RESEARCH PAPERS OF WROCŁAW UNIVERSITY OF ECONOMICS No. 91
Econometrics 28 2010

Barbara Namysłowska-Wilczyńska, Artur Wilczyński
Wrocław University of Technology

3D ELECTRIC POWER DEMAND FORECASTING AS A TOOL FOR PLANNING ELECTRICAL POWER FIRM'S ACTIVITY BY MEANS OF GEOSTATISTICAL METHODS

Abstract: Geostatistical methods were applied to forecasting area – time (3D) electrical power demand. Spatial analyses based on node load data for two kinds of electrical power networks, i.e. the 220/400 kV network covering the whole area of Poland and the 110 kV network for a selected subarea of Poland, were carried out. The 20-year power variation structure for the two kinds of networks was analyzed using the directional variogram function. Power demand forecasts for 1 year and 5 years were made using ordinary block kriging. The results of the power estimation and forecasting of averages Z^* and the estimation standard deviation σ_k show that the employed techniques are useful and effective. Therefore they are recommended for use by power firms.

Key words: geostatistical (3D) modelling, area – time forecasting, electrical loads, directional variogram, ordinary kriging.

1. Introduction

The short- and long-term planning of a public utility's activity or development often requires the use of 3D (area – time) forecasting techniques. This applies particularly to companies which service large areas, e.g. network companies such as telecommunications companies and power companies, including electric power companies. The latter are the subject of analysis in this paper.

For its operations an electricity provider needs a proper network infrastructure adequate to the demand for this energy at an appropriate time and place.

Long-term area – time forecasts are useful for planning the development of the 220/400 kV transmission network used for transporting electricity over longer distances or the distribution network which transmit this energy within smaller areas.

Short-term forecasts are needed to plan the operation of the networks 24 hours, 1 week and 1 year in advance.

It would be interesting and very useful for planning economically effective and safe electrical power networks to answer the questions [Willis 2002]:

– where are power demands increasing?

– how much do they vary depending on the location?
– what is the geographical direction of the variation?

The development of area – time forecasts of power demands could reduce the risk of wrong investment decisions concerning (transmission and distribution) electrical power networks, taken in a situation when market mechanisms are being implemented in the electrical power sector. Area – time models of power demand variation distribution over a given area for the particular hours in the 24-hour period can also be used in demand side management (DSM) [Willis 2002]. An analysis of the power demands shows where and when a significant increase in power occurs and within which subareas it amounts to zero or to a minimum. This is an important signal for the planners. Areas in which power demands can be subject to some adjustment (e.g. periodic reduction) by means of DSM tools can be determined. Such an analysis can show the planners how all these factors may affect the shape and condition of the electrical power network in the future.

This paper proposes a research methodology for the 2D and 3D modelling and forecasting of electrical power demand, which could be the basis for the modern planning of the development of power firms operating networks in the conditions of developing market mechanisms.

2. Research methodology

2.1. Introduction

Geostatistical methods, i.e. the directional variogram function and the ordinary (block) kriging [Namysłowska-Wilczyńska, Wilczyński 2008; Wilczyński et al. 2007], were employed to model and estimate average power demands in 3D and then to forecast them for 1-10 years. Until now geostatistical methods have been used for the 2D as well as the 3D modelling of phenomena in such fields as geology [Namysłowska-Wilczyńska 2006, 2007], mining [Journel, Huijbregts 1978], environmental protection [Namysłowska-Wilczyńska 2006], the civil engineering [Newsletters], the power industry [Namysłowska-Wilczyńska, Wilczyński 2004, 2005, Wilczyński 2004], forestry [Newsletters], fishery [Newsletters], economics [Namysłowska-Wilczyńska et al. 2003, Namysłowska-Wilczyńska, Wilczyński 2003], agriculture, oceanology, epidemiology, climatology, and hydrology [Newsletters].

2.2. Subject of analyses

The studies into the possibility of developing area – time forecasts of power demands were carried out on the basis of load data (the values of power) coming from two kinds of electric networks. The investigations covered the whole area of Poland (the powers flowing from 101 nodes of the 220/400 kV network) and a subarea of Poland (the powers flowing from 30 nodes of the 110 kV network). The network node power data were for the winter load peak hour of 5 p.[1] The databases include geographic coordinates X and Y, specifying the locations of the measurements carried out over the 20-year period and the consecutive numbers of the measurements and coordinate Z (time). Since no proper amount of original input data was available for the calculations, the actual powers were supplemented with simulation data.

For the kriging calculations the considered areas were covered with elementary grids. For the nodes of the 110 kV network the elementary grid superimposed on the analyzed (in 3D) supply area had the elementary block dimensions: 5 km × 2.5 km × 1 year and the number of elementary blocks along the particular axes was: X – 47, Y – 60 and Z – 30 (Figure 1).

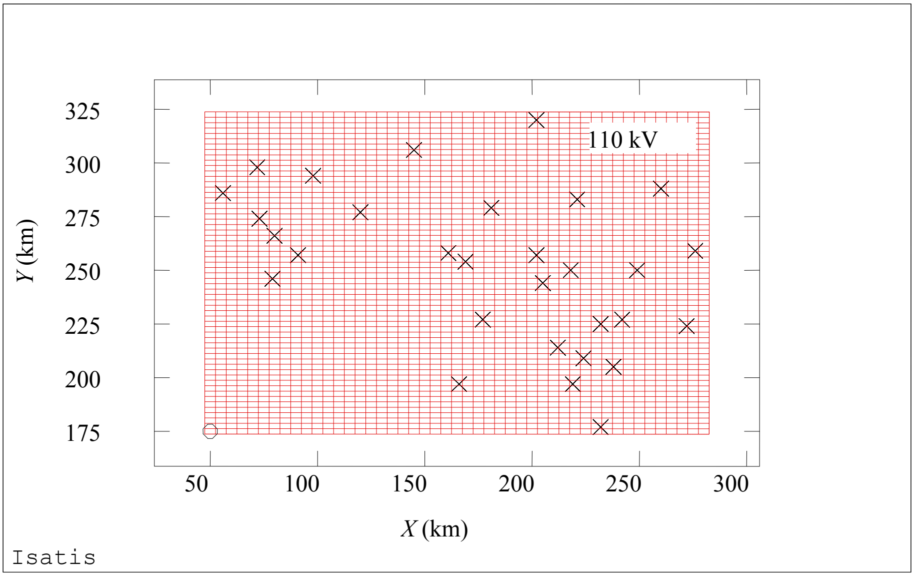

Figure 1. Grid of elementary blocks for area supplied by 110 kV network, with marked locations of nodes

Source: in-house study.

The primary statistical parameters, calculated on the basis of the set of original data on the power demands in the nodes of the 110 kV network, used for the estimation and forecasting are shown in Table 1. It is apparent that there is a large range between the minimum and maximum values of the power P drawn from the nodes, whereby the standard deviation (S) is high. Coefficient V indicates that power P variation (Table 1) is high in the analyzed area in the considered period.

[1] The databases were prepared in ASCII, as required by geostatistical software ISATIS ver. 7.0.6 (purchased from Geovariances & Ecole des Mines de Paris, France, by the Institute of Geotechnics and Hydrotechnics at Wrocław University of Technology) used in this research.

Table 1. Global statistics for power demands in nodes of 110 kV electrical power network

Number of electric-power nodes n	Minimum power P_{min} [MW]	Maximum power P_{max} [MW]	Average power P [MW]	Standard deviation S [MW]	Coefficient of variation V [%]
30 × 20 = 600	1.31	300.71	33.29	71.57	215

Source: in-house study.

Table 2 shows the basic statistics for the geostatistical power parameters determined for the 110 kV electrical power network for the analyzed (in 3D) supply area covered with the adopted elementary grid.

Table 2. Global statistics of estimated power for values for 110 kV distribution network in (process history) years 1-20

Estimated parameter	Sample size n	Minimum estimated value Z^*_{min} [MW]	Maximum estimated value Z^*_{max} [MW]	Average Z^* [MW]	Standard deviation S [MW]	Coefficient of variation V [%]
Estimated value Z^*	107,209	10.48	293.50	41.84	56.83	136.00
Standard deviation of estimation σ_k	107,209	0.78	8.96	4.46	1.69	38.00

Source: in-house study.

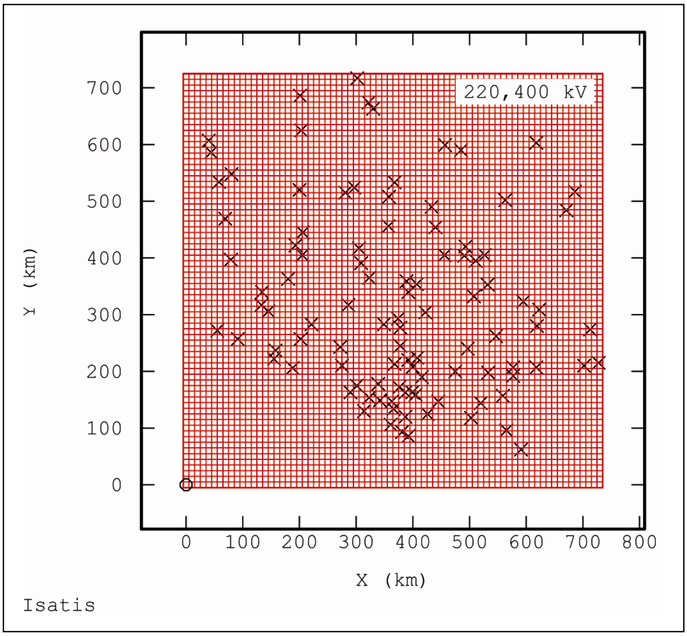

Figure 2. Grid of elementary blocks for area supplied from 220/400 kV network, with marked locations of nodes

Source: in-house study.

The high variation coefficient V calculated from estimated averages Z^* reaches a lower value (136%) (Table 2) in comparison with its very high value (215%) calculated on the basis of the original power data (Table 1).

In the case of the 220/400 kV network, the elementary block dimensions of the grid were 10 km × 10 km × 1 year and the number of elementary blocks along the particular axes was: X – 74, Y – 73 and Z – 30 (Figure 2).

The primary statistical parameters, calculated on the basis of the set of data on the power demands in the nodes of the 220/400 kV network, used for the estimation and forecasting are shown in Table 3.

Table 3. Global statistics for power demands in nodes of 220 kV/400 kV electrical power network

Number of electric-power nodes n	Minimum power P_{min} [MW]	Maximum power P_{max} [MW]	Average power P [MW]	Standard deviation of power S [MW]	Coefficient of variation V [%]
101 × 20 = 2021	1.00	666.00	229.57	120.19	52.00

Source: in-house study.

The primary statistics for the investigated power demand processes, i.e. standard deviation S and variation coefficient V (Table 3), indicate great variation in the analyzed quantity (power) in the investigated area.

Table 4 shows the primary statistics for the geostatistical power parameters, determined for the 220/400 kV power network for the investigated (in 3D) supply area covered with the adopted elementary grid.

In the case of both geostatistical parameters, i.e. average values Z^* and standard deviations σ_k, obtained from estimation for the Poland area, one notices high and low coefficient V values, falling into the group of so-called very large and average variation, particularly lower for standard deviation of estimation σ_k (Table 4).

Table 4. Global statistics for estimated power values in (process history) years 1-20 for 220/400 kV transmission network (ordinary block kriging)

Estimated parameter	Sample size n	Minimum estimated value Z^*_{min} [MW]	Maximum estimated value Z^*_{max} [MW]	Average Z^* MW]	Standard deviation S [MW]	Coefficient of variation V [%]
Estimated average Z^*	204,795	19.72	587.24	207.64	320.46	154.00
Standard deviation of estimation σ_k	204,795	3.44	90.80	63.46	16.02	25.00

Source: in-house study.

2.3. Analysis of directional variograms

The basic tool of geostatistics is the variogram, which is used to determine the kind of surface or spatial correlation between the analyzed variables. The variogram is modelled by an analytical mathematical function, which is referred to as a geostatistical model [Armstrong 1998; David 1977; Isaaks, Srivastava 1989; Namysłowska-Wilczyńska 2006]. The variogram function is assumed for the investigated variable. The function allows one to obtain the best (as regards minimum estimation variance (estimation error)) picture of the variation of the regionalized variable in 1D, 2D or 3D [Armstrong 1998; David 1977; Isaaks, Srivastava 1989; Namysłowska-Wilczyńska 2006].

An empirical variogram, showing the correlation between variables arranged on a surface (in 2D), represents the following relation:

$$\gamma^*(h) = \frac{1}{2n_h}\sum_{i=1}^{n_h}[z(x_i + h) - z(x_i)]^2, \tag{1}$$

where: $z(x_i + h)$, $z(x_i)$ – electrical power values in points x_i and $x_i + h$, i.e. separated by distance h; n_h – the number of pairs (x_i, $x_i + h$) of power values in points separated by distance h, used to calculate semivariogram function $\gamma^*(h)$.

The empirical variogram shows the character of the variation of a studied regionalized variable (power in the nodes). This variation is best illustrated by an omnidirectional (isotropic) variogram (with all the measuring data taken into account) or a directional variogram calculated on the basis of measurements oriented along specified directions (zones). Averaged variograms do not give a full picture of variation differentiation in space. For this reason, directional variograms (which show variation in the particular directions) are calculated.

In this research the directional variogram was used to investigate power variation along time axis Z and to make forecasts.

When modelling the surface variation of the investigated variable, the above form of variogram should be extended by a component representing changes along time axis Z.

Then the *isotropic variogram* determined in the horizontal plane has this form [Wackernagel 1998]:

$$\gamma(h) = \gamma_0\left(\sqrt{h_1^2 + h_2^2 + h_3^2}\right), \tag{2}$$

and the third (time) component is:

$$\gamma(h) = \gamma_1(h_3). \tag{3}$$

The variogram describes the character of the variation of the regionalized variable – the power in the nodes of the electrical power networks. In order to analyze and estimate the considered regionalized variable in 3D one must built a variogram model depicting the surface variation in 2D, and then extend it by the time variable, i.e. expressing changes along the time axis for the 20-year period.

A directional variogram, calculated along time axis Z (i.e. for 20 years), was used to characterize the power variation structure and then to make forecasts.

2.4. Estimation by means of kriging

Kriging is the technique of interpolation performed using the weighted average. In kriging a set of weights assigned to the values of the analyzed variable (power samples or observations) minimizes the estimation variance of the estimate (the so-called kriging variance), which is calculated as a function of the adopted variogram model and the mutual location of the samples, and in relation to the point or block being the subject of estimation [Armstrong 1998; David 1977; Isaaks, Srivastava 1989; Namysłowska-Wilczyńska 2006]. Kriging is used for "local estimation" since it takes into account data from the nearest neighbourhood.

Weighted (moving) average Z^* is estimated using this relation:

$$Z_k^* = \sum_{i=1}^{n} w_{ik} z_i, \tag{4}$$

where: z_i – the value of power in point i, for $i = 1, ..., n$; w_{ik} – a kriging weight coefficient assigned to sample i.

The selection of kriging coefficients (kriging weights) w_{ik} is a critical step. Unweightedness condition Z_k^* is fulfilled if:

$$E\left(Z_k^* - m\right) = 0,$$

hence the constraints that the sum of weights is equal to 1:

$$\sum_{i=1}^{n} w_{ik} = 1, \tag{5}$$

and that the variance is minimum:

$$\sigma_E^2 = E\left[\left(Z_k^* - m\right)^2\right] = \min, \tag{6}$$

are introduced.

Having a system of kriging equations [Namysłowska-Wilczyńska 2006; Wackernagel 1998] one can determine weight kriging coefficients w_{ik} assigned to given samples within and near the estimated area. The coefficients are used to calculate the average kriging error whose variance is defined by the formula:

$$\sigma_k^2 = \sum w_i \bar{\gamma}(S_i, A) + \lambda - \bar{\gamma}(A, A), \tag{7}$$

where: $\bar{\gamma}$ (A, A) – the average variogram value between each two points of block A;
$\bar{\gamma}$ (S_i, A) – the average variogram value for all the segments connecting measuring point S_i with calculation block A within which the average of the investigated quantity is estimated; λ – the Lagrange multiplier.

3. Directional variograms of power demands in nodes of 110 kV and 220/400 kV networks

In view of the research goal, which was to demonstrate the possibility of short- and long-term forecasting using geostatistical methods, empirical variograms along time axis Z (20 years) were calculated. The directional variograms calculated on the basis of node power demands for the 110 kV distribution network and the 220/400 kV transmission network, including the geostatistical models (analytical functions) used for the variograms approximating, are shown in Figures 3 and 4.

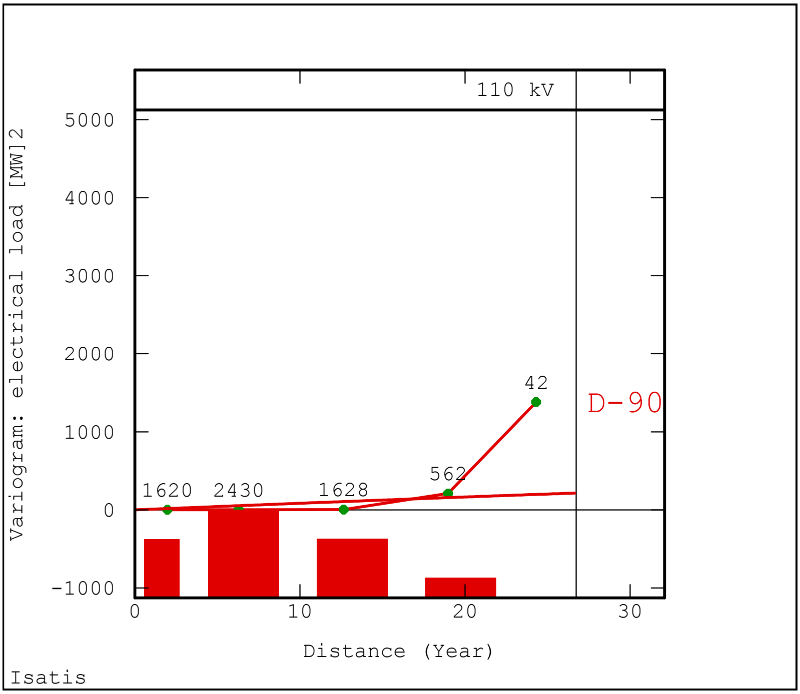

Figure 3. Directional variogram (along time axis Z) of power demands in nodes of 110 kV distribution network, approximated by theoretical model (against histogram of distribution of number of power measurement pairs)

Source: in-house study.

No nugget effect C_0 appeared in the directional variogram (approximated by the spherical model) for the power demands in the nodes of the 110 kV network and the variogram shape shows a weak upward trend (Figure 3). The range of influence a of the variogram is 67.62 years and its sill variance C reaches 382.95 $[MW]^2$. The directional variogram indicates that the load values in the nodes of the 110 kV network are mutually correlated for the period of ca 15 years.

Table 5. Results of calculations connected with cross-validation of theoretical model of directional variogram of power demands in nodes of 110 kV network (test data)

Analyzed parameter	Sample size n	Test data			
		Mean error [MW]	Error variance $[MW]^2$	Mean standardized error	Standardized error variance
Power demand	600	−0.005	1.273	−0.006	1.000

Source: in-house study.

The results of calculations carried out on the basis of the 110 kV network node load data according to the cross-validation procedure, taking into account ordinary point kriging and the moving kriging neighbourhood, show the fitted (spherical) model to be in agreement with the directional variogram (Tables 5 and 6). The standardized error variance values are in limits of 0.41-1.00, depending on the kind of data used for the calculations, i.e. the test data (n = 600, Table 5) and the robust data (n = 578, Table 6).

Table 6. Results of calculations connected with cross-validation of theoretical model of directional variogram of power demands in nodes of 110 kV network (robust data)

Analyzed parameter	Sample size n	Robust data			
		Mean error [MW]	Error variance $[MW]^2$	Mean standardized error	Standardized error variance
Power demand	578	0.043	0.470	0.029	0.408

Source: in-house study.

The directional power demand variogram determined for the nodes of the 220/400 kV network shows a clearer trend in nonrandom variation (Figure 4) than the variogram investigated for the 110 kV network (Figure 3).

The Cauchy model was used to approximate the power demands directional variogram in the nodes of the 220/400 kV network. No C_0 effect appeared in this variogram. The variogram's very large range of influence of 96.41 years is conspicuous. Sill variance C amounts to 4845.89 $[MW]^2$. The correlation between the load values, evident in the directional variogram, is due to the much shorter time horizon of ca 7.5 years (Figure 4) than in the case of the corresponding variogram for the 110 kV network (Figure 3).

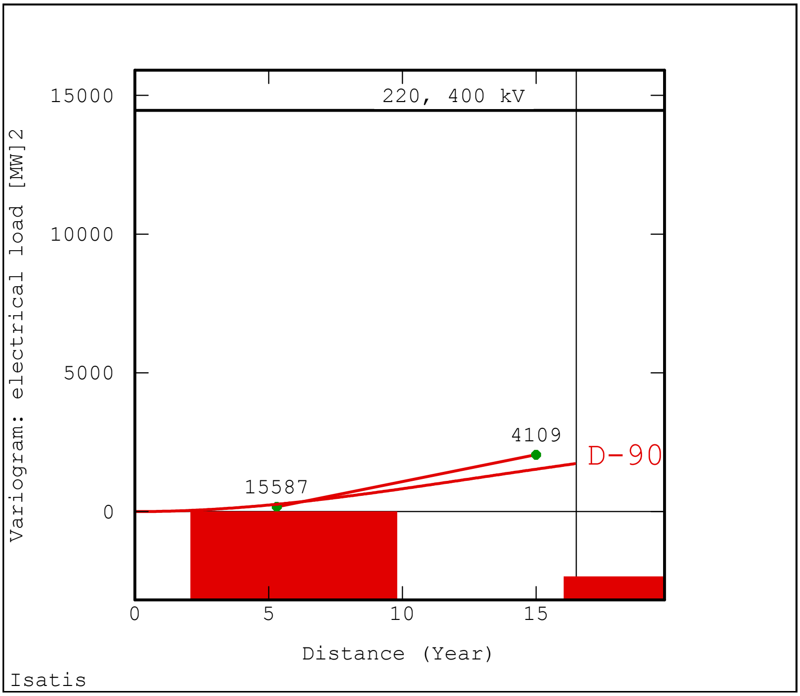

Figure 4. Directional variogram (along time axis *Z*) of power demands in nodes of 220/400 kV transmission network, with fitted theoretical model

Source: in-house study.

Table 7. Results of calculations connected with cross-validation of theoretical model of directional variogram of power demands in nodes of 220/400 kV network (test data)

Analyzed parameter	Sample size n	Test data			
		Mean error [MW]	Error variance $[MW]^2$	Mean standardized error	Standardized error variance
Power demand	2019	−0.784	61.61	−0.015	1.000

Source: in-house study.

Table 8. Results of calculations connected with cross-validation of theoretical model of directional variogram of power demands in nodes of 220/400 kV network (robust data)

Analyzed parameter	Sample size n	Robust data			
		Mean error [MW]	Error variance $[MW]^2$	Mean standardized error	Standardized error variance
Power demand	1984	−0.764	48.926	−0.011	0.385

Source: in-house study.

The results of calculations carried out on the basis of the 220/00 kV network node load data according to the cross-validation procedure, using ordinary point kriging and the moving kriging neighbourhood, show the theoretical (Cauchy) model approximating the shape of the analyzed directional variogram to be correct. The standardized error variance would reach the reference value of 1 and only 0.385 when respectively the test data (n = 2019, Table 7) and the robust data (n = 1984, Table 8) were used.

4. Area – time forecast of power demands for 110 kV network, made using ordinary block kriging

Figures 5 and 6 show raster maps of the distributions of power values Z^* in the nodes of the 110 kV network, forecasted for 1 year and 5 years. The maps were calculated using ordinary (block) kriging, taking into account the geostatistical parameters of the directional variogram model (Figure 6) and the moving kriging neighbourhood. The global statistics for the 1 year and 5 year forecasts are shown in Tables 9 and 10.

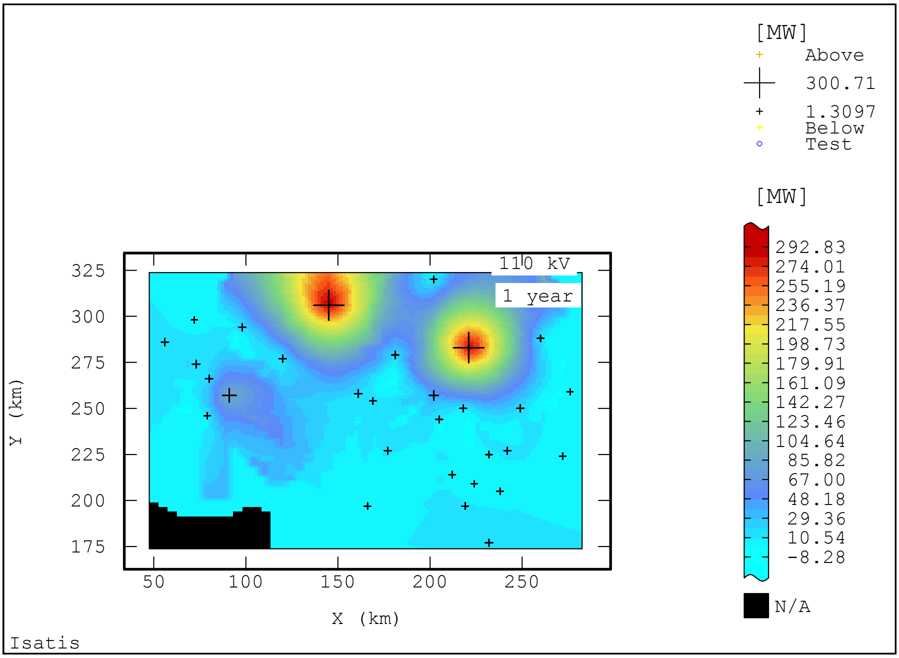

Figure 5. Raster map showing distribution of forecasted (for 1 year) power demands Z^* in nodes of 110 kV network for selected area of western part of Poland (forecast based on the results of ordinary block kriging); highest forecasted values Z^*: 255.19 ÷ 292.83 MW, lowest forecasted values Z^*: 10.54 ÷ 48.18 MW

Source: in-house study.

The estimation method was ordinary (block) kriging. This technique is used to estimate the block average for an elementary grid node (the block centre) as weighted average Z^* of sample values from a local neighbourhood (a samples searching area or the centre of an ellipse or circle, located in the block). Simultaneously with each estimated averages Z^* (kriging estimates), the estimation standard deviations – kriging deviations σ_k or kriging estimation variances σ_k^2 are calculated.

Table 9. Global statistics of forecasted (for 1 year) power demands in nodes of 110 kV network (ordinary block kriging)

Geostatistical parameter	Number of elementary grid nodes n	Minimum estimated value X_{min} [MW]	Maximum estimated value X_{max} [MW]	Average X [MW]	Standard deviation S [MW]	Variation coefficient V [%]
Estimated average Z^*	57,138	10.54	293.15	41.76	57.05	137
Standard deviation of estimation σ_k	57,138	0.78	8.96	4.50	1.69	38

Source: in-house study.

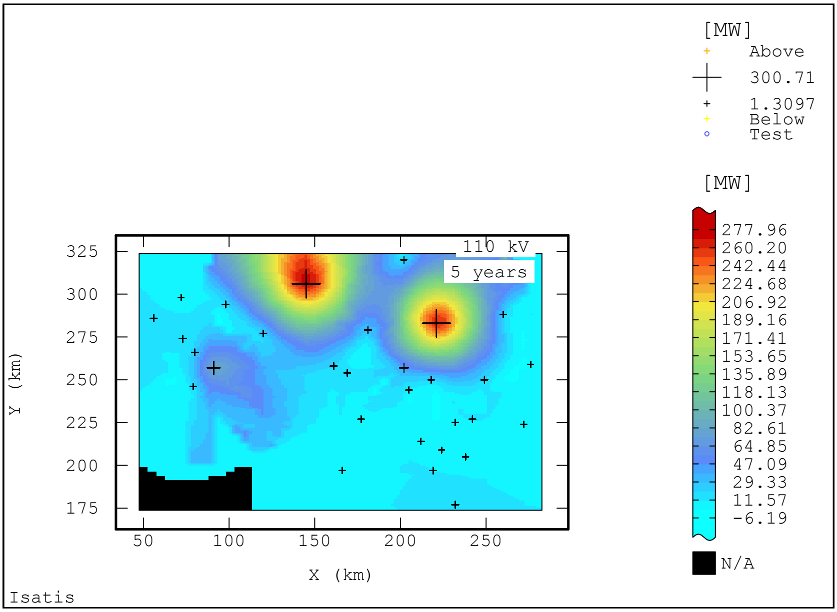

Figure 6. Raster map showing distribution of forecasted (for 5 years) power demands Z^* in nodes of 110 kV network for selected area of western Poland
(forecast based on the results of ordinary block kriging); highest forecasted values Z^*: 242.44 ÷ 277.96 MW, lowest forecasted values Z^*: 11.57 ÷ 47.09 MW

Source: in-house study.

The high values of variation coefficient V for forecasted (for 1 and 5 years) averages Z^*, reaching 136-137% (Tables 9 and 10), indicate extreme variation of averages Z^*. Whereas the other geostatistical parameter – standard estimation (forecast) deviation σ_k – does not vary so much as for averages Z^*. The coefficients (V) of variation of deviations σ_k reach 37-38%, falling into the range of average variation (Tables 9 and 10).

Table 10. Global statistics of forecasted (for 5 years) power demands in nodes of 110 kV network (ordinary block kriging)

Geostatistical parameter	Number of elementary grid nodes n	Minimum estimated value X_{min} [MW]	Maximum estimated value X_{max} [MW]	Average X [MW]	Standard deviation S [MW]	Variation coefficient V [%]
Estimated average Z^*	68,008	11.57	293.15	41.90	57.04	136
Standard deviation of estimation σ_k	68,008	0.78	8.96	4.51	1.68	37

Source: in-house study.

For the fifth year of the forecast based on the power demand data for the 110 kV nodes, the average of values Z^* is only slightly higher (Table 10) than the one for the first year (Table 9), but also higher than the average of values Z^* for the analyzed history (1-20 years) of the process. Also the lower limit of minimum values Z^* is set higher (Table 10).

5. Area – time forecast of power demands for 220/400 kV network, based on ordinary block kriging

Figures 7 and 8 show the raster maps of the distributions of forecasted (for 1 year and 5 years) power values Z^* in the nodes of the 220/400 kV network. The maps were calculated using ordinary block kriging, taking into account the parameters of the geostatistical directional variogram model (Figure 7). The global statistical parameters for the 1-year and 5-year forecasts are shown in Tables 11 and 12.

If the forecasts for the geostatistical parameters of the power demands in the nodes of 220/400 kV for one and five years are compared, a distinct upward trend in Z^* values (Tables 11 and 12) becomes apparent against the estimation results for the analyzed history (1-20 years) of the process. Higher minimum estimated values Z^*, maximum estimated values Z^* and estimated averages Z^* were obtained for the fifth forecast year (Table 12). It turns out that more accurate forecasting is possible on the basis of the power demands in the nodes of the 220/400 kV network.

Table 11. Global statistics for forecasted (for 1 year) power demands in nodes of 220/400 kV network (ordinary block kriging)

Geostatistical parameter	Number of elementary grid nodes n	Minimum estimated value X_{min} [MW]	Maximum estimated value X_{max} [MW]	Average X [MW]	Standard deviation S [MW]	Variation coefficient V [%]
Estimated average Z^*	104,895	19.80	587.67	210.53	362.46	172.00
Standard deviation of estimation σ_k	104,895	3.44	90.80	63.46	16.02	25.00

Source: in-house study.

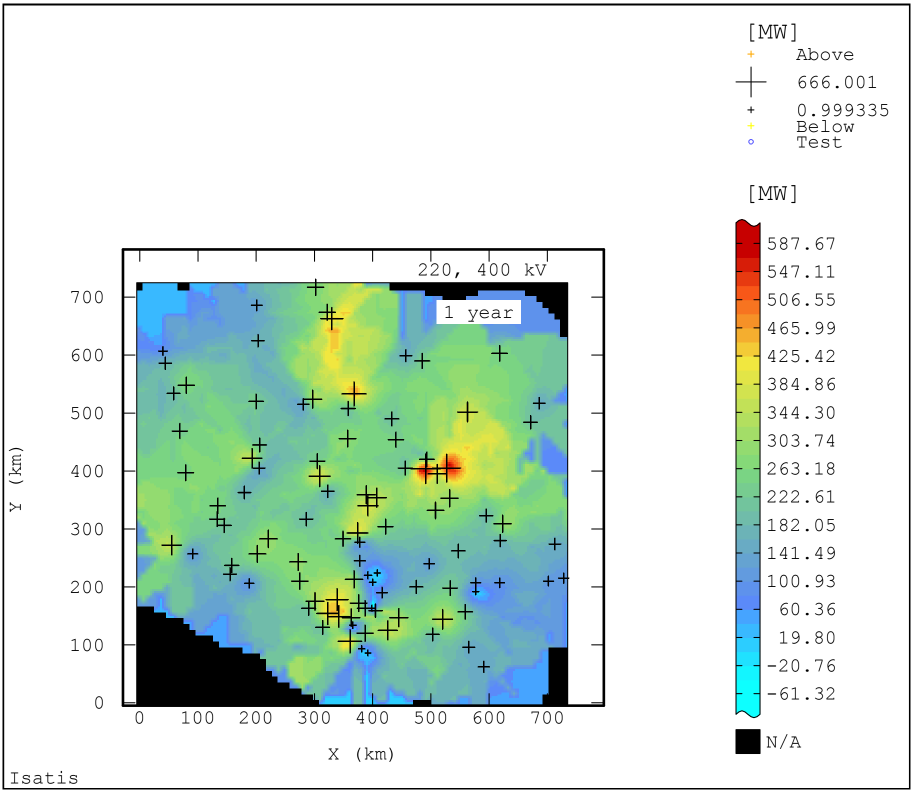

Figure 7. Raster map showing distribution of forecasted (for 1 year) power demands Z^* in nodes of 220/400 kV networks for whole area of Poland
(forecast based on the results of ordinary block kriging); highest forecasted values Z^*: 506.55 ÷ 587.67 MW; lowest forecasted values Z^*: 19.80 ÷ 100.93 MW

Source: in-house study.

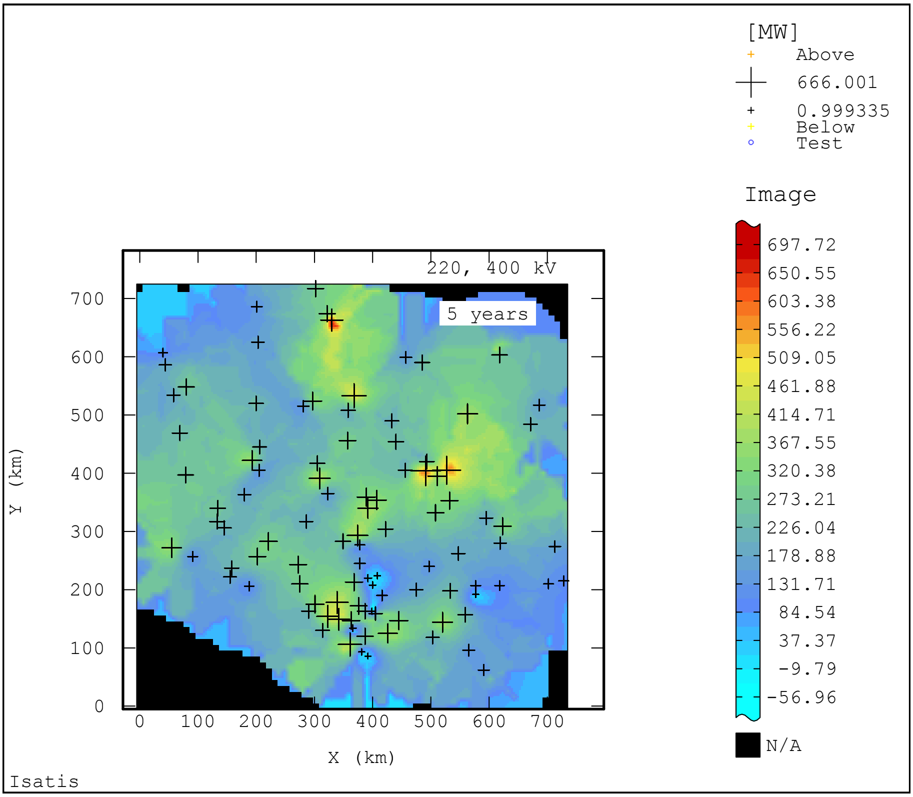

Figure 8. Raster map showing distribution of forecasted (for 5 years) power demands Z^* in nodes of 220/400 kV network for whole area of Poland
(forecast based on the results of ordinary block kriging); highest forecasted values Z^*: 603.38 ÷ 697.72 MW; lowest forecasted values Z^*: 37.37 ÷ 131.71 MW

Source: in-house study.

Table 12. Global statistics for forecasted (for 5 years) power demands in nodes of 220/400 kV network (ordinary block kriging)

Geostatistical parameter	Number of elementary grid nodes n	Minimum estimated value X_{min} [MW]	Maximum estimated value X_{max} MW]	Average X [MW]	Standard deviation S [MW]	Variation coefficient V [%]
Estimated average Z^*	124,872	37.37	697.72	211.57	334.00	158.00
Standard deviation of estimation σ_k	124,872	3.44	91.46	63.47	16.02	25.00

Source: in-house study.

Regardless of the time horizon, high values of variation coefficients V for forecasted averages Z^* (136–172%), indicating the latter's very large variation in the analyzed space – time space, were obtained (Tables 9-12). This applies to the nodes of both the 110 kV network and the 220/400 kV network. The variation coefficients V of the forecast deviations σ_k indicate average and relatively small changes of the σ_k values in the nodes of respectively the 110 kV network (37-38%) and the 220/400 kV network (25%), regardless of the time horizon (Tables 9-12).

6. Conclusions

The aim of this research was to investigate the possibility of applying geostatistical methods to forecast the surface distribution of electrical loads in a specified time period (interval). The results of forecasting the power demand in areas supplied by selected nodes of the 110 kV network (in western part of Poland) and in areas supplied from the nodes of the 220/400 kV network (for the whole area of Poland) have been presented.

The obtained results indicate that the proposed approach is useful for forecasting. The following observations have been made:

– the use of the moving kriging neighbourhood during estimation and forecasting gives better results than the use of all the data (the unique kriging neighbourhood),
– from among the tested estimation methods the technique of ordinary block kriging yields the most accurate estimates and forecasts,
– the investigations have a preliminary character and they should be continued to qualitatively improve the forecasts,
– further investigations should focus on fitting the theoretical function better to the description of the directional variogram, carrying calculations for different parameters of the kriging neighbourhood and verifying the usefulness of still other estimation kriging methods,
– the forecast model should include a component (e.g. a zero-one component) representing a deterministic factor, e.g. one taking into account the fact that an industrial facility is to be built in a given area or a large electricity consumer is to close down.

The 3D geostatistical model (which incorporates time through axis Z) developed for two kinds of electrical power network allows one to carry out various spatial analyses for all kinds of test variants, such as: modelling and estimating load variation as well making area – time forecasts for the nodes of a spatial (3D) elementary network as or its part. It is also possible to make forecasts for subareas of nodes, specified through indicators of their location in area (along axes X, Y) and in time (along axis Z).

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PROGNOZOWANIE (3D) ZAPOTRZEBOWANIA NA MOC ELEKTRYCZNĄ JAKO NARZĘDZIE W PLANOWANIU DZIAŁALNOŚCI FIRMY ENERGETYCZNEJ Z ZASTOSOWANIEM METOD GEOSTATYSTYCZNYCH

Streszczenie: metody geostatystyczne zastosowano do prognozowania obszarowo-czasowego (3D) zapotrzebowania na moc elektryczną. Analizy przestrzenne przeprowadzono na podstawie danych stanowiących obciążenia w dwóch rodzajach sieci elektroenergetycznych, tj. w węzłach sieci 220 oraz 400 kV dla całego obszaru Polski i w węzłach sieci 110 kV dla wytypowanego podobszaru Polski. Strukturę zmienności mocy dla tych dwóch rodzajów sieci analizowano w okresie 20 lat, z wykorzystaniem funkcji wariogramu kierunkowego. Opracowano prognozy obciążeń elektrycznych, z zastosowaniem krigingu zwyczajnego blokowego, z wyprzedzeniem czasowym, wynoszącym 1 rok i 5 lat. Uzyskane wyniki szacowania i prognozowania wartości średnich Z^* i standardowego odchylenia estymacji σ_k mocy wskazują na efektywność i przydatność użytych technik polecanych do wykorzystania w działalności firm energetycznych.