SOPRONI EGYETEM

LÁMFALUSSY SÁNDOR KÖZGAZDASÁGTUDOMÁNYI KAR

KONFERENCIAKÖTET

Conference Proceedings

Nemzetközi tudományos konferencia a Magyar Tudomány Ünnepe alkalmából

International Scientific Conference on the Occasion of the Hungarian Science Festival

Sopron, 2025. november 6.

6 November 2025, Sopron

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DEVELOPMENT TRAJECTORIES AND NEW DIVIDES IN TIMES OF SUSTAINABILITY TRANSITIONS

Szerkesztők / Editors:
RESPERGER Richárd, SZÉLES Zsuzsanna, TÓTH Balázs István

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SOPRONI EGYETEM KIADÓ

UNIVERSITY OF SOPRON PRESS

SOPRON, 2026

Mottó: **„200 év a tudás és a társadalom szolgálatában"**
/ Motto: „200 years to knowledge and service to society"

Felelős kiadó / Executive Publisher**: Prof. Dr. FÁBIÁN Attila**
a Soproni Egyetem rektora / Rector of the University of Sopron

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ISBN 978-963-334-579-5 (pdf)

DOI: https://doi.org/10.35511/978-963-334-579-5

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DOI: 10.35511/978-963-334-579-5-s7-4

Integrating AI-driven Macroeconomic Forecasting with Exchange Rate Hedging: The Case of Japanese Yen

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Abstract:
The Foreign Exchange market is the largest and most liquid market, and it is considered a highly volatile market, which poses a significant risk for investors, governments, and global companies. The use of macroeconomic indicators such as inflation, economic growth, and interest rates on exchange rate predictions is valuable, as stated in traditional economic models, Interest rate parity, and purchasing power parity. However, machine learning models demonstrated higher accuracy in predicting macroeconomic indicators by capturing non-linearity and rapid market shocks, which traditional models might miss. The primary goal of this study is to evaluate how effective AI and ML models are in predicting exchange rates through macroeconomic indicators, which have a significant impact on exchange rate movements. In this paper, the application of artificial intelligence has been used, specifically a long short-term memory neural network model, which makes predictions more accurate. For analysis, we will use USD/JPY due to the volatility of the yen in recent years. The empirical findings, derived from monthly data spanning 1996 to 2024, indicate that AI-enhanced models substantially exceed traditional econometric methods in predicting fluctuations in the USD/JPY exchange rate. The study also uses simulated hedging strategies, which lead to less exposure to changes in the exchange rate.

Keywords: exchange rate volatility, artificial intelligence, machine learning, Japanese yen, financial risk management
JEL Codes: C45, C53, F31, F37

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1. Introduction

The growth of the economy was significantly influenced by international trade. It has even shaped the way we live since ancient times. Now, each global trade transaction has an impact on the Foreign Exchange (Forex) Market, which enables the buyers and sellers to get their cash in a desirable currency. This makes the forex market the largest and most liquid market in the world, involving trillions of dollars being traded daily. This huge market is decentralized and consists of participants such as governments, central banks, corporations, hedge funds, etc. Because of its characteristics forex market is considered one of the most volatile markets. Therefore, it poses a major risk for investors, governments, and global companies (Baruník et al., 2017).

After the collapse of Bretton Woods, the exchange rate fluctuations and their impact on economic areas became a more attractive topic, and many studies have been carried out to measure the possible outcomes of this subject. Forecasting exchange rates is an important component of financial markets and international trade, functioning as an indispensable instrument for firms, investors, and regulators. The capacity to precisely forecast exchange rate fluctuations has significant consequences.

It facilitates the formulation of efficient currency hedging plans for enterprises, safeguarding against unforeseen exchange rate swings that could threaten profitability (Nihro Jabal & Majeed Allawi, 2020).

The use of macroeconomic indicators such as inflation, economic growth, and interest rates on exchange rate predictions is proven to be valuable, as stated in traditional economic models, Interest rate parity (IRP), and Purchasing power parity (PPP). These assumptions have been fundamental in understanding the movement of exchange rates. This paved the way for researchers to analyze and prove the impact of the main economic indicators on exchange rates (Vámos & Novák, 2018).

While the traditional economic models provided a valuable long-term foundation for understanding the movement of exchange rate volatility, they had limitations. The main disadvantage of these models is the emphasis on linearity. Recent developments in AI and ML have the capability to fill this gap. Machine learning models demonstrated higher accuracy in the prediction of macroeconomic indicators by capturing non-linearity and rapid market shocks, which traditional models might miss.

The primary goal of this study is to evaluate how effective AI and ML models are in predicting exchange rates through macroeconomic indicators, which have a huge impact on exchange rate movements. In this paper, the years spanning from 1996 to 2024 are analyzed using the USD/JPY conversion rate to predict the Japanese Yen using the main macroeconomic indicators. Japanese Yen is chosen because of its high volatility in recent years and unique characteristics. In the second part of the paper, we then analyze how these predictions can improve hedging techniques to enable the switch to a proactive state from a static one. Simulated hedging strategies are analyzed to produce superior results.

Our results emphasize the necessity of having integrated prediction models equipped with AI and ML models, and hedging strategies to better manage the risks against exchange rate volatility.

2. Literature Review

Barton et al., (2002) state that uncertainty prevails in the current economy. Every corporation engages in risk management to some degree, regardless of its products or services. It is not feasible to establish a firm that does not take risks. Without risk, it is impossible to make money. As a firm evolves, so do the associated risks. Stakeholders are increasingly demanding that companies identify and mitigate their business risks. As such, financial risk management plays a key role for companies. One of the main risks companies face is the exchange rate volatility.

The Foreign Exchange (FOREX) market is the largest and most liquid market, where, on average, trillions of dollars are traded daily. Since it is considered a highly volatile market, it poses a significant risk for investors, governments, and global companies (Baruník et al., 2017).

After the collapse of Bretton Woods, the exchange rate fluctuations and their impact on economic areas became a more attractive topic, and many studies have been carried out to measure the possible outcomes of this subject. Forecasting exchange rates is an important component of financial markets and international trade, functioning as an indispensable instrument for firms, investors, and regulators. The capacity to precisely forecast exchange rate fluctuations has significant consequences.

It facilitates the formulation of efficient currency hedging plans for enterprises, safeguarding against unforeseen exchange rate swings that could jeopardize profitability.

Unexpected exchange rate fluctuations can threaten profitability. In the past, classical econometric models were the most common way to forecast exchange rates. The most popular were the autoregressive integrated moving average (ARIMA), vector autoregressive (VAR), and random walk models. These models primarily used historical data and statistical methods to forecast future exchange rate movements. ARIMA is a time series model that uses past data points to predict future values based on their relationships. VAR models also showed the relationships between different time series variables. This was useful for studying the impact of various economic factors, such as inflation and interest rates, on exchange rates. The random walk model, which posits that future exchange rate movements are random and do not follow any pattern, was also often used for forecasting (Poon & Granger, 2003).

While these models provided a valuable foundation for understanding the movement of exchange rate volatility, they had limitations. The main disadvantage of these models is the emphasis on linearity. Because of the likelihood of establishing a misleading correlation, linear regression is an unsuitable strategy for studying time series. Therefore, we see a rise in the focus on AI and ML models in exchange rate forecasting. Deep learning models such as long short-term memory (LSTM), support vector machines (SVM), and neural networks have filled the gap left by traditional models. These machine learning models can include both structured and unstructured data, such as inflation rates and GDP growth, news articles, social media sentiment, and geopolitical events. This gives a full picture of what causes exchange rate volatility. A recent study found that artificial intelligence and machine learning models did better than traditional approaches at predicting exchange rates (Abouzaid & Boussedra, 2025). This study, focusing on EUR/USD forecasting (2014–2024) evaluated an LSTM, a random forest, and a multilayer perceptron, concluding that the LSTM attained the highest predicted accuracy with an R-squared of 0.92. All the machine learning models produced robust short-term projections, demonstrating that machine learning can adeptly capture exchange rate changes, even when conventional macroeconomic indicators have minimal explanatory power in the short term. That shows the model was able to predict the exchange rate with limited power from main macroeconomic variables, which aligned with the famous research from (Meese & Rogoff, 1983) that simplistic random walk can outperform traditional economic models, but now ML models challenge this orthodoxy. Combining economic augmentation with AI gives the best results. As the results state in the study (Abouzaid & Boussedra, 2025), Macro-augmented LSTM models have substantially enhanced EUR/USD predictions after abrupt economic occurrences (e.g., interest rate increases or inflationary shocks). This indicates a hybrid forecasting method that combines data-driven machine learning algorithms with economic insights to achieve both accuracy and interpretability.

The core challenge for hedging decisions is the dependence on the expectation of future exchange rate movements. If one can perfectly predict the movement, they can be better prepared for the hedging decisions. This would enable the users to switch from reactive to predictive decision-making in this process. Forecasts are not always accurate, and an inaccurate projection can result in less-than-ideal hedging, such as hedging too little, which leaves the company vulnerable if the currency swings negatively, or hedging too much, which incurs needless expenses if the currency stays favorable. Forecasting and hedging are therefore naturally related; improved predictive data should facilitate improved hedging tactics. In the recent study (Pagnottoni & Spelta, 2024), the use of several trained ML models containing currency return components in time series has produced a method for the prediction of exchange rate movement. Their backtests involving the years between 2008 and 2022 demonstrate that integrating machine learning projections of currency components produced superior hedged results compared to static or simplistic methods. The analysis of diverse model performance indicators resulted in substantial currency risk hedging for global stock portfolios enabled through precise predictions of global factor returns, particularly those obtained by nonlinear machine learning models. Automated portfolio management using machine learning not only provides superior protection against currency risk but also improves portfolio returns compared to linear forecasting approaches. This provides scientific evidence that incorporating AI forecasts into hedging strategies enhances their value. Another illustrative example is a pilot project implemented by Citigroup and Ant International for a well-known airline, where AI was used to improve the airline's currency hedging strategy. The outcomes were remarkable: the airline saw a 30% decrease in hedging expenses and enhanced its prediction precision to over 90% by employing AI-driven models to optimize the timing and magnitude of its currency hedges (Reuters, 2025).

However, the use of artificial intelligence and machine learning models has its limitations. Despite their forecasting effectiveness, machine learning models often lack clarity and interpretability in their results. Complex, uncertain models trained on large datasets often have limited interpretability, making it difficult to assess which characteristics most influence forecasts. Future research could focus on improving the clarity of machine learning models' forecasts, an important area in this context, helping to determine the factors that determine portfolio weightings (Pagnottoni & Spelta, 2024).

Another issue in AI and ML models is the risk of overfitting. This significant challenge transpires when a model internalizes patterns present solely in historical data, hence failing to generalize to novel or unknown data. Economic and financial data often contain significant random noise caused by unexpected events such as policy changes, crises, or fluctuations in market sentiment. As a result, adaptive machine learning models such as neural networks or random forests can demonstrate exceptional performance on historical data but may produce inaccurate forecasts for the future (Gogas & Papadimitriou, 2021).

3. Research Methodology

Methods of the research are prepared to identify the best approaches for forecasting the Japanese exchange rate based on the macroeconomic indicators with the help of modern Artificial Intelligence techniques. Macroeconomic indicators such as real GDP growth, inflation rate, and trade balance are used since they are some main drivers of the exchange rate movement (Jamil, et al., 2023). This section describes the dataset and its techniques, identifies the research methods, and outlines the approaches to analysis employed.

3.1. Research Design

This research employs a quantitative, data-driven research design to forecast the AI-adopted USD/JPY exchange rate prediction. It is divided into 2 stages: First, Advanced AI models are employed to predict exchange rates using merged historical daily data from Yahoo Finance and annual macroeconomic data from the International Monetary Fund (IMF) for the period of 1996 to 2024. Additionally, traditional statistical methods are also applied to get a comparison of the results of the first stage. In the second stage, hedging strategies are proposed to maintain relative stability in the local exchange rate based on the results of the study. The most significant macroeconomic variables are identified, and the proposed hedging strategies are suggested according to globally recognized approaches. Shinzo Abe's economic decisions (2012-2020), major global external shocks such as the pandemic (2020-2022) and rising US interest rates (2022-2024) are connected to the quantitative results and suggestions.

3.2 Data source and Variables

IMF World Economic Outlook (WEO) (International Monetary Fund, 2025) Dataset and Yahoo Finance (Yahoo Finance, 2025) The daily exchange rate for Japan is one of the two datasets that are utilized in the writing of this article. The World Bank of Economics (WOE) offers yearly macroeconomics data beginning in 1980; however, because the research covers the period from 1996 to 2024, the analysis only covers that thirty-year period. Yahoo Finance offers daily USD/JPY exchange rates, and research adopts the close rate for each day.

The temporal frequency of the two datasets is different, and that is why it requires the implementation of a frequency alignment technique for accurate merging. The IMF WEO macroeconomic statistics are reported annually, whereas the exchange rate data are provided daily. To facilitate integrated modeling, yearly macroeconomic values were unsampled to a daily frequency by distributing each macroeconomic observation across all trade days within the respective year. Each daily measurement of the exchange rate correlates with the macroeconomic conditions of that year.

The primary dependent variable for the analysis is the daily exchange rate of the Japanese yen against the US dollar (USD/JPY). The exchange rate represents the value of one dollar in yen. To provide better accuracy, the daily rates are transformed to monthly, which additionally assists in reducing overfitting in the prediction. Some other important independent variables:

- *Real GDP Growth:* It shows the strength and expansion of the Japanese economy for each year. Higher growth rate usually brings capital and appreciates the exchange rate (Habib et al., 2017).
- *Inflation rate:* It represents the price change in the country within a year. Differences in inflation between countries – here Japan and the USA – impact the Purchasing Power Parity (PPP) and change the exchange rate (Krugman et al ., 2018)
- *Trade Balance:* This variable in the dataset is represented by the percentage of GDP. The trade balance indicates a net export surplus for the country and has a positive correlation with the exchange rate (Petrović & Gligorić, 2010). A positive trade balance in Japan will lead to a rise in demand for the Yen.

3.3. Quantitative Analysis and AI models

Before any quantitative analysis, exploratory data analysis (EDA) is applied to show the basic relationship between dependent and independent variables. Initially, descriptive statistics were investigated to understand the variables and see the mean, median, distribution, and detect potential outliers. Additionally, the Augmented Dickey-Fuller (ADF) is adopted in order to check the stationarity. Stationary factors are changed or transformed by using logarithms. At the same time, highly correlated variables should be removed to avoid multicollinearity.

Traditional statistical methods are the basis for the comparison for forecasting and an accuracy check. That is the reason why Multiple Linear Regression (MLR) and Random Forest are used. Each model has its own advantages; for example, MLR is good at predicting non-linear relationships, whereas Random Forest creates multiple tree-based decisions and aggregates results to reduce overfitting and increase accuracy (James et al., 2013).

Long Short-Term Memory (LSTM) Neural Network is the main algorithm of the research, and it is another base part for the comparison. Its unique structure enables the retention and utilization of information over longer durations, rendering it appropriate for time-series prediction and the modeling of dynamic systems, and that is why it is well-suited for exchange rate prediction (Malashin et al., 2024).

The final merged dataset is divided into two distinct parts for training and testing, 80% and 20%, respectively. Five-fold cross-validation is employed in order to avoid overfitting and to get more accurate results. Root Mean Squared Error (RMSE), Mean Squared Error (MAE), Mean Absolute Percentage Error (MAPE), and Directional Accuracy (DA) are used for the evaluation and testing accuracy of the final models.

3.4. Hedging strategies suggestion based on analysis

Progressing from the previous sections where predictive models were developed, this study combines the exchange rate forecasts based on AI models with the comparison of different hedging strategies for Japanese Yen against USD. The two frameworks that are analyzed include the static forward hedge and the AI-informed dynamic hedge.

The static hedge uses a one-to-one fixed forward position to cancel out currency exposure, which is the traditional way commonly used in corporate risk management (Bartram et al., 2009). Even though it is easy to operate, this type of model ignores the changing macroeconomic and market information. On the other hand, the dynamic hedge utilizes the forecaster's exchange rate produced by AI and modifies the hedge ratio in line with the predicted yen value change (Bollerslev et al., 2018).

4. Analysis and Results

The analysis started with data cleansing and feature selection. Daily data and macroeconomic indicators have been merged via frequency alignment techniques. Each day value possesses an equivalent annual worth, accordingly. Exploratory data analysis reveals trends in near values from 1996 to 2024, as seen in *Figure 1*. The Yen strengthened against the USD until 2012, with the exchange rate increasing from around 0.0075 to around 0.013.

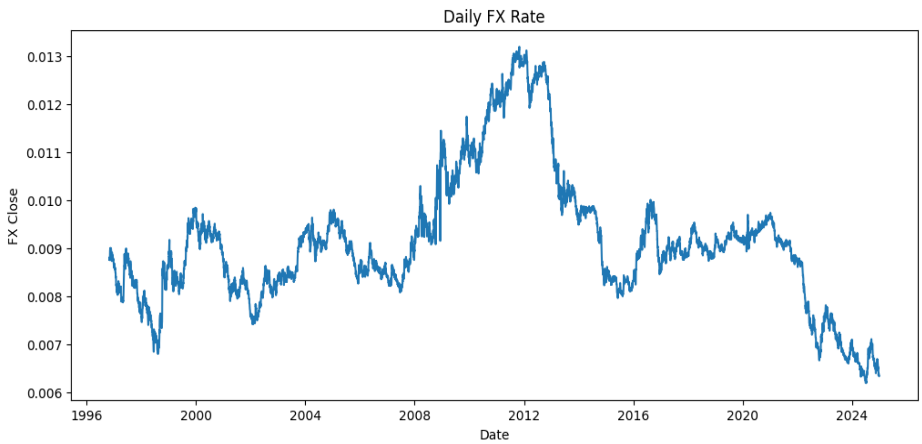

Figure 1: Yen Close price between 1996 and 2024
Source: Yahoo Finance (2025)

To assess the volatility of the currency rate, a visualization was provided below. *Figure 2* illustrates that the Yen exhibits little or consistent volatility rates during these years.

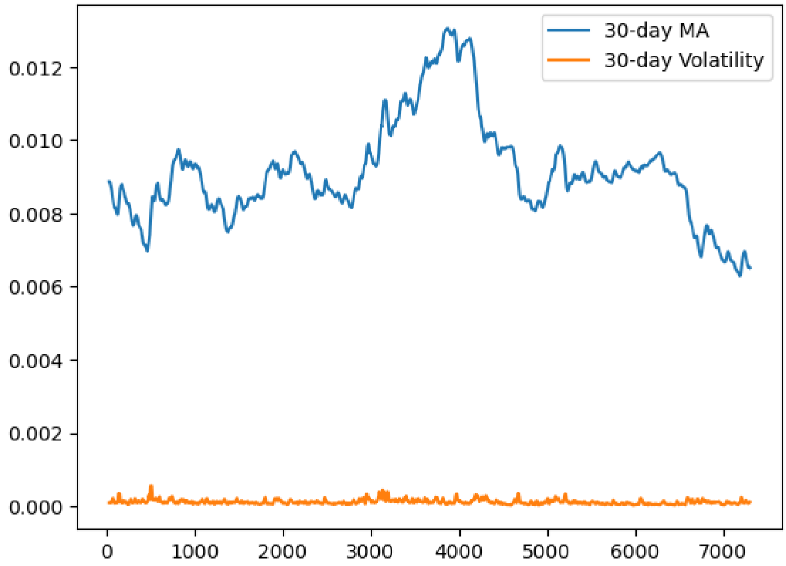

Figure 2: Volatility between 1996 and 2024
Source: Yahoo Finance (2025)

As a next step, correlation was checked, and highly correlated values were dropped in order to avoid overfitting in the modelling part. CPI, Current Account, Expenditure, Export, Goods Imported, Net borrowing/Net lending, Output Gap, Structural balance, and Unemployment rate have been selected as main indicators for analysis. All variables in the correlation matrix are lower than 0.9 after all cleaning (*Figure 3*). Additionally, the Augmented Dickey-Fuller (ADF) is adopted in order to ensure all variables are stationary. The ADF test results indicate that the majority of the series are likely non-stationary, signifying that their statistical properties, including mean and variance, fluctuate over time, as evidenced by elevated p-values and ADF statistics exceeding the critical values. Close (FX rate for close price), CPI, Current Account, Expenditure, Net lending/net borrowing, Structural balance, and Unemployment rate do not reject the null hypothesis of a unit root. Export, Goods Imported, and Output Gap, on the other hand, are probably stationary because their ADF statistics are below the critical values and their p-values are very low, which means that the null hypothesis can be rejected. This means that only a small number of series change around a constant mean, while most show trends or patterns that last over time.

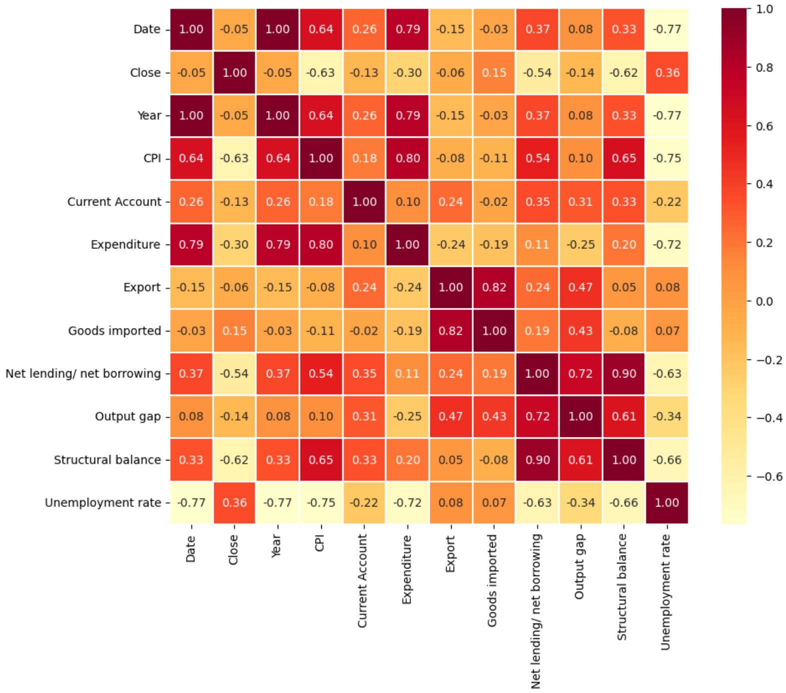

Figure 3: Correlation matrix
Source: Own representation

The log-difference transformation is applied to convert a series into growth rates, stabilizing its variance. It also helps remove trends, making non-stationary series more stationary. This makes the data suitable for time series modeling and statistical analysis.
A box plot is created to detect outliers and see the distribution of the Close price of JPY in the time series (*Figure 4*). It shows the median of the Close Rate is around 0.009. Even if there are some outliers, it is usually recommended to keep outliers in the market dataset since they often reflect real market behavior (Shehadeh et al., 2022). Therefore, outliers are kept for accurate modelling.

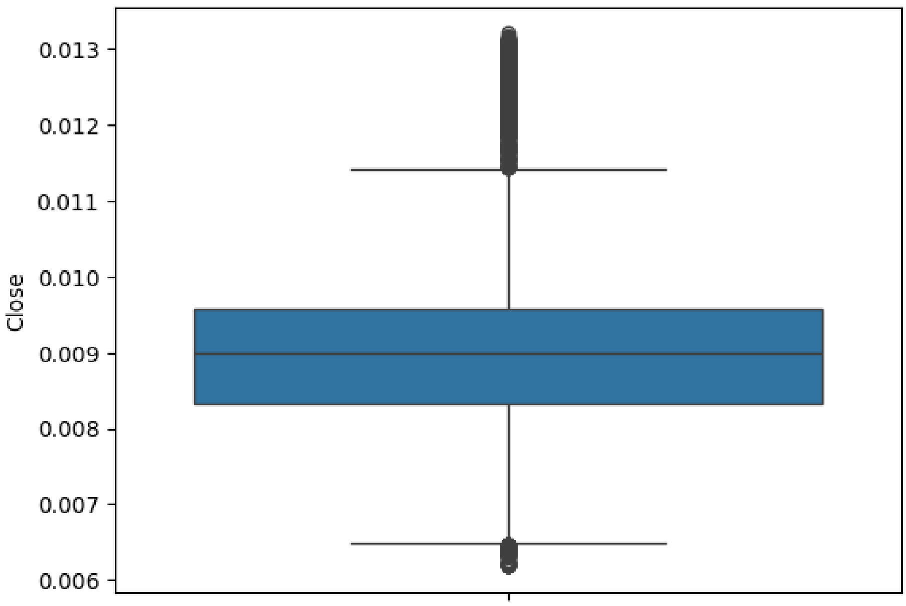

Figure 4: Box Plot of Close Rate
Source: Own representation

4.1. Modelling and Prediction

Initially, multiple linear regression was applied to see how a very traditional model predicts the Close price. With an around 0.81 R^2 coefficient and with extremely low MAE = 0.000471, RMSE = 0.000597, MSE = 3.56×10^{-7} shows the model performs well. Next, the ARIMA method is applied, and all five autoregressive terms were statistically significant, and the model's error variance was very small, which means that it made accurate short-term predictions. Residuals had a very high kurtosis and a small negative skewness, which meant that there were some extreme values. However, the Ljung-Box test showed that there was no significant autocorrelation left. The predictions were very accurate, with a mean squared error (MSE) of 2.34×10^{-6} and a mean absolute error (MAE) of 0.00116. There are some warnings about convergence and the covariance matrix that make it important to be careful when looking at coefficient confidence intervals. Overall, though, the model does a good job of capturing the main patterns in the data (*Figure 5*).

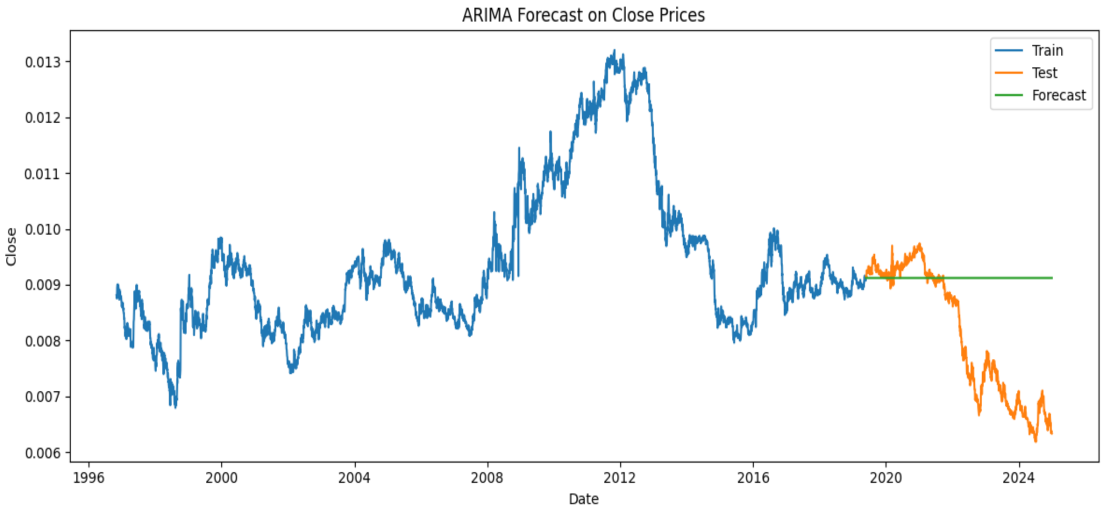

Figure 5: ARIMA Method Results
Source: Own representation

As a next model, Random Forest has been applied, and it outperformed compared to previous models. Cross-validation results show the model performance to be consistent across folds, with the RMSE ranging from 0.00022 to 0.00024, averaging 0.000226. Corresponding R^2 values were very high, lying within the range of 0.972 to 0.976 and averaging 0.974, hence suggesting that most of the variance in the data has been explained by the model. It predicts well on the test set by giving an RMSE of 0.000225, an R^2 of 0.974, and an MSE of 5.06×10^{-8}, performing with the best result until now (*Figure 6*).

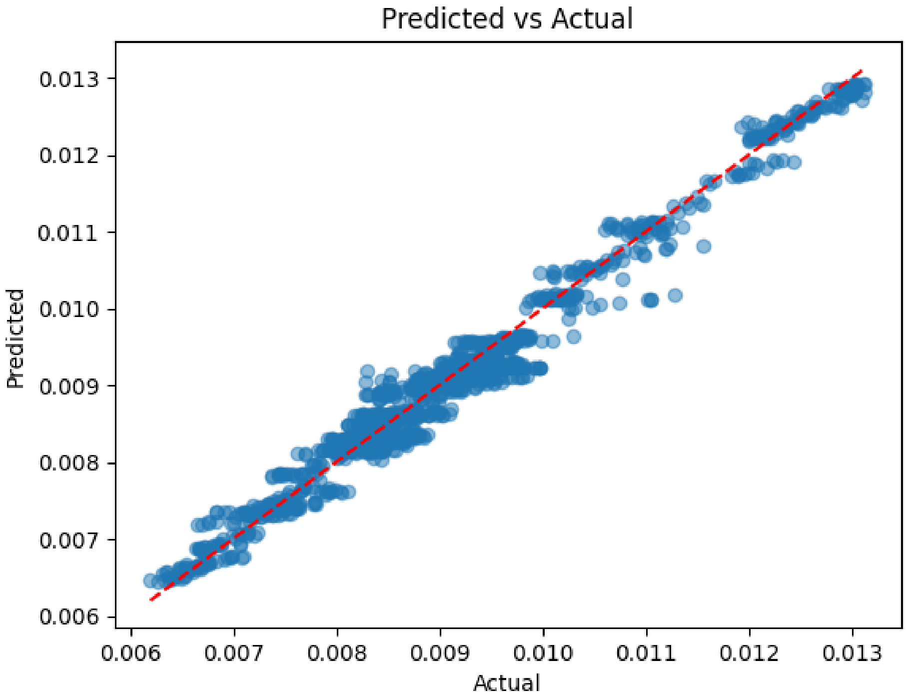

Figure 6: Random Forest Prediction Result
Source: Own representation

Last but not least, the LSTM model has been applied to conclude the final part. During the 55 epochs of training, the model progressively lessened the training loss and mean absolute error (MAE), and at the same time, significantly performed in the validation set with a minimum validation loss of 4.31×10^{-5} and MAE of 0.0050. The results suggest that the model managed to extract the underlying patterns from the data very well and that both short- and long-term dependencies were captured.

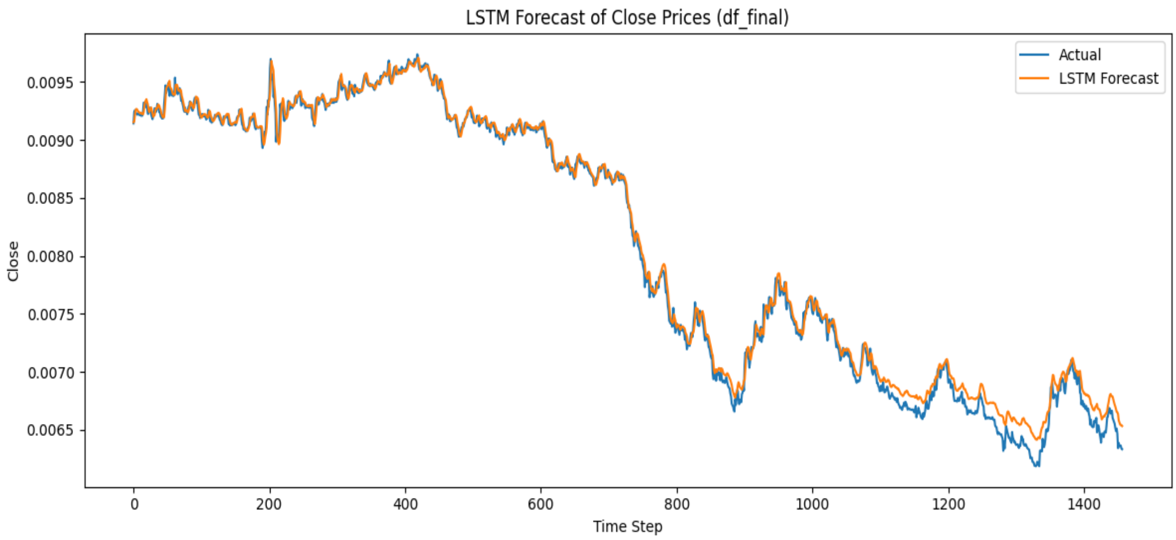

Figure 7: LSTM Model Performance
Source: Own representation

Overall, it outperforms compared to previous models and did a good job of predicting the Close price for JPY against USD (*Figure 7*).

4.2. Hedging Strategies Comparison

This part of our analysis focuses on comparing static hedging against dynamic hedging. As mentioned earlier, traditional hedging strategies heavily depend on static methods. Our analysis of the predictive exchange rate will help us to develop simulated approaches to test the switch to dynamic hedging. For simplicity, we chose a 6-month period with high volatility to see the difference between the two approaches.

Static hedging is mainly identifying risk setting in the beginning and starting the portfolio where you remain in the place for the entire period with almost no reaction. This kind of approach is called "set and forget". Dynamic hedging, on the other hand, gives the option to respond to the market by becoming reactive. Predictive dynamic hedge strategy enables earning time by getting notified before the market reacts (Xu & Rutkowski, 2025).

Our prediction analysis on the Long Short-Term Memory network model involving train and test data outperforms the traditional models. We will take this model as the basis for a dynamic hedge position.

The static hedge strategy will be the 6-month forward position for a fictional company A having 10 million USD in cash revenue. The period used for the simulation with high volatility for JPY is from April 2022 to October 2022 (*Figure 8*).

Figure 8: Japanese Yen to USD Spot Exchange Rate
Source: FRED (2025)

4.2.1. Static Hedging

Company A, using a Static hedging strategy, has a 10 million USD cash inflow. The USD/JPY exchange rate stood at 122.60. They will have a cash outflow in 6-month periods in Yen; therefore, they want to prevent the risk they might face in the future. 6-month forward rate is approximately 124.073. To simplify the comparison, the full amount is used for the forward contract. The forward rate is calculated using the standard formula:

$$Forward\ ate\ = Spot\ Rate\ \times \left(\frac{1 + iusd \times T}{1 + ijpy \times T}\right)$$

4.2.2. Dynamic Hedging

Now, company B, which is also in the same situation, uses a dynamic hedging strategy to reduce the exchange rate volatility risk associated with the cash outflow of JPY in 6 months. Based on the predictive dynamic strategy, the company is using 50% lock on the forward rate/ 50% Spot. Therefore, 50% of the portfolio follows the same approach as company A, where the other half is used on the spot market. The formula to calculate the dynamic hedge based on the test results, R-squared 99% is stated below:

$$Predicted\epsilon\ Spot = Actual\ Spot + \epsilon$$
$$\epsilon \sim \mathbb{N}(0, \sigma^2)$$

4.2.3. Dynamic against Static Hedging

According to the results of the comparison, dynamic hedging outperforms static hedging in short-term high volatility environments. The static hedging prevents the company from reacting to the market behavior and locks its responsiveness ability, whereas dynamic hedging helps the company to counteract the market shocks and give responsive actions.

The *Table 1* summarizes the results of both hedging strategies.

Table 1: Static vs Dynamic Hedging

Component	**Static Hedge (100% Forward)**	**Dynamic Hedge (50% Forward + 50% Spot, RÂ²=99%)**
USD Exposure	10,000,000 USD	10,000,000 USD
Hedging Split	100% Forward	50% Forward, 50% Spot
Forward Rate (Fixed)	124.07	124.07
Actual Spot Rate	145.50	145.50
Predicted Spot Rate (LSTM, RÂ²=99%)	N/A	145.997
JPY from Forward Contract (Fixed)	1,240,700,000	620,350,000
JPY from Spot/Prediction (Variable)	-	727,500,000

Source: Own representation

5. Conclusions

This research examines the integration of Artificial Intelligence into macroeconomic forecasting and exchange rate hedging, using the Japanese yen in the volatile USD/JPY currency pair as an example. As it was mentioned before, classic theories such as purchasing power parity and interest rate parity have helped to understand the mechanisms of exchange rates. However, they are not always effective in rapidly changing markets or significant changes in the global financial system. To fill this gap, the study applied advanced statistical models to predict exchange rate dynamics by using macroeconomic factors over several decades.

The results show that AI models such as long short-term memory (LSTM) networks and ensemble methods such as random forests provide more accurate forecasts than traditional linear models. These machine learning methods better predict the complex and dynamic relationships between macroeconomic indicators and exchange rates than traditional methods. More importantly, when applying these predictions to hedging strategies, dynamic AI-based hedging models have proven to be more adaptive and responsive than static ones. This clearly demonstrates the value of using data-driven predictions to manage risk in a rapidly changing market.

However, despite these positive results, a number of challenges remain. First, it is still difficult to understand how AI models work. They are quite accurate, but it is not always clear which elements are involved in generating the predictions. This can make them less attractive to financial decision makers who need clear justifications and logical reasons for their risk management plans. Moreover, there is a risk of overfitting, particularly in the case of market data that may contain random noise and infrequent shocks. Even after validation and model adjustment procedures, AI models trained on old data may prove ineffective against new, unforeseen events. Third, the modeling of hedging techniques in the study is theoretical and context-dependent; practical application, paradoxically, requires further customization to take into account the risks, operating costs, and regulatory requirements of a specific company.

In summary, the study confirms the growing importance of artificial intelligence in improving forecasting accuracy and hedging effectiveness in foreign exchange markets. As companies and government officials seek more effective ways to combat foreign exchange risk, macroeconomic understanding and AI skills are a welcome step. However, it is crucial that these models be made more transparent, reliable, and scalable so that they can be more widely used and trusted in making real-world financial decisions.

References

Abouzaid, O., & Boussedra, F. (2025). Artificial intelligence and exchange rate forecasting: Assessing predictive accuracy and macroeconomic sensitivity. *Frontiers in Applied Mathematics and Statistics*, *11*, 1654093. https://doi.org/10.3389/fams.2025.1654093

Barton, T. L., Shenkir, W. G., & Walker, P. L. (2002). *Making enterprise risk management pay off: How leading companies implement risk management*. Financial Times/Prentice Hall.

Bartram, S. M., Brown, G. W., & Fehle, F. R. (2009). International evidence on financial derivatives usage. *Financial Management*, *38*(1), 185–206. https://doi.org/10.1111/j.1755-053X.2009.01033.x

Baruník, J., Kočenda, E., & Vácha, L. (2017). Asymmetric volatility connectedness on the forex market. *Journal of International Money and Finance*, *77*, 39–56. https://doi.org/10.1016/j.jimonfin.2017.06.003

Bollerslev, T., Patton, A. J., & Quaedvlieg, R. (2018). Modeling and forecasting (un)reliable realized covariances for more reliable financial decisions. *Journal of Econometrics*, *207*(1), 71–91. https://doi.org/10.1016/j.jeconom.2018.05.004

Federal Reserve Bank of St. Louis. (2025). Japanese yen to U.S. dollar spot exchange rate [Data set]. FRED. https://fred.stlouisfed.org/series/DEXJPUS

Gogas, P., & Papadimitriou, T. (2021). Machine learning in economics and finance. *Computational Economics*, *57*(1), 1–4. https://doi.org/10.1007/s10614-021-10094-w

Habib, M. M., Mileva, E., & Stracca, L. (2017). The real exchange rate and economic growth: Revisiting the case using external instruments. *Journal of International Money and Finance*, *73*(Part B), 386–398. https://doi.org/10.1016/j.jimonfin.2017.02.014

International Monetary Fund. (2025). *World economic outlook (WEO)* [Data set]. https://data.imf.org/en/Data-Explorer?datasetUrn=IMF.RES:WEO(9.0.0)&INDICATOR=NGDP_R

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning: With applications in R*. Springer. https://doi.org/10.1007/978-1-4614-7138-7

Jamil, M. N., Rasheed, A., Maqbool, A., & Mukhtar, Z. (2023). Cross-cultural study of macro variables and their impact on exchange rate regimes. *Future Business Journal*, *9*(1), 9. https://doi.org/10.1186/s43093-023-00189-1

Krugman, P. R., Obstfeld, M., & Melitz, M. J. (2018). *International economics: Theory and policy* (11th ed.). Pearson.

Malashin, I., Tynchenko, V., Gantimurov, A., Nelyub, V., & Borodulin, A. (2024). Applications of long short-term memory (LSTM) networks in polymeric sciences: A review. *Polymers*, *16*(18), 2607. https://doi.org/10.3390/polym16182607

Meese, R. A., & Rogoff, K. (1983). Empirical exchange rate models of the seventies. *Journal of International Economics*, *14*(1–2), 3–24. https://doi.org/10.1016/0022-1996(83)90017-X

Nihro Jabal, S., & Majeed Allawi, K. (2020). The impact of exchange rate fluctuation risk on corporate profits: A review. *International Journal of Research in Social Sciences and Humanities*, *10*(4), 451–459. https://doi.org/10.37648/ijrssh.v10i04.043

Pagnottoni, P., & Spelta, A. (2024). Hedging global currency risk: A dynamic machine learning approach. *Physica A: Statistical Mechanics and Its Applications*, *649*, 129948. https://doi.org/10.1016/j.physa.2024.129948

Petrović, P., & Gligorić, M. (2010). Exchange rate and trade balance: J-curve effect. *Panoeconomicus*, *57*(1), 23–41. https://doi.org/10.2298/PAN1001023P

Poon, S.-H., & Granger, C. W. J. (2003). Forecasting volatility in financial markets: A review. *Journal of Economic Literature*, *41*(2), 478–539. https://doi.org/10.1257/jel.41.2.478

Reuters. (2025, July 18). *Citi, Ant International pilot AI-powered FX tool for clients to help cut hedging costs*. https://www.reuters.com/business/finance/citi-ant-international-pilot-ai-powered-fx-tool-clients-help-cut-hedging-costs-2025-07-18/

Shehadeh, A., Alwadi, S. M., & Almaharmeh, M. I. (2022). Detecting and analysing possible outliers in global stock market returns. *Cogent Economics & Finance*, *10*(1), 2066762. https://doi.org/10.1080/23322039.2022.2066762

Vámos, I., & Novák, Z. (2018). Four currencies outside the eurozone. *International Journal of Business and Economic Sciences Applied Research*, *8*(3), 97–108. https://www.econstor.eu/bitstream/10419/144667/1/848642856.pdf

Xu, H., & Rutkowski, M. (2025). *Pricing and hedging of cross-currency equity protection swaps* [Preprint]. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.5686728

Yahoo Finance. (2025). USD/JPY (JPY=X) historical data [Data set]. https://finance.yahoo.com/quote/JPY%3DX/history/

Web resources were last accessed on 31 March 2026.