Energy Proceedings
Vol 42, 2024
ISSN 2004-2965

Unraveling Energy Consumption patterns: Insights through Data Analysis and Predictive Modeling

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ABSTRACT

Most of the utility meters in Sweden are connected using the Internet of Things (IoT) technology. This opens new possibilities for understanding society's energy consumption dynamics and making citizens aware of their power consumption usage. In this study, we investigate the patterns of electricity consumption using machine learning methods. We collected metered data from Kalmar Energi company, the electrical grid for Kalmar city in Sweden. In addition, we collected the Kalmar weather and electricity price data from the Swedish Meteorological and Hydrological Institute (SMHI) and Nordpool, the European leading power market, respectively. We comprehensively analyze the electricity consumption data to assess the changes in overall electricity demand during the year 2021 in the city of Kalmar. This information can be of significant benefit to other regions seeking to improve their sustainability and energy consumption practices. For analysis and energy consumption prediction, we utilize two forecasting models, i.e., Random Forest (RF) and XGBoost. RF model results show a high level of accuracy with the achieved R-squared (R^2) value of 0.91 compared to XGBoost value of 0.87.

Keywords: energy consumption, machine learning, energy forecasting, Internet of Things

NONMENCLATURE

Abbreviations	
IoT	Internet of Things
SMHI	Swedish Meteorological and Hydrological Institute
ECP	Energy Consumption Prediction
RF	Random Forest
XGBoost	Extreme Gradient Boosting

1. INTRODUCTION

With the acceleration of urbanization, the energy consumption of buildings is projected to continue rising, and it currently makes up over one-third of the global total energy consumption [1]. As a result, energy conservation and creating sustainable buildings have become key focuses for countries worldwide. Researchers have suggested various measures to conserve building energy, such as employing renewable energy sources and utilizing high-performance building envelopes, to tackle this problem. An efficient and intelligent control is among the most effective measures to minimize energy consumption throughout a building's lifespan, as highlighted by [2]. Accurate and reliable prediction of building energy consumption holds immense importance for the optimal scheduling and control of predictive building systems, owing to its significant entropy [3,4]. There are two primary categories of building energy consumption prediction (ECP) methods, as outlined in reference [5]: physical models and data-driven models. Physical models rely on the analysis of energy consumption and utilize the heat-transfer process and outdoor meteorological conditions to make predictions [6]. Detailed information related to the building's exterior walls, doors, windows, ground, and other aspects, as well as heat sources within the building, are essential for physical models. However, obtaining such information can often be challenging, which restricts the widespread use of physical models [7]. As the Internet of Things (IoT) continues to evolve, technologies for monitoring building energy consumption are becoming more sophisticated. This

This is a paper for 15th International Conference on Applied Energy (ICAE2023), Dec. 3-7, 2023, Doha, Qatar.

development, coupled with the availability of a vast amount of historical data, has enabled the swift progress of data-driven energy consumption prediction models [8]. One of the most popular data-driven approaches for BECP is machine-learning models, which have emerged due to their ability to model intricate and non-linear relationships without the need for expert knowledge [9]. Artificial neural networks [10], support vector machines (SVMs) [11], decision trees [12], random forests (RFs) [13], extreme gradient boosting (XGBoost) [14], and other similar techniques are among the methods being used. This study employs a methodical data analysis approach and leverages predictive models, specifically Random Forests (RF) and XGBoost, to offer valuable insights [15]. The central objective of this study is to comprehend energy consumption patterns, elucidating the relationships between external factors, such as temperature and price as well as formulating predictive models to anticipate future power utilization trends. The main contributions of this study are as follows:

- Investigate the patterns of electricity consumption with the correlation of weather and price data.
- Develop an accurate forecasting model for electrical loads that mirrors real-world consumption trends.

The rest of the paper is organized as follows. Section 2 covers the literature review and previous research. Section 3 presents materials and methods in which we provide our methodology, data description and visualization, and model development. Section 4 evaluates the models' accuracy and interprets the prediction results. Section 5 presents the discussion and conclusions.

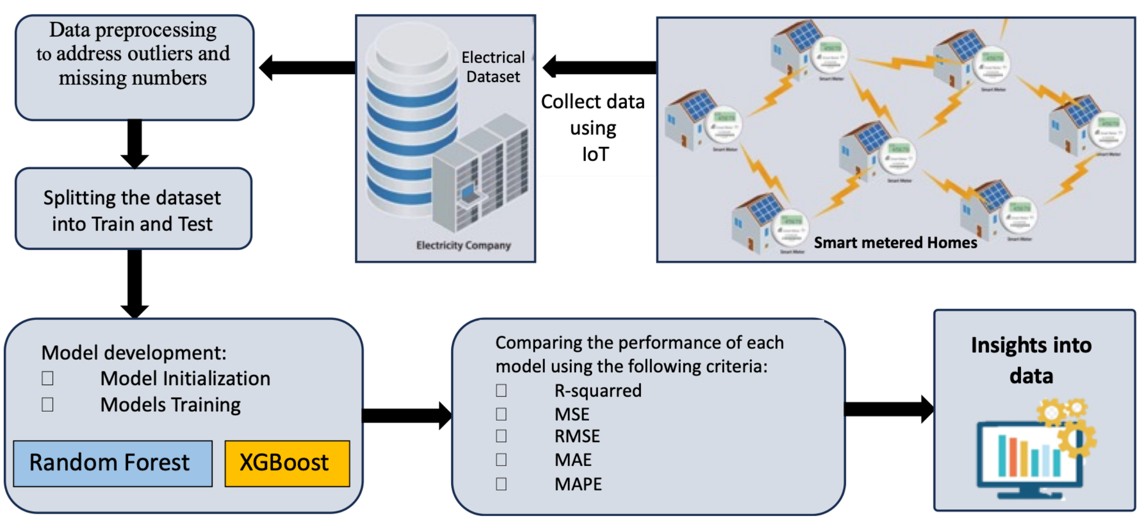

Fig. 1 Workflow used for electric load forecasting using RF and XGBoost.

2. LITERATURE REVIEW

The study [16] provides an extensive overview of machine learning methods for predicting energy consumption in the context of load forecasting. The authors discuss various machine learning approaches, analyze their pros and cons, and highlight their applications in power usage prediction. In the study [17] authors developed a machine learning model for power load estimation, aiding grid maintenance and electricity trading. It combines a precise Gated Recurrent Unit (GRU) with a RF model to simplify the model. The lighter GRU enhances efficiency but slightly sacrifices accuracy compared to the original model. The authors [18] introduced a power consumption forecasting method using the XGBoost algorithm. They applied it to user data from an industrial park and their results showcased the method's remarkable accuracy, adaptability, and suitability for future power grid planning. However, authors in [19] employed RF, XGBoost, and Linear Regression models and considered environmental and temporal factors such as temperature and time of day. Among these models, the RF approach was found to be the most effective. Authors in [20] analyzed power consumption patterns in a university campus over the course of one calendar year. The authors compared power usage on weekdays and weekends, as well as in academic and residential buildings. They also considered the impact of temperature as an external factor affecting the power usage in that area with a New England climate. In our proposed study, we are applying RF and XGBoost model for power consumption analysis with the

Table 1 Statistics of the dataset.

	CUSTOMER	HOUR0	HOUR1	HOUR2	...	HOUR22	HOUR23	One Day Power	Temp
Count	319523	319523	319523	319523	...	319523	319523	319523	319523
Mean	1.139779e+09	0.0076	0.0075	0.0075	...	0.0081	0.0078	0.2417	8.2339
Std	2.340728e+08	0.0589	0.0584	0.0574	...	0.0608	0.0596	1.7437	7.8239
Min	1.060599e+09	0.0000	0.0000	0.0000	...	0.0000	0.0000	0.0000	12.8000
25%	1.060615e+09	0.0003	0.0003	0.0003	...	0.0004	0.0004	0.0155	2.4000
50%	1.060679e+09	0.0015	0.0015	0.0015	...	0.0016	0.0016	0.0534	8.0000
75%	1.060792e+09	0.0041	0.0041	0.0041	...	0.0045	0.0042	0.1430	14.8000
Max	2.074248e+09	2.3380	2.3090	2.2590	...	2.4570	2.4130	68.3080	23.7000

consideration of environmental and price factor for a city-wide area.

3. MATERIALS AND METHODS

3.1 Data description and pre-processing

The research data were obtained from the IoT-connected utility meters installed by Kalmar Energi company, the electrical grid for Kalmar city in Sweden. The energy consumption data belongs to five areas namely, Kvarnholmen, Varvsholmen, Berga, Malmen, and Stensö, and includes apartments, houses, industries, office buildings, restaurants, care centers, and hospitals. The research data consists of electrical load data recorded on an hourly basis from 1st January to 31 December 2021. This dataset comprises a total of 332,790 rows. During raw data acquisition, various issues may arise, including sensor malfunctions and interruptions in data transmission signals, leading to null values or outliers within the dataset. Therefore, preprocessing is imperative as a preliminary step before data analysis. The null values and duplicate entries on hourly energy consumption have been removed from the dataset. This deduplication process resulted in a dataset containing 319,523 rows. Our methodology is shown in Figure 1.

Table 1 displays the dataset's status following initial preprocessing. In Table 1, CUSTOMER represents the ID assigned to energy meter. HOUR0 ~ HOUR23 is the user's energy consumption in megawatt each hour of the day. One Day Power is the total amount of energy consumed by the user in the day and Temp is the average temperature for the day.

To have a general view of the data, we showed the number of areas with the number of customers in each area in Table 2.

Then, we diagrammed the data based on the distinct areas, with the annual energy consumption for each of the five areas presented in Figure 2. Observations from

Table 2 The number of customers in each area of Kalmar.

Area	Number of Customers
Kvarnholmen	401
Berga	278
Malmen	255
Stensö	53
Varvsholmen	43

the figure reveal a notably higher energy consumption in the Stensö area compared to the other areas.

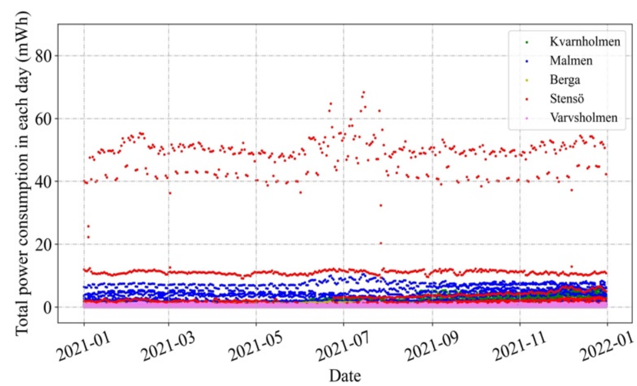

Fig. 2 Power consumption distribution of five areas in Kalmar.

Regarding the low number of customers in this area, the discrepancy can be attributed to the predominance of villa-type residences and industrial facilities within the Stensö area.

3.2 Data Visualization

In this study, we have chosen to focus exclusively on the Kvarnholmen area as our primary case study. Before visualizing the relation between the external parameters such as temperature and price with power consumption, first we visualize the hourly-total, daily-total, and daily-average power consumption in Kvarnholmen to getting a first flavour of the data.

We have partitioned the day into two distinct segments: the residential phase, denoted as "home-time," and the occupational phase, referred to as "work-time." Our analysis, as depicted in the hourly graph

(Figure 3), reveals a notable disparity in power consumption between these two periods. During work-time, power usage exhibits a noticeable rise, primarily attributable to the simultaneous operation of various entities such as restaurants, companies, and industries. These entities use higher energy, way more than home activities like cooking, doing laundry, and using household appliances.

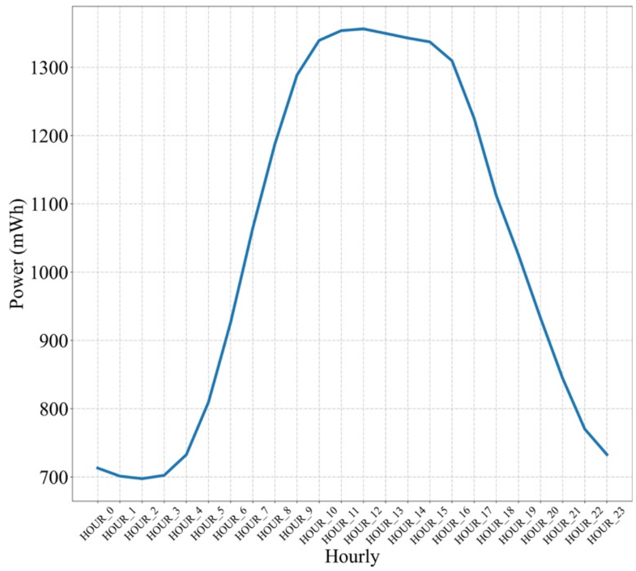

Fig. 3 Hourly total power consumption in Kvarnholmen.

Of particular interest is the interval between 11 a.m. and 2 p.m., the graph shows a small decrease in power usage. This slope corresponds to the lunchtime period, during which power-intensive activities within the studied area are temporarily suspended. This nuanced fluctuation in power consumption reflects the dynamic nature of daily energy demand and underscores the impact of commercial and industrial operations on the overall power grid.

Figures 4 and 5 provide insights into the daily total power consumption and daily average power consumption across all customers, respectively. Notably, a consistent pattern emerges across both figures,

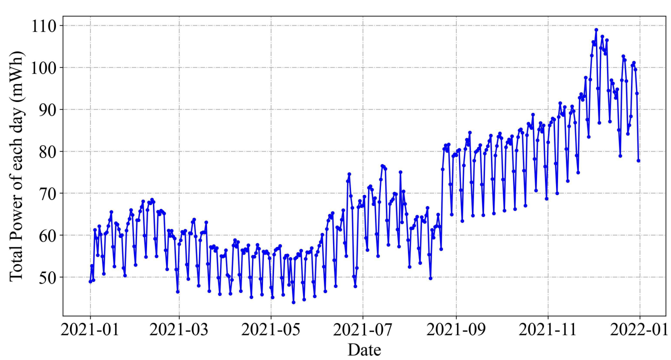

Fig. 4 Daily-total power consumption in Kvarnholmen.

characterized by a consumption range spanning from a minimum observed in May to a peak of 110 mWh recorded in December (Figure 4).

The average consumption exhibits a narrower range, fluctuating between 0.12 mWh in the middle of May to 0.28 mWh in December (Figure 5). From late July to the end of August, which is typically vacation time, we can observe a noticeable drop in power usage.

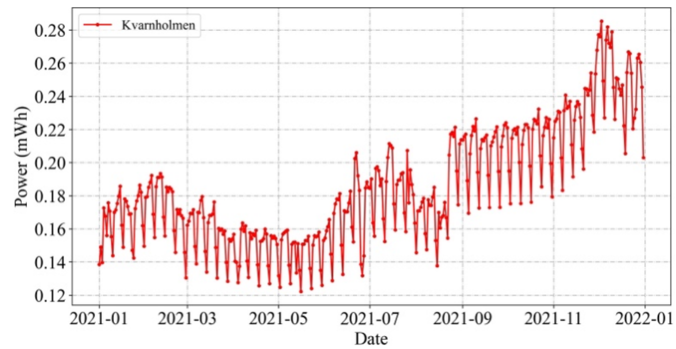

Fig. 5 Daily average power consumption in Kvarnholmen.

3.2.1 *Temperature and power consumption*

A comprehensive study was conducted on the daily average energy consumption and temperature fluctuations within the Kalmar city center area, explicitly focusing on Kvarnholmen over a year. The Kvarnholmen area, characterized by a substantial mix of residential and commercial zones, exhibits energy consumption levels that represent the average within the area—depicted in Figure 6.

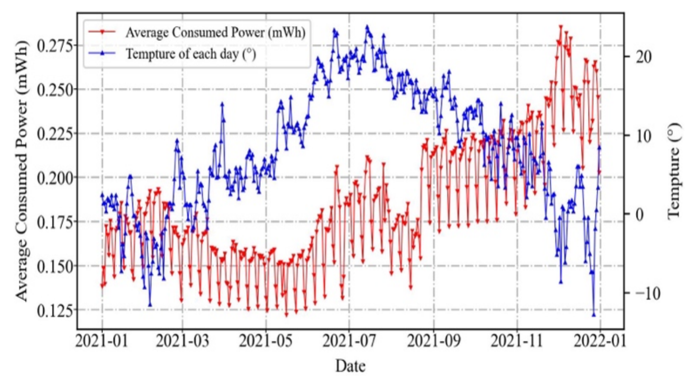

Fig. 6 Tracking power consumption and temperature trends in Kvarnholmen.

The discernible contrast between winter and summer is evident in the temperature fluctuations. During the summer, there is a noticeable decrease in energy consumption, partly attributed to less need for heating and longer daylight. Conversely, energy consumption rises during the extended winter nights, further substantiating the correlation between energy usage and temperature variations, particularly in response to seasonal changes.

3.2.2 Customer numbers and power consumption

At the end of August, more buildings were constructed in the city center, which is reflected in the increasing number of customers in this area. Figure 7 illustrates a clear relationship between the growth in customer numbers and power consumption. This is consistent with common knowledge that an increase in customers typically leads to a greater demand for various services, including electricity for residential and commercial use.

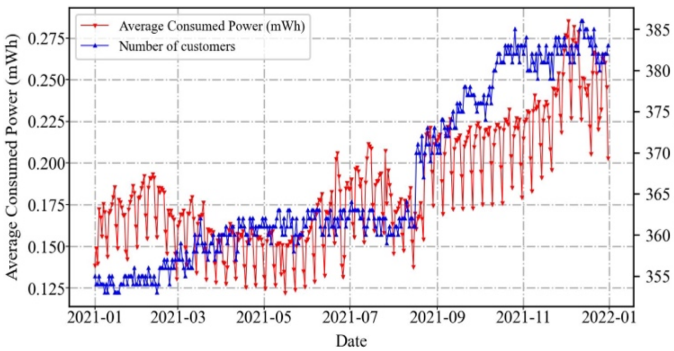

Fig. 7 Tracking average power consumption and customer trends in Kvarnholmen.

3.2.3 Price and power consumption

The currency depicted in Figure 8 is the Swedish Krona (SEK), which equals 0.1 Euro in the year 2021. The recorded average price exhibits fluctuations, reaching its lowest point at approximately 200 SEK per month by the end of September and peaking in December at a value exceeding 4000 SEK.

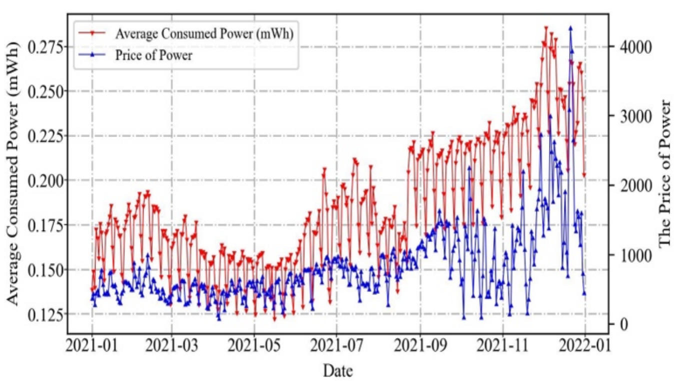

Fig. 8 Tracking power consumption and price trends in Kvarnholmen.

The average power consumption shown in Figure 8 also indicates fluctuations in average price. For instance, as the average power consumption line reaches its lower interval from April to mid-May, the corresponding average price in SEK also exhibits a lower value, hovering around 200 SEK. Conversely, in December, when the average power consumption reaches its peak, the average price in SEK surges to more than 4000 SEK. These fluctuations in price and consumption patterns reveal a potential relationship between energy demand and cost.

3.3 Model Development

To enhance the precision of predicting user energy consumption, thereby aiding the company's decision-making process, we chose the data from the Berga area to construct our model. We selected Berga because it is a residential area, which makes the data more consistent and simpler to analyze.

The RF based on a decision tree is selected to build the model. Our hypothesis posits that users can make independent choices regarding energy consumption and are likely to adjust depending on environmental factors such as temperature and socioeconomic factors encompassing household income and energy prices.

To account for the influence of temperature and price, we had to utilize the Swedish Meteorological and Hydrological Institute (SMHI) [21] API for gathering temperature data, and we accessed energy average price data for each day from the Nordpool [22] API, which is a prominent European power market provider.

We have pinpointed three key input variables for our model: customer ID, temperature, and price. These variables will predict the daily total energy consumption, serving as the model's output parameter.

The division of the dataset into a training set and a test set follows a ratio of 7:3, resulting in 255 rows allocated to the training set and 110 rows to the test set (in total, 365 rows which is the average power consumption in one year). A 5-fold cross-validation approach was employed to optimize the model's hyperparameters. After optimization, the hyperparameters $\max\_depth$ and $n\_estimators$ were determined to have their optimal values set at 5 and 50, respectively.

To comprehensively compare the prediction performance of the two models, *Mean Square Error (MSE)*, *Root Mean Square Error (RMSE)*, *Mean Absolute Error (MAE)*, *Mean Absolute Percentage Error (MAPE)*, and *R-Square* (R^2) are used to evaluate the accuracy of the models. The evaluation index formulas are as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i' - y_i)^2 \quad (1)$$

$$RMSE = \sqrt{MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i' - y_i)^2} \quad (2)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i' - y_i| \quad (3)$$

$$MAPE = 100\%.\frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i' - y_i}{y_i}\right| \quad (4)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i' - y_i)^2}{\sum_{i=1}^{n}(\overline{y_i} - y_i)^2} \quad (5)$$

Where n is the number of samples; y_i is the true value; y_i' is the predicted output value of the model; and $\overline{y_i}$ is the average value of the samples. Further details regarding the development can be found in [23].

4. RESULTS AND ANALYSIS

The model evaluation results, as presented in Table 3, indicate that the achieved R-squared (R^2) value of 0.91 demonstrates a high level of accuracy.

As shown in Table 3, the RF model generally performs better than the XGBoost model in terms of prediction accuracy and explaining the variance in the data. It has lower MSE, RMSE, MAE, MAPE, and a higher R2 value, suggesting that it provides more accurate and reliable predictions.

Table 3 The RF and XGBoost model evaluation results.

Model	RF	XGBoost
MSE	0.7028	1.8796
RMSE	0.8383	1.3710
MAE	0.6492	1.0408
MAPE	5.3251	6.8080
R^2	0.9173	0.8770

We also comprehensively analyzed the results by employing a correlation matrix encompassing power consumption, temperature, and price variables, partitioned into two distinct parts. The first part involved an in-depth correlation analysis within a specific area, focusing primarily on Berga. Subsequently, the second part comprised a broader correlation analysis encompassing all the studied areas.

4.1 Correlation Analysis of One Area-Berga

We conducted a correlation analysis utilizing the Pearson correlation coefficient to examine the relationship between temperature and hourly power consumption across various temporal segments. We analyze the correlation matrix in two aspects: 1) Hourly power consumption correlation, and 2) temperature and price correlation with power consumption, respectively. Firstly, we investigated correlations among different hours of the day.

Our findings revealed (Figure 9) that during home-time hours, specifically from 12 a.m. to 6 a.m. and from 5 p.m. to 12 a.m., there exists a high degree of positive correlation, exceeding 90 percent. These strong correlations manifest as dark-red colors within the correlation matrix, signifying a robust and direct association between these hours. In contrast, the correlation between home-time and the interval spanning from 6 a.m. to 5 p.m., corresponding to work hours, demonstrates comparatively lower values, with levels hovering around 60 to 87 percent. Similarly, work-time hours exhibit a notably strong correlation, reaching approximately an average of 80 percent.

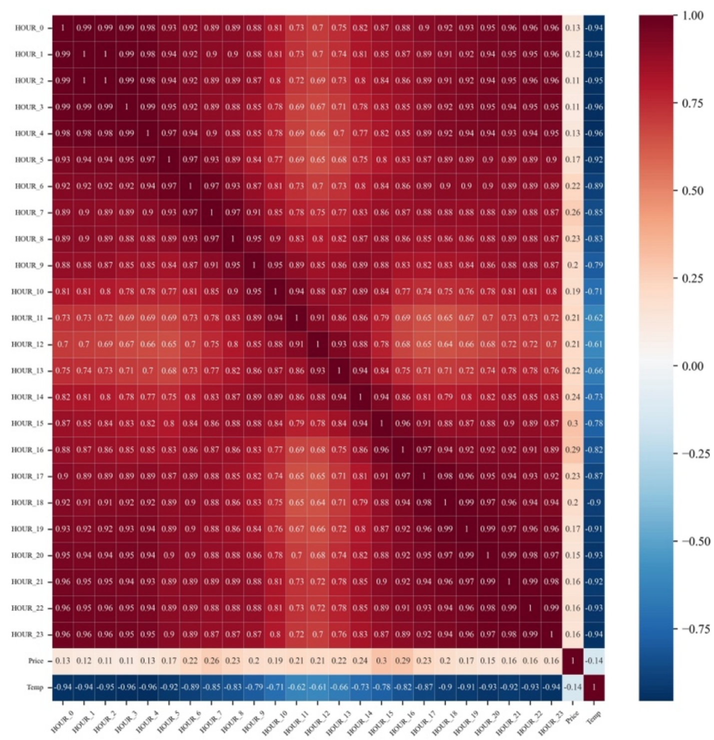

Fig. 9 Correlation between hourly power consumption in Berga.

4.1.1 Temperature and power consumption

We explored the correlation between hourly power consumption and temperature within the matrix. These analyses unveiled an inverse relationship, indicating that higher temperatures coincide with reduced power consumption. Specifically, we observed that during the hours between 12 a.m. to 6 a.m. and from 6 p.m. to 12 p.m., there exists a more pronounced inverse correlation between temperature and power consumption when compared to the hours spanning from 6 a.m. to 5 p.m. This disparity suggests that individuals tend to utilize more power while at home and awake, as opposed to when they are asleep or at work. Furthermore, the correlation coefficient for the first part of home-time (12 a.m. to 4 a.m.) is lower than that of the latter part (4 p.m. to 12 a.m.), signifying that energy consumption is influenced by the temperature more during the active hours when residents are awake and engaged in daily activities.

4.1.2 Price and power consumption analysis

We examined the relationship between hourly power consumption and price, as indicated by the yellow line in the correlation matrix. Our analysis reveals that the price coefficient exhibits a positive shift, increasing from 0.11 to 0.17 during the hours of 12 a.m. to 5 a.m. and 7 p.m. to 12 p.m. However, between 6 a.m. and 6 p.m., this coefficient experiences a more substantial change, rising from 0.2 to 0.3. Despite these fluctuations, the overall impact of price on power consumption during these intervals remains minimal and may not be considered significant.

4.2 Correlation Analysis of All Areas

Figure 10 reveals distinct patterns in the correlation between power consumption, temperature, and price across different areas. In Berga, there exists a strong correlation of approximately 90% between power consumption and temperature, indicating that power usage in this area is significantly influenced by changes in

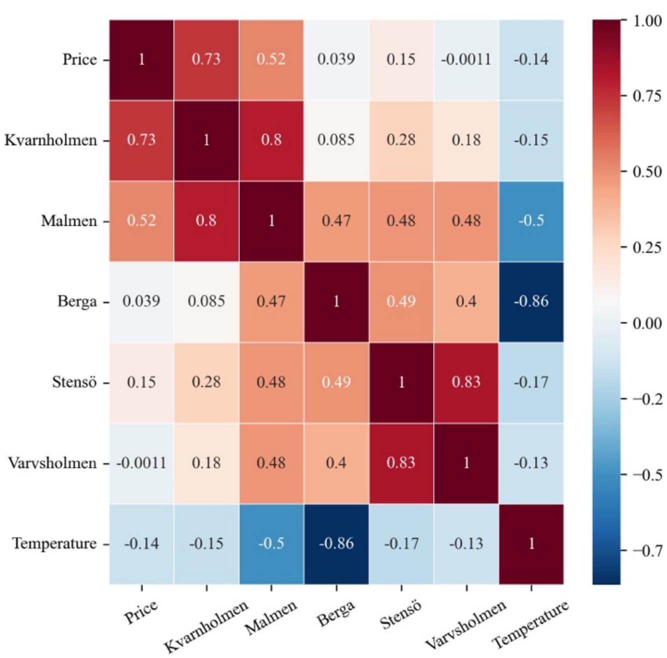

Fig. 10 Correlation between hourly power consumption with temperature and price in all areas.

temperature. Additionally, there is a weak negative correlation (-0.17) between power consumption and price in Berga, implying that higher prices are associated with a slight decrease in power usage.

Conversely, Kvarnholmen demonstrates a low correlation (-0.075) between power usage and temperature, suggesting that energy consumption in the city center remains relatively stable regardless of weather conditions. Kvarnholmen exhibits the highest positive correlation coefficient (0.71) between power usage and price. This signifies a strong positive relationship, implying that power consumption also increases significantly in Kvarnholmen as electricity prices rise.

Malmen displays moderate correlations, with a correlation coefficient of approximately -0.47 between power consumption and temperature, and a corresponding positive correlation of about +0.47 between power consumption and price. These findings suggest that temperature has a moderately noticeable effect on power consumption in this area, and as prices increase, power usage tends to rise moderately. In contrast, both Stensö and Varvsholmen exhibit very weak relationships between power usage and both temperature and price. Temperature and price fluctuations have minimal influence on power consumption in these areas.

5. DSDISCUSSION AND CONCLUSION

Our study aimed to uncover insights that could inform energy management and policy decisions to understand the factors influencing power consumption in various areas of Kalmar, Sweden. In our dataset encompassing hourly power consumption records for five distinct areas in Kalmar, Sweden, comprising a total of more than 300,000 data points, we encountered certain limitations that merit consideration in our analysis. Our dataset includes essential information such as customer ID, area, 24-hour power consumption, date, temperature, and price. However, we need more critical details regarding the building type (residential or commercial) and the specific heating systems employed within these structures.

These missing pieces are important as they can influence power consumption patterns significantly. For instance, residential and commercial buildings often exhibit distinct energy usage profiles due to differing operational hours, occupancy patterns, and heating methods. Additionally, the type of heating system, whether local or central, can introduce substantial variations in power consumption.

This contextual information is necessary to perform a more detailed and accurate analysis. It hampers our capacity to draw precise conclusions regarding the factors contributing to power consumption trends in the studied areas. Despite these constraints, our study endeavors to derive meaningful insights from the available data, recognizing that further research incorporating additional data attributes could enhance the depth and accuracy of our analysis.

Our study highlights the importance of leveraging advanced data analytics and machine learning methods to inform decision-making and better understanding of energy consumption. This understanding is crucial for addressing challenges related to energy sustainability. Our analysis unveiled essential changes in electricity demand, offering valuable insights into consumption trends in Kalmar using two predictive models, RF and XGBoost, to aid in understanding and forecasting these patterns.

These insights are pivotal in guiding future energy policies and management strategies for Sweden. This study is also significant beneficial for other regions or countries to improve their energy consumption usages, ultimately contributing to a more sustainable and resilient energy future.

ACKNOWLEDGEMENT

This work was supported by the European Regional Fund, Kalmar Region, Kronoberg Region, and Linnaeus University.

DECLARATION OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. All authors read and approved the final manuscript.

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