# Description of electricity consumption by using leading hours intra-day model

Krzysztof Karpio[1[0000-0003-0621-3499]], Piotr Łukasiewicz[1[0000-0002-1169-3282]], Rafik Nafkha[1[0000-0002-9534-8880]] and Arkadiusz Orłowski[1[0000-0002-6755-1830]]

Institute of Information Technology, Warsaw University of Life Sciences SGGW, Poland
{Krzysztof_karpio, piotr_lukasiewicz, rafik_nafkha, arkadiusz_orlowski}@sggw.edu.pl

**Abstract.** This paper focuses on parametrization of one-day time series of electricity consumption. In order to parametrize such time series data mining technique was elaborated. The technique is based on the multivariate linear regression and is self-configurable, in other words a user does not need to set any model parameters upfront. The model finds the most essential data points whose values allow to model the electricity consumptions for remaining hours in the same day. The number of data points required to describe the whole time series depends on the demanded precision which is up to the user. We showed that the model with only four describing variables, describes 20 remaining hours very well, exhibiting dominant relative error about 1.5%. It is characterized by a high precision and allows finding non-typical days from the electricity demand point of view.

**Keywords:** time series, data mining technique, electricity consumption modeling, multivariate linear regression.

## 1 Introduction

The load curve of the power system can be considered as a random function of a random variable of its load. The power system load curve is formed as a result of the superposition of consumers individual load curves and is the sum of the components of random functions. It should be emphasized that these are functions that have only one implementation during the considered time interval, and they are also correlated and are subject to an increase during the year, which is also a random variable. Functions of the load of component consumers of the system, and thus functions of the system load, are influenced by non-accidental factors [1-3]: (1) Location of the considered area (climate, changes in the angle of sunlight beams, changes in the times of sunrise and sunset). (2) Features of the power system, the most important of which are: the structure of consumers, the dynamics of economic development, the statutory number of working hours within a day and the system of shifts binding in a given country. The above-mentioned factors of a non-accidental nature constitute a set of features that determine the course of the system load in terms of the process average.

The load curve of the power system is also influenced by random factors, such as changes in temperature [4-6], rainfall, wind speed [7], errors of receiving devices,

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_30

changes in the structure of electricity consumers, etc. The life rhythm of the population, its connection to the variability of seasons, traditions and customs, and the nature of the work performed by people to regulate the rhythm of the working and non-working days, become enhanced in the variation of the load curve of the power system and are the main cause of the phenomenon called load variability.

Electricity consumers load variation have always been the basis of modeling electricity demand. Initially, planning and forecasting electricity consumption was mainly related to the assurance of electricity delivery. Due to the specific nature of electricity, as it cannot be permanently stored, means that its demand and supply should be equal. The first electricity consumption models were, therefore, oriented towards forecasting electricity demand. Depending on the purpose of model preparation, many types and classes of models can be distinguished. The models used in the electricity management can be divided into two basic groups. A group of analytical and forecasting models and a group of forecasting models. The most intensively developed and studied models are prognostic models [8]. Currently, models based on artificial neural networks [9-12] and genetic algorithms [13] are most often used in forecasting, due to the fact that prognostic effects obtained with their use provide best results [14-15]. However, the disadvantage of these types of models, is that they do not have information about reasons of the problems. Based on that, it is difficult to determine which of the factors has the strongest impact on the shape of the load.

In the case of electricity consumption analysis and modeling, the most commonly used models are: regression [16, 17], economic processes and time series [17-19], which, however, inform about certain tendencies, but not about the causality of the phenomenon. In such situation, econometric models that describe phenomena while taking into account many external factors are useful.

Time-series and regression have been extensively used in modelling for decades. In electrical engineering, regression techniques are used to model the electric load as a function of load consumption in relationship with different dynamics like seasonal patterns, meteorological conditions, day type, customer social class etc. Different regression techniques (linear, multiple linear, quadratic, and exponential regression models) with the hour-by-hour load data based upon a specific day, and considered temperature as the variant parameter were used to perform the hour by hour model for a Grid Station in Pakistan [20]. A multiple regression model was performed for monthly electricity demand of New South Wales [21]. The climatic variables such as temperature, humidity, and rainy days appear as the most affective the electricity demand consumption in this case. The multivariate linear regression is used to model electricity consumption of Jordian Industrial sector as function of variables such as number of establishments, number of employees, electricity tariff, prevailing fuel prices, and production outputs [22].

Undoubtedly, the involvement of many variables provides better explanations which of the factors most strongly influences the shape of the load. This, however, requires collecting a lot of data, tedious work with processing it and introduction of increasingly powerful processors. According to the econometric methodology, there is a gap between the best (meaning the best compatibility) model and the most economical approach. The constructed model should be as simple as possible, i.e., contain the smallest

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_30

possible number of variables, and explain the fluctuations of the analyzed dependent variable as precise as possible. Usually, the first choice for modeling is a linear regression model estimated by the least squares' method. This method enables deterministic dependencies modeling. The ability to describe a given phenomenon in terms of deterministic components lets us predict most of the variability. In this paper, we present a method that finds a subset of the points that are enough to recreate the entire electricity demand curve for a given time allocation. It turns out that it is enough to know 4 appropriate points to parameterize e.g. one day time series of electricity consumption with very good accuracy. With 5 points, the accuracy is already super good. The method uses the multivariate linear regression technique.

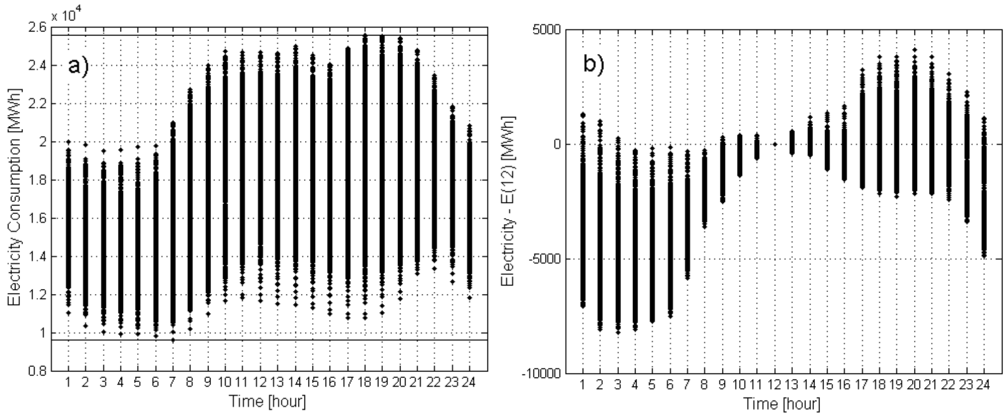
## 2 Motivation

Electricity consumption depends on many factors like day/night, weekdays/weekends, working days/holidays. One must also keep in mind the seasons and environmental conditions like temperature and humidity. Let us note that hour is the important factor too. The Figure 1a contains all possible electricity consumptions at each hour (the data is described in the following chapter). The consumption varies between $0.98 \times 10^4$ and $2.57 \times 10^4$ MWh, thus, having the range of $1.56 \times 10^4$. However, ranges for the single hours are smaller for night hours, they are only about $0.9 \times 10^4$ MWh. It is due to two groups of reasons: (1) not all combinations of factors' values exist and (2) behaviors of people are typical. First, there is a night at 7 o'clock only during autumn or winter, very low temperatures can possibly exist during summer, but they are extremely unlikely. Secondly, activities of people, business and public transportation are very limited during the night. Those behaviors lead to the relatively low electricity consumption regardless of current temperature or humidity. Moreover, the electricity demand does not change rapidly between hours. Even, if a number of people start a job at the same time they get up at different hours, travel to work for various times and arrive to the workplace at similar but still different hours. All of those make changes of electricity demands to spread for a few hours even the factors change rapidly, what is visible in Figure 1a. The lowest electricity consumptions are concentrated around 6:00 o'clock and it takes about 5 additional hours to reach the first local maximum. We can point out that the electricity consumptions at different hours are not independent on one another. The dependence between electricity consumptions at various hours is visible in Figure 1b. One showed there the differences between current electricity demands and electricity consumption at 12:00 o'clock. We have a zero value at 12:00 o'clock but the widths of ranges are not growing rapidly when going away of 12:00. Moreover, these ranges are not symmetrical around zero. They exhibit bigger values after the 12:00 and significantly smaller before. The base hour has been chosen arbitrary but in general we observe the following behavior. If the electricity consumption is $x$ [MWh] at the hour $n$, then one observes the expected electricity consumptions at hours $n-1$ and $n+1$ in some range around $x$ [MWh]. This range will be significantly narrower than the total dispersion of electricity consumptions at those hours. Such an „inertia" of electricity consumption provides the idea that we can describe time series within the whole day

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_30

by the consumptions at a relatively small number of hours regardless of other factors. In our earlier work [23] we studied many possible factors potentially influencing electricity consumption. Now, the only independent variable which we take into account is hourly electricity consumption.

**Fig. 1.** a) Electricity consumption vs hour. Two horizontal lines indicate maximum and minimum electricity consumption; b) Difference between the current electricity




demand and the electricity consumption at 12 o'clock vs hour

## 3 The data

This study was carried out based on the historical data representing total electricity consumption in Polish power system [24]. The consumption is denoted on the hourly basis covering the time span between January 1st 2008 and June 23rd 2015, what corresponds to 2,731 days. Each consumption is accompanied by additional attributes listed in Table 1.

The electricity consumption is accompanied by the additional 10 attributes, including Hour. The majority of the attributes: Year, Month, Day as well as nDay, and nWeek are derived from dates (originally in the data set). The date was also complemented by the Holiday attribute, which is similar to nDay but additionally to weekends it takes into account also holidays. Some of the hours are during sunlight some are not. The Night_Day attribute reflects the presence of the sunlight. There are hours when this attribute changes its value during the year. The Night_Day is also influenced by time changes between winter and summer. The last two attributes are continuous: temperature and humidity. The data set contains whole days, and it holds 55,536 data points. The power system load is presented as the time series in Figure 2a. The vertical line on May 3rd 2014 represents the split of the data into the learning and test data subsets. The learning data subset was used during the model construction and tuning. The other data subset was used for testing and during model evaluation. The first data part contains 2,314 days and the second one consists of 416 days.

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_30

**Table 1.** List of all features/variables used in the model

| Symbol | Type | Description |
|---|---|---|
| Ener | continuous | Electricity [MWh] |
| Hour | discrete | The hour |
| Year | discrete | Year's number |
| Month | discrete | Month's number |
| Day | discrete | Day of the month |
| nDay | discrete | Day of the week |
| nWeek | discrete | Week of the year |
| Holiday | boolean | Holiday or working day |
| Night_Day | boolean | Night or day |
| Tem | continuous | Temperature |
| Hum | continuous | Humidity |

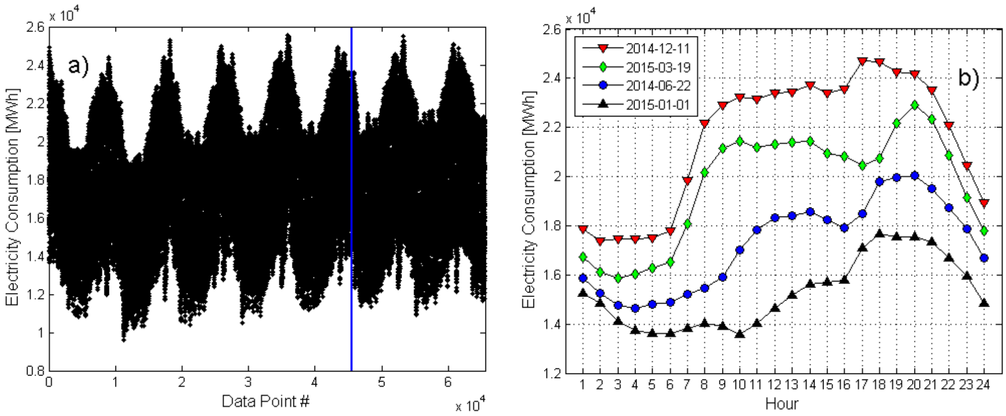



**Fig. 2.** a) The whole data series; b) Electricity consumption during selected days.

The individual days and weeks are not visible but annual periodicity is clear. The high power demands take place during winters, low – during summers. There is a visible weak rising trend, but the data was not correct for the trend. The data is smeared vertically due to various days of the week, holidays, temperature, humidity and so on as was mentioned earlier. The Figure 2b contains sample daily time series of electricity consumption for selected four days. The attributes of presented days are listed in Table 2.

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_30

**Table 2.** The attributes of the selected days

| No | Data | nDay | Working Day | Month |
|---|---|---|---|---|
| 1 | 2014-12-11 | Thursday | Yes | December |
| 2 | 2015-03-19 | Thursday | Yes | March |
| 3 | 2014-06-25 | Wednesday | Yes | June |
| 4 | 2015-01-01 | Thursday | No | January |

The highest power demand is on (1) 2014-12-11, which is weekday in winter (December). It is a regular working day. Next, (2) 2015-03-19 is also a regular working day but during March, month almost always significantly warmer than December. Slightly lower demand is experienced on (3) 2014-06-25, the day in June, during summer. Probably, because it is significantly warmer day than two previous ones, electricity consumption is significantly lower. In this case there is no second maximum at evening hours. Even lower electricity demand is on (4) 2015-01-01 which is the New Year. The electricity consumption starts rising very late and its maximum is at about 18 o'clock. Although, we are looking at time series for various seasons, days of the week, etc. we can still see common features. There is a local minimum during night hours followed by a rising power demand. Next, we can observe small local maximum, wide plateau or slow rise. Afterwards, the power consumptions drop a little bit or at least stop rising and then rise again towards local maximum. At the end of a day there is a significant drop in the power consumption. Described common features and visible smoothness of daily time series lead to the idea of the model which is presented below.

# 4 Model Construction

## 4.1 The model

The model presented herein is based on a linear multidimensional regression and is self-configurable – no model parameters have to be set up front. Its purpose is to find the most essential data points (hours) whose values allow to model the electricity consumptions for remaining hours within the same day. The whole data set consists of the time series of hourly electricity consumption.

In order to build and configure a model, we use a learning subset of data (see Figure 2a). The remaining data is used for testing purposes of the final model. The described variables are hourly electricity consumptions $E(h)$, $h = 1, 2,\ldots, 24$. The construction of the model is performed in successive steps. Each step expands the model by changing the type of one variable from described to describing. During each step another hour is chosen till one reaches a demanded accuracy. The procedure starts with 24 described variables corresponding to 24 hours in step zero. One calculates a root of the mean error squared (standard deviation) for each variable:

$$s(h) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(E_i(h) - \overline{E(h)}\right)^2} \tag{1}$$

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_30

where, $E_i(h)$ – electricity consumption at hour $h$ in $i$-th day, $\overline{E(h)}$ – average electricity consumption at hour $h$, $N$ – total number of analyzed days. The mean electricity consumption and standard deviation are plotted vs hour in Figure 3.

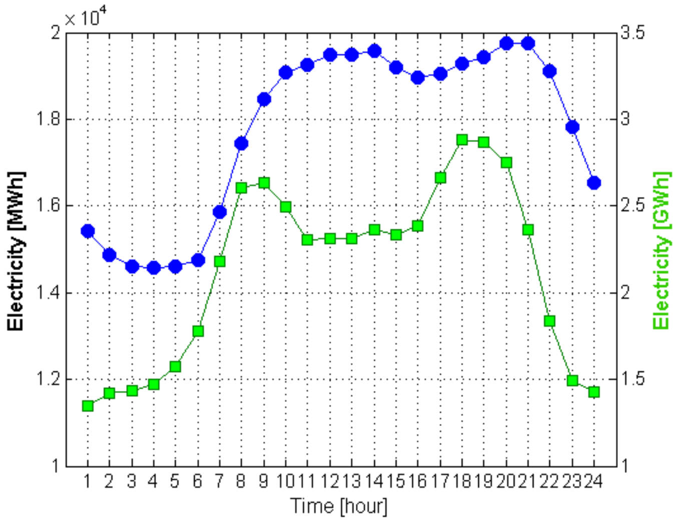



**Fig. 3.** Mean energy consumption (blue circles) and standard deviation (green squares) vs hour.

Now, the first step starts and the hour for which $s(h)$ is the biggest is chosen, in our case 18 o'clock. This hour is denoted by h1 and an electricity consumption at this hour by $E_i(h_1)$. The chosen variable is used to construct 23 linear regressions of the form:

$$E_i(h) = a_{1h}E_i(h_1) + a_{0h} + \varepsilon_i \tag{2}$$

where $h = 1, 2,\ldots, 24$ and $h \neq h_1$, $i = 1, 2,\ldots, N$ and $a_{1h}$, $a_{0h}$ are model parameters. For each linear model root of the mean squared error (3) is calculated.

$$\sigma(h) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(E_i(h) - \hat{E}_i(h)\right)^2} \tag{3}$$

where the error $E_i(h) - \hat{E}_i(h)$ is the difference between theoretical and empirical value. In the second step the hour corresponding to the biggest $\sigma(h)$ – the most poorly described variable is chosen: $h_2 = 9$ (see Figure 4). Now, there are 2 describing and 22 described variables. The 22 linear regressions of the form (4)

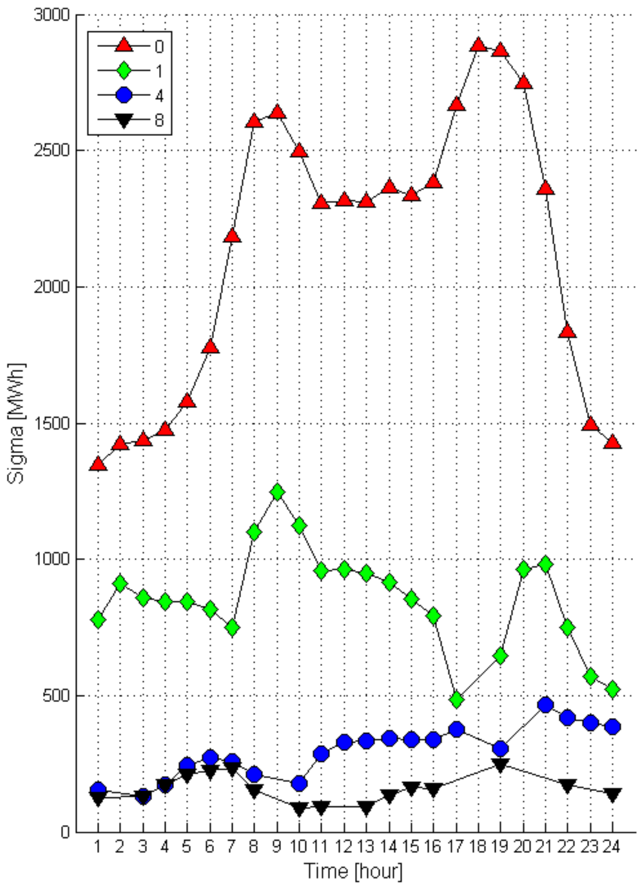
$$E_i(h) = a_{2h}E_i(h_2) + a_{1h}E_i(h_1) + a_{0h} + \varepsilon_i \tag{4}$$

are built and another set of $\sigma(h)$ is calculated. During the third step, the third describing variable is chosen and 21 models are calculated. The procedure is repeated till only one described variable will remain or when demanded accuracy will be reached. The values of $S(h)$ and $\sigma(h)$ are presented in Figure 4. One showed values for steps: 0 and 1 as well as another sample steps: 4 and 8. One can notice that the values of $\sigma(h)$ for the first step are significantly smaller than those obtained during the previous step. In the following

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_30

steps the values of $\sigma(h)$ became smaller. During each step more accurate models are constructed, each with one more describing variable but for the price of dropping the number of described variables.

**Fig. 4.** Values of $S(h)$ for the step zero and $\sigma(h)$ for the steps: 1, 4, and 8.




The procedure finishes with one linear regression with 23 describing variables and only one described variable. The biggest, mean and the smallest $\sigma(h)$ for modeled hours vs step number are plotted in Figure 5.

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_30

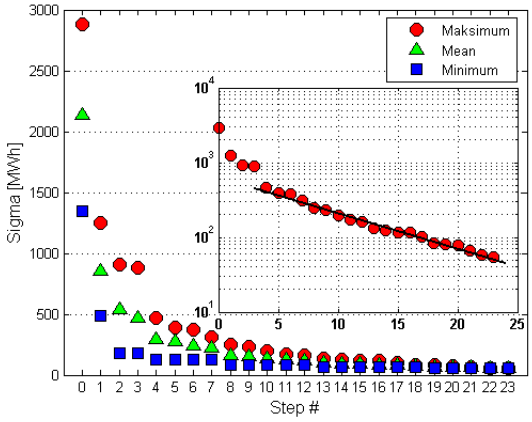



**Fig. 5.** Values of $S(h)$ for the step zero and $\sigma(h)$ vs step number. There are maximum, mean, and minimum values for each step. Inserted plot shows maximal values vs step number in log scale. Line represents linear fit to data points starting with step 4.

The biggest $\sigma(h)$, which are taken into account during each step are also plotted in logarithmic scale. The progress during the first steps is very big and became smaller afterward. For example, having 4 describing variables the most poorly described hour has the root of the mean squared error below 500. That means a $\sigma(h)$ dropped almost 6 times in comparison to the starting step when it was almost 3000. We want the error to be as small as possible. On the other hand, we want to have as few describing variables as possible possessing a model with big support. In the Figure 5 we see that, starting from 4 variables the maximum sigma drops systematically according to the exponential law. It seems that the optimal number of steps is 4, when we get high accuracy while having a small number of describing variables and big support (20 described variables). One should keep in mind we take into account the biggest $\sigma(h)$, while taking into account mean $\sigma(h)$ we would get even better results – they would drop from about 2200 to about 250 so approximately 9 times. However, the interpretation of the maximal $\sigma(h)$ is clearer: a time series is described with the accuracy equal or better than a given sigma. For comparison, we present $\sigma(h)$ for 4-th and 8-th step in Figure 4. Having 4 and 8 describing variables we would have the poorest described variables with sigma equal to about 500 and 250 respectively.

### 4.2 Testing the model

The last stage is the test of the model with 4 describing variables. The model is based on variables related to the electricity consumptions at: $h_1 = 18$, $h_2 = 9$, $h_3 = 2$, and $h_4 = 20$. They were selected at first four successive steps. The model is described by the formula:

$$E_i(h) = a_{4h}E_i(h_4) + a_{3h}E_i(h_3) + a_{2h}E_i(h_2) + a_{1h}E_i(h_1) + a_{0h} + \varepsilon_i \quad (5)$$

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_30

We use test data set – the last 9 984 hours that corresponds to 416 days. We compared empirical time series of electricity consumptions for one day with those provided by the model. Results for sample days are presented in Figure 6. The red markers indicate empirical, black – theoretical data, and open circles indicate describing variables. Attributes of the selected days were listed in Table 2.

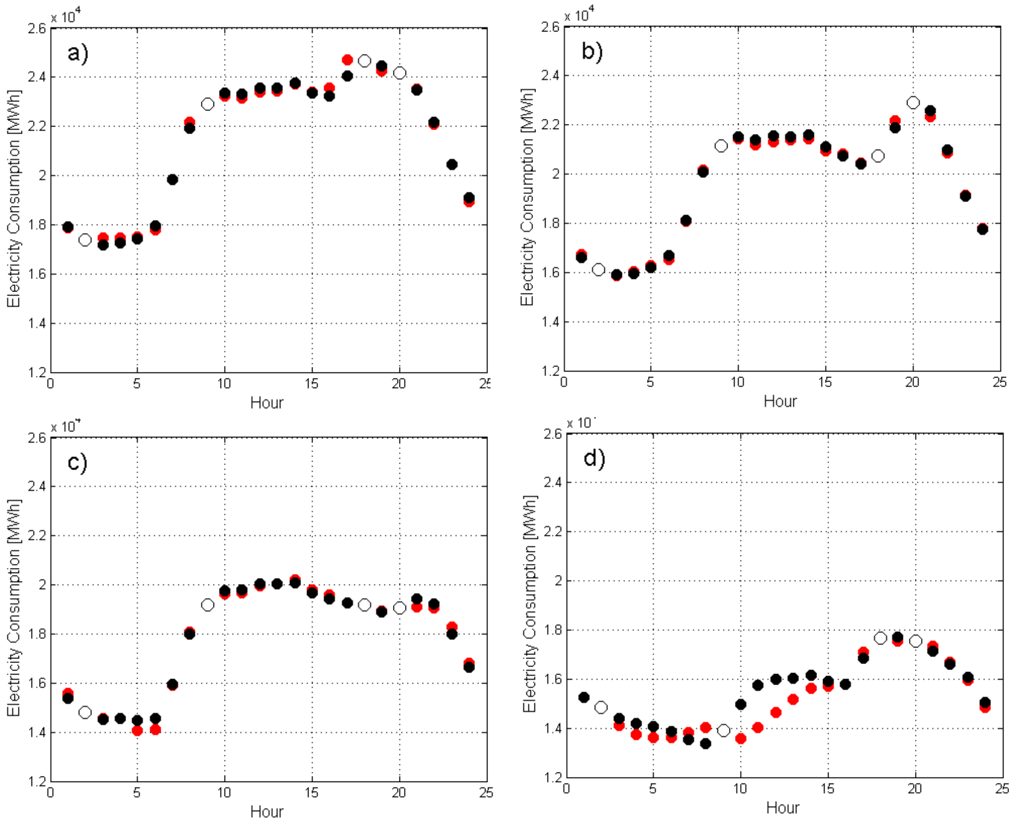



**Fig. 6.** Empirical (red dots) and theoretical (black dots) electricity consumptions for selected days: (a) 2014-12-11, (b) 2015-03-19, (c) 2014-06-25, (d) 2015-01-01. Theoretical values are provided by the model (5) with 4 describing variables indicated by open circles.

Although presented plots are for different days of weeks, seasons and environmental conditions (thus having various shapes), the model describes data well. However, some discrepancies are visible. The shapes of the empirical and theoretical plots are similar to each other. Let note that the majority of the differences are between −1% and 1%. The biggest differences are for New Year 2015-01-01 10:00 and 14:00 o'clock (see Figure 6). In order to investigate the model quality in the complex manner, we defined the model quality measure given by the formula (6):

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_30

$$Q(i) = \sqrt{\frac{1}{20}\sum_{h=1}^{24}(E_{ih}-\hat{E}_{ih})^2} \Big/ \frac{1}{20}\sum_{h=1}^{24}\hat{E}_{ih}, \tag{6}$$

where, $h \neq h_1$, $h_2$, $h_3$, $h_4$ and $i = 1, 2, \ldots N$. Measure (6) is a relative root of the mean squared error. Figure 7a contains values of the quality measure $Q(i)$ for the full range of the test data set. Presented results indicate a very high quality of the model in the entire data range. Moreover, there is no visible trend of values of $Q(i)$. The distribution of the measure values is presented in Figure 7b, while the distribution of the log-values is in Figure 7c. One can notice that the distribution of the measure values has a shape similar to a log-normal. The distribution starts at about 0.5%, has the maximum at 1.5% and falls rapidly thereafter. Almost all measure values (95%) are within the range of 0.5% - 2.8%, however there are a few high spikes, the highest reaches almost 7%. We investigated attributes of days related to the highest six values of the quality measure: 7%, and three around 5% and two about 3.5%. They are listed in the Table 3.

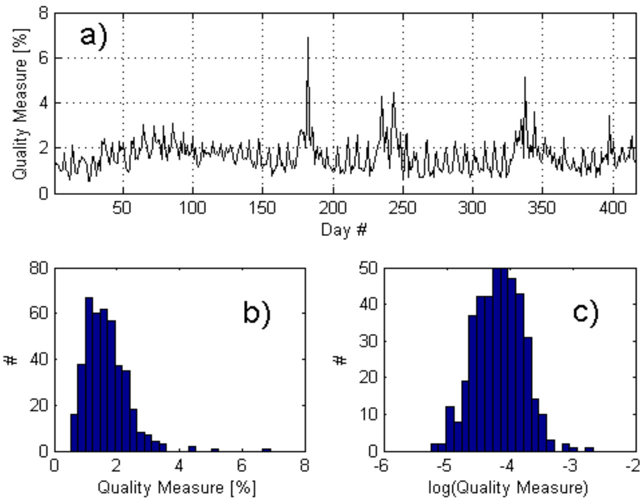



**Fig. 7.** a) Quality measure $Q(i)$ for each day in test data set; b) Distribution of quality measure values; c) Distribution of logarithm of quality measure values.

**Table 3.** Days with the highest values of the quality measure. All the days are holydays (names in brackets)

| Data | Week Day | $Q(i)$ [%] |
|---|---|---|
| 2014-11-01 | Saturday (All Saints' Day) | 6.89 |
| 2014-12-24 | Wednesday (Christmas) | 4.31 |
| 2015-01-01 | Thursday (Labour Day) | 4.43 |
| 2015-04-05 | Sunday (Easter) | 5.11 |
| 2015-04-12 | Sunday (Orthodox Easter) | 3.59 |
| 2015-06-04 | Thursday (Corpus Christi) | 3.44 |

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_30

If the days with the highest values of the measure are not typical, that would explain the differences between the model and data. The first spike is on the first of November – a holiday. All Saints' Day is celebrated solemnly in Poland. It is a bank holiday during which people travel a lot to visit family graves. Additionally, in 2014 this day was on Saturday, which favored trips. That's why the spike in this case was so strong. We deal with not a typical day. The second spike is in Christmas Eve which occurred on Wednesday. It is worth to point out that during Christmas, next two days are non-working days in Poland, thus, there was so called long-weekend: Thursday-Sunday. The next spike was related to the New Year, which was on Thursday. There is a common practice in Poland to take the next day off and have a long weekend. The fourth spike occurred during Easter Sunday, while the next day is also a bank holiday in Poland. The last two spikes are lower than previous ones. The first one corresponds to Orthodox Easter, holiday celebrated by the biggest religious minority in Poland. The next day is also celebrated by them. The last spike occurs on Thursday (Corpus Christi bank holiday) and it makes a long weekend possible. All the most deviated days are related to the bank holidays which are the first days of groups of non-working days. They surely cannot be regarded as typical. To conclude, the elaborated model can be used to distinguish non typical days from the electricity consumption point of view.

## 5 Conclusion

In this work, the hourly electricity consumption was investigated. In order to describe shapes of time series during each day, the data mining model was elaborated. The model uses the multivariate linear regression technique. Its aim is to find points in data series which will describe remaining data points in the same day. The construction of the model is performed in steps and every step improves the accuracy but lowers support. It is up to the user when to stop a construction of the model and, thus, obtaining required precision. The accuracy was measured as a maximum root of the mean squared error. Based on the Polish data, we showed that the model with 4 describing variables, describes 20 hours remaining very well, exhibiting dominant relative error about 1.5%. The model describes data very well, independently on season, temperature time series, humidity, or day of the week. It is characterized by a high precision and allows finding non-typical days from the electricity demand point of view.

During future studies this model will be used for classification of the daily electricity demand profiles as well as for finding non-typical electricity consumptions. The model will be also used for identification factors influencing electricity consumption at different hours of day. We also expect to obtain good results during a prognosis of the electricity demand.

## References


1. Pérez-Arriaga, I. J.: Regulation of the Power Sector. (I. J. Pérez-Arriaga, Ed.), Springer, London, (2013).



ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_30

2. Khatoon, S., Ibraheem, Arunesh, Kr. S., and Priti,: Effects of various factors on electric load forecasting: An overview. In: 6th IEEE Power India International Conference (PIICON), pp. 1-5, Delhi, (2014).
3. Kremers, E.: Modelling and Simulation of Electrical Energy Systems through a Complex Systems Approach using Agent-Based Models. KIT Scientific Publishing, Germany 2013.
4. Neng, S., Jingjing, Z., Wenjie, Z.: Energy Efficiency Measures and Convergence in China. Taking into Account the Effects of Environmental and Random Factors. Polish Journal of Environmental Studies , Vol. 24 Issue 1, pp. 257-267(2015).
5. Li, J., Yang, L., Long, H.: Climatic impacts on energy consumption: Intensive and extensive margins. Energy, Econ. 71, pp.332–343 (2018).,
6. McCulloch, J., Ignatieva, K.: Forecasting High Frequency Intra-Day Electricity Demand Using Temperature, SSRN Electronic Journal, (2017).
7. Xie, J., Hong, T.: Wind Speed for Load Forecasting Models. Sustainability, 9(5), pp.795 ( 2017).
8. Kalimoldayev, M., Drozdenko, A., Koplyk, I., Abdildayeva, M. A., Zhukabayeva, T.: Analysis of modern approaches for the prediction of electric energy consumption, Open Eng. 10, pp. 350–361 (2020).
9. Manowska, A.: Using the LSTM Network to forecast the demand for Electricity in Poland. Appl. Sci. 10, 8455 (2020).
10. Del Real, A.J., Dorado, F., Duran, J.: Energy Demand Forecasting Using Deep Learning: Applications for the French Grid. Energies, 13,2242 (2020).
11. Kang, T., Lim, D.Y., Tayara, H., Chong, K.T.: Forecasting of power demands using deep learning. Appl. Sci. , 20, 7241 (2020).
12. Ciechulski, T., Osowski, S.: Deep Learning Approch to Power Deman Forecasting in Polish Power System. Energies 13, 6154 (2020).
13. Elias Barrón, I., De, J., Rubio, J.d.J., Martinez, D., Vargas, T., Garcia, V., Mújica-Vargas, D., Meda Campaña, J., Pacheco, J., Gutierrez, G.: Genetic Algorithm with Radial Basis Mapping Network for the Electricity Consumption Modeling. Appl. Sci. 10, 4239 (2020).
14. Gajowniczek, K., Nafkha, R., Ząbkowski, T.: Seasonal Peak Demand Classification with Machine Learning Techniques. Applied Mathematics & Computer Science (ICAMCS) 2018 International Conference, pp. 101-1014 (2018).
15. Dudek, G.: Neural networks for pattern-based short-term load forecasting: A comparative study. Neurocomputing 205, pp. 64–74 (2016).
16. Dudek, G.: Pattern-based local linear regression models for short-term load forecasting. Electr. Power Syst. Res. 130, pp. 139–147 (2016).
17. Fan, G.F., Qing, S., Wang, H., Hong, W.C., Li, H.J.: Support vector regression model based on empirical mode decomposition and auto regression for electric load forecasting. Energies , 6, pp. 1887–1901 (2013).
18. Divina, F., Torres, M.G., Vela, F.A.G., Noguera, J.L.V.: A comparative study of time series forecasting methods for short term electric energy consumption prediction in smart buildings. Energies, 12, 1934 (2019).
19. De Gooijer, J.G., Hyndman, R.J.: 25 years of time series forecasting. Int. J. Forecast. 22, pp. 443–473 (2006).
20. Halepoto, I.A., Uqaili, M.A., Chowdhry, B.S.: Least square regression based integrated multi-parameteric demand modeling for short term load forecasting. Mehran University Research Journal of Engineering and Technology. 33(2), pp. 215-226 (2014).


ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_30

21. Vu, D.H., Muttaqi, K.M., Agalgaonkar, A.P.: A variance inflation factor and backward elimination based robust regression model for forecasting monthly electricity demand using climatic variables, Applied Energy, 140, pp. 385-94 (2015).
22. Ghandoor, A., Samhouri, M.: Electricity Consumption in the Industrial Sector of Jordan: Application of Multivariate Linear Regression and Adaptive Neuro-Fuzzy Techniques. Journal of Mechanical and Industrial Engineering, 3, 1, pp. 69-76. Jordan (2009).
23. Karpio, K., Łukasiewicz, P., Nafkha, R,: Regression Technique for Electricity Load Modeling and Outlined Data Points Explanation. International Multi-Conference on Advanced Computer Systems, ACS 2018. Advances in Intelligent Systems and Computing, vol 889. pp. 56-67. Springer (2019).
24. Polish power system dataset. http://www.pse.pl/index.php?dzid=77. Accessed 12 Aug 2017

ICCS Camera Ready Version 2021
To cite this paper please use the final published version:
DOI: 10.1007/978-3-030-77970-2_30