Intelligent Computing and Foreign Exchange Rate Prediction: What We Know and We Don't

Tasadduq Imam
Central Queensland University (Rockhampton), QLD 4702, Australia, t.imam@cqu.edu.au

Abstract

While exchange rate prediction has come a long way since the developments of early macroeconomic models and has embraced a number of intelligent computing (i.e., computational intelligence) methodologies in recent undertakings, there remain a number of uncertainties and debates around the characteristics of these different models. Further, while finance community is primarily focused on linear models due to interpretability, computational intelligence community has mainly focused on the time series aspects – leading to a gap between the two communities. This article provides a contemporary survey on the different exchange rate models from both the finance and computational intelligence domains. As illustrated, while computational intelligence has considerably progressed in this area, there still remains a number of research issues before these models will be well-accepted by the finance community. Thus, this article serves both as a comprehensive survey and link to future research opportunities for the domain

Keywords: *Foreign Exchange Rate Prediction, Computational Intelligence, Prediction Models*

1. Introduction

Foreign exchange rate prediction is a specific challenge that has interested researchers in the finance domain for several years. There have been views that the dynamics of exchange rate is chaotic and a prediction model is only as good as a random walk model [1]. In the very recent years, this negative view has partially changed mainly due to achieving better insights [2] and the application of computational intelligence in this area [3]. To date, however, a comprehensive review on the intelligent computing technologies being applied in exchange rate determination is lacking. Further, there is a gap between the views of the Finance and Computational Intelligence communities in regards to exchange rate prediction. Computational intelligence based community have primarily focused on time-series aspects of these data and developed models with a view to improving prediction performance. Finance community, on the other hand, most often imposes importance on model interpretability and tends to advocate the linear models due to the ease of conceptualization.

This article outlines the contemporary progress of both finance and intelligent computing community in the exchange rate prediction domain and highlights the issues yet to be addressed. The rest of this article is organized as follows. Sections 2-5 discuss on the exchange rate modeling from finance perspective. Starting from the models in the mid-1970s, the progress towards the current stage, including the debates around performances against the random walk, linear and nonlinear modeling issues and incorporation of microeconomic information along with the traditional macroeconomic approach are detailed in these sections. Section 6 reviews the intelligent computing approaches in the domain, with particular focus on the two dominant strategies in the context. Section 7 outlines the knowledge achieved from the varied undertakings and also provides directions of future research. Lastly, Section 8 concludes the article with an overall summary.

2. Early Studies in Exchange Rate Modeling

Dynamics and characteristics of exchange rates have drawn attention of the researchers for many years. The very early studies reflected on varied macro-economic models to conceptualize the exchange rate dynamics. Several of these works posed a monetary view of the economy [4]; i.e. these works considered exchange rates to be the relative prices of the two nation's currencies and viewed the movements as the impact of reaching equilibrium for demand and supply of assets within international context. Dornbusch [5], for example, reflected on capital mobility, varied adjustment speeds of the asset markets, and economic expectations to explain the exchange rate's variability. Frenkel [6] related money, asset prices and expectations to exchange rate. Giddy [7] identified a theoretical equilibrium for exchange rates within a set of assumptions and integrated four different postulates, involving interest rate, inflation rate and exchange rate, into a single framework. Kouri [8] investigated the interaction between exchange rate, expectations and balance of payments through a dynamic model. Bilson [9] provided evidences to the validity of monetary approach in exchange rate determination. Officer [10] examined the long-term predictive capacity of purchasing power parity based exchange rate forecast models.

These monetary models differed, not only in terms of the macro-economic factors considered, but also in the assumption of monetary systems. Two such notable systems were the flexible price view and sticky price view. In the first view, the asset prices were assumed to be flexible over the time [6], in contrast to the sticky view that assumed asset prices to be fixed over a short period of time [11]. The second approach was, thus, relevant to the Keynesian view of economy [4]. There have also been works that combined the flexible price view and sticky price view to relate exchange rates with nominal interest rate and inflation [12].

Parallel to the monetary approaches, early works also encompassed alternative thought that exchange rate markets are efficient, i.e., follow the Efficient Market Hypothesis [13]. The particular view posed by the researchers in this context was exchange rate markets are weakly efficient, i.e., at a particular time the rate already reflects the historical information, and a prediction model is worthless [14], [15]. However, Caves and Feige [14] argued that historical prices may not be the only contributing factor within a weakly efficient market assumption, and presented a bivariate model that incorporates both of the monetary and efficient market views towards the determination of exchange rates.

Along with these different works, the early periods also saw the emergence of other economic views like, portfolio theory [16] and elasticity approach [17] in regards to exchange rate characterization.

Thus, overall, the early periods in exchange rate research domain emphasized particularly in developing models that are interpretable from finance domain, and allow conceptualizing the determinants and effects in the varied macro-economic perspectives.

3. Debate about Predictability and Random Walk Hypothesis

Meese and Rogoff [1], in a seminal work, compared the performances of earlier exchange rate models, including the then well-popular flexible and sticky price view models, and highlighted that the prediction accuracy of these exchange rate frameworks on out-of-sample data was as good as a random walk model. This work led to the recognition of random walk hypothesis in the exchange rate prediction domain, and created a long debate among the researchers.

It is to be noted, however, the poor predictability of earlier exchange rate models had already drawn attentions of the researchers before the publication by Meese and Rogoff [1]. Frenkel [18], for instance, recognized the weaknesses of purchasing power parity, as utilized in the earlier models, to explain the unexpected patterns in exchange rate, and advocated "news" as a key factor in this respect. Flood [19] also highlighted the bottleneck of purchasing power parity and asset views in characterizing exchange rate volatility, but was inconclusive in regards to the cause. Meese and Singleton [20] pointed to the defensive views by the proponents of monetary model in respect to exchange rate's volatility, and highlighted the influence of non-stationary exogenous processes.

Since the publication by Meese and Rogoff [1], further research provided insights in this context. Backus [21], for example, concluded that empirical support behind the monetary, sticky-price and portfolio models are weak and exchange rates closely follow the random walk. Wolff [22] compared the results of published exchange rate models and highlighted that the univariate timeseries models fail to beat the random walk. Urrutia [23] performed variance ratio tests and concluded, based on data for exchange rates of four currencies, that exchange rates follow the random walk.

There have also been efforts to challenge the random walk views, and to derive solutions to the problem. Hakkio [24] argued that the tests of random walk hypothesis have low power. Somanath [25] claimed that consideration of lag in exchange rate models performed better than the random walk models. Schinasi and Swamy [26] reported that incorporating variable coefficient in the exchange rate models resulted in improved forecast over the random walk model. Gandolfo et al. [27] pointed out that single equation based exchange rate models are outperformed by random walk models and advocated the concept of "economy-wide macroeconomic models". Kim and Mo [28] explored multi-variate cointegration and noted that random walk models are beaten by the monetary models in the long run. Fritsche and Wallace [29] noted the better performance of error correction based models over the random walk. Lisi and Medio [30] proposed a Singular Spectrum Analysis based model to outperform the random walk approach.

Overall, the exchange rate literature since the early 1980s to late 1990s noticeably focused on the debate about random walk hypothesis and prediction model developments to beat the random walk.

4. Nonlinear Exchange Rate Models

While majority of the works described earlier related exchange rate dynamics to the other factors in terms of linear models, researchers also explored non-linear aspects in modeling. The works were motivated by the weaknesses of the linear models and poor fits to the data. Hsieh [31] indicated the presence of nonlinearities in five major currencies' exchange rates and highlighted that a generalized AutoRegressive Conditional Heteroskedasticity (GARCH) model well explained these nonlinearities. Higgins and Bera [32] proposed a nonlinear ARCH model and highlighted the potentials in exchange rate determination. Bleaney and Mizen [33] demonstrated that a cubic model outperformed the forecasts of linear models foe five major currencies over the period of 1973-1994.

There have also been works that challenged the trend in nonlinear modeling. Meese and Rose [34-35], for example, highlighted that the poor performance of existing models cannot be attributed to the inherent nonlinearity. Chinn [36] observed that nonlinear models perform only marginally better than linear models. Sarantis [37] noticed nonlinearity in the exchange rates of eight industrial countries, but achieved negligible improvements for nonlinear models over the linear models.

And, as in the case of linear model, researchers in this context also faced the challenge of outperforming the random walk model. Brooks [38], for instance, explored a set of linear and non-linear models to forecast daily Sterling changes and noted very modest improvements over the random walk models. Creedy et al. [39], on the other hand, proposed a parametric non-linear model that considered up to the fourth moment of data and provided better forecast than the random walk for US/UK exchange rates. Soofi and Cao [40] proposed a nonlinear deterministic technique for Peseta/Dollar exchange rates and noted improvements over the random walk model.

Overall, shifting from linear modeling to nonlinear aspects to realize and improve the prediction accuracy is a considerable change in the exchange rate domain. A later section will illustrate that the recent advancements in intelligent computing techniques have also played a role in this regard, and an increasing number of research is employing these techniques with a view to reducing uncertainty and improving predictability for the domain.

5. Recent Works in Exchange Rate Modeling

Recent works have seen the development and incorporation of different macro-economic factors, and focuses on varied economies, as well as increased applications of computational techniques. The computational intelligent perspective is detailed in the next section. This section briefly reflects on the contemporary works in the domain that have been of particular interests to the finance community.

A noticeable recent research is the focus on microeconomic factors in exchange rate modeling. In a relevant work, Evans and Lyons [41] present an exchange rate model that incorporates order flow, a microeconomic information, and observe the model's better predictability than the random walk. Lyons [42] provides a review on the key microeconomic information in this context – order flow and spreads. In another work, Evans and Lyons [43] show that the microeconomic exchange rate model outperformed both the macroeconomic based models and random walk. Rime et al. [44] demonstrate that order flow has a close relationship with the macroeconomic factors and play a role in outperforming the macroeconomic models. In a recent work, Evans and Rime [45] outline a model that considers microeconomic information like the trading between agents and dealers in addition to other economic variables to capture the exchange rate dynamics, and also highlights how the dealer centric views of the proposed microeconomic model addresses the issues faced by the macroeconomic models.

Another notable progress is clearer insights about the exchange rate dynamics and increasing number of research refuting the random walk hypothesis in different contexts. Kilian and Taylor [46] reflect that the non-linear relationship between exchange rates and macroeconomic factors results in random walk outperforming the other models at short horizon. However, the work also indicates that the purchasing power parity based models, along with the consideration of nonlinearity, considerably capture the exchange rate fluctuations at medium-term time span. Faust et al. [47] highlight that exchange rate models are sensitive to data revisions and sampling period, and, depending on these factors, the comparison results against the random walk vary. Clarida et al. [48] present a nonlinear term-structure based forecast model that outperforms the random walk models. Engel et al. [49] conclude that exchange rate models are generally beaten by the random walk especially at short horizon. The work also indicates that incorporation of "panel estimation" and long horizon consideration results in a better forecast by the exchange rate models over the random walk models. Evans [2] provides a comprehensive review in regards to the progress and development of varied exchange rate models, and points out the characteristics of newer models that have resulted in better performances than random walk. While these works generally have noted better performance than random walk at longer horizon, Yuan [50], in a recent research, has proposed a "multi-state Markov-switching model with smoothing techniques" which beats the random walk at short horizon.

Overall, the noticeable progress in the recent era has been deeper understanding of the validity of random walk hypothesis, wider acceptance of microeconomic structures, and increased employments of nonlinear modeling.

6. Intelligent Computing in Exchange Rate Prediction

Now that the previous sections have covered the exchange rate modeling from varied perspective and domains, this section focuses on the main theme of this article – progresses of intelligent computing in exchange rate prediction. In the context of this article, intelligent computing refers to the intelligent and informative processing of data towards achieving insightful knowledge and/or developing computational frameworks for realizing the dynamics of a deterministically uncertain phenomenon. As has already been indicated in the prior sections, the field of exchange rate modeling and prediction comprises uncertainty and researchers are in disagreement in regards to the best modeling criteria. So, a number of recent works have focused on employing computational intelligence techniques and intelligent system [51], [52] frameworks to derive better performing models or to gain better realization of the exchange rate dynamics. The following subsections review these studies in terms of the computational intelligence (a.k.a., intelligent computing) methods being applied.

6.1. Artificial Neural Network (ANN)

Of the different computational intelligence techniques being applied in the exchange rate domains, the dominant method has been the Artificial Neural Network (ANN). An ANN simulates the biological network through a set of nodes distributed across input, output and user specified number of hidden layers, weighted connections between the nodes, activation functions and a training process [53], [54]. A characteristic feature of the ANN is its ability to capture nonlinear functional relationship between predictors and the response variables, and, thereby, resulting in high performing prediction models in various domains.

ANN has found recognition as a potential modeling tool in the exchange rate prediction domain since the early 1990s. In a very early related work, Refenes et al. [55] demonstrate the application of an error backpropagation ANN in predicting the exchange rate between US Dollar and Deutsche Mark, and note considerable prediction performance. The work also highlights the implementation of both single-step and multi-step ahead forecasts. An extension to this work provides further insights on the ANN design strategy and symmetric squashing functions are shown to derive quicker convergence [56].

Further down the track, researchers have derived conflicting results in respect to the use of ANN in exchange rate modeling. Several works pose a positive view in this respect. Pi [57], for instance, realizes the dependency structure in the context of multivariate exchange rate time series, and highlights, through a feed-forward ANN, that consideration of dependency structure refutes the random walk hypothesis. Staley and Kim [58] reflect on the feasibility of ANN in predicting Canadian Dollar/ US Dollar exchange rates, and note the ANN model to explain some of the variances in data with a modest prediction performance. Hann and Steurer [59] report that the performance of ANN in exchange rate prediction is superior to the linear models provide the time-structure of data and nonlinearity are taken into consideration. Verkooijen [60] extends the concept of structural macroeconomic models in the context of ANN and observe that the ANN model either outperforms or performs comparably to the linear models. The comparison of performances against the random walk, however, is inconclusive. Andreou et al. [61] consider the chaotic nature of exchange rate time series and achieve good prediction performance using ANN and local approximation technique.

There have also been works that disfavor or fail to see the potential of ANN in this domain. Kuan and Liu [62], for instance, employ a network selection strategy based on predictive stochastic complexity and investigate the performances of feedforward and recurrent ANN. However, the prediction outcomes of the ANN are only modestly better than the random walk models. Plasmans et al. [63] make a considerable contribution by highlighting the lack of long-run relationships between exchange rates and macroeconomic factors (as generally considered in the financial domain), and pose a cynical view in regards to employing feedforward ANN to predict exchange rates. Qi and Wu [64] indicate that ANN based models considering market fundamentals fail to beat the random walk, while disregarding the fundamentals improves the ANN's predictability to some degree.

The studies since the early 2000s, however, have focused on improving the prediction characteristics of the ANN models from varied angels. A particular approach is the institution of ensemble frameworks and hybrid techniques. Zhang and Berardi [65], for instance, demonstrate that an ensemble of ANN having different architectures outperforms the single network for the British Pound/US Dollar exchange rates. The work, though, admits that the performance improvement as against the random walk is minor. Kodogiannis and Lolis [66] explore the ANN and fuzzy based techniques in exchange rate forecasting and outline the potentials of hybrid methods. Nag and Mitra [67] propose an ANN and genetic algorithm hybrid method, and achieve superior performance over the traditional techniques. Zhang [68] combines the Autoregressive Integrated Moving Average (ARIMA) and ANN in a hybrid technique, and notes improved forecasting performance for the British Pound/US Dollar exchange rates. Anastasakis and Mort [69] combine parametric (ANN based) and non-parametric self-organizing approaches, and note promising results for the combined method over the individual exchange rate models. Chang et al. [70] employ a genetic algorithm based feature selection and weighting along with back-propagation ANN, and observe improved exchange rate prediction performances over the model employing all the features. Sheikhan and Movaghar [71] utilize Genetic Algorithm (GA) to determine the ANN parameters and demonstrate potential of the hybrid approach. Chen [72] combines fuzzy and ANN techniques and achieves promising outcomes.

There have also been an increased number of studies on considering varied aspects of the time-series data and specialized ANN architecture selection. Leung et al. [73], for instance, observe that General Regression Neural Network (GRNN) outperforms competing ANN structures and random walk in predicting exchange rates for a set of currencies. Yu et al. [74] integrate adaptive smoothing technique in ANN learning and note exchange rate forecast improvements over the multilayer feed-forward ANN. Xie et al. [75] recognize that different ANN architectures produce different outcomes for the varied economies and highlight recurrent ANN as the most suitable model to capture CNY/USD exchange rate. Majhi et al. [76] propose a set of low complexity ANN frameworks as potential exchange rate forecast strategies. Dunis et al. [77] compare varied ANN architectures in Euro/US Dollar exchange rate prediction and report the Gaussian Mixture model's potentials. Lye et al. [78] indicate that the generalized regression neural network outperform the multilayer feed-forward ANN for Chinese exchange rate prediction. Sermpinis et al. [79] note Psi Sigma NeuralNetwork (PSN), a special ANN architecture, model's superiority in forecasting Euro/US Dollar exchange rates.

Other than the aforementioned works, literature also comprises a vast amount of other studies incorporating ANN in exchange rate prediction. A relevant brief survey is in the article by Li and Ma [80]. A further comprehensive survey is in Yu et al. [81]. Another interesting article is the one by Li and Lin [82], which outlines the problems of employing ANN in exchange rate domain including the controversy regarding the type and size of data samples and long term predictability.

Overall, ANN stands as a significant intelligent computing process in the context of modeling and forecasting exchange rates.

6.2. Support Vector Machine (SVM)

Support Vector Machine (SVM) has recently established itself as a robust intelligent computing technique, possessing high generalization performance in varied domains [83–85]. Central to the SVM's mechanism is the mapping of input space to a high-dimensional feature space through the use of special functions termed kernels and performing a quadratic optimization towards identifying a reduced set of points (termed as support vectors) and corresponding weights that detail a linear model in the high-dimensional feature space. Contrary to the ANN, SVM produces unique results and is considerably less prone to overfitting the data.

SVM has recently drawn considerable interests of the exchange rate researchers. In an early work in this respect, Kamruzzaman et al. [86] investigate a set of SVM kernel functions in the context of Australian Dollar's exchange rate against six major currencies and recommend the choice of kernel based on historical patterns of the individual currencies. In another relevant study, Kamruzzaman and Sarker [87] observe the superiority of SVM model over ANN model. In a similar research, Cao et al. [88] demonstrate the potential of SVM in exchange rate forecasting and also reflect on the issue of parameter selection for SVM learning. Ullrich et al. [89] investigate SVM models in forecasting Euro exchange rate directions and highlight SVM as a promising learning technique in the context of financial time series. Liu and Wang [90] report LS-SVM, a variation of SVM technique, as a potential strategy in exchange rate prediction. Alamili [91] note the advantages of SVM over ANN in financial forecasting.

As is the case of ANN, researchers have attempted hybrid strategies, ensemble techniques and consideration of data aspects in the context of SVM as well. Hong [92] provides a hybrid structure comprising linear and non-linear kernel based SVM, with parameters being estimated through genetic programming. The work has been reported to outperform the existing exchange rate forecast models. Ince and Trafalis [93] present a hybrid model integrating parametric and non-parametric approaches, and point to the superiority of SVM based model over the ANN based model. Ni and Yin [94] employ both the recurrent Self Organizing Map (RSOM) (a variant of ANN) and the SVM, with RSOM partitioning the data space into disjoint regions and SVM making predictions through regression approach. The proposed model is shown to outperform the GARCH model. Yu et al. [95] demonstrate the combination of SVM and ANN in a hybrid strategy and achieve promising results. He et al. [96] present a SVM based ensemble of varied modeling approaches and note better outcome than the ANN ensemble. Wang et al. [97] present another hybrid structure with SVM regression approach aggregating forecasts from multiple classifiers. This work also demonstrated promising results. Lu et al. [98] employ Independent Component Analysis (ICA) to reduce noise in the data and achieve better exchange rate forecasting for SVM. Hung and Hong [99] utilize ant-colony optimization to determine SVM parameters for exchange rate forecasting, and observe promising outcomes. Huang et al. [100] incorporates chaos-model with SVM and note higher performance for the hybrid method over the SVM, ANN and chaos based ANN models. Pai et al. [101] combine Rough Set Theory (RST) and Directed Acyclic Graph Support Vector Machines (DAGSVM), considering the ability of RST in outlying important features and the generalization capacity of SVM, in exchange rate prediction. The results indicate that the hybrid approach perform better than the individual models. Fu [102] uses Empirical Mode Decomposition (EMD) to address the non-stationary and irregularity issue of exchange rate information, utilizes SVM in training the decomposed subsets and aggregates the predictions. The hybrid approach is shown to achieve effective predictability for Euro/Chinese Renminbi exchange rate forecasts. Similar works that exploits the SVM regression approach with the concepts in signal processing have also been proposed, including the wavelet based transformations [103], [104] and slantlet based denoising [103]. These methods have also been claimed to achieve better prediction performance than existing models. Pang et al. [105] integrate the concept of correlation with SVM and report potentials of the approach as compared to the SVM model.

Overall, the use of SVM in exchange rate domain has been relatively recent and majority of the works have been published within the last few years. A noticeable trend in this respect is the integration of different techniques with SVM within hybrid frameworks. Also, noticeable is the reportedly better results than the competing strategies for many of the SVM based methods.

6.3. Other Computational Intelligence Methods

While ANN and SVM dominate the computational intelligence perspective within the exchange rate modeling domain, other computational intelligence techniques have also found applications in this area. Two such well explored methods are Fuzzy Logic and Genetic Algorithm. Both of these methods have been combined with ANN and SVM to develop different hybrid models, as has been outlined in the previous two subsections. In addition to these, the two methods have also been employed from other perspectives.

Fuzzy logic deals with the probabilistic set membership and linguistic variables to address uncertain and ambiguous conditions, and have been applied in financial timeseries processing domain[106–109]. Tseng et al. [110] combine the concepts of ARIMA and Fuzzy regression towards the development of a Fuzzy ARIMA model, and report effectiveness of proposed model over the traditional ARIMA model in forecasting Taiwanese Dollar/US Dollar exchange rates. de los Angeles Hernandez Medina and Mendez [111] explore a set of Fuzzy logic based methods for predicting the Mexican Peso/US Dollar exchange rates, and show the potentials of these methods. Leu et al. [3] utilize the distance between fuzzy logic relationships to propose a novel exchange rate model, and demonstrate that it outperforms both the random walk and ANN models.

Genetic Algorithm (GA) is a heuristic search method, which is motivated by the characteristics of biological genes like mutation, survival and natural selection, and has been applied in wide range of domains to address wide range of issues [112], [113]. GA has found popularity in exchange rate modelling as well. Neely and Weller [114] investigate GA in the context of exchange rate volatility and note its superior performance than GARCH in terms of Mean Absolute Error (MAE). Lawrenz and Westerhoff [115] employ GA to simulate the microeconomic characteristics of foreign exchange market and realize the behavioural aspects of the exchange rate. Alvarez-Diaz and Alvarez [116] utilize GA to find the best functional approximation of time variability for several exchange rates. In another work, Álvarez-Díaz and Álvarez [117] apply GA along with ANN and data fusion approach to realize the evolution of exchange rate returns. The work, however, points to minor improvements in forecasting even with the employments of sophisticated methods.

In addition to these two methods, researchers have also employed other intelligent computing strategies in exchange rate modelling domain. These include the employment of Random Forest to capture the RMB exchange rate dynamics [118], Bayesian approaches to address diverse exchange rate issues [119–122], Association Rule Mining to realize the co-movements between exchange rates and stock indexes [123], and multi-agent based modelling [124], [125].

A particular recent research is the one by Imam et al. [126]. This work relates the exchange rates for Australian Dollar (AUD) against the US Dollar (USD) through a set of computational intelligence models and the linear model. In addition to historical exchange rate information, the work also considers the respective stock market indices in the model design. It is shown that while computational intelligence model stands out as the best predictor when considering historical exchange rates, incorporation of economic factors like the stock market indices result in linear model standing out as the best predictor. The work further highlights that the AUD/USD exchange rate is well approximated by a linear model that considers historical information of both the stock market indices and the exchange rate. In other words, the work shows effectiveness of computational intelligence method for AUD/USD exchange rate only when univariate exchange rate timeseries considered, and favours linear modelling when other economic factors are taken into consideration.

Overall, the computational intelligence endeavours in exchange rate domain notably vary in terms of perspectives, and focus primarily on the timeseries characteristics of exchange rate information.

7. What We Know and We Don't

The previous sections have provided a contemporary review on exchange rate modeling and prediction literature from various angels. Fig. 1 indicates the various strategies under the different groups. As shown, and also discussed in the earlier sections, exchange rate models in literature can be broadly categorized into two aspects – those based on economical aspects and those on computational intelligence aspects. Many of these economical aspect models incorporate the macroeconomic information (in a linear or non-linear structure), while microeconomic information has also been considered in recent studies. ANN and SVM are the two computational intelligence strategies that have found wide applications in this domain, while several literatures have reflected on random walk models to be as good as the economic aspect based and computational intelligence based models. This section draws from these existing literatures to point out the knowledge gained so far and indicates the potential future research undertakings.

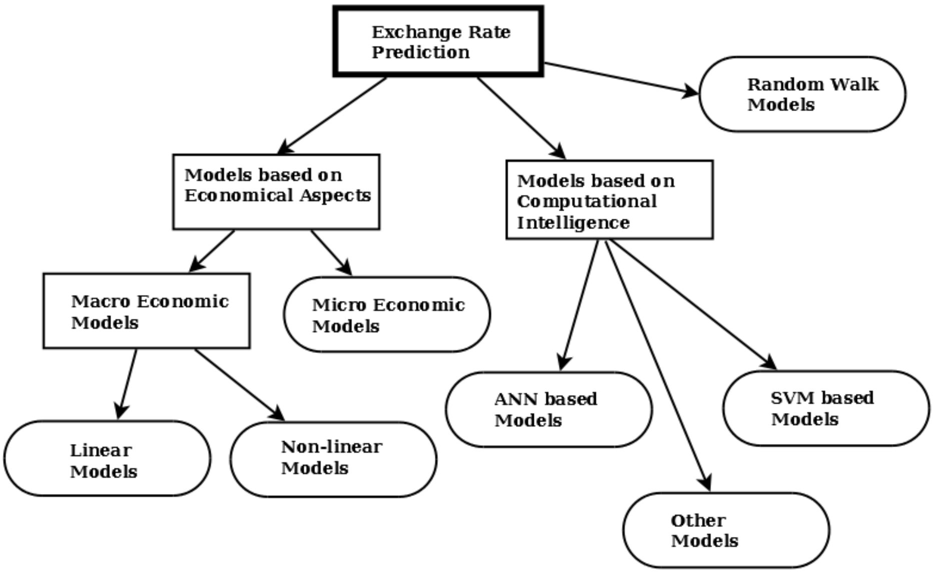

Figure 1 Broad Classification of Exchange Rate Models

7.1. Observations from the Reviews (i.e., What We Know)

First of all, a distinction in views between the researchers in computational intelligence domain and the researchers in the other domain is evident. As notable, computational intelligence community accepts that exchange rate information is a timeseries and the related works mainly emphasize on the technical processing of timeseries information towards achieving high prediction accuracy. Interpretations of the models from finance domain perspective are generally limited. Other researchers (i.e., finance community), in contrast, are well focused on interpretation, and structured models comprising varied economic factors are generally investigated. It is due to the ease of interpretation, linear models are so popular in the finance domain.

A second observation is the issue of random walk hypothesis for both the finance and computational intelligence domains. While some of the recent works have either refuted the hypothesis or indicated that the hypothesis is true only for short horizon through the incorporation of varied economic factors and robust model development, the decision in this regard is still inconclusive.

A particular recent trend is the wider use of nonlinear models, in contrast to the widely popular linear models. Even though linear models are well accepted among the finance researchers in varied aspects, the performance of these models in exchange rate domains have not been satisfactory. It is this issue which has led the substantial development of intelligent computing techniques in this domain, with a view to addressing the non-linear aspects of the data.

Another noticeable observation is the increasing number of hybrid approaches, particularly in the computational intelligence contexts. This trend indicates the difficulty of accurate prediction in exchange rate domains. As have been indicated in some of the literatures, exchange rate timeseries is often chaotic, noisy and non-stationary [98], [100], [102]. These attributes cause the prediction by single model to be hard, and often inferior to the random walk. A single model approach, which can generalize well in capturing dynamics of the different exchange rates in different economical contexts, is still a challenge.

7.2. Future Research Potentials (i.e., What We Don't Know)

A noticeable research potential for the intelligent computing community lies in the development of a model that can be well interpreted from the finance domain perspective. Dependencies among variables, explanations of the response variable's volatility, and statistical significance of the estimated parameters are some of the key model attributes generally sought by the finance community. The inherent goal is the human-interpretable knowledge generation. Interestingly, many of the computational intelligence methods applied in the exchange rate domains are not easily interpretable and do not provide the aforementioned information. Also, intelligent computing methods that are human interpretable, like the rule based algorithms and association rule mining, have found only limited focus. Thus, research opportunities exist in this context.

A second research opportunity is due to the findings by Cheung et al. [127]. The work indicated that the performances of exchange rate models are specific to the currencies and the time periods in consideration. In other words, no single model is generally the best fit for capturing the dynamics of all the exchange rates. Although the work focused on a selected set of models, this appears to be the case from the varied economies and models that have been explored in exchange rate literature. However, this issue is still inconclusive from theoretical perspectives. The phenomenon implies that we still don't clearly know what factors within the economy and other characteristics, along with historical information can influence the exchange rates for a currency pair. An intelligent computing research may be able to shed further lights in this respect.

As indicated in the previous subsection, challenge still remains to develop a single model based approach, in contrast to a hybrid approach, for exchange rate modeling. Another issue discussed in the previous subsection is the inconclusiveness about the random walk hypothesis.

Another challenge is the incorporation of microeconomic information within the computational intelligence approach. As highlighted in Section 5, microeconomic models have recently been proposed and shown to better capture the dynamics of exchange rate than the macroeconomic models. However, the incorporation of microeconomic information in computational intelligence model is still limited and opportunities exist to explore this issue. In relation to this, while intelligent computing community has seen an outburst of hybrid models involving varied computational intelligence methods in the exchange rate domain, there is yet a comprehensive study that performs a hybrid of the economic structure model and a computational intelligence model. Such a development may address the issue of interpretability, as sustained by the computational intelligence models, while also provide deeper insights in the exchange rate dynamics. In respect to this, another research opportunity remains due to the fact that there is yet a comprehensive contemporary study that has focused on comparing the exchange rate prediction models based on economical aspects and those based on computational intelligence strategies.

A last research opportunity is due to the recent work by Imam et al. [126]. The work provides a comparison among set of intelligent computing methods and notes that incorporation of economic factors along with exchange rate information deems the linear model as better predictor than the intelligent computing methods. It's interesting to further investigate if this is the case for other economical contexts, or whether the computational intelligence methods can be improved in this respect.

8. Conclusions

This article has provided a contemporary review on progress in the exchange rate prediction and modeling from both the finance and intelligent computing focus. It is shown that these two communities vary in terms of the approach and expected outcomes. As noted, finance community is generally focused on realizing the structural relationship to explain exchange rate dynamics, while computational intelligence community emphasizes on better processing of exchange rate timeseries. ANN and SVM are noted to be the dominant intelligent computing methods in this domain. Further, the article also highlights the weaknesses in the different methods and points to newer research opportunities, particularly in the area of computational intelligence. As indicated, a number of research opportunities exist including design of interpretable intelligent computing models, development of an exchange rate model that generalizes over currency and economical contexts, addressing controversies against the random walk hypothesis, formulation of hybrid frameworks involving both the structural modeling and intelligent computing strategies, and further investigations into the linear and nonlinear modeling issue. Overall, the article stands on a unique ground by combining surveys from two different disciplines towards a common issue and pointing to potential research undertakings.

Acknowledgments

The author would like to thank the anonymous reviewers for their suggestions.

9. References

[1] R. A. Meese and K. Rogoff, "Empirical exchange rate models of the seventies: Do they fit out of sample?," *Journal of international economics*, vol. 14, no. 1, pp. 3–24, 1983.

[2] M. D. D. Evans, *Exchange-rate dynamics*. Princeton University Press, 2011.

[3] Y. Leu, C.-P. Lee, and Y.-Z. Jou, "A distance-based fuzzy time series model for exchange rates forecasting," *Expert Systems with Applications*, vol. 36, no. 4, pp. 8107–8114, May 2009.

[4] J. Duffy, *CliffsQuickReview Economics*. John Wiley & Sons, 1993.

[5] R. Dornbusch, "Expectations and exchange rate dynamics," *The Journal of Political Economy*, pp. 1161–1176, 1976.

[6] J. A. Frenkel, "A monetary approach to the exchange rate: doctrinal aspects and empirical evidence," *the scandinavian Journal of economics*, pp. 200–224, 1976.

[7] I. H. Giddy, "An integrated theory of exchange rate equilibrium," *Journal of Financial and Quantitative Analysis*, vol. 11, no. 5, pp. 883–892, 1976.

[8] P. J. . Kouri, "The exchange rate and the balance of payments in the short run and in the long run: A monetary approach," *The Scandinavian Journal of Economics*, pp. 280–304, 1976.

[9] J. F. . Bilson, "The current experience with floating exchange rates: An appraisal of the monetary approach," *The American Economic Review*, pp. 392–397, 1978.

[10] L. H. Officer, "Effective exchange rates and price ratios over the long run: a test of the purchasing-power-parity theory," *Canadian Journal of Economics*, pp. 206–230, 1980.

[11] J. F. . Bilson, "The Monetary Approach to the Exchange Rate: Some Empirical Evidence," *Staff Papers-International Monetary Fund*, pp. 48–75, 1978.

[12] J. A. Frankel, "On the Mark: A Theory of Floating Exchange Rates Based on Real Interest Differentials," *The American Economic Review*, vol. 69, no. 4, pp. 610–622, Sep. 1979.

[13] E. F. Fama, "Efficient Capital Markets: A Review of Theory and Empirical Work," *The Journal of Finance*, vol. 25, no. 2, pp. 383–417, May 1970.

[14] D. W. Caves and E. L. Feige, "Efficient foreign exchange markets and the monetary approach to exchange-rate determination," *The American Economic Review*, vol. 70, no. 1, pp. 120–134, 1980.

[15] M. P. Dooley and J. Shafer, "Analysis of short-run exchange rate behavior: March 1973 to November 1981," *Floating exchange rates and the state of world trade and payments*, pp. 43–70, 1984.

[16] J. A. Frankel, *Tests of monetary and portfolio balance models of exchange rate determination*. University of Chicago Press, 1984.

[17] A. C. Stockman, "A theory of exchange rate determination," *The Journal of Political Economy*, pp. 673–698, 1980.

[18] J. A. Frenkel, "Flexible Exchange Rates, Prices, and the Role of 'News': Lessons from the 1970s," *Journal of Political Economy*, vol. 89, no. 4, pp. 665–705, Aug. 1981.

[19] R. Flood, *Explanations of exchange rate volatility and other empirical regularities in some popular models of the foreign exchange market*. National Bureau of Economic Research Cambridge, Mass., USA, 1981.

[20] R. A. Meese and K. J. Singleton, "Rational expectations and the volatility of floating exchange rates," *International Economic Review*, vol. 24, no. 3, pp. 721–733, 1983.

[21] D. Backus, "Empirical models of the exchange rate: Separating the wheat from the chaff," *Canadian Journal of Economics*, pp. 824–846, 1984.
[22] C. C. P. Wolff, "Models of exchange rates: A comparison of forecasting results," *International Journal of Forecasting*, vol. 4, no. 4, pp. 605–607, 1988.
[23] J. L. Urrutia, "Variance ratio tests of random walk for foreign exchange rates," *Economics Letters*, vol. 38, no. 4, pp. 457–465, Apr. 1992.
[24] C. Hakkio, "Does the exchange rate follow a random walk? A Monte Carlo study of four tests for a random walk," *Journal of International Money and Finance*, vol. 5, no. 2, pp. 221–229, Jun. 1986.
[25] V. S. Somanath, "Efficient exchange rate forecasts: Lagged models better than the random walk," *Journal of International Money and Finance*, vol. 5, no. 2, pp. 195–220, Jun. 1986.
[26] G. J. Schinasi and P. A. V. B. Swamy, "The out-of-sample forecasting performance of exchange rate models when coefficients are allowed to change," *Journal of International Money and Finance*, vol. 8, no. 3, pp. 375–390, Sep. 1989.
[27] G. Gandolfo, P. C. Padoan, and G. Paladino, "Exchange rate determination: Single-equation or economy-wide models?: A test against the random walk," *Journal of Banking & Finance*, vol. 14, no. 5, pp. 965–992, Nov. 1990.
[28] B. J. C. Kim and S. Mo, "Cointegration and the long-run forecast of exchange rates," *Economics Letters*, vol. 48, no. 3–4, pp. 353–359, Jun. 1995.
[29] C. P. Fritsche and M. Wallace, "Forecasting the exchange rate PPP versus a random walk," *Economics Letters*, vol. 54, no. 1, pp. 69–74, Jan. 1997.
[30] F. Lisi and A. Medio, "Is a random walk the best exchange rate predictor?," *International Journal of Forecasting*, vol. 13, no. 2, pp. 255–267, Jun. 1997.
[31] D. A. Hsieh, "Testing for Nonlinear Dependence in Daily Foreign Exchange Rates," *The Journal of Business*, vol. 62, no. 3, pp. 339–368, Jul. 1989.
[32] M. L. Higgins and A. K. Bera, "A Class of Nonlinear Arch Models," *International Economic Review*, vol. 33, no. 1, pp. 137–158, Feb. 1992.
[33] M. Bleaney and P. Mizen, "Nonlinearities in Exchange-Rate Dynamics: Evidence from Five Currencies, 1973–94," *Economic Record*, vol. 72, no. 216, pp. 36–45, 1996.
[34] R. A. Meese and A. K. Rose, "Nonlinear, nonparametric, nonessential exchange rate estimation," *The American Economic Review*, vol. 80, no. 2, pp. 192–196, 1990.
[35] R. A. Meese and A. K. Rose, "An Empirical Assessment of Non-Linearities in Models of Exchange Rate Determination," *Review of Economic Studies*, vol. 58, no. 3, pp. 603–619, May 1991.
[36] M. D. Chinn, "Some linear and nonlinear thoughts on exchange rates," *Journal of International Money and Finance*, vol. 10, no. 2, pp. 214–230, Jun. 1991.
[37] N. Sarantis, "Modeling non-linearities in real effective exchange rates," *Journal of International Money and Finance*, vol. 18, no. 1, pp. 27–45, Jan. 1999.
[38] C. Brooks, "Linear and non-linear (non-) forecastability of high-frequency exchange rates," *Journal of forecasting*, vol. 16, no. 2, pp. 125–145, 1997.
[39] J. Creedy, J. Lye, and V. L. Martin, "A non-linear model of the real US/UK exchange rate," *Journal of Applied Econometrics*, vol. 11, no. 6, pp. 669–686, 1996.
[40] A. S. Soofi and L. Cao, "Nonlinear deterministic forecasting of daily Peseta–Dollar exchange rate," *Economics Letters*, vol. 62, no. 2, pp. 175–180, Feb. 1999.
[41] M. D. D. Evans and R. K. Lyons, "Order flow and exchange rate dynamics," National Bureau of Economic Research, 1999.
[42] R. K. Lyons, *The microstructure approach to exchange rates*. Citeseer, 2001.
[43] M. D. D. Evans and R. K. Lyons, "Meese-Rogoff Redux: Micro-Based Exchange Rate Forecasting," National Bureau of Economic Research, Working Paper 11042, Jan. 2005.
[44] D. Rime, L. Sarno, and E. Sojli, "Exchange rate forecasting, order flow and macroeconomic information," *Journal of International Economics*, vol. 80, no. 1, pp. 72–88, 2010.
[45] M. Evans and D. Rime, "Micro approaches to foreign exchange determination," *Available at SSRN 1935812*, no. 2011/05, 2011.
[46] L. Kilian and M. P. Taylor, "Why is it so difficult to beat the random walk forecast of exchange rates?," *Journal of International Economics*, vol. 60, no. 1, pp. 85–107, May 2003.

[47] J. Faust, J. H. Rogers, and J. H. Wright, "Exchange rate forecasting: the errors we've really made," *Journal of International Economics*, vol. 60, no. 1, pp. 35–59, May 2003.
[48] R. H. Clarida, L. Sarno, M. P. Taylor, and G. Valente, "The out-of-sample success of term structure models as exchange rate predictors: a step beyond," *Journal of International Economics*, vol. 60, no. 1, pp. 61–83, May 2003.
[49] C. Engel, N. C. Mark, and K. D. West, "Exchange rate models are not as bad as you think," National Bureau of Economic Research, 2007.
[50] C. Yuan, "Forecasting exchange rates: The multi-state Markov-switching model with smoothing," *International Review of Economics & Finance*, vol. 20, no. 2, pp. 342–362, Apr. 2011.
[51] A. Konar, *Computational Intelligence: Principles, Techniques and Applications*. Springer, 2005.
[52] C. Grosan and A. Abraham, *Intelligent Systems: A Modern Approach*. Springer, 2011.
[53] B. Yegnanarayana, *Artificial Neural Networks*. PHI Learning Pvt. Ltd., 2004.
[54] D. Graupe, *Principles of Artificial Neural Networks*. World Scientific, 2007.
[55] A. N. Refenes, M. Azema-Barac, and S. A. Karoussos, "Currency exchange rate forecasting by error backpropagation," in *Proceedings of the Twenty-Fifth Hawaii International Conference on System Sciences, 1992*, 1992, vol. iv, pp. 504 –515 vol.4.
[56] A. N. Refenes, M. Azema-Barac, L. Chen, and S. A. Karoussos, "Currency exchange rate prediction and neural network design strategies," *Neural Computing & Applications*, vol. 1, no. 1, pp. 46–58, 1993.
[57] H. Pi, "Dependency Analysis and Neural Network Modeling of Currency Exchange Rates," *First International W or k shop on Neural Networ k s in the Capital M ar k ets, London Business School*, 1993.
[58] M. Staley and P. Kim, "Predicting the Canadian spot exchange rate with neural networks," in *Computational Intelligence for Financial Engineering, 1995.,Proceedings of the IEEE/IAFE 1995*, 1995, pp. 108 –112.
[59] T. H. Hann and E. Steurer, "Much ado about nothing? Exchange rate forecasting: Neural networks vs. linear models using monthly and weekly data," *Neurocomputing*, vol. 10, no. 4, pp. 323–339, Apr. 1996.
[60] W. Verkooijen, "A neural network approach to long-run exchange rate prediction," *Computational Economics*, vol. 9, no. 1, pp. 51–65, 1996.
[61] A. S. Andreou, G. A. Zombanakis, E. F. Georgopoulos, and S. D. Likothanassis, "Forecasting Exchange-Rates via Local Approximation Methods and Neural Networks," 1998.
[62] C.-M. Kuan and T. Liu, "Forecasting Exchange Rates Using Feedforward and Recurrent Neural Networks," *Journal of Applied Econometrics*, vol. 10, no. 4, pp. 347–364, Oct. 1995.
[63] J. Plasmans, W. Verkooijen, and H. Daniels, "Estimating structural exchange rate models by artificial neural networks," *Applied Financial Economics*, vol. 8, no. 5, pp. 541–551, 1998.
[64] M. Qi and Y. Wu, "Exchange Rates and Fundamentals: Evidence from Out-of-Sample Forecasting Using Neural Networks," *Computational Finance*, pp. 271–286, 1999.
[65] G. P. Zhang and V. L. Berardi, "Time series forecasting with neural network ensembles: an application for exchange rate prediction," *Journal of the Operational Research Society*, pp. 652–664, 2001.
[66] V. Kodogiannis and A. Lolis, "Forecasting Financial Time Series using Neural Network and Fuzzy System-based Techniques," *Neural Computing & Applications*, vol. 11, no. 2, pp. 90–102, 2002.
[67] A. K. Nag and A. Mitra, "Forecasting daily foreign exchange rates using genetically optimized neural networks," *Journal of Forecasting*, vol. 21, no. 7, pp. 501–511, 2002.
[68] G. P. Zhang, "Time series forecasting using a hybrid ARIMA and neural network model," *Neurocomputing*, vol. 50, pp. 159–175, Jan. 2003.
[69] L. Anastasakis and N. Mort, "Exchange rate forecasting using a combined parametric and nonparametric self-organising modelling approach," *Expert Systems with Applications*, vol. 36, no. 10, pp. 12001–12011, Dec. 2009.
[70] J.-F. Chang, C.-M. Kuan, and Y.-W. Lin, "Forecasting Exchange Rates by Genetic Algorithms Based Back Propagation Network Model," in *Fifth International Conference on Intelligent*

Information Hiding and Multimedia Signal Processing, 2009. IIH-MSP '09, 2009, pp. 791 – 794.

[71] M. Sheikhan and B. Movaghar, "Exchange rate prediction using an evolutionary connectionist model," *World Applied Sciences Journal, Special Issue of Computer & IT*, vol. 7, pp. 8–16, 2009.

[72] T. Chen, "Applying a Fuzzy and Neural Approach for Forecasting the Foreign Exchange Rate," *International Journal of Fuzzy System Applications*, vol. 1, no. 1, pp. 36–48, 2011.

[73] M. T. Leung, A.-S. Chen, and H. Daouk, "Forecasting exchange rates using general regression neural networks," *Computers & Operations Research*, vol. 27, no. 11–12, pp. 1093–1110, Sep. 2000.

[74] L. Yu, S. Wang, and K. Lai, "Adaptive Smoothing Neural Networks in Foreign Exchange Rate Forecasting," in *Computational Science – ICCS 2005*, vol. 3516, V. Sunderam, G. van Albada, P. Sloot, and J. Dongarra, Eds. Springer Berlin / Heidelberg, 2005, pp. 523–530.

[75] C. Xie, B. Sun, J. Zhang, and Y. Xiang, "Which neural network is appropriate for CNY/USD exchange rate series forecast," *International Journal of Computational Science*, vol. 3, pp. 535–553, 2009.

[76] R. Majhi, G. Panda, and G. Sahoo, "Efficient prediction of exchange rates with low complexity artificial neural network models," *Expert Systems with Applications*, vol. 36, no. 1, pp. 181–189, Jan. 2009.

[77] C. L. Dunis, J. Laws, and G. Sermpinis, "Higher order and recurrent neural architectures for trading the EUR/USD exchange rate," *Quantitative Finance*, vol. 11, no. 4, pp. 615–629, 2011.

[78] C. T. Lye, T. H. Chan, and C. W. Hooy, "Forecasting Chinese Foreign Exchange with Monetary Fundamentals using Artificial Neural Networks," in *3rd Int Conf Inf Finance Eng*, 2011, vol. 12, pp. 560–564.

[79] G. Sermpinis, C. Dunis, J. Laws, and C. Stasinakis, "Forecasting and trading the EUR/USD exchange rate with stochastic Neural Network combination and time-varying leverage," *Decision Support Systems*, vol. (in press), 2012.

[80] Y. Li and W. Ma, "Applications of Artificial Neural Networks in Financial Economics: A Survey," in *2010 International Symposium on Computational Intelligence and Design (ISCID)*, 2010, vol. 1, pp. 211 –214.

[81] L. Yu, S. Wang, and K. K. Lai, *Foreign-Exchange-Rate Forecasting with Artificial Neural Networks*. Springer, 2007.

[82] M. Li and S. Lin, "Several Problems of Exchange Rate Forecasting Using Neural Network," in *International Symposium on Intelligent Information Systems and Applications*, 2009.

[83] T. Joachims, *Making large-Scale SVM Learning Practical. Advances in Kernel Methods-Support Vector Learning, B. Schölkopf and C. Burges and A. Smola*. MIT-press, 1999.

[84] V. N. Vapnik, *The nature of statistical learning theory*. Springer-Verlag New York Incorporated, 2000.

[85] J. Shawe-Taylor and N. Cristianini, *Kernel methods for pattern analysis*. Cambridge university press, 2004.

[86] J. Kamruzzaman, R. A. Sarker, and I. Ahmad, "SVM based models for predicting foreign currency exchange rates," in *Third IEEE International Conference on Data Mining, 2003. ICDM 2003*, 2003, pp. 557 – 560.

[87] J. Kamruzzaman and R. A. Sarker, "Application of Support Vector Machine to Forex Monitoring," *IEEJ Transactions on Electronics, Information and Systems*, vol. 124, no. 10, pp. 1944–1951, 2004.

[88] D.-Z. Cao, S.-L. Pang, and Y.-H. Bai, "Forecasting exchange rate using support vector machines," in *Proceedings of 2005 International Conference on Machine Learning and Cybernetics, 2005*, 2005, vol. 6, pp. 3448 –3452 Vol. 6.

[89] C. Ullrich, D. Seese, and S. Chalup, "Foreign Exchange Trading with Support Vector Machines," in *Advances in Data Analysis*, R. Decker, H.-J. Lenz, H.-H. Bock, W. Gaul, and M. Vichi, Eds. Springer Berlin Heidelberg, 2007, pp. 539–546.

[90] L. Liu and W. Wang, "Exchange rates forecasting with least squares support vector machine," in *Computer Science and Software Engineering, 2008 International Conference on*, 2008, vol. 5, pp. 1017–1019.

[91] M. Alamili, "Exchange Rate Prediction using Support Vector Machines," M. Sc. Thesis, DELFT UNIVERSITY OF TECHNOLOGY, 2011.
[92] W. C. Hong, "A hybrid support vector machine regression for exchange rate prediction," *International journal of information and management sciences*, vol. 17, no. 2, pp. 19–32, 2006.
[93] H. Ince and T. B. Trafalis, "A hybrid model for exchange rate prediction," *Decision Support Systems*, vol. 42, no. 2, pp. 1054–1062, Nov. 2006.
[94] H. Ni and H. Yin, "Recurrent Self-Organising Maps and Local Support Vector Machine Models for Exchange Rate Prediction," in *Advances in Neural Networks - ISNN 2006*, vol. 3973, J. Wang, Z. Yi, J. Zurada, B.-L. Lu, and H. Yin, Eds. Springer Berlin / Heidelberg, 2006, pp. 504–511.
[95] L. Yu, S. Wang, and K. K. Lai, "Forecasting foreign exchange rates using an SVR-based neural network ensemble," *Advances in Banking Technology and Management: Impacts of ICT and CRM*, pp. 261–277, 2008.
[96] K. He, C. Xie, and K. K. Lai, "Multi Scale Nonlinear Ensemble Model for Foreign Exchange Rate Prediction," in *Fourth International Conference on Natural Computation, 2008. ICNC '08*, 2008, vol. 7, pp. 43 –47.
[97] Z.-B. Wang, H.-W. Hao, X.-C. Yin, Q. Liu, and K. Huang, "Exchange Rate Forecasting Using Classifier Ensemble," in *Neural Information Processing*, vol. 5863, C. Leung, M. Lee, and J. Chan, Eds. Springer Berlin / Heidelberg, 2009, pp. 884–891.
[98] C.-J. Lu, T.-S. Lee, and C.-C. Chiu, "Financial time series forecasting using independent component analysis and support vector regression," *Decision Support Systems*, vol. 47, no. 2, pp. 115–125, May 2009.
[99] W. M. Hung and W. C. Hong, "Application of SVR with improved ant colony optimization algorithms in exchange rate forecasting," *Control and Cybernetics*, vol. 38, no. 3, pp. 863–891, 2009.
[100] S.-C. Huang, P.-J. Chuang, C.-F. Wu, and H.-J. Lai, "Chaos-based support vector regressions for exchange rate forecasting," *Expert Systems with Applications*, vol. 37, no. 12, pp. 8590–8598, Dec. 2010.
[101] P.-F. Pai, S.-Y. Chen, C.-W. Huang, and Y.-H. Chang, "Analyzing foreign exchange rates by rough set theory and directed acyclic graph support vector machines," *Expert Systems with Applications*, vol. 37, no. 8, pp. 5993–5998, Aug. 2010.
[102] C. Fu, "Forecasting Exchange Rate with EMD-Based Support Vector Regression," in *2010 International Conference on Management and Service Science (MASS)*, 2010, pp. 1 –4.
[103] K. He, K. K. Lai, and J. Yen, "A hybrid slantlet denoising least squares support vector regression model for exchange rate prediction," *Procedia Computer Science*, vol. 1, no. 1, pp. 2397–2405, May 2010.
[104] F.-Y. Liu, "The hybrid prediction model of CNY/USD Exchange Rate Based On Wavelet And Support Vector Regression," in *2010 2nd International Conference on Advanced Computer Control (ICACC)*, 2010, vol. 4, pp. 561 –565.
[105] S. Pang, L. Song, and N. Kasabov, "Correlation-aided support vector regression for forex time series prediction," *Neural Computing & Applications*, vol. 20, no. 8, pp. 1193–1203, 2011.
[106] L. A. Zadeh and J. Kacprzyk, *Fuzzy logic for the management of uncertainty*. Wiley, 1992.
[107] D. McNeill and P. Freiberger, *Fuzzy logic*. Simon & Schuster, 1993.
[108] J. F. Baldwin, *Fuzzy logic*. Wiley, 1996.
[109] O. Castillo and P. Melin, "Simulation and forecasting complex financial time series using neural networks and fuzzy logic," in *2001 IEEE International Conference on Systems, Man, and Cybernetics*, 2001, vol. 4, pp. 2664 –2669 vol.4.
[110] F.-M. Tseng, G.-H. Tzeng, H.-C. Yu, and B. J. C. Yuan, "Fuzzy ARIMA model for forecasting the foreign exchange market," *Fuzzy Sets and Systems*, vol. 118, no. 1, pp. 9–19, Feb. 2001.
[111] M. de los Angeles Hernandez Medina and G. M. Mendez, "Modeling and Prediction of the MXNUSD Exchange Rate Using Interval Singleton Type-2 Fuzzy Logic Systems," in *2006 IEEE International Conference on Fuzzy Systems*, 2006, pp. 2305 –2308.
[112] L. D. Chambers, *The Practical Handbook of Genetic Algorithms: New Frontiers*. CRC Press, 1995.
[113] M. Affenzeller, S. Wagner, and S. Winkler, *Genetic Algorithms and Genetic Programming: Modern Concepts and Practical Applications*. CRC Press, 2009.

[114] C. J. Neely and P. A. Weller, "Predicting Exchange Rate Volatility: Genetic Programming vs. GARCH and Risk Metrics^{TM}," *Federal Reserve Bank of St. Louis Working Paper Series*, 2001.
[115] C. Lawrenz and F. Westerhoff, "Modeling Exchange Rate Behavior with a Genetic Algorithm," *Computational Economics*, vol. 21, no. 3, pp. 209–229, 2003.
[116] M. Alvarez-Diaz and A. Alvarez, "Forecasting exchange rates using genetic algorithms," *Applied Economics Letters*, vol. 10, no. 6, pp. 319–322, 2003.
[117] M. Álvarez-Díaz and A. Álvarez, "Genetic multi-model composite forecast for non-linear prediction of exchange rates," *Empirical Economics*, vol. 30, no. 3, pp. 643–663, 2005.
[118] W. Lv and R. Zhang, "A regression model on effective exchange rate of RMB based on Random Forest," in *2011 International Conference on E -Business and E -Government (ICEE)*, 2011, pp. 1 –3.
[119] A. S. Chen and M. T. Leung, "A Bayesian vector error correction model for forecasting exchange rates," *computers & operations research*, vol. 30, no. 6, pp. 887–900, 2003.
[120] J. H. Wright, "Bayesian Model Averaging and Exchange Rate Forecasts," *SSRN eLibrary*, Sep. 2003.
[121] J. Osiewalski and M. Pipień, "Bayesian comparison of bivariate ARCH-type models for the main exchange rates in Poland," *Journal of Econometrics*, vol. 123, no. 2, pp. 371–391, 2004.
[122] C. M. Lo and J. Morley, "Bayesian Analysis of Nonlinear Exchange Rate Dynamics and the Purchasing Power Parity Persistence Puzzle," Working Paper, University of New South Wales, 2011.
[123] S. Liao, P. Chu, and Y. You, "Mining the co-movement between foreign exchange rates and category stock indexes in the Taiwan financial capital market," *Expert Systems with Applications*, vol. 38, no. 4, pp. 4608–4617, Apr. 2011.
[124] G. Zimmermann, R. Neuneier, and R. Grothmann, "Multi-agent FX-Market Modeling Based on Cognitive Systems," in *Artificial Neural Networks — ICANN 2001*, vol. 2130, G. Dorffner, H. Bischof, and K. Hornik, Eds. Springer Berlin / Heidelberg, 2001, pp. 767–774.
[125] D. Zhang, S. Simoff, and J. Debenham, "Exchange Rate Modelling Using News Articles and Economic Data," in *AI 2005: Advances in Artificial Intelligence*, vol. 3809, S. Zhang and R. Jarvis, Eds. Springer Berlin / Heidelberg, 2005, pp. 467–476.
[126] T. Imam, K. Tickle, A. Ahmed, and W. Guo, "Linear Relationship Between The AUD/USD Exchange Rate And The Respective Stock Market Indices: A Computational Finance Perspective," *Intelligent Systems in Accounting, Finance and Management*, vol. 19, no. 1, pp. 19–42, 2012.
[127] Y.-W. Cheung, M. D. Chinn, and A. G. Pascual, "Empirical exchange rate models of the nineties: Are any fit to survive?," *Journal of International Money and Finance*, vol. 24, no. 7, pp. 1150–1175, Nov. 2005.