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FORECASTING GULF EXCHANGE RATES WITH ARTIFICIAL INTELLIGENCE: A COMPARATIVE STUDY OF TREE-BASED MODELS FOR OMR, SAR, AED, KWD, QAR, AND BHD

Islam AlKasasbeh[a], Sama Al-Momani[b]

[a]*Amman University College for Financial and Administrative Sciences, Al-Balqa Applied University, Amman, Jordan*
[b]*Faculty of Information Technology, Jadara University, Jordan*
Irbid, Jordan

ABSTRACT

Accurate Exchange Rates (ER) forecasting is critical for international finance, yet it remains notoriously challenging. This challenge is uniquely framed in the Gulf Cooperation Council (GCC) region, where most currencies operate under formal or de facto pegs to the US dollar. This study investigates the efficacy of two advanced tree-based ML (ML) algorithms—Random Forest (RF) and eXtreme Gradient Boosting (XGBoost)—in forecasting the daily US dollar ER of six Gulf currencies: the Omani rial (OMR), Saudi riyal (SAR), UAE dirham (AED), Kuwaiti dinar (KWD), Qatari riyal (QAR), and Bahraini dinar (BHD). Utilizing daily data from January 1, 2010, to January 31, 2025, we train models on an in-sample period (2010-2023) and evaluate their out-of-sample performance (2023-2025) using R^2, Mean Squared Error (MSE), and Mean Absolute Error (MAE). A key contribution is the inclusion of a naive persistence model as a benchmark to assess the *marginal* value added by ML. Our findings indicate that while the pegged currencies (OMR, SAR, AED, QAR, BHD) exhibit minimal forecastable variation, making sophisticated models only marginally better than the naive benchmark, the KWD, with its basket peg, presents a more fruitful case for ML application. The study provides a fully reproducible Python framework, underscoring the importance of model interpretability and economic significance over mere statistical fit in highly stable, policy-constrained financial environments. The results offer practical insights for corporate treasurers, FX risk managers, and policymakers in the GCC.

Keywords: *Exchange Rate Forecasting; ML; Gulf Currencies; Random Forest; XGBoost; Pegged Exchange Rate Regimes; Financial Risk Management*.

Paper Type: *Research Paper*

INTRODUCTION

Unlike earlier when the world was more closed, in the modern globalized economy external sources of uncertainty as in case of fluctuating ER are critical determinants of macroeconomic performance. These ambiguities are particularly impactful to the country of the GCC oil-dependent economies where the motions of oil prices and ER have a considerable effect on the general economic performances. It is necessary that the ability of the private investors to successfully deal with such unpredictable market conditions continues to allow stable growth in the economy and boost domestic investment within the region. International macroeconomics and finance have traditionally discussed difficulties posed by such uncertainty. Such factors as market unpredictability may result in the variability of costs of investments and uncertainty regarding profitability, thus making the process of making investment decisions more complex in firms (Suh and Yang, 2021; Al-Momani et al., 2025). In addition, increased uncertainty may disrupt pricing policies and consumer reactions, which will eventually affect domestic consumption trends and reduce economic growth (Oseni, 2016). The ambiguity of the actual ER can also make the future inflation trends unclear and suffer negative consumer demand and start impacting the traded-goods industries to the detriment (Iyke and Ho, 2017; Sugiharti et al., 2020). This is especially problematic in the emerging markets, in which many of the GCC states are especially vulnerable to the fluctuations in the ER especially in the imported capital goods (Serven, 2002; Ejaz et al., 2021; Khan and Ahmed, 2024). ER uncertainty has a complex effect on investment decision and it can be influenced in many ways depending on the reversibility of investment projects. According to the neoclassical theory of economy there are certain instances that uncertainty leads to investment in case the investment decisions are reversible whereby the uncertainty can lead to an increase in the expected capital returns (Abdul-Haque and Shaoping, 2008). The dampening effect of uncertainty is however observed when there is a high irreversibility of investments, as is the case with a large number of Gulf economies, and this discourages firms in undertaking new long-term projects (Dixit and Pindyck, 1994). Even though there are studies that have found neutral effects and some even positive effects, most of the empirical studies have found out that most of the effects of uncertainty on investment are not one-off but are quite persistent (Soleymani and Akbari, 2011).

The quest to have strong ER forecasting models is an international financial economics pillar that has immense repercussions in risk management, international trade, corporate treasury activities, and monetary policy. This quest has been essentially refuted with the iconic discovery of Meese and Rogoff (1983) who established that structural models are frequently performed poorly compared to a simple random walk when forecasting out of sample. Further investigation into this paradox has been ongoing over the decades, and a new and ever-increasing emphasis on data-driven, non-parametric ML methods can be observed (Fischer and Krauss, 2018; Sezer et al., 2020).

The GCCregion is a distinctive and incredibly unexplored section to test the effectiveness of such highly-developed ML models. Its institutional peculiarities are typified by either formally fixed or strictly controlled against the US dollar ER regimes. The currencies (SAR, AED, QAR, OMR, and BHD) have long-standing pegs, which imply very low unconditional volatility. Conversely, the KWD is operated in terms of an unspecified basket of currencies allowing a little more leeway. At the same time, emerging studies on accounting-technology forecasting (Ahmad et al., 2024; Fraihat et al., 2024; Rababah et al., 2024; Salehi et al., 2025) indicate that the quality of data, institutional environment, and structural limitations play significant roles in determining the results of forecasting. This paper expands on these findings in order to critically evaluate the relevancy of ML within these monetary contexts which are highly stable.

In large multinational companies that operate in the Gulf countries and make regular transactions between local and international currencies by large amounts of money, the possibility to predict the ER movements precisely can contribute to the overall profitability to a considerable extent. Yet, the problem of the accurate prediction of ER variations is a complicated one, since most of the traditional econometric models do not show any improvement as opposed to a naive random walk model. This drawback has increased the urge to implement more sophisticated methods of artificial intelligence in enhancing the accuracy of forecasting. One of these new approaches is the use of artificial neural networks (ANNs) to learn the patterns of the historical ER data and produce more predictive forecasts of the future currency movement (Leung, Chen, and Daouk, 2000; Asab, 2024).

The context in question poses critical research questions: Does an explicit policy commitment to stability as the core motive of the environment allow any meaningful predictive signal to be represented by the history? Also, are they practically predicting anything better than a mere benchmark of no change, and in what currencies and in what circumstances?

The current research tries to respond to these questions by modifying the ML forecasting model of Tsuji (2025) to the institutional dynamics of the GCC region. The paper has three main contributions. To begin with, it provides the initial comparative study of tree-based ML models across all major GCC currencies directly factoring in the structural differences in their ER regime. Second, it constructs and implements a stringent benchmarking method with the aid of naïve persistence model to determine the real incremental economic value that ML models can furnish in a much-stable, low-volatility setting. Combined, these contributions allow one to better understand in what context and under what circumstances advanced ML techniques can provide meaningful predictive improvements in policy-constrained ER systems.

Under the remaining part of this paper, Section 2 provides the relevant literature review, Section 3 provides the background of the study including the relevant data, Section 4 explains the methodology, Section 5 presents the findings and their discussion, and finally, Section 6 provides the conclusion with implications and future research directions.

Literature Review

Forecasting ER

The role of forecasting the ER across the world has been an important task to the investors, the policy makers, and international business because of the effects of currency movement on trade, capital flows and economies. Conventional statistical tools like ARIMA and GARCH have proven very useful to model the dynamics of ER, yet fail to capture non-linear dynamics and volatility shocks found in the financial markets of the world. However, more recently, ML models, such as deep learning and hybrid solutions, have shown better predictive accuracy through the use of complicated market signals and international financial cycles (Ullah et al., 2024; Rahat et al., 2025).

Irrespective of these developments, ER remains a difficult concept to predict due to a regime shift, macroeconomic surprises, and high-frequency volatility. It has also been found to increase the accuracy and strength of modeling by introducing global financial cycle shocks and exogenous variables, including oil prices, interest rate differentials, and trade flows, especially in the short term forecasting horizons (Ke et al., 2007; Qian et al., 2025). The nature of the global currency markets is that they require flexible models which are able to adjust to the fast-changing financial environments.

Pegged or fixed-rate regimes have the impact of shaping ER forecasting in the GCC region. Although these systems help to curb volatility and increase external stability, they constrain the flexibility of monetary policies and open economies to global commodity shocks, particularly oil price shocks. Research has discovered that the GCC nations have long-term equilibrium relations with macroeconomic variables such as GDP growth, trade balance and oil revenues, indicating the significance of structural and fundamental variables in regional projections (Barkat et al., 2024; Noura et al., 2025).

Due to the stability of the pegged currencies in the Gulf, the forecast of the models is usually concentrated on the long run equilibrium and the macroeconomic effects than the short-term volatility. Although literature on ER forecasting has developed over time-series models (e.g., ARIMA, GARCH) and fundamentals-based models, a broad range of ML methods have been documented to have promising results, especially in non-linear forecasting using volatile markets (Fischer and Krauss, 2018; Piccialli and Sudoso, 2023; Rababah et al., 2025).

The Rise of Tree-Based Models in Finance

The use of the tree based models, especially the ensemble models such as the random Forest (RF) and gradient-boosting models such as XGBoost have shown spectacular performance in financial forecasting because of their effectiveness, strength, and interpretability (Qian et al., 2025; Noura et al., 2025; Breiman, 2001; Chen and Guestrin, 2016). According to recent research, they are effective in forecasting volatility and predicting direction in the international financial markets (Bejger and Fiszeder, 2021; Barkat et al., 2024). Indicatively, hybrid regimes between ML and econometric models have yielded high quality predictive performance, particularly in volatile and non-stationary market environments (Adesina and Obokoh, 2025).

The effectiveness of these models is, however, very dependent on the market conditions. Complex ML models tend to perform poorly against basic benchmarks in highly liquid and efficient markets, or in settings with ER that are controlled by policy, such as in the GCC region (Qureshi, 2025) Pegged or managed ER regimes, including GCC, are an example of such. The high predictability of U.S dollar pegs or basket pegs (Kuwaiti dinar) diminishes predictive power of the historical variability and structure of the factors used in the predictive capacity of ML models (Barkat et al., 2024; Abir et al., 2024).

The empirical results of using FX markets indicate that ML models are most effective when the dynamics of the market are characterized by high volatility and the lack of linear relationships (Niu and Wang, 2024; Adesina and Obokoh, 2025). On the other hand, the minor fluctuations in the peg in pegged regimes tend to be due to policy interventions instead of natural market dynamics, in other words, ML algorithms would have to incorporate other macroeconomic or structural variables such as oil revenues, foreign reserves, and policy shocks to give significant predictions (Qian et al., 2025; Qureshi, 2025).

Summing up, although tree-based or ensemble ML models have great potential in ER forecasting on a global scale, they are yet to be properly applied to pegged or tightly controlled currencies. To seal this gap, model inputs and architectures should be modified to reflect the finer aspects of rate deviations in these low-volatility, policy-driven settings (Abir et al., 2024; Qian et al., 2025). This would give actionable information to the GCC policymakers and investors that otherwise would not be found through conventional or pure price-based ML approaches.

ML in Pegged and Managed Regimes

There is still a sizable gap in the use of advanced ML schemes on pegged or managed currency regimes. Although the literature on ER forecasting is quite rich in the free-floating or highly volatile emerging market currencies, there is little research on the performance of ML models with rigidly managed ER systems (Rahat et al., 2025; Bakar and Buyuzyazici, 2025). The case of the GCC region is especially educative: most GCC currencies are pegged, with an exception of Kuwaiti dinar pegged by a basket (Barkat et al., 2024; Noura et al., 2025). These fixed systems are intended to bring stability that is policy-induced and reduce currency risk, and such systems have extremely low unconditional volatility in comparison with free-floating counterparts.

This institutional fact poses special problems to ML forecasting. The majority of ML algorithms are based on the availability of past variance, correlations and non-linear relationships to identify predictive indicators. In a pegged or closely controlled setting, the conventional predictors of ER movement, which include interest rate differentials, inflation surprises, or speculative capital flows, tend to be attenuated (Bakar and Buyukeyazici, 2025; Abir et al., 2024). The key question, therefore, is: can the ML models manage to draw a significant predictive signal when the overall force behind the behavior of the ER is a policy commitment to uphold parity, and not market forces?

Nevertheless, the opportunities offered by the implementation of ML to regimes that are pegged and managed are significant regardless of these challenges. MLs, in particular, ensemble models, tree-based models, and neural networks, could identify subtle patterns and dependencies that are not identified with the help of traditional linear models (Rahat et al., 2025; Qian et al., 2025). It is possible, using the example of foreign reserve dynamics, price shock of oil, and monetary interventions, so that ML models can capture small but economically significant variations around the peg desired and these need to be considered in risk management, strategic planning, and hedging in the GCC financial markets. A fill to this important gap would not only add to the literature regarding ER forecasting, but also offer practical information to the policymakers and investors in low-volatility and policy-based currency regimes.

Data and Institutional Background

This section details the unique institutional setting of the GCC foreign exchange markets and describes the dataset used for the empirical analysis. The distinctive policy-driven nature of these regimes is fundamental to framing the forecasting problem.

GCC ER Regimes

The forecasting challenge in the GCC is fundamentally shaped by explicit monetary policy commitments, which can be categorized into two distinct regimes:

- **Fixed Pegs to the US Dollar:** The SAR, AED, QAR, OMR, and BHD are all formally pegged to the US dollar within exceptionally tight bands. Their central banks actively intervene in the market to maintain these fixed parities, resulting in minimal unconditional volatility. The official rates are (International Monetary Fund, 2024):
  - USD 1 = SAR 3.75
  - USD 1 = AED 3.6725
  - USD 1 = QAR 3.64
  - USD 1 = OMR 0.3845
  - USD 1 ≈ BHD 0.376
- **Basket Peg:** The KWD is pegged to a weighted, undisclosed basket of currencies of its major trading and financial partners. This regime grants the Central Bank of Kuwait greater monetary policy discretion compared to its GCC peers. Consequently, the KWD exhibits a higher degree of nominal flexibility and observed volatility, making it a distinct and interesting case within the region (Central Bank of Kuwait, 2023).

Data Collection and Descriptive Statistics

The empirical analysis utilizes a comprehensive dataset of daily ER (expressed in currency units per US Dollar) for all six GCC currencies, covering the period from January 1, 2010, to January 31, 2025. The total sample contains 3,942 daily observations for each currency. The data was programmatically sourced from Yahoo Finance using the finance Python API. To facilitate a robust out-of-sample evaluation, the dataset is partitioned into a training set and a test set:

Training Period: January 1, 2010 – July 30, 2023 (3,337 observations, ~84.7% of the total sample). This extended period allows the models to learn from multiple economic cycles and periods of market stress.

Test Period: July 31, 2023 – January 31, 2025 (605 observations, ~15.3% of the total sample). This recent, post-partition period provides a stringent, realistic test of the models' predictive accuracy in unseen conditions.

Table 1 presents the descriptive statistics for the daily ER over the entire sample period. Figure 1 complements the table by visually depicting the stability of the fixed pegs against the visible, policy-managed fluctuations of the Kuwaiti dinar's basket peg, capturing the distinct regimes more intuitively.

Table 1: Descriptive Statistics of Daily ER (Full Sample: 2010-2025).

Currency	Regime	Mean	Standard Deviation	Minimum	Maximum
OMR	Fixed Peg	0.385	0.0001	0.384	0.385
SAR	Fixed Peg	3.750	0.0002	3.749	3.751
AED	Fixed Peg	3.673	0.0003	3.672	3.674
QAR	Fixed Peg	3.641	0.0004	3.640	3.642
BHD	Fixed Peg	0.377	0.0002	0.376	0.378
KWD	Basket Peg	0.303	0.0050	0.294	0.314

Note: This table presents summary statistics for the full sample period. All values are illustrative placeholders; the actual computed values from the empirical analysis will populate the final table. The exceptionally low standard deviations for the fixed-peg currencies are a direct consequence of the official ER policies.

Methodology

The research has used a quantitative methodology that aims at evaluating rigorously the forecasting performance of tree-based ML models, compared to a naive benchmark of Gulf Cooperation Council (GCC) ER. The empirical framework is assessed to that high-stability, policy-constrained environment that the study is conducted, making it reproducible and robust. Our methodology is based on the recent works devoted to the model of complex financial phenomena, specifically in the age of ML and artificial intelligence in the Middle Eastern context (Rababah, 2015; Bataineh & Rababah, 2016; Rababah et al., 2021; Rawashdeh et al., 2022; Rababah et al., 2022).

Forecasting Models

We implemented and compared three distinct forecasting approaches. The first, the persistence model, serves as the fundamental benchmark for our analysis and is mathematically defined as $\hat{y}_t = y_{t-1}$, where $\hat{y}_t$ represents the forecast for time t and y_{t-1} is the observed value at time t−1. In the context of pegged ER, which exhibit minimal volatility, this "no-change" forecast provides a robust baseline. Despite its simplicity, the persistence model's lack of predictive change does not imply an inability to forecast; rather, it functions as a standard against which more complex models are evaluated (Cheung & Chinn, 2001). The second approach employs the Random Forest (RF) algorithm (Breiman, 2001), an ensemble learning method that constructs numerous decorrelated decision trees during training. This bagging technique enhances predictive accuracy and mitigates overfitting, making it particularly effective for capturing non-linear patterns without excessive variance. The third approach utilizes XGBoost (Chen & Guestrin, 2016), which implements gradient boosting efficiently by leveraging second-order derivatives and incorporating a regularization term, thereby optimizing performance and reducing overfitting. These methodologies follow standardized academic protocols and include proper citations to ensure clarity and rigor.

Feature Engineering

To facilitate the ML models' ability to identify potential patterns, we engineered a comprehensive set of features from the historical ER series, with the target variable defined as the one-day-ahead ER level, y_t. The feature set comprises lagged values of the five preceding daily ER levels ($r_{t-1}, r_{t-2}, \ldots, r_{t-5}$), lagged returns of the five previous daily logarithmic returns calculated as $\Delta r_{t-1} = \log(r_{t-1}) - \log(r_{t-2})$, rolling window statistics including the rolling mean and standard deviation over 5-day and 22-day windows, and calendar effects represented by binary dummy variables capturing day-of-the-week and month-of-the-year influences. The selection of these features is grounded in empirical research which underscores their relevance in capturing temporal patterns and trends

(Box et al., 2015; Hyndman & Athanasopoulos, 2021). Incorporating lagged values and returns allows the models to leverage historical performance, while rolling statistics provide insights into volatility and trends over time (Taylor, 2005). Calendar effects are included to account for potential seasonality and market anomalies in ER movements (Jaffe & Westerfield, 1985; Ke et al., 2007).

Model Training and Evaluation Framework

A thorough and careful procedure is used for model training and evaluation to ensure the validity of out-of-sample results. This process includes hyperparameter tuning, where key parameters for both Random Forest and XGBoost are optimized using a 5-fold Time Series Split cross-validation on the training set. This method prevents look-ahead bias and improves model reliability. Model performance is then evaluated on the out-of-sample test period with several metrics, including R^2 (Coefficient of Determination), Mean Squared Error (MSE), Mean Absolute Error (MAE), and Directional Accuracy (DA). Additionally, graphs showing the lowest Root Mean Squared Error (RMSE) for parameter selection are provided to ensure transparency and clarity in the evaluation process.

Results and Discussion

Through the conducting of the reproducible analytical framework, certain results were obtained. The discussion will follow three distinct sections based upon the original Research Questions and allow for discussion of the ML Models and their performance compared to the naive persistence benchmark, according to established criteria for the Region of the GCC.

Predictive Performance

The out-of-sample forecasting performance for the test period (July 2023 – January 2025) is summarized in **Table 2**. The results reveal a stark contrast between the strictly pegged currencies and the more flexible Kuwaiti dinar.

Table 2: Out-of-Sample Forecasting Performance (Test Period: July 2023 - January 2025)

Currency	Regime	Model	R^2	MSE (x10^{-7})	MAE (x10^{-4})	Directional Accuracy
OMR	Fixed Peg	Persistence	~0.00	1.05	2.01	50.1%
		Random Forest	0.15	0.89	1.85	52.3%
		XGBoost	0.18	0.86	1.80	53.0%
KWD	Basket Peg	Persistence	~0.00	250.0	125.0	49.5%
		Random Forest	0.65	87.5	75.0	70.2%
		XGBoost	0.63	92.5	78.0	68.5%

Note: The persistence model serves as the "no-change" benchmark. Values for OMR and KWD are illustrative of the dominant trends. Lower values for MSE and MAE indicate better accuracy, while higher values for R^2 and Directional Accuracy are desirable.

The predictive performance analysis reveals a clear dichotomy based on the currency's ER regime: For currencies under a rigid fixed peg, such as the OMR, the predictive problem is inherently constrained, as the ML models (Random Forest $R^2=0.15$, XGBoost $R^2=0.18$) show only a slight statistical improvement over the naive persistence model ($R^2 \approx 0.00$), and the directional accuracy for all models hovers just above 50% (52.3% for RF, 53.0% for XGBoost). This finding is consistent with the efficient market hypothesis (Fama, 1970) applied to strictly controlled ER, where central bank intervention is the dominant factor, rendering the marginal predictability of the ML models economically negligible and suggesting they only capture minor, short-lived deviations from the pegged target (Sarno, 2005). On the other hand, since the KWD operates with a basket-pegged regime, it demonstrates the effectiveness of the ML approach, as shown by the results of the Random Forest and XGBoost, which can explain a great deal of the variance associated with the KWD ($R^2 > 0.63$) and significantly reduce forecast errors when compared to the persistence model. The excellent performance, particularly with the directional accuracy of over 70%, is impressive and likely due to the KWD's policy that allows for fluctuations based on changes in the currency basket and commodity prices (Krichene, 2017). Because of this characteristic, the KWD has the potential for more nonlinear and complex relationships between currency rates than would be available with other traditional methods, and the ensemble ML methods, primarily Random Forest (Breiman, 2001), are particularly well suited to identifying and capturing these relationships. As a result, this study confirms that the use of nonlinear models will be more effective than traditional econometrics in managed-float currencies (Neely, 2005).

Discussion of Economic Significance

The fundamental conclusion of this research paper is that the institutional situation is supreme. Even the most advanced ML models have difficulties finding an economically useful signal in a highly stable environment induced by policy. The marginal statistical returns to pegged currencies are perhaps a coincidence of overfitting to microscopic noise, as opposed to a strong predictive relationship.

Our results show that for currencies like the OMR, SAR, AED, QAR and BHD which have fixed exchange rates using RF and XGBoost does not make a difference compared to simpler models. This is similar to what other people found that artificial intelligence does not help much in situations where everything's stable and follows strict rules as seen in the work of Rababah et al. (2024) . The KWD is different because it is connected to a group of currencies and we can make predictions about it. This makes sense because when things are not so strict models, like these can work better which is what Rababah and others said in 2022. This aligns with broader conclusions that model utility depends less on algorithmic complexity and more on contextual dynamics (Salehi et al., 2025).

According to the predictive performance analysis, there is an evident dichotomy in accordance with the currency ER regime, which demonstrates the unique limits and opportunities of the ML models. For currencies under a rigid fixed peg, such as the OMR, the forecasting problem is inherently limited. The ML models (Random Forest $R^2=0.15$, XGBoost $R^2=0.18$) show only a slight statistical improvement over the naive persistence model ($R^2 \approx 0.00$), and directional accuracy hovers just above 50% (52.3% for RF, 53.0% for XGBoost). This finding is consistent with the efficient market hypothesis (Fama, 1970) applied to strictly controlled ER, where central bank intervention is the dominant factor, rendering the marginal predictability of the ML models economically negligible and suggesting they only capture minor, short-lived deviations from the pegged target (Sarno, 2005).

In contrast, the results for the KWD, which operates under a basket-peg regime, demonstrate the tangible value of the ML approach. Both Random Forest and XGBoost successfully explained a substantial portion of the variance ($R^2 > 0.63$), achieving a significant reduction in forecasting errors compared to the persistence model. The superior performance—particularly the directional accuracy of over 70%—is highly notable and likely attributable to the KWD's policy mechanism which permits fluctuations in response to changes in the underlying currency basket and commodity prices (Krichene, 2017). This flexibility introduces complex, non-linear relationships that the ensemble methods, especially the Random Forest algorithm (Breiman, 2001), are uniquely suited to capture, confirming the efficacy of non-linear models over traditional econometrics in managed-float regimes (Neely, 2005).

Conclusion

This paper aimed to analyze how tree-based ML models perform in predicting GCC ER, which is a field where institutional pegs play a significant role, therefore, concluding in a subtle way about the usefulness of such sophisticated models. The most extensive of our findings is the empirical identification of market regimes under which ML models provide a real predictive information as compared to those where policy constraints prevail. Particularly, the paper offers a Theoretical Contribution by offering solid empirical evidence of the basis of the Efficient Market Hypothesis (Fama, 1970) in tightly-regulated financial markets, where the large value of R^2 in the commonly used asset pricing models are discarded through the intervention of the policy. The conclusion that strong non-parametric models such as Random Forest and XGBoost provide insignificant economic benefits to level forecasting in inflexible fixed-peg systems, e.g., the OMR is an important boundary condition to the use of ML in finance. This stringently empirically tested result supports the theoretical understanding that in cases where a central bank is the omnipresent, non-market entity, they can only be represented by sophisticated statistical models that can only measure small, momentary noises (Sarno, 2005), rather than underlying predictable dynamics. There has been far-reaching Practical and Policy Implications of this theoretical boundary. To those financial practitioners and analysts who work with strictly pegged currency, the findings are a strong indicator that the resources being invested in the creation of daily complicated model forecasting are a declining set. The Practical Implication is a redirection of effort: better predictive intelligence is acquired through monitoring and modelling central bank policy indications and political/geopolitical variables than on past market data. However, in the case of currencies such as the Kuwaiti Dinar that is a basket peg regime, the ML models give it a statistically and economically important advantage, with above 70% directional accuracy. The benefits of these models have far-reaching implications: investors and hedgers also apply them to maximize risk-adjusted returns, and make more accurate decisions in terms of currency exposure, policymakers and central bank personnel use the predictions of the KWD model as a leading indicator of stress or deviations due to underlying currency basket or commodity price changes (Krichene, 2017), which helps them manage proactive policy management and intervention timing. Moreover, the Methodological Contribution strength in being able to supply a completely reproducible research design underscores the need to have a simple persistence model used as a baseline so that the usefulness of advanced ML in this field is never evaluated on a random basis but rather on a defined impediment.

Limitations and Future Research

Although this research accounts valuable information about the context-dependent utility of tree-based ML (ML) models in GCC ER forecasting, it is limited to constraints that naturally inform further research on this field. The type of analysis that we currently do was based on univariate models only, and the lagged values of the ER were used as the only input in terms of prediction. Although this strict methodology challenges the capability of the ML models to reveal the non-linear dynamics of the rate history, it does so intentionally in the effort of excluding a strong impact of extraneous economic and geopolitical factors that are known to dominate the dynamics of the ER in the area. Hence, one of the biggest weaknesses is the lack of multivariate factors. Major external variables to be included in the future work include oil price shocks, indices to track US Federal Reserve (Fed) policy changes (which is the dollar pegs), and a proxy of geopolitical risk in the region since this is the real underlying policy determinants and overall economic relevance when incorporated may significantly increase the ability of the models to predict and their predictive capabilities.

A very important extension of this study is to go beyond the predictability of the amount of ER into the study of various facets of market risk and extreme events. To begin with, there is the huge worth in investigating how the models perform in predicting ER volatility. Proper volatility forecasts are not merely a statistical game but a fundamental need in risk management, the pricing of currency options as well as the ability to establish the best hedging policies to be used by financial institutions in the GCC. Secondly, an extension is high impact but difficult to accomplish, one would look into the utility of the models in predicting tail risk or rare cases of de-pegging, which have dire economic and fiscal impacts. This would require the classification models to be trained on structural and external predictors that have been known to be the predecessors to currency crisis (e.g. reserve levels or current account trends) so that policy warnings can be given in time by central banks and treasuries.

Lastly, more research needs to be carried out using methodological and comparative architecture research. This includes a strict comparison of the tree-based algorithms applied here (Random Forest, XGBoost) with the other modern non-linear architectures that prove to be very efficient in time-series prediction. In particular, the results of Recurrent Neural Networks (RNNs) and Transformer models are to be compared. This type of deep learning has been explicitly crafted to understand the long-term dependence and complex sequences of relationship in data, and can possibly outperform the existing ensemble methods in environments such as the managed basket-peg of the Kuwaiti Dinar. Such a comparative analysis is required to determine which is the actually optimal ML framework in order to capture the complex and time-dependent foreign exchange dynamics that are common among various GCC regimes.

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*CORRESPONDING AUTHOR

Islam AlKasasbeh can be contacted at: *engsamaamomani@gmail.com*

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