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Modeling Stock Market Exchange Prices Using Artificial Neural Network: A Study of Amman Stock Exchange

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Abstract

Stock market represents an essential part of the economy in the Middle East, it is significant for shareholders and investors to estimate the stock price and select the best trading opportunity accurately in advance. This paper utilizes artificial neural network in the modeling of stock market exchange prices. The network was trained using supervised learning. Simulation was conducted for seven case study companies from Amman Stock Exchange representing both the service and manufacturing sectors. The case study companies were selected from different categories varies according to the degree of stock market stability. The model was evaluated by stock market brokers through the use of a questionnaire that was distributed in Amman Stock Exchange, the majority of the participants found the results acceptable. The use of ANN provides fast convergence; high precision, and strong forecasting ability for real stock prices which it turn will bring high return and reduce potential loss to stock brokers.

Keywords: Artificial Neural Network; Supervised Learning; Simulation; Stock Market; Amman Stock Exchange; Prediction

1. Introduction

Stock market is the market involved with the issuance and trade of shares either through exchanges or over-the-counter which is also known as equity market, it provides companies with access to capital and investors with a segment of ownership in the company and the prospective of gains based on the company's future performance [1-2].

Stock market represents an essential part of the economy in the Middle East; however, stock markets in the Middle East are usually small and deeply regulated. Lack of reliable information, insider trading, accounting practices, and governments interference are among the problems that are encountered by investors. Some Middle East markets have limit foreigners to invest in the stock market except in some bourses, as those of Egypt, Lebanon, and Israel [3].

Apparently, it is significant for shareholders and investors to estimate the stock price and select the best trading opportunity accurately in advance. This will bring high return and reduce potential loss to investors. Traditional methods for stock price forecasting are based on the statistical methods, intuition, or on experts' judgment. Time series analysis, Autoregressive Moving Average (ARMA) models, Autoregressive Conditional Heteroskedasticity (ARCH) models, and Autoregressive Integrated Moving Average (ARIMA) models [4] are usually used for forecasting the stock market prices, however, their performance depends on the stability of the prices (i. e. if the prices time-series exhibits memory), as more political, economical and psychological impact factors get into the picture, the problem becomes non linear, and need a more heuristic or nonlinear methods like ANN, Fuzzy logic and Genetic Algorithms [5-6].

Jordanian stock market faces continuous fluctuating values due to political and economical factors; it also witnesses a noticeable sharp growth in the last few years. Thus, it is imperative for the Jordanian stock brokers to employ new analysis tools. The motivation of this research was to introduce the concept of ANN into the Jordanian business sector and utilize it in forecasting the Jordanian stock market prices.

A lot of research had been conducted for using ANN in stock market prices forecasting, Hassoun [7] defines ANN as "parallel computational models comprised of densely interconnected adaptive processing units, they are viable computational models for a wide range of problems including pattern classification

, speech synthesis and recognition, adaptive interfaces, function approximation, image compression, associative memory, clustering, forecasting and prediction, combinatorial optimization, nonlinear system modeling, and control". ANN can outperform other methods of forecasting due to its remarkable ability to derive meaning from complicated or imprecise data, it had been used successfully to extract complex patterns and trends [8]. Literature shows that ANN can be used in prediction, classification, data association, data conceptualization, and data filtering [9].

Steiner and Wittkemper [10] had developed a portfolio optimization model embedded in the nonlinear dynamic capital market model based on ANN. An economic approach to the analysis of highly integrated financial markets and econometric methods had been developed by

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Poddig and Rehkugler [11]. Donaldson and Kamstra [12] proposed a methodology for forecasting future stock prices and return volatilities for fundamentally valuing assets such as stocks and stock options.

2. Amman Stock Exchange

Amman Stock Exchange (ASE) is a private non-profit institution with administrative and financial autonomy that was established in March 1999 and authorized to function as an exchange for the trading of securities by a board of directors. It includes in its membership 70 Jordanian brokerage firms. The ASE is an active member of the Union of Arab Stock Exchanges, Federation of Euro-Asian Stock Exchanges, World Federation of Exchanges, and an affiliate member of the International Organization for Securities Commissions [13].

3. ANN Mathematical Model

The neuron can be modeled mathematically as shown in Fig. 1, where:

The cell inputs are $x_1(t),...,x(t)_n$

The cell output is $y(t)$

The dendrite or input weights are $v_1,....,v_n$

The firing threshold or bias weight is v_0

The cell function or activation function is f

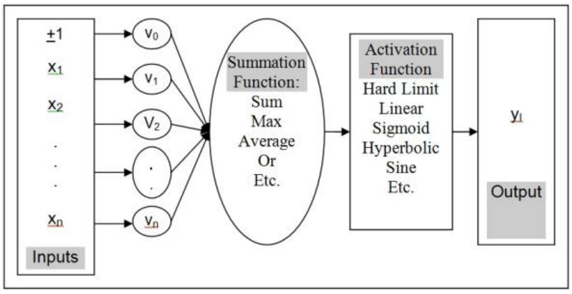

Figure 1: Neuron mathematical model.

The output can be expressed as [14]:

$$y(t) = f(\sum_{j=1}^{n} v_j x_j(t) + v_0). \tag{1}$$

Eq. (1) can be streamlined by defining the augmented column vector of the cell inputs $\bar{x}(t) \in \Re^{n+1}$ and the input weights $\bar{v}(t) \in \Re^{n+1}$ as [14]:

$$\bar{x}(t) = [1 \quad x_1 \quad x_2 \quad ... \quad x_n]^T, \quad \bar{v}(t) = [v_0 \quad v_1 \quad v_2 \quad ... \quad v_n]^T \tag{2}$$

Then Eq. (1) can be written in matrix notation as [14]:

$$y = f(v^T x). \tag{2}$$

One layer ANN is commonly used which has L cells, all fed by the same input signals $x_j(t)$, and producing one output per neuron $y_l(t)$. This network can be modeled as [14]:

$$y_l = f(\sum_{j=1}^{n} v_{lj} x_j + v_{l0}); l = 1,2,..., L. \tag{4}$$

However, most of the ANN consists of more than one layer, where the second layer input is the first layer output and so on. The cases presented in this paper needed two and three layers, the output for the network consists of three layers can be written based on Eq. (4) as follows:

$$y_l = f_3(\sum_{l=1}^{n3} v_{kl} f_2(\sum_{o=1}^{n2} v_{io} f_1(\sum_{p=1}^{n1} v_{jp} x_p + v_{j0}) + v_{i0}) + v_{k0}) \tag{5}$$

Where:

f_1, f_2, f_3: are the activation functions for layer 1, layer 2, and layer 3 respectively.

$n1, n2, n3$: are the number of input signals for layer 1, layer 2, and layer 3 respectively.

L : is the number of outputs for layer.

$v_{n2n1}, v_{n3n2}, v_{Ln3}$: are the input weights for layer 1, layer 2, and layer 3 respectively.

v_{n20}, v_{n30}, v_{L0}: are the bias weights for layer 1, layer 2, and layer 3 respectively.

$l = 1,2,..., L.$

The network used for stock market prices forecasting model build from two or three layers, 13 inputs and only one output; the variables of Eq. (5) were set as follows:

y: The price in JD's for the 14th working day of the month.

$x_1 - x_{13}$: The stock market prices for the first 13th days of the month.

The other variables were set according to the case study.

4. Training an ANN

Once a network has been structured for a particular application, that network is ready to be trained. To start this process the initial weights are chosen randomly. Then, the training, or learning, begins.

There are three approaches to training or learning: Supervised learning, unsupervised learning, and reinforcement learning. The vast bulk of networks utilize supervised learning. Unsupervised and reinforcement learning are used to perform some initial characterization on inputs. However, in the full blown sense of being truly self learning, it is still just a shining promise that is not fully understood and in need for further research.

4.1. Supervised Learning:

Supervised learning, or learning with a teacher, or associative learning is where the network is supplied with a training data set that includes a set of inputs and its corresponding output or target, ANN adjusts their weights using one observation at a time. Learning is achieved by minimizing a criterion function which is the average square error between the network outputs and the target.

4.2. Reinforcement Learning:

The learning process in reinforcement learning is designed to maximize the expected value of a criterion function by using trial and error. That is if the action improves the state of affairs then the tendency to produce this action is reinforced while if it deteriorate the state of affairs, then the tendency to produce it is weakened [7]. The training data does not includes a target; instead, it includes a performance judge or a utility function that reports how good the current network output [15].

4.3. Unsupervised learning:

In this case the network is adapted without giving it any kind of directive feed back, in other words there are no target information in the training data or a performance judge, rather the learning objective is to find out the features inherent in the training data [16-18].

Stock market forecasting is done by approximating the function or the relationship between inputs and output, thus supervised learning is more appropriate for our application compared to the other two, furthermore, supervised learning is more mature and accurate than the other two learning approaches.

5. Simulation Results

To test the efficiency and effectiveness of the model a Software program was developed using MATLAB for this purpose. The weights and biases of the network were automatically initialized to small random numbers by the software. Seven Jordanian companies from different sectors were used as case studies. For each company, a full year was used for training the network; each month was used as a different pattern. The data starting from February and ending with January were used for the training; the validation was done by using the next year prices starting from February and ending with January.

Different training functions, activation functions, number of layer, and number of neurons were tried till the error converged to the set value which is 10-6. The performance function used was the mean square error (MSE). MSE is the average squared error between the network outputs and the target.

5.1. Case 1: Arab Engineering Industry

The training was done using one step secant backpropagation, a two layers network was used with Hyperbolic tangent sigmoid activation function for the first layer and hard limit activation function for the second layers, the first layers consists with 14 neurons and 1 neuron for the second layer. The stock market prices for this company during the year in Jordanian Dinars (JD) are shown in Fig. 2, after entering these data into the simulation software, the error resulting during the training is shown in Fig. 3. As shown in the figure the network was able to train the data with 9.7245×10^{-7} in only 11 epochs. To put things into perspective, the output of the network is plotted against the target as shown in Fig. 4, after the network passed the validation stage, the network was used to forecast the prices for the next year starting from February till January, Fig. 5 reveals the forecasted prices against the actual prices, as shown in the figure the forecasted price is very close to the actual one.

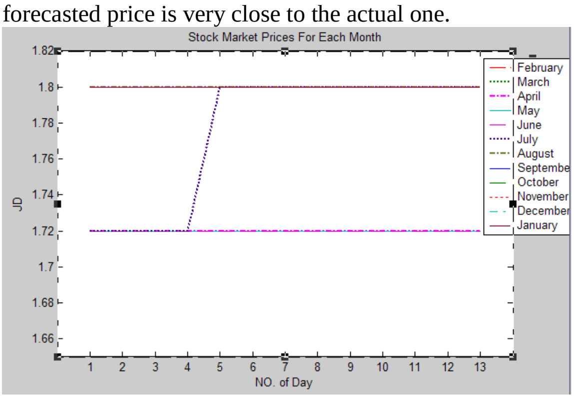

Figure 2: Stock market prices for Arab Engineering Industry Company.

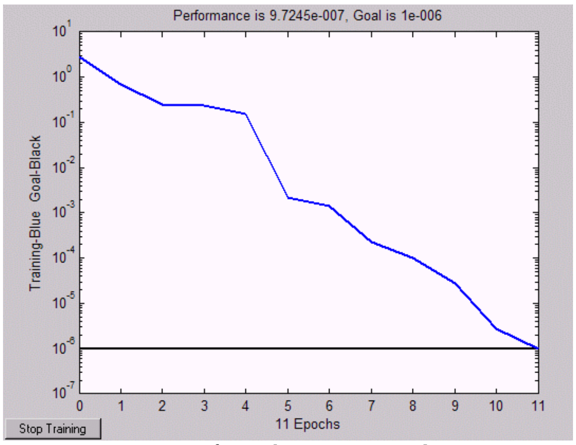

Figure 3: Training error for Arab Engineering Industry Company.

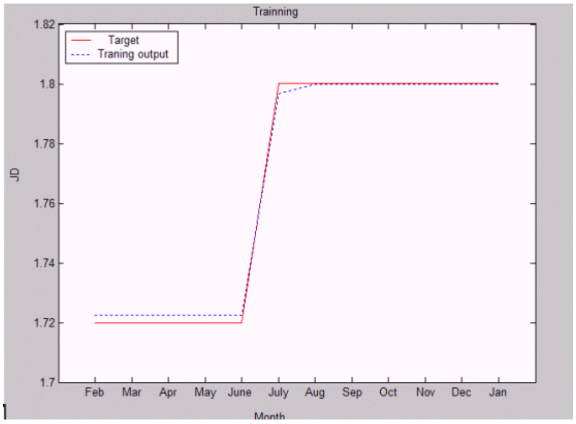

Figure 4: Training output against the target for Arab Engineering Industry Company.

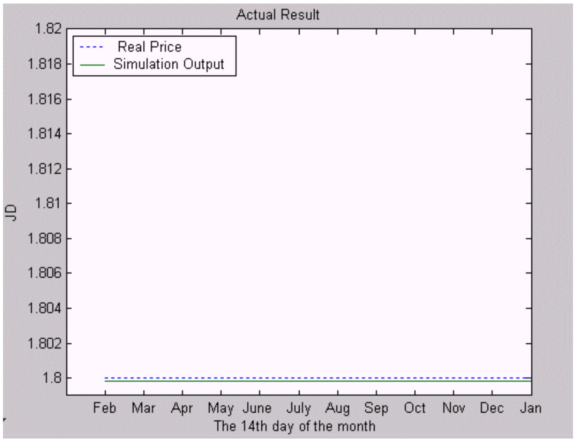

Figure 5: Forecasted prices against the actual prices for the Arab Engineering Industry Company.

5.2. Case 2: Nutriadar: Jordanian Drug Company:

The same training function was used, however, this time three layers contain (14,10,1) neurons respectively was needed to converge to a small training error, the first and second layers used positive linear transfer activation function, while the third layer used a hard limit transfer activation function. The stock market prices for this company are shown in Fig. 6, as revealed from the figure this company exhibit a noticeable variation of the prices among days in each month, which make the forecasting job more difficult, after entering these data into the simulation software, the error resulting during training is shown in Fig. 7. As shown in the figure the network was able to train the data in 1000 epochs that took only 30 seconds. The output of the network is plotted against the target as shown in Fig. 8, the figure prove that the network output matches the actual prices, after the network passed the validation stage, the network was used to forecast the prices for the next year, Fig. 9 reveals the forecasted prices against the actual prices. This time the forecasted price was slightly different than the actual prices, however, the gap did not exceed .08 JD (1 JD=$1.40).

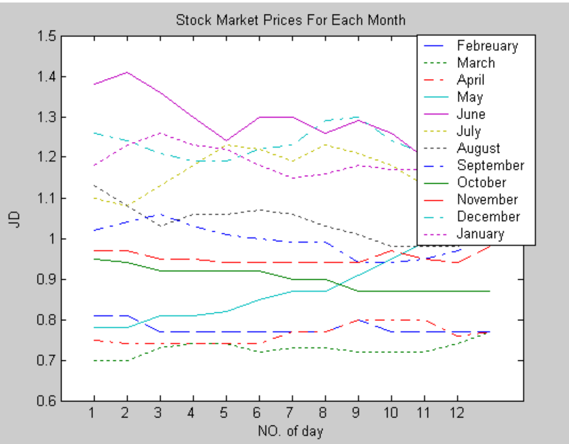

Figure 6: Stock market prices for the Nutriadar Company.

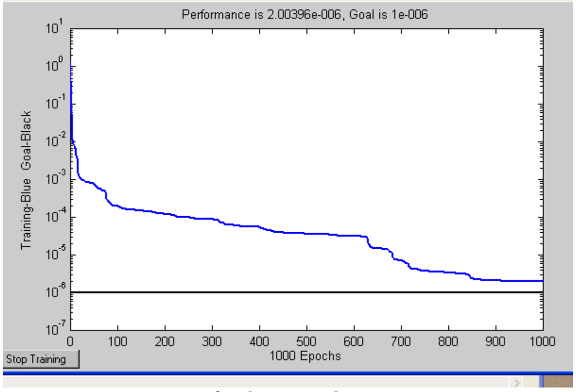

Figure 7: Training error for the Nutriadar Company.

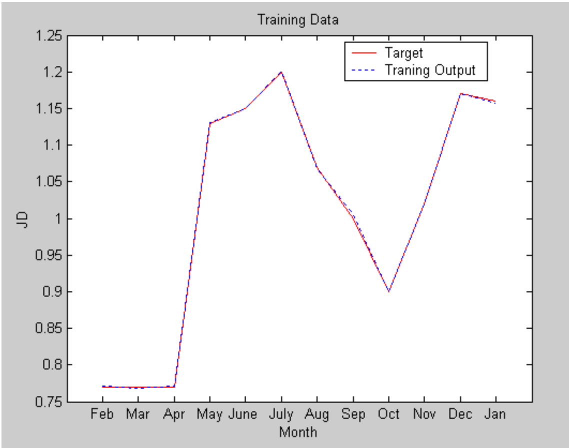

Figure 8: Training output against the target for the Nutriadar Company.

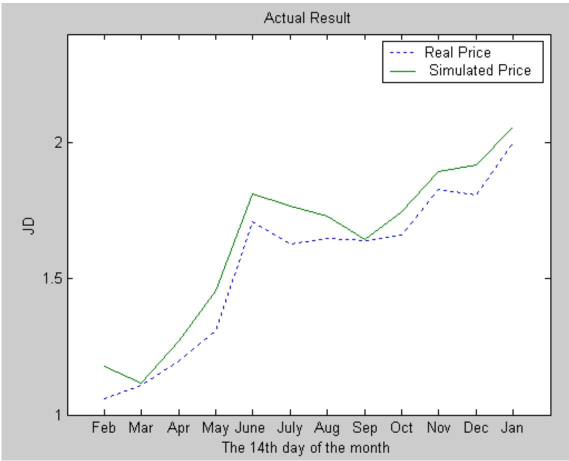

Figure 9: Forecasted prices against the actual prices for the Nutriadar Company.

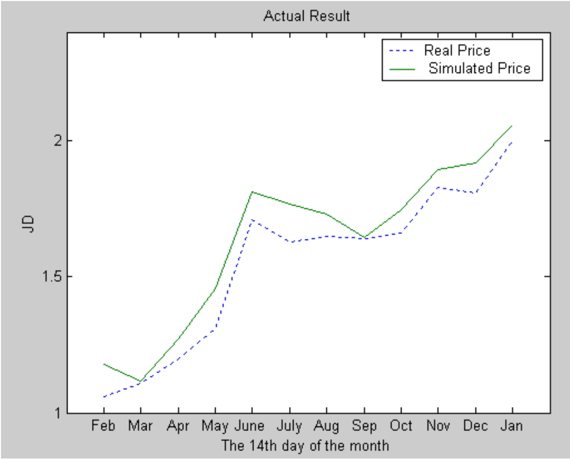

Figure 9: Forecasted prices against the actual prices for the Nutriadar Company.

5.3. Case 3: Jerusalem Insurance Company:

The training was done using one step secant backpropagation, two layers contain (14,1) neurons respectively was needed to converge to a small training error, the first layer used positive linear transfer activation function, while the third layer used a hard limit transfer activation function. The stock market prices for this company are shown in Fig. 10, as revealed from figure, the stock prices vary during the months, its also varies from month to another, after entering these data into the simulation software, the error resulting during the training is shown in Fig. 11. As shown in the figure the network took 174 epochs and 20 second to reach a performance level of 10-8. The output of the network is plotted against the target as shown in Fig. 12, the network output is very close to the actual prices, after the network passed the validation stage, the network was used to forecast the prices for the next year, Fig. 13 reveals the forecasted prices against the actual prices. This time the forecasted prices are close to the actual prices.

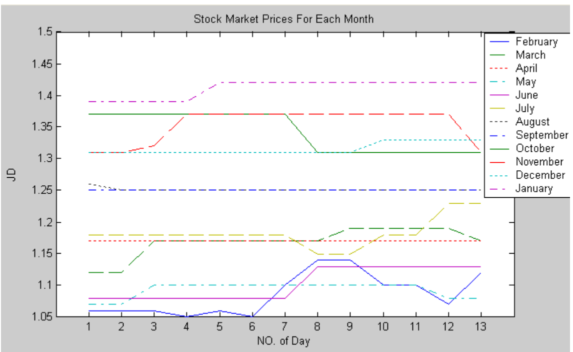

Figure 10: Stock market prices for Jerusalem Insurance Company.

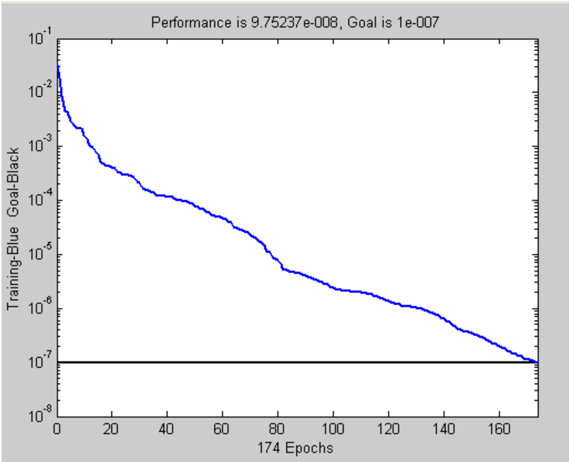

Figure 11: Training error for Jerusalem Insurance Company.

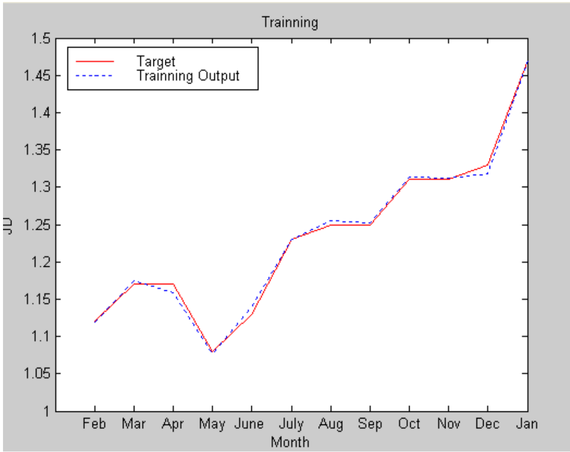

Figure 12: Training output against the target for Jerusalem Insurance Company.

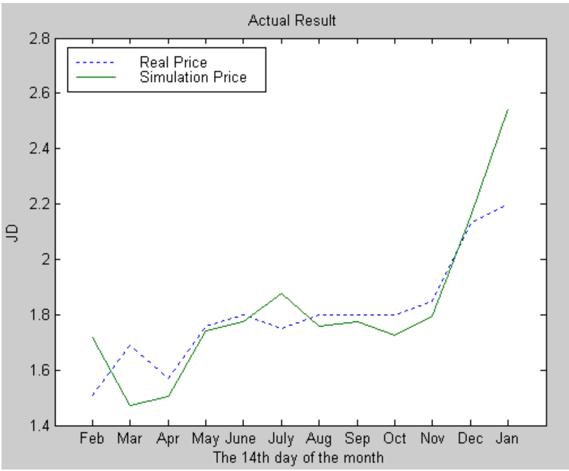

Figure 13: Forecasted prices against the actual prices for Jerusalem Insurance Company.

5.4. Case 4: United Glass Industries:

The training was done using one step secant backpropagation, two layers contain (14, 1) neurons respectively was needed to converge to a small training error, a two layers network was used with Hyperbolic tangent sigmoid activation function for the first layer and hard limit activation function for the second layers. The stock market prices for this company during the year is shown in Fig. 14, which shows that the stock prices are very stable, its varies from month to another but in very small amount (maximum change was 0.050 JD), entering these data into the simulation software resulted in an error of 10-7 in only 10 epochs as shown in Fig. 15. The output of the network is plotted against the target as shown in Fig. 16, the network output matches exactly the actual prices, after the network passed the validation stage, the network was used to forecast the prices for the next year, Fig. 17 reveals the forecasted prices against the actual prices. The forecasted prices are very close to the actual prices except for the last month (January) where the actual price has a small drop.

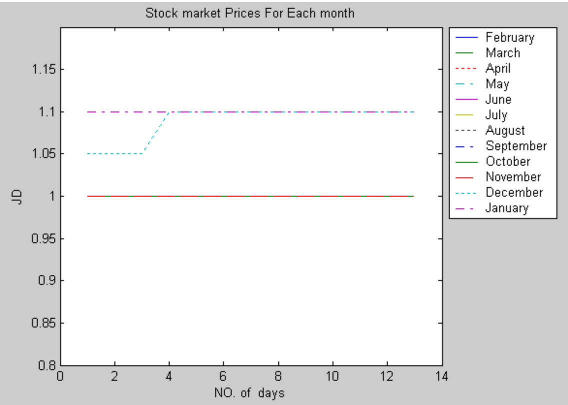

Figure 14: Stock market prices for United Glass Industries Company.

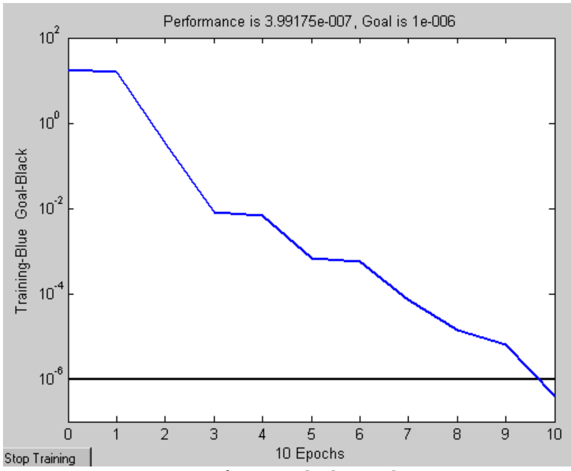

Figure 15: Training error for United Glass Industries Company.

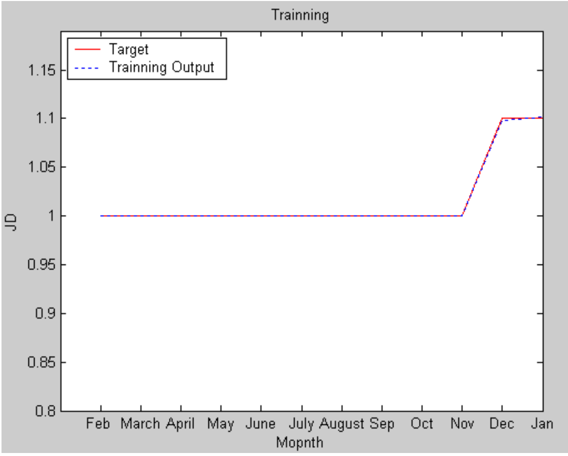

Figure 16: Training output against the target for United Glass Industries Company.

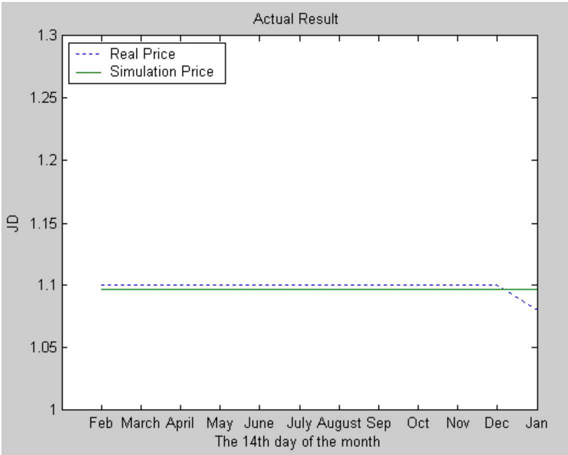

Figure 17: Forecasted prices against the actual prices for United Glass Industries Company.

The rest of the seven case studies were very close to the ones presented before where the network was able to train very quickly the data and produce a very good forecast, except for one case that will be presented next.

5.5. Case 7: Jordan Petroleum Refinery:

A three layers ANN was used in this case of (14,7,1) neurons on the three layers, the training was done using one step secant backpropagation, the first and second layers used positive linear activation function, while the third layer used hard limit activation function. The stock market prices for this company during the year are very volatile and vary substantially from month to month or even during the same month as shown in Fig. 18. The performance level could reach 10-3 within 90 second through 1000 epochs.

After 1000 epochs, the training mean square error was 10-3 which is far from the specified error of 10-6 as shown in Fig. 19. The output of the network is plotted against the target as shown in Fig. 20, this time the network output slightly differs from the target, although it exhibits the same pattern, finally, using the network to forecast the prices of the next year resulted in very good forecast for the first four months (February-June) as shown in Fig. 21, after June the actual prices jumps from 15 JD's to 4 JD's, the forecasted prices jumps too at the same time but with different amplitude (from 14 to 1 JD) then it follow the same pattern of the actual price but with a gap that is less than 2 JD's. Further investigation into this case reveals that the company broke the shares in order to increase the supplied quantity of them which caused the prices to drop to 3 JD's.

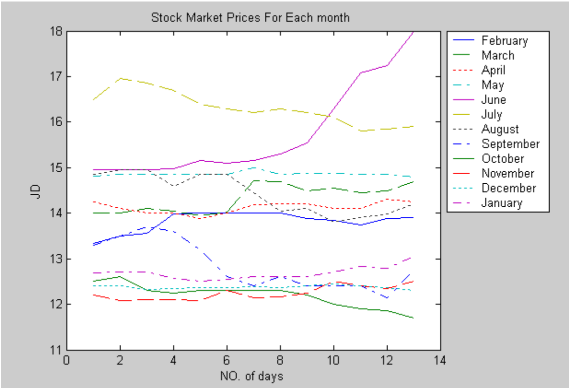

Figure 18: Stock market prices for Jordan Petroleum Refinery Company.

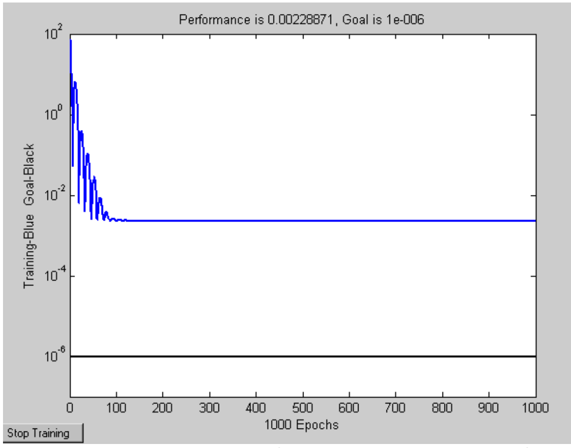

Figure 19: Training error for Jordan Petroleum Refinery Company.

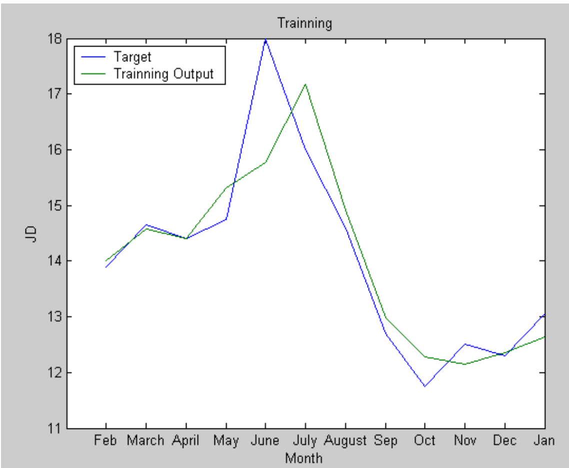

Figure 20: Training output against the target for Jordan Petroleum Refinery Company.

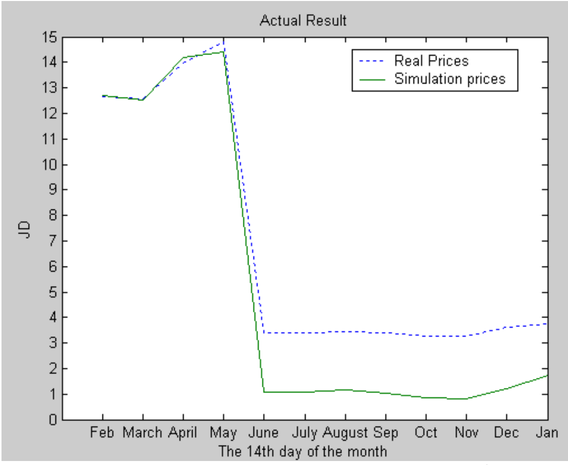

Figure 21: Forecasted prices against the actual prices for Jordan Petroleum Refinery Company.

6. Discussion

The results obtained from the software were very accurate for six out of seven cases, which prove that this is a valid technique for stock market price forecasting.

In the last case the results shows that although the network did not give a good forecast due to the significant drop in the actual Stock market prices but it followed the same pattern of the actual price, which means that even when the actual stock prices change dramatically for any assignable cause, the network was able to catch up and the forecast change at the same month and even with the same pattern as the actual data. This proves that this method can give a very good indication about market trends.

7. Model Evaluation by Stock market brokers

The model was evaluated by stock market brokers through the use of a questionnaire that was distributed in Amman Stock Market, the questionnaire was designed so that it can be filled in no more than two minutes, it first presents the forecasting results obtained from the network and then asked the participant to answer seven multiple choice questions, focus on the techniques currently used by the broker, and whether he want to use the network in the future, only seven questionnaires were returned.

In response to a question asking "Would you depend on the ANN technique for forecasting Amman Stock Market prices?", five out of the seven participants who answered the questionnaires stated that they would depend on ANN technique, while two of them stated that they would partially depend on ANN technique.

In response to another question "Do you believe that this technique will be applicable to all categories of companies (volatile, stable)?", six participants decided that the ANN technique will be applicable to all companies categories, while one participants believed that it is not applicable to all categories of companies.

8. Conclusions

This paper utilizes artificial neural network in the modeling of stock market exchange prices. The model was developed using a feed forward neural network with two to three layers; the network was trained using one step secant backpropagation, the activation functions used were hyperbolic tangent sigmoid, positive linear and hard limit transfer function. Simulation software developed by MATLAB was used to evaluate the network performance for seven Jordanian companies selected from service and manufacturing sectors. The companies have different degree of stock prices stability. The network was trained on a whole year data; the network was able to produce the output within a MSE of $0.0023*10^{-8}$ from the target. The network performance was evaluated using the stock market prices of the following year, the network output was very close to the actual data, except for one case, for which the company broke it's shares in the middle of the year, however, even in that case the network output drops dramatically to values close but not exactly the same as the ones of the actual data. The results of the network were further evaluated by stock brokers from Amman stock market; the majority of the responses stated that they may depend on ANN technique and that they believe that the technique is applicable to all categories of companies.

The model is significant in view of the fact that stock market represents an essential part of the economy in the Middle East. Using the developed ANN model can help shareholders and investors to estimate the stock price and select the trading chance that will maximizes their profits more accurately in advance compared to the currently used methods.

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