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Integrating Economic Indicators and Machine Learning for Exchange Rate Forecasting

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Abstract – This study presents an integrated framework for forecasting the USD/JPY exchange rate using ensemble machine learning techniques – CART-Ensembles and Arcing. The analysis employs monthly macroeconomic data from October 1987 to April 2025. Key predictive variables include differentials in interest rates, inflation, unemployment, and government bond yields between the United States and Japan. After a preliminary time-series analysis and feature selection, ensemble models were developed for four distinct time periods. Each model performs step-by-step forecasts up to four months ahead (January–April 2025), achieving exceptionally high predictive accuracy, with coefficients of determination (R^2) above 0.98 and mean absolute percentage errors (MAPE) below 1%. The results demonstrate that combining macroeconomic fundamentals with advanced ensemble learning methods significantly enhances the accuracy, robustness, and reliability of exchange rate forecasting. These findings provide policymakers and investors with a robust analytical tool for anticipating short-term currency fluctuations under varying macroeconomic conditions.

Keywords – Ensemble Machine Learning Methods, Macroeconomic Indicators, Exchange Rate Forecasting

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1. Introduction

Foreign exchange markets play a crucial role in the functioning of the global economy, as they influence international trade, capital flows, labour markets, purchasing power, and the overall national economic policy. Exchange rate dynamics are primarily driven by fundamental macroeconomic indicators, such as inflation, unemployment, GDP, and official interest rates, as well as the yields on local and international debt instruments. These interactions produce complex effects on economic stability [1-3]. Central banks and governments strive to maintain sustainable growth, low unemployment, controlled inflation, and optimal public debt levels, with the strength of the national currency often serving as a direct indicator of economic health. Exchange rate forecasting has long been a significant topic in academic literature. High accuracy and efficiency in this process are of strategic importance for financial markets, national budgets, and international trade.

The application of modern mathematical and statistical methods in the study of economic processes, as well as macro- and microeconomic dependencies, provides valuable insights into currency and financial markets [4,5]. Many of the current approaches combine classical techniques with machine learning to achieve higher predictive accuracy. For example, in [6], the authors propose an ensemble model combining linear and nonlinear techniques (Box–Jenkins ARIMA methods and neural networks) for forecasting major currency pairs (EUR/USD, GBP/USD, USD/JPY). The study shows that the hybrid model is more precise than each of the individual methods. In [7], the predictive power of Random Forests is demonstrated for forecasting four major exchange rates (USD/CAD, GBP/USD, AUD/USD, EUR/USD). Study [8] proposes a new hybrid model of Fuzzy AutoRegressive Integrated Moving Average (FARIMA) integrated with probabilistic neural classifiers (FARIMAH), achieving a more accurate model for financial

forecasting with incomplete data. Empirical results from exchange rate market forecasting indicate that the proposed model effectively improves forecasting accuracy, especially when dealing with scarce data over a short time period. The authors' approach also shows improved performance in the presence of unstable or anomalous data. In [9], a combined model incorporating logistic regression, a random forest classifier, and a Gaussian Naïve Bayes classifier is developed to identify optimal times for buying and selling the euro against the dollar, achieving an accuracy of 94.8%. In [10], the authors propose a new method for predicting USD exchange rates against GBP, JPY, EUR, and CNY by combining Long Short-Term Memory (LSTM) with a bagging ensemble strategy (LSTM-B), aiming to improve both forecasting accuracy and trading profitability. Further studies, such as [11], evaluate the performance of advanced machine learning methods for trading the EUR/USD exchange rate at the ECB fixing. Five supervised classification algorithms (K-Nearest Neighbours, Naïve Bayes, Artificial Neural Networks, Support Vector Machines, and Random Forests) are applied to predict the one-day-ahead movement of the exchange rate using only autoregressive variables. Their performance is compared with two traditional approaches (Naïve Strategy and MACD), showing that SVM and Random Forest yield the highest returns and Sharpe ratios. Paper [12] focuses on the foreign exchange market, known for its high volatility and large transaction volumes, emphasising the importance of accurately predicting currency pair movements for effective investment strategies. It presents a comparative analysis of various machine learning models for forecasting the daily directional movement of the EUR/USD pair, evaluating both decorrelated and non-decorrelated feature sets via Principal Component Analysis. The work in [13] highlights that previous exchange rate forecasting research has typically relied on either shallow or deep features, with limited investigation into their combined potential. To address this, it proposes a novel ensemble learning method, Adaptive Linear Sparse Random Subspace (ALS-RS), which leverages the complementary strengths of both feature types.

Ensemble learning represents a class of machine learning techniques that combine multiple base models to achieve superior predictive performance compared to individual models [14,15]. By aggregating diverse learners – either homogeneous, as in bagging methods (e.g., Random Forest), or heterogeneous, as in stacking and boosting approaches – ensemble methods can reduce variance, bias, or both, depending on the strategy employed. This approach is particularly effective in financial time series forecasting, where high volatility and noise can lead to instability in single-model predictions. In the context of exchange rate forecasting, ensemble learning makes it possible to integrate models that capture different aspects of the data (such as linear and nonlinear relationships and short- and long-term dependencies), thereby enhancing overall prediction accuracy and robustness.

The primary objective of this study is to develop high-performance machine learning models for predicting the USD/JPY exchange rate, while examining the impact of key macroeconomic indicators for both countries. For this purpose, time series analysis is combined with CART Ensemble and Arcing methods.

2. Data and methods

2.1. Data collection

In this study, we use official data provided by the Bloomberg Professional Terminal. The dataset is arranged by month and spans the period from October 1987 to April 2025. The USD/JPY exchange rate (*EX_USDJPY*) is treated as a dependent variable, while a set of macroeconomic indicators serves as predictors. Table 1 summarises the variables used, along with their descriptive statistics. An important characteristic of the data in Table 1 is that all time series are measured simultaneously, which makes real-time forecasting particularly challenging.

Table 1. Descriptive statistics of the data used[1].

Variable	Description	Measure	Mean	Median	Std. deviation
FX_USDJPY	US dollars to Japanese yen Exchange Rate	Rel. units	114.69	112.69	17.57
IR_US	Fed Interest Rate	%	3.23	3.00	2.58
IR_JP	BOJ Interest Rate	%	0.79	0.15	1.47
INF_US	US Inflation Rate	%	2.81	2.7	1.62
INF_JP	Japan Inflation Rate	%	0.72	0.3	1.37
UNEM_US	US Unemployment Rate	%	5.69	5.4	1.69
UNEMJ_P	Japan Unemployment Rate	%	3.52	3.4	1.03
BOND_US	US 10-Year Government Bond Yield	%	4.49	4.25	2.18
BOND_JP	Japan 10-Year Government Bond Yield	%	1.92	1.36	1.91

[1]All percentages are measured on a monthly basis.

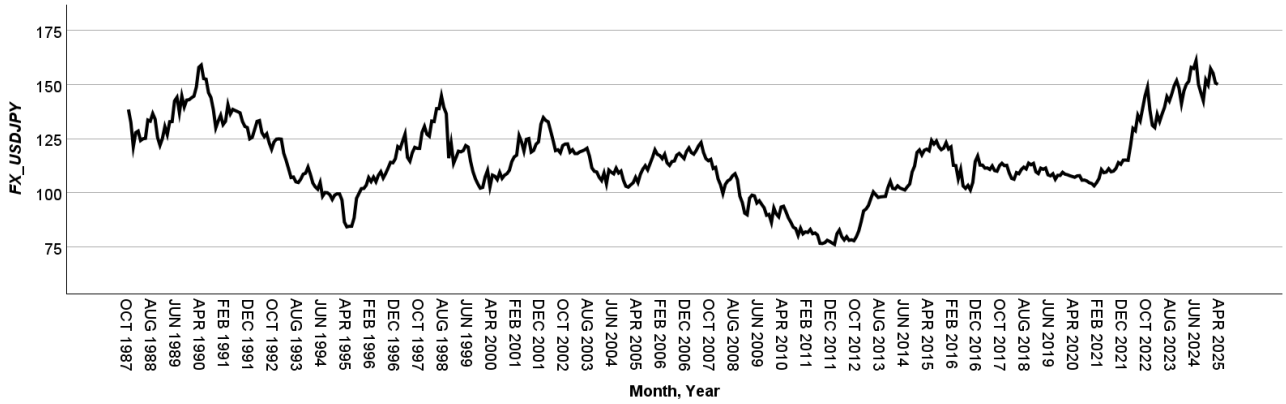


Figure 1. USD/JPY exchange rate from October 1987 to April 2025.

Figure 1 displays the time series of the dependent variable FX_USDJPY, from which three distinct phases of the Japanese yen can be observed:

(1) a period of yen appreciation (1990 – 2011), during which the exchange rate steadily declined to around 75–80 JPY per USD;
(2) a period of significant depreciation (2012 – 2020), when the rate rose sharply, exceeding 125 JPY per USD around 2015; and
(3) a post-2022 period marked by a clear trend of yen weakening.

2.2. Methods and Model Evaluation Measures

The modelling framework is carried out through a two-stage procedure consisting of feature selection followed by model specification. In the first stage, a time-series analysis is conducted on the differential dynamics of the macroeconomic indicators for the two economies, using standard approaches such as the parametric univariate Box–Jenkins ARIMA methodology [15] and partial autocorrelation function (PACF) analysis. Once the relevant predictors (features) are determined for modelling and forecasting *FX_USD/JPY*, we apply the powerful ensemble machine learning techniques of CART-Ensembles and Arcing. The CART Arcing method (Adaptive Resampling and Combining), commonly known as Arcing, is an ensemble approach in which multiple decision trees (CART – Classification and Regression Trees) are generated and combined to improve predictive accuracy in both classification and regression tasks. Arcing belongs to the class of boosting algorithms, of which the best-known example is Arc-x4, proposed in [16]. While traditional ensemble methods with Bagging assign equal probability to each observation when creating bootstrap samples, Arcing adjusts these probabilities dynamically, based on how frequently each observation has been misclassified in previous trees. This allows the model to focus more heavily on complex cases. Each successive tree is thus trained in a way that improves upon the performance of the preceding ones. The weight assigned to each observation is updated according to the formula: $w_{t+1}(V_i) = \frac{1+m(V_i)^4}{\sum_i(1+m(V_i)^4)}$, where $m(V_i)$ denotes the number of times observation V_i was misclassified by the models built up to iteration $1, 2, \ldots, t$.

The primary hyperparameters of the Arcing ensemble include: the number of trees in the ensemble (T), form of cross-validation (CV), the minimum admissible size of parent nodes ($m1$) and child nodes ($m2$), and the number of predictors randomly selected at each node split. The principal advantages of Arcing-based ensembles lie in their higher predictive accuracy, resistance to overfitting, and robustness to noise.

To evaluate model performance, we use the following statistical measures: Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination R^2:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2}{n}}, \quad (1)$$

$$MAPE = \frac{1}{n}\sum_{k=1}^{n}\left|\frac{P_k - Y_k}{Y_k}\right|, \quad (2)$$

$$R^2 = \frac{\{\sum_{k=1}^{n}(P_k - \bar{P})(Y_k - \bar{Y})\}^2}{\sum_{k=1}^{n}(P_k - \bar{P})^2 \sum_{k=1}^{n}(Y_k - \bar{Y})^2}, \quad (3)$$

where Y_k and P_k are the values of the dependent and predictor variables, respectively, and $\bar{Y}$ and $\bar{P}$ are their means. Finally, n is the sample size.

3. Modelling Results

3.1. Feature Selection

Differences (differentials) between macroeconomic indicators of two countries reflect their relative economic conditions and form the basis

of many classical and modern models of exchange rate determination. According to the Interest Rate Parity (IRP) theory, the expected change in the exchange rate between two countries is determined by the difference in their nominal interest rates, i.e. the interest rate differential. A higher interest rate in one country tends to attract capital inflows, leading to appreciation of the domestic currency [17]. The theory of Purchasing Power Parity (PPP) predicts that the exchange rate should adjust in line with inflation differences between countries (the inflation differential): a country with higher inflation will experience depreciation relative to a lower-inflation partner [18]. Although not directly related to the exchange rate, the unemployment differential between two countries serves as an indicator of economic activity, as lower unemployment often implies a prospect of higher interest rates in the future, which in turn affects the currency [19]. Finally, the bond yield differential reflects both interest rate risk and expectations of economic stability and inflation: higher yields tend to attract foreign capital and strengthen the currency [20].

In the present study, to examine the influence of macroeconomic indicators on the USD/JPY exchange rate, the following variables were defined:

- *IR_DIFF = IR_US – IR_JP* (Interest Rate Differential)
- *INF_DIFF = INF_US – INF_JP* (Inflation Differential)
- *UNEMP_DIFF = UNEMP_US – UNEMP_JP* (Unemployment Differential)
- *BOND_DIFF = BOND_US – BOND_JP* (Bond Yield Differential)

Since exchange rate movements are jointly determined with macroeconomic indicators, selecting appropriate predictors is essential for constructing an effective forecasting exchange rate model.

Figure 2 presents the PACFs of the differenced macroeconomic indicators for the USA and Japan. As observed from the graphs, all four variables under consideration (*IR_DIFF, INF_DIFF, UNEMP_DIFF, BOND_DIFF*) exhibit a pronounced first lag, indicating a very strong and statistically significant partial autocorrelation (close to 1), i.e., a dependency between the current time series and the same series shifted by one lag. For the variable *IR_DIFF*, lags 2, 3, and 4 are also significant, and for *INF_DIFF*, lags 2 and 13 are significant. All of these are potential predictors for constructing a model of the USD/JPY exchange rate. We denote the lagged variables as *LIR_DIFF, LINF_DIFF, LUNEMP_DIFF,* and *LBOND_DIFF* for the first lag, and as *Lk_<var>* for the k-th lag of the corresponding variable.

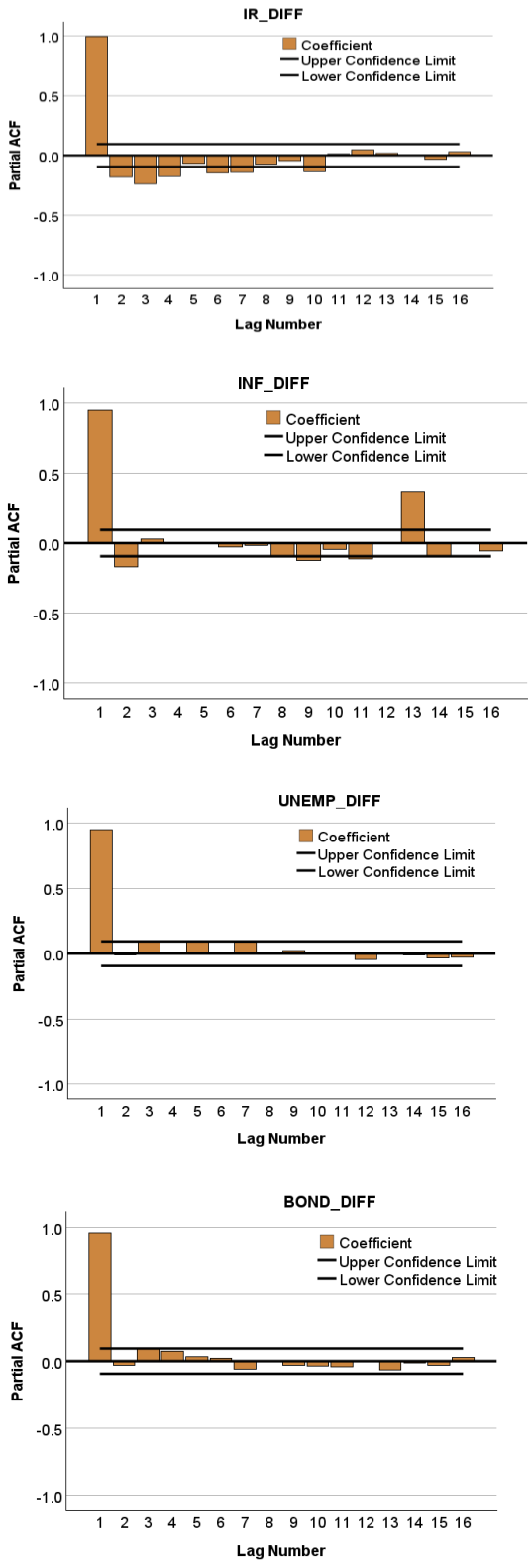


Figure 2. PACF of the differentials and macroeconomic indicators of the USA and Japan.

Figure 3 presents the PACF of the dependent variable *FX_USDJPY*. The strongest partial autocorrelation appears at the first lag, exceeding the boundaries of the confidence interval, which indicates that the previous value of the exchange rate (*LFX_USDJPY*) is a significant predictor of its current

value. The other lags are close to zero and lie within the confidence limits, i.e., they are not statistically significant. This suggests that there is no substantial dependence between earlier values of the variable and its current value.

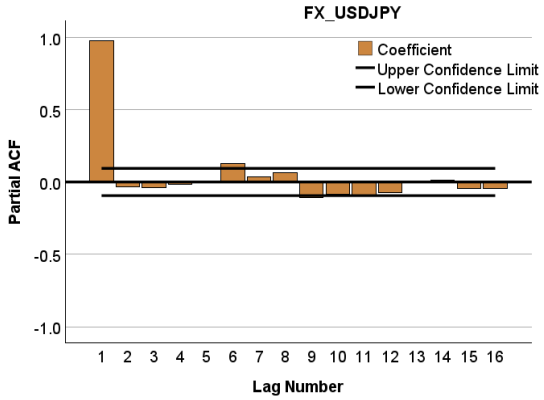


Figure 3. PACF of the USD/JPY exchange rate.

For completeness of this study, Table 2 reports the univariate SARIMA *(p, d, q) (P, D, Q)* models of the main variables. A *SARIMA* model consists of two main components: a non-seasonal part *(p, d, q)* and a seasonal part *(P, D, Q)*, which together capture both short-term dynamics and seasonal patterns in the time series data. The non-seasonal components are: *p* (autoregressive order), i.e., the number of lagged observations included in the model (AR part); *d* (degree of differencing), i.e., the number of times the data is differenced to achieve stationarity; and *q* (moving average order), i.e., the number of lagged forecast errors in the prediction equation (MA part). The seasonal components *(P, D, Q)* are, respectively: *P* (seasonal autoregressive order), i.e., the number of seasonal lagged observations (e.g., 12 months ago); *D* (seasonal differencing), i.e., the number of seasonal differences required to remove seasonal trends; and *Q* (seasonal moving average order), i.e., the number of seasonal lagged forecast errors.

Table 2. Statistics of the obtained univariate SARIMA models for differential dynamics of the macroeconomic indicators.

Variable	SARIMA $(p,d,q)(P,D,Q)_s$	Ljung-Box statistic	R^2
FX_USDJPY	(0, 1, 5) $(0,0,0)_{12}$	0.288	0.957
IR_DIFF	(0, 1, 9) $(0,0,0)_{12}$	0.568	0.990
INF_DIFF	(0, 1, 1) $(0, 0, 1)_{12}$	0.580	0.942
UNEMP_DIFF	(1, 1, 2) $(0,0,0)_{12}$	0.986	0.904
BOND_DIFF	(0, 1, 0) $(1, 0, 1)_{12}$	0.665	0.918

The Ljung-Box (L-B) statistics of all models are insignificant; therefore, we can assume the models are adequate [15]. Additionally, the models exhibit excellent performance with a high R^2 accuracy rate. The key takeaway from Table 2 is that all variables exhibit a differencing order of $d = 1$, indicating that they are non-stationary in levels but become stationary after their first differencing. This property supports the use of lagged versions of these variables as meaningful predictors in a future model construction.

3.2. Construction and Evaluation of CART-Ensembles and Arcing Models

We model the USD/JPY exchange rate across several time periods, denoted as: Period I (January 1987 – April 2025), Period II (January 2000 – April 2025), Period III (January 2012 – April 2025), and Period IV (January 2020 – April 2025). Period I encompasses all available data on the exchange rate and macroeconomic indicators, totalling $n1 = 451$ cases. Period II captures the exchange rate dynamics in the third millennium, with $n2 = 304$ cases. Period III corresponds to the period when the weakening of the yen began, with $n3 = 160$ cases. Period IV covers the post-COVID period, marked by a clear trend of yen depreciation, with $n4 = 64$ cases. To demonstrate the robustness of the obtained models, for each period, we remove the last four monthly USD/JPY observations and predict them step by step, one month ahead, using the selected model.

For each period, multiple models were constructed using different selections of hyperparameters for the Arcing ensemble and various groups of lagged variables. Based on statistical measures, predictive performance, predictor significance, and residual analysis, we selected the following set of lagged variables: *LFX_USDJPY, LIR_DIFF, L3_IR_DIFF, LINF_DIFF, LUNEMP_DIFF, LBOND_DIFF*. The models were built using the following hyperparameter settings: number of trees in the ensemble $T = 30, 40, 50, 60, 70$; type of cross-validation (CV) – CV5 and CV10; minimum observations in parent and child nodes of each tree of each ensemble $m1{:}\,m2 = 5{:}\,5$; and number of randomly selected predictors for building each tree – 3. The Arcing models that achieved the best statistical performance and predictive accuracy on the test set were obtained for all four periods using $T = 60$ trees, CV10 cross-validation, and minimum cases in parent and child nodes $m1{:}\,m2 = 5{:}\,5$.

For each of the four periods, we constructed four models to predict the USD/JPY exchange rate – separately for January, February, March, and April 2025. Since the four models for a given period exhibited similar statistical performance, Table 3 presents the metrics for the weakest model, which we denote as Mi, where i corresponds to the period number. The other models for the same period achieved better performance, as indicated by the symbols "<" and ">".

Table 3. Statistics of the CART-Ensembles and Arcing models.

Model	RMSE	MAPE	R^2
M1	< 2.593	< 0.019	> 0.978
M2	< 1.328	< 0.011	> 0.994
M3	< 1.382	< 0.011	> 0.995
M4	< 1.684	< 0.011	> 0.992

The results in Table 3 indicate excellent model performance, with a coefficient of determination up to 98% and MAPE of 1%.

Table 4 presents the step-by-step forecasts of the models for the four periods, spanning January 2025 to April 2025.

Table 4. Predicted values of the models for the period January 2025 – April 2025.

Predicted	M1	M2	M3	M4	Real value
January 2025	153.52	153.36	152.72	153.67	155.19
February 2025	152.83	152.71	151.89	152.37	150.63
March 2025	151.78	151.88	151.72	152.03	149.96
April 2025	150.93	150.74	150.23	151.05	143.07

The predicted values for models *M1*, *M2*, *M3*, and *M4* fit the actual data with approximately 88%, 93%, 99%, and 95% respectively.

Figure 4 illustrates the sequence plot of the original USD/JPY data together with the values predicted by model *M3*. Following the vertical line are the step-by-step forecasts produced by model *M3* one month ahead, applied to the months of January, February, March, and April 2025, respectively.

For greater clarity, Figure 5 displays the actual data and the values predicted by model *M3* over the last 16 months, with the step-by-step forecasts again marked by a vertical line.

Figure 6 shows the quality of fit between the original USD/JPY data and the predictions of model *M3*, along with the 95% confidence intervals. An excellent approximation is observed, including the extreme values.

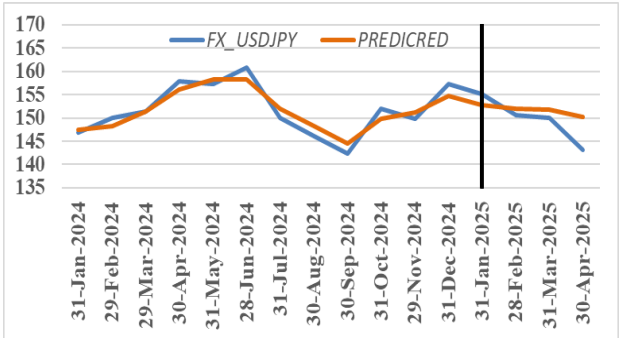


Figure 5. Original USD/JPY data and forecasts from model M3 for the period January 2024 – April 2025.

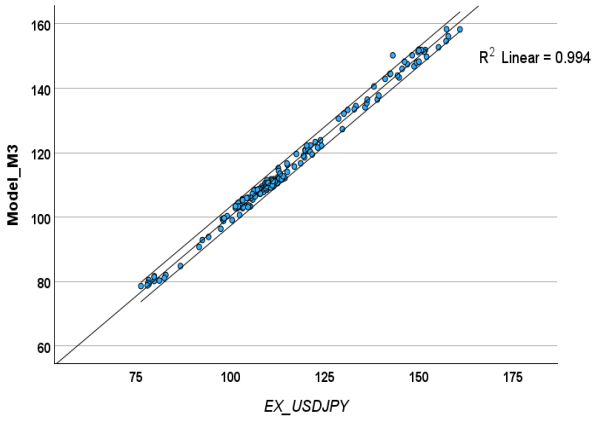


Figure 6. Scatter plot of the USD/JPY data and predictions from the M3 Arcing model.

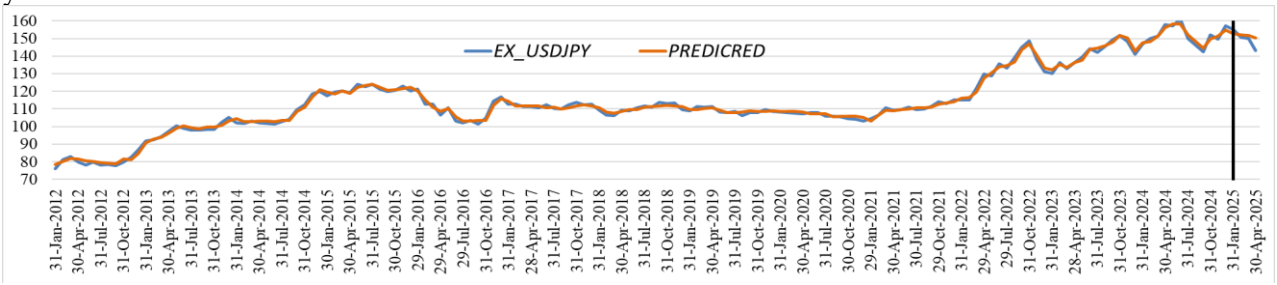


Figure 4. Original USD/JPY data and forecasts from model M3.

3.3. Variable importance

The CART-Ensemble and Arcing method allows us to determine the relative influence of the predictors in the model. For each of the four periods, the models constructed for step-by-step prediction of the last four monthly values determine the same ranking of predictors. The models for the different periods determine the order of predictor influence as shown in Table 5. For all models, the first variable with a weight of 100 points is the lagged dependent variable LFX_USDJPY. The next most important variable for models *M1* and *M2* is the lagged interest rate differential at one and three lags, and both have almost equal influence percentages. With a difference of up to 5%, the bond differential variable follows, then the unemployment differential, and finally the inflation differential. For models *M3* and *M4*, the only difference is that the bond differential precedes, by up to 5%, the lagged interest rate differential variables at one and three lags.

Table 5. Relative variable importance of predictors in the models.

Variable	Relative importance in %			
	M1	M2	M3	M4
LFX_USDJPY	100	100	100	100
LIR_DIFF	35	49	72	80
L3_IR_DIFF	35	45	68	78
LBOND_DIFF	28	42	80	90
LUNEMP_DIFF	25	35	80	65
LINF_DIFF	15	15	20	45

3.4. Reliability Evaluation of the Forecasts

Following [19,20], we need to evaluate the reliability of all forecasting models. To this end, an Auto-Correlation Function (ACF) plot can be used to check for the presence of autocorrelation in the model residuals. We verify whether the residuals are identically distributed, asymptotically independent, and whether there is no serial correlation remaining in the model errors.

The ACF of the residuals of model *M3* in Figure 7 shows no deviations outside the confidence intervals. The residual plots for the other models exhibit similar behaviour. We can therefore conclude that the selected predictors accurately forecast the USD/JPY exchange rate, regardless of the chosen time period.

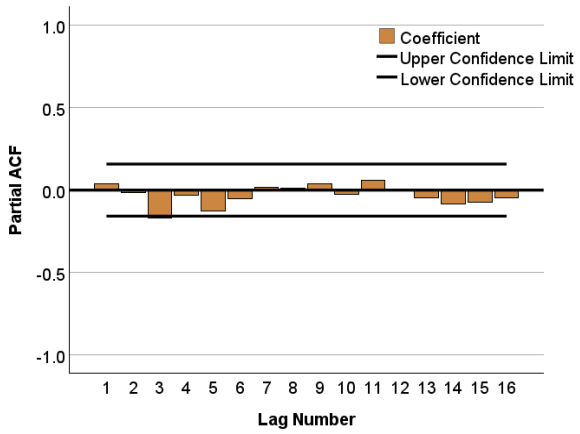


Figure 7. Autocorrelation function of M3 residuals.

From an economic perspective, the results indicate that differentials in interest rates, inflation, and bond yields remain key drivers of USD/JPY movements. The persistent dominance of interest rate and bond yield differentials implies that monetary policy asymmetries between the Federal Reserve and the Bank of Japan are the main determinants of exchange rate fluctuations. The strong predictive contribution of these variables also highlights the sensitivity of the yen to shifts in global capital flows and policy expectations. These findings suggest that ensemble learning models not only achieve high forecasting accuracy but also effectively capture the economic structure underlying exchange rate formation.

4. Conclusion

This study demonstrates the high performance of the CART-Ensembles and Arcing method for forecasting the exchange rate. The main contribution of this study lies in applying the Arcing ensemble method with a carefully selected set of macroeconomic predictors. The results confirm that the method maintains strong statistical properties across varying time periods.

In this article, we established the dependence of changes in the USD/JPY exchange rate on the differentials of various macroeconomic indicators for the two countries. Accurate prediction of future exchange rate values cannot be achieved without considering the key macroeconomic indicators of both economies.

Future research could extend this framework to other major currency pairs (e.g., EUR/USD, GBP/JPY) or combine ensemble learning with deep neural architectures such as LSTM or Transformers to better capture nonlinear temporal dependencies. Incorporating sentiment indices, geopolitical risk indicators, and policy uncertainty measures could also enhance the robustness of exchange rate predictions.

Acknowledgements

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References

[1] Byrne, J. P., Korobilis, D., & Ribeiro, P. J. (2016). Exchange rate predictability in a changing world. *Journal of International Money and Finance, 62*, 1–24. https://doi.org/10.1016/j.jimonfin.2015.12.001

[2] Mishkin, F. S. (2012). *Economics of money, banking, and financial markets* (10th ed.). Prentice Hall.

[3] Parkin, M. (2011). *Economics* (10th ed.). Prentice Hall.

[4] Elliott, G., & Timmermann, A. (Eds.). (2013). *Handbook of economic forecasting* (Vol. 2). North Holland.

[5] Fabozzi, F. J., & Mann, S. V. (2012). *The handbook of fixed income securities.* McGraw-Hill Education.

[6] Tripathi, M., Kumar, S., & Inani, S. K. (2021). Exchange rate forecasting using ensemble modeling for better policy implications. *Journal of Time Series Econometrics, 13*(1), 43–71. https://doi.org/10.1515/jtse-2020-0013

[7] Tsuji, C. (2022). Exchange rate forecasting via a machine learning approach. *iBusiness, 14*(3). https://doi.org/10.4236/ib.2022.143009

[8] Khashei, M., Rafiei, F. M., & Bijari, M. (2013). Hybrid fuzzy auto-regressive integrated moving average (FARIMAH) model for forecasting the foreign exchange markets. *International Journal of Computational Intelligence Systems, 6*, 954–968. https://doi.org/10.1080/18756891.2013.809937

[9] El Mahjouby, M., Taj Bennani, M., Lamrini, M., Bossoufi, B., Alghamdi, T. A. H., & El Far, M. (2024). Machine learning algorithms for forecasting and categorizing euro-to-dollar exchange rates. *IEEE Access, 12*, 74211–74217. https://doi.org/10.1109/ACCESS.2024.3404824

[10] Sun, S., Wang, S., & Wei, Y. (2020). A new ensemble deep learning approach for exchange rates forecasting and trading. *Advanced Engineering Informatics, 46*, 101160. https://doi.org/10.1016/j.aei.2020.101160

[11] Theofilatos, K., Likothanassis, S., & Karathanasopoulos, A. (2012). Modeling and trading the EUR/USD exchange rate using machine learning techniques. *Engineering, Technology & Applied Science Research, 2*(5), 269–272. https://doi.org/10.48084/etasr.200

[12] Guyard, K. C., & Deriaz, M. (2024). Predicting foreign exchange EUR/USD direction using machine learning. In *Proceedings of the 2024 7th International Conference on Machine Learning and Machine Intelligence (MLMI '24)* (pp. 1–9). Association for Computing Machinery. https://doi.org/10.1145/3696271.3696272

[13] Wang, G., Tao, T., Ma, J., Li, H., Fu, H., & Chu, Y. (2021). An improved ensemble learning method for exchange rate forecasting based on the complementary effect of shallow and deep features. *Expert Systems with Applications, 184*, 115569. https://doi.org/10.1016/j.eswa.2021.115569

[14] Zhou, Z.-H. (2012). *Ensemble methods: Foundations and algorithms.* CRC Press. https://doi.org/10.1201/b12207

[15] Opitz, D., & Maclin, R. (1999). Popular ensemble methods: An empirical study. *Journal of Artificial Intelligence Research, 11*, 169–198. https://doi.org/10.1613/jair.614

[16] Breiman, L. (1998). Arcing classifiers. *The Annals of Statistics, 26*(3), 801–849. https://doi.org/10.1214/aos/1024691079

[17] Obstfeld, M., & Rogoff, K. (1996). *Foundations of international macroeconomics.* MIT Press.

[18] Taylor, A. M., & Taylor, M. P. (2004). The purchasing power parity debate. *Journal of Economic Perspectives, 18*(4), 135–158. https://doi.org/10.1257/0895330042632744

[19] Engel, C., & West, K. D. (2005). Exchange rates and fundamentals. *Journal of Political Economy, 113*(3), 485–517. https://doi.org/10.1086/429137

[20] Bernoth, K., & Erdogan, B. (2012). Sovereign bond yield spreads: A time-varying coefficient approach. *Journal of International Money and Finance, 31*(3), 639–656. https://doi.org/10.1016/j.jimonfin.2011.10.006