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INTELLIGENT AUTOMATION OF THE FORECASTING PROCEDURE FOR THE OPERATIONS OF ELECTRIC POWER ENTERPRISES

Kotov I.A., Shvets D.V.

ІНТЕЛЕКТУАЛЬНА АВТОМАТИЗАЦІЯ ПРОЦЕДУРИ ПРОГНОЗУВАННЯ ДІЯЛЬНОСТІ ЕЛЕКТРОЕНЕРГЕТИЧНИХ ПІДПРИЄМСТВ

Котов І.А., Швець Д.В.

The article investigates a highly relevant scientific and practical problem related to the development of intelligent automation systems for forecasting the operations of electric power enterprises under conditions of high information uncertainty and incomplete input data. Decision-makers face increasing responsibility within a competitive business environment. This necessitates the urgent implementation of novel mathematical computational models and intelligent information technologies. The research focuses on automating the forecasting process for electric power enterprises. The primary goal is to develop a software application based on formal, structural-functional, and logical models.

In this work, a comparative review of existing forecasting methods has been conducted, highlighting time-series methods, exponential smoothing, simple and moving averages. Special attention is paid to the development of the fuzzy forecasting system architecture, which accounts for both the probabilistic nature of the parameters and the specific characteristics of the electric power industry. The development cycle of the fuzzy model is described in detail, including the stages of fuzzification of input variables, the formation of a comprehensive knowledge base, the configuration of the inference engine based on fuzzy rules, and the final defuzzification process to obtain real-world values for long-term strategies. To limit the confidence interval of the parameters, various membership functions (Gaussian, triangular, and exponential) are applied. Additionally, the model incorporates reliability indicators for the components of the electric power complex. It is proposed to use the constructed knowledge base in conjunction with statistical forecasting results to refine the trend of the investigated parameter.

During the modeling process, three key regions of failure rate were identified. This distribution improved the accuracy of evaluating the equipment's technical condition and the probability of an application failure event. The study's result is a software complex that has been created and fully tested, utilizing artificial intelligence modules and a neural network-based forecasting architecture. The conducted forecasting experiments on retrospective data have confirmed the high efficiency, stability, and adequacy of the developed system and its evaluation results. Ultimately, this approach significantly minimizes potential financial risks and optimizes resource allocation.

Keywords: *forecasting, automation, knowledge base, model, membership function, reliability, intellectualization*

Introduction. In recent years, the interest in and significance of forecasting have sharply increased [1]. This interest is exhibited by both the academic community and forecasting practitioners. The rapid development and emergence of free software particularly facilitate the advancement of this field. Therefore, particularly in recent times, a significant shift toward the creation of innovative information systems to execute and support forecasts has been observed [2].

The role of forecasting is constantly growing. The reason for this lies in the continuous increase in the responsibility for potentially erroneous actions on the part of decision-makers. The primary and most crucial area for implementing new forecasting methods and tools is the production sector, including electric power enterprises and complexes. The operations of electric power enterprises are based on operational, medium-term, and long-term forecasts.

There are numerous categories of forecasting methods, including statistical, time series, critical, and target forecasting. The principal ones among these are statistical and time series methods [2].

Forecasting errors result in significant economic losses within power systems. Concurrently, an additional adverse factor impacting forecasting quality is the unreliability and incompleteness of input data. Under such conditions, acquiring a valid and reliable forecast of enterprise operations constitutes a complex and pressing issue.

Consequently, there is a need to implement novel mathematical computational models and intelligent information technologies. These enable the forecasting of electric power enterprise operations using historical data, aiming to provide management with timely information to deploy control strategies that improve performance under uncertainty [3].

In this study, the object of research is the automation process of forecasting the operations of electric power enterprises under conditions of information uncertainty. The research subject comprises structural, functional, mathematical, and logical models, along with the software modules of the intelligent automation system for forecasting the operations of industrial enterprises, particularly electric power enterprises, under conditions of uncertainty.

A comparative literature review in the field of forecasting was conducted, during which the principal features of forecasting that formed the basis for the design of a software solution were identified [1, 3, 4]. It was deemed necessary to incorporate fundamental methods and indicators, such as: graphical data representation, selection of proven forecasting methods (exponential smoothing forecasting methods: SES, Holt, Damped, Naive), representation of statistical indicators and forecasting errors, development of an algorithm to identify an optimally tuned forecasting method, and representation of forecasts alongside the primary qualitative characteristics of the time series. Furthermore, forecasting technological advancements in the technology sector, particularly in the electric power industry, is radically transforming the structure and operations of these enterprises, as well as how they justify their decisions and formulate strategies to enhance competitiveness in a continuously changing environment.

The proposed research direction possesses novelty, which lies in the fact that the developed intelligent automation software complex differs from existing counterparts in that, based on novel structural, functional, mathematical, and logical models, it ensures an intelligent forecasting process accounting for the uncertainty of input parameters within the industrial environment of electric power enterprises. Introduction. In recent years, the interest in and significance of forecasting have sharply increased [1]. This interest is exhibited by both the academic community and forecasting practitioners. The rapid development and emergence of free software particularly facilitate the advancement of this field. Therefore, particularly in recent times, a significant shift toward the creation of innovative information systems to execute and support forecasts has been observed [2].

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The aim of the research is to develop a software application for the intelligent automation of the forecasting process for the operations of electric power enterprises under conditions of uncertainty, based on formal, structural-functional, and logical models of the automated forecasting system.

Based on the conducted analysis, the following research tasks are formulated: to develop the main approaches to the implementation of intelligent systems for evaluating enterprise operations; to develop forecasting models under conditions of uncertainty based on time series; to develop operation algorithms for the knowledge base model of the automated system; to develop data management software modules for the automated system; to conduct research on the operation of the knowledge base of the forecasting software system; to conduct modeling of interactive human-machine interaction with the forecasting software system.

Presentation of the main research material. Forecasting has become highly popular in recent years across numerous scientific fields. The rapid development and emergence of free software particularly facilitates the advancement of this area. In this context, the aim of the work is to develop an automated, intelligent forecasting system for the operations of electric power enterprises, serving as a foundation for further research and a widely applicable tool.

The essence and general strategy of forecasting can be illustrated graphically. A graphical example of a mathematical approach to forecasting using regression approximation is shown in Fig. 1.

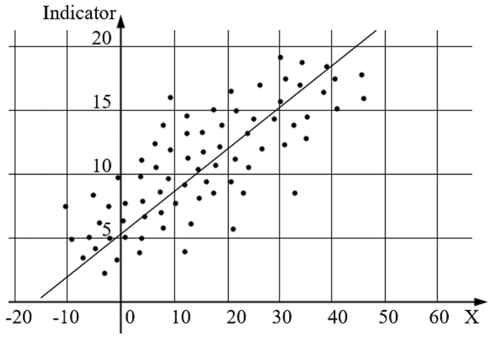


Fig. 1. Graphical example of linear regression approximation for forecasting

Let us briefly describe the necessary stages of the forecasting process that were utilized during the development of the software complex:

Step 1. Problem definition. This involves a profound understanding of the situation, how the forecasts will be used, who will use them, and how the corresponding method will be adapted to the data.

Step 2. Information gathering. The collection of historical data regarding the considered elements is highly important, as they constitute the foundation upon which the corresponding forecasting method will be developed and adapted, thereby yielding the forecast result.

Step 3. Exploratory analysis. The objective of this step is to identify the pattern in the data and, in general, extract vital information from the available historical data. A common method for achieving the aforementioned is data visualization via its graphical representation. This step also indicates which quantitative methods are appropriate to employ.

Step 4. Model selection and adaptation. This step entails selecting and adapting an appropriate quantitative model to the specific data. There are numerous factors to consider. Various simulations are frequently required.

Step 5. Use and evaluation of the forecasting model. After carefully selecting an appropriate forecasting model for each case and estimating its parameters, the model must generate forecasts that are subsequently evaluated.

Based on the previous considerations, let us briefly consider some implementations of the forecasting procedure. The so-called *naive method* provides a forecast for the next time period equal to the value recorded in the previous time period. The mathematical formula describing this forecasting method is as follows (1).

$$x_t(m) = x_{t-1.} \tag{1}$$

Historical data can be smoothed in various ways. Some of these include the simple average and the moving average.

The simple average method involves calculating the mean of all observations and using it for forecasting. Thus, the forecast is generated based on the following formula (2).

$$F_{t+1} = \frac{1}{t}\sum_{i=1}^{t} Y_i^2 \tag{2}$$

Moving average. One way to control the influence of past observations on the forecast when the moving average method is selected is to determine the length of the moving average to use when deriving the forecast. The term "moving average" is utilized to describe the process because, as a new observation emerges, a new average value of the most recent observations of the selected length is calculated. The relation used for the moving average method takes the form (3).

$$F_{t+1} = \frac{1}{k}\sum_{i=t-k+1}^{t} Y_i^2 \tag{3}$$

An extension of the simple average methods comprises the weighted average forecasting methods. That is, not all observations have equal weight in the derivation of forecasts. It is often the case that the most recent observations provide the best indicator for forecasting a future outcome.

The intellectualization of forecasting necessitates the detailed elaboration and definition of the forecast generation processes and the subsequent management of forecast results. In turn, the forecast results management process requires incorporating new observational data and formalizing the outcomes of managerial decision-making [3]. Based on these considerations, a diagram of the correlation and interrelation between the forecasting processes and the management of forecast results has been formulated and is depicted in Fig. 2.

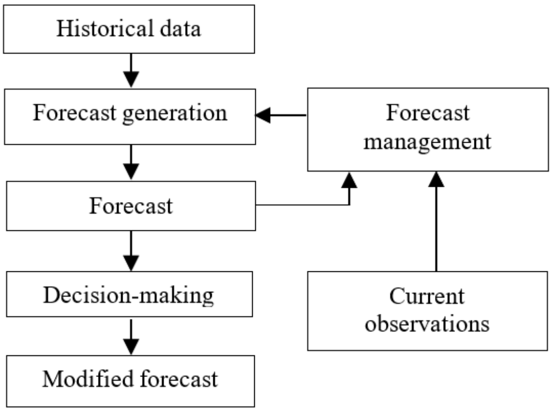


Fig. 2. Correlation between forecast generation and forecast results management

It is evident that, in the decision-making process, the developer or user requires an approximate estimate of the probability of parameter values or the reliability of the expert system [3, 4]. To overcome this problem and limit the parameter confidence intervals, various fuzzy membership functions (triangular, trapezoidal, exponential, and Gaussian) are used. An example of a Gaussian membership function is presented in Fig. 3.

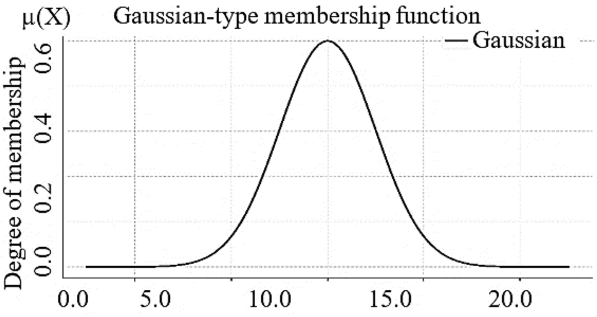


Fig. 3. Example of a Gaussian membership function

In evaluating the reliability of components of the electric power complex, one of the crucial functions in reliability analysis, as it demonstrates changes in the probability of failure over the system's service life, is the time to failure (TTF). In practice, the TTF indicator possesses a characteristic bathtub shape. The upper and lower bounds of fuzzy numbers for the probability of the forecasting result occurrence can be obtained by assuming triangular fuzzy and exponential fuzzy failure rates, respectively.

Consequently, let us assume that the fuzzy exponential TTF constitutes the minimum or lower bound for modeling. In contrast, the triangular fuzzy failure rate constitutes the maximum or upper bound of the modeling results. This curve comprises three regions: decreasing failure rate (DFR), random failure rate (RFR), and increasing failure rate (IFR). In the bathtub curve with a low operating time for the TTF system, based on three fuzzy distributions, the three failure rate regions (IFR, RFR, and DFR) are characterized by random component failures. The TTF system may exhibit a relatively extended period of random failures. Furthermore, the probability of an application failure event (EDS) is derived from the PAND gate as the system's final output.

At the subsequent stage of the work, the structure of the fuzzy forecasting system was established. This structure accounts for the specifics of both the probabilistic nature of the forecasting parameters and the electric power industry, which is considered the object of research.

The methodology for developing fuzzy systems is employed. It is of paramount importance to properly design the fuzzy system's architecture. The transformation of real-world values into the fuzzy domain using membership functions is called fuzzification of input variables in a fuzzy system. This process is the most critical.

Following fuzzification, it is necessary to possess a knowledge base (a set of information that will enable imparting "intelligence" to the system) to subsequently determine the inference engine or the fuzzy inference process, which is the most critical component of the entire fuzzy model, since this specific part will execute the whole process based on the available information. After evaluating the fuzzy rules that link the fuzzy variables, it is typically necessary to convert the obtained values back to their original, real-world values, as these are required to obtain real values derived from the fuzzy sets defined within the output variable. In other words, defuzzification is necessary. Fuzzy models utilized in process control or information technologies generally undergo the same application development cycle, as illustrated in Fig. 4.

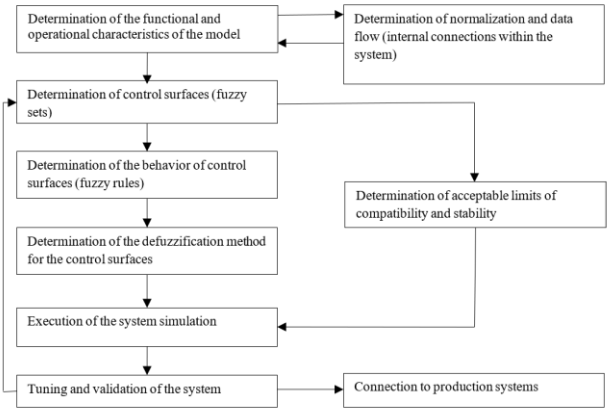
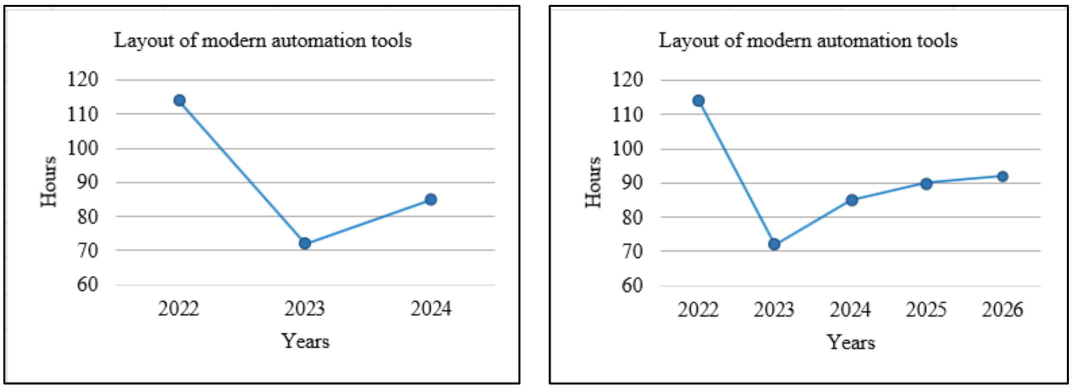


Fig. 4. Development cycle of the fuzzy forecasting system

Table

Input data array of the enterprise operations for forecasting

Functional parameters	Time duration, h			Parameter change, %	
	2022	2023	2024	2022/2023	2023/2024
1	2	3	4	5	6
Resource planning	23	21	15	109,52	140,00
Calculation of indicators	13	11	12	118,18	91,67
Control measures	21	15	9	140,00	166,67
Preparation of new documents	17	17	4	100,00	425,00
Accounting for depreciation costs	5	5	5	100,00	100,00
Calculation of resource allocation	29	23	13	126,09	176,92
Phased planning	15	13	7	115,38	185,71
Distribution of managerial workload	23	21	11	109,52	190,91
Drafting of legal documents	9	31	31	29,03	100,00
Preparation of long-term contracts	25	21	15	119,05	140,00
Control activities	8	5	9	160,00	55,56
Development of informational processing methods	5	5	5	100,00	100,00
Market promotion measures	23	25	25	92,00	100,00
Accounting of counterparty data	8	6	6	133,33	100,00
Tracking of counterparty loyalty	33	15	7	220,00	214,29
Implementation of modern software systems	13	17	19	76,47	89,47
Configuration of modern automation tools	114	72	85	158,33	84,71
Support and development of automated systems	13	17	17	76,47	100,00
Generalization and systematization of data arrays	114	97	54	117,53	179,63



a b

Fig. 5. Forecasting the process of configuring modern automation tools:
a – retrospective data as a basis for analysis and forecast, b – forecast based on the knowledge base

A large volume of data characterizing the operations of the electric power enterprise within a specific time period is processed in the automated system. These data serve as the input data array for processing and forecast generation [1, 2]. Table presents a partial input data array for forecasting the operations of an electric power complex.

Based on the examined concepts, approaches, and models, a forecasting software system for enterprise operations in the electric power complex under conditions of incomplete information about operational parameters has been developed. A series of forecasting experiments was conducted using the available data. The processing of the obtained forecasting data results, incorporating subsequent defuzzification operations, demonstrated the adequacy of the constructed models and the forecast evaluation results.

Examples of specific operational results of the intelligent forecasting system are presented below. Fig. 5 depicts the input data and forecasting results for the configuration process of modern automation tools.

The test results of the developed software complex demonstrated that the implementation of artificial intelligence system modules, based on knowledge of the operational specifics of electric power enterprises, as supplementary tools, enhances the efficiency of evaluation and the adequacy of the forecasting results [4, 5].

Conclusions. The necessity of forecasting in the modern and competitive business environment increasingly concerns enterprise executives. Particularly in recent times, a significant shift toward the development of novel, intelligent information systems for forecasting support has been observed. In this context, the need to consider a broader set of parameters for forecasting in both research and operational spheres becomes evident.

To achieve the aim of the work, the software system's knowledge base and the structure of the forecasting neural network were constructed [6]. The knowledge base was adopted as a foundation, and the forecasting system's operation was modeled using the available parameters. The acquired data permit the following conclusions to be drawn: an analysis of intelligent system methods for forecast implementation was conducted; the problem of constructing a forecast for enterprise operations under conditions of uncertainty was formulated; the structures of the intelligent system's knowledge base for forecasting purposes were established; forecasting models under conditions of uncertainty based on time series were developed; a forecasting software system for the operations of electric power enterprises was developed; data management software modules for the automated system were developed; the knowledge base of the forecasting software system was constructed; a study of the developed forecasting system was conducted, which demonstrated the efficiency and adequacy of the software complex.

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Котов І.А., Швець Д.В. Інтелектуальна автоматизація процедури прогнозування діяльності електроенергетичних підприємств

У статті досліджується актуальна науково-практична проблема розроблення систем інтелектуальної автоматизації процедури прогнозування діяльності електроенергетичних підприємств в умовах високого рівня інформаційної невизначеності та неповноти вихідних даних. Зростання відповідальності осіб, які приймають управлінські рішення в конкурентному бізнес-середовищі, зумовлює гостру необхідність впровадження нових математичних обчислювальних моделей та інтелектуальних інформаційних технологій. Об'єктом дослідження є процес автоматизації прогнозування функціонування електроенергетичних підприємств, а метою - розробка відповідного програмного застосунку на основі формальних, структурно-функціональних і логічних моделей.

У роботі здійснено порівняльний огляд існуючих методів прогнозування, серед яких виділено методи часових рядів, експоненціального згладжування, просте та ковзне середнє. Приділено увагу розробці архітектури нечіткої системи прогнозування, яка враховує імовірнісний характер параметрів та специфіку електроенергетичної галузі. Описано цикл розроблення нечіткої моделі, що включає етапи фазифікації вхідних змінних, формування бази знань, налаштування машини виводу на основі нечітких правил та остаточної дефазифікації для отримання реальних значень. Для обмеження довірчого інтервалу параметрів застосовано різні функції приналежності (Гаусові, трикутні, експоненціальні). Додатково в моделі враховано показники надійності компонентів електроенергетичного комплексу. Запропоновано використовувати побудовану базу знань спільно з результатами статистичного прогнозування для уточнення руху досліджуваного тренду параметрів.

У процесі моделювання було виділено три ключові області частоти відмов. Зазначений розподіл дозволив підвищити точність оцінки технічного стану обладнання та ймовірності виникнення події відмови в застосуванні. Результатом дослідження є створений та протестований програмний комплекс, який використовує модулі штучного інтелекту та структуру прогнозуючої нейронної мережі. Проведені прогнозні експерименти на ретроспективних даних підтвердили високу ефективність, стабільність та адекватність розробленої системи. Зазначений підхід суттєво мінімізує потенційні фінансові ризики та оптимізує розподіл ресурсів.

***Ключові слова**: прогнозування, автоматизація, база знань, модель, функція належності, надійність, інтелектуалізація*

Котов Ігор Анатолійович – доктор технічних наук, професор, кафедра моделювання і програмного забезпечення, Криворізький національний університет, вул. Віталія Матусевича. 11, м. Кривий Ріг, Україна, 50027,
ORCID: 0000-0003-2445-6259
e-mail: rioexito@knu.edu.ua,

Швець Дмитро Валерійович – кандидат технічних наук, доцент, кафедра моделювання і програмного забезпечення, Криворізький національний університет, вул. Віталія Матусевича. 11, м. Кривий Ріг, Україна, 50027,
ORCID: 0000-0001-5126-6405
e-mail: dmitriy.shvets@knu.edu.ua,

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