Finance Stock Price Prediction by Artificial Neural Networks: A Study of Jordanian's Stock Prices (J.S.P)

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Abstract:
This paper presents a study of artificial neural networks for use in stock price prediction. The data from an emerging market Jordanian's Stock Prices (J.S.P), are applied as a case study. Software was developed by using MATLAB to simulate the performance and efficiency of the algorithm. Simulation was conducted for seven Jordanian companies from service and manufacturing sectors. The companies were sampled from different categories which vary according to the degree of stock stability.
A multilayer perception (M.L.P) neural network model is used to determine and explore the relationship between some variables as independent factors and the level of stock price index as a dependent element in the stock market under study over time. The results show that the neural network models can get better outcomes compared with parametric models like regression and others traditional statistical techniques. Our test also shows that useful predictions can be made without the use of extensive market data or knowledge, and in the data mining process, neural networks can explore some orders which hide in the market structure.
Keywords: *stock price index, multilayer perception, back propagation, parametric models, Pridiction***.**

1. Introduction:
Neural networks are powerful forecasting tools that draw on the most recent developments in artificial intelligence research. They are non-linear models that can be trained to map past and future values of time series data and thereby extract hidden structures and relationships that govern the data. Neural networks are applied in many fields such as computer science, engineering, medical and criminal diagnostics, biological investigation, and economic research. They can be used for analyzing relations among economic and financial phenomena, forecasting, data filtration, generating time-series, and optimization *(Garcia and Gencay, 2000; and Hamm and Brorsen, 2000; Hawley, Johnson, and Raina, 1990; Shtub and Versano, 1999.)*
Traditional methods for stock price forecasting are based on the statistical methods, intuition, or on experts' judgment. Time series analysis, Arema / Arma model are usually used for forecasting the stock prices. However, their performance depends on the stability of the prices, 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, or Genetic Algorithms *(Greene, 2003; Investor Words, 2005).*
(Refenes et al, 1994) indicate that conventional statistical techniques for prediction have reached their limitation in applications with nonlinearities in the data set. Artificial neural networks (A.N.N), a computing system containing many simple nonlinear computing units as neurons interconnected by links, is a well-tested method for financial analysis on the stock market. Neural networks have been shown to be able to decode nonlinear financial time series data, which adequately describe the characteristics of the stock markets (Lapedes *et al, 1987*). Examples using neural networks in equity market applications include recognition of patterns in trading charts, rating of corporate bonds, estimation of the market price of options and futures, and the indication of trading signals of buying and selling, etc. Feed-forward back propagation neural networks are the most commonly used networks and meant for the widest variety of the efficiency of the markets, returns follow a random walk. If these hypotheses come true, it will make all prediction methods worthless.
The research done here would be considered a violation of the above two hypothesis for short- term trading advantages in, Jordanian's Stock Price, which is considered by some Jordan researchers such as *(Hammad et al, 2006)* to be inefficient than the mature markets. In fact, even the stock price movements of U.S *(Fama, 1965),* and Japan *(Ang, 1978),* have been shown to conform only the weak from of the efficient market hypothesis. The second school's view is the so-called fundamental analysis. It looks in depth at the financial conditions and operating results of applications in these field of science.
This paper shows that without the use of extensive market data useful and proper prediction can be made. It begins with general discussion of the possibilities of common stock price forecasting in an emerging stock market, like Jordanian's Stock Prices (J.S.P). It is followed by a section neural network, subsequently, a section is devoted to a case study on the stock price Index in Jordanian's Stock Prices (J.S.P), pointing to the promises and problems of such an experiments. At last, a conclusion which also discusses areas for future research is included at the end of the paper

2- Analogy between artificial neuron and biological neuron:

The biological neuron is the basic building block of the nervous system. The human nervous system consists of billions of neurons of various types and lengths relevant to their location in the body *(rumelhard, 1986).* The Fig 1 shows a schematic of an oversimplified biological neuron with three major functional units: dendrites, cell body and axon. The cell body has a nucleus that contain information about heredity traits; the dendrites receive signals from other neurons and pass them over to the cell body; and the axon, which branches into collaterals, receives signals from the cell body and carries them away through the synapse to the dendrites of neighboring neurons.

Because a neuron has a large number of dendrites/synapses, it can receive and transmit many signals at the same time; these signals may either excite or inhibit the firing of the neuron *(basher, 2000).* This basic system of signal transfer was the fundamental step of early neuro-computing development and the operation of the building unit of Artificial Neural Networks.

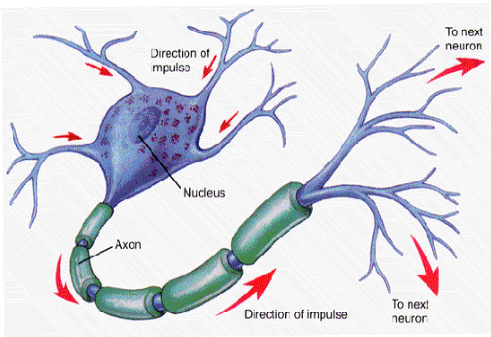

Fig 1. Schematic of biological neuron
(basher, 2000).

Source: Brown & Benchmark Introductory Psychology Electronic Image Bank, 1995. Times Mirror Higher Education Group, Inc.

The basic analogy between artificial neuron and biological neuron is that the connections between nodes correspond to the axons and dendrites, the connection weights represent the synapses and the threshold approximates the activity in the soma.

3- Literature Review:

There is a growing body of literature based on the comparison of neural network computing to traditional statistical methods of analysis. ***(Hertz et al, 1991)*** offer a comprehensive view of neural networks and issues of their comparison to statistics. *(Hinton 1992)* investigates the statistical aspects of neural networks. *(Weiss et al, 1991)* offer an account of the classification methods of many different neural and statistical models.

The main focus for the artificial neural network technology, in application to the financial and economic fields, has so far been data involving variables in non-linear relation. Many economists advocate the application of neural networks to different fields in economics (*Kuan and White, 1994; Bierens, 1994*; *Lewbel, 1994*). According to *(Granger 1991)* non-linear relationships in financial and economic data are more likely to occur than linear relationships. New tests based on neural network systems therefore have increased in popularity among economists. Several authors have examined the application of neural networks to financial markets, where the non-linear properties of financial data provide many difficulties for traditional methods of analysis *(Omerod, et al, 1991; Grudnitski et al, 1993; Kaastra et al, 1995; Witkowska, 1995).*

(Yoon et al, 1990) compare neural networks to discriminate analysis with respect to prediction of stock price performance and find that the neural network is superior to discriminate analysis in its predictions. and find that a neural network models perform better than discriminate analysis in predicting future assignments of risk ratings to bonds.

(Trippi et al, 1992) apply a neural network system to model the trading of Standard and Poor 500 index futures. They find that the neural network system outperforms passive investment in the index. Based

on the empirical results, they favor the implementation of neural network systems into the mainstream of financial decision making.

4- The Stock Market Prediction:

Prediction in stock market has been a hot research topic for many years. Generally , there are four schools of thought in terms of the ability to profit from the stock market. The first school believes that no investor can achieve above average trading advantages based on the historical and present information. The major theories include the ***Random Walk Hypothesis*** and the *Efficient Market Hypothesis (Peters 1991).*

The Random Walk Hypothesis states that prices on the stock occurs without any influence by past prices. The Efficient Market Hypothesis states that price on the stock occur without any influence by past prices. The Efficient Market Hypothesis states that the market fully reflects all of the freely available information and prices are adjusted fully and immediately once new information becomes available. If this is true then there should not be any benefit for prediction, because the market will react and compensate for any action made from these available information. In the actual market, some people do react to information immediately after they have received the information while other people wait for the confirmation of information. The waiting people do not react until a trend is clearly established. Because of a specific company and the underlying behavior of its common stock. The value of a stock is established by analyzing the fundamental information associated with the company such as accounting, competition, and management.

The third school's view is technical analysis, which assumes the stock market moves in trends and these trends can be captured and used for forecasting. It attempts to use past stock price and volume information to predict future price movements. The technical analyst believes that there are recurring patterns in the market behavior that are predictable. They use such tools as charting patterns, technical indicators, and specialized techniques like Elliot Waves and Fibonacci series *(Plummer 1991).* Indicators are derived from price and trading volume time series. Unfortunately, most of the techniques used by technical analysts have not been shown to be statistically valid and many lack a rational explanation for their use.

The fourth school's view is dynamic systems and chaotic behavior of stock price. From this standpoint, stock price movements have a very complex and nonlinear relations to some variables which advanced mathematical modeling of its can be done *(Abdoh, 1996).* One of the challenges of modern capital market analysis is to develop theories that are capable of explaining the movements in asset prices and returns.

The study of stock market has led financial economists to apply statistical techniques from chaos theory for analyzing stock market data. Based on these new techniques, recent empirical studies document nonlinearities in stock market data. Our main result is that stock price structure is many complex and neural network model is appropriate for capturing all the nonlinear dynamic relationships in Jordanian's stock Exchange.

5- Neural Network and its Usage in Stock Price Prediction:

5.1- Artificial Neural Network

A neural network is a collection of interconnected simple processing elements (P.E). Every connection of neural network has a weight attached to it. Artificial neural network is a system loosely modeled on the human brain. The field goes by many name, such as connectionism, paralleled distributed processing, neurocomputing, natural intelligent systems, machine learning algorithms, and artificial neural networks. It is an attempt to simulate within specialized hardware or sophisticated software, the multiple layers of simple processing elements called neurons. Each neuron is linked to certain of its neighbors with varying coefficients of connectivity that represent the strengths of these connections. Learning is accomplished by adjusting these strengths so cause the overall network to output appropriate results. The back propagation algorithm has emerged as one of the most widely used learning procedures for multilayer networks. The basic unit of neural networks, the artificial neurons, simulates the four basic functions of natural neurons. All natural neurons have four basic components, which are dendrites, soma, axon and synapses. Basically, a biological neuron receives inputs from other sources, combines them in some way, performs a generally nonlinear operation on the result, and then output the final result. Artificial neurons are much simpler than the biological neuron; the figure2. shows the basics of artificial neurons.

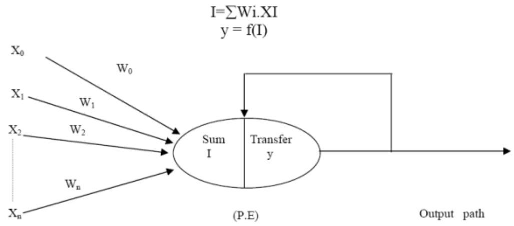

Figure2. Simple artificial neural network

The typical back propagation neural networks usually has an input layer, some hidden layers and an output layer.Figure3 shows a one- hidden layer neural network. The units in the network are connected in a feed forward manner, from the input layer to the output layer. The weights of connections have been given initial values. The error between the predicted output value and the actual value is back propagated through the network for the updating of the weights. This method is proven highly successful in training of multilayered neural networks. The network is not just given reinforcement for how it is doing on a task. Information about errors is also filtered back through the system and is used to adjust the connections between the layers, thus improving performance. This a supervised learning procedure that attempts to minimize the error between the desired and the predicted outputs. *(Haykin 1994).*

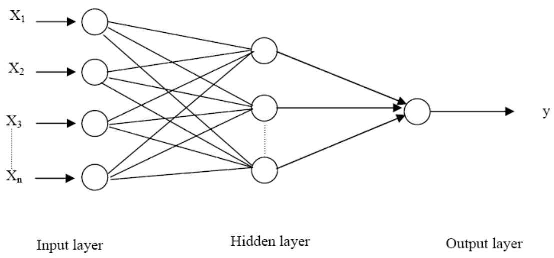

Figure3. A neural network with one hidden layer

The output value for a unit; is given by the following functions:

$$O_j = G\left(\sum_{i=1}^{m} w_{ij} x_j - \theta_j\right)$$

where xi the output value of ith unit in a previous layer, wij, is the weight on the connection from the unit, θj is the threshold, and m is the number of units in the previous layer. The function G( ) is a sigmoid hyperbolic tangent function:

$$G(Z) = \tanh(Z) = \frac{1 - e^{-Z}}{1 + e^{-Z}}$$

G( ) is a Commonly used activation function for time series prediction in back propagation *(Chapman 1994).*

5.2- Design of Neural Network

The developer must go through a period of trial and error in the design before coming up with a satisfactory design. The design issues in neural networks are complex and are the major concern of system developers. Designing a neural network consists of:

- Arranging neurons in various layers.
- Deciding the type of connections among neurons for different layers, as well as among the neurons within a layer.
- Deciding the way a neuron receives inputs and produces output.

- Determing the strength of connection within the network by allowing the network learn the appropriate values of connection weights by using a training data set. The process of designing a neural network is an iterative process.

5.3- Financial time series forecasting with neural networks

Based on the technical analysis, past information will affect the future. So, there should be some relationship between the stock prices of today and future. The relationship can be obtained through a group of mapping of constant time interval. Assume that ui represents today's price, γI represents the price after ten days. If the prediction of a stock price after ten days could be obtained using today's stock price, then there should be a functional mapping ui to γI, where $vi = \Gamma i\ (ui\ )$ Using all (ui, vi) pairs of historical data a general function Γ( ) which consists of Γi( ) could be obtained. ν=Γ(u) More generally, U which consists of more information in today's price could be used in function Γ( ). Neural networks can simulate all kinds of functions, so they also can be used to simulate this Γ( ) function. The U is used as the inputs to the neural network.

There are three major steps in the neural network based forecasting proposed in this research: ***preprocessing, architecture***, and ***postprocessing***. In preprocessing, information that could be used as the inputs and outputs of the neural networks are collected. These data are first normalized or scaled in order to reduce the fluctuation and noise.

In architecture, a variety of neural network models that could be used to capture the relationships between the data of inputs and output are built, Different models and configurations using different training and fore casting data sets are experimented. The best models are then selected for use in forecasting based on such meseaures as out- ofsample hit rates. Sensitive analysis is then performed to find the most influential variables fed to the neural network. Finally, in post processing, different trading strategies are applied to the forecasting results to maximize the capability of the neural network prediction *(Hornik 1989).*

5.4- Measurements of neural network training

The Normalized Mean Squared Error (NMSE) is used as one of the measures to decide which model is the best. It can evaluate and compare the predictive power of the models. The definition of NMSE is

$$NMSE = \frac{\sum_k \left(X_k - \hat{X}_k\right)^2}{\sum_n \left(X_k - \bar{X}_k\right)^2}$$

Where Xk and *k X*ˆ represent the actual and predicted Value respectively, and *X k* is the mean of Xk. Other evaluation messieurs includes the calculation of the correctness of gradients. NMSE is one of the most wildly used meseaurments. It represents the fit between the neural network predictions and the actual targets. We argue that NMSE is a very important signal for pattern recognition.

5.5- Neural Network Topologies

The arrangement of neural processing unit and their interconnections can have a profound impact on the processing capabilities of the neural networks. In general, all neural networks have some set of processing units that receive inputs from the outside world, which we refer to appropriately as the "input units". Many neural networks also have one or more layers of "hidden" processing units that receive inputs only from other processing units. A layer or "slab" of processing units receives a vector of data or the outputs of a previous layer of units and processes them in parallel. The set of processing units that represents the final result of the neural network computation is designated as the "output units". There are three major connection topologies that define how data flows between the input, hidden, and output processing units. These main categories- feed forward, limited recurrent, and fully recurrent networks- which we are used the feed-forward networks. Feed – forward networks are used in situations when we can bring all of the information to bear on a problem at once, and we can present it to the neural network. In this type of neural network, the data flows through the network in one direction, and the answer is based solely on the current set of inputs.

In Figure 4, we see a typical feed- forward neural network topology. Data enters the neural network through the input units on the left. The input values are assigned to the input units as the unit activation values. The output values of the units are modulated by the connection weights, either magnified if the connection weight is positive and greater than 1.0, or being diminished if the connection weight is between 0.0 and 1.0. If the connection weight is negative, the signal is magnified or diminished in the opposite direction.

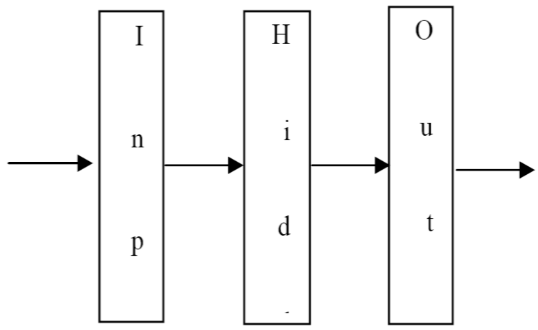

Figure 4: Feed- forward neural networks.

Each processing unit combines all of the input signals into the unit along with a threshold value. This total input signal is then passed through an activation function to determine the actual output of the processing unit, which in turn becomes the input to another layer of units in a multi- layer network. The most typical activation function used in neural networks is the S- shaped or sigmoid (also called the logistic) function. This function converts an input value to an output ranging from 0 to 1. The effect of the threshold weights is to shift the curve right or left, thereby making the output value higher or lower, depending on the sign of the threshold weight. As shown in Figure 3, the data flows from the input layer through zero, one, or more succeeding hidden layers and then to the output layer. In most networks, the units from one layer are fully connected to the units in the next layer. However, this is not a requirement of feed- forward neural networks. In some cases, especially when the neural network connections and weights are constructed from a rule or predicate form, there could be less connection weights than in a fully connected network. There are also techniques for pruning unnecessary weights from a neural network after it is trained. In general, the less weights there are, the faster the network remember that “feed- forward” is a definition of connection topology and data flow. It does not imply any specific type of activation function or training paradigm.

5.6- Neural Network Models

The combination of topology, learning paradigm (supervised or no supervised learning), and learning algorithm define a neural network model. There is a wide selection of popular neural network models. For data mining, perhaps the back propagation network and the Kohonen feature map are the most popular. However, there are many different types of neural networks in use. Some are optimized for fast training, others for fast recall of stored memories, others for computing the best possible answer regardless of training or recall time. But the best model for a given application or data mining function depends on the data and the function required. A back propagation neural network uses a feed- forward topology, supervised learning, and the (what else) back propagation learning algorithm. This algorithm was responsible in large for the reemergence of neural networks in the mid 1980s.

Back propagation is a general purpose learning algorithm. It is powerful but also expensive in terms of computational requirements for training. A back propagation network with a single hidden layer of processing elements can model any continuous function to any degree of accuracy (given enough processing elements in the hidden layer). There are literally hundreds of variations of back propagation in the neural network literature, and all claims to be superior to “basic” back propagation the other. Indeed, since back propagation is based on a relatively simple form of optimization known as gradient descent, mathematically astute observers soon proposed modifications using more powerful techniques such as conjugate gradient and Newton’s methods. However, “basic” back propagation is still the most widely used variant. Its two primary virtues are that it is simple and easy to understand, and it works for a wide range of problems.

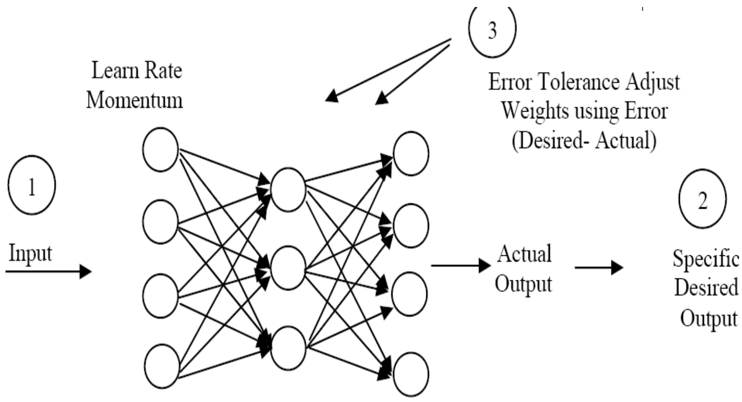

Figure 5. Back propagation network

The basic back propagation algorithm consists of three steps (see Figure 5). The input pattern is presented to the input layer of the network. These inputs are propagated through the network until they reach the output units. This forward pass produces the actual or predicted output pattern. Because back propagation is a supervised learning algorithm, the desired outputs are given as part of the training vector. The actual network outputs are subtracted from the desired outputs and an error signal is then the basis for the back propagation step, whereby the errors are passed back through the neural network by computing the contribution of each hidden processing unit and deriving the corresponding adjustment needed to produce the correct output. The connection weights are then adjusted and the neural network has just "learned" from an experience. Back propagation is a powerful and flexible tool for data modeling and analysis suppose you want to do linear regression. A back propagation network with no hidden units can be easily used to build a regression model relating multiple input parameters to multiple outputs of dependent variables. This type of back propagation network actually uses an algorithm called the delta rule, first proposed by Widrow and Hoff. Adding a single layer of hidden units turns the linear neural network into a nonlinear one, capable of performing multivariate logistic regression, but with some distinct advantages over the traditional statistical technique. Using a back propagation network to do logistic regression allows you to model multiple outputs at the same time. Confounding effects from multiple input parameters can be captured in a single back propagation network model. Back propagation neural networks can be used for classification, modeling, and time-series forecasting. For classification problems, the input attributes are mapped to the desired classification categories. The training of the neural network amounts to setting up the correct set of discriminate functions to correctly classify the inputs. For building models of function approximation, the input attributes to correctly classify the inputs. This could be a single output such as a pricing model, or it could be complex models with multiple outputs such as trying to predict two or more functions at once. Two major learning parameters are used to control the training process of a back propagation network. The *learning rate* is used to specify whether the neural network is going to make major adjustments after each learning trial or if it is only going to make minor adjustments. *Momentum* is used to control possible oscillations in the weights, which could be caused by alternately signed error signals. While most commercial back propagation tools provide the most impact on the neural network training time an performance.

6-Simulation Results:

To test the efficiency and effectiveness of the model a software program was developed using MATLAB. 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 2002 and ending with January 2003 was used for the training, the validation was done by using another year which starts with February 2003 and ends with January 2004.

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. The weights and biases of the network were automatically initialized to small random numbers by the software.

7- Case study:

Case 1: Arab Engineering Industry

The training was done using one step secant back propagation, 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 layer consists of 14 neurons and the second layer consists of one neuron. The network was trained using the stock prices for this company during the year starting February 2002 and ending January 2003, the network was able to train the data with a MSE of 9.7245*10-7 in only 11 epochs. To put things into perspective, the output of the network was plotted against the target as shown in Fig. 6, after the network passed the validation stage; the network was used to forecast the prices for the year starting from February 2003 until January 2004. Fig. 7 reveals the forecasted prices against the actual prices, as shown in the figure the forecasted price is very close to the actual one.

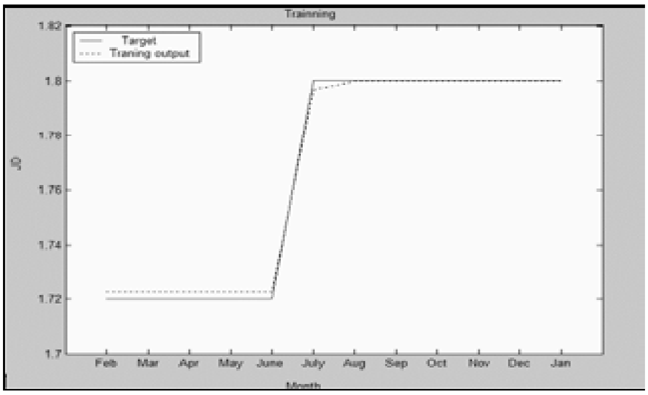

Figure 6: Training output against the target for Arab Engineering Industry Company.

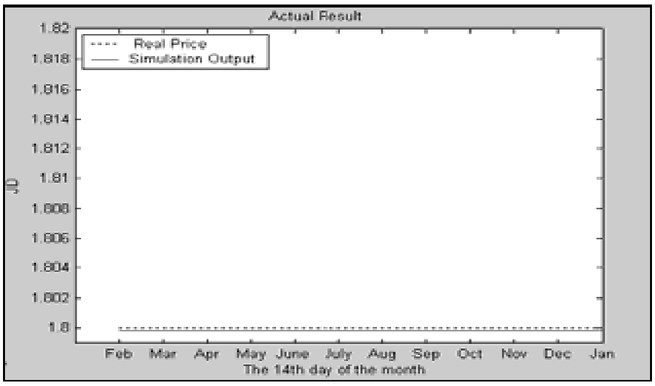

Figure 7: Forecasted prices against the actual prices for the Arab Engineering Industry Company.

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 company stock prices exhibits a noticeable variation between the days of each month, which make the forecasting job more difficult. 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 year starting from February 2003 until January 2004. 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).

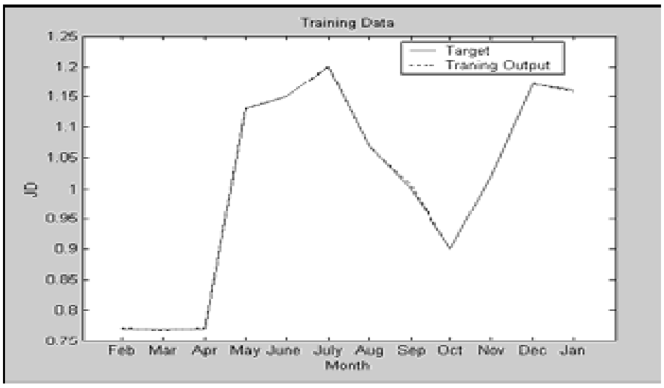

Figure 8: Training output against the target for the Nutriadar Company.

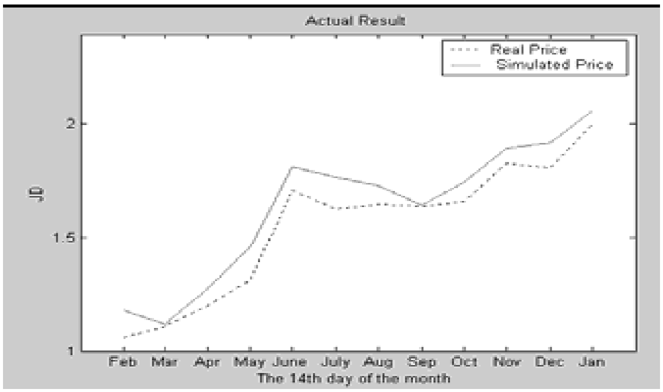

Figure 9: Forecasted prices against the actual prices for the Nutriadar Company.

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

Case 3: Jordan Petroleum Refinery
A three layers ANN was used consist of (14,7,1) neurons respectively, the training was done using one step secant back propagation, the first and second layers used positive linear activation function, while the third layer used hard limit activation function. The stock prices for this company during the year starting February 2002 and ending January 2003 are very volatile and varies substantially from one

month to month and even during the same month. The training mean square error reaches 10-3 within 90 second in 1000 epochs. The output of the network against the target is shown in Fig 10. As shown in the figure the network output slightly differs from the target, although it exhibits the same pattern. The network was used to forecast the prices of the year starting from February 2003 until January 2004. The forecasted prices against the actual prices are shown in Fig 11. The network was able to produce a very good forecast for the first four months (February-June), after June the actual prices fall from 15 JD's to 4 JD's. As shown in the figure the forecasted prices fall 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 difference of less than 2 JD's. Further investigation into this case reveals that the company broke the shares which caused the prices to drop.

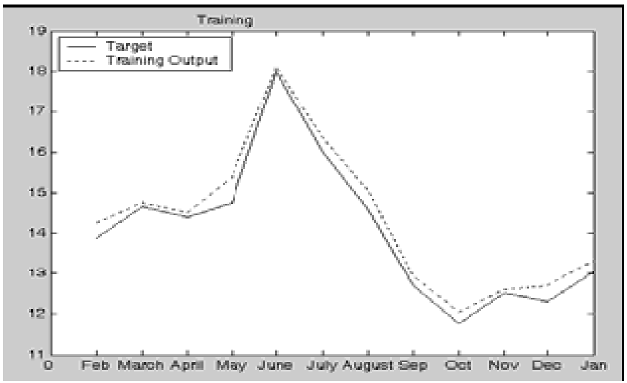

Figure 10: Training output against the target for Jordan Petroleum Refinery Company.

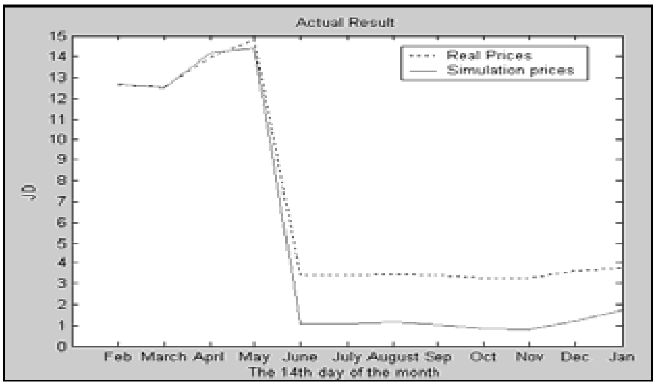

Figure 11: Forecasted prices against the actual prices for Jordan Petroleum Refinery Company.

8- Discussion:

The results obtained from the software were accurate for six out of seven cases, thus, ANN can be used for forecasting stock prices. In the last case, the network did not give a good forecast but it was able to detect the pattern of the change in prices. Even when the actual stock prices change dramatically for assignable causes, the network was able to detect that and the forecast change at the same month and even with the same pattern as the actual data. Therefore, ANN can give a good indication about the trends of stock prices.

9- Validation of the neural network:

To compare the performance of an artificial neural network to linear regression, a regression equation was computed form the same data used for training the neural network. The equation then was used to predict stock price index from the same recall data set used to evaluate the neural network. The performance of each approach was tested to determine which tool is the better predictor. To test the significance of the difference in predictive ability of the two models, a matched sample pairs statistical procedure was used to test the hypothesis that the mean difference between the predictive between the model is zero (i.e. there is no difference between the predictive abilities of the two models). The p-value0.00089 is--, which is an evidence that the neural network out perform the regression model for predicting stock price index.

A procedure analogous to step- wise regression was used to investigate the significance of each determinant of models. The results show that neural network has best performance for predicting stuck price network has was significantly better able to explain the relationship between Inputs and output. In analyzing ongoing relationships between Inputs and outputs, neural network has three primary advantages over regression analysis:

1. Neural network development does net require knowledge of underlying relationships between the input and output variables (both linear and non- linear). Since the network "learns" relationships hidden in the data. These complex relationships are discovered and automatically assimilated into the weights connecting the nodes of the network. These weights contain the "learned information" from the network training phase and are analogous to regression coefficients.

2. The associative abilities of neural networks make them more robust to missing and inaccurate data, since the knowledge of relationships between variables is distributed across numerous network connections. Regression, on the other hand, cannot tolerate missing data and works poorly with inaccurate data since all relation- ship knowledge is stored in a single beta coefficient.

3. Neural networks performance is not diminished by the multicollinearity problem of regression analysis- Non- standard conditions, violations of assumptions, high influence points, and transformations can all be handled by the neural networks.

10- Conclusion and Future Research:

This paper reports an empirical work which investigates the usefulness of artificial neural networks in fore casting the (J.S.P). The performance of several back propagation neural networks applied to the problem of predicting the Jordanian's stock market index was evaluated. The delayed index levels and some technical indicators and fundamental elements of macroeconomics were used as the inputs of the neural networks, while the current index level was used as a output. With the prediction, significant power. The significance of this research is as follows:

1- It shows that useful prediction could be made for MATLAB without the use of extensive.

2- It shows how annual return could be achieved by using the proposed model.

3- To improve neural network's capabilities, a mixture of technical and fundamental factors as inputs over different time period is used. The characteristics of emerging market such as Jordanian's stock exchange should be further researched to facilitate better market using neural networks. The forecasting results can then be applied to the trading of index linked stocks under consideration of the transaction costs.

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