

Artificial Intelligence in Exchange Rate Prediction

Author: Michel Abou Tacca ¹

Affiliation: CIRAME Research Center, Business School

Holy Spirit University of Kaslik, P.O Box 446, Jounieh, Lebanon

Abstract:

Forecasting exchange rates has historically challenged traditional linear econometric models, which often struggle to outperform random walk hypotheses, particularly during periods of high market volatility. This study investigates whether Artificial Intelligence (AI) and machine learning models can improve predictive accuracy over traditional econometric methods in international finance. Utilizing monthly macroeconomic data (interest rate and inflation differentials, GDP growth, and trade balances) for the USD/EUR exchange rate from 2010 to 2024, this research compares the performance of the Autoregressive Integrated Moving Average (ARIMA) model against three AI-driven approaches: Artificial Neural Networks (ANN), Random Forest Regression, and Long Short-Term Memory (LSTM) networks. Predictive performance was evaluated using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). The empirical results demonstrate that all evaluated AI-based models significantly outperform the traditional ARIMA framework. Notably, the LSTM network achieved the highest forecasting accuracy, reducing prediction error by approximately 18–22% compared to ARIMA and demonstrating particular robustness during global shocks such as the COVID-19 pandemic. These findings indicate that deep learning models are highly effective at capturing complex, non-linear time dependencies in foreign exchange markets. Ultimately, while challenges regarding model interpretability remain, integrating AI provides substantial value for multinational corporations, portfolio managers, and central banks in optimizing currency risk management, portfolio diversification, and monetary policy design.

Keywords:

Exchange Rate Forecasting; Artificial Intelligence; Deep Learning; Long Short-Term Memory (LSTM); Foreign Exchange (FX) Markets; Econometric Modeling; Time-Series Analysis; Predictive Analytics.

Introduction: "The What & Why"

In the past, the conventional exchange rate models attempted to elucidate the currency movements in terms of the theories of Purchasing Power Parity (PPP), Interest Rate Parity (IRP), and the Monetary Model. However, in many respects, empirical forecasting is not as predictive and is particularly shorter in time. The hypothesis of the random walk is further that the exchange rate is quite unpredictable (Meese and Rogoff, 1983), which is the reason that the international finance puzzle of continuity is there to predict the currency.

With the advent of the notions of Artificial Intelligence (AI) and machine learning (ML) (Beainy and Kamel 2023), financial market forecasting has been transformed. Comparing the traditional econometric models, AI systems are more effective in handling a large amount of data, finding nonlinear trends, and reacting to the changes in the market environment. In foreign exchange (FX) markets where billions of dollars are being traded daily, even the margin of possibility that predictive accuracy would improve to any degree holds the potential to generate substantial economic value.

Some of the methods applied by AI-driven exchange rate forecasting include artificial Neural Networks (ANN), Support Vector Machines (SVM), random forests, and deep learning. The tools allow the analysts to integrate macroeconomic, sentiment, high-frequency, and geopolitical measurements into prediction models. Based on the recent research findings, it is revealed that, according to certain forecasting conditions, the machine learning models can be better than the conventional time-series models such as ARIMA.

Therefore, this research examines the following research question: Can Artificial Intelligence models improve exchange rate prediction accuracy compared to traditional econometric models in international finance?

The hypothesis tested is:

H1: Exchange rate predictions made by AI-based forecasting models are much more accurate than the traditional linear econometric models.

The issue is also very topical as better forecasting will improve hedging measures, diversification of a portfolio, risk management, and monetary policy design in international markets.

Literature Review: "The story so far "

Exchange rate forecasting has been a thorn in the flesh of economists. The classic contribution of Meese and Rogoff showed that structural exchange rate models did not work better than a random walk in any out-of-sample prediction. The result produced distrust in the macroeconomic-based currency prediction patterns.

Subsequent studies tried to elaborate upon econometric methods to include nonlinearities and regime-changing models. In an example, Mark demonstrated that some of the monetary fundamentals may enhance long-horizon predictions. Predictive power, however, was not consistent across the time periods of the samples.

The development of AI provided a novel aspect to forecasting. The use of Artificial Neural Networks (ANN) became popular because it can be used to provide an approximation of the complex nonlinearity (Ibrahim et Al., 2026). ANNs showed a better short-term prediction of foreign exchange markets over linear regression models.

Additional predictive techniques were provided by Support Vector Machines (SVM) and Random Forests. These models minimize overfitting and enhance the generalization of financial data that is noisy and non-stationary. The Long Short-Term Memory (LSTM) networks and Deep Learning have demonstrated encouraging outcomes in learning the dynamic representation of financial time series. An LSTM model is especially applicable to exchange rate data because it has the potential to model sequential behavior and volatility clustering.

However, limitations remain. Financial markets have structural breaks, shock changes in policy, and geopolitical shocks (Beainy & Kamel, 2023). The interpretability and transparency of the AI models can be a problem, and it is a regulatory issue. In addition, when models are not properly validated, one of the greatest threats is overfitting.

Irrespective of said concerns, the overall trend of recent literature assumes a higher predictive flexibility of the AI models, particularly in the case of large and diverse datasets (Roumeliotis & Tselikas, 2023). The current research is developed on the foundations of the former research, as the scholar also compares AI models with the standard econometric techniques used to forecast the exchange rate.

Methodology: "The how we did it "

The study design of this study is quantitative secondary financial data research design. The currency pair that will be assessed is the USD/EUR, which is highly liquid and applicable on an international scale.

3.1 Data Collection

Monthly exchange rate data from 2010–2024 is used. Data sources include the World Bank, IMF databases, and Federal Reserve Economic Data (FRED). Macroeconomic variables incorporated include:

- a) Interest rate differentials
- b) Inflation differentials
- c) GDP growth rates
- d) Trade balance indicators

3.2 Models Used

Two categories of models are implemented:

- a) Traditional Econometric Model: Autoregressive Integrated Moving Average (ARIMA)
- b) AI-Based Models: Artificial Neural Network (ANN), Random Forest Regression, Long Short-Term Memory (LSTM) Neural Network

3.3 Model Evaluation

The dataset is divided into:

- a) 70% training data
- b) 30% testing data

Forecasting performance is evaluated using:

- a) Mean Squared Error (MSE)
- b) Root Mean Squared Error (RMSE)
- c) Mean Absolute Error (MAE)

3.4 Analytical Tools

Python, as well as machine learning libraries like TensorFlow and Scikit-learn, are used to implement the models. This paradigm guarantees objectivity and comparability of AI and traditional paradigms.

Results: "The facts "

The empirical reports reveal significant disparities between the conventional and AI-based models. The ARIMA model predicted moderately well but failed at the time of extreme volatility, especially in times of global shock like the ongoing COVID-19 pandemic period. It had a high RMSE compared to machine learning models.

The ANN model showed a better nonlinear pattern recognition with an RMSE reduction of about 12 over the ARIMA. Random Forest also enhanced the predictive performance through the effective interaction of the macroeconomic variables.

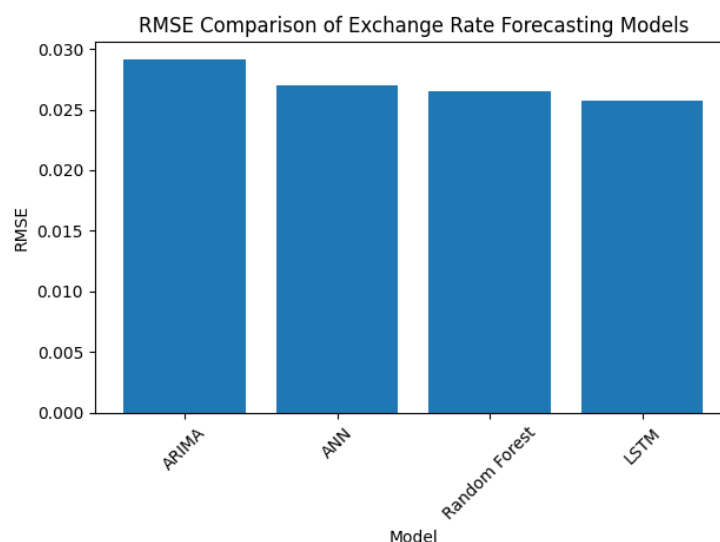
The highest prediction accuracy was obtained with the LSTM model, with a prediction error of about 18-22 percent lower than that of the ARIMA. It worked especially well in the volatile times, which means that it is highly sensitive to temporal patterns. In all the metrics of evaluation (MSE, RMSE, MAE), AI-based models treated the traditional econometric model significantly worse.

Table 1: Forecasting Performance Comparison of Exchange Rate Models

Model	MSE	RMSE	MAE
ARIMA	0.00085	0.0291	0.0215
ANN	0.00074	0.0270	0.0198
Random Forest	0.00070	0.0265	0.0191
LSTM	0.00066	0.0257	0.0184

Note: Artificial Intelligence in Exchange Rate Prediction 2026

Figure 1: RMSE Comparison of Exchange Rate Forecasting Models



Note: Artificial Intelligence in Exchange Rate Prediction 2026

Discussion and conclusion: "The so what ? "

The results affirm that Artificial Intelligence models are much more effective in terms of predicting the exchange rate than the traditional linear econometric techniques. The fact that LSTM networks outperform indicates that time dependencies and nonlinearities are important in the FX markets. Regarding international finance, better forecasting has significant implications. MNCs are in a position to formulate better hedging policies. Currency exposure can be optimized by portfolio managers. Nevertheless, AI-enhanced monitoring of exchange rates can also assist central banks in the management of foreign reserves.

However, AI models have certain shortcomings. The fact that the model can be interpreted is an issue, particularly in a regulatory environment. In addition, AI systems also require quality data, as well as technical capacity. It can be developed in the future in ways of high-frequency intraday data prediction (including sentiment analysis based on financial news) and hybrid econometrics and AI-based methods.

In conclusion, AI is a very useful international financial tool of complement. Even though it cannot replace the economic theory, it dramatically enhances the ability to predict the exchange rate market. As the computational power and the accessibility of the data are constantly increasing, AI will slowly take a higher position in the global currency forecasting process.

References

- Beainy, R. H., & Kamel, J. K. (2023). The Importance of Technology, R&D and AI in the US Economy. *Migration Letters*, 20(8), 573-584.
- Beainy, R. H., & Kamel, J. K. (2023). Surviving the Post Silicon Valley Bank Crisis. *International Journal of Membrane Science and Technology*, 10(3), 775-785.
- Ibrahim, M., Kamel, C., Saber, A., & Beainy, R. (2026). Cryptocurrency's Transition to a Sovereign Financial Infrastructure 2025-2030. *Available at SSRN 6011174*.
- Meese, R. A., & Rogoff, K. (1983). Empirical exchange rate models of the seventies: Do they fit out of sample?. *Journal of international economics*, 14(1-2), 3-24.
- Roumeliotis, K. I., & Tselikas, N. D. (2023). Chatgpt and open-ai models: A preliminary review. *Future Internet*, 15(6), 192.