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New Approaches to Forecasting Budget Revenues of the Russian Federation Based on Reservoir Computing

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ABSTRACT

The relevance of this study stems from the need to enhance the accuracy of forecasting tools in determining future budget revenues for the Russian Federation, given the dynamic macroeconomic environment shaped by sanctions. In the current situation, it is essential to respond quickly to the changes taking place. This requires the use of various frequency data in predictive models and the search for new, more accurate forecasting methods. The object of the study is the dynamics of federal budget revenues. The subject of the research is to examine the applicability of reservoir computing in forecasting federal budget revenues in the Russian Federation. The purpose of the study is to identify the feasibility of using reservoir computing models in forecasting federal budget revenues in the Russian Federation. Empirical and theoretical methods were employed in the research process. These methods allowed us to understand the essence of reservoir computing, interpret the predictive results obtained, and select the best hyperparameters. As a result, a model based on reservoir computing was proposed by the author, taking into account the dynamics of monthly and daily factors in the development of the Russian economy. It is concluded that the world's first experience in using reservoir computing in forecasting federal budget revenues in the Russian Federation has improved the quality of the model. The characteristics of the resulting model are significantly better than analogues calculated using other methods. The high fragmentation of the Russian data and the short length of the time series have also been revealed, which was eliminated by shortening the time period for training models and imputing missing values in the data.

Keywords: federal budget revenue forecasting; reservoir computing; machine learning; data preprocessing; PCA

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INTRODUCTION

The last decade has seen significant changes in the global economy, driven by a number of factors. Due to the development of technology, the pace of transformation and the number of changes are increasing, leading to increased instability.

At the same time, many countries are shifting their budgetary policies towards medium-term planning, rather than short-term forecasts. This is reflected in the development of various restrictive tools [1, p. 435].

Exceeding revenues over expenditures and reducing the size of budgetary borrowing is becoming one of the most significant goals for the future development of the global economy. The study [2, p. 2460] demonstrates that stabilizing budget revenues contributes to their growth and attracts investors for business expansion.

Existing budget forecasting models often underestimate revenue and do not make effective use of available information. This is due to the fact that budget revenues are characterized by variability, which is influenced by economic activity, political and administrative factors, as well as tax adjustments. Overestimating budget revenues can lead to a restriction on corporate and personal spending, a decrease in investment activity, and an increase in the debt burden, slowing the pace of economic growth in countries. Conversely, underestimating projected revenues can result in insufficient tax collection and payment [3, p. 210], causing a budget deficit and preventing the implementation of important social projects.

Effective budget planning in the Russian Federation and the successful implementation of national projects and programs requires an accurate assessment of the necessary revenues for their realization. In such circumstances, financial forecasting faces strict requirements related to improving the accuracy of forecasts of federal budget revenues and the effectiveness of their calculation, which will influence the quality of decision-making processes.

A significant part of forecasting models used in Russia are based on dynamic stochastic general equilibrium (DSGE) models. These models assume that a large number of indicators are taken into account, but as practice has shown, they cannot reliably predict major shocks, such as the global financial crisis of 2007. These models are based on the rational expectations of economic agents [4, p. 124], and their results are largely determined by the calibration and identification of parameters. They depend on the correct setting of many exogenous variables, and do not take into account information asymmetry or imperfect markets. This makes it difficult to interpret the results, and studies often note inconsistencies with empirical data [5, p. 81].

The use of machine learning (ML) technologies in budget forecasting is limited by the complexity of the interaction between various economic factors and the need to process large volumes of diverse data. Training neural networks requires a significant amount of computational resources [6, p. 050803], which drives the search for simplified methods for their training.

Reservoir computing (RC), which is one of the machine learning options, has solved this problem. RC evolved by combining certain models of recurrent neural networks encompassing liquid state machines (LSM), echo state networks (ESN), and delayed and feedback reservoirs. RC's simplify learning by focusing on learning weights connected to the output layer (also called the readout layer). A related concept is back propagation of error over time, a reservoir readout layer learning algorithm that unwraps a recurrent neural network over time and processes it as a fast neural network over a sequence, adjusting the weights depending on the error at the output.

The presented analysis of works on reservoir calculations allows us to significantly expand the methodological forecasting tools in the field of public finance and improve the quality of forecasts by increasing the accuracy of estimates. This will help to improve the balance of fiscal policy and provide additional benefits in the form of increased investment.

The purpose of this study is to prove the expediency of using reservoir calculations in forecasting budget revenues of the Russian Federation and to substantiate the resulting advantages. To achieve it:

• a review of research on reservoir computing has been conducted, their focus and tasks have been determined;

• the reservoir computing model has been described;

• the author's model has been built, and the procedure for selecting hyperparameters for it has been carried out in order to improve the quality of forecasting federal budget revenues.

MATERIALS AND RESEARCH METHODS

The information base is based on research materials conducted as part of fundamental research on the topic "The digital ecosystem of financial and economic forecasts in public finance management" in 2023–2025. It also includes scientific work on econometric modeling and machine learning methods.

The use of various methods for forecasting federal budget revenues in various countries is studied in the works of a number of authors [7, p. 25; 8, p. 1215]. They most often substantiate the effectiveness of using author's models and forecasting methods at certain stages of economic development. In most studies, the choice of a model from a variety of design options is based on the calculation of various errors [9, p. 134698].

Scientific research by Russian and foreign scientists devoted to reservoir computing does not address the issues of forecasting federal budget revenues, nor does it reveal the specifics of data preprocessing for model formation and configuration.

The RC model with configured hyperparameters will improve the quality of forecasts of budget revenues of the Russian Federation and improve budget planning.

The model uses preprocessed monthly and daily data to improve the quality of forecasts. The experiments carried out by the authors make it possible to justify the choice of a model based on minimizing the size of errors, which reduces the discrepancy between its actual and predicted values.

During the research and selection of hyperparameters of the reservoir computing model, methods of comparative analysis, description of the methodology of reservoir computing, experiment were used to build a model, form hypotheses, generalize accumulated theoretical data and explain the practical results obtained.

THE RESULTS OF THE STUDY. RESERVOIR CALCULATIONS AND THEIR USE IN MODERN PRACTICE

Reservoir calculations were developed by H. Jaeger [10, p. 6]. RC is used when the system under study has chaotic or complex spatiotemporal behavior. The use of reservoir calculations in order to predict budget indicators is a new area of research (*Table 1*).

RC research is primarily theoretical in nature, but practical application in the financial field started with the work of P. Tziatzios in 2019 [15]. Later, a study showed the effectiveness of using this method for forecasting macroeconomic indicators, using the example of the US GDP [8, p. 1215].

CHARACTERISTICS OF THE RC MODEL

The RC is based on a recurrent artificial neural network with a pool of interconnected neurons (*Fig. 1*). The RC architecture consists of an input layer of the $d_r \times d_x$, reading matrix (W^{in}) of the $d_x \times 1$ states of the vector x, a randomly selected inner layer of the $d_r \times d_r$ matrix for the internal states of the $d_r \times 1$ vector r, and a trained reader the output layer of the matrix (W^{out}) $d_x \times d_r$. The essence of RC boils down to reservoir modeling. The quality of the model is changed by adjusting the hyperparameters.

Table 1

Comparative Characteristics of RC Research

Author	The direction of research	The problem being solved
H. Jaeger, H. Haas [11, p. 78]	It is proved that in echo-state networks, the learning method is easy to use and allows efficient calculations	The engineering task of leveling the communication channel
J. Pathak, B. Hunt, M. Girvan, Z. Lu, E. Ott [12]	The effectiveness of using machine learning to predict spatiotemporal chaotic systems of a large attractor dimension is shown	Description of the reservoir calculation algorithm
D.J. Gauthier, E. Bollt, A. Griffith, W.A.S. Barbosa [13, p. 1]	RC is proven to be the best-in-class machine learning algorithms for information processing of dynamic systems	Descriptions of the reservoir computing algorithm
J.A. Platt, A. Wong, R. Clark, S.G. Penny, H.D.I. Abarbanel [14]	Problems with the selection of RC hyperparameters have been identified, which can be solved using a method based on generalized synchronization	Description of the algorithm that allows you to select hyperparameters in RC and determine the quality of the resulting reservoir
P. Tziatzios [15]	A reservoir calculation tool, Echo State Networks (ESN), is described, which is used to predict real, raw financial data	Stock market forecast and indices
G. Ballarin, P. Dellaportas, L. Griliryeva, M. Hirt, S. Huellen, J.-P. Ortega [8, p. 1215]	Using the example of forecasting US GDP, the effectiveness of a multi-frequency network of echo states in comparison with a dynamic factor model and a reduction in computational costs are proved	Forecast of US macroeconomic indicators
A. Santos, R.R. Lima, J.L. Alves, D.W. Misturini, J.B. Florindo [9, p. 134698]	The superiority of the author's model in the stock market is proved, which involves combining the initial time series data when calculating RC with Hurst indicators calculated using sliding windows	Forecast of S&P 500, NASDAQ, DJIA, etc.

Source: Developed by the authors.

RC's can be divided, depending on the architecture used, into:

- Single (single-reservoir)
- Multi-reservoir:

– Hierarchical with several subsystems. Input data is fed into the first subsystem, which then transmits it to the other subsystems.

– Parallel, where two independent subsystems (reservoirs) receive the same input signal. Both subsystems provide output data with different hyperparameter settings.

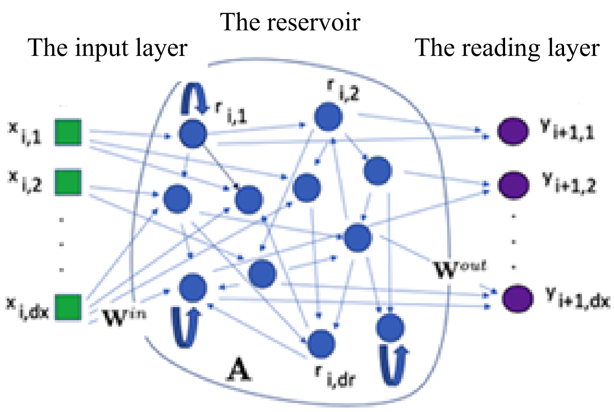

Fig. 1. **RC Architecture [17]**

Source: Developed by the authors.

Table 2

Data for Modeling the Forecast of Federal Budget Revenues

Code	Naming of the indicator	Type of conversion	Source
	Monthly		
QD	Federal budget revenues	The logarithm of the income of the first difference *	The Ministry of Finance of the Russian Federation
QR	Federal budget expenditures	FOD**	
M1	Industrial Production Index	FOD	Rosstat
M4	Real accrued salary		
M5	Commissioning of residential buildings		
M7	Retail sale of basic goods		
M11	Real effective ruble exchange rate	–	The Bank of Russia
M12	Key rate of the Bank of Russia	FOD	
M14	The difference between the yield of the Moscow Exchange index of corporate bonds Rated BBB and the coupon-free yield of government bonds (% per annum) for 0.25 years		The Moscow Stock Exchange
M15	The difference between the yield of the broad market Moscow Exchange index and the coupon-free yield of government bonds (% per annum) for 0.25 years		
M2	Production capacity utilization		Rosstat
M3	Unemployment rate		
M6	Dynamics of the volume of paid services to the population		
M8	Consumer price and tariff indices for goods and services	–	
M9	Consumer Confidence Index	-	
M10	Producer price indices for industrial goods	FOD	
M13	The difference between the yield of the Moscow Stock Exchange index of corporate bonds Rated AAA and the coupon-free yield of government bonds (% per annum) for 0.25 years		The Moscow Stock Exchange
M16	The difference between the yield of the Moscow Exchange index of corporate bonds (less than 1 year) and the coupon-free yield of government bonds (% per annum) for 0.25 years		
M17	The difference between the yield of the Moscow Exchange index of corporate bonds (3–5 years) and the coupon-free yield of government bonds (% per annum) for 0.25 years	-	
M18	Government Bond Index (3–5 years)	FOD	
M19	Index of government bonds (5–10 years)		
M20	The difference between the yield of the Government Bond Index (5–10 years) and the government bond index for less than 1 year		

Table 2 (continued)

Code	Naming of the indicator	Type of conversion	Source
Daily			
D1	Moscow Exchange Index	FOD	The Moscow Stock Exchange
D2	The difference between the profitability of the Moscow Blue-chip Exchange index and the Moscow Information Technology Exchange index		
D3	The RTS Index		
D4	Index of the Moscow Stock Exchange of the electric power industry		
D5	Index of the Moscow Stock Exchange of the consumer sector		
D6	Brent crude oil price		
D7	Gold price	GARCH***	
D8	The price of the Russian Wheat Index Novorossiysk		
D9	Natural gas price		
D10	The difference between the yield of a futures contract for Brent crude oil and the price of Brent crude oil	FOD	
D11	The difference between the yield of a gold futures contract and the gold price		
D12	The difference between the yield of a futures contract for the Russian Wheat Index Novorossiysk and the price of the Russian Wheat Index Novorossiysk		
D13	The difference between the yield of a natural gas futures contract and the price of natural gas		

Source: Developed by the authors.

Note: * or modeling without PCA; ** first-order differentiation; *** the method of generalized autoregressive conditional heteroscedasticity.

THE DATA FOR BUILDING THE MODEL AND THE PROCESS OF THEIR PREPROCESSING

The research revealed a list of indicators used in the Eurozone and the USA for forecasting macroeconomic indicators [8, p. 1218] and budget system revenues [16; 17, p. 179; 18, p. 109; 19, p. 21]. By analogy, the Russian data were selected for analysis (*Table 2*).

It has been revealed that the quality of the Russian data limits the ability to train the model. A full time series of daily and monthly data has been available since 2021, but part of the time series has been fragmented due to holidays, weekends, and the temporary suspension of trading on the Moscow Stock Exchange in 2022.

To prepare the data for training, a pre-processing process was performed using the following steps: 1) assessing data completeness, 2) excluding variables with gaps that cannot be filled, 3) combining daily and monthly arrays using interpolation, 4) checking for stationarity, 5) transforming data, 6) determining multicollinearity between indicators, and 7) reducing the dimension of the data using

Table 3

Comparative Assessment of the Quality of Federal Budget Revenue Forecasting Models

Model	Tank Settings	Mean Squared Error	Root Mean Square Error	Root Mean Square Percentage Error
The autoregressive model	–	7274.772	85.292	1.693
Single-Tank Tank Computing Models (S-MFESN				
with 30 neurons	ρ = 0.5 γ = 1 α = 0.1	7267.801	85.251	1.693
with 120 neurons		7278.529	85.251	0.999
Two-tank Tank Computing Models (M–MFESN):	The reservoir for monthly data is 100 neurons, daily 20 neurons:			
Model A	monthly; ρ = 0.5 γ = 1.5 α = 0 daily: ρ = 0.5 γ = 0.5 α = 0.1	10 525,614	102.594	1.005
Model B	monthly: ρ = 0.08 γ = 0.25 α = 0.3 daily: ρ = 0.01 γ = 0.01 α = 0.99	8403.114	91.670	1.447

Source: Developed by the authors.

Principal Component Analysis (PCA) to obtain an array for training the forecast models.

THE RESULTS OF MODELING THE FORECAST OF FEDERAL BUDGET REVENUES USING RC AT THE FIRST STAGE OF THE STUDY

The simulation was carried out in two stages. At the first stage, steps 1–5 of the preprocessing algorithm were used for data preprocessing.

The study predicted the monthly revenues of the federal budget of the Russian Federation. The script presented in [4] is used as a basis. A forecast with four different settings was obtained, the quality of which is compared with the result of the autoregressive model (*Table 3*).

Table 4

The Values of Forecast Errors

Model	Reservoir_size	Leak_rate	Spectral_radius	Input_scaling	MSE	RMSE	Mean Absolute Percentage Error
1.1.1–1.1.4	600	0.7	0.8	0.7	163 282.13	404.08	15.20
1.2.1–1.2.4			1.2	0.9	158 336.33	397.91	14.87
1.3.1–1.3.4		0.9	0.8	0.7	148 112.22	384.85	14.65
1.4.1–1.4.4			1.2	0.9	151 409.88	389.11	14.30
2.1.1–2.1.4	850	0.7	0.8	0.7	138 175.45	371.72	11.99
2.2.1–2.2.4			1.2	0.9	143 011.06	378.17	12.59
2.3.1–2.3.4		0.9	0.8	0.7	138 545.47	372.22	12.66
2.4.1–2.4.4			1.2	0.9	145 373.28	381.28	13.02
3.1.1–3.1.4	1100	0.7	0.8	0.7	121 197.68	348.13	12.09
3.2.1–3.2.4			1.2	0.9	114 798.47	338.82	11.65
3.3.1–3.3.4		0.9	0.8	0.7	116 681.23	341.59	12.21
3.4.1–3.4.4			1.2	0.9	116 039.69	340.65	12.10

Source: Developed by the authors.

The model with one tank produced the best results, with the smallest error. The error size was slightly higher in the autoregressive model, but using a model with a single reservoir for 120 neurons reduced the relative RMS error by 69.5%.

Models with two tanks had more significant errors, but their configuration did not significantly affect the quality characteristics. This suggests that further data preprocessing may be necessary to improve the results.

THE CONSTRUCTION OF THE AUTHOR'S RC MODEL AT THE SECOND STAGE OF THE STUDY

At the second stage, the data preprocessing process continued to build a revenue forecasting model for the federal budget of the Russian Federation. Principal Component Analysis (PCA) was used for this purpose. The following algorithm was assumed:

1. Formation of a complete set of stationary data without gaps.
2. Calculation of correlation and covariance matrices for variables to evaluate relationships in the data and justify the use of the principal component method.
3. Selection of relevant variables for analysis of the main components.
4. Conversion of timestamps to numerical format.
5. Visualization of principal components and eigenvalues.
6. Saving the first 11 principal components out of 17 to preserve the data structure.
7. Reconstruction and preservation of the dataset with addition of timestamps and original time series for the target variable.

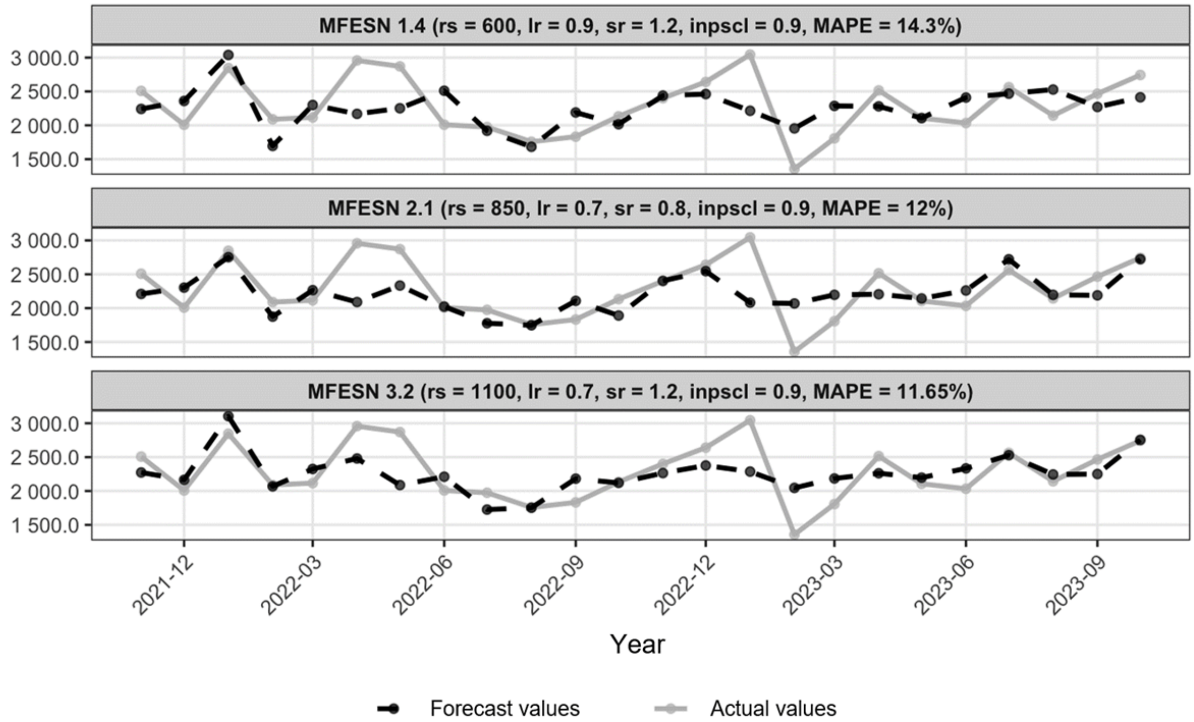

Fig. 2. **Visualization of the Best Models by MAPE Value**

Source: Developed by the authors.

The architecture of the model used in the study was employed for calculations [8, p. 1221]. The experiment involved 12 different combinations (*Table 4*), and random_seed was not recorded in order to test the stability of the predictions made by the models. Each model was trained four times with inference, and the predicted values and forecast errors were saved.

Three models were selected based on the size of the resulting indicator (MAPE) values: ESN 1.4, ESN 2.1, ESN 3.2. It has been revealed:

1. Increasing the size of the reservoir improves the quality of the forecast regardless of the combination of other hyperparameters, since larger reservoirs provide higher computing power and the ability to store complex time dependencies in economic data.

2. Improved prediction quality in most hyperparameter configurations occurs by reducing the rate of state leakage (leak_rate).

3. Increasing the forecast of economic patterns when using large reservoirs is carried out by increasing the spectral radius to 1.2, despite approaching the edge of chaos, due to the generation of richer nonlinear dynamics. This statement is true for models with 600 and 1100 neurons.

All the studied models showed no signs of significant instability when using a spectral radius of 1.2, considering the consistency of the error size for each model. There is no need to adjust the regularization value. Among the three tank sizes, the models with the best forecasting quality are characterized by an increased sensitivity to the input signal (input_scale = 0.9).

Analyzing the forecast values of the three selected models over time, we can draw the following conclusions:

- ESN 1.4 demonstrates the highest stability with a coefficient of variation of MAPE = 74.7%, which is significantly lower than that of models with larger reservoirs (ESN 2.1: 101.5%, ESN 3.2: 96.5%). Therefore, larger reservoirs are more sensitive to input data and can produce both highly accurate and significantly inaccurate forecasts.
- ESN 2.1 has an average accuracy of 12.0% MAPE with a high coefficient of variation

Table 5

Comparative Assessment of the Quality of Predictive Models

Model	MSE	RMSE	MAPE
ESN 3.2	114798.47	338.82	11.65
ARIMA	452857.36	672.95	34.16
LSTM	151076.36	388.68	13.55

Source: Developed by the authors.

of 101.5%. It achieves 73.9% accuracy in the direction of the trend and provides more forecast values with an MAPE of less than 5% compared to other models.

• ESN 3.2 outperforms other models in terms of predicting the direction of change: 82.6% accuracy compared to 73.9% for ESN 2.1 and 60.9% for ESN 1.4.

Visualization of the selected models (*Fig. 2*) and their comparison with actual data indicate the feasibility of using them to forecast federal budget revenues over a horizon of up to three months. However, using them over a longer horizon is not recommended due to a significant averaging of predicted values and an increase in error.

The models (ESN 1.4, ESN 2.1, and ESN 3.2) experience difficulties in predicting minimum values of federal budget revenues below 1,600 billion rubles, with MAPE reaching 44–53%. This indicates a limitation of the models and requires further investigation. A similar issue exists when forecasting revenues exceeding 2,800 billion rubles; when using these models, MAPE ranges from 19% to 21%.

The ESN 3.2 model was recognized as the best, having hyperparameters: reservoir_size: 1100; spectral_radius: 1.2; sparsity: 0.5; noise: 0.01; input_scaling: 0.9; leak_rate: 0.7; residual_scale: 0.1; warmup: 200; ridge_alpha: 1e-5; random_state: 3.

The size of the errors obtained using the selected ESN 3.2 model was compared with similar values of ARIMA and LSTM trained on the same data set (*Table 5*).

The author's model based on reservoir calculations is characterized by a minimum error size. In particular, LSTM's MSE is 24% higher than ESN's, and ARIMA's is 74.65% higher.

CONCLUSIONS

Improving the accuracy of budget revenue forecasts is essential for effective government budget planning. This task is complicated by economic fluctuations and the interaction with government policies. Geopolitical tensions, risks, and the uncertainty and instability of the global economy have a significant impact on the process.

Existing predictive models cannot accurately predict budget revenues, which are a stochastic process. To improve the quality of predictions, it is necessary to integrate new machine learning techniques. This study aims to use advanced machine learning technologies, such as RC technology, to forecast federal budget revenues more accurately. This will contribute to the creation of a budget that does not restrict the corporate and private sectors, stimulating investment activity.

The conducted research allowed us to draw the following conclusions:

1. The contribution of this study is to identify the feasibility of using RC models in forecasting federal budget revenues. It is the world's first attempt to use the method in public finance. The use of a model using hyperparameters defined by the authors will improve the accuracy of calculations by 24%

compared to LSTM and by 74.65% according to ARIMA for a two-year forecast period. The results of the study were obtained under the conditions of a number of limitations presented in [7, p. 32].

2. The use of PCA for ESN 3.2 made it possible to significantly reduce the dimension of the training data array while maintaining performance, significantly increase computing resources, memory capacity and quality of the model, and improve the ability to simulate stochastic time series dynamics. The increase in the spectral radius made it possible to achieve more pronounced trend dynamics due to the long-term retention of information. Increasing the scale of the input data made it possible to improve the model's response to input signals and the condition of the reservoir, which led to an improvement in the quality of the author's model in conditions of limited data.

3. The model reduces computing resources without loss of accuracy. Further research should include testing large reservoirs and developing models for various planning horizons.

4. The model is recommended for practical use in ministries and departments with the possibility of operational adjustments in real time.

5. The importance of the model proposed by the authors for the fiscal policy of the Russian Federation is to improve the quality of management decisions while minimizing the resources allocated by reducing the error in forecasting budget revenues, and calculating taxes and payments necessary to replenish the budget more correctly. This will make it possible to more efficiently redistribute available resources for various purposes: achieving economic growth, stabilizing prices, reducing inflation, increasing employment due to increased institutional confidence, etc. The model's ability to update revenue streams in real time, use high-frequency data, and meet the requirements of a balanced budget allows it to be quickly adjusted to reflect the latest economic changes.

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