IABC Robotic Evolutionary Model for the Foreign Exchange Rate Prediction in Central America Trading Agreement Events

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Abstract—**Taiwanese economy is extremely export-oriented. However, Taiwan also starts to actively look for opportunities for participation, because of the slowdown of multinational liberalizations, and as a result of the advance of the regional economic integration trend. As an example, Taiwan vigorously participates in FTAs with countries in Asia and Central America. International economic conditions are significantly important to the international trade and the volume of export/import volume, which is affected by the foreign exchange rate. If contemporary researchers could take full advantage of the exchange rate forecasting, Taiwan could maximize its trade surplus, thus boosting the economic growth. Conventional foreign exchange rate forecasting is usually provided by analyzing many financial indices or with the time-series method. Our goal is to produce the foreign exchange rate forecasting result by the robotic way with an evolutionary computing method called Interactive Artificial Bee Colony algorithm. Based on the event study methodology, the selected agreements include four FTA that are ECFA, BIA, ASTEP and ANZTEC, and the observation period setting is 70 days of pre-event period and 70 days of post-event period. This paper uses time series model (GARCH、EGARCH) and Interactive artificial bee colony (IABC) to establish the exchange rate predicting models. In addition, we adopt Mean Absolutely Percentage Error (MAPE) to compare the accuracy of exchange rate prediction. There are many exchange rate predicting models and the most frequently one to conduct maybe the time series model. This research reveals that even the IABC is relatively new it is the model has the best predictive ability among all the models.**

Keywords—Event study; free trade agreement; GARCH; EGARCH; IABC

I. Introduction

Taiwan has a very small territory with limited natural resources. For this reason, Taiwanese economy is extremely export-oriented. In international trade, exchange rates are the most important adjustment lever. If Taiwan could take full advantage of the exchange rate trend, Taiwan could maximize its trade surplus, thus boosting the economic growth. Given the importance of international trade to Taiwanese economy, this study investigated the respective impact of signing four free trade agreements that are ECFA, BIA, ASTEP and ANZTEC on exchange rate forecasting models, and offers some insight to central banks and investors in foreign exchange markets (forex, FX, or currency market).

In the past, the foreign exchange rate forecasting is mostly produced by the time-series methods and is operated by the human economist. In recent years, scholars start to use artificial intelligence method to compose the robotic mechanism or software to deal with the forecasting problem [12-13]. In our work, we choose IABC to be the artificial intelligence method. The reason we choose IABC algorithm to compose the artificial intelligence model is that IABC is a younger algorithm and is with less computing complexity than other existing methods. Nevertheless, using only the artificial intelligence methods to compose the robotic mechanism for the foreign exchange rate forecasting is not very efficient because the mechanism does not consider the event effects in the real-world as the human economist does. Based on this point of view, we use not only the artificial intelligence method, but also the event study method in this paper.

Although the event study methodology has been widely used in many financial and management fields, only few related researches used information entropy concerning various type of news report as a factor for exchange rate forecasting. After 1990, scholars (Kwok) [1] started to apply event studies to foreign exchange market research. The event study methodology can be used to test a null hypothesis and investigate whether the occurrence of a certain event will cause the fluctuation of exchange rates and abnormal returns. This hypothesis doesn't use any Macroeconomic Index as factors in building exchange rate predicting models. It is based on two hypothesizes. The first one is it regards the determination of exchange rate as is very similar to the valuation of ordinary asset. The concept is built on the background that after 1975, the improved international capital mobility allows people to freely hold and allocate both domestic and foreign assets. That is, exchange rates are determined by supply and demand in foreign exchange markets. Such a method is called the asset market approach. The followings are the two branches of the asset market approach: British economist John Maynard Keynes's monetary approach and American economist William Branson's portfolio balance approach. The second hypothesizes is it is root in the efficient-market hypothesis (EMH). Emanuele Bajo (2010) [2] defined the event study methodology as the basic method to test for "semi-strong form efficiency". The semi-strong form efficiency of the EMH states that stock prices reflect all publicly available information. For this reason, abnormal trading volume is seen as a signal of upcoming announcements by investors. In this research we examine whether there will be unusual changes in exchange rate and abnormal returns, after the signing of free trade agreements.

There are many exchange rate predicting models and the most frequently one to conduct maybe the time series model Time series modeling may be considered a classic analysis tool in economics and finance. The spirit of such modeling lies in its idea that all current data is somehow connected with historical data. One of the most famous one is Autoregressive conditional heteroskedasticity (ARCH) models which were proposed in one paper published in Econometrica by Professor Robert Engle (1982) [3]of the University of California, San Diego. In that paper, Engle claimed that ARCH models can be used to solve the problem with the volatility of time series. Thereafter, ARCH models have been developed very fast in quantitative economics. After Engle (1982) introduced ARCH models, Tim Bollerslev (1986) [4] improved them and developed generalized autoregressive conditional heteroscedasticity (GARCH) models. GARCH models are an extension of ARCH models. GARCH models assume that the current conditional variances are a function of both the preceding period's conditional variances and the squares of the error terms, the plus or minus sign of the error terms does not affect these conditional variances. For this reason, GARCH models are not able to depict the asymmetric feature shown by the volatility of the conditional variances of returns. However, In fact, many distributions of returns have the leptokurtic feature. Moreover, residuals of stock market returns affect returns asymmetrically. That is to say, GARCH models are not able to explain the negative correlation between stock returns and changes in volatility. To improve GARCH models, Dan Nelson (1991) [5] introduced exponential generalized autoregressive conditional heteroscedasticity (EGARCH) models. Pei-Fen Chang (2014) [6] built exchange rate forecasting models from the perspective of market microstructure. In her study, she used 1-minute and 5-minute interval observations of exchange rates during the period from January 2006 to December 2007. Using these data, Chang tried to compare forecasting performance of symmetric and asymmetric GARCH models targeted at the exchange rate between the U.S. dollar and the euro and that between the U.S. dollar and the Japanese yen under the effect of order flows. This empirical study yielded two important findings: (1) volatility of exchange rates is asymmetric and (2) among the GARCH family models, EGARCH models have the best forecasting performance and obviously are able to capture volatility and the leverage effect.

Compare to other exchange rate predicting models, artificial intelligence methodologies also have been gradually adopted to do researches in finance recently. The artificial bee colony (ABC) algorithm is the recent collective intelligence methodology used to optimize numerical problems. It was introduced by Dervis Karaboga in 2005[7] Li Bao and Jian-chao Zeng (2009) [8] pointed out that the advantages of such an algorithm include its simple concept, good usability, and low requirement on the number of parameters. Proven by experiments, ABC can be employed to conduct business researches. This research adopted a refined one, Interactive Artificial Bee Colony, to build the exchange rate forecasting model. Pei-Wei Tsai et al. (2008) [9] added the concept of universal gravitation into ABC, thus creating the interactive artificial bee colony (IABC) algorithm. Compared with ABC, IABC provides honeybees with a larger exploration zone and is less likely to get stuck in local optima. Through the use of five benchmark functions, Tsai et al. (2008) further compared the respective efficiency and accuracy of ABC, IABC, and Particle Swarm Optimization (PSO) to solve optimization problems. The results indicate that IABC has the best optimization problem-solving ability among the three algorithms. In 2016, Tsai et al. utilize the IABC model with the Consumer Confidence Index (CCI) and several other conventional microeconomics factors as the input to construct the foreign exchange rate forecasting model [11]. In their study, the newly added CCI element improves the prediction accuracy for the foreign exchange rate forecasting. Nevertheless, focusing on only the microeconomics factors and other variables should still have some undiscovered potentiality for us to analyze. Thus, we use only the microeconomics factors in our model and try to find out the stability of the forecasting result when facing the impact on signing the trade agreements between Taiwan and the Central America countries.

This study intends to investigate how the exchange rate prediction accuracy under the impacts of four FTAs with this three models, time series model (GARCH, EGARCH) and IABC, in order to provide some insights to central banks and investors in foreign exchange markets. After all, exchange rate plays an important role in such a small open economy as Taiwan.

II. Experiment Design and Experimental Resluts

A. Time Series Models (GARCH and EGARCH)

To find out which exchange rate forecasting model has the best predictive ability, this paper examines and compares the accuracy of the exchange rate forecasting models adopted in this study under the effect of four free trade agreements (FTAs). First, the time series data are tested to see whether they are stationary using two unit root tests, the augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. Next, the Box-Jenkins approach is used to build an ARIMA model. The AIC (Akaike information criterion) value and the SC (Schwarz criterion) value are the criteria for choosing lag periods.

$$JB = \frac{T-n}{6}\left[s^2 + \frac{(k-3)^2}{4}\right] \tag{1}$$

The Jarque-Bera test is a goodness-of-fit test to see whether sample data have the skewness (s) and kurtosis (k) that match a normal distribution. Assume that the number of estimated parameters is n, and that the total number of sample residuals is T. Then, built are volatility models, ARCH, GARCH, and EGARCH models in this study.

The GARCH model equations displaying this phenomenon are as follows:

$$Y_t \middle| \Omega_t \sim N\left(X_t \alpha, \sigma^2\right) \tag{2}$$

$$\varepsilon_t = Y_t - X_t \alpha \tag{3}$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-1}^2 > 0 \tag{4}$$

where $\alpha_i \geq 0$ and $\beta_j \geq 0$.

The EGARCH model equations are given as follows:

$$Y_t = X_t^b + \varepsilon_t \tag{5}$$

$$\varepsilon_t \middle| \Omega_{t-1} \sim N\left(0, \sigma^2\right) \tag{6}$$

$$\ln \sigma_t^2 = \alpha_0 + \sum_{i=1}^{q}\left[\alpha_i\left(\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| - E\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right| + r\,\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right)\right] + \sum_{j=1}^{p} \beta_j \ln \sigma_{t-i}^2 \tag{7}$$

After the creation of volatility models, a diagnostic test is conducted on these models to check whether the standardized residuals already meet the requirement to be white noise. Finally, the mean absolute percentage error (MAPE) is adopted to analyze and compare the predictive ability of the exchange rate forecasting models. Also, the Ljung-Box Q statistic is used to see whether these models are white noise:

$$\mathrm{Q(P)} = \mathrm{n(n+2)}\sum_{k=1}^{p} \frac{1}{n-k} p_k^2 \sim \mathrm{X}^2(P) \tag{8}$$

In this equation, n is the sample size. k denotes the lag periods. Such a statistic is a chi-square distribution with p degrees of freedom (DOF).

MAPE is the criterion to compare the predictive ability of the exchange rate forecasting models.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \frac{\left|\hat{S}_t - S_t\right|}{S_t} \tag{9}$$

In this equation, n is the sample size. Whereas $\hat{S}_t$ is the expected exchange rate of period t, and S_t is the actual exchange rate of such a period.

B. Interactive Artificial Bee Colony Algorithm

In the second experiment of this paper, the interactive artificial bee colony (IABC) algorithm is adopted to build exchange rate forecasting models. This experiment examines and analyzes the accuracy of the four exchange rate forecasting models targeted at the exchange rate between the New Taiwan dollar and the U.S. dollar under the impact of four FTAs between Taiwan and four Central American countries. Before making predictions using IABC, we need to conduct the unit root test, the autocorrelation test, and the normality test on the time series data of the signing of the four FTAs. The following is the procedure of this IABC experiment:

Step 1. Initialization: Set up the initial three parameters, including the size of employed bees (*SN*) and the maximum cycle number (*MCN*). When the fitness value of a particular food source cannot be improved in a predefined number of iterations (*limit*), the employed bee attached to it becomes a scout bee and leaves the food source to randomly look for a new food source. Randomly put each employed bee at a position in the solution space. Such a position can be expressed as follows:

$$X_{ij} = X_{\min}^{j} + rand \cdot \left(X_{\max}^{j} - X_{\min}^{j}\right) \tag{10}$$

where X_{ij} is the initial value of the i^{th} employed bee in dimension *j*. $X_{\min}^{j}$ is the minimum value in dimension *j*. On the contrary, $X_{\max}^{j}$ is the maximum value in dimension *j*. $rand$ is a random number in the range of [0, 1].

Step 2. Move the Employees: Select a new food source for each employed bee to move to according to equation (11), and then determine the nectar amount (profitability) of that food source.

$$V_{ij} = X_{ij} + r \cdot \left(X_{ij} - X_{kj} \right) \tag{11}$$

where V_{ij} is the new position of the i^{th} employed bee in dimension j, whereas X_{ij} is the original position of that bee. X_{kj} is the position of the randomly selected onlooker bee k in dimension j, and $r \in [0,1]$ is a random variable. All employed bees and onlooker bees follow Eq. (11), to search for a new food source. Each employed bee has the information (profitability) related to its food source and shares such information with onlooker bees by performing the waggle dance on the area of the comb. k 1,2,…,SN represents the size of food sources, and $j\in$ 1,2,⋯,D denotes the dimension of the solution (search dimension). This equation can also be interpreted from another perspective. From such perspective, k and j are randomly chosen.

Step 3. Move the Onlookers: Use roulette wheel selection, Eq. (12), to calculate the probability of a food source being chosen and determine which food source an onlooker bee should move to and help searching.

$$P_i = \frac{f(\theta_i)}{\sum_{k=1}^{S} f(\theta_k)} \tag{12}$$

where P_i is the probability of the i food source being selected, and $f(\theta_i)$ is the profitability of that food source. SN represents the size of food sources.

Step 4. Move the Scouts: When the fitness value of a particular food source cannot be improved in a predefined number of iterations (limit), the employed bee attached to it becomes a scout bee and leaves the food source to randomly look for a new food source following Eq. (12). The original food source is abandoned and replaced by the new one.

Step 5. Update the Best Food Source Found So Far: Memorize the food source with the highest profitability so far. Also, such profitability should be recorded as the best solution of the algorithm.

Step 6. Termination Checking: Check whether the number of iterations reaches the maximum cycle number. If so, the termination condition is satisfied. Then, terminate the algorithm and output the best solution found so far. Otherwise, go back to step 2.

Exchange rate predictions will be generated by the IABC model. MAPE is used as the criterion to evaluate and compare its predictive ability with the GARCH (1, 1) model and the EGARCH model.

III. Experiments and Experimental Results

These experiments adopt as events the signing of four FTAs between Taiwan and such Central American countries as ECFA, BIA, ASTEP and ANZTEC. The event period is defined as the 70 days before the event and the 70 days after the event. Exchange rate forecasting models are built through the uses of time series models (GARCH and EGARCH) and the IABC model. Finally, we use MAPE as the criterion to evaluate the predictive ability of the exchange rate forecasting models. The following figures present the predictive ability of the three models based on MAPE. The vertical axis represents percentage changes in errors, and the horizontal axis denotes monthly averages. The blue bar represents the GARCH model, the orange bar denotes the EGARCH model, and the green bar represents the IABC model. The details are described as follows:

This research adopts MAPE proposed by Lewis (1982) [10] to evaluate the predictive ability of the exchange rate forecasting models. The smaller MAPE values indicate the better forecasting quality. Actually, a value should be as close to 0 as possible.

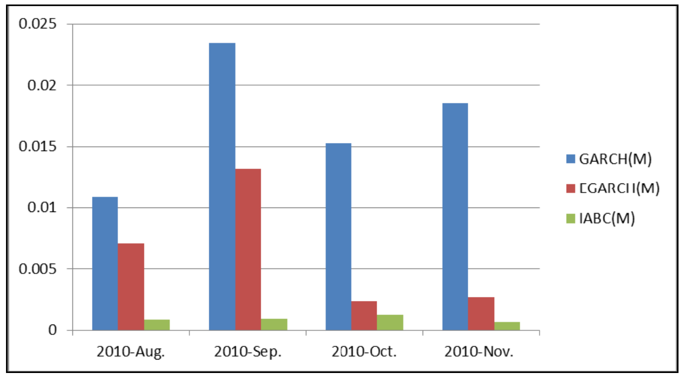

Fig. 1. The comparison of three models' MAPE on the event of ECFA

From Figure 1, all of the GARCH, EGARCH and IABC models obviously fall within the standard range, suggesting that all these three models have a pretty good predictive ability. The IABC model has smaller MAPE values in all time intervals. This phenomenon means that it has an even better predictive ability that the time series models. The EGARCH model has smaller MAPE values than the GARCH model in August, September, October and November indicating that in these three months, the EGARCH model has better forecasting performance than the GARCH model.

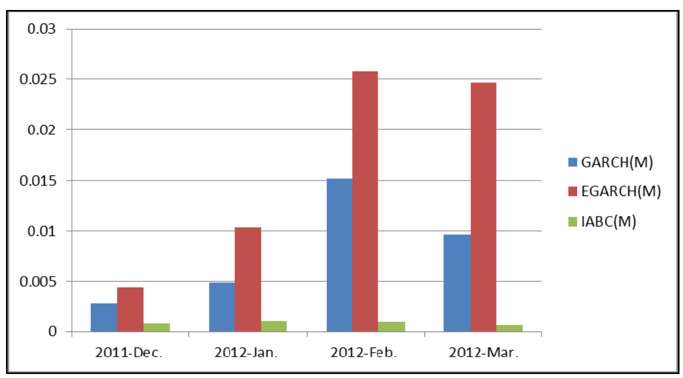

Fig. 2. The comparison of three models' MAPE on the event of BIA

This research adopts MAPE proposed by Lewis (1982) to evaluate the predictive ability of the exchange rate forecasting models. The smaller MAPE values indicate the better forecasting quality. Actually, a value should be as close to 0 as possible. From Figure 2, all of the GARCH, EGARCH and IABC models obviously fall within the standard range, suggesting that all of these three models have a pretty good predictive ability. The IABC model has smaller MAPE values in all time intervals. This phenomenon means that it has an even better predictive ability that the time series models. The GARCH model has smaller MAPE values than the EGARCH model in December, January, February and March, indicating that in these four months, the GARCH model has better forecasting performance than the EGARCH model.

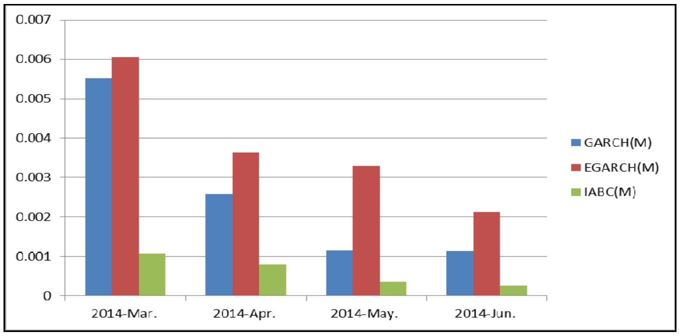

Fig. 3. The comparison of three models' MAPE on the event of ASTEP

This research adopts MAPE proposed by Lewis (1982) to evaluate the predictive ability of the exchange rate forecasting models. The smaller MAPE values indicate the better forecasting quality. Actually, a value should be as close to 0 as possible. From Figure 3, all of the GARCH, EGARCH and IABC models are within the standard range, indicating that these three models have a pretty good predictive ability. The IABC model has smaller MAPE values in all time intervals. This phenomenon suggests that it has an even better predictive ability than the time series models. The GARCH model has smaller MAPE values than the EGARCH model in March, April, May and June, indicating that in these four months, the GARCH model has better forecasting performance than the EGARCH model.

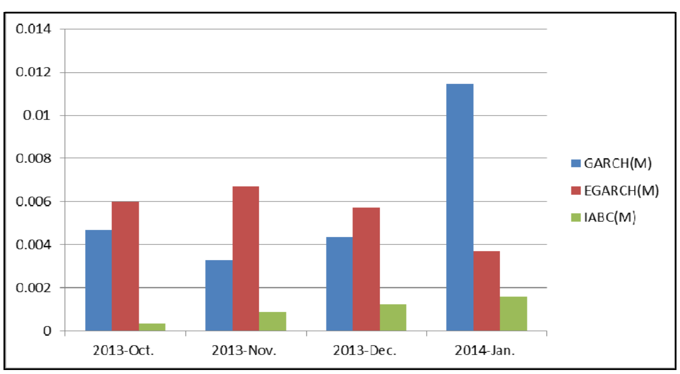

Fig. 4. The comparison of three models' MAPE on the event of ANZTEC

This research adopts MAPE proposed by Lewis (1982) to evaluate the predictive ability of the exchange rate forecasting models. The smaller MAPE values indicate the better forecasting quality. Actually, a value should be as close to 0 as possible. From Figure 4, all of the GARCH, EGARCH and IABC models are within the standard range, indicating that these three models have a pretty good predictive ability. The IABC model has smaller MAPE values in all time intervals. This phenomenon suggests that it has an even better predictive ability than the time series models. The GARCH model has smaller MAPE values than the EGARCH model in October, November, and December, indicating that in these three months, the GARCH model has better forecasting performance than the EGARCH model. On the contrary, the EGARCH model has a smaller MAPE value than the GARCH model in January, suggesting that in this month, the EGARCH model has better forecasting performance than the GARCH model.

IV. CONCLUSIONS AND FUTURE WORKS

This paper utilizes time series models (GARCH and EGARCH) and the interactive artificial been colony (IABC) algorithm to construct exchange rate forecasting models, and uses the mean absolute percentage error (MAPE) to compare the accuracy of these models. The experimental results reveal that all of the GARCH, EGARCH and IABC models obviously fall within the standard range, suggesting that all these three models have a pretty good predictive ability. Even so, the IABC model has the best predictive ability among all the models. Although IABC mode presents the best forecasting result among GARCH and EGARCH models, there is still a drawback of the proposed method: IABC is like other evolutionary computing algorithms, it requires time to evolve. Moreover, in the process of finding the near best solutions, it may be trapped in the local optimal, sometimes. How to shrink the evolution time and avoiding being suffered from the local optimal solutions can be further improved. In the future work, we plan to use a wider diversity of exchange rate forecasting models to study which model has the best predictive ability.

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