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Comparison of Risk Factors for Investing in Tehran Stock Exchange Using Smart Neural Network (Forecasting Tehran Stock Exchange with Neural Networks)

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Abstract

In the stock market, predicting the trend of price series is one of the most widely investigated and challenging problems for investors and researchers. Risk managers need to decide when to leave a portfolio unhedged to generate profit and when to hedge in order to control downside risk. There are multiple time scale features in financial time series due to different durations of impact factors and traders' trading behaviors. While science and technology parks and towns and development centers have been established before 2002 in Iran and their number have been continually increased, there has been only a seminar presented by Tehran Securities and Exchange Organization, in Agricultural Bank , 2001, about venture capital in the country. Gradually, venture capital have been presented as a new mechanism for financing to entrepreneurs and a bill has been represented to cabinet by Management and Planning Organization to define an annual definite budgetary in a general manner. The industry of venture capital has been under attention by many organizations and science centers during recent years. The Institute of Elites' technological development, on behalf of Centre for Innovation and Technology Cooperation, Presidency of Islamic Republic of Iran, Management and Planning Organization of Iran, Industrial Development and Renovation Organization of Iran, Centre for New Industries of Iran. In this paper, we extend the field of expert systems, forecasting, and model by applying an Artificial Neural Network. ANN model is applied to forecast market volatility. The results show an overall improvement in forecasting using the neural network as compared to linear regression method.

Keywords: Venture Capital, Predictive Model, Neural Network, Fuzzy Logic, Tehran Stock Exchange

Introduction

Considering the changes that have been made in different levels of new technologies of the country and has made Iran, superior and worthy-at least in the Middle East- in terms of top talents, the need to review the various systems of entrepreneurship financing and to support useful and high-yield projects is quite palpable. There are many reasons to define an organized and systematic structure for modeling in the field of investment and the growth of new ideas and outstanding designs. We know that the main point is the existence of initial capital and starting a business in the financing structures of such projects; Therefore, if the owner of the original plan or idea maker fails to provide the required initial financial resources and even the necessary guarantees for the investor, he will actually be involved in the first and most serious issue. In this case, the main concern, if it can be assumed that he can handle management and market issues and situation analysis, is how to provide these resources and spend a lot of time and energy, which requires complex processes in banks and other state-owned companies. There are various other important reasons that require us to pay special attention to the category of investment with its conventional view in the world of venture capital, some of which are as follows:

1. Starting a new business is not something that is fruitful in terms of leisure and self-fulfillment needs and the emergence of talents in the long and even short term, but it is necessary to plan and projects within a single organizational framework by defining organizational structure and defining models. Business necessity should be designed by the selected and managers of the company and they should seriously prepare themselves for activity and competition in the sensitive conditions of the market and with competitors and in the changing environment of modern technologies. In the risky investment model, serious attention has been paid to these parameters and the appointment of a capable board of directors who are familiar with the relevant industry for monitoring, control and management designed in a completely dynamic manner.
2. Many entrepreneurs and even commercial companies and enterprises in setting up new production units or services are not as familiar with the current investment and operational literature in companies. These people are not expert in preparing executive plans and using principled agreements and licenses, employing outstanding consultants, financial estimates and technology and market assessments, etc.. Therefore, they should provide the conditions to step into the new field of experience by creating partnerships with groups, companies and individuals and networks known to their industry. These ideals are achieved when they are designed with the necessary preparations in the management and investment environment in the country and use the capable scientific and executive forces in their business.
3. In the old systems, the financing processes continued in a passive manner and only with initial examinations of the plan and with lending by financial institutions; But now in the current world, the main capital of the company is provided by a number of shareholders and venture capitalists, and earning a return and receiving more operating profit is more important and attractive for them than just returning the capital and paying the loan installments. If we look at the past financing systems, we see that many, and perhaps it is better to say, over 90% of these companies and their managers are not present in a competitive environment that believe in more activity for the growth of the company. This means that because they have designed the company with a passive system of loans, they themselves do not have an active and significant desire to fight problems and change the situation in their favor. They overshadow the will of the managers of such companies, which deprives them of

the necessary and sufficient movement and morale. Paying company loans and finding a way to get out from under the burden of commitments and guarantees, along with the fear and anxiety that take over the existence of these people from the first moment of starting a business cannot be ignored and denied. In the method of securing the financial structure of the company through long-term loans, in addition to the proper management of costs and allocation of money to the current expenses of the company is not done optimally, it is imagined that the company is successful in earning money and capital. Because cash payments have already been approved and agreements have been reached, and if the company is able to meet its repayment obligations, how much better otherwise it should have been careful right now so that the situation does not get worse. In such circumstances, the managers and owners of the company prepare themselves for a test that their life and main capital are not in danger and deprive them of the ability to bear risk and move seriously. The author suggests that project owners need to be more responsible and committed to the future and economic condition of the company than has ever been the case; Of course, the presence of shareholders, efficient managers and strategic partners can be considered as a solution to solve these problems, which is quite evident in the risky investment literature of the design of this organization.

4. In venture capital, decision-making and management of the company's plans will not be based on specific personal decisions and tastes, but the patterns, methods, aspects of affairs and its competence will be reviewed and analyzed by expert boards and shareholders' interests will be intelligently processed in the company. Thus, in this system, economics, technology and other micro and macro parameters that are included in the mission and long-term goals of the company that make the company's survival possible or impossible.

What is venture capital investment like in our country?

Venture capital has recently been introduced in scientific and research circles in our country.

This type of investment provides financing for start-ups that need the initial costs of developing and expanding their business.

The atmosphere of uncertainty that prevails in such plans has caused investors from different private and public sectors to face various risk parameters including management risk, product, technology, market, financial, operational and executive, organizational, strategic, environmental.

Creating a suitable structure and business modeling such projects with regard to the mentioned risks have always faced investors on the one hand and entrepreneurs on the other hand with some risks. Creating added value in investable companies and benefiting from the financial and legal benefits of such companies in the early years of starting a business have caused number of risky investors increases. According to this general rule, which is common in finance and investment, returns increase rationally as risk increases? As mentioned, the high risk and high returns that arise from such start-ups are the only factors that can be the distinguishing point between many investment centers and investing individuals and individuals. The individuals are generally divided into two categories based on their personality and financial ability: Risk-taking and risk-averse, but it should be noted that these two categories are two ends of the same spectrum and people manage different risks with their expected returns. In Iran, there is still a risky company or investment fund that no profession has entered this field and it is predicted that we will gradually see the presence of these funds in the coming years. Identifying the infrastructure needed to create, sustain and develop a venture capital in a region or country is important enough. It seems that in order to achieve the desired situation for the realization of venture capital in Iran, building a platform and creating infrastructure in the following three axes is significant, each of which has multiple and extensive branches and they should be identified, studied and followed up:

a. Financing
b. Financial and investment knowledge
c. Legal issues

Part 1 - Financing - It is proposed to use a model based on which venture capital is created by forming a "Joint Venture Capital Investment Fund of Iranian Industries" with the participation of various enterprises interested in venture capital.

With the formation of the fund, it seems that the first serious move will be made by the private sector, not the public sector. Why should we believe in the scientific ability and bold spirit of our country's managers and experts and make the most of all the power and energy that can be used in this field?

The implementation of this idea can be the engine of other risky investment activities in the country. The formation of the Iranian Venture Capital Association, as is the case in most countries in Europe, the United States and Asia, can become a powerful network for providing various financial services and investment and entrepreneurial growth. In the second part - financial knowledge and investment - although there are talented and hard-working graduates in the financial and technical fields of engineering, understanding the investment processes by investors and executives requires experience and updating specialized information. Technology evaluation, technology valuation, risk assessment and feasibility study of projects, formulation of appropriate business strategies and design of appropriate models are the most important factors required in venture capital that enable the fund or venture capital company to be able to organize the optimal portfolio.

In the third part - legal issues - Unfortunately, in Iran, intellectual property rights still lack the necessary laws and regulations. This fundamental weakness is a major stepping stone to entrepreneurship in most areas of investment. Although there are many experts and legal advisors in the country, but if the legal support of the government in this matter don't create a safe and appropriate environment for entrepreneurs, unfortunately, the realization of the first two issues that we addressed will not help us.

Literature Review

Selective Hedging

Hedging is usually performed to reduce the risk associated with holding a risky asset (Kofman & McGlenchy, 2005). (Working, 1953) defines hedging as using the futures market to reduce risk in a cash market position. A portfolio of risky assets can for example be combined with a position in a futures contract which is highly negatively correlated. Thus, fluctuations in the risky asset are offset by opposite fluctuations in the hedging instrument. Therefore, hedging is used as protection against adverse price movement. However, favourable price movements in the risky assets are also offset by losses in the hedging instrument. There are several views on the purpose of hedging in the literature. (Working, 1953) states that the main objective of hedging is profit maximisation, which is achieved by speculating on changes of the basis. The basis if the difference between the futures price and the cash price of a commodity. (Ederington, 1979) argues that the objective of hedging is risk reduction which is achieved by minimizing the portfolio variance. (Howard & D'Antonio, 1984) and (Howard & D'Antonio, 1987), state that the purpose of hedging is to optimise the risk-return trade off. Please refer to (Floros & Vougas, 2004), for a detailed review of the hedging literature. The term "selective hedging" describes a dynamic hedging strategy which establishes hedge positions based on the hedgers market expectations. In a selective hedging strategy, the risky asset can be fully protected, partly protected or not protected at all. For example, if a hedger expects his assets to rise in value because of favourable market conditions, he might decide to leave the assets unprotected to be able to take full advantage of the gain in value. If volatile market conditions are expected, the hedger can decide to protect the risky asset through hedging. As an alternative to selective hedging, small investors could decide to simply sell their assets instead of hedging. However, large institutions like banks or superannuation funds cannot sell all their assets since the selling itself would have a large negative impact on the market. Large institutions can use financial derivatives as short term protection under uncertain market conditions (Hull, 2006). The overall objective of selective hedging is to achieve downside protection and allow upside gain (Huu, 2002). (Topaloglou et al., 2008) use a dynamic stochastic programming model to manage risk in assets price and exchange rates in a international portfolio context. The study finds that selective hedging strategies are effective in controlling risk and generating stable return path. (Kim et al., 2001), investigate local polynomial kernel forecasts for the management of price risks in hog and corn futures markets. The study indicates that combining hedging with forecasts can potentially enhance price risk management. (McCarthy, 2003), compares strategies for managing foreign exchange exposures and finds that a selective hedging strategy based on the random walk model performs well in the analysed markets. (Eun & Resnick, 1997), also state that the Random Walk model is a good estimate of foreign exchange rates when analyzing minternational equity investments. (Simpson, 2004), analyses the performance of five selective hedging strategies with foreign exchange future contracts. The author states that a strategy based on large deviations of prices compared to the purchasing power parity performs best in the examined market. (Simpson & Dania, 2006) examine conditional hedging strategies for Euro currency exposures. It is found that selective hedging strategies can outperform strategies that always hedge and never hedge. Using such a strategy leads to a better risk-return trade off for investors.

Neural Network Models

Artificial Neural Networks aim to automatically learn and recognise patterns in large amounts of data. There is a great variety of machine learning techniques within the literature. The popularity of ANN based forecasting has been growing steadily over the last years. Examples of ANN based techniques are local linear wavelet neural networks (Chen et al., 2005), probabilistic neural networks (Chen et al., 2003), stochastic neural networks, chaotic neural networks and tapped delay neural networks. Evolutionary & optimization techniques are based on particle swarm optimization (Majhi et al., 2008), bacterial foraging optimization and genetic algorithms. Very common in the recent literature are variations of ANNs and hybrid systems. There is a clear trend to use established ANN models and enhance them with new training algorithms or combine ANNs with emerging technologies into hybrid systems.

Forecasting Timeframe

In the context of hedging, time-frames of one week or longer are usually preferred. (Butterworth & Holmes, 2001), use daily and weekly hedging time-frames and find that hedging performance increases as the hedge duration rises from a day to a week. The finding that hedging effectiveness tends to increase when the investment period increases is consistent with previous studies (Benet, 1992). (Chen et al., 2002) state that "possible explanation for this phenomenon is that trading noise in the market will be cancelled out in longer investment horizons as the true underlying relationship between the spot and futures prices emerges". (Kenourgios et al., 2008), use weekly data in their study and justify their decision by stating that a weekly time-frame implies that hedgers in the market rebalance their futures positions on a weekly basis. Therefore, futures can be used for risk reduction without incurring excessive transaction costs.

Input Variables

Choosing the right input variables is essential for Artificial Neural Networks. Even the best machine learning technique can only learn from an input if there is actually some kind of correlation between input and output variable. The majority of reviewed papers rely in some form on lagged index data. The most commonly used parameters are daily opening, high, low and close prices. Also often used are technical indicators which are mathematical transformations of lagged index data. The most common technical indicators found in the literature are the simple moving average (SMA), exponential moving average (EMA), relative strength index (RSI), rate of change (ROC), moving average convergence / divergence (MACD), William's oscillator and average true range (ATR). In addition to data purely derived from past index data, some studies use economic data in order to forecast the stock index. (Stansell & Eakins, 2004), forecast the change in sector stock indices with neural networks. 19 economic variables are used as inputs variables. The authors state that input data needs to fulfill certain criteria in order to be usable in the forecasting process. The information has to be available on a consistent and timely basis, and there should be a rational economic justification for believing that the variable has an effect on the predicted index. (Kofman & McGlenchy, 2005), analyse the sensitivity of US stock market indices to the commodity prices of the US dollar, oil, and gold. The authors argue that the companies which form a stock index incur capital costs for borrowing funds and energy costs for producing and transporting goods. Capital costs are influenced by the value of the US dollar and energy costs are affected by changes in the major energy commodity, oil.

In addition, changes in the gold price are used as a proxy for the belief of future inflation. (Ederington, 1979), use the spreads of long-term bond yields over short-term bond yields as input parameter. The authors state that it may have some power to forecast stock returns since this variable has also a business cycle pattern. In general it is stated that an independent variable must be observable (available and published) before the prediction can be made. "Constructing the data set in this manner ensures that the generation of out-of-sample forecasts will be similar to those made in the real world. It is because only observable, but not future unobservable, data can be used as inputs to the forecasting models." (Floros & Vougas, 2004), Additional economic variables found in the literature are the unemployment rate (Stansell & Eakins, 2004), and the value of US stock indices for non-US studies. Huang, (Huang et al., 2005) use the S&P 500 data and the USD/JPY exchange rate to predict the NIKKEI 225 index. (Jaruszewicz & Mandziuk, 2004) also try to predict the NIKKEI index and use data from the US NASDAQ and German DAX indices. (Pan et al., 2005), use the S&P 500 index as input to predict the Australian AORD index. Witkowska & Marcinkiewicz (Witkowska & Marcinkiewicz, 2005), use the USD/PLN exchange rate as well as the US DJIA, German DAX and Japanese NIKKEI indices in order to predict Warsaw index futures. This suggests that there is a lead-lag relationship between established economies and small markets. The majority of studies try to forecast the stock index directly.

Methodology

In this study, the aim is to determine the comparison of the relationship between variables.

The neural network acts as a "living mind" in application meaning it judges from its abstract observations. Therefore, the neural network spends some time training and then is used operationally.

A neural network model is created in order to predict changes in the tset 200 futures contract. In order to determine the number of neurons in the hidden layer, we follow the methodology described by Vanstone and Finnie (Vanstone & Finnie, 2009).

In neural network training, the more complete the observation, the more accurate what is abstracted will be. Of course, it is possible that some of the observations were misleading and not consistent with the general method of observations.

Therefore, what is provided to the neural network as educational examples should be refined and matched as much as possible. The neural network memorizes what it observes in the form of its internal parameters. In fact, the repetition of each observation changes the internal parameters of the network in order to maintain the relationships governing the observations. What is kept in the neural network's mind is not individual observations but the general method and perception of observations. This is why sometimes the neural network reacts in a re-encounter with educational examples, with negligible error, but it has the stability and practicality that in dealing with the general public of similar examples, it performs well and with negligible error. Observations or educational examples of neural networks can be accompanied by a preliminary judgment or without a preliminary judgment. In other words, neural network training can be with or without a teacher. In teaching by the teacher, what is taught to the network as an educational set is accompanied by the judgment that the teacher expects, therefore, the examples are taught with a predetermined judgment so that in the future the network, in case of encountering new examples according to the training procedure. In some cases, the samples are provided to the neural network without initial judgment, so that it can be categorized by successive observations and finally general abstraction from them.

The neural network has internal characteristics indicating its potential and capacity. As a living mind is very capable, progressive, and successful in some cases, and multiplies and fails in others in a degraded dimension, the neural network also functions differently depending on its internal structure in dealing with various issues. A neural network may be very good at solving one problem and very bad at another. Therefore, choosing the network structure in accordance with the issue is of great importance.

Just as circumstances affect the outcome of training, so does the learning of the neural network. Proper selection of initial values of network parameters will be very effective as a result of its training.

A neural network, after a period of use, needs retraining to deepen and expand its knowledge.

Training will be very effective if it includes new examples or examples that have not been well-trained before.

Neural networks are divided into different types in terms of topology, structure and learning methods, and each of them performs well in specific applications. The multilayer perceptron neural network is one of the most common application networks by inverse diffusion learning method. In theoretical discussions, it has been proven that the MLP network is able to model and simulate any nonlinear system if the appropriate internal structure is selected correctly.

The structure of the neural network consists of a number of perceptron with a specific function that are located in separate layers. Each perceptron, due to its weight coefficients ، aggregates the output of all perceptrons of the previous layer and sends it to the next layer through a functional function. The neural network has an input layer, an output layer, and at least one hidden layer. The number of perceptrons in each layer varies depending on the network structure and the problem.

Back Propagation computational learning algorithms are very diverse with different outcomes and functions. In the simplest algorithm, the network weight coefficients to minimize the network target function change, so that the error gradient changes each time. The weighting training step is changed as follows.

Wk +1 = wk – akgk

Wk is the vector of network weight coefficients, gk is the network output error gradient and ak is the network learning coefficient. This method, called the gradient reduction algorithm, can be implemented either incrementally or as learning packages. In incremental mode, the error gradient is calculated after each observation of one of the training samples and the weighting coefficients are improved. In the learning packages, this is done after observing a complete course of training samples and calculating the total gradient. In most cases, the incremental method performs better than the closed method.

In addition to the two methods, new computational methods with the two objectives of increasing computing speed and reducing computational volume have also been presented. These methods are known as fast learning methods. The rapid methods themselves are divided into two groups: methods based on abstract techniques or based on numerical optimization techniques. In methods based on abstract techniques, the coefficient of learning varies during the training stages, this coefficient become smaller and smaller during the training steps to achieve the minimum error gradient in less time. In methods based on multiple optimization techniques, using the Levenberg-Marquardt speed computational method or the new Quasi Newton method, the Conjugate Gradient, like calculations to reach the minimum error gradient, increases while reducing computational volume and computation.

In addition, some inverted diffusion training computational methods have been proposed to achieve maximum learning with special attention to network generalizability in the face of new examples, which are called improved network generalizability methods. In these methods, since the goal is to achieve maximum power of expansion and generalization of network learning in dealing with new examples, the neural network divides the training set into two subsets of training and training test. At the end of each training step, the network immediately measures the network performance of the training test suite and the training continues until appropriate performance of the test samples is achieved.

Results

Simulation environment, data and evaluation parameters

The data set used in this simulation includes investments made by companies listed on the stock exchange in 2020, with a record of 500 investments selected as a sample. This data consists of two parts: training data and test data to evaluate the accuracy of the model in forecasting. Of all the devices, 350 investment records will be used as training data and 150 investment data as test datasets to evaluate project performance. Each investment record is assigned a numerical value as the amount of investment risk. The design evaluation parameter is the mean square error (MSE) and the explanatory index (R2) of the proposed combined category. The system characteristics and parameters used in the implementation are shown in (Table 1).

Table 1. Simulation parameters

Simulation parameter	content
The total number of data records	500
Number of selected features	14
Educational data set size	350
Test data set size	150,120,،90,60,30
Type of neural network training method	MLP.ANN
Number of clusters in SOM	4

Analysis of the accuracy of the proposed design

In order to compare the proposed design with existing tools, it is necessary to determine the accuracy of these tools on their data set, so in this section, the MLP neural network is used first to predict investment risk. In this step, we present the 12 characteristics of corporate investment records as input neurons to the neural network. The output of the network will also be the amount of investment risk. Here, the neural network has the task to provide conditions in the model training stage by determining the weights, so that the predicted amount of investment risk has the least difference with their actual amount. The neural network, after training, is evaluated to test performance with test data. In the implemented model, the neural network consists of an input layer (consisting of 12 neurons), 3 latent layers and an output layer (consisting of one neuron), the schematic of which is shown in (Figure 1).

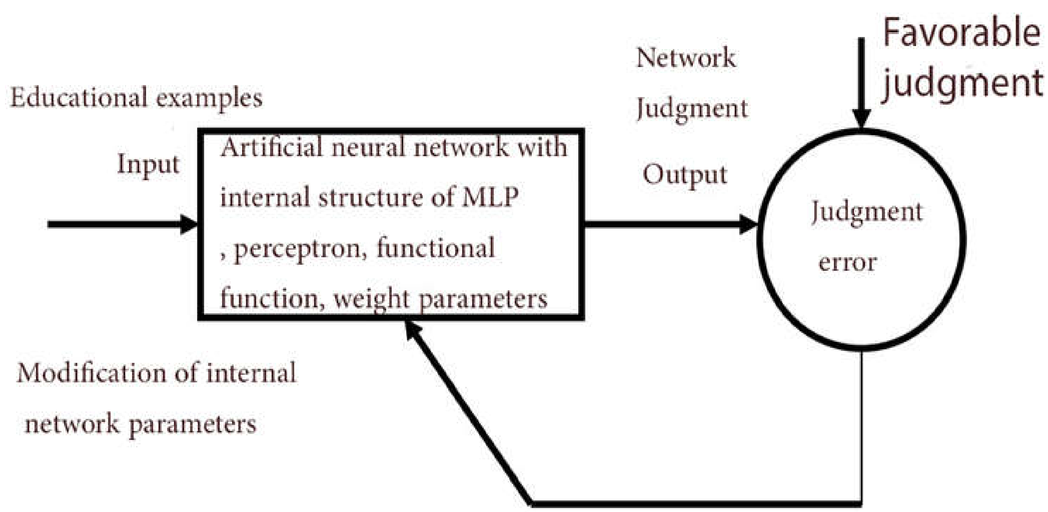

Figure 1. Scheme of neural network

After training the network, we will now examine the accuracy of the design and its related parameters, including the mean squared error, gradient, regression coefficients, and error histogram. The main function of neural networks is the amount of MSE error that we want to minimize. The lower the standard square error, the more accurately the model was able to predict. Figure (2) shows the iteration 7that as the best performance of the design, with a minimum detection error of less than 0.024.

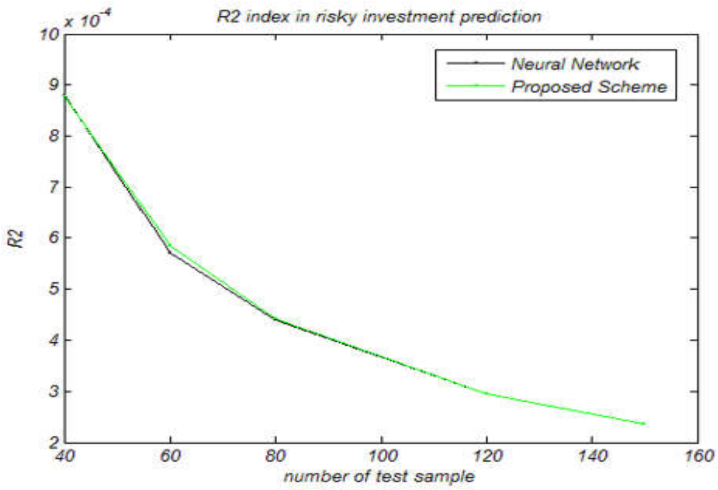

Figure 2. Comparison of the average square error of the proposed design in determining the amount of investment risk

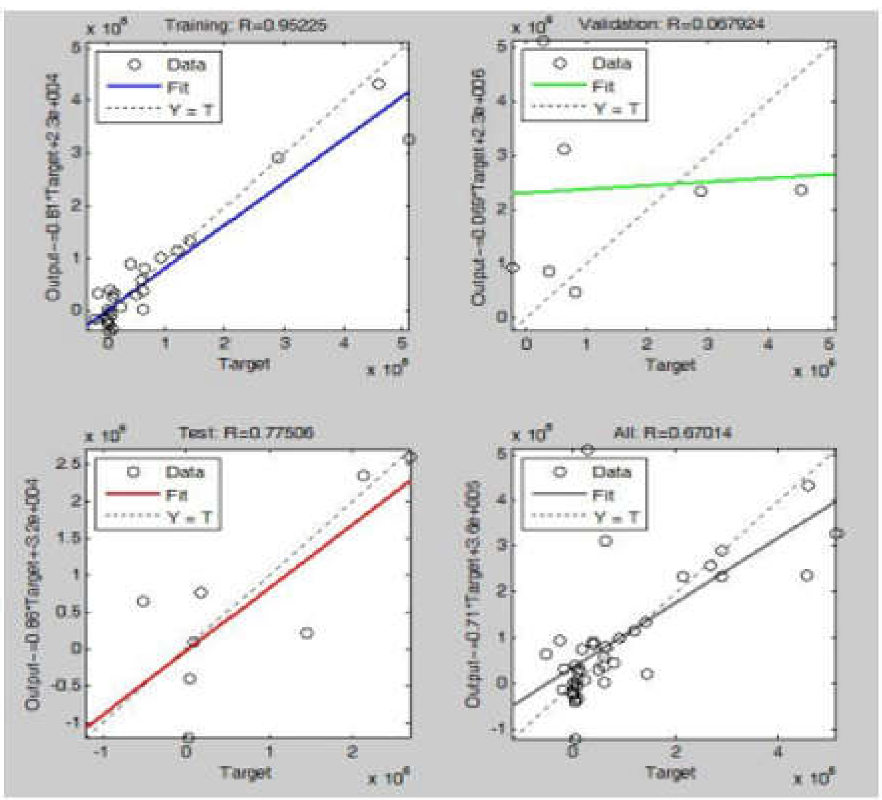

Figure 3. Comparison of the proposed plan explanation index in determining the amount of investment risk

The closer the value of R2 is to one, the better the result. (Figure 3) shows that the value of this coefficient R2 in the proposed design is higher than the baseline design using neural network (Table 2).

Table 2. Out-Of-Sample Result

Strategy Reduction	Sharpe Return	Variance	Annualized	Max DD
Never Hedge	0.34	0	3.97 %	-51.88 %
Always Hedge	0.29	0.98	0.85 %	-6.94 %
Premium	0.77	0.43	8.40 %	-.35.90 %
Volatility	0.87	0.44	9.61 %	-10.67 %
ANN 3 Nodes	1.38	0.60	13.45 %	-17.92 %

The ANN model was able to reduce the maximum draw down compared to the unhedged portfolio from -51.88% to -17.92% while improving the annualized rate of return (Figure 4).

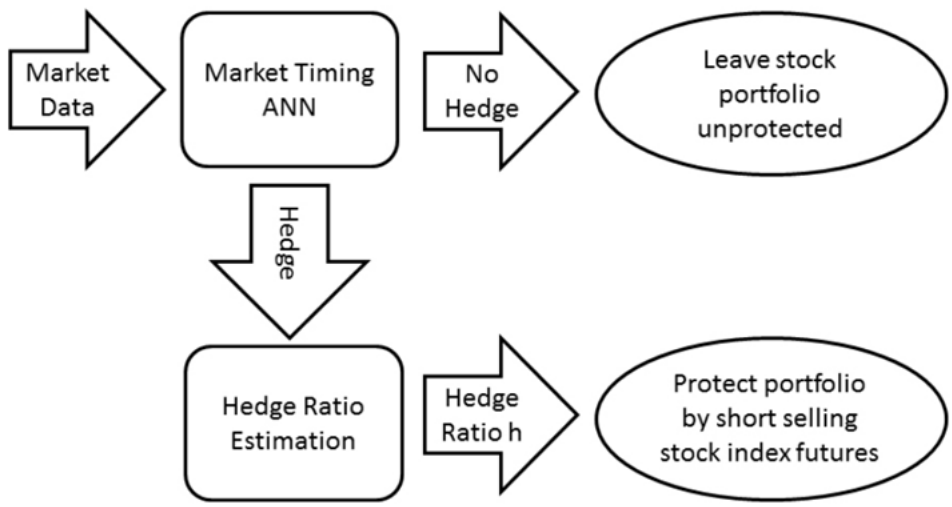

Figure 4. Flowchart: ANN based hedging

The (Figure 5) represents the prediction of the network based on input data, as well as their comparison with real results. The red plot represents the neural network forecast, whereas the blue one shows the real data.

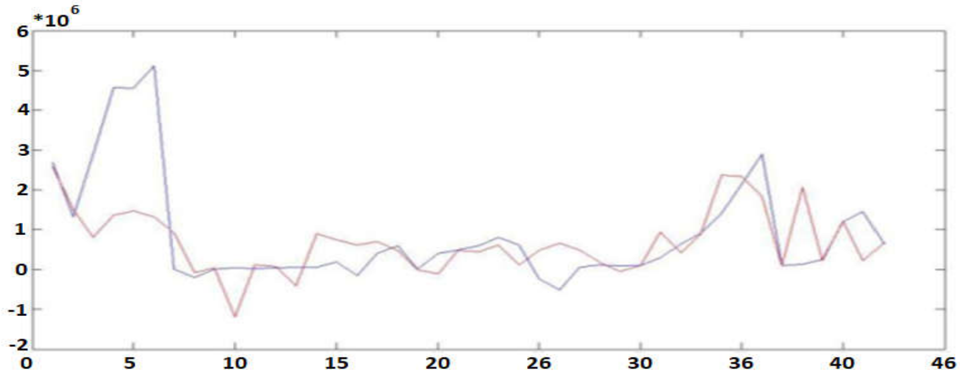

Figure 5. The prediction of the network based on input data in comparison with real data

Discussion

This paper developed a neural network based selective hedging strategy for the tehran stock market. The simulation results indicate that Artificial Neural Networks provide a flexible and effective decision support tool for risk managers in the share market. The neural network based model seems to be suitable to notify investors of unfavorable market conditions. A limitation of this study is the use of the stock index as a proxy for a diversified portfolio. It would be useful to see how the model performs with less correlated portfolios in a cross-hedging scenario. Also, we used a binary hedging approach in this study, which means that we were either fully invested or fully hedged. Another possibility would be to constantly hedged, but to adjust to hedge ratio according to the expected market conditions. We leave this as a future research direction.

Conclusion

Forecasts are instrumental to successful management and integral to economic planning. Market volatility, as a significant macroeconomic variable influencing various internal and external sectors of the economy, plays a decisive role in economic policy-making, much balance of payments and international competitiveness. Changes in market volatility affect various sectors of a country. It is thus essential for developing economic and financial policies to model and predict its future variations. Given the significance of forecasting market volatility, the present study focused on designing a neural network for predicting market volatility in the Iranian economy. The results of this study were indicative of the smaller error in the neural network forecast than the linear regression forecast. Therefore, it is suggested to the government to use neural network methods as far as possible in the process of formulating the country's economic policies. It is also proposed to increase investment through the creation of a stable and secure macroeconomic environment that will be effective in creating and maintaining such an environment: A) Replace financial discipline instead of financial instability in the state budget, B) Stability in the implementation of government policies, C) Eliminate fluctuations in government-controlled economic variables, Since the present study uses a neural network for prediction, it can be used in future studies of other neural network tools and by combining other linear and nonlinear patterns such a Hopfield neural network, radial neural network, probabilistic neural network and so on.

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