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The use of quantitative methods as measures for forecast electricity demand on the local market in a short time horizon

Abstract. *The article builds a model of an hourly system for short-term forecasting of electricity demand on the local market of the Krakow area in 2019-2022. Including quantitative methods. The time series representing the hourly system-wide electricity demand was decomposed. A comprehensive statistical analysis of the data was performed in order to select the best optimization method used to select the optimal coefficients of the developed method of estimating the quality of forecasts. In addition, the results of numerical experiments aimed at determining the impact of the y parameter value on the quality of forecasts for various forecast horizons were presented, and the relationships between the number of historical data and the quality of forecasts were established. Due to the periodic nature of the examined time series, a detailed analysis of seasonality and periodicity of a given signal was carried out using spectral analysis and autocorrelation. This analysis allowed the author create an effective tool for accurate local electricity demand forecasting in the time horizon "an hour before delivery". On the basis of data from the distribution company, the built system was verified. An analysis of profits and losses after applying the selected forecasting model was made. The proposed concept of the model is an effective analytical tool of the analyzed problem, which will make it easier for operators of energy companies to effectively support their decisions in forecasting electricity demand.*

Streszczenie. *W artykule zbudowano model godzinowego systemu do krótkoterminowego prognozowania zapotrzebowania na energię elektryczną na lokalnym rynku obszaru Krakowa w latach 2019-2022. Z wykorzystaniem metod ilościowych dokonano dekompozycji szeregu czasowego reprezentującego godzinowe ogólnosystemowe zapotrzebowanie na energię elektryczną. Wykonano wszechstronną analizę statystyczną danych w celu wyboru najlepszej metody optymalizacyjnej służącej do doboru optymalnych współczynników opracowanej metody szacowania jakości prognoz. Dodatkowo zaprezentowano wyniki eksperymentów numerycznych mających na celu ustalenie wpływu wartości parametru y na jakość prognoz dla różnych horyzontów prognoz oraz ustalono związki między liczbą danych historycznych a jakością prognoz. Ze względu na okresowy charakter badanego szeregu czasowego została przeprowadzona szczegółowa analiza sezonowości oraz okresowości danego sygnału przy pomocy analizy spektralnej oraz autokorelacji. Analiza ta pozwoliła autorowi stworzyć skuteczne narzędzie do dokładnego lokalnego prognozowania zapotrzebowania na energię elektryczną w horyzoncie czasowym „godzina przed dostawą". Na podstawie danych ze spółki dystrybucyjnej dokonano weryfikacji zbudowanego systemu. Dokonana została analiza zysków i strat po zastosowaniu wybranego modelu prognostycznego. Zaproponowany koncepcja modelu jest skutecznym narzędziem analitycznym analizowanego problemu, które ułatwi operatorom spółek energetycznych, skuteczne wspomaganie podejmowanych decyzji w prognozowaniu zapotrzebowania na energię elektryczną. (**Wykorzystanie metod ilościowych jako mierników do prognozowania zapotrzebowania na energię elektryczną na lokalnym rynku w krótkim horyzoncie czasowym**).*

Keywords: power engineering, forecasting, electricity demand, electricity production.
Słowa kluczowe: elektroenergetyka, prognozowanie, zapotrzebowanie na energię elektryczną, produkcja energii elektrycznej.

Introduction

One of the basic problems that must be solved at each stage of electricity generation and trading is obtaining a precise forecast of electricity demand in the energy system (both national and local). The energy security of the state as well as the profit of electricity producers and distributors depend on the result of this forecast. Forecasting the short-term demand for electricity over the next 24 hours is essential for ensuring its safe operation and, consequently, for the continuity of electricity supply.

Forecasting the demand for electricity has long been one of the basic tasks of distribution companies that purchase electricity on the wholesale market in order to meet the demand of consumers on the local market. Knowing the demand forecast and wanting to reduce the price risk on the wholesale market, companies try to conclude contracts in market segments low risk (bilateral contracts) or limitable risk (stock exchange transactions) and avoid the most risky balancing segment. As a result, by concluding appropriate contracts, companies determine their contractual position, deviations from which are the basis for settlements in the balancing segment of the energy market. Distribution companies incur the greatest loss when purchasing electricity on the balancing market, which results from the underestimation of the load forecast. Similarly, electricity producers, when they are unable to deliver the contracted amount of energy to the system, must buy it on the balancing market. The need to reduce the costs of purchase and sale of electricity in the balancing segment by reducing the amount of energy purchased there prompted the author to undertake research. The aim of the work is to build an hourly system for short-term forecasting of electricity demand for local electricity market. For the development of the local electricity market, short-term forecasts with a horizon of 1 to 2 hours are needed. These forecasts (especially one hour before delivery) must be subject to the smallest possible error, as decisions on balancing activities on the local electricity market will be made on the basis of this forecast. This error should be less than 1% to minimize the financial risk associated with the purchase of energy. The task of the built system will be to support decision-making regarding the management of the local hourly electricity market, which will contribute to reducing the forecast error and improving financial results.

The study describes the possibilities of predicting demand and prices on the retail electricity market using artificial intelligence tools. This knowledge allows for economic optimization both in entities operating on the demand and supply side. Further optimization of the market requires reducing peak demand in particular, which is possible, among others, by based on an energy forecasting system. The content of this article gives a fresh and innovative look at the essence of energy forecasting processes, taking into account the benefits of energy production and the financial benefits for generation plants incurred from its generation. The forecasting models used in the work, with particular emphasis on seasonal models, have become a good tool for energy forecasting. The conducted analyzes give promising results, they show that it is worth dealing with the further development of market mechanisms not only at the national level, but also at the local market electric energy. Scientific achievements in the field of forecasting, both in economics and in technical sciences, are perfect for forecasting seasonal time series representing the demand for electricity on the local electricity market. The creation of a local hourly electricity market is possible and profitable, and the mutual cooperation of electricity producers and distribution companies can bring financial benefits to each of the parties to this market. Although the presented considerations refer to the realities and legal regulations prevailing in one of the selected European Union countries - Poland, these considerations can be used in practice in other regions of the world. At the same time, the content of the considerations provides a basis for further development of research on these processes in order to promote energy forecasting policies and techniques.

Analysis of statistical data on electricity demand - the essence of the research problem

In the case of short-term power system load forecasting, both autoregressive methods have been used for years properties of moving averages and exponential smoothing as well as methods using machine learning and artificial intelligence. Forecasting the value of power, energy, load, etc. is crucial for planning the operation, development and modernization of the power system. Artificial neural networks, thanks to good-quality prediction and freedom in the selection of factors determining the forecast, are particularly useful in the case of short-term forecasts [1,2]. They have the ability to detect the relationship between input and output data without a known relationship between them. It is also important that artificial neural networks, thanks to their ability to generalize, can work with inaccurate and even incomplete data. Power requirement electricity in the power system is characterized by high fluctuation [3-5]. The key in this case are: daily, weekly, annual and long-term variability [6]. For the purposes of illustrating the volatility of electricity demand, it is also possible to distinguish seasonal variability (which results in annual variability), quarterly variability (seasons) and monthly variability (part of seasons). Continuity of demand for electric power and the still "insufficient" (in the sense of high power/capacity) development of energy storage facilities results in the inability to store it in large quantities, which makes it necessary to cover the demand for electric power on an ongoing basis exactly at the moment of occurrence of this demand [7,8].

The paper analyzes the electricity demand data using time series, seasonality analysis, the impact of external factors and the stationarity of the time series. Time series of electricity demand was constructed from data representing the hourly demand for electricity. These data represent the demand on the Małopolska electricity market in the period from January 1, 2019 to October 31, 2022. Figure 1 presents all the data collected for the analysis.

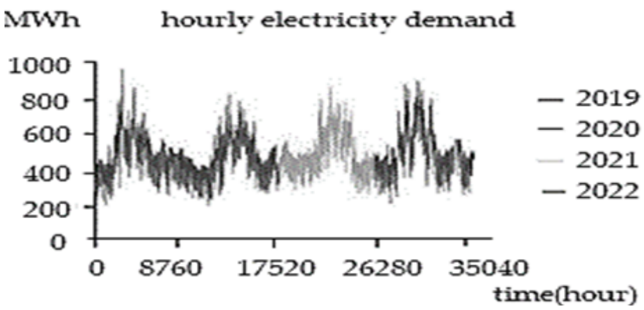

Fig.1. Hourly demand for electricity in 2019-2022 on the local energy market in Lesser Poland

After analyzing the statistics from the percentage changes in annual energy sums for this period, it can be concluded that the amount of energy needed changed in a very small range, i.e. a maximum of 2.7%. Since the aim of the work is short-term forecasting, the annual cycle was omitted in the analysis [9,10]. Also, the sum of the monthly demand for electricity did not change significantly in those years, as shown in Figure 2. In this figure, the presented series shows tendencies to annual cyclical fluctuations. These fluctuations are related to the recurring seasons.

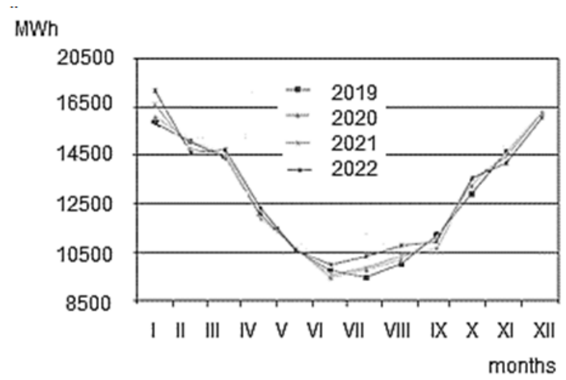

Fig.2. Monthly sums of demand for electricity in 2019-2022 on the local energy market

In order to detect seasonality, the collected data for a shorter period of time was analyzed (Figure 3). It was noticed that the energy demand in different months and days of the week in terms of hourly average value is different. This happens in all months of the year, which is mainly due to the decrease in demand on these days in the business sector [11]. Therefore, it is justified to analyze data divided into two sets, i.e. weekdays (working days) and holidays (Saturday, Sunday and holidays).

Fig.3. Average hourly electricity demand in 2021

Subsequently, the following was performed: autocorrelation analysis using the autocorrelation function between the values of a series of data spaced apart by k points and an analysis of partial autocorrelation, i.e. correlation of the series with itself, shifted by a specific delay *k* of observations, while eliminating the correlation effect for all shifts from 1 to *k-1*. In order to detect seasonality in the examined time series, the following were determined: covariance matrix and partial autocorrelation coefficients $\varphi_{i,j}$ recursive method using the differential operator ∇_z^{-1} from formula (1). The results of the analysis of the partial autocorrelation function are shown in Figure 4.

$$\varphi_{p+1,p+1} = \frac{r_{p+1} - \sum_{j=1}^{p} \varphi_{pj} \cdot r_{p+1-j}}{1 - \sum_{j=1}^{p} \varphi_{pj} \cdot r_j} \tag{1}$$

$$\nabla^{-1} z_i = D(-1) z_i = z_i - z_{i-1} = (1 - B) \cdot z_t$$

where: φ_{pj} – partial correlation coefficients, r_j - correlation coefficient of the *j*-th explanatory variable with the output,

r_{pj}- is the correlation coefficient of the i-th and j-th explanatory variable$B$ – backshift operator $Bz_i = z_{i-1}$ oraz $B^m z_i = z_{i-m}$.

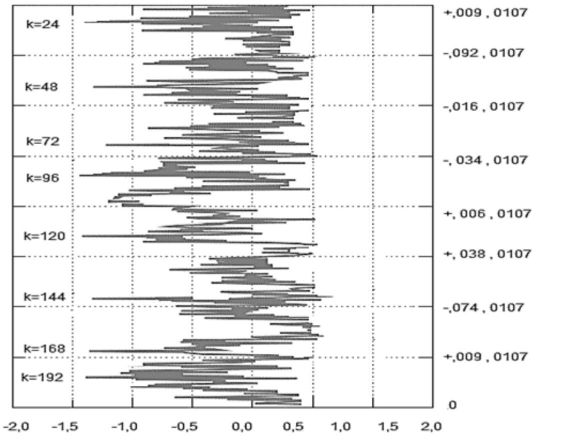

Fig.4. Plot of differentiated partial autocorrelation (k = 200, D-1, D-24) for data for 2021

From Figure 4, it was observed that the selected time series representing the demand for electricity for 2021 has several periods of seasonality. The basic period is k = 24 hours, i.e. a daily cycle. The next period is k = 168 hours, i.e. a weekly cycle. Annual fluctuations were not visible here, because the time series taken for analysis represented data from only one year. The above analysis also shows that the seasonality detected in this way is very strong and cannot be completely removed by the differentiation operation [12]. Therefore, a spectral analysis was then performed to detect seasonality in the time series using the spectral density estimator, i.e. the periodogram. Periodogram values can be interpreted in terms of variance (sum of squares) corresponding to variations of a particular frequency or period. For the vector {x1, x2, ..., xn}, the periodogram is defined by the formula (2) [13,14]:

(2) $$I_n(\omega_k) = \frac{1}{n}|\sum_{i=1}^{n} x_i \exp[-2\pi i(t-1)\omega_k|^2$$
$$for\ \omega_k = \frac{k}{n} \quad k = 1,2,\dots n/2$$

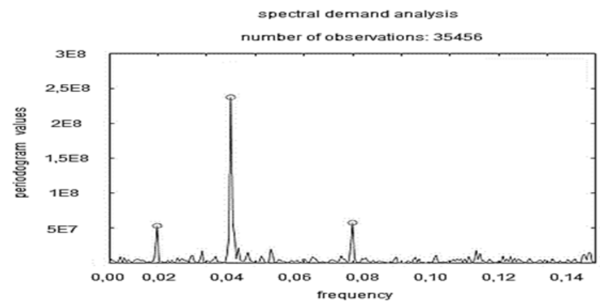

Fig.5. Spectral analysis plot for the entire time series

The analysis of Figure 5 shows that the examined time series shows periodicity in its course. The highest values are for the period corresponding to the year, week and day. There is also a lot of other harmonic data, which is a result of the complexity of this time series, but these three main periods confirm previous chart observations and autocorrelation analysis. In addition, two sets of data for the so-called holidays and weekdays, which was confirmed by the calculation of hourly averages for these days. Subsequently, the time series was decomposed, i.e. the trend function was determined, taking into account the degree of fit. Since the analyzed time series has two significant periods T1 = 24 hours and T2 = 168 hours, a seasonal decomposition should be performed for these periods. Figure 6 shows the decomposition effect for the additive model.

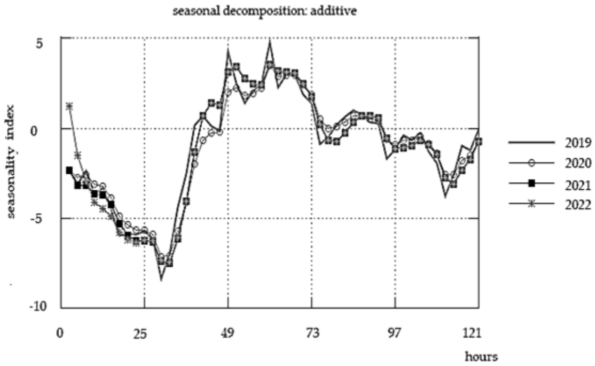

Fig.6. Seasonal model charts for 2019-2022

From the analysis of Figure 6, it can be concluded that the years 2019-2022 are very similar to each other, and 2019 is a bit different from them. It can also be seen that the biggest difference occurs in both the additive and multiplicative models. Due to the fact that after taking into account the criterion of minimizing the random factor, the additive model turned out to be better than the multiplicative model, therefore further analyzes were carried out for the additive model. Its results are presented in Table 1.

Table 1. Results of decomposition of the time series into components resulting from the influence of the trend, seasonality and random factors for data from 2019-2022

	Year 2019	Year 2020	Year 2021	Year 2022
R^2	0.5544	0.6949	0.5291	0.5186
R_{pop}^2	0.8166	0.8283	0.8209	0.8392
Random factor e(t)	5.11%	5.12%	5.63%	4.87%
Seasonality	15.11%	12.34%	29.97%	20.95%
Trend	55.32%	69.49%	52.91%	51.86%

The analysis of Table 1 shows that the effect of random factors in the examined time series is at the level of about 4%. Determining these factors and identifying them and describing them in the form of an analytical function is almost impossible. These factors include two main groups: natural factors and socio-cultural factors. Natural factors are primarily the influence of climate, i.e. changes in meteorological parameters. Socio-cultural factors are related to various mass events, e.g. cultural, religious, sports, political, etc. While the first group, i.e. meteorological parameters, is easy to measure and identify as a phenomenon, finding an analytical description of the impact of these parameters is very difficult. Temperature is a parameter that changes quite predictably throughout the year, which makes it easy to determine and evaluate the trend function. But there are large fluctuations around this line in particular periods (weeks months), especially transitional, i.e. winter, spring, etc. Moreover, there is an inverse relationship between these parameters. The coefficient of determination R2 was used to detect the correlation between these variables. It determines the strength of the linear relationship between the explanatory variable - ambient temperature and the variable forecast value - energy demand. After preparing statistics for the regression analysis for 2021 based on hourly data and determining the dependence of electricity demand for a given period, an analysis of daily averaged data was carried out. The result of this analysis is the value of the R2 coefficient at the level of 0.6019. The value of the F(1.241) statistic verifying the hypothesis about the significance of the coefficient of determination R2 is greater than F, so the null hypothesis of the lack of linear dependence should be rejected and the alternative hypothesis accepted. Therefore, the results should be considered significant. If there is a need to test other metrological parameters and their influence on the size demand, this analysis should be performed similar to the above analysis for ambient temperature.

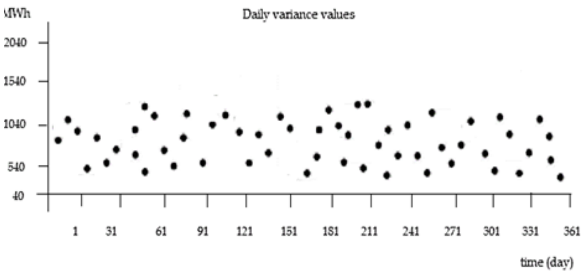

Fig.7. Daily statistics for 2021 using the adjusted series

For the complete data analysis, the stationarity of the time series was also examined. After analyzing the data, it was found that both the mean value of the action (trend) and the variance change over time. As a result, the analyzed series is not stationary, because its first moments change in time. Therefore, the method of correcting the time series by subtracting the seasonality coefficients calculated in the seasonal decomposition process from the original series was used. Then, the series was differentiated by the value of D(-24) and the periodic component selected using the additive model with a period of 168 hours was subtracted from the series. Then, the model was reprocessed with the differentiation operator D(-1), which resulted in the stabilization of the variance and the mean over time. The results of this analysis are shown in Figure 7.

Short-term forecasting in the energy sector

In this part of the analysis, the hourly electricity demand for the local area of Poland was forecasted using the following models: naive, exponential smoothing, artificial neural networks, multiple regression and the SARIMA model. Due to the extensive scope of this part of the research and the extensive analysis of their results, the author decided that for a better illustration of this part of the research, it would be appropriate to show only a comparative analysis of the results of all built models, rather than their individual interpretation. Table 2 summarizes the results for the best models in each of the analyzed methods.

The SARIMA model gives the best results both in terms of the mean value of the relative error and the autocorrelation analysis. These models have some limitations. The condition for forecasting based on time series is the skillful perception of certain regularities in past events. Deepening the observation with a qualitative and quantitative measurement of these regularities and the selection of rules according to which they will be extrapolated into the future is the basis for using this type of forecasting.Comparing all built models, it can be observed that in all cases the distribution of model residuals deviates from the ideal normal distribution. However, in the ARIMA seasonal model, these differences start to become visible only beyond the ±2σ range. We are dealing here with the so-called fat tails (Figure 8). This is the result of large errors made when forecasting demand on holidays.

Table 2 List of the best models

Model	ME - Mean Error, MWh	MAE - Mean Absolute Error	MSE - Mean Squared Error	MPE - Mean Absolute Percentage Error	MAPE - Mean Absolute Percentage Error, %	SDE - Standard Deviation of Errors, MWh	DW - Durbin–Watson statistics
Naive	-0.002	15.46	227.7	-0.001	3.56%	24.23	0.67
Exponential smoothing	0.0013	12.49	235.4	-7E-02	2.75%	17.51	1.23
SSN	0.1276	10.17	110.6	-4E-02	1.51%	13.78	1.45
Regression	0.0024	12.68	220.4	-2E-02	2.45%	17.19	0.67
SARIMA	0.0122	9.36	101.6	-5E-04	1.29%	9.34	1.65

Table 3 Comparison of SARIMA models

Model No	Weeks	ME - Mean Error, MWh	SS - sum of sqared, MWh	MSE - Mean Squared Error, MWh	SDE - Standard Deviation of Errors, MWh	MAPE - Mean Absolute Percentage Error, %	DW - Durbin–Watson statistics
1	1-6	0.1211	84742	86.40	8.64	0.97%	1.89
2	7-12	-0.0510	75804	77.31	7.19	0.96%	1.89
3	13-18	0.0017	12150	99.83	8.11	1.87%	1.91
4	19-24	0.1009	74624	76.02	7.84	1.32%	1.87
5	25-30	-0,0342	79414	79.81	8.84	1.30%	1.88
6	31-36	-0.0053	77086	78.63	8.24	1.56%	1.95
7	37-42	-0.0220	67604	68.94	7.67	1.11%	1.56
8	43-48	0.0174	99838	99.45	9.32	1.09%	1.91
9	46-51	0.0008	88094	99.79	8.81	1.15%	1.89

Table 4 Model validation results for 2021

Forecast, week	Calibration, week	ME - Mean Error, MWh	SS - Sum of sqared, MWh	MSE - Mean Squared Error, MWh	SDE - Standard Deviation of Errors, MWh	MAPE - Mean Absolute Percentage Error, %	DW - Durbin–Watson statistics
7	1-6	-0.0201	20816	181.13	12.74	1.15	2.36
8	2-7	-0.1287	20478	68.87	8.44	0.98	2.03
9	3-8	0.0814	13142	87.42	8.24	1.09	2.11
10	4-9	-0.2794	13437	131.11	8.22	1.03	1.36
11	5-10	0.1793	16567	168.54	9.14	1.36	1.52
12	6-11	-0.3404	16567	134.51	10.21	1.18	1.84
….	….	….	…..	…..	….	…..	…..
50	44-49	-0.0676	18421	171.56	10.11	1.09	2.31
51	45-50	0.0478	21400	145.21	9.14	1.14	2.14
52	46-51	-0.0578	31587	165.41	8.14	0.94	2.01

Table 5. Comparison of forecasting results an hour before delivery y(t)1 and a day before delivery y(t)24 for October 12, 2022

		Forecast made a day in advance			Forecast made an hour earlier		
t	y(t)	Predictive model one day earlier, $y(t)^{24}$	Absolute forecast error, e	PE - Percentage Error	Predictive model one hour earlier, $y(t)^{1}$	Absolute forecast error, E	PE - Percentage Error
	[MWh]	[MWh]	[MWh]	[%]	[MWh]	[MWh]	[%]
1	783	755.19	38.03	5.27	786.18	-4.18	-0.57
2	759	713.95	45.27	6.38	748.96	21.26	2.68
3	742	658.04	43.15	6.12	753.67	-12.45	-2.54
4	741	682.18	45.25	6.23	732.34	9.54	2.14
5	752	715.42	47.87	6.85	754.47	-3.75	-1.42
6	781	744.19	48.54	6.98	770.54	1.54	0.14
7	841	814.45	37.65	4.67	830.32	0.83	0.12
8	872	847.99	34.76	4.67	877.55	-5.32	-0.83
9	800	868.46	52.23	6.32	899.65	9.34	1.54
10	923	882.47	50.93	6.97	926.43	-3.22	-0.36
11	925	886.17	49.43	5.78	926.54	-1.34	-0.24
12	919	898.65	31.35	3.56	937.32	-17.42	-2.65
13	921	898.12	21.19	2.65	922.55	-3.21	-0.65
14	955	943.45	22.32	2.76	969.64	-5.32	-0.54
15	942	942.15	2.56	1.23	938.54	-6.43	0.54
16	898	-34.45	-33.91	-4.13	899.43	2.45	-0.34
17	905	-64.78	-34.56	-7.65	898.65	-1.54	0.84
18	984	22.95	-64.32	2.54	977.32	5.43	2.56
19	1010	985.47	21.38	4.13	1015.04	19.64	-0.43
20	1035	-62.87	39.34	-7.43	1019.54	-0.25	-9.76
21	932	-58.63	-62.87	-7.32	860.43	-65.32	3.21
22	847	-33.45	-58.32	-4.12	827.65	21.23	2.11
23	825	-6.75	-4.32	-1.76	814.66	4.32	0.65
24	795	3.48	-1.92	0.37	804.22	0.23	0.04

Table 6 List of normal distribution parameters for percentage errors (PE) of the forecast

Forecasting model	Mean standard deviation of PE	PE standard deviation	Distributor		F(-1)-F(1)
			F(-1)	F(1)	
	[MWh]	[MWh]	[%]	[%]	[%]
A day ahead	0.0371	2.41	27.37	59.84	11.4
One hour ahead	0.0201	0.23	11.21	65.66	43.3

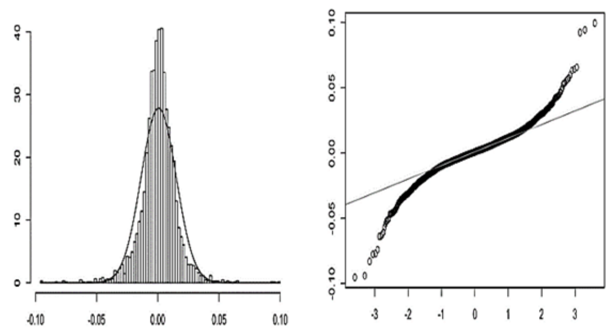

Fig.8. Residual distribution for the ARIMA model

Great care should be taken when forecasting demand on church and public holidays. Building a statistical model for these days with a small error is difficult due to the small amount of data. The best way to forecast demand on non-working days is an expert system combined with statistical data analysis. The hourly values of the MAPE relative error are shown in Figure 9. These data show how the prediction errors look like in individual hours. On the graph showing the hourly MAPE error, lines are marked at the level of 1%. This limit is the goal set for the forecasting model so that it can be useful for supporting decisions when purchasing energy on the hourly market. You can see that for no hour the error is below this line, and the total error of the model is 1.74%.

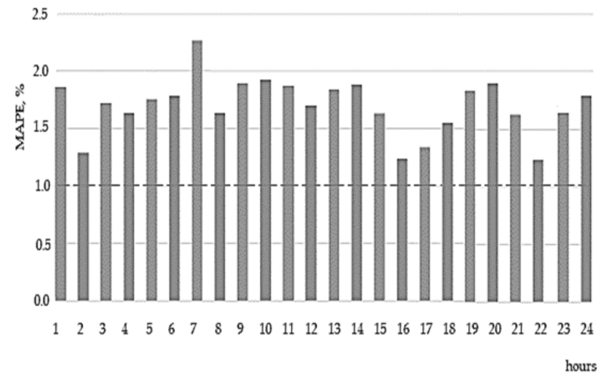

Fig.9. Hourly relative error values for the ARIMA model

However, this model was built for a seasonal factor calibrated for the whole year. Better results will be obtained using the adaptive method of estimating model parameters. This method consists in calculating the parameters of the ARIMA model each time for a new day. For the calibration of the seasonal component, data from the last 6 weeks was used instead of the whole year. A comparison of models whose parameters were estimated using the adaptive method is presented in Table 3.

Comparison of MAPE percentage errors for selected periods for the model calibrated for the whole year and for the model calibrated for 6 weeks using the adaptive method showed that for each of the selected periods the adaptive model has a smaller error and standard deviation. Still, the percentage error is not always less than 1%, but it is already approaching this value. After eliminating holidays that generate large errors, achieving 1% error is possible excluding morning and evening rush hours.

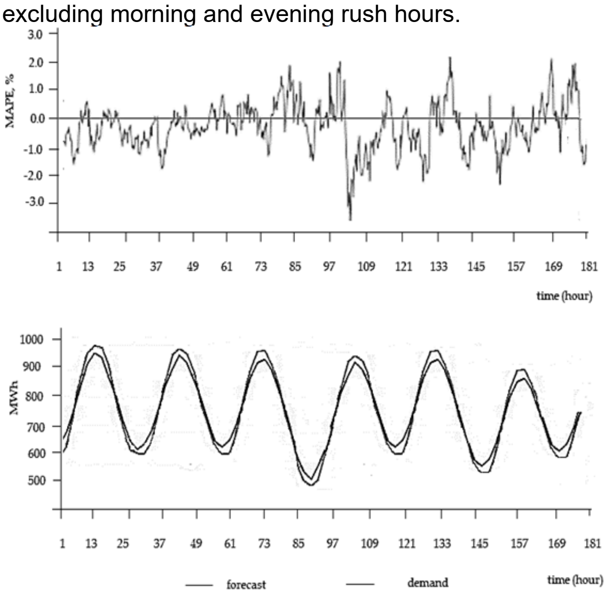

Fig.10. Forecast one hour ahead for a sample period in 2021

The selected SARIMA model was checked on the data for which its parameters were estimated, both the seasonal component and the parameters of the SARIMA model. In order to check whether the model is correct, its validation was performed, i.e. the correctness of the forecasts for other data was checked (Table 4). In the analyzed case, the built model was used to build forecasts for the next week, i.e. once a week the model parameters were calibrated and estimated on the basis of previous 6 weeks. This calibration can be performed once a day to improve results.

The model validation results (Table 4) are worse than the residual analysis for the data on the basis of which the model was calibrated and estimated (Table 3). However, the validation results show that the model "adjusted" well to the new dataset. Figure 10 shows the results of the hour-ahead forecast for the week with the smallest relative MAPE percentage error.

The use of a short-term forecasting model in creating a local hourly electricity market

Long-term contracts are very beneficial for electricity producers, as they not only guarantee that the energy they produce will be sold, but also guarantee a high price per MWh. These contracts undoubtedly contributed to the modernization of the Polish energy sector from the point of view of ecology, but they have a very negative impact on the development of the free electricity market. However, market participants are trying to overcome these disadvantages. As of today, contracting the quantity purchased as well as produced energy is performed for a day (broken down into 24 hours). The exchange segment, i.e. Towarowa Giełda Energii S.A., is already working on introducing the hourly market. On this market, it would be possible to trade electricity an hour before it was delivered. Forecasting the demand for electricity for the next day (i.e. with a horizon of 10-35 hours) is burdened with an error much greater than ±1% [20]. These models are usually medium an error of 1.9-5.7% depending on the hour to which this forecast applies. The further the hour, the greater the error, because the horizon of the forecast increases. Table 5 presents the forecast for October 12, 2022, which was the basis for creating the energy purchase schedule for that day. Comparison of forecast errors at hour t (t=1.2,…,24) for the forecasting model one day earlier (y(t)24) with the forecasting model one hour earlier (y(t)1) clearly shows that it is possible to scheduling adjustments based on a forecasting model one hour before delivery

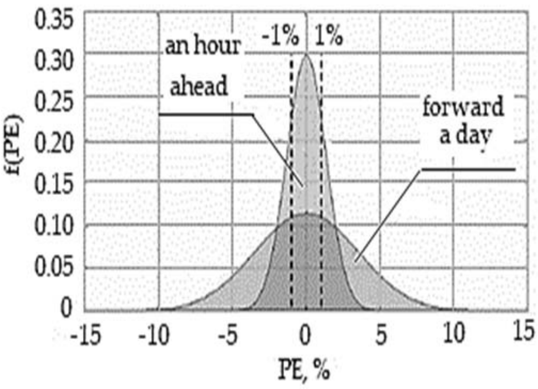

Fig.11. Plot of the ideal normal distribution for PE percentage errors with marked limits of ±1%

Analyzing the results of comparing percentage errors for forecasts made in day n-1 and one hour before delivery. It can be concluded that the forecast errors (PE) one hour before delivery are clearly smaller. However, you can also see that it is not the other way around at certain times. Also, the signs of error do not always coincide, which means that one forecast overestimated demand and the other underestimated. However, for the whole day, the error average is always better for the model one hour before delivery. Analyzing the data of the compiled parameters of the normal distribution (Table 6) for the percentage errors (PE) of the forecast, it can be observed that the model has a higher standard deviation a day earlier and only 11.4% of the PE errors of the model fall within the ±1% error range. For the forecast one hour before delivery, this percentage is already 43.3%.

As can be seen from Figure 11, approximately 55% of the PE errors of the one hour ahead forecasting model are within ±1%, but compared to the one day ahead forecasting model, this is a much better result. This provides a basis for an attempt to create an hourly electricity market based on this model. The algorithm of the procedure consists of five main stages calculated every hour in the *n-1* trading day. In stage 1, forecast electricity demand for each hour of the next 24 hours. As a result, a graph containing 24 forecasts for each hour will be created. In the next step, the forecast should be calculated for each subsequent hour of the day *n*. The forecast is made an hour earlier using the SARIMA(1,1,1)(1,1,1)$_{24}$ model. Then we compare the obtained result $y(t)^1$ with the forecast from the chart for the same hour $y(t)^{24}$. If less energy has been ordered than it results from the forecast y(t)1, we go to the next stage, otherwise we end further calculations, because the forecast shows that we have too much energy. In the next step, if less energy has been ordered, we calculate the modulus of relative percentage error (APE) based on formula (3). As a reference value, we take the result of the model's forecast for one hour ahead $y(t)^1$ [15].

$$APE = \left|\frac{y(t)^1 - y(t)^{24}}{y(t)^1}\right| \cdot 100\% \tag{3}$$

If the APE is less than 1%, we finish further calculations, as it follows from the forecast that we are in a safe price band on the balancing market. If the APE is greater, in the next step, the amount of missing energy Δy(t) that we need to balance the hour t should be calculated on the basis of the formula (4) [16]:

$$\Delta y = y(t)^1 - y(t)^{24} \tag{4}$$

If t is not an hour with an increased forecasting risk, we go to the next stage, i.e. the decision to purchase or produce the missing energy. If the distribution company has its own energy sources and the ability to start them quickly, it should be done and the balancing should be completed for hour t. If not, energy must be purchased from a local producer, e.g. a CHP or power plant [17-18]. An important element at this point is also the determination of the purchase price. The proposed solution is to set the price based on the price for a given hour on the power exchange multiplied by a certain price adjustment factor. In order to satisfy both sides of the transaction, this factor should be greater than 1, its value may also be variable depending on the hour for which the price is calculated. Figure 12 shows a reduced amount of energy purchased on the balancing market after applying the presented balancing procedure.

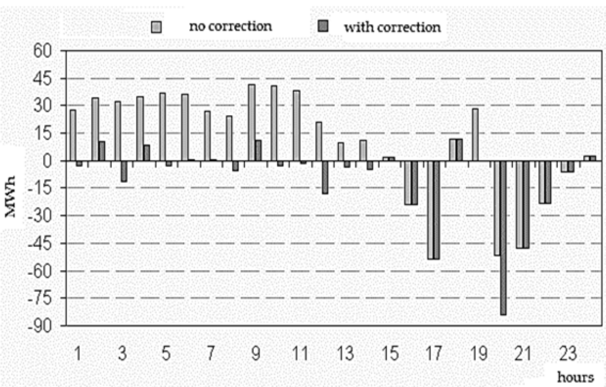

Fig.12. The amount of energy purchased on the balancing market using the balancing model without adjustment and using the adjustment algorithm

As part of further research, the financial results for several options of the analyzed procedure were analyzed. In the algorithm, the price coefficient and the balancing cut-off hours used in checking the condition at the stage of purchasing the missing energy were changed. It can be concluded that regardless of the variant of switching off the hours that has been chosen, the model with the correction always brings profits for the price factor of 1.2 and 1.3. Increasing the price factor to the value of 1.4 resulted in a decrease in profits, and even for one variant, balancing resulted in losses. It can therefore be concluded that the proposed adjustment factor of 1.2 is a good solution for each of the parties. In addition, the application of this balancing procedure resulted in a decrease in energy purchased or sold on the balancing market outside the range of ±1%. Most energy can now be balanced on the local market at a negotiated price. The proposed purchase price from a local producer is the price of 1 MWh on the power exchange for a given hour, increased by 20%.

Summary and final conclusions

The analyzes and research carried out in the work have shown that the autoregressive methods, both naive and mathematically advanced (ARIMA), allow to obtain acceptable forecasts and accurate forecasts, and the developed method is competitive in terms of its efficiency. Naive methods are easy to use and allow to achieve qualitatively acceptable forecasts in a very short time. Mathematically advanced methods require more time to calibrate the forecasting model, which is compensated by obtaining accurate forecasts. Technological and legislative changes taking place on the global and European electricity markets, within which power system operators operate, indicate that the research area undertaken in the work is important and is a response to the challenges resulting from the identified changes. The developed method is in line with trends and potential threats and is a tool responding to them practical needs of power system operators.The developed mathematical model using the method of forecasting short-term demand for electric power in power systems, with particular emphasis on the National Power System, is characterized by commensurability and rationality of expenditures in relation to the expected level of quality. For the purpose of the work, the concept of a mathematical model was developed and its practical implementation was built to implement the problem of forecasting short-term demand for electric power in power systems, which is conceptually based on the values of the coefficients of the partial autocorrelation function and thus uses an autoregressive approach. The model takes into account the required independence of the forecasting model from external data and ensures the use of only information from historical values of the course of the time series of electric power demand in the power system.The developed method allows for greater efficiency than most of the selected autoregressive models subjected to comparative analysis, while maintaining the least time consumption while meeting the assumed acceptability criterion.

The conducted analyzes give promising results, they show that it is worth dealing with the further development of market mechanisms not only at the national level, but also at the local electricity market. Achievements of science in the field of forecasting, both in economics and in technical sciences, are perfect for forecasting seasonal time series representing the demand for electricity on the local electricity market. The creation of a local hourly electricity market is possible and profitable, and the mutual cooperation of electricity producers and distribution companies can bring financial benefits to each of the parties to this market.

The author of the work will focus future activities primarily on three aspects that will increase the accuracy of forecasts:

• data preprocessing - proper data preparation affects both the network learning process itself and the accuracy of the models. It is necessary to find records and supplement them if necessary. An important issue is also the filtration of registered data from the power plant. It is not without significance to prepare a training and verification set in the process

• ”conscious” use of deep learning neural networks dedicated to forecasting. The selection of input streams, determination of the appropriate structure and type of network will shorten the learning process and the hardware requirements associated with it.

• finding methods to increase the accuracy of forecasts and adapting them to the specificity of operation and the spatial size of the power plant. Numerical weather forecasts are usually generated with a limited resolution of the forecast grid and for altitude 10m above sea level

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