Prediction of Stock Price Resilience, using Artificial Neural Networks (MLP) in companies listed on the Tehran Stock Exchange

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ABSTRACT

Over the past few years, the growth and development of the capital market of countries and the introduction of new tools, mechanisms, and phenomena in it, have enhanced the importance of the capital market in the economy. Predicting Stock Price Resilience is one of the key issues for estimating the use of new techniques such as neural networks that have been considered by researchers. Artificial neural networks are mathematical models inspired by the human nervous system and brain. In this research, the researcher aims to predict Stock Price Resilience in the Iranian Stock Exchange using the multilayer perceptron model of artificial neural networks. The present study has an applied approach that pays special attention to providing a purposeful method in designing stock price resilience forecasts. The statistical population is the companies listed on the Tehran Stock Exchange in the period 2009-2019. The dynamic artificial neural network structure design is done in the MATLAB software environment. Comparison of AR and ARMAX statistical methods and NAR and NARX networks has been used to predict the average Stock Price Resilience for the next year. The results show that in estimating Stock Price Resilience, the highest amount of R2 is present in NARX, NAR, ARMAX, AR models, respectively. This means that the best models for estimating Stock Price Resilience are listed in order. Based on the criteria of mean square error, total square error, coefficient of explanation, prediction error of the NARX model for the stock price parameter is very low, so this model has a much higher accuracy in predicting the stock price resilience than other models so Which is a lower amount of prediction error.

Keywords: Prediction, Stock Price Resilience, Artificial Neural Networks, NAR, NARX.

1. Introduction

Stock markets movements can have a substantial impact on the economy and individuals. A collapse in share prices can highly dysfunctional the economy. For instance, the stock market crash of 1929 was the principal reason triggering the Great Depression of the 1930s (Tejvan, 2020). When the stock prices are high, more companies are likely to issue an Initial Public Offering (IPO) to raise capital through transfer ownership. This increased investment leads to more remarkable economic growth (Premkumar, 2020). Stock price Prediction and examining the price behavior of securities is a category that financial academics and investors are always looking for optimization (Heidari Zare and Kordloui, 2010). The importance of this issue stems from the fact that stock price forecasting in financial markets is one of the important variables in the field of investment decisions, securities pricing (derivatives), and risk management (Badiei et al, 2017). The stock market is turbulent, yet using artificial intelligence to make calculated predictions is possible and advisable before investing (Chhajer et al, 2022). On the other hand, talking about stock price forecasting and recognizing its behavior is a long and complicated matter (Babajani et al, 2019, Jin and Kwon, 2021). The existence of various factors in researchers' studies such as political, economic, and psychological and the study of the resilience of this market to shocks indicate the existence of a nonlinear and chaotic system (Amiri et al., 2010). Chhajer et al. (2022) analyzed stock price prediction using neural network and support vector machines.

Chang (2006-185) and Wang (2011-468) emphasize the use of intelligent techniques to overcome the limitations of traditional analysis and improve stock price forecasting. Because of the non-linearity of the price trend, the prevailing uncertainty and the unevenness of the component data have made it difficult for researchers to accurately and without error predict prices (Babajani et al, 2019). Financial forecasting can be tagged as data-intensive, noisy, non-stationary, and unstructured and hidden relations (Kshirsagar, 2018; Solanki et al, 2021). According to Easley et al (2008), stock prices can be broken down into two components. Components of a permanent or random trend that reflects the underlying value of a stock that fluctuates or even shocks as new information enters. In other words, the entry of new information indicates a change in the fundamental value of stocks. The other component is a transient or fixed component that contains a temporary change in price that deviates from its fundamental value. This component makes it possible to calculate resilience so that the duration of the stock's return to its original value after a deviation from it will be calculated according to the speed of the transient price effect. Warf et al (2020) consider resilience to withstand environmental shocks and stresses while maintaining key system functions. Rehak (2020) defines resilience as the state through which the system reduces impending damage, minimizes the effects of active threats, and accelerates accountability, recovery, and facilitates adaptation to destructive events. Numerous studies have identified the factors of capital market resilience: organizational structure and processes (Andersson et al., 2019), hope for the future (Hasanzadeh et al., 2020), staff capabilities (Barasa, 2018), attention to learning And education (Kuang & Liao (2020), information sharing (Kurtz & Varvakis (2016), futurism (Ramezani & Camarinha-Matos, 2020), identification and analysis of shocks, threats and risks ahead (Ebrahimi et al., 2017), Variety of available designs and choices (Klibi et al., 2010), resilience to change (Manfield, 2016), agility (Darvishmotevali et al., 2020), collaboration between units within the organization (Hasanzadeh et al., 2020) , Integration between intra-organizational units (Gibson & Tarrant, 2010), networks and communication channels with influential decision-making groups (Dorobantu et al., 2017), organizational culture and values (Barasa, 2018), technology acceptance (Gibson & Tarrant, 2010), Creativity and Innovation (Barasa et al., 2018) and Attention to Improvement and Development (Hasanzadeh et al., 2020) are examples of these factors. In a general classification, the models used in the research background about stock price forecasting are divided into the following four general categories: **A. Statistical models:** such as audit analysis, logistic regression, decision tree, and probit. The main problem with statistical methods is that they limit some assumptions that are far from being assumed in the real world. Name the limiting assumptions (Beckwith, 2008, 608; Edirisinghe & Zhang, 2008, 315). **B- Research methods in operations:** such as linear programming and integer programming. In these methods, they define the problem model by defining an objective function, which is usually to minimize the level of credit risk, as well as defining a set of constraints. Then, by using an optimization algorithm in research methods in operations, they try to solve the mentioned problem (Kumar, 2007, 125; Chang, 2004, 62). **C- Artificial intelligence methods:** including genetic algorithms, neural networks, fuzzy devices, and intelligent devices that the superiority of these methods over statistical methods, the lack of limiting assumptions (Li, 2014, 109; Affenzeller, 2009, 232). **D) Hybrid methods:** In such methods, first, using a feature selection algorithm, a subset of features that cause the most effective of the independent variable on the dependent variable are selected and considered as the input of the main model. Then, based on one of the main prediction models, another method is developed to develop and improve the prediction of the original model (Babajani et al, 2019). Here in this paper, three algorithms have been discussed — ANN. ANN or Artificial Neural Network is an algorithm designed to understand complicated issues that cannot be undertaken by basic machine learning algorithms or accessible neural networks. ANNs are built in a more complex and complicated web of interconnectivity than the human brain. The method is based on algebraic equations aiming to channel information to a model or time-series line (Dhenuvakonda et al, 2020). Figure 1 shows the prediction implementation process in this study. Therefore, considering the importance of "*Stock Resilience*" among investors in the stock exchange organization, the researcher with the approach of neural networks has addressed the issue of stock price resilience at the level of companies operating in the Iranian Stock Exchange to be able to choose the appropriate model.

Bibliometric analysis (1975-2021)

Bibliometrics is a method of quantifying scientific publications using statistical techniques (Zhang et al., 2015). This tool has been used as a common tool of systematic analysis in various disciplines that aims to assess the status of research and trends in a particular subject and also to identify future research orientations to guide researchers (Fu et al., 2010). From this technique, scientific publications can be identified through a series of methods such as the output of various journals, countries, institutions, authors and citation analysis, and paths that focus more on content analysis and research development (Liu et al., 2011) To retrieve the records of this research, a search was made in the Core Collection section of the WoS database on September 21, 2021, without any time limit. Keywords The basis of data collection was formed by studying the titles and keywords of the articles and according to the previous knowledge of the field of stock price resilience.

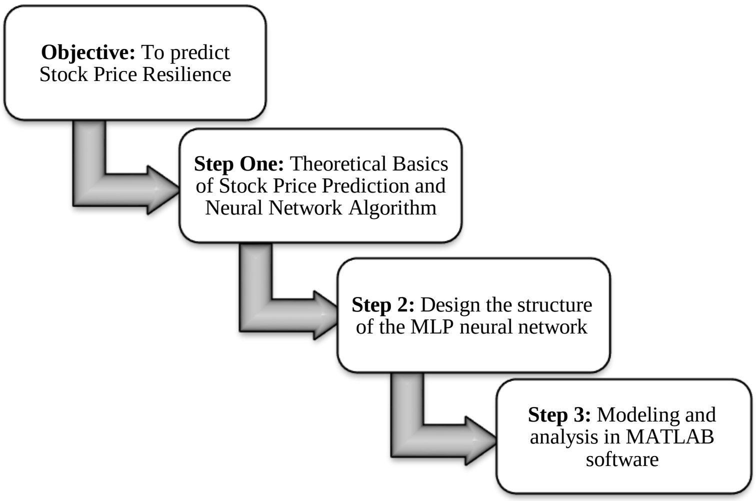


Figure 1. Modeling and prediction process in research

Search Formula

- **T1: TOPIC 1-1:** (stock price) *AND* **TOPIC 1-2:** (Resilience)

Timespan: All years. **Indexes:** SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI, CCR-EXPANDED, IC: The result includes 90 articles from 1975 to 2021.

- **T2: TOPIC 2-1:** (stock price) *AND* **TOPIC 2-2:** (Neural Network)

Timespan: All years. **Indexes:** SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI, CCR-EXPANDED, IC: The result includes 1616 articles from 1975 to 2021.

It is also worth noting that searching for keywords in a combination of the above two phases did not yield any results. As it turns out, the emission field is TOPIC. The data obtained as CSV from WoS in Excel and txt files are used by VOSviewer software to calculate and find different topics in a two-dimensional map. The results of the first search for the most keywords in the articles show that the word resilience with 21 repetitions and total communication power of 86, is the highest among articles from 1975 to 2021. Also, the words management with 16 repetitions and turbulence with 11 repetitions are in the next categories (Figure 2):

Also, the most references to Walker (2010) documents with 79 references in an article entitled Incorporating Resilience in the Assessment of Inclusive Wealth: An Example from South East Australia. Table 1 shows the most citations to authors and the power of communication between articles:

As it turns out, the power of communication between documents is very low. The results of the study also show that the most referrals based on the leading countries in this field are the United States with 23 documents and 387 referrals. Australia with 6 articles and 198 citations and the United Kingdom with 14 articles and 132 citations have the highest number of citations by country (Figure 3)

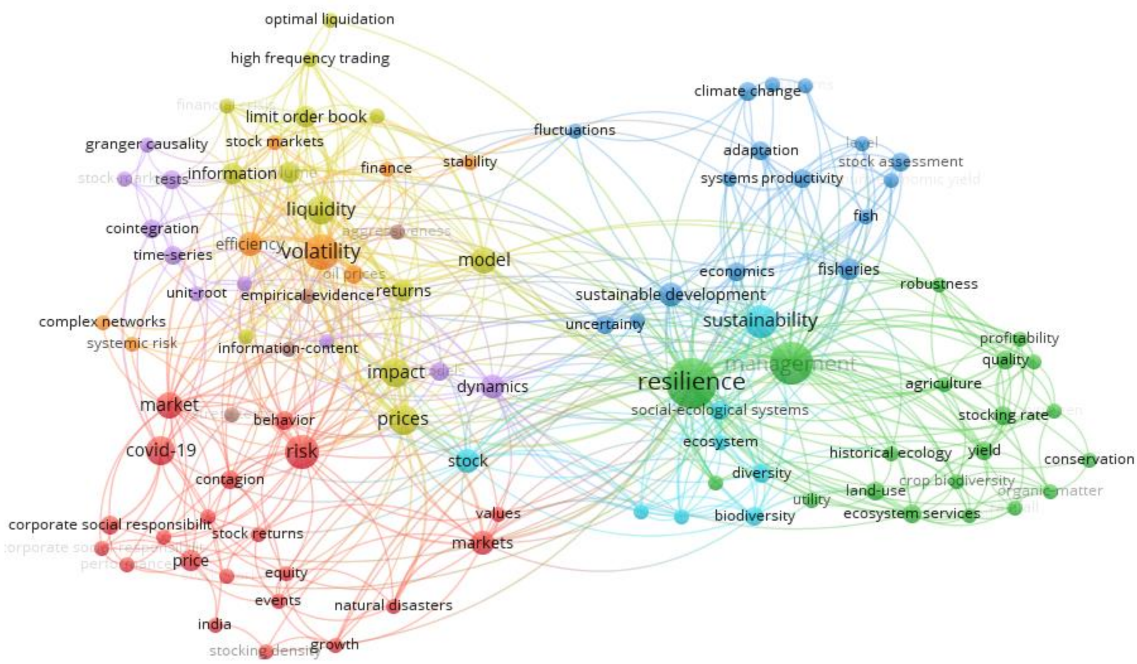


Figure 2. Most repetitive keywords in stock price search and resilience

Table 1. Relationship between documents, references and their relationship in articles in search of stock price and resilience

Row	Documents	Citations	Links
1	Walker (2010)	79	2
2	Perrings (2000)	26	1
3	Matsusshita (2018)	4	1

Row	Documents	Citations	Links
4	Xu (2017)	34	1
5	Obizhaeva (2013)	170	1
6	Dal masi peron (2012)	54	0

Figure 3. Most documents based on countries in search of stock prices and resilience

The second search is examined below. The results showed that the word prediction with 69 repetitions is the most meaningful among keywords. Also, neural networks with 61 repetitions, stock price forecast with 54 repetitions, artificial neural network with 50 and neural networks with 47 repetitions were in the next categories (Figure 4):

Also, the most referrals are based on documents related to Kara (2011) with 282 referrals, Pie (2005) with 413 referrals and Guchen (2016) with 107 referrals (Table 2)

Figure 5 illustrates the relationship between documentation and references in the search between stock prices and the neural network:

Also, in the second search (Figure 6), China had the most articles in this field with 173 documents and 1303 citations. The United States with 48 documentaries and 1331 citations, Taiwan with 46 documentaries and 1404 citations, India with 51 documentaries and 711 citations and Turkey with 13 documentaries and 526 citations are in the following categories:

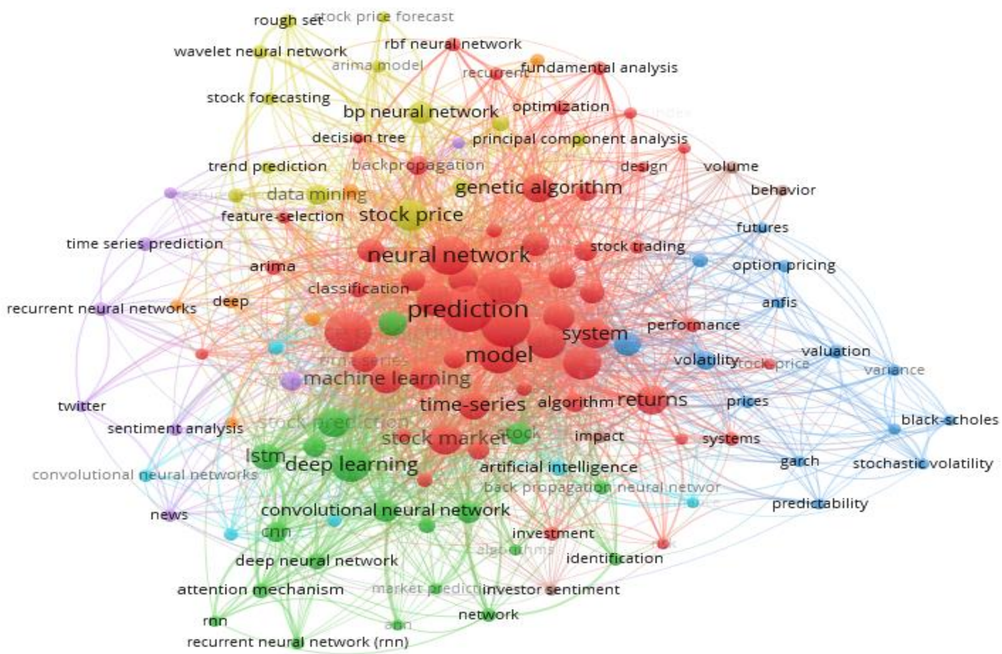


Figure 4. Most repetitive keywords in stock price search and neural network

Table 2. Relationship between documents, references and their relationship in articles in search of stock prices and neural network

Row	Documents	Citations	Links
1	Kara (2011)	282	32
2	Pai (2005)	413	17
3	Gocken (2016)	107	17
4	Wang (2011)	175	16
5	Handavandi (2010)	202	16
6	Saad (1998)	271	16

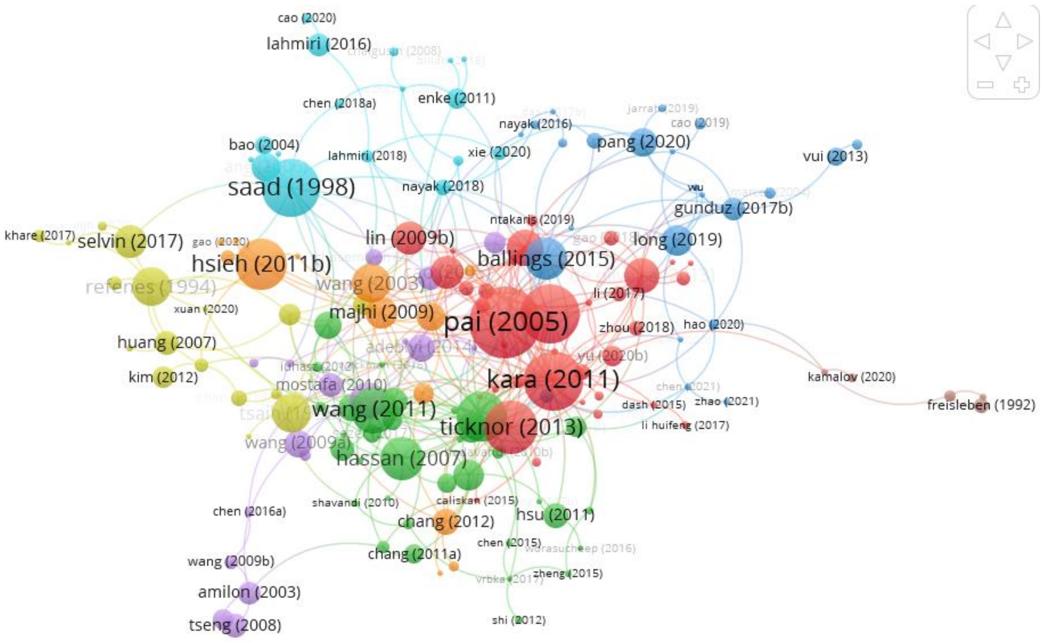


Figure 5. Relationship between documents, references and their relationship in articles in search of stock prices and neural networks

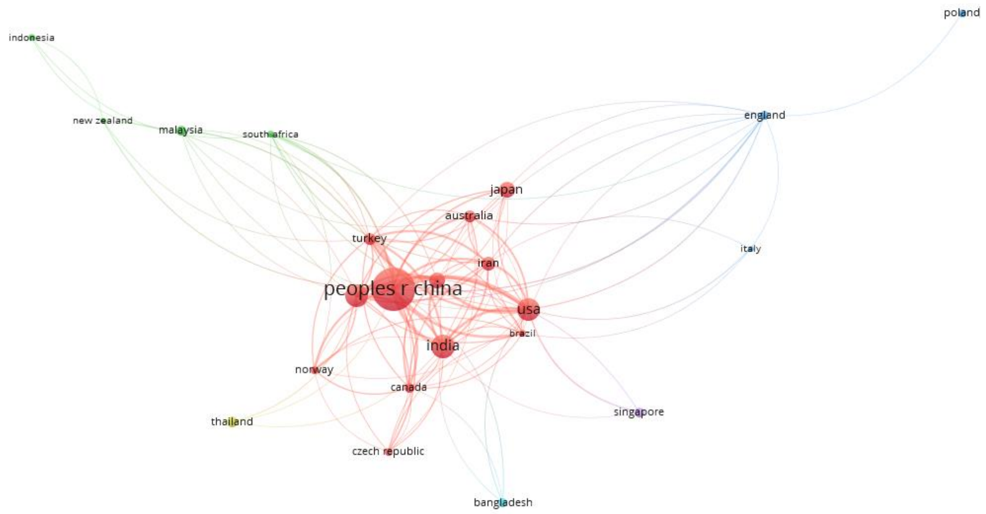


Figure 6. Relationship between most countries' documents and their references in articles in search of stock prices and neural networks

The Effect of important factors in the Iranian Market

A) Currency

In Iran, the impact of the exchange rate on price fluctuations has proven to be a principle, and it has shown itself more than ever in the economic crisis of the early 1990s and the last two years; These crises, with the intensification of sanctions against Iran, had a double impact on the country's economic situation, and both eventually led to a recession. However, more research is needed in this area to understand the various dimensions of price fluctuations caused by the weakening of the national currency. Although the domestic economy is increasingly affected by the currency shock, it is clear that the speed and intensity of the impact of currency fluctuations in each sector have their characteristics. A recent study by the Institute for Monetary and Banking Studies suggests that agriculture and industry are hit faster than any other sector by currency shocks, with 1.97 seasons in agriculture and 2.6 seasons in industry. As the foreign exchange market became more turbulent, production costs and final prices rose. Meanwhile, in the transportation, education, health, and social work sectors, after a one-year break and after 5.2 seasons, they change their prices according to the situation in the foreign exchange market. The industry sector, on the other hand, is experiencing an impact equivalent to 0.93 of the currency shocks; In simpler terms in the field of industry, the price effect on the final product is almost equivalent to the changes that have taken place in the foreign exchange market. The transportation, warehousing, and communications sector is also in the next position after the industry with an efficiency of 0.74%. The education sector also accepts only the effect of 0.033% of the currency shock and the weakening of the national currency, which is the sign of the least impact. On the other hand, firms whose products are highly dependent on imports have more foreign exchange expenditures from their resources, and those that use the dollar as their reference currency for imports suffer more from currency fluctuations.

B) Bourse

The stock market is one of the components of financial markets and as a part of the economy, it is subject to it. If this market is not coordinated with other sectors, there will be problems and shortcomings in its performance. The stock market downturn and boom affect not only the national economy but also the global economy (Najarzadeh et al., 2009). An examination of the past trends in the Iranian capital market shows that the Joint Comprehensive Plan of Action has affected analysts' expectations of the country's economic variables, and these expectations have also had an effect on the country's capital market. At the beginning of the Joint Comprehensive Plan of Action, we saw that with the hope of opening up in the Iranian economy, there was an expectation of economic growth, and as the economy improved, it was hoped that the dollar would not fluctuate much and eventually grow as much as Iran's domestic inflation. These expectations also affected the stock market, and of course, there was an overreaction among capital market residents. At first, we saw price increases in some companies that were thought to have the most positive impact from the Joint Comprehensive Plan of Action. But after it became clear that the effect of the Joint Comprehensive Plan of Action openings would not be immediately apparent in corporate profits and that other unresolved barriers, such as the FATF and the possibility of using Swift, remained, market participants, revised their corporate earnings analysis and the capital market moved in the same direction. There was a decline. After the withdrawal of the United States from the Joint Comprehensive Plan of Action, there were inflation expectations and an increase in the dollar exchange rate among market participants, which led to the growth of companies' stock prices following other assets. The important point is that despite the negative growth rate of the economy during the US withdrawal from the Joint Comprehensive Plan of Action, but given that the nominal economic growth rate in which inflation is also present on the capital market, in the capital market with rising prices as a result, we faced expectations of high inflation and rising dollar rates. This time, too, the market was not immune to hyper-reaction, and the price growth of many stocks did not match their income and profits, and the capital market continued to face price corrections.

C) Banking industry

For many years, the tip of the arrow of economic sanctions against our country has been the banking industry. In fact, sanctions have had a real impact on Iran's economy since they directly targeted the sector. The global financial crises of 2007-2009 show that increasing stress in financial markets is of great importance for analyzing and forecasting economic activity and can have severe adverse effects on the real activity of the economy in terms of production, employment, and welfare (Van Roye, 2011).

Stock price Predicting in research

Stock price forecasting is traditionally done using linear models such as AR, ARMA, and ARIMA and its variations (Box GEP et al, 2015). In these models, the stock price is used as a time series as an independent variable for forecasting. For multivariate models, company characteristics (returns, sales, different financial ratios, etc.) (Ballings et al, 2015), stock trading volume (Bessembinder and Kaufman, 1997), stock price trends over some time, and the number of times the name of a particular company is considered (Table 3).

Table 3. Literature on stock price prediction (Jin and Kwon, 2021)

Method	Determinants	Data Frequency	Ref
SVM	Single words, bigram, polarity, noun phrase	Daily	Hagenau et al (2013)
ANN, SVM, linear regression	Economic info, financial ratios	Yearly	Ballings et al (2015)
MLP, RNN, CNN	Close price	Daily	Di Persio and Honchar (2016)
ANN, genetic algorithm			Qiu and Song (2016)
LSTM	Rate of return		Fischer et al (2018)
CNN	Open and close prices		Hoseinzade et al (2019)
CNN	Close price	Monthly	Sezer and Ozbayoglu (2019)
ARIMA, LSTM, CNN	DJIA index closed	Daily	Deng et al (2019)
SVM, CNN	Close price	Every 30 minutes	Sim et al (2019)
LSTM, CNN		Daily	Jin et al (2018)
LSTM, CNN	Four commodity futures and two equity indices closed	Every 5 minutes	Wang and Wang (2015)

Recently, attempts have been made to predict stock prices using nonlinear models. Various classification algorithms such as ANNs,naïve Bayes, support vector machines (SVM), and random decision forests have been used. Nonlinear classifiers perform better than existing linear models in predicting stock prices (Di Persio and Honchar, 2016). Among the various options, artificial neural networks (ANNs) have provided good predictive performance and have become widely used as financial forecasting tools (Shastri et al, 2019). For example, a comparison between ANN and SVM classifiers showed that ANNs outperformed SVMs in forecasting on the Istanbul Stock Exchange (Kara et al, 2011). To improve the predictive performance of ANNs, specific features must be easily extracted. Thus, feature engineering methods such as principal component analysis (PCA) are currently used to improve the performance of ANNs (Zhong and Enke, 2017). However, ANN networks do not always perform well. In another study, ten technical indicators were used to measure the up and down movements of stocks using the classifiers ANN, SVM, random forest, and naïve Bayes. The authors found that the stochastic forest model performed better than the others (Patel and Shah, 2015). In some studies, neural networks have been described as a miracle for prediction, and the advantages of these networks over the methods of sales strategy or random step hypothesis have been identified (Safari Dehnavi & Shafiee, 2020). Monajemi et al (2010) used a fuzzy neural network and its combination with a genetic algorithm and showed that this method has better results than a fuzzy neural network. Pourzamani & Nouraldin (2011) used linear genetic algorithm, nonlinear genetic algorithm, and neural network and showed that neural network has good results. Etemadi & Baghaei (2012) used a neural network to address the issue of corporate profitability and using a neural network in 86% of cases, corporate profitability was obtained correctly. Pourzamani (2016) used the method of linear and nonlinear genetic algorithm and showed that the prediction accuracy of the nonlinear genetic algorithm from 1992 to 2012 had better results than a linear genetic algorithm. Alian & Hejazi (2017) and Saghriharvani & Mahoutchi (2017) performed index forecasting using neural networks and Pourzamani & Miralavi (2018) performed stock forecasting using neural network and metaheuristic algorithms. Samadipour et al (2020) in predicting the index using the classification method that has examined the growth or decline of stocks. Takhar and Chadari (2021) with the approach of DNN and CNN predicted the stock market between 2017 and 2020. Farahani and Razavi (2021) have predicted stock prices with the ANN approach and metaheuristic algorithms and time series models. Selvato and Mishra (2019) used stock neural networks to predict stock prices in the Indian market. Sean and Shafiq (2020) predict stock market prices in the Canadian market with the approach of deep learning systems. Safari Dehnavi and Shafiei (2020) used the fuzzy neural network approach and the proposed algorithm to predict stock prices in the Iranian stock market.

Shahvaroughi Farahani and Razavi Hajiagha (Shahvaroughi Farahani and Razavi Hajiagha, 2021) Today, the stock market serves an essential purpose and may be used to indicate economic strength. To forecast stock price index values using an artificial neural network (ANN) that has been trained utilizing many novel metaheuristic algorithms like social spider optimization (SSO) as well as the bat algorithm (B.A.) is described. As input variables, some technical indicators were used. They then utilized genetic algorithms (G.A.) as a heuristic method for feature selection and indication selection.

Jamous et al (2021) As mentioned before, artificial neural networks (ANNs) have already been used to forecast stock market closing prices. However, standalone ANNs have several constraints, which result in reduced prediction accuracy. This constraint is overcome via the use of hybrid models. As a result, the literature reported on a mixture of artificial intelligence networks & particle swarm optimization for effective stock market prediction (Thakkar and Chaudhari, 2021).

Selvamuthu et al (2019) conducted a study to remove the barrier of time series data by using the ANN algorithm. The algorithm incorporates analyzing and hence predicting stock exchanges' price movements. The aim was to find if the algorithm would forecast stock prices despite its dynamic nature and liable to quick changes. The abundance of data and technological enhancement makes it possible to form algorithms that can work and how one wishes. The study employs three algorithms: Levenberg–Marquardt (L.M.), Scaled Conjugate Gradient (SCG), and Bayesian Regularization. The results showed that SCG gave the best validation in 103 (54) iterations and L.M. in 10 (13) tick datasets. However, referring to the time barrier again, SCG was quicker than L.M. Bayesian Regularization gave the least squared error over all datasets.

Moghaddam et al (2016) experimented with the ability of ANN to predict the NASDAQ. Two networks for the NASDAQ index prediction were developed and validated. The methods used in the study took into context both short-term and historical stock prices along with daily data. ANN has performed better in bankruptcy prediction, discriminant analysis, and logistic regression. ANN can predict better than statistical methods as it is related complexly among input variable data and financial data. The model used input parameters as previous four to nine days (working). The model output displayed nothing to do with the number of days as inputs in the prediction process.

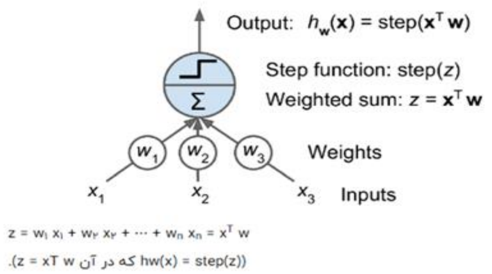
Trifonov et al (2017) examined the ANN algorithm under the contract with National Science Fund in Bulgaria. The research included extensive experimenting with the network parameters. They could confidently state that choice of input, pre-processing of data, variables, and the network's structure had a significant impact on the working of the algorithm. After running the test multiple times, the researchers concluded that the Neural Network Algorithm is considerably accurate in predicting the movement of the prices a day before the actual price change. Systems designed with Neural Networks are universal and can be applied to any number of financial devices using the most basic technical indicators as input data.

Shahvaroughi Farahani and Razavi Hajiagha (2021) tested ANN on the NSE (National Stock Exchange, India). A prediction model was built using Multilayer Perceptron (MLP) Neural Network technique. The years 2015, 2016, and 2017 were used to train and test the MLP prediction model. The results were in contrast with the studies and researches done above. The MLP neural network showed promising results and had just a Median Normalized Error of 0.05995, a Median Standard Deviation of 6.39825. MLP neural network is considered to predict the companies listed under the LIX15 index of the NSE (National Stock Exchange, India), and the results were satisfactory.

Perceptron Network

Perceptron is a machine learning algorithm that (like a support vector machine) is supervised in the field of learning. This algorithm is considered to be one of the first artificial neural network algorithms to be used in this field. Perceptron is a type of binary classification algorithm, which means that this algorithm can decide whether a member belongs to a particular category or class. This algorithm is also known as an online algorithm because it conducts its studies sequentially, one at a time. In addition, the perceptron is considered a linear classifier. The following algorithm makes its predictions based on the weighted linear composition of the input data to the algorithm.

Perceptron is one of the simplest ANN architectures introduced to the world in 1958 by Frank Rosenblatt. This artificial neural network is based on a different neuron called the TLU. TLU is an abbreviated form of the term Threshold Logic Unit, which means logical threshold unit. It Means unit linear threshold. In TLU, inputs are not binary, but numbers. In this neuron, each input has a specific weight. The TLU calculates the weighted sum of its inputs and uses this information as the basis for its predictions. For a more specialized look at the problem, see the following calculations:



In fact, the most common and widely used step function used in TLU; Is a function of Heaviside. In some cases, the sign function is used.

$$heaviside\ (z) = \begin{cases} 0\ if & z < 0 \\ 1\ if & z \geq 0 \end{cases}$$

$$sgn\ (z) = \begin{cases} -1\ if & z < 0 \\ \ 0\ if & z = 0 \\ +1\ if & z > 0 \end{cases}$$

Each TLU alone can be used for binary classification. but how? The TLU calculates the weighted sum of the inputs, then the output of the class is positive if the result is greater than a threshold value, and the output of the class is negative if it is less than the threshold. A neural network with a neuron has limited capabilities. That's why Rosenblatt formed a layer of TLUs to improve performance. Perceptron is a neural network made up of a layer of TLUs.

Types of perceptron neural networks

Perceptron artificial neural networks can generally be divided into two main types:

A. Single-layer perceptron neural networks

The Single-layer perceptron neural networks (Figure 7) is a simple type of perceptron network. This type of perceptron neural network receives a certain amount of input data. At each stage, one of the input data enters the neural network. With a set of weights (WW) and a bias value, the Single-layer perceptron neural networks produces output commensurate with the input data and weights. The input data to the Single-layer perceptron neural networks, in the network training phase, is called training data.

B. Multilayer perceptron neural networks

Multilayer perceptron neural networks (Figure 8) are a group of artificial feed neural networks. In a multilayer perceptron neural network, there will be at least three layers of nodes, which are:

- Input Layer
- Hidden Layer
- An output layers

In this type of artificial neural network, the outputs of the first layer (input) are used as the inputs of the next layer (hidden); This continues until, after a certain number of layers, the output of the last hidden layer is used as the output of the output layer. All layers between the input layer and the output layer are called "hidden layers". Multilayer perceptron networks, like monolayer perceptron neural networks, also contain a set of weights that must be adjusted for neural network training and learning.

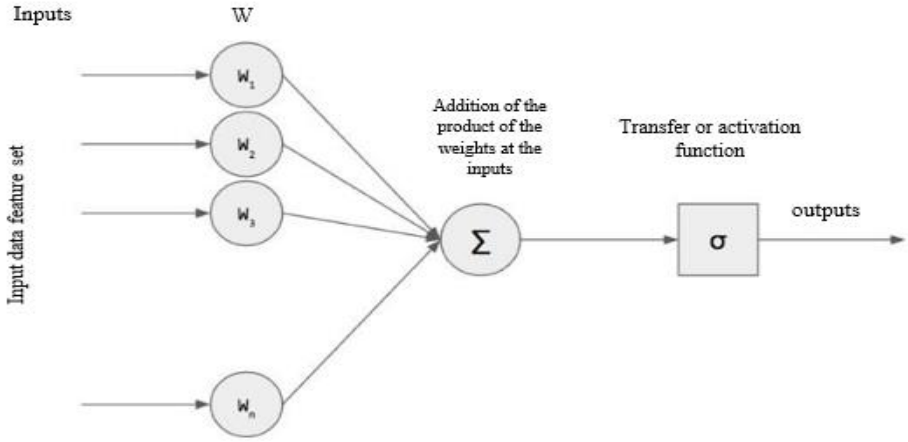


Figure 7- Single layer perceptron network

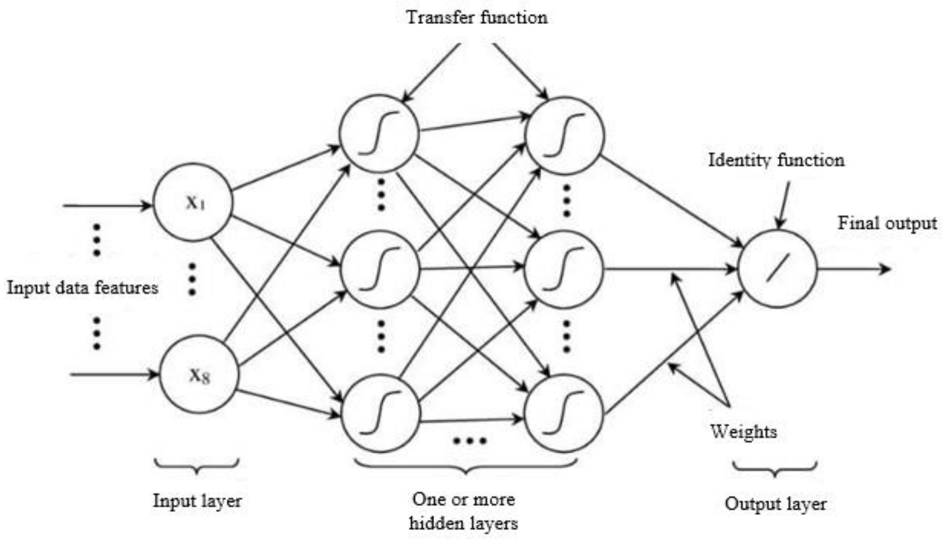


Figure 8- Multilayer perceptron network

The output in the last layer is called the Predicted Output. In all supervised learning algorithms, the actual output of the training data is predetermined. These outputs are called Expected Outputs. Expected outputs are used to measure the performance of the neural network system. Based on the expected output and predicted output values, the amount of "loss" of the multilayer perceptron neural network is calculated, but how does this happen?

Methodology

The present study has an applied approach that pays special attention to providing a purposeful method in designing stock price resilience forecasts. In this study, the statistical population is the companies listed on the Tehran Stock Exchange in the period 2009 to 2019 that meet the following conditions.

1) The fiscal year ending March 20 of each year.
2) Have not changed their fiscal year during the research period.

3) The information of their financial statements from 2009 to 2019 should be fully available.
4) Not to be part of investment and financial intermediation companies (banks and leasing).
5) The trading of the company's shares during the research period has not been stopped for more than 6 months on the Tehran Stock Exchange. Based on the above conditions, companies in the period 2009 to 2019 have been selected.

The research modeling process is as shown in Figure 9. Excel spreadsheet software has been used to prepare the necessary variables for use in the model related to the hypothesis. First, the collected information was entered in the worksheets created in the environment of this software, and then the necessary calculations were performed to obtain the variables of this research. After calculating all the necessary variables for use in the models of this research, these variables were combined in a single worksheet to be transferred to the software used in the final analysis. In this research, MATLAB software has been used for final analysis.

Prediction with Intelligent Learning Algorithms: Neural Network

Neural networks are one of these new methods. In this process, first, the neural network is taught with the existing statistical data of the past and the results obtained from them in real courses, and with this process, it tries to find the hidden pattern in this data. This means that the network tries to understand the nonlinear law of the existing time series. In the next step, several past data series when their results are known is given to the network to compare the proposed network solution with the existing solution and measure network performance. If network performance is desirable, it can be used in practice to predict future time-series data. Implementation of these networks with a variety of programming tools such as MATLAB, Java, Excel, etc. is possible.

The NAR neural network had a linear autoregressive (AR) portion and a nonlinear portion of the neural network preceded by ANN reversal propagation. This network prepares input and target data for network training and testing. In this model, the future outputs of the time series y (t) are predicted as a nonlinear function based on the past values of the output of the series. The structure of the NAR network is shown in Figure (10) below. The equation of the NAR model is as follows.

$$y(t) = f\left(y(t-1), y(t-2), \ldots, \mathrm{y}(t-d)\right)$$

Which is equal to the number of output delays and represents the time (days). Y (t) is the predicted output value at time t, which depends on the previous output values. F is a nonlinear function that is approximated using a multilayer perceptron artificial neural network (MLP).

To predict the average Stock Price Resilience for the next year using the NAR network, we first identified the target data, selected approximately 80% of the data for network training, 10% of the data for evaluation, and 10% of the network test. As mentioned in the previous section, the NAR neural network makes predictions based only on-target data. And has endogenous inputs. Endogenous inputs are inputs that enter the model with a delay line from the network output. The network uses the number of outputs (average Stock Price Resilience in the past month) to forecast the month here (365) or the next year. The structure designed for this network using trial and error has 20 neurons in the hidden layer and 8-time delays when this model of the neural network is obtained through trial and error. It is important to note that the NAR network uses a series-parallel structure in the learning phase and the target data is entered into the model and then in the prediction phase the network becomes a closed-loop network (parallel structure). Figure (11) shows the structure of the NAR network in the learning phase. Figure (12) shows the structure of the NAR network in the average Stock Price Resilience prediction phase.

The average Stock Price Resilience forecast by NAR method per year is a function of the average Stock Price Resilience in the last 8 to 10 years, so stock price values in previous years as network input and Stock Price Resilience in the next 12 months (approximately one year) are considered as network output. In this network, LEVENBERG-MARQUARDT learning algorithm and TANH function, HYPERBOLIC TANGENT in the hidden layer, and linear function in the network output layer are used. In this method, using the initial random weight set, training begins with a maximum of 1000 repetitions. The training procedure is performed using the number of neurons specified in different layers and the specified structure. After the network is trained using the training data, the test data is used to evaluate it. Then regression diagrams obtained from real and predicted data are drawn and by comparing the values of the correlation coefficient (R2) the accuracy of the network is checked. This study shows the appropriate accuracy of the trained neural network in predicting the desired values for the test data (Figure 13).

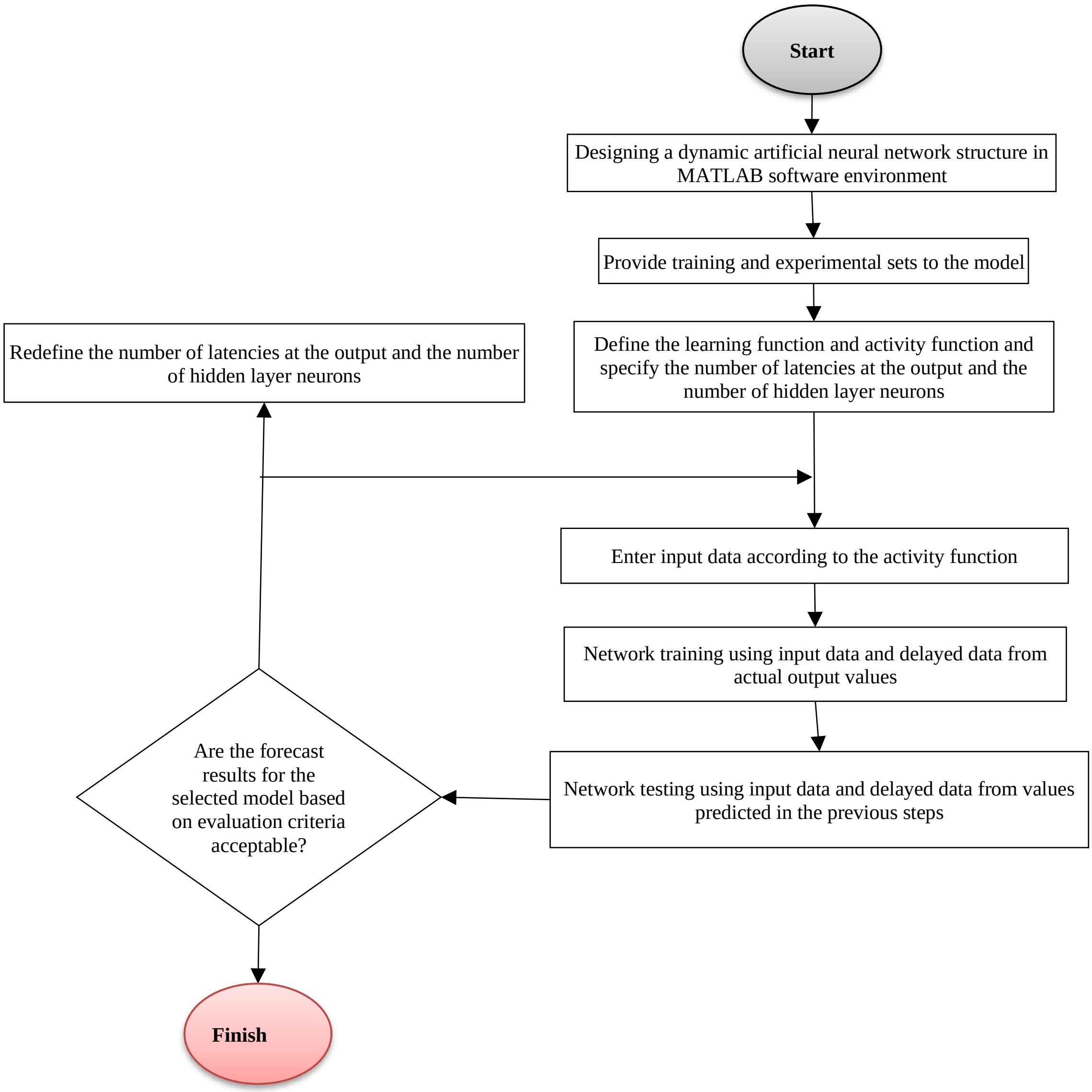


Figure 9 - Research modeling and forecasting process

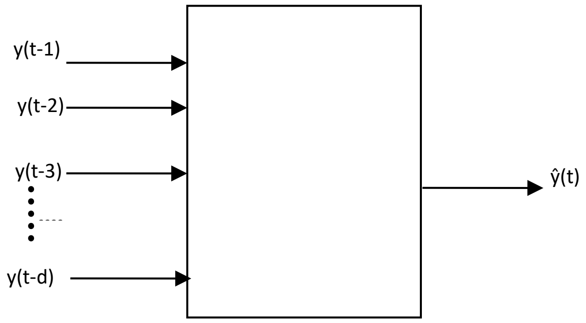


Figure 10 - Structure of the NAR model

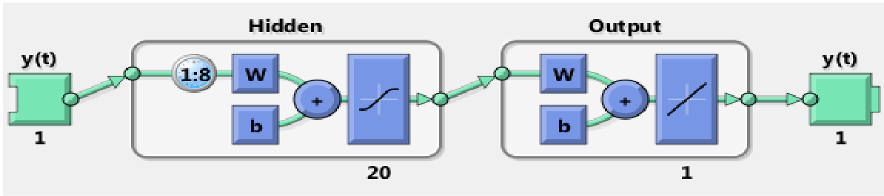


Figure 11- NAR network structure in the stage of learning the stock price resilience parameter

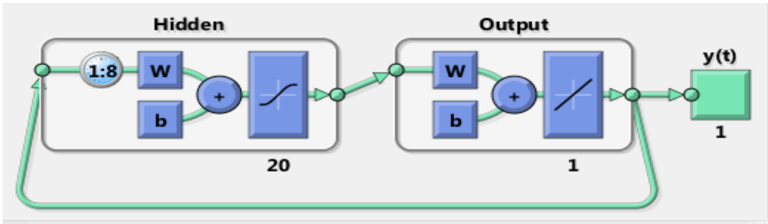


Figure 12 - NAR network structure in the average stock price resilience prediction stage

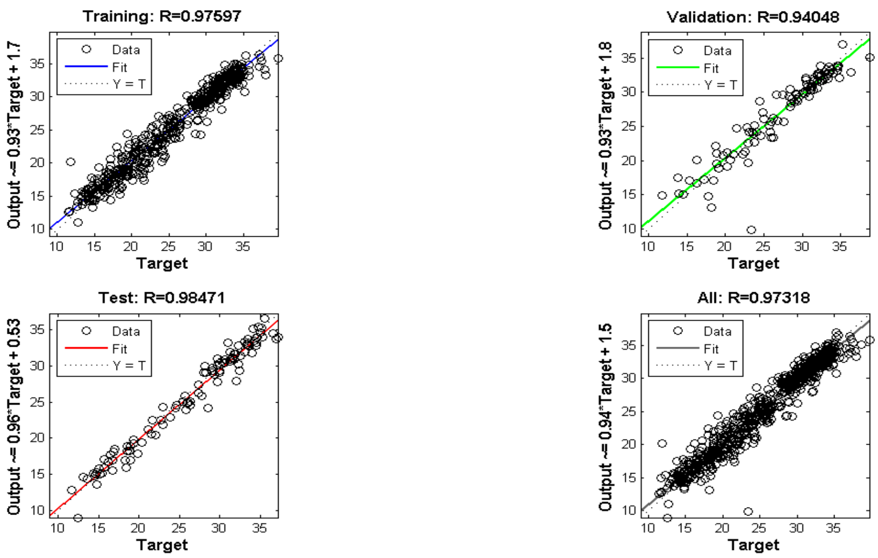


Figure 13- Network regression diagrams between network output and target related to training, evaluation and test data

As can be seen in Figure (13), according to the designed model, the correlation coefficient between the target vector and the output during training, evaluation and testing are 0.97, 0.94 and 0.98, respectively, which indicates the accuracy of the model.

Also, the appropriate accuracy of the trained dynamic neural network (NAR) in predicting the optimal values for the training data as well as the test is as follows (Figure 14):

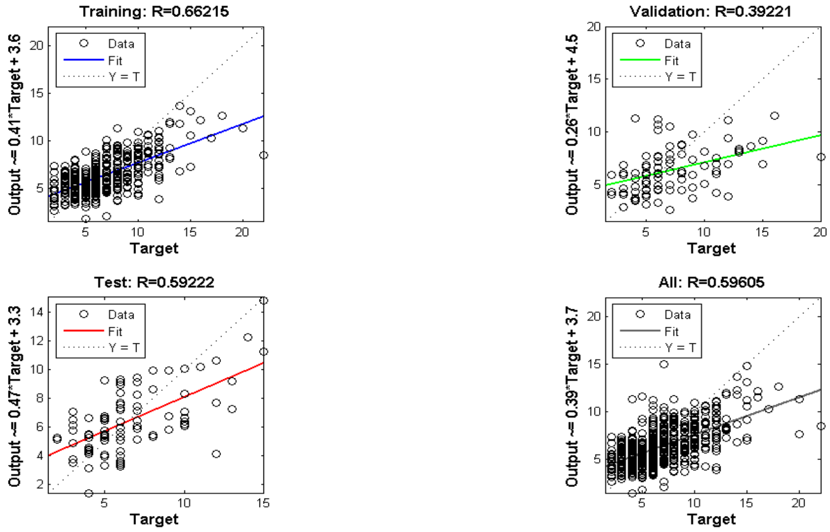


Figure 14- Network regression diagrams between network output and target related to training, evaluation and test data

Figure (15) also shows the mean square error diagram for the training, assessment, and test data sets. This diagram shows the efficiency and power of network learning, and up to the repetition of the 15 best performances of the assessment set has taken place and no over-fitting has occurred.

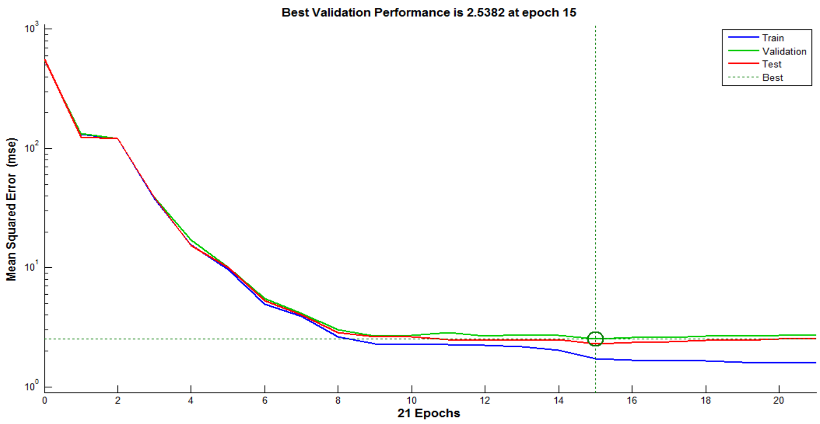


Figure 15 - Square average error diagram for training, assessment and test data sets

At the end of the training, stock price resilience is predicted by the NAR neural network. Figure (16) shows a graph of actual and predicted values.

Figure 16 - Comparison of the predicted average values of Stock Price Resilience by the NAR neural network with the actual values of the data.

Table (4) evaluates the performance results of this network to predict the average Stock Price Resilience in 12 months, which is approximately equivalent to the next year. As can be seen, this means that 97% of the changes are explained by the NAR neural network. This indicates that the NAR neural network has a very high prediction accuracy and cannot fit well with only 3% of changes in Stock Price Resilience variables.

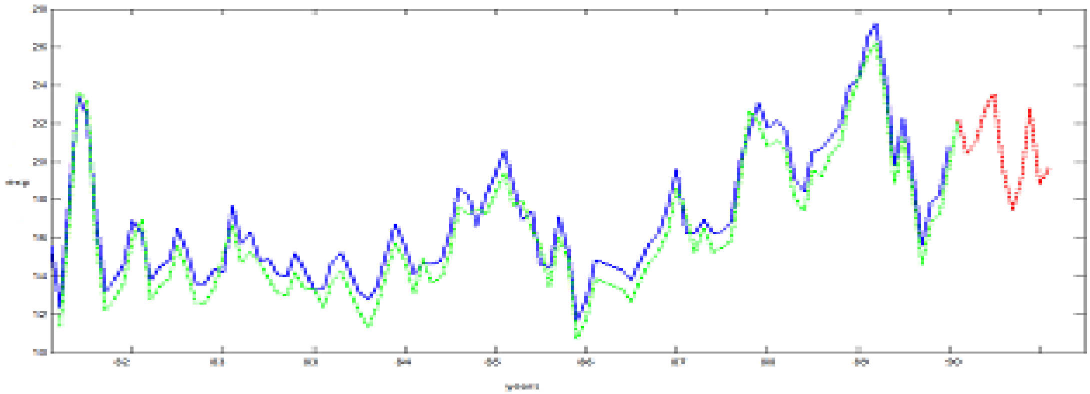


Table 4 - Evaluation of NAR artificial neural network performance in predicting average stock price resilience

MODEL	MSE	RMSE	R^2
NAR	0.34	0.59	0.97

NARX Fit Estimation

First, the structure of the NARX artificial neural network is designed in a MATLAB software environment. In designing a network, it is generally better to first create an experimental setting in which any possible case is included in reality. The training set is used for network learning and training and the pilot set is used to evaluate the network after training. Choosing the right training package is very important in the next performance of the network. If this set does not include all possible scenarios, it cannot have extensive learning of the whole system at the time of training, and when testing this educational weakness of the network, which is due to incorrect selection of the training set is identified. Therefore, of the available stock price data, 70% of the data was used for network training and 15% of the data was used for network evaluation and testing. The first step in modeling is to select the number of inputs and outputs previously used in the model, i.e., to determine. This is usually done experimentally using trial and error. Here, the values are set to 4 and 6, respectively. Also, in the present study, the initial selection of weights and biases are considered automatically. The training function of this network is Levenberg-Marquardt. The number of neurons required in the lattice layer to solve a problem in neural networks is not generally known and must be determined experimentally. However, it can be argued that if the number is too small, learning may not be complete. This condition is known as incomplete fitting, which means that there are no weights and biases by which the network can produce logical outputs close to the correct answers. Therefore, in this section, with different tests, the best number of neurons in the hidden layer was obtained. The number of neurons is 26 with 1 hidden layer and is implemented with the activation function of the hidden layer of the hyperbolic tangent and the activation function of the linear output layer to predict the average stock price parameter. Below is the architecture of the NARX network in the learning phase and the prediction phase.

According to the above diagrams, the network coefficient of explanation is equal to 0.989 and as can be seen, due to the accuracy of the network in forecasting, the curves of real and predicted data completely overlap. This shows the good performance of this network in forecasting the average stock price.

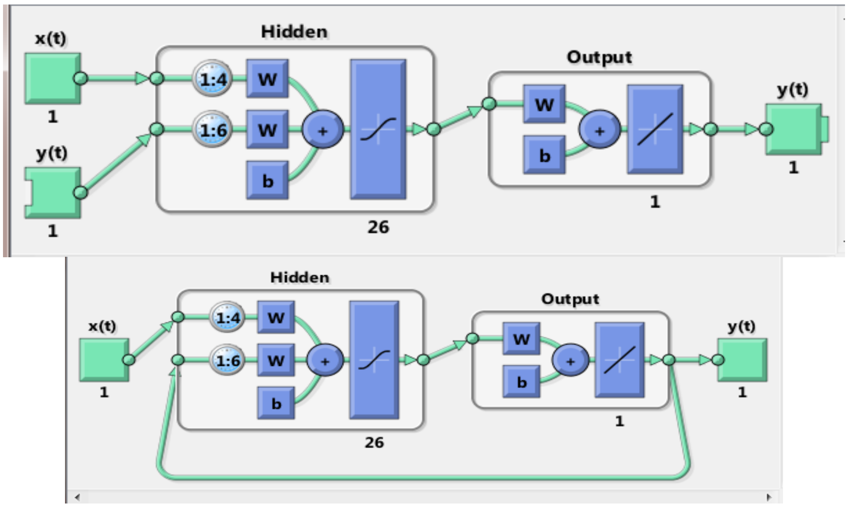


Figure 17 - NARX network architecture in the learning phase and the forecasting phase

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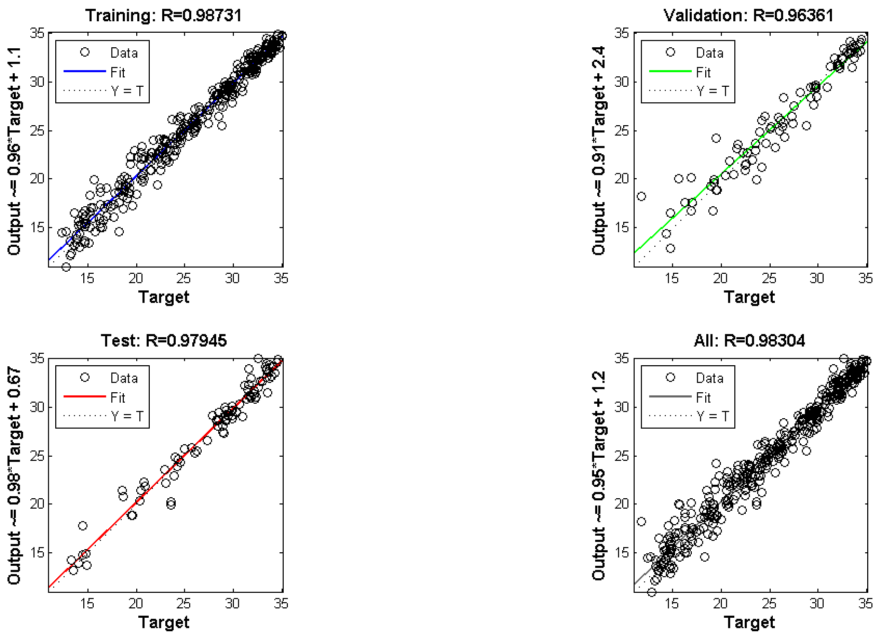

Figure 18 - NARX network fitting results

Table 5 - Performance evaluation of NARX neural network model

MODEL	RMSE	MSE	R^2
NARX	0.35	0.12	0.98

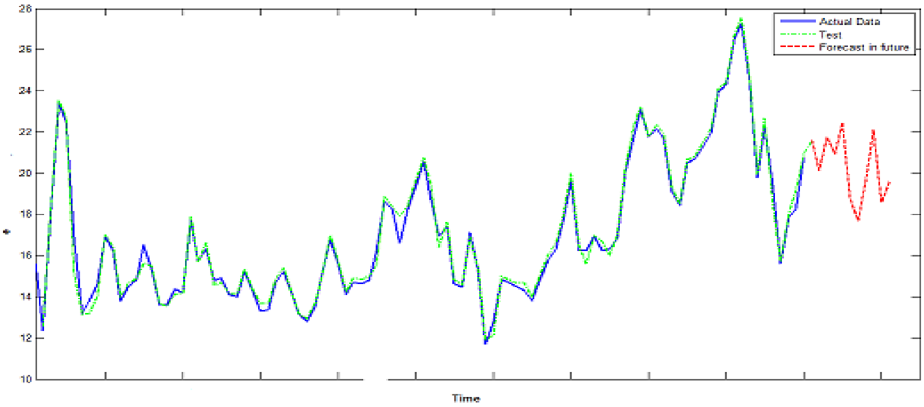

Figure 19 - Actual data values

Results

The stock market has been one of the most important avenues for investing money and growing it over time. Machine Learning Models have proved to provide more precise results about future price movements. However, there are several obstacles faced in between to get the optimum results from these algorithms. Stock market prediction is highly avoided due to the chaotic data presentation. Finding the desirable data suitable for the algorithm in use. Predicting the stock market requires forming a model that requires high knowledge in Coding and Software. This type of knowledge is not available in abundance to people and also needs specialized training. So, there is no large pool of people who can create an algorithm with their preferences and filters to predict the stock market prices and create a fully functional model to predict the stock market; it is necessary to train it accordingly, and this period is generally long. So, a person whose principal occupation is not investing would careless to do so. A professional investor could only assess a machine learning model that helps predict future price movements' worth as it is the main job. He will have no issues directing his time in developing something that works in his best interests. Creating an ML predicting model is a costly affair. Dedicated and trained personnel are required along with expensive technology to maximize the output. People are unaware of A.I. prediction; they do not know what sites provide reliable data or which sources top investors trust for their investments. Major mass is just investing in stock without the necessary expertise, whereas a stock should be analyzed first and then bought. The world needs to start smart investing. This leads to the next obstacle, which is the mentality. In third-world countries like India, Myanmar, Indonesia, etc., people are not comfortable with a machine guiding them to invest their money. The citizens think in the typical old-fashioned way. There is no trust in intricate machinery that can solve complex equations; the mass follows advice from small brokers/investors from personal yet unreliable sources. Broader application base and awareness are the need of the hour to promote machine learning and its benefits to the users.

In this study, AR and ARMAX statistical models and dynamic artificial neural networks including NARX and NAR were selected to predict Stock Price Resilience. To compare the performance of statistical models and neural networks in predicting Stock Price Resilience, Table (6) summarizes these results:

Table 6- Comparison of the efficiency of statistical models and neural networks in predicting stock price resilience

MODEL	R^2	MSE	RMSE
AR	0/95	2.25	1/50
NAR	0/97	0/34	0/59
ARMAX	0/95	1/98	1/41
NARX	0/98	0/12	0/35

As can be seen in Table (6), in terms of Stock Price Resilience, the highest amount of R2 is present in NARX, NAR, ARMAX, AR models, respectively. This means that the best models for estimating Stock Price Resilience are listed in order. Based on the mean squared error criteria, the sum of the square error, the coefficient of explanation, the prediction error of the NARX model for the stock price parameter is very low, so this model has much higher accuracy in predicting the stock price resilience than other models. So that the amount of prediction error is lower.

Among the two statistical models, since the ARMAX model uses the Stock Price Resilience parameter that correlates with the parameter under study, it has been more accurate in predicting than the AR model. Therefore, this model has the lowest error compared to other statistical models. Also in neural network models, the results of the NARX model have higher predictive accuracy than the NAR model in predicting stock price resilience and have less error. Of course, in terms of predictive accuracy, there is not much difference between NAR and NARX models. Figures (20) and (21) compare statistical methods and neural networks, respectively. Finally, because the time series of the stock price resilience parameter has a certain approximately periodic pattern (sine wave), so most models with 90% accuracy were able to simulate the trend of changes in the time series.

Therefore, according to the results, in general, it can be said that dynamic artificial neural network models are superior to statistical models in predicting stock price resilience.

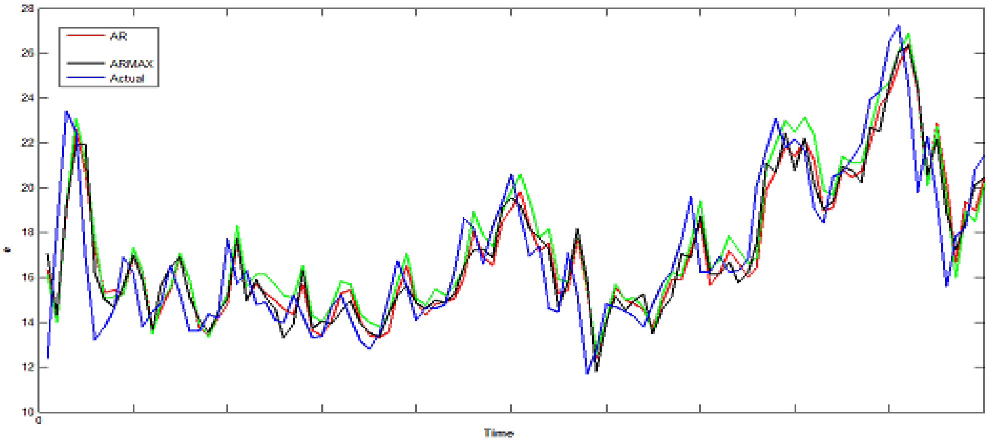

Figure 20 - Comparison of statistical methods (AR, and ARMAX) in predicting stock price resilience

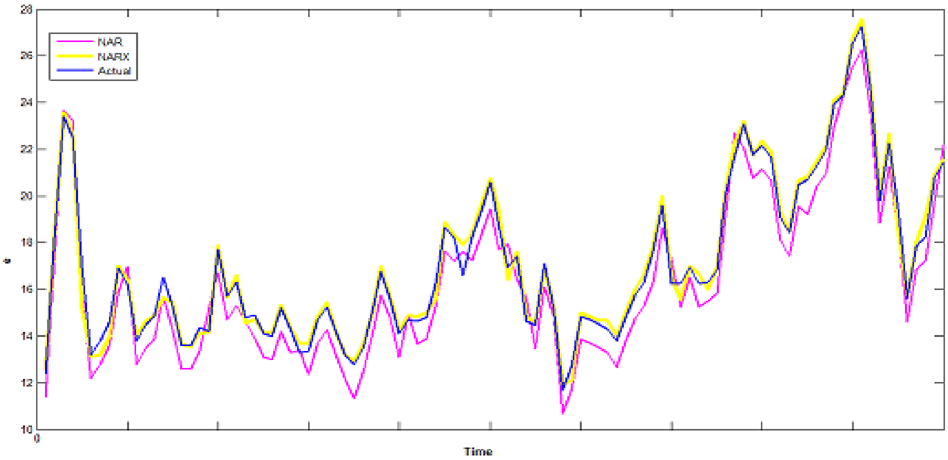

Figure 21- Comparison of neural network methods in predicting stock price resilience

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