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A Nonlinear Autoregressive Model with Exogenous Variables Neural Network for Stock Market Timing: The Candlestick Technical Analysis

E. Ahmadi*[a], M. H. Abooie[a], M. Jasemi[b], Y. Zare Mehrjardi[a]

[a] Department of Industrial Engineering, Yazd University, Yazd, Iran
[b] Department of Industrial Engineering, Khajeh Nasir Toosi University of Technology, Tehran, Iran

PAPER INFO	ABSTRACT
	In this paper, the nonlinear autoregressive model with exogenous variables as a new neural network is used for timing of the stock markets on the basis of the technical analysis of Japanese Candlestick. In this model, the "nonlinear autoregressive model with exogenous variables" is an analyzer. For a more reliable comparison, here (like the literature) two approaches of Raw-based and Signal-based are devised to generate the input data of the model. The correct predictions percentages for periods of 1- 6 days with the total number of buy and sell signals are considered. The result proves that to some extent the approaches have similar performances while apparently, they are superior to a feed-forward static neural network. The created network is evaluated by the measure of Mean of Squared Error and the proposed model accuracy is calculated to be extremely high. *doi*: 10.5829/idosi.ije.2016.29.12c.10

1. INTRODUCTION

Developing a model for predicting returns in order to make investment decisions is an important goal for academics and practitioners. Typically, the financial services industry relies on three main approaches to make investment decisions: 1- The fundamental approach that uses fundamental economic principles like economic, industry, and company conditions to form portfolios; 2- The Technical Analysis (TA) approach; and 3- The mathematical approach that is based on the mathematical model. The first two approaches dominate practice because of their applicability [1] and our paper focuses on the TA.

TA, also known as Charting has been a part of financial practice for many years. TA studies the historical data surrounding price and the volume movements of the stock by charts as the primary tool to forecast future price movements [2].

*Corresponding Author's Email: elham.ei86@gmail.com (E. Ahmadi)*

In recent years, TA has proven to be powerful for evaluating stock prices and is widely accepted among financial economists and brokerage firms. This is due to the fact that it offers a relative mixture of human, political, and economic events [2].

This paper focuses on Japanese Candlestick technical trading strategies. Candlestick is a short-term timing technique that generates signals according to the relationships between open, high, low, and close prices [3]. The technique was originally developed by Munehisa Honma in the 1700s. Honma used historical data from the Dojima Rice Exchange in Osaka, Japan, to analyze the rice market since the 1600s. His analytical skills led to the development of candlesticks. Further analysis of candlestick patterns became the foundation of today's candlestick chart techniques. Candlestick charts are more graphically stimulating than bar charts. It is believed that the patterns of one or more candlesticks can describe market conditions and emotion [4]. Many studies have analyzed the applications and advantages of candlestick charts for predicting the stock markets and its reliability is now highly established; such as Lee and Jo [5], Kamo [4],

Xie et al. [6], Lan et al. [7], Chen et al. [8]. It is now accepted that stock markets are nonlinear dynamic systems; so linear approaches cannot identify the relationships in the time series of stock prices. However, an appropriate nonlinear model such as an intelligent system technique may be able to discover complex nonlinear relationships and handle the uncertainty and imprecision common in the stock market [2]. Artificial neural network (ANN), as the main approach in the field of Artificial Intelligence (AI), has attracted much interest over the past decade for its ability to forecast financial performance [8].

In this study, ANN is used as a computational intelligence because it typically performs well for classification, recognition, and forecasting of financial data and is capable of dealing with uncertain, fuzzy, or insufficient data that fluctuate rapidly in very short periods of time [2]. Many types of research have used ANNs in modeling and prediction of time series data [9-17]. Most of the reported research has focused on using feed forward neural network [18]. These networks do not have any feedback connections in their architectures. Therefore, they do not take into account the temporal dependencies between the data. Recurrent neural networks (RNNs) are widely used to deal with many dynamical and non-linear problems, including time series prediction [19-21]. RNNs are computationally more powerful than feed-forward networks and valuable approximation result has been obtained for prediction problems [18]. One of the most convenient forms among RNNs for prediction purposes is a nonlinear autoregressive model with exogenous variables (NARX) which is a quite general formulation where the current output value is made dependent on the past values of the input and output signals through a suitable nonlinear static function [20]. This type of ANN has been used in the work of Mahmoud et al. [18], Huo and Poo [22], Pisoni et al. [20], Andalib and Atry [19] as the prediction model, Sahooa et al. [23] for determination of the nonlinear systems, and Ardalani-Farsa and Zolfaghari [24] for the prediction and analysis of the chaotic time series. In this study, the key point about the model is the application of Japanese Candlestick technique.
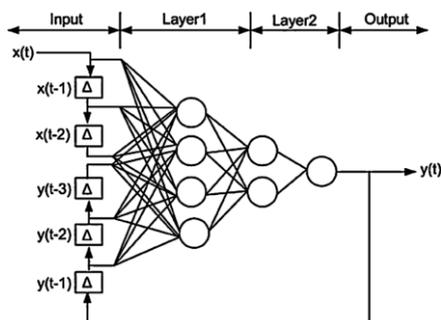
Figure 1. NARX network with two input delays and three output delays

This study uses the NARX neural network in the field of Candlestick TA and compares the outputs with a feed-forward neural network.

The rest of the paper is organized as follows: section 2 reviews the literature of RNNs, NARX, and optimal architecture of an ANN; section 3 introduces the prediction model; section 4 presents the experimental results and finally section 5 focuses on the conclusions.

2. MATHEMATICAL MODEL

2. 1. RNN   Generally, neural networks are two kinds of static and dynamic. Static networks have no feedback elements and no delays; the output is calculated directly from the current inputs and they assume that the data is concurrent and no sense of time can be encoded. These networks can thus lead to instantaneous[21].

Dynamic networks may be difficult to train but are more powerful than static networks. As they have memory in form of delays or recurrent loops, they can be trained to learn sequential or time varying patterns. This makes them networks of choice for various applications like financial predictions, channel equalization, sorting, speech recognition, fault detection etc. Since we are dealing with a time series it is necessary to use dynamic networks. Dynamic networks are of two types: the ones with feed forward connections and taps; and those with feedback or recurrent networks [25].

2. 2. The NARX Network   NARX is an important class of discrete-time nonlinear systems. Not only are NARX neural networks computationally powerful in theory, but they have several advantages in practice. For example, it has been reported that gradient-descent learning can be more effective in NARX networks than in other recurrent architectures with ''hidden states'' [22]. The key advantages of NARX network over other recurrent neural networks are its generalization and convergence at learning long-term dependencies. By long term dependencies, we mean the ability of the network to remember information that is stored for a long period of time [18].

Figure 1 shows the typical architecture of NARX network. In this model, Multi-Layer Perceptron (MLP) is used to approximate the following function.

$$y(t) = f(x(t-1), x(t-2), ..., x(t-D_x), y(t-1)), y(t-2), ..., y(t-D_y)) \qquad (1)$$

where, x(t) and y(t) are respectively the input and the output of the model at time step t, while Dx and Dy are respectively the input and the output memory orders with $D_x \geq 1$, $D_y \geq 1$ and $D_y \geq D_x$. Also, f is a non-linear function of the input and output of the model. The

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1. Accelerating the pace of engineering and science, documentation Center. (2013).http://www.mathworks.com/help/matlab.

predicted output y (t) is regressed on the input value (exogenous) x (t − 1) and the output value y (t − 1). In this case, since one of the inputs of NARX is the output of the network, this makes NARX network represents the dynamical characteristic of a system efficiently. In this paper, a series–parallel NARX network is trained and used as the prediction model.

2. 3. Optimal Architecture of an ANN   When developing a neural network model for prediction purposes, specifying its architecture in terms of the number of input, hidden, and output neurons and weight training are important tasks. Weight training in ANNs is usually formulated as a minimization of an error function, such as MSE between target and actual outputs averaged over all training data by iteratively adjusting connection weights. Most training algorithms, such as back propagation (BP) and conjugate gradient are based on gradient descent.

Among the literature regarding using the ANNs as the prediction tool, most of them focus on back-propagation Neural Network. BP is characterized by very poor convergence. Several improvements for BP, such as the quick-propagation algorithm, resilient error back propagation, etc. were developed. Much better results can be obtained using second order methods such as Newton or Levenberg–Marquardt. The Levenberg–Marquardt back propagation is a powerful optimization technique was introduced to the neural net research because it provided methods to accelerate the training and convergence of the algorithm. It utilizes the BP procedures in which derivatives are processed from the last layer of the network to the first [26].

3. METHODOLOGY

3. 1. Structure of the Model   The purpose of this study is to use the NARX neural network for prediction while first the data preparation and then pre-processing are done before the data is manipulated to train the network and to simulate. After this stage, network is trained by the LM algorithm and the best structure is selected. Then, the predicted values by the network, the prediction error, and network performance are calculated based upon the MSE. After network training for proper evaluation, inputs are divided into three categories of training, validation and testing. Network performance is calculated for these categories. Also, the NARX neural networks with closed loop and removal delay are created and the performance of these two networks are calculated.

After network training and testing by training data, data checking is used for prediction as the final test. Finally, predicted signals by the network and the percentages of correct signals are determined.
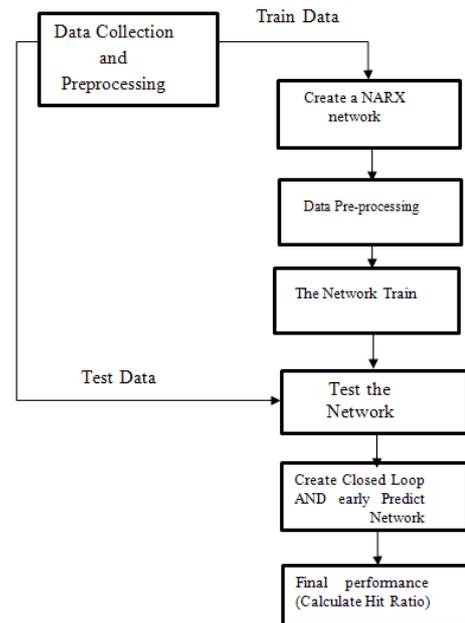
Figure 2. Structure of the model

Figure 2 shows the general structure of the model while it will be discussed in details in the following parts.

3. 2. Create a Nonlinear Autoregressive Network with External Input   At this stage, the basic structure of the NARX neural network includes input delays, feedback delays, and hidden layer size which are determined and the NARX network is created on the basis of the specified values.

3. 2. 1. Data Pre-processing

3. 2. 1. 1. Prepare the Data for Training and Simulation   In this step, the input time series are prepared for simulation or training of the network. Before preparation, the data are converted to a standard neural network format. Time-series data is converted from a matrix representation to standard cell array representation. Here data is defined in standard neural network data cell form. Converting this data does not change it [23].

The prepared data simplifies the normally complex and error prone task of reformatting input and target time series. It automatically shifts input and target time series as many steps as are needed to fill the initial input and layer delay states. If the network has open loop feedback, then it copies feedback targets into the inputs as is needed to define the open loop inputs. Each time a new network is designed, with different numbers of delays or feedback settings, prepares can be called to reformat input and target data accordingly.

Also, each time a network is transformed with open loop, close loop, remove delay or add delay, this function can reformat the data accordingly [25].

3. 2. 1. 2. Data Pre-processing   Data quality is a critical issue in prediction. To increase the accuracy of the prediction, we may perform data pre-processing techniques such data transformation [26]. Data preprocessing is an essential step in working with any ANNs [16].

Using transformed data is more useful in most heuristic methods especially when dealing with forecasting problems. A pre-processing method should contain the capability of transforming pre-processed data into its original scale (called post-processing).

One of the most useful data transformation techniques is data normalization. There are different normalization algorithms, such as Min–Max normalization, Z-score normalization, and sigmoid normalization. In this paper, we use Min–Max normalization which is a common approach in this field. The Min–Max normalization scales the numbers in a data set to improve the accuracy of the subsequent numeric computations. If Xold, Xmax, Xmin are the original, maximum and minimum values of the raw data, respectively and Xmax, Xmin, are the maximum and minimum of the normalized data, respectively, then the normalization of Xold called Xnew, can be obtained by the following transformation function [27]:

$$X_{new} = \frac{X_{old} - X_{min}}{X_{max} - X_{min}}(X^{*}_{max} - X^{*}_{min}) + X^{*}_{min} \qquad (6)$$

As a method to evaluate the usefulness of the model, we observe the results that calculate the difference in price between the result of the model and real target after a time unit. In this study for short-term forecasting of stock price movements, a 6-day stock market movement is used as the evaluation time unit. The price difference after 6 days indicates whether the model is successful or not. The Hit Ratio is defined as:

$$HitRatio = \frac{Number \quad of \quad Successes}{Total \quad Number \quad of \quad Successes} \qquad (7)$$

If the Hit Ratio of the pattern is 51% or larger, the model can be approved. It means that investment according to the rule can result in a good profit [5].

3. 2. 3. Train and Test the Network   The network is trained by the selected training function and the best structure of the network is selected. For the test network, MSE, as a performance function is calculated by the target data and outputs and prediction error, are also identified. To test the network, the network performance is calculated by test, validation and training data.

3. 2. 4. Closed Loop Network and Early Prediction Network   In this stage, a close loop NARX network is created. The close loop converts neural network open-loop feedback to a closed one. The function replaces the feedback input with a direct connection from the out layer. This function takes a neural network and closes any open-loop feedback. In this stage, closed Loop Performance is calculated.

Furthermore, another neural network is created for remove delay. Remove delay returns the network with input delay connections that are decreased, and the output feedback delays that are increased, by the specified number of delays, n. The result is a network which behaves identically, except that outputs are produced in n time steps later. In this stage, early Prediction Performance is calculated.

3. 2. 5. Test Net with Testing Data   Checking data are used to test the trained neural network and the predicted values or network output is obtained.

3. 2. 6. Calculate Hit Ratio   Finally, buy and sell signals and their total number are determined and correct signals are calculated during a 6-days period. By these obtained values, Hit Ratio as the main performance criteria is computed.
The semi-codes of the model are as follows:
 (1) Load data (Train Data and Test Data)
(2) Create a Nonlinear Autoregressive Network with External Input
 – Specifying Network Architecture: Input Delays, Feedback Delays, Hidden Layer Size
 – create an NARX network
(3) Choose Input and Feedback Pre/Post-Processing Functions
(4) Prepare the Data for Training and Simulation
(5) Setup Division of Data for Training, Validation, Testing
(6) Choose a Training Function
 – Choose Levenberg-Marquardt;
 (7) Choose a Performance Function
 – Choose Mean Square Error(MSE);
(8) Train the Network: Training Neural Network using Levenberg - Marguardt Algorithm
(9) Test the Network
 – Calculate outputs
 – Calculate errors
 – Calculate network performance
 – Plot error of train data
 – Recalculate training, validation and test
(10) View the Network
 (11) Create closed loop AND early predict network
 – Closed Loop Performance
(12) Early prediction network
 – Early Prediction Performance
(13) Test Network with other Data
 (14) Calculate Hit Ratio:

–   Identify buy and sell signals and calculate Total number of signals
–   Calculate number of correct signals (success)
–   Calculate Hit Ratio

4. RESULTS AND DISCUSSION

4. 1. Input Data   In this study the training data are based upon two applied approaches of Jasemi et al. [28]. Applied approach for input is shown in Figure 3. The first approach (Raw database) is based on raw input features including 15 items and 1 output. In this approach the focus is on open (O_i), high (H_i), low (L_i) and close (C_i) prices of the stock in the ith day due to the Japanese candlestick during last 3 days while to cover the stock price trend the close prices of the stock during the last 7 days are also included. The second approach (Signal based) is based on the reverse signals of Japanese candlestick technique including 24 input features and 1 output. This package covers the important factors of decision making in the technique. These approaches in 48 data sets are applied to train and test the introduced model that are past daily data of General Motors stocks in NYSE. Every input data is divided into two categories of training data and testing data. For more detail about input data refer to the study of Jasemi et al. [28].

4. 2. Experiment Results   The input data of our experiments are daily stock prices of General Motors Company at New York Stock Exchange from 2000 to 2009. 48 datasets are applied for learning and checking. In this study, input Delays, feedback Delays and hidden Layer Size, 1:2, 1:2, 30 is considered, respectively. Division of data for Training, Validation, Testing are 70%, 15%, 15% respectively and the numbers of train epochs are considered to be 100.

The goal is to develop NARX model for TA approach. First, the training data is loaded. A tapped delay line is used with two delays for both the input and the output, so training begins with the third data point. The series-parallel NARX network is created.
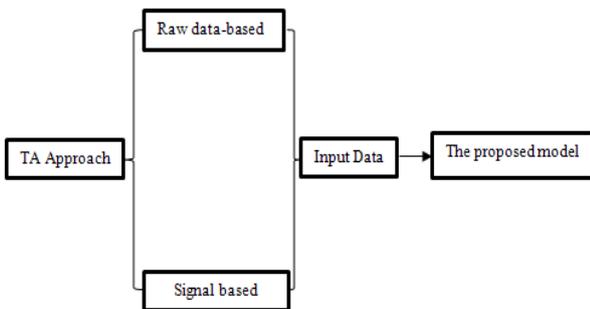
Figure 3. The general approach in this model
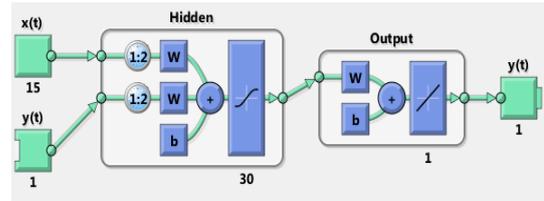
Figure 4. NARX neural network with Raw Database
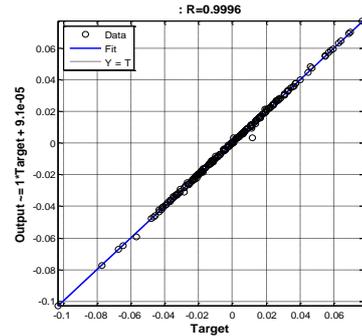
Figure 5. The linear regression of targets relative to outputs

30 neurons are used in the hidden layer and train LM is used for the training function, and then data is prepared. After training, the result is displayed in Figure 4. Figure 4 shows NARX neural network for the Raw approach as a graphical diagram. This structure is the same in NARX neural network for the Signal approach and only the number of input is different.

After completing parameters estimation validating the results against another set of data is necessary. For this purpose data was divided into three sets.

As mentioned before, MSE is used as the performance criteria. Network performance is calculated for signal approach and raw approach by training, validation, data testing and also data checking. Network performance is great and MSE value is low. Thus, the prediction accuracy is extremely high.

The linear regression between the network output and the actual output is calculated and is plotted for all data sets. Figure 5 shows this plot for data set 1 of Raw database (2000 for training and 2001 for checking) as an example. The linear regression value is 0.9996 for this data set and the regression model among these two variables is as follows:

$$Output = 1 \times T \arg et + 9.1e - 0.5 \qquad (8)$$

A histogram plot with normal fit for error of training data is another output of the model; this plot is shown in Figure 6 for data set 1. This plot is also shown in Figure 7 for error of checking of the data. The model plots a histogram of the values in the vector data using specified number of bins then superimposes a fitted normal distribution.

It can be seen that the errors are very small. However, because of the series-parallel configuration, these are errors for only a one-step-ahead prediction. A more stringent test would be to rearrange the network into the original parallel form (closed loop) and then to perform an iterated prediction over many time steps. The structure of this network is shown in Figure 8.
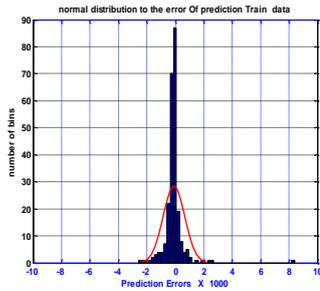
Figure 6. Histogram with normal fit to the error of prediction
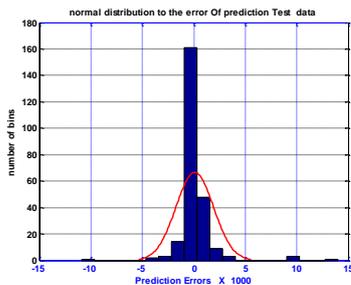
Figure 7. Histogram with normal fit to the error of prediction Test data
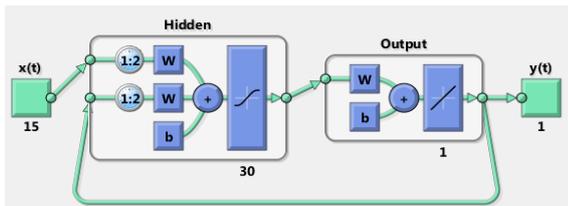
Figure 8. NARX neural network (close loop) with Raw databased
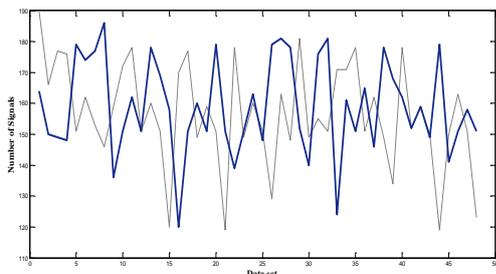
Figure 9. The total number of signals that are produced by the approaches for each dataset

TABLE 1. The final result in comparison with other prediction model

	Total Hit Ratio	Hit Ratio Approach 1	Hit Ratio Approach 2
Supervised Feed Forward NN [26]	74.2%	74.8%	73.6%
Wrapper ANFIS-ICA [27]	86%	85%	87%
NARX NN	89%	89%	89%

Furthermore, by remove delay, the NARX network is used to predict the next output a time step (one step) ahead of when it will actually appear. Here, minimal tap delay is now 0 instead of 1.

In this study like Lee and Jo [5] and Jasemi et al. [28], a six-day stock market movement as the evaluation time unit is decided; that is each time a bull signal is followed by an actual upturn or a bear signal is followed by an actual downturn within 6 days; the signal is considered as a success. The correct signals are achieved by comparing the predictions with real happenings of the stock market. The complete list of the results is shown in appendix A. Figure 9 shows the total number of identified signals by the two approaches in different datasets. By the help of this figure, it can be verified that which of these approaches are better.

Lee and Jo [5] believe that if the hit ratio is above 51%, the model is regarded as useful and feasible. The total hit ratio of our new model is 89% while raw and signal data-based approaches have a hit ratio of 89% and are both equally successful.

The Number of identified signals by raw and signal approaches are shown in Figure 9. The correct percentage prediction for a 1 day period is shown as 0.32 and 0.33 for raw and signal approaches, respectively. In comparison with Jasemi et al.'s study [28], our model is much better. The hit ratio of Jasemi et al.'s model is 74.2% while this value in our model is 89% and this result is excellent. The Two approaches are equally successful in the current study while in the study by Jasemi et al. [28], the raw approach was better than the other approach.

5. CONCLUSION

In this paper, a new approach for modeling of TA by neural networks on the basis of the ancient investment technique of Japanese Candlestick is employed. NARX is used as an RNN while long-term dependencies exist. Although embedded memory can be found in all the recurrent networks, it is explained that why it is particularly prominent in NARX models.

Two approaches are used as input to the NARX neural network on the basis of the Japanese Candlestick

charts patterns. These two approaches are studied in 48 different datasets with different training and checking periods and NARX neural network predictions. For this TA, the NARX neural network operates as an analyzer. Finally, the number of buy and sell signals and their correctness percentage is calculated.

In this study, the NARX neural network is examined on the basis of two criteria of hit ratio and MSE. According to the experimental results, it is proved that the network performance is excellent and better than the feed-forward static neural network. Moreover, the new model has a better hit ratio than the basic study of Jasemi et al. [28]. On the other hand, the Raw-based and signal-based approaches have similar performances with no significant difference between recognition of the buy and sell signals.

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7. Appendix A

Table A 1: The complete list of the results is brought here. The columns of 1 to 6, column 7 and column 8 show the correct signals in 1, 2, 3, 4, 5, and 6 day periods, the total number of correct signals and the total number of the emitted signals by the system, respectively.

TABLE A 1. The complete list of the results

Raw Data base

No	1	2	3	4	5	6	7	8
1	68	42	29	20	13	9	181	190
2	47	46	21	19	13	9	155	166
3	68	46	22	17	5	1	159	177
4	66	43	18	14	14	8	163	176
5	51	41	15	12	8	7	134	151
6	50	31	20	15	13	10	139	162
7	50	31	20	11	11	10	133	153
8	35	28	22	17	9	6	117	146
9	47	45	18	19	13	8	150	159
10	67	45	22	17	4	1	156	172
11	67	43	18	15	14	8	165	178
12	50	39	15	12	10	7	133	151
13	50	31	20	15	13	10	139	160
14	46	33	21	13	11	10	134	151
15	36	25	20	12	7	3	103	120
16	66	45	22	17	3	1	154	170
17	66	43	18	15	14	8	164	177
18	49	42	16	12	12	8	139	149
19	49	31	20	15	13	10	138	159
20	48	32	18	12	12	12	134	151
21	33	25	20	13	7	3	101	119
22	67	43	18	15	14	8	165	178
23	49	40	15	11	10	7	132	149
24	49	31	20	15	13	10	138	160
25	47	30	17	11	11	10	126	151
26	36	23	21	14	7	5	106	129
27	47	46	21	19	14	9	156	163
28	44	37	25	14	8	7	135	148
29	68	43	18	15	15	8	167	181
30	50	40	15	11	9	7	132	149
31	48	30	21	13	11	10	133	155
32	47	30	19	10	11	10	127	151
33	43	34	23	17	13	7	137	171
34	66	45	22	17	4	1	155	171

Raw Data base

No	1	2	3	4	5	6	7	8
35	67	43	18	15	14	8	165	178
36	50	40	15	12	10	7	134	151
37	52	32	22	16	14	11	147	162
38	46	30	17	11	11	10	125	149
39	36	25	21	14	7	6	109	134
40	67	43	18	15	14	8	165	178
41	64	42	21	12	5	3	147	152
42	49	31	20	15	13	10	138	159
43	46	30	18	11	11	10	126	150
44	34	23	18	12	6	3	96	119
45	49	40	15	11	10	7	132	150
46	49	32	20	16	13	10	140	163
47	47	30	18	11	11	10	127	151
48	35	25	18	13	6	3	100	123

Signal Data base

No	1	2	3	4	5	6	7	8
1	38	28	26	20	11	7	130	164
2	53	28	17	10	10	7	125	150
3	47	27	20	14	12	9	129	149
4	50	37	18	12	9	6	132	148
5	69	42	19	14	15	8	167	179
6	68	46	22	16	5	1	158	174
7	52	49	20	21	13	9	164	177
8	67	39	31	18	13	9	177	186
9	36	25	22	15	9	7	114	136
10	46	40	15	13	10	8	132	151
11	49	31	21	14	13	10	138	162
12	49	40	15	12	10	7	133	151
13	67	43	18	15	14	8	165	178
14	66	45	22	17	3	1	154	169
15	47	45	18	19	12	8	149	158
16	35	23	20	12	6	4	100	120
17	47	30	18	11	11	10	127	151
18	50	31	20	15	13	10	139	160
19	50	40	15	12	10	7	134	151
20	68	43	18	15	14	8	166	179
21	49	35	20	14	12	4	134	151
22	36	26	24	16	7	9	118	139
23	47	30	18	11	11	10	127	151
24	50	31	20	15	13	10	139	163
25	48	40	15	11	10	7	131	148
26	69	43	18	15	14	9	159	179
27	49	32	26	24	13	6	150	181
28	56	35	24	14	15	13	157	178
29	50	30	20	11	12	9	132	152
30	46	38	18	13	8	7	130	140
31	64	40	19	16	16	11	166	176
32	70	46	23	16	6	3	164	181
33	36	34	16	15	12	5	118	124
34	43	32	24	17	8	6	130	161
35	47	30	19	12	11	10	129	151
36	50	33	22	17	14	11	147	165
37	47	40	15	12	11	7	132	146
38	68	43	19	18	15	11	174	178
39	65	46	22	17	5	3	158	168
40	40	31	25	16	12	8	132	162
41	47	32	19	13	11	10	132	152
42	49	31	21	15	14	10	140	159
43	49	40	15	11	11	7	133	149
44	68	43	19	16	14	9	169	179
45	37	27	23	14	6	6	113	141
46	47	30	19	12	11	10	129	151
47	50	30	21	15	17	10	143	158
48	50	40	15	13	13	7	138	151

A Nonlinear Autoregressive Model with Exogenous Variables Neural Network for Stock Market Timing: The Candlestick Technical Analysis

E. Ahmadi[a], M. H. Abooie[a], M. Jasemi[b], Y. Zare Mehrjardi[a]

a Department of Industrial Engineering, Yazd University, Yazd, Iran
b Department of Industrial Engineering, Khajeh Nasir Toosi University of Technology, Tehran, Iran

چکیده

در این مقاله، مدل اتورگرسیو غیرخطی با متغیرهای خارجی به عنوان یک شبکه عصبی جدید برای زمان بندی بازارهای سهام بر اساس تحلیل فنی شمعدان ژاپنی به کار رفته است. در مدل، اتورگرسیو غیرخطی با متغیرهای خارجی یک تحلیل گر است. اینجا (همانند ادبیات) دو رویکرد مبتنی بر دادهای خام و سیگنال برای ایجاد داده های ورودی تعبیه شده اند. درصد صحت پیش بینی برای دوره های زمانی ۱-۶ روزه با تعداد کل سیگنال های خرید و فروش در نظر گرفته شده است. نتایج اثبات می کند که رویکردها تا حدی عملکرد مشابه ای دارند در حالی که آن ها از شبکه عصبی پیشرو برتری دارند. شبکه ایجاد شده توسط معیار میانگین مربع خطا ارزیابی می شود و صحت مدل پیش بینی بسیار بالا محاسبه شده است.

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