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DEVELOPMENT OF MATHEMATICAL MODELS TO SUPPORT DECISION-MAKING REGARDING THE FUNCTIONING OF CRITICAL INFRASTRUCTURE IN THE INDUSTRY OF ENERGY SUPPLY

The object of research is the energy supply company and the processes of generation and supply of electric energy. The paper examines the problems of building mathematical models for forecasting the operation of a critical infrastructure object in the conditions of a changing security environment, characterized by unpredictability, the presence of uncertainties of various types, the appearance of new threats, their combinations, changes in the form, duration, nature of their influence. In the work, the main attention is paid to the study of the functioning of critical infrastructure in the field of energy supply. Based on the study of the functioning of the energy company system, methods of dealing with uncertainties at the stage of data preparation for analysis and during the preliminary construction of models are presented, in particular, statistical and probabilistic approaches, modeling of the studied processes, alternative methods of estimating model parameters, etc. The complexity of preparing the input data set is related to the fact that it is necessary to ensure the representativeness and variability of the data sets, given that a significant number of factors must be included in the model according to the requirements of regulatory documents, which can lead to multicollinearity of the input variables. The paper proposes an analytical toolkit based on the use of mathematical models and their combinations, intended for use in specialized decision support systems. In the course of the research, a number of numerical experiments were conducted, in which the proposed methodology was worked out on the materials of the enterprise – the object of the critical infrastructure of the energy sector. SAS Energy Forecasting software was used to build the models. The best forecasting results are obtained using generalized linear models (GLM), in particular the GLM model in the form of ARIMAX (a moving average autoregressive model that includes an integrated trend component and external regressors). The proposals presented in the work will allow to increase the efficiency of the functioning of the energy sector, including the determination of the goals, tasks and benchmarks of its operation in regular mode for certain periods of time, as well as in the field of development of universal and special mechanisms for ensuring stability in the mode of response to threats and critical situations.

Keywords: *critical infrastructure, mathematical models, decision-support system, threats, critical situation.*

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1. Introduction

The state of threat, critical situation in the conditions of the military conflict has not become a temporary short-term phenomenon, but the conditions for the functioning of critical infrastructure facilities. Threats and crises are long-lasting, and overcoming them requires time and significant resources. Therefore, the tasks of guaranteeing the ability of the critical infrastructure to function effectively both in regular mode and in crisis and critical situations, its rapid recovery after the impact of threats of any type, prediction and prevention of possible crisis situations, have acquired a new meaning [1]. Therefore, new approaches to support decision-making in the management of critical infrastructure are needed, which can be used as part of a single multi-level system of national stability in the development of universal protocols for responding to threats and crisis situations, adapted to the conditions of the relevant industries. Their implementation requires appropriate analytical tools, methods of analysis, forecasting and planning measures to protect critical infrastructure and ensure the ability to overcome the consequences of critical situations and threats, decision-making in conditions of uncertainty and time constraints [1].

Mathematical models are widely used in the global practice of information and analytical activities both by individual subjects of critical infrastructure and in the relevant state information and analytical systems. Ukraine is no exception [2, 3]. In particular, the information and analytical system «SOTA» [4], which works with BigData, provides storage, combination and analysis of data from more than 20 directions, from various sources in order to increase reliability, effective monitoring of the state of national security, has been implemented into the system of the Main Situation Center of the country. in order to effectively coordinate the activities of state bodies. IAS «SOTA» [4] is a complex multi-layered information and analytical system of the highest level of information protection, has a flexible, open architecture that allows creating new functional modules in accordance with the tasks that arise during the implementation of state policy in the field of national security. However, the analytical component of the system needs to be refined from the point of view of expanding the range of used models, in particular, mathematical, methods of processing input data and the block for building forecasts.

A significant part of the subjects of critical infrastructure – business structures use their own developments or ready-made information and analytical systems of well-known global developers of analytical software. Ready-made solutions are expensive, but have powerful modeling and predictive components, built using the most modern information technologies. However, they are used exclusively as part of the information systems of the specified business structures. Own developments are carried out by specialists of enterprises and institutions using MS Excel tools, programming languages C++, Python, etc. They often have a very limited set of mathematical models. In addition, they take into account only the specific conditions of specific enterprises, which leads to the impossibility of using them to assess threats, identify and predict potential vulnerabilities of other enterprises, even those belonging to the same industry.

The issue of identifying potential threats, vulnerabilities, forecasting disasters and their consequences, forming protocols for responding to them is relevant, but also difficult. These issues are difficult not only for Ukraine, international organizations also take an active part in solving them. In particular, studies of these problems are conducted within the framework of the United Nations Office for Disaster Risk Reduction (UNDRR) [5] and the Center for Research on the Epidemiology of Disasters (CRED) [6]. A single the International Disasters Database (EM-DAT) is being formed [7]. In the European system of prevention, preparedness and response to terrorist attacks directed against elements of the critical infrastructure of the EU, the European Program for the Protection of Critical Infrastructure and the European Information Network for the Prevention of Threats to Critical Infrastructure are used [8, 9]. An example of the use of modern information and analytical systems for critical infrastructure research is the Critical Infrastructure Interdependency Modeling System (CIMS) [10], which was developed by the Idaho National Laboratory. Recently, considerable attention has also been paid to the tasks of disaster prevention management, in particular, the use of artificial intelligence in solving them, a number of publications are devoted [11, 12]. However, at the moment, Ukraine does not yet have a significant amount of its own developments, and those abroad need adaptation.

Therefore, *the aim of research* is to create a predictive toolkit, the basis of which is new models and methods of mathematical modeling, modern information technologies, intended for use in the decision support system in the management of critical infrastructure. This will make it possible to increase the efficiency and effectiveness of responding to relevant threats, obtain high-quality forecasts and propose options for solutions in situations of critical threats (or the potential occurrence of threats), perform an analysis of the consequences of the proposed options for solutions.

2. Materials and Methods

Solving the problem of implementing a comprehensive science-based approach to reforming the system of national stability and its leading link – critical infrastructure is both an urgent practical issue and a matter of fundamental research. The main attention should be paid to the study of the state and dynamics of this complex stratified system under the influence of various groups of external and internal factors in conditions of uncertainty and risk caused by their influence. Therefore, the task of developing modern tools and methodical approaches to solving the entire complex of problems: from analyzing the situation and preparing data, modeling the occurrence of threats, forecasting the occurrence, predicting their consequences, risks, recovery prospects, etc. is important. Among the areas of activity that are of critical importance for the sustainable functioning of the state and society, the energy sector should be singled out – the uninterrupted functioning of which is decisive for the national economy and population. This led to the choice of the research object, which is the energy supply company and the processes of generation and supply of electric energy.

The study of the operation of selected critical infrastructure objects was carried out comprehensively, in the section of separate vertical and horizontal levels of management, taking into account information and management connections between them. Considerable attention is paid to the formation of a criterion base for analysis and methodical approaches to modeling and forecasting the risks of crisis situations, etc. The proposed method is presented in Table 1.

Since the studied system functions under conditions of uncertainties of various types, in particular, statistical, situational, structural, probabilistic, etc., the proposed method involves the processing of uncertainties of various types under their simultaneous influence.

The forecast is built for the selected forecasting horizon, if several modes of operation of the object are considered, then the forecast is built for each scenario of the corresponding mode of operation of the system (Fig. 1).

Since SAS Energy Forecast [13] uses a step-by-step model building technique, one-stage models are built first, as a rule, these are generalized linear models, each of which is distinguished by additional regressors included in the model. Each of the models has a training and testing period, *MAPE* statistics are used to evaluate the quality of the model [14, 15]. After the best model is determined, the residuals of the model are analyzed. Two-stage models are built taking into account the results of the analysis of the residuals of one-stage models.

Table 1

The method of applying mathematical models and their combinations for forecasting the functioning of the critical infrastructure facility of the energy sector

Stage	Stage characteristics			
Loading input data	Loading time series of historical data			
Data diagnostics	Identification of anomalies and their processing (exclusion, smoothing)			
Pass processing	Filling in the blanks			
Formation of a set of additional factors	Factors essential for the analysis of the investigated processes are added (data provided at the request of the user, reference data, data on exogenous process parameters, expert assessments, data supplementing information about the analyzed process)			
Type of forecasting	Very short term	Short term	Medium term	Long term
Peculiarities of building a forecast	For each hour, cycles in the middle of the day are taken into account	A day (week) ahead, taking into account cycles and patterns in the middle of the week	Trend component, trend and combined factor with other regressors, derived indicators	Additional factors are taken into account, the user (for the long term)
Inclusion of additional factors	Additional regressors describing the process	Additional regressors describing the process	Additional user factors are taken into account	Depending on the subject area
Forecast horizon	From 1 to 24 hours	From a day to a month	From 1 month to 3 years	More than 3 years
Mode of operation of the facility	Regular	Functioning in a crisis situation	Restoration	
Scenario	Optimistic, realistic, pessimistic			
Construction of candidate models	At each forecasting horizon, a model is built for each operating mode based on historical data and additional data provided by the user			
Stage 1	One-stage models (exponential, multivariate regression, comb regression models, autoregressive, generalized linear models, etc.)			
Stage 2	Two-stage models (regression and autoregressive models. models with the inclusion of a trend component and taking into account residuals (the difference between the actual and predicted value), which are included in the model in the form of a moving average, provided that there is a correlation (autocorrelation) between the residuals and the target variable. Models class of exponential smoothing – Holt, Theil-Wage, Brown, Winters (with additive or multiplicative seasonal component), taking into account the damping trend and other modifications Generalized linear models, neural networks, probabilistic models and fuzzy methods			
Selection of the best candidate model	Selection based on the results of stage 1 and stage 2, based on: mean absolute percentage error (*MAPE*), maximum *MAPE*, coefficient of determination (R^2), root mean square error (*RMSE*)			
Construction of the forecast	The best candidate models are used, input data: time series of the investigated processes and additional factors that are significant at this forecasting horizon			

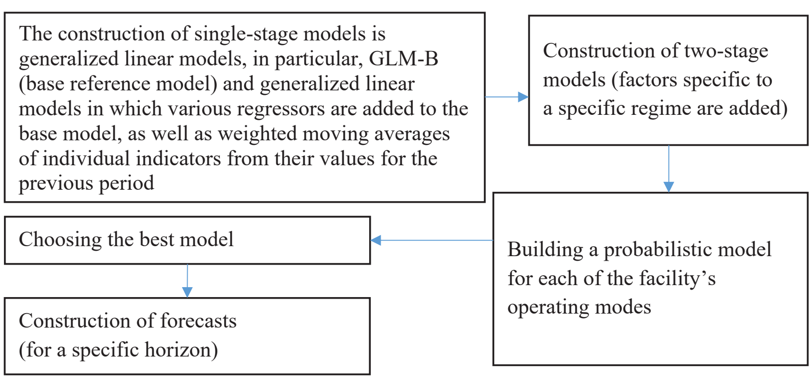

Fig. 1. Scheme of probabilistic forecasting

SAS Energy Forecasting software includes the following models:
- GLM UCM (generalized linear model of unobserved components);
- neural network;
- exponential smoothing models (from the models of this class, the best one is chosen) are models of exponential smoothing, double exponential smoothing, exponential smoothing with seasonality, exponential smoothing with a linear trend (Holt model);
- Winters model with additive or multiplicative seasonality;
- model taking into account the drifting trend;
- GLM model in the form of ARIMAX;
- combined model (some combination of forecasts of several models) [13, 14, 16, 17].

Special attention in the work is paid to the study of the input data set, as it is necessary to ensure both the representativeness and variability of the data sets, taking into account that a significant number of factors must be taken into account based on the requirements of regulatory documents, which may be the cause of multicollinearity of the input variables. To solve this problem, it is proposed to use the method of structural-parametric adaptation based on regression models and neural networks (Fig. 2).

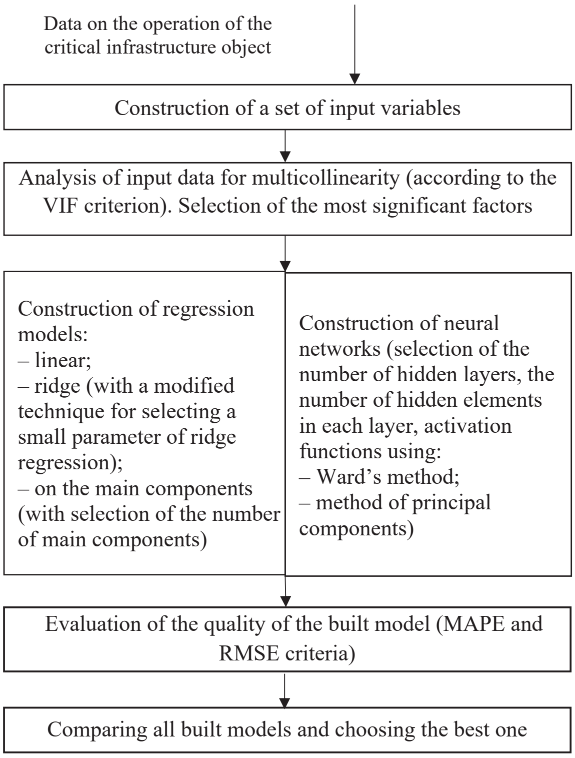

Fig. 2. Scheme of application of the method of structural-parametric adaptation based on regression models and neural networks

If there are doubts about the completeness and reliability of the input data, it is suggested to use the method of studying the similarity of time series proposed in [18].

The use of probabilistic statistical methods to create and apply structurally unified models in the space of states is a feature of the methodology. To do this, the task of evaluating the structural elements and parameters of the model is first solved. The structure of the model is evaluated based on the study of the regularities of the process, the use of statistical tests to check the presence of nonlinearity, integration, heteroskedasticity, analysis of correlation functions and visual analysis of data. At the same time, several of the most likely structures of candidate models are selected. Then the parameter estimates of the candidate models are calculated, the best one is selected using the appropriate statistical characteristics of model adequacy. Assessment of the quality of forecasts is carried out automatically either by separate quality criteria or using an integral quality criterion that includes 2–5 separate statistical quality criteria. The effectiveness of the application of this method was verified during solving practical problems of forecasting the functioning of the energy infrastructure segment.

3. Results and Discussion

The study of the functioning of the energy infrastructure segment was performed on the materials of one of the Ukrainian energy companies using the SAS Energy Forecasting software. To select and diagnose models, data from January 1, 2015 to September 30, 2017 were used, as a forecasting horizon – data from October 1, 2017 to December 31, 2017, as well as from January 1, 2015 to September 30, 2021, as a forecasting horizon – from October 1, 2021 to December 31, 2021. The simulation results are summarized in the Tables 2, 3.

The input data sets were preliminarily examined for the detection of omissions, abnormal values, data analysis, daily energy load values change significantly throughout the year, there are seasonal increases and periods of low electricity consumption, and periods when there is a similarity in the processes taking place in the energy market were also identified. The forecast is made taking into account the fact that the energy market operates according to the rules of the day-ahead market and the intraday market. Diagnostics of the input data was performed at the stage of preliminary analysis and after the initial construction of the models.

Table 2

Comparison of built power system load models according to the average absolute error in percentage (*MAPE*) criterion, %

Model name	Prediction results			
	Very short term (24 hours ahead)	Short term (2 weeks ahead)	Medium term (for 3 months ahead)	Long term
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
ARIMAX GLM model	2.39	1.97	1.57	3.09
Combined model	2.44	2.03	1.75	1.82

Table 3

Statistical characteristics of models for forecasting peak power system load values – mean absolute error in percentage (*MAPE*), %

Model name	Prediction results		
	Short term (2 weeks ahead)	Medium term (for 3 months 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
ARIMAX GLM model	2.31	2.41	3.38
Combined model	2.40	2.01	3.86

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The situation of gaps in the studied time series and the possibility (feasibility) of their filling was considered at the stage of data preparation, the presence of anomalous values at the stage – during data preparation and after the initial construction of models. The peculiarity of the stage of primary construction of models is that a set of various models is built on the forecasting horizon chosen by the user, among which the best models are determined (according to statistical characteristics), as well as anomalous values and reasons for their appearance are analyzed.

The neural network built for modeling the power system load and peak load values (Table 2, Table 3) has the architecture [19, 20]:

– one vertex for each input variable;
– one hidden layer;
– the number of hidden vertices is equal to the number of input variables;
– there is a connection between all input vertices and hidden ones;
– hyperbolic tangent activation function;
– learning algorithm – Levenberg-Marquardt with inverse error propagation.

The obtained results for medium and long-term forecasting indicate that the GLM-B class models give better results, while for very short-term and short-term forecasting, the suitable GLM model ARIMAX is better.

Let's note that in long-term forecasts for a quarter or years, it is necessary to take into account economic crises that lead to the reduction of enterprises and companies, and as a result, the consumed electricity. When using temperature for load forecasting, it is also necessary to realize that a fairly accurate weather forecast for today can be calculated one day ahead, and significantly worse two weeks ahead. For more than this period, it is better not to use weather forecasts in models, or to switch to probabilistic models.

For the case of short-term forecasting at hourly time intervals, the models were trained on data from January 1, 2015 to September 31, 2017, and tested on the segment from October 1 to December 31. Before starting the simulation, a graphical and statistical analysis of the data was performed quite carefully for the presence of typical patterns and differences in behavior under different conditions. Thus, it was found out that the lowest consumption occurs at 4–5 o'clock at night, and the highest from 11 a.m. to 8 p.m. The main reason for the decline in workload on weekends compared to working days is the closure of business centers, offices, and enterprises.

Based on the recommendations of experts and international experience in building models, information on weekends and public holidays was used as regressors. In addition, on the example of the Easter and New Year holidays, it was shown that it is necessary to take into account the days before and after the holidays. At the same time, as it turned out, large sports events do not significantly affect the load level of the energy system.

The analysis of data in daily and monthly cross-sections for «temperature» and «load» indicators revealed a dependence in the form of an inverted phase depending on the time of year. Therefore, the «temperature» indicator must be taken into account in the model in the form of a third-order polynomial together with specialized combined variables built on the basis of the «temperature» indicator: «temperature and month», «temperature and hours of the day», «temperature and day of the week».

A more detailed analysis of the simulation results showed that, in general, 93 % of the previous load value is taken into account in the next one, while there is a trend in the time data, and mixing into the model regressors describing holidays increases the accuracy of forecasting according to the *MAPE* criterion by 0.04 %.

It should be noted that for a long-term forecast for a quarter or several years, it is necessary to take into account crisis situations that lead to a reduction in electricity consumption.

The results obtained during the conducted research, tested in one of the energy companies of Ukraine, can be implemented in the work of similar companies. The conditions of martial law did not affect the conduct of the research and the obtained results.

In general, the methodology proposed in the work is intended for use at an enterprise in the energy industry. However, it can be adapted for use as part of the analytical module of the decision support system of situational centers, information and analytical systems of national critical infrastructure entities. The use of the proposed methodology in the work of the State Service for the Protection of Critical Infrastructure requires expanding the range of models used and taking into account macroeconomic factors. The use of the presented methodology in the specified information and analytical systems will contribute to the automation of most processes during the selection of the optimal solution, will ensure its validity both in regular mode and in the mode of threats and critical situations, which is especially relevant for the period of martial law.

In the future, it is proposed to use the factors presented in the Green Book of Israel and the Green Book of Ukraine to determine the parameters of the criticality level assessment. The criticality of objects and functions of critical infrastructure is proposed to be determined by considering different levels of the management system, choosing the level of detail, depending on the criticality of the situation, simulating the behavior of the system, identifying and classifying development problems, external and internal factors that cause them. In addition, the proposed approach provides for the expansion of the toolkit to support quick decision-making in conditions of uncertainty and critical threats due to the use of optimization methods, automation of most processes during the selection of the optimal solution.

4. Conclusions

The following simulation results were obtained as a result of the conducted research. The power system load models turned out to be the best:

– GLM ARIMAX model, *MAPE* value 2.39 % (very short-term forecasting (24 hours ahead));
– GLM ARIMAX model, *MAPE* value 1.97 % (short-term forecast for 2 weeks ahead);
– GLM-B, *MAPE* value 1.46 % (medium-term forecast for 3 months ahead); and the error of forecasting the *MAPE* peak load was 2.41 %;
– GLM-B, *MAPE* value 1.61 % (long-term forecasting based on two-year retrospective data).

The probabilistic forecasting model for 29 days ahead, for the average value of the forecast based on the obtained three scenario models, also showed good results: the value of MAPE statistics on hourly values was 1.52 %, and on daily values – 1.23 %.

For forecasting the peak load on the power system, the following models turned out to be the best:

– for short-term forecasting for 2 weeks ahead, GLM ARIMAX model (*MAPE*=2.31 %);

– for medium-term forecasting for 3 months ahead – combined model (*MAPE*=2.01 %);

– long-term forecasting based on retrospective two-year data – GLM-BRWH model (*MAPE*=2.63 %).

The proposed approach involves expanding the toolkit for supporting quick decision-making in conditions of uncertainty and critical threats through the use of mathematical modeling, intelligent data analysis, and artificial intelligence. This will allow to optimize and speed up the decision-making process in the management of a critical infrastructure object, in particular in a critical (or crisis) situation, including in the event of cascading effects caused, in particular, by military actions.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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Data availability

The data will be made available on reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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