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ORIGINAL RESEARCH

A Hybrid-SFLA-Based Hyper-Parameter Tuning Algorithm in SVR for Exchange Rate Prediction

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Abstract

This paper proposes a hybrid machine learning-based approach to forecast the exchange rate between the Indian Rupee and the US dollar. The prediction of the exchange rate is carried out by support vector regression (SVR) and a hybrid-shuffled frog leaping algorithm (HSFLA). SVR predicts the exchange rate, whereas the hybrid-SFLA is used to tune the hyper-parameters. Hybrid-SFLA is an improvement over SFLA where random movement of particles is carried out using levy flight distribution. The proposed work has been compared with state-of-the-art hybrid prediction models that have applied different meta-heuristic algorithms. To measure predictive efficiency, root mean square error, mean absolute percentage error, Theil's U, and average relative variance have been used, and the proposed HSFLA outperformed the other methods.

Keywords Exchange rate · SVR · Hybrid-shuffled frog leaping algorithm (HSFLA) · Memetic algorithm

Introduction

The exchange rate is the price of foreign currency with respect to the domestic currency and is dependent on factors impacting flow of foreign currency in and out of the domestic economy. Foreign currency flows through the current account and capital account of the balance of payments. Components of the current account include exports–imports of goods and services, whereas foreign direct investment and foreign portfolio investment are the major components of the capital account. The combination of these two accounts is reflected in foreign exchange reserves which are used by central banks to control exchange rate volatility. Exports of an economy are determined by the extent of international competitiveness of the industrial, agricultural, and services sectors, and imports reflect consumption and production patterns. The movement of foreign currency through the capital account depends on the relative attractiveness of the domestic economy as an investment destination and factors governing such movement are present in the covered interest arbitrage condition.

A macroeconomic approach to exchange rate determination is given in Messe and Rogoff [1], and a financial market approach is given in Datta Chaudhuri and Ghosh [2]. For a broader understanding of the determination of the exchange rate, one can refer to the literature on macroeconomics and trade theory by Fleming [3], Balassa [4], Samuelson [5], Meade [6], Caves and Jones [7], and Dornbusch [8]. The exchange rate volatility is of concern to policymakers as it has macroeconomic effects on the domestic economy. Intervention by the central bank to avoid destabilizing effects on the exchange rate is often required. This requires the accumulation of forex reserves, which takes time. It may be recalled that India ran out of foreign currency reserves in 1990–91, which ushered in a new era of macroeconomic

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policy-making. Currently, Sri Lanka has run out of foreign currency reserves and has sought the help of the International Monetary Fund. Extreme exchange rate instability can put pressure on the reserves' position and have serious consequent macroeconomic effects. It is, thus, important to have in place a framework with which movements in the exchange rate can be understood, the sources of instability can be identified, and efficient forecasts can be made. This will help policymakers in taking proactive action before things go out of control.

The ongoing Russia–Ukraine war has led to a significant increase in fuel prices in India and has had a detrimental effect on the balance of trade. Tightening of fiscal support and consequent hardening of rates of interest in the US has led to significant outflow of dollars in the capital account. These have resulted in depreciation of the Indian rupee from around Rs. 74 to the US dollar in the month of February 2022 to around Rs. 79.30 plus in July 2022. As per reports, this has caused a reduction in reserves of around six billion US dollars. The implied volatility index (INDIA VIX) has increased for around 15 levels on an average, to around 30 in the last few months.

The purpose of the discussion above was to emphasize that movement in the exchange rate, besides being caused by factors in the current account and the capital account, can also be affected by macroeconomic shocks, both at home and abroad. Thus, a framework for understanding and forecasting the exchange rate has to consider all these factors. An added dimension of the exchange rate is that it is also a financial asset. The literature on exchange rate forecasting has focused on macroeconomic factors, the covered interest arbitrage condition, market volatility at home and abroad, crude oil price volatility, market sentiment and also lagged values of the exchange rate itself. There are a number of methods which have been used for forecasting. The lag variables were considered as an input in Zhang and Berardi's [9] neural network ensemble prediction of the British pound to the US dollar exchange rate. Using an artificial neural network framework, Yusuf and Perwej [10] explored forecasting the Indian rupee to the US dollar exchange rate where the selection of several input nodes and hidden layers is the concern. To forecast future exchange rate values, lagged exchange rate values are used. Lam et al. [11] propose a Bayesian model for predicting the exchange rate following the work of Rogoff [1]. A wide range of explanatory factors was considered, including stock price, long-term interest rate, change in stock price, term spread, interest rate in short-term basis, price of oil and change in the price of oil, exchange rate return in the predominant period, earlier period return of exchange rate sign, real GDP seasonally adjusted, and the change reflected by seasonally adjusted real GDP. The parameters range also includes seasonally adjusted money supply, change in same followed by the price levy for consumer. Numerous parameters are measured in comparison to those of other countries. Down the line, in another forecasting model, six nonlinear ensemble architectures were used by Ravi et al. [12].

The only input variables used in this article are the lagged values of the exchange rates themselves, even though various forecasting techniques are used. In 2011 for estimating the Indian Rupee against US Dollar exchange rate, both Bayesian vector auto regression (BVAR) and vector auto regression (VAR) were used by Dua et al. [13]. Along with future exchange rates, they also take into consideration capital account and current account variables, following Messe and Rogoff [1]. The index of Nasdaq, Daily Exchange Rate of Euro against New Zealand USD, price of Gold Spot-USA, government Bonds average return in USA zone and Euro zone for 5 years, price of Crude Oil and previous day Exchange Rate of Euro against US Dollar were taken as input variables in the analysis of Pacelli's work (2012). In the same for comparison and prediction, GARCH, ARCH, and CNN models were used [14].

The present study is for the Indian economy and the time period under consideration is 19/10/2011–18/6/2021. It covers the time period before the new BJP government came to power, the period under two terms of the BJP government, the period of macroeconomic slowdown during 2017–2019, and also the first and second waves of the COVID-19 pandemic period. Figures 1, 2, 3, 4, 5 and 6 show the movement in dependent variable, the Indian Rupee US Dollar exchange rate, and the movement in the independent variables over the time period of the study. It is evident that the there are differences in pattern of movement in the variables and Table 1 reports the statistical properties of the exchange rate. Figures 1, 2, 3, 4, 5 and 6 show movements in the exchange rate, volatility of the exchange rate, nifty returns, IT sector returns, pharma sector returns, and Indian VIX. The diagrams are shown to indicate volatility and time dependence of the variables. They demonstrate that macroeconomic factors have affected India VIX and sectoral returns have been

Table 1 Descriptive statistics and fundamental properties of dependent variable

Measures	Values
Minimum	48.653
Maximum	77.57
Mean	64.4523
Median	64.89
Mode	55.648
SD	6.383
Skewness	−0.4177
Kurtosis	−0.4761
Adf test statistic	−1.355
JB test statistics	90.55012
Hurst exponent	0.841

Fig. 1 Movement in the exchange rate during 19/10/2011–18/6/2021

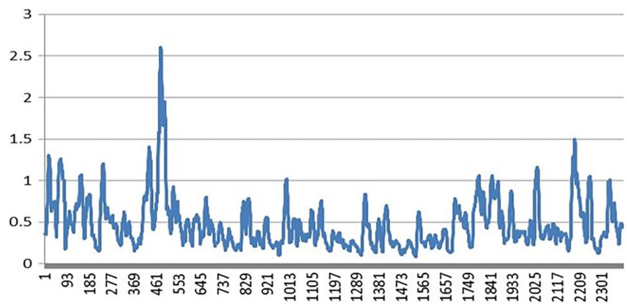


Fig. 2 Movement in volatility of the exchange rate during 19/10/2011–18/6/2021

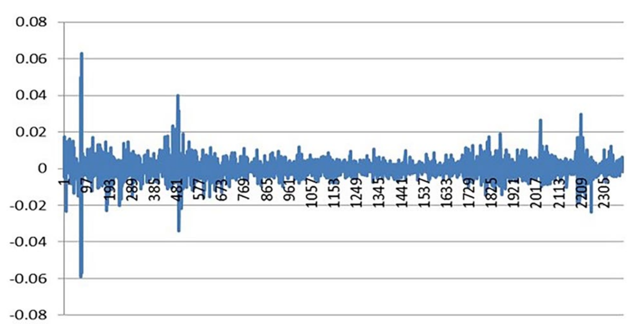


Fig. 3 Movement in Nifty returns during 19/10/2011–18/6/2021

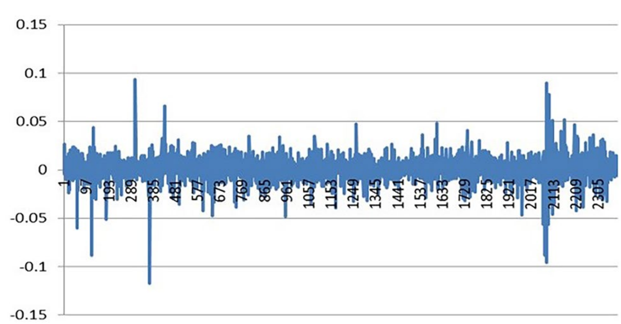


Fig. 4 Movement in IT returns during 19/10/2011–18/6/2021

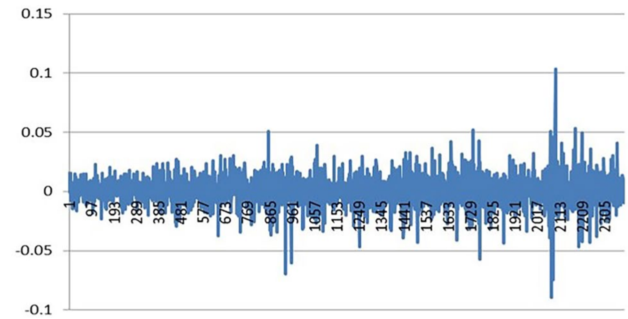


Fig. 5 Movement in Pharma sector returns during 19/10/2011–18/6/2021

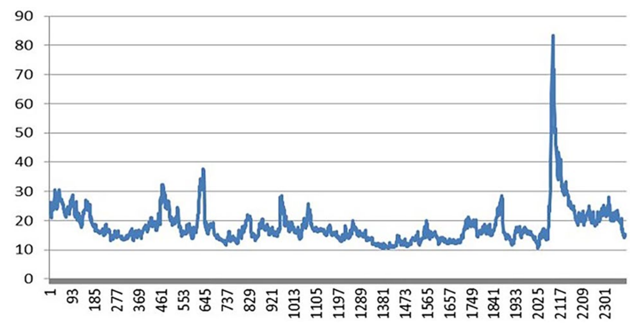


Fig. 6 Movement in India VIX during 19/10/2011–18/6/2021

quite volatile at times. The figures justify use of our proposed method, as against frameworks using linear methods.

In this paper, we include macroeconomic factors, variables drawn from the capital and current account of the balance of the payments, the covered interest arbitrage condition, past and expected domestic and foreign macroeconomic volatility, crude oil price volatility and also technical indicators to incorporate the financial asset aspect of foreign exchange as variables explaining movement in the Indian Rupee in contrast to US Dollar exchange rate. The present study on prediction of the exchange rate is carried out by support vector regression (SVR) and a hybrid-shuffled frog leaping algorithm (HSFLA). Accordingly, the plan of the paper is as follows. "Related work" discusses related works in the area. The proposed methodology is elaborated in "Proposed methodology (SVR–HSFLA prediction model)", the results are presented in "Results and discussion" and "Conclusion" concludes the paper.

Related Work

A.I. and ML have been used in several prediction models to forecast exchange rates. Andreou and Zombanakis [15] anticipated the exchange rate of the Euro against the

Japanese yen and the US dollar using artificial neural network. According to Rescaled range Statistics (R/S), their research revealed that time series exhibit random behavior. The neural network model used in their proposal produce good predictions in terms of mean square error (MSE), mean absolute error (MAE), mean relative error (MRE), and normalized root mean squared error (NRMSE). To predict the exchange rate, different sets of predictors have been used in a multivariate framework. Using the GARCH extended machine learning models, Garg [16] presented a novel framework where random forests, regression trees, least absolute shrinkage and selection operator (LASSO), SVR, and Bayesian additive regression trees (BART) have been used. In 2015 to predict exchange rates, the knowledge guided artificial neural network (KGANN) structure was applied by Jena et al. [17]. Premade et al. [18] put forth a unique technique that uses differential empirical mode decomposition (EMD) to boost the forecasting abilities of SVR [18]. According to the results, the recommended framework performed better than Markov switching regression models and Markov switching GARCH. A comparison was conducted by Majhi et al. [19] between Wilcoxon artificial neural network (WANN) and Wilcoxon functional link artificial neural network (WFLANN) for exchange rate forecasting.

While Wong et al. [20] applied wavelets to forecast the US dollar exchange rates against the Deutsche mark, later in another proposal, fuzzy wavelet model has been used for exchange rate forecasting between Indonesian IDR and US dollar by Septiarini [21]. A few subsequent works in this area are Tao [22], Lebaron [23], Baetaens et al. [24], Kaashoek and Van Djik [25]. In a recent study, Das, Mishra, and Rout proposed an ELM-Jaya hybrid model to forecast USD to INR and USD to EURO based on statistical measure [26]. In the area of machine learning, hybrid models have drawn attention to prediction because of their higher accuracy than traditional models. In Wafa [27], hyper-parameter tuning of artificial neural network (ANN) using particle swarm optimization (PSO) is done to forecast energy prices with an accuracy of 96%. In the area of exchange rate prediction, Hamori [28] proposed a random forest (R.F.) and CNN-based model. In 2021, Jonathan applied extreme gradient boosting and CNN to predict exchange rates for ten currency pairs of OECD countries [29]. An improvement over frog leaping algorithm along with a computationally efficient functional link artificial neural network (CEFLANN) has been used by Das [30] to forecast the exchange rate for USD against CAD, USD against CHF, and USD against JPY. In another exchange rate prediction model [31], PSO is used to tune the hyper-parameters of support vector regression (SVR) and its prediction accuracy is greater than the autoregressive integrated moving average (ARIMA). Mahmoud et al. [32] proposed another SVR-based prediction model where the shuffled frog leaping algorithm (SFLA) was applied to tune hyper-parameters of SVR. In 2019, Li and Yan combined the shuffled frog leaping algorithm and bacterial foraging algorithm to improve the local search of particles [33]. Leavy flight random walk applied over a group of particles to upgrade the position [34] which improve the global search ability and surpass the SFLA. When this hybrid-SFLA is applied to tune SVR for more accurate balancing between SVR parameters. It outperforms PSO and SFLA-based hyper-parameter tuning methods in reducing errors and, therefore, improves prediction accuracy.

In contemplation of higher forecasting accuracy, the present study is an Indian rupee US dollar exchange rate prediction model combining SVR and hybrid-SFLA. When SVR parameters are optimized using meta-heuristic procedures, the prediction error is reduced [32]. In this study, the hyperline parameters of SVR are tuned in a balanced order by the hybrid-SFLA [33]. The explanatory factors that we use include macroeconomic variables, volatility indicators, lagged exchange rate values, and technical indicators. We emphasize that the exchange rate, while affected by macroeconomic factors, is also a financial asset traded in the market. Thus, technical indicators are introduced to capture the financial asset aspect of foreign currency.

Proposed Methodology (SVR–HSFLA Prediction Model)

In this section, we have discussed the methodology of the hybrid learning model. Support vector regression (SVR) and hybrid-SFLA are applied to train the dataset. In SVR, hyper-parameters accurately determine the prediction accuracy of the model which are interrelated with each other. Tuning hyper-parameters of SVR by nature-inspired algorithms is a novel idea. In recent studies, PSO and SFLA are used to tune these hyper-parameters and minimizes errors in prediction [31, 32]. PSO is a bird flocking algorithm, whereas the shuffled meta-heuristic optimization method enables the local search of particles as well as exchange of global information between groups by involvement of a population of possible solutions. From this point of view, SFLA is better in tuning SVR parameters [35]. However traditional SFLA, discussed in "Tuning hyper-parameters of SVR", could improve the local search when merged with Levy flight algorithm. Levy flight is a random search process and been widely used in metastatic algorithms [34]. In each memeplex to improve worst frogs position levy flight randomization upgrade over a portion of particles is applied [33]. The hybrid approach improves the credibility of global search rather than the tradition SFLA. In the present work, hybrid-SFLA is used to balance the adjustment parameters of the SVR model. The entire process is discussed in "Shuffled frog leaping algorithm (SFLA)" and Fig. 7 shows the overall process diagrammatically.

In 2019, Li and Yan combined the SFLA and lavy flight algorithm to improve the local search of particles [33]. Leavy flight update strategy was applied to improve the search in global space and surpass the SFLA. When this hybrid-SFLA is applied to tune SVR, it outperforms PSO and SFLA-based hyper-parameter tuning methods. The hybrid-SFLA algorithm finds the optimal values for the hyper-parameters.

We have discussed the feature selection algorithm in "Support vector regression (SVR)". In "Tuning hyper-parameters of SVR", we have discussed the SVR-based prediction model, where we tuned the hyper-parameters using the hybrid-SFLA algorithm.

Support Vector Regression (SVR)

This supervised algorithm is used for classification, regression, and clustering. In the paper, the regression model is the backbone of prediction. In 1990 Vapnik et al. introduced the SVM model [36] to serve the purpose of creating a maximum separating plane or optimal hyper-plane. The SVM regression mode, known as SVR, is used to identify an optimal hyper-plane. Hyper-planes work as decision boundaries that help to predict the continuous output. Distance of data points from the optimal hyperline is to be minimum [37]. Vapnik's-ϵ insensitive loss function is used in SVR. For a sample dataset ui, vi, where $i = 1, ..., n$. Ui is the input vector and vi is the target vector. The loss function is formulated in Eq. (1).

$$L_\epsilon(v, g(u)) = \left\{ \begin{array}{ll} 0 & |v - g(u)| \le \epsilon \\ |v - g(u)| - \epsilon & otherwise \end{array} \right\}. \tag{1}$$

The regression function is defined in Eq. (2).

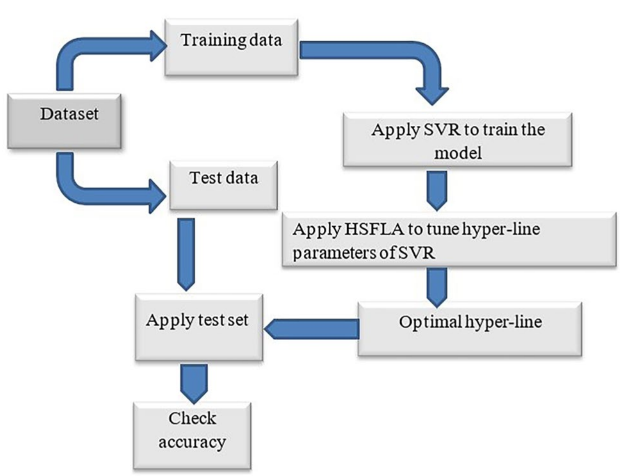


Fig. 7 SVR–HSFLA prediction framework

$$g(u) = w.u + b. \tag{2}$$

Here, $w \in z$ and $b \in R$ is bias term and (w, u) is dot product of w and u vectors. $||w||^2$ is to be minimized for better fatness. According to Eqs. (1) and (2), any regression problem is represented in Eq. (3).

$$\min_{w,b,\xi,\xi^*} \frac{1}{2}||w||^2 + c\sum_{i=1}^{n}(\xi + \xi^*), \tag{3}$$

$$\text{subject} \quad to \left\{ \begin{array}{l} v_i - (w.u_i + b) \le \epsilon + \xi \\ (w.u_i + b) - v_i \le \epsilon + \xi_i \\ \xi_i, \xi_i^* \ge 0; i = 1, 2, ..., n \end{array} \right\}. \tag{4}$$

In Eq. (4), ξ and ξ^* are slack variables used for calculating training samples which are outside ϵ-insensitive area. Basic objective function is represented in Eq. (4). The initial function is extended to a Lagrange function therefore to achieve a non-linearity a kernel function is formed. Available kernel functions are: linear, sigmoid, polynomial, and radial basis function (RBF). RBF is mostly used to fulfill the purpose and in case of SVR also the same is followed.

$$K(u_i, u) = \exp(-\gamma||u_i - u_j||^2). \tag{5}$$

Equation (5) shows the involvement of γ to control the smoothness of the decision boundary. Resultant of the process is an optimal regression function following Eq. (6).

$$g(u) = \sum_{i=1}^{n}(\underline{\alpha_i}, \overline{\alpha_i})K(u_i, u) + b, \tag{6}$$

where $0 \le \underline{\alpha_i}$ and $\overline{\alpha_i} \le c$. The kernel function is represented by $K(u_i, u)$. $\underline{\alpha_i}$ and $\overline{\alpha_i}$ are Lagrange multipliers.

Tuning Hyper-Parameters of SVR

In SVR, tuning the hyper-parameters accurately determines the prediction accuracy of the model. These parameters are interrelated with each other. Each particle is expressed in terms of three parameters: C, σ and ϵ. C is the regularization parameter engaged in maximizing tube size margin and minimizing errors. σ is the function bandwidth whereas ϵ used to reflect accuracy based on training data. Higher value of C causes overfitting, whereas smaller value effects in under-fitting while training [38]. For a RBF kernel, both σ and C need to be optimized simultaneously. As radius of the tube is regulated by ϵ in the regression function and the value of ϵ has a strong relation with the amplitude of the noise in training data, therefore, it is hard to predict the amount od noise present in the dataset. The present study focuses on balancing these parameters simultaneously within optimized range applying HSFLA. In this study, the optimized range of ϵ is considered within 0.001–0.2 and the value of C has been considered within 0.01–2000. Ranges of ϵ and C have been considered based on the range taken by earlier researches like [37, 39].

$$C = \max(|\bar{y} + 3\sigma_y|, |\bar{y} - 3\sigma_y|) \text{ and } \epsilon = 3\sigma\sqrt{\frac{\ln(n)}{n}}. \tag{7}$$

In Eq. (7), $\bar{y}$ denotes mean of y values whereas σ_y is standard deviation of y values. ϵ is calculated using k-nearest neighbor method and n is the number of training data.

Shuffled Frog Leaping Algorithm (SFLA)

The present research has applied the hybrid-SFLA to tune the SVR parameters which is a continuation of SFLA. In 2003, Yusuf and Lansey reported a new meta-heuristic algorithm [40] combining memetic algorithm (M.A.) [41] and particle swarm optimization (PSO) [42]. Mahmoudi et al. proposed a SVR-hyperparameter tuning model using SFLA where C, σ and ϵ. C is tuned using SFLA [43]. SFLA is a population-based heuristic search algorithm mainly used for optimization. Here, each frog is considered as a particle. An objective function ranks the frogs in ascending/ descending order. After that, the frogs are divided into K memeplexes. If there are M frogs, M/K frogs are allocated in each memeplex. Following this, the frog with the best fitness value is put into the first memeplex and the next to the second memeplex. The process is continued till Mth frog is assigned to Mth memeplex. The next step is carried out in such a way that $(M + 1)$th frog is allocated to the first memeplex again. Once this is over, from each memeplex, the best frog is identified as X_{kb} and the worst one is identified as X_{kw}. In the entire set, the best frog is known as the global best and is identified as X_g. In each iteration, along with the allocation process, the leaping of frogs to upgrade their position is taken place. The worst frog in each memeplex moves toward the best or optimal one. At the end of each iteration, if it is found that the new position is better than the previous one, it is upgraded. The continued until a predefined threshold of the iteration number or a satisfactory objective value is obtained.

Hybrid-Shuffled Frog Leaping Algorithm (HSFLA)

An improvement over the SFLA [40] is carried out here by modifying the exchange procedure in leaping. Here in this proposal for the first time hybrid-SFLA is used to tune the regularization parameter of SVR. The hybrid-SFLA tries to improve the frog's position in the worst position in every iteration [33]. Equations (8), (9), and (10) show the movement of X_{kw}.

$$D_K^t == \text{rand}(X_{kb} - X_{kw}), \tag{8}$$

$$D_{\text{Min}} \le D_K^t \le D_{\text{Max}}, \tag{9}$$

$$X_{Kw}^{t_1} = X_{Kw}^t + D_K^t. \tag{10}$$

Here, D_K^t is the movement of the frog with the worst value within the memeplex K for tth iteration. rand indicates a random value generated between 0 and 1. Minimum and maximum changes allowed for the worst frog are denoted by D_{Min} and D_{Max}. $X_{Kw}^{t_1}$ and X_{Kw}^t denotes the positions of the worst frog in t_1th and tth iterations, respectively. The hybrid form of SFLA is explained here:

Step 1: For a total sample size of $F = mn$, m indicates the number of memeplexes, and n denotes the number of frogs in each memeplex.

Step 2: For a virtual sample, the feasible space is denoted as $U(1), U(2), \ldots U(F)$. $U(i) = (U_i^1, U_i^2, \ldots U_i^{kd})$ is a candidate solution with K cluster centers.

Step 3: Arrange frogs in descending order like $X = U(i), f(i), i = 1, \ldots\ldots F$, where i =1 is the best frog, and its position is stored in P_x, i.e., $P_x = U(1)$.

Step 4: Arrange frogs in memeplex. X is partitioned into $Y_1, Y_2, \ldots. Y_m$ so that each partition contains n frogs.

Step 5: In the process of memetic evaluation for each memeplex, $Y^l, l = 1, \ldots.., m$, each iterate for N times. Once the local search is complete, the evaluation of the global search starts as follows:

Step 5.1: Set two counter variables named im and iN, these are to count number of memeplexes and evolutionary steps, respectively. N counts maximum steps in individual memeplex. In each memeplex, the P_{b} denotes the frog with best target value whereas, P_{w} is the worst and P_{g} holds the global best fitness. Equations (11) and (12) are to improve the position of P_{w} after each cycle.

$$D_i = \text{rand}(m) \times (P_{\text{b}} - P_{\text{w}}). \tag{11}$$

Equation (11) computes the new position.

$$P_{\text{w}} = \text{present} \quad \text{position}.P_{\text{w}} + D_i, \tag{12}$$

where $D_{\max} \ge D_i \ge -D_{\max}$. Dmax and Dmin are the maximum and minimum allowed movements in the frog's position and rand function produces a random value between 0 and 1.

Step 5.2: If the updated position is better than the former, an up-gradation is followed replacing the previous frog with the upgraded one. A decreasing order of fitness is followed to keep frogs in a queue. Unlike the SFLA (discussed in "Shuffled frog leaping algorithm (SFLA)") the levy flight is applied over a group of frogs to improve the global search accuracy. Levy flight is not applied over the entire population, only half of the population having better solution is updated as per SFLA whereas, the rest updates their positions by using Levy flights to increase global search ability using Eq. (13).

$$x_i^{t+1} = x_i^{(t)} + \alpha \oplus \text{Levy}(\lambda) i = 1, 2, ..., n. \tag{13}$$

In Eq. 13, tth location of x_i is $x^{(t)}$. $\oplus$ is the point-to-point multiplication operator. α controls the step length. Levy(λ) is a random search path followed by the limit given in Eq. (14).

$$\text{Levy} \sim u = t^{-\lambda} \quad 1 < \lambda \le 3. \tag{14}$$

The random step length distribution of the Levy flight is simulated by the Mantegna algorithm using Eq. (15).

$$\left\{\begin{array}{l} s = \frac{\mu}{|v|^{1/\beta}} \\ \mu \sim N(0, \sigma_\mu^2) \\ v \sim N(0, \sigma_v^2) \\ \sigma_\mu = \left\{ \frac{\Gamma(1+\beta) sin(\frac{\pi\beta}{2})}{\Gamma[\frac{(1+\beta)}{2}]\beta 2^{\frac{(\beta-1)}{2}}} \right\}^{1/\beta} \\ \sigma_y = 1 \end{array}\right\}. \tag{15}$$

In Eq. (15), μ and v are Gaussian distribution variables, Γ denotes the standard gamma function and β is 1.5. The location update is done using Levy flight and defined in Eq. (16).

$$X_{g+1,i} = X_{g,i} + \alpha \frac{\mu}{|v|^{1/\beta}} (X^{g,i} - P_g). \tag{16}$$

For equal fitness of individual particles, adaptive migration is applied using Eq. 17.

$$\text{Pred}(i) = 1 - (\frac{S-i}{S-1})^2. \tag{17}$$

S indicates the population size and i is the serial number. It concludes that lower fitness is inversely proportional to the migration probability.

Step 5.3: On achieving a better solution, the frog with worst solution is replaced by the new one. Otherwise, the process is repeated. A randomly generated new solution with arbitrary fitness continues if no improvement is observed.

Step 5.4: If $iN < N$, increase i and repeat Step 5.1. Do the same for m if $im < m$ and repeat from Step 5.1. Otherwise, apply global search to shuffle memeplex.

Step 6: When the threshold is met, replace $Y1, ..., Ym$ into X so that $X = Yk, k = 1, ..., m$. Arrange X in decreasing order.

Step 7: Stop if convergence criteria are met; otherwise, go to step 4.

Step-wise decryption of SVR–HSFLA

Step 1. Normalize the exchange rate dataset and remove redundant data.

Step 2. Split the dataset into training data(x) and test data(y).

Step 3. Apply SVR on dataset x to predict the exchange rate.

Step 4. To set an optimal range of σ, ϵ and C apply HSFLA for tuning (Detail of the entire process is in "Tuning hyper-parameters of SVR").

Step 5. Set a sample size of $F = mn$ comprising memeplex(m) and number of frogs(n). A randomly generated new solution with arbitrary fitness continues if no improvement is observed.

Step 6. If a better solution is achieved, stop HSFLA as per the convergence criteria. Otherwise repeat step 3 to 6. (Detail in "Hybrid-shuffled frog leaping algorithm (HSFLA)")

Step 7. Test the predicted exchange rate against dataset y.

Step 8. Check prediction accuracy.

Results and Discussion

We describe the variables used in the analysis in "Variables" and compare our results with alternative algorithms in terms of efficiency measures in "Results".

Variables

This paper presents an approach to forecasting the Indian rupee—US dollar exchange rate. The Indian Rupee vs US. Dollar exchange rate (E) is the dependent variable where t is the time subscript.

The independent/explanatory variables are Et-1, Et-2, Et-3, the lagged values of the exchange rate; EV, EV1, EV2, EV3, the volatility in the exchange rate and its lagged values; NIFTY R, market returns in the Indian stock market representing overall Indian macroeconomic sentiment and DJIA R, market returns in the US stock market reflecting overall macroeconomic sentiment in the rest of the world. ITR, AUTO R, FMCG R, METAL R, and PHARMA R are the returns of the indices of the I.T. sector, the Auto sector, the FMCG sector, the Metal sector, and the Pharma sector, respectively, in India. These explanatory variables are included to represent the performance of the different sectors of the Indian economy and their role in exchange rate determination. While the IT and the Pharma sectors are foreign exchange earners, the Auto, FMCG, and Metal sectors are users of foreign exchange. The movement in these indices also reflects the macroeconomic scenario as they form an important part of GDP. The model has been trained over a volume of 2770 dataset.

The other explanatory variables are IVIX, IVIX1, IVIX2, and IVIX3, the implied volatility index of the Indian market, and its lagged values. They reflect expected market volatility.

CVIX, CVIX1, CVIX2, and CVIX3 are the implied volatility index of the US market and its lagged values. CRUDV, CRUDV1, CRUDV2, and CRUDV3 are the volatility of crude oil prices and their lagged values. These are included as Indian imports consist primarily of crude oil, and its volatility significantly affects the exchange rate. Technical indicators used as explanatory variables are Momentum = (E-E1), moving average convergence divergence (MACD) of E defined as the difference between 26-Day exponential moving average (EMA) and the 12-Day EMA, and 9-Day EMA of the spread. The latter is called the trigger line. This is a commonly used technical indicator used by traders.

The explanatory variables used in the study represent the macroeconomic environment of the Indian economy and that of the US, the current account and capital account of the balance of payments, and the financial asset aspect of foreign exchange. We have a unified framework of macroeconomic variables covering interest arbitrage conditions and trading methods. On the macroeconomic side, we also focus on sectoral performance reflected in sectoral indices. Besides the above, we explicitly consider expected market volatility at home and abroad and volatility in crude prices. Thus, our choice of explanatory variables is quite comprehensive.

Table 1 shows descriptive statistics and fundamental properties of the target variable. Dependent variables were SD: standard deviation, ADF test: Augmented Dickey–Fuller test, and J.B. test: Jarque–Bera test. Table 1 reflects that the ADF test statistic is non-significant. J.B. test statistic is significant at 1% level, which implies non-normality. Hurst exponent is significant at 1%, and the level implies past values influence present values, which justifies the use of lags. ADF and J.B. test statistics indicate that the time series is non-stationary and non-parametric. Hurst exponent indicates that the series was persistent during the period.

Results

In implementation, we have used Python programming in a core i3 processor with 8 G.B. of primary memory. The prediction accuracy of SVRHSFLA is compared against state-of-the-art methods. Somewhere regression model is solely applied without tuning hyper-parameters, and some recent studies where regression model is used as a primary prediction algorithm along with hyper-parameter tuning. It is an evident from the results that tuning the parameters of SVR by a heuristic algorithm enhances the prediction accuracy. Here, we have compared SVRHSFLA with SVR, PSOSVR [31], SVRSFLA [32]. Mean absolute percentage error (MAPE), root mean squared error (RMSE), Theil's U, and average relative variance (ARV) are used to calculate the prediction error on SVR and three other different hybrid methods. A lower range of RMSE and MAPE tends to result in higher forecasting accuracy. Equations (18) and 19 give details of RMSE and MAPE. Table 2 shows MAPE (%), RMSE, Theil's U, and ARV observed for SVRHSFLA. When SVRHSFLA is compared with the regression model without tuning hyperline parameters using MAPE (%), an improvement of 35% is observed. It is reflected in Table 3. In Table 4, MAPE (%), RMSE, Theil's U, and ARV observed for state-of-the-art methods are tabulated.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} ||y(i) - \bar{y}(i)||^2}{N}}, \tag{18}$$

where the number of data points is denoted by N. $y(i)$ is the i_{th} measurement, and $\bar{y}(i)$ is its corresponding prediction.

$$M = \frac{1}{n}\sum_{t=1}^{n} |\frac{A_t - F_t}{A_t}|, \tag{19}$$

$$\mathrm{ARV} = \frac{\sum_{i=1}^{N}(P_i - A_i)^2}{\sum_{i=1}^{N}(P_i - \tilde{A})}, \tag{20}$$

$$\mathrm{Theil'sU} = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(A_i - P_i)^2}}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}A_i^2} + \sqrt{\frac{1}{N}\sum_{i=1}^{N}P_i^2}}. \tag{21}$$

MAPE is a forecasting accuracy measurement method normally represented using percentages. Theil's U measures

Table 2 Prediction accuracy measurement metrics for SVRHSFLA

	MAPE (%)	RMSE	Theil's U	ARV
SVRHSFLA	2.735	0.325	0.002355	0.00181

MAPE (%), RMSE, Theil's U, and ARV

Table 3 MAPE (%), RMSE, Theil's U, and ARV observed with regression model without tuning hyperline parameters

	MAPE (%)	RMSE	Theil's U	ARV
SVR	4.212	0.875	0.007523	0.0683
SVRHSFLA	2.735	0.325	0.002355	0.00181

Table 4 Accuracy comparison using MAPE (%), RMSE, Theil's U, and ARV

	MAPE (%)	RMSE	Theil's U	ARV
SVR	4.212	0.875	0.007523	0.0683
PSOSVR	3.741	0.713	0.003111	0.0046
SVRSFLA	3.223	0.584	0.002541	0.002118
SVRHSFLA	2.735	0.325	0.002355	0.00181

the accuracy by comparing actual data and forecast data. Theil's U value range between 0 and 1. A value closer to 0 indicates better accuracy by the model, whereas > 1 value indicates a worse prediction. ARV takes the average value and indicates the range of changes between actual and prediction data value nearer to 0 indicates better prediction. Equations (20) and 21 give details of ARV and Theil's U, respectively. A_i denotes actual data, whereas P_i denotes the predicted data.

Figures 8 and 9 show prediction errors with respect to MAPE and RMSE, Theil's U and ARV consecutively. MAPE observed for SVR is 4.258%, and RMSE for the same is 0.87. When SVR hyperline parameters are adjusted using optimization algorithms, the prediction error is reduced. Hybridization of SVR with PSO and SFLA gives better prediction accuracy with MAPE 3.74% and 3.22% consecutively. SVRHSFLA outperforms other models where the error rate is reduced by 36% when compared against SVR with a MAPE of 2.73%. RMSE observed for SVRHSFLA is 0.325, which is minimum when compared against SVR, PSOSVR, and SVRSFLA. In Fig. 10, predicted accuracy against actual data is plotted where the actual value is indicated in blue whereas the red line indicates the test value for 239 data.

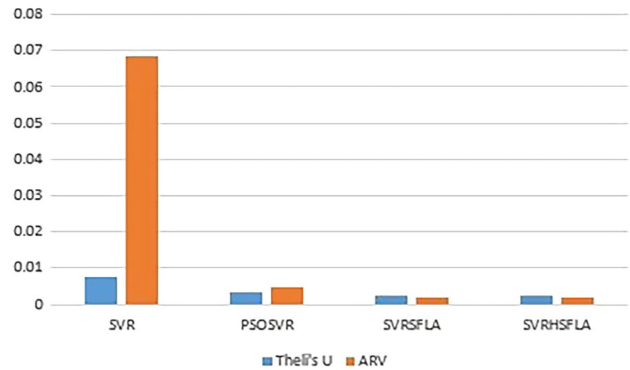
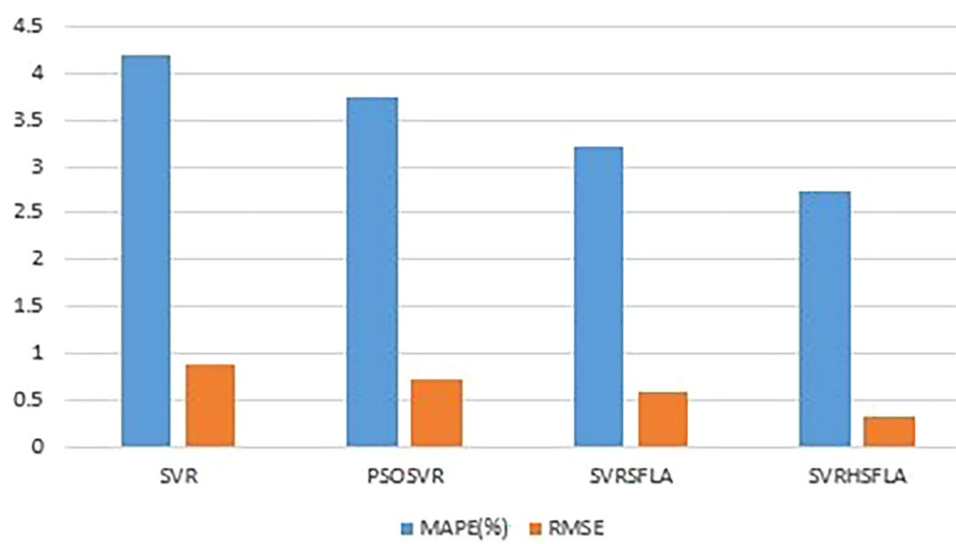


Fig. 9 Prediction accuracy of SVR, PSOSVR, SVRSFLA, and SVRHSFLA using Theil's U and ARV

Conclusion

In this study, we have focused on tuning SVR parameters in a balanced manner using the new hybrid-SFLA method and have applied it to forecasting the exchange rate. Forecasting the exchange rate is important for India as payments for imports of crude oil constitute more than 80% of its import payments. The recent Russia–Ukraine war has revealed the sensitivity of the rupee–dollar exchange rate to crude oil price movement and the consequent depletion of forex reserves. The hardening of interest rates in the US has also caused the Indian rupee to depreciate recently. In another example, the ongoing economic crisis in Sri Lanka has shown how an economy dependent on tourism and exports of tea can get severely affected by pandemic-like shocks leading to zero forex reserves resulting in inability to pay for petroleum imports and a slowing down of the economy. The present paper highlights the importance of these factors that can affect the exchange rate through the choice of appropriate variables, chosen from both the current account and the capital account of the balance of payments, differential returns, crude price volatility, exchange rate volatility, and implied volatility at home and abroad. The inclusion of technical indicators brings out the exchange rate's financial asset aspect and traders' role. The persistence in the time series has necessitated the use of lags. The paper also incorporates factors affecting foreign exchange demand and supply emanating from sectors like the I.T., AUTO, FMCG, METAL,

Fig. 8 Prediction accuracy of SVR, PSOSVR, SVRSFLA, and SVRHSFLA using MAPE (%) and RMSE



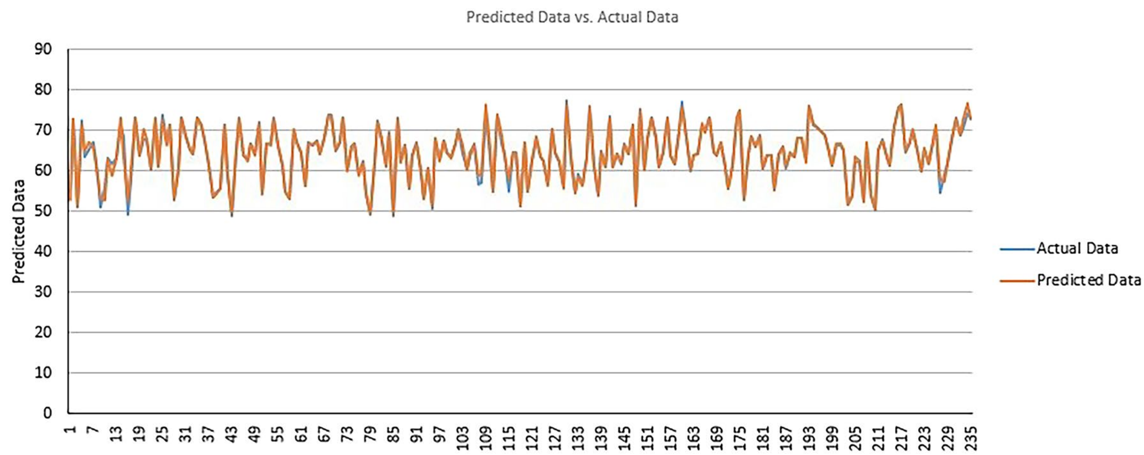


Fig. 10 Actual value (blue) and predicted value (red)

and PHARMA. While the IT and the Pharma sectors are foreign exchange earners, the Auto, FMCG, and Metal sectors are users of foreign exchange. The movement in the sectoral returns reflects the macroeconomic scenario as they form a significant part of GDP. In terms of predictive accuracy, the proposed hybrid-shuffled frog leaping algorithm performed better than the other algorithms measured by test statistics like MAPE, RMSE, Theil's U, and ARV. Our future work will focus on testing our algorithm on other exchange rates, incorporating the relevant variables reflecting fundamental factors of trading partners. We also intend to examine whether including more technical indicators improves predictive efficiency.

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.The authors have no conflicts of interest to declare that are relevant to the content of this article. All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript. The authors have no financial or proprietary interests in any material discussed in this article. Finally, the authors declare that they have no conflict of interest.

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