Application of Genetic Algorithms in the Fundamental and Technical Models of Exchange Rate Optimization: A Case Study for Iran

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Abstract: Genetic Algorithms (GAs) are very likely to be the most widely known type of Evolutionary Algorithms (EAs). GAs are adaptive methods that can be used in searching and optimization problems which work by imitating the principles of natural selection and genetics.The aim of this article is to examine the explaining power of models of exchange rate determination for Iran's Rial against the US Dollar using monthly data from January 1992 to December 2008. In this framework, we have estimated absolute and relative purchasing power parity, Mundell-Fleming, sticky and flexible prices, equilibrium exchange rate and portfolio balance as fundamental models and Auto Regressive (AR), Moving Average (MA), Auto Regressive with Moving Average (ARMA) and Mean Reversion (MR) as technical models. Then, we've put each fundamental and technical model into the genetic algorithm system for measuring their optimal weight. These optimal weights have been measured according to three criteria Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). Based on results obtained, it seems that fundamental models of exchange rate determination explain the behavior of Iran's Rial against the US Dollar exchange rate better than technical models. Furthermore these criteria introduce equilibrium exchange rate and portfolio balance as optimal models.

INTRODUCTION

Addressing data uncertainty in mathematical programming models has been a central problem in optimization for a long time. There are two principal methods that have been suggested to address data uncertainty over the years: (a) Stochastic Programming (SP) and (b) Robust Optimization (RO). SP models produce plans which have higher capabilities to prevent from losses and catastrophic failures. Models such as these have been developed for a variety of applications, including electric power generation, financial planning, telecommunication network planning, supply chain management, oil industry and energy system [1]. Stochastic Programming models can include both anticipative and adaptive decision variables. An anticipative variable is tantamount to those decisions that must be made here-and-now and cannot depend on future observations/partial realizations of the random parameters. An adaptive variable corresponds to wait-and-see decisions after some/all of the random parameters are observed. The most famous type of Evolutionary Algorithms (EAs) is genetic algorithms. GAs have been applied to optimization problems in many fields, from optimal control problems, to job scheduling, transportation problems, pattern recognition, machine learning. GAs are robust algorithms that are capable of optimizing multi-model, noisy, dynamic functions. In their application to complex design problems, however, simple GAs may converge slowly, assessments may be computationally intensive, or GAs may fail because of convergence to an unacceptable local optimum. Considerable research effort has been made to improve the efficiency of GAs, which has resulted in developed genetic algorithms. When used in economic modeling, genetic algorithm describes the evolution of a population of rules, representing different possible beliefs, in response to experience. In a parallel to population

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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. 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 pay-off that agents receive by employing them. Genetic algorithm patterns successfully mimic the behavior of human subjects in strictly controlled laboratory settings. There are a myriad of methods in optimal approaches to get an optimal solution in manyfields. In recent years, GAs and their combined techniques have been applied extensively to financial application areas. *Dempsterand Leemans* [2] 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 aredynamically optimized to maximize a trader's utility. *Chun and Park* [3] proposed a regression case-based reasoning technique where concepts are examined against the backdrop of a practical application involving the prediction of Korean stock price index.

Shin and Lee [4] proposed a GA approach to bankruptcy prediction modeling, which is capable of extracting rules that are easy to grasp for users like expert systems. Some technical trading rules using GA have been used to analyze the profit from financial market and some researches combined neural network, GA and knowledge-based techniques [5, 6]. *Tsakonas, et al.* [7] demonstrated the efficient use of hybrid intelligent systems for solving the classification problem of bankruptcy. The evolutionary neural logic networks are consisted of an innovative hybrid intelligent methodology, by which evolutionary programming techniques are used for obtaining the best possible topology of a neural logic network. *Bhattacharyya, et al.* [8] added semantic constraints to the genetic operators in their application for investing foreign exchange markets. Their model represents a domain-related structuring of the representation and incorporation of semantic restrictions for genetic programming based on search for trading decision models. *Shin and Han* [9] investigated an integrated thresholding design of the optimal or near-optimal wavelet transformation by genetic algorithms (GAs) to represent a significant signal most suitable in artificial neural network models.

In the past few years researchers in the area of exchange rate economics have turned their attention to the analysis of transaction data in foreign exchange (FX) markets. Until late 1990s no detailed data on foreign exchange transactions were available for researchers and it was not possible to conduct any empirical study of microstructure aspects of FX markets with detailed information on the trading activity of their participants. More recently, however, improved data, captured by trading platforms and data vendors, has given researchers and practitioners access to detailed information on individual transactions between FX traders. The abysmal results of the empirical investigations of the models of exchange rate determination, developed in the 1970s, question the validity of the traditional asset market approach. In fact, plenty of empirical evidence shows how asset market models of exchange rate determination completely fail to explain exchange rate movements in the short-run and can only indicate long-run trends [10, 11].

In international economics literature, there are two approaches to the determination of exchange rates. The first one, the fundamental approach, predicts exchange rates based on factors offered by the framework which is itself provided by exchange rates determination models. The second approach is the so-called single-variable approach that uses only the past behavior of exchange rate to predict their future trend and, due to lack of attention to other macroeconomic variables, this procedure is known as the technical approach [12].

The work of *Meese and Rogoff* [10] showed that fundamental exchange rate models were not able to beat the simple random walk in out-of-sample prediction. According to survey studies technical analysis is the most widely used trading technique in foreign exchange markets. Since the 1990s the importance of technical analysis has increased more considerably than other trading practices like the orientation to fundamentals or to customer orders. More recently, between 30 and 40 percent of professional currency traders use technical systems as their most important trading technique. Since technical trading systems are widely used in currency markets, they are continuously monitored even by those traders who do not believe in technical analysis. By observing the transactions and open positions indicated by the most popular technical systems, a trader can draw conclusions about the behavior of other actors and their potential price effects. To put it differently: monitoring technical models helps the trader to deal with Keynes' ''beauty contest'' problem, i.e. how to form expectations about other traders' expectations [13]. Therefore, to check

out which model or models are the best option(s) to evaluate the behavior of exchange rates, a tool which is capable of addressing the needs of the present research is required. Apparently, Genetic Algorithms (GA), as a new technique and a powerful tool in solving complex optimization problems, which can also find the best model among exchange rate models, can serve this function. Therefore, the aim of this research is to select the best model of exchange rate.

The rest of the paper proceeds in the following steps: Section 2 will introduce Material and Methods which includes Introduction to Genetic Algorithms and models of exchange rate determination. Section 3 presents results and discussion. Finally, section 4 is this paper's references.

MATERIAL AND METHODS

Introduction to Genetic Algorithms: During the last two decades there has been a growing interest in algorithms which are based on the principle of evolution/survival of the fittest. A common term, accepted recently, refers to such techniques as evolutionary computation methods. Genetic algorithms, evolutionary programming, evolution strategies and genetic programming are among the best known algorithms in this class. There are also many hybrid systems which incorporate various features of the above paradigms and consequently are hard to classify; they are referred to just as evolutionary computation methods. In general, any abstract task to be accomplished can be thought of as solving a problem, which, in turn, can be perceived as a search through a space of potential solutions. Since usually we are after "the best" solution, we can view this task as an optimization process. For small spaces, classical exhaustive methods usually suffice; for larger spaces special artificial intelligence techniques must be employed. The methods of evolutionary computation are among such techniques; they are stochastic algorithms whose search methods model some natural phenomena: genetic inheritance and Darwinian strife for survival [14]. Figure 1 shows the common structure of genetic algorithms.

In these algorithms a population of individuals (potential solutions) undergoes a sequence of unary (mutation type) and higher order (crossover type) transformations. These individuals strive for survival. A selection scheme, biased towards fitter individuals, selects the next generation. This new generation contains a higher proportion of the characteristics possessed by the "good" members of the previous generation; in this
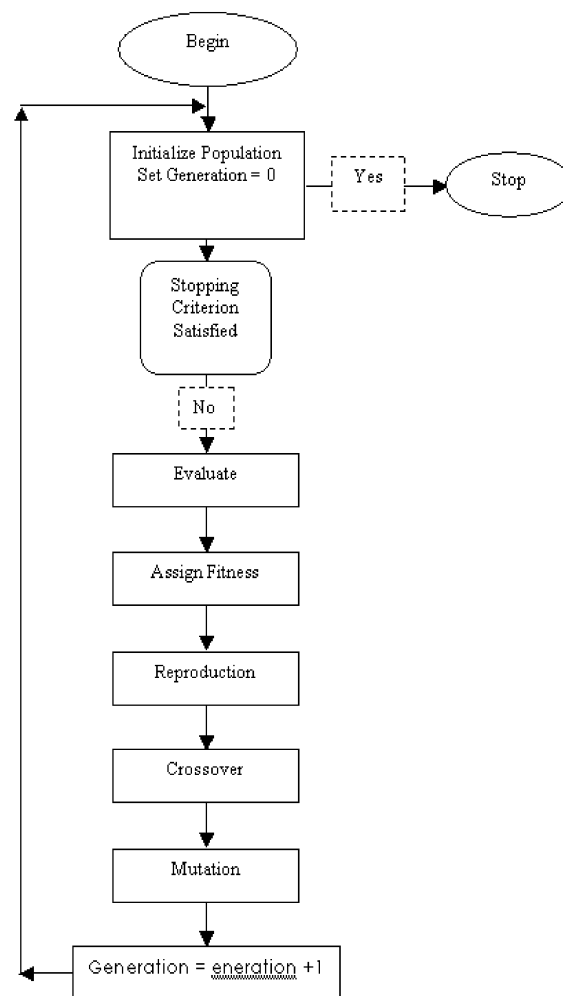

Fig. 1: Flow chart of all GAs used for comparative study

way good characteristics are spread over the population and mixed with other good characteristics. After a number of generations, the program converges and the best individual represents a near-optimum solution [15].

In this section, for the purpose of convenience in our subsequent discussion, genetic algorithms with double strings for multidimensional 0-1 knapsack problems proposed by *Sakawaand Shibano*[16] are revisited with some modifications and their computational efficiency and effectiveness are examined through computational experiments.

Problem Formulation: As is well-known, a multidimensional 0-1 knapsack problem is formulated as:

Minimize cx

Subject to $Ax \leq b$

$$x_j \in \{0,1\}, j = 1,...n \qquad (1)$$

Where $c = (c_1,....,c_n)$ is an n-dimensional row vector, $x = (x_1,....,x_n)^T$ is an n-dimensional column vector of 0-1 decision variables; $A = [a_{ij}]$, $i = 1,..., m$ $j = 1,..., n$ is an $(m \times n)$ coefficient matrix and $b = (b_1,....,b_n)^T$ is an m-dimensional column vector.

It should be noted here that, in a multidimensional 0-1 knapsack problem, each element of c is assumed to be non-positive and each element of A and b is assumed to be nonnegative.

Coding and Decoding: For solving 0-1 programming problems through genetic algorithms, an individual is usually represented by a binary 0-1 string of length n [17]. For handling m constraints defined by $Ax \le b$ in a multi-dimensional 0-1 knapsack problem, the most straightforward technique is to transform the constrained problem into an unconstrained problem by penalizing infeasible solutions, namely, penalty term is added to the objective function for any violation of the constraints. Based on the concept of penalty functions, it is possible to define the fitness function of each individual s by:

$$f(s) = \begin{cases} -cx & if \ Ax \le b \\ 0 & if \ Ax \le b \end{cases} \qquad (2)$$

$$f(s) = -cx - \theta . \max_{i-1,...,m} \left\{ 0, \frac{a_i x - b_i}{b_i} \right\} \qquad (3)$$

where a_i, $i = 1,.....,m$, is an n-dimensional i the row vector of the coefficient matrix A; b_i, is an i the element of a vector b; and θ is a positive parameter to adjust the penalty value.

The fitness function equation (2) or (3) is defined for preventing to generate solutions by imposing penalties on individuals that violate the constraints.

For multidimensional 0-1 knapsack problems, Sakawa *et al.* [18] proposed a double string representation as shown in Table 1, where $g_{s(j)} \in \{0,1\}, s(j) \in \{1,...,n\}$ and $s(j) \ne s(j')$ for $j \ne j'$.

In a double string, regarding $s(j)$ and $g_{s(j)}$ as the index of an element in a solution vector and the value of the element, respectively, a string s can be transformed into a solution $x = (x_1,....,x_n)$ as:

$$x_{s(j)} = g_{s(j)}, j = 1,...,n. \qquad (4)$$

Table 1: Double String

Index of variables	s(1)	s(2)	......	s(n)
0-1 value	$g_{s(1)}$	$g_{s(2)}$	......	$g_{s(n)}$

Unfortunately, however, because this mapping may generate infeasible solutions, the following decoding algorithm for eliminating infeasible solutions has been proposed [18]. In the algorithm, n, j, $s(j)$, $g_{s(j)}$ and $p_{s(j)}$ denote length of a string, a position in a string, an index of a variable, 0-1 value of a variable with index $s(j)$ decoded from a string and a $s(j)$ the column vector of the coefficient matrix A, respectively.

Fitness and Scaling: For multidimensional 0-1 knapsack problems, it seems quite natural to define the fitness function of each individual s by:

$$f(s) - \frac{cx}{\sum_{j-1}^{n} c_j} \qquad (5)$$

Where s denotes an individual represented by a double string and x is the phenotype of s. Observe that the fitness is normalized by the minimum of the objective function and hence the fitness $f(s)$ satisfies $0 \le f(s) \le 1$.

In a reproduction operator based on the ratio of fitness of each individual to the total fitness such as an expected value model, it is frequently pointed out that the probability of selection depends on the relative ratio of fitness of each individual. Thus, several scaling mechanisms have been introduced [17]. Here, a linear scaling is adopted.

In the linear scaling, the fitness f_i of an individual is transformed into f_i' according to:

$$(f_i' - a).(f_i + b) \qquad (6)$$

Where the coefficients a and b are determined so that the mean fitness f_{mean} of the population should be a fixed point and the maximal fitness f_{max} of the population should be equal to $c_{mult} . f_{mean}$. The constant c_{mult} usually set as $1.2 \le c_{mult} \le 2.0$, means the expected value of the number of the best individual in the current generation is surviving in the next generation.

Genetic Operators
Reproduction: Using several Multi-objective 0-1 programming test problems, *Sakawa et al.* [18] investigated the performance of each of the six

reproduction operators - ranking selection, elitist ranking selection, expected value selection, elitist expected value selection, roulette wheel selection and elitist roulette wheel selection and as a result confirmed that elitist expected value selection is relatively efficient.

Elitist expected value selection is a combination of elitism and expected value selection as mentioned below.

Elitism: If the fitness of a string in the past populations is larger than that of every string in the current population, preserve this string into the current generation.

Expected Value Selection: For a population consisting of N strings, the expected value of the number of the i the string s_i in the next population

$$N_i - \frac{f(s_i)}{\sum_{i-1}^{N} f(s_i)} \times N \tag{7}$$

is calculated. Then, the integral part of N_i denotes the deterministic number of the string s_i preserved in the next population. The decimal part of N_i is regarded as probability for one of the string S_i to survive; in other words, $N - \sum_{i-1}^{N} [N_i]$ strings are determined on the basis of this probability.

Mutation: It is well-recognized that a mutation operator plays a role in local random search in genetic algorithms. Here, for the lower string of a double string, mutation of bit reverse type is adopted. The original inversion for double strings is extended to deal with the substrings not only between h and k but also between k and h. Examples of bit-reverse type mutation and version are illustrated in Figure 2.

Number of observations (in genetic algorithms: population size) in the efficiency of genetic algorithms is an effective and decisive parameter. For example if the number of observations to be considered is smaller than normal size, it may lead to early convergence [20]. Therefore, considering the efficiency of problem solving and algorithm execution time, according to empirical literature, the population size would be appropriate if it is between 25 to 300 [21].

Crossover: If a single-point or multi-point crossover operator is applied to individuals represented by double strings, an index $s(j)$ in an offspring may take the same
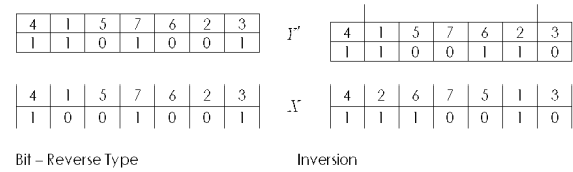

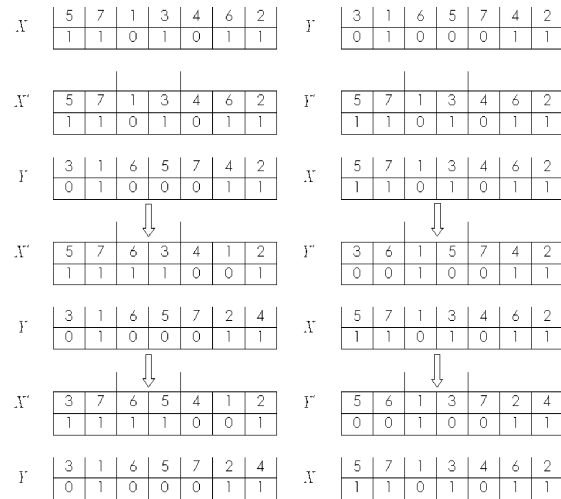Fig. 2: Examples of bit-reverse type mutation and inversion

Fig. 3: Examples of partially matched crossover (PMX)

number that an index $s(j')(j \neq j')$ takes. Recall that the same violation occurs in solving traveling salesman problems (TSPs) or scheduling problems through genetic algorithms. One possible approach to circumvent such violation, the crossover method called partially matched crossover (PMX) is useful. The PMX was first proposed by *Goldberg and Lingle* [19] for tackling a blind traveling salesman problem. It enables us to generate desirable off springs without changing the double string structure, unlike the ordinal representation. However, in order to process each an element $g_{s(j)}$ in the double string structure efficiently, it is necessary to modify some points of the procedure. Figure 3 shows examples of PMX.

Models of Exchange Rate Determination: Theories and models of exchange rate determination are divided into two categories of fundamental and technical models. In this point we aim to introduce fundamental models which are absolute and relative purchasing power parity, Mundell-Fleming, sticky and flexible prices, equilibrium exchange rate and portfolio balance; also, Auto Regressive (AR), Moving Average (MA), Auto Regressive with Moving Average (ARMA) and Mean Reversion (MA) are introduced as technical models.

Fundamental Models of Exchange Rate Determination:
Purchasing power parity (PPP), as one of the basic approaches to fundamental models of exchange rate determination, has undergone considerable testing over the past few decades. This theory holds that exchange rates should be determined by countries' price levels [22]. The notion underlying PPP is that deviations from parity represent profitable commodity arbitrage opportunities, which, if exploited, will tend to force exchange rate towards parity. This model has been viewed as an equilibrium condition as well as an exchange rate determination theory [23].

Another fundamental model to explain exchange rate behavior is Mundell - Fleming Model (MFM) that has dominated attempts to explain the behavior of exchange rates for a long time. This model was introduced by two economists named Mundell and Fleming who extended Keynesian model in the context of open economy. In this model, exchange rate is determined based on capital account, current account and balance of supply and demand forces. A good number of studies of this model point to the fact that the most influential factors on the exchange rate are domestic income, money market variable (domestic money supply), domestic government spending, domestic real interest rates and domestic taxes [24].

Mundell - Fleming model was criticized for their non-compliance with economic realities and with monetary models. Monetary models are studied within the two frameworks of Flexible Price Model (FPM) and Sticky Price Model (SPM). In sticky price model that is associated with *Dornbusch's*[25] work, the short - run exchange rate stands higher than its own long-term equilibrium, a situation which is known as overshooting [26]. In this system, there are jump variables (exchange rate and interest rate) that compensate for the stickiness of other variables (price level).

The monetary model of exchange rate is the standard instrument of analysis in international finance. In a way this is surprising as the empirical support for this model of exchange rate behavior is dubious, if data are used for the Post-Bretton Woods period. The Flexible Price Model starts from the definition of the exchange rate as the relative price of two currencies and attempts to model that relative price in terms of the relative supply of and demand for the currencies.

The next fundamental model is Equilibrium Exchange Rate Model (EERM). The EERM approach, presented by *Williamson* [27], is based on a complete macroeconomic model of an economy and/or a partial equilibrium model of foreign trade. In this setup the FEER is defined as a level of the RER that is consistent with the simultaneous attainment of internal and external equilibrium. In most studies internal equilibrium is defined as closed output gap and external equilibrium as the current account equal to its exogenously set target.

Evans and Lyons [28] propose an alternative channel of transmission from order flow to exchange rates. According to their portfolio-shift model trade innovations affect exchange rates through a portfolio-balance effect, given that FX dealers are willing to absorb an excess demand (supply) of foreign currency from their customers only if compensated for by a shift in the exchange rate.

Technical Models of Exchange Rate Determination:
Technical models are entirely different from fundamental exchange rate models. The failure of traditional macro-based models of exchange rate determination in explaining at least some part of exchange rate fluctuations has stimulated economists to develop new approaches which focus on the micro-foundations of transaction behavior and price dynamics. Over the past decade two approaches have become increasingly important. One of the technical approaches for analyzing the behavior of exchange rates has been established based on efficient market hypothesis. In this model, the opportunities to obtain any non-normal profits in the market have been deleted; rational expectations play a decisive role, here. For testing the efficient market hypothesis, use of random walk hypothesis in forecasting exchange rates is being increasingly accepted as one of the more effective methods [29].

Following *Mark* [31], experimental tests for absolute and relative purchasing power parity are expressed via the below equations, respectively:

$$S_t = \beta_0 + \beta_1 \, (P_t/P_t^*) + U_t \qquad (8)$$
$$\Delta s_t = \beta_0 + \beta_1 \Delta \, (P_t/P_t^*) + U_t \qquad (9)$$

To apply Mundell - Fleming model, the following regression is used [32]:

$$S_t = \beta_0 + \beta_1 Y_t + \beta_2 G_t + \beta_3 (i\text{-}\Pi^e) + \beta_4 T_t + \beta_5 \, M_t + U_t \qquad (10)$$

The regression equation used to estimate sticky price model and adopted by *Papell*[33],*Rogoff*[26] is:

$$S_t = \beta_0 + \beta_1 Y_t + \beta_2 M_t + \beta_3 i_t + \beta_4 \Pi_t + U_t \qquad (11)$$

So, to estimate and check the behavior of exchange rates by resorting to flexible price model this regression can be used [34]:

$$S_t = \beta_0 + \beta_1 (M_t - M_t^*) + \beta_2(Y_t - Y_t^*) +$$
$$\beta_3 (i_t - i_t^*) + \beta_4 (\Pi_t - \Pi_t^*) + U_t \qquad (12)$$

One widely-used and comprehensive econometric model in equilibrium exchange rate context is as follows [35]:

$$S_t = \beta_0 + \beta_1(G_t/ Y_t) + \beta_2 i_t^* + \beta_3 TOT_t +$$
$$\beta_4 LIB_t + \beta_5 NFA_t + U_t \qquad (13)$$

In portfolio balance model, we use the below regression [36]:

$$S_t = \beta_0 + \beta_1 M_t + \beta_2 M_t^* + \beta_3 NFA_t + \beta_4 NFA_t^* + U_t \qquad (14)$$

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

(AR): $$\qquad S_t = \beta_0 + \beta_i \sum_{i=1}^{P} S_{t-i} + U_t \qquad (15)$$

(MA): $$\qquad S_t = \beta_0 + \beta_1 S_{t-1} + \theta_j \sum_{j=1}^{q} U_{t-j} \qquad (16)$$

(ARMA): $$\qquad S_t = \beta_0 + \beta_i \sum_{i=1}^{P} S_{t-i} + \theta_j \sum_{j=1}^{q} U_{t-j} \qquad (17)$$

(MR): $$\qquad (S_t - \bar{S}) = \varphi(S_{t-1} - \bar{S}) + U_t \qquad (18)$$

In these equations, S_t and $P_t(P_t^*)$ indicate the logarithm of domestic (foreign) price level and the logarithm of exchange rate, respectively. $Y_t(Y_t^*)$ and $i_t(i_t^*)$ are respectively the logarithm of domestic (foreign) income and domestic (foreign) interest rate. G and T indicate the logarithm of domestic government expenditure and the logarithm of tax revenue, respectively. $M_t(M_t^*)$ is the logarithm of domestic (foreign) money supply. Π_t (Π_t^*) indicates domestic (foreign) inflation rate. TOT_t and LIB_t are respectively terms of trade and trade liberalization index. Finally, $NFA_t(NFA_t^*)$ is the logarithm of domestic (foreign) net foreign assets.

In this study, after estimating each and every one the fundamental and technical models, the models enter the genetic algorithms system for being evaluated for their weights. Optimal weights of each model will be measured

according to these three criteria: mean square error (MSE), mean absolute percentage error (MAPE) and root mean square error (RMSE).

Let A and $\hat{A}$ be the actual and fitted exchange rate respectively, three criteria are then defined as:

$$MSE = \frac{1}{n} \sum_{t=1}^{n} (A_t - \hat{A}_t)^2 \qquad (19)$$

$$MAPE = \left[\sum_{t=1}^{n} \left| \frac{(A_t - \hat{A}_t)}{A_t} \right| / n \right] \times 100 \qquad (20)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (A_t - \hat{A}_t)^2} \qquad (21)$$

In other words, the objective function in genetic algorithms is determined through the procedure that the model which has a higher mean square error (MSE), mean absolute percentage error (MAPE) or root mean square error (RMSE), will be given less weight.

RESULTS AND DISCUSSION

We have used monthly data from January 1992 to December 2008 for Iran's Rial against US Dollar for estimation purposes. End-of-period exchange rate data were collected from and certified by the Federal Reserve Bank of New York. Gross Domestic Product (GDP), government expenditure and taxes, total exports and imports were collected from the IMF's International Financial Statistics, OECD's main economic indicators and WDI (World Development Index). Money supply, interest rates and consumer price indices are drawn from Central Bank of Iran. Net foreign assets are used as the sum of export and import. All data are measured in constant 2000. The consumer price indices also use 2000 as base year. Results of regressions estimation for Models of Exchange Rate determination (Technical and Fundamental) are summarized in Table 2.

Table 3 below summarizes the performance of the exchange rate models. Results based on genetic algorithms show that fundamental models of exchange rate have produced better results than the technical models of exchange rates. Equilibrium exchange rate model, portfolio balance model and monetary models (sticky and flexible) were identified as the best models of

Table 2: Results of estimations for Models of Exchange Rate Determination

	Fundamental Models		Technical Models								
	APPP	RPPP	MFM	SPM	FPM	EERM	PBM	AR	MA	ARMA	MR
INTERCEPT	0.2*	0.09**			0.06			9.58**	8.78**	9.59**	
Trend		-0.003				0.0001*					
P/P*	0.008										
Δ(P/P*)		-0.01**									
Y			-0.02	-0.07**							
G			0.06**								
T			0.02**								
M			-0.004	0.001			0.01*				
M*							0.005				
i				0.07**							
i*						0.001*					
Π				0.02							
i - Π			-0.02								
(M - M*)					-0.01*						
(Y- Y*)					-0.04						
(i- i*)					-0.0005						
(Π- Π*)					-0.03						
G/ Y						0.008					
TOT						-0.02**					
LIB						-0.10					
NFA						0.05**	-0.01**				
NFA*							0.03				
S(-1)	0.97**		0.98**	0.98**	0.97**	0.98**	0.97**				
AR(1)								0.99**		0.99**	
MA(1)									0.95**	-0.02	
DS(-1)											0.66**
DS(-2)											0.33**
R²	0.9960	0.211	0.9961	0.9961	0.9960	0.9962	0.9961	0.9960	0.7197	0.9960	0.960
F	25008**	0.810	8791**	10331**	10201**	7643**	12902**	50890**	522**	25341**	13452**
D.W	2.02	2.05	2.12	2.03	2.05	2.08	2.07	2.05	0.22	2.00	1.93
SC	18.73	15.57	11.72	18.31	16.20	11.46	14.42				
FF	2.77	0.21	0.86	1.06	1.17	2.95	1.37				
HS	1.74	1.54	1.81	1.66	1.59	1.65	1.66				

APPP (Absolute Purchasing Power Parity), RPPP (Relative Purchasing Power Parity),
MFM (Mundell - Fleming Model),SPM (Sticky Price Modes),
FPM (Flexible Price Model),EERM (Equilibrium Exchange Rate Model),
PBM (Portfolio Balance Model),AR (Auto Regressive),
MA (Moving Average),ARMA (Auto Regressive with Moving Average)
MR (Mean Reversion)DW (Durbin-Watson Test)
R² (R- Square)
*: Significant at 10 percent.**: Significant at 5 percent.

Table 3: Performance Matrix for Exchange Rate Models Using Genetic Algorithm

		Criteria									
		MSE			MAPE			RMSE			Result
Model		Amount	Weight	Rank	Amount	Weight	Rank	Amount	Weight	Rank	Final Ranking
Fundamental	APPP	0.000511	0.098797	6	0.001304	0.096426	2	0.001587	0.094850	6	5
	RPPP	0.001471	0.096538	10	0.003441	0.090568	10	0.002692	0.091262	10	10
	MFM	0.000502	0.098819	5	0.001375	0.096233	8	0.001572	0.094897	5	6
	SPM	0.000498	0.098827	3	0.001355	0.096287	6	0.001567	0.094915	3	4
	FPM	0.000498	0.098828	2	0.001369	0.096248	7	0.001566	0.094917	2	3
	EERM	0.000495	0.098835	1	0.001354	0.096289	5	0.001562	0.094930	1	1
	PBM	0.000501	0.098821	4	0.001287	0.096471	1	0.001571	0.094901	4	2
Technical	AR	0.000515	0.098787	8	0.001321	0.096380	3	0.001593	0.094828	8	8
	MA	0.036010	0.015245	11	0.019819	0.045680	11	0.013319	0.056768	11	11
	ARMA	0.000515	0.098788	7	0.001328	0.096359	4	0.001593	0.094830	7	7
	MR	0.000971	0.097715	9	0.002532	0.093059	9	0.002187	0.092902	9	9

exchange rate determination; also moving average model, relative purchasing power parity and mean reversion model were the weakest models of exchange rate determination.

Briefly we have examined the explaining power of the fundamental and technical models of exchange rates for Rial/USD using monthly data from January 1992 to December 2008. For this purpose, fundamental and technical exchange rate models and factors affecting them were presented based on their own theoretical frameworks. Next, genetic algorithms and how it works was described briefly. In the next step, exchange rate determination models were estimated. Later, optimal weights of these models were extracted using genetic algorithms. Weight of each model was calculated according to the three criteria of mean square error (MSE), mean absolute percentage error (MAPE) and root mean square error (RMSE), in a way that, if a model has larger amounts of these three criteria, it will have less weight. The results showed that according to mean square error (MSE), equilibrium exchange rate, sticky and flexible price models well explained the behavior of exchange rate. Mean absolute percentage error (MAPE) criterion introduced Portfolio Balance, absolute Purchasing Power Parity and Autoregressive models as optimal models. Also, according to root mean square error (RMSE), equilibrium exchange rate, sticky and flexible price provided sensible explanations for the behavior of exchange rate. Therefore, it seems that fundamental models of exchange rate determination have higher explanatory power than technical models. In other words, Rial/USD exchange rate for the period 1992 to 2008 is affected by the fundamental variables, especially "net foreign assets", "Commodity terms of trade" and "foreign and domestic money supply", not by its past valuesin Iran economy. We finally note that these results are consistent with findings from *Frankel and Moosa* [37] *and Taylor and Allen* [30]. Exploring new approaches are left for future research.

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