

Comparing Prediction Methods of Artificial Neural Networks in Extracting Financial Cycles of Tehran Stock Exchange based on Markov Switching and Ant Colony Algorithm

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Abstract

The stock exchange is considered to be an important establishment to finance long term projects, on one hand, and to collect savings and finance of private section. The stock exchange can be a safe and secure place to invest surplus funds to purchase corporate stocks. As recession and prosperity in this market can have a great role in stockholders` decision-making, it becomes vital to predict these cycles. In this paper, using model MSMH(4)AR(2), we extract the financial cycles of the market. Then, using the ant colony algorithm, we determine the most significant predictors and predict the market financial cycles using neural networks. The results show that the PNN model performs better in predicting the future market with respect to the criteria of mean squared error, the root mean squared error, the model accuracy and kappa coefficient.

Keywords: Market Financial Cycles, Bear Market, Bull Market, Artificial Intelligence, Markov Switching Model.

Introduction

Investing in stock market constitutes an important part of the economies at the national level. Undoubtedly, the greatest part of the investment is exchanged through stock markets over the world and national economies are influenced by the stock market performance. Also, this market is accessible for professional investors and the public as an investing benchmark (Samadi and Bayani, 2011).

The great economic crises led to the increasing attention to economic cycles, financial cycles and global exchanges between them in the last decade (Hana, 2018). Market efficiency and its prediction have become of great interest as studied in different researches while market financial cycles prediction is less investigated. The division of market situation into bear and bull markets similar to recession and prosperity periods is defined in economic main activities (Hamilton, 2011; Pagan & Sossounov, 2003). In the bear market, stocks are not of attraction and the price of stock decreases. If the future situation is predicted, an investor can transfer his capital without risk. Therefore, the increasing importance of assets in the economy necessitates the continuous investigation of this market. There are two parametric and non-parametric approaches to identify financial cycles. As there is no agreement on the definition and identification of bear and bull markets between the authorities and decision-makers, Markov switching parametric approach has been used to differentiate market financial cycles (Gonzalez et al., 2005).

In this paper, using the Markov switching model, we extract market financial cycles and then the most important predictor variables of market with ant colony algorithm (ACO) are derived and predict the future situation of market using probability neural networks (PNN), radial basis function (RBF), multi-layer perceptron (MLP), and artificial neural fuzzy inference system (ANFIS).

Literature review and theoretical basis

1- Bear and Bull stock market

Financial markets show up and downtrends known as bear and bull regiment, with different opportunities of investment. Financial market investors are seriously eager to predict market periods in order to allocate their assets (Nyberg, 2013). Using precise analyses of bulls and bears, investors can improve their decision-making time to do investing (Candelon et al., 2008). Chauvet and Potter (2000) define the bull and bear markets as the following: In stock market terminology, the bull (bear) market is the market in which there is seen to be an increasing (decreasing) trend of prices (Pagan & Sossounov,

2003).

2- Predictor variables of market financial cycles

The predictor variables of prosperity and recession of the market are divided into market financial variables and macro-economic variables. As an optimal start to analyze investment and finally decide on investment depends on the historical trend of market and firms financially, it seems necessary to scrutinize the internal information (Hejazi & Fatemi, 2005).

2-1- Market financial variables

There are five financial variables of the prospective situation of the market:

Book to Market Ratio: this index shows the liquid flow in the market and can contain valuable information. Fama and French (1992) concluded that the ratio of book to market value is of a great relationship with stock efficiency. In another word, the stocks with a higher ratio of booking value to market value imply higher efficiency compared with the ones with a lower ratio (Pontiff & Schall, 1998; Lewellen, 1999; Chen et al., 2017).

Earning to Price Ratio: calculation ease, lack of intervention for mental factors and comparability are the benefits of applying this ratio which has made it a common tool of evaluation of the market. Basu's findings (1977) showed that firms with higher E/P or lower P/E have greater efficiency than those with lower E/P (Hejazi & Fatemi, 2005). In the study carried out by Chen et al. (2017), there was established a positive relationship of this index with market prosperity.

Dividend to Price Ratio: This ratio is called division profit to price. The division profit of each share (DPS) shows the profit the firm pays for each share. The findings of Barakchian et al. (2016) show that the ratio of division profit to price is of great potentiality in predicting the market. Despite the extensive research, there is not found any consensus on the effect of division profit on the value of the firm. Gordon (1959) believes that division profit increases the stockholder's wealth. Miller and Scholez (1978) concede that division profit is of no effect on stockholder's wealth. Lipson (1998) expresses that division profit is a good sign of profiting situation of the firm and the firm management does not establish the division profit unless it assures that the division profit can be kept the same from the prospective revenue of the firm (Khoshtinat & Sarebanha, 2003).

Sales to Price: Barbee, Mukhreji, and Rains (1996) stated that the ratio S/P is more reliable than efficiency as it is not affected by the accounting

methods influencing profit and book value. Based on the Gordon growth model, with the increase of revenue to the price in the market, there is better efficiency and greater prosperity.

Stock Variance: According to fluctuation feedback, if the fluctuations of stock efficiency have value as stock risk index, the increase of stock efficiency fluctuation leads to the increase of expected stock efficiency, in turn, causing the reduction of stock value. In fact, investors assume more risks with greater efficiency; therefore, the stock efficiency is affected by fluctuation, the increase of which results in a reduction in stock price and efficiency (Sias & Whidbee, 2010).

2-2- Macroeconomic variables

There are found four macroeconomic variables to predict the prospective situation of the market:

Raw oil price: the fluctuation of oil price affects the price and the stock efficiency and also indirectly on the capital market. Regarding the dependency of governmental budget and subsidiary on oil revenues, the change in oil price has a great influence on Iran economy especially in the capital market (Bordbar & Heidari, 2017). The studies can be divided into four main groups. The first group contains the studies supporting the negative relationship between oil price and stock market efficiency, reasoning that increases in oil price lead to the enhanced energy costs for production firms which, in turn, decreasing the profits of stock firms and their values. Chio and Lee (2009) and Jammazi and Aloui (2010) have supported this trend. In national studies, Samadi et al. (2007) investigated the effect of oil and gold world price index on TEPIX¹.

The second group of studies as seen in El-sharif et al. (2005) and Narayan and Narayan (2010), proves that there is a positive relationship between oil price and stock market efficiency in that the increase of oil world prices increase the investors' income and demand to purchase stock and thereby increases the imports of raw materials and technology to the country. This increases the profiting and cash flow of prospective incomes of the firms and can have a positive effect on the price and efficiency of stock (Torabi & Hooman, 2010).

The third group confirms both negative and positive relations, direction of

¹ Tehran Price Index

which depends on the fact whether the country imports or exports oil, as mentioned in the studies of Park and Ratti (2008) and Killian and Park (2007). The increase of oil price leads to the increase of GNP for oil-exporting countries, but it must be noted that developing countries are the final oil products and derivative consumers which import the oil due to the inability to process the raw oil. Therefore, the increase in oil price raises the final price of finished products by industrial countries which increases the real value of imports in developing countries such as Iran. Therefore, it is expected that there is a negative relation between the increase of oil revenues and the increase in the stock market index.

The fourth group proves that there is not any significant relationship between oil price and market efficiency. The findings of Apergis and Miller (2009) show that oil shocks do not have any effect on stock efficiency, consistent with those of Miller and Ratti (2009) and Al-Janabi et.al. (2010).

Inflation rate: the relationship between the inflation rate and the stock market varies from one country to another regarding the economic structure of the country. Chen et al. (2017) confirmed the positive relationship between inflation rate and recession in the market. The increase in inflation leads to the reduction of power purchase. With the reduction of power purchase, the interest rate increases, thereby affecting the stock value which increases the recession in the market. In contrast, some studies highlight the positive relationship between inflation and market efficiency, but if inflation and price rise of stock firm products is greater than the growth of production costs, the profits of firms increase and inflation can have a positive effect on stock value through the cash flow of prospective revenues. Evidently, the result of these two opposite effects determines the effect of inflation on price and stock efficiency (Torabi & Hooman, 2010).

Gold price: Gold coin is considered to be an alternative for investment (Samadi & Bayani, 2011). Baur and Lucy (2010) expressed that gold can neutralize the financial risks and protects investors in chaos financial markets. Capie et al. (2005) believed gold can be an immunizing tool to protect the investors' portfolio.

Exchange rate: in developing countries such as Iran, the exchange rate is believed to be an influential economic variable. Both the stock market and the foreign exchange market are affected by economic fluctuations and reflect the changes rapidly (Saleh, 2008). The empirical studies have paid attention to this subject, the results of which vary regarding the country, study period and operational definition. For example, Skouie and Sohrabian (1992), Adjasi et al.

(1998), Wu (2000), Ramasamy and Yeung (2002) and Chiang and Yang (2003) can be mentioned. Miller and Show fang (2001) showed that the exchange rate fluctuation leads to fluctuation in stock efficiency and reduction of the exchange rate has a negative effect on stock efficiency. Adam and Tweneboah (2008) studied the effect of macro-economic variables on the stock market, concluding that there is a negative relationship between stock price and exchange rate (PourEbadalhan et al., 2014). Barghi Oskoei et al. (2014) showed that the external exchange rate variable change and raw oil price are positive with a delay and their effect on stock price is negatively significant with two delays.

Methodology of Research

The data related to macro-economic variables including oil price, inflation rate, gold price and exchange rate were extracted from the statistics bureau of the central bank of Iran and technical information center of Iran(www.tici.info). Also, the data related to the variables of stock market including TEPIX, a book to market, earnings to price, dividend to price, sales to price and stock variance were extracted from the database of Tehran stock market, dating back to Farvardin 1380 through Day 1396, on a monthly basis. Each of the variables was considered with a delay of 3, 6, and 12 months. The data were analyzed with SPSS 22, MATLAB 2017 and OxMetrics 7.

1- Extracting market financial cycles using the Markov switching model

There are several studies regarding the application of the Markov switching model to explain the switching behavior of stock market regiment. This model was introduced by Terner (1989) to explain the behavior of regiment transmission of the stock market. This study showed the benefit of the Markov switching model in explaining regiment transmission in mean and variance of stock efficiency. Schaller and Norden (1997) investigated the severe regiment switching in the behavior of stock efficiency and presented hard evidence on the regiment transmission of the market stock regiment, including change in mean, variance, or both. Maheu and Mccurdy (2000), using the regiment switching model, identified two different high-efficiency regiment(stable regiment) and low efficiency (fluctuating regiment) through the investigation of non-linear structure in conditioned mean and variance of the USA stock market efficiency.

The assumptions of the Markov switching model are as following: the regiment occurring in t period is not observable and depends on a non-

observable process (s_t). In a two-regiment model, it is assumed that S_t adopts the values 1 and 2. A two-regiment model AR(1) can be shown as follows.

$$y_t = \varphi_{0,s_t} + \varphi_{1,s_t}y_{t-1} + \varepsilon \tag{1}$$

To complete the model, the features of process S_t should be specified. In the Markov switching model, S_t is considered to be a Markov process of the first order, showing that S_t is only dependent on the previous regiment S_{t-1} . In the sequel, the transition probabilities from one situation to another are introduced to complete the model:

$$\begin{aligned} p\left(s_t = \frac{1}{s_{t-1}} = 1\right) &= p_{11} \\ p\left(s_t = \frac{1}{s_{t-1}} = 2\right) &= p_{12} = 1 - p_{11} \\ p\left(s_t = \frac{2}{s_{t-1}} = 2\right) &= p_{22} \\ p\left(s_t = \frac{2}{s_{t-1}} = 1\right) &= p_{21} = 1 - p_{22} \end{aligned} \tag{2}$$

In the above relationships, P_{ij} is the transmission probability of Markov chain from the situation i in $t-1$ to situation j in t . P_{ij} must be non-negative and satisfy the following conditions:

$$\begin{aligned} p_{11} + p_{12} &= 1 \\ p_{21} + p_{22} &= 1 \end{aligned} \tag{3}$$

Matrix P , called the transition matrix, can be defined as the following.

$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} \tag{4}$$

The elements on the main diagonal show the stability of the situation but other elements indicate the change of situation (Souri, 2013). The model can be generalized into the case including m regiments and P delays, where there appear some general situations divided into four classes depending on which part of the autoregressive model is related to the regiment and is transferred: change in mean, change in intercept, change in autoregressive parameters, and change in variance inconsistency. The combination of these cases can bring about other cases as observed in Table 1.

Table 1. Summary of different cases of MS-AR models

		variable mean	Fixed mean	Variable intercept	Fixed intercept
Fixed A_i	Fixed σ	MSM	linear M	MSI	Linear
	variable σ	MSMH	MSH	MSIH	MSH
Variable A_i	Fixed σ	MSMA	MSA	MSIA	MSA
	variable σ	MSMAH	MSAH	MSIAH	MSAH

Regarding the previous studies such as Hana(2018), Chen et al. (2017) and Kole and Van Dijk (2017) the market situation is non-observable as a discrete variable which depends on the past change of stock efficiency (change of mean and Variance of price logarithm).

$$r_t = \mu_{st} + \sigma_{st}\varepsilon_t \quad (5)$$

Before introducing the financial cycles in the stock market using the Markov switching model, it is necessary to investigate the data stationary. In this section, using the efficiency of data logarithm related to TEPIX and utilizing Augmented Dickey-Fuller and Philips-Perron tests, we will examine the data stationary. If the absolute value of calculated statistics is less than the absolute value of critical value, the null hypothesis that there is a unit root in variables is accepted. The results are summarized in Table2.

Table2. Unit root test

Variable	Augmented Dickey-Fuller test	Philips-Perron test
the efficiency of TEPIX logarithm	-7.805	-7.705

At the error level 0.05, the critical value is -2.87. The optimum delay length is determined using the Schwarz information criterion. Since the absolute value of statistics of ADF and PP is greater than that of critical values, the presence of unity root in data is rejected and the data are stationary.

Regarding the literature, MSMH model which makes the market trend dependent on mean and variance of the past market is chosen. In order to determine the number of regiments and proper delay length, the Akaike information criterion (AIC) and likelihood ratio have been used. The results are summarized in Table3.

Table 3. Determine the number of regiments and proper delay length

Madel	AIC	Log-Likelihood
MSMH(2)AR(1)	-3.42	349.154
MSMH(2)AR(2)	-3.42	438.582
MSMAH(2)AR(3)	-3.40	346.428
MSMH(2)AR(4)	-3.39	344.185
MSMH(3)AR(1)	-3.426	353.694
MSMH(3)AR(2)	-3.421	352.455
MSMH(3)AR(3)	-3.407	350.296
MSMH(4)AR(1)	-3.376	352.695
MSMH(4)AR(2)	-3.401	355.415
MSMH(4)AR(3)	-3.392	352.877

Based on the above table, the greatest likelihood ratio is related to the four-regiment model and the lowest Akaike criterion belongs to the delay length 2; therefore, MSMH(4)AR(4) is chosen.

Having estimated the model, we should examine the classic assumptions. If these assumptions are confirmed, the results can be trusted and there is a possibility to interpret them.

Table 4 shows the output results of the model. Based on the LR test used to investigate the adherence of market efficiency from 4 regiments, the null hypothesis of linearity is rejected and the existence of 4 regiments in Tehran stock exchange is confirmed. Therefore, it is assured that the recession and prosperity model of Tehran stock market can be estimated with the Markov switching model. According to Akaike information criterion which is -3.401 for delay length 2, less than other delay lengths, and also based on greatest significant coefficients, the least error variance and the maximum likelihood, the model can be used to determine the cycles of the stock market. The output of model MSMH (4)AR (2) is observed in the following table.

Table 4. The results of estimating Markov switching model for dependent variable of market efficiency

Variable	Coefficients	Standard deviation	t	Sig
AR-1	0.367***	0.0901	4.08	0.000
AR-2	-0.273***	0.0798	-3.42	0.001
Constant(0)	0.0333***	0.0082	4.05	0.000
Constant(1)	-0.00431**	0.0035	-1.20	0.032
Constant(2)	0.918***	0.019	4.77	0.000
Constant(3)	-.0422***	0.016	-2.63	0.009
log-likelihood	355.415			
AIC	-3.401			
Normality Test	1.950 (0.2771)			
ARCH Test	0.00481 (0.9448)			
Linearity LR-test Chi ² (6)	45/554 (0.000)***			

As seen in Table 4, the dispersion (variance) in regiment 2 (severe prosperity) is greater than that of other regiments. Figure 1 shows the smoothed conditional probabilities of locating in each of four regiments.

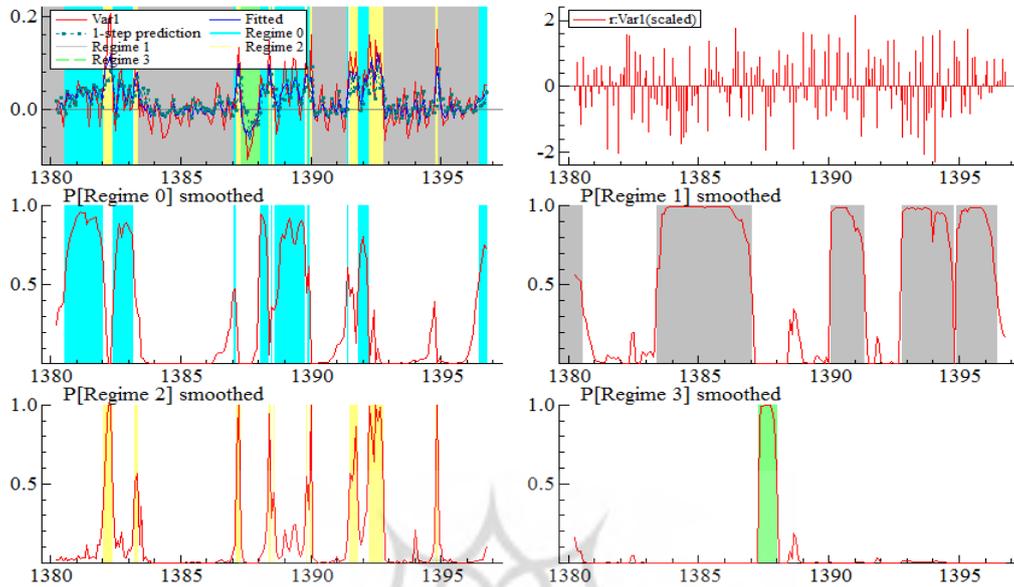


Fig 1. Smoothed conditional probabilities of locating at zero regiments (moderate prosperity), regiment 1(moderate recession), regiment 2 (severe prosperity), regiment 3(severe recession)

Table 5 shows the probability of stability and transition from a regiment to another. .Based on the results, the probability of stability in the moderate and severe prosperity regiment is 0.84 and 0.60, respectively. The probability of stability in the moderate and severe recession regiment is 0.94 and 0.84, respectively.

Table 5. The probability of stability and transition from a regiment to another

	Moderate prosperity & t	Moderate recession & t	Severe prosperity & t	Severe recession & t
Moderate prosperity & t+1	0.84187	0.040128	0.14296	0.16115
Moderate recession & t+1	0.00000	0.94249	0.20964	0.00000
Severe prosperity & t+1	0.15813	0.017382	0.59636	0.00000
Severe recession & t+1	0.00000	0.00000	0.051051	0.83885

In the sequel, the summary of four regiments is presented separated by month. As the results of Table 6 shows the Tehran stock market was in moderate prosperity, moderate recession, severe prosperity and severe recession for 59 months, 107 months, 24 months and 9 months.

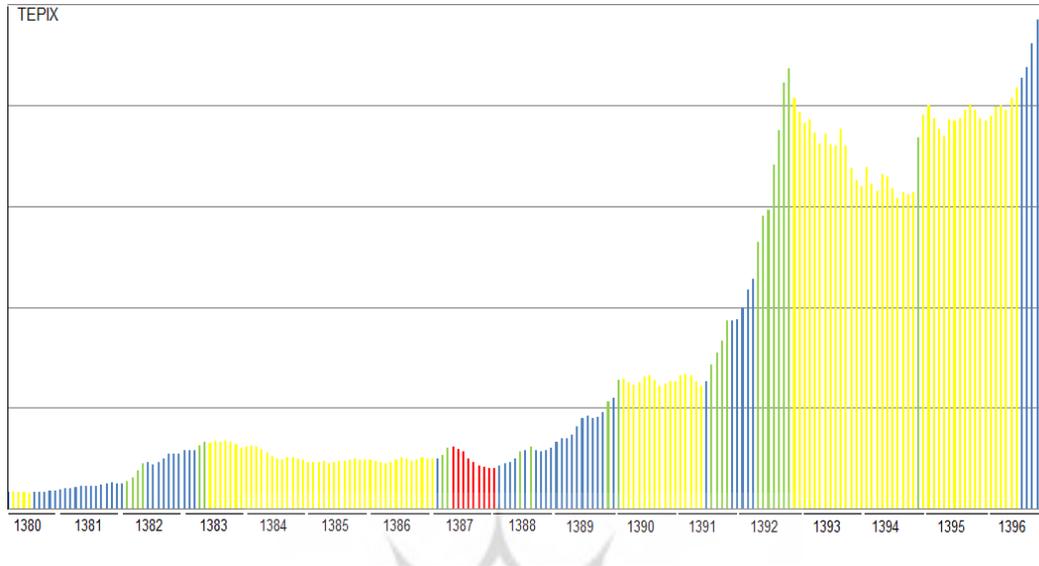


Fig 2. Extraction of Financial periods in the market using MS algorithm

In Fig 2, the periods of moderate and severe recession are presented in yellow and red and those of moderate and severe prosperity in blue and green respectively.

Table 6. The regiments of model MSMH(4) AR(2)

Regiment 0 (moderate prosperity)		Regiment 1 (moderate recession)		Regiment 2 (severe prosperity)		Regiment 3.(severe recession)	
80/8-82/1	18	80/4-80/7	4	82/2-82/5	4	87/5-88/1	9
82/6-83/3	10	83/6-87/1	44	83/4-83/5	2		
87/2	1	90/2-91/5	16	87/3-87/4	2		
88/2-88/5	4	92/11-94/10	24	88/6	1		
88/7	1	94/12-96/6	19	88/8	1		
88/9-89/10	14			89/11	1		
89/12	1			90/1	1		
91/6	1			91/7-91/10	4		
91/11-92/3	5			92/4-92/10	7		
96/7-96/10	4			94/11	1		
Total: 59 months Mean: 5.9 months		Total: 107 months Mean: 21.4 months		Total: 24 months Mean: 2.4 months		Total: 9 months Mean: 9 months	

2- Extracting the most important predictor variables Using Aco algorithm

Ant colony algorithm is one of meta heuristic search algorithms. Like other evolutionary search methods with one population, this method starts in a parallel way, then; the competency of each population is determined with a cost function. This continues to get convergence in the algorithm. The ant's colony algorithm was designed and introduced in 1991 by Dorigo (Dorigo & Stuzzele, 2004). Inspired by ant's behavior, this algorithm serves to find the shortest path.

$$J = \begin{cases} \arg \max_{r \in T_k(i)} \{[\lambda(i, r)] \cdot [v(i, r)]^\beta\} & \text{if } q \leq q_0 \\ J & \text{o.w.} \end{cases} \quad (6)$$

Suppose k is an artificial ant the task of which is to create a path. This ant meets all the customers and returns to the initial point. Along with the k th ant, there appears a list of $T_k(i)$ including all the customers not having been met. The k th ant located at i th customer goes to the j th customer based on equation (6). $\lambda(i, r)$ shows the effect pheromone on the arch between two customers. $v(i, r)$ is an innovative value obtained from the inverse of the distance between i and r customers and β is a parameter which shows the relative importance of $v(i, r)$. q is the value generated between 0 and 1 and q_0 is the parameter determined by the user between 0 and 1. J is a random variable, generated based on the probability distribution function in equation (7), in which $p_k(i, j)$ is the probability of selecting the j th customer.

$$P(KI, j) = \begin{cases} \frac{[\lambda(i, j)] \cdot [v(i, j)]^\beta}{\sum_{r \in T_k(i)} [\lambda(i, r)] \cdot [v(i, r)]^\beta} & \text{if } j \in T_k(i) \\ 0 & \text{o.w.} \end{cases} \quad (7)$$

Equation (8) is used to update the pheromone effect locally when the K th ant goes from the customer i to customer j . In this equation, P is the parameter of fading the local pheromone effect on the path, between zero and one and λ_0 is the initial pheromone value on the path.

$$\lambda(i, j) = (1 - \rho)\lambda(i, j) + \rho\Delta\lambda(i, j) + \rho\Delta\lambda(i, j), \quad (8)$$

$$\Delta\lambda(i, j) = \lambda_0$$

After the ants produce their paths, global pheromone trail update is carried out, based on equation (9) in which is the parameter of fading the effect of total pheromone on the path, between zero and one. Also, L_{gb} is the length of the best path from the beginning of the solution.

$$\lambda(i, j) = (1 - \alpha)\lambda(i, j) + \alpha \frac{1}{L_{gb}} \quad (9)$$

Before the application of ACO algorithm, we normalized the data using the following rule.

$$X_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (10)$$

X_i = the normalized input values, x_i = the main input values, x_{min} = the smallest input value, x_{max} = the greatest input value.

In this research, 70% of the data are used to train the network. The training data are used to find the relationship between input and outputs observed by model. 15% of data are used to validate and 15% to per from the test. Having implemented the ACO algorithm, we found the following results:

The results of which are seen in fig 3 after 500 iterates a proper convergence. The algorithm error with 11 variables is at the least value (0.0269). To be sure for choosing the effective variables, the model was repeated 5 times

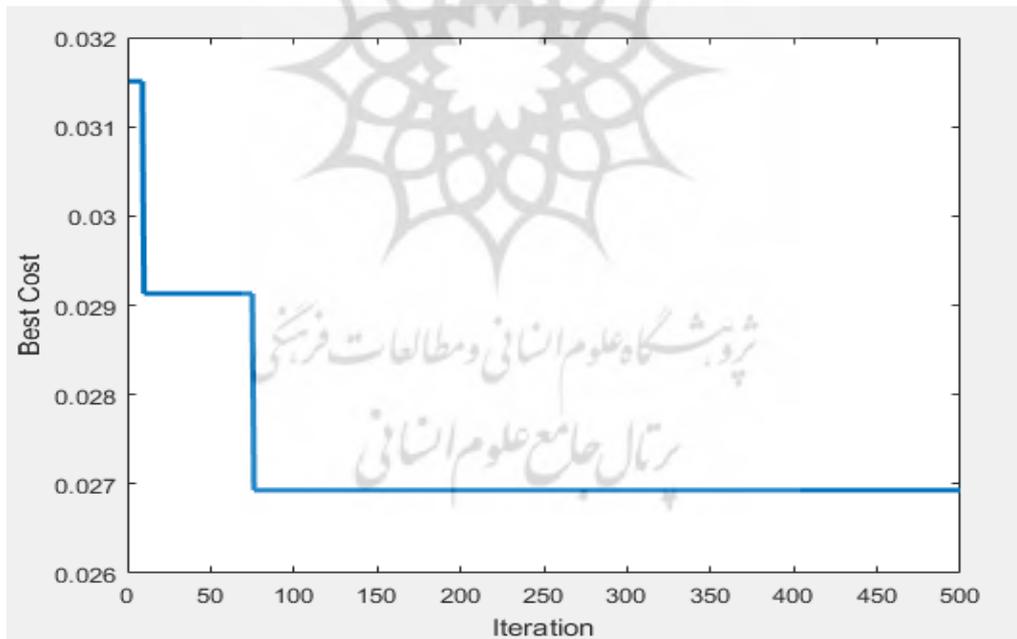


Fig3. the path pared by the evaluation function to reach the optimum value by ACO algorithm

Table 7 shows the effective variables in predicting the prospective situation of the stock market based on priorities.

Table7. The effective variables in predicting by ACO algorithm

Effective variable	Priority	Effective variable	Priority
Coin Price (-6)	1	Book to Market (-3)	7
Exchange Rate (-6)	2	Earning to Price (-6)	8
Sales to Price (-12)	3	Book to Market (-6)	9
Coin Price (-12)	4	Inflation Rate (-12)	10
Dividend to Price (-12)	5	Oil Price (-12)	11
Oil Price (-3)	6		

3- Predicting market financial periods using ANFIS, MLP, RBF, and PNN networks

3-1- Artificial Neural Fuzzy Inference System

In this inferential system, the combination of neural networks and fuzzy logic is used to non-linearly map the inputs to outputs, which is a powerful total to predict complex phenomena (Güler & Übeyli, 2005). This network is shown with 5 layers. ANFIS provides a fuzzy inference system is shown in the following figure. For simplicity, it is assumed that the FIS of interest has two inputs X and Y, and one output. For the first order Sugeno fuzzy model, the if-then rules are as follows.

Rule 1: if x is A_1 , and y is B_1 , then $f_1 = p_1x + q_1y + r_1$

Rule 2: if x is A_{21} , and y is B_2 , then $f_2 = p_2x + q_2y + r_2$ (11)

One of the non-fuzzification methods is to use the mean of centers, the rule of which is shown in the following:

$$f = \frac{w_1f_1 + w_2f_2}{w_1 + w_2} = \bar{w}_1 f_1 + \bar{w}_2 f_2 \quad \text{st} \quad \bar{w}_1 = \frac{w_1}{w_1 + w_2}, \quad \bar{w}_2 = \frac{w_2}{w_1 + w_2} \quad (12)$$

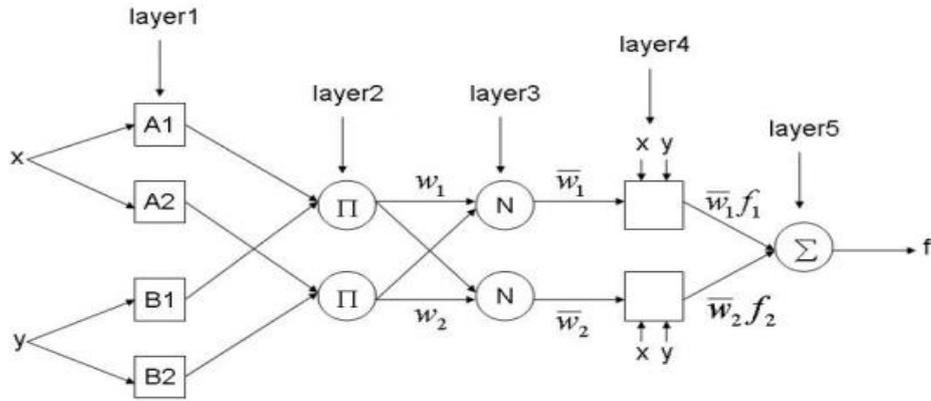


Fig4. ANFIS Structure

Layer1. In this layer, the degree of membership of input nodes to different fuzzy intervals is specified with membership function.

$$O_{1,i} = \mu_{A_i}(x), \quad i = 1,2$$

$$O_{1,i} = \mu_{B_{i-2}}(y), \quad i = 3,4 \tag{13}$$

Layer2. Each node in this layer, calculates the degree of activity of a rule.

$$O_{2,i} = w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \quad i = 1,2 \tag{14}$$

Layer3. in this layer, the activity degree of the ith rule is normalized as the following.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{\sum_{i=1}^2 w_i}, \quad i = 1,2 \tag{15}$$

Layer4. In this layer, the output of each node is as follows:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i), \quad i = 1,2 \tag{16}$$

Layer 5. in this layer, the final value of output which is the sum of the previous layer nodes is calculated as the following.

$$O_{5,i} = \sum_{i=1}^2 \bar{w}_i f_i \tag{17}$$

3-2- Multilayer perceptron

One of the simplest types of perceptron networks is the single-layer one. In this network, weights and biases can be trained for a certain purpose.

The learning rules to implement are “perceptions learn rules”. Perceptron networks are of great importance as they are able to evolve with input vectors, especially in solving simple problems of classification (Kia, 2016).

The multi-layer perceptron networks include several simple perceptions for which a hidden layer exists between input and output layers. A manufacturer must determine how monolayers and neurons should be chosen in each layer (with scientific guess or trial and error). Different learning algorithms are used in MLP, the most common of which are DELTA and backpropagation.

3-3- Radial Basis Function Network

Radial bases functions (RBFs) need more neurons than BPs, but they enjoy less design time. They are of better efficiency when the learning vectors are in a great number. In these networks, first, the center of input space is calculated and then the inputs which are near this space are responded to. Thus, these networks respond to the inputs locally (Nademi, 2017). The superiority of RBF networks to multilayer perceptron is to remove the problem of local minimum, as the only parameters which are adjusted in this type of learning are a linear mapping of hidden layer to the output layer. The linearity of this relationship is a guarantee of error level squared; therefore, there would appear a minimum which is specified easily.

3-4- Probabilistic Neural Networks

Probabilistic neural networks (PNNs) are one of the RBF networks used for classification problems. When an input vector is applied to the network, the first layer determines the distance of the input vector from the training inputs, thereby providing a vector the elements of which show the distance between the training inputs and outputs. Using the output of the first layer, the second layer produces a vector of probabilities as the output of the network. Finally, the competitive transition function in the second layer chooses the maximum of probabilities and assigns one to it with zero for the rest (Kia, 2016). The difference of this network from others lies in the second layer which is of the competitive type. The target outputs should be entered in terms of index vectors of zero and one values. In this section, when an input is applied to this network, the distance between this input and other inputs is calculated and a vector is produced, the elements of which show the distance of that input to the training set. This operation repeats for other inputs. Finally, the sum of distances calculated is transferred to the output layer in a probability vector. The respective function performs on the vector to give the outputs (Nademi, 2017).

3-5- The Evaluation of Models

The evaluation of the power of each model is carried out using 4 criteria of mean squared error, root mean squared error, model accuracy, and coefficient Kappa. The calculation rules are introduced in the following.

The rule of calculating the mean squared error and root mean squared error has been mentioned in relations 18 and 19 in which y_i is the value of real outputs and \hat{y}_i is the predicted value.

$$MSE = \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{N} \quad (18)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{N}} \quad (19)$$

The confusion matrix is used in artificial intelligence for learning algorithms with the supervisor, although used in unsupervised learning. Each column of the matrix shows a case of predicted value while each row represents the true case. Out of artificial intelligence, this matrix is called the contingency matrix or error matrix. The confusion matrix is defined in a binary classification as follows.

Table 8. The confusion matrix

		Actual class	
		Positive	Negative
Predicted class	Positive	TP	FP Type 1 error
	Negative	FN Type 2 error	TN

The general accuracy of the model is obtained from the following rule (Stehman, 1997).

$$pr(a) = \frac{TP+TN}{N} \quad (20)$$

The general accuracy only shows the compatibility of classified data with the reference data and there is no information on confidence level showing the compatibility measurement between repeated scales. Neither can two confusion matrices be compared with the general accuracy while kappa statistics solves these problems. Kappa is formed in terms of general and random compatibility, showing how a classification can be better than a random classification. The kappa calculation is mentioned in the following.

$$K = \frac{\text{Pr}(a) - \text{Pr}(e)}{1 - \text{Pr}(e)} \quad (21)$$

In the above relationship, pr (a) is the observed agreement between the model output and real value, equal to general accuracy, the rule of which was explained in (20). Pr (e) is the putative probability of agreement chance in that the multiplication of the calculated values in per cent by model and real output in each class is computed separately and finally the sum obtained from classes represents pr(e) (Stehman, 1997).

$$\text{Pr}(e) = \left(\frac{TP + FN}{N} \times \frac{TP + FP}{N} \right) + \left(\frac{FP + TN}{N} \times \frac{FN + TN}{N} \right) \quad (22)$$

In the interpretation of kappa coefficient, it can be said that if this coefficient is less than 0.4, between 0.41 and 0.75 and greater than 0.76, the agreement is considered to be low, relatively desirable to good and high, respectively. The calculations related to kappa coefficients are carried out with SPSS22.

Predicting Market Financial Periods using ANFIS, MLP, RBF, and PNN

The network outputs are seen in the following table when 70% of training data and 30% of test data are used.

Table9. MSE and RMSE of networks in terms of experimental and training data

PNN		RBF		MLP		ANFIS		
Test data	Training data							
0.0614	0.0075	0.0776	0.0671	0.0917	0.0364	0.4680	8.7419e-12	MSE
0.2478	0.0866	0.2786	0.2590	0.3028	0.1908	0.6841	2.9567e-06	RMSE

Regarding Table 9, the network ANFIS and RBF have the least and greatest error in training data and the network PNN and ANFIS have the least and greatest error in test data, respectively. It is seen that the model PNN in training and test data outperforms better than other models.

Table 10. Networks confusion matrix

Accuracy and the Coefficient Kappa	severe recession	severe prosperity	moderate recession	moderate prosperity	Actual class	Model
					Observed class	
Accuracy: 72.6% Kappa: 0.583	0	8	43	54	moderate prosperity	ANFIS
	0	1	60	0	moderate recession	
	0	15	0	0	severe prosperity	
	9	0	0	0	severe recession	
Accuracy: 84.7% Kappa: 0.738	3	8	0	43	moderate prosperity	MLP
	0	4	102	7	moderate recession	
	2	12	1	4	severe prosperity	
	4	0	0	0	severe recession	
Accuracy: 83.2% Kappa: 0.722	3	7	0	43	moderate prosperity	RBF
	0	7	100	6	moderate recession	
	0	9	3	5	severe prosperity	
	6	1	0	0	severe recession	
Accuracy: 95.3% Kappa: 0.921	0	4	0	52	moderate prosperity	PNN
	0	2	102	1	moderate recession	
	0	18	1	1	severe prosperity	
	9	0	0	0	severe recession	

Also, PNN has the highest accuracy and the coefficient Kappa is the most accurate model in predicting financial cycles of the market, followed by models MLP, RBF, and ANFIS. Of 54 months of moderate prosperity, of 103 months of a moderate recession, of 24 months of severe prosperity and finally of 9 months severe recession, ANFIS, MLP as well as PNN, and PNN present the most precise classification respectively.

Discussion and Conclusion

This research aimed to predict the financial cycles of the market in a three-month interval. Using the model Markov switching and TEPIX, we extracted the market financial cycles from Farvardin 1380 to Day 1396. The model output shows that in this period, the market had 59 months of moderate prosperity, 107 months of a moderate recession, 24 months of severe prosperity and 9 months of severe recessions.

In the next stage, the financial predictor variables of the market and macroeconomics variables were considered for 3, 6, and 12-month delays. Initially, using algorithm ACO, 11 variables of 27 were chosen as the most influential ones.

Based on the output of algorithm ACO, the financial variables of market include sales to price with a 12-month delay, the dividend to price with a 12-month delay, the book to market with 3 and 6-month delays, earning to price with the 6-month delay and macroeconomic variables including gold price with the 6 and 12-month delays, exchange rate with the 6-month delay, oil price with 3 and 12-month delays and inflation rate with a 12-month delay are capable of predicting the prospective situation of market. As the results show, the financial variables of the market and macroeconomics variables influence in long term and middle term on market financial cycles but the book to market and oil price have short term effects.

In the final stage, the prediction of the prospective three-month situation of the market is carried out with the networks ANFIS, MLP, RBF and PNN. The results showed that MSE and RMSE of test data of PNN model are 0.0614 and 0.2478 less than those of other models. Also, the accuracy of this model is 95.3% and the Kappa coefficient is 0.921 showing good agreement. The model PNN classified 52 months of 54 months of moderate prosperity, 102 months of 103 months of moderate recessions, 18 months of 24 months of severe prosperity and 9 months of 9 months severe recession correctly. Some suggestions are expressed for further work.

Regarding the fact that models Pagan & Sossounov (2003) and Lunde and Timmermann (2004) are considered in predicting market financial cycles, it is suggested that the comparison of market financial periods is done in terms of these two models.

Gonzales et al. (2005) investigated the market financial cycles with the index of transaction volume and compared the transaction volume increase in

each of bear and bull periods. It is suggested that the index of transaction volume be paid attention to in each financial cycle.

Since the effect of change of macroeconomic variables on the efficiency and the price of firm stocks varies in terms of different industries, it is suggested that in future studies it be carried out in the industries of the country.

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