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THE FEATURES OF THE PREDICTIVE COMPUTING MODELING POWER SYSTEM LOAD IN TERMS OF REFORMING ENERGY MARKET

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ABSTRACT

The development of the country's energy system, its reform is one of the key issues not only for the development of the national economy, but also for national security. Ukraine does not stay away from the global tendencies of integration of energy systems, increase of energy efficiency, increase of the share of renewable sources in the structure of energy consumption. Therefore, the power market segment has a special place in the energy market as one of the most powerful export-oriented industries. Therefore, considerable attention is paid to the formation of an efficient electricity market infrastructure, optimization of its distribution and generation system, implementation of its rational use system and reduction of electricity prices. That is why the tasks of strategic and operational management of the load on the grid are important for both business entities and state and regional authorities. The lack of an effective science-based system of analysis and forecasting of grid load, generation and consumption of electricity is one of the factors that significantly impede the implementation of reforms in the energy sector. That is why the creation of a decision support system based on the predictive modeling subsystem is especially timely and relevant. The proposed system is universal and can be used in different countries of the world, as it is tailored to take into account the national peculiarities of the energy market of the country, its creation uses the experience of leading scientific institutions and energy generating companies, and its ability is tested through a large number of numerous experiments.

Keywords: *Prognostic Modelling, Consumption, Energy, Power Load, Nonlinear Processes, Generalized Linear Model*

1. INTRODUCTION

The issue of balanced environmental management is inextricably linked to the need to ensure efficient management of production and consumption of energy resources, both in particular country and in the regions of the world. After all, during the late XX and early XXI centuries, significant changes took place both in terms of increasing of the volumes of generation and consumption of energy resources and changing of their structure [1–3]. According to the prognosis of the International Energy Agency [1], global demand for energy resources will be increased, herewith the share generated from renewable energy sources will be greater, and the attention paid to increasing the share of renewable energy sources has risen from year to year. This will affect the changes in the structure of both energy generation and energy consumption. That is, significant changes are expected in the energy market. The “Energy and Climate Program for 2030” [4] and the “European Energy Security Strategy” [5] provide that a fundamental transformation of the energy system will take place under the creation of a single Energy Union, whereby a single efficient energy market will be formed, where pricing will occur on the basis of competition and regulation at European Union level with free access to the market for both consumers and suppliers.

For a long time, a significant share in the structure of production and consumption of

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energy resources concern to electricity; almost half of the growth of the world volume of primary energy consumption ensures owing to the increase in production of electricity according to the «World Energy Outlook 2014» (WEO 2014) [6]. As noted in [4], the share of electricity in the final consumption will increase from 16% in 2003 to 23% in 2050 (56% of growth by 2035) at an average annual rate of 2.2%. Therefore, the issue of improving the management of the formation of a balanced electricity market and its rational use based on prognosis of its generation and consumption is becoming more relevant.

A considerable number of works by both Ukrainian and foreign scientists is dedicated to the issues of prognosis the energy market [7-40]. However, appreciable attention in most of them has been paid to prognostic modelling of the financial components of the energy market. These solutions are based on regression analysis of time series of statistic data of the financial-and-economic indicators and volumes of energy supply and use [7–21]. Less attention has been paid to optimizing of energy consumption and identifying of the reserves of its reducing. First of all, it is connected with the complexity of processing of large amounts of data from energy generating and electricity distributing companies. These large volumes of structured and unstructured data require the use of specific data mining tools to collect and accumulate them in the form applicable for analysis. In addition, a necessary condition for obtaining qualitative results of prognostic modelling is to provide flexibility and adaptability of the used methods, which would allow to take into account as much as possible local and national features of the energy market, the nature of the processes dynamics that cause in certain periods sharp changes in the load on the electric power system or its individual subsystems: their randomness and unsteadiness. In addition, it is important not only to propose the use of individual prognostic methods to solve "point" problems, but also to formulate a common methodology of analyzing and prognosis of the structure and dynamics of the energy market that can be used to solve complex problems related to optimization of its functioning. Therefore, the development of a methodology for prognostic modelling of electric power system load, generation, consumption and supply of electricity with the use of appropriate analytical tools, especially in the conditions of its reformation is a timely issue not only for individual countries, but also for united regional energy systems.

2. ANALYSIS OF LITERARY DATA AND PROBLEM STATEMENT

A significant number of publications on this topic prove the urgency of the problem of improving the efficiency of energy market management. Most papers [2–5, 7–21, 27–40, 45–47, 53] address the issue on prognosis of electric power system load in the course of planning of generation and consumption of electric energy. It should be noted that a particular attention is paid to prognosis of peak loads on the electric power system and development of proposals to reduce electricity consumption during such periods, using different approaches for this that take into account, first of all, the specificities of the national energy market. In particular, researchers from the Western University of London and the University of the Suez Canal [26] propose a Hephaestus method developed by them based on using of transfer learning, a multivariate regression model with seasonal correction and trend correction to predict electricity consumption. Using of this method allowed improving the quality of prognosis by 11.2%. The advantage of the Hephaestus method, according to the developers [26], is the effectiveness of its application even with small sets of input data, which they offer to supplement with measurements from similar objects made for over a longer period. T. Pedersen [27] proposes a model designed for prognosis of hourly electricity demand on the energy market of the Northern European countries. This model is based on annual, weekly and daily trends, as well as temperature fluctuations. Its peculiarity is also taking into account economic trends and opportunities for changes in energy consumption under the influence of economic growth. Australian researchers from Monash University [28] also proposed software that allows processing of nonlinear connections between different variables-factors of the energy market and electricity consumption, and build short- , medium- and long-term prognoses of electricity demand on the country's energy market based on semi-parametric additive models, which can be divided into two parts: "long-term" and "half-hour", which are evaluated separately. The

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model [28] takes into consideration long-term changes in the economy, demographics, technological development, climate change, etc., and considerable attention is paid to the prognosis of peak electricity demand, which allows to plan the required capacity during these periods and to develop more accurate short-term prognoses of electricity consumption. Another variant of prognosis of peak electricity demand for integrated resource planning is the development of the scientists from the laboratory of Ernest Orlando Lawrence Berkeley [29].

Emphasis on prognosis of wholesale electricity prices using a seasonal ARIMA model and electricity price modelling in real time based on an energy consumption scheme that provides price defining for electricity during the periods of peak loads was done by Indian researchers [30]. They note that the use of home electricity controllers is effective for ensuring balanced electricity consumption according to the results of prognostic modelling [30]. Scientists from Slovakia [31] propose to use cluster analysis for determining of aggregate electricity consumption by all consumers and note that the best results were obtained by applying combinations of regression models taking account seasonality and holidays. Not only seasonal variations but also temperature corrections with appropriate correction coefficients developed for different types of energy, in particular, new ones based on the concept of "warm-up days" are proposed to use in the work [32]. Brazilian researchers [33], taking into account the specifics of the development of the country's energy system, developed a one-dimensional model of short-term prognosis with time interval of 15 minutes, forward on 15 days, that is 1440 steps. Methods of exponential smoothing, in particular, the Holt-Winters method with two exogenous corrections taking account day-offs and extreme temperatures were used in the model.

Researchers from Dubai [34] like the Brazilian ones suppose that monthly peak loads on the electricity grid is important for the rapidly expanding energy market, as it allows to plan further development of the country's energy system in the future. The models of exponential smoothing (linear trend with multiplicative seasonality) and the Box–Jenkins model with root transformation (1,1,1) -(0,1,1) proved to be the best models, as their research showed.

The KNIME analytical platform, presented as a modelling tool in the work [35], allows using different approaches, including autoregressive models with seasonal correction, neural networks, data mining facilities, a wide range of statistical approaches, etc. We select those from the models-candidates which produce the best results to build prognosis. Value of root-mean-square error is the selection criterion.

It is worth noting the experience of Ukrainian scientists [3, 12, 13, 17, 36–40], in particular, the work of Kovalenko M. V. [38] for prognosis of the consumption of fuel-and-energy resources in the operational management of energy supply of a large city. This paper proposes the use of three model groups of etalon and connected energy consumption, which is relevant in the context of combined use of heat and electricity during the heating season.

T. O. Tereshchenko, Yu. S. Yamnenko [39] and others in MicroGrid systems concluded that a method that combines the use of digital filters and neural networks is promising for the Ukrainian energy market having reviewed the prognostic models of energy consumption, including electricity. Applying of systematic approach using a set of models for prognosis of the region's energy consumption is proposed in some papers of Ukrainian scientists [40]. The balance of fuel-and-energy resources in terms of the levels of the macroeconomic system of the country is at the bottom of the approach, and it is also proposed to take into account both external influence and the model of energy intensity of the economy, models of energy consumption of industries and regional energy consumption [36, 40].

Therefore, summarizing the above, it should be noted that prognosis of energy consumption and development of the energy market is a problem of interest to researchers from many countries. Despite the variety of proposed methods for solving this problem, virtually all the recommendations are connected with seasonality, nonlinearities of the studied processes, the need to process data gaps, however, all of these methods need to be improved by applying a wider range of models, complementing by the prognosis methods of peak loads and season fluctuations. Just the interest of many players on the energy consumption market in continuation of the study in this segment of researches became a starting point of the work and, in our opinion, made the paper relevant based on the mentioned factors.

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3. STATEMENT OF THE PROBLEM

The purpose of the work is the study and development of information technology of prognostic modelling of electric power system load taking into account prognosis horizon, intended to improve the efficiency of managing of the energy market functioning in terms of its transition to saving consumption and indicative pricing. The article discusses the solutions that are based on the use of different methods of prognostic modelling for short-, medium- and long-term prognosis, implemented by means of SAS Energy Forecasting, a specialized software [41, 42].

Proposed information technology should ensure acceptable quality of prognoses in the presence of different-type data, time series containing gaps, anomalous values, etc.

It is necessary to solve such following problems to achieve a set purpose as:

- to study the peculiarities of the domestic and foreign energy market;
- to consider variants of problem solutions of energy consumption prognosis proposed by researchers from around the world;
- to develop a methodology for using the models of different types and their combinations for prognostic modelling of energy consumption depending on the prognosis horizon;
- to study the use of SAS Energy Forecasting software;
- to develop practical recommendations concerning pricing management on the energy market;
- to check the efficiency of the proposed system on the example of specific tasks.

Using of the proposed methodology will allow improving the quality of pricing management in the energy market.

4. MATERIALS AND METHODS

Many methods are used to make prognosis of electricity consumption, but there is no unified universal and tested in practice one. It is connected with the fact that the energy market of each country has features common to the world community, groups of countries, etc. and their own unique peculiarities. There is also a very powerful mathematical prognostic machine that allows getting prognoses of high quality. Therefore, it is important to ensure automatical selection of the best model from a large number by using standard statistical tests, followed by manual selection of models for the most important or problem series when studying such a difficult process as operation of electric power system. This requires both appropriate analytical tools and involvement of the competent experts in the branch of energy market. The difficulties in prognosis of the electric power system load are also caused by the fact that electricity consumers are different-type groups of consumers who use electricity during a day, month, year unevenly and non-synchronously, formation of energy pricing for them is also occurred in a different way, and often social-and-political factors are crucial, especially for the population.

Regression models are "traditional" for prognosis of electric power system load. Their use is described in the works [43-48]. They are the models with additive and multiplicative seasonal component, taking into account the trend dump and other modifications.

Models of exponential smoothing group are also widely used to model time series and, their corresponding modifications if there is a trend and seasonality. Winters's model with a multiplicative seasonal component showed the best results in prognostic modelling of the components of the energy market among the methods of exponential smoothing group [47–49]. In a general form, the corresponding formula is as follows [50] (1):

$$\hat{y}(t+h) = ((a(t)+h\cdot b(t))\cdot s(t-p+1+(h-1)\bmod(p)), \quad (1)$$

where $\hat{y}(t+h)$ – prognosis for the period h forward, p – length of the seasonality period, *mod* – function of the remainder of a division operation, for example, 12 *mod* 5 = 2.

The first equation describing a smoothed trend [50] (2):

$$a(t) = \alpha(\frac{y(t)}{s(t-p)} + (1-a)\cdot(a(t-1)+b(t-1)). \quad (2)$$

The second equation used to estimate the trend [50]:

$$b(t) = \beta\cdot(a(t)-a(t-1)) + (1-\beta)\cdot b(t-1). \quad (3)$$

The third equation for estimating seasonality [44] (4):

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$$s(t) = \gamma \cdot (\frac{y(t)}{a(t)}) + (1-\gamma) \cdot s(t-p) \, . \qquad (4)$$

Auto-regression models, as noted [43-49], are most commonly used for long-term prognosis of the components of the energy market.

Neural networks [51], used in some cases are also popular among researchers, since such models are characterized by the complexity in architecture choosing, the need for a large training sample and resource capacity of the learning process, the risk of network "overlearning" and the difficulty in results interpreting, etc. Specialized probabilistic models [52], including Markov's chains, are also used for prognosis in the energy market branch. In some cases, fuzzy methods are also used [53]. However, regression models are the most common, which are not only easy to use but in many cases they also provide prognoses of high quality.

A linear regression model with normally distributed errors can be written as [50] (5):

$$Y_i = \beta_o + \beta_1 \cdot x_{i1} + \beta_2 \cdot x_{i2} + ... + \beta_{p-1} \cdot x_{i,p-1} + e_i \, , \qquad (5)$$

where $\beta_0,...,\beta_{p-1}$ – the parameters, $x_{i1},...,x_{i,p-1}$ – known values of variables at the time moments, i, e_i – independent, normally distributed remainders with parameters $N(0,\sigma^2)$, $i = 1, \ldots, n$.

Target variable is described by the equation [50] (6):

$$E[Y] = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_{p-1} x_{p-1} \, , \qquad (6)$$

where $x_1, \ldots, x_{p-1}$– variables- regressors.

Generalized linear models [42, 54] are the most common for building short-term prognoses of electric power system load, as it was shown by the analysis of publications and practical implementations in specialized software packages [55].

Their simplicity and sufficiently high quality of forecasting are the advantages of using them for short-term prognosis of the dynamics of electric power system load. It should be noted that the use of one or other group of models depends on the prognosis horizon, the presence of sufficiently long time series of the indicators of state and dynamics of the energy market that affect the pricing formation for electricity, as well as the competencies of the analyst, etc.

Generalized linear models (GLM) [55] are a broad group of statistical models that summarize classic linear models by two directions. The first one is that the target variable may have a distribution different from normal. It can be any distribution that belongs to exponential dispersion models. The second one is that some monotone transformation of mathematical expectation is a linear function from the regressor.

The ordinary linear model is a partial case of the GLM model. The main task of the linear model is to model the value of the mathematical expectation of the target variable based on the regressors values.

In the general case, the GLM model is a more advanced version of equation [49] (5), which is written as (7):

$$g(E(Y_i)) = \beta_o + \beta_1 \cdot x_{i1} + \beta_2 \cdot x_{i2} + ... + \beta_{p-1} \cdot x_{i,p-1} + e_i = X\beta \qquad (7)$$

where $g(E(y)) = g(\mu) = X\beta -$ a coupling function that must be monotonic but not identical to linear regression [50, 55].

The general form of a function for the density or probabilistic exponential family of the GLM model can be written as [49] (8):

$$f(y|\theta) = \exp\{\frac{y\theta - b(\theta)}{a(\theta)} + c(y,\varphi)\} \, , \qquad (8)$$

where θ – mid position parameter, and φ – b straggling parameter.

X-12-ARIMA and TRAMO-SEATS models [56] also have practical importance for prognosis of energy consumption and they are structural models of time series which are some alternative if they take into account the complete processing of calendar and load peaks and include an appropriate diagnostic set. Consistent use of a specific unified set of seasonal correction packages, in [45, 48, 56] 's opinion, will improve the transparency and comparability of time series adjusted for seasonal variations for different countries.

It is usually used the following as criteria for determining of the adequacy of the constructed mathematical mode [50]:

RMSE – root mean square error (9).

$$RMSE = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^{n} (A_i - F_i)^2} \, . \qquad (9)$$

R^2 – coefficient of determination (10):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(A_i - F_i)^2}{\sum_{i=1}^{n}(A_i - \overline{A})^2}, \qquad (10)$$

ME – mean error (11):

$$ME = \frac{1}{n} \cdot \sum_{i=1}^{n}(A_i - F_i) \qquad (11)$$

MAE – mean absolute error (12):

$$MAE = \frac{1}{n} \cdot \sum_{i=1}^{n}\left|A_i - F_i\right|. \qquad (12)$$

$MAPE$ – mean absolute percent error (13):

$$MAPE = \frac{100}{n} \cdot \sum_{i=1}^{n}\left|\frac{A_i - F_i}{A_i}\right|, \qquad (13)$$

where n – number of observations, A_i actual(real) i-th value, $\overline{A}$ – mathematical expectation of actual values, F_i – forecasting i-th value.

It should be noted that this study uses *MAPE* statistics, often used at the enterprises of energy industry [41–43] as the most comprehensible when comparing and independent from tolerance range, to make the decision concerning choosing the best mathematical model.

5. EXPERIMENT

This article proposes a methodology of prognosis of electric power system load for an energy generating company. The SAS Energy Forecasting software [42] package was used as a tool of simulation modelling. Partially, this method of prognostic modelling is presented in our work [57]. But this article focuses on building computer models for short-term prognosis unlike our previous study. The following are distinguished according to the International Industry Standard on Energy [1, 47], depending on the prognosis horizon:

- very short-term prognosis – from 1 to 24 hours
- short-term prognosis – from 1 to 14 days
- medium-term prognosis – from 14 days to 3 years
- long-term prognosis – from 4 to 50 years.

Energy market operates as a component of the national and global markets, under the influence of many factors that characterize its dynamics and structure at different time intervals and different levels of its functioning. Therefore, it is necessary to use prognostic models that will not only differ in structure but also use different input parameters, taking into account the differences in the cycles of energy power system load: hourly, daily, monthly and annual for short-, medium- and long-term prognoses.

It should be predicted that certain structural-and-dynamic changes will occur on the country's energy market, common to the macroeconomic system as a whole, for medium- and long-term prognoses of electric power system load. These changes can occur under realistic, pessimistic or optimistic scenarios of the development of the national economy. Various methods can be used to build the scenarios, which involve the use of both quantitative and qualitative indicators, in particular social-and-demographic, economic, and social-and-political in some cases. The lack of long enough time series of statistical data is the main problem happened while developing scenarios. After all, we need comparable statistical data for at least the same 10-year retrospective period, as well as the corresponding 10-year scenarios of the development of the energy company and the country's economy to build prognoses for the decade forward.

It is impractical to use time series of air temperature as an input variable when building long-term prognoses of electric power system load; macroeconomic indicators are more informative and they characterize the general tendencies of the development of the national economy, features of its sectoral structure, prospects of generation and consumption of electricity by domestic consumers and enterprises. Scenarios of the development of energy generative and energy consumption companies, as well as territorial units and regions are also important. Statistics of gross domestic product, the number of population, the amount of workers employed in production is used for this purpose. Supporting the opinion of the researchers [47, 48], it should be noted that the following aggregated indices in long- and medium-term prognostic modelling in order to ensure the comparability of statistical data [58] for different years, are advisable to use [48, 58] (14):

$$I = 0{,}28 \cdot GDP + 0{,}32 \cdot NP + 0{,}4 \cdot WP, \qquad (14)$$

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where *GDP* – gross domestic product; *NP* – number of population; *WP* – amount of workers employed in production.

In addition, temperature values and load distribution during the day are irrelevant when constructing long-term prognoses, since such detalization is too excessive within the models used for macroeconomic planning and forecasting.

But it should be noted that indicators of air temperature, energy consumption, etc. need considerable attention in the short-term prognosis of energy consumption, in agreement with the opinion of many researchers. In addition, in the general case, the experts [42–48, 53–56] recommend to consider pre-holiday, holiday and after-holiday dates, hours of the day, air temperature, geographical location in the model. Therefore, preliminary preparation of time series of these indicators is of particular importance in this case. After all, there are often anomalies in studies when time series may contain too high values of the temperature (for example, 255 degrees Celsius on January 25, 2015) or that may not occur at the appropriate time of the year on the specific territory (45 degrees Celsius on December 6, 2015 in Ukraine). It is necessary to refer to other databases where there is correct information or to replace the anomalous value by calculating as the mean value between known neighbors in these cases, as well as in the cases of data gaps. Available retrospective statistical information can be used to deal with gaps in the time series of air temperature values when developing short- and medium-term prognoses. For example, if there is thirty-year statistics of air temperature measurements done every hour during a day, then prognosis of load is calculated for each of the thirty values corresponding to a specific hour, taking into account seasonal peaks, holidays and working days. Then a prognosis weighted value can be obtained. Thus, the corresponding task can be come to development of 8760 (by the number of hours in a standard 365-daily year or 8784 hours in a leap year) individual models for each hourly value of load on the electric power system.

The peculiarities of prognostic modelling of electric power system load is that the aggregate value for the previous periods except the air temperature value is used in a form of a model regressor; the formula is used which by its nature is a mean value of the temperature for the previous 24 hours for the case of short-term prognosis (by hours) (15):

$$T_{\alpha}(t)=\sum_{k=1}^{24}\frac{T(t-k)}{24}. \quad (15)$$

The following formula when calculating a weighted value for the monthly data is used (16)

$$T_{\alpha}(t)=\sum_{k=1}^{n}\frac{T(t-k)}{n}, \quad (16)$$

where n – the number of hours in the corresponding month, for example, 744 hours (31 days for 24 hours) for January.

In a general case, specially selected smoothing coefficients α can be used, which s more weight to the "fresher" value of the air temperature (17):

$$T_{w}(t)=\frac{\sum_{k=1}^{n}\alpha^{k-1}T(t-k)}{\sum_{k=1}^{n}\alpha^{k-1}}. \quad (17)$$

Gaps and anomalous values can also occur in time series of electric power system load. These problems can be related to both errors in the filling of databases by a human-operator and technical failures of the information registration systems. Practical experience of analyzing the statistical data of energy companies shows that there can be missing data completely for one and sometimes two days in a row every year in the time series of indicators. The reason for this is the regular annual technical work, and information does not enter into the database as a result of this. In these cases, specialized methods on renewing or forecasting of relevant data based on previously known hourly values must be applied.

The international practice of constructing of mathematical load models [45–48] recommends to take into account holidays, major sporting events, concerts, and other events that affect the mass behavior of the population regarding energy consumption. However, application of international experience without taking into account the specificity of the country can lead to significant errors of the model, which in the future becomes a financial loss for energy companies. This is confirmed by the results of a relevant study: if the electric power system load is presented graphically using stock charts (Fig. 1), then the volume and dynamics of the power system load [58, 59] during a week and day can be seen.

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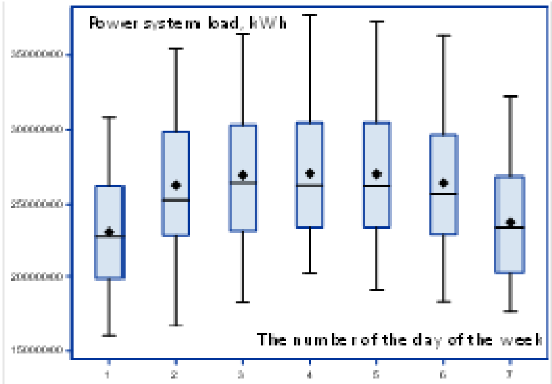

Figure 1: Chart of the power system load during typical working week in Ukraine (the figure shows: 1-Sunday, etc.)

If you can notice from Fig.1, the maximum load is in the middle of the week, and the minimum one – at the weekends.

There is great interest in the electricity supply companies for load prognosis of every hour during a day, in addition to forecasting the value of the load during a day. After all, availability of prognosis of power cuts and load peaks is important for both energy generating companies and consumers. For the first, it will help to prevent power outages, secondly – to develop adequate measures to motivate consumers to save electricity, to reduce consumption during peak hours, to distribute electricity generation between different capacities, to turn on peak and half-peak block units, etc. Prognostic models used to solve this problem are developed taking into account the daily fluctuations in prices for electricity and daily load on the energy system [58, 59] (Fig. 2).

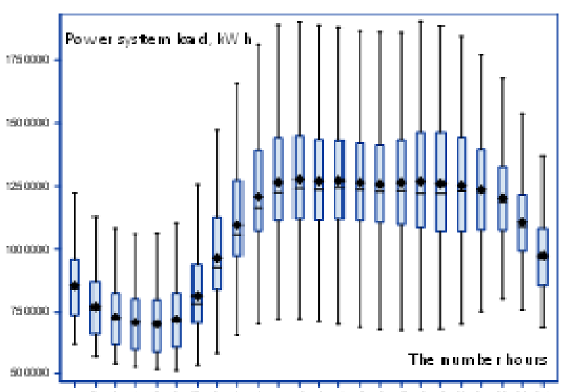

Figure 2: Chart of the hourly load power during the day

As can be seen from Fig. 2, the minimum load is fixed at 4-5 a.m., and the maximum - from 11 a.m. to 20 o'clock (8 p.m.).

It is proposed to use single-stage (GLM-B, GLM-BR, GLM-BRW, GLM-BRWH, GLM-WeBRWH) and two-stage models (UCM, neural networks, models of exponential smoothing, GLM ARIMAX and combined models) for very short-term prognosis. The best model is selected, the lighter load value is added to the best model, and the model coefficients are estimated on a training sample. If a two-stage model is preferable, then the coefficients of the model are estimated on the residual period.

For the Ukrainian energy market, major sports events do not significantly affect the level of electric power system load according to the research. Thus, the typical situation may be when the load on the day of the UEFA Champions League final in 2015 is almost exactly the same as a regular Saturday. However, there is a significant difference in the load on the electricity grid on the days of holidays marked in the national holiday calendar.

Table 1 Shows mean of values system power load for days of the week, aggregated by quarters [58, 59].

Table 1. Dynamics of the average power system load in the days of the week throughout the year, kWh

Day of the week	Quarters of the year			
	1	2	3	4
Monday	1250889	923659	962924	1235508
Tuesday	1269983	971538	975017	1264412
Wednesday	1258977	996129	975709	1276478
Thursday	1255583	991599	977955	1264600
Friday	1240089	963754	963183	1234308
Saturday	1132154	857896	856869	1099644
Sunday	1101928	820446	838255	1077186

The study of the connections between the power system load and air temperature is also important [58, 59] (Fig. 3).

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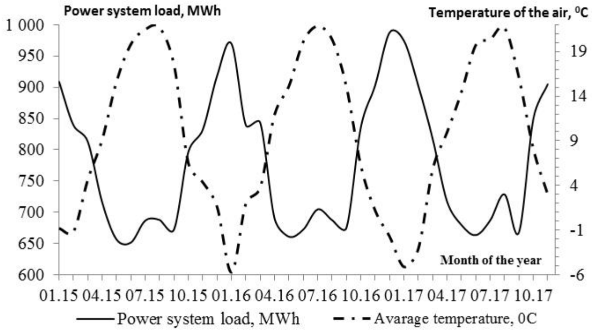

Figure 3: Chart of dependence of average temperature of the air and total power system load by months during 01.2015 - 11 2017

The study of the connection between the air temperature and load on the electric grid in the daily and monthly sections (Fig. 3) shows that the temperature and load are in reverse phase one to another depending on the time of the year. That is why, the temperature is included in the form of the polynomial of the third degree [58] (Fig. 4), also specialized combined variables based on the air temperature and month, the air temperature and hour of the day, the air temperature and the day of the week are created in the model for short-term prognosis which takes into account the air temperature.

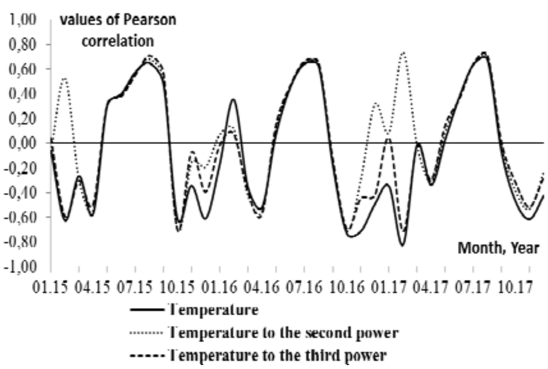

Figure 4: Graf of values of Pearson correlation between system power load and air temperature to the second and to the third power during 01.2015 - 11. 2017

There are significant Pearson correlation estimates between electric power system load and air temperature of the second and third degree according to Fig. 4. This means that the load on the electric power system increases in the winter months when the temperature falls, and in the summer - when the temperature increases. This is quite obvious from ordinary human logic, because the consumers switch on heating equipment in winter and air conditioners and other cooling means in summer. Experts recommend that the air temperature can be included in the model to make prognosis concerning the load of the electric power system in the form of the current value of the air temperature as of the corresponding hour, the previous value as the difference between the current value and the previous one, the minimum, maximum and mean values [47] per day or several hours and other derived indicator.

In general, the mathematical model in addition to historical data must also take into account macroeconomic indicators by different scenarios, the presence of public holidays. The proposed information technology allows implementing mentioned and similar mathematical models.

However, at the proposed system is not discovered the possibility of using scenario analysis for the short-term perspective, state and dynamics of the socio-economic system, prompt processing of input data. Therefore, it is further proposed to develop data mining technology, including for the processing of large data sets, obtained from various sources, in particular, and in real time. For this purpose, it is envisaged to implement an on-line system for processing of primary information, its structuring and accumulation, checking for the presence of gaps and incorrectly entered data, etc. Also it is proposed to use probabilistic modeling and elements of expert systems to select the most relevant socio-economic factors for the energy market and to use them in predictive modeling and scenario construction.

6. RESULTS

The proposed method of prognosis of electric power system load was used in the system of decision-making support to determine the need for electricity generation for the energy generating company. A training sampling provided by the company, which included data from January 1, 2015 to September 30, 2017, and validation sampling from October 1, 2017 to December 31, 2017 was analyzed in the study [58].

A four-month validation period is sufficient to develop models of several groups simultaneously: very short-term and medium-term.

The following types of models are used for prognosis:

- regression and autoregressive models;

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- models with using trend component and taking into account residuals (difference between real and prognostic values) included in the model in the form of moving mean, if there is a correlation between the residuals and the target variable;
- models of exponential smoothing group - Holt, Brown, Winters (with additive or multiplicative seasonal component), taking into account trend dump and other modifications;
- generalized linear models;
- neural networks;
- separate probabilistic models and fuzzy methods.

The process of developing of prognostic models was implemented as follows. At first, the input data is loaded, then the user selects the interval at which models and prognosis horizon will be learned. Further, the system automatically builds a set of models, and the user receives a set of tables with static characteristics of these models and a table with the values [47] of the electric power system load that interpret by the system as anomalous.

SAS Energy Forecasting [42], specialized industry software, for automatic calculation of GLM values [58] of the ARIMAX model was used. Its advantages are a wide range of tools for prognostic modelling and visualization of the results.

For example, the general structure of ARIMAX model provided by a training data-set of GLM company is a follow (18):

$$Y = \beta_0 + \beta_1 \cdot Trend + \beta_2 \cdot Y(t-1) + \beta_3 \cdot WeekDay \cdot Hour + \beta_4 \cdot Month + \beta_5 \cdot T_0 \cdot Month + \beta_6 \cdot T_0^2 \cdot Month + \beta_7 \cdot T_0^3 \cdot Month + \beta_8 \cdot T_0 \cdot Hour + \beta_9 \cdot T_0^2 \cdot Hour + \beta_{10} \cdot T_0^3 \cdot Hour + \beta_{11} \cdot T_1 \cdot Month + \beta_{12} \cdot T_1^2 \cdot Month + \beta_{13} \cdot T_1 \cdot Hour + \beta_{14} \cdot T_1^2 \cdot Hour + \beta_{15} \cdot T_\alpha \cdot Month + \beta_{16} \cdot T_\alpha^2 \cdot Month + \beta_{17} \cdot T_\alpha \cdot Hour + \beta_{18} \cdot T_\alpha^2 \cdot Hour, \quad (18)$$

where β_0 – the free member of the model, actually average value by all measurements of the load in the sample; *Trend* - trend component of the model; Y(t-1) - autoregressive component of the model, the value of the load at the previous moment of the time; *WeekDay* – day of the week (1 – Sunday, 2 – Monday, …, 6 – Saturday); *Hour* – hour of the day (goes from 1 to 24); *WeekDay · Hour* – combined variable that, in fact, reflects all values matching *WeekDay* and *Hour*, on the whole 168 different combinations of the day of the week and the hour (7 days multiply by 24 hours); *Month* – month of the year (goes from 1 to 12); T_0 – temperature value in the estimated time period t; T_1 – temperature value in the previous time period t-1, i.e lag 1; T_2 – temperature value in the previous time period t-2, i. e lag 2; T_α – average weighted value of the temperature; T_0^2, T_0^3, T_1^2, …, T_α^2 – temperature value in an appropriate degree; $T_0 \cdot Month$ – combined variable that displays the average value of the temperature per month, 12 different combinations in total (by the number of months in a year); $T_1 \cdot Month$ – combined variable that displays the average value of the temperature in the previous month, 12 different combinations in total; $T_\alpha \cdot Month$ – combined variable that displays average weighted value of the temperature for the previous 12 months, 12 different combinations in total; $T_0 \cdot Hour$ – combined variable that displays temperature value at the current time, 24 different combinations in total; $T_1 \cdot Hour$ – combined variable that displays temperature value for a previous hour, 24 different combinations in total; $T_\alpha \cdot Hour$ – combined variable that displays average weighted value of the temperature for the previous 24 hours, 24 different combinations in total.

Table (2) shows the first tree values of the 435 values [58] of the model coefficients estimates.

As it can be seen from Table 2 the previous load value (β_2), namely, about 93% of the previous load value is taken into account in the following one, and there is a slight trend in the data. The last 432 coefficients actually describe all possible combinations of the situations, taking into account the volumes of electricity consumption for a certain hour of a day, month, day of the week, air temperature and various combinations of factors. A complete result table consisting of 435 estimates of GLM parameters of the ARIMAX model is presented in [58].

Table 2. The first three of the 435 values of the coefficients of the GLM ARIMAX

Para-meter	Description	Value of the estimation	Standard model error	T - statistic	p- value
β_0	the free member of the model	35861,18	15030,7	2,39	0,0170
β_1	trend	0,1317	0,0175	7,52	0,0001
β_2	previous load value	0,9336	0,0023	414,1	0,0001

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Qualitative variables, unlike quantitative ones, are shown in the form of design variables in the model. For example, let's have a WeekDay variable that gets seven values: 1 – Sunday, 2 – Monday, .., 7 – Saturday. The WeekDay variable can be represented as six indicator design variables using the following rules:

X_1 = 1, if WeekDay = "Sunday",
X_1 = 0, if WeekDay is not "Sunday",
X_2 = 1, if WeekDay = "Monday",
X_2 = 0, if WeekDay is not "Monday",
X_3 = 1, if WeekDay = "Tuesday",
X_3 = 0, if WeekDay is not "Tuesday",
X_4 = 1, if WeekDay = "Wednesday",
X_4 = 0, if WeekDay is not "Wednesday",
X_5 = 1, if WeekDay = "Thursday",
X_5 = 0, if WeekDay is not "Thursday",
X_6 = 1, if WeekDay = "Friday",
X_6 = 0, if WeekDay is not "Friday".

Although the WeekDay variable acquires seven values, it can be described by six design variables. Because when $X_1 = 0$, $X_2 = 0$, $X_3 = 0$, $X_4 = 0$, $X_5 = 0$, $X_6 = 0$ the value of *WeekDay* is "Saturday ", and, in terms of regression modeling, the corresponding coefficient is taken into account in the free member of the model.

The model with the multiplicative seasonality showed the best results among the methods of exponential smoothing. This model is a simpler variant compared to the earlier-mentioned Winters' model in view of the multiplicative seasonality. The main difference between the models is that there is no need to include the trend component in the model [47]. Table 3 shows the obtained values of the coefficients estimates of the equation with the corresponding statistical characteristics.

Table 3: The parameters of smoothing seasonal multiplicative model

Para-meter	Estima-tion	Standard model error	T - statistic	p - value
α	0,8972	0,003688	243,2693	0,0001
γ	0,999	0,039808	25,09517	0,0001

The model in the form of equation (3) that includes an additional component $\beta_{19} \cdot Holliday$ similar to the GLM of the ARIMAX model was built. The values of the Holliday variable were formed on the basis of the list of national holidays, which is approved annually by a resolution of the Cabinet of Ministers of Ukraine [60]. The model construction took into account the list of holidays in 2015-2018, as well as the before-holiday days, the days following the holidays and postponing of working days on other dates.

The following architecture of neural network to model the load was used:
- one node for each input variable;
- one hidden layer;
- the number of hidden node is equal to the number of input variables;
- there is a connection between all input and hidden node;
- activation function – hyperbolic tangent;
- learning algorithm - Levenberg-Marquardt algorithm with inverse error propagation.

Table 4 shows the results of comparison of model estimates for short-term prognosis.

Table 4: Comparison of quality of mathematical models of hourly forecasting of power system load

Name of the model	ME	MAE	MAPE, %
GLM model ARIMAX	-1414.69	29874.34	2.43
Exponential smoothing with multiplicative seasonality	-2786.98	30813.06	2.55
Neural network	-2443.8	39752.53	3.19
GLM model taking into consideration holidays	1364.21	29246.59	2.39

As it can be seen from Table 4, the best results are obtained using the GLM model with taking into account holidays, where the MAPE error is the smallest.

The calculated values of the statistics were received from the prognosis results on the validation segment from October 1 to December 31, 2017.

Figure 5 shows the example of the obtained prognoses for one of the 92 days of the validation segment.

Figure 5: The results of hourly forecasting of power system load

Auto-regression models are one of the fairly common approaches to forecasting the month ahead in the classical analysis of time series, and this model of the twelfth order for the case of usage monthly data for prognostic modelling in energy is as follows (19):

$y(t)$ = 602546044 – 0,0219 · $y(t – 1)$ – 0,0257 · $y(t – 2)$ – 0,0548 · $y(t – 3)$ – 0,1528 · $y(t – 4)$ – 0,0029 · $y(t – 5)$ – 0,0886 · $y(t – 6)$ – 0,0184 · $y(t$

$$-7) - 0{,}1687 \cdot y(t-8) - 0{,}0642 \cdot y(t-9) + 0{,}0013 \cdot y(t-10) + 0{,}0827 \cdot y(t-11) + 0{,}7646 \cdot y(t-12) \quad (19)$$

where $y(t)$ - energy consumption per month.

Table 5 shows the obtained values of the estimates of the equation coefficients with the corresponding statistical characteristics.

Table 5: The value of smoothing parameters for the Winters model with multiplicative seasonality

Para-meter	Estima-tion	Standard model error	T - statistic	P - value
α	0,4294	0,1272	3,3767	0,0019
β	0,0983	0,0327	3,0077	0,0050
γ	0,1298	0,0262	4,9467	0,0000

Table 6 shows statistical characteristics of the auto-regression model AP (AR) (12).

Table 6: Statistical characteristics of autoregressive model AR(12)

Name of the characteristics	Model name	
	AR(12)	Winters' model with multiplicative seasonality
R^2	0,95	0,83
RMSE, MW	24866068	24873314
MAPE, %	2,64	2,6

The results of prognostic modelling are presented in Fig. 6, real and prognostic values are compared.

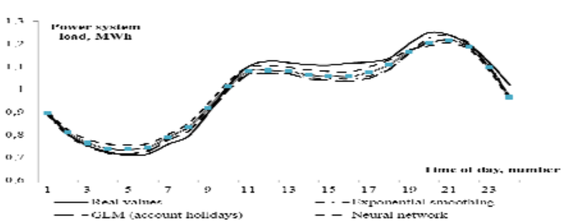


Figure 6: The real and predicted monthly autoregressive power system load model

As it can be seen from Fig. 6, the maximum load is observed in December and January, and a significant decrease is from May to September by an average of 30%.

The model for prognosis of quarterly energy load is as follows (20):

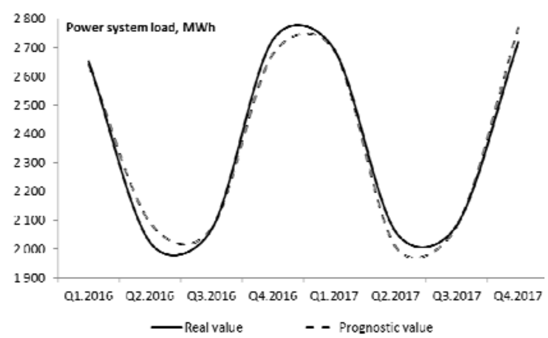
$$y(t) = 1861428237 + 0{,}03931 \cdot y(t-1) - 0{,}4818 \cdot y(t-2) + 0{,}0833 \cdot y(t-3) + 0{,}5842 \cdot y(t-4) \quad (20)$$

where $y(t)$ - energy load for the quarter.

Table 7: Statistical characteristics of autoregressive model AR(4)

Name of the characteristics	Value
R^2	0,98
RMSE, MW	39 503 917
MAPE, %	6,9

Figure 7 presents quarterly real and prognostic indicators of the electric power system load



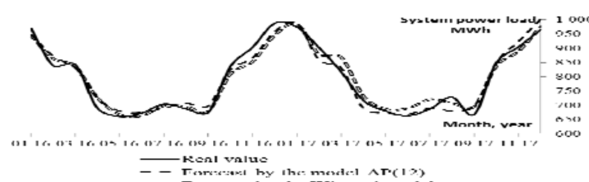


Figure 7: Comparison of the results of predictive modeling of the quarterly power system load and real indicators

As it can be seen from Fig. 7, the maximum load on the electric power system is in the first and fourth quarters of the year, while its decrease is observed in the second and third quarters by an average of 25%.

A model using the aggregate index and macroeconomic indicators for 2011–2017 [59] was developed for the long-term prognosis of

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the electric power system load by different scenarios (21):

$$Y(t) = 79{,}88 + 1{,}096 \cdot Y(t-1) - 3{,}864 \cdot I, \quad (21)$$

where Y – electric power system load, I – index.

The parameter estimates of the developed model are presented in Table 8.

Table 8 – Statistical characteristics of long-term forecasting model parameter estimates

Para-meter	Estima tion	Standard model error	T-statistic	p-value
Free member	79,88	13.24239	6,03	0.0018
Y(t-1)	1.096	0.02405	45,59	<.0001
Index	-3.868	0.64050	-6,04	0.0018

As it can be seen from Table 8, the p-value for the developed model is much less than the critical alpha by 0.05, which indicates the adequacy of the selected estimates of the model parameters. In such a case, the general statistical characteristics of the model: $R^2 = 0.98$, MAPE=0.2%.

The results of long-term prognosis of the electric power system load performed according to different scenarios are presented in Table 9.

Table 9: The results of long-term forecasting of the electric power system load for 2018-2020 performed according to different scenarios

Year	Power load, MWh	Type of the scenarios		
		Base	Pessimistic	Optimistic
2011	8,457			
2012	8,646			
2013	8,835			
2014	9,024			
2015	9,179			
2016	9,469			
2017	9,557			
2018	9,795	9,85	9,76	9,93
2019		10,08	10,00	10,17
2020		10,33	10,24	10,42

Prognostic models for peak loads of the electricity power system (Table 10) of high quality while using the proposed methodology were developed.

Table 10: Analysis of the results of the forecasting the peak power system load

Model name	The value of the MAPE for models, %:		
	short-term (forecasting for 2 weeks ahead)	middle-term (forecasting for 3 weeks ahead)	long-term
GLM-B	3,87	5,10	3,20
GLM-BR	3,99	4,85	2,77
GLM-BRW	3,99	4,85	2,77
GLM-BRWH	4,10	4,87	2,63
GLM UCM	2,60	2,32	3,24
Neural network	3,30	6,60	11,21
Exponential smoothing	2,53	2,45	4,20
GLM ARIMAX	2,31	2,41	3,38
Combined model	2,40	2,01	3,86

As it can be seen from Table 10, there is no model that is universal for all prognosis cases. Thus, the GLM model of ARIMAX model was found to be the best model for prognosis of 2 weeks ahead, the combined model was good for forecasting of 3 months ahead, the GLM-BRWH MAPE model occurred the best one for long-term prognosis.

That is, the use of the proposed information technology is substantiated and justified. The general scheme of implementation of this information technology in SAS is presented in fig. 8.

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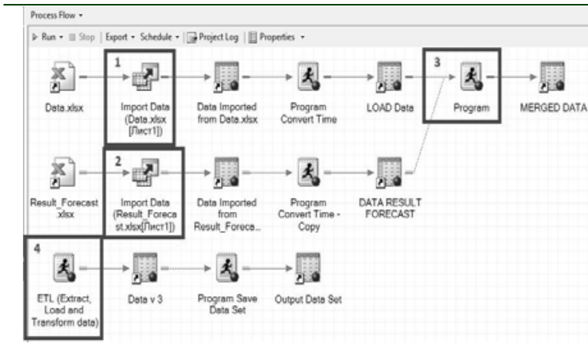

Figure 8: Scheme of implementation of information technology of forecasting of power system load, implemented in SAS Energy Forecasting 4.1

Usage of SAS Energy Forecasting, specialized software, allows you to implement a great number of different models in a unified software environment, to choose the best one for prognosis, to perform preliminary data preparation. Another advantage of this technology is the ability to integrate it with third-party solutions such as SAP HANA, Hadoop and various platforms for storing large amounts of data. In the future, it will be implemented in the proposed information technology.

7. DISCUSSION

The necessity of transition to new conditions of functioning, the presence of uncertainties of different kinds, obligatoriness to take into consideration the national features and to build forecasts of nonlinear non-stationary processes of the energy market for different forecasting horizons in the absence of the well-developed methodology of the forecasting energy markets under the conditions of dynamic changes, make this study especially relevant.

The real support system for making decisions for the energy market is represented in this research. It could be used both for forecasting energy consumption and the load of the energy system, and for pricing in the energy market.

Unlike many studies that consider the benefits of predictive modeling of the energy market using models of a certain type [18-40], this paper proposes the use of an adaptive approach, which involves the construction of a large number of models-candidate of different types, as well as ensembles of the models, which significantly improves the quality of forecasting for different types horizons.

This study continues and significantly expands the one presented in [57]. First, this study implemented information technology that automatically selects the best candidate models by utilizing a specialized solution for the SAS Energy Forecasting energy industry. Secondly, the methodology of adaptive forecasting modeling of the energy market for all forecasting horizons foreseen by the energy industry standards is elaborated.

Information technology that implements mathematical approaches and methods for long-, medium- and short-term load prognosis was proposed in the research. Real statistical data from one of Ukraine's energy companies to perform computational experiments and estimation of equation coefficients were used. The generalization of the results of the computational experiment is presented in Table 11.

Table 11: Value of the MAPE for different classes of models, %

Name of the model	Very short term model, twenty four hours ahead	Short-term model, two weeks ahead	Middle-term model three months ahead	Long-term model
GLM-B	3,62	2,97	1,46	1,61
GLM-BR	3,32	2,74	2,15	1,67
GLM-BRW	3,32	2,74	2,15	1,67
GLM-BRWH	3,27	2,79	2,09	1,83
GLM UCM	2,68	2,05	1,70	3,13
Neural network	3,19	2,59	2,08	3,88
Exponential smoothing	2,55	2,01	1,86	3,15
GLM ARIMAX	2,39	1,97	1,57	3,09
Combined model	2,44	2,03	1,75	1,82

The criterion for comparing the quality of the developed models is the indicator of mean error in percentage.

Statistical data from the website of the State Statistics Service of Ukraine – GDP, total amount of population and number of people

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working in production to build a long-term mathematical model by annual intervals were used. Index that reflects the state of general economic development and the amount of population based on these indicators was calculated.

The received model has the characteristics of R^2 is equal 0,98, MAPE is equal 0,2%.

The auto-regression model of the twelfth order and Winters' model with multiplicity seasonality under middle-term prognosis by a monthly data segments was developed, for which the MAPE statistics were 2.64% and 2.6%, respectively. Less accurate results were obtained under short-term prognosis by quarter data; the auto-regression error of the fourth order reached the MAPE statistic value to 6.9%.

Note that it is necessary to take into account the economic crises that lead to the reduction of enterprises under long-term prognoses for the quarter or years. You should also be aware when using temperature for load prognosis, that the exact weather forecast for today can be a day ahead, and much worse two weeks ahead. Weather forecasts over this period should not be used, or you should take probabilistic models.

In the case of short-term prognosis by hourly time segments, models training was based on data from January 1, 2015 to September 31, 2017, and testing was from October 1 to December 31. The graphical and statistical analysis of the data for the presence of typical patterns and differences in behavior under different conditions was thoroughly performed before the beginning of the modelling. It was found that the minimum consumption occurred at 4-5 o'clock in the morning, and the maximum - from 11 a.m. to 20 o'clock (8 p.m.). The main reason for the decline in load at the weekends when compared to working days is the closure of business centers, offices, enterprises.

Information concerning weekends and public holidays as regressors while developing the models based on the recommendations of experts and international experience was used. In addition, it was showed that it is also necessary to consider before- and after-holidays on the example of Easter and the New Year. However, as it turned out, important sports events do not significantly affect the load level.

Analysis of the data in daily and monthly sections of temperature and load found dependence in the form of reversed phase depending on the time of a year, as a consequence, the temperature should be taken into account in the model in the form of a third-order polynomial together with specialized combined variables based on the temperature and month, temperature and hour of a day, temperature and day of a week.

Four models for short-term prognosis in the form of neural network, exponential model with multiplicate seasonality, GLM models of ARIMAX and GLM models taking account holidays were developed, the statistical characteristics of MAPE are 3.19%, 2.55%, 2.43% and 2.39%, respectively.

More detailed analysis of the results showed that a total of 93% of the previous load value is taken into account in the following, with a trend in the time data, and adding of regressors describing holidays into the model increases the accuracy of prognosis by MAPE criterion by 0.04%.

In contrast to previous work, which focused only on constructing models for long-term forecasting of power system load, in this study is covered different forecasting horizons, justified the use of different methods of forecasting modeling of energy market indicators. The peculiarities of the national energy market are also investigated, and it is found that the more significant factors influencing changes in the load of the grid are changes in climatic parameters. Greater attention is paid to short- and short-term forecasting of grid load, since in the conditions of switching to daily energy planning there is a need to formulate applications for electricity consumption and tariffs based on schemes based on different differentiated rates [60–64].

The main advantages of the proposed information technology are its versatility, flexibility, adaptability. The use of multimodel approach, preliminary data preparation allows obtaining of much better prognosis results, and the use of SAS Energy Forecasting, the software, allows taking into account the sectoral characteristics of the company or industry of the national economy under study.

8. CONCLUSIONS

The changes that are taking place on the energy market today need to pay attention to both rational use of energy resources and anticipation of changes in their use by different groups of consumers, opportunities for wider use of renewable energy sources. It is also important that the processes occurring in the energy market are closely related with socio-economic development and technological progress.

The nature of the development of these nonlinear and non-stationary processes is difficult to predict. This is due to the large number of various uncertainties that require the use of a wide range of modern information technologies.

These information technologies should allow for the pre-processing of structured and unstructured real-time data from different sources, and their accumulation for later use. It is also important to choose optimal forecasting tools to support decision-making in the management of generation and distribution of energy resources, and to generate economically reasonable prices for them for different consumer groups.

Such tools include the adaptive approach in predictive modeling, the use of mathematical models of different classes and their combinations, data mining tools for input processing, and more. In addition, it should be noted that there is a need for an effective quality control system at all stages of forecasting that uses traditional and combined indicators and quality criteria for input, models and forecasts.

Such measures, as shown by the study, allow achieving high quality results even in conditions of missing observations and relatively short data sets. The optimal criterion for assessing the quality of predictive modeling of power system load, as shown by the study is the mean absolute percentage error (MAPE) [41–43] that is easy for analyzing and comparing alternative results. Practically in all cases of modeling it showed high quality or acceptable results.

To achieve a set purpose of this research there were solve such following problems:

1. As the study of the peculiarities of the domestic and foreign energy market show, the similar trends in the development of energy generation and energy consumption take place in the domestic and global energy markets both. The processes characteristic of the modern energy market are characterized by non-linearity and non-stationarity, the presence of uncertainties of different types. Therefore, forecasting the development of these processes in order to make optimal management decisions requires the development of new and improvement of existing methods of predictive modeling, automation of the construction of models-candidates and preliminary processing of input data.

2. The analysis of information sources showed that most energy market researchers propose to use certain types of models to forecast individual components of the energy market. Our study presents a technique of universal adaptive forecasting, which can be used both for the prediction of individual components and the development of the energy market as a whole, since it provides for the use of scenario modeling and automatic selection of models depending on the forecasting horizon.

3. The method of adaptive forecasting of the energy market on the example of forecasting the load of the grid for the short, medium, and long term is proposed in the paper. According to the study, different factors are the most significant in different forecasting horizons. In particular, the quality of the long-term forecast is influenced by macroeconomic factors and the medium and short-term prospects by meteorological conditions and seasonal phenomena. Therefore, for long-term forecasting it is better to use scenario modeling in combination with regression models, and for short- and medium-term forecasting, model compositions, in particular using generalized linear models.

4. The best tool for predicting the development of the energy market is the SAS Energy Forecasting package, as it contains a wide range of models that have been tested in the energy market of different countries and provides the ability to automatically select the best candidate models and model ensembles and data mining tools for input preparation data - time series of indicators of the state and dynamics of the energy market.

5. Based on the models proposed for forecasting peak loads in the grid, it is possible to develop a tariff system based on differentiated rates, which will bring you closer to uniform and balanced energy consumption during the day. In general, using the proposed methodology will allow improving the quality of pricing management in the energy market.

The scientific novelty of this study is the development of techniques for the use of specialized software, in particular, SAS Energy Forecasting in decision support systems for the automatic selection of models and their ensembles, depending on the horizon of forecasting and data gaps. It has been found that, depending on the forecast horizon, the

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better results could obtained by the usage of the models of different types. In particular, the construction of mathematical models for long-term forecasting of the load of the grid is better performed according to a specific scenario, using the compositions of the models, the input variables of which, in addition to the indicators of the development of the energy market are macroeconomic indicators. It is best to use model ensembles and generalized linear models to predict peak loads. It is noted that the prerequisite for building the quality models for any forecasting horizon is preliminary data processing using data mining, including filling in the gaps.

In the future developments it will be possible and useful to further incorporate the features of intelligence systems, decision support systems approach to data and with the elements of expert systems.

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