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Review

Soft computing hybrids for FOREX rate prediction: A comprehensive review

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ABSTRACT

Foreign exchange rate prediction is an important problem in finance and it attracts many researchers owing to its complex nature and practical applications. Even though this problem is well studied using various statistical and machine learning techniques in stand-alone mode, various soft computing hybrids were also proposed to solve this problem with the aim of obtaining more accurate predictions during 1998–2017. This paper presents a comprehensive review of 82 such soft computing hybrids found in the literature. Almost all authors in this area demonstrated that their proposed hybrids outperformed the stand-alone statistical and intelligent techniques in terms of accuracy. It is conspicuous from the review that artificial neural network based hybrids turned out to be more prevalent, more pervasive and more powerful. This observation is corroborated by the fact that both evolutionary computation based hybrids as well as fuzzy logic based hybrids also contained some architecture of neural networks as a predominant constituent. The review concludes with a set of insightful remarks and future directions that are very much useful to budding researchers and practitioners alike.

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1. Introduction

The Foreign Exchange (FOREX) rate is the price of one currency paid in terms of another. It is the most important price in any country's economic system and is a measure of the economic health of that country. The exchange rates have the tremendous influence on the trade relationship of one country with another, which in turn, affect the common man's standard of living. A country with lower currency rate has to make its exports very cheap and its imports very expensive in foreign currency market thereby affecting its economy. It can revisit its economic policies and change them suitably based on the accurate prediction of FOREX rate. These changes help in maintaining trade relationships properly which, in turn, lead its economy to be stronger. Thus, the prediction of FOREX rate is paramount, and it should never be underestimated (Hoag and Hoag, 2002).

Financial time series is a collection of chronologically recorded observations of the financial variable(s). For example, the daily FOREX rate of a currency pair is a univariate financial time series. Compared to other time series, the financial time series are intrinsically non-stationary and chaotic (Yao and Tan, 2000). A time series is said to be chaotic if and only if it is nonlinear, deterministic and sensitive to initial conditions (Dhanya and Nagesh Kumar, 2010). The prediction of a chaotic time series engages with the prediction of future behavior of the chaotic system by utilizing the current and past states of that system.

In addition to these, financial time series prediction is a highly complicated task as a financial time series exhibits the following characteristics:

1. Financial time series often behave nearly like a random-walk process, making the prediction almost impossible (from a theoretical point of view) (Hellstrom and Holmstrom, 1998).
2. Financial time series are usually very noisy, i.e., there is a large amount of random (unpredictable) day-to-day variations (Magdon-Ismail et al., 1998).

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Table 1
Constituents of soft computing used in hybrids.

Constituent of soft computing	Basic idea	Merits	Demerits
Artificial Neural Network (ANN)	Capable of learning patterns from examples using various algorithms mimicking human learning	Suitable for diverse tasks of classification, clustering, forecasting, optimization and function approximation	Optimal parameter combination of a training algorithm is found by fine tuning. A lot of training data and time are needed.
Evolutionary Computation (EC)	Imitates the Darwin's principles of evolution in order to solve nonlinear, non-convex global optimization problems	Capable of finding the near global optimal solution of an nonlinear, non-convex function without getting entrapped in local minima	Convergence process is slow,while convergence to the global optimal solution is not guaranteed unless improved by a suitable direct search method.
Fuzzy Logic (FL)	Fuzzy sets can model the imprecision and the ambiguity in the data. FL brings the human experiential knowledge into the model via suitable fuzzy mathematics.	Capable of deriving human understandable fuzzy 'if-then' rules; It has low computational complexity	Often, the selection of a membership function is not scientific and unique.
Support Vector Machine (SVM)	Finds a hyperplane which separates the d-dimensional data perfectly into two classes.	Training is relatively easy and scales relatively well to high-dimensional data and yields the global optimal solution.	Need to choose a good kernel function
Chaos Theory	Characterizes a dynamical system by transforming it into its equivalent phase-space.	It models underlying deterministic complex behavior in a system.	It is not clear how much data are required to construct the phase space set and susceptible to initial conditions.

3. Statistical properties of the financial time series are different at different points in time as the process is time-varying (Hellstrom and Holmstrom, 1998).

Time series forecasting involves collecting historical observations of a variable, analyzing them to develop a model capturing the underlying process of data generation and utilizing that model to predict the future. Whenever a single model fails to find all characteristics of a Time series and a bunch of models, in their stand-alone mode, cannot find the true process of generating data in, it is better to build hybrid models (Terui and Van Dijk, 2002). A hybrid is either homogeneous or heterogeneous depending on whether only nonlinear models comprise it or a combination of linear and nonlinear models comprise it (Taskaya-Temizel and Casey, 2005).

Several researchers demonstrated that hybrid or ensemble models do yield better results compared to the constituent stand-alone models. Reid (1968) and Bates and Granger (1969) laid the foundation for proposing various hybrid time series models. Bates and Granger (1969) concluded that suitably combining different forecasting models can yield better predictions than the stand-alone models. Similarly, Makridakis et al. (1982) reported that a hybrid or an ensemble of several models is commonly needed to improve forecasting accuracy. Pelikan and De Groot (1992), and Ginzburg and Horn (1993) reported that the combination of several artificial neural networks (ANNs) improved time series forecasting accuracy. An excellent comprehensive review of various hybrid prediction models and annotated bibliography can be found in Clemen (1989). Usually, a good hybrid prediction model can:

1. Improve the forecasting performance.
2. Overcome deficiencies of the constituent stand-alone models.
3. Reduce the model uncertainty (Chatfield, 1996).

Soft Computing (SC) is a collection of various computational techniques from computer science and some engineering disciplines. It is aimed at exploiting the tolerance for imprecision, uncertainty, partial truth, and approximation to achieve tractability, robustness and low solution cost. The idea of hybridizing two or more machine learning techniques emanated from the fact that each one of them in their stand-alone mode has merits and demerits. Once hybridized, their demerits would be nullified, while merits would be amplified (Zadeh, 1994). It is founded on the fact that the human mind can store and process information which is commonly unclear, ambivalent and lacking in categorization. It can model and analyze complex systems arising in bioscience, medicine, the humanities, management sciences, and all fields of science and engineering (Galindo, 2008).

The Table 1 presents the constituents of SC such as Artificial Neural Network (ANN), Evolutionary Computation (EC), Fuzzy Logic (FL), Support Vector Machine (SVM) and Chaos Theory that are used in predicting FOREX rate time series along with their respective merits and demerits. The constituents of SC, in general, include fuzzy computing, neural computing, evolutionary computing, SVM, decision trees, chaos, probabilistic reasoning and rough sets. Some of the hybrid systems (or Hybrids) include neuro-fuzzy, neuro-genetic, neuro-fuzzy-genetic, fuzzy-neural, fuzzy-genetic, etc. to mention a few.

It is interesting to note that even though some past reviews (Bahrammirzaee, 2010; Cavalcante et al., 2016; Huang et al., 2004; Li and Ma, 2010; Mochon et al., 2008; Yu et al., 2007a) covered the use of intelligent techniques to financial time series prediction appeared in the literature, to the best of our knowledge, no study performed a comprehensive review of the use of hybrid intelligent techniques also known as soft computing techniques exclusively to the problem of FOREX rate prediction. Therefore, this paper attempts to fill that gap in the literature by presenting a comprehensive review of various Soft Computing hybrid forecasting models for FOREX rate prediction appeared during 1998–2017. This is necessitated because in other fields such as bankruptcy prediction (Ravi Kumar and Ravi, 2007; Verikas et al., 2010) and software engineering (Mohanty et al., 2010) such reviews caught the attention of the researchers and proved to be useful to them, while FOREX rate prediction area does not have a single such paper.

The objectives of the current review paper are as follows:

Table 2
Acronyms used in the paper.

Acronym	Interpretation	Acronym	Interpretation
AAE	Average Absolute Error	ICA	Independent Component Analysis
ACO	Ant Colony Optimization	k-NN	k-Nearest Neighbor
ANN	Artificial Neural Network	LSSVR	Least-Squares SVR
APE	Absolute Percentage Error	Max AE	Maximum Absolute Error
AR	Annualized Return	MACD	Moving Average Convergence/ Divergence
ARMA	Autoregressive Moving Average	MAFE	Mean Absolute Forecast Error
ARIMA	Autoregressive Integrated Moving Averages	MAPE	Mean Absolute Percentage Error
ARMSE	Absolute Root Mean Square Error	MARS	Multivariate Adaptive Regression Splines
BFO	Bacterial Foraging Optimization	MD/MDD	Maximum Drawdown
BPNN/BPN	Back propagation Neural Network	MF	Membership Function
BVAR	Bayesian Vector Autoregression	MKL	Multiple Kernel Learning
CART	Classification and Regression Tree	ML	Machine Learning
CC	Correlation Coefficient	MLP	Multi-layer Perceptron
CD	Correct Downtrend	MRE	Mean Relative Error
CDC	Conservative Dual- Criteria	MSE	Mean Squared Error
CGP	Cartesian Genetic Programming	MTF	Multivariate Transfer Function
CP	Correct Uptrend/ Correct Prediction	NMSE	Normalized Mean Square Error
CSO	Cat Swarm Optimization	NRMSE	Normalized Root Mean Squared Error
CTR	Correct Trend Rate	PCA	Principal Component Analysis
DBN	Deep Belief Network	PNN	Probabilistic Neural Network
DE	Differential Evolution	PSN	Psi Sigma Neural Network
DENFIS	Dynamic Evolving Neuro-Fuzzy Inference System	RBF	Radial Basis Function
Dstat	Directional change statistic	RE	Relative Error
DWT	Discrete Wavelet Transform	RLSE	Recursive Least Squares Estimator
EC	Evolutionary Computation	RMSE	Root Mean Squared Error
ELM	Extreme Learning Machine	RNN	Recurrent Neural Network
ES	Exponential Smoothing	RPNN	Ridge Polynomial Neural Network
FBLMS	Forward Backward Least Mean Square	RSQ	R-Square
EMD	Empirical Mode Decomposition	SC	Soft Computing
FL	Fuzzy Logic	SMAPE	Symmetric MAPE
GA	Genetic Algorithm	SNR	Signal to Noise Ratio
GARCH	Generalized Auto Regression Conditional Heteroskedasticity	SVM	Support Vector Machine
GLAR	Generalized linear auto-regression	SVR	Support Vector Regression
GMDH	Group Method of Data Handling	TAFE	Total Absolute Forecast Error
GMM	Generalized Method of Moments	TE	Total Error
GP	Genetic Programming	VAR	Vector Autoregression
GRNN	General Regression Neural Network	RW	Random Walk
HMM	Hidden Markov Model	PSO	Particle Swarm Optimization
IC	Independent Component	NSGA-II	Non-dominated Sorting GA-II
QR	Quantile Regression	RF	Random Forest
QRRF	Quantile Regression RF	LASSO	Least Absolute Shrinkage Selection Operator

1. To systematically analyze the current state-of-the-art of soft computing models for FOREX rate prediction.
2. To identify gaps in the current research efforts towards involving hybrid intelligent forecasting models in FOREX rate prediction, which will hopefully stimulate fruitful research in new exciting and hitherto unexplored areas.

The remainder of this paper is organized as follows: various earlier reviews are presented in Section 2. Section 3 presents the overview of the review methodology. The Sections 4–8 present ANN-based hybrids, EC-based hybrids, FL-based hybrids, SVM-based hybrids and Chaos-based hybrids respectively. Each of these sections describes corresponding hybrids. Section 9 discusses overall observations and gaps found in the literature. Finally, Section 10 presents various conclusions and future directions. Table 2 presents various acronyms, Table 3 presents the currency codes and Table 4 presents the performance metrics used in the paper.

2. Earlier reviews

In the past, there have been excellent reviews of financial time series prediction using ANNs alone. Huang et al. (2004) presented a survey of FOREX rate prediction using ANNs and directed the future research towards formulating hybrid ANN models that integrate ANN with complementary technologies so that ANN can enhance their self-adaptation to different situation. Similarly, Yu et al. (2007a) presented a survey including 45 journal articles from 1971 to 2004 in detail involving ANN and suggested the researchers that the hybrid and ensemble ANNs are the potential research topics for FOREX rate prediction. Mochon et al. (2008) discussed the motivation of using various SC techniques in finance and presented a short introduction of several application areas including FOREX rate prediction. Li and Ma (2010) surveyed the application of ANNs in forecasting various financial market prices, including FOREX market. Similarly, Bahrammirzaee (2010) presented a comparative survey of ANNs, expert systems and hybrid intelligent systems in finance including exchange rate prediction. It is noteworthy that the author presented very few hybrid intelligent systems in exchange rate prediction. Recently, Cavalcante et al. (2016) presented an overview of the most important primary studies applying computational intelligence techniques for solving financial market problems.

The current review is different from the extant reviews mentioned above as follows:

1. None of the previous reviews exclusively included hybrid intelligent methods, meaning that they considered a majority of stand-alone systems also.

Table 3
Currency codes used in the paper.

Code	Currency
AUD	Australian Dollar
CAD	Canadian Dollar
CHF	Swiss Franc
CNY	Chinese Yuan
DEM	Deutsche Mark
EUR	Euro
FF	French Franc
GBP	British Pound
HKD	Hongkong Dollar
INR	Indian Rupees
IRR	Iranian Rial
JPY	Japanese Yen
KRW	Korean Won
MOP	Macanese Pataca
MXN	Mexican Peso
MYR	Malaysian Ringgit
NTD	New Taiwan Dollar
PHP	Philippine Peso
RMB	Yuan Renminbi
ROL	Romanian Lei
RUB	Russian Ruble
SGD	Singapore Dollar
USD	United States Dollar

Table 4
Performance measures used.

Performance measure	Description
$SSE = \sum_{t=1}^{N} {e_t}^2$	SSE measures the sum of squared errors. Less value results in more accurate predictions.
$MSE = \frac{SSE}{N}$	MSE measures the mean of squared errors. Less value results in more accurate predictions.
$RMSE = \sqrt{MSE}$	RMSE measures the square root of mean of squared errors. Less value results in more accurate predictions.
$NMSE = \frac{1}{N} \sum_{t=1}^{N} \frac{{e_t}^2}{(y_t - \overline{Y})^2}$	NMSE measures the mean of normalized squared errors. Less value results in more accurate predictions.
$NRMSE = \sqrt{NMSE}$	NRMSE measures the square root of mean of normalized squared errors. Less value results in more accurate predictions.
$MAD = \frac{\sum_{t=1}^{N} \lvert y_t - \overline{Y} \rvert}{N}$	MAD measures the average distance between each data value and mean. Less value results in more accurate predictions.
$MAE = \frac{\sum_{t=1}^{N} \lvert e_t \rvert}{N}$	MAE measures the mean of absolute errors. Less value results in more accurate predictions.
$MAPE = \frac{100}{N} \sum_{t=1}^{N} \lvert \frac{e_t}{y_t} \rvert$	MAPE measures the mean of absolute errors in percentages. Less value results in more accurate predictions.
$U = \frac{\sqrt{\frac{1}{N} SSE}}{\sqrt{\frac{1}{N} \sum_{t=1}^{N} {y_t}^2} + \sqrt{\frac{1}{N} \sum_{t=1}^{N} \hat{y}_t^2}}$	Theil's Inequality coefficient (U) measures the closeness of predictions to actual values. The value of U closer to zero results in more accurate predictions.
$Dstat = \frac{1}{N} \sum_{t=1}^{N} a_t * 100\%$ where $a_t = \begin{cases} 1, & \text{if}(y_{t+1} - y_t) * (\hat{y_{t+1}} - \hat{y}_t) \geq 0 \\ 0, & \text{otherwise} \end{cases}$	Dstat Measures the direction movement of financial variable. Higher value results in more accurate predictions.
$RE = \sum_{t=1}^{N} \lvert \frac{e_t}{y_t} \rvert$	RE measures the ratio between the absolute error and the actual data. Less value results in more accurate predictions.
$MRE = \frac{1}{N} (RE)$	MRE measures the percentage of accuracy of predictions expressing it in a stricter way. Less the value more accurate the predictions. $CTR = \frac{1}{N} \sum_{t=1}^{N} \frac{b_t}{N}$
where $b_t = \begin{cases} 1, & \text{if}(y_{t+1} - y_t) * (\hat{y_{t+1}} - y_t) \geq 0 \\ 0, & \text{otherwise} \end{cases}$	CTR measures the prediction effect of the algorithm. Higher the value more accurate the predictions are.
$TE = \sum_{t=1}^{N} \lvert e_t \rvert$	TE measures the total error. Less the value more accurate the predictions are.
$RSQ = 1 - \frac{\sum_{t=1}^{N} {e_t}^2}{\sum_{t=1}^{N} (y_t - \overline{Y})^2}$	RSQ measures how close the data are to the fitted regression line.
$SNR = 10 * log(\frac{max({y_t}^2) * N}{SSE})$	SNR Measures how much noise is in the data. Less the value more accurate the predictions are.
$CC = \frac{N \sum_{t=1}^{N} y_t \hat{y}_t - \sum_{t=1}^{N} y_t \sum_{t=1}^{N} \hat{y}_t}{\sqrt{N \sum_{t=1}^{N} {y_t}^2 - (\sum_{t=1}^{N} y_t)^2} \sqrt{N \sum_{t=1}^{N} {\hat{y}_t}^2 - (\sum_{t=1}^{N} \hat{y}_t)^2}}$	CC Measures the capability of predicted series whether it follows the upward or downward jumps same as actual series. A CC value near 1 shows that both have same jumps. However, a negative CC sign points out that the predicted series follows the same ups or downs of the actual series with a negative mirroring.

y_t=Actual observation at time t; $\hat{y}_t$=Predicted value at time t; $e_t = y_t - \hat{y}_t$;$\overline{Y}$=Mean of actal observations

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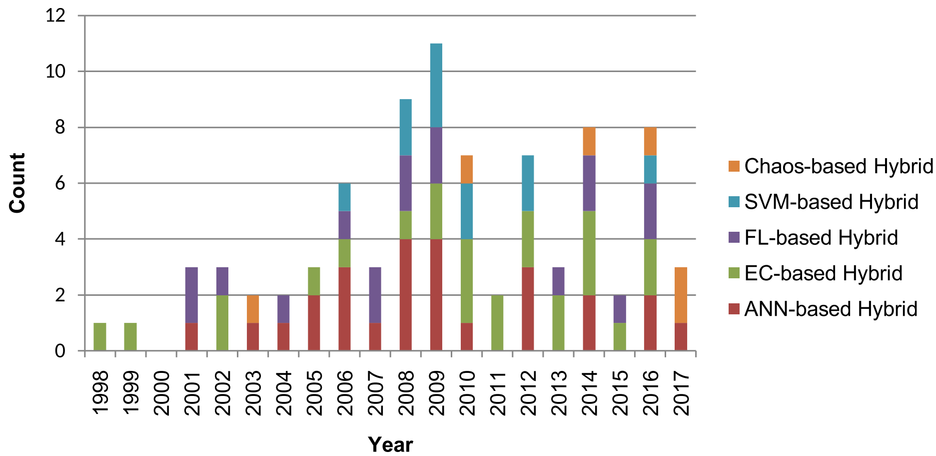

Fig. 1. Year-wise distribution of papers included in the review.

2. The whole gamut of the soft computing hybrids including loosely-coupled (i.e. components integrated in a serial fashion so that the output of one component becomes the input to the next one) and tightly-coupled (i.e. components that are so seamlessly combined that individually they cannot yield any output whatsoever) systems is considered here, which is conspicuously absent in the previous reviews.
3. Then, our review is highly focused on FOREX rate time series prediction only, while others considered other financial time series too.
4. Most importantly, the last review appeared in 2010, which makes our current attempt up-to-date. Further, our survey indicates that a total of 29 papers appeared during and after 2010, contributing to 35% of the total papers reviewed, which is substantial.
5. Finally, the most striking aspect of our review is the suggestion of a host of novel future research directions which would be extremely useful to new researchers and practitioners in this area.

3. Review methodology and taxonomy

Since the past reviews are replete with FOREX rate prediction using ANN and since soft Computing hybrids made foray into all fields including FOREX rate Prediction, in this paper, we present a comprehensive review of all such works appeared between 1998 and 2017. We found 82 peer-reviewed research papers falling in the proposed theme from various sources such as ScienceDirect, IEEE Explore Digital Library, ACM Digital Library, Google Scholar, Springer Link, Taylor & Francis and Wiley Online Library. Thus, non-refereed journals, non-refereed conferences are excluded from the review. The Fig. 1 presents the year-wise distribution of papers collected and reviewed. In general, the FOREX rate prediction models are classified into three categories: statistical models, stand-alone SC constituent techniques (machine learning techniques) based models and various SC-based hybrids.

Statistical methods especially exponential smoothing methods are found to be robust in the study of time series (Gardner, 2006). Statistical forecasting models such as ARIMA are linear models whereas financial time series, in general, and FOREX rate time series, in particular, are nonlinear. So, they can not fit nonlinear data very well. However, there are special cases in which linear models could fit financial time series.

In the context of exchange rate prediction, in 1983, Meese and Rogoff (1983) proposed and applied a Random Walk (RW) model. They concluded that all conventional exchange rate models do not perform well in out-of-sample forecasting than a single RW. In 1996, Hann and Steurer (1996) compared ANN with the linear model in predicting FOREX rates. They reported that ANN does not show much improvement over linear models when experimented on monthly data.

Stand-alone intelligent techniques are also applied to FOREX rate Prediction. In 1993, Refenes et al. (1993) described an application of MLP in forecasting FOREX rates. They came out with an interesting fact that the MLP trained using backpropagation algorithm is the effective ANN for time series prediction. They concluded that MLP could learn the training set near perfectly, and yield accurate predictions. Similarly, in 2007, Santos et al. (2007) compared the models of MLP, RBF neural network (RBFNN) and Takagi–Sugeno (TS) fuzzy system with traditional ARMA and ARMA-GARCH models. They concluded that nonlinear models outperformed linear models.

The afore-mentioned online databases are searched with the keywords “FOREX rate prediction hybrid”, “exchange rate forecasting hybrid”, and “exchange rate prediction” combined with SC constituents for collecting the papers with the concerned theme. The collected papers are classified into (i) hybrids purely dedicated to FOREX rate prediction (ii) hybrids related to financial time series prediction in general with FOREX rate as one of its datasets and (iii) hybrids related to general time series prediction with FOREX rate as one of its datasets. This broader categorization is needed in order to review all the papers in the area.

Based on the key role of a constituent of a SC hybrid model, the literature is divided into five groups as follows. In other words, in each of these groups, the absence of the leading constituent can lead to worse predictions than the reported ones. The taxonomy of the present review includes the following hybrids:

1. ANN-based Hybrid Model
2. EC-based Hybrid Model
3. FL-based Hybrid Model
4. SVM-based Hybrid Model
5. Chaos-based Hybrid Model

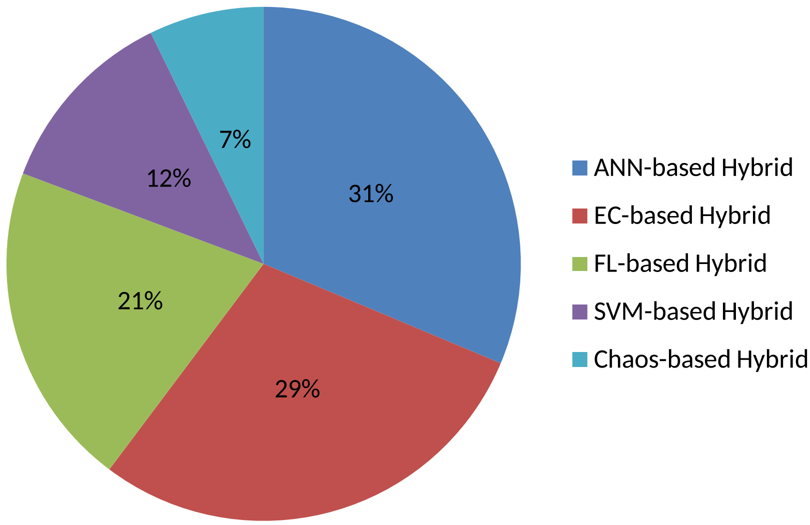

Fig. 2. Distribution of soft computing hybrids included in the review.

Table 5
Distribution of the papers included in the review.

Type of hybrid	Total papers	Number of papers in journals	Number of papers in conferences
ANN-based hybrid	26	11	15
EC-based hybrid	23	11	12
FL-based hybrid	17	8	9
SVM-based hybrid	10	2	8
Chaos-based hybrid	6	2	4

The Fig. 2 presents the distribution of research papers covering these soft computing hybrids for FOREX rate prediction. The Table 5 presents the information about the number of papers appeared in both journals and proceedings of various conferences. Further, Table 6 presents peer-reviewed conference-wise distribution of papers and Table 7 presents peer-reviewed journal-wise distribution of papers that are included in the present review.

4. Artificial Neural Network (ANN)-based hybrid models

ANN is a massively parallel distributed system having many simple processing elements (neurons or computing elements or nodes). Its function depends on its architecture, connection weights, and the processing performed at its nodes. It resembles human brain through the knowledge acquired by a learning methodology and synaptic weights used to store the knowledge (Haykin, 1994). Researchers choose ANN as FOREX rate prediction tool because of several distinguishing features of ANN that made it valuable and attractive in forecasting (Refenes et al., 1997). These include:

1. ANN is a class of nonlinear models with good generalization capability (Zhang et al., 1998).
2. ANN is a universal function approximator that can approximate any continuous measurable function to an arbitrary degree of accuracy (Hornik et al., 1989; White, 1990).
3. ANN is the data-driven, self-adaptive method with few restrictive assumptions. It implies that it also remains as accurate and robust in the non-stationary environment as it is in the stationary one. In various situations of financial forecasting, where the data is plentiful, but the primary data generating method is frequently unknown, this distinctive feature is extremely advantageous (Qi and Zhang, 2001; Yu et al., 2007b).
4. ANNs use fewer parameters compared to traditional polynomial, spline, and trigonometric expansions which use exponentially many parameters to achieve the same approximation rate (Panda and Narasimhan, 2007). However, ANN is treated as black box because it can not disclose the interaction with the environment to reach an outcome.

In this section, ANN refers to Multi-layer Perceptron (MLP) also known as back propagation trained NN (BPNN) unless otherwise stated. Other types of ANN apart from MLP were also employed in various hybrids.

4.1. Description

Various ANN-based hybrids were reported in literature addressing the problem of FOREX rate prediction (see Table 8). The brief description of each of these hybrids is as follows.

Zhang and Berardi (2001) created the ANN ensembles by just varying the initial random weights that are not as efficient as the conventional Keep-The-Best (KTB) model. Ensemble models of different ANNs performed well in a variety of situations. Empirical findings from this study indicated that partition ensembles significantly outperformed the basic ensemble using the same training sample. The authors concluded that the serial ensemble model was a more promising approach in time series forecasting applications including FOREX rate.

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Table 6
Names of the conferences included in the review.

Name of conference	Number of papers reviewed
International Conference on Computational Science (ICCS)	4
International Joint conference on Neural Networks (IJCNN)	4
International Conference on Natural Computation (ICNC)	2
International Conference on Swarm Intelligence (ICSI)	2
The IEEE International Conference on Fuzzy Systems (FuzzIEEE)	2
International Symposium on Neural Networks (ISNN)	2
IEEE Info-tech and Info-net (ICII)	1
World Automation Congress (WAC)	1
IEEE Symposium on Computational Intelligence and Data Mining (CIDM)	1
International Wireless Communications, Networking and Mobile Computing (WiCOM)	1
Hybrid Artificial Intelligence Systems (HAIS)	1
IEEE International conference on Intelligent systems design and applications (ISDA)	1
IEEE International Conference on Communication Systems (ICCS)	1
IEEE International Conference on Developments in eSystems Engineering (DeSE)	1
International Workshop on the Agent-Based Approaches in Economic and Social Complex Systems (AESCS)	1
International Joint Conference on Computational Sciences and Optimization (CSO)	1
The International Conference on Neural Processing (ICONIP)	1
International Conference on Computational Intelligence, Modelling and Simulation (CSSim)	1
International Conference on Innovative Computing, Information and Control (ICICIC)	1
International conference on Rough Sets, Fuzzy Sets, Data Mining and Granual Computing (RSFDGrC)	1
IEEE International Conference on Advanced Computer Control (FICACC)	1
Global Congress on Intelligent Systems (GCIS)	1
International Conference on Electronics and Information Engineering (ICEIE)	1
International Conference on Business Intelligence and Financial Engineering (BIFE)	1
The International Conference on Engineering Applications of Neural Networks (EANN)	1
IEEE-International Conference on Advances in Engineering, Science and Management (ICAESM)	1
IEEE Iranian Conference on Electrical Engineering (ICEE)	1
IEEE Conference on Nobert Wiener in the 21st Century (21CW)	1
International Conference on Future Information Engineering (FIE)	1
Recent Advances in Information Technology (RAIT)	1
International Conference on Frontiers in Intelligent Computing: Theory and Applications (FICTA)	1
IEEE International Conference on Control, Instrumentation, and Automation (ICCIA)	1
IEEE Power, Communication and Information Technology Conference (PCITC)	1
International Conference on Communication and Electronics Systems (ICCES)	1
International Conference on Computational Intelligence and Cybernetics	1

Table 7
Names of journals included in the review.

Name of journal	Number of papers reviewed
Neurocomputing	4
Expert Systems with Applications	4
Computational Economics	3
Decision Support Systems	2
Fuzzy Sets and Systems	2
Journal of Operational Research Society	2
Computers and Operations Research	2
Journal of Forecasting	1
Swarm and Evolutionary Computation	1
Empirical Economics	1
European Journal of Operational Research	1
Applied Soft Computing	1
Neural Computing and Applications	1
Decision technologies for computational finance	1
Economic Modelling	1
International Review of Financial Analysis	1
Journal of Statistics and Management Systems	1
Journal of King Saud University-Computer and Information Sciences	1
International Journal of Innovative Computing, Information and Control	1
Academy of Accounting and Financial Studies Journal	1
Intelligent Decision Technologies	1
International Journal of Computer Information Systems and Industrial Management Applications	1

Zhang (2003) proposed a combined approach to forecasting the time series using the both ARIMA and ANN. The authors concluded that although the combination of several ANNs could improve the forecasting accuracy, combining distinct models should be carried out. Furthermore, they also inferred that the overfitting problem could be best solved using ANNs by fitting the ARIMA model first to the data.

Chen and Leung (2004) introduced two-stage Error-Correction Neural Network (ECNN) hybrids to correct errors in FOREX forecasting and trading. In Stage-1, the estimates of FOREX rates were generated using a time series model and, in Stage-2, General Regression Neural Network (GRNN) corrects the errors of the estimates. The authors revealed that the proposed approach not only predicted FOREX rate better but also resulted in superior investment returns when compared with single-stage models.

Table 8
ANN-based hybrid FOREX rate prediction models(chronological order).

Year	Author(s)	Hybrid model(s)	Models compared with	Winner	FOREX data used	Performance metrics used
2001	Zhang and Berardi (2001)	Neural Network ensemble	KTB	Neural Network ensemble	Weekly data of GBP/USD from DataStream International	MSE, MAE
2003	Zhang (2003)	ARIMA+ANN	ARIMA, ANN	ARIMA+ANN	Weekly data of GBP/USD	MSE, MAD
2004	Chen and Leung (2004)	ECNN+MTF, ECNN+BVAR, ECNN+GMM	MTF, BVAR, GMM, GRNN	ECNN+GMM	Daily data of CAD/USD, JPY/USD, GBP/USD from International Monetary Fund(IMF)	RMSE, Theil's U, RSQ
2005	Yu et al. (2005a)	Ensemble of GLAR and ANN	GLAR, ANN	Ensemble of GLAR and ANN	Daily data of DEM/USD, JPY/USD, USD/GBP from http://fx.sauder.ubc.ca/	NMSE, Dstat
2005	Yu et al. (2005b)	ASNN	MLFN	ASNN	Daily data of DEM/USD, JPY/USD, USD/GBP from http://fx.sauder.ubc.ca/	NMSE, Dstat
2006	Ince and Trafalis (2006)	Two-stage model including ARIMA, VAR, SVR, MLP	MLP, SVR	Two-stage model including ARIMA, VAR, SVR, MLP	Daily data of EUR/USD, GBP/USD, JPY/USD, AUD/USD	MSE, MAE
2006	Lai et al. (2006a)	ES+BPNN	ES, BPNN	ES+BPNN	Daily data of EUR/USD, JPY/USD from http://fx.sauder.ubc.ca/	RMSE, Dstat
2006	Lai et al. (2006b)	Triple-phase nonlinear ensemble predictor	ANN, Regression	Triple-phase nonlinear ensemble predictor	Daily data of GBP/USD from Datastream (http://www.datastream.com)	RMSE
2007	He and Shen (2007)	Bootstrap method of ANNs	Single ANN	Bootstrap method of ANNs	Daily data of AUD/USD, GBP/USD, CAD/USD, EUR/USD, JPY/USD, CHF/USD	NMSE
2008	Ghazali et al. (2008)	DRPNN	MLP, RPNN	DRPNN	Daily data of GBP/EUR, JPY/GBP from DataStream	AR, MD, NMSE
2008	Jia et al. (2008)	MEPIP+FNT	GGGP+HOFNT, GEP+HOFNT	MEPIP+FNT	Daily data of EUR/USD, GBP/USD, JPY/USD from Pacific Exchange Rate Service	NMSE
2008	Li et al. (2008)	SVR Network	SVR	SVR Network	Daily data of JPY/USD	SSE, MAE, CP, CD
2008	Yu et al. (2008)	RBF-based ensemble	RBF, regression	RBF-based ensemble	Daily data of GBP/USD, EUR/USD, DEM/USD, JPY/USD from Pacific Exchange Rates Services	NMSE, Dstat
2009	Chaudhuri and De (2009)	Neuro-Fuzzy Regression Model	ANN, Fuzzy ARIMA	Neuro-Fuzzy Regression Model	Daily data of INR/USD	MAE, MSE
2009	Mahdi et al. (2009a)	SOMLP	MLP, FLNN	SOMLP	Daily data of USD/GBP, JPY/USD, USD/EUR	NMSE, SNR, CDC, AR
2009	Mahdi et al. (2009b)	SMIA	MLP, FLNN	SMIA	Daily data of USD/GBP, JPY/USD, USD/EUR	AR, MDD, SNR, MSE
2009	Majhi et al. (2009)	FLANN, CFLANN	LMS	FLANN	Monthly data of GBP/USD,INR/USD, JPY/USD from www.forecasts.org	APE
2010	Hua et al. (2010)	FLANN+KR	AES, FLANN	FLANN+KR	Monthly data of JPY/USD, GBP/USD, INR/USD from www.forecasts.org	MAPE
2012	Khashei and Bijari (2012)	ARIMA+PNN ANN+PNN	ARIMA, ANN, ARIMA+ANN	ARIMA+PNN ANN+PNN	Daily data of GBP/USD	MSE, MAE
2012	Sermpinis et al. (2012a)	Ensembles of MLP, RNN, PSN, ARMA	Naïve, ARMA ,MLP, RNN, PSN	Mixed results	Daily data of EUR/USD	MAE, MAPE, RMSE, U,
2012	Mohapatra et al. (2012)	MLANN+WN	MLANN	MLANN+WN	Monthly data of INR/USD, JPY/USD	MAPE
2014	Adhikari and Agrawal (2014)	RW+FANN+EANN	RW, FANN, EANN	RW+FANN+EANN	Daily data of INR/USD from Pacific FX database, USD/GBP from Federal Reserve Bank	MAE, MSE, SMAPE
2014	Zhang et al. (2014)	CDBN+FG	CDBN, BP+FG	CDBN+FG	Daily data of EUR/USD, GBP/USD	Profit
2016	Wang et al. (2016)	ANN-ARIMA	Fuzzy, ANN, ANN-ARMA	ANN-ARIMA	Daily data of EUR/USD	MAE, MSE, RMSE
2016	Rout and Dash (2016)	FLRBFNN	linear, nonlinear, hybrids	FLRBFNN	Daily data of EUR/USD INR/USD, CAD/USDAUD/USD	MAE, MAPE, RMSE
2017	Yang and Lin (2017)	EMD+PSR+ELM	ARIMA,BPNN,ELMPSR+ELM,EMD+ELM	EMD+PSR+ELM	Daily data of USD/TWD, EUR/TWD GBP/TWD AUD/TWD	MAE, MAPE, RMSE

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Yu et al. (2005a) presented a hybrid, GLAR+ANN, to forecast FOREX rates. The proposed hybrid model consists of four steps: (i) construct Generalized Linear Auto-regression (GLAR) model, (ii) compute the nonlinear components from the GLAR model, (iii) develop ANN to model the nonlinear components and (iv) combine obtained forecast results. The authors concluded that the nonlinear ensemble model was an efficient tool to forecast FOREX rate to obtain greater forecasting accuracy.

Yu et al. (2005b) implemented Adaptive Smoothing Neural Network (ASNN) for FOREX rate prediction. Compared with MLP, the ASNN model converged faster as it used adaptive smoothing techniques to fine tune the learning parameters. It also generalized well. The authors concluded that the ASNN was an effective alternative approach to forecast FOREX rate.

Ince and Trafalis (2006) presented a two-stage forecasting model for FOREX rate prediction. In the first stage, both ARIMA and co-integration analysis were used to select the number of inputs. Later, ANN and Support Vector Regression (SVR) were applied in tandem. Comparison of these models highlighted the importance of selecting right inputs to forecasting models. Further, they also revealed that the SVR could outperform the ANN for two input selection methods.

Lai et al. (2006a) implemented a hybrid consisting of Exponential Smoothing (ES) and BPNN to predict financial time series. The forecasts from both models were synergized to yield better forecast, and it turned out that the hybrid outperformed the stand-alone BPNN and ES.

Lai et al. (2006b) proposed triple-phase nonlinear ensemble predictor to forecast financial time series. This ensemble is formed by selecting the appropriate predictors (using PCA) out of the arbitrary number of neural predictors generated. The SVR method was used as an arbitrator to form the ensemble. The authors stated that the ensemble could be a practical approach to financial time series prediction.

He and Shen (2007) predicted FOREX rate using various bootstrap based multiple ANN models. A bootstrap mechanism was used to train multiple ANNs. After training, the test data was presented to them. Finally, an aggregator function was employed to ensemble the results from these ANNs. The authors concluded that proposed bootstrap could significantly reduce the errors on the test data.

Ghazali et al. (2008) extended Ridge Polynomial Neural Network (RPNN) and named it as Dynamic RPNN (DRPNN). It had faster learning capability, incremented the profit, yielded smaller prediction error and reduced network complexity. The authors justified that DRPNN was the best alternative for financial time series prediction.

Jia et al. (2008) predicted FOREX rates using Multi Expression Programming and Immune Programming based Flexible Neural Tree (MEPIP+FNT) which was a flexible MLFANN. This work demonstrated that Multi Expression Programming (MEP) best helps in evolving the architecture and parameters of ANN simultaneously.

Li et al. (2008) introduced SVR network with two layers including transformation layer and prediction layer, to deal with the high noise, non-stationary FOREX rate prediction problem. The SVRs in the transformation layer form a modular network. In the prediction layer, the transformed outputs from the preceding layer were used as the inputs to the SVR. The authors directed the readers to focus on proper partition mechanism.

Yu et al. (2008) predicted FOREX rate using a multi-stage nonlinear RBF neural network ensemble. In the proposed ensemble, in stage-1, many single RBFNNs were produced. In stage-2, some of these networks were selected to form an ensemble with the help of Conditional Generalized Variance (CGV) minimization method. Finally, prediction task was accomplished using another RBF network. The authors claimed that this ensemble yielded improved predictions. The business practitioners can also formulate effective investment strategies and portfolios for FOREX markets using the proposed approach.

Chaudhuri and De (2009) proposed Neuro-fuzzy regression model that combined the advantages of both ANN and Fuzzy regression. The proposed model yielded accurate predictions with fewer observations and incomplete datasets. The proposed Neuro-fuzzy regression model turned out to be more accurate for both point and interval forecasts.

Mahdi et al. (2009a) proposed Self-organized MLP (SOMLP), an adaptive neural network inspired by the immune system. The authors conducted two sets of experiments. In the first set, the data was normalized and fed as input to ANNs as non-stationary data. In the second set, the ANNs accept stationary data transformed from the non-stationary data. The predictions obtained from SOMLP demonstrated that all ANNs with stationary data as input generated profit and all ANNs with non-stationary data as input failed to generate any profit.

Majhi et al. (2009) presented two novel ANN models namely Functional Link ANN (FLANN) and Cascaded FLANN (CFLANN). These ANNs have one/two-neuron architectures and accept nonlinear inputs. The FLANN is a nonlinear adaptive model, and it can approximate a known financial time series through supervised training. The algorithm used in this method is an optimum method for computing the gradients of the error performance obtained from the single layer. The algorithm is robust with respect to noisy data. In CFLANN, two single layer FLANN structures were cascaded in series. The authors concluded that proposed ANN models could perform better.

Mahdi et al. (2009b) presented a novel application of the SOMLP inspired by Immune Algorithm, namely SMIA, to predict financial time series. A new training algorithm inspired by immune system with weight decay was used. The authors concluded that SMIA with weight decay training could not outperform the FLANN model on all the financial datasets tested. However, it yielded highest returns from daily exchange rates.

Hua et al. (2010) presented a fusion model of FLANN based on Kernel Regression (KR) to model and predict exchange rates. The KR was used to smooth the noise. Later, the sine and cosine expansions expand the smoothed datasets. The nonlinearly expanded smoothed datasets were then input to the FLANN model. The authors concluded that FLANN+KR outperformed AES and stand-alone FLANN.

Khashei and Bijari (2012) proposed ARIMA+PNN and ANN+PNN hybrids. The PNNs in the proposed models helped to modify the estimated values of the actual time series. The authors concluded that the proposed methods were the effective ways that can help construct accurate hybrid models than basic time series models.

Sermpinis et al. (2012a) investigated the trading and statistical performance using forecast combinations of ANN and PSN. They explored the application of Kalman filters in combining the obtained ANN forecasts. A time-varying leverage strategy was applied to yield better predictions using the proposed models and combinations. The authors concluded that the PSN outperformed all models by producing better statistical accuracy as well as outstanding trading performance.

Mohapatra et al. (2012) proposed a hybrid neural network comprising Multilayer ANN and rank based Wilcoxon Norm (WN). Their work demonstrated that the proposed MLANN+WN was robust in the presence of outliers and yielded better predictions.

Adhikari and Agrawal (2014) proposed a novel hybrid combining the Random Walk (RW), Feed forward ANN (FANN) and Elman ANN (EANN) models to forecast in-sample financial data, including exchange rates. The methodology proceeds as follows: first, linear component was modeled using RW. Then, the residual set was computed. Then, FANN and EANN structures were fit to the residual set. Later, the desired number of future observations through RW model and the remaining residuals through FANN/EANN models were forecasted separately. Later, the approximation of the nonlinear part was computed. Finally, the desired combined forecast vector was computed. The authors concluded that the proposed approach improved the overall forecasting accuracy after RW was applied for the linear part and neural networks for nonlinear residuals.

Zhang et al. (2014) proposed a hybrid model combining Fuzzy Granulation (FG) with Continuous-valued Deep Belief Networks (CDBN) for predicting the fluctuation range of FOREX rate. The authors concluded that the proposed model was more profitable compared to the classical approach and a newly proposed efficient neural network.

Wang et al. (2016) investigated a prediction model combining an ARIMA and a three-layer ANN (ANN-ARIMA). In their work, nine descriptors were also used to train ANN. The authors concluded that ANN-ARIMA could outperform the global modeling techniques in terms of profit returns.

Rout and Dash (2016) proposed a novel compact Functional-link RBFNN (FLRBFNN) to improve prediction performance. The proposed model also included prominent trading indicators, the moving average convergence/ divergence, and relative strength index. The authors concluded that the FLRBFNN architecture outperformed all other models using statistical accuracy and trading efficiency measurements.

Yang and Lin (2017) proposed an approach combining empirical mode decomposition (EMD) and phase space reconstruction (PSR) with extreme learning machine (ELM). In this approach, first, the input series was decomposed into one residual component and several components of intrinsic mode function (IMF) using EMD. Later, phase space was reconstructed from residual time series. After reconstruction, the dataset was partitioned into training and test sets. Finally, ELM was used to predict residual component, and the regression model was used for each IMF. Both predictions were combined to obtain final predicted value. The authors concluded that the proposed approach could yield better predictions.

4.2. Remarks

After reviewing 26 various ANN-based hybrids, it is observed that:

1. MLP was the most often used architecture probably because of its universal approximator property.
2. Seldom, they were hybridized with ARIMA models.
3. GMDH, world's first deep learning architecture, was conspicuously absent while GRNN was rarely exploited.
4. Various ANNs such as Single Multiplicative Neural Network, Pi-sigma Neural Network, Quantile Regression Neural Network, and Spiking Neural Network were not applied at all.
5. Deep learning architectures were also least exploited.

5. Evolutionary Computation (EC)-based hybrid models

Evolutionary Computation (EC) is the field comprising various techniques that import biological evolutionary principles into algorithms (implemented on computers) which are used for searching optimal solutions to a problem. It is founded on the Darwinian principle of the "survival of the fittest" (Bäck and Schwefel, 1993). An evolutionary algorithm (e.g., GA (Holland, 1975) or PSO (Kennedy and Eberhart, 1995)) searches or operates on a given population of potential solutions to find the optimum solution that approaches some specification or criteria and evolves toward better results. Evolutionary algorithms have capabilities of efficient search space exploration with population models corresponding to the problem. They can capture the non linear dependencies among the system variables (Sharma and Srinivasan, 2007). They are extremely powerful and versatile too in that they can be employed to solve feature selection, classification, regression, clustering, association rule mining and outlier detection problems in data mining (Krishna and Ravi, 2016). These are easily adaptable by modifying user-defined parameters, easy to implement and work well with incomplete, noisy data and non-convex, non-unimodal decision spaces. Therefore, researchers employed various evolutionary algorithms in predicting exchange rates.

5.1. Description

Various EC-based hybrids were proposed for FOREX rate prediction problem (see Table 9). A brief description of each of these hybrids is as follows.

Adamopoulos et al. (1997) proposed two different approaches to forecast financial time series. The first one involved the RBF training using a Kalman filter, whereas the second approach used GA to optimize the parameters of the RBF network. The authors reported that the proposed RBF Network with GA could yield better predictions.

Shazly and Shazly (1999) proposed a hybrid system, ANN+GA, for forecasting the spot FOREX rate. The authors claimed that an ANN could easily predict the direction of change and turning points if it was trained genetically. The results reported that the forecasts obtained by proposed hybrid were better than the forecasts using the forward and future rates.

Andreou et al. (2002) presented a new hybrid algorithm namely GA+MLP+EKF, for exchange rates forecasting, wherein GA was employed to determine the optimal structure of MLP and a localized version of the Extended Kalman Filter (EKF) for training. It achieved a remarkable prediction success in both, one-step-ahead and multi-step-ahead predictions. A demerit of the algorithm is a small sensitivity in periods characterized by highly frequent and abrupt fluctuations.

Nag and Mitra (2002) forecasted exchange rates using the genetically optimized neural network (GANN). The GA using robust cost functions was used to obtain optimal parameters for this architecture. It helped the GANN to yield better predictions than conditional heteroskedastic models and fixed-geometry neural network (FGNN) models. However, the authors reported that Max Absolute Error (AE) values were more for GANN and these could be further minimized.

Álvarez-Díaz and Álvarez (2005) employed GP and ANN separately to forecast FOREX rates, and the results were then genetically fused. The authors concluded that fusing GP and ANN did not result in great improvement in results.

Chen et al. (2006) presented a Flexible Neural Tree (FNT) model to forecast FOREX rates. The FNT was created and evolved by utilizing the predefined instruction sets, and Extended Compact Genetic Programming (ECGP) was used to develop its structure. The PSO was used for optimizing the free parameters of the FNT. The authors concluded that the FNT provided a good solution for FOREX rate forecasting.

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Table 9
EC-based hybrid FOREX rate prediction models (chronological order).

Year	Author(s)	Hybrid model(s)	Models compared with	Winner	FOREX data used	Performance metrics used
1997	Adamopoulos et al. (1997)	RBF Network+GA	RBF Network+ Kalman	RBFNetwork+GA	Daily data of USD/GRD, GBP/GRD, DEM/GRD, FF/GRD	Actual vs Predicted
1999	Shazley andShazley Shazly and Shazly (1999)	GA+ANN	–	GA+ANN	Quarterly data of GBP/USD, DEM/USD, JPY/USD, CHF/USD obtained from the Wall Street Journal and OECD Financial Statistics	MAFE, TAFE
2002	Andreou et al. (2002)	GA+MLP+EKF	MLP, stationary models and Naïve estimators,	GA+MLP+EKF	Daily data of USD/GRD, DEM/GRD, FF/GRD, GBP/GRD	NRMSE, CC, MRE
2002	Nag and Mitra (2002)	GANN	FGNN	GANN	Daily data of DEM/USD, JPY/USD, USD/GBP from the Reuters data stream	AAE, MAPE, MSE, Max AE, RSQ
2005	Alvarez-Diaz and Alvarez Álvarez-Díaz and Álvarez (2005)	GP+ANN	GP, ANN	GP+ANN	Weekly data of JPY/USD, GBP/USD from the Pacific Exchange Rate Service	NMSE
2006	Chen et al. (2006)	FNT	MLFN, ASNN	FNT	Daily data of EUR/USD, GBP/USD, JPY/USD from Pacific Exchange Rate Service	NMSE, Dstat
2008	Abbod and Deshpande Abbod and Deshpande (2008)	GA+PSO+GMDH	LR, GMDH, PSO+GMDH, GA+GMDH	GA+PSO+GMDH	Daily data of EUR/USD from the www.oanda.com	MAPE, RMSE
2009	Sheikhan and Movaghar (2009)	GA+ANN	ARIMA, ANN, ARIMA+ANN, ARIMA+FL+ANN	GA+ANN	Daily data of EUR/USD, EUR/GBP	MSE, NMSE
2009	Chang et al. (2009)	PSOBPN	PSO, BPN	PSOBPN	Daily data of NTD/USD	RMSE, MSE, MAE
2010	Chang and Lee (2010)	PSOBPN, GABPN	PSO, GA, BPN	PSOBPN	Monthly data of NTD/USD	RMSE, MSE, MAE
2010	Nayakovit et al. (2010)	ANN+MGA	RLS+TS, RW, LR, ARIMA, ANN	ANN+MGA	Daily data of USD/GBP and weekly data of USD/GBP	RMSE, MAPE
2011	Chang (2011)	GA+GA,GA+PSO GA+BPN	Regression Model	GA+GA	Monthly data of NTD/USD	MSE, MAE, RMSE
2011	Chang and Hsieh Chang and Hsieh (2011)	PSOBPN	PSO, BPN	PSOBPN	Daily data of NTD/USD	RMSE, MSE, MAE
2011	Li et al. (2011)	PSO+RLSE+PSO	PSO, PSO+RLSE	PSO+RLSE+PSO	Daily data of USD/CNY	RMSE
2012	Ravi et al. (2012)	Ensembles of BPNN, WNN, MARS, SVR, DENFIS, GMDH and GP	BPNN, WNN, MARS, SVR, DENFIS, GMDH, GP	Ensembles of GP and GMDH	Daily data of JPY/USD, DEM/USD, GBP/USD from http://fx.sauder.ubc.ca/	NRMSE, Dstat
2012	Sermpinis et al. (2012b)	ARBF+PSO	Naïve, ARMA, MACD, MLP, RNN, PSI	ARBF+PSO	Daily data of EUR/GBP from European Central Bank	MAE, MAPE, RMSE, Theil-U
2013	Li and Suohai (2013)	AFSASVR	SVR, GASVR, PSOSVR	AFSASVR	Daily data of USD/RMB, EUR/RMB, JPY/RMB, HKD/RMB, GBP/RMB, MYR/RMB, RUB/RMB,	TE, RE, ARMSE, CTR
2013	Sermpinis et al. (2013)	ARBF+PSO	k-NN, ARMA, MCAD	ARBF+PSO	ARBF+PSO Daily data of EUR/USD, EUR/GBP and EUR/JPY from European Central Bank	MAE, MAPE, RMSE, Theil-U, PT-statistic
2014	Rehman et al. (2014)	Application of RCGPANN	HMM, Naïve Bayes, ARMA, MLP, HFERFM, AFERFM	RCGPANN	Daily data of JPY/USD, NZD/USD, CAD/USD, KRW/USD, IDR/USD	MAPE
2014	Pulido et al. (2014)	T-1 Fuzzy+PSO T-2 Fuzzy+PSO	T-1 Fuzzy T-2 Fuzzy	T-1 Fuzzy+PSO T-2 Fuzzy+PSO	Daily data of USD/MXN	Prediction Error
2014	Rout et al. (2014)	ARMA+DE, ARMA+PSO, ARMA+BFO, ARMA+CSO, ARMA+FBLMS	Among themselves	ARMA+DE	Daily data of INR/USD, JPY/USD,GBP/USD from www.forecasts.org	MAPE, RMSE
2015	Deng et al. (2015)	MKL+GA	14 methods	MKL+GA	Minute-by-minute data of target pair USD/JPY using USD/CHF, GBP/USD, EUR/USD	RMSE
2016	Jiang and Wu Jiang and Wu (2016)	Variants of GA-SVR	Among themselves	Mixed results	daily USD/CNY, EUR/CNY, JPY/CNY	MSE
2016	Sidehabi et al. (2016)	GA-NN	ASTAR,SVM	Mixed results	EUR/USD	RMSE

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Abbod and Deshpande (2008) proposed a hybrid GMDH using GA and PSO namely GA+PSO+GMDH. GMDH provided better speed and accuracy after both algorithms were combined. In the proposed model, the GMDH could best map the input to output after many iterations, and the optimization algorithm was applied to the data. The authors concluded that a low accuracy GA could find the rough global minima and PSO could find a more accurate minima.

Chang et al. (2009) adopted the PSO for selecting the optimal number of input neurons of BPN. In the proposed methodology, the whole dataset was divided into six periods of sliding windows. Later, superior variables were selected using PSO. Finally, exchange rates were forecast using BPN with the selected variables. The authors concluded that PSOBPN could achieve the optimal variable selection and better forecast ability. It could also closely match the trend of fluctuation. However, this study employs PSO-based linear model. They suggested the use of non-linear PSO model and further adoption of other evolutionary methods for comparative study.

Sheikhan and Movaghar (2009) proposed a rich evolutionary connectionist model, GA+ANN, for FOREX rate prediction, where GA performs both structure and parameter optimization and determines the optimum learning rate and momentum rate. The authors reported that the proposed hybrid outperformed other time series forecasting models.

Chang and Lee (2010) proposed GA-based BPN and PSO-based BPN for forecasting FOREX rate. In this work, the whole data divided into six periods of sliding windows. Later, GA/PSO helped in selecting the superior variables. Finally, the FOREX rate was forecast by BPN with the selected variables. The authors concluded that the proposed hybrid models could not perform well. They suggested the use of nonlinear PSO model and ACO.

Nayakovit et al. (2010) proposed ANN+MGA for predicting FOREX rate. The Meiosis Genetic Algorithm (MGA) involves meiosis cell division, selected strain, the selected chromosome simulation, mutations, crossover, and selection of progeny to parents instead of models. The proposed hybrid outperformed Regularized Least-Squares Time Series (RLS-TS), RW, ARIMA, and ANN.

Chang (2011) proposed various hybrid FOREX rate forecasting models with GA such as GA+GA, GA+PSO, and GA+MLP. The author employed GA for selecting the optimal variable weights for macroeconomic factors and concluded that GA+GA model was best among proposed models albeit consuming more time for convergence. The authors recommended further adoption of nonlinear model in GA and application of the proposed models to other currencies for long-term prediction.

Chang and Hsieh (2011) constructed a new forecasting model namely PSOBPN for forecasting FOREX rates. In this hybrid, PSO was employed for selecting the optimal number of input neurons, and then BPN was used to predict FOREX rates. The authors concluded that PSOBPN yielded better predictions and suggested the use of nonlinear PSO model for future research.

Li et al. (2011) proposed a neuro-fuzzy self-organizing system (NFS) to solve the financial forecasting problem. A novel hybrid learning algorithm using PSO and RLSE namely PSO+RLSE+PSO was proposed for the purpose of learning. It was a two-stage method in which, PSO and RLSE methods collaborate in a hybrid way for fast learning of NFS in stage-1, and PSO method was employed in stage-2 to update the consequent parameters whereas earlier parameters were kept fixed using the results in stage-1. The authors concluded that proposed approach performed extremely well.

Ravi et al. (2012) presented six nonlinear ensemble architectures involving BPNN, WNN, MARS, SVR, DENFIS, GMDH, and GP. Their results indicated that both GMDH and GP based ensembles could perform well. However, they did not consider the optimal lagged variables in the prediction model scientifically. Instead, they tried different lag values as a sensitivity analysis.

Sermpinis et al. (2012b) introduced a hybrid neural network architecture namely Adaptive RBF(ARBF)+PSO and a fitness function for forecasting FOREX returns. In ARBF+PSO, PSO was used to obtain the optimal parameters for training the RBFNN. It was also used to locate the minimum number of hidden nodes of hybrid. The authors defined multi-objective fitness function to evaluate the particles of PSO such that it can select more profitable predictors for ARBF+PSO.

Li and Suohai (2013) proposed Artificial Fish Swarm Algorithm based SVR (AFSASVR) for FOREX rate prediction. SVR with Gaussian kernel function was used to develop the prediction model. AFSA was used to optimize the model parameters including penalty factor and kernel function variance. It was concluded that AFSASVR could efficiently be used in FOREX rate prediction.

Sermpinis et al. (2013) introduced a hybrid ARBF+PSO, a time-varying trading strategy using Glosten, Jagannathan, and Runkle (GJR) forecast and an ANN fitness function to forecast financial time series. The authors argued that the proposed hybrid, same as in Sermpinis et al. (2012b), can be trained with optimal parameters to augment both statistical accuracy and trading efficiency. The work was similar to Sermpinis et al. (2012b) and was extended by working on more datasets and comparing with more benchmark models.

Rehman et al. (2014) proposed a novel approach to FOREX rate prediction based on Recurrent Cartesian Genetic Programming evolved ANN (RCGPANN). The CGP was the algorithm deployed for the forecasting. The RCGPANN outperformed other forecasting models because of the following reasons: (1) the RCGPANN could select the finest possible features and good network architecture, (2) it could decide whether recurrent connection or a feed-forward connection were needed. They concluded that an ANN with feature selection was a viable approach to predict FOREX rates.

Pulido et al. (2014) proposed the design of PSO of an ANN ensemble with type-1 and type-2 fuzzy integration of responses namely T-1 Fuzzy+PSO and T-2 Fuzzy+PSO. In this ensemble, PSO optimizes the structure of ANN. The authors concluded that hybrid outperformed other fuzzy integrations without PSO.

Rout et al. (2014) proposed hybrid prediction model namely DE+ARMA, where Differential Evolution (DE) optimizes the parameters of ARMA. It was concluded that the proposed hybrid outperformed other hybrids. However, the authors also recommended further in-depth investigation in terms of selection of features, adoption of abrupt fluctuations to model and learning algorithm.

Deng et al. (2015) developed a hybrid model combining Multiple Kernel Regression (MKR) with GA. First, MKR was applied to FOREX rate for a particular training period for obtaining the optimal parameters and weights. Then, GA was used for optimizing the trading strategy as per predicted FOREX rate changes. The authors concluded that average profit obtained was positive with statistically high confidence.

Jiang and Wu (2016) predicted CNY exchange rates using hybrids of GA and SVR with a range of kernel functions. The intuitive and statistical performances of the hybrid model with linear, radial basis, polynomial and sigmoid functions were presented. The authors concluded that the hybrid model was effective for studying the in-sample and out-sample CNY FOREX rate prediction.

Sidehabi et al. (2016) proposed a hybrid of Genetic Algorithm-Neural Network (GA-NN) to predict FOREX rate. The authors concluded that Adaptive Spline Threshold Autoregression (ASTAR) and GA-NN methods predicted well.

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5.2. Remarks

After reviewing 24 EC-based hybrids, it is found that:

1. GA was employed very often to train a neural network for forecasting FOREX rate, whereas other evolutionary algorithms such as DE and ACO were not applied at all. Sometimes, GP was also employed to train neural networks. PSO was rarely employed for the same purpose. A robust algorithm like DE would be a better alternative for this purpose.
2. EA trained WNN, PSNN and Single Multiplicative NN were never applied to this problem.

6. Fuzzy Logic (FL)-based hybrid models

Fuzzy Logic (FL), a generalization of Boolean logic, was founded on the concept of partial truth i.e. truth values between "completely true" and "completely false". It deals with approximate reasoning instead of exact reasoning. Its importance lies in the fact that many types of human logic, particularly the logic based on common sense, are by nature approximate (Zadeh, 1965). The forecasting processes are very complicated because they include political, social, psychological, economic, and other phenomena. Many variables are difficult to measure; they are characterized by imprecision, uncertainty, vagueness, semi-truth, approximation, nonlinearity, etc. The advantage of the use of fuzzy logic is in processing these data (Dostál, 2013).

6.1. Description

Various FL-based hybrids were proposed to solve the problem of FOREX rate prediction (see Table 10). They are briefly described as follows.

Abraham and Chowdhury (2001) presented an intelligent FOREX monitoring system using Takai–Sugeno type neuro-fuzzy system and compared its performance with an ANN trained by the scaled conjugate gradient algorithm. The authors concluded that neuro-fuzzy system outperformed ANN in terms of better training time, obtaining more accurate predictions and easy interpretability of the results in terms of 'if-then' rules. The authors suggested that performance can be improved by supplying more training data. Their work can be extended towards short-term forecast (daily, hourly, etc.) using more intelligent systems.

Tseng et al. (2001) developed a fuzzy ARIMA (FARIMA) model to forecast next ten observations of the FOREX market. It combined the advantages of both fuzzy regression and the ARIMA model while nullifying their limitations. The FARIMA provided the best and worst possible situations based on which one can make decisions. The authors concluded that the FARIMA was appropriate when the needed number of observations was less than what ARIMA model needed.

Abraham (2002) presented a study of FOREX prediction using a hybrid CART-MARS. In this hybrid, CART initializes the prediction model, while MARS performs variable selection. After that, stand-alone MARS model was used for final prediction. This hybrid was useful when there was no expectation of many variations in the FOREX data. He concluded that the proposed hybrid was fast and accurate, while the neuro-fuzzy soft computing model was very robust and with easy interpretability using fuzzy if-then rules after experimenting on the same data used in Abraham and Chowdhury (2001).

Neagoe et al. (2004) applied the Fuzzy-Gaussian Neural Network (FGNN) with four layers to predict the daily FOREX rate. They concluded that FGNN architecture constructed the fuzzy system rule by rule and could eliminate redundant nodes.

Medina and Mendez (2006) proposed the Interval Singleton Type-2 Fuzzy Logic System (IT2SFLS) which used the recursive least-squares (RLS)-back propagation hybrid learning method (IT2SFLS-1 (RLS-BP)) to predict FOREX rate. They concluded that the hybrid could yield best predictions, and the baseline T1 SFLS-1 (BP) yielded the worst predictions.

Chen and Lin (2007) proposed a hybrid model, called Fuzzy BPN to predict NTD/USD. It consisted of fuzzy-interval membership function to improve the performance of BPN while retaining the nonlinear capabilities of ANN. The authors concluded that Fuzzy BPN was a viable substitute to forecast FOREX rate.

Zhang and Wan (2007) proposed a novel statistical fuzzy interval neural network (SFINN). It took statistical interval input and yielded better FOREX rate predictions. The fuzzy interval neural learning algorithm was used to predict future FOREX rates.

Khashei et al. (2008) proposed a new hybrid comprising ANN and Fuzzy ARIMA for forecasting time series. The proposed hybrid obtained accurate results even under incomplete data conditions. It worked well even when a little historical data available. Finally, it provided both the best and the worst possible situations to make good decisions.

Mendez and Hernandez (2008) presented the application of the interval type-1 non-singleton type-2 fuzzy logic system that used the recursive least-squares (RLS)-back propagation hybrid learning method (IT2NSFLS-1 (RLS-BP)) to predict FOREX rate. They concluded that the hybrid forecasting model yielded best predictions, and the baseline T1 NSFLS-1 (BP) yielded the worst predictions. The difference between the works of Medina and Mendez (2006) and Mendez and Hernandez (2008) is that Medina and Mendez (2006) had dealt with the prediction of same exchange rates using Singleton T2FS whereas Mendez and Hernandez (2008) had dealt with Non-singleton T2FS.

Khashei et al. (2009) proposed a method to forecast time series using ARIMA, ANNs and Fuzzy regression model to forecast point estimates of financial time series. The ARIMA models were linear models with data limitation. But, the proposed model had nonlinear ANNs, and it invoked the application of the fuzzy numbers and fuzzy logic in ARIMA model and obviated the need of having large amounts of historical data. The proposed model was more flexible for forecasting even when less data available.

Leu et al. (2009) proposed a distance-based fuzzy time series (DBFTS) model to predict 1,3,5,7-day ahead forecasts of FOREX rates. The existing FTS model entailed exact match of the fuzzy logic relationships (FLRs). But, the DBFTS model used the Euclidean distance between two FLRs to select matching prediction rules. To predict the FOREX rate, a two-factor DBFTS model was constructed with FOREX rate as its first factor and the candidate variables which affect the variation of FOREX rates as the second factor. The authors concluded that the proposed model outperformed RW model and ANN.

Fallahzadeh and Montazeri (2013) presented a hybrid neuro-fuzzy system, IT2FCMFNS, which consists of interval type-2 fuzzy c-means clustering, MLP and interval type-2 fuzzy model, to predict FOREX rate. The authors claimed that proposed model could handle the fluctuations to a high degree of accuracy.

Table 10
FL-based hybrid FOREX rate prediction models (chronological order).

Year	Author(s)	Hybrid model(s)	Models compared with	Winner	FOREX data used	Performance metrics used
2001	Abraham and Chowdhury (2001)	Takagi–Sugeno type Neuro-Fuzzy model and ANN using Scaled conjugate gradient	Among themselves	Neuro-fuzzy system	Monthly average data of USD/AUD, GBP/AUD, SGD/AUD, NZD/AUD	RMSE
2001	Tseng et al. (2001)	FARIMA	ARIMA	FARIMA	Daily data of USD/NTD	Actual Vs Predicted
2002	Abraham (2002)	Application of MARS, CART, CART+MARS, ANN, Neuro-fuzzy model	Among themselves	CART+MARS and Neuro- Fuzzy Model	Monthly average data of USD/AUD, GBP/AUD, SGD/AUD, NZD/AUD	RMSE
2004	Neagoe et al. (2004)	Application of FGNN	AR model	FGNN	Daily data of USD/ROL	RMSE
2006	Medina and Mendez (2006)	IT2SFLS-1 (RLSBP)	T1 SFLS (BP), IT2 SFLS(BP)	IT2SFLS-1 (RLS-BP)	Daily data of MXN/USD from http://pacific.commerce.ubc.ca/xr	RMSE
2007	Chen and Lin (2007)	FuzzyBPN	BPN, AR+GARCH	FuzzyBPN	Daily data of NTD/USD from Central Bank of China	MSE
2007	Zhang and Wan (2007)	SFINN	–	Gives closer predictions	Daily data of JPY/USD, GBP/USD, HKD/USD	Actual Vs Predicted
2008	Khashei et al. (2008)	ANN+Fuzzy ARIMA	ANN, Fuzzy ARIMA and other works	ANN+Fuzzy ARIMA	Daily data of USD/IRR	MAE, MSE
2008	Mendez and Hernandez (2008)	IT2NSFLS-1 (RLS-BP)	T1 NSFLS (BP), IT2 NSFLS(BP)	IT2NSFLS-1 (RLS-BP)	Daily data of MXN/USD from http://pacific.commerce.ubc.ca/xr	RMSE
2009	Khashei et al. (2009)	Hybrid of ARIMA, ANN and Fuzzy regression	ANFIS, ARIMA, ANN and other works	Hybrid of ARIMA, ANN and Fuzzy regression	Daily data of USD/IRR and EUR/IRR	MAE, MSE
2009	Leu et al. (2009)	DBFTS	RBFNN, RW	DBFTS	Daily data of NTD/USD, JPY/USD, CNY/USD, KRW/USD from Central Bank of Taiwan	MSE, Dstat
2013	Fallahzadeh and Montazeri (2013)	IT2FCMFNS	FLIT2FNS TIFCMFNS	IT2FCMFNS	Daily data of EUR/USD, USD/CHF	MSE
2014	Bagheri et al. (2014)	ANFIS+QPSO, ANFIS-QPSO-WT-DTW	Neuro-fuzzy	ANFIS+QPSOANFIS-QPSO-WT-DTW	Daily data of EUR/USD GBP/USD,USD/JPY USD/CHF	MAPE, MAE
2014	Gharleghi et al. (2014)	Cointegration based neuro-fuzzy system	Vector Error Correction Model	Cointegration based neuro-fuzzy system	Daily data of MYR/USD PHP/USD,SGD/USD	RMASE,MAPE, MAE
2015	Parida et al. (2015)	FLFNN	FNN, FLFNN, RBFNN, BPNN	FLFNN	Daily data of EUR/AUD, EUR/INR, EUR/JPY, EUR/CAD, EUR/USD, EUR/CNY	MAPE,MSERMSE
2016	Sharma et al. (2016)	ANFIS	–	Mixed results	Daily data of CNY/USD, JPY/USD, INR/USD	MAPE
2016	AmirAskari and Menhaj (2016)	MFRM	ANFIS, MLPRBF	MFRM	Daily data of USD/CHF	MSE,MAPE,RMSE

Bagheri et al. (2014) forecasted FOREX rate using ANFIS networks with Quantum-behaved PSO (QPSO). In their approach, first, the decomposed wavelet time series was used as an ANFIS input data for forecasting future market prices. The QPSO was used for tuning the ANFIS membership functions. They also proposed the hybrid namely Dynamic Time Warping (DTW)-Wavelet Transform (WT) to automate pattern extraction. The authors concluded that the hybrid could yield better results.

Gharleghi et al. (2014) proposed a cointegration-based neuro-fuzzy system, which was a combination of a cointegration technique, a Fuzzy Inference System (FIS) and ANN. The sign of the coefficients in the long-run equation was used to construct the FIS. The results from the FIS were fed as inputs to the ANN in order to predict the FOREX rate returns. The authors concluded that hybrid consistently outperformed the Vector Error Correction Model.

Parida et al. (2015) proposed Functional-Link Fuzzy Neural Network (FLFNN) to predict FOREX rate. The normal Fuzzy Neural Network (FNN) comprised a linear combination of inputs in the consequent part of the TSK-type fuzzy rules. However, to improve forecasting accuracy, the consequent part used the output from an FLNN to provide an expanded nonlinear input dimension. The authors concluded that the FLFNN could yield robust predictions.

Sharma et al. (2016) proposed the application of ANFIS to predict the FOREX rate. The ANFIS was employed for deriving a rule base, and the rule base was used for testing the data. The authors concluded that ANFIS could better predictions only on one exchange rate.

AmirAskari and Menhaj (2016) proposed Modified Fuzzy Relational Model (MFRM) to predict FOREX rate. In MFRM, a new method was introduced for implementing a general N-dimensional fuzzy relational matrix showing the fuzzy relationship between input and output variables. They concluded that the proposed model outperformed MLP, RBFNN, and ANFIS.

6.2. Remarks

After reviewing 17 FL-based hybrids, it is found that:

1. Various Neuro-fuzzy Inference Systems such as DENFIS and ANFIS were rarely employed.
2. Fuzzy SVM was never used to solve this problem at all.
3. Takagi–Sugeno (TS) fuzzy inference system Takagi and Sugeno (1985) was rarely used.

7. Support Vector Machine (SVM)-based Hybrid Models

Machine learning techniques including SVM focus on the development of self-taught computer programs to grow and change when exposed to new data. Researchers choose regression version of SVM namely SVR in prediction tasks as it produces very accurate forecasting model. It has guaranteed convergence to the global minimum, overfitted less and was robust to noise. The ϵ-SVR is a regression model which aims at finding a function $f(x)$ that has atmost ϵ deviation from the actual target values Basak et al. (2007); Smola and Scholkopf (2004); Vapnik et al. (1997).

7.1. Description

Various SVM-based hybrids were proposed to solve the FOREX rate prediction problem (see Table 11). They are briefly described as follows.

Ni and Yin (2006) proposed a two-stage hybrid system for out-of-sample FOREX rate prediction. In the first stage, it used the Recurrent Self-organizing Map (RSOM) for partitioning the original data into a few disjoined regions. Later, SVMs were invoked to make the predictions. The hybrid did not require prior knowledge of the data. The authors concluded that the hybrid could make a certain degree of profits.

He et al. (2008b) proposed the Multi-Scale Non-linear Ensemble (MSNE), namely Wavelet decomposed support vector regression model, to analyze and model the out-of-sample complex FOREX rate behaviors. The wavelet analysis modeled the multi-scale heterogeneity property in MSNE and the ARMA modeled the autocorrelation property. SVR-based nonlinear ensemble framework in combination with ICA helped MSNE to improve the model specification stability. In this ensemble, the global optimum solution was obtained faster and more reliably.

He et al. (2008a) proposed the Wavelet Denoising SVR (WDNSVR) model for out-of-sample FOREX rate prediction. In this ensemble, first, the wavelet-based denoising algorithm separates data from noises. After that, ARIMA models the conditional mean for both the data and the noises. Later, PCA reduces the dimensionality for the forecast matrix of individual forecasts. Finally, ensembling of aggregate conditional mean forecasts of ARIMA models obtained from PCA transformed forecast matrix was carried out. The authors concluded that the ensemble significantly improved the forecasting accuracy and reliability.

Lu et al. (2009) demonstrated the application of ICA-based SVR time series prediction model. In this model, ICA transformed the actual time series into a set of independent components (ICs). Then, the prediction models were built using SVR for ICs. The authors concluded that the proposed application yielded better predictions than the single SVR and RW models.

Ni and Yin (2009) described a hybrid model of recurrent SOM (RSOM), SVR, GA and several common trading rules. In this hybrid model, RSOM partitions the time series into consistent groups. Then, the SVRs model those grouped samples. Finally, the best fitting local models make predictions. The GA integrates the trading rules with the local regressive models. The authors concluded that the hybrid could yield better results.

Wang et al. (2009) investigated the impact of non-numerical information on FOREX rate changes. First, the authors employed a fuzzy comprehensive evaluation model which, in turn, could quantify the non-numerical information. Later, they designed a single classifier that could address the impact of FOREX rate changes associated with this information. The authors also proposed various diverse classifiers to deal with numerical information and SVM integrated all these classifiers. The authors concluded the work by questioning the number of economic indicators that were needed to be incorporated for accurate forecasting.

He et al. (2010) proposed a novel Slantlet Denoising Least Square SVR (SDLSSVR) model. In this model, the denoising algorithm separates Data Generating Process (DGP) that exhibits different characteristics. The Slantlet analysis performed denoising. While conducting

Table 11
SVM-based hybrid FOREX rate prediction models (chronological order).

Year	Author(s)	Hybrid model(s)	Models compared with	Winner	FOREX data used	Performance metrics used
2006	Ni and Yin (2006)	RSOM+SVM	SOM+MLP, GARCH	RSOM+SVM	Daily data of GBP/USD from the PACIFIC Exchange Rate Service	MSE, Profit earned, CP
2008	He et al. (2008b)	MSNE	RW, ARMA	MSNE	Daily data of EUR/USD from Global Financial Data (GFD)	MSE, Theil's U
2008	He et al. (2008a)	WDNSVR	ARMA, RW	WDNSVR	Daily data of EUR/USD from Global Financial Data (GFD)	MSE, C-W Test P-T Test
2009	Lu et al. (2009)	ICA+SVR	SVR, RW	ICA+SVR	Daily data of NTD/USD	MSE, MAPE, Theil's U (DA)
2009	Ni and Yin (2009)	SOM+SVR+GA	SOM+SVR, SOM+MLP, GARCH	SOM+SVR+GA	Daily data of GBP/USD	Profitability(ROI)
2009	Wang et al. (2009)	Classifier ensemble+SVM	Ensemble without non-numerical information	Classifier ensemble+SVM	Daily data of JPY/USD from http://www.federalreserve.gov/release/	MAE, Dstat
2010	He et al. (2010)	SDLSSVR	ARMA, RW, LSSVR, SDARMA	SDLSSVR	Daily data of EUR/USD from Global Financial Data (GFD)	MSE, C-W Test, P-T Test
2010	Liu (2010)	SVM+DWT	SVM	SVM+DWT	Daily data of CNY/USD from the Board of Governors of the Federal Reserve System	RMSE
2012	de Brito and Oliveira (2012)	SVR+GHSOM	SVR	SVR+GHSOM	Daily data of EUR/USD, GBP/USD from OANDA	ROI, MD
2012	Lin et al. (2012)	EMD+LSSVR	EMD+ARIMA, LSSVR, ARIMA	EMD+LSSVR	Daily data of USD/NTD, JPY/NTD, RMB/NTD obtained from the Central Bank of Taiwan and Yahoo Finance	RMSE, MAPE, MAD, Dstat, CP, CD

the process of forecasting, the LSSVR model corrected the error specifications. The SDLSSVR outperformed the benchmark models such as ARMA, RW, LSSVR and Slantlet Denoising ARMA (SDARMA).

Liu (2010) presented a hybrid model comprising SVM and DWT to predict FOREX rates. In this model, the DWT decomposed the time series data into five different scales. Different kernel functions were selected for SVR to make predictions using different scales. Finally, the predicted values of different scales were reconstructed. The author also highlighted the limitations of work such as its ability to predict only one-step-ahead predictions, the need for the selection of optimal parameters and the need for exploration of other SVM kernels too.

de Brito and Oliveira (2012) proposed SVR+GHSOM. In this model, Growing Hierarchical SOM (GHSOM) network divided the dataset into regions that have similar statistical distribution to avoid the problem of non-stationarity and SVR makes forecasts for those regions. Their experiments indicated that, regardless of time frame (i.e., intraday or interday), the hybrid yielded lower rates of MD, i.e., the risk involved was lower for the hybrid than SVR. The work can be extended by incorporating technical indicators as inputs with the aim of improving profitability.

Lin et al. (2012) proposed EMD-based Least Squares SVR (LSSVR) forecasting hybrid for predicting FOREX rates. In this proposed model, the actual FOREX rate is decomposed into quite a few intrinsic mode functions (IMFs) and one residual component using EMD. Later, LSSVR is used to forecast the IMFs and also residual value separately. The predictions of all components obtained were summed to obtain final forecasting result. This final result turned out to be a better forecast.

7.2. Remarks

From this section on SVM-based hybrids, we observed the following:

1. Despite the successful applications of SVR in various domains owing to its capability to produce accurate predictions, it is surprising that it is under-utilized in FOREX rate prediction domain.
2. Multi-kernel SVR was never used.
3. Kernel methods like kernel-NN and kernel-QR almost never employed.
4. EC methods were employed very less in SVM-based hybrids.

8. Chaos-based hybrid models

Chaos Theory is the study of deterministic, nonlinear and dynamic systems that evolve from some initial conditions. A small change in the initial setup of a chaotic system may lead to drastically different behavior Poincaré (1890). The chaotic systems are difficult to predict or control, like weather, stock market, and so on. Frank and Stengos (1988) and Scheindman and Lebaron (1989) found that chaotic behavior existed in financial markets including the stock market, FOREX market and futures market.

Chaos is a seemingly random and unpredictable behavior occurring in a deterministic system. It can be modeled by reconstructing the corresponding phase space from the univariate time series with the help of both lag and embedding dimension. This approach was mathematically explained by Takens (1981). Once phase space is reconstructed, a prediction model can be applied on phase space.

8.1. Description

A few Chaos-based hybrids (see Table 12) appeared in literature addressing the problem of FOREX rate prediction. They are briefly described as follows.

Pavlidis et al. (2003) proposed a hybrid for predicting financial time series. In this hybrid, first, False Nearest Neighbors (FNN) method was employed to obtain optimal chaos parameters viz., lag and embedding dimension. Later, unsupervised K-windows algorithm clustered the time delayed vectors. Later, DE/PSO was used to train a different and cluster-specific feedforward neural network (FNN). Then, each cluster contained the test set patterns identified. Finally, predictions for each test pattern were generated. The authors concluded that the proposed hybrid could achieve better results when both DE and PSO were used.

Huang et al. (2010) proposed a Chaos-SVR model to predict FOREX rates. First, state space was reconstructed from time series using optimal chaos parameters viz., lag and embedding dimension. Later, SVRs were used for forecasting. The authors concluded that Chaos-SVR could acquire the dynamics of FOREX rate.

Pradeepkumar and Ravi (2014) proposed two intelligent chaos-based hybrids to predict exchange rates including ANN (MLP/GRNN/GMDH) + PSO/ Polynomial Regression (PR)and PSO+ANN/PR. In these hybrids, initial predictions were obtained using corresponding models, and the predictions obtained were fine tuned later. The presence of chaos was tested, and if present, it was modeled using optimal lag and embedding dimension. The reconstruction of phase space from the data had led the hybrids to predict better than traditional forecasting models. However, the work can also be extended using Multi-objective optimization.

Pradeepkumar and Ravi (2016) proposed Chaos-based Quantile Regression Random Forest (Chaos+QRRF) model for exchange rate prediction. In the proposed hybrid, first, the presence of chaos was tested, and if present, it was modeled by reconstructing the phase space with optimal lag and embedding dimension. Later, QRRF was invoked on the reconstructed data to make accurate predictions. The authors reported that Chaos+QRRF could outperform Pradeepkumar and Ravi (2014) and other models.

Pradeepkumar and Ravi (2017) proposed Chaos-based Multi-variate Adaptive Regression Splines (Chaos+MARS) model to predict FOREX rates. In the proposed hybrid, first, the presence of chaos is tested, and if present, it was modeled by reconstructing the phase space with optimal lag and embedding dimension. Later, the reconstructed data was fed to MARS for prediction purpose. The authors concluded that the proposed hybrid outperformed Pradeepkumar and Ravi (2014) and other models.

Ravi et al. (2017) proposed two different three-stage chaos-based hybrids for financial time series prediction namely Chaos+MLP+MOPSO and Chaos+MLP+NSGA-II. In the proposed hybrids, optimal lag and embedding dimension were used to reconstruct the phase space, if chaos was present and MLP was used to obtain initial predictions and then Multi-objective PSO/NSGA-II based auto-regressive error model was employed to fine tune the initial predictions obtained. The authors concluded that the proposed hybrids outperformed Pradeepkumar and Ravi (2014, 2017).

Table 12
Chaos-based hybrid FOREX rate prediction models (chronological order).

Year	Author(s)	Hybrid model(s)	Models compared with	Winner	FOREX data used	Performance metrics used
2003	Pavlidis et al. (2003)	Hybrid methodology of Chaos theory, Clustering, ANN, and EC	FNN	Hybrid model	Daily data of JPY/USD, USD/GBP from (www.oanda.com)	Mean predictive accuracy
2010	Huang et al. (2010)	Chaos+SVR	SVR, BPNN, Chaos+BPNN	Chaos+SVR	Daily data of EUR/USD, GBP/USD, NZD/USD, AUD/USD, JPY/USD, RUB/USD from Datastream provided by Morgan Stanley Capital International (MSCI).	RMSE, MSE, MAE
2014	Pradeepkumar and Ravi (2014)	Chaos+ANN+PSO/PR, Chaos+PSO+ANN/PR	MLP, GRNN, GMDH, PSO	Both hybrids (Mixed results)	Daily data of JPY/USD, GBP/USD, EUR/USD from US Federal Reserve System (http://www.federalreserve.gov/releases/h10/hist/)	MSE, MAPE
2016	Pradeepkumar and Ravi (2016)	Chaos+QRRF, Chaos+QR, Chaos+RF	Among themselves	Chaos+QRRF	Daily data of JPY/USD, GBP/USD, EUR/USD from US Federal Reserve System (http://www.federalreserve.gov/releases/h10/hist/)	MSE, MAPE
2017	Pradeepkumar and Ravi (2017)	Chaos+CART, Chaos+CART-EB, Chaos+TreeNet, Chaos+LASSO, Chaos+RFTE, Chaos+MARS	Among themselves	Chaos+MARS	Daily data of JPY/USD, GBP/USD, EUR/USD from US Federal Reserve System (http://www.federalreserve.gov/releases/h10/hist/)	MSE, MAPE
2017	Ravi et al. (2017)	Chaos+MLP+MOPSO, Chaos+MLP+NSGA-II	Among themselves	Chaos+MLP+NSGA-II	Daily data of JPY/USD, GBP/USD, EUR/USD Gold Price (USD)from US Federal Reserve System (http://www.federalreserve.gov/releases/h10/hist/)	MSE, Dstat, Theil's U

8.2. Remarks

From this section, we observe the following:

1. Chaos-based hybrids were the least explored among the 5 types of hybrids that the current review is divided into. Till 2014, there were only two works related to Chaos-based hybrids reported. Later, the present authors Pradeepkumar and Ravi (2014, 2016, 2017), and Ravi et al. (2017) published four works related to Chaos-based hybrids. They developed various two-stage chaos-based hybrids in which Chaos Theory is used to reconstruct phase space from one-dimensional array and later, intelligent technique is used to obtain predictions using reconstructed phase space. Among the proposed two-stage hybrids, the authors reported that Chaos+QRRF outperformed all other two-stage hybrids.
2. Similarly, the authors also implemented various three-stage hybrids and reported that Chaos+MLP+NSGA-II outperformed all other three-stage hybrids. It can be concluded that there is still a lot of scope to develop various chaos-based hybrids for FOREX rate prediction.

9. Discussion

The current review discovered many useful insights, and accordingly, the following interesting observations are made, some of which can be seen as gaps in the past research efforts.

1. In 2009, many good contributions of various new hybrid models were made. In all other years, except 2000, good amount of work was reported. It is interesting to note that during 2008–2010, 29 papers out of 82 reviewed appeared amounting to 35%. Incidentally, this phase also coincided with the worldwide economic downturn, when several financial institutions failed. The spurt in research in FOREX rates forecasting indicates that researchers investigated not only market risk but also bankruptcy risk, which spans credit risk and operational risk.
2. It is interesting to note that the traditional Box–Jenkins paradigm of time series forecasting that advocates modeling the deterministic part namely the trend by least squares estimation and the stochastic part by ARIMA models is slowly giving way to more robust and comprehensive methodology, wherein chaos (if present) is modeled first before modeling the deterministic and stochastic parts by powerful nonlinear techniques such as neural network architectures and evolutionary algorithms in tandem. This, in essence, made the ARIMA models redundant to some extent because ANN and SVM are more powerful than the ARIMA as reported in several papers. This paradigm shift will continue to bring some groundbreaking methodologies into the realm of FOREX rate prediction.
3. It is noteworthy that earlier, statistics-based hybrid forecasting models (e.g., ARIMA+ANN) were used for FOREX rate prediction. Later, however, soft computing based hybrid intelligent forecasting models (e.g., ANN+PSO) replaced them, which in turn yielded more accurate predictions. This departure coincided with the same approach followed in other engineering disciplines (Ram and Davim, 2017; Saba et al., 2017; Weron, 2014).
4. It is quite strange that the potential of Fuzzy logic based hybrids involving ANFIS, DENFIS in forecasting FOREX rates have not yet been fully exploited. This is a glaring gap in the literature.
5. Further, Fuzzy SVR is not yet explored in this area. It can perform fuzzy nonlinear regression by combining the power of fuzzy logic in modeling imprecision and accurate prediction capability of SVR.
6. Another striking observation is that ANN-based hybrid models dominated the arena of FOREX rate prediction. Here, ANN meant mostly MLP. However, there is a tremendous scope to apply other powerful neural network architectures.
7. The EC used in various ANNs helped them yield accurate predictions. The evolutionary algorithms played a key role in obtaining optimal parameters so that ANN could be trained better resulting in accurate predictions.
8. It is worth noting that none of the papers reviewed here considered exogenous variables in addition to the time series of FOREX rates to accurately predict them.
9. A lot of work was carried out in predicting exchange rates of different currencies such as JPY, GBP, EUR/USD. Different durations of data such as daily, weekly and monthly prices were experimented. However, intraday exchange rate forecasting needs to be explored, which requires stream data mining principles and online, one-pass algorithms for prediction. In addition, this requires big data framework such as Apache Spark and its ecosystem to tame streaming data.
10. Finally, it is conspicuous from the review that ANN-based hybrids turned out to be more prevalent, more pervasive and more powerful. This observation is corroborated by the fact that both EC-based hybrids and FL-based hybrids, do also contain some architectures of ANNs as a predominant constituent.

10. Conclusions and future directions

10.1. Conclusions

The paper presented a comprehensive review of 82 works reported on FOREX rate prediction using soft computing hybrid techniques during 1998–2017, This is a unique review paper, which focuses exclusively on the FOREX rate prediction using soft computing hybrids. The idea of application of SC hybrids for this domain attracted the attention of the researchers and practitioners more during the latest financial crisis of 2008–2010. This trend indicates that researchers investigated not only bankruptcy risk, which spans credit risk and operational risk but also market risk that subsumes interest rate risk and FOREX rate risk. We are confident that the present review is going to be very useful to young researchers as well as practitioners.

10.2. Future directions

Based on the present comprehensive review, we advocate the following research directions for future, which could be helpful to the budding researchers and practitioners:

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1. The hybridization of Chaos, Fuzzy regression and fuzzy SVR can be explored to see if the better forecast of FOREX rates can be obtained.
2. Moreover, the hybrids involving SVM and EC have to be investigated in future. Also, the hybrids involving FL and EC are worth to be investigated.
3. The evolutionary techniques other than GA and PSO such as ACO (Dorigo et al., 2006), DE (Storn and Price, 1997), etc. are to be explored to form new hybrid forecasting models. Further, the utilization of metaheuristics such as Simulated Annealing (Kirkpatrick et al., 1983), Tabu Search (Glover, 1989; 1990), etc. also need to be investigated.
4. Quantum-inspired evolutionary algorithms (Han and Kim, 2002) hold a lot of promise in classification and prediction because of their superior exploration strategy. They should be explored in future as little or no work is reported in this area concerning financial time series prediction.
5. The potential of powerful ANN architectures such as ELM (Huang et al., 2006), Spiking Neural Network (Maass, 1997), Functional Link Network (Pao and Takefuji, 1992), Higher order Neural Networks (Shin and Ghosh, 1991; 1995), etc. also need to be investigated in the context of the problem. Further, one can still propose novel ANN-based hybrid models and ensembles of ANN involving wavelet neural networks, GMDH, Pi-Sigma Networks etc.
6. Deep learning architectures (Deng, 2012), which exhibited tremendous promise in Image Processing, need to be explored and applied in this context.
7. The EC-driven rule-based techniques are also worth exploring in this context.
8. The application of HMM (Baum and Petrie, 1966; Rabiner, 1989) is conspicuously absent in all of the papers that are reviewed. Therefore, researchers can look into hybrids involving HMM-based hybrids.
9. The online versions of existing algorithms and kernel methods need to be investigated in the context of the problem. This line of research is going to be exciting in current times when big data has caught everyone by storm in various domains including finance.
10. In FOREX rate prediction, there was a lot of work carried out in predicting exchange rates of different currencies such as JPY, GBP, EUR/USD. Different durations of data such as daily, weekly and monthly prices were experimented. However, intraday exchange rate forecasting needs to be explored.
11. The Quantile Regression (QR)-based hybrids (Cannon, 2011; Koenker and Bassett, 1978; Meinshausen, 2006; Taylor, 1999) are also need to be explored in the context of predicting financial time series.
12. Financial news and political events based FOREX rate prediction with the help of any of the five types of hybrids are worth exploring, preceded by modeling the underlying chaos, if present. Then, the financial or political textual data generates exogenous textual variables.

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