The Comparison between IABC with EGARCH in Foreign Exchange Rate Forecasting

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Abstract. Foreign exchange rate forecasting catches many researchers interests in recent years. Problems of the foreign exchange rate forecasting model selection and the improvement on forecasting accuracy are not easy to be solved. In this paper, the forecasting results obtained by conventional time-series models and by the Inter-active Artificial Bee Colony (IABC), which is a young artificial intelligent meth-od, are compared with each other with 4 years historical data. The sliding win-dow strategy is used in the experiment for both the training and the testing phases. In our experiments, we use continuous previous three days data as the training set, and use the training result to forecast the foreign exchange rate on the fourth day. In addition, we evaluate the forecasting accuracy with three criteria, namely, Mean Square Error (MSE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). The experimental results indicate that feeding macroeco-nomic factors to IABC as the input data is capable to produce higher accurate data in the foreign exchange rate than the conventional time-series models such as EGARCH.

Keywords: IABC, Foreign Exchange Rate Forecasting, Time-series, EGARCH.

1 Introduction

Foreign exchange rate forecasting is an important issue in finance. The forecasting result is quite sensitive to the selected forecasting model is one of the key factor re-sulting in the forecasting accuracy. In addition, the foreign exchange

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rate is quite sensitive to many factors such as price index, interest rates, money supply, balance of trade, and so forth. As the matter of fact, the forecasting accuracy is directly affected by the selection of the referenced variables and information fed into the forecasting model. Although the monetary theory model has higher accuracy than the random walk method [13] has been revealed, the performance of the monetary theory model is still limited [6]. Furthermore, most of the literatures focus on the long-term ex-change rate forecasting, only a few literatures discussed about the short-term, i.e. the daily exchange rate forecasting topic. It implies that the existing foreign exchange rate forecasting models are not sharp at short-term responses.

For the investors, who involve in the foreign exchange market, the profit comes from the short-term investment is much worth than from the long-term investment. Hence, the urgent need of new foreign exchange rate forecasting model for short-term prediction becomes clear. Answering to the need, we propose a new foreign exchange rate forecasting model based on Interactive Artificial Bee Colony (IABC) optimiza-tion, which is a young swarm intelligence algorithm, for the short-term foreign ex-change rate prediction. Our model requires the last 3 continuous historical data as the input for producing the predicted result for the next day.

The rest part of this paper is composed as follows: the literature review is given in section 2, our proposed method and the experiment design are described in section 3, the experiment design is depicted in section 4, the experimental results are given in section 5, and finally, the conclusion is made in section 6.

2 Literature Review

In this section, we first focus on the foreign exchange rate theory. A brief review on EGARCH is given in the next paragraph and is followed by the brief review on IABC algorithm.

2.1 Foreign Exchange Rate Theory

Many different theories of foreign exchange rate determination, including Purchas-ing Power Parity (PPP), monetary model, Interest Rate Parity (IRP), balance of pay-ment model, portfolio balance model, and etc. are proposed in finance history. The brief review of the models listed above are given as follows:

2.2 Purchasing Power Par (PPP) and Monetary Model

The PPP theory claims that the exchange rate between two countries currencies are equal to the ratio of their price levels because the Purchasing Power of a countrys currency is reflected in the countrys price level, the money price of a reference bas-ket of goods and its services. The PPP theory is generated based on the concept of the arbitrage across goods markets and the law of one price [9]. The PPP theory is a foun-dation of many other economic models, e.g. the

Monetary model. Monetary School uses the monetary supply and the demand side to define the exchanges of exchange rates. This model is proposed based on the PPP theory [12].

2.3 Interest Rate Parity Theory

The interest pate parity (IRP) theory establishes the joint between the spot currency market and the forward currency market with foreign and domestic market. The IRP is maintained by the arbitrage.

2.4 Portfolio Balance Model (PBM)

The PBM can be treated as an extension of the monetary model. PBM is proposed by Tobin, who claims that people having different assets should undertake different returns and risks. These two items should be assessed by their own returns and risks in order to determine the optimal asset portfolio. This model also treats the expected returns of different financial assets existing in different countries as the primary fac-tors which affect the exchange rate. The main factors which affect these expected returns are the interest rates of domestic, foreign financial assets and the expectation of exchange rate between domestic and foreign countries.

2.5 Balance of Payment Model

The balance of payment model indicates that the equilibrium exchange rate should be the one, which makes the surplus or the deficit of balance from the payment of the country equals to zero. If the terms described above do not equal to zero, the ex-change rate must be fluctuated [4].

Many practical exchange rate forecasting models are introduced in the past, for in-stance, balance of payment model [4], monetary model [12] and purchasing power parity model [9]. These models use a single structural model to find out which factor gives the effect on the foreign exchange rate. In recent years, researchers working in the related research field usually use the models mentioned above with macroeco-nomic factors to construct the linear model for simulating the exchange rate fluctua-tion for the exchange rate forecasting.

2.6 Time-Series Model: EGARCH

Bollerslev (1986) proposed a Glossary-ARCH (GARCH) [3] model based on Engles (1982) AutoRegressive Conditional Heteroskedastic (ARCH) class of models. Alt-hough the ARCH model works well in analysis of the heteroscedasticity difference of a time series, the prediction is still not accurate in some cases. The GARCH is a time series regression model, which is designed especially for the financial data. The GARCH model not only construct the model for the time series data, but also create models for the modeling error. This results in the

GARCH model present good results in the analysis and the prediction of the volatility. This information is quite im-portant and useful for the investors and can be treated as a leading index.

Although GARCH model provides information of the volatility, it is still not able to depict the leverage effect in the data. Hence, Nelson (1991) propose the Exponen-tial General Auto-Regressive Conditional Heteroskedastic (EGARCH) model [14] to overcome this problem. An EGARCH(p,q) model can be described as follows:

$$\log \sigma_t^2 = \omega + \sum_{k=1}^{q} \beta_k g(Z_{t-k}) + \sum_{k=1}^{p} \alpha_k \log \sigma_{t-k}^2 \ . \tag{1}$$

$$g(Z_{t-k}) = \theta Z_t + \lambda[|Z_t|t - E(|Z_t|)] \ . \tag{2}$$

where σ_t^2 indicates the conditional variance, α, β, ω, θ are coefficients, respectively, and Z_t comes from the generalized error distribution or the standard normal varia-ble. The sign and the magnitude of Z_t are capable to donate separate effects on the volatility in Eq. (2). This is particularly useful in an asset pricing context [16]. In addition, the parameters are bounded with less restrictions because the value of $\log \sigma_{t-k}^2$ may be negative.

2.7 Swarm Intelligence and the Interactive Artificial Bee Colony (IABC)

Swarm intelligence is an artificial intelligence technique based on the study of collective behavior [2]. Many of the algorithms in swarm intelligence are developed based on simulating the behaviors of the creatures in the Mother Nature. Swarm intel-ligence is symbolically made up of a population of simple agents interacting locally with one another and with their environment. Even though there is no centralized control structure indicating how individual agents should behave, local interactions between such agents often lead to the emergence of global behavior.

We have seen many successful applications using swarm intelligence methods to solve problems in optimization. For example, Particle Swarm Optimization (PSO) algorithm has successfully been used to design antennas [21] and to construct param-eters in neural network systems [10]; Ant Colony Optimization (ACO) algorithm has successfully been used to solve the Traveling Salesman Problem (TSP) [8] and the routing problem of networks [17]; Artificial Bee Colony (ABC) algorithm has suc-cessfully been used to solve the lot-streaming flow shop scheduling problem [15]; Cat Swarm Optimization (CSO) algorithm has successfully been used to discover proper positions for information hiding [19] and to adjust parameters for the Support Vector Machine (SVM) [11]. Moreover, many researchers have led in the idea of par-allelizing the optimization methods by splitting the artificial agents into independ-ent groups such as the Island-model genetic algorithm [20], the parallel genetic algo-rithm [1], the ant colony system with communication strategies [5], and the parallel particle swarm optimization algorithm with communication strategies [7]. The paral-lelized group of artificial agents increases the accuracy and extends the global search capacity than the original structure.

The Interactive Artificial Bee Colony is proposed by Tsai et al. in 2008. [18] It is evolved from the Artificial Bee Colony Optimization (ABC), and it is developed based on researchers notice that the moving pattern of the bee of original algorithm to search nectar is linear movement, and it will narrow the explore scope, so we put forward to join law of universal gravitation to improve the shortcomings of the origi-nal colony algorithm. The gravitations between the onlooker and the selected em-ployed bees are concerned, thus, it can be calculated by applying equation. To im-plement the IABC optimization, the procedures are given as follows:

Step 1. Initialization: Put n_e percentage of the populations into the solution space randomly, then calcu-late their fitness values, which called the nectar amounts, where means the ratio of employed bees to the whole population. In case these populations are positioned into the solution space, they will be the employed bees.
Step 2. Move the Onlookers: Calculate the probability of selecting a food source by Eq. (3), choose a food source to move to by roulette wheel selection for every onlooker bees, and then decide the nectar amounts of them. The movement of the onlooker bees follows Eq. (4).

$$P_i = \frac{F(\theta_i)}{\sum_{k=1}^{S} F(\theta_k)} \ . \tag{3}$$

$$x_{ij}(t+1) = \theta_{ij}(t) + \sum_{k=1}^{n} \tilde{F}_{ik_j} \cdot [\theta_{ij}(t) - \theta_{kj}(t)] \ . \tag{4}$$

where x_i represents the position of the i^{th} onlookers, t denotes the iteration number, θ_k represents the randomly chosen employed bee, j is the dimension of the solution, and $\tilde{F}_{ik_j}$ is the normalized gravitation.

Step 3. Move the Scouts: Supposing the fitness values of the employed bees is limited, which means they do not be improved by a continuous predetermined number of iterations, those nectar are abandoned and these employed bees become the scouts. To move the scouts, Eq. (5) is applied.

$$\theta_{ij} = \theta_{jmin} + r(\theta_{jmax} - \theta_{jmin}) \ . \tag{5}$$

where r is a random number and $r \in [0, 1]$.
Step 4. Update the Best Food Source: Memorizing the best fitness value and the best position, which are found by the bees.
Step 5. Termination Checking: Stop when the amount of the iterations satisfies the termination condition, and then terminate the program and output the results; on the contrary, go back to *Step 2* to restart.

2.8 Our Proposed Method and Experiment Design

To establish a new exchange rate forecasting model, we first collect the factors for the reference and then utilize IABC to find the optimum weighting distribution for con-structing the predicted daily exchange rate. Eight macroeconomic factors including Consumer Price Index, M1, M1B, Commercial Paper Rate, Federal Fund Rate, Bal-ance of Trade, Foreign Investment, and Stock Return are taken with the NTD/USD exchange rate to be the reference data. According to the collected historical data in the database, most of the factors only provides monthly records. Only the NTD/USD exchange rate has both monthly and daily records. The weekly record of Stock Return can also be found in the database. Hence, our reference information is composed of totally 13 elements including the monthly records of the eight macroeconomic factors and the NTD/USD exchange rate, the weekly record of the Stock Return, 2 daily records of the NTD/USD exchange rate and the Stock Return, and one constant, which is set to 1 in the experiment.

We use IABC to train a set of considering weightings correspond to the reference information. The goal is to output the estimated foreign exchange rate, which should approach the exact foreign exchange rate as much as it can. Hence, the prediction error is used in the fitness function to train the considering weightings. The goal of this optimization process is to produce a set of considering weighting by minimizing the prediction error. The fitness function used in IABC is listed in Eq. (6):

$$minf(W) = \sum_{t-1}^{n} |(\sum_{d=1}^{D} w_d \times v_{t,d}) - R_{real,t}| \ . \tag{6}$$

where $f(W)$ indicates the fitness function, $W = \{w_1, w_2, ..., w_D\}$ is the set of the considering weights, n denotes the number of past dates of which the reference information is taking part in the optimization process, D is the total number of reference infor-mation (D is set to 13 in our experiment), v denotes the reference information, and R_{real} stands for the real foreign exchange rate.

The trained considering weights are output as the prediction parameter and the predicted foreign exchange rate for the next date is calculated by Eq. (7):

$$R_{pd,t+1} = \sum_{d=1}^{D} w_d \times v_{t,d} \ . \tag{7}$$

where R_{pd} denotes the predicted foreign exchange rate.

In addition, the forecasting accuracy is evaluated by the Mean Absolute Error (MAE), the Mean Square Error (MSE), and the Root Mean Square Error (RMSE) by Eqs. (8)-(10):

$$MAE = \sum \frac{|\hat{S}_t - S_t|}{n} \ . \tag{8}$$

$$MSE = \sum \frac{(\hat{S}_t - S_t)^2}{n} \ . \tag{9}$$

$$RMSE = \sqrt{\sum \frac{(\hat{S}_t - S_t)^2}{n}} \,. \tag{10}$$

where $\hat{S}_t$ is the forecast exchange rate at day t; S_t represents the exchange rate at day t, and n is the number of data.

The historical data from the first trading day in February in 2005 to the last trading day in 2008 is included in our experiment. The collected data is examined by the basic test at the first beginning. The test result indicates that the collected data fits the criteria of the regular data and is suitable for the usage in our experiment. Since our proposed method is for forecasting the daily exchange rate and we only require the last three days' data for training, the sliding window strategy is employed in our experiment to run over totally 2922 days. Same strategies is also applied with the EGARCH model. The concept of the sliding window strategy is depicted in Fig. 1:

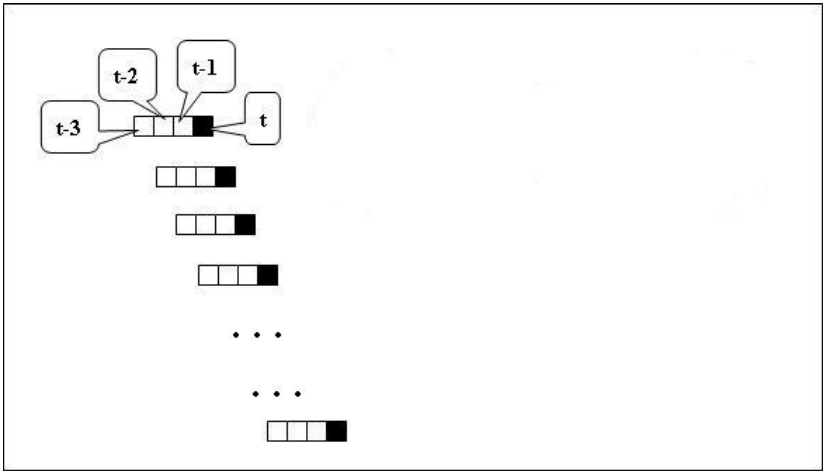

Fig. 1. The Concept of the Sliding Window Strategy

Here we give two examples to demonstrate how to use the sliding window strate-gy in the experiment. As shown in Fig. 1, if we are going to predict the exchange rate on day t, the reference data should be collected from the latest past three days, i.e. from days $(t-3)$ to $(t-1)$. On the other hand, if we want to predict the exchange rate on day $(t+1)$, the reference data should be collected from days $(t-2)$ to t.

The parameter setting for IABC is listed as follows: the population size is 16, the agents are equally divided into 4 independent groups, and the initial range is set to $[-1, 1]$. Half of the agents play the role of onlookers. The optimization process is set to run 120 iterations with 30 independent runs. The best result over all runs is output-ted as the final result.

2.9 Experimental Results

The prediction results produced by the IABC forecasting model and the EGARCH model are drawn year-by-year in Fig.2 with the actual foreign exchange rage. The vertical axis shows the foreign exchange rate; and the horizontal axis shows the date in a year. The experimental results show that the forecasting result obtained by the IABC forecasting model almost stick together with the actual foreign exchange rate from the beginning to the end in year 2005 and 2008. In year 2006 and 2007, the forecasting result obtained by the IABC forecasting model show the oscillation in some days. It may be caused by the failure to find the near best solution, but trapped in the local optimum. On the other hand, the forecasting results obtained by the EGARCH model shows more oscillation and larger oscillation amplitude over all forecasting results.

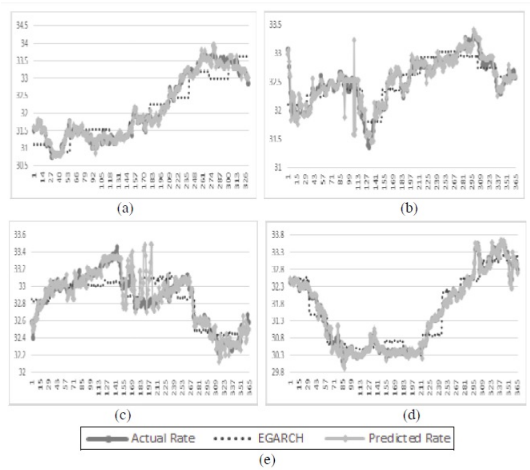

Fig. 2. The actual foreign exchange rate and the forecasting results obtained by the IABC forecasting model and the EGARCH model: (a) results in 2005, (b) results in 2006, (c) results in 2007, (d) results in 2008, (e) the graphic symbols

Table 1 shows the compare on forecasting results from IABC trained foreign ex-change rate forecasting model and the conventional EGARCH forecasting models with MAE, MSE, and RMSE.

Our proposed IABC forecasting model presents the lowest MSE and RMSE values over all experiment data. The MAE value is larger than the EGARCH model in 2006. It is caused by the failure to find the near best solution around the 100th days in 2006.

2.10 Conclusions

In this paper, we propose a new daily foreign exchange rate forecasting model with IABC algorithm. IABC plays the role to construct the forecasting exchange

Table 1. Satisfaction Capability Index of the Investment Performance

Year	Forecasting Model	MSE	MAE	RMSE
2005	IABC result	8.365×10^{-3}	6.321×10^{-2}	9.146×10^{-2}
	EGARCH result	1.237×10^{-1}	2.778×10^{-1}	3.518×10^{-1}
2006	IABC result	1.735×10^{-2}	7.389×10^{-2}	1.317×10^{-1}
	EGARCH result	4.312×10^{-2}	1.673×10^{-1}	2.077×10^{-1}
2007	IABC result	1.609×10^{-2}	7.147×10^{-2}	1.269×10^{-1}
	EGARCH result	2.905×10^{-2}	1.444×10^{-1}	1.704×10^{-1}
2008	IABC result	9.339×10^{-3}	5.792×10^{-2}	9.664×10^{-2}
	EGARCH result	8.906×10^{-2}	2.307×10^{-1}	2.984×10^{-1}

rate by finding the optimum combination and the weighting distribution from the past three continuous day's information. The forecasting results are compared with the classical conventional time-series model, e.g. the EGARCH model. The experimental results indicate that our proposed method provides the forecasting result with high accuracy. Although the vibrations of the forecasting result sometimes appears, it still doesnt cause much drop on the accuracy. The vibration may be overcame by increasing the population size or the iteration number. In the future, we plan to further use IABC to reduce the number of the referred factors. By doing so, the computational cost is able to be reduced.

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