Journal of System Management (JSM)
Online ISSN: 2538-1571, Print ISSN: 2322-2301
Doi: 10.30495/JSM.2022.1965914.1679
8(4), 2022, pp. 65-80

Received: 20/08/2022
Accepted: 21/09/2022

RESEARCH ARTICLE **Open Access**

Designing an Optimal Model Using Artificial Neural Networks to Predict Non-linear Time Series (case Study: Tehran Stock Exchange Index)

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Abstract

Investing in stocks is fraught with long risks that make it tough to manage and predict the choices out there to the investor. Artificial Neural Network (ANN) is a popular method which also incorporates technical analysis for making predictions in financial markets. The purpose of this work is an applied study which is conducted using description based on testing as method. The discussion is established on analytical-computational methods. In this research, the documents and statistics of the Tehran Stock Exchange are used to obtain the desired variables. Descriptive statistics and inferential statistics, as well as Perceptron multi-layer neural networks are utilized to analyze the data of this research. The results of this research show the confirmation of the high prediction accuracy of the Tehran Stock Exchange index compared to other estimation methods by the presented model, which has the ability to predict the total index with less than 1.7% error.

Keywords: Total stock index; Forecast; Artificial neural networks; Tehran Stock Exchange

Introduction

Nonlinear time series are generated by nonlinear dynamic equations. They display features that cannot be modeled by linear processes: time-changing variance, asymmetric cycles, higher-moment structures, thresholds and breaks (Beheshti et al., 2022). One of the best examples for non-linear time series is the stock price index, the stock market is a means to buy and sell equities and securities. It is the backbone of any economy. Although, some believe stock market is completely random. Prediction of stock market price is one of the most important issues in finance. Many researchers have been given their idea how to forecast the market price in order to make gain using different techniques, such as technical analysis, statistical analysis, with different methods. Many researchers have been successful at predicting stock prices to a great extent (Lopez et al., 2017). It helps companies raise the capital that empowers the world. More than 75% of the stock trading in United States exchanges and other countries is done by automated trading systems. And now in 2022, this number is even greater. Stock prediction systems can help investors to identify right stock(s) to invest in. The reasons why stock prediction is difficult are, (1) Stock

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price movement are very noisy, hence a machine learning algorithm may over fit, (2) Some undocumented event may also cause the stock prices to change suddenly, and (3) Confidence in prediction (Khojasteh et al., 2019). Nowadays, artificial neural networks (ANNs) have been applied in order to predict exchange index prediction. ANN is one of data mining techniques that are learning capability of the human brain. Data patterns may perform dynamics and unpredictable because of complex financial data used. ANNs have been used in stock market prediction during the decade. Artificial neural networks are structurally composed of two main parts, a structure of hidden layers of the network and two sets of input data, in this research our focus is on the internal structure of the network and considering that generally in most estimations of a The type of neural network used, we are trying to provide a more accurate estimate of the movement of the stock market index by providing an optimal model. The prime motive to apply Neural Networks in Stock Market prediction is as follows: (1) Stock data is highly complex and hard to model, so a non-linear model is beneficial. (2) A large set of interacting input series is often required to explain a specific stock, which suits Neural Network (Paidar et al., 2021). In this research, we intend to provide an optimal model for predicting stock price trends by creating a new structure of different computing layers for an artificial neural network and focus that Multi-Layer Perception (MLP) networks are layered feed-forward networks typically trained with back propagation.

Theoretical Foundations

1) Prediction

One of the important management tools is the use of different forecasting methods. In order to make decisions, managers need to estimate future events using past information. In literature prediction is defined as calculating and guessing future conditions and situations. The person who is faced with these calculations often relies on current statistics and information and relies on personal vision to predict the future. A prediction clarifies what may happen in the future. Most predictions are based on experience or knowledge. There is no guarantee that the predictions will be accurate, however, forecasting is crucial for planning. Howard Stevenson writes about forecasting in business: "...forecasting has at least two characteristics: important and difficult."(Ayodele, Aderemi, 2014)

2) Artificial Neural Network

NNs are simplified models of real nervous systems that are used in solving various problems in science. The range of application of these networks is vast, including but not limited to classification applications, interpolation, estimation, detection. Perhaps the most important advantage of these networks is their versatility despite being easy to use (Marcel, Kristjanpoller, 2020).

Artificial NN is a data processing system that is based on the human brain function and processes data with many small processors that function in interconnected and parallel networks to solve a problem. In these networks, with the help of programming, a data structure is designed that can act as a neuron. Hence, this data structure is called a neuron. After creating networks between these neurons and applying a training algorithm to them, they train the network (Raymundo, Cuevas, 2008).

3) Working with artificial neural networks

Working with any artificial NN consists of three stages: training, generalization and execution. In the training stage, the network learns the patterns in the input data set. Each NN uses a specific rule. Generalization is the ability of the neural network to produce acceptable responses to inputs that are not members of the training set. At the stage of execution, the NN is used for the specific function that it is designed for (Jun Zheng, 2010).

4) Perceptron neural network

This NN is built on a computing unit called perceptron. A perceptron takes a vector of inputs with real numbers and calculates a linear combination of the input data. If the result is greater than a threshold value[16], the output of the perceptron will be equal to 1, otherwise it will be equal to -1. Perceptron NNs, especially multilayer perceptron, are among the most practical NNs and are capable of executing a nonlinear mapping with any designated accuracy by selecting the appropriate number of layers and neurons (Ayodele, Aderemi, 2014).

Literature Review

Atsalikis and Valavanis (2009) collected and classified researches in the field of finance using soft computing methods. This review shows that the main subject of experimental researches is predicting the return of the stock market index in various countries, and most of the methods used in them have been soft computing techniques. These studies can be classified into three groups. The first class includes research that uses data from developed countries such as Europe, America, etc. The second class is researches that focus on predicting the index of emerging markets such as Greece, Istanbul, etc. The third category is research that is not focused on a specific stock market, but targets independent shares or portfolios. Based on this, the research review is presented below. Table 1 shows some of the most important researches on stock market index.

Table 1.
Related Work

Exchange	Authors	Technique	Outcomes
Istanbul Stock Exchange	Yumlu, Gurgen and Okai(2004, 2005)	Predicting changes and comparing methods	IGARCH model has better performance than MLP and RNN.
Indonesia Stock Exchange	Situngkir and Surya(2005)	Stock price prediction	Achieving more accurate predictions
Athens Stock Exchange	Atsalikis and Valavanis(2006)	Better specification of the prediction model Stock trends	Nero fuzzes' best performance suggested system has in the stock market.
Tehran Stock Exchange	Jafari and Izadi (1390)	Examining the scale characteristics of the index The entire Tehran Stock Exchange	Prices in Tehran Stock Exchange They have correlation and memory.
	Mohammadi and tabasi (1391)	Examining the uneven changes of the stock exchange Bahadar Tehran	Cusp model compared to the alternative model It is more explanatory.
	Abbasi and Naderi(1391)	Predicting the performance of the price index and Cash return	Superiority of MFNN and ANFIS based models Data analyzed using wavelet analysis Against data level deployment
	Abu nouri(1392)	Investigating the relationship between the inflation rate and the index Stock market performance	Existence of asymmetric relationship between variables Research
Turkish stock exchange	Celik and Ergin(2014)	Finding the best volatility prediction model	The superiority of predictive models based on

Exchange	Authors	Technique	Outcomes
			High frequency compared to GARCH models and MIDAS and HAR-RV-CJ
Toronto Stock Exchange	Olson and Mossman(2003)	Comparison of forecasting methods	The superiority of artificial neural network
Tokyo Stock Exchange	Huang and Nakamori(2005)	Investigating the predictability of movement direction Prices	Superiority of SVM and hybrid models
Cyprus Stock Exchange	Constantinou and Kazandjian	Forecast analysis of the Cyprus Stock Exchange	Rejecting the assumption of linearity
New York Stock Exchange	Melina and Soto(2012)	Minimizing the prediction error of ANFIS	Achieving ANFIS model with less error compared to artificial neural network models
Free	Kim et al.	Hybrid long short-term memory	Stock price forecasting
Free	Sedighi et al	Hybrid stock prediction model by combining ABC, ANFIS, and SVM	Stock price forecasting
Free	Senapati et al	Hybrid model for stock price prediction using ANN and PSO	Stock price forecasting

The number and type of variables used in the above researches have been different. The most common variables that have been used for the input of prediction models in these studies are: opening value, closing value, minimum value and historical data. These simple variables generally lead to soft calculation methods with relatively low time and calculation cost Get the right predictions. Despite this, in the studies where the stock market indexes of a country have been the target variable, macro variables such as dollar price, euro price and gold price have also been paid attention to. In general, the forecasting techniques in these researches are focused on the methods of artificial neural networks. The criteria used in experimental research to evaluate the performance of forecasting models are classified into the following two categories: (1) statistical criteria (2) non-statistical criteria. Statistical criteria include root mean square error, RMSE and mean square error MSE, mean value the absolute error is MAE, a non-statistical measure of hit rate in most researches. The main decision criterion for measuring the economic aspect is the results of forecasting models. Also, in most of the investigated studies, the effect of network structure on the performance of models has been less investigated. Therefore, it seems that by using soft computing methods, it may be possible to provide acceptable forecasts of the stock market index of various markets, including the Tehran Stock Exchange.

Conceptual Model of Research

1) Conceptual model of artificial neural network

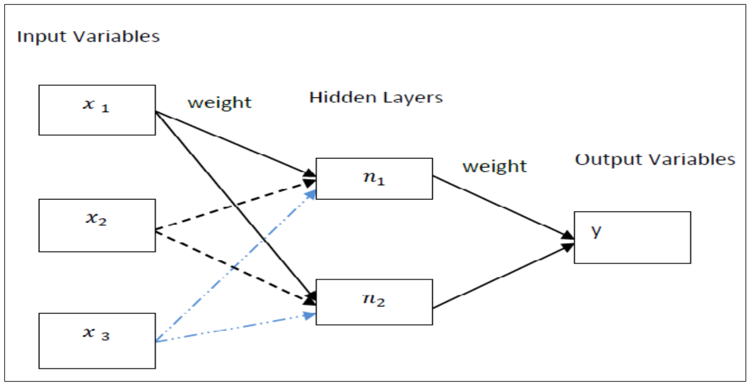

Figure 1. Conceptual model of research for artificial NN.

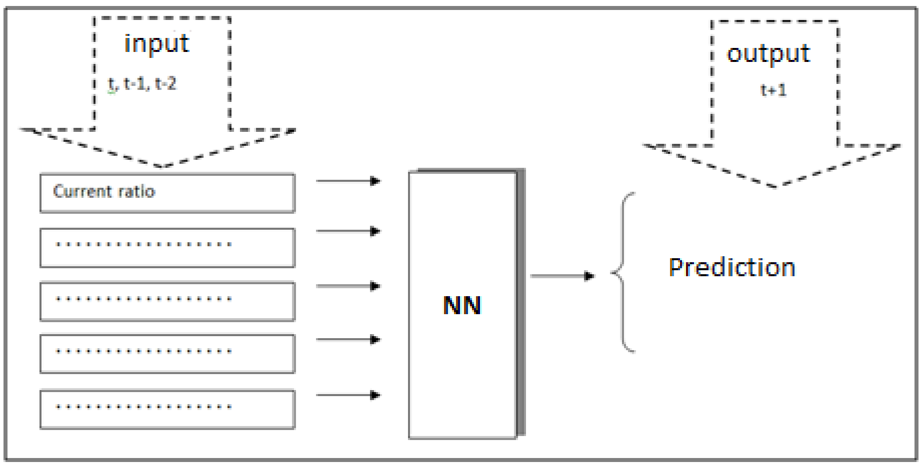

Figure 2. Employing the information from 30 years ago and feeding it into the network for forecasting

Method

This research is exploratory and practical in terms of its purpose, and according to its nature, goals, number and type of variables in the current research, the methodology of this research is descriptive based on survey since the researcher's goal in conducting this research is to describe the prediction of the total stock index of the TSE. This research is analytical-mathematical in terms of investigation method, modeling in terms of statistics, and in terms of the method of data collection, it is an experimental research based on the analysis of information collected from It is the desired statistical population. To cover the discussion of research theory, the method of data collection in this research is relied on specialized and general books, specialized articles and publications, and the analyzed data is obtained from the documents of the past 30 years (from 1990 to 2020) available in the Central Bank and Statistics Center of the Islamic Republic of Iran. The statistical population and statistical sample in this research is the statistical data (time series) related to the stock index of the TSE, during the last 30 years (from 1990 to 2020), available in the Statistics Center and the Central Bank of the Islamic Republic of Iran. The descriptive statistics of the data are utilized to analyze the data and information in the documents. Then the research findings based on the NN technique and artificial intelligence are provided according to the conceptual model provided for prediction. Afterwards, Dickey Fuller test is employed to compare the linear results with the non-linear results of the NN, followed by the test of hypothesis using Student's t-test and correlation. In this work, descriptive statistics and inferential statistics have been conducted using MATLAB and SPSS programs to analyze the data.

After the revolution, the base year for calculating the total index was designated to 1990, which was established during the time of Rajaei Salmasi, and by the end of that year, it closed at 189 units. Finally, during the second administration of Mr. Rouhani, the stock market index reached 1,500,000 followed by a sharp drop in 2020 reached 1,265,234 units in December 2020 (the end of the research study period) after severe fluctuations.

Table 2

Descriptive statistics of information related to the total index of TSE in the last 30 years

Variables	Value	Unit
Total stock index (Dec 2020)	12652341	unit
Mean (30 years)	260158	unit
Median	24849	unit
Standard deviation	454218	unit
Maximum	1447120	unit
Minimum	189	unit

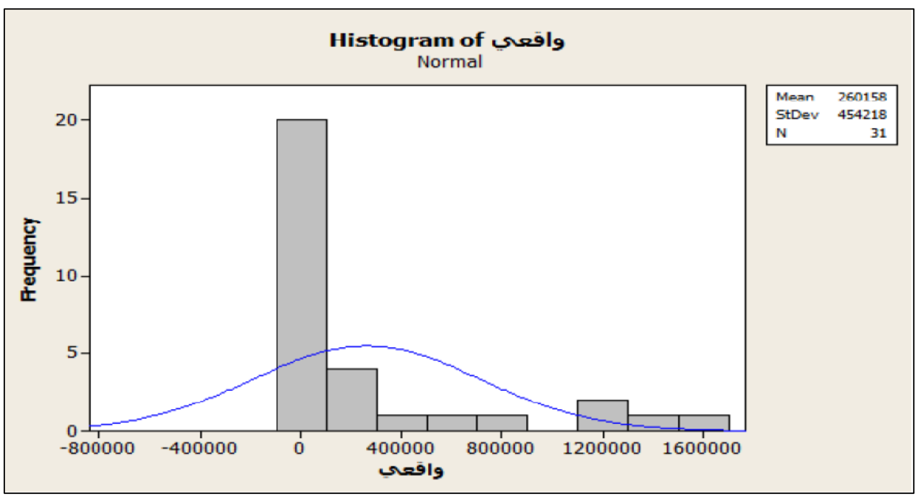

Chart 1. Histogram of the total index of TSE from 1990 to 2020.

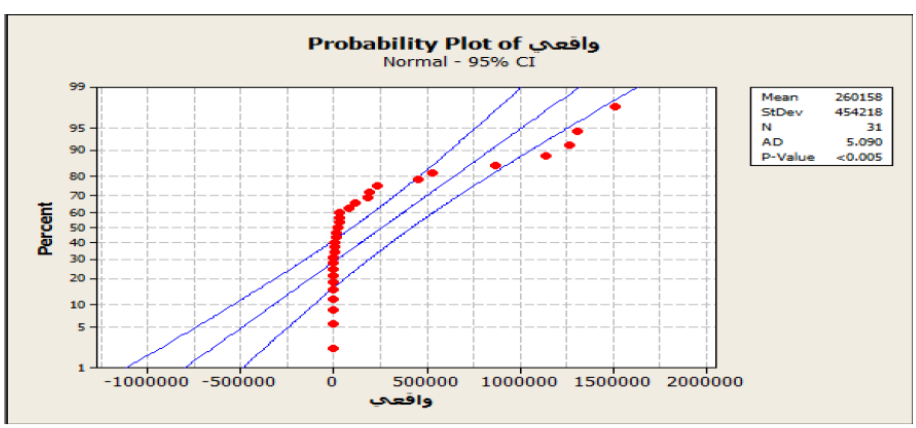

Chart 2. Scattering of the total index of Tehran Stock Exchange from 1990 to 2020.

Descriptive statistics of total index from 1990 to 2020 (Table 2) and scatter charts and histograms (Charts 1 and 2) show that the total index had severe fluctuations during this period since the standard deviation of the total index was 454218 units. The average of the index during this period was equal to 260158 units. Also, the large distance between the lower and upper limits of the average at 95% confirms this case. The scatter diagram (Chart 2) shows the significance of the changes (significance level is equal to 0.005 and less than 5 percent) during the time series. Finally, the mentioned changes indicate a lot of turbulence in the country's macroeconomics during the last thirty years. In this research, there are two separate sections, one of which is related to the intended general index forecasting population, and the other is related to determining the forecasting pattern of the total index in TSE. The investigation of Kolmogorov-Smirnov[23] test on the real total index data from 1990 to 2020 shows that the distribution of the data is not a normal distribution since the significance level is equal to 0.01 and is less than 0.05. In other words, the data have a significant difference with normal distribution, and this issue reconfirms the existence of excessive scattering of the total index during the time series.

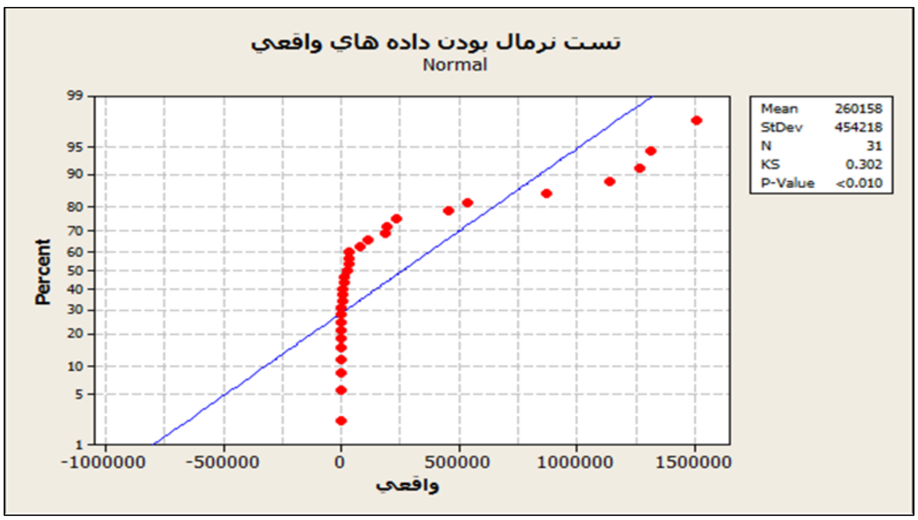

Chart 3. Test of normality of the TSE real total index from 1990 to 2020.

Research Question

At what level is the prediction of stock index of TSE using NNs? Quantitative results of artificial NN modeling have been used in this research using MATLAB to create NN after reporting error and modeling the changes of the total index. Due to the large number of data (11160 daily indicators for 16 years), TSE index prediction was done using 6000 data, 80% of which was used for training, 15% for evaluation and 5% of data for testing the model. The criterion used to confirm the root mean square error model is based on the test data. In order to obtain the best values of the model parameters, the following steps have been implemented. First, the learning rate and the number of training sessions were determined as 0.3 and 8000, respectively. Then the effect of different amounts of processing elements in the hidden layer has been analyzed. Based on the values of the appropriate processing elements obtained from step one, the effect of different learning rates on the results of the model has been investigated in the second step. In the third step, two tests have been performed for 1 and

2 hidden layers in order to draw conclusions about the best number of hidden layers. Finally, the selected model is trained in the above steps during 8000 training courses to reduce the probability of the process being stuck at local minimum points. First, the neural network model with a learning rate of 0.3, and the number of training courses of 8000 and six different processing element values has been created. The results are shown in Table 3. By entering the data of the first variable, the network randomly divides these data into three groups. The first group that is used for training and hence is called the training group. The network is trained using the information of this group and improves itself by trial and error, that is, if an error occurs, it goes back (post-error propagation algorithm) and then moves forward (forward network) and this time it tries to avoid making that error again. The second group is the validation group, in which we randomly enter the information of several companies into the network in order to evaluate the performance of the designed network. The third group is called the test group and is used to test the results of the network.

Table 3.

The number of experiments, processing elements and the number of hidden layers

Number of training courses: 8000, Number of hidden layers: 1					
Experiment	**Processing elements**	**Data**	**MSE**	**RMSE**	**R^2**
1	1	Learning	132733441	11521	%79.2
		Learning	211469764	14542	%81.1
2	2	Learning	427716	654	%97.7
		Learning	467856	684	%84.6
3	3	Learning	292681	541	%85.2
		Learning	96721	311	%99.8
4	4	Learning	71520849	8457	%79.9
		Learning	43414921	6589	%88.8
5	5	Learning	131400369	11463	%89.0
		Learning	114383025	10695	%91.2
6	6	Learning	17926756	4234	%76.7
		Learning	175561	419	%79.9

As it can be seen in Table 3, the minimum root mean square error is equal to 311, which happened with the number of processing elements of three. Therefore, three processing elements should be used in testing other parameters. In the second step, conducting six experiments with different learning rates and three test elements, the accuracy of the model is investigated.

Table 4

The second step, the number of experiments, processing elements and the number of hidden layers

Number of training courses: 8000, Number of hidden layers: 1, Number of processing elements: 3					
Experiment	**Learning rate**	**Data**	**MSE**	**RMSE**	**R^2**
1	. /01	Learning	132733441	1205	%99.1
		Learning	211469764	1008	%82.4
2	. /05	Learning	427716	477	%99.8
		Learning	467856	413	%97.1
3	. /1	Learning	292681	892	%92.4
		Learning	96721	1327	%88.3
4	. /3	Learning	71520849	645	%79.7

Number of training courses: 8000, Number of hidden layers: 1, Number of processing elements: 3					
Experiment	**Learning rate**	**Data**	**MSE**	**RMSE**	**R^2**
		Learning	43414921	652	%81.3
5	. /5	Learning	131400369	2499	%89.0
		Learning	114383025	1879	%91.2
6	. /7	Learning	17926756	1921	%86.8
		Learning	175561	4174	%79.9

From Table 4 it can be inferred that the lowest mean square root of error, which is 413, was obtained at a learning rate of 0.0526. Therefore, in the next step, three processing elements, a learning rate of 0.05 and the number of one and two hidden layers are used. At this stage, first, the model is set with three processing elements, a learning rate of 0.05, and 8000 training rounds.

Table 5.

The third step, the number of experiments, processing elements and the number of hidden layers

Number of training courses: 8000, Number of hidden layers: 1 and 2, Number of processing elements: 3					
Experiment	**Learning rate**	**Data**	**MSE**	**RMSE**	**R^2**
1	1	Learning	427716	477	%99.8
		Learning	467856	413	%97.1
2	2	Learning	427716	635	%99.6
		Learning	467856	563	%93.3

Table 5 shows that the lowest root mean square error, which is equal to 413, occurs in the model with one hidden layer. The results of investigating the NN model are carried out with the following parameters in Table 6.

Table 6.

Parameters of the designed artificial NN.

Number of data	6000
Learning data	4800
Evaluation data	900
Transfer function	Sigmoid
Number of processing elements	3
Learning rate	. /05
Number of hidden layers	1
Number of training courses	8000

Chart 4 and Table 7 summarize the results of the post-propagation NN model with the best performance obtained with the aforementioned parameters in Table 6.

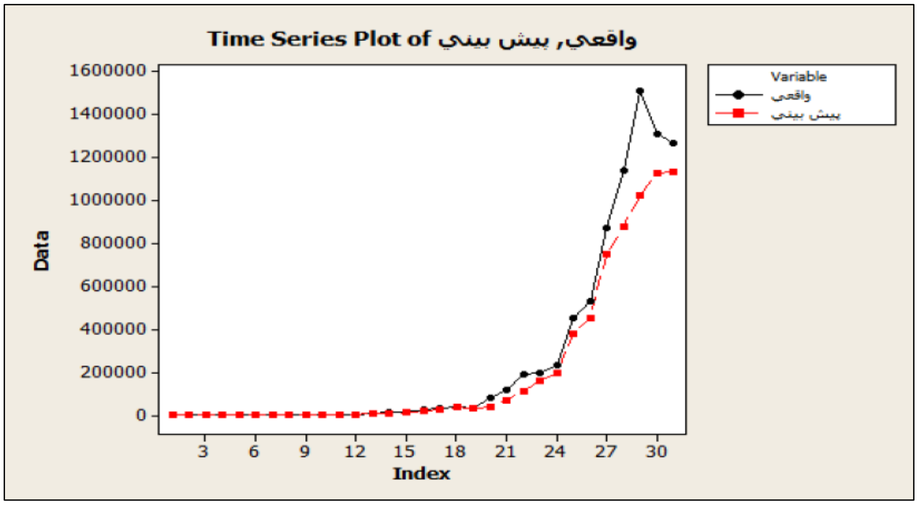

Chart 4. Comparative plot of actual and forecast total index from 1990 to 2020.

Table 7.
Comparison of actual and forecast total index from 1990 to 2020

Number of processing elements: 3, Learning rate: 0.05, Number of hidden layers: 1			
Row	Predicted value for next periods (month)	RMSE	R^2
1	**1275685**	**489**	**981٠/**
2	**1285613**	**552**	**934٠/**
3	**1290080**	**509**	**944٠/**
4	**1323687**	**688**	**929٠/**
5	**1325001**	**571**	**942٠/**
6	**1329964**	**609**	**937٠/**

The difference between real data and data predicted by the designed model

Paired t-tests and correlation are used to show the difference between real data and predicted data:

Table 8.
Difference between real data and data predicted by the designed model

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	forcast	2.09E5	31	365774.534	65695.046
	real	2.60E5	31	454217.934	81579.949

```
Paired T for واقعي - پيش بيني

             N     Mean   StDev  SE Mean
واقعي        31   260158  454218    81540
پيش بيني     31   208556  365775    65695
Difference   31    51601  102047    18328


95% CI for mean difference: (14170, 89032)
T-Test of mean difference = 0 (vs not = 0): T-Value = 2.82  P-Value = 0.109
```

Paired Samples Test

	Paired Differences					t	df	Sig. (2-tailed)
	Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference: Lower	Upper			
Pair 1 forcast - real	-5.160E4	102046.827	18328.151	-89032.240	-14170.083	-2.815	30	.109

Considering that the significance level is more than 0.05 (0.109), the hypothesis H0 is accepted, meaning that there is no significant difference between the predicted values and the actual values. In other words, the predicted values are in line with the actual values, the accuracy of which has been confirmed in question one. Also, according to the results of the Pearson correlation test, there is a high correlation (0.992) between the real data and the predicted data, and it also illustrates that there is significant correlation between the real and predicted data (significance level is 0.000):

Table 9.
Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	forecasts & real	31	.992	.000

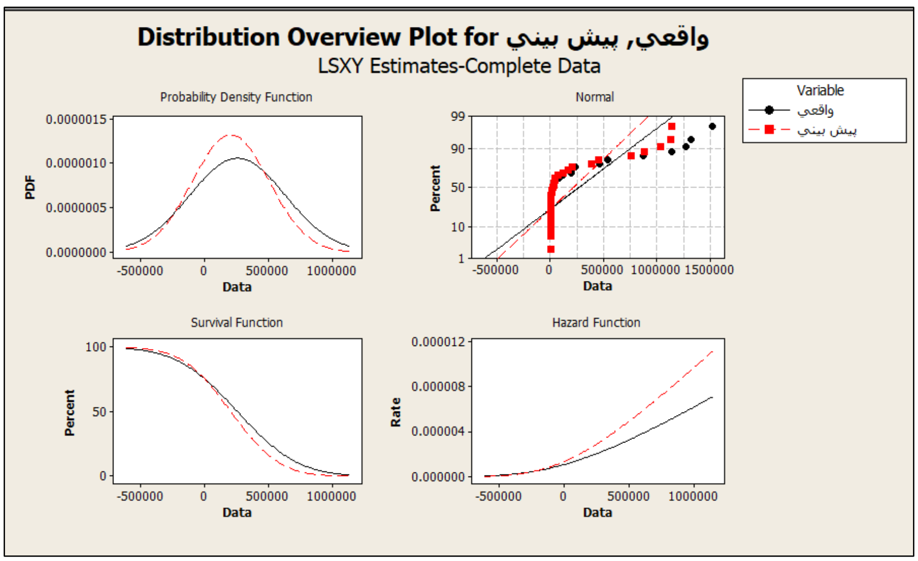

Diagram 5. The difference between real and predicted data by the presented model.

The dependence of TSE index on a non-linear process

The artificial NN model can be used as a test to find the dynamic non-linear process, including the chaotic process, in the data. Artificial NN models are flexible non-linear models that are able to estimate and predict complex non-linear time series with acceptable accuracy. NN models often include three layers; input, intermediate and output layers. The input data is directly or indirectly linked to the output layer through transfer functions in the middle layer. The direct connection of the linear part and the connection through the middle layer define the non-linear part of the model. Some tests have been proposed in the literature to investigate the predictability and non-linearity of time series, which are Keenen, Tsai and Ramsey rearrangement tests, Nietzsche bi-spectral test and Dickey Fuller test. Since Dickey Fuller test is more accurate, this test has been implemented to detect linearity and non-linearity of the data. The Dickey-Fuller test is one of the most widely used tests to investigate the stationary features in experimental work. This method is based on the assumption that the time series variables used are stationary. The first step in determining if a variable is stationary is to observe the time series graph of that variable. It is possible to detect the presence of a random trend in a time series simply through the unit root test. The result of Table 8 show that at the significance level of 1%, 5% and 10% at the absolute value of Dickey-Fuller's statistic number for the growth of the stock price index of TSE, are greater than the critical values and is stationary. Thus, the H0 hypothesis based on the existence of a unit root is rejected. The results of the tests indicate that the process of the stock price index in the TSE market in the period from 1990 to 2020 is a product of a specific dynamic non-linear process and can be predicted in the short term. After performing the tests and confirming that the stock price index is not random and has a non-linear structure, followed by justifying the presence of chaos in this series (the absolute value of the test statistic is greater than the critical values), A NN model is used to predict the stock price index in future periods.

Table 10.

The results of the unit root test that attest to the non-linearity of the time series of the TSE market index

Parameter under study	Statistic DFT experiment	MacKinnon critical value	Significance level
Stock price index	- ۱۶/۳۵	- ۳/۲۴	۱%
		- ۲/۶۹	۵%
		- ۲/۵۱	۱۰%

Evaluation of the proposed model

Figure 3 shows that the output of the software after feeding the last variable into the network, the test sample yields 100% correct prediction and 0% error in the prediction of the total stock index and the training sample also yields 100% correct prediction and 0% error. The validation sample has 88.9% correct prediction and 11.1% error. The overall result after entering the first variable results in 0.981% correct prediction and 1.7% error and a root mean square error value 489 in predicting the total stock index of TSE. According to the results of the multi-layer perceptron NN outputs at each stage, it can be concluded that the network has a maximum error of 1.7% in predicting the total stock index of the TSE using artificial NN highlighting the high predictive power of the model. Therefore, the power of the presented model is proved.

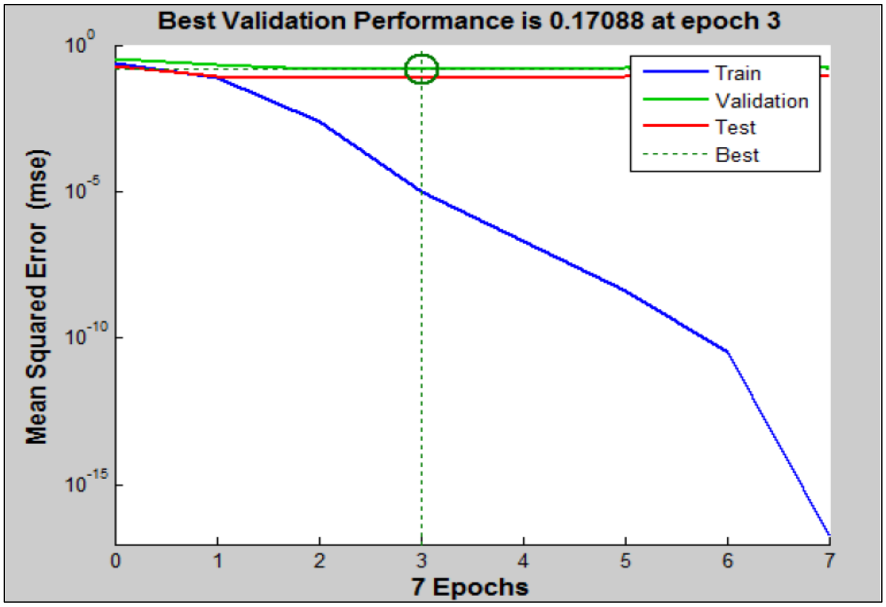

Diagram 6. Error function.

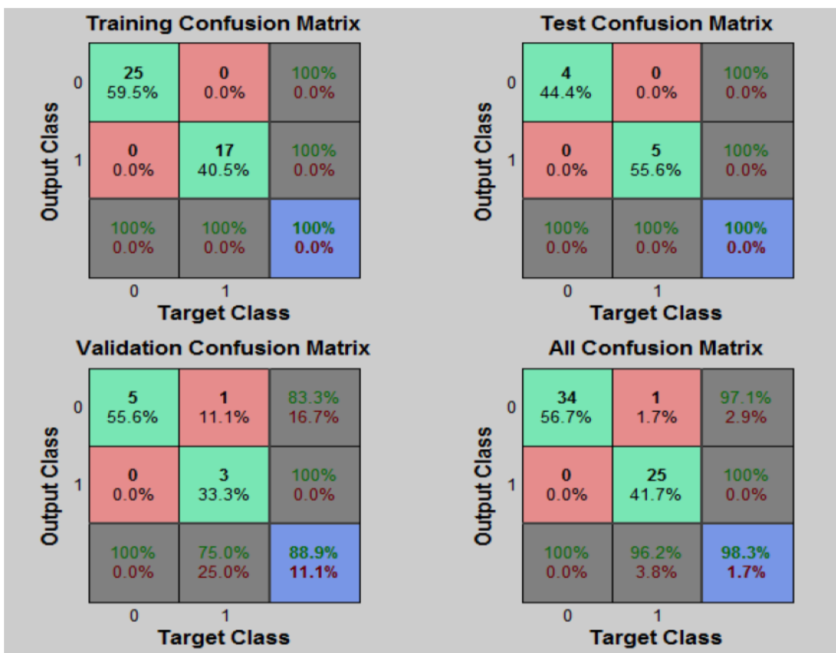

Figure 3. Software output of the designed model and corresponding prediction performance.

Table 11.
Rating the forecasting performance

MAPE	Judging the prediction performance
Less than 10%	High accuracy
11% to 20%	Good prediction
21% to 50%	Defendable prediction
More than 50%	Inaccurate prediction

The difference between the predicted results and the real data show that the presented model is able to predict the total stock index with 98.1% and the non-linearity of the price index of the TSE was confirmed by statistical calculations. Furthermore, the evaluation of the model using error functions was presented schematically.

Conclusion

By changing the structure of artificial neural network layers and minimizing the error squares, we were able to provide an optimized model to provide a more accurate estimate of the trend of the Tehran Stock Exchange index. In detail the results obtained from the Kolmogorov-Smirnov test indicate that the data of the TSE total index from 1990 to 2020 does not have a normal distribution because the significance level is equal to 0.01 and is less than 0.05; in other words, the data have a significant difference with the normal distribution, and which reconfirms the existence of excessive scattering in the total index during the time series. In the next step, using 4800 training data and 900 evaluation data and using sigmoid function and the number of three processing elements with a learning rate of 0.05 and a hidden layer with 8000 training courses, the results of the post-error propagation NN model has the best performance. This model resulted in a least root mean square error of 413 calculated with the aforementioned parameters. These results are consistent with the research results of Prokhoff and Wench (2000), who designed a system that predicts significant short-term changes in stock prices to estimate good profit opportunities. It is also consistent with the results of Ayodele Adebiyi's (2014) research, which used a hybridization method with a combination of variables from technical and fundamental analysis of stock market indices to predict future stock prices in order to improve existing methods. In the next step of the research, using t-test and correlation test, it was shown that there is no significant difference between the predicted values and the actual values, hence, the predicted values are in line with the actual values. Also, using the Dickey-Fuller test, the results of the tests indicated that the stock price index of the TSE market between years 1990 to 2020 is a product of a certain dynamic non-linear process and can be predicted in the short term. After performing the tests and confirming that the stock price index is non-random and has a non-linear structure, and the presence of chaos in this series was confirmed by the fact that the absolute value of the test statistic is greater than the critical values. In order to predict the stock price index in future, NN model was implemented. The evaluation of the prediction model was investigated using error function graphs, and based on the results of the error functions, the final result after entering the first variable showed that 98.1% of the prediction is correct and only 1.7% error exists in predicting the total stock index of TSE. According to the results of the multi-layer perceptron NN outputs at each stage, it can be concluded that the network has a maximum error of 1.7% in predicting the total stock index of the TSE using artificial NN, which corroborates the high prediction power of the model.

Practical Suggestions

Future researchers are recommended to continue this research in the fuzzy environment and compare the results of fuzzy artificial NN with non-fuzzy ones. Besides, in order to check the accuracy of the results of this research, a comparative study can be done on the use of genetic algorithm compared to artificial NN in order to make a more accurate judgment about the best method of predicting the total stock index. Considering the high variance and standard deviation of the data during the last 31 years in the total capital market index and according to the chaos theory, if the data is obtained from a chaotic non-linear dynamic system, it is possible to accurately modeling and forecast the future behavior of the system in short term since the irregular behavior of a chaotic system is a result of its non-linearity. If it is proven that the data generating system is chaotic, it is possible that the non-linear dynamic models can be used to obtain high accuracy predictions. Conducting this research and comparing its results is one of the researcher's recommendation to other colleagues as a future path of research to accurately predict the TSE market index.

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