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PREDICTING FEDERAL REVENUE COLLECTION FOR THE BRAZILIAN GOVERNMENT: AN APPLICATION OF TIME SERIES AND NEURAL NETWORKS[*]

PREVISÃO DA ARRECADAÇÃO DE RECEITAS FEDERAIS PARA O GOVERNO BRASILEIRO: UMA APLICAÇÃO DE SÉRIES TEMPORAIS E REDES NEURAIS

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ABSTRACT

Accurate revenue forecasting is critical for fiscal stability, yet traditional models struggle with volatility. This study innovates by comparing the classic SARIMA model against an Autoregressive Neural Network (NNAR) to forecast Brazilian federal tax revenue (1994-2025). The NNAR model demonstrated clear superiority, reducing the prediction error by 19.7%. This provides a more accurate and robust machine learning tool for budgetary planning and fiscal transparency.

Keywords: SARIMA Models. Forecasting. Neural network.

RESUMO

A precisão na previsão de receitas é vital para o planejamento fiscal, mas modelos tradicionais são limitados. Este estudo inova ao comparar o modelo clássico SARIMA com uma Rede Neural Autorregressiva (NNAR) para prever a arrecadação federal brasileira (1994-2025). Os resultados demonstram a superioridade do *machine learning*, com o modelo NNAR reduzindo o erro de previsão em 19,7%, fornecendo uma ferramenta mais acurada e robusta para a gestão orçamentária.

Palavras-chave: Modelos SARIMA. Previsão. Redes neurais.

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1. Introduction

Tax collection is one of the main sources of revenue available for financing public policies carried out in Brazil by the three federative entities: the Union, states, and municipalities. The federative pact defined by the 1988 Constitution establishes that both tax collection and the execution of public policies are tasks shared by the three entities. In this design, the Union holds the largest share of the tax revenue pool—just over 25% of GDP when considering the sum of taxes, social contributions, and other revenues (Tesouro Nacional, 2024).

The 1988 Constitution also determines that part of the Union's revenue be distributed to states and municipalities, precisely to finance the country's main public policies, which are executed primarily by subnational entities. The State Participation Fund (FPE) and the Municipal Participation Fund (FPM) are fundamental revenues for these entities—especially the FPM for municipalities, representing, roughly, 2/3 of their total revenue.

The impact (on the Brazilian economy) of public policy execution by subnational entities, partially financed by federal transfers, should not be overlooked: for every BRL 1 spent by the Union on intermediate consumption, states and municipalities spend BRL 5.68; likewise, for every BRL 1 spent by the Union on investments, states and municipalities spend BRL 4.45; finally, for every job in the Union, there are almost ten in these subnational entities (Santos, 2024).

Therefore, for the execution of the main public policies carried out in the country, it becomes extremely important to adequately estimate the magnitude of federal revenues. In this regard, the role of the Special Secretariat of the Federal Revenue of Brazil (SRFB) is noteworthy. The purposes, obligations, and competencies of the SRFB can be found in the Ministry of Economy Ordinance No. 284 of July 27, 2020. Among these competencies, the forecasting and analysis of federal revenues to support the preparation of the Union's budget proposal must be emphasized.

Thus, presenting a credible theoretical framework for the preparation of the Union's budget proposal is one of the main objectives of federal revenue forecasting, seeking responsibility in the fiscal management of public accounts, especially after the advent of Complementary Law No. 101, of May 4, 2000, known as the Fiscal Responsibility Law. In this context, this law explicitly highlights revenue forecasting as one of the essential requirements for responsible fiscal management, prohibiting the voluntary transfer of revenues to any federative entity that fails to observe this mandate.

According to Art. 12 of Complementary Law No. 101, revenue forecasts must be based on technical and legal standards, considering changes in current legislation, variations in the price index, economic growth, or any other relevant factor. Furthermore, it is understood that such forecasts must be accompanied by a statement of their evolution over the last three years, the projection for the two years following the one they refer to, and the calculation methodology and assumptions used.

Based on the information from Ministry of Economy Ordinance No. 284 and Complementary Law No. 101, it is clear that a robust estimation of public revenue collection is an essential condition for preparing the government's annual budget and, consequently, necessary for balancing public accounts. In this sense, to carry out the budgetary forecasting task, the SRFB uses a method called the "Indicator Method" (*Método dos indicadores*), which is based on applying specific indices to the revenue collected in a given period to forecast the revenue for the following period (Siqueira, 2002).

In studies by Siqueira (2002), ARIMA (Autoregressive Integrated Moving Average) models from the Box-Jenkins methodology were used to forecast federal tax revenues from 1989 to 2000, finding that the ARIMA models were superior to the Indicator Method used by the SRFB. Similarly, in works by Castanho (2011), Holt-Winters exponential smoothing models, also from the Box-Jenkins methodology, were used to forecast the ICMS (a state-level tax) series for the state of Espírito Santo, comparing the predictive power of the adjusted models using the mean absolute percentage error.

Several studies in different contexts seek to compare forecasting techniques to capture complex patterns in time series. For example, Lam and Oshodi (2016) applied both methods to forecast construction cost indices, while Ahmar and Boj (2021) analyzed the COVID-19 infection fatality rate in Brazil. In another field, Luzia et al. (2023) focused on forecasting Brazilian agricultural commodity prices. In all these distinct fields, the authors highlighted that neural network models were more accurate than ARIMA models (especially in the short term), suggesting that the ANN's ability to handle non-linearities is a robust advantage across different domains.

Given this scenario, this study proposes an advancement in the predictive analysis of federal revenues. While the traditional literature on this topic has focused on linear models (Box-Jenkins), this research innovates by applying Artificial Neural Networks (ANNs), a methodology capable of capturing the complex and non-linear patterns inherent in tax collection, which are often overlooked by classic models. The objective is to quantify the gain in accuracy achieved by this more robust approach. To do this, we compared the predictive power of the SARIMA and ANN models using the Root Mean Squared Error (RMSE), analyzing the historical series from January 1994 to August 2025 and reserving the final 10% of the data for model validation (test set).

2. Public Revenue Forecasting

According to Alves (2015), the Public Budget is an important tool for planning government actions and fiscal management. In turn, budget elaboration through the legislative process aims to share the decision on the allocation of public resources between the government and the parliament.

The budget proposal is, initially, based on projections and estimates of macroeconomic variables that affect public revenues and expenditures, such as interest rates, inflation, and GDP growth. During the budget's execution, these variables may deviate from what was estimated, thus requiring a readjustment of the budgetary expenditure configuration to maintain the primary surplus targets established in the Budgetary Guidelines Law (*Lei de Diretrizes Orçamentárias*) and to maintain the balance of public accounts (Alves, 2015).

The revenues collected by the government provide the necessary resources for the development of public policies by the government. For the execution of public policies, knowledge of federal revenues becomes extremely important. In this regard, the Special Secretariat of the Federal Revenue of Brazil (RFB) is noteworthy, as one of its functions is to forecast these federal government tax collections.

Through the Ministry of Economy (ME) Ordinance No. 284 of July 27, 2020, it is possible to observe the purposes, obligations, and competencies provided for the Special Secretariat of the Federal Revenue of Brazil. Among these purposes and obligations, it should be emphasized that this Special Secretariat of the RFB is responsible for forecasting, monitoring, analyzing, and controlling the revenues under its administration, in addition to coordinating and consolidating the forecasts of other federal revenues, to support the preparation of the Union's budget proposal (Brasil, 2020).

Public revenue forecasts are of paramount importance for the preparation of the government's annual budget, as well as a mechanism to guide and limit public spending. According to Siqueira (2002), such forecasts can be applied both to the total aggregate revenue and to its individual sources, such as those originating from consumption taxes or property taxes, among others. In this sense, there are various forecasting techniques available, whose processes may involve qualitative and quantitative techniques.

According to Siqueira (2002), qualitative methods are based on conjectures about the future collection of certain revenues, being denominated as conjectural or non-extrapolative approaches. This technique uses an individual or a small group of people with the objective of making assessments of probable future circumstances and analyzing their effects on the revenue to be forecasted. Furthermore, qualitative techniques do not present mathematical formality, rigorous hypotheses, and numerical data, as is the case with quantitative methods.

Quantitative methods use mathematical models, based on numerical (past) data to make forecasts for a response variable. Such methods seek to make explicit the hypotheses to be tested and the procedures used to generate the forecasts, in addition to assigning a margin of error to the forecasts, providing confidence intervals for the data. The work of Azevedo et al. (2017) found that forecasts of consumption taxes, such as the Tax on Circulation of Goods and Services (ICMS), generated by time series showed better accuracy when compared to the estimates from the federative entities.

In the study by Chain et al. (2015), the use of quantitative techniques aimed to estimate a predictive model for ICMS collection by the government of Minas Gerais, in order to compare some time series techniques, such as models from the Box-Jenkins family. Furthermore, in studies by Bernardino et al. (2021), the use of time series models was also observed in generating estimates for ICMS revenues for the state of Sergipe, the results of which pointed to the advances that the Box-Jenkins family models brought to the analyzed forecasts.

In general, the most used methodologies for forecasting tax revenues are the models from the Box-Jenkins family, as seen, for example, in Siqueira (2002), Chain et al. (2015), Azevedo et al. (2017), Pereira, Sampaio, and Guilherme (2019), and Bernardino et al. (2021).

The main hypothesis of the time series technique is that the patterns associated with the past values of a data series can be used to project future values.

2.1 Box-Jenkins Time Series Models

The methodology of financial time series analysis aims to forecast future values based on statistical experience, that is, quantitative methods (Morettin, 2017). Among time series models, the Autoregressive Integrated Moving Average (ARIMA) models stand out for constructing forecasting models. The general formula for the ARIMA model, considering \$d\$ differences of the original series X_t for it to become stationary, is given by:

$$\phi(B)\Delta^d X_t = \theta_0 + \theta(B)a_t$$

where $\phi(B)$ is the autoregressive operator of order p, and $\theta(B)$ is the invertible moving average operator of order q (Morettin, 2017).

ARIMA models can be extended for use in seasonal series, known as Seasonal Autoregressive Integrated Moving Average (SARIMA) models. The representation of a $SARIMA\ (p, d, q)(P, D, Q)_S$ model using the lag operator B and D differences is given by (Morettin, 2006):

$$\phi(B)\Phi\left(B^S\right)(1-B)^d\left(1-B^S\right)^D X_t = \theta(B)\Theta\left(B^S\right)a_t$$

where $\phi(B)$ is the autoregressive operator of order p; $\Phi(B^s)$ is the seasonal autoregressive operator of order P; $\theta(B)$ is the invertible moving average operator of order q; $\Theta(B^s)$ is the invertible seasonal moving average operator of order Q; $(1 - B)^d$ is the difference operator of order d; $(1 - B^s)^D$ is the seasonal difference operator of order D (Morettin, 2017).

The assumptions that must be analyzed in $SARIMA(p, d, q)(P, D, Q)_S$ models relate to invertibility and stationarity. Regarding stationarity, a process is stationary if the roots of the characteristic equation, $\phi(B)$, lie outside the unit circle; or, it can be said that a process is stationary when it develops over time around a constant mean. Regarding the invertibility of a process, it is necessary that all roots of the polynomial $\theta(B)$ lie outside the unit circle.

To verify stationarity, the Dickey-Fuller test can be used, where the hypotheses are: $H_0: \phi = 0$ against $H_1: \phi < 0$. Thus, it is being tested whether the process is stationary. Economic and financial series are generally not stationary, but when differenced, they can become stationary. Thus, before fitting any model to a series, it is necessary to check for its stationarity, so that the data do not have a mean that changes over time.

According to Morettin (2017), the Box-Jenkins methodology includes three stages: identification, estimation, and verification (diagnostic checking), to select the appropriate model for the given process. In this manner, the identification of the model to be fitted to the data is primarily based on the estimated autocorrelations and partial autocorrelations, which suggest the orders of the model. The objective of identification is to determine the p, d and q values of the ARIMA (p, d, q) model, consisting of three fundamental steps: (i) verify if the series' variance is constant; (ii) take differences of the series to obtain a stationary series; and (iii) identify the resulting ARMA (p, q) process by analyzing the estimated autocorrelations and partial autocorrelations (Morettin, 2017).

After identifying the model, the next step is the estimation of its parameters, which, in turn, can be done by an estimation method, such as the method of moments or the maximum likelihood method. Finally, the last stage refers to the validation of the fitted model, which can be done by analyzing the residuals. If the model is adequate, these should be approximately uncorrelated.

2.2 Artificial Neural Networks

Artificial Neural Networks (ANNs) can be divided into three parts, called layers, which are named as follows: the input layer, responsible for receiving information (data); the hidden layer, composed of neurons that seek to extract features associated with the process; and the output layer, also composed of neurons, responsible for producing and presenting the final results of the network (Russel & Norvig, 2022).

Deep neural networks are acyclic graphs that compute a function through the successive processing of layers. The depth of the network refers to the number of layers. Among the main types of deep architectures are: (i) single-layer feedforward, (ii) multilayer feedforward, and (iii) feedback networks (Goodfellow, Bengio, & Courville, 2016).

In a single-layer feedforward architecture, there is an input layer that projects onto an output layer of neurons, but not the other way around. In other words, this network forms a directed acyclic graph with designated input and output nodes. Each node computes a function of its inputs and passes the result to its successors in the network. Information flows through the network from input nodes to output nodes, with no loops. The flow of information always proceeds in a single direction—from the input layer to the output layer (Russel & Norvig, 2022).

Multilayer feedforward networks are distinguished by the presence of one or more hidden layers. The function of the hidden neurons is to intervene between the external input and the network's output in a useful manner. By adding one or more hidden layers, the network becomes capable of extracting higher-order statistics. The source nodes in the network's input layer provide the respective elements of the activation pattern (input vector), which constitute the input signals applied to the neurons in the second layer. The output signals of the second layer are used as input for the third layer, and so on throughout the rest of the network. Feedback networks (recurrent networks) differ from feedforward networks by the existence of at least one recurrence/feedback loop (Goodfellow, Bengio, & Courville, 2016).

Hyndman et al. (2020) proposed a feedforward neural network with a single hidden layer and lagged inputs to perform univariate time series forecasting in R software. Thus, a feedforward neural network is fitted using lagged values of the time series (y) as inputs and a single hidden layer with a user-defined number of nodes. The network is trained for one-step-ahead forecasting, and multi-step forecasts are computed recursively.

For non-seasonal data, the fitted model is called an NNAR(p,k) model, where k is the number of hidden nodes. This is analogous to an AR(p) model but with nonlinear functions. For seasonal data, the fitted model is called an NNAR(p,P,k)[m] model, which is analogous to an ARIMA(p,0,0)(P,0,0)[m] model but with nonlinear functions (Hyndman et al., 2020).

In the study by Safi and White (2017), the forecasting accuracy of two methods (ARIMA and ANN) was compared using data from the Palestine Stock Market. The results indicated that ANN models produced more accurate forecasts for the dataset analyzed. Furthermore, the results suggested that ANNs become more accurate as more information is fed into the model and that these ANNs can often be preferable to assuming an ARIMA model when the true model is nonlinear (Safi & White, 2017). Similarly, Sekadakis et al. (2022) found that neural network methods outperformed ARIMA models in predicting driving behavior and its correlation with the strictness of COVID-19 response measures.

3. Methods

The data used in this study were obtained from the Institute for Applied Economic Research (IPEA) and refer to the gross collection of federal government taxes from January 1994 to August 2025. Regarding data analysis and processing, an initial descriptive analysis of the series under study was conducted. Next, the historical series was deflated using the monthly IPCA (Broad National Consumer Price Index) in order to use real values in the time series analyses of the models studied.

First, descriptive analyses of the data were carried out using statistical measures and time series plots. Then, the processes of model identification, estimation, and validation were performed using the R programming language (R Core Team, 2025). Using the time series of real values, statistical tests were applied to forecast the future behavior of the revenue from the aforementioned taxes, namely: i) Stationarity test, a time series is said to be stationary when it evolves randomly over time around a constant mean; ii) Residual autocorrelation test, residuals are said to be white noise if they are uncorrelated.

The stationarity test adopted was the Augmented Dickey-Fuller (ADF) Test, whose null hypothesis states the existence of a unit root, that is, $H_0: \phi = 0$ against $H_1: \phi < 0$. Therefore, it tests whether the process is stationary. If H_0 is not rejected, it is assumed that the series is non-stationary; otherwise, the series is stationary.

Subsequently, the appropriate model for forecasting was identified: the ARIMA model, based on the autocorrelation function (ACF) and the partial autocorrelation function (PACF). Parameter estimates were obtained using the Exact Maximum Likelihood Method. Next, the Ljung-Box test was applied to test the white noise hypothesis for the model residuals.

To compare the SARIMA model, neural network models based on ARIMA structures were employed. The constructed network considers the structure of an ARIMA model but also incorporates the structure of a neural network so that the model can learn from the dataset and achieve better forecasting performance. The implementation of the model was carried out using the R programming language (R Core Team, 2025) through the *forecast* package (Hyndman et al., 2020).

Finally, to evaluate the model, part of the sample corresponding to 95% was used for training and the remaining 5% for testing, based on the Root Mean Square Error (RMSE). The RMSE is the measure used to represent the differences between the values predicted by a model and the values actually observed, which are called prediction errors when calculated for sample data,

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} \quad (x_i - \hat{x}_i)^2}{n}}$$

in which x_i is the actual time series, $\hat{x}_i$ is the series predicted by the applied model, and nnn is the number of predicted values. Thus, to compare the ARIMA model with the neural network model, the RMSE was used. The analyses were developed in the R programming language and are available on GitHub (https://github.com/leobiazoli/federal-revenue).

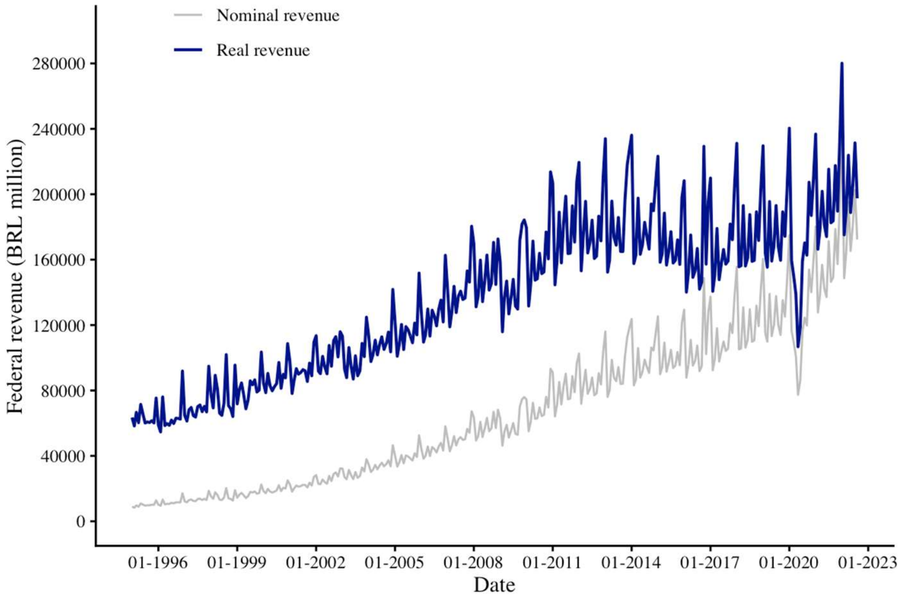
4. Analysis and Discussion of Results

Federal government tax revenues show a clear upward trend over the years, resulting in a non-constant mean over time, a visual characteristic of non-stationarity. In addition to the trend, the series (Figure 1) exhibits strong intra-year seasonality, notably with "peaks" in January. These peaks are consistent with the Brazilian tax calendar, which concentrates the payment of annual adjustments (e.g., corporate income tax) and other obligations at the beginning of the year. The presence of these components (trend and seasonality) in federal revenue is a well-documented finding; **Siqueira (2002)**, for example, had already identified these patterns and was a pioneer in proposing the Box-Jenkins (ARIMA) methodology for forecasting this same series.

The series is also susceptible to exogenous shocks, as observed by the abrupt decline in mid-March 2020 (onset of the COVID-19 pandemic), a phenomenon also noted at the municipal level by Fujiwara et al. (2020). The real revenues series (Figure 1), deflated by the IPCA, also reflects this long-term trend.

Given the clear visual non-stationarity, the original series requires differencing. The Augmented Dickey-Fuller (ADF) test was applied *after the first differencing (d=1)*, yielding a p-value of 0.01. This result ($p < 0.05$) rejects the null hypothesis (of a unit root) *for the differenced series*, confirming that the original series is stationary after one difference, i.e., Integrated of order 1, I(1). Additionally, tests confirmed the presence of a seasonal component (justifying D=1). Therefore, a SARIMA model was the appropriate approach, considering the orders indicated in the autocorrelation and partial autocorrelation functions.

Figure 1 – Time Series of Federal Government Tax Revenues



Source: Author's elaboration. Data source: IPEA, 2025.

The first adjusted model is a $\boldsymbol{SARIMA(5,1,2)_{12}}$, with a first-order difference operator and a first-order seasonal difference operator. Since this model was used for comparison with the neural network model, the last 37 months were set aside for testing against the fitted values. Thus, using the predicted values from this model, a comparison with the actual values was made, and the RMSE was calculated as 29,878.76. A graph was also generated to visualize the differences between the predicted and actual values (Figure 2). Subsequently, the time series forecast was performed considering all available monthly observations.

Table 1 – Parameters of the Adjusted ARIMA Model

Coefficients	Estimates	Standard error	z	Pr(>|z|)
ϕ_1	-0.6127	0.0605	-10.1273	< 2.2e-16
ϕ_2	0.0298	0.0731	0.4077	0.6835
ϕ_3	0.0978	0.0700	1.3971	0.1624
ϕ_4	-0.0431	0.0669	-0.6442	0.5194
ϕ_5	-0.4513	0.0501	-9.0080	< 2.2e-16
θ_1	0.0873	0.0500	1.7460	0.0808
θ_2	-0.8122	0.0489	-16.6094	< 2.2e-16
μ	446.8765	128.5837	3.4753	0.0005

Source: Author's elaboration.

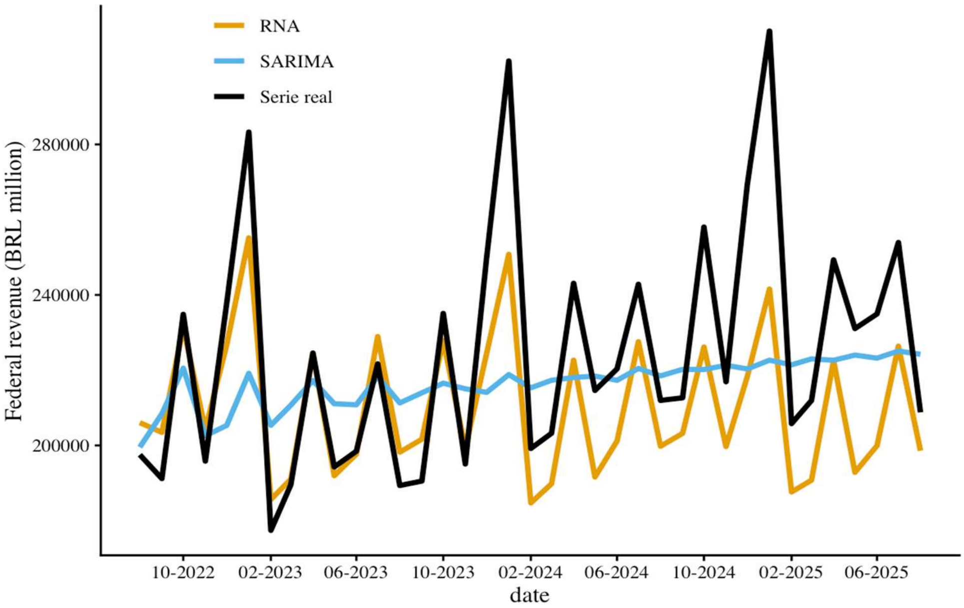
The Box–Pierce test makes it possible to verify whether the residuals of the series are independent; therefore, the null hypothesis indicates independence in a given time series. When applying the Ljung–Box test to the SARIMA model, it was observed that there is no evidence to reject the null hypothesis, suggesting that the residuals are uncorrelated (p-value = 0.9967).

Table 2 presents the predicted values of the fitted time series model for the months from August 2022 to August 2025. As shown in Figure 2, the SARIMA model was able to partially capture the pattern followed by tax revenues, as was the artificial neural network (ANN) model. As previously mentioned, the root mean square error (RMSE) of the SARIMA model was 29,878.76, whereas for the NNAR model, the RMSE was 23,983.70. The reduction in error was approximately 19.7% when comparing the two forecasting models used in this study, we observe that the NNAR model can generate good short-term estimates for forecasting federal public revenues.

The 19.7% reduction in the root mean square error (RMSE) is not merely a marginal statistical improvement. In the context of public accounting and budget planning—where revenue estimates form the basis for the *Lei Orçamentária Anual* (LOA, Annual Budget Law) and the *Lei de Diretrizes Orçamentárias* (LDO, Budget Guidelines Law)—forecasting errors directly affect resource allocation and fiscal stability. A smaller forecast error, such as that provided by the NNAR model, implies a planning process more consistent with reality, reducing the need for severe budget contingencies or excessive optimism in expenditures. Therefore, the result provides empirical evidence that adopting machine learning models can offer more accurate support for public management decision-making, increasing transparency and the reliability of fiscal projections.

The superior performance of the NNAR model is consistent with a growing body of literature demonstrating the ability of neural networks to capture complex dynamics that linear models, such as SARIMA, cannot (Zhang, 2003; Makridakis et al., 2018). SARIMA models are robust in capturing linear trends and seasonalities; however, tax revenue is often subject to nonlinearities, such as abrupt structural changes, asymmetric economic cycles, and exogenous shocks (like the COVID-19 pandemic, which is evident in the series). The NNAR architecture, acting as a universal function approximator, can learn these nonlinear patterns directly from the data, explaining its predictive advantage. The fact that the NNAR(32,20) model required a large number of lags (32) and hidden nodes (20) suggests the high complexity and strong nonlinearity of Brazil's tax revenue series, justifying the SARIMA model's failure to compete in terms of accuracy.

Figure 2 – Comparison of Models for the Federal Government Revenue of Brazil



Source: Author's elaboration.

The neural network model was used as an alternative method for forecasting federal government tax revenues. Consequently, forecasts were generated for the same period as the SARIMA model. As shown in Figure 2, the ANN series produced values closer to the original series and successfully followed the time series patterns from August 2022 onward. For seasonal data, the fitted ANN model is called an NNAR(32,20) model, which is analogous to an AR(32,20) model but with nonlinear functions. In the NNAR model, the number of hidden layers used for forecasting and model generation was 20.

The superiority of the NNAR is not surprising and lies in its architecture. The SARIMA model, by definition, is linear and assumes that seasonality and trend repeat constantly. Federal revenue, however, is subject to severe non-linearities: economic shocks, abrupt changes in tax legislation, and asymmetric business cycles, which a linear model fails to capture well. The neural network model employed an autoregressive model of order 32 and operated with 20 hidden nodes, producing the predicted values for the time series shown in Table 2. This architecture stands in stark contrast to the more parsimonious, linear SARIMA model. The NNAR's ability to "learn" these intricate, long-memory patterns, which the Box-Jenkins methodology simplifies or misses entirely, is a primary driver of its superior accuracy.

Table 2 – Predicted Values for the Time Series According to the Analyzed Models

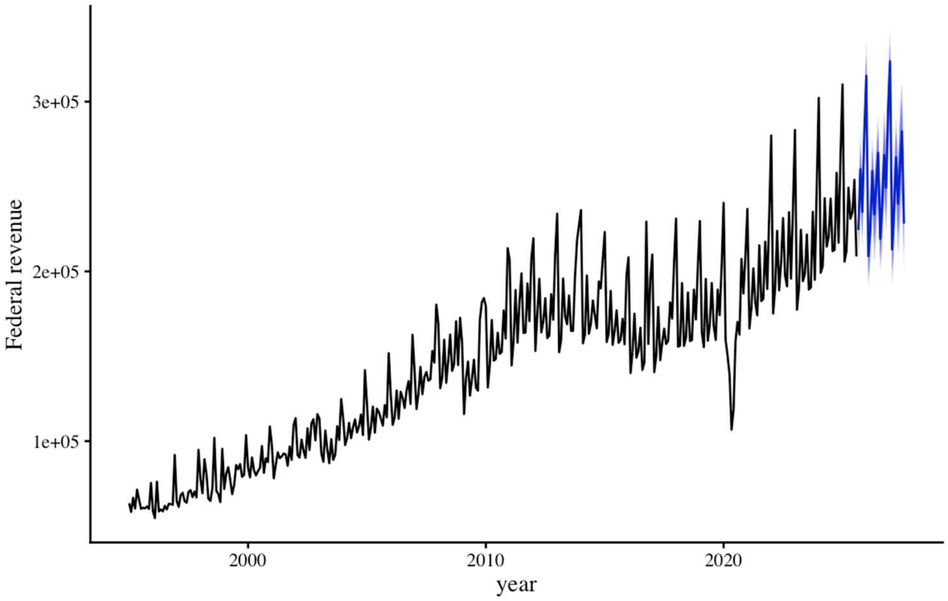
Month	RNA			SARIMA		
	Mean value	Lower limit	Upper limit	Mean value	Lower limit	Upper limit
09/2024	203209.8	169047.6	238438.6	220213.3	175196.2	265230.4
10/2024	226162.8	192164.0	260287.1	220168.8	174945.0	265392.6
11/2024	199688.3	164482.1	235636.4	221303.6	175854.3	266752.9
12/2024	218379.3	186055.9	254572.5	220327.6	174609.4	266045.7
01/2025	241572.4	209370.0	272991.1	222652.4	176760.8	268543.9
02/2025	187635.7	153378.4	219836.9	221417.7	175262.7	267572.7
03/2025	190764.0	155435.6	224672.0	223003.8	176637.8	269369.7
04/2025	222501.5	187562.4	255887.1	222637.1	176048.2	269225.9
05/2025	192843.0	158675.0	224991.8	224013.1	177217.5	270808.8
06/2025	199942.0	164556.4	234036.3	223202.9	176157.6	270248.1
07/2025	226384.3	191457.8	260750.9	225077.9	177847.8	272307.9
08/2025	198587.8	162907.3	233274.9	224224.1	176750.5	271697.7

Source: Author's elaboration.

A closer examination of the forecast values in Table 2 illustrates this difference clearly. The SARIMA model's predictions are overly "smoothed" and stable, hovering consistently around the 220k-225k range. It identifies the general trend (drift) but completely fails to capture the expected monthly volatility. The NNAR model, conversely, forecasts a much more dynamic and realistic path, successfully anticipating significant fluctuations, such as the characteristic seasonal peak in January (241,572.4) followed by a dip in February (187,635.7). This ability to model the non-linear seasonality and asymmetric shocks, rather than just a linear trend, explains its better fit and lower error.

In this way, it was observed that the NNAR model provided a better fit to the federal government tax revenue data, achieving a lower error than that obtained with the Box–Jenkins family model. Furthermore, as shown in Figure 2, the adjusted model was able to capture the patterns exhibited by the time series. Figure 3 presents the 24-month out-of-sample forecast generated by the Autoregressive Neural Network (NNAR) model, which was found to be the most accurate in this study. The black line represents the historical federal revenue series, while the solid navy blue line indicates the mean point forecast. The shaded blue areas illustrate the 80% and 95% prediction intervals, quantifying the uncertainty of the estimate. The NNAR model's projection suggests a continued growth trend, while also capturing the complex seasonal patterns the model was able to learn.

Figure 3 – Comparison of Models for the Federal Government Revenue of Brazil



Source: Author’s elaboration.

In conclusion, the results demonstrate that the NNAR model's superiority is not merely statistical (as reflected by the lower RMSE) but fundamentally practical. While the SARIMA model is limited to a smoothed, linear projection, failing to forecast volatility (Table

2), the NNAR(32,20) proves its ability to learn and replicate the complex, non-linear dynamics of tax revenue. The out-of-sample forecast (Figure 3) validates this finding, presenting a prognosis that is not just accurate but economically plausible, as it captures and extends the series' volatile seasonal patterns.

5. Final Considerations

Revenues derived from tax collection are of utmost importance for the planning and implementation of federal government public policies. Therefore, public revenue forecasts must be robust, providing predicted values as close as possible to actual values to support the preparation of the annual budget proposal (LOA) and maintain alignment with the Fiscal Responsibility Law.

In this context, the objective of this study was to compare a classic econometric model (SARIMA) with a machine learning approach (NNAR). The main contribution of this work lies in the empirical demonstration that the Artificial Neural Network methodology, capable of modeling complex non-linear patterns, significantly outperforms the linear model.

The NNAR model presented an error (RMSE) 19.7% lower than that of the SARIMA model, a substantial improvement that goes beyond a mere statistical gain. This reduction in error represents a more reliable tool for budgetary planning, with the potential to reduce the incidence of budget freezes (contingency measures) resulting from revenue overestimations.

The results demonstrate that although tax collection is affected by public policies that complicate modeling, the flexible architecture of neural networks can capture these dynamics with greater precision. The adoption of NNAR models for forecasting federal revenue proves to be a viable and superior alternative to the indicators method or classic linear models, contributing as a more reliable decision-support tool for public managers.

However, this study has limitations that pave the way for future research. First, the NNAR model, while accurate, operates as a "black box", making the direct economic interpretation of the factors influencing the forecast difficult, which presents a challenge for transparency in public administration. Second, the analysis was univariate, using only lagged values of the series itself. It is known that revenue is affected by macroeconomic variables;

therefore, the inclusion of exogenous variables (such as GDP growth, the SELIC interest rate, IPCA inflation, and consumer confidence indices) in multivariate models could contribute to further increasing predictive accuracy and will be the subject of future studies.

REFERENCES

AHMAR, Ansari Saleh; BOJ, Eva. Application of neural network time series (Nnar) and arima to forecast infection fatality rate (ifr) of covid-19 in Brazil. **JOIV: International Journal on Informatics Visualization**, v. 5, n. 1, p. 8-10, 2021.

ALVES, Gustavo HT. O orçamento federal entre a realidade e a ficção: as armadilhas à transparência da despesa pública no Brasil. **Revista da Controladoria-Geral da União**, v. 7, n. 11, p. 128-54, 2015.

AZEVEDO, Ricardo Rocha; DA SILVA, José Marcos; GATSIOS, Rafael Confetti. Análise crítica dos modelos de previsão de série temporal com base no icms estadual. **Revista de Gestão, Finanças e Contabilidade**, v. 7, n. 1, p. 164-184, 2017.

BERNARDINO, Wilton et al. PREVISÃO DA ARRECADAÇÃO DE ICMS PARA O ESTADO DE SERGIPE: MODELAGEM A PARTIR DA METODOLOGIA DE BOX E JENKINS. **Latin American Journal of Business Management**, v. 12, n. 1, 2021.

Brasil. Ministério da Economia. Gabinete do Ministro. **Portaria nº 284, de 27 de julho de 2020**. Brasília, 2020.

Castanho, BJ da S. Modelos para previsão de receitas tributárias: o ICMS do estado do Espírito Santo. 2011. *Tese de Doutorado*. Dissertação (Mestrado em Economia) - Centro de Ciências Jurídicas e Econômicas, Universidade Federal do Espírito Santo, Vitória, 2011.

CHAIN, Caio Peixoto et al. Contribuição da modelagem de valores atípicos na previsão da arrecadação do ICMS do Estado de Minas Gerais. **Exacta**, v. 13, n. 2, p. 239-249, 2015.

FUJIWARA, Ricardo Shigueru; CHROPACZ, Franciely; OFFMANN, Denis. Administração Tributária Municipal e a Covid-19: Um estudo do impacto nas receitas tributárias e nos serviços públicos. **Boletim de conjuntura (boca)**, v. 3, n. 8, p. 86-100, 2020.

GOODFELLOW, Ian et al. **Deep learning**. Cambridge: MIT press, 2016.

HYNDMAN, Rob J. et al. Package ‘forecast’. Disponível em: https://cran. r-project. org/web/packages/forecast/forecast. pdf, 2020.

HYNDMAN, Rob J.; KHANDAKAR, Yeasmin. Automatic time series forecasting: the forecast package for R. **Journal of statistical software**, v. 27, p. 1-22, 2008.

LAM, Ka Chi; OSHODI, Olalekan Shamsideen. Forecasting construction output: a comparison of artificial neural network and Box-Jenkins model. **Engineering, Construction and Architectural Management**, v. 23, n. 3, p. 302-322, 2016.

LUZIA, Ruan; RUBIO, Lihki; VELASQUEZ, Carlos E. Sensitivity analysis for forecasting Brazilian electricity demand using artificial neural networks and hybrid models based on Autoregressive Integrated Moving Average. **Energy**, v. 274, p. 127365, 2023.

MAKRIDAKIS, Spyros; SPILIOTIS, Evangelos; ASSIMAKOPOULOS, Vassilios. The M4 Competition: Results, findings, conclusion and way forward. **International Journal of forecasting**, v. 34, n. 4, p. 802-808, 2018.

MORETTIN, Pedro A. **Econometria financeira: um curso em séries temporais financeiras**. Editora Blucher, 2017.

MORETTIN, Pedro Alberto; TOLOI, Clélia Maria de Castro. Análise de séries temporais. 2022.

PEREIRA, Alan Frank Rodrigues; DE SOUZA SAMPAIO, Francisco Jean Carlos; GUILHERME, Hiponio Fortes. Estimativa da arrecadação própria municipal: um estudo da previsão dos impostos de municípios paraibano e potiguar através das séries temporais.

Brazilian Journal of Development, v. 5, n. 6, p. 5675-5699, 2019.

R CORE TEAM et al. R: A language and environment for statistical computing. **R foundation for statistical computing, Vienna, Austria**, 2025.

SAFI, Samir K.; WHITE, Alexander K. Short and long-term forecasting using artificial neural networks for stock prices in Palestine: a comparative study. **Electronic Journal of Applied Statistical Analysis**, v. 10, n. 1, p. 14-28, 2017.

SANTOS, Cláudio Hamilton Matos dos. Modelos vetoriais de correção de erros trimestrais para os componentes da demanda agregada, para as importações e para a carga tributária bruta. 2024.

SEKADAKIS, Marios et al. Driving behavior and its correlation with COVID-19 response measures: a neural network forecasting analysis. **Journal of transportation engineering, Part A: Systems**, v. 148, n. 10, p. 04022083, 2022.

SIQUEIRA, M. L. *Modelo de séries temporais para a previsão da arrecadação tributária federal*. 2002. Dissertação de Mestrado. Universidade Federal de Pernambuco.

STUART, R. J.; NORVIG, P. Inteligência Artificial–Uma Abordagem Moderna. **Barueri (SP): Editora GEN LTC**, 2022.

Tesouro Nacional. (2024). **Estatísticas Fiscais do Governo Geral** (Resultados 2023 (anual e trimestral)) [Relatório]. Tesouro Nacional. https://thot-arquivos.tesouro.gov.br/publicacao/49432

ZHANG, G. Peter. Time series forecasting using a hybrid ARIMA and neural network model. **Neurocomputing**, v. 50, p. 159-175, 2003.