FOREX meet A.I.[⋆]

Marco Fisichella[1,*], Filippo Garolla[b]

[a] *L3S Research Center of Leibniz University of Hannover, Germany*
[b] *Austria*

Abstract

This template helps you to create a properly formatted LaTeX manuscript.

Keywords: `elsarticle.cls`, LaTeX, Elsevier, template
2010 MSC: 00-01, 99-00

1. Introduction

People are involved more and more in trading of currencies these days. Amongst those markets, of the biggest buying and selling platforms are cryptocurrency trading and the FOREX marketplace. Although cryptocurrency promises better returns than foreign exchange, FOREX gives solid, especially secured, and relatively regulated trading in comparison to cryptocurrency trading. As a result, in latest years, the foreign exchange (FOREX) market has attracted pretty a lot of interest from researchers all over the world. Different kinds of studies have been performed to accomplish the task of predicting future FOREX currency prices accurately.

Researchers have been involved primarily in neural networks models, pattern-based approaches, and optimization techniques. The emergence of artificial neural networks performed a massive function in foreign exchange rate prediction. During our evalutaion of related works, we discovered that many deep learning algorithms, such as gated recurrent unit (GRU) and long short term memory (LSTM), have been explored and exhibit massive potential in time sequence prediction.

The foreign exchange market, is the world's largest foreign money trade market with over 5.1 trillion of trade exchange per day. It is recognized to be very complicated and volatile. Currency trading occurs 24 h a day, however the buying and selling time is divided into 4 fundamental time zones. Each of these zones has its specific opening hours and closing hours. FOREX is divided into three specific categories: majors, cross-rates, and exotics. Majors are the most traded currencies which are priced in opposition to the USD and occupy the majority of the FOREX market. Our work is primarily based on Majors.

[⋆] Fully documented templates are available in the elsarticle package on CTAN.

[*] Corresponding author
Email address: `mfisichella@L3S.de` (Marco Fisichella)

Each forex pair has its opening price, highest price, lowest price, and closing price based on the trading session. For security reasons, it is now not possible for one person to at once go to, register with, and purchase from the FOREX market, but each individual needs to use third party like brokers, who are humans or corporations that have admission to the FOREX market and are capable to buy or sell currencies. In the FOREX market, solely two alternatives are available, either buying currencies or selling if they have brought any currencies previously.

Recent years have viewed a lot of researches in the FOREX market foreign money rate prediction. Predicting the FOREX market has been a key goal of investigators over the preceding couple of decades. There are two methods to forecast the market: undamental research and technical research. Fundamental research considers many factors, such as the financial system and political state of a country, the popularity of a company, all inner and exterior buying and selling news, etc. Technical research concentrates predicting the FOREX market based totally on historic data, in particular, the highest price, lowest price, opening price, and closing price of a currency and the volume traded on a particular day.

The remainder of the paper is arranged as follows.

2. Related Works

Numerous hybrid techniques have been examined in preceding years. Based totally at the papers we reviewed, according to the principle set of rules the studies prioritised, the papers can be cut up into going in conjunction with the following categories: regression strategies, optimization strategies, neural networks, and others. Those classes had been made in keeping with the popularity of the principle method of the forecasting system in the past years.

To INSERT In conclusion, these techniques are not appropriate for all currency pairs and may provide better effects for only a few randomly selected ones, as we can see inside the proposed papers.

Some pattern-based approaches are contradictory to each other.

2.1. Regression Methods

Raimund et al. [1] proposed a hybrid model for foreign exchange prediction that makes use of wavelet models along with support vector regression (SVR). Before everything, they used a discrete wavelet transform (DWT) technique to interpret facts from their forex dataset. Then the data were used as the input of support vector regression (SVR) for predicting the foreign exchange prices. They analysed the overall performance of their system with ARIMA and ARFIMA models. The effects confirmed that their system performs higher than ARIMA and ARFIMA models.

Taveeapiradeecharoen et al. [2] proposed a version for time series inspection and prediction; this is based on compressed vector autoregression. At the start, they used random compression method to decrease a big wide variety of foreign exchange data into a smaller form. After that, they used the Bayesian model averaging (BMA) approach to establish the load of each random compressed datum to attain the intersecting parameters. Their approach can provide out of sample forecasting till fourteen days previous to the real time. They concluded that their system was not suitable to predict all of the 30 forex currencies. Their proposed study outperformed the existing benchmark of Bayesian autoregression for specific 6 foreign money pairs.

A huge range of forecasting models have been proposed via the authors of the paper [3], by applying linear kernel SVR to historical data for EUR/USD, GBP/USD, and USD/JPY currency pairs received from high-frequency trading. Previous successive timeframes are used as features to predict the movement of rates in future/next time frame. Upon building models, they found a easy rule that supplied high-quality results.

After reviewing recent papers, it's evident that support vector regression turned into the most used approach included in our reviewed papers. Compressed vector autoregression, the CRT regression tree, and partial least squares regression had been additionally utilized by researchers. However, there are different algorithms which include lasso regression, logistic regression, and multivariate regression which have been abandoned in later years. The reviewed literature shows that the system primarily based on a regression model performed higher than ARIMA and ARFIMA models [1], and the model performance may additionally growth [4] when a regression model is combined with other techniques. However, when operating with a huge number of foreign money pairs, it is able to become hard with regression techniques, as most of the currency pairs return a higher MSE [2].

2.2. Optimization Techniques

Chandrinos et al. [5] proposed a technical system for FOREX that was stimulated by using the Donchian channel method. the primary reason in their method become to create profitable portfolios for FOREX buying and selling strategy. They first constructed the modified Renko bars (MRBs) via combining their trading guidelines. Their changed MRBs proved to be more correctly responsive than the normal candlesticks used in FOREX. They created an optimization level used by eight currency pairs. To acquire their optimization stage, they used three search-derivative-free global optimization strategies. These algorithms were the swarm optimization algorithm, also referred to as dividing a hyperrectangle (DIRECT), along side multilevel coordinate search (MCS), and pity beetle (PBA). They examined their optimization method and primarily based on the total return they built two kinds of portfolios: an equally weighted portfolio and a Kelly criterion-based portfolio. They evaluated the performance in their approach primarily based at the geometric return, arithmetic mean, and Sharpe ratio. They found out that the proposed version isn't always suitable for three currency pairs, whilst for the others they attain from 29% until over 200% general return.

Pradeepkumar et al. [6] advised a model for foreign exchange prediction that became primarily based on a quantile regression neural network (QRNN) and particle swarm optimization. They used PSO to train the QRNN and named the version PSO-QRNN. They used 8 pairs currencies. They used seven unique algorithms for the overall performance evaluation of their model: group method of data handling (GMDH), multilayer perceptron (MLP), random forest (RF), a quantile regression neural network (QRNN), generalized autoregressive conditional heteroskedasticity (GARCH), quantile regression random forest (QRRF), and a general regression neural network (GRNN). Once they executed the Diebold–Mariano (DM) evaluation check on all of the test results, they found that their proposed PSO-QRNN version completed higher than all models on datasets. For the rest of the datasets, QRRF and QRNN carried out better than other approaches.

Das et a. [7] proposed a hybrid approach that turned into build the use of extreme learning machine's on-line sequential version and krill herd (KH). The krill herd (KH) was devoted to features reduction. They compared their proposed system with a recurrent backpropagation neural network (RBPNN) and extreme learning machine (ELM). They considered 3 elements: (i) without features reduction (ii) with statistical features reduction, and (iii) with optimized features reduction strategies. For optimized features reduction strategies, they used bacteria foraging optimization (BFO), krill herd, and particle swarm optimization techniques. They used four foreign currency pairs. For RMSE their approach performed first-class. However, in MAE overall performance, their proposed model didn't provide the satisfactory effects.

For foreign exchange buying and selling approach optimization, a genetic set of rules become employed by the authors of the paper [8] to evolve a various set of profitable buying and selling rules based totally on weighted moving average approach. They used a time series with 4147 observations inside a range of sixteen years from 2000 to 2015 and they used the close prices of four foreign money pairs. Developed approach yields acceptably high returns on out-of-sample data. The rules acquired using their genetic algorithm result in appreciably better returns than the ones produced by exhaustive search.

In conclusion, these techniques are not appropriate for all currency pairs and may provide better effects for only a few randomly selected ones, as we can see inside the proposed papers.

2.3. Neural Network

Ni et al. [9] proposed a model that predicts the time series of foreign exchange using the C-RNN approach. C-RNN uses a convolutional neural network and recurrent neural network. They used a statistics-driven method to study the changing characteristics of FOREX. They used the past 10 years records until 2018 for nine currency pairs. 2000 datapoints were contained in their dataset. Using a convolutional neural network and long short-term memory, evaluating RMSE, they discovered that their proposed C-RNN version offers much less mistakes than LSTM and CNN.

Chandrinos et al. [5] proposed a model referred to as the artificial intelligence risk management system (AIRMS) this is based on machine studying. They advanced two risk management structures: One with a neural network (AIRMS-ANN) and the other with the decision tree approach (AIRMS-DT). They used five FOREX currencies and the technical indicator and historical time-series data as the input to their proposed model. They divided the output signal into two categories: profitable and not profitable. When they categorized the output signal only as profitable, they were given an growth of 50% profit over the 2-category labelled version. As assessment metrics, they used the F1 measure for both models. Each AIRMS-ANN and AIRMS-DT carried out well on average and outperformed each other in some cases. Whilst evaluating the Kelly criterion portfolios, the decision tree once more beat the neural network with respect to total return.

Dash et al. [10] proposed a model that makes use of a higher order neural network for FOREX prediction. They used a shuffled frog leaping approach with the Pi–sigma neural network for predicting dynamic and non-linear FOREX prices. Three currencies had been used for imposing their model. The ISFL algorithm was used for estimating the hidden parameters and improving the prediction price. ISFL algorithm is a progressed model of the shuffled frog leaping algorithm (SFLA) wherein convergence the speed of the network is enhanced along side the predictive potential of the network. They compared the performance of their approach with a range of different ones. Their model furnished higher accuracy in conjunction with higher statistical performance.

Recent study conducted by Ahmed et al. [11] suggests that a significant enhancement inside the prediction of FOREX prices may be executed through incorporating domain information in the system of training machine learning models. The proposed approach integrates the foreign exchange Loss feature (FLF) into a long short-time memory model called FLF-LSTM, that minimizes the difference between the actual and predictive average of foreign exchange candles. The usage of $10,078$ 4-hour candles of EURUSD pairs highlighted that, compared to the classic LSTM version, the proposed FLF-LSTM model shows a lower overall mean absolute error rate by 10.96%.

The neural network became pretty popular in recent years. Many algorithms, inclusive of the modular neural network and deep belief model are yet to be explored. The reviewed literature implies that neural network-primarily based models may be equipped with unique types of procedures, which proves the versatility of those models. but, in some systems, a big network length can also have an effect on the result.

2.4. Rest of the Methods

In this section, we present the rest of methods proposed in literature. Far from being an exhaustive collection of all approaches, we wanted to analyse the most recent works in this field and give the reader an overviews of the remaining methods found in literature.

The genetic algorithm and SVM hybrid version had been quite extensively used strategies. The best function of the SVM is that it could be used as a classifier [12] and a regressor for forecasting [13]. The literature advised that after a SVM is incorporated with the genetic algorithm the model can yield a greater return of investment [12]. Nevertheless, on occasion selecting the wrong kernel may offer a huge difference within the end result [13]. Moreover, some approaches rely on the choice of learning model, inputs, and selection mechanisms.

Another perspective is shown by researches exploiting the chaos theory. Studies prove that chaos's extensive applicability can be used in a broader way. Lee et al. [14] indicates that chaos theory can successfully be used as both an economic time series predictor and as a trading strategy optimizer. The issue is deciding on the input parameters. The methods are selected based totally on the dynamics underlying the selected data and what type of evaluation is meant for the system. That makes the system tremendously complex and not always accurate.

Pattern-based techniques have seen pretty a recognition. Recurrent reinforcement learning (RL), dynamic model averaging (DMA), dynamic conditional correlation (DCC), and so forth., were explored through the researchers. Pattern-based methods also proved their flexible adaptability. A few systems can alternate the statistics of the predictors by using the object properties [15] that can be carried out to layout a selection of time series structures. However, some pattern-based approaches are contradictory to each other, as some systems carry out nicely and offer excellent outcomes with a specific algorithm [16], at the same time as other systems perform just the opposite [17]. Additionally, some pattern-based models are only capable of predicting the changes over a short-time period and do no longer guarantee success for longer period of prediction time [18].

Finally, the rest of the strategies incorporate several kinds of methods which have been applied for the forecasting of the FOREX marketplace. It became determined that Bayesian autoregressive trees (BART), random forest (RF), naive Bayes (NB), ARIMA, and many others have been implemented and explored. A number of these algorithms have been carried out individually, whereas a few have been carried out in a hybrid version. Natural language processing become not often explored, however techniques such as NLP based on sentiment analysis that relies upon on news headlines [19] can easily be misguided using wrong news. As a result, right security measures need to be carried out on these methods.

3. Preliminaries

3.1. Trading System: Meta Trader 5

3.2. Technical indicators

In our trading system, XX technical indicators are used as the basis of trading rules. These technical indicators are: Adaptive Moving Average, Average Directional Moving Index, Bollinger Bands, Double Exponential Moving Average, Envelope Moving Avarage, Parabolic SAR, Fractal Adaptive Moving Avarage, Standard Deviation, Triple Exponential Moving Average, Avarage True Range, Bears Power, Bulls Power, MACD (Moving Average Convergence Divergence), Stochastic oscillator, William' Percentage Range, Momentum, RSI (Relative Strength Index), and Heiken Ashi Candles.

4. Trading Strategies

4.1. Trading Simulation Layer

This layer is used to simulate any buying and selling rule on the given time series data with respect to specific currency pairs in order to generate buy/sell/StopLoss/TakeProfit signals (hereafter explained) and calculate net profit as well as different statistics (number trades/deals, total net profit, number of ticks, balance drawdown absolute/max/relative, consecutive wins/profit, consecutive losses, and many others.) at the end of the simulation. Our trading simulation system adopts a realistic approach to compute the net profit: we use a demo account with a trading broker [1] simulating the placement of buy/sell positions. Our choice to go through a demo trading account is fundamental for realistically computing the gain and loss of our proposed approach. Finally, the net profit of the simulated trading rule is used as fitness value for the GA layer.

CHECK Market Order page 82 ans SL and TP page 83. Riscrivere prox linea

The simulation and calculation of net profit of a trading rule is given in Algorithm 1.

[1]https://www.icmarkets.com/en/open-trading-account/demo/

Algorithm 1: Feature Analysis using feature burst distributions

Input: A set of extracted features F; a set of articles A; a fixed threshold τ

Output: all the feature burst distributions θ_{type}, i.e. θ_v, θ_d, and θ_l

begin

- N := count the number of articles within A;
- D := count the number of distinct date t, according to articles' timestamps, in A;
- $P[|F|]$:= array storing the dominant period P_f for each feature $f \in F$;
- $S[|F|]$:= array storing the dominant power spectrum S_f for each feature $f \in F$;
- $FeatureDistributions[|F|][D]$:= matrix storing the vectors of feature trajectories y_f for each feature f over the dates t;
- $FourierFeatureDistributions[|F|][D]$:= matrix storing the decomposition of the vectors of feature trajectories y_f into the sequence of complex vectors via the discrete Fourier transform DFT;
- **for** *each distinct date t in A* **do**
  - $N(t)$:= count the number of articles at date t;
- **for** *each feature f in F* **do**
  - DF_f := count the total number of articles containing entity f;
  - **for** *each distinct date t in A* **do**
    - $DF_f(t)$:= count the number of articles containing feature f at date t;
    - DF-IDF := $\frac{DF_f(t)}{N(t)} * \log\left(\frac{N}{DF_f}\right)$;
    - Store DF-IDF into $FeatureDistributions[f][t]$;
- Compute $FourierFeatureDistributions$ using DFT on $FeatureDistributions$;
- **for** *each feature f in F* **do**
  - *type* := type of feature f;
  - $P[f]$:= compute the dominant period P_f of the corresponding feature;
  - $S[f]$:= compute the dominant power spectrum S_f of the corresponding feature;
  - **if** $S[f] \geq \tau$ **then**
    - **if** $P[f] > \lceil \frac{P}{2} \rceil$ **then**
      - Model the feature by a Gaussian distribution (aperiodic feature f_{ap});
    - **else**
      - Model the feature by a mixture of $K = \lfloor P/P_f \rfloor$ Cauchy-Lorentz distributions (periodic feature f_p);

4.2. A.I. Convolutional Layer

4.3. The GA layer: a Genetic Algorithm for variables' parameters selection

The unstable and chaotic structure of exchanges in FX market complicates forecast analysis. This leads to the utilization of optimisation methods. There are many heuristic methods, such as genetic algorithm (GA), simulated annealing (SA), etc. to resolve optimisation problems. Heuristic algorithms are extensively used for solving problems of high computational complexity, alternatively of going via all of the options, which takes up a considerable quantity of time. GA is one of the most popular heuristic optimisation approach that generates options which evolve in time [20]. GA is based totally on evolution and genetics. Heuristic strategies yield nearly but not necessarily optimal solution with reasonable computational effort and time.

Genetic algorithm refers to the heuristic algorithm, which offers an acceptable answer to the hassle in the majority of virtually practically significant cases, however the correctness of the decisions has no longer been tested mathematically, and is used most frequently for problems, the analytical solution of which is very hard or even impossible.

GA contains the concepts, borrowed from nature. These are the ideas of heredity and variability. Heredity is the capacity of organisms to transmit their traits and evolutionary characteristics to their offspring. Thanks to this capability, all living organisms pass the characteristics of their species in their offspring.

The variety of genes in living beings assures the genetic variety of the population and is random, considering nature would not have a manner of knowing in advance which characteristics may be most useful for the future (weather exchange, famine, dryness and so forth.). This variability allows the appearance of creatures with new features, which could live in the new environmental conditions and transmit the new traits to the offspring.

In GA there are two types of variations carried out within the algorithm: (i) the mutation, which is the variability arising due to the emergence of mutations; (ii) combination which arises from the aggregate of genes with the aid of mating.

The *gene* is the basic unit of information transfer: a structural and functional unit of heredity, which controls the development of a particular features or trait. We are able to call one variable of the function the gene. The gene is represented via a actual quantity: a real number. The set of gene- variables of the studied characteristic is the characterizing characteristic of the *chromosome*.

The chromosome representation of the Slow Stochastic Oscillator rule is illustrated in Table 1 as an example, where K Period, D Period and Slowing are the genes.

K Period	D Period	Slowing
10	3	6

Table 1: Chromosome representation of the Slow Stochastic Oscillator rule.

All samples of the identical evolutionary era are mixed into a population. Furthermore, the population is arbitrarily divided into two identical colonies: the parent and the descendant colonies. Due to crossing the parental species, which are decided on from the whole population, and different operators of the GA, there is a colony of offspring, which is identical to half the scale of the population.

In our work, the GA algorithm layer is implemented within the MetaTrader 5 platform [2]. Hereafter we report the steps on how the GA layer works:

1. Firstly, a range of values as function of start-stop-step values is defined for each gene of a chromosome.
2. Secondly, the chromosomes which represent the parameter combos are randomly generated to shape an initial proto-population.
3. Thirdly, for each chromosome the fitness value is computed and sent to be simulated into the Trading Layer.
4. Finally, we run the main loop of the GA until the selected number of offspring iterations are generated:
    - Making ready the population for reproduction, after disposing of chromosome duplicates.
    - Isolation and protection of the reference chromosome (with the best fitness cost).
    - For each mating and mutation, new parents are picked up on every time, getting ready the population for the subsequent era.
    - Evaluation of genes of the best offspring with the genes of the reference chromosome. If the chromosome of the best offspring is higher than the reference chromosome, then replace the reference chromosome.

We experimented with several parameters' values in order to tune the GA. For sake of clarity, there are no universal parameters' values, and it is a good practice to assign them on the basis of the domain. We varied the scale of the population, which range between 64 and 256, and the threshold value of the epochs number. We did not choose too large values, since this did not accelerate finding solution to the problem. As a result, we have observed the subsequent parameter settings for GA pretty exceptional for our problem (Table 2):

Number of chromosomes in the colony	100
Number of epochs without progress	50
Probability of mutation of each gene in %	5

Table 2: GA parameter settings.

The following optimization criteria were considered for GA and used with the fitness metric:

- Balance max - the highest value of the balance.
- Net Profit max - the highest value of the net profit.

[2] https://www.metatrader5.com/en/trading-platform

- Expected Payoff max - a statistically calculated value showing the average return of one deal.
- Drawdown max - difference between the initial deposit and the minimal level below initial deposit throughout the whole testing period.
- Recovery Factor max — the highest value of the riskiness of the strategy, i.e. the amount of money risked by the Expert Advisor to make the profit it obtained.
- Sharpe Ratio max — the highest value of the efficiency and stability of a strategy. It reflects the ratio of the arithmetical mean profit for the position holding time to the standard deviation from it.

For our GA layer, we decided to use as fitness metric the net profit. In conclusion, the output of the GA layer is a chromosome which has the greatest fitness value discovered.

5. Filippo Experiments

Dataset. If the document class *elsarticle* is not available on your computer, you can download and install the system package *texlive-publishers* (Linux) or install the LaTeX package *elsarticle* using the package manager of your TeX installation, which is typically TeX Live or MikTeX.

Algorithm descriptio. Once the package is properly installed, you can use the document class *elsarticle* to create a manuscript. Please make sure that your manuscript follows the guidelines in the Guide for Authors of the relevant journal. It is not necessary to typeset your manuscript in exactly the same way as an article, unless you are submitting to a camera-ready copy (CRC) journal.

Experiments. The Elsevier article class is based on the standard article class and supports almost all of the functionality of that class. In addition, it features commands and options to format the

- document style
- baselineskip
- front matter
- keywords and MSC codes
- theorems, definitions and proofs
- lables of enumerations
- citation style and labeling.

References

[1] M. S. Raimundo, J. Okamoto, Svr-wavelet adaptive model for forecasting financial time series, in: 2018 International Conference on Information and Computer Technologies (ICICT), 2018, pp. 111–114. doi:10.1109/INFOCT.2018.8356851.

[2] P. Taveeapiradeecharoen, K. Chamnongthai, N. Aunsri, Bayesian compressed vector autoregression for financial time-series analysis and forecasting, IEEE Access 7 (2019) 16777–16786. doi:10.1109/ACCESS.2019.2895022.

[3] C. Serjam, A. Sakurai, Analyzing predictive performance of linear models on high-frequency currency exchange rates, Vietnam Journal of Computer Science 5 (2) (2018) 123–132. doi:10.1007/s40595-018-0108-x.
URL https://doi.org/10.1007/s40595-018-0108-x

[4] S. Achchab, O. Bencharef, A. Ouaarab, A combination of regression techniques and cuckoo search algorithm for forex speculation, in: Á. Rocha, A. M. Correia, H. Adeli, L. P. Reis, S. Costanzo (Eds.), Recent Advances in Information Systems and Technologies, Springer International Publishing, Cham, 2017, pp. 226–235.

[5] S. K. Chandrinos, N. D. Lagaros, Construction of currency portfolios by means of an optimized investment strategy, Operations Research Perspectives 5 (2018) 32–44. doi:https://doi.org/10.1016/j.orp.2018.01.001.
URL https://www.sciencedirect.com/science/article/pii/S2214716017301148

[6] D. Pradeepkumar, V. Ravi, Forecasting financial time series volatility using particle swarm optimization trained quantile regression neural network, Applied Soft Computing 58 (2017) 35–52. doi:https://doi.org/10.1016/j.asoc.2017.04.014.
URL https://www.sciencedirect.com/science/article/pii/S1568494617301862

[7] S. R. Das, Kuhoo, D. Mishra, M. Rout, An optimized feature reduction based currency forecasting model exploring the online sequential extreme learning machine and krill herd strategies, Physica A: Statistical Mechanics and its Applications 513 (2019) 339–370. doi:https://doi.org/10.1016/j.physa.2018.09.021.
URL https://www.sciencedirect.com/science/article/pii/S0378437118311476

[8] S. Galeshchuk, S. Mukherjee, Forex trading strategy optimization, in: E. Bucciarelli, S.-H. Chen, J. M. Corchado (Eds.), Decision Economics: In the Tradition of Herbert A. Simon's Heritage, Springer International Publishing, Cham, 2018, pp. 69–76.

[9] L. Ni, Y. Li, X. Wang, J. Zhang, J. Yu, C. Qi, Forecasting of forex time series data based on deep learning, Procedia Computer Science 147 (2019) 647–652, 2018 International Conference on Identification, Information and Knowledge in the Internet of Things. doi:https://doi.org/10.1016/j.procs.2019.01.189.
URL https://www.sciencedirect.com/science/article/pii/S1877050919302066

[10] R. Dash, Performance analysis of a higher order neural network with an improved shuffled frog leaping algorithm for currency exchange rate prediction, Applied Soft Computing 67 (2018) 215–231. doi:https://doi.org/10.1016/j.asoc.2018.02.043.
URL https://www.sciencedirect.com/science/article/pii/S1568494618301029

[11] S. Ahmed, S.-U. Hassan, N. R. Aljohani, R. Nawaz, Flf-lstm: A novel prediction system using forex loss function, Applied Soft Computing 97 (2020) 106780. doi:https://doi.org/10.1016/j.asoc.2020.106780.
URL https://www.sciencedirect.com/science/article/pii/S1568494620307183

[12] B. Jubert de Almeida, R. Ferreira Neves, N. Horta, Combining support vector machine with genetic algorithms to optimize investments in forex markets with high leverage, Applied Soft Computing 64 (2018) 596–613. doi:https://doi.org/10.1016/j.asoc.2017.12.047.
URL https://www.sciencedirect.com/science/article/pii/S1568494618300036

[13] T. N. T. Thu, V. D. Xuan, Using support vector machine in forex predicting, in: 2018 IEEE International Conference on Innovative Research and Development (ICIRD), 2018, pp. 1–5. doi:10.1109/ICIRD.2018.8376303.

[14] R. S. Lee, Cosmos trader – chaotic neuro-oscillatory multiagent financial prediction and trading system, The Journal of Finance and Data Science 5 (2) (2019) 61–82. doi:https://doi.org/10.1016/j.jfds.2019.01.001.
URL https://www.sciencedirect.com/science/article/pii/S2405918818300990

[15] E. Bartoš, R. Pinčák, Identification of market trends with string and d2-brane maps, Physica A: Statistical Mechanics and its Applications 479 (2017) 57–70. doi:https://doi.org/10.1016/j.

physsa.2017.03.014.
URL https://www.sciencedirect.com/science/article/pii/S0378437117302273

[16] P. Taveeapiradeecharoen, N. Aunsri, Dynamic model averaging for daily forex prediction: A comparative study, in: 2018 International Conference on Digital Arts, Media and Technology (ICDAMT), 2018, pp. 321–325. doi:10.1109/ICDAMT.2018.8376549.

[17] A. V. Contreras, A. Llanes, A. Pérez-Bernabeu, S. Navarro, H. Pérez-Sánchez, J. J. López-Espín, J. M. Cecilia, Enmx: An elastic network model to predict the forex market evolution, Simulation Modelling Practice and Theory 86 (2018) 1–10. doi:https://doi.org/10.1016/j.simpat.2018.04.008.
URL https://www.sciencedirect.com/science/article/pii/S1569190X18300571

[18] A. Wilinski, Time series modeling and forecasting based on a markov chain with changing transition matrices, Expert Systems with Applications 133 (2019) 163–172. doi:https://doi.org/10.1016/j.eswa.2019.04.067.
URL https://www.sciencedirect.com/science/article/pii/S0957417419303033

[19] S. Seifollahi, M. Shajari, Word sense disambiguation application in sentiment analysis of news headlines: an applied approach to forex market prediction, Journal of Intelligent Information Systems 52 (1) (2019) 57–83. doi:10.1007/s10844-018-0504-9.
URL https://doi.org/10.1007/s10844-018-0504-9

[20] M. Ozturk, I. H. Toroslu, G. Fidan, Heuristic based trading system on forex data using technical indicator rules, Applied Soft Computing 43 (2016) 170–186. doi:https://doi.org/10.1016/j.asoc.2016.01.048.
URL https://www.sciencedirect.com/science/article/pii/S1568494616300369