Technical modeling exchange rate by using genetic algorithm: A case study of the Iran’s Rial against the EU Euro

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Genetic algorithms (GAs) are computer programs that mimic the processes of biological evolution in order to solve problems and to model evolutionary systems. In this study, we apply GAs for technical models of exchange rate determination in exchange rate market. In this framework, we estimated autoregressive (AR), moving average (MA), autoregressive with moving average (ARMA) and mean reversion (MR) as technical models for the Iran’s Rial against the European Union’s (EU) Euro (Rial/Euro) using monthly data from January 1992 to December 2008. Then, we put these models into the genetic algorithm system for measuring their optimal weight for each model. These optimal weights have been measured according to four criteria; R-squared ($R^2$), mean square error (MSE), mean absolute percentage error (MAPE) and root mean square error (RMSE). Results showed that for explanation of the Iran’s Rial against the European Union’s Euro exchange rate behavior, autoregressive (AR) and autoregressive with moving average (ARMA) are better than other technical models.

Key words: Genetic algorithm, technical models, exchange rate, Rial/Euro.

INTRODUCTION

Building a forecasting model for exchange rates has always been a challenging area of research to applied econometricians and statisticians. A good forecasting of a financial time series requires strong domain knowledge and good analysis tools. Trading techniques based on technical analysis are widely used in financial markets. This is particularly true for the currency markets as surveys reveal. Roughly 90% of market participants base their trading at least in part on technical analysis, and between 30 and 40% of professionals use technical analysis as their most important trading technique. Moreover, the importance of technical analysis has increased more strongly over the 1990s than other trading practices like the orientation on fundamentals or on customer orders. Studies on the profitability of technical currency trading cannot fully explain the extent of the popularity of technical rules in practice. Although these studies find technical trading systems to be profitable when tested in sample, they also find the out-of-sample performance to be significantly worse. Moreover, some studies find that the profitability of trading rules based on daily data has declined over time (Schulmeister, 2005). The quantitative approaches try to identify trends using statistical transformations of past amounts. These models produce clearly defined buy and sell signals. Many well-established methods, such as autoregressive (AR), autoregressive moving average (ARMA) and generalized autoregressive conditional heteroscedasticity (GARCH), have been successfully applied for financial forecasting. Recently, many researchers have focused on developing computational intelligence methods for forecasting financial time series. Experience the few past decades denotes significant growth of exchange rate literature and considering the importance of exchange rates as an...
important variable in open economy. Exchange rate has become a vast area of research for economists (Preminger and Franck, 2007).

Ever since the seminal paper by Meese and Rogoff (1983), it has been a difficult task to predict the short-run movements of nominal exchange rates. They found that at horizons up to one year, none of the foreign exchange models could outperform the predictions of a random walk model. Remarkably, this was true even when the predictions of the models were based on realized, and not predicted, values of the explanatory variables, meaning that the out-of-sample fits of the models were surprisingly poor. According to Cheung et al. (2005), there is still no single foreign exchange model that has outperformed the predictions of other models, including the random walk. It is, however, possible to find a specific model that do well for a certain exchange rate series, but not for other time series. Technical models often produce a sequence of either buy or sell signals when they are trading and hold the same - long or short - position when they are not trading. Hence, technical currency trading exerts an excess demand (supply) on exchange rate formation. It is therefore interesting to explore the interaction between the aggregate trading behavior of different models and exchange rate dynamics. These technical models are used in various kinds such as auto regressive (AR), moving average (MA), auto regressive with moving average (ARMA) and mean reversion (MR). Therefore, to check out which technical model or models are the best options to evaluate the behavior of exchange rates, a tool that is able to address the research is needed.

To solve this problem, we can use the genetic algorithms (GA) as a new technique and a powerful tool in solving complex optimization problems that can find the best model among exchange rates models. The genetic algorithm has been increasingly employed to model the behavior of economic agents in macroeconomic models. The genetic algorithm learning has been used both as an equilibrium selection device, and as a model of transitional, out-of-equilibrium dynamics. When used in economic modeling, the genetic algorithm describes the evolution of a population of rules, representing different possible beliefs, in response to experience. In a parallel to population genetics, these rules undergo a selection process whereby more successful ones become more numerous in the population. The rules are subjected to random mutations and to recombination of their parts. In turn, such newly-created rules contribute to the diversity of the population. There are several advantages in modeling of agents' adaptation in this way. Genetic algorithms impose low requirement on the computational ability of economic agents. They allow for modeling the heterogeneity of agents' beliefs. Survival of decision rules depends on their performance, measured by the payoff that agents receive by employing them. Genetic algorithm patterns successfully mimic the behavior of human subjects in controlled laboratory settings (Arifovic, 1996). So, the aim of this paper is finding the best model of technical exchange rate.

Dempster and Leemans (2006) developed an automated foreign exchange trading system based on adaptive reinforcement learning. The parameters that govern the learning behavior of the machine learning algorithm and the risk management layer are dynamically optimized to maximize a trader's utility. Chun and Park (2006) proposed a regression case-based reasoning technique where the rationale is the trading (trading) on the backdrop of a practical application involving the prediction of Korean stock price index. Nag and Mitra (2002) in their paper used a hybrid artificial intelligence method, based on neural network and genetic algorithm, for modeling daily foreign exchange rates. A detailed comparison of the proposed method with non-linear statistical models is also performed. The results indicate superior performance of the proposed method as compared to the traditional non-linear time series techniques and also fixed-geometry neural network models.

MATERIALS AND METHODS

Efficient markets

The idea that the expected risk-adjusted excess return on foreign exchange is zero implies a sensible statement of the efficient markets hypothesis in the foreign exchange context: exchange rates reflect information to the point where the potential excess returns do not exceed the opportunity cost of holding the asset. Under the efficient markets hypothesis, only current information can help predict exchange rates; past exchange rates are of no help in forecasting excess excess exchange returns - that is, if the hypothesis holds, technical analysis will not work. How do prices move in the hypothetical efficient market? In an efficient market, profit seekers trade in a way that causes prices to move instantly in response to new information, because any information that makes an asset appear likely to become more valuable in the future causes an immediate price rise today. If prices do move instantly in response to all new information, past information, like prices, does not help anyone make money. If there were ways to make money with little risk from past prices, speculators would employ it until they bid away the money to be made (Neely, 1997). Because the efficient markets hypothesis is frequently misinterpreted, it is important to clarify what the idea does not mean. It does not mean that asset prices are unrelated to economic fundamentals. Asset prices may be based on fundamentals like the purchasing power of the EU euro or Iran Rial. Similarly, the hypothesis does not mean that an asset price fluctuates randomly around its intrinsic (fundamental) value. If this were the case, a trader could make money by buying the asset when the price was relatively low and selling it when it was relatively high. Rather,
“efficient markets” means that at any point in time, asset prices represent the market’s best guess, based on all currently available information, as to the fundamental value of the asset. Future price changes, adjusted for risk, will be close to unpredictable (Fortune, 1991).

Genetic algorithm

Genetic algorithm (GA) derives its name from the pioneer Holland (1973) who got his inspiration from the way of natural evolution. Genetic algorithms (GA) are global optimization algorithms based on the mechanism of natural selection and genetics. A standard GA optimization problem is formulated as:

\[ \text{Optimize } \quad F(x) \]
\[ \text{Subject to } \quad x \in \Omega = \{0,1\}^n \quad [1] \]

The function to be optimized, \( F : \Theta \rightarrow \mathbb{R} \), is called the fitness function. To start the genetic search, an initial population (\( P_0 \)) of \( N \) members are selected from \( \Theta \) each with, say, \( n \) bits (each bit is either \( 0 \) or \( 1 \)). The members of this initial population are evaluated for their fitness. Members of a current generation are selected to survive in the next generation by designing a probability experiment in which each member is assigned a probability of survival proportional to their fitness value. Members found fit to survive are next chosen for crossover (mating) to fill the next generation. In order to fully explore the search space, a mutation operation on these strings (chromosomes) is applied. The mutation operator is a stochastic bit-wise complementation applied with a priori probability. Mutation helps to diversify the search procedure and introduces new strings into the population and forces diversity in the population allowing more search space to be sampled, thus allowing the search to overcome the local minima and also help to combat the effects of destructive crossover. The whole process of selection, crossover and mutation is repeated until the convergence criterion is achieved (Nag and Mitra, 2002). To apply the standard genetic algorithm to any arbitrary optimization problem given by:

\[ \text{Optimize } \quad G(y) \]
\[ \text{Subject to } \quad y \in \Omega \subset \mathbb{R}^n \quad [2] \]

We proceed as follows: First, a correspondence between the search space \( \Omega \) and the space of binary strings \( \Theta \) is established through an invertible mapping \( M : \Omega \rightarrow \Theta \). Finally, an appropriate fitness function \( F(\chi) \) is established, such that the optimizer of \( F \) corresponds to the optimizer of \( G \).

The parameter space \( \Omega \) in the present problem consists of the number of input units, the possible combination of input units, the number of hidden layers, the number of hidden neurons for each layer, the type of transfer function (for hidden units and output units), the value of the learning rate, the momentum rate parameter and the weight vector. The proposed procedure of genetic neural network model building is carried out through the following iterative steps (Nag and Mitra, 2002).

Reproduction

During the reproductive phase of the GA, individuals are selected from the population and recombined, producing offspring which will comprise the next generation. Parents are selected randomly from the population using a scheme which favors the more fit individuals. Good individuals will probably be selected several times in a generation; poor ones may not be at all.

Crossover

Crossover takes two individuals and cuts their chromosome strings at some randomly chosen position, to produce two “head” segments and two “tail” segments. The tail segments are then swapped over to produce two new full length chromosomes. The two offspring each inherit some genes from each parent. Crossover is not usually applied to all pairs of individuals selected for mating. A random choice is made, where the likelihood of crossover being applied is typically between 0.6 and 1.0. If crossover is not applied, offspring are produced simply by duplicating the parents. This gives each individual a chance of passing on its genes without the disruption of crossover (Spears, 1993).

Mutation

Mutation is applied to each child individually after crossover. It randomly alters each gene with a small probability (typically 0.001). The traditional view is that crossover is the more important of the two techniques for rapidly exploring a search space. Mutation provides a small amount of random search space has a zero probability of being examined.

Convergence

If the GA has been correctly implemented, the population will evolve over successive generations so that the fitness of the best and the average individual in each generation increases towards the global optimum. Convergence is the progression towards increasing uniformity. A gene is said to have converged when 95% of the population share the same value. The population is said to have converged when all of the genes have converged. As the population converges, the average fitness will approach that of the best individual. GA differs from more traditional optimization techniques in four important ways:

i. GA uses objective function information to guide the search, not derivative or auxiliary information.

ii. GA uses a coding of the parameters used to calculate the objective function in guiding the search, not the parameter themselves.

iii. GA searches through many points in the solution space at one time, not a single point.

iv. GAs uses probabilistic rules, not deterministic rules, in moving from one set of solutions (a population) to the next (Goldberg, 1989).

Number of observations (in genetic algorithms: population size) in efficiency of genetic algorithm are effective and decisive parameters. For example, if the number of observations to be considered is smaller than normal size, it may lead to early convergence (Fish et al., 2004). Therefore, considering the efficiency of problem solving and algorithm execution time, in empirical literature, the appropriate population size would be 25 to 300 (Wang and Hsu, 2008).

Technical modeling exchange rate

To estimate technical models, different regressions can be used
such as:

Auto regressive model

\[ S_t = \beta_0 + \beta_1 S_{t-1} + \theta \sum_{j=1}^{q} U_{t-j} \]  \[3\]

Moving average model

\[ S_t = \beta_0 + \beta_1 S_{t-1} + \theta \sum_{j=1}^{b} U_{t-j} \]  \[4\]

Auto regressive with moving average model

\[ S_t = \beta_0 + \beta_1 \sum_{i=1}^{p} S_{t-i} + \theta \sum_{j=1}^{q} U_{t-j} \]  \[5\]

Mean reversion model

\[ (S_t - \bar{S}) = \varphi (S_{t-1} - \bar{S}) + U_t \]  \[6\]

In these equations, \( S_t \) is the Log exchange rate in time \( t \). In this study, after estimating each fundamental and technical model, weighting enters the genetic algorithms system. Optimal weights of each model will be measured according to these four criteria: R-squared (\( R^2 \)), mean square error (MSE), mean absolute percentage error (MAPE) and root mean square error (RMSE). Let \( A_t \) be the actual, mean and fitted exchange rate respectively, four criteria are then defined as:

\[ R^2 = \frac{1}{n} \sum_{i=1}^{n} (A_t - \hat{A}_t)^2 \]  \[7\]

\[ MSE = \frac{\sum_{i=1}^{n} (\hat{A}_t - A_t)^2}{\sum_{i=1}^{n} (A_t - \bar{A})^2} \]  \[8\]

\[ MAPE = \left( \frac{\sum_{i=1}^{n} (A_t - \hat{A}_t)}{A_t} \right) \times 100 \]  \[9\]

\[ RMSE = \sqrt{\frac{\sum_{i=1}^{n} (\hat{A}_t - A_t)^2}{\sum_{i=1}^{n} (A_t - \bar{A})^2}} \]  \[10\]

In other words, the objective function in genetic algorithms is so determined that model which has higher \( R^2 \), mean square error, mean absolute percentage error or root mean square error, will be given less weight. The fitness functions used in the genetic algorithm are as follows (Vose, 1991):

\[ P(k) = \frac{\max(CRI_{i}) - CRI_{k} + 1}{\sum_{i=1}^{n} (\max(CRI_{i}) - CRI_{i} + 1)} \]  \[11\]

In equation (11), the probability of selection of chromosome \( k \) is \( P(k) \). \( CRI \) consists four criteria (\( R^2 \), MSE, MAPE and RMSE) corresponding chromosome \( k \), max (CRI) is maximum criteria in population and finally, \( M \) is number of exchange rate models. Table 1 demonstrates the parameter settings of GA.arResult and Discussion

We use monthly data from January 1992 to December 2008 for the Iranian Rial against European Union’s Euro for the estimation. The exchange rate data are end-of-period exchange rates and data for exchange rate was collected and certified by European Central Bank. We now turn to estimating the exchange rate models. In next step, optimal weights of each model have been determined according to four criteria (\( R^2 \), MSE, MAPE, RMSE) using genetic algorithms. All other parameters (population size, number of generations) were kept constant for all experiments. Table 2 summarizes the performance of the exchange rate models. Results based on genetic algorithms shows that auto regressive (AR) and auto regressive with moving average (ARMA) have better results than the other technical models of exchange rates relatively. Also, mean reversion model (MR) was the worst model of technical exchange rates determination. Technical analysts believe that their methods will permit them to beat the market. Economists have traditionally been skeptical of the value of technical analysis, affirming the theory of efficient markets that holds that no strategy should allow investors and traders to make unusual returns except by taking excessive risk. There are not too many papers that incorporate technical analysis in a foreign exchange model, and we believe there are two reasons for this. The first is that most researchers do not believe that technical approaches can survive in the market, and the second reason is that even if some researchers are aware of the use of technical rules in exchange rate markets, most of them argue that it is of utmost importance to explain why these traders survive in the market. The aim of applying this article is to test explaining the power of the technical models of exchange rates for Rial / Euro using monthly data from January 1992 to December 2008. In this regard, genetic algorithms and how it work was described briefly. Then, optimal weights of these models were extracted using genetic algorithms. Weight of each model was selected according to four criteria R-squared (\( R^2 \)), mean square error (MSE), mean absolute percentage error (MAPE) and root mean square error (RMSE); So that, if a model has larger amounts of these four criteria, it will be less weight. The results showed according these criteria: auto regressive (AR) and auto regressive with moving average (ARMA) well explain behavior of exchange rate. Also according to R-squared (\( R^2 \)), mean square error (MSE) mean absolute percentage error (MAPE) and root mean square error (RMSE) worst model is mean reversion (MR). In other words, Rial / Euro exchange rate for the period 1992 to 2008 is affected by its past values.
Table 1. Parameter setting of GA.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Setting</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population size</td>
<td>204</td>
</tr>
<tr>
<td>Number of generations</td>
<td>50</td>
</tr>
<tr>
<td>Initialization method</td>
<td>Encoding method</td>
</tr>
<tr>
<td>Percentage of elite</td>
<td>0.2</td>
</tr>
<tr>
<td>Selection method</td>
<td>Tournament selection</td>
</tr>
<tr>
<td>Crossover method</td>
<td>Uniform crossover</td>
</tr>
<tr>
<td>Crossover rate</td>
<td>0.8</td>
</tr>
<tr>
<td>Mutation method</td>
<td>Single point mutation</td>
</tr>
<tr>
<td>Mutation rate</td>
<td>0.05</td>
</tr>
</tbody>
</table>

Table 2. Performance matrix for technical models of exchange rate using genetic algorithm.

<table>
<thead>
<tr>
<th>Model</th>
<th>Criteria</th>
<th>Weight</th>
<th>Rank</th>
<th>R²</th>
<th>Weight</th>
<th>Rank</th>
<th>MSE</th>
<th>Weight</th>
<th>Rank</th>
<th>MAPE</th>
<th>Weight</th>
<th>Rank</th>
<th>RMSE</th>
<th>Weight</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR</td>
<td>R²</td>
<td>0.43629</td>
<td>1</td>
<td>0.41376</td>
<td>1</td>
<td>0.32928</td>
<td>2</td>
<td>0.40280</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MA</td>
<td>MSE</td>
<td>0.11148</td>
<td>3</td>
<td>0.17036</td>
<td>3</td>
<td>0.31904</td>
<td>3</td>
<td>0.16398</td>
<td>3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ARMA</td>
<td>MAPE</td>
<td>0.43205</td>
<td>2</td>
<td>0.37937</td>
<td>2</td>
<td>0.33717</td>
<td>1</td>
<td>0.37847</td>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MR</td>
<td>RMSE</td>
<td>0.02017</td>
<td>4</td>
<td>0.03650</td>
<td>4</td>
<td>0.01451</td>
<td>4</td>
<td>0.05475</td>
<td>4</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

AR: auto regressive; MA: moving average; ARMA: auto regressive with moving average; MR: mean reversion; R²: R-squared; MSE: mean square error; MAPE: mean absolute percentage error; MAPE: root mean square error.

REFERENCES