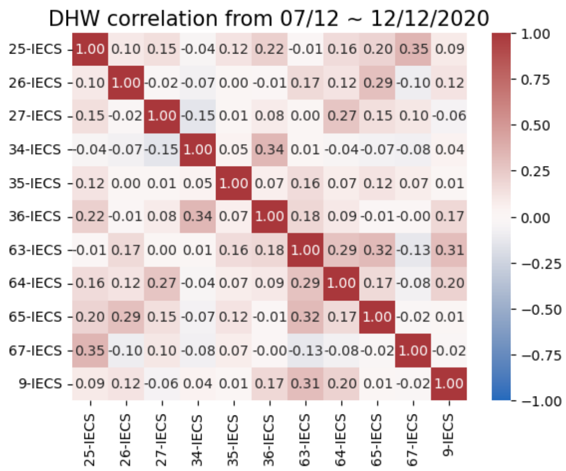

Figure 25: Correlation analysis

Subsequently, to proceed, we aim to identify the highest correlation values and the corresponding apartments. Initially, the apartment 25 shows a correlation of 0.22 with the apartment 36 and 0.35 with the apartment 67. The apartment 26 has a correlation of 0.29 with the apartment 65. The apartment 27 exhibits a correlation of 0.27 with the apartment 64 but notably varies from the apartment 34, displaying a correlation of -0.15. The apartment 34, in turn, has one of the highest correlation values with the apartment 36 reaching 0.34. Lastly, the apartment 63 demonstrates notable correlation values with three other apartments: 0.29 with the apartment 64, 0.32 with the apartment 65 and 0.31 with the apartment 9. Our objective is to compare these correlation values with those obtained from the analysis covering one more day.

Continuing our analysis, we extend the time series correlation to encompass six days, from December 7th to December 13th, 2020. The correlation Figure 26 shows the relationship between all the apartments, revealing that none of them exhibit correlations surpassing the 0.5 threshold. Nevertheless, we aim to identify any differences in correlation coefficients between the previous analysis and this extended one.

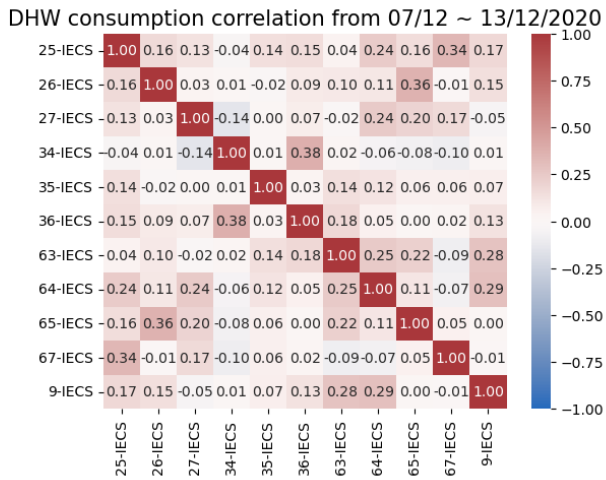

Figure 26: Correlation analysis

The apartment 25 maintains a high correlation with the apartment 67, although the correlation factor changes for the apartment 36 as it becomes lower. Notably, the apartment 63 shows a shift in the correlation coefficient, now displaying a higher value. The observation suggests that the correlation values are subject to change over time. The apartment 26 appears to sustain a ‘high’ correlation with the apartment 65. The apartment 67 maintains a ‘high’ correlation with the apartment 64 and continues to differ significantly from the apartment 34. On the other hand, the apartment 34 shows the highest correlation with the apartment 36, reaching 0.38. Moreover, the apartment 63 maintains notable correlation values with the same three apartments as before: 0.25 with the apartment 64, 0.22 with the apartment 65 and 0.28 with the apartment 9. Lastly, the apartment 64 develops a higher correlation rate with the apartment 9, a change not previously observed.

In conclusion, the correlation values show variability over days, yet high correlation values persist for most apartments. However, it is important to note that this analysis is an extension of the previous one, and we intend to compare the initial coefficients with those obtained from another week independent of December 7th to December 12th.

The analysis now shifts to the week from December 14th to December 19th, as showed in the Figure 27. As observed previously, the correlation coefficients once again fail to surpass the 0.5 threshold. Furthermore, comparing the coefficients between the week of December 7th and the week of December 14th reveals significant changes.

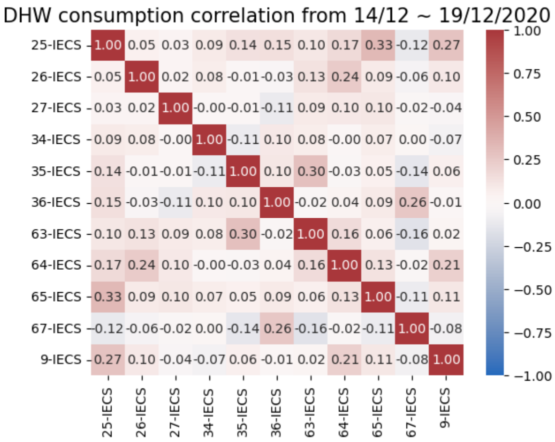

Figure 27: Correlation analysis

Indeed, the apartment 25 which previously exhibited a ‘high’ coefficient with the apartment 67 now shows a value of -0.12, indicating a considerable difference in consumption over a one-week interval. Notably, the consumption is now more correlated with the apartment 65, a trend like the previous observation. The correlation between the apartment 26 and 65 is also lower than before. Additionally, the apartment 63 which previously had some of the highest coefficients with three other apartments, now demonstrates very low coefficients.

These observations underscore the dynamic nature of apartment consumptions, with correlation coefficients showing constant changes. Even with a one-week interval, both analyses yield results that differ significantly from one another.

Before adjusting our approach, we aim to explore the variations in correlation coefficients between two different months, specifically comparing December with June. The results are shown in the Figure 28.

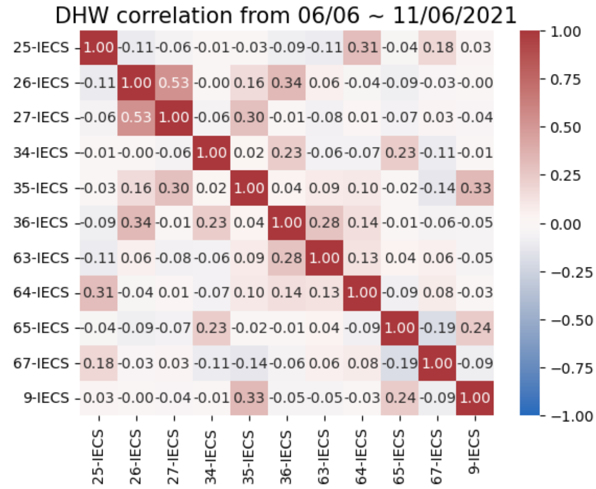

Figure 28: Correlation analysis

Surprisingly, one apartment, the 26, appears to surpass the 0.5 threshold when correlated with the apartment 27 in June, whereas the coefficient was near 0 for the same pair in December. This highlights the fact that the variation of correlation during different months makes it challenging to identify consistent patterns based on time series data.

Interestingly, the apartment 25 maintains a ‘high’ correlation coefficient with the apartment 64, similar to the December observation. However, the apartment 34 and 36, which displayed a ‘high’ correlation coefficient in the week of December 7th and June, do not exhibit the same pattern in the week of December 14th. This suggests that establishing a consistent correlation between these apartments is not possible.

In conclusion, identifying patterns between apartments based on time-series data proves to be difficult, and our initial hypothesis appears unsuitable.

iv. Correlation analysis of the apartments together using each apartments’ hourly-mean of a ten-day period

We now aim to explore if patterns emerge when examining the average consumption of apartments over ten days with a one-hour sampling interval.

To achieve this, we gather the data and resample it to an hourly frequency for each day. Consequently, for each apartment, we obtain ten values for each hour and the next step involves working out the mean of these ten values for every hour. This process provides us with the mean consumption over a span of ten days for each hour. Our analysis consists of studying and comparing these mean values for each apartment, seeking patterns between them.

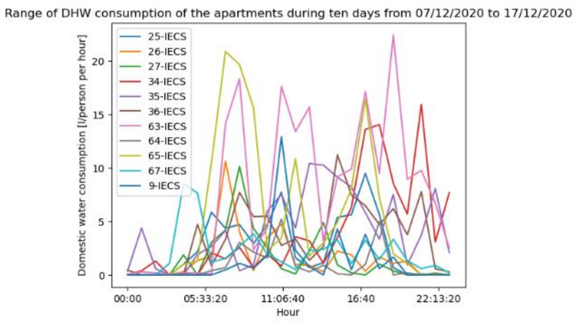

Figure 29 : Hourly average of the DHW consumption for each apartment

The initial results, presented in Figure 29 for the period from December 7th to December 17th, 2020, reveal that the consumption shows two peaks, one in the morning and another in the late afternoon. A notable pattern is observed between the apartments 65 and 63, where the peak values seem to align in time and are nearly equivalent. However, this observation is based on the mean values of consumption. To enhance our understanding, we introduce the concept of band error values. Since each data point has its standard deviation, plotting these error bands can illustrate the range of values covered by all the apartments. This approach helps identify patterns and discern if certain apartments share similar consumption values. The mean values along with their error bands are showed in Figure 30.

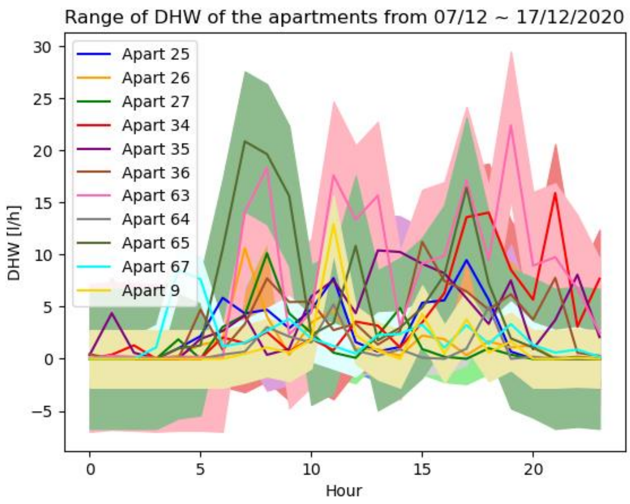

Figure 30 : Range of the DHW consumption with their band errors of the apartments

As observed previously, the apartments 65 and 63 show shared values, with the error band overlapping. Additionally, there is a resemblance between the apartment 9 and 67 in the late afternoon. However, due to the wide error bands of the apartment 63 and 65, identifying further patterns becomes challenging. To address this, the error bands for these apartments are removed in the Figure 31 .

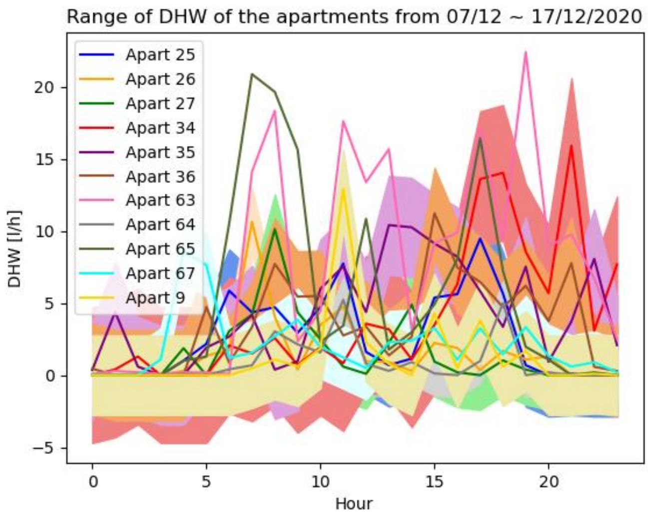

Figure 31 : Range of the DHW consumption with their bands errors for each apartment excluding the apartments 63 and 65

Further examination reveals that the apartment 9 (in yellow) and 25 (in blue) share common peaks at the same time. The blue line illustrating the apartment 25 remains mostly within the error band of the apartment 9. These are the primary observations from the current visualization. The next step involves comparing these visual patterns with the correlation values to verify if there is indeed a correlation between the apartments.

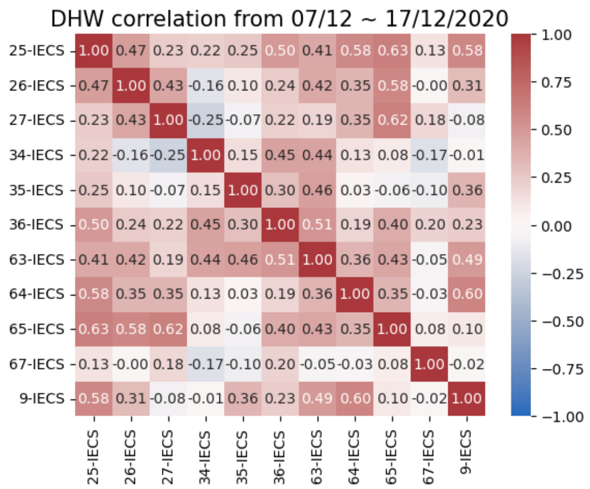

Figure 32 : Correlation analysis

In Figure 32, the correlation coefficients between each apartment are presented. Notably, using a threshold of 0.5, contrary to the previous time-series analysis, certain mean values appear to be correlated. As anticipated, the apartments 25 and 9 exhibit a correlation of 0.58, surpassing the threshold. Moreover, the apartment 25 shows correlations with the apartments 36, 64 and 65. To form a group, the relationship between the apartments 9, 36, 64 and 65 is explored. While the apartment 36 is correlated with the apartment 63 and 25, it lacks correlation with the apartment 9, 64 and 65. However to constitute a group, all apartments within it should be correlated with each other. The apartment 64 correlates with the apartment 9, reaching a correlation 0.6. Lastly, the apartment 65 does not show correlation with either the apartment 9 or 64. From this analysis, it is deduced that a preliminary group of apartments sharing patterns can be formed, consisted of the apartment 9, 25 and 64.

Interestingly, the apartments 26, 27 and 63 are correlated with only one other apartment, suggesting the formation of pairs of apartments. The first pair includes the apartments 26 and 65, the second comprises the apartments 27 and 65 and the last pair is composed of the apartments 63 and 36. Meanwhile, the remaining apartments seem to operate on their own, lacking similar patterns with correlation coefficients consistently below 0.5.

Now the goal is to examine whether the groups formed earlier remain the same with a change of one day in the data. Figure 33Figure 33 illustrates the correlation coefficients between the apartments from December 8th to December 18th, 2020.

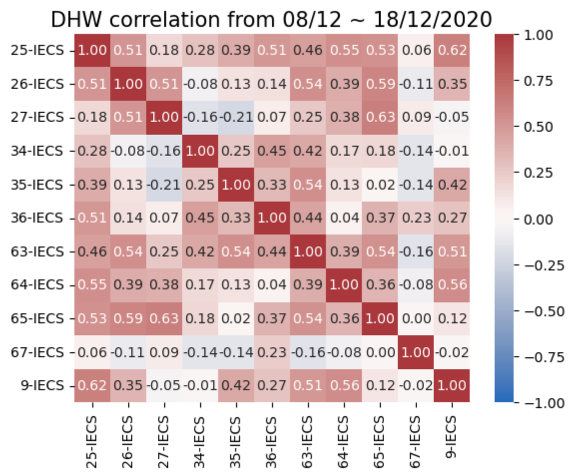

Figure 33: Correlation analysis

Notably, the apartment 25 still exhibits correlations with the apartments 36, 64, 65 and 9. However, the correlation coefficients, although similar, differ from the previous analysis. Additionally, this time, the apartment 25 appears to be correlated with the apartment 26 as well, a connection that wasn't present before. Considering the previous coefficient was near the threshold, this change is not surprising, given the slight alteration in data from the earlier analysis.

Now let's compare the correlations among the other apartments to determine if the same groups persist in the analysis. The apartment 26 correlates with the apartments 25, 27, 63 and 65. In the previous analysis, it was only correlated with the apartment 65, but, as mentioned earlier, the coefficients were already close to the threshold. The apartment 64 maintains its correlation with the apartment 9, as seen before, and with the apartment 25. The apartment 65 correlates with the apartments 26, 27 and 63. Independently, the apartment 9 shows correlation with the apartments 63, 64 and 25. The apartment 36 however, is only correlated with the apartment 25 which diverges from the previous analysis. This observation underscores that even with a one-day change, the coefficients can change, impacting the observed patterns.

From this analysis, three groups emerge. The first comprises the apartments 25, 64 and 9, which aligns with the findings from the previous analysis, which is reassuring. The second group consists of the apartments 25, 26 and 65, and given the previous correlation between the apartments 26 and 65, this result is not unexpected. A third group emerges with the apartments 26, 27 and 65, where the correlation between the apartments 27 and 65 was noted in the earlier analysis.

Notably, smaller groups of two can also be identified. The apartments 35 and 65 are correlated, marking a change from the previous analysis. This observation suggests that the groups established over a ten-day span may not consistently remain accurate or identical. It implies a dynamic nature, subject to change over time, which could potentially lead to misinterpretations in predictive modeling. Despite this variability, utilizing the correlation from ten days prior might offer insights into potential groupings for the following day. Newt, we aim to explore variations observed in another month. The study of the month of June is now showed in Figure 34.

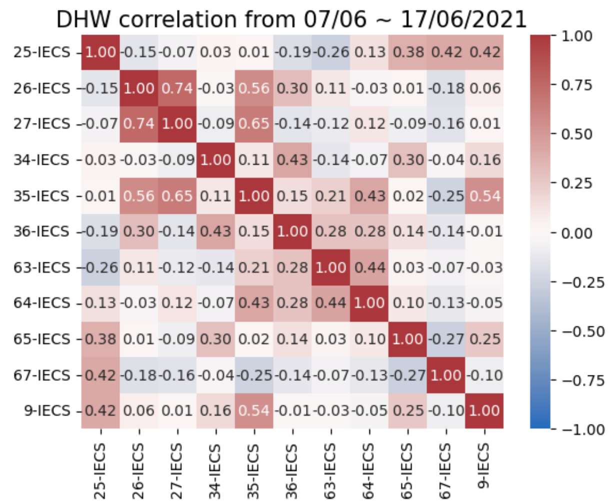

Figure 34: Correlation analysis

The aim of this examination is to discern disparities between the earlier observations and those derived from another month. We seek to see whether the groups previously identified remain the same or undergo significant changes.

A notable shift is observed in the apartment 25, which is not correlated with any other apartment this time. This observation contrasts to the previous analysis, where it shows high correlations, and underscores the dynamic nature of the relationship between the consumption. On the other hand, the apartment 26 is still correlated with the apartment 27. Additionally, the apartment 26 is correlated with the apartment 35, and intriguingly, the apartment 35 also shares a correlation with the apartment 27. Consequently, a first group can be formed, comprising these three apartments. However, this time, they do not exhibit the same relationship observed with the apartment 65 in the previous analysis. In this case, it appears that this is the only group that can be identified, except for a pair consisting of the apartments 35 and 9. The remaining apartments do not manifest correlations with one another, marking a significant change from the previous analysis.

We now aim to validate our hypothesis of forming group based on the correlation ten days before the forecasting. Similar to our December analysis, we shifted our assessment one day after to examine if we could identify consistent groups. The Figure 35Figure 35 represents the correlation between the apartments from June 8th to June 18th.

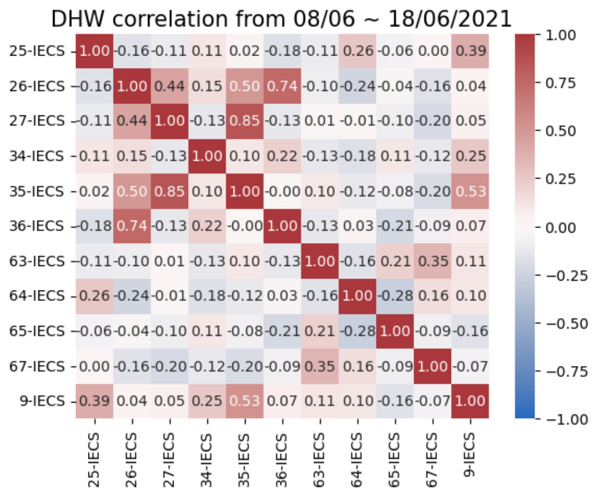

Figure 35: Correlation analysis

It appears that the apartment 26 still exhibits a correlation with the apartment 35. However, it is now linked with the apartment 36 instead of the apartment 27. Interestingly, the apartment 35 maintains its correlation with both apartments 26 and 27 but not with the apartment 36. Additionally, it continues to show correlation with the apartment 9.

This observation emphasizes the challenge of forming the same group as in our previous analysis. To make accurate forecasting, it becomes clear that we have to examine the past results and correlations, enabling the formation of groups. Forecasting the consumption one month in advance with an hourly resampling over ten days seems challenging. Nevertheless, forecast the future consumption of a group becomes more feasible by analyzing the consumption patterns of prior days.

v. Correlation analysis of the apartment together using the three-hours mean of a ten-day period

Our current objective is to identify patterns by examining the average consumption of apartments over a span of ten days, with a three-hour sampling interval. Our goal is to observe daily variations divided into distinct periods. To start our study, we look at the Figure 36, which provides information about the DHW consumption.

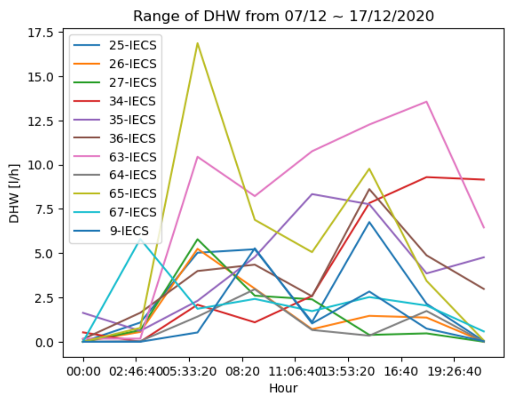

Figure 36 : Range of DHW consumption for each apartment with a resample of three-hour

As observed previously, the highest overall consumption still occurs in the late afternoon. Notably, the apartments 35, 36 and 65 appear to share the same pattern in the late afternoon, while the apartments 26 and 27 exhibit an identical pattern in the morning. To discuss these initial visualizations, we plan to conduct a correlation analysis. As said in the protocol, our attention is directed towards a specific ten-day period. The initial analysis focuses on the timeframe from December 7th to December 17th and is illustrated in Figure 37.

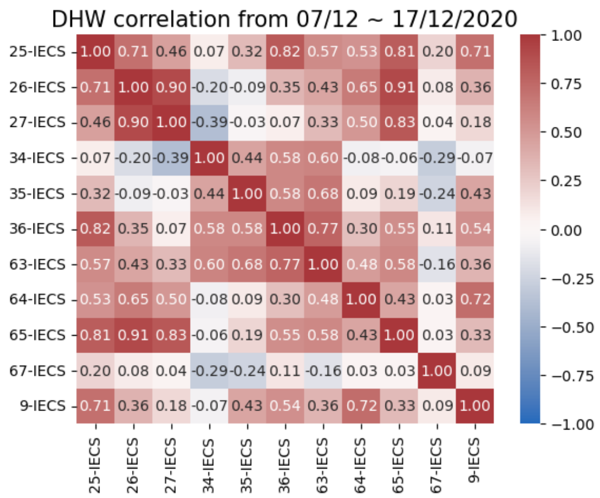

Figure 37 : Correlation analysis

In Figure 37, the correlation analysis for a three-hour resampling reveals anticipated patterns among apartments. The apartment 25 exhibits a high correlation with the apartments 36 and 65, with correlation coefficients of 0.82 and 0.81 respectively, surpassing by far our threshold of 0.5. Furthermore, the apartment 25 shows a notable correlation with the apartment 26 and 9, with correlation coefficients of 0.71. Additionally, it is also correlated with the apartments 63 and 64, although the coefficients are slightly lower, falling below 0.6.

Moving to apartment 26, it is strongly correlated with the apartments 25, 27, 63 and 65, reaching high coefficients around 0.9, far above the threshold.

The apartment 36 exhibits correlations with the apartments 25, 34, 35, 63, 65 and 9, even though the majority of the correlation coefficients are lower compared to those observed previously. Specifically, they are around 0.55, except for the correlations with the apartments 25 and 63.

The apartment 63 appears to share patterns with the apartments 25, 34, 35, 36 and 65. While the apartment 64 is correlated with the apartments 25, 26, 27 and 9. Then, the apartment 65 exhibits correlation with the apartments 25, 26, 27, 36 and 63. Lastly, the apartment 9 shows some correlation with the apartments 25, 36 and 64.

Based on this initial analysis, the most significant group comprises the apartments 25, 36, 63 and 65. Further examination suggests the formation of additional groups, such as the apartments 26, 27 and 65. Notably, the apartments 34 and 35 stand out as the only apartments correlated with two others, while the apartment 67 lacks any correlation with the other apartments.

In the upcoming analysis, we aim to observe how these groups evolves by shifting our data analysis by one day. The data for analysis spans from December 8th to December 18th.

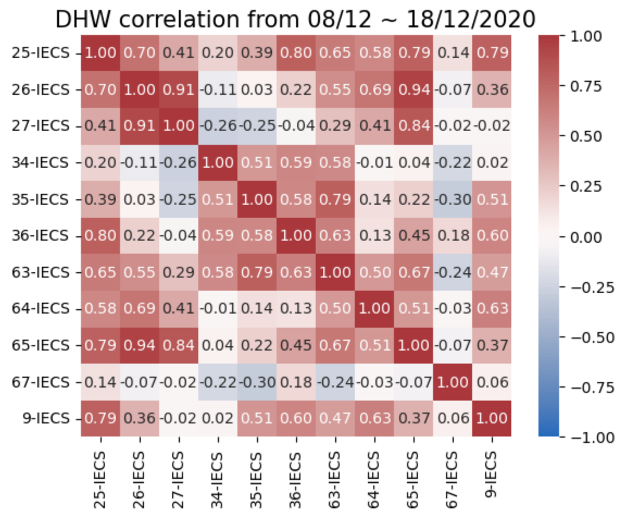

Figure 38 : Correlation analysis

In Figure 38, the correlation analysis among each apartment in the study case is done. The apartment 25 maintains its high correlation with the apartments 36 and 65, with coefficients still around 0.8, showing minimal change from the previous analysis. Interestingly, the apartment 9 now exhibits an even higher correlation with the apartment 25 compared to the previous analysis. Additionally, the apartment 9 continues to show strong correlations, around 0.7, with apartments 26 and 63. This indicates that the correlation between apartments 25 and 26 remains relatively stable, while the correlation with the apartment 63 increases. Notably, the correlation for the apartment 64 remains nearly the same.

Additionally, our objective is to examine whether the previously identified group remain consistent. The initial group encompasses the apartments 25, 36, 64 and 65 changes as the apartment 36 is no longer correlated with the apartment 65. This highlights the dynamic nature of domestic hot water consumption and its continuous fluctuations. However, the second group, consisting of the apartments 26, 27 and 65, persists in this analysis. It's notable that the correlation coefficients in this case were higher than those observed from December 7th to December 17th.

Our focus now shifts to observing the correlation between each apartment based on an analysis for another month. To achieve this, we shift our analysis month to June. The initial analysis, presented in Figure 39, covers the period from June 7th to June 17th.

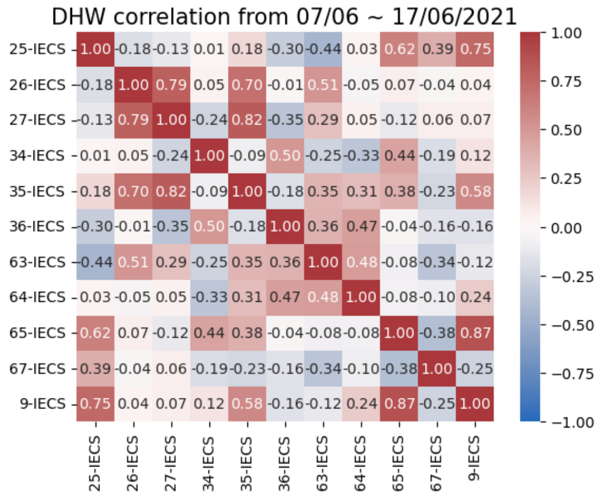

Figure 39 : Correlation analysis

In comparison to the month of December, there is a lower level of correlation among the apartments in June, as evident from the visual inspection of the figure. The color tone is now more centered around 0 on the scale, whereas in the previous analysis, it leaned more towards 0.75. Despite this shift, the apartment 25 remains correlated with the apartments 65 and 9, although not with others.

Examining the correlation between apartments 9 and 65 reveals a very high correlation, allowing the formation of a first group encompassing the apartments 25, 65 and 9.

The apartment 26 remains correlated with the apartment 27, and in this analysis, it is also linked to the apartments 35 and 63. Notably, the correlation coefficients are nearly equal to the previous ones. The apartment 27 seems to be correlated with the apartment 35 but not with the apartment 63, forming another group comprising the apartments 26, 27 and 63.

The apartments 34 and 36 continue to be correlated with each other exclusively maintaining the same pattern as in the previous analysis. However, the apartment 36, which was correlated with several apartments in December, now only correlates with the apartment 34.

The final observation is that the apartments 64 and 67 still lack correlations with other apartments in the study case. Interestingly, this remains consistent for the apartment 67, while for the apartment 64, it marks a change from the previous analysis.

The dynamic nature of the analysis, which represents the primary challenge in predicting consumption, is clear in this examination. Furthermore, it becomes apparent that the approach of grouping apartments based on correlation does not yield consistent results. The changing correlation patterns among apartments indicate that they are not consistently correlated with each other.

vi. Correlation analysis for the apartment with itself

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