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Incorporating the Markov chain concept into fuzzy stochastic prediction of stock indexes

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ABSTRACT

In this paper we incorporate the Markov chain concept into fuzzy stochastic prediction of stock indexes in order to attain better accuracy and confidence. By the fuzzy stochastic method, parameters for prediction are produced using a fuzzy linguistic summary, whereas by our proposed model, parameters are determined using both a fuzzy linguistic summary and the probabilities of stock indexes rising or falling. This model, whose performance having been tracked for three months, has proved to be significantly better for stock index prediction.

1. Introduction

Forecasting stock indexes has always been a topic of interest for most stock investors, dealers and brokers. Nevertheless, finding out the best time to buy or to sell has remained very difficult because there are numerous factors to take into consideration that may affect the stock market [24].

In the past decades, artificial neural networks (ANNs) have been explored by many researchers for stock price prediction [2,3,6,12,19,21,25,28–30,33,34,36]. These models use information such as market indexes, technical indicators, and fundamental factors of companies as inputs. However, the applicable input factors of the ANNs are hard to define and select [37]. Another popular method is the use of genetic algorithms (GAs) [1,4,8,10,18,20]. But the method has its limitations owing to the tremendous noise and complex dimensionality of stock data [18]; besides, the bulk of data itself may interfere with the learning of patterns.

There are many other approaches to stock prediction. Time series analysis techniques and multiple regression models, for example, are widely used [17]. Also, Lee and Jo [24] use a candlestick chart to predict stock market timing, applying the reinforcement learning theory to stock price prediction; Lam and Mok [22] employs intraday and AHIPMI data. The acronym is a compound of the Nasdaq-100 After-Hours Indicator (AHI) and the Pre-Market Indicator (PMI). There are also studies using the Markov chain: Hassan and Nath [14] applies the Hidden Markov Model (HMM) to forecast airline stock prices; Bauerle and Rieder [5] suggests a Markov-modulated process; Zhang [38] argues that the Markov process can represent general market conditions.

Particularly relevant to the present study is the fuzzy stochastic method, which has attracted a growing amount of attention in computer communities due to its successful use in many applications, such as the fuzzy stochastic model [7], the fuzzy stochastic optimization [26,31], and many other applications [13,16,27,32]. Worthy of special note is a study of Wang [35] which presents a fuzzy stochastic prediction method for real-time predicting of stock prices, employing a fuzzy linguistic summary system [9] to produce prediction parameters. In the present research, to attain better accuracy and confidence, the Markov chain concept [11] is incorporated into that fuzzy stochastic process, with the parameters to be determined using both fuzzy linguistic summarization and the probabilities of stock indexes rising or falling.

Compared to the ANNs method, the approach of this study has a major advantage: it generates a highly accurate result, requiring only one input of data. That is, for instance, only the first hour's stock index data is used as the input leading to the predicting of the probable index at any given hour, while the ANNs way would need more than one input. Furthermore, unlike regular statistical techniques, the present approach requires no calculation of the standard deviation of the prediction.

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2. The prediction model

Treating the stock market situation as a random process, Wang [35] proposes a fuzzy stochastic model for real-time predicting of stock prices: $X(n+1) = X(n)e^r$ where $r = \sum_{n=1}^{n=J} \mu(t_{n+1}) - \mu(t_n)/J$ and $n = 1, 2,\ldots, J \in N$; N represents natural numbers. Furthermore, the function $\mu(t_n)$ is a kind of membership function defined as $\mu(t_n) = (x/y)^2$ where x is the object value at a specific hour, t_n, on one day, and y is the highest value at the hour on the same day. In the present study, the concept of the Markov chain is borrowed to adjust the parameter r of the fuzzy stochastic prediction model.

2.1. The concept of the Markov chain

A Markov chain is a discrete-time stochastic process that describes at successive times the states of a system [15]. The system's state at each successive time is discrete, $n = 0, 1, 2,\ldots$ For each time n, let random variable X_n be the current state of the system. A considerable simplification occurs if, given the complete history $X_0, X_1,\ldots, X_n$, the next state X_{n+1} depends only upon X_n. That is, as far as predicting X_{n+1} is concerned, the knowledge of $X_0, X_1,\ldots, X_{n-1}$ is redundant if X_n is known. If the system has this property at all times n, it is said to have the *Markov property*. The probability of $X_n = i$, denoted by $a_i(n)$, is the *state probability*. The probability from $X_n = i$ to $X_{n+1} = j$, denoted by p_{ij}, is the *transition probability*. A stochastic process $\{X_n, n \geq 0\}$ on state space S is said to be a Markov chain if i and j belong to S,

$$a_i(n+1) = \sum_{j=1}^{k} a_j(n)\, p_{ji}, \quad i = 1, 2, \ldots, k, \tag{1}$$

And $a_i(n)$ and p_{ji} are satisfied with

$$\sum_{i=1}^{k} a_i(n) = 1, \quad n = 1, 2, \ldots, k, \tag{2}$$

$$p_{ji} \geq 0, \quad i, j = 1, 2, \ldots, k, \tag{3}$$

$$\sum_{j=1}^{k} p_{ji} = 1, \quad i = 1, 2, \ldots, k. \tag{4}$$

2.2. Proposing the prediction model

The proposed prediction model is for stock dealer usage. Since the data is grouped by the hour, the random variable X_n is used to express the situation of stock index at the nth hour. $X_n = 1$ represents the stock index rising; $X_n = 2$, the stock index falling, where $n = 1, 2, 3,\ldots$ and X_n is the system situation of the stock index. $y_i(n)$ denotes the probability ($i = 1, 2$) of the state in situation i at the nth hour, as $y_i(n) = P(X_n = i)$. p_{ij} expresses the probability ($i = 1, 2$; $j = 1, 2$) of the transfer of state from a certain hour in situation i and to the next hour in situation j, as $p_{ij} = P(X_{n+1} = j | X_n = i)$. X_{n+1} depends only on X_n and p_{ij}, being irrelevant to $X_{n-1}, X_{n-2},\ldots$. Thus, according to the total probability formula, the following is obtained:

$$y_1(n+1) = y_1(n)\, p_{11} + y_2(n)\, p_{21} \tag{5}$$

$$y_2(n+1) = y_1(n)\, p_{12} + y_2(n)\, p_{22} \tag{6}$$

We use r_{ij} to express the change rate ($i = 1, 2$; $j = 1, 2$) from a certain hour's state in situation i to the next hour's state in situation j, as $r_{ij} = \sum_{n=1}^{n=k} \mu(t_{n+1}) - \mu(t_n)/k$. The $\mu(t_n)$ is defined as $\mu(t_n) = (x/y)^2$ where x is the object value at a specific hour, t_n, on one day, and y is the highest value at the hour on the same day. The parameter r of the prediction model is obtained by using Eqs. (5) and (6):

$$r = \begin{cases} r_{11}\, p_{11} + r_{21}\, p_{21} & \text{when the stock index is on the rising trend} \\ r_{12}\, p_{12} + r_{22}\, p_{22} & \text{when the stock index is on the falling trend} \end{cases} \tag{7}$$

3. The experiment

The stock index data is downloaded and reformatted into a relational database [9]. A portion of the reformatted data is shown in Table 1.

3.1. Computing rising/falling probabilities of the stock index

In this section, we shall compute p_{11}, p_{21}, p_{12} and p_{22} in Eqs. (5) and (6).

To tell if the stock index will rise or fall over the next period, we use the last one year's stock index data as shown in Table 2, for example, to generate Table 3. In Table 3, "1" indicates the stock index rising and "0" represents a fall, i.e., "1" is given when the stock index value is greater than, or equal to, that in the previous period (rising), and "0" is shown when the value is smaller than that in the previous period (falling). For example, in Table 2, the value at 10:00, 03012006 is 6585.66 (marked bold), which is greater than the value 6546.06 at 09:00 the same day. Hence, in Table 3, we enter "1" in the cell for 10:00, 20060301 to indicate a rise of value from the preceding hour.

Now we can compute p_{11}, p_{21}, p_{12} and p_{22} over a particular period of time. We use (times of appearance of (1, 1)/total number of entries) to obtain p_{11}; (times of appearance of (0, 1)/total

Table 1
The reformatted stock index data.

Date	Time	Stock index	μ_{index} (time)
03012006	09:00	6546.06	0.975899
03012006	10:00	6585.66	0.987742
03012006	11:00	6596.18	0.9909
03012006	12:00	6603.83	0.993199
03012006	13:00	6626.40	1
03012006	14:00	6613.97	0.996252

Table 2
A portion of the stock index data.

Date	Time					
	09:00	10:00	11:00	12:00	13:00	14:00
⋮	⋮	⋮	⋮	⋮	⋮	⋮
03012006	6546.06	**6585.66**	6596.18	6603.83	6626.40	6613.97
03022006	6613.39	6668.21	6659.00	6649.83	6648.78	6642.96
03032006	6642.96	6610.84	6618.42	6604.42	6565.38	6553.66
03062006	6553.66	6574.11	6541.58	6559.52	6567.56	6575.78
03072006	6575.78	6534.57	6524.71	6533.17	6515.19	6494.15
⋮	⋮	⋮	⋮	⋮	⋮	⋮

Table 3
The stock index rising or falling over the next period.

Date	Time					
	09:00	10:00	11:00	12:00	13:00	14:00
⋮	⋮	⋮	⋮	⋮	⋮	⋮
03012006	**0**	**1**	1	0	1	0
03022006	**0**	**1**	0	1	0	0
03032006	0	0	1	1	0	0
03062006	**0**	**1**	0	1	0	1
03072006	1	0	1	1	0	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮

Table 4
The probabilities of all cases in different time periods.

Date time	Probability			
	p_{11}	p_{12}	p_{21}	p_{22}
Time = 09:00 to 10:00	0.4048	0.3333	0.0714	0.1905
Time = 10:00 to 11:00	0.4048	0.3333	0.0714	0.1905
Time = 11:00 to 12:00	0.2856	0.1904	0.3334	0.1906
Time = 12:00 to 13:00	0.4047	0.2143	0.1429	0.2381
Time = 13:00 to 14:00	0.2616	0.2860	0.1902	0.2622

Table 5
Stock index change rate from 09:00 to 10:00.

Date/μ_{index}	Time	
	09:00	10:00
⋮	⋮	⋮
03062006	0.98644826	0.99138831
03292006	0.99274475	0.98482256
04102006	0.99556475	0.99595821
04122006	0.98497863	0.99154325
04242006	0.98837260	0.99171410
⋮	⋮	⋮
Average μ	0.98962180	0.99108529
Change rate from 09:00 to 10:00	0.99108529 − 0.98962180 = 0.001-0.00146349	

number of entries) to obtain p_{21}; (times of appearance of (1, 0)/total number of entries) to obtain p_{12}; and (times of appearance of (0, 0)/total number of entries) to obtain p_{22}. For example, as shown in Table 3, from 09:00 to 10:00, the times of appearance of (0, 1), marked bold, are three, and the total number of entries are six. Hence p_{21} is 3/6 = 0.5. In the same way, we can easily obtain p_{11}, p_{12}, and p_{22} of Eq. (3). The probabilities of a rise or fall at different hours are shown in Table 4.

3.2. Computing the rising/falling change rate of the stock index

In this section, the stock index change rates of all the cases, i.e., r_{11}, r_{21}, r_{12}, and r_{22}, of Eq. (7) are computed. For example, the change rate from 09:00 to 10:00 of the case (0, 1), $r_{21,}$ is computed by selecting the data of μ_{index} (09:00) < μ_{index} (10:00). The results so obtained are shown in Table 5. *Average* μ is the average of all μ_{index} at a given hour. In this case, *Average* μ (09:00) is 0.98962180 and *Average* μ (10:00) is 0.99108529. The change rate, $r_{21,}$ from 09:00 to 10:00 is equal to *Average* μ (10:00) − *Average* μ (09:00) = 0.00146349. In the same way are obtained the stock index change rates in other cases, i.e., r_{11}, r_{12}, and r_{22}, as shown in Table 6.

3.3. Computing the parameter and obtaining the predicted value

The parameter r is defined in Eq. (7) in Section 2.2. When the stock index is on the rise, $r = r_{11}p_{11} + r_{21}p_{21}$ is used as the parameter; otherwise, $r = r_{12}p_{12} + r_{22}p_{22}$ serves as the parameter. Table 7 is generated by Eq. (7) combining Tables 4 and 6.

Table 7
Parameter r from 09:00 to 14:00.

Time	Rising parameter r	Falling parameter r
09:00–10:00	0.001235	−0.00387
10:00–11:00	0.002088	−0.00275
11:00–12:00	0.001695	−0.00136
12:00–13:00	0.002633	−0.00164
13:00–14:00	0.001479	−0.00253

Table 8
The predicted values and their deviations in May 2, 2006.

Date	Time	Actual stock index	Predicted values	Deviations (%)
05022006	09:00	7171.77	–	–
05022006	10:00	7189.89	7180.633	0.1287467
05022006	11:00	7213.17	7204.918	0.1144016
05022006	12:00	7168.75	7203.331	0.4823863
05022006	13:00	7162.07	7156.99	0.0709307
05022006	14:00	7199.60	7144.003	0.7722196

The stock index during the next hour can be predicted using the prediction function $X(n+1) = X(n)e^r$ [35]. For example, based on the known Taiwan stock indexes, 7171.77 at 09:00 and 7174.93 at 09:01, on May 2, 2006, the stock index for the other hours on the same day can be predicted. The stock indexes at 09:00 and at 09:01 shows that the market is on the rise, and according to Table 7, the parameter r from 09:00 to 10:00 is 0.001235. By substituting the parameter into the predicting function $X(n+1) = X(n)e^r$, the predicted value for the next hour can be obtained: $X(10{:}00) = 7171.77e^{0.001235} = 7180.633$. The deviation from the actual value is |7180.633 − 7189.89|/7189.89 = 0.1287467%. The predicted values for the other hours on the same day can be obtained in the same way, as shown in Table 8.

3.4. Results of the experiment

The testing data is collected from the Taiwan Stock Exchange website on a minute basis (http://www.tse.com.tw/docs/market/t13sa120.htm). The trading hours are from 9:00 a.m. to 13:30 p.m., from Monday through Friday. The data from January 2003 to March 2006 are used as training examples and the data from April 2006 to Jun 2006 as testing examples. To simplify data processing, the data is grouped by the hour and reformatted accordingly, as shown in Table 1.

As the system begins running, the change rates (r_{11}, r_{12}, r_{21}, r_{22}) and the rising/falling probability (p_{11}, p_{12}, p_{21}, and p_{22}) of all the time periods are computed, respectively (Tables 4 and 6).

After several experiments intended to test the accuracy of the new method, which incorporates the Markov concept, the results were found to be very similar to the example given in Section 3.4. And in the three months trials that followed, the deviations remained consistently from 0.0025% to 1.03%. By contrast, when the former fuzzy stochastic prediction method [35] was applied,

Table 6
Stock index change rates in four cases.

Date time	Change rate			
	r_{11}	r_{12}	r_{21}	r_{22}
Time = 09:00 to 10:00	0.00119090	−0.00934263	0.00146349	−0.00394757
Time = 10:00 to 11:00	0.00457040	−0.00515758	0.00333165	−0.00541578
Time = 11:00 to 12:00	0.00166747	−0.00321723	0.00365443	−0.00394750
Time = 12:00 to 13:00	0.00507807	−0.00402646	0.00404340	−0.00327150
Time = 13:00 to 14:00	0.00307117	−0.00343180	0.00355350	−0.00588958

Table 9
A portion of the predicted values and their deviations in three-month trials.

Actual stock index	New method		Former method		Better or Not
	Predicted values	Deviations (%)	Predicted values	Deviations (%)	
⋮	⋮	⋮	⋮	⋮	⋮
7306.39	7322.043	0.00214239	7322.038	0.002141708	1
7278.96	7298.748	0.002718551	7298.798	0.00272542	0
7235.17	7259.836	0.003409116	7313.15	0.010777906	0
7225.19	7230.376	0.000717833	7230.391	0.000719784	0
7202.95	7227.572	0.003418356	7227.58	0.0034194	0
7177.54	7210.092	0.004535292	7210.087	0.004534609	1
7176.35	7170.033	0.000880254	7170.082	0.00087341	1
7187.09	7157.495	0.004117782	7210.058	0.003195732	1
7156.65	7182.328	0.003588038	7182.342	0.003589995	0
7145.20	7159.01	0.001932717	7159.017	0.001933759	0
7087.96	7152.285	0.009075245	7152.28	0.009074559	1
7069.90	7080.547	0.001505917	7080.595	0.001512778	0
7116.94	7051.325	0.009219579	7103.108	0.001943531	1
7067.83	7112.225	0.00628125	7112.239	0.006283213	0
7096.16	7070.16	0.003663902	7070.168	0.003662866	1
7134.56	7103.196	0.004396018	7103.192	0.004396695	0
7116.83	7127.098	0.001442769	7127.147	0.001449629	0
7030.20	7098.132	0.009662813	7150.258	0.017077528	0
7034.10	7025.542	0.001216605	7025.556	0.001214657	1
7024.27	7036.419	0.001729609	7036.427	0.001730651	0
⋮	⋮	⋮	⋮	⋮	⋮
Sum					298

Fig. 1. A portion of contrasted prediction results obtained using the old fuzzy stochastic prediction method and the new one.

the deviations were from 0.0098% to 1.71%. Table 9 is a portion of the results obtained using both the methods. In the column "Better or Not", "0" is given when our new method is found to be better than the old one; otherwise, "1" is given.

Compared to its former counterpart, as Table 9 shows, our proposed method proves to be significantly better in 298 out of the 330 trials conducted per hour on each trading day during the three-month period of the experiment; see also Fig. 1 for a contrast of the outcomes of both methods.

4. Conclusion

The former fuzzy stochastic prediction method, although found to be better and more effective than other predicting methods [35], fails to consider the rising and falling probabilities of stock indexes. Our proposed new model, with the Markov chain concept incorporated into the prediction, combines the advantages of fuzzy linguistic summarization approaches and has proved able to consider simultaneously both the change rates and rising and falling probabilities of stock indexes. It is no surprise that this model is far more reliable than its predecessors in prediction accuracy, although some might argue that it is just a little more sophisticated or smarter. Moreover, as far as practical day trading is concerned, our predicting device not only helps improve profit performance; more importantly, it can also be used to determine stop-losses with greater confidence. Further exploration in this area might be desired, however, that aims at the betterment of this model itself or puts forward new approaches and perspectives.

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