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Problems of forecasting output

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Abstract

This article shows the need to revive the scientific interest and practical use of science-based planning methods in solving the problems of effective development of the economy of the country as a whole, and its individual regions and industries. The analysis of works devoted to methods of forecasting and planning, research and application of science-based planning method—program-target method is presented, as a result of which the conclusion is made about the necessity of using the capabilities of artificial intelligence to solve the problems of strategic planning. The results of machine learning (ML) of the neural network SARIMAX are presented. A comparative analysis of the use of neural networks SARIMAX and LST for output forecasting is made. Conclusions are drawn about the possibilities of using neural networks for the development of regional socioeconomic systems and branch systems in the conditions of mobilization economy.

Keywords

Analysis of forecasting methods, machine learning methods, socioeconomic systems, forecasting, neural networks, SARIMAX

I. Introduction

Forecasting is one of the management functions. As noted by Academician Alexander Alexandrovich Dynkin and Professor Vladimir Dmitrievich Milovidov, “Strategic planning, its methods, forms and institutions have gone through a long path of evolution and have been modernized in accordance with changing historical conditions. At the same time, each of their new evolutionary transformations required a significant concentration of intellectual and organizational abilities of a wide range of specialists who summarized the accumulated experience and formulated new ideas and approaches to solving complex tasks to achieve strategic goals of social development, including security, state-building, and human economic activity” [1]. During the years of the transition of our country’s economy to market-based management methods, scientifically based strategic planning tools were not practically used, and liberal views of economic activity were implemented. In the current situation, when it is necessary to solve the issues of industrial revival, it is necessary to turn to those scientific developments that were made during the planned economic development of our country. Dynkin and Milovidov show that the greatest interest in the problems of planning in English-language sources was in the early 1990s [1]; at the same time, liberal economic views were actively promoted in our country, while Russian-language publications on planning issues reached a maximum by 2009. Thus, this indicates that Russian scientists continued to study the problems of effective long-term development. Strategic planning can solve the tasks of planning the socioeconomic system, the task of mobilizing all types of resources for the production of the necessary products. We agree with the concept of Lazhentsev that to solve the tasks of strategic development, it is advisable to turn to the method of program-targeted management. Lazhentsev notes that this model was most fully applied in the implementation of the program for the Development of the Economy of the Komi Republic (1993–2004). As a result of the implementation of this program, it was possible to move the issues "from the dead point" construction of the Timan bauxite mine, the Yareg mining (petroleum titanium), and other projects [2]. These results were achieved thanks to the program-oriented management, revealing that scientists and practitioners were united [3].

Blokhin and Kuvalin note that the changing geopolitical situation requires not only the revision of certain high-level documents but also the consolidation of the entire strategic planning system. To do this, it is advisable to carry out an inventory of existing documents to remove anachronisms from them, suggesting that the interaction of foreign business with Russia is extremely positive and this will allow removing several outdated provisions of strategic documents and updating their indicators [4].

We support this opinion, as an analysis of the industrial development programs of the Southern Federal District has shown that there is no single program for the development of the district's industry or industries. There is no single format for the development program of the subjects of the district, i.e., no single indicators. For example, the industrial development program of the federal city of Sevastopol identifies specific indicators that need to be fulfilled, but there are no such indicators in the development programs of the Rostov Region, the Volgograd Region, and the Krasnodar Territory [3]. The lack of a standard form makes it difficult to assess the implementation of development programs for both the subjects of the district and the district as a whole. This state of affairs in the context of active digitalization of accounting processes and interdepartmental interaction makes it difficult both to strategically plan the system and to evaluate the results obtained, which must be used to make managerial decisions.

As Academician Ivanter notes, "The prevailing development of large and largest businesses in the country, a steady increase in business consolidation in many significant markets around the leading group require a transition from market regulation institutions to the controlled development of oligopolous market relations, regulation of the use of institutional rents received by large businesses operating in the best institutional conditions, to achieve significant nationwide or for a given market purpose" [5].

a. Analysis of the results of previous work

An analysis of scientific papers on economic planning in our country has allowed us to identify a number of views. The collective work of the Institute of National Economic Forecasting of the Russian Academy of Sciences emphasized that the target results of Russia's spatial development should be achieved "not so much through budget transfers and subsidies, but through investments in carefully selected projects that accelerate the socio-economic development of regions" [5].

If we talk about this approach, then we need to talk about it not only in relation to regions but also cities of federal significance, because the rules should be the same in the country. We partially agree with the authors because budget transfers and subsidies are also a source of money supply, which generates demand and gives impetus to the development of the economy. The projects are aimed at the implementation of a specific task and can be used with a program-target management method. To implement the control of indicators with the program-target method of strategic planning, it is necessary to have a system of indicators with quantitative values. For example, consider one of the indicators of effective development of the region—the share of innovative goods, works, and services in the total volume of exports of goods, works, and services. This indicator is an official statistical indicator, however, none of the industrial development programs of the subjects of the Southern Federal District.

Figure 1 shows the dynamics of the share of innovative goods, works, and services in the total volume of exports of goods, works, and services [6]. It can be seen that the value of this indicator exceeds five times the average Russian value in the North Caucasus Federal District and four times in the Far Eastern Federal District. It is not possible to analyze the reasons for such a serious breakthrough.

Consider the following indicator—the energy intensity of GRP (a general indicator of the economic activity of a region, characterizing the process of production of goods and services for final use) (Figure 2) [6]. This indicator is also absent in the development programs of the subjects of the Southern Federal District; as an indicator, it provides information on the amount of conventional fuel per 10,000 rubles. This indicator can be used to assess production efficiency and develop measures to stimulate production in the context of energy saving.

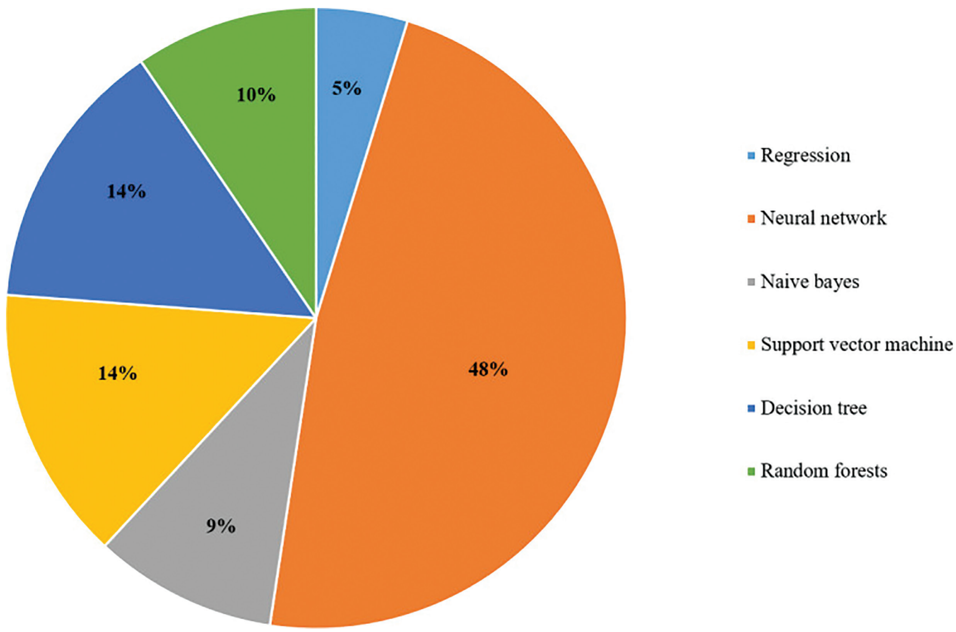

Figure 1: Supervised learning algorithms used for big data analysis in selected articles.

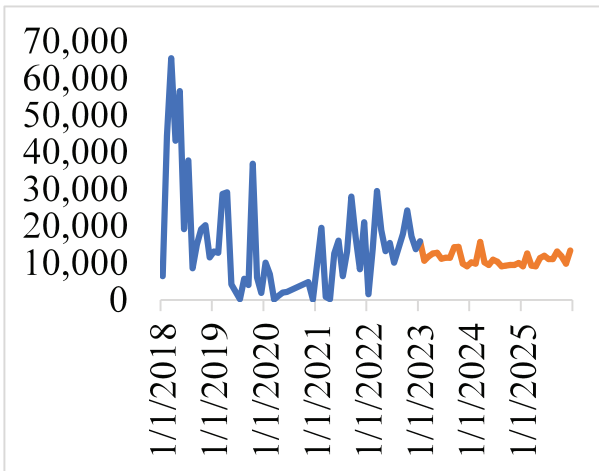

Figure 2: The results of forecasting the output of the 73 mm casing, tubing, and coupling using the SARIMAX model.

It is also not possible to analyze the reasons for the increase in energy intensity according to the available data.

The authors analyzed the methods of production planning presented in foreign sources (Table 1).

An analysis of forecasting methods has shown that their use requires quantitative data and appropriate information resources, which may not always be available.

One of the ways to solve the above problems is to use the capabilities of artificial intelligence, which can be used to implement a software-targeted management method.

Machine learning (ML), knowledge-based reasoning methods, decision-making algorithms, and search methods and optimization theory are the four main categories of big data, analytical methods. The main achievements of these methods

Table 1: Analysis of the mathematical and statistical forecasting methods

Name of the method	Brief description of the method	Advantages of the method	Disadvantages of the method
Exponential smoothing [7]	A time-series forecasting method based on weighing past observations with exponential attenuation.	Easy to implement Takes into account recent observations	It is sensitive to emissions/ anomalies Does not take into account trends
Linear regression [8]	A method based on the search for a linear relationship between independent and dependent variables.	Easy to interpret Effective for linear dependencies	Suitable only for linear dependencies Sensitive to emissions/ anomalies
ARIMA [9]	A method that allows us to model time series taking into account autoregression, moving average and seasonality.	Takes into account the complex structure of time series Adapts to different types of data	Requires defining model parameters Difficult to interpret
Forecasting based on ML [10]	Using ML algorithms for forecasting based on historical data and external factors.	Takes into account complex nonlinear dependencies Takes into account many input features	Requires a large amount of data for training Requires a lot of computing resources
Holt-Winters method [11]	A method that extends exponential smoothing to account for seasonality and trend.	It takes into account trends and seasonality Suitable for data with explicit cyclic behavior	Requires parameter settings Strong dependence on initial conditions
Prediction by the k-nearest neighbor method [12]	A method based on the fact that objects with similar attributes have similar values of the target variable.	Easy to implement Does not require assumptions about the data structure	Sensitive to emissions Requires setting the k parameter
Principal component method [13]	A method that reduces the dimensionality of data by projection onto a subspace with maximum variance.	Effective for a large number of signs Reduces the effect of multicollinearity	May lose its interpretability Does not take into account the dependencies between variables
Facebook prophet [8]	A method developed by Facebook to predict time series based on seasonality, holidays and trends.	Easy to use It takes into account seasonality and holidays	It does not always show good results on short time series Does not take into account external factors
Neural network method [14]	A method using ANNs for prediction based on learning from historical data.	Takes into account complex nonlinear dependencies Works with different types of data	Requires a large amount of data for training Difficult to set up and interpret
Random forest method [15]	A method based on constructing an ensemble of decision trees and averaging their predictions.	Resistant to retraining and works with a large number of signs	Prone to overtraining with suboptimal parameter settings Takes time to learn
Time-series method SARIMA [16]			
Hybrid models [17]	Methods that combine several different forecasting methods to improve the accuracy of forecasts.	Work with a variety of data characteristics Improve forecast accuracy	Require additional configuration Difficult to implement

(Continued)

Table 1: Continued

Name of the method	Brief description of the method	Advantages of the method	Disadvantages of the method
Gaussian processes [18]	Methods that simulate random processes, including time series, using Gaussian distributions.	Take into account uncertainty in forecasts Simulate nonlinear dependencies	Require computing resources to evaluate Difficult to interpret
Bayesian methods [19]	Methods based on Bayesian statistics for modeling and forecasting.	Take into account the uncertainty in the forecasts Allow us to update forecasts based on new information	Require the definition of *a priori* distributions Complex calculations
Gradient boosting [20]	A method based on the construction of an ensemble of weak models, with each subsequent model correcting the errors of the previous one.	High prediction accuracy Resistant to overtraining	Demanding on resources Difficult to configure parameters
LSTM [21]	A method that uses RNNs with LSTM to analyze sequential data.	Takes into account long-term dependencies Effective when working with sequential data	Requires a large amount of data for training Requires computing resources
Method of graphical models [22]	A method that models dependencies between variables in the form of a graph, where nodes represent variables and edges represent dependencies.	Allows us to take into account the structure of dependencies between variables Works with different types of data	Requires specification of the graph structure Difficult to interpret
Quantile regression [23]	A method that allows us to estimate not only the average value of the target variable but also its quantiles.	Allows us to estimate the confidence intervals of forecasts Takes into account different levels of uncertainty	Requires more data to accurately estimate quantiles High sensitivity to emissions/anomalies
Method of extreme cases [24]	A method based on the analysis of extreme (extreme) data values to predict rare events or extreme conditions.	Effective in predicting rare events Used for risk assessment	Requires a large amount of data on extreme values Difficult to interpret
Time-series decomposition method [25]	A method that divides a time series into components (trend, seasonality, and residuals), and then predicts each component separately.	Takes into account various characteristics of time series Effective in predicting nonstationary series	Requires setting the parameters of the decomposition method Difficulties in analyzing the results
Graph neural networks [26]	A method that combines graph models and neural networks for data structure analysis and forecasting.	Takes into account complex dependencies between variables Works with graph data	Requires a large amount of data for training Difficult to set up
Temporary neural autoencoder [27]	A method using neural autoencoders to study the internal structure of time series and their subsequent prediction.	Takes into account complex dependencies in the data Works with different types of time series	Requires a lot of computing resources Requires a large amount of data for training

ANNs, artificial neural networks; LSTM, long short-term memory; ML, machine learning; RNNs, recurrent neural networks.

are as follows. Artificial intelligence reduces the time needed to analyze big data. Repetitive tasks can be performed using machine intelligence. Reducing errors and increasing the degree of accuracy are other advantages of big data analysis based on artificial intelligence.

Figure 1 demonstrates the popularity of various teaching methods in big data analytics, which clearly shows that neural networks, support vector machines (SVMs—a set of similar "supervised learning" algorithms used for classification and regression analysis problems), and decision trees are the most popular ones [28].

Thus, an analysis of works devoted to the study of the role of artificial intelligence showed that no works present the results of using artificial intelligence to build a forecast of industrial output. This article presents such results.

II. Methods and Materials of the Research

Artificial intelligence is used for various purposes; for example, it draws beautiful pictures. However, the capabilities of artificial intelligence are not used for the tasks of strategic development of the national economic complex.

Initially, John McCarthy defined AI as a field of science that deals with computer modeling [29].

According to research from Precedence, the AI market will grow to more than $1.5 trillion by 2030 [2]. If optimistic forecasts come true, then, by 2030, the share of AI in China's GDP will be 26.1%, North America 14.5%, and UAE 13.6% [30].

The National Strategy for the Development of Artificial Intelligence has been approved in Russia to develop AI. In 2021, the Federal Project "Artificial Intelligence" began and, as part of the project, 24.6 billion rubles will be invested in this sector over 5 years. Only in 2021, approximately 3% of the National Project budget (4.7 billion) was spent on the implementation of this project [31]. According to the updated National Strategy for the Development of Artificial Intelligence, the share of priority sectors of the economy with a high readiness to implement AI should increase from 12% to 95%.

In Russia, according to the National Strategy for the Development of Artificial Intelligence for the period until 2030, artificial intelligence is defined as "a set of technological solutions that allows you to simulate human cognitive functions (including self-learning and searching for solutions without a predetermined algorithm) and obtain results when performing specific tasks that are comparable with the results of human intellectual activity" [32].

Thus, the country faces enormous challenges. The use of artificial intelligence, ML, and distance learning is implemented in modern transport systems [33], predictive maintenance [34], gesture and speech recognition [35], robotic surgery [36], medical applications [37], military robotics [38], agriculture [39], service robotics [40], robotics production, etc.

As for the use of artificial intelligence in solving socioeconomic problems, there are limited examples of effective use. Forecasting financial and economic time series has never been an easy task due to its sensitivity to political, economic, and social factors. Recently, various studies have suggested a special type of ANNs (artificial neural networks) as artificial intelligence systems, without which it is no longer possible to imagine the future of humanity. They can recognize, analyze, predict, and find analogies and detect problems, called recurrent neural networks (RNNs), which it is a deep learning model that is trained to process and transform sequential inputs into specific sequential outputs, as well as improve the accuracy of predicting the behavior of financial data over time. The results presented in [41] show that GRU gives overall better results, especially for univariate out-of-sample forecasting of exchange rates and multivariate out-of-sample forecasting for stock market indices.

Also, Ekhlakov and Sudakov note that GRU (a gating mechanism in RNNs for entering or forgetting certain features, but does not have a context vector or output gate) uses fewer training parameters and therefore less memory and runs faster than long short-term memory (LSTM), with the LSTM module being more accurate for a larger dataset [42].

The literature indicates that among numerous methods, ML is increasingly applied and used to develop new artificial intelligence technologies.

The most commonly used tools to evaluate the performance of artificial intelligence methods were accuracy, specificity, as well as generalizability, robustness, computational cost, and speed. The most commonly used ML is a subsection of AI that supports the development of algorithms and models in solving problems by generalizing many similar examples. In ML, a system collects information, learns from it, and then uses what it learns to make decisions. The algorithms used were artificial neural networks (ANNs), followed by SVM, which is a set of similar "supervised learning" algorithms used for classification and regression analysis problems, k-means, and Bayesian methods. Some studies have used hybrid methodologies to exploit the strengths of different methods and compensate for the weaknesses of specific methods. The areas of expertise assessed are the development of next-generation software and systems for data acquisition and management, with fault diagnosis being the application area with the largest solution offerings, followed by robotics, autonomous computing, and driving. This review showed that classification problems are the most commonly used methods of the so-called intelligent systems, either statistical algorithms or artificial intelligence. The literature also suggests that AI-based DL platforms (a set of ML methods, the training of which occurs based on representations [representation learning]) require less information, which improves the solution of complex decision-making problems, making them an alternative solution with the greatest AI methodological offerings [43].

III. Research Results and Discussion

An analysis of some of the capabilities of artificial intelligence has shown that using this toolkit it is possible to make forecasts for a system that is weakly structured and has dynamic, computational, evolutionary, and internal and external complexities. In this study, we present the results of product output forecasting using the SARIMAX model (an extension that includes an external regression component).

When choosing a model for forecasting product prices several months in advance, it was decided to use the SARIMAX (Seasonal AutoRegressive Integrated Moving Average with eXogenous factors) model. This choice is based on several key factors.

First, SARIMAX models are well suited for analyzing and forecasting time series such as product prices. They take into account both trends and seasonal patterns in the data, making them an ideal choice for forecasting product prices.

Second, SARIMAX allows us to take into account the influence of external factors on a time series, which can be useful in forecasting prices that are susceptible to external economic factors.

Thus, the SARIMAX model was selected as the model for forecasting product prices 36 months in advance based on its ability to account for seasonal patterns and external factors in the data.

The Python programming language was used to develop and configure the forecasting model using the Pandas, NumPy, Statsmodels, and scikit-learn libraries.

The model development process began by loading data from the “data2.csv” file. Then, the data were scaled using standardization to normalize the values.

Later, the data were divided into training and test sets for subsequent model training.

To train the model, SARIMAX was used with the parameters order (0,1,1) and seasonal order (0,0,1,36). These parameters were selected based on preliminary data analysis.

The model was trained on a training dataset using SARIMAX. During the training process, the model automatically adjusted its parameters to minimize the prediction error.

After training the model, prediction was carried out on a test dataset. To do this, we used model predictions based on the training data. Then, the forecasts were scaled back to obtain the original price values.

After successfully training the model, product forecasting was carried out 36 months in advance using the get_forecast method (number of steps = 36).

The predicted values were back-scaled to obtain the original prices. The resulting models are presented in Figure 2 and Figure 3. Figure 2 presents the results of forecasting industrial production of 73 mm casing, tubing, and coupling using the SARIMAX model. These products are used in the production of plastic pipes. Figure 3 presents the results of predicting casing and coupling using the SARIMAX model, which is used to connect plastic pipes. Thus, the use of the SARIMAX model makes it possible to forecast the production of components for plastic pipes.

The results of forecasting product output using the SARIMAX model and the LSTM network (an ANN containing LSTM modules instead of or in addition to other network modules) are close, but not the same. This also indicates the need for further research and comparison of predicted values with actual ones.

The authors’ goal is to train a neural network to make production forecasts. Machine learning was carried out using data from the production of plastic pipes. The results obtained from the SARIMAX model and the LSTM network were close in accuracy but not identical. This divergence underscores the strengths and limitations of each approach. While SARIMAX excels in capturing linear patterns and seasonality, LSTM networks can model nonlinear relationships more effectively. However, the neural network’s performance depends heavily on the quality and quantity of data used for training, as well as the tuning of hyperparameters. The observed differences

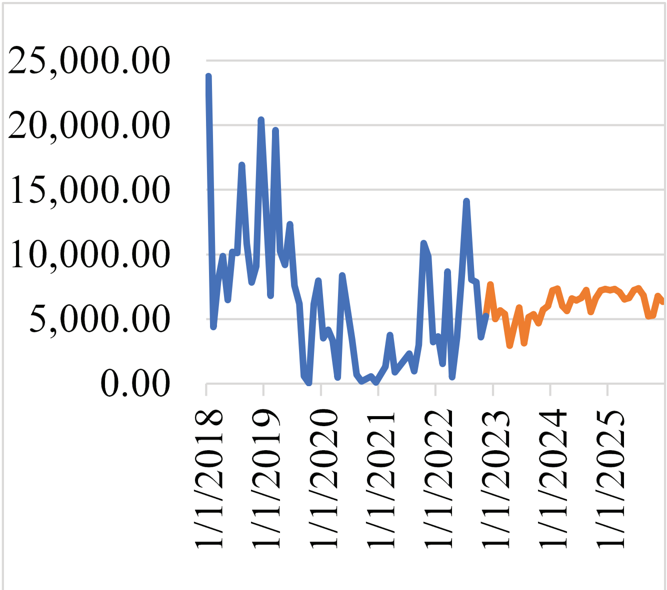

Figure 3: Results of forecasting the output of the casing coupling using the SARIMAX model.

in predictions suggest that both approaches have potential, but further research is required to refine their accuracy and applicability.

The primary objective of this research was to train an LSTM neural network to provide reliable forecasts of plastic pipe production. Machine learning training was conducted using historical production data, encompassing variables such as production volume, input materials, and external influencing factors. The use of production data allowed the neural network to learn patterns and dependencies unique to the manufacturing process. By continuously comparing the predicted values from both the SARIMAX and LSTM models with actual production figures, the study aims to identify the most effective forecasting strategy.

The findings of this study highlight the necessity of combining statistical and ML approaches to enhance forecasting accuracy in industrial production. The SARIMAX model provides a strong baseline with its interpretability and ability to handle seasonality, while the LSTM network introduces the capability to learn nonlinear patterns and adapt to complex dynamics within the data. Future work will focus on optimizing the neural network's architecture, exploring hybrid modeling approaches that combine the strengths of SARIMAX and LSTM, and conducting extensive validation using additional datasets. By doing so, the goal of achieving highly accurate and reliable production forecasts can be realized, ultimately contributing to improved planning, resource allocation, and efficiency in the manufacturing industry.

IV Conclusion

Based on the study, it is advisable to use the capabilities of artificial intelligence to analyze indicators for the application of program-targeted management. The indicators, such as the share of innovative goods, works, and services in the total volume of exports of goods, works, and services, GDP (a macroeconomic indicator that reflects the market value of all final goods and services (i.e., not intended for use in production or further resale) produced over a specified period in all sectors of the economy on the territory of a particular state), and energy intensity (GRP) (a general indicator of the economic activity of a region, characterizing the process of production of goods and services for final use) can be analyzed using artificial intelligence, and we can determine factors that influence changes in the indicators. However, as Gennady Krasnikov, President of the Russian Academy of Sciences, notes, "'Is an artificial neural network good?'" Yes, but the problems associated with cybersecurity, when your images and voice can be faked and used against you, are bad… the real threat today is when you can't control your gadgets, someone else will do it" [44].

As Ganasia rightly notes in his work, “The popularity of the term ‘artificial intelligence’ is largely explained by its erroneous interpretation, in particular, when it denotes a certain artificial entity endowed with intelligence, which is supposedly able to compete with people” [45]. This is one of the most common misconceptions, since there is only one existing example for association and comparison, i.e., human intelligence [46].

Therefore, to solve the issues of forecasting product output, appropriate specialists are needed with the skills of planning, analyzing business activities, working with artificial intelligence, and having a database on the nomenclature and quantity of products. The combination of all the above resources will make it possible to develop industrial development programs both at the regional and national levels with precise quantitative values.

Thus, the result obtained in this article suggests that the use of neural networks can make it possible to build predictive models of industrial output for many years to come and, accordingly, determine the need for resources for the production of these products. This allows us to plan the need for resources in the enterprise.

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