TEKA. COMMISSION OF MOTORIZATION AND ENERGETICS IN AGRICULTURE – 2013, Vol. 13, No. 2, 67–72

Selection of decisive variables for the construction of typical end user power demand profiles

Krzysztof Nęcka

Department of Power Engineering and Agricultural Processes Automation, Agricultural University of Cracow
Balicka Str. 116B, 30-149 Kraków, Poland, e-mail: krzysztof.necka@ur.krakow.pl

Received May 16.2013; accepted June 28.2013

Summary. This study provides a description of the impact of critical variables of various grouping methods on the quality of the developed hourly power demand schedule. The adequacy of various indicators reflecting the course of power consumption was checked against the appropriate classification of daily load profiles in the clustering process. According to the performed simulations, the lowest MAPE and ΔESR error values of 14,01% and 12,65% were achieved with the EM concentration analysis algorithm and the following variables: daily peak and average daily load of electric power, shape coefficient, interval, variance, daily load variation rate and production output quantity. Furthermore, it was observed that within the data clustering performed on basis of the EM algorithm more homogeneous groups of week days were obtained, provided that the input variables had been standardised.

Key words: concentration analysis,load profile, load variation rates, short-term forecast.

INTRODUCTION

As of 1st July 2007 all end recipients, that is customers purchasing electricity for own needs, are entitled to freely choose the electricity supplier [13]. Since the freeing of the electricity prices until the end of October 2012 over 61 500 of industrial and commercial customers and almost 64 thousand households have used the right to change the electricity provider [18]. Customers who have exercised this right may become schedule-based recipients, provided that they are equipped with a measurement and billing system, with a possibility to register the real hourly power consumption values [8]. In such case they are obliged to develop a commercial consumption schedule which specifies the amounts of power demand in the specific hours of day and night '*n*'. This schedule must be submitted in a format determined in the power supplies contract to the distribution system on the day '*n*-1' before 7.30 am. It is mainly the quality of the developed load schedule which determines whether instead of expected profit additional expenses will be incurred due to the necessity to make additional deals in the power balancing market [12]. On the day '*n*+1' a clearance of differences generated by the real consumption diverging from the ordered power in the specific hours of the '*n*' day is performed. Such clearance is carried out on basis of dynamically changing prices of electric power on the balance market in the specific hours of the '*n*' day.

As an alternative for acting as a schedule-based customer within the SMEs sector, and in order to lower the electricity costs, it is possible to remain a tariff customer and renegotiate the so-far terms of contract, together with the re-selection of power demand and tariff group [14, 16]. While negotiating the unit price of electric power with the current or new supplier it is advantageous to have an own hourly power demand profile which enables the customer to reduce the balance difference against the allocated standard power consumption profile.

The knowledge of the typical hourly power demand profiles of end customers is thus essential both from the point of view of power suppliers and customers [20, 22]. Currently, as electricity is regarded as merchandise, the appropriate classification of daily load profiles and their effective analysis gains high economic and technical importance. The developed power demand profiles may be used by the end user among other for the creation of a commercial operating schedule and the selection of an optimal tariff group. On the other hand, power distribution companies use the load curves in order to formulate their pricing strategies, develop tariffs and undertake measures for the improvement of efficiency of their distribution grids.

After the emerging of microprocessor devices for constant measurement and recording of power consumption, the access to data required for the construction of typical hourly power demand profiles has become very simple. Extensive databases are thus available, but the question arises how to obtain the greatest possible amount of information to construct an optimal hourly load profile out of such a great collection of power demand variation data.

The purpose of this study is to determine an optimum set of decisive variables for the determination of typical hourly power demand profiles of end users generating the lowest total amount energy subject to clearance on the balancing market.

MATERIAL AND METHOD

The objective of this study was accomplished on basis of own research in a medium-size family company established in 1990. The company runs a modern poultry slaughterhouse with a cold store in the Małopolskie voivodeship. The main scope of its business is slaughter and sales of poultry in the national market, as well as Slovakia and Ukraine.

The study goal was achieved on basis of own research results of 24-hour measurements and automatic recording of average active power load and power consumption at 15-minute intervals, carried out for one year by means of a specialist AS-3 Plus grid parameter analyser manufactured by the Twelve Electric company from Warsaw. The measurement results were then compiled into one-hour time intervals and saved in a worksheet as a database. Each record of the created database included also information on the date and hour of the specific power consumption and the number of production output quantity of a given day. The collected data provided the basis to determine the indicators depicting the daily fluctuation of load and develop the daily load profiles.

In order to create homogeneous day groups of the greatest hourly power consumption match rate, the adequacy of the *k*-average grouping method and EM method was checked, with the application of various distance measures between clusters.

The quality evaluation of developed load profiles was performed by (*APE*) with the use of differences between the forecast hourly power demand determined on their basis and the real consumption, with the consideration of the value of relative forecast tolerance (APE), average relative forecast tolerance (*MAPE)* and percentage share of balance power in the total power consumption (ΔESR):

$$APE = \frac{\left|E_t - E_t^p\right|}{E_t} \cdot 100, \tag{1}$$

$$MAPE = \frac{1}{n} \cdot \sum_{t=1}^{n} \frac{\left|E_t - E_t^p\right|}{E_t} \cdot 100, \tag{2}$$

$$\Delta ESR_t = \frac{\sum_{t=1}^{n}\left|E_t - E_t^p\right|}{E_c} \cdot 100, \tag{3}$$

where:
E_t – real electric power consumption in *t* hour,
E_t^p – forecast electric power consumption in *t* hour,
E_c – real electric power consumption in the examined period,
n – number of monitoring hours.

RESEARCH RESULTS

In the first stage of research, one common load profile of all days of the year was developed on basis of raw data. As the next step, the number of developed profiles was increased for an ever narrower number of days, taking into account calendar days, that is month name, type of day (working or holiday) and day name. In the last stage it was assumed that on the day preceding the planned electricity supplies, that is day *n-1*, the facility would inform the seller whether slaughtering of poultry was planned on day *n*, without providing the production output quantity. The quality evaluation results of the specific profiles are presented in Table 1.

According to the performed analyses, the development of a single common hourly profile of power consumption for all days of the year will have an average value of relative forecast tolerance of 40%, while the share of power to be cleared on the balancing market will amount to 30% of total power consumption. As expected, the calendar data improved the quality of developed typical profile models. On basis of these information the lowest values of indicators reflecting the quality of the hourly power demand schedule were obtained by constructing separate load schedules for working days and holidays, regardless of the specific months of the year. For the analysed load profiles, the value of the MAPE tolerance ranged from 20,79% to 24,25%. On the other hand,

Table 1. Quality of daily load profile developed with the consideration of the calendar

Type of schedule	*MAPE* [%]	ΔESR [%]
Common schedule for all days of the year	39,75	31,51
Separate load schedules for working days and holidays	24,25	20,69
Separate load schedules for working days and holidays, taking into account whether slaughter activities were planned on a given day	22,80	19,90
Separate load schedules for working days, Saturdays, Sundays and holidays	22,91	19,80
Separate load schedules for the specific days of the week	22,63	19,57
Separate load schedules for working days and Saturdays, Sundays and holidays, taking into account whether slaughter activities were planned on a given day	21,66	19,42
Separate load schedules for working days and holidays in the summer, winter and spring-autumn	22,67	19,33
Separate load schedules for working days and holidays in the specific months	20,79	17,78
Separate load schedules for working days and holidays in the specific months, taking into account whether slaughter activities were planned on a given day	18,13	15,38

the share of energy to be cleared in the balancing market amounted to 17,78%-20,69% of total power consumption in the facility. Thanks to the use of information whether on a given day poultry slaughtering activities were to be carried out, it was possible to lower the values of indicators evaluating the quality of estimate profiles approximately by further 2%. The reason why the quality of performed hourly consumption forecast has improved was the correct classification of the specific day types into the groups of working days and holidays. Poultry slaughtering was not performed on every working day and also there were holidays on which slaughtering-related processes were running.

Nevertheless, all the so-far developed typical hourly power consumption profiles were highly erroneous. Their main reasons include changes of load profile for working days depending on the production output quantity and the occurrence of days with modified production technology. The first variable can be quite easily considered while developing the load curves, as daily production records were maintained in the facility. The information on switching between the production of whole or portioned poultry meat were unfortunately not recorded.

In the next stage of research the determination of typical days was performed, so that the respectively developed daily load curves would allow to determine hourly power demand forecasts generating smaller amounts of power proportion to be cleared in the balancing market. The results of this research will also be used to identify the days with the corresponding production process.

In order to create typical load profiles, the most effective indicators reflecting the daily load variation were searched for out of the ones described in the literature [1, 2, 3, 4, 5, 9, 10, 11, 17, 19]. Due to the great number of available indicators, their preliminary selection was performed on basis of their importance, variability and mutual correlation strength.

The importance analyses of the specific indicators was performed on basis of convexity of the cumulative distribution function. Examination of convexity of the empiric cumulative distribution function was performed according to the following algorithm [15]:

a) specific load variation indicators $X_j (j = 1, 2,...,m)$ were subjected to normalisation according to formula 4, as a result of which vectors were obtained with feature values contained within <0,1>:

$$x_{ij} := \frac{x_{ij} - \min\limits_i x_{ij}}{\max\limits_i x_{ij} - \min\limits_i x_{ij}}, \quad i = 1,2,...,n; \; j = 1,2,...,p, \tag{4}$$

b) transformed values of the specific features were sorted ascending and a median was determined:

$$M_{ej} = \frac{x_{ij\left(\frac{n}{2}\right)} + x_{ij\left(\frac{n}{2}+1\right)}}{2}, \tag{5}$$

c) value of the t_j indicator was found:

$$t_j = 1 - \sum_{(i:x_{ij} \le o,5)} w_{ij}, \qquad \mathrm{j} = 1,2,..., \mathrm{p}, \tag{6}$$

where:

$$w_{ij} = \frac{1}{n}.$$

Evaluation of importance of the specific indicators performed on basis of value t_j. This parameter may be regarded as an inhibitor, as together with its growth the feature importance falls. For further analyses, only such load variation rates were selected in case of which t_j was lower than the adopted threshold value of 05.

In order to evaluate the variation of the specific indicators, the ε variation rate was used, calculated with the relationship (7) and it was required that the features are more changeable than the arbitrarily adopted value of ε=20% [15]:

$$\varepsilon_j = \frac{s_j}{X_{jsr}}, \tag{7}$$

where:
S_j – standard deviation of the load fluctuation rate,
$X_{j\acute{s}r}$ – average value of the load fluctuation rate.

In order to eliminate unfavourable phenomena occurring in case of common varying of coefficients, it was required that the linear correlation power between the specific indicators reflecting the load variation used for the development of a typical load profile had to be lower than 0,8.

As the presented requirements for the development of typical hourly power demand profiles are met, the following indicators were selected:

daily power consumption: $$A_d = \int_{i=1}^{T_d} P_i dt, \tag{8}$$

daily peak load: P_{ds},
daily average load P_{dsr},
peak load hour: t_{ps},

unevenness indicator of daily power demand: $$m_o = \frac{P_{do}}{P_{ds}}, \tag{9}$$

daily peak compensation grade: $$l_{ds} = \frac{P_{ds}}{P_{dsr}}, \tag{10}$$

daily load shape coefficient: $$k = \frac{P_{srkw}}{P_{dsr}},$$

daily load interval: $$R = P_{ds} - P_{do},$$

daily load variance: $$s^2 = \frac{1}{24}\sum_{i=1}^{24}\left|P_i^2 - P_{dsr}{}^2\right|, \tag{11}$$

standard deviation of daily load: $$s = \sqrt{s^2},$$

average deviation of daily load: $$d = \frac{1}{24}\sum_{i=1}^{24}\left|P_i - P_{dsr}\right|, \tag{12}$$

fluctuation rate of daily load: $$V = \frac{s}{P_{dsr}},$$

daily load median: $$M_e = \frac{P_{\left(\frac{n}{2}\right)} + P_{\left(\frac{n}{2}+1\right)}}{2}, \tag{13}$$

geometrical average of daily load:
$$G_e = (P_1 \cdot P_2 \cdot \ldots \cdot P_{24})^{\frac{1}{24}}, \quad (14)$$

average harmonious daily load:
$$H = \frac{24}{\sum_{i=1}^{24} \frac{1}{P_i}}, \quad (15)$$

where:
P_i, P_j - load in hour i (j),
i, j = 1, 2, ..., 24,
T_d= 24 hours.

Due to the fact that many coefficients depicting the load fluctuation fulfilled the requirements during the cluster analysis performed in the *Statistica 10.0* application, attempts were made to determine the most effective indicators by means of the „*Selection of variables and analysis of causes*" module available in the programme. The cluster analyses were performed with the *k*-average method and EM method, belonging to the non-hierarchical category. The classic algorithm of *k*-averages was popularised by Hartigan [6, 7]. The essential idea of this algorithm is to assign an observation of a set number of *k*-clusters in such a manner that a minimum internal differentiation and maximum inter-group differentiation is achieved. During the cluster analysis performed with *k*-averages also the influence of the following observation distance measures was examined:

– Euclidean – distance $(x, y) = \sum_{i=1}^{n} \sqrt{(x_i - y_i)^2}$,

– city (Manhattan, City block) – distance:
$$(x, y) = \sum_{i=1}^{n} |x_i - y_i| ,$$

– Chebyshev – distance $(x, y) = maksimum|x_i - y_i|$.

The EM method algorithm for cluster analysis was described in detail by Witten and Frank [21]. Its basic idea relies on the determination of the probability density function for the specific variables. Then, the average value is determined, together with standard deviation for each created cluster, so that the reliability of observed distribution is maximised. In the EM method, the distances between clusters are calculated with the Euclidean measure.

In the specific analyses the optimum cluster quantity was determined on basis of a crosscheck multiplied with *v*. This method consists of dividing data into random-selected v-separable parts. In the next step, an analysis for the preliminarily adopted *k* value is performed in order to find a prediction for *v*-of this data group by using for this purpose *v-1* of a part of data as reference cases. As we know the dependent variable data in the data cluster for which the prediction was made, the prediction tolerance can be calculated. The accuracy rate is counted as a percentage of properly classified cases. Then the entire procedure is repeated for all *v* data segments. At the end of the cycle the errors are averaged and model quality measures are determined. The above procedure is repeated for various *k* values. As an optimum number of clusters *k* value was adopted with regard to which the best model quality was obtained.

Table 2. Quality description of a daily load profile developed on basis of power demand fluctuation indicator cluster analysis

Grouping method	Input variable, formula no.	Cluster interval	Number of clusters	*MAPE* [%]	Δ*ESR* [%]
k-average algorithm	8-24	Euclidean	5	17,34	14,73
k-average algorithm	8-24 after standardisation	Euclidean	5	17,34	14,73
k-average algorithm	9,16,23,24	Euclidean	5	18,43	15,68
k-average algorithm	24	Euclidean	9	19,93	16,16
k-average algorithm	9,10,14–16,19, 23, 24	Euclidean	5	17,47	14,8
k-average algorithm	8-24	Manhattan	5	21,39	17,3
k-average algorithm	8-24 after standardisation	Manhattan	5	17,28	14,72
k-average algorithm	9,16,23,24	Manhattan	6	18,04	15,12
k-average algorithm	24	Manhattan	9	18,61	15,04
***k*-average algorithm**	8-10,14-16, 19, 23, 24	Manhattan	5	16,11	14,1
k-average algorithm	8-10,14-16, 19, 23, 24 after standardisation	Manhattan	5	18,31	15,29
k-average algorithm	8-24	Chebyshev	5	18,19	15,16
k-average algorithm	8-24 after standardisation	Chebyshev	5	18,19	15,16
k-average algorithm	9,16,23,24	Chebyshev	5	18,48	15,55
k-average algorithm	24	Chebyshev	9	18,61	15,04
k-average algorithm	9,10,14-16,19,23, 24	Chebyshev	5	17,19	14,68
EM algorithm	8-24	Euclidean	3	19,4	16,13
EM algorithm	8-24 after standardisation	Euclidean	5	16,02	14,16
EM algorithm	9,10,17,23,24	Euclidean	2	21,36	17,64
EM algorithm	13,14,21-23 after standardisation	Euclidean	5	15,18	13,58
EM algorithm	24	Euclidean	1	39,74	31,51
EM algorithm	21 after standardisation	Euclidean	2	26,23	21,49
EM algorithm	8-10, 14 -16, 23, 24	Euclidean	3	19,88	16,52
***EM* algorithm**	8-10,13,14,19-23 after standardisation	Euclidean	7	14,01	12,65

In table 2, the error values of hourly power demand forecast errors are listed, as obtained on basis of various indicator combinations depicting the power demand and various distance measures between the observations.

By using indicators depicting the fluctuation of load for the purpose of determining days with a similar load profile, both the average relative percentage tolerance and the power cleared on the balancing market was reduced. By using the *k*-average algorithm for analysing purposes the lowest MAPE and ΔESR error values of 14,01% and 12,65% were achieved by using the following indicators for the development of typical daily load profiles: daily peak and average daily load of electric power, shape coefficient, intervals, variance, daily load variation rate and production output quantity. Also an over 1% error rate reduction was observed in case of analyses where the clusters observation interval was Manhattan.

The same set of variables in the cluster analysis with the EM method has allowed to obtain load profiles that were less consistent with real data, while forecasts created on their basis generated higher amounts of power to be balanced out. It was however noticed that for the EM algorithm one can achieve much more homogeneous week day clusters, and therefore develop load profiles which may generate forecasts involving a relatively small error risk ($MAPE$ = 14,01%, ΔESR = 12,65%), provided that the input data are standardised. The desired impact of standardisation of exogenous variables on the quality of hourly power demand forecasts was not clearly stated for the *k*-average algorithm.

CONCLUSIONS

According to the performed analyses, the development of a single common hourly profile of power demand for all days of the year will have an average value of relative forecast tolerance of 40%, while the share of power to be cleared on the balancing market will amount to 30% of total power consumption.

Thanks to the use of calendar data for the development of typical profiles, the *MAPE* tolerance was reduced below 25%. On the other hand, the share of energy to be cleared in the balancing market remained below 21% of total power consumption in the facility. Furthermore, thanks to the use of information whether on a given day poultry slaughtering activities were to be carried out (without information on their extent), it was possible to lower the values of indicators evaluating the quality of estimate profiles approximately by further 2%.

By using indicators depicting the fluctuation of load for the purpose of determining days with a similar load profile, both the average relative percentage tolerance and the power cleared on the balancing market was reduced. Within the performed research the lowest MAPE and ΔESR error values of 14,01% and 12,65% were achieved with the EM concentration analysis algorithm and the following variables: daily peak and average daily load of electric power, shape coefficient, interval, variation, daily load fluctuation rate and production output quantity. The obtained tolerance (error) level will act as a point of reference while developing hourly power demand forecasts both for conventional and alternative models.

REFERENCES

1. **Bieliński W. 1998:** Typowe wykresy obciążeń elektroenergetycznych wybranych odbiorców. Materiały V Konferencji Naukowo-Technicznej „Rynek energii elektrycznej REE'98". Nałęczów. 307-314.
2. **Chojnacki A. Ł. 2008**: Zmienność obciążeń w układach sieciowych SN zasilających odbiorców komunalnych na terenach miejskich oraz wiejskich. V Ogólnopolska Konferencja Naukowa PTETiS „Modelowanie i Symulacja". Kościelisko 23-27 czerwca. 125-128.
3. **Chojnacki A. Ł. 2009**: Analiza dobowej, tygodniowej i rocznej zmienności obciążeń elektroenergetycznych w sieciach miejskich oraz wiejskich. Przegląd elektrotechniczny. Nr 06. 9-12.
4. **Derecka M., Bieliński W. 2002:** Nowe charakterystyki zmienności mocy pobieranej przez odbiorców. Materiały VI Konferencji Naukowej „Prognozowanie w elektroenergetyce PE'2002". Częstochowa. 39-47.
5. **Dudek G. 2004:** Wybrane metody analizy szeregów czasowych obciążeń elektroenergetycznych. Materiały VII Konferencji Naukowej „Prognozowanie w elektroenergetyce PE'2004". Częstochowa. 116-125.
6. **Hartigan J. A. 1975:** Clustering Algorithms**,** New York: John Wiley & Sons.
7. **Hartigan J. A., Wong M. A. 1978:** Algorithm 136. A *k*-means clustering algorithm. Applied Statistics. *28*. 100.
8. Instrukcja Ruchu i eksploatacji sieci dystrybucyjnej. Enion Grupa TAURON
9. **Kaźmierczyk A., Chojnacki A. Ł. 2011:** Analiza dobowej i tygodniowej zmienności obciążeń mocą czynną i bierną elektroenergetycznych sieci dystrybucyjnych SN, miejskich oraz terenowych. Energetyka. Nr 1. 29-37.
10. **Łyp J. 2003:** Metodyka analizy i prognozy obciążeń elektroenergetycznych systemów lokalnych. Rozdział w książce pt. „Zastosowania metod statystycznych w badaniach naukowych II". StatSoft. Kraków. 91-104.
11. **Łyp J., Kurach M. 2011:** Problematyka prognozowania sezonowej zmienności obciążeń szczytowych krajowego systemu elektroenergetycznego. Rynek Energii. Nr 1(92). 97-100.
12. **Majchrzak H, Mroziński A., Pozniak R. 2005:** Wpływ funkcjonowania rynku bilansującego na koszty ponoszone przez uczestników rynku energii elektrycznej. Energetyka. Nr 6. 376-380.
13. Ustawa z dnia 10 kwietnia 1997 r. Prawo energetyczne. Dz.U. z 1997 r. nr 54 poz. 348 wraz z późniejszymi zmianami.
14. **Nęcka K. 2012:** Analiza efektywności zmiany grupy taryfowej na przykładzie oczyszczalni ścieków. Inżynieria Rolnicza. Nr 2 (136). 257-266.
15. **Ostasiewicz W. (red). 1999:** Statystyczne metody analizy danych. Wydawnictwo Akademii Ekonomicznej we Wrocławiu.

16. **Połecki Z., Michalak G. 2012:** Minimalizacja kosztów zakupu energii elektrycznej odbiorcy przemysłowego. Materiały konferencyjne VIII Konferencja Naukowo-Techniczna Optymalizacja w Elektroenergetyce.
17. **Popławski T. 2005:** Problematyka analizy zmienności i prognoz obciążeń w systemach elektroenergetycznych w warunkach transformacji rynku. Rozdział w Monografii: Metody i systemy komputerowe w automatyce i elektrotechnice. ISBN 83-7193-288-X. Wydawnictwo Politechniki Częstochowskiej. Częstochowa. 144-149.
18. Raport Urzędu Regulacji Energetyki styczeń 2013. [online]. [dostęp 27-03-2013]. Dostępny w Internecie: http://optimalenergy.pl/blog/aktualnosci/raport-urzedu-regulacji-energetyki-styczen.
19. **Trojanowska M. 2010:** Analysis of the power and electricity demand in the dairy plant. Journal of Research and Applications in Agricultural Engineering. Vol. 55(2). 113-116.
20. **Trojanowska M., Nęcka K. 2009:** Determination of typical electric power loads for rural end users. TEKA Komisji Motoryzacji i Energetyki Rolnictwa Vol. IX. Lublin. 357-363.
21. **Witten I. H., Frank E. 2000:** Data Mining: Practical Machine Learning Tools and Techniques. New York: Morgan Kaufmann.
22. **Zalewski W. 2010:** Statystyczna analiza zmienności obciążeń w sieciach rozdzielczych. Economy and Management. Nr 4. 206-213.

DOBÓR ZMIENNYCH DECYZYJNYCH DO BUDOWY CHARAKTERYSTYCZNYCH PROFILI ZAPOTRZEBOWANIA ODBIORCÓW KOŃCOWYCH NA MOC I ENERGIĘ ELEKTRYCZNĄ

Streszczenie. W pracy przedstawiono wpływ zmiennych decyzyjnych oraz różnych metod grupowania na jakość opracowanego grafiku godzinowego zapotrzebowania na energię elektryczną. Sprawdzono przydatność różnorodnych wskaźników opisujących zmienność zużycia energii elektrycznej do właściwej klasyfikacji dobowych profili obciążenia podczas tworzenia skupień. Z wykonanych symulacji wynika, że najniższe wartości błędów MAPE i ΔESR o wartościach 14,01% i 12,65% uzyskano wykorzystując do analizy skupień algorytm EM i następujące zmienne: dobowe obciążenie szczytowe oraz średnie, dobowe zużycie energii elektrycznej, współczynnik kształtu, rozstęp, wariancję, współczynnik zmienności obciążenia dobowego oraz czystą ilość sztuk produkcji. Ponadto zaobserwowano, że w analizie skupień wykonywanej w oparciu o algorytm EM uzyskano bardziej jednorodne grupy dni tygodnia pod warunkiem, że zmienne wejściowe zostały poddane standaryzacji.

Słowa kluczowe: analiza skupień, profil obciążenia, prognoza krótkoterminowa, wskaźniki zmienności obciążenia.