Adv. Math. Fin. App., 2026, **11**(1), P. 17-34

Advances in Mathematical Finance & Applications
www.amfa.iau-arak.ac.ir
Print ISSN: 2538-5569
Online ISSN: 2645-4610
Doi: https:10.71716/amfa.2026.41211066

Original Research

Hybrid Modeling Approaches for Forecasting the Yield of Iranian Islamic Treasury Bonds

Pegah Shahrokhi [a], Seyyed Mohammad Hasheminejad [b, *], Seyyedeh Atefeh Hoseini [c]

[a] *Department of Accounting and Finance, Firuzkuh Branch, Islamic Azad University, Firuzkuh, Iran*
[b] *Department of Business Management, Tehran Medical Science Branch, Islamic Azad University, Tehran, Iran*
[c] *Department of Accounting, Firuzkuh Branch, Islamic Azad University, Firuzkuh, Iran*

ARTICLE INFO
Article history:
Received 2025-07-04
Accepted 2025-08-15
Keywords:
Yield Estimation
Regression
Treasury Bonds
Multiple Linear Regression

ABSTRACT

Forecasting financial variables, especially the returns of debt instruments, plays a vital role in economic decision-making and risk management. Although the forecasting literature in financial markets is extensive, few studies have focused on predicting the returns of Islamic Treasury Bonds with unconventional structures. Moreover, despite the importance of these bonds, very limited work has been done using machine learning in the debt market. This study aims to predict the returns of Islamic Treasury Bonds using three models: Multiple Linear Regression (MLR), Multilayer Perceptron Neural Network (MLP), and Radial Basis Function Neural Network (RBF). Monthly data from 2018 to 2023 were collected using Excel and Python. The training and evaluation of the models were carried out in MATLAB. Eleven influential variables were selected based on previous studies and expert opinions. The models' performance was evaluated using Root Mean Square Error (RMSE) and the coefficient of determination (R^2). The findings indicate that the Multilayer Perceptron Neural Network model has higher accuracy in predicting the returns of Islamic Treasury Bonds compared to Multiple Linear Regression and Radial Basis Function models. These results suggest that neural network models can serve as more effective tools in financial and economic analyses, significantly enhancing forecasting accuracy.

1 Introduction

Nowadays, productive investments are considered one of the fundamental pillars in achieving sustainable national development. To realize this goal, it is essential to provide financial resources aligned with the investment needs of various economic sectors. Alongside the equity and derivatives markets,

* Corresponding author. Tel.: +989122574744
E-mail address: *m.hasheminejad@iautmu.ac.ir*

the debt market represents one of the three main pillars of the capital market, with its primary objective being the establishment of mechanisms for short-, medium-, and long-term financing for both the private and public sectors. The debt market, or bond market, is a platform where fixed-income securities are traded and plays a significant role in government financing [2]. Given the substantial volume of outstanding debt and the increasing need for investment in infrastructure, the government is compelled to mobilize new financial resources. A combination of underinvestment of oil revenues and inefficiencies in the tax system has led to budget deficits and revenue constraints. Furthermore, the adoption of expansionary and supportive fiscal policies has resulted in increased government expenditures. To service debt obligations, cover budget deficits, and finance infrastructure projects, the government resorts to financing instruments such as borrowing from the central bank and issuing debt securities, including Islamic Treasury Bonds. However, borrowing from the central bank often results in undesirable consequences, such as increases in the monetary base and inflation, rendering debt securities a preferable financing tool [29]. Although Islamic Treasury Bonds are issued primarily to finance government expenditures, their yield rates effectively represent the risk-free interest rate in the economy and serve as a benchmark for valuing other financial instruments. The risk-free rate is crucial as it influences the expected returns of economic agents and investors, ultimately affecting asset pricing. Therefore, accurate knowledge of the yields on these bonds aids analysts, investors, and policymakers in risk management and informed decision-making. Consequently, forecasting the yield rates of these securities holds significant importance.

Various methods have been used to predict fixed-income securities yields. Most prior studies have employed parametric models such as Nelson-Siegel, which typically consider variables like yield rate and time to maturity. However, in recent years, with increasing uncertainty in financial markets and declining predictive power of traditional models, machine learning methods have gained significant attention due to their superior ability to model complex and nonlinear relationships. Recent studies have applied machine learning methods extensively in financial and economic domains. Nonetheless, the majority of these studies focus on equity markets, while the debt market, particularly Islamic Treasury bonds, has received less attention. For example, Agrawal et al. (2013), Ballings et al. (2015), and Booth et al. (2014a) predicted stock returns using neural networks. Similarly, Dunis et al. (2016) applied machine learning models in the stock market, but none addressed fixed-income securities. In the fixed-income domain, Castellani and Santos (2006) employed a multilayer perceptron neural network to forecast US Treasury bond yields, but the prediction accuracy was low, with models performing only slightly better than a simple one-month lag predictor. Dunis and Morrison (2007) predicted government bond yields in the UK, US, and Germany using neural networks and Kalman filter models, incorporating various variables such as short-term interest rates, stock price indices, exchange rates, and commodity prices. They regarded neural network regression as a promising alternative to traditional industry techniques. Kanevski et al. (2008) used machine learning and spatial statistical models to reconstruct yield curves from limited data points. Although initial results were promising, further validation under different market conditions is necessary. Sambasivan and Das (2017) compared multivariate time series, dynamic Nelson-Siegel, and dynamic Gaussian process models for yield prediction, concluding that model performance varies across different maturities and no single model excels under all conditions [28]. Domestically, studies have mainly focused on stock markets. For instance, Tehrani and Moradpoor (2012) compared multilayer perceptron and radial basis function neural networks in predicting the Tehran Stock Exchange index, finding better in-sample performance for RBF and better out-of-sample performance for MLP [34]. Similarly, Khalafi et al. (2023) compared static and dynamic artificial neural networks for stock return prediction, concluding that dynamic models provided higher predictive accuracy [19].

To the best of the authors' knowledge, no comprehensive study has applied artificial neural networks for forecasting Islamic Treasury Bond yields in the Iranian market. Most existing models rely on parametric approaches and a limited set of variables. This research aims to bridge this gap by employing a broader set of financial and economic indicators and applying machine learning models to this underexplored area. For this reason, in the current study, three models—Multiple Linear Regression (MLR), Multilayer Perceptron (MLP), and Radial Basis Function (RBF)—have been selected. MLR is a simple and interpretable model that allows direct analysis of the effect of each variable and serves as a benchmark for comparison. MLP is widely used due to its high prediction accuracy and ability to learn complex patterns. RBF offers a favorable balance between prediction accuracy and training speed. The combination of these three methods enables a comprehensive evaluation of yield forecasting performance. The main objective of this study is to compare the forecasting accuracy of MLR, MLP, and RBF models in predicting the yield rates of Islamic Treasury Bonds. This research contributes to the literature by being the first to implement machine learning models in yield estimation for Islamic Treasury Bonds in the Iranian market using an expanded set of input variables. The study not only fills a critical research gap but also provides practical insights for policymakers and investors.

2 Theoretical Fundamentals and Research Background

2.1 Nature and Characteristics of Debt Instruments

Debt instruments are contractual agreements in which the borrower commits to repaying a specific amount of money—typically in cash—at predetermined intervals. The maturity of these instruments denotes the period from the inception of the debt to its final settlement. Short-term debt instruments generally exhibit lower price volatility and are subject to minimal risk. These instruments serve as common tools for financing, widely utilized in financial markets due to their relative stability and predictability [2].

2.2 Functional Role of Debt Instruments in Economic Policy

Beyond their financial structure, debt instruments play a critical role in economic policy implementation. One of the fundamental functions of the debt market is to facilitate government financing through market-based mechanisms while also enabling the management of outstanding liabilities. Moreover, central banks can conduct monetary policy by engaging in open market operations purchasing and selling debt securities to influence liquidity and interest rates. In the absence of an active debt market, central banks are compelled to issue debt directly, incurring costs related to issuance, marketing, interest payments, and buybacks. These expenses can undermine the effectiveness of monetary policymaking and reduce the overall efficiency of macroeconomic management [2].

2.3 Advantages of Establishing a Debt Market in the Economy

Establishing a debt market in an economy offers numerous benefits, the most important of which include:

- Assisting in price discovery based on risk, return, and maturity of debt instruments
- Strengthening the implementation of government fiscal policies
- Enabling the central bank to conduct monetary policy
- Increasing liquidity in money and capital markets
- Establishing a logical relationship between risk and return
- Properly guiding liquidity and preventing the growth of unhealthy markets
- Enhancing transparency in financial markets
- Creating diversity in financial instruments
- Reducing pressure on the banking network and the central bank in financing
- Assisting in the discovery of the yield curve

These functions play a fundamental role in the economy, and without an active debt market, other financial markets cannot effectively fulfill these roles. For example, the debt market helps the government to finance its needs through market mechanisms and manage past liabilities. Additionally, the central bank can implement its monetary policies through the buying and selling of debt securities in this market. In the absence of an active debt market, the central bank is forced to issue debt directly, which entails costs related to issuance, marketing, interest payments, and buybacks. These expenses can pose obstacles to effective monetary policymaking. However, despite the significant benefits of the debt market and its irreplaceable role in the economy, the debt market in the country lacks sufficient depth. The shallow depth of this market has caused it to inadequately meet the needs of financial system stakeholders. This issue highlights the necessity of deepening the market and diversifying existing instruments based on risk, return, and maturity [2].

2.4 Practical Features of Islamic Treasury Bonds in Iran

Islamic Treasury Bonds (ITBs) possess several operational features that distinguish them from conventional fixed-income instruments:

- **Zero-Coupon Structure:** ITBs do not provide periodic interest payments. Instead, investors benefit from the difference between the discounted purchase price and the bond's face value at maturity.
- **Government Guarantee:** These bonds are guaranteed by the Ministry of Economic Affairs and Finance. The National Treasury considers the repayment of these bonds as a top-priority government obligation, equivalent in urgency to the payment of public employee salaries.
- **Secondary Market Liquidity:** Once admitted to the Iran Fara Bourse (IFB), ITBs become tradable, and their prices are determined based on market supply and demand. Transaction fees are in line with other fixed-income securities traded on the same platform.
- **Tax Exemption:** According to annual budget laws and Article 7 of the Law on Development of New Financial Instruments and Institutions, ITBs are exempt from all forms of taxation.
- **Debt Settlement Mechanism for Contractors:** Contractors with confirmed government claims may request settlement through ITBs. After being introduced to the designated bank by the relevant governmental authority and completing the necessary documentation, contractors receive the bonds, which can then be sold through any IFB-licensed brokerage.
- **Redemption Process:** The Central Securities Depository of Iran (CSDI) handles the redemption of ITBs at face value upon maturity via the designated agent banks [33].

2.5 Challenges of Government Debt Instruments in Iran with a Focus on Islamic Treasury Bonds

Despite the increasing use of Islamic Treasury Bills (ITBs) as a financing tool, Iran's debt market still faces a number of structural and operational challenges that limit its effectiveness:

- **Lack of a Structured Issuance Calendar:** Unlike developed economies where annual auction calendars are pre-announced by the Treasury (e.g., the U.S. or U.K.), there is no official schedule for issuing government bonds in Iran. Ad-hoc issuance and occasional cancellations due to concerns about market impact undermine investor confidence and secondary market stability.
- **Limited Maturity Diversification:** The government typically issues debt with uniform maturities, preventing the construction of a reliable yield curve. A diversified maturity structure could reflect investor preferences more effectively and enhance market depth.

- **Institutional Coordination Deficit:** There is insufficient coordination between the Ministry of Economic Affairs and Finance and the Central Bank. As these entities pursue different policy objectives (fiscal vs. monetary), uncoordinated issuance may lead to sudden increases in interest rates, undermining macroeconomic stability.
- **Low Incentives for Government Issuance:** Compared to bank borrowing, bond issuance imposes higher explicit and implicit costs on the government, including transparency requirements and political resistance tied to capital market sensitivity. As a result, the government tends to favor banking channels.
- **Insufficient Public Disclosure and Market Education:** A lack of clear communication by regulatory bodies regarding the type, timing, and impact of Islamic debt instruments leads to investor confusion and mispricing in the market.
- **High Duration and Absence of Coupon Payments:** Most ITBs are long-term zero-coupon bonds, resulting in high duration and increased sensitivity to economic shocks. This structure discourages risk-averse investors, leading to reduced demand.
- **Low Liquidity in the Secondary Market:** Although government bonds are assumed to be highly liquid instruments, Iranian debt securities often suffer from poor tradability due to shallow market participation and limited market-making infrastructure.
- **High Price Volatility and Speculative Behavior:** Volatility in the bond market hinders accurate yield discovery and increases market risk. Inadequate forecasting of macroeconomic indicators such as exchange rates and inflation further complicates investment decisions.

These issues highlight the need for comprehensive reform in Iran's debt market infrastructure, including improved coordination, transparent issuance mechanisms, and regulatory support for deepening market liquidity [37].

2.6 Multiple Linear Regression (MLR)

Multiple Linear Regression is a statistical method used to model the relationship between a dependent variable and several independent variables. This model assumes a linear relationship between the dependent and independent variables and seeks to estimate parameters that best explain the variation in the dependent variable by minimizing the sum of squared errors. The general formula for the multiple linear regression model is given by equation (1):

$$(y) = a_0 + a_1x_1 + a_2x_2 + ... + a_nx_{n+} \epsilon \tag{1}$$

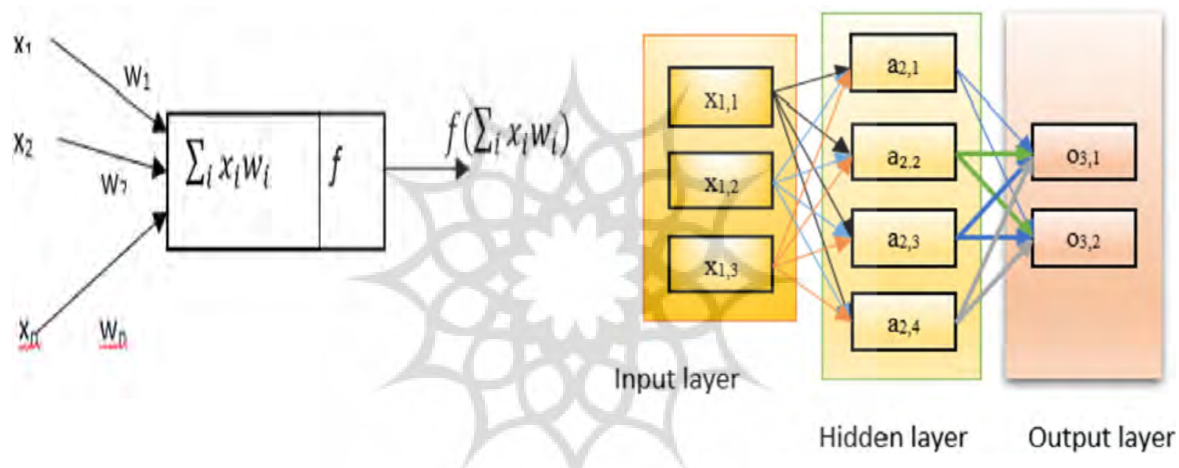
In this model, y represents the dependent variable, x1, x2 , ... , xn are the independent variables, a1,a2 ,...,an are the regression coefficients, and ϵ is the error term of the model. Foundational studies such as Montgomery et al. (2012) recommend the use of multiple linear regression as a simple, interpretable, and effective method for modeling relationships between independent and dependent variables [25].

2.7 Multi-Layer Perceptron (MLP) Architecture

The Multilayer Perceptron (MLP) architecture consists of at least three layers: an input layer, an output layer, and one or more hidden layers. As illustrated in Fig. 1(a), each layer is composed of basic processing units called neurons. A mathematical representation of a neuron is depicted in Fig. 1(b). According to this figure, the operation of a neuron can be described by the following equation:

$$y = f\,(\Sigma wi\ xi + b) \quad (2)$$

In the above equation, xi denote inputs; y represents the output; wi denote the neuron's synaptic weights; represents the bias; and is the activation function, which may be a sigmoid or linear function. The weights and bias parameters are the model parameters which can be learned during an iterative training mechanism so that the RMSE between the model output and the observed value get minimized. Studies such as Tayebi et al. (2019) have shown that the Multilayer Perceptron (MLP) architecture is a powerful and effective method for modeling complex and nonlinear phenomena [33].



(a) (b)

Fig. 1: (a) Basic Artificial Neuron. (b) A Feed Forward Neural Network with One Hidden Layer [33]

2.8 Radial Basis Function (RBF) Architecture

Unlike MLPs (Multilayer Perceptrons), Radial Basis Function (RBF) networks utilize linear parameters for prediction purposes. A basic three-layer feedforward RBF network is illustrated in Figure 2. In this architecture, the input passes through a set of basis functions, most commonly Gaussian functions defined by their mean and standard deviation. The output of the j-th hidden node is given by the following equation:

$$H\,j(X) = \exp\left(- (\lVert X - Uj \rVert^2) / s^2 \right) \quad (3)$$

In this formula, $\lVert X - U\,j \rVert$ represents the Euclidean distance between the input vector $X = (x_1, x_2, ..., x_n)$ and the center of the j-th hidden node $Uj = (u_1,j, u_2,j, ..., u_n,j)$.

This Euclidean distance determines the activation level of the Gaussian function. The output layer computes the final network output by applying a linear combination of the hidden layer outputs, as described below [30].

$$F(X) = \Sigma wj\ H\ j\ (x) \quad (4)$$

There can be as many nodes in the hidden layers as there are data instances in the training set, but a too large training set is best to be represented by a lower number of carefully selected data instances. An alternative method to lower the number of nodes is to use a clustering approach, i.e. by locating the RBF centers at the centers of clusters**.**

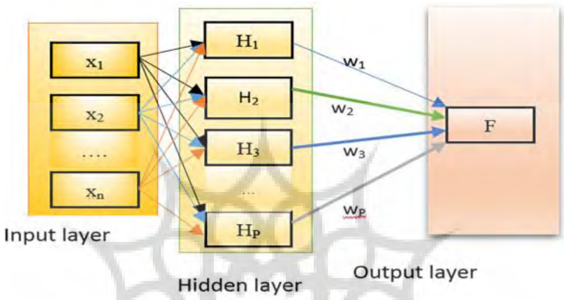


Fig. 2: Sample RBF Network Architecture [33]

2.9 Literature Review

Bilio et al. [5] in their study titled *"Bond Supply Expectations and the Term Structure of Interest Rates"*, examine the impact of anticipated bond supply on interest rates and the formation of the yield curve. The authors demonstrate that forward guidance and projected information regarding government bond issuance can significantly influence long-term interest rates. Junier et al. [24] in their article titled *"Risks and Risk Premia in the U.S. Treasury Market"*, investigate the risk–return relationship in the U.S. Treasury market using a term structure model that incorporates multi-source volatility effects while maintaining bond prices in closed form. Their findings reveal a strong positive relationship between risks and risk premia over the period 1966–2018. Although interest rate risk is identified as the primary driver, macroeconomic risks also play a crucial role, and omitting them leads to unstable estimations. Atsushi [32] in his study titled *"Estimating the Yield Curve Using the Nelson-Siegel Model: Evidence from Daily Yield Data"*, applies the Nelson-Siegel framework to model the yield curve based on time-to-maturity and days-to-maturity variables using daily yield data. Khodayari et al. [21] aimed to enhance the accuracy of financial market volatility forecasting by applying an Artificial Neural Network (ANN) model. Comparing the performance of the ANN with that of traditional linear regression, the authors found that the neural network approach provided better forecasting results with reduced prediction errors. Their findings highlight the potential of artificial intelligence techniques in improving the effectiveness of market forecasting models**.** Ghasemzadeh et al. [14] explored the modeling and forecasting of financial market volatility by comparing traditional methods such as linear regression with datadriven and intelligent approaches. Their study revealed that machine learning models particularly Artificial Neural Networks significantly improve the accuracy of volatility forecasts. The findings underscore the value of advanced computational tools in analyzing financial time series**.** Nunes et al. [28] estimated the UK bond yield curve using a hybrid model that combines regression techniques with Artificial Neural Networks. The study incorporated variables such as credit ratings, equity, currency, commodities, and financial market volatility. The results indicated that the Multi-Layer Perceptron (MLP) model, when fed with the most relevant features, delivered the best forecasting performance across all prediction horizons**.** Ehteshami et al. [13] focused on stock trend forecasting as a crucial factor in making optimal investment decisions. Using data mining algorithms, they analyzed the stock trends of 180 firms listed on the Tehran Stock Exchange from 2009 to 2015. Their results indicated that these algorithms can effectively forecast negative stock returns, with the Random Forest algorithm outperforming the Decision Tree method. Additionally, stock returns over the past three years and sales growth were identified as key variables for predicting negative stock returns. Razaghi et al. [30] in their article titled "Comparing the Efficiency of ARIMA and *AFRIMA Models in Forecasting Interest Rates and Islamic* Treasury Bond Yields", forecasted the interbank interest rate and Islamic treasury bond yields as indicators of interest rates in Iran, aiming to facilitate interest rate risk management. Their evaluation of the forecasting accuracy, based on monthly data of interbank rates and average Islamic treasury bond yields, demonstrated that the ARIMA model outperformed the AFRIMA model in predicting both datasets. The findings of some researchers showed that there is a significant relation between the stock market uncertainty changes in an economic boom and the investment risk in general, which is not significant in terms of the economic turndown. The Investment risk during both economic boom and recession is decreased by the unexpected increase in profit of each share and propagation of positive news. Although the risk is increased by the spread of negative forecasts in relation to shares [38].

3 Methodology

3.1 Research Procedure

This study is applied research with a descriptive-analytical approach. Using real data, the performance of forecasting models, including neural networks and regression, was evaluated through various statistical indices. The statistical population of this research consists of all Islamic Treasury bills issued by the Government of the Islamic Republic of Iran from the beginning of 2018 to the end of 2023. Data collection was conducted in two stages. The first stage involved a literature review using scientific books, Persian and English articles, and theses. The utilized sources were mainly extracted from domestic databases such as NoorMags, SID, and IranDoc, as well as international databases including Scopus, ScienceDirect, and Google Scholar. The focus of this stage was on identifying theoretical frameworks related to forecasting the returns of Treasury bills, artificial intelligence, indices for comparing forecast accuracy, and key variables affecting the yield rate of Treasury bills. The second stage was dedicated to gathering the required data from official sources such as the Iran Fara Bourse website, the Central Bank, and the Technology Management of Tehran Stock Exchange [9-16-35]. The main research question is focused on determining which of the multiple linear regression, multilayer perceptron (MLP) neural network, or radial basis function (RBF) neural network methods has higher accuracy in predicting the yield rate of Islamic Treasury bills. In this study, eleven variables were selected as influential factors in predicting the yield rate of Islamic Treasury bills. The process of identifying and selecting these variables was carried out in three stages. In the first step, through a systematic review of domestic and international prior studies, five frequently recurring and influential variables were identified and selected. The sources included reputable scientific articles such as Castellani and Santos (2006), Dunis and Morrison (2007), Rezende and Ferreira (2010), Nunes et al (2019) **[**8-12-10- 28**].** These variables are: the number of days remaining to maturity, the percentage growth of the Tehran Stock Exchange overall index, the percentage growth of the dollar price in the free market, the average one-month return volatility, and the duration of securities .In the second step, to complete the set of variables and to utilize the opinions of capital market experts, Delphi sessions were held with the participation of 10 specialists in the field of debt securities. In this stage, eight new variables were proposed and, after several rounds of consensus, were added to the final list. These variables include: the spread between the average rate of government bonds and corporate bonds, the spread between the rates of government bonds with the longest and shortest maturities, the spread of each security's rate from the average rate of debt securities, the spread of each security's rate from the previous security's rate, the spread of each security's rate from the next security's rate, the spread of each security's rate from the average interbank interest rate of the same month, the ratio of the trading volume of each security to the total volume of debt securities, and the ratio of the trading value of each security to the total trading value of debt securities. The third step included implementing the fuzzy Delphi method for final consensus and confirmation of the selected variables. Ultimately, among the identified variables, eleven variables were approved by the experts' consensus and entered into the forecasting model. These variables include: duration of debt securities, the spread between the rates of government bonds with the longest and shortest maturities, the spread of each security's rate from the average rate of debt securities, the spread of each security's rate from the previous security's rate, the spread of each security's rate from the next security's rate, the spread of each security's rate from the average interbank interest rate of the same month, the average one-month return volatility, the ratio of the trading volume of each security to the total volume of debt securities, the ratio of the trading value of each security to the total trading value of debt securities, the percentage growth of the dollar price in the free market, and the percentage growth of the Tehran Stock Exchange overall index. Monthly data were collected directly from the mentioned sources using Microsoft Excel software and Python programming language. Subsequently, forecasting was performed using three methods: multiple linear regression, multilayer perceptron (MLP) neural network, and radial basis function (RBF) neural network with MATLAB software. The results were evaluated using statistical indices including the coefficient of determination (R^2) and root mean square error (RMSE). These indices were calculated as follows: The coefficient of determination (R^2) measures the proportion of variance explained by the model:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y_i})^2}{\sum_{i=1}^{n}(y_i - y^-)^2} \tag{5}$$

where yi is the actual value, $\hat{y_i}$ is the predicted value, and y^- is the mean of actual values.

Root Mean Square Error (RMSE): where N is the number of observations.

$$RMES = \sqrt{\frac{\sum_I (y_i - \hat{y_i})^2}{N}} \tag{6}$$

3.2 Forecasting Models Used in the Study

3.2.1 Multi-Layer Perceptron (MLP) Neural Network

The Artificial Neural Network model was implemented using MATLAB programming. Specifically, a three-layer perceptron network was designed, consisting of an input layer, an output layer, and two hidden layers. The network input variables included: bond duration, the spread between rates of the bonds with the highest and lowest maturities, the spread of each bond’s rate relative to the average market rate, the spread compared to the previous bond, the spread compared to the next bond, the spread relative to the average interbank interest rate in the same month, the average one-month return volatility, the ratio of each bond's trading volume to the total market volume, the percentage change in the free-market USD exchange rate, and the percentage growth of the Tehran Stock Exchange's overall index. The network output was defined as the return rate of government-issued Islamic treasury bills. The input layer consisted of 11 neurons, corresponding to the 11 independent variables. The output layer had 1 neuron, representing the dependent variable (bond return). The hidden layer initially included 8 neurons, but the final structure was determined through a trial-and-error process. This process began with a basic architecture (one input layer, one hidden layer, one output layer), and then the number of hidden neurons was gradually increased. The model's performance for each configuration was assessed using evaluation metrics such as the Root Mean Square Error (RMSE). After several iterations, it was concluded that using two hidden layers, each with 8 neurons, yielded the best performance for the dataset in this study. For training the MLP network, the backpropagation learning algorithm was employed. This algorithm was selected due to its effectiveness in optimizing weights and providing a predictable cost function in complex problems. During the backpropagation process, the derivative of the final error with respect to the weights is calculated using the chain rule, allowing for the minimization of model error by updating weights. The choice of this algorithm was motivated by its proven efficiency in nonlinear and regression problems similar to this study, particularly when using nonlinear activation functions such as sigmoid.The sigmoid activation function was used in the hidden layers. The data was randomly divided into training and testing sets, with 80% assigned to training and 20% to testing. The training data was randomly selected first, and the remaining data was allocated to testing. The backpropagation algorithm, using the sigmoid function, optimized the network weights based on the training data. This learning process was repeated for 20 epochs to achieve optimal performance. After training, the model was evaluated using the test data, and the predicted values were compared with the actual outcomes. Performance metrics including the Root Mean Square Error (RMSE) and coefficient of determination (R^2) were calculated to assess the model’s prediction accuracy.

3.2.3 Multiple Linear Regression (MLR)

The Multiple Linear Regression (MLR) model was implemented using MATLAB programming. In this model, the input variables included: bond duration; the spread between the rates of government bonds with the highest and lowest maturities; the spread of each bond's rate relative to the average rate of all bonds; the spread of each bond's rate compared to the previous and next bonds; the spread of each bond's rate relative to the average interbank interest rate for the same month; the average one-month return volatility; the ratio of each bond's trading volume to the total market volume; the percentage change in the free-market USD exchange rate; and the percentage growth of the Tehran Stock Exchange overall index. The output variable was defined as the return on government-issued Islamic treasury bills. The model coefficients were estimated using the normal equation for linear regression. The dataset was divided into two subsets: 80% for training and 20% for testing. After training the model on the training set, predictions were generated for the test set and compared to the actual observed values. The model's performance was evaluated using standard statistical indicators, specifically the Root Mean Square Error (RMSE) and the coefficient of determination (R^2).

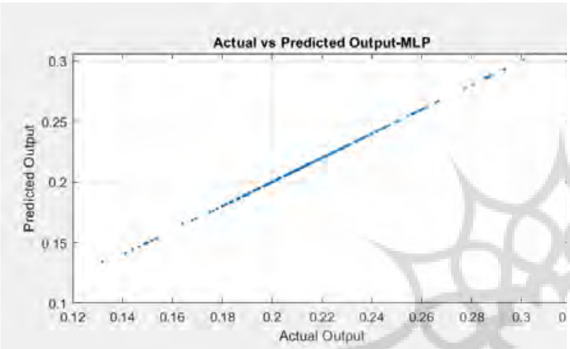
3.2.2 Radial Basis Function (RBF) Neural Network

The implementation of the Radial Basis Function (RBF) neural network model was carried out using MATLAB. The structure of the RBF network consisted of three layers: an input layer, a hidden layer, and an output layer. The input layer received 11 economic and financial features, including the spread between government bond rates, the spread of each bond relative to the previous and next bonds, the average one-month return volatility, the percentage change in the free-market USD exchange rate, and other related variables. Consequently, the input layer contained 11 neurons, matching the number of input variables. The hidden layer consisted of neurons using radial basis (Gaussian) activation functions, which are capable of modeling complex nonlinear relationships in the data. In this study, the number of neurons in the hidden layer was fixed at 8 neurons. The output layer included a single neuron responsible for producing the model's final prediction, which corresponds to the return on government-issued Islamic treasury bills. The newrb function in MATLAB was used to train the RBF network. This function automatically adjusts the network's parameters to minimize prediction error and optimize the network's weights. In this study, the target error for training was set to 0.00000001. The dataset was randomly divided into 80% training data and 20% test data. The network was trained using the training set, and parameter optimization was conducted through the newrb algorithm, which adaptively determines key network parameters such as the number of neurons and the spread value. The training process was limited to 20 learning iterations (epochs) to ensure a balanced model suitable for prediction. After training, the `sim` function was used for prediction. This function operates as the forward-pass inference mechanism of the neural network, transforming input values into predicted outputs based on the optimized network parameters obtained through training. The performance of the trained model was then evaluated on the test data. The predicted values were compared against the actual outcomes using two evaluation metrics:

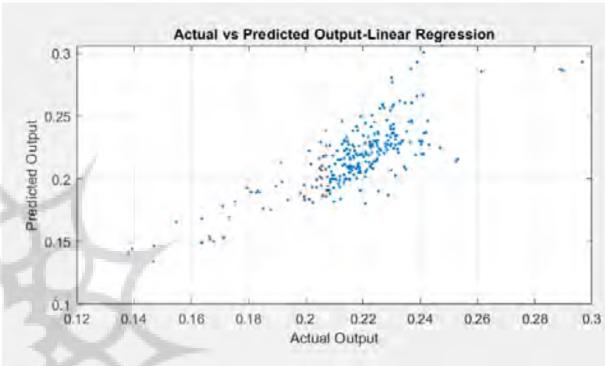
Root Mean Square Error (RMSE) and the coefficient of determination (R^2), to assess the model's forecasting accuracy.

4 Finding

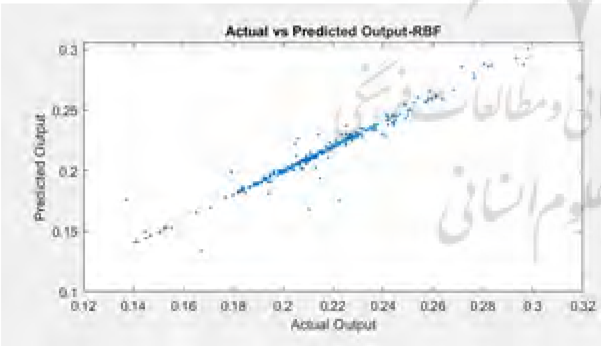
In this section, the performance of the MLP, RBF, and MLR models is evaluated. As previously mentioned, MATLAB software was used to implement all three methods. To obtain a more realistic assessment of the proposed system, the training and testing process was repeated 20 times, and the evaluation metrics were computed for each trial. Finally, the average and standard deviation of the evaluation parameters were reported. The metrics used in this study are R^2 and RMSE. Figures 2(a), 2(b), and 2(c) show the predicted versus observed values for a single trial, corresponding to the MLR, MLP, and RBF models, respectively. In addition, Figure 3 presents a comparison of the distributions of observed and predicted values for all three models.



(b)MLP model



(a)MLR model



(c)RBF model

Fig. 3: (a), (b) and (c) The Scatter Plots of Observed Versus Predicted Values in Testing Data, Using MLR, MLP, RBF Models, Respectively

In Figure 3(a), the dispersion of data points around the ideal line y=x suggests that the model is generally capable of predicting bond yields. However, the spread of points from the ideal line indicates the presence of prediction errors at certain points. The overall upward trend implies a positive correlation between actual and predicted values. Nonetheless, some points are significantly distant from the ideal line, reflecting limitations of the model in fully capturing the variations in bond yields. In contrast, Figure 3(b) shows that most data points lie closely along the ideal line y=x, indicating high accuracy in prediction. This demonstrates that the MLP model successfully learned the underlying patterns in the data and generated predictions with minimal error. Similarly, Figure 3(c) shows that the data points are generally distributed near the ideal line y=x, reflecting high predictive accuracy of the RBF model. Although some deviations exist, the overall pattern reveals a strong correlation between the observed and predicted values.

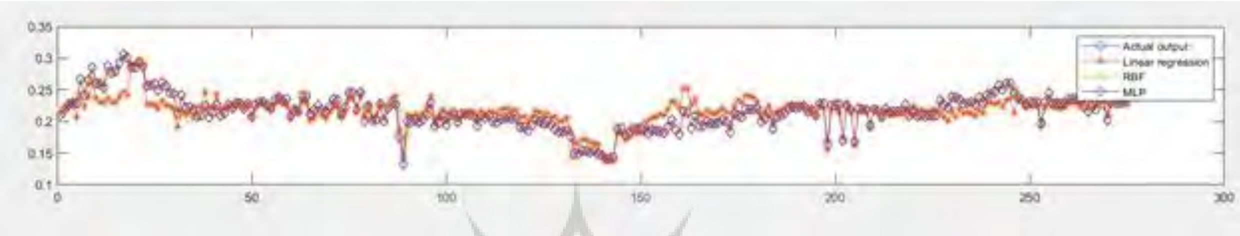


Fig. 4: Distribution Of the Observed Values and The Predicted Ones, Using MLR, MLP and RBF models, For Testing Data

Figure 4 further compares the performance of the three models in predicting observed values. It can be seen that the MLP model provides the best fit, closely following the trends and fluctuations in the data. The MLR model, on the other hand, shows greater deviation from actual values, indicating lower accuracy. The RBF model performs reasonably well and is effective in capturing data fluctuations.

Table 1 presents the mean and standard deviation of R^2 and RMSE values obtained from the test sets after multiple experimental runs. The evaluation procedure was applied equally across all three models.

Table 1: Evaluation of the MLR, MLP and RBF models in various experiments. Means and standard deviations of the RMSE and R2 parameters obtained after 20 runs in testing data.

Test	R2		RMSE	
	mean	Std.	mean	Std.
MLR	0.6450	0.0468	0.0187	0.0086
MLP	0.9582	0.0754	0.0047	0.0047
RBF	0.9380	0.0381	0.0067	0.0026

A comparison of model performance reveals that the MLP neural network significantly outperforms the others. The mean coefficient of determination (R^2) for the MLR model is 0.6450, indicating that approximately 64% of the variance in bond yields is explained by the model. While this result is acceptable, better performance is expected in predictive tasks. In contrast, the MLP model achieves a mean R^2 of 0.9582, meaning it explains about 95% of the variance in the dependent variable, indicating high precision and strong model fit. The R^2 value for the RBF model is 0.9380, showing it can explain 93% of the variation in bond yields—an impressive indication of the model's ability to extract relationships between input and output variables. In terms of the standard deviation of R^2, the MLR model has a value of 0.0468, suggesting relative stability in its predictions. For the MLP and RBF models, the standard deviations are 0.0754and 0.0381respectively. Although these values suggest slightly more variability in performance, both models maintain high predictive accuracy.The comparison of mean RMSE values also clearly demonstrates the superiority of the MLP model. The average RMSE for the MLR model is 0.0187, while the corresponding values for MLP and RBF are 0.0047and 0.0067, respectively. This indicates a significantly lower prediction error for the MLP model. The standard deviation of RMSE for the MLR model is 0.0086, indicating consistent error behavior. For MLP and RBF, the standard deviations are 0.0047and 0.0026, respectively. While these values show higher variability, the overall prediction error of the MLP model remains considerably lower than that of both MLR and RBF. In conclusion, the multilayer perceptron model outperformed both multiple linear regression and the radial basis function model in predicting bond yields, in terms of both coefficient of determination and prediction errors.

5 Discussion and Conclusions

In this study, machine learning was applied to the Islamic debt securities market—a domain that has received relatively less research attention compared to other financial sectors. This research is the first comprehensive study utilizing multilayer perceptron (MLP) neural networks and radial basis function (RBF) models for predicting the yields of Islamic treasury bonds, while also employing a more diverse set of input variables compared to previous studies. A review of the literature shows that researchers such as Nunes et al. (2019) and Gorsen et al. (2011) have reported successful performance of neural network models, particularly MLP, in financial data forecasting. In Iran, studies by Rezaqhi et al. (2023) and Jamshidi et al. (2019) indicate that machine learning models outperform traditional methods like multiple regression in terms of accuracy and flexibility in financial prediction. The findings of this research indicate that the MLP model achieved the highest accuracy with the lowest root mean square error (RMSE) and the highest coefficient of determination (R^2). The RBF model also showed acceptable performance, though it lagged slightly behind the MLP. The multiple linear regression model, used as a baseline, showed the weakest performance in predicting the yields of Islamic treasury bonds. The results further demonstrate that the MLP model's superior performance stems from its ability to learn complex and nonlinear relationships among variables. Additionally, using a diverse set of input variables selected based on systematic literature review and expert opinions played a critical role in enhancing model performance. These findings are consistent with previous financial forecasting studies emphasizing the advantage of neural networks over linear methods. An important aspect of this research is the careful selection of input variables, identified through a systematic review and fuzzy Delphi method with market experts an approach that has been key to improving machine learning model accuracy. However, the study also faces limitations. For testing neural network models, the dataset was randomly split into training and testing subsets using MATLAB software. Statistically, there is always a possibility that different splits could yield varying results. Moreover, macroeconomic conditions such as recession, boom, or economic shocks during the study period (2018–2023) were not incorporated into the models, which might have impacted the outcomes. Given the results, the use of artificial neural networks is recommended as an effective tool for predicting debt securities yields and managing risk in the debt market. Future research is encouraged to evaluate the stability and accuracy of these models under different economic conditions and extend the study to other types of debt instruments such as Sukuk, participation bonds, and Murabaha securities. Furthermore, international comparisons of model performance in Iran with countries having similar economic and debt market structures particularly Islamic or emerging markets could open new horizons for research and policymaking.

References

[1] Agrawal, J., Chourasia, V., and Mittra, A., State-of-the-art in stock prediction techniques, *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, 2013; 2(4): 1360–1366.

[2] Ahmadi, S. M. R., Mahdavi, M. H., and Ahmadi Shadmehri, M. T., Debt securities as a tool for financing oil industry projects, *Financial Economics Quarterly*, 2018; 45: 213–242., (in Persian).

[3] Ballings, M., Van den Poel, D., Hespeels, N., and Gryp, R., Evaluating multiple classifiers for stock price direction prediction, *Expert Systems with Applications*, 2015; 42(20): 7046–7056. Doi: 10.1016/j.eswa.2015.05.013

[4] Bayat, S., and Misami, H., Diagnosis of the debt securities market and presenting deepening solutions in Iran, *Proceedings of the Annual Conference on Monetary and Exchange Rate Policies*, 2016; Tehran, Iran, (in Persian).

[5] Billio, M., Busetto, F., Dufour, A., and Varotto, S., Bond supply expectations and the term structure of interest rates, *Journal of International Money and Finance*, 2025; 250: 103217. Doi: 10.1016/j.jimonfin.2024.103217

[6] Booth, A., Gerding, E., and McGroarty, F., Performance-weighted ensembles of random forests for predicting price impact, *Quantitative Finance*, 2015; 15(11): 1823–1835. Doi: 10.1080/14697688.2014.983539

[7] Broomhead, D. S., and Lowe, D., Multivariable functional interpolation and adaptive networks, Complex Systems, 1988.

[8] Castellani, M., and Santos, E. A., Forecasting long-term government bond yields: an application of statistical and AI models, ISEG, *Departamento de Economia*, 2006.

[9] Central Bank of the Islamic Republic of Iran. [Internet]. Tehran: Central Bank of the Islamic Republic of Iran. Available from: https://www.cbi.ir

[10] de Rezende, R.B., and Ferreira, M.S., Modeling and Forecasting the Yield Curve by an Extended Nelson-Siegel Class of Models: A Quantile Autoregression Approach, 2010.

[11] Dunis, C. L., Middleton, P. W., Karathanasopolous, A., and The ofilatos, K., Artificial Intelligence in Financial Markets: Cutting Edge Applications for Risk Management, Portfolio Optimization and Economics, *New Developments in Quantitative Trading and Investment, London*, Palgrave Macmillan UK, 2016. Doi: 10.1057/978-1-137-48880-0

[12] Dunis, C. L., and Morrison, V., The economic value of advanced time series methods for modelling and trading 10-year government bonds, *European Journal of Finance*, 2007; 13(4): 333–352. Doi: 10.1080/13518470600880010

[13] Ehteshami, S., Hamidian, M., Hajihah, Z., and Shokrollah, S., Forecasting stock trend by data mining algorithm, *Advances in Mathematical Finance and Applications*, 2018; 3(1): 97–105.

[14] Ghasemzadeh, M., Mohammad-Karimi, N., and Ansari-Samani, H., Machine learning algorithms for time series in financial markets, *Advances in Mathematical Finance and Applications*, 2020; 5(4): 479–490. Doi: 10.22034/amfa.2020.1894677.1383

[15] Haykin, S., Neural Networks and Learning Machines, 3rd ed., *Upper Saddle River*, NJ, Pearson, 2009.

[16] Iran Fara Bourse. [Internet]. Tehran: Iran Fara Bourse. Available from: https://www.ifb.ir

[17] Kanevski, M., Maignan, M., Pozdnoukhov, A., and Timonin, V., Interest rates mapping, *Physica A*, 2008; 387(15): 3897–3903. Doi: 10.1016/j.physa.2008.02.031

[18] Kanevski, M., and Timonin, V., Machine learning analysis and modeling of interest rate curves, In: European Symposium on Artificial Neural Networks, *Computational Intelligence and Machine Learning* (ESANN), 2010.

[19] Khalafi, S., Mosavi, M. S., and Omidi, A., Comparison of Artificial Neural Networks in Predicting Stock Returns, *Journal of New Research Approaches in Management and Accounting*, 2023; 7(89): 753, (in Persian).

[20] Kheradiyar, S., Maleki, M., and Asgarpour Reza, A., Asnad-e Khazaneh-ye Eslami: Abzari Novin dar Tamin-e Maliyat [Islamic Treasury Bills: A Novel Instrument in Financing], *Studies in Accounting and Auditing*, 2020; 34: 67–87, (in Persian).

[21] Khodayari, M., Yaghoubnejad, A., and Khalili Araghi, M., A comparison of financial market volatility estimation using regression and neural network models, *Journal of Financial Economics Quarterly*, 2020; 14(52): 223–240, (in Persian).

[22] Khodayari, M. A., Yaghobnezhad, A., and Khalili Eraghi, M., A neural-network approach to the modeling of the impact of market volatility on investment, *Advances in Mathematical Finance and Applications*, 2020; 5(4): 569–581. Doi: 10.22034/amfa.2020.1879320.1298

[23] Kutner, M. H., Nachtsheim, C. J., and Neter, J., Applied Linear Regression Models, New York, McGraw-Hill, 2005.

[24] Li, J., Sarno, L., and Zinna, G., Risks and risk premia in the US Treasury market, *Journal of Economic Dynamics and Control*, 2024; 158: 104788. Doi: 10.1016/j.jedc.2023.104788

[25] Montgomery, D. C., Peck, E. A., and Vining, G. G., Introduction to Linear Regression Analysis, 5th ed., Wiley, 2012.

[26] Mousavian, S. A., and Khademolhosseini Ardakani, M., Financial engineering of bonds, *Islamic Economics Journal*, 2012; 45, (in Persian).

[27] Nassirizadeh, H., et al., Kasr-e Boudjeh va Tavarrom dar Eqtesad-e Iran taye Salhaye 1342–1375 [Budget Deficit and Inflation in Iran's Economy During 1963–1996], 2001; 2, (in Persian).

[28] Nunes, M., Gerding, E., McGroarty, F., and Niranjan, M., A comparison of multitask and single task learning with artificial neural networks for yield curve forecasting, *Expert Systems with Applications*, 2019; 119: 362–375. Doi: 10.1016/j.eswa.2018.11.012

[29] Rashidi, D., Vaez Barzani, M., and Bakhshi, R., Comparative analysis of the effects of borrowing from the central bank, bonds, and Islamic treasury bills to finance the government budget deficit on selected macroeconomic variables, *Iranian Economic Research Quarterly*, 2022; 38: 203–237, (in Persian).

[30] Razaghi, M., et al., Comparison of the efficiency of ARIMA and AFRIMA methods in forecasting interest rate9s and government treasury bond yields, *Danesh Sarmayegozari Scientific Research Quarterly*, 2023; 3: 481–504, (in Persian).

[31] Sambasivan, R., and Das, S., A statistical machine learning approach to yield curve forecasting, Paper presented at the International Conference on Computational Intelligence in Data Science (ICCIDS), *IEEE*, 2017; pp. 1–6.

[32] Sekine, A., Estimating the yield curve using the Nelson-Siegel model: evidence from daily yield data, *Public Policy Review*, 2022; 18(1): 1–14. Doi: 10.22034/amfa.2022.1894677.1383

[33] Sepehvand, M., Garshasbi Fakhr, S., and Asayesh, H., Determining the Demand for Islamic Treasury Bills in Iran Fara Bourse Market, *Journal of Islamic Economics and Banking*, 2024; 11(45): 135–157. (in Persian)

[34] Tayebi, H. A., et al., Modeling of reactive orange 16 dye removal from aqueous media by mesoporous silica/crosslinked polymer hybrid using RBF, MLP and GMDH neural network models, *Journal of Molecular Structure*, 2019; 1189: 514–523. Doi: 10.1016/j.molstruc.2018.10.040

[35] Tehrani, R., and Moradpour, S., Prediction of stock market index return using radial basis function neural network models, *Journal of Financial Engineering and Securities Management*, 2012; Issue 10, (in Persian).

[36] Tehran Stock Exchange. [Internet]. Tehran: Tehran Stock Exchange. Available from: https://www.tse.ir

[37] Tohidi, M., Fereydooni, M. M., Afghahi, S. M., and Rabbani, M., Determining Challenges of Government Securities in the Capital Market and Providing Policy Solutions, *Journal of Securities Exchange*, 2023; 16(63): 223–254.

[38] Zanjirdar, M., Moslehi Araghi, M., The Impact of Changes in Uncertainty, Unexpected Earning of Each Share and Positive or Negative Forecast of Profit Per Share in Different Economic Condition, Quarterly Journal of Fiscal and Economic Policies,2016;4(13): 55-76.