A fuzzy portfolio trading system in the foreign exchange market based on technical analysis

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Abstract

Technical trading rules are extensively used by foreign exchange (forex) traders. Despite the essential need to the forex diversification, it is not addressed by academic researches to generate forex portfolio trading systems based on technical indices. This paper aims to develop an interpretable and accurate Takagi-Sugeno-Kang (TSK) system for forex portfolio trading. The system uses technical indices of the forex rates and delivers the preferred portfolio composition among multiple foreign currencies. The proposed model considers the transaction cost and trading risk, which are the two important factors in the high frequency trading strategies. The proposed model was implemented to develop a trading system for portfolio trading among the five of the most traded currencies in the Tehran forex market. Four experiments were designed to examine the performance of the proposed model in different market trends, in terms of the portfolio return and risk adjusted return. According to the experimental results, the proposed model is able to extract profitable portfolio trading systems in this market, especially when the market is in the downward trend.

Keywords: Forex portfolio trading system, Technical analysis, TSK fuzzy rule based system, Tehran foreign exchange market.

1. Introduction

Access to the foreign exchange (forex) market and trading in this market is now simple, without a large initial capital requirement and high leverage. Therefore, foreign currency market is an attractive market for individual traders and there are the greatest trading volumes in this market in comparison with the other financial markets [1]. Furthermore, technical trading rules are extensively used by forex traders. According to [2], up to 40 percent of forex traders rely on technical analysis as their main trading tool. On the other hand, the efficient market hypothesis (EMH) states that technical trading rules should not yield superior returns to traders, especially in the markets having vast trading volume and virtually lack of private information about fundamentals in markets such as forex. However, the results of the empirical studies on the profitability of technical trading rules in the forex markets are inconsistent. While some studies confirmed the EMH in different trading frequencies [3, 4], some others concluded the contrary [5-7]. Recently, some experiments investigated the effects of trading frequency and currency diversification on the profitability of forex technical trading rules. According to the experiments, high frequency trading has a beneficial role in the performance of technical analysis [8]. The effects of forex portfolio diversification in the major and emerging currency markets have also been investigated [9, 10]. Neely and Weller conclude that dynamic trading strategies and rule-currency diversification improve the profitability of the trading strategy [9]. However, in these studies the well-known forex technical rules were only used and the portfolio composition was determined according to the return and volatility of the forex rates in the previous periods [9, 10]. In this study, we propose a model to develop forex portfolio trading systems with dynamic strategy for daily trading based on the technical analysis. In this model, the effective factors on the performance of high frequency trading such as transaction cost and trading risk are considered. Since the forex market is a chaotic, noisy and nonlinear dynamic system [11], it is rather difficult to construct a forex portfolio trading system through the simple linear or mathematical ways. The artificial intelligence (AI) techniques seem to be more professional in dealing with the complex nonlinear and dynamic behaviour of forex rate trends. Furthermore, Takagi-Sugeno-Kang (TSK) systems have shown a powerful capability to describe nonlinear mappings for modelling dynamic systems. This fuzzy modelling method is selected when the main objective is the output precision of the system [12]. However, the interpretability of the TSK systems is lower than other fuzzy modelling methods [13]. Interpretability improvements while maintaining the accuracy of the TSK systems has been investigated by several studies [14-16]. Also, a TSK fuzzy rule based system with a new structure has been introduced by the authors to develop a more interpretable and accurate system [17]. In this structure, the TSK rules are represented in disjunctive normal form with variable structured consequents when the absence of some input variables is allowed in the antecedent and consequent parts. Here, we propose a hybrid AI model to develop a TSK system with this structure for forex portfolio trading among the most traded currencies in Tehran Forex market. Finally, the performance of our developed system is evaluated in terms of return and risk.

2. Our proposed model

This section introduces our proposed model to develop forex portfolio trading system based on hybrid AI techniques. In our design, the crisp technical indices are used to forecast the future behaviour of each forex rate and the proportion of the foreign currency in the portfolio composition is suggested based on the forecasts. Since different forex rates fluctuate in different patterns in the forex market, a single TSK system is developed for each foreign currency, separately. The overall framework of our proposed model to develop forex portfolio trading system is presented in Figure 1. The steps of the model are described in the following.

Step 1. Denoising the forex time series

As a pre-processing stage, the noise within the original forex time series is removed using wavelet transformation. The wavelet transformation is selected because it is able to deal with the non-stationarity involved with forex rates time series. Regarding the properties of Haar wavelet and its successful application in finance [18-20], it is used to decompose the forex series and to eliminate the noise.

Step 2. Selecting the most influential technical indices

In our proposed model, a lot of technical indices are considered as the possible input variables. The potential input variables include 6-day moving average (MA6), 12-day exponential moving average (EMA12), 6-day bias (BIAS6), moving average convergence divergence (MACD), 6-day relative strength index (RSI6), 14-day relative strength index (RSI14), 13-day rate of change (ROC13), true strength index (TSI), 9-day stochastic oscillators (%D9, %K9), psychological line (PSY). So far, some of these technical indices have been considered for forex rate prediction [3, 7, 9, 21]. In this work, stepwise regression analysis is applied to select the most influential subset of technical indices and to remove some indices with low explanation ability of the model.

Step 3. Assigning fuzzy membership functions (MFs) to the selected indices

The selected technical indices are introduced to the system with their MFs. The MFs are assigned according to Adeli-Hung algorithm (AHA) [22]. In this algorithm, each technical variable is clustered using a topology and weight change neural network named Adeli-Hung clustering (AHC). The AHC algorithm flowchart is shown in the step 3 of Figure 1. Then a triangular membership function is defined for each cluster as (1).

$$\mu_j(X_i) = f[D(X_i, C_j)] = \begin{cases} 0 & if \quad (X_i, C_j) > k \\ 1 - \frac{D(X_i, C_j)}{k} & if \quad (X_i, C_j) \le k \end{cases} \tag{1}$$

where $D(X_i, C_j)$ is the Euclidean distance between the *i*th data (X_i) and the *j*th cluster center (C_j) and *k* is a threshold which is selected based on the desired number of clusters (i.e., linguistic labels).

Step 4. Developing interpretable and accurate TSK systems for forex portfolio trading

To learn the accurate and interpretable TSK rule bases with the new structure [17], genetic programming (GP) with the context free grammar is used. GP has been applied to forecast the trend of the forex rates and technical trading in this market as well as other financial markets [3, 5, 8, 23]. Different studies report a promising ability of GP in developing technical trading strategies [5, 8, 23]. In these studies, trading rules are evolved in GP evolutionary process with a tree structure. However, in our design, GP should learn multiple TSK rule bases for multiple forex portfolio trading. Among the two approaches for genetic learning of rule bases, we use the Pittsburgh approach in which the whole rule bases are coded by one GP individual with multi tree structures. With this approach, the interaction between different forex rates is properly considered in the evolutionary process [24, 25]. The basic steps of multi tree GP algorithm are shown in the step 4 of Figure 1.

Figure 2 shows an example of a GP chromosome that encodes a portfolio trading system for five foreign currencies, where the TSK system for each currency includes n rules. One of the trees representing the second rule of the TSK system for the second currency is highlighted for example. This tree is interpreted as follows:

$$\text{IF ((BIAS6 isr } A_1 \text{)AND (K9 isr } A_3 \text{)) AND ((D9 isr } A_2 \text{) OR (D9 isr } A_2 \text{)}$$

$$\text{THEN } y_{2,2} = (\text{D9} * 2) + (\text{BIAS6} - \text{ROC13})$$

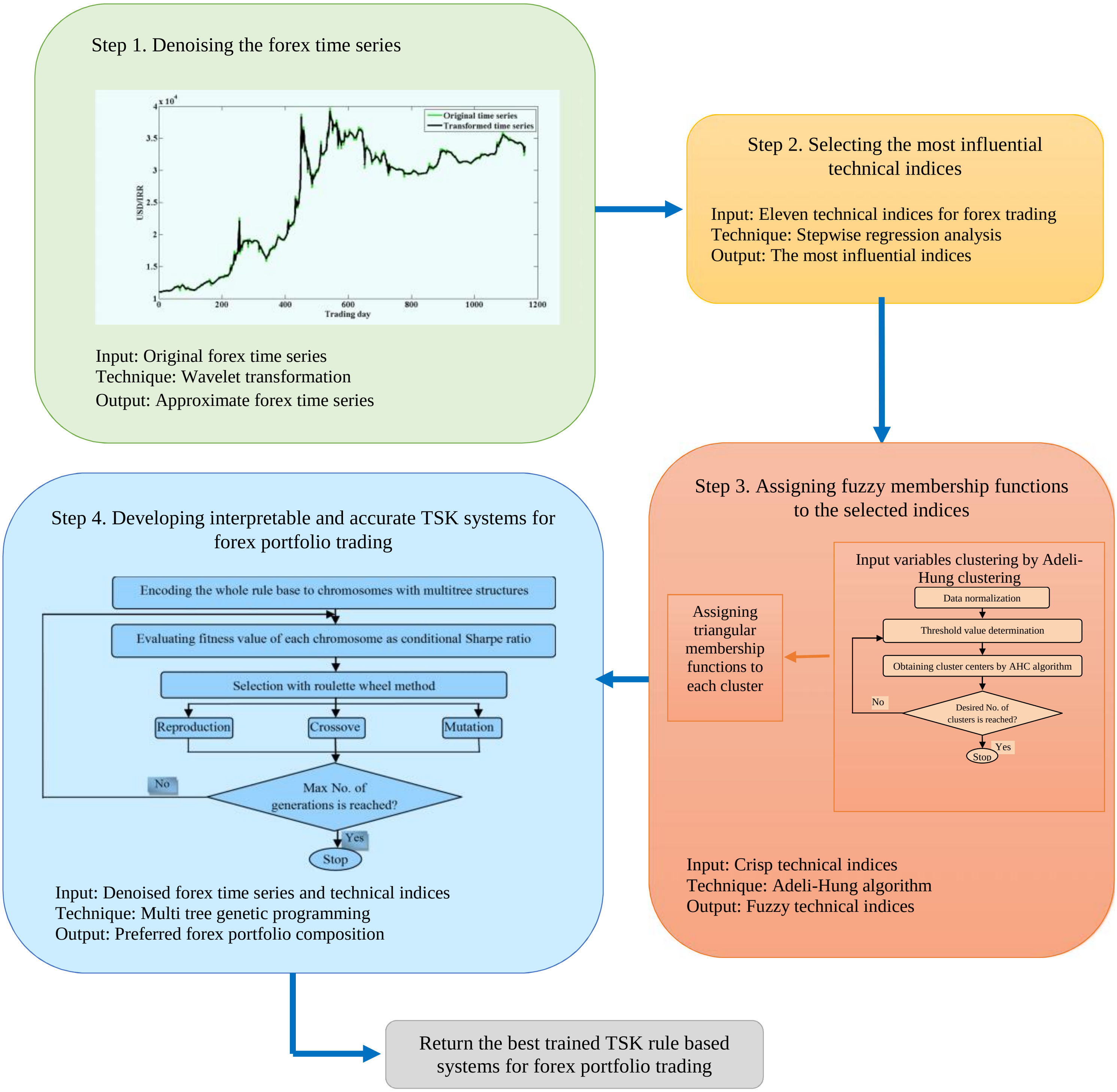

Figure 1. The overall framework of the proposed model to develop forex portfolio trading system based on technical analysis

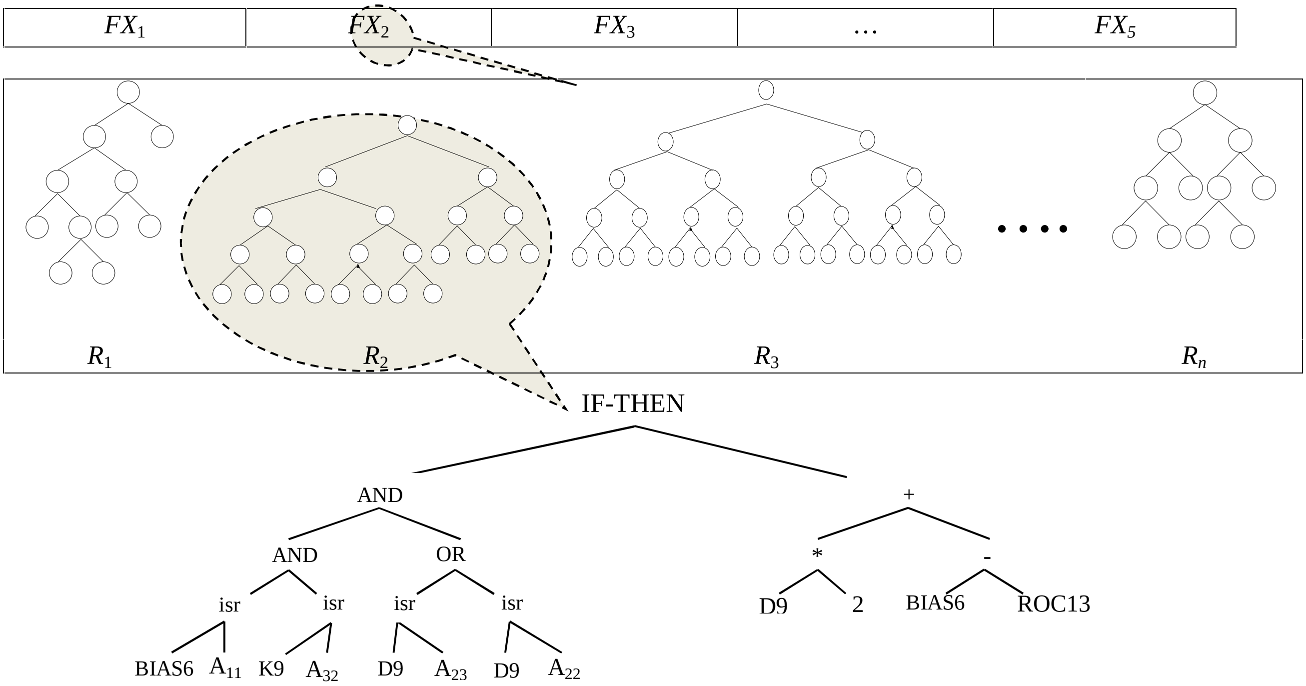

Figure 2. A multitree GP chromosome representing 5 TSK rule based systems for 5 currencies portfolio trading.

This rule states that when the 6-day BIAS of the second forex rate is low and its 9-day %K is medium and its 9-day %D is high or medium then the output of the second rule for the second currency is calculated as $y_{2,2} = (\mathrm{D9} * 2) + (\mathrm{BIAS6} - \mathrm{ROC13})$. The crisp output of the second currency's TSK rule base is determined as a weighted average of the individual rules outputs, when the weight of each rule is its degree of firing. The output of this rule base is normalized with respect to the outputs of the other TSK rule bases in the same individual and the weights of the currencies are updated based on the five TSK rule bases results. The GP chromosomes are evaluated by the cumulative conditional Sharpe ratio of their corresponding portfolio trading system as (2). Conditional Sharpe ratio is a risk adjusted measure that uses conditional value at risk as its risk measure.

$$f \qquad f\imath \qquad = \sum_{i-1}^{n} \frac{R_i - r_f}{C \qquad {}_{1-\alpha}} \qquad (2)$$

where t is the number of portfolio rebalancing in the period, R_i is the return of ith rebalancing considering related transaction costs, r_f is the risk free rate and $\mathrm{CVaR}_{1-\alpha}$ is the conditional value at risk over the ith rebalancing time horizon with $100(1-\alpha)$ % confidence level.

3. Experimental results

The proposed model was implemented to develop a forex portfolio trading system in Tehran foreign exchange market. Five currencies from the most traded currencies in Tehran market are considered: United States Dollar (USD), Euro, Great Britain Pound (GBP), Swiss Franc (CHF) and Japanese Yen (JPY). The daily exchange rates of these currencies in Tehran market at 11:00 AM were used and the spread between Bid-Ask quotes were taken into account. Four experiments with the sliding window approach were considered to investigate the performance of the developed system in different market conditions, i.e. bull and bear markets. Table 1 reports the training and testing periods of the four experiments.

Table 1. The training and testing periods of the four experiments

Training period	Testing period
September, 22, 2011- March, 20, 2012	March, 21, 2012- September, 21, 2012
March, 21, 2012- September, 21, 2012	September, 22, 2012- March, 19, 2013
September, 22, 2012- March, 19, 2013	March, 20, 2013- September, 21, 2013
March, 20, 2013- September, 21, 2013	September, 22, 2013- March, 19, 2014

The time series for each currency were denoised using Haar wavelet with four levels. Five technical indices of BIAS6, %D9, %K9, TSI and ROC13 were selected as the most effective variables in the forex rate prediction. Three fuzzy sets were assigned to each of the selected indices which were interpretable by linguistic labels of low, medium and high. Figure 3 shows the triangular fuzzy sets of the selected indices for USD/IRR during the investigated period.

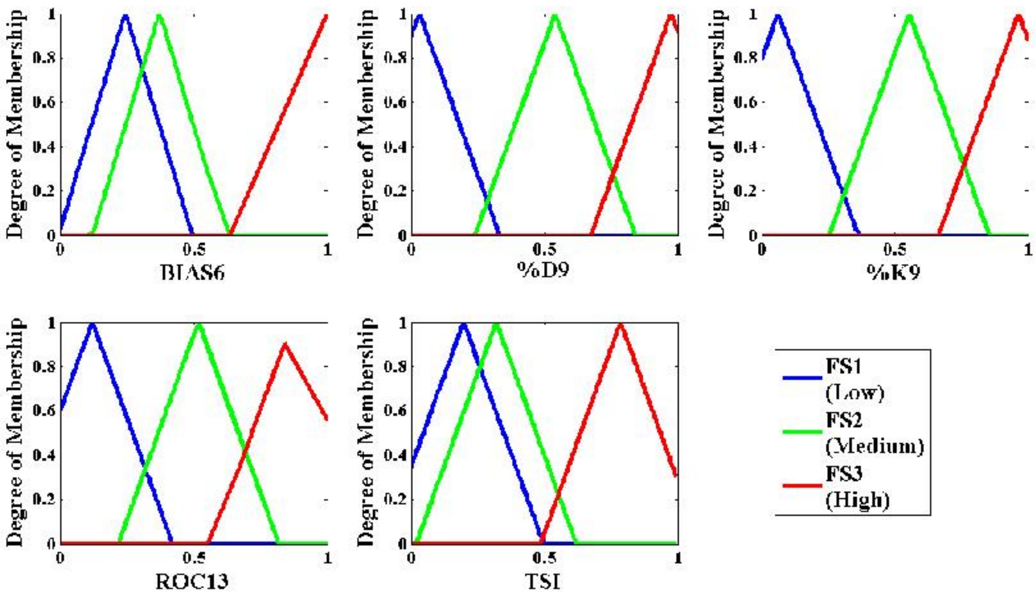

Figure 3. The fuzzy sets of the selected technical indices for USD/IRR.

Finally, the TSK systems were generated using multitree GP with the parameter settings as shown in Table 2. In our primary experiments, Taguchi method was used to select the GP parameters as well as the number of rules in each TSK system and the interval of the numeric constant in the consequent part of TSK rules.

Table 2. Parameter settings of the TSK systems and multitree GP in Tehran Foreign Exchange market

Number of rules in one TSK rule base	7
The interval of the numeric constant in TSK rules	[0, 10]
Population size	70
Number of generations	200
Initialization method	Ramped half and half
Selection method	Roulette wheel
Max initial tree depth	5

Crossover rate	0.6
Mutation rate	0.5
Max following tree depth	6
CVaR confidence level	95%

The performance of the proposed model for forex portfolio trading was evaluated in terms of the cumulative conditional Sharpe (CSharpe) ratio and rate of return (ROR). The proposed model is compared with the equally weighted portfolio of the five currencies with the buy and hold strategy, which is a benchmark strategy. Table 3 shows the experimental results along the four mentioned testing periods. According to this table, our proposed model shows a good performance for dynamic portfolio trading in the Tehran forex market. It reached to the average cumulative CSharpe ratios of 10.2, 14.7, 5.2 and 1.4, which are much higher than the buy and hold portfolio. Also, the proposed model outperformed the buy and hold in terms of ROR. The developed forex portfolio trading system yielded remarkable profits with rates of 32.4%, 41.6%, 1% and 7% on average. The acquired RORs in the first and the second periods are fantastic RORs for six months investment. It should be noted that in these periods the market was in up trend. The lowest ROR of 1% belongs to the third period in which the market was in down trend. According to our experiments, the proposed model can generate profitable forex portfolio trading systems in all market conditions. However, the capability of the model is more prominent in bear markets.

Table 3.Performance of our proposed model and a benchmark strategy in Tehran forex market in terms of conditional Sharpe ratio (rate of return)

	1st test period[a]	2nd test period[b]	3rd test period[c]	4th test period[d]
Buy and Hold strategy	0.55 (29.6%)	0.67 (32.4%)	-0.58 (-13.1%)	0.32 (2.8%)
Our proposed system	10.2 (32.4%)	14.7 (41.6%)	5.2 (1%)	1.4 (7%)

[a]1st period:March, 21, 2012- September, 21, 2012. [b]2nd period: Sept**ember**, 22, 2012- March, 19, 2013.
[c]3rd period: March, 20, 2013- September, 21, 2013. [d]4th period:**September, 22, 2013- March, 19, 2014.**

The performance of the proposed model can be further investigated using Figure 4. This figure shows the ROR trend of the developed TSK system, the equally weighted portfolio with naïve buy and hold strategy and the single forex investment with the buy and hold strategy, throughout the overall testing period of two years. The TSK portfolio trading system outperformed the buy and hold portfolio as well as the single foreign currencies. However, the ROR curve of the equally weighted portfolio is usually under the ROR curve of the single currencies. The only exception is the JPY ROR, which shows a remarkably good performance in the first period and vice versa in the other three periods.

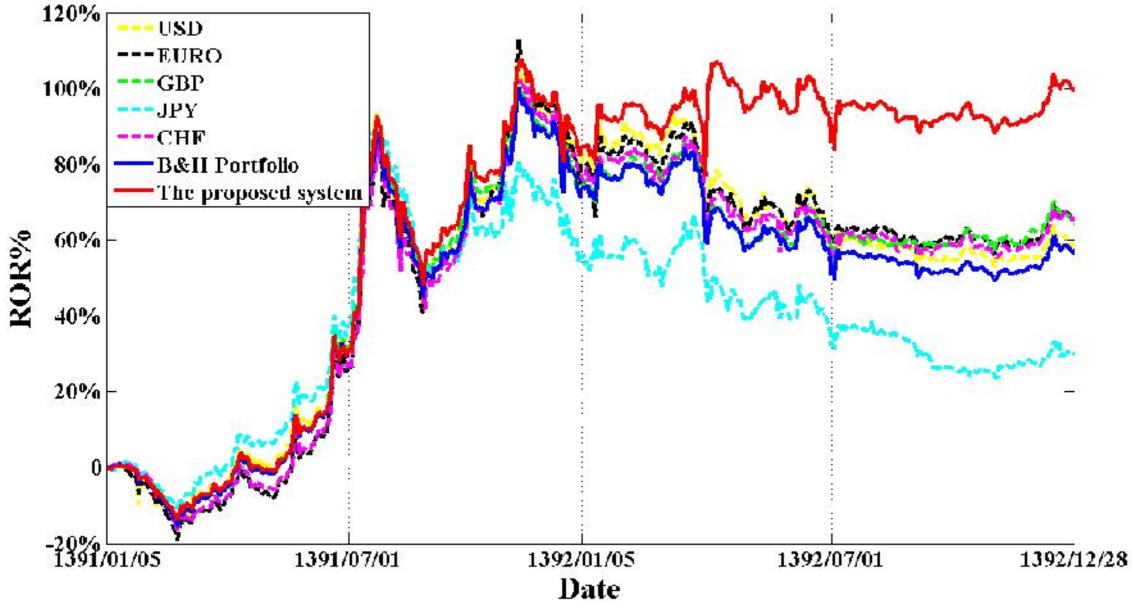

Figure 4. ROR trend of the developed TSK system for portfolio trading in the Tehran Foreign Exchange versus the buy and hold strategy

4. Conclusion

This paper presents a hybrid artificial intelligence model to develop a portfolio trading system for forex traders. Regarding the importance of the interpretability in the trading systems as well as its profitability, a TSK system with the new structure was developed for forex trading. In this structure, the TSK rules are in disjunctive normal form and the absence of some input variables is allowed. Additionally, the consequent part of the TSK rules is not restricted to the first order or the higher order polynomials. The developed trading system directly induces the preferred portfolio weights from technical indices. According to the authors' knowledge, this is the first study to develop a forex portfolio trading system based on technical indices. Our proposed model has some strengths. First, the noises within forex time series are removed and the most important technical indices are selected in two pre-processing steps, to improve the performance of the system. Second, the system induces the preferred portfolio weights from technical indices of forex rates considering the forex correlations. Third, the model extracts an interpretable and profitable portfolio trading system from historical forex rates. Forth, the transaction cost and risk are considered in the model. The proposed model was implemented in the Tehran forex market and a trading system is developed for portfolio selection among five most traded currencies in this market. Four experiments with different training and testing periods were designed to examine the performance of the model in different market trends. According to the experimental results, the proposed model can generate profitable forex portfolio trading systems, especially in downward trends. Consequently, it is possible to discover patterns in the forex time series using multi tree GP and also the forex technical trading is profitable in an emerging market like the Tehran forex market.

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