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Prospective Models of Financial Forecasting of Budget Revenues

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ABSTRACT

The **subject** of the study is the choice of a model for financial forecasting of budget revenues, which allows the most correct assessment and obtaining a forecast value for the next period. The **purpose** of the study is to identify promising models of financial forecasting of budget revenues of the Russian Federation. DSGE models used since the 60s of the twentieth century have failed to identify a number of crises and timely predict the level of changes in government revenues in the United States, the Eurozone, and Russia, which did not allow for prompt adjustment of the policy pursued in the field of public revenue management. The **novelty of the study** consists in identifying the shortcomings of the modern methodology of financial forecasting associated with the obsolescence of the approaches used and the need to search for new models that allow you to quickly refine the prognostic results. The study used such **methods** as measuring predictive values and the size of their errors, analyzing and comparing the results obtained using methods and models of machine and deep learning. As a **result** of the study of predictive methods and models of machine and deep learning used in real business, the stock market and public finance, the most promising of them were selected. The main selection criteria were the possibility of modeling nonlinear relationships of parameters, the efficiency of calculation, the minimality of error, and the absence of a problem with retraining. In the course of the study, the expediency of time series decomposition was revealed, which made it possible to minimize predictive errors and choose the most accurate model for forecasting budget revenues of the Russian Federation. The results of the study can be used to form a system of predictive indicators used to develop a dashboard system for civil servants in order to improve the accuracy and efficiency of their decisions.

Keywords: predictive model; financial forecasting; budget revenue forecasting; neural networks; vivlet transformation

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INTRODUCTION

Significant changes in the global economic and political situation necessitate prompt responses to ongoing transformations. The digitalization of a substantial number of processes in the national economy, the increase in instability, and the rapid development of technologies present fundamentally new challenges to the system of public administration. As a result, there is an acute need for methods that allow for the prompt forecasting of key financial indicators in the public sector to make management decisions in real-time based on them.

In a significant number of Russian studies, the main focus was on issues of planning budget indicators based on the norms of the Budget Code of the Russian Federation [1, p. 186], assessing the reliability of forecasts [2, p. 2020], their cognitive modeling [3, p. 179], as well as the quality of forecasting [4, p. 40]. The issues of selecting the methodological framework for forecasting key indicators are actively being developed [5, p. 599]. It has been proven [6, p. 5] that for the purposes of forecasting macroeconomic indicators, a significant number of methods can be applied. Some methods involve the use of a large amount of data, macroeconomic and financial indicators, which have varying levels of availability. Others, on the contrary, show good results under conditions of limited samples. A number of indicators are high-frequency, while others do not possess this property. The paradigm of machine and deep learning has been actively developing recently. The analysis and comparison of models presented in this work will allow for the selection of the most promising ones for use in predictive purposes.

The **purpose** of the paper is to identify the most promising methods for forecasting the revenues of the Russian Federation's budget. To achieve this:

- a review of studies has been conducted, showing the key reasons driving the shift from DSGE to alternative models;
- the main forecasting methods have been identified, and their characteristics have been provided;
- the process of selecting a model for forecasting budget indicators is presented.

REASONS FOR THE SHIFT FROM DSGE TO MACHINE LEARNING MODELS

Today, DSGE models are used for forecasting, which are actively criticized for: instability of results, increased sensitivity to data quality, inability to account for uneven loading of production capacities and the degree of their renewal [7, p. 205]; the complexity of implementation due to the absence of a nonlinear trend; reliance on the hypothesis of rational expectations, despite the proven formation of waves of optimism and pessimism associated with the irrationality of decision-making, etc. [8, p. 125]. There are studies summarizing individual critical remarks on the DSGE model [9, p. 77]. They present the main reasons that contribute to the transition to alternative forecasting models in the public sector. The authors point to the difficulty of explaining the duration and depth of recessions. Rapidly evolving DSGE models have failed to predict a number of crisis phenomena and the consequences of the pandemic (2007, 2008, 2020, etc.) due to the need for regular model calibration, superficial evaluation results, and their poor ability to capture changes in market trends. In the early 2000s, studies began to emerge that forecasted budget revenues using autoregression methods, mixed data models, and others [10]. In the forecasting of macroeconomic indicators, vector autoregression, integrated autoregressive moving average models, and reservoir computing [6] started to be used. This led to the emergence of alternative forecasting model options for central banks and finance ministries in several countries, based on machine learning (ML) and deep learning (DL) methods and algorithms. They reduce the use of statistical (econometric) models, which yield decent results when there are linear relationships between indicators, as these do not capture a significant portion of the signals [11, p. 187]. These models demonstrate sensitivity to relationships between indicators, require the exclusion of multicollinearity and heteroscedasticity, and the assessment of residual autocorrelation, showing high predictive ability when forecasting budget revenues in a stable situation.

In most countries, the time series for forecasting government revenues is limited to 30–40 years, and there is a need to consider a significant number of factors in the models. These aspects are taken into account in machine learning and deep learning methods and algorithms, whose effectiveness depends on the sample size. Their application involves tuning parameters and hyperparameters that affect the quality of the model. At present, they are recognized as some of the most promising.

FINANCIAL MODELING OF BUDGET REVENUES: SEQUENCE AND MODEL SELECTION

Definition of the Base for Financial Forecasting of Budget Revenues

The stage involves collecting data for forecasting and placing it in a unified database. This allows for an increase in data processing speed, which impacts the efficiency of the modeling process. This database contains three levels according to the ANSI-SPARC architecture: external, conceptual, and internal. The technical description of the physical implementation of the database is beyond the scope of this study.

Deep and Machine Learning Models Tested for Budget Revenue Forecasting: Characteristics, Advantages, and Disadvantages

In the study, machine and deep learning models and algorithms (*Table 1*) were tested, which work with data in the presence of a certain type of noise, can identify and account for nonlinear relationships between individual data groups, and are free from multicollinearity considerations. A comparative characterization of the models is presented in *Table 2*. Understanding the mechanism of the model allows for taking into account the necessary information processing features for the specific situation when forecasting government revenues, and the hyperparameters can be adjusted accordingly.

To improve the accuracy of forecasts, time series decomposition is used. Within this framework, a time series is divided into several components: trend, seasonality, cyclicality, residuals, or noise. Time series decomposition allows for: separating raw data into different components to enhance the quality of time-based analysis, identifying anomalies, conducting data visualization, and improving the quality of time series forecasting.

The disadvantages of the method include:

- the need for assumptions about components that may be disrupted by changes in dynamics and external factors;
- the need to identify data that distort trends, reduce decomposition accuracy, and affect component reliability;
- the possibility of obtaining a low-quality predictive model when using standard decomposition methods;
- the impracticality of using the approach for irregular or noisy data;
- the dependence of the accuracy of the obtained forecast results on the correct selection of parameter values [12].

A trend represents a long-term movement or general direction in which the analyzed data increases, decreases, or stabilizes over time. Different trends can be used: upward, downward, or stable. Understanding them will allow determining the overall trajectory of the data movement.

Cyclicality represents recurring patterns that do not have a fixed period. The trend and the cyclical component are usually combined into a single trend-cyclical component. The specific functional relationships between these components vary.

Table 1

Comparative Characteristics of Machine Learning Methods and Models

Comparison criteria	Linear and generalized regression models	Decision trees	Random Forest	KK-nearest neighbors	Support Vector machines	Neural networks	Naive Bayes	Gradient boosting	Extreme gradient boosting
The possibility of forecasting a time series	+	+	+	+	+	+	+	+	+
The necessity of accounting for the effect of variable collinearity	+	–	–	–	–	–	–	–	–
The possibility of identifying and accounting for nonlinear relationships	+	+	+	+	+	+	+	+	+
Building a classification based on data characterized by a specific type of noise	–	–	–	–	–	–	+	+	+
Labor intensity in model training	–	–	–	–	–	+	–	+	–
The complexity of interpreting the results of the calculation of parameter value selection	–	–	–	–	+	+	+	+	+

Source: Developed by the authors.

Seasonality allows for the identification of recurring patterns or fluctuations in data that occur over specific intervals of time, such as monthly, quarterly, or annual cycles. In our case, the season of the year has an impact, as cash flow depends on obligations imposed by the tax code and other regulatory documents, among other factors. Identifying these patterns enables a more accurate forecasting process and describes the cyclicality of the data.

Residuals represent the remaining random variations or deviations in the data after identifying the trend, cyclical, and seasonal components. They are noise. It is impossible to predict them in time series. The assessment conducted is necessary to understand the overall variability of the data.

For decomposing time series, it is common to use methods such as classical decomposition, moving average decomposition, seasonal and trend decomposition using LOESS, singular spectrum analysis, and seasonal extraction in ARIMA time series. After performing the calculations, all elements of the time series are combined, which improves the quality of the forecast.

To clean the time series from noise and random outliers, the wavelet transform method will be used in the work. It allows for filtering and preprocessing the data, which will subsequently be used for building the forecast.

Each of the methods and algorithms is appropriate for forecasting the studied time

Table 2

Characteristics of the Models Used in Calculations for Forecasting Budget Revenues of the Russian Federation

Name of the model	The mechanism of operation of the model	Hyperparameters	Advantages of the model	Model Type
Gradient Boosting Regressor	The essence of the algorithm: creating a forest with a fixed number of decision trees. The model fitting begins with determining the average value of the target indicators. Next, a forecast is added based on subsequent trees. In the following stages, decision trees are fitted to predict the negative gradients of the samples. The gradients are updated in each iteration	• the number of trees; • maximum depth of the tree; • scalability speed; • loss function	• applicable for poorly trained and poorly predictive models	Ensemble model
CatBoost Regressor	It is built on the assumption of the mean value of the target variable. It involves the formation of an ensemble of decision trees. Each new tree minimizes the errors or residuals of the previous ones. The trees are grown by introducing the rule: all nodes at the same level are checked by the same predictor with the same condition. The leaf index is calculated using bitwise operations	• depth of the tree; • learning speed; • number of iterations	• has advanced features compared to Gradient and XGBoost algorithms, enhancing its reliability, speed, and accuracy; • used for integrating data types into a unified structure, categorical functions, and processing non-numeric values; • has open source code	Extreme gradient boosting
Extra Trees Regressor	In the calculations, the initial dataset is used. The selection of "cut" points for node splitting is done randomly. The algorithm determines the best subset of features, which allows for maintaining optimization in the model when adding randomization	• the number of features considered at each • decision node; • minimum number of samples for the node; • the number of trees in the forest	• the number of features considered at each decision node; minimum number of samples for the node; • the number of trees in the forest is used to improve the performance of calculations; • has a simple decision tree construction algorithm; • contains a small number of key hyperparameters, easy to configure; • characterized by low systematic error and high model fitting speed	Random forest method, decision tree

Table 2 (continued)

Name of the model	The mechanism of operation of the model	Hyperparameters	Advantages of the model	Model Type
LTSM	The architecture of the model consists of an input, hidden, and output layer. They regulate the state and response of the cell. The input and output layers control reading and write access, while the hidden layer resets the contents of the memory cells as soon as they become outdated. The cell state is updated upon receiving information. The learning algorithm in the model is local in space and time. It is trained to overcome minimal time delays exceeding 1000 discrete time steps	• standard cell; • number of epochs; • function g, regulating the cell input; • function h, regulating the output of the cell	• allows solving complex tasks with a long delay; • improves the quality of the model based on non-stationary data through preprocessing; • leads to improved modeling results when used in conjunction with convolutional neural networks; • allows not to conduct tests for stationarity, seasonality, etc.	Neural network
Gated Recurrent Units	The model is based on two vectors that determine the type of information transmitted to the output. A feature of the vectors is the ability to store old information. The update gate determines the amount of preceding information. It is defined by the current input and the previous hidden state, expressed by a sigmoid activation function. The output values of the update gate are between 0 and 1. The reset gate evaluates the size of the ignored information. The reset gate determines the values using the current input and the previous hidden state, expressed by a sigmoid activation function. The hidden state is determined after calculating the update and reset gates. It represents new information. The "calculated state" is then combined with the previous hidden state. As a result, the current hidden state is formed, combining old and new information. The application of the update and reset gates helps solve the vanishing gradient problem in recurrent neural networks	• size of the input vector; • size of the hidden layer	• captures dependencies by using retrospective information from the data array in the model; • solves the vanishing gradient problem; has a simple modification unlike LSTM; • allows obtaining quality results with a small sample size; has fewer parameters than LSTM; • requires minimal computational power	Neural network

Table 2 (continued)

Name of the model	The mechanism of operation of the model	Hyperparameters	Advantages of the model	Model Type
N-BEATS	The architecture of the model is formed by combining blocks into a hierarchical structure. In a branched architecture, the blocks are characterized by fully connected equations. Each block receives data at the input. At the output, two signals are generated: 1) direct forecast; 2) inverse forecast. Each block receives data, generates a forecast, and performs an inverse transformation. The input data for the next block is formed by subtracting the output data of the inverse forecast of the previous block from its input data. The resulting residue is processed by the network. The forecasts of the blocks are combined into the final result — a general forecast	• planning horizon; loss function; • the number of past lags of the model; • integer values for each type of stack (seasonality, trend, identity); • integer value determining the number of harmonic terms for the seasonal stack type; • integer value, for the degree of the trend polynomial; • categorical value determining the type of normalization; • floating-point value representing the learning rate for the model optimization process	• has a transparent model structure and high interpretability of results; • is characterized by increased performance, high accuracy, and minimal training time compared to other deep learning architectures	Neural network

Source: [10, 13–18].

series. They differ in terms of the level of study, the accuracy of the forecast results obtained with their help, and the ability to account for the individual characteristics of the time series.

SELECTION OF A PREDICTIVE MODEL

The selection of budget revenue forecasting models calculated by the authors is based on a number of criteria. These include: approximation accuracy; cross-validation; expert evaluation.

To justify the criteria used in the work, a number of studies were reviewed. Each of them employed cross-validation and expert evaluation methods. Significant differences in the studies [10, 13, 19–22] were related to the indicators based on which the model selection was made. As a result, the errors used for selecting the model for forecasting the revenue of the Russian Federation's budget were identified.

RESULTS OF FINANCIAL MODELING OF THE RUSSIAN FEDERATION'S BUDGET REVENUES

The choice of methods and algorithms in the study is determined by the necessity to avoid adhering to the stationarity of time series. Calculations were performed in Python and Wolfram Mathematica 12.0. The models are built on the basis of 80% of the sample used. The remaining 20% of the sample were set aside to verify the quality of the obtained forecasts. Monthly budget revenues were used as regressors in the models. The results are presented in *Table 3*.

Table 3

Errors and Coefficient of Determination of Forecast Models of Budget Revenues of the Russian Federation

No.	Name of the model	MAE	RMSE	MAPE	R 2
1	Модели машинного обучения				
1.1	CatBoost Regressor	57.87	70.32	0.24	–
1.2	Gradient Boosting Regressor	61.41	76.17	0.25	–
1.3	Extra Trees Regressor	71.15	82.36	0.27	–
2	Модели глубокого обучения				
2.1	Gated Recurrent Units, GRU	131	168	17	0.66
2.2	LTSM	119	144	17	0.69
2.3	N-BEATS	92	115	14	0.76

Source: The calculation was made by the authors based on data from the Ministry of Finance of the Russian Federation. URL: https://minfin.gov.ru/ru/statistics/fedbud (accessed on 24.03.2024).

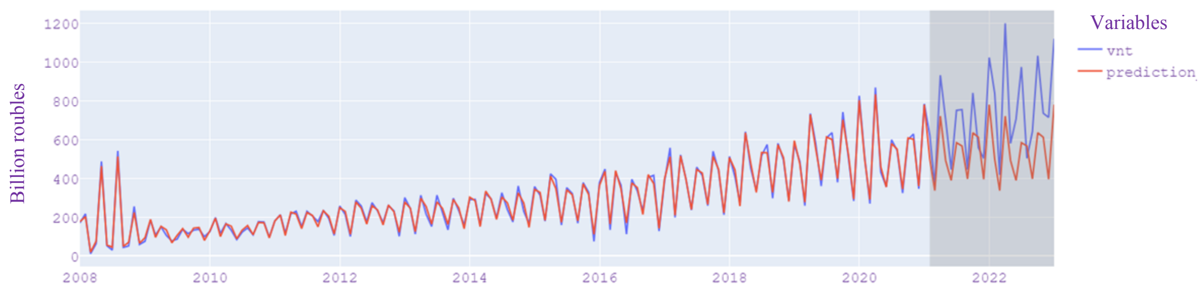

Fig. 1. **Budget Revenue Forecast Using the Catboost Model**

Source: Developed by the authors.

The criterion for selecting a predictive model is the minimum error magnitude (MAE, RMSE, MAPE). For deep learning models, the value of the coefficient of determination (R^2) was taken into account. Among the machine learning models, the CatBoost Regressor algorithm showed the best results. The size of the three errors according to the algorithm is minimal. Among deep learning models, N-BEATS has the smallest errors. The coefficient of determination for this model is the highest. Next, a comparison of error sizes between CatBoost Regressor and N-BEATS was conducted. The advantage of the first algorithm has been identified. Budget revenue forecasts obtained from test samples showed that the CatBoost Regressor predicts the training sample well, clearly capturing the dynamics of changes, but does not work on the test sample (*Fig. 1*). It is evident that the forecast (red trend line) for 2021–2023, made on the test sample, significantly differs from the actual federal budget revenues (blue trend line), demonstrating model overfitting. Therefore, its use for forming a predictive model requires correction. In subsequent studies, normalized samples that have undergone data preprocessing will be tested, including first differences, logarithms of first differences, and 2011 prices, as well as models with retuned hyperparameters (*Table 2*).

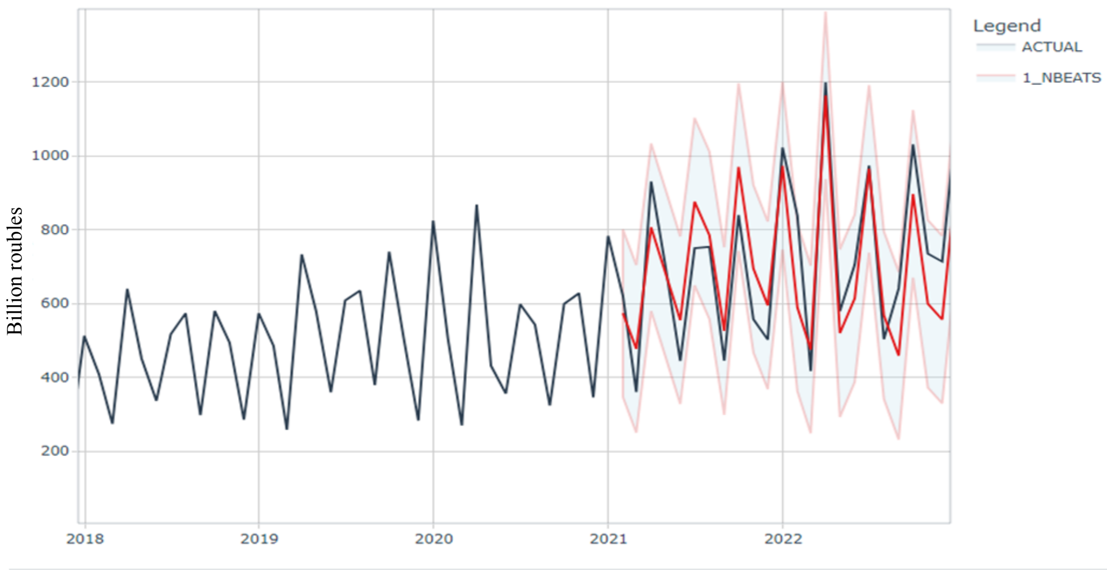

Fig. 2. **Budget Revenue Forecast Using the N-BEATS Model**

Source: Developed by the authors.

The forecast using the N-BEATS model shows that it better captures the trend in the test sample (2021–2023) (*Fig. 2*). The deviations of the forecast (red trend line) from the actual federal budget revenue (blue trend line) are minor. They fall within the confidence interval (represented by the pale red boundary). The predictive ability of the model is higher. The model makes mistakes in the fall of 2022 due to the presence of anomalous data behavior. This is due to a significant increase in domestic production and a sharp decline in import revenues, as, on the one hand, the policy of import substitution was activated, and on the other hand, sanctions were imposed against Russia. We also note the increase in the volatility of other revenues during this period.

The forecasted values fall within the confidence interval, and there is no autocorrelation of the residuals. Therefore, the N-BEATS model is advisable to use for forecasting in the public sector, which proves the proposed hypothesis.

Next, we will consider an approach that allows minimizing predictive errors.

The ambiguity of the obtained results led the authors to the necessity of using a preliminary decomposition procedure for the time series, which was tested on the revenues of the budgets of the subjects of the Russian Federation taken from the period from 01.2013 to 03.2023. The source of the data is the website of the Treasury of Russia.[1]

The study used aggregated values of the revenues of the consolidated budgets of the subjects of the Russian Federation. In the future, it is planned to develop models for forecasting the revenues of the budgets of specific subjects of the Russian Federation. Short-term forecasting of revenue receipts throughout the financial year, on a monthly basis, is a key contribution to effective Treasury Cash Management. The seasonal nature of these revenues must align with the planned budget support payments for expenditure obligations throughout the financial year,[2] as well as the need to attract

[1] Federal Treasury. Consolidated Budgets of the Subjects of the Russian Federation and the Budgets of Territorial State Off-Budget Funds. URL: https://roskazna.gov.ru/ispolnenie-byudzhetov/konsolidirovannye-byudzhety-subektov/ (accessed on 24.03.2024).

[2] Main directions of budgetary, tax, and customs-tariff policy for 2024 and the planning period of 2025 and 2026: approved by the Ministry of Finance of Russia. URL: https://www.consultant.ru/document/cons_doc_LAW_429950/ (accessed on 24.03.2024).

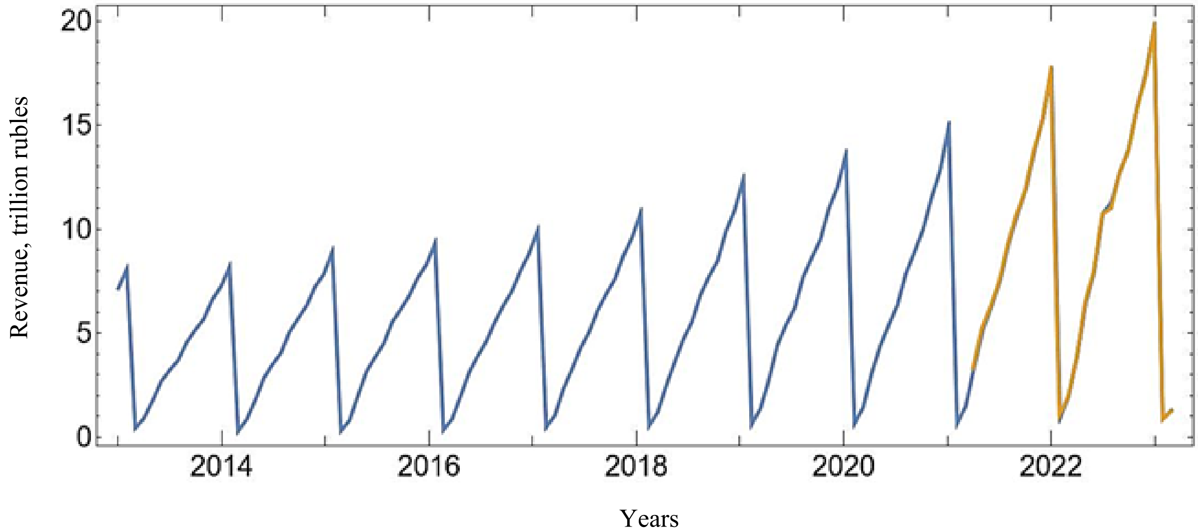

Fig. 3. **Real and Projected Monthly Aggregated Revenues of the Budgets of the Subjects of the Russian Federation**

Source: Developed by the authors.

Note: The blue line represents real data (period 01.2013–03.2023), the yellow line represents predicted values (period 03.2021–03.2023). The study was conducted in 2023 using the initial data available at that time.

short-term financing to cover any short-term budget deficits. The expected seasonal nature of revenue collection is also crucial for monitoring the targeted revenue collection indicators throughout the financial year.

Their forecast using the preliminary time series decomposition procedure through discrete wavelet transform (family of ReverseBiorthogonalSplineWavelet) allowed for the identification of high predictive accuracy of the model (R^2 = 99.9%).

Several different families of wavelets were tested. The calculations used a forecasting procedure based on interpolation and extrapolation of time series data. The calculations were made using series decomposition based on DWT. The highest forecast accuracy was achieved using the ReverseBiorthogonalSplineWavelet 8.8 family. The results are shown in *Fig. 3*.

When comparing N-BEATS and the model built on the basis of the preliminary time series decomposition procedure using discrete wavelet transformation according to the R^2 criterion, the advantage of the latter is evident. Therefore, the hypothesis proposed by the authors is proven. The method has the highest predictive potential.

The use of the proposed model will allow civil servants to make responsible and well-founded decisions.

Revenue forecasting models serve three interconnected but distinct budgetary purposes. First, they are in demand for preparing medium-term budgets (both federal and regional budgets); second, for short-term cash management during the financial year; and third, for expenditure forecasting.

Reasonable revenue forecasts are necessary to achieve sustainable funding for public projects and programs and to avoid large unplanned and potentially unacceptable budget deficits that may arise over the next year.

An important aspect of revenue forecasting is its connection to short-term and medium-term budget stability. A bias towards revenue optimism and political pressure to spend budget amounts or beyond them generally lead to deficits exceeding target levels.

Therefore, revenue collection policies and forecasting strategies should be coordinated with budget management strategies to better account for the variability of expenditures and revenues in both the short-term and medium-term perspectives.

CONCLUSION

Financial forecasting is one of the most important aspects in the context of increasing instability and growing sanctions pressure. The contribution of this research lies, firstly, in the attempt to use alternative DSGE methods and models to minimize the identified weaknesses. Secondly, the work allows for the comparison of machine learning and deep learning methods and models to identify the most promising ones for further use. Specific aspects that need to be considered when choosing models for calculations have been identified. Thirdly, the study demonstrates the feasibility of using the N-BEATS method for financial forecasting of budget revenues. The effectiveness of applying the procedure of preliminary decomposition of a non-stationary nonlinear time series using discrete wavelet transforms has been proven. The procedure used for forecasting allowed increasing its accuracy from 65–80% to 99%. At the same time, the selection of the most accurate method was carried out using a traditional approach.

The study has limitations. Firstly, the methods and models compared are used for forecasting purposes to predict budget revenue indicators since January 2011, which is due to the limited data on the monthly revenues of the federal budget provided by the Ministry of Finance of Russia. Secondly, only open data from official sources were used for the forecast. Thirdly, calculations were conducted on monthly data, as the developed models assumed obtaining forecasts in real-time. This allowed the model to be trained and its quality to be tested. For indicators of other frequencies, the models were not tested due to a significant reduction in the sample size, which could negatively affect their predictive power.

The results obtained by the authors indicate the need for further research. It is necessary to seek ways to improve the accuracy of forecasts for the indicators of the federal budget of the Russian Federation. To this end, it is advisable to test preliminary decomposition of time series with discrete wavelet transforms from various families.

In the long term, it is advisable to develop a system of forecasting methods and models using machine learning to predict aggregated revenue and expenditure items of federal and regional budgets with the aim of creating a dashboard system based on them. This would allow government officials to receive real-time information on forecast indicators to make managerial decisions on reallocating funding for specific activities within the framework of national projects in the Russian Federation, distributing available financial resources for the upcoming year, and more.

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