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Prediction of Stock Market Prices Using Hybrid Intelligent System

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Declaration

I hereby declare that this thesis is my own work which has been done after registration for the degree of master at Arab American University, and contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. except where otherwise indicated.

Dedication

Thanks for those who gave me everything to see me here, thanks to those who gave me the strength to complete this way, thanks to my parents.

Acknowledgments

I would like to express my sincere gratitude to my advisor Prof. Dr. Mohammed Awad for the continuous support and related research, for his patience, motivation, and immense knowledge. His guidance helped me all the time. Thanks to my co-supervisor, Dr. Rami Hodrob who has provided me with support, encouragement, and guidance during this thesis.

Abstract

The main aim of the stock market is to provide a safe environment for trading in order to achieve better services to investors and maintain their investments. The stock market in any country plays an important role in the national economic development and gross domestic product (GDP). Hence, the process of the prediction of the stock market returns is of high importance attention. If the stock market predictions come true, they will definitely help the investors formulate their investment strategies on solid and scientific grounds. Consequently, the concepts of the stock market parameters that affect the market that we have to consider with the mathematical methods used to predict the econometrics emerge and to quantify the uncertainty through multivariate causal criteria with the support of the randomization of the market. The variables of the market like share price, interest rates, exchange rates, inflation, etc, can be predicted using intelligent and smart methods, which allow the investors to invest their money in a more secure and reliable way.

In this thesis, we presented an optimized hybrid model that combines the multilayer perceptron neural networks with genetic algorithms (MLPNNs-GAs) to predict the status of the Palestinian stock market on Al-Quds Index as the main indicator. In addition, the stock market data of three biggest Palestinian companies (Paltel, Padico, and Bank of Palestine) will be used to predict its stock prices. In this research, the idea behind combining artificial neural networks (ANNs) with GAs is that characteristics of data in stock prices have high volatility, nonlinear in type. And as we know, without imposing a particular relationship in the data, ANNs has the ability to learn unobserved relationships in the data. Genetic algorithms (GAs) are used to optimize the weights for the NNs, and GAs will pick the best weights in order to optimize performance and get the best-predicted minimum mean square error (MSE) value. The GAs process applied using the best combination methods of the GAs main steps. Furthermore, we applied another two models of different neural networks

methodologies; multilayer perceptron neural networks trained using Levenberg-Marquardt back propagation (MLPNNs-LM) and the recurrent neural networks RNNs-LM trained using Levenberg-Marquardt back propagation too and compared the performance of the three applied models in term of MSE.

The experimental results obtained from the proposed MLPNNs-GAs model and the other applied NNs models (MLPNNs-LM and RNNs-LM), showed that the performance of the hybrid model (MLPNNs-GAs) outperforms the MLPNNs-LM and RNNs-LM models in forecasting the closed price of the 4 datasets which present the stock market (Padico, Paltel, Palestine Bank, and the Al-Quds index), where the MLPNNs-LM model produce better accuracy than RNNs-LM in general.

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List of Abbreviations

MLPNNs	Multilayer Perceptron Neural Networks
ANNs	Artificial Neural Networks
GAs	Genetic Algorithms
NNs	Neural Networks
RNNs	Recurrent Neural Networks
MLPNNs-GAs	Multilayer Perceptron Neural Networks with Genetic Algorithms
MLPNNs-LM	Multilayer Perceptron Neural Networks with Levenberg-Marquardt
RNNs-LM	Recurrent Neural Networks with Levenberg-Marquardt
MSE	Mean Square Error
SVM	Support Vector Machine
BPNNs	Back Propagation Neural Networks
MLPFFNNBP	Multilayer Perceptron Feed Forward Neural Network Back Propagation
LMA	Levenberg Marquardt Algorithm
FFNNs	Feed Forward Neural Network
GN	Gauss-Newton
PEX	Palestine Exchange
AI	Artificial Intelligence
Paltel	Palestine Telecommunications Company
Padico	Palestine Development and Investment Company
BOP	Bank of Palestine

Chapter One:

Introduction

1. Introduction

The stock markets are spaces of fundamental importance for the development of economies and their good management implies the transition from saving to investment through the purchase and sale of shares. These actions are so important that they are influenced by economic, social, political and cultural variables. Therefore, it is reasonable to consider the value of an action in an instant not as a deterministic variable but as a random variable, considering its time trajectory as a stochastic process [1]. Predicting the movements of the stock market has been a complex task for years. This issue has aroused the interest of researchers and investors around the world, who have tried to anticipate the levels of return. Consequently, these researchers will be able to make decisions regarding the reduction of risks, which might be faced during the investment process. Thanks to the economic importance and the interest of the investors to anticipate the stock market, many researchers have focused their efforts on understanding the phenomena that influence the volatility of the shares. Despite some noticeable advances, it is still far from being an exhausting line of research and there are still a lot of fields to explore because there are still no consistent techniques that work in a sustained manner. The current situation has shown the need to speculate the prices of shares based on feasible values to avoid any economic crises and improve the returns of the investments [2]. Due to the development of societies, the increasing complexity of the economy and ongoing conflict and instability, a number of researchers and investors found out that predicting the direction of the stock market index is quite challenging. The stock market of the country is usually analyzed in terms of advanced knowledge based on mathematics, computer science, and economics. Specifically, forecasting the trends of the financial market and the stock exchange has become a necessity to help the investors make appropriate decisions when planning for the future, which will ultimately create new opportunities for profit and protection against potential losses. This forecasting depends on time series, which can be defined as a set of observations arranged according to their occurrences and consequently their causes and consequences are analyzed to determine their trends to build future expectations and make the relative decisions. Regarding the theoretical perspective of the modeling and forecasting of this type of financial time series, there are two common positions. The first assumes that the price of a financial asset has sufficient and useful information that makes it more predictable, which means that its past behavior tends to repeat itself in the future. The second is the Efficiency Market Hypothesis, which states that it is not possible to predict future prices from past prices. It ensures that markets reflect all available information and cannot follow a trade rule that provides additional benefits. Accepting the Efficiency Market Hypothesis would imply that it is impossible to exceed the market average. However, in practice, this was refuted by investors like Warren Buffet and Peter Lynch, who managed to exceed the market average for more than 20 years [3].

There are two approaches with which stock markets can be analyzed: fundamental analysis and technical analysis. The first is a numerical based on time series to estimate the values reached by stocks with past returns. The second is a study of the factors that affect supply and demand. It is done through the analysis, collection, and interpretation of the information delivered by the companies through their reports, balance sheets, statements or news. So far, the works published in this regard deals with these two approaches separately using econometric, statistical or computational techniques to make short, medium or long term predictions. [2].

Several researchers have proposed a prediction model to predict the trends of the stock exchange in different international stock markets. Some of them depend on their studies on individual models such as neural network, genetic algorithms, particle swarm optimization algorithm and Neuro-Fuzzy system [4], others depend on hybrid approaches that use a parallel combination of two or more methods from Artificial Intelligence (AI) [5]. The basic idea of the hybrid model is to overcome the weaknesses of the single models and take advantages of each model and generate more accurate results. In this thesis, one of the intelligent models which combines two intelligent methods; artificial neural network, and evolutionary algorithms used to predict the stock market price; namely, multilayer perceptron neural networks with genetic algorithms model (MLPNNs-GAs). It should be noted that coupling ANNs with GAs leads to the emergence of ANNs. Therefore, and since GAs is used for the optimization process, GAs was used to select the initial weight to be replaced in the last NNs structure. The number of weights and basis are determined according to the structure and number of layers in the NNs, and the GAs is responsible for reducing cost function called MSE (the difference between outcome and actual values of target).

The datasets were taken from the Palestinian stock market to predict the future stock market prices. We will study the price time series of the shares in these stock markets as per the historical data exchange intervals with the goal of finding patterns of these markets, which will be used to predict the future stock markets price series. The input variables consists of the daily time series closing prices in studied stock markets and the output will be the forecast period for the next time series. The researcher's ultimate objective is predicting the financial time series corresponding to the Palestinian market through one or hybrid models of intelligent systems. This process start by structuring the architecture of the neural networks then the hybrid system, training the proposed models, predicting the future values and comparing the performance of the proposed model with another two ANN’s models (MLPNNs-LM model and RNNs-LM model). Both two ANN’s models are usually trained with the back propagation method and have proven themselves over the year to be suitable and reliable for predicting the complicated financial indexes as compared to linear models (Arima) [6,7]. In addition, the stock market has highly changeable and data of stock nonlinear in type and ANN’s is used to solve nonlinear problems. RNNs-LM differs from MLPNNs-LM in input data it takes input from both the past and the present, while in MLPNNs outcome of a neuron of a given layer becomes the input to neurons of the next layer only. Matlab software tools and the library will be used to simulate the proposed model in this thesis.

1.1 Problem Statement

The prediction of the price of shares in the capital market has been of great interest to stockbrokers and investors, due to the profits obtained by stock transactions. Prediction based on time series has been extensively used in research, where one of the most influenced fields has been the financial field. There are several models of time series whose purpose is to predict future data from historical data. However, in such a dynamic as is the stock market, the data obtained to make the series of time have non-linear behaviors, which would affect the effectiveness of the prediction. The Palestinian stock market is leading our country to the global investment map so, there's a special role of the stock market prediction in protecting investors and the growth of the economic prosperity. On one hand, several studies are deployed to predict the Palestinian Stock market performance using some of the statistical techniques like ARIMA model [8], where few of them that have applied Artificial

Neural Networks (ANNs) as a prediction model [9]. On the other hand, there's no study that has applied a hybrid model such as ANNs and evolutionary algorithms (genetic algorithms, particle swarm optimization algorithm, Neuro-Fuzzy system) on the Palestinian Stock market datasets and it has been found that not much accurate information is available on this research topic. Hence there’s a need for a more efficient and suited prediction model that helps in forecasting the non-linear data to improve the forecasting accuracy of Palestinian stock market and related decision-making.

1.2 Objectives

The main objective of this work is applying a hybrid artificial intelligence model, which consists of "MLPNNs-GAs" to improve the prediction accuracy of the stock market price in the Palestinian Stock Market (Padico, Paltel, Palestine Bank, and the Al-Quds index). The study aims to achieve the following specific objectives:

- Collecting historical data about the selected banks and their explanatory variables at a certain time interval.
- Performing a pre-processing of the obtained historical data.
- Implementing the gist of the work, which is the hybrid model which consists of "MLPNNs-GAs". This proposed model "MLPNNs-Gas" novelty lies in constructing a model, where weights of ANN are evolving by genetic algorithms through the use of the best combination of the methods of the GAs steps.
- Applying other two artificial intelligence models (i.e. MLPNNs-LM and RNNs-LM) models to compare with the performance of the previous three considered models according to the MSE factor.

- Studying different NNs methodologies including their architectures and training using Levenberg-Marquardt algorithm to select the NNs parameters; this will be used to forecast the next stock exchange with minimal prediction errors.
- Identifying and analyzing which companies are the most favorable to predict and which ones will be its explanatory variables.

1.3 Contribution

This particular study has presented different hybrid intelligent methods which are expected to have the following contributions:

- Improving the forecasting accuracy value and primarily the efficiency in predicting the stock exchange in the financial market of the Palestinian Stock Market.
- The novelty of the proposed hybrid model "MLPNNs-Gas” will make it possible to compare the selection of different combination methods of the GAs main steps in terms of MSE values and then come up with the best group that improves the performance of our model.
- Comparing the performance of the suggested model with the other two models (MLPNNs-LM) and the (RNNs -LM) will probably help to find the most efficient model for the prediction of the stock market price in the Palestinian Stock Market.

1.4 Thesis Structure

The rest of the thesis is organized as follows: In the next chapter (chapter 2) we will introduce a topics background related to our thesis subject, we started with a general introduction about the stock market, the importance of stock market and prediction, and description of used data set, then we will present the used prediction method of stock market and the time series. After that, we present a brief introduction of

Artificial Neural Network (ANNs) and evolutionary algorithm (genetic algorithm) focus on models that are used in our work which are MLPNNs-LM and RNNs-LM and MLPNNs-GAs. Finally, we will show the related researches that use intelligent systems to forecasts stock prices.

In the third chapter, we will construct and implement the proposed model and describe in details this model and other applied models (MLPNNs-LM and RNNs-LM), also introduce the performance function MSE. The training algorithm Levenberg–Marquardt algorithm that is used by all applied models will be illustrated.

In chapter 4 the process of preparing collected stock exchange datasets and data normalization is introduced. The results obtained from the applied models are described; system results and discussion are presented with testing and evaluation. Finally After studying, designing and developing our system. In chapter 5 we will provide a summary and conclusions of results, the results will justify our work, also important recommendations will be presented.

Chapter Two: Background

2. Background

Predicting the stock market parameters has been an important issue in the field of investment and attracting the researchers. This process has become a complex problem due to the enormous number of conditions and variables that surrounds this evaluation process. Through ANNs with suitable learning algorithms able to predict future values in the stock market. So this research aims to help persons or agencies that decide to invest in the stock market through the management of purchase or sale of shares of a company to make decisions regarding the time to buy or sell based on the knowledge obtained from the historical values of the shares in the stock exchange.

2.1 Stock Market

A financial market is a market in which an investor's needs are fulfilled. It allows capitalists to buy and sell financial assets in order to mobilize their surpluses. It also has a contribution to social and economic development. Four centuries ago in Europe, the industry burned and at that time, what is called the industrial revolution had been started. In conjunction with this time period, the stock market started to be common. A British explorer called Sebastian Cabot proposed the first modern shareholding enterprise [10], this enterprise proposed to find a new trade route to China and the Orient from North East. Starting a huge business require a lot of money and partners, so many of the pioneer traders alliance to start these businesses. Every share of money of these traders was represented by a unit of ownership, later these units called shares and that was the beginning of joint stock companies [10]. The stock market is an organized market and it can be a very complicated market place. It is an important measure of a country's economic movement [11]. Stock markets can be classified as follows [11]:

- Money market: The money market is the specialized market on immediate and short-term funding where the money is exchanged in the form of cash. The advantage of securities in this market is the high liquidity. The main source of funds in this market is bank deposits and depositors have the right to recover their deposits at any time. These deposits maturity date is usually less than a year.
- Capital market: The Capital market is the specialized market on offering and requesting long-term funds in order to mobilize and facilitate the flow of financial surpluses towards those with a deficit. The market deals with securities related to venture capital financing. These deposits maturity date is usually more than a year. It's divided into two types:
    1. Spot markets which include two types of markets according to the issue date. First, primary markets or issue market in which the new issues of securities are traded and offered in the market for the first time. Second, the secondary market in which the securities that have been issued in the primary market. Secondary market includes organized market and unorganized market.
        - The organized market which is called the Stock Exchange. It has a specific place in which securities trading can be done in accordance with the laws of the official body that deals with securities.
        - The unorganized market which is also called Over-The-Counter (OTC) market doesn't have official systems in which the securities that are dealt with are not meeting the legal

requirements. This market has a number of intermediaries scattered in different places within the state.

2. The futures market: are the markets where the transactions of buying or selling securities are taken a place in the present and the delivery is taken a place in the future.

There are many functions performed by the stock exchange/market [10]:

1. Funding Investments.
2. Mobilizes savings: it mobilizes the development of savings through the promotion of investment in securities which will benefit the holder of profits and thus lead to higher stock prices. The stock market also channels savings to serve the national economy.
3. Helps to transfer funds from the surplus economic categories (lenders) to the economically disadvantaged (borrowers).
4. Helps to predict price trends and thus guide investors to the best-advertised prices
5. Directs resources to the most profitable areas with high efficiency, leading to economic prosperity.

Several factors affect the future investments and have high effects in whether go markets up or down which include wars, natural disasters, conflicts, anxiety over inflation or deflation, and changes and development of technologies. And because the investment process is risky and difficult to estimate, investors need methods to predict the future so they can be guided to make the right decision with a high level of confidence, whether to enter or exit the market. The financial forecast is based on the development of a set of estimates and results relating to future conditions and events that may be positive or negative and that can be met by making plans depending on it.

The estimates are developed based on scientific and statistical methods. Using historical data, estimates help in determining the changes in the environment surrounding investors and thereby assist them in making investment decisions which in turn contribute to reaching profits with minimum risks. The forecasting methods are selected based on their complexity, limitations, requirements, and accuracy so that the best results can be achieved, the highest accuracy with the smallest errors.

2.2 Datasets Description

The thesis applied the daily and weekly closing price data for four applied datasets from the Palestinian Stock Exchange excluding holidays, which included the daily closing price data for three of the biggest companies from the stock exchange, these companies were selected among the most active and traded companies in the Palestine Exchange (period from 2010-2017 for Padico and Bank of Palestine companies and from 2011-2017 for Paltel company). And the weekly closing price data for the main index of Palestinian Stock Exchange which is Al-Quds Index (period from 2010-2017).

At 13:30 pm, officially in Palestine Exchange (PEX), the closing prices are established for different symbols and the trading session ends. In order to review data and print reports members will have the availability to the trading system when entering the closing session [12].

2.2.1 Palestine Exchange (PEX) and the Main Index (Al-Quds-index)

It is often found surprising Palestine has a stock exchange market which plays an important role in the financial market of the country. The stock exchange was established as a private joint stock company in 1995 and was the first trading session in 1997 and in 2010 it became a public shareholding company. The main objective of the Palestinian stock exchange is to provide an efficient investment environment based on fairness and transparency. According to [7], the most surprising news is that in 2005, Palestine security exchange was having the best performance in the world along with its major index that is Al Quds rising by over 300% though there was having an ongoing conflict as well as instability in the region. In 2008, this Al Quds index has lowered down by 16% affecting the financial market of Palestine and stock exchange level decreased [13]. However, in 2009, it has been noted that this Al Quds index has increased by 11.62% for reaching the point level of 493.00 at the end of 2009 compared with the points in 2008 being 441.66. This increase has taken place irrespective of the political stability that happened in the country during this year [12]. Later, at the end of the year, it has been found that the peak of the index had gathered 557.3 points. In 2009, the best performing stock exchange in Palestine was Palestine Poultry (increased by 90%), industrial investment (75%), Establishment of Arab Real Estates (50%), electric company (53%) as well as Al Quds Bank (34%). In 2013, it has been found that the financial market of Palestine was trading stocks on the exchanges and the Palestine Stock Exchange was including several other securities to secure its financial market in the future. In 2016 it has got full membership in the Federation of Stock Exchanges [12]. The behavior of Al-Quds Index daily closed price data duration from 2010 to2017 Illustrated in figure 2.1. We will use these values to predict the closing price for the next year (2018).

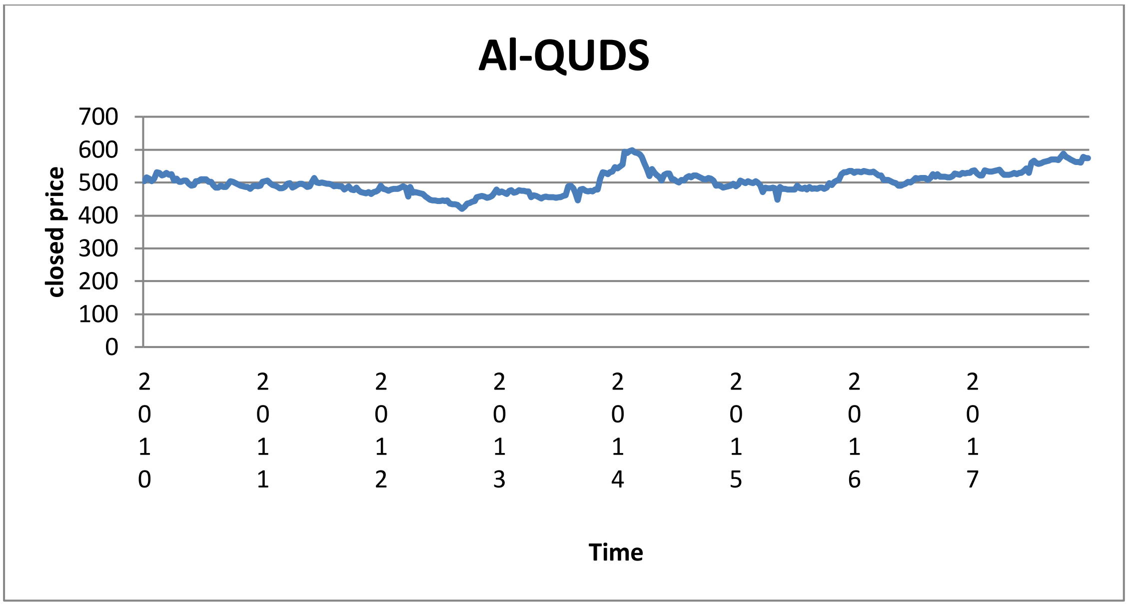

Figure 2. 1: Al-Quds Index Daily Closed Price Data

2.2.2 Palestine Telecommunications (Paltel) Company

It was established as a public joint stock company in 1995. The company's stock was stated for trading on Palestine Stock Exchange in 1997. The company provides various services including fixed and cellular telecommunication and internet services at the highest quality standards approved worldwide. In terms of employment capacity, the Palestinian Telecommunications Group is considered as within the Palestinian private sector institutions [14].

Figure 2.2 illustrates Paltel Company daily closed price data (duration from 2011-2017). We will use these values to predict the closing price for the next year (2018).

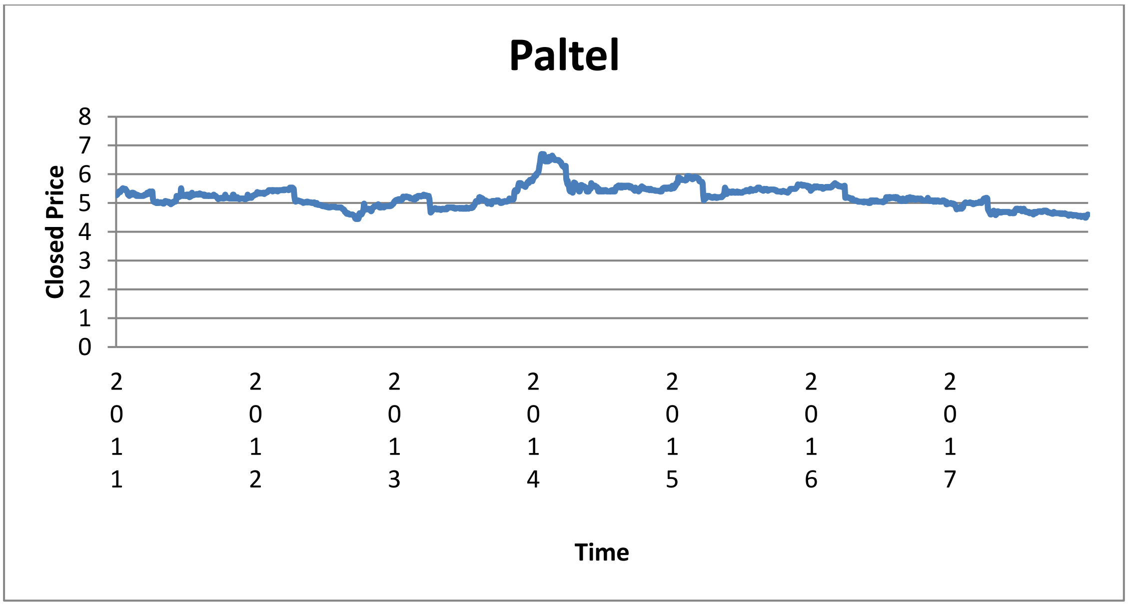

Figure 2. 2: Paltel Company Daily Closed Price Data

2.2.3 Palestine Development and Investment (Padico)

In 1993, the company was established as a foreign shareholding company with the aim of contributing to the construction and development of the Palestinian economy and creating job opportunities in Palestine. The company's capital is 250 million shares with a par value of US $1 per share. Since 1997, its shares have been traded on the Palestine Stock Exchange [15].

The company invests in large projects in various vital and basic economic sectors and seeks to expand geographically in different governorates of Palestine. Its investments fall into three main categories: Category I (Subsidiary Investments:(Padico Holding's shareholding in these companies is more than 50% of its capital. Category II (Associate Investments): Padico Holding owns a shareholding of between 20% and 50%. The third category (investments in other companies): Padico Holding shareholding in these companies is less than 20%. In contrast to the two previous categories, Padico has insufficient representation to participate in and influence the development of financial and operational strategies and policies [15].

As shown in Figure 2.3 daily closed price data for Padico Company are illustrated (duration from 2010-2017). We will use these values to predict the closing price for the next year (2018).

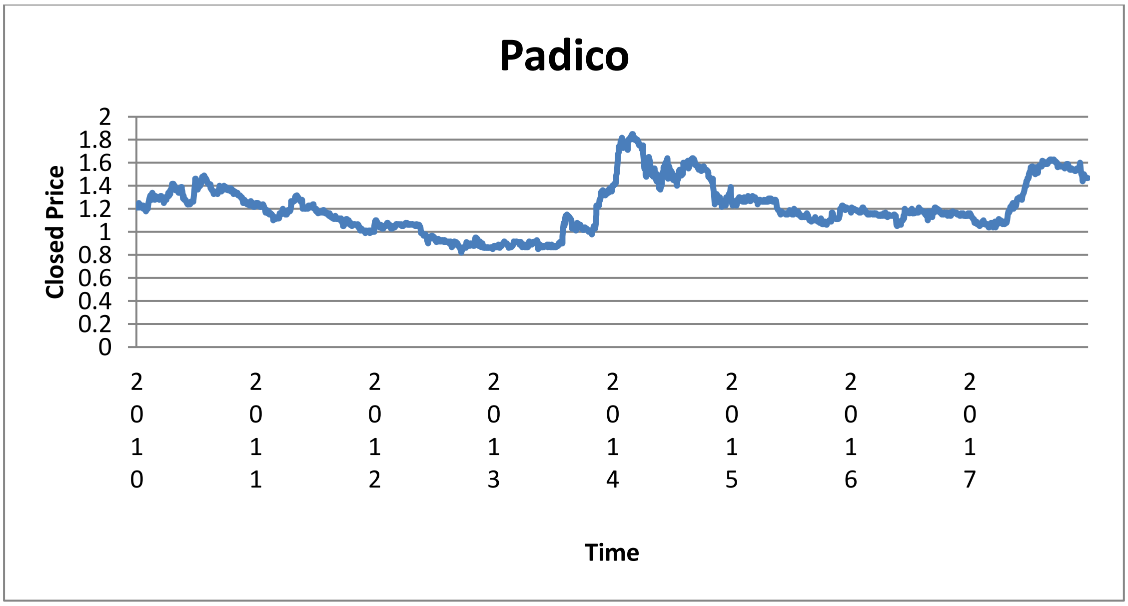

Figure 2. 3: Padico Company Daily Closed Price Data

2.2.4 Bank of Palestine

It was established in 1960 as an institution; in 2005 the bank's shares were listed as the second largest listed company with a market value of approximately 15% of the market capitalization. In terms of a number of branches and offices, it is considered to be one of the largest banks. Its purpose is to spread locally, regionally and internationally. In 2007, Al-Wasatah Securities Company, which is a member of the Palestine Securities Exchange, opened PalPay in 2011 to develop and innovate modern and sophisticated electronic payment mechanisms [16].

Figure 2.4 illustrated daily closed price data for Bank of Palestine Company (duration from 2010-2017). We will use these values to predict the closing price for the next year (2018).

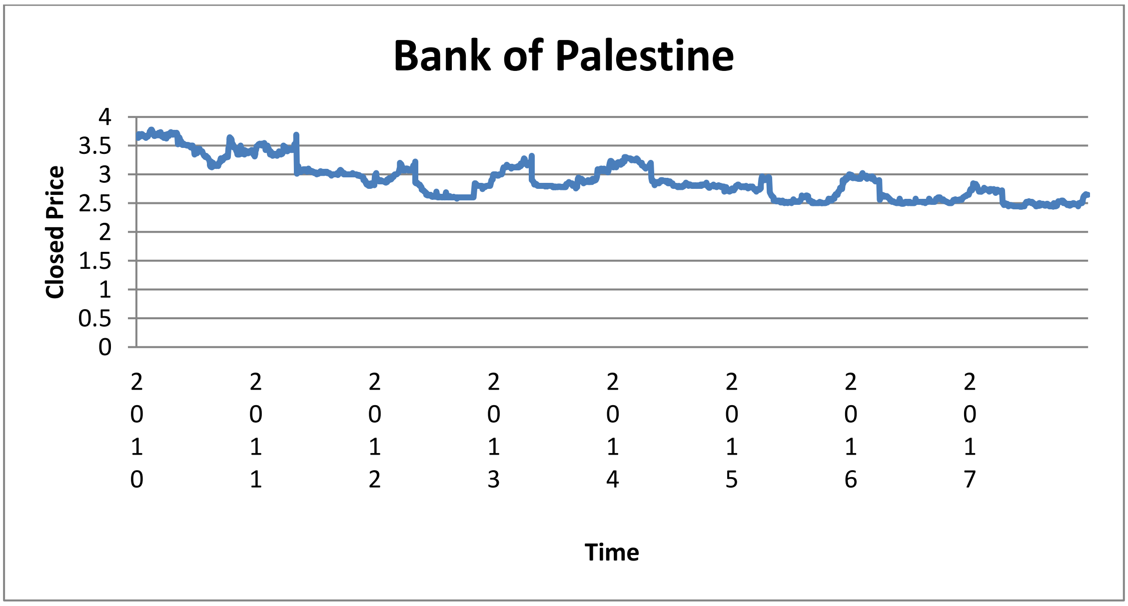

Figure 2. 4: Bank of Palestine Company Daily Closed Price Data

2.3 Stock Market Prediction

There's a variety of prediction models in future expectations such as stock market, including traditional models and machine learning models (i.e Neural Network) models. Traditional models have high-efficiency modeling which reflects the behavior of the series (Seasonal, non-seasonal, regular behavior, Irregular behavior) and interprets the dependent variable by time, but it has a shortage in interpreting the nonlinear systems and this makes the forecasting process a very complex task. ANNs models have the ability to process data with no need to a certain structure or models proposed before .it simulates the nervous system in humans in its construction and work mechanism and has the ability of formation nonlinear complex systems. So prediction using ANNs gives better results than traditional models. using ANNs methods and evolutionary algorithms are widely used to estimate market value series

According to [17] neural network has proved to be one of the most used technologies which have been widely regarded for its advantages over regression as well as classification of forecasting of the stock market. The authors in [18] added on this perspective that among several neural methods, the artificial neural method has been found to be one of the effective methods to predict a country's stock market. A simplified description of ANNs prediction techniques such as MLPNNs-LM and RNNs-LM and hybrid model MLPNNs-GAs are introduced in this chapter.

2.3.1 Time Series Forecasting

A time series is a number of observations taken sequentially in a certain time interval, characterizing each observation with the period in which it was taken. Therefore, a series of time can be described as a stochastic process indexed by the time variable. To make a forecast based on time series, information from past periods is required; therefore, the main objective is to achieve a dependence on historical data. Analyzing a series of time can be found structures and patterns in the historical data that give rise to models capable of predicting their behavior.

Time series forecasting in finance is the most valuable data science applications. Time series can be applied at any sequential observation at a regular interval (i.e. hourly, daily, weekly, monthly, quarterly, etc). Time series techniques are valuable to predict anything have a continuous change over a period of time, using the data collected from the past. In time series analysis the main goal is to forecast the future behavior using the patterns of the past data. A set of vectors $y(t)$, t= 0,1,2,... where the time elapsed presents as t and $y(t)$ is a random variable [19].

There are a lot of statistical forecasting techniques that employ patterns of historical data to forecast future outcomes. One of the simplest techniques called simple moving average (SMA) [20]. Essentially, a simple moving average is considered as the prediction for the next period and it is equal to the average of a set of prices security over the last "m" periods. Also Autoregressive Integrated Moving Average (ARIMA) is one of the statistical techniques that use time series analysis to forecast future behavior [20]. ARIMA depends on three parameters P the autoregressive average, D the integrated average and Q the moving average parts of the data. Add to that, ARIMA take the trends, cycles and non-stationary aspects of a data set in consideration when creating a future behavior or prediction [20].

Another method is the exponential smoothing which is the widely used statistical method for predictive modeling, if a series with no seasonality and do not have an evident trend, simple exponential smoothing is appropriate to use. While the series with a strong tendency component used Holt-Winters technique [21].

A time series of stationary time is one whose properties do not depend on the time in which the series is observed. Where a continuous time series of $X_t, t \in R$ for a finite set of time $(t_1, t_2, \dots, t_n)$ and for $S \in R$, which present the time step so:

$$F(X_{t1}, X_{t2} \dots, X_{tn}) = F(X_{t1+s}, X_{t2+s}, \dots X_{tn+s}) \qquad (2.1)$$

With the note that, it is very difficult to find a strictly stationary process in real life. Even if it is found, it is equally difficult to prove that it is.

2.3.2 Artificial Neural Networks

The principle of artificial neural networks came similar to the neural networks of human that consist of nerve cells and links connect cell. It simulates the human in storing knowledge [22]. As we know the human get the experience with the passage of time through activating specific links in nerve paths when an event occurs. The purpose is to develop a method to perform different computational and complex tasks more quickly than traditional methods. The application of artificial neural networks includes pattern recognition and classification, prediction and financial analysis, and optimization [22].

Neurons in artificial neural networks are corresponding to the neural network in the human brain. In ANN the connection between a neuron and another is characterized by a link to a value called weighting.

An artificial neuron is a function $\mathrm{fj}(\mathrm{x})$ is calculated by using the following general formula:

$$\mathrm{yj} = \mathrm{fj}(\mathrm{x}) = \sigma(\langle \mathrm{wj}, \mathrm{x} \rangle + b\mathrm{j}). \qquad (2.2)$$

Where x=(x1,,…,xd) is the input, $w=(w_{j,1},_{\dots},w_{j,d.})$ is the weight, b_j is the neuron bias values, and σ is the transfer function; also called(activation function). The activation function can be: step, sigmoid function (or logistic), *tanh* and others of activation functions [23].

- *Step function:* $$\sigma(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases} \qquad (2.3)$$

- *Sigmoid* function: $$\sigma(x) = \frac{1}{1 + e^{-x}} \qquad (2.4)$$

- *Tanh function:* $$\sigma(x) = \tanh(x) = \frac{2}{1 + e^{-2x}} - 1 \qquad (2.5)$$

The mostly used activation function the sigmoid since it is differentiable and allows to keep values in the range [0, 1], [24]. Neural Network types can be classified based on topology as a single layer, multilayer and recurrent (networks that contain more than one layer). Information in the neural network can flow feed-forward direction or feedback NNs direction. The general structure of NNs illustrated in figure [2.5].

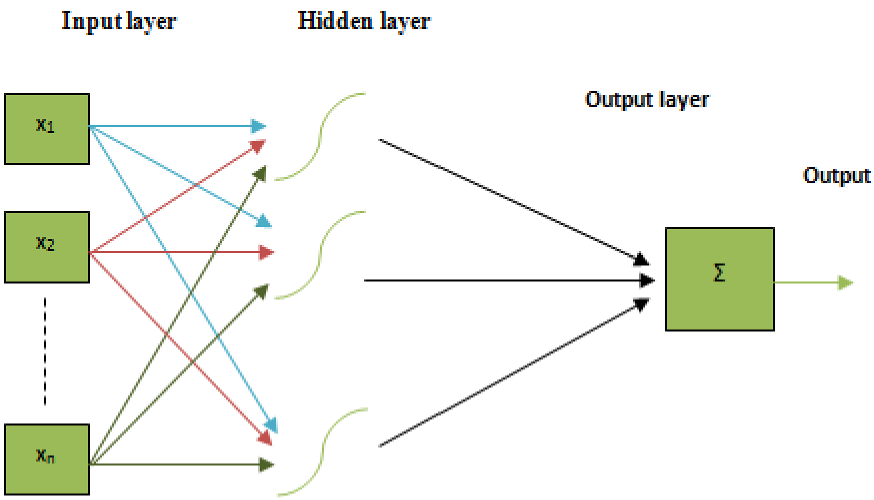

Figure 2. 5: General structure of an Artificial Neural Network

2.3.2.1 Multilayer Perceptron Neural Networks (MLPNNs)

MLPNNs usually contain at least three layers; the first layer called input layer that does not perform any processing and only it transfers data to the next layer (hidden layer), the final layer is called an output layer, and one or more hidden layers. Processing is done in the hidden layers and the output layer. The general structure of the MLPNNs illustrated in figure [2.6].

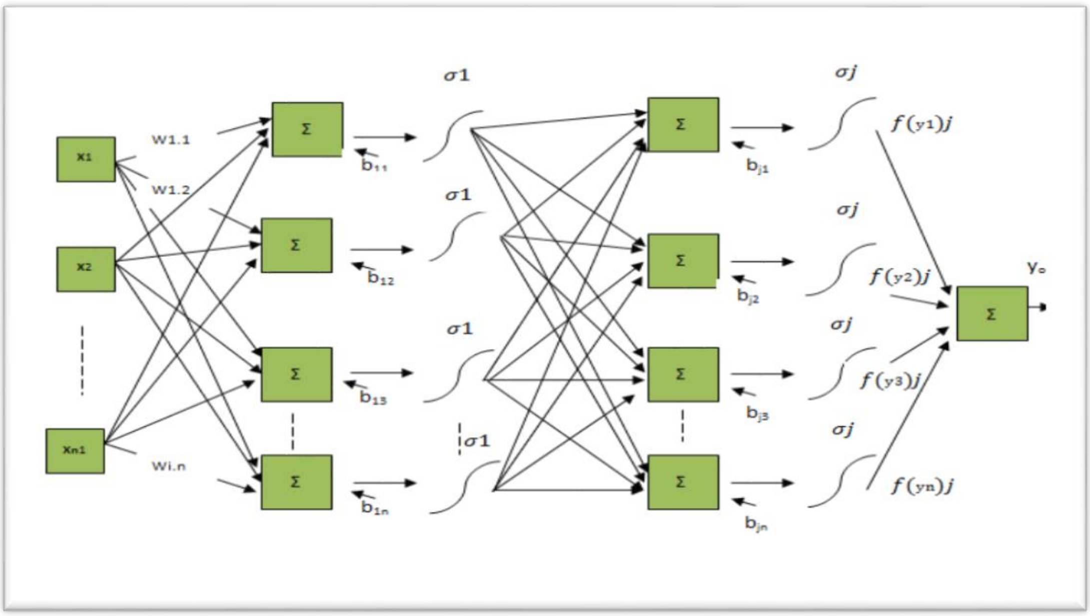

Figure 2. 6: Multi-layer Perceptron NNs

In the architecture of MLPNNs, each neuron of a layer is linked only to all neurons of the next layer which means the output of a layer only become the input to the next layer and can't be input to the neuron of the same layer or previous layer moving from the input layer to the output layer [25]. The outcome of the MLPNNs is calculated by using this formula [26].

$$z_j^n = \sigma\left(\sum_{i=1}^{n} K_{jk}^n \, z_k^{n-1} + b_j^n\right) \qquad (2.6)$$

Where K_{jk}^n is the weight from the k^{th} neuron in the $n-1^{th}$ layer to the j^{th} neuron in the n^{th} layer, b_j^n is the bias of the j^{th} neuron in the n^{th} layer, z_k represents the input data vector, z_j^n represents the outcome value of the j^{th} neuron in the n^{th} layer and σ is the activation function.

The objective of training NN is to reduce outcome errors through updating NN weights in order to decrease the difference between the actual target and desired outcome, so improved performance; one method is used for calculating this difference is the Sum of Square Error (SSE) function.

$$Er = \frac{1}{2}\sum_{j=1}^{m}\sum (Ta_a - Op_a)^2 \qquad (2.7)$$

Where Ta_a is the real value, Op_a is the forecasted value, m represent the total number of input data. And the gradient descent algorithm is used to update weights which illustrated in these formulas:

$$\Delta K_{ia}^{nm} = -\mu i \frac{dEr(K_{ia}^m)}{dK_{ia}} \qquad (2.8)$$

Where μi is the learning rate determine how should change weights to decrease the error function (E), K is the weight, and dEr represents the derivative of the error function and it determine the direction to reduce the error (increase w or decrease it) [27].

2.3.2.2 Recurrent Neural Networks (RNNs)

Another type of NNs is called recurrent neural networks (RNNs). RNNs are considered as a robust method that is widely used for sequential such as financial data [28]. The idea behind this network is coming to overcome the shortcoming of other algorithms; neurons in RNNs contain a short-term memory which gives the possibility to remember the values obtained from the previous neurons and then apply these values in the future .so this algorithm has two inputs, the present, and the immediate past. Which is essential since the sequential data contains important information about what is coming next, here in the case of prediction a series of results that based on each other, the model must be aware of all previous predictions. Hence a nonlinear time series that depends on knowledge of the previous information and previous computations can be effectively processed by this network [29].

In the architecture of RNNs, data can be processed from the input layer to the outcome layer. This is similar to the direction of feed forward network. Also, data can be processed in the reverse direction of the feed-forward network from outcome layer to the input layer through the existence of feedback loops. Hence unlike feed-forward network outcome of a neuron becomes the input to the neuron of the next layer and is used as feedback inputs themselves and neuron of the previous layer (the outcome of a neuron is used as feedback inputs for other neurons) [30].

2.4 Genetic Algorithms

In 1960s John Holland described Genetic Algorithms firstly, then in 1960s and 1970s Holland developed and improved it with his students at the University of Michigan

[31]. Genetic algorithms are part of evolutionary computing that depends on simulating nature. Applications of genetics are represented in search problem and optimization (find optimal solution from group of possible solutions for a specific problem) [32], when there's a complex problem, large group of solutions will be there, some of these solutions are efficient and others less, in addition to the existence of an optimal solution that will be difficult to reach . Here came the principle of genetics algorithm that based on generating a large number of a possible solution to be applied for a specific problem, here only the strong survive, which means that the best solutions stay and bad solutions are neglected. And the more efficient solutions are mixed to get a new population that holds attribute of their parent's and check the new solutions to know the efficiency of these solutions and how they are close to the optimal solution. The quality of solutions will evolve by repeating the process to a specific number until the optimal solution reached [33]. The general structure of a genetic algorithm is illustrated in the following figure [33]:

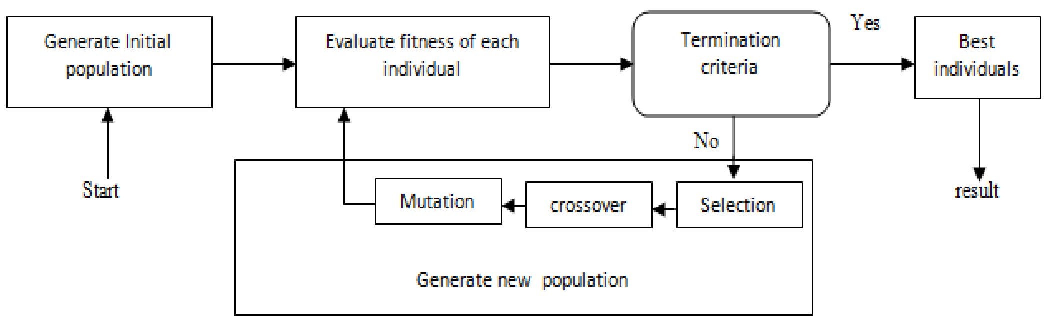

Figure 2. 7: General structure of the genetic algorithms

Combine MLPNNs with evolutionary algorithms such as GAs to forecast stock exchange with the back-propagation method. They are well appropriate to the problem of training MLPNNs, and this can be done in several various cases. One case that used in this thesis is letting GAs determine the optimal weights for the applied MLPNNs. Therefore optimize the Neural Networks.

2.5 Learning Algorithms

One of the most distinguishing characteristics of ANNs is their ability of learning relationship and the behavior between inputs and outputs to produce outcome closes to the desired outcome of any given input values [30]. The methods of teaching the network are divided into supervised learning and unsupervised learning. According to [34] in both methods the network is given a group of carefully chosen examples (training set), but in the strategy of supervised learning the training data is displayed as pairs (input and their corresponding target) and the weights are adjusted by knowing the difference between the target and the output [34], the dataset used as a teacher in this algorithm, pairs of input and output are used iteratively to make prediction. Learning process stop at acceptable level of performance, the common types of this strategy are classification and regression, while the strategy of unsupervised learning provides only input without providing the target on the network, then learning methods are constructed based on the ability of this network to detect the attributes of the objects presented without the need for prior knowledge in the required output, hence in this algorithm there is no teacher like supervised learning [34]. Clustering is a common type of this strategy which is used for understand and exploratory data analysis through looking for structure or hidden pattern that has not been considered before, so here not looking for something specific as in supervised learning [34] and [35].

The supervised learning methods have high ability in prediction and the outcomes produced by this type are more accurate than unsupervised so we used this type in our work. All applied models (MLPNNs-LM, RNNs-LM, and MLPNNs-GAs) with Levenberg Marquardt training algorithm. Since the back propagation (BP) algorithm has preeminent learning ability and its broad applicable to many businesses problems which made it the most popular neural network training algorithm for financial time series.

2.6 Related Work

This thesis will discuss an important problem concerned with the research topic. The problem is investigating the method used for forecasting the economic condition of an economy. In time series forecasting, the main problem is the use of effective methods that fit with the time series depending on the nature of data. It is likely to note that all financial data are non-linear type and the use of traditional statistical methods such as regression analysis and ARIMA models may generate problems. Using these methods can lead to inaccurate data and forecasting of the future economy might not be appropriate as thought [36]. Thus, it is important to take into account the necessary and most efficient methods when data of non-linear type, also the complex problem is solved by using artificial intelligent models with no need to algorithm solution and logical methods, which is the sphere of traditional and statistical methods [37].

During the last years, many researchers tried to predict the stock markets in different countries using intelligent methods. Many researchers depend on the Palestinian Stock Exchange Market in their studies and other researchers depend on their studies of datasets collected from international Stock Exchange Markets. In [38] the authors compare between ARIMA Models and Artificial Neural Networks models (MLPNNs) in forecasting Al Quds indices of Palestine Stock market for three years. The predicted result obtained from this research with the using of multilayer perceptron neural networks with back propagation outperforms the forecasting result obtained using ARIMA (P=0, D=1, Q= 1).

In [9] the researchers compared the prediction accuracy for two different methods (ANN and ARIMA) using data collected from the Palestinian stock market, were used: daily, moderate and short-term. The results indicate that the ANN models produced the results of the most accurate forecasts. The authors conclude that ANN and ARIMA produce forecasts result better when the data set is bigger, where ANN is usually produced better forecasting results.

In [39] the authors used two approaches ARIMA and Support Vector Machine (SVM) based models, to predict the time series PATEL'S stock market price dataset. The result showed that the SVM produces a better result of forecasting than ARIMA model.

The research paper in [4] investigated the application of SVM in financial forecasting compared with ARIMA and ANN. The data set was collected from Al-Quds Index of the Palestinian Stock Exchange Market to forecast two-month future points. They concluded that SVM produces a better result of forecasting than the other two models.

In this paper [5] the authors compared the accuracy of three hybrid intelligent systems in forecasting ten international stock market, they used genetic algorithms with adaptive time-delay neural networks (ATNN), time delay neural networks (TDNN), and they used the Neuro-Fuzzy inference system (ANFIS).the obtained results showed that the ANFIS model produced the most accurate forecasts results in forecasting future price of seven international stock market from the ten and when comparing GA-TDNN and GA-ATDNN. GA-TDNN usually produced better forecasting results.

In [40] the authors investigated the predictability of Istanbul stock market returns with Adaptive-Network-Based Fuzzy Inference System (ANFIS). The results reveal that the model successfully forecasts the monthly returns of the ISE National 100 Index with an accuracy rate of 98.3%.

This research [41] proposed an intelligent stock market forecasting system which is nonlinear fuzzy-neural network model to discover patterns in nonlinear and chaotic systems. The dataset record of BEXIMCO Ltd. which is a member of Chittagong Stock Exchange in Bangladesh.

In [42] the authors study the usage of long short-term memory (LSTM) networks to forecast the future trends of stock prices based on the price history, alongside technical analysis indicators. The obtained results are promising, getting up to an average of 55.9% of accuracy when predicting if the price of a specific stock is going to go up or not in the near future.

This study [43] was conducted to a comparison of analyzing trends prediction accuracy between the forecast with Google Trends data, and the forecast without Google. Through proposed a hybrid forecasting method namely ISCA-BPNN model, to forecast the stock price trend for S&P 500 and DJIA Indices. , they combined sine cosine algorithm (ISCA) with BPNN in order to optimize the weights and basis for BP network. The obtained results showed the suitability of this hybrid model and conclude that Google Trends enhancing a stock prediction.

In this study [44] the authors compared the performance of five Artificial Neural Network: FFNN, ESN, CRBM, TDNN, and CNN. These methods are also compared to SVM. When applied for a short-term stock market price forecast. Stock data is taken from rising and declining markets and listed at (NYSE) or (NASDAQ). And their result showed that FFNN, CNN, and SVM have better results and generating positive Profits. And Low profits for other methods.

The author in [45] conducted a study to forecast the exact movements of the daily stock market prices using artificial neural networks (ANNs) model. Data set is taken from the Libyan Stock Market. The obtained results are encouraging with this model, since when predicting the trend of movement in its best case getting up to an average of 91% of accuracy.

This paper [46] presented a PSOQRNN (Particle Swarm Optimization (PSO)-trained Quantile Regression Neural Network) model to prediction volatility and instability from financial time series. The performance of this model was compared with the other seven volatility predicting models: GARCH, MLP, GRNN, GMDH, RF, QRRF, and QRNN. The data for testing the performance of these proposed models came from eight financial datasets. The results showed that in terms of (MSE), PSOQRNN outperformed these models.

The authors in [47] developed an adaptive single layer second-order neural network with GAs based training (ASON-GAs) and compared performance with another two developed methods ANN, and RNN. They demonstrate that the proposed model does better-forecasting accuracy in handling the uncertainties and nonlinearities.

In this study [6] the authors compare the performance of four types of deep learning (DL) models (MLP, RNN, LSTM, and CNN). Also, compare between DL and ARIMA models in forecasting two various stock markets (NSE) and (NYSE). They demonstrate that DL models are exceeded by ARIMA models. And CNN model does better-forecasting accuracy than the other three models.

In [48] the researchers proposed an SVM optimized by particle swarm optimization based on uncertain knowledge (PSO-UK). And compared the prediction accuracy between PSO-UK-SVM and PSO-SVM in Forecasting SSE composite index. The results indicate that PSO-UK-SVM produced the results of the most accurate forecasts.

In [49] the authors depend on BP neural network to propose a forecast model of the Shanghai composite index. This model has higher accuracy with strong robustness and higher capacity of fault tolerance. They found that the model was good at forecasting.

According to [50] a hybrid intelligent system has been proposed, based on ANNs and a neuro-fuzzy system for analyzing the trend prediction of the market. The results showed the efficiency of this hybrid intelligent system.

2.7 Summary

Table2. 1: Papers and reports on Prediction stock market.

<table>
<tr><th>Year</th><th>Author</th><th>Application method</th><th>Result</th><th>Dataset</th></tr>
<tr><td>2013</td><td>Okasha & Yaseen.[38]</td><td>ARIMA compared with Artificial Neural Networks.</td><td>Neural network model outperform ARIMA model</td><td rowspan="4">Palestinian Stock Market</td></tr>
<tr><td>2014</td><td>Okasha.[4]</td><td>SVM compared with ARIMA; ANN.</td><td>SVM produces a better result of forecasting than the other two models.</td></tr>
<tr><td>2017</td><td>Safi & White.[9]</td><td>ANN compared with ARIMA.</td><td>ANN and ARIMA produce forecasts result better when the data set is bigger, where ANN is usually produced better forecasting results.</td></tr>
<tr><td></td><td>Basal. [39]</td><td>ARIMA compared with SVM.</td><td>SVM produces a better result of forecasting than ARIMA model.</td></tr>
<tr><td>2001</td><td>Abraham & Mahanti.[50]</td><td>Hybrid intelligent system based on ANNs and a neuro-fuzzy system.</td><td>The results showed the efficiency of this hybrid intelligent system.</td><td>International</td></tr>
</table>

2010	Boyacioglu & Avci.[40]	Adaptive-Network-Based Fuzzy Inference System (ANFIS).	The model successfully forecasts the monthly returns of the ISE National 100 Index with an accuracy rate of 98.3%.	Stock Market
2012	Xin, , Yuhong, & Keyi.[48]	PSO-UK-SVM compared with PSO-SVM.	PSO-UK-SVM produced the results of the most accurate forecasts.	
2014	Masoud.[45]	(ANNs) model.	Predicting the trend of movement in its best case getting up to an average of 91% of accuracy.	
2015	Miah, Hossain, M. Z., Hossain, M. A., & Islam.[41]	intelligent stock market forecasting system nonlinear fuzzy-neural network.	The proposed model is able to handle the quantitative and qualitative factors that affect the stock price.	
2016	Lahmiri.[5]	ANFIS compared with GA-TDNN and GA-ATDNN.	ANFIS model produced the most accurate forecasts results in forecasting future price of seven international stock market from the ten and when comparing GA-TDNN and GA-ATDNN. GA-TDNN usually produced better forecasting results.	
2017	Aamodt & Torresen.[44]	Compared the performance of five Artificial Neural Network: FFNN, ESN, CRBM, TDNN, and CNN	FFNN, CNN, and SVM have better results and generating positive Profits. And Low profits for other methods.	
2017	Pradeepkumar & Ravi.[46]	PSOQRNN compared with seven predicting models: GARCH, MLP, GRNN, GMDH, RF, QRRF, and QRNN.	PSOQRNN outperformed these models.	
2017	Yuan & Su.[49]	BP neural network.	The model was good at forecasting.	
2018	Nelson, Pereira &	LSTM networks.	Results are getting up to an average of	

	deOliveira.[42]		55.9% of accuracy when predicting if the price of a specific stock is going to go up or not in the near future	
2018	Hu,Tang, Zhang &Wang.[43]	Hybrid forecasting method (ISCA-BPNN model).	The obtained results showed the suitability of this hybrid model and Google Trends enhancing a stock prediction	
2018	Nayak, Misra, & Behera.[47]	ASON-GAs compared with ANN, and RNN.	The proposed model does better-forecasting accuracy in handling the uncertainties and nonlinearities.	
2018	Hiransha, Gopalakrishnan, Menon & Soman.[6]	ARIMA compared with MLP, RNN, LSTM, and CNN.	DL models are exceeded by ARIMA models. And CNN model does better-forecasting accuracy than the other three models.	

A few researchers focused on prediction of the stock market of Palestine, and after review of this particular research topic, we found that few studies have applied Artificial Neural Network (ANN) as a prediction model and there's no study that has applied a hybrid model such as ANNs and evolutionary algorithms. Therefore, there's an urgent need for a more efficient model that helps forecast the non-linear data that will help improve the forecasting accuracy of Palestinian stock market and decision-making, hence in this research, we want to use different hybrid intelligent methods to predict the future values based on the time series of daily and weekly closed price values in Palestine Stock Exchange Market. In addition to this, the researcher will also apply NNs models (i.e. MLPNNs-LM and RNNs-LM) models to predict the future values from the Palestine Stock Exchange market time series. And compare the performance of all applied models according to the MSE factor.

Chapter Three: Proposed Methodology and Applied Models

3. Proposed Methodology and Applied Models

3.1 Introduction

In this chapter, we use neural networks (Multilayer perception neural networks and Recurrent neural networks) to predict the stock market price, after that we use a hybrid system that combines neural networks with evolutionary algorithms as illustrated in figure [3.1]. Another important part of the analysis will be to determine the statistical and economic significance of the predictive capacity of evolutionary algorithms and neural network techniques in decreasing the prediction mean square error.

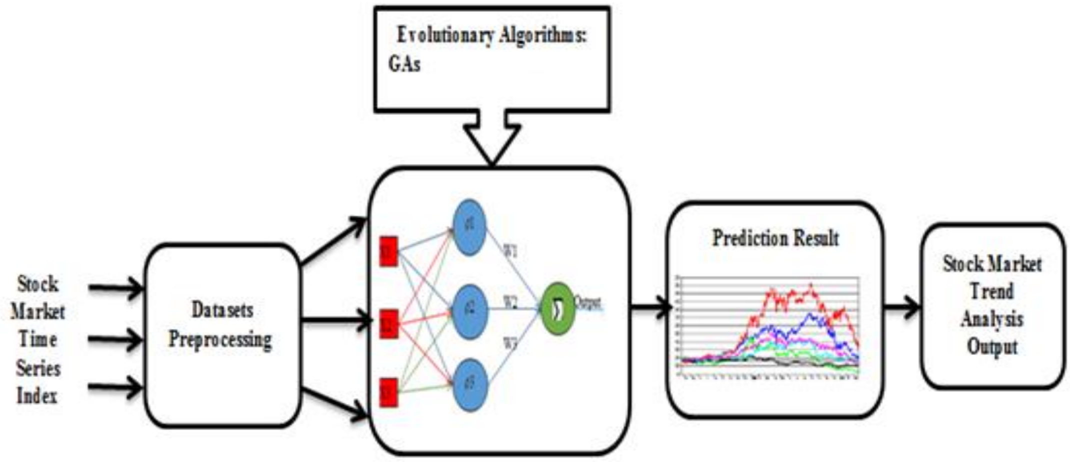

Figure 3. 1: General Structure of the Proposed System

The general procedure that was used in conducting experiments illustrated in figure [3.2]. Where the input data, which presents a time series of the stock market behavior of the biggest companies, will be the input of the model together with the time series of the Al-Quds Index, which presents the behavior of the companies in the Palestine stock market. Then the data will be passed on a pre-processing step, where the data will be normalized and divided based on the time period. Training and testing data will be used to check the performance evaluation of the three applied models.

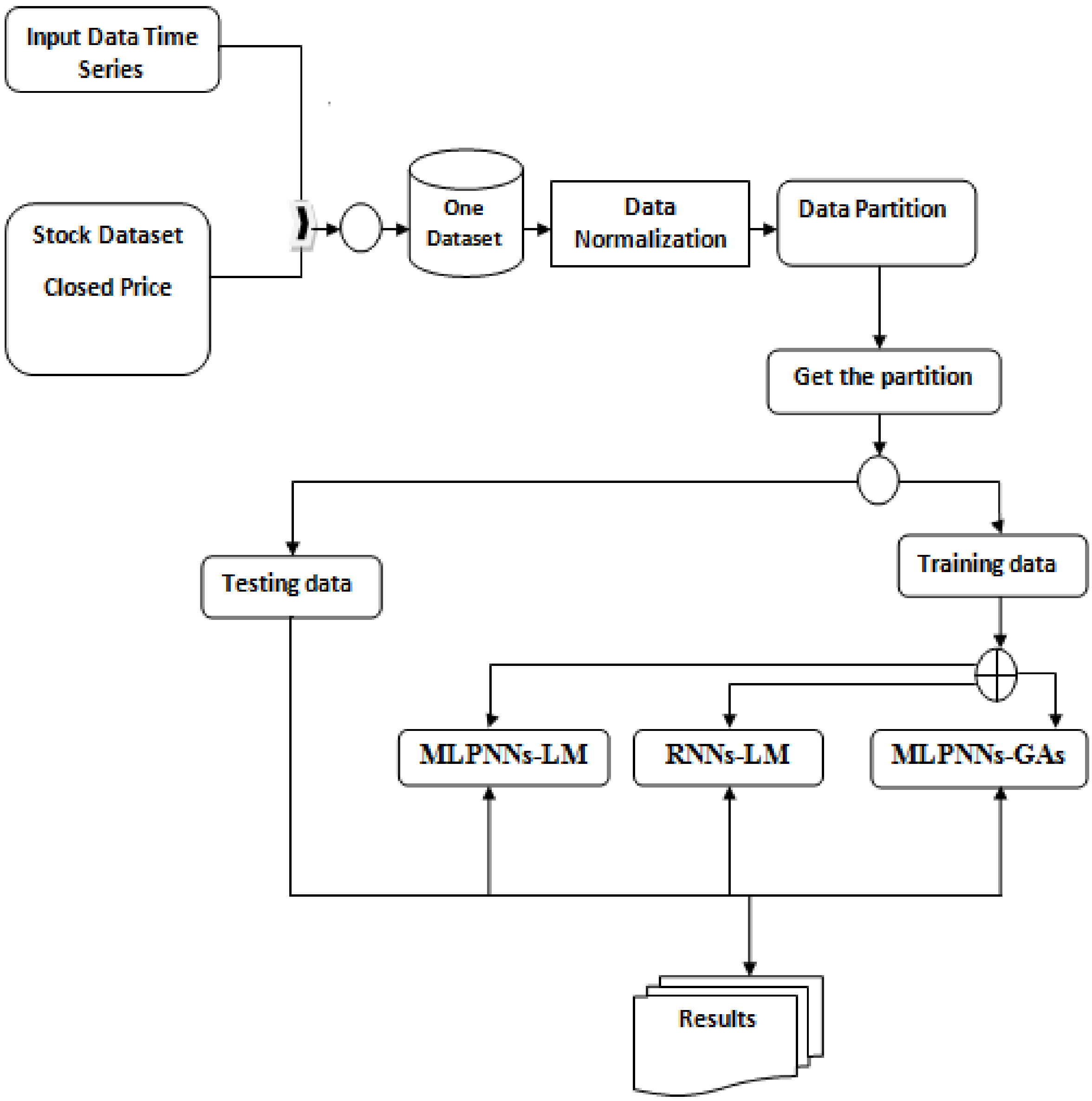

Figure 3. 2: Flow chart of the general procedure that was used in conducting experiments.

This work will concentrate on improving the prediction process of the stock market price. We used the mean square error (MSE) for evaluating the models of (MLPNNs-LM, RNNs-LM, hybrid (MLPNNs-GAs)) and calculated the mean square error using the following equation:

$$MSE = \frac{1}{m} \sum_{a=1}^{m} \sum (Ta_a - Op_a)^2 \qquad (3.1)$$

Where m represents the total number of input data, $\mathrm{Ta_a}$ is the actual value, and $\mathrm{Op_a}$ is the forecasted /predicted value.

And we calculate the error between output and target as follow:

$$\text{Error} = \sum (Ta_a - Op_a) \qquad (3.2)$$

3.2Applied Models

This section will present the procedures for the prediction models, which will come up with results that will be discussed in the following chapter as per the error metrics. In the first part of the methodology, MLPNNs-LM will be presented in detail. Secondly, procedures will be formulated for RNNs-LM. Third, the procedures of the optimized model using GAs to optimize the MLPNNs parameters will be formulated to develop a model prediction of the result.

3.2.1 Multilayer Perceptron Neural Networks Model

This model has two phases: feed forward bass and the backward bass. The steps of computing the outcome of the input layer, the following layer and the outcome layer are done in the forward pass. In this phase, random weights are used, so the real and desired outcome is not convergent. Backward bass made the difference between a real and desired target (gradient decent error) are small enough through updating the weights in order to decrease the outcome of performance function [51]. General formulas for computing outcome of the first hidden layer y1 of the MLPNNs are:

$$\text{outc}_{y1} = \sigma^1(\sum_{i=1}^{m} X_i . K_{iy1}) \qquad (3.3)$$

Where m represent the total number of input data, X_i represent the input vector and K represent the weight vectors. The general formula for computing the outcome of the final outcome layer y2 is illustrated in equation [3.4] here outc_{y1} is input to the final outcome layer y2.

$$\text{outc} = \sigma^2(\sum_{j=1}^{m} \text{outc}_{y1} . K_{jy2}) \qquad (3.4)$$

Where σ^1 and $\sigma^2$are the transfer functions for the hidden and the outcome layers, which computed using these formulas:

$$\sigma^1 = \frac{1}{1+e^{-x}} \qquad (3.5)$$

$$\sigma^2 = X \qquad (3.6)$$

We calculate the error that occurs for each neuron as follows:

$$EN_Y = (y_k - y_g)\sigma^{s'}(Y) \qquad (3.7)$$

Where EN is the error between the target outcome and desired outcome, σ s'(Y) represents the derivative of the transfer function in each layer of the MLPFFNNBP, for the sigmoid σ s'(Y) equals= $y_g(1 - y_g)$. In equation [3.8] the process of weights update is illustrated

$$K_Y(t+1) = K_Y(t) + \alpha . EN_Y . y_g \qquad (3.8)$$

Where α represents the learning rate, $K_Y(t)$ represents the value of current weight, and K_Y (t+1) represents a value of new weight. for training the MLPFFNNBP we used fastetst back propagation method (Levenberg Marquardt algorithm). Figure [3.3] represents general process for MLPFFNNBP model.

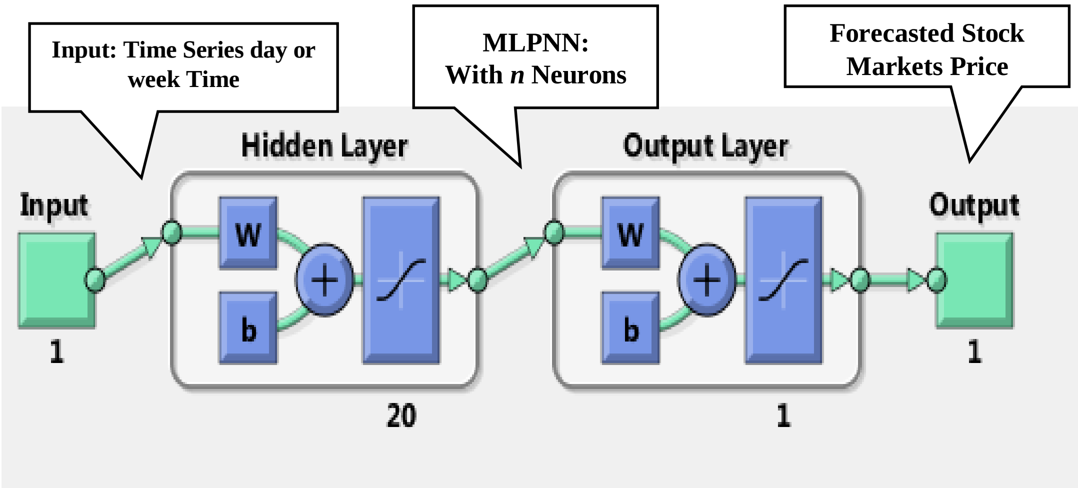

Figure 3. 3: Proposed Stock Markets Price using MLPNN

3.2.1.1 Levenberg Marquardt algorithm

In the optimization problems with neural networks, one of the efficient training algorithms used to determine and adapt the best weights in order to minimize network error is the Levenberg-Marquardt algorithm (LMA) [52]. A nonlinear least squares problem are solved using this method. It finds a minimum of a function by blinding both minimizations methods, the gradient descent and the Gauss-Newton (GN) [35]. LMA method has advantages over gradient descent and the GN, such as fast convergence, training is stable and at each iteration direction. LMA has two possible options, which make it stronger than GN [53], but this algorithm has complex calculations. The idea of this algorithm works in two cases: if the algorithmic parameter (λ) is away from the nearest of the minimum (optimal value), the LMA use an approximate gradient-descent and Newton method if the algorithmic parameters are adjacent (close) to their optimal value [54]. The LMA will go towards the GN method as soon as possible. The procedure of the LMA method [55]:

1. *Initialize network parameters (weights; K).*
2. *Calculate and evaluate sum square error (SSE)*
3. *Calculate the Jacobian matrix (X) according to the first partial derivatives of the network outcomes or the transfer functions with respect to the network. X is an $N \times M$ matrix. N and M are respectively the numbers of training patterns and weights.*
4. *Calculate the gradient error.*
5. *Approximate The Hessian (HE) using the cross-product Jacobian.*
6. *($JT\, X+\lambda\, iN$) Δ= gradient error is solved to find Δ.*
7. *Adjust weights using Δ*
8. *Recompute the sum square error (SSE) using the adjusted weights.*
9. *When the sum square error is increased should change the weight vector to the previous value, increase λ, and adjusted using step2. But should rely on the weight vector and decrease λ if the sum square error is reduced.*
10. *Using step 2 the algorithm is repeated according to the new weights, in order to have the sum square error (SSE) lower than the predicted value.*

The computation approximation of the Hessian is expressing in the following Equation:

$$\mathrm{HE} = \mathrm{J}^{T}\mathrm{X} \qquad (3.9)$$

$$\mathrm{gg} = \mathrm{J}^{T}\ \mathrm{Je} \qquad (3.10)$$

Where equation [3.10] expressed the computation of its gradient. Note that X represents the Jacobian matrix and a vector of network error indicates by Je. Equation [3.11] expressed behaves of LMA as Newton.

$$K_{M+1} = K_{M-}\ [J^{T}X + \lambda i_{N}]^{-1} J^{T}\ \mathrm{Je} \qquad (3.11)$$

K_{M+1} represent a new weight that computed as gradient function and K_M represents current weight using Newton algorithm. And λ is used in the training process (updated at each iteration in order to reduce the sum of squared errors) iN represent the identity matrix of order N. The general process for MLPFFNNBP is illustrated as shown in figure [3.4].

Model 1: The general procedure that was used MLPFFNNBP

Start Training *MLPNNs*

Initialize *MLPNNs* parameters

- *Load Training Dataset*
- *enter initial Neuron number*
- *Initialize the Network Weights W randomly*
- *Initialize Network Bias b randomly*

While Error less than or equal threshold value θ

- *Compute Forecast result* y_g
- *Compute Mean Square Error between forecast and target outcomes.*
- *Compute ΔW for all weights from the outcome to hidden layer.*
- *Compute ΔW for all weights from the hidden to input layer.*
- *Adjust the Weights of the network.*
- *Add 5 Neurons at a time.*

Compute Mean Square Error.

Start Testing Phase

- *Set Network Weights to measure in training level*
- *Compute forecasted outcome using testing data*
- *Compute Mean Square Error*

Figure 3. 4: MLPNNs-LM Model

3.2.2 Recurrent Neural Networks-LM (RNNs-LM) Model

In RNNs the decision at neurons of hidden layer h affected by the decision of h-1 layer. Because of that, the current input depends on the merges of all previous inputs of recurrent neurons that stored previously. So there are correlations between the current, next and previous data steps in RNNs. It is like human decision making that depends on all previous and present data to decide to do or not and how to do [56].Graphical representation details of recurrent neural networks is illustrated in figure[3.5].

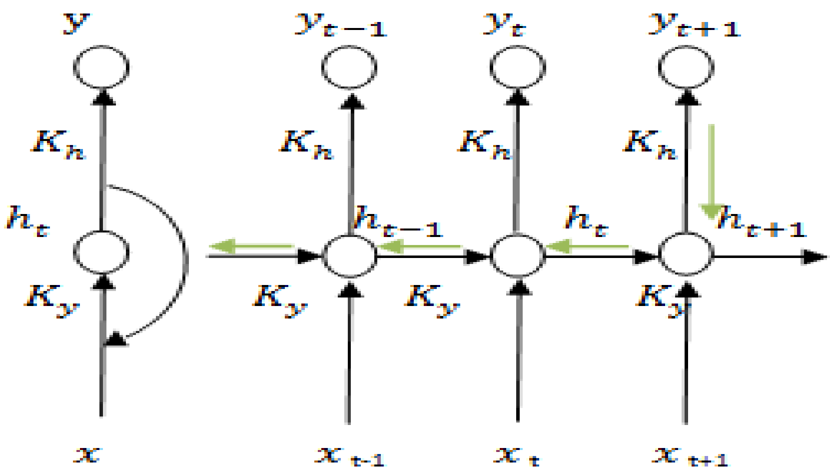

Figure 3. 5: Shows a pictorial representation of recurrent neural networks.

The predicted outcome of the recurrent network. Input to hidden layer calculated by using this formula [57]:

$$h_t = \sigma_h(K_h x_t + U_h\, h_{t-1} + b_h) \qquad (3.12)$$

This predicted output (h_t) will be the input of the outcome layer (y_t), so the predicted hidden to outcome layer calculated by using this formula:

$$y_t = \sigma_y\big(K_y h_t + b_y\big) \qquad (3.13)$$

Where x_t is an input vector, h_t hidden layer vector, y_t is an outcome vector, K_h input to the hidden layer weight matrix, K_y hidden to outcome layer weight matrix, and σ_h and σ_y are activation functions. Also here for training the RNNs-LM we used Levenberg Marquardt Algorithm. General process for RNN is illustrated in figure [3. 6].

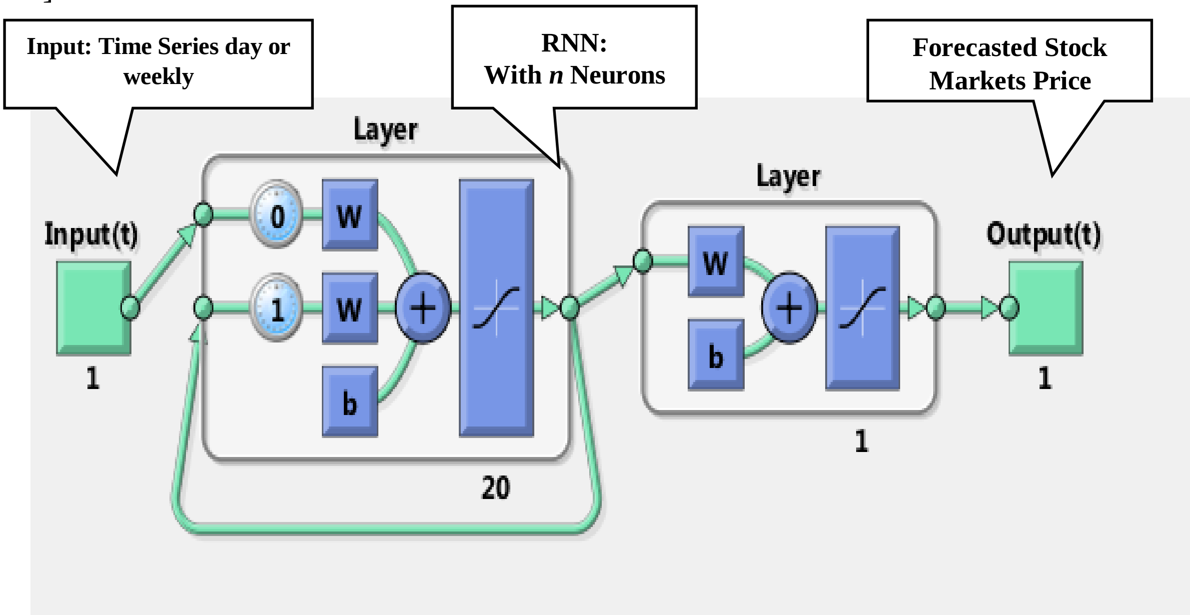

Figure 3. 6: Proposed Stock Markets Price using RNN.

The general process for RNNs-LM is illustrated as shown in figure [3.7].

Model 2: The general procedure that was used RNNs-LM

Start RNNs –LM

Initialize RNNs-LM parameters

- *Load Training Dataset*
- *Enter the number of hidden layers*
- *Enter the neurons in each layer*
- *Enter the transfer function in each layer (sigmoid)*
- *Enter the training function*
- *the weight/bias learning function*
- *select the performance function(MSE)*

Start Training Phase

Defines activation function (Levenberg-Marquardt back-propagation).

Compute Mean Square Error between forecast and target outcomes.

Start Testing Phase

- *Load Testing Dataset*
- *Set Network Weights to measure in training level*
- *Compute forecasted outcome using testing data*
- *Compute Mean Square Error between forecast and target outcomes.*

Figure 3. 7: RNNs-LM Model

3.2.3 MLPNNs-GAs Model

Before starting the process of training, the parameters in NNs have to be determined and adjusted until reaching the best solution that has the smallest value of error. For this particular problem, the entities in a GAs reach the optimal genome/ parameters in NNs, since they evaluate each individual independently. And this makes GAs fitting to improve and evolve NNs. Improving can be done through evolve topology of NNs, parameters, and the number of hidden layers [57]. That’s why we used the Optimization method (genetic algorithm) in my work, to optimize parameters through optimized weights of NNs. Details of MLPNNs-Gas model is illustrated in figure [3.8].

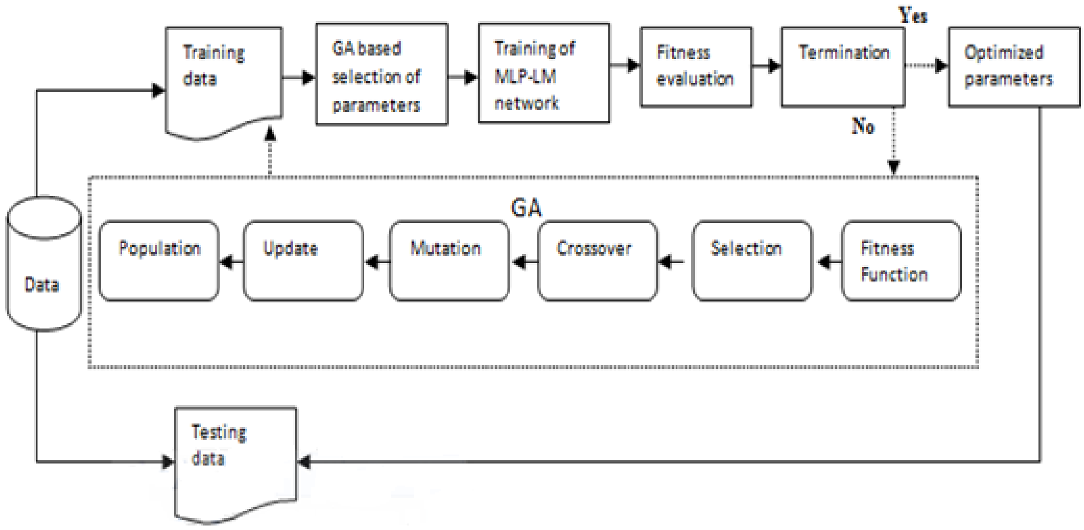

Figure 3. 8: MLPNNs-GAs model architecture

There's a factor such as the selection of fitness function and the value of genetic algorithm parameters affect the effectiveness and performance of the algorithm. As shown in figure [3.8] architecture of MLPNNs-GAs model include extract weight using GAs to use them as initial weights for the MLPNNs-LM.

The procedure of GAs-weight extraction:

1. Input number of generation, number of population, preprocessing dataset, and number of the neuron.
2. Apply basic operation of a genetic algorithm.
3. Output (GA-weights) to use as initial weights for the neural network.

As shown in figure [2.1] in chapter two the basic process of GA is as follow:

- Initialization: the genetic algorithms generate initial population (chromosomes/parent) randomly in the first step, each chromosome contain a number of genes and in my work, every gene represents the weights of NNs (start from weigh1 represent by gene1 until weight n represent by gene n) as illustrated in the following figure.

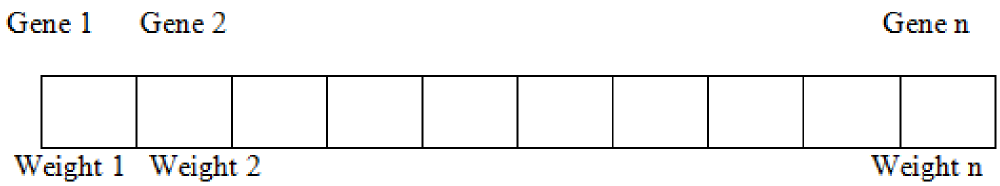

Figure 3. 9: Chromosome illustration of the weights

As shown in the figure [3.9] above, all weights are denoted as the values of genes. If NNs contain x input neurons, h hidden and s outcome neurons, then the chromosome must contain *(x+s) h* genes.

- In the second step, the fitness function is evaluated for each chromosome to evaluate performance. As we know the fitness function is considered as a basic link between the algorithm and the problem. In our work, the fitness function used is Mean Square Error (MSE).
- The third step includes applying the selection, the aim is to choose only the most two efficient chromosomes that fit with the problem with the aim of giving the best qualities to the next generation. So the chromosome that outputs the smallest MSE has a higher opportunity to be selected.
- After that crossover and mutation are applied in the fourth and the fifth steps, that include exchange the selected gene and change gene in a solution for the possibility to produce a better solution.

- Then in six-step compare with the performance of efficient chromosomes that selected in step3. Finally, repeating the process (from step3-step6) to a specific number until the optimal solution reached.

In our work the crossover rate ranges (0.5 – 0.9) and migration fraction has been changed (.001, .002, .003, .01, .02, .03, .1, .2, .3). We select these values by try and error and as we noted in the previous studies these values were the best. For this experiment, population and generations have been changed together as shown in table [3.1].

Table 3. 1: change number of population and generations

Population-size	10	10	20	30	40	50	50	60	70	80	100
Generation	20	40	40	60	70	80	90	100	120	140	160

Also, the combination of genetic algorithm functions such as crossover, mutation, selections has been changed to select the best groups of these functions that have minimum MSE values as shown in table [3.2].

Table 3. 2: Genetic Algorithms functions

Group	Selection Fcn	Crossover Fcn	Mutation Fcn
Group1	Roulette	Scattered	Adaptive feasible
Group2	Stochastic uniform	Constraint dependent	Uniform
Group3	Uniform	Two point	Gaussian
Group4	Tournament	Heuristic	Constraint dependent
Group5	Remainder	Two point	Adaptive feasible

Then for prediction closed price, we use in the MLPNNs-GAs model specified a group of genetic algorithms function, selecting a group that has reduce the cost function (MSE) these groups contain: Uniform Selection function, Gaussian Mutation function, and Two point Crossover function.

3.2.3.1 Uniform Selection Function

Relating selection to fitness is the most important idea of selection. In genetic algorithms, there is a significant role which is the selection of the individuals to produce the consecutive generation. The fitness arises for each individual by the probable selection. In our work, we used Uniform Selection, FUSS (fitness uniform selection scheme) can be defined as a fitness value f which is selected uniformly in the interval [fmin,fmax] where fmin/fmax are the smallest/highest fitness values in the existing population. After that a fitness for individual $i \in P$ which is so close to f is selected and add a copy to P. So it is not necessary for this strategy to drive the population toward higher fitness. Therefore, preserving diversity [58].

3.2.3.2 Gaussian Mutation Function

The mutation is the process of changing between specific genes within one solution or chromosome for the possibility to produce better chromosomes. In Gaussian mutation each gene Ki is mutated with the mutation rate Pn in the following way [59]:

$$K_i^{t+1} = K_i^t + N(0, \sigma) \qquad (3.14)$$

$N(0, \sigma)$ Represents the normal distribution (mean equal zero and with σ standard deviation. In the classical GAs the Mutation rate keeps constant. However, when the varies of Mutation rate based on the algorithmic convergence, the method becomes more efficient [54]. Compute the mutation rate is as follow [59]:

$$p_n^d = Pav + \mu \qquad (3.15)$$

Pav Is the average mutation rate and is calculated by using this formula

$$\text{Pav} = \frac{\text{Pma} + \text{Pmi}}{2} \qquad (3.16)$$

and

$$\mu = 3\,\sigma\left(\frac{x}{z}\right) \qquad \mu \in [0, 3\sigma] \qquad (3.17)$$

Where Pmi and Pma are the minimum and maximum values of the mutation rate, x is the value of fitness frequency distribution with M generation, linking coefficient represent by z.

3.2.3.3Two Point Crossover Function

A crossover takes two parents A and B and produces two new children A' and B' .Type of crossover classified to be one point, two point, multi point and uniform. We used two-point crossover for the aim of prediction in our work, which select two random positions, then exchange or alter the bit strings between these two positions as shown in the following figure [60].

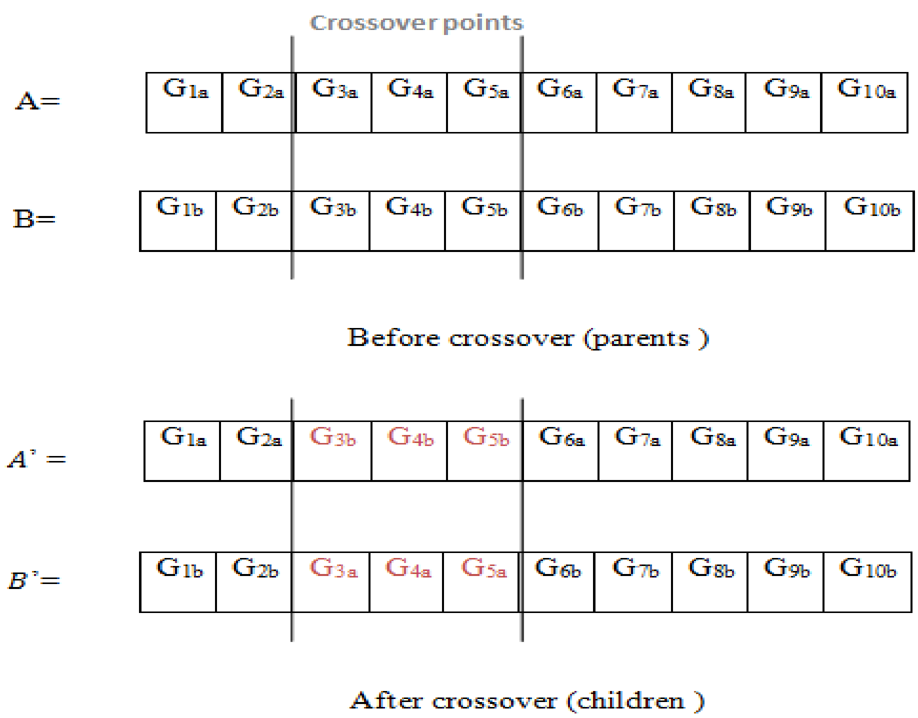

Figure 3. 10 Two-point crossover operation

Model 3: The general procedure that was used MLPNNs-GAs

Load Training Dataset

Start Training Phase

Start Genetic Algorithm to extract the weight:

Step1: Initialize parameters:

- *Enter number of generation number of population.*
- *Preprocessing dataset.*
- *Enter number of the neuron.*

Step2: Apply basic operation of a genetic algorithm:

- *Initialize population*
- *Evaluate fitness function to find the optimal solution*

Repeat

- *Apply uniform selection*
- *Apply Gaussian Mutation function.*
- *Apply Two point Crossover function.*
- *Evaluate fitness until population has converged.*

Step3: Get optimal weights to apply for the MLPNNs.

Compute Mean Square Error.

Start Testing Phase

- *Set Network Weights to measure in training level*
- *Compute forecasted outcome using testing data*
- *Compute Mean Square Error*

Figure 3. 11: MLPNNs-GAs Model

3.3 Summary

In this chapter, we constructed and implement the proposed model and described it in details in addition to other applied models (MLPNNs-LM and RNN-LM). For prediction closed price in the proposed model MLPNNs-GAs we selected best combination of genetic algorithm functions (Uniform Selection function, Gaussian

Mutation function, and Two point Crossover function) that has reduce the cost function (MSE). We also introduced and illustrated the performance function MSE and the training algorithm Levenberg–Marquardt algorithm used by all the applied models.

Chapter Four: Experiments And Results

4. Experiments and Results

In this chapter, the process of preparing collected stock exchange datasets is introduced. Then we will explain and describe accurately how the results were obtained for the three applied models with numerical and graphical results. The network targets are the actual daily time series closing prices for the companies and weekly time series closing prices for Al-Quds index. And, the network output is the forecast period for the next time series. Data have been split into two parts using Cross-validation, the first one with 70% of Input-Target pairs from the total data for training and 30% for the second part (testing). Prediction of future closing price results in all experiments is considered under normal situations away from political situations.

4.1 Stock Exchange Datasets

The first step includes collecting the most suitable and sufficient datasets from the Palestinian stock market. It was obtained from three companies in addition to the Al-Quds index. These companies are respectively (the stock of Palestine Telecommunications Company (Paltel), the stock of Palestine Development and Investment Company (Padico), and the stock of Bank of Palestine (BOP). Since we used different datasets, size of the input data vector, target data vector and output data vector different for each dataset.

The second step is the Pre-processing datasets step which firstly includes solving the problem of missing data for each dataset; we replaced missing data by the average value of the data at the same date of other applied years. Secondly, we do normalization in order to adapt the data to the output range of the logistic activation function. It was scaled in the range 0-1 using the following general formula [49]:

$$d_i = \frac{(d - \min(d))}{(\max(d) - \min(d))} \quad (4.1)$$

Where d is the original value and d_i is the normalized value, $\min(d)$ and $\max(d)$ are the maximum and minimum values of the original dataset.

After Pre-processing datasets, data have been split into two parts using Cross-validation, the first one with 70% of Input-Target pairs from the total data for training and 30% for the second part (testing). Here, the size of input data for the test and training in each Company is different from the others due to the difference in period (how many years and how many days in the year) for each company. as shown information about data are illustrated in details in table [4.1].

Table 4. 1: Datasets description

Company Name	Period	Prediction type(Weekly or Daily)	How many values in all years (input vector)	How many values in the year	Train (70%)	Test (30%)
Padico	2010-2017 (8 years)	Daily	1912 value	239 value	1338	574
Paltel	2011-2017 (7 years)	Daily	1763 value	239 value	1234	529
Bank of Palestine (BOP)	2010-2017 (8 years)	Daily	1928 value	241 value	1350	578
Al-Quds index	2010-2017 (8 years)	Weekly	348 value	48 value	269	115

4.2 Experiment Procedure

In this his thesis, MATLAB (R2014a) was used to analyze the predictive model's design. The process of analysis conducted using r Windows 7 with Core i5-3230M

CPU 2.6GHz, 4GB RAM memory. In MATLAB, which is a numerical computing environment depends on matrices, the model performance error (MSE) was calculated by writing script files to develop our applied models and performance function. The input data in MATLAB regardless of its type (numeric, character, or logical true or false data) is stored as a matrix or n-dimensional array of any size with a minimum of 0-by-0 in size.

MATLAB allows plotting of data and functions, algorithms accomplishment, building user interfaces and communicate in another language with programs. It also provides graphical user interfaces (GUIs) that allow the user to simply manage and design neural networks. Implementing, visualizing, simulating and designing neural networks tools in MATLAB are located in the Neural Network Toolbox [61]. This thesis used built-in activation functions that MATLAB provides; Logistic Sigmoid (tansig), linear (purelin), and Tangent Sigmoid (logsig).

The results were obtained for three applied models in three stages. The first stage includes determining general characteristics of a hybrid model of neural networks and genetic algorithms for four datasets. In this stage, data has been used for Padico to determine the best parameter for GAs (Crossover fraction, Migration fraction, population size, generations, and the best group of functions; Selection Fcn, Crossover Fcn, Mutation Fcn) that gives the best performance. The second stage involves applying RNNs-LM model for each dataset and applying the MLPNNs-LM method in the third stage. A number of neurons in each stage have been changed in each dataset incrementally starting from 5 neurons to 50 neurons with adding 5 neurons at a time.

4.2.1 Padico Company

As we describe before to reduce the time complexity of genetic algorithms we used the dataset for Padico to define the general characteristic of MLPNNs-Gas model and applying it for all datasets, and starting of select the best group which contain the best combination of genetic algorithm functions as illustrated in table [4.2].

Table 4. 2: Compares the results of applying the hybrid models (MLPNNs-GAs) with changing functions of GAs.

Selection Fcn	Crossover Fcn	Mutation Fcn	Mse-Train	Mse-Test
Roulette	Scattered	Adaptive feasible	0.0013	0.0087
Stochastic uniform	Constraint dependent	Uniform	0.0011	0.0080717
Uniform	Two point	Gaussian	0.0011	0.0051
Tournament	Heuristic	Constraint dependent	0.0013	0.0059
Remainder	Two point	Adaptive feasible	0.0013	0.0052

The experiment runs for 20 neurons, migration fraction=.1, crossover fraction =.7, population size=10, and generation =10. As shown from all groups that were applied in MLPNNs-GAs model, minimum MSE values for training represents by both Group2 and Group 3 and Group3 have minimum MSE values for testing. So we consider Group3 to represent the best combination.

Then the second step in this stage included determine the best generation and population size, the experiment runs for migration fraction=.1, crossover fraction =.7, and with the using of the best group that obtained in the previous step (Group3) as shown in table [4.3]. It is obvious from the table [4.3] best or minimum MSE in both train and test when population size= 40 and 70 generations. After that increasing number of population and generations haven't made improvement in the MSE for training and testing.

Table 4. 3: Compares the results of applying the hybrid models (MLPNNs-GAs) with changing population and generations.

Number of generations	Number of Population	MSE-Train	MSE-Test	Number of generation reached
20	10	0.0011	0.0081128	20
40	10	0.001	0.0013	40
40	20	0.0008	0.0013	40
60	30	0.0008	0.001	60
70	40	0.0007	0.0008296	70
80	50	0.0008	0.00083	51
90	50	0.0009	0.0013	68
100	60	0.0007	0.000911	60
120	70	0.0008	0.0009585	82
140	80	0.0007	0.000971	87
160	100	0.0009	0.0014	89

The third step includes determining the best migration fraction, as illustrated in figure [4.1].

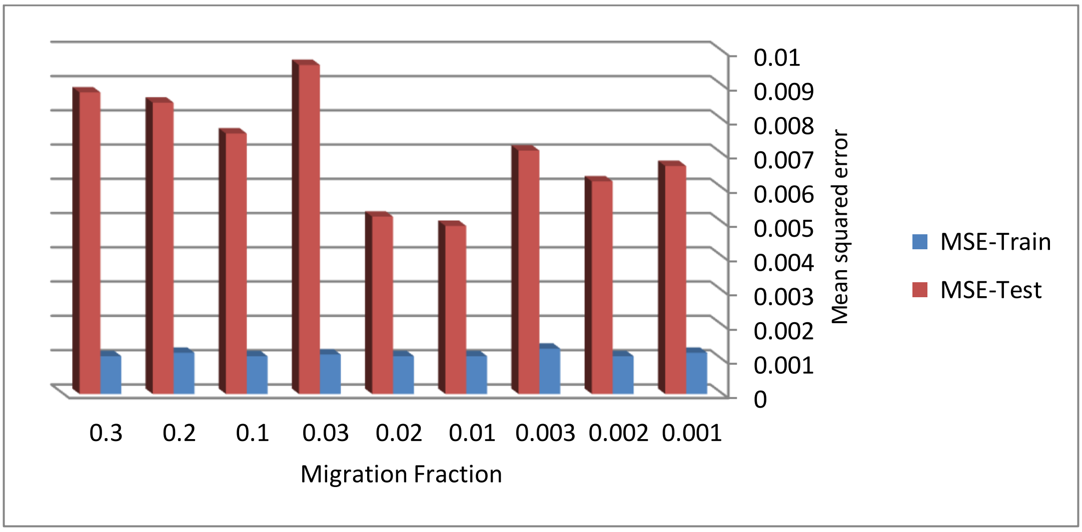

Figure 4. 1: Compares the results of applying the hybrid models (MLPNNs-GAs) with Migration fraction set to (.001-.3).

The example runs for 40 population size, 70 generations, 20 neuron, crossover fraction =0.1, and Group3. Best or minimum MSE in both train and test when migration fraction=.01 (MSE train= 0.0011, MSE test= 0.0049). We noticed a fluctuation in the MSE when changing Migration fraction.

The fourth step includes determining the best crossover fraction as illustrate in figure [4.2].

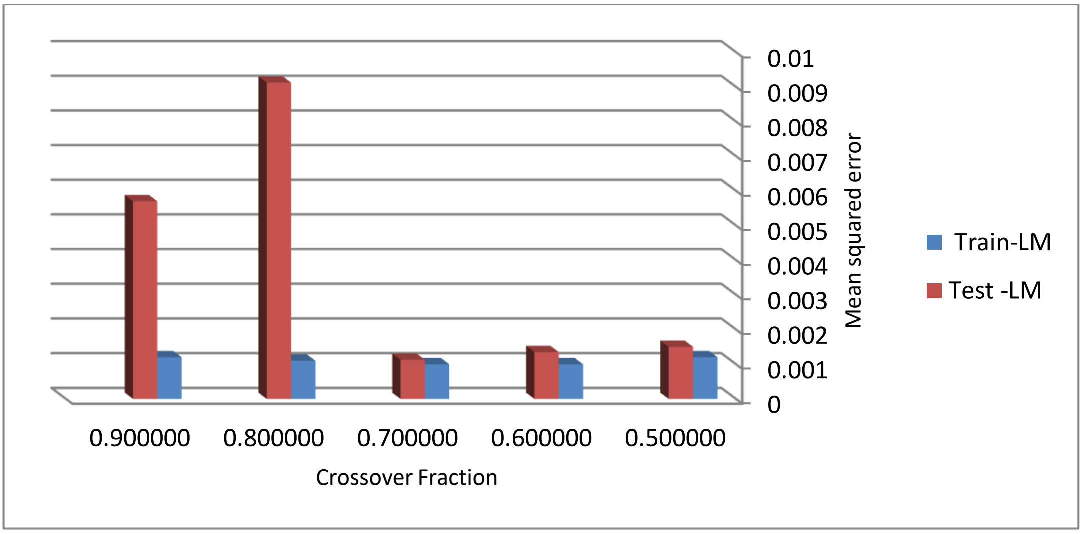

Figure 4. 2: Compares the results of applying the hybrid models (MLPNNs-GAs) with crossover fraction set to (.001-.3).

The example runs for 40 population size, 70 generations, 20 neurons, Migration fraction=.01, and Group3. Best MSE in both train and test when crossover fraction =.7 (MSE train= 0.001, MSE test= 0.00113). After .7 crossover fraction MSE for testing and training can't be improved.

After that, we used population size 40, 70 generations, migration fraction=.01, crossover fraction=.7 and Group3 that have minimum MSE for Padico data as general characteristics of the hybrid model (MLPNNs-GAs) for all datasets, in addition to change the number of neuron from (5- 50) neurons with adding 5 neurons at a time, as shown in table [4.4]. And select the best number of neuron that has minimum MSE for each dataset to use it for prediction next year.

Table 4. 4: General characteristics of the hybrid model (MLPNNs-GAs) for four datasets.

Company Name	Al-Quds Index	Paltel	Padico	Bank of Palestine

Number of generations	70	70	70	70
Number of Population	40	40	40	40
number of neuron	50	50	45	40
Measure of performance	MSE	MSE	MSE	MSE
Selection Fcn	Uniform	Uniform	Uniform	Uniform
Mutation Fcn	Gaussian	Gaussian	Gaussian	Gaussian
Crossover Fcn	Two point	Two point	Two point	Two point
Migration Fraction	0.01	0.01	0.01	0.01
Crossover Fraction	0.7	0.7	0.7	0.7

Results of MSE from the hybrid model (MLPNNs-GAs) are illustrated in table [4.5].

Table 4. 5: Results from the hybrid model (MLPNNs-GAs).

Value	Company name	Mse-Train	Mse- Test	Number of generation genetic reached
1912	Padico	0.000506	0.00064	68
384	Al-Quds Index	0.0010	.0011	52
1763	Paltel	.0005	0.0009	63
1928	Bank of Palestine	0.0008	0.002	54

As shown in table [4.5] for each applied datasets number of generation genetic reached is less than determined generation number (70) which means genetic reached the best solution with no need to increase generation number.

To predict the daily closed price for the next year (2018), we calculated the average mean values of 8 years from (2010-2017).

4.2.1.1 MLPNNs-GAs

In this experiment, we apply the first model (MLPNNs-GAs) on the data set of Padico Company. Compares the results of applying the MLPNNs-GAs on Padico with changing number of neurons (5-50) are illustrated in table [4.6]. As shown in the below table a good improvement for the testing error have been noticed when increasing number of neurons and at 45 neurons we have the minimum MSE for both training and testing (MSE train= 0.0006, MSE test= 0.0006), then after 45 neurons error for testing become worst. Figure [4.3] illustrates real data and outputs of the training phase for Padico Company using MLPNNs-GAs model.

Table 4. 6: Results of Padico MSE for MLPNNs-GAs model.

Number of Neurons	Mse-Train	Mse-Test
5	0.003	0.0081
10	0.0017	0.0079
15	0.0014	0.0079
20	0.0011	0.0011
25	0.0009	0.001
30	0.0009	0.00094
35	0.0008	. 0009
40	0.0006	0.00063
45	0.0006	0.0006
50	0.0006	0.00076

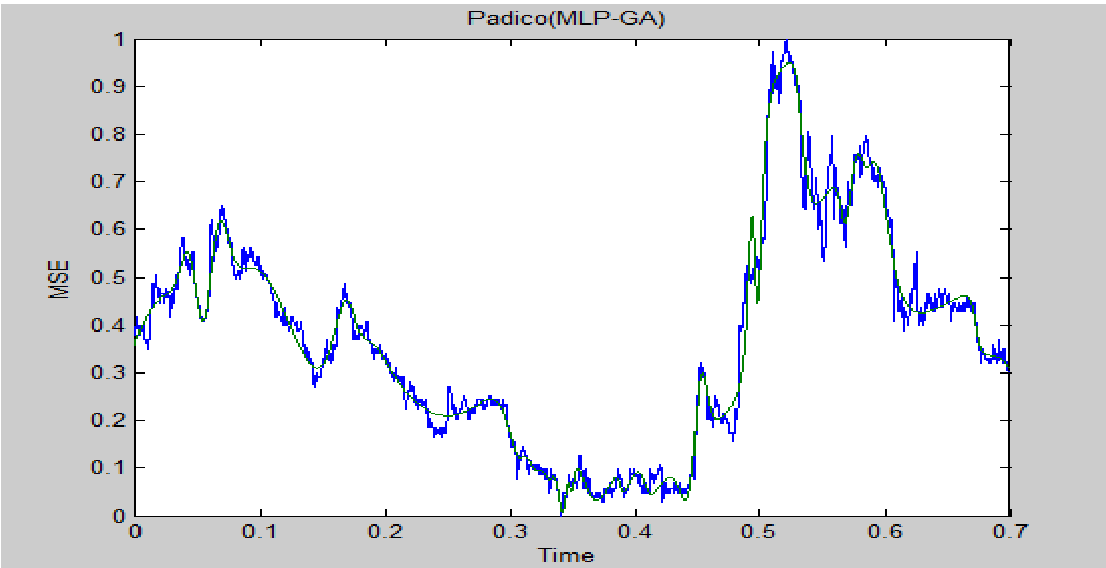

Figure 4. 3: Real and predicted Padico Company values using (MLPNNs-GAs) model.

As illustrated in figure [4.3] the real and predicted values of Padico Company are nearly close to each other. This indicates that the used method MLPNNs-Gas is an effective method that can be used in forecasting the stock pricing. Thus, using this method in prediction will give high certainty for the investors to advance their choices in stock portfolio investment. The prediction of Padico stock prices for the next year of 2018 is illustrated in figure [4.4] which shows the stability of the prediction of Padico stock prices for the coming year. This indicates that we will have stable prices around the mean stock price of Padico, which equals (mean=0.378) for the next year according to the behavior of Padico stock prices for the past eight years, away from any unstable political situation that might arise in the near future.

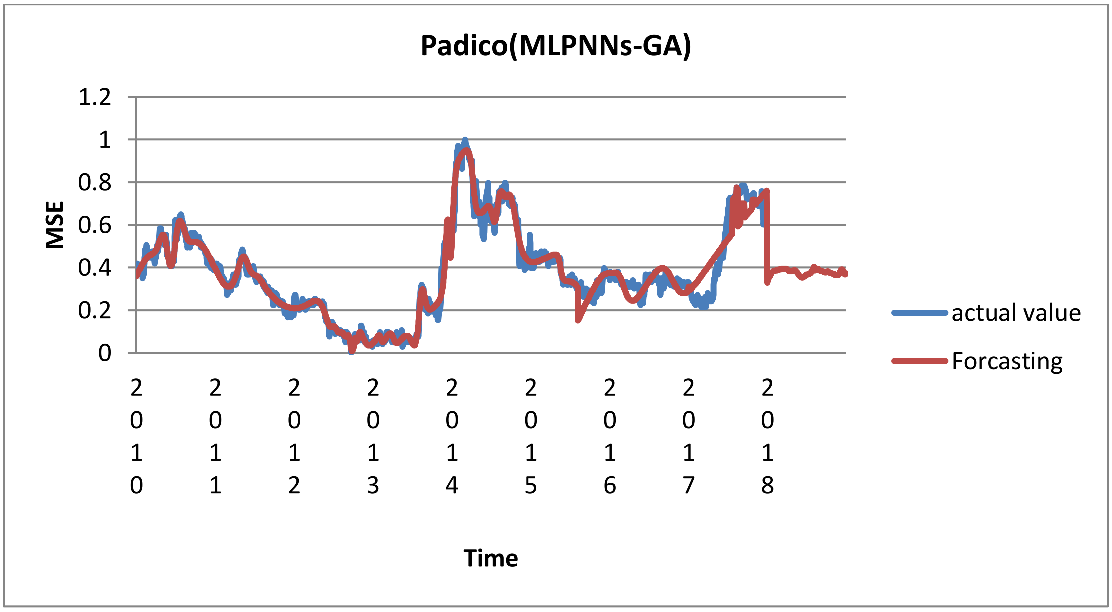

Figure 4. 4: Real and predicted Padico Company values for the next year using (MLPNNs GAs) model -.

4.2.1.2MLPNNs-LM

In this experiment example, we use the MLPNNs- LM applied on the data set of the Padico Company. As illustrated in table [4.7] we show that increasing number of neurons until 25 neurons make a slight improvement in the testing error, while increasing number of neurons until 35 neurons make a slight improvement in the training error and with 50 neurons, we have obtained the minimum MSE(MSE train= 0.00068, MSE test= 0.00079). Figure [4.5] illustrated real data and outputs of the training phase for Padico Company using the MLPNNs -LM model.

Table 4. 7: Results of Padico MSE for MLPNN-LM model

Number of Neurons	Mse-Train	Mse-Test
5	0.0059	0.006
10	0.0019	0.0021
15	0.0017	0.0018
20	0.0013	0.0015
25	0.001	0.001
30	0.00096	0.0012
35	0.00074	0.001
40	0.00081	0.000866
45	0.00072	0.00096
50	0.00068	0.00079

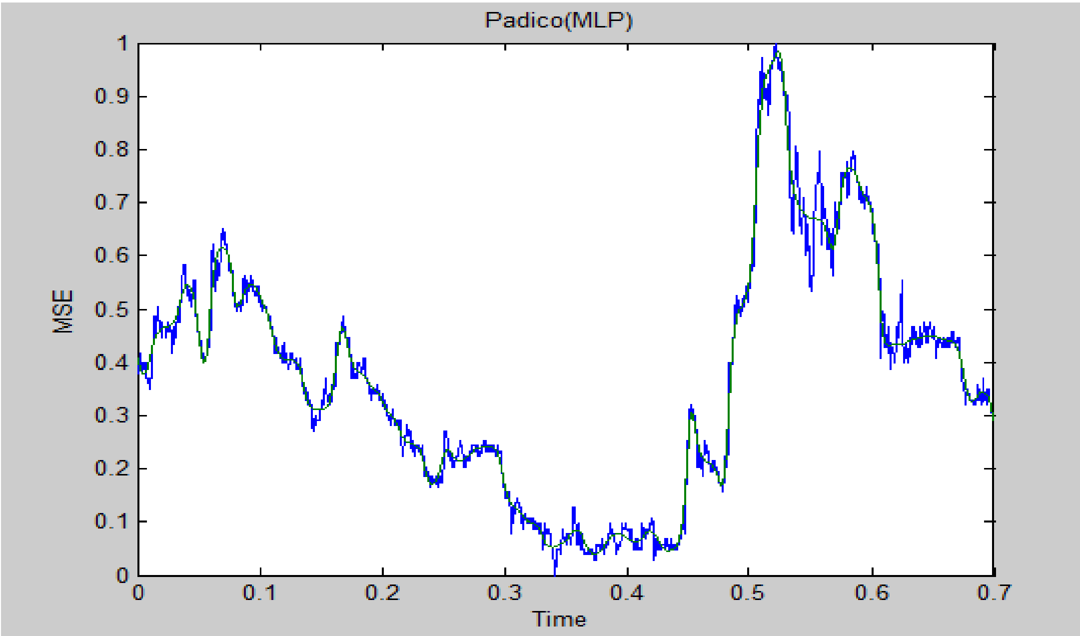

Figure 4. 5: Real and predicted Padico Company values using (MLPNNs-LM) model.

As shown in the figure above the real and predicted values of Padico Company are corresponding, which means that this model is appropriate for the prediction of the stock pricing. The prediction of the next year for Padico Company using the MLPNNs -LM model is illustrated in figure [4.6], which indicates that Padico stock prices for 2018 will have stable prices around the mean stock price. The obtained results are close to the results obtained from MLPNNs-GA, which are convergent with the real and predicted values of Padico Company and the prediction of the coming year for Padico Company.

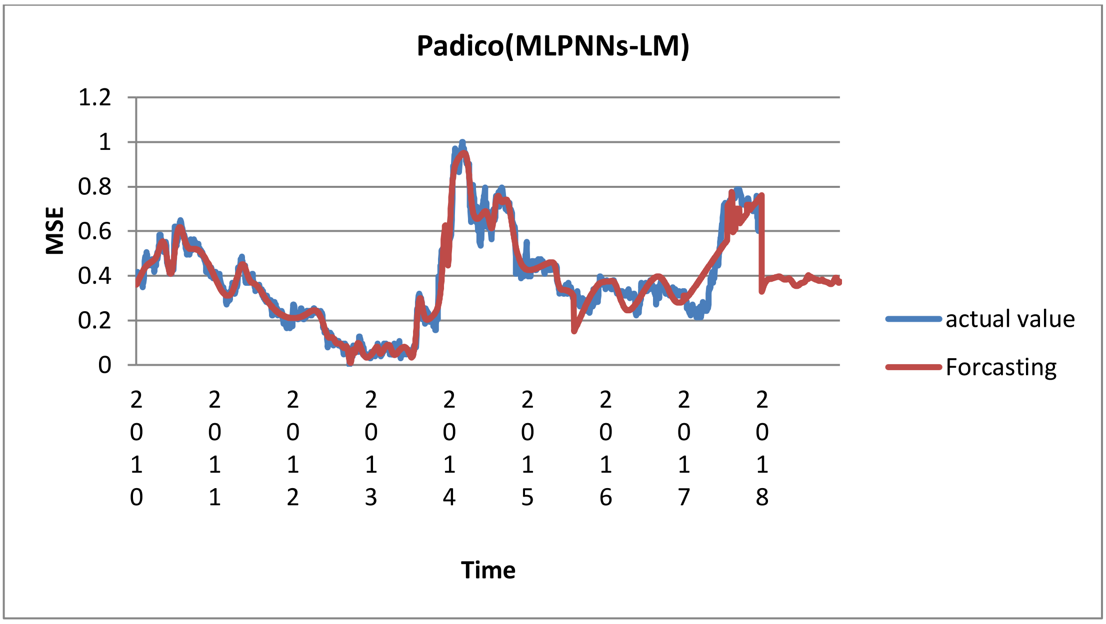

Figure 4. 6: Real and predicted Padico Company values for the next year using (MLPNNs-LM) model.

4.2.1.3 RNNs-LM

The last experiment example on Padico Company includes applying the RNN-LM model in this dataset of company. As we show in table 4.8 increment number of neurons make a variation in the MSE, it doesn't make slightly improvement. And the best error for training and testing obtained with 30 neurons (MSE train= 0.0013, MSE test= 0.0014). Figures [4.7] illustrated real data and outputs of the training phase for Padico Company using RNNs-LM model. And a diagram for prediction next year using RNNs-LM model is illustrated in figure [4.8].

Table 4. 8: Results of Padico MSE for RNN-LM model

Number of Neurons	Mse-Train	Mse-Test
5	0.00404	0.0046
10	0.0022	0.0024
15	0.0036	0.004

20	0.002	0.0023
25	0.0035	0.00369
30	0.0013	0.0014
35	0.0036	0.0037
40	0.0036	0.0041
45	0.0034	0.004
50	0.00365	0.0038

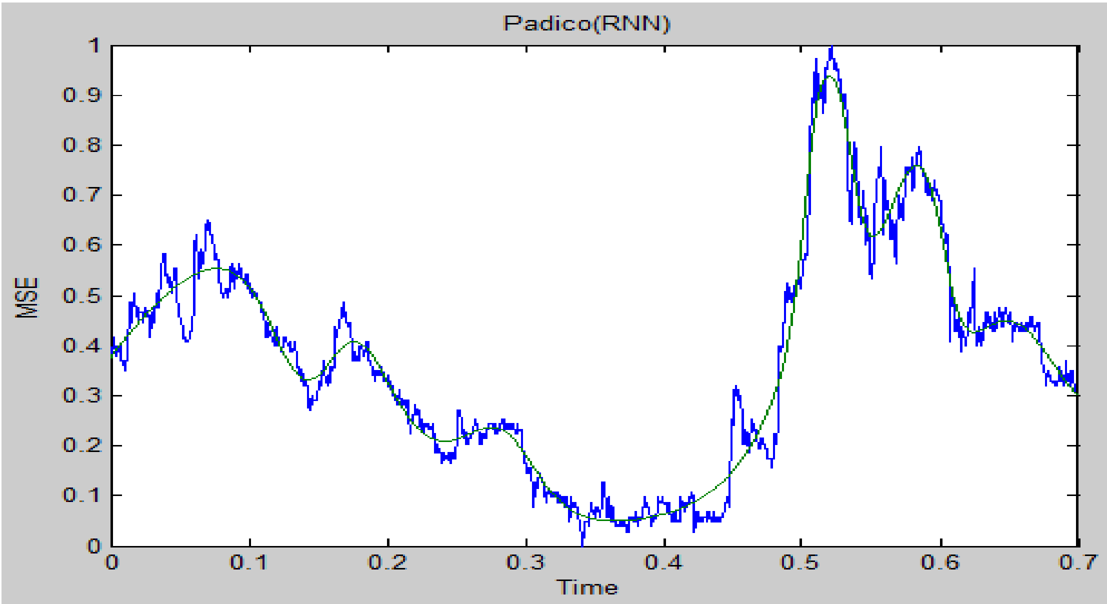

Figure 4. 7: Real and predicted Padico Index values using (RNN) model.

As shown in the figure above [4.7] we haven't received good convergence in the actual and predicted values using this model as the other models applied before (MLPNNs-GAs and MLPNNs-LM). The prediction of the next year for Padico Company using the MLPNNs -LM model is illustrated in Figures [4.8], which, as the previous applied models, indicate that Padico stock prices for 2018 will have stable prices around the mean stock price that equals 378.

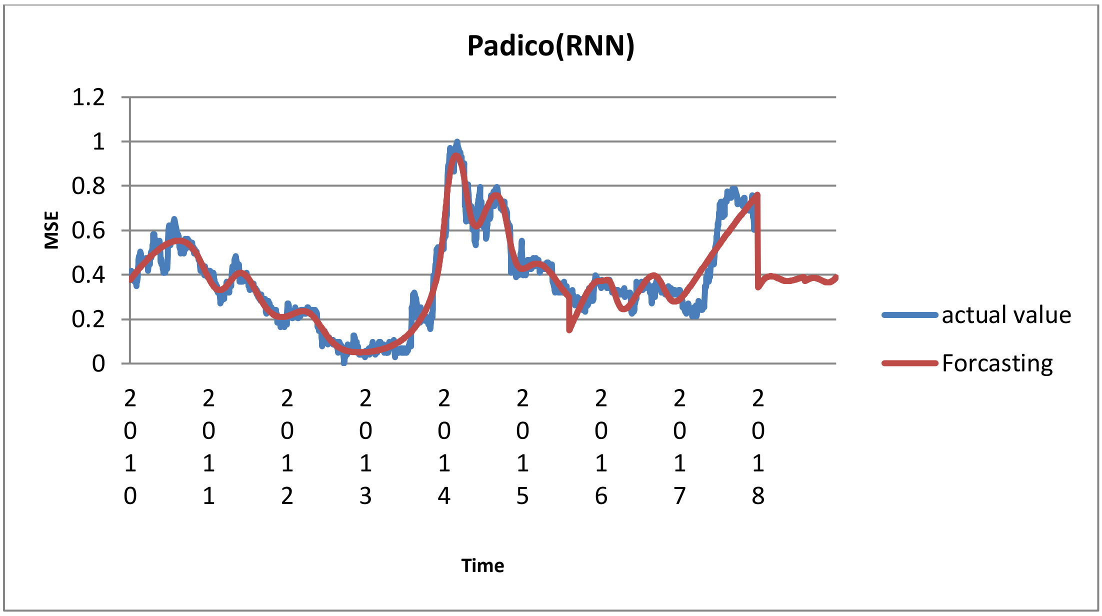

Figure 4. 8: Real and predicted Padico Company values for the next year using (RNNs-LM) model.

As illustrated in figures (4.4, 4.6 and 4.8) for Padico Company using the three methods MLPNNs-GAs, MLPNNs-LM and RNNs-LM, all of these methods give nearly the same perdition for the next year of 2018. The forecasting results indicate that we will have stability of Padico stock prices for the coming year around the mean stock price according to the behavior of Padico stock prices for the past eight years. As the three used methods give nearly the same prediction, then the investors can take these results in their consideration when they make their investment choices.

4.2.2Paltel

We calculated the average mean values of seven years from (2011-2017) to predict Patel company daily closed price for the next year (2018).

4.2.2.1MLPNNs-GAs

MLPNNs-Gas model was applied to Paltel Company. Table 4.9 shows that increment number of neurons from 5 neurons until 35 neurons give good enhancement in the testing error. And the best testing error at 35 neuron (MSE train= 0.0007, MSE test= 0.001) then MSE becomes worst in testing error. The actual data and outputs of the training phase for the Paltel Company using MLPNNs-GAs model are shown in figure [4.9].

Table 4. 9: Results of Paltel company MSE for MLPNNs-Gas model

Number of Neurons	Mse-Train	Mse-Test
5	0.0032	0.01461
10	0.0017	0.0275
15	0.00012	0.0273
20	0.001	0.0263
25	0.0007	0.0246
30	0.0006	0.00234
35	0.0007	0.001
40	0.0006	0.0035
45	0.0006	0.0013
50	0.0006	0.0011

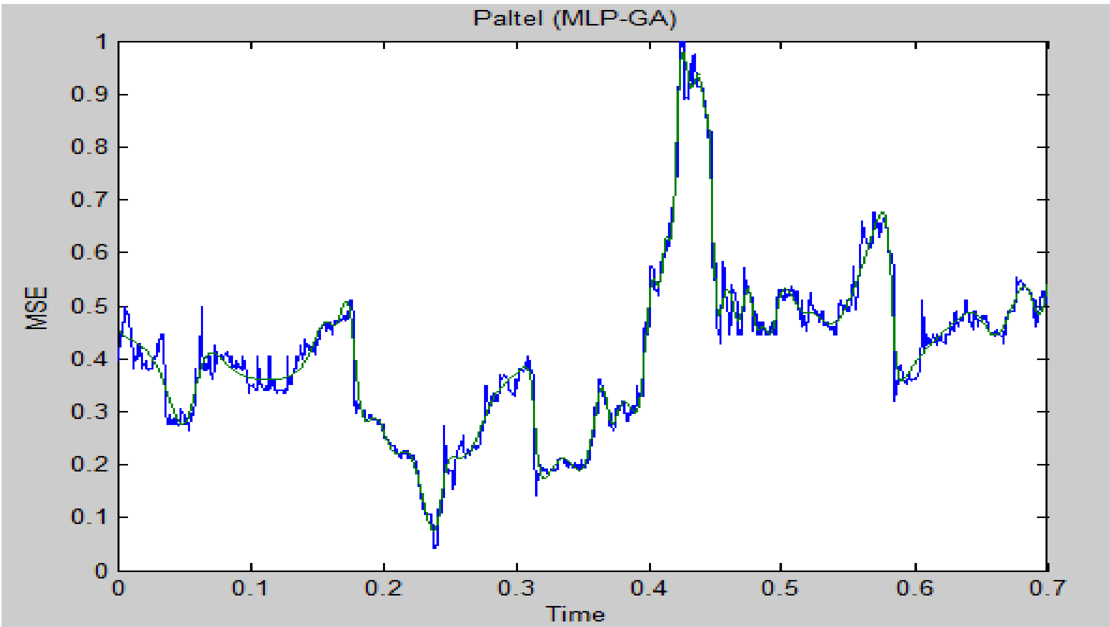

Figure 4. 9: Real and predicted Paltel Prices values using (MLPNNs-GA) model.

From the figure above [4.9], it is clear that the predicted data nearly closes to the actual data. Figure [4.10] clarifies the prediction of the next year (2018) for Paltel

Company stock prices. This indicates that stock prices in the next year will increase, then decrease at the beginning of the second half of 2018 to converge stable prices that will be less than the mean of Paltel stock prices for the past seven years, which equals 0.369.

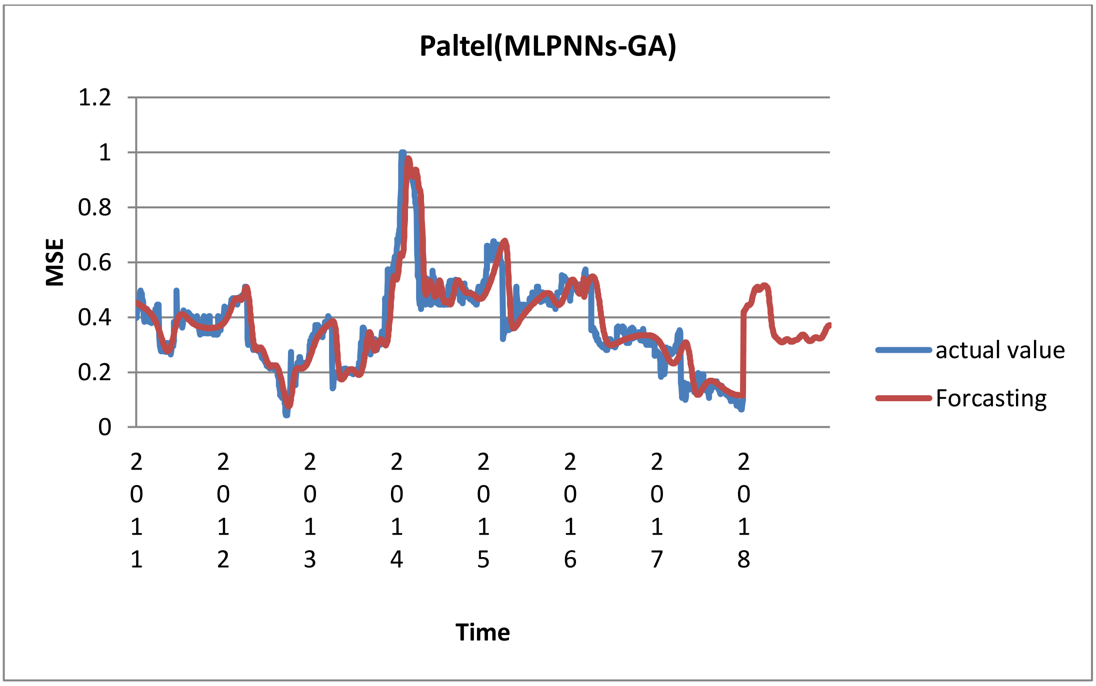

Figure 4. 10: Real and predicted Paltel Company values for the next year using (MLPNNs-GAs) model.

4.2.2.2MLPNNs-LM

The second experiment was applying MLPNNs-LM model to Paltel Company. Table4.10 shows that the increment number of neuron gives excellent enhancement in MSE. The best error for training and testing obtained with 50 neurons (MSE train= 0.00066, MSE test=0.00067). Actual data and outputs of the training phase for the Paltel Company using the MLPNNs -LM model are presented in figure [4.11].

Table 4. 10: Results of Paltel company MSE for MLPNNs-LM model

Number of Neurons	Mse-Test	Mse-Train
5	0.0037	0.0044
10	0.0028	0.0033
15	0.0013	0.0016
20	0.0011	0.0012
25	0.0011	0.0012
30	0.001	0.0012
35	0.00095	0.0011
40	0.00071	0.001
45	0.00069	0.00091
50	0.00066	0.00067

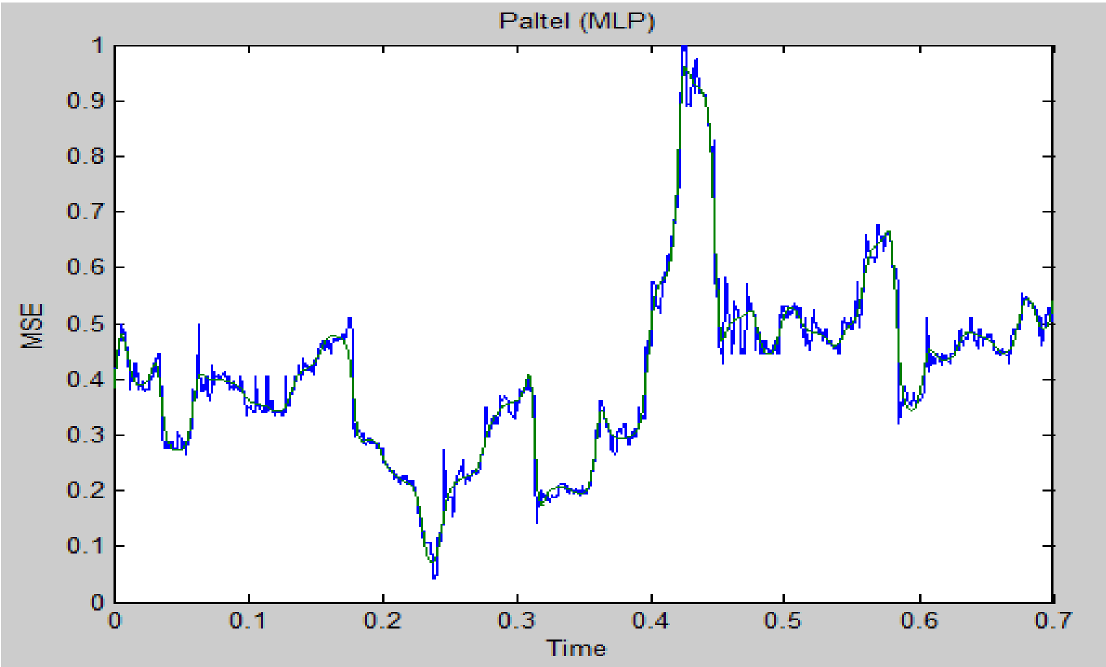

Figure 4. 11: Real and predicted Paltel Company values using (MLPNNs-LM) model.

Figure 4.11 shows that the real and predicted values of Paltel Company are close to each other same as the convergence obtained from model applied before. The prediction of the next year for Paltel Company using the MLPNNs -LM model is illustrated in figure [4.12], which also indicates Paltel stock prices for 2018 will have an increase in prices then a decrease at the end of the year.

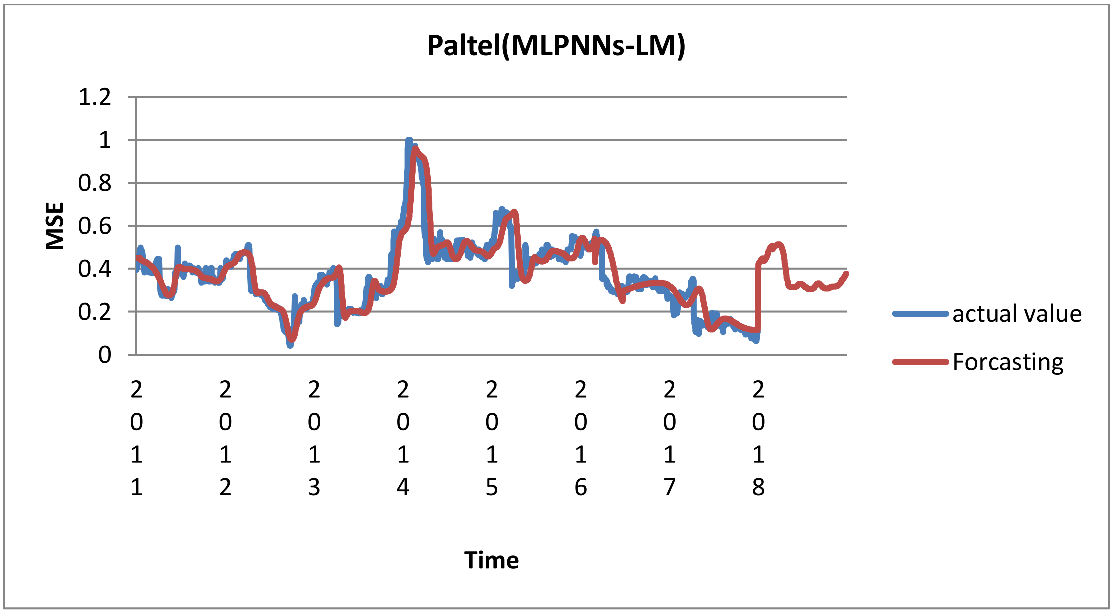

Figure 4. 12: Real and predicted Paltel Company values for the next year using (MLPNNs-LM) model.

4.2.2.3RNNs-LM

This experiment conducted to apply RNNs-LM model on Paltel company .Table 4.11 illustrate that increase number of neurons gives variation in enhancement performance function and best performance for testing and train have been obtaining at 50 neurons (MSE train= 0.0023, MSE test=0.0024). Figure [4.13] presents real data and outputs of the training phase for the Paltel company using RNNs-LM model.

Table 4. 11: Results of Paltel company MSE for RNNs-LM model

Number of Neurons	Mse-Train	Mse-Test
5	0.0039	0.0041
10	0.0046	0.005
15	0.003	0.003
20	0.0023	0.0027
25	0.0024	0.0029
30	0.0046	0.0048
35	0.0046	0.0041
40	0.0038	0.0039
45	0.0026	0.0034
50	0.0023	0.0024

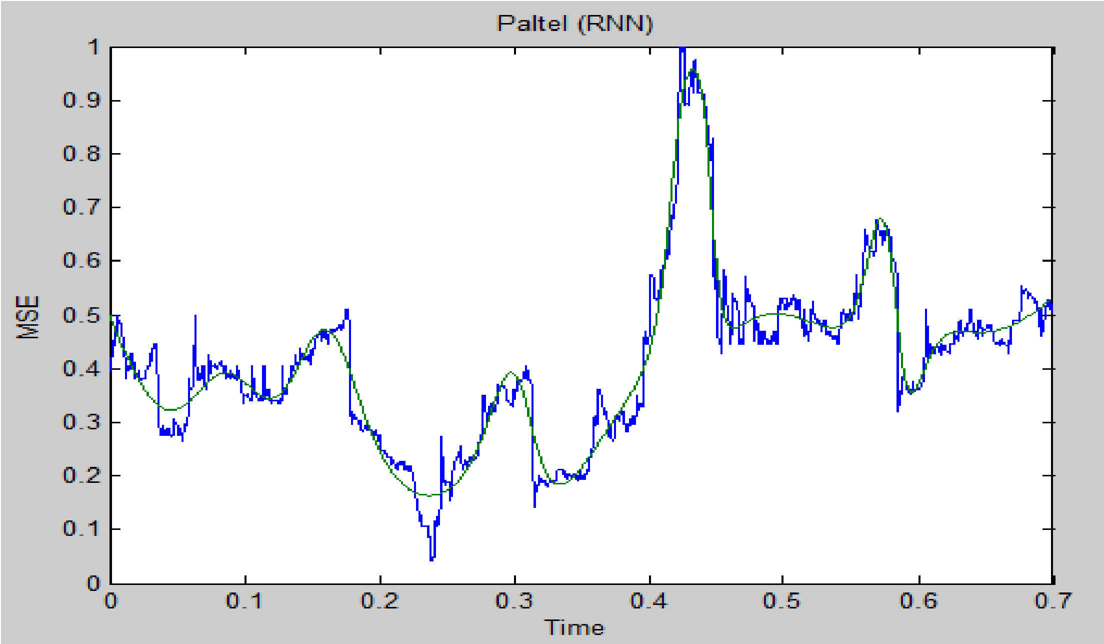

Figure 4. 13: Real and predicted Paltel Company values using (RNNs-LM) model.

It's clear from the above figure [4.13] the values of the actual and predicted Paltel Company are close to each other, but are not as accurate as MLPNNs-Gas and MLPNNs-LM models. The prediction of the next year 2018 is described in figure [4.14], which indicates Paltel stock prices for 2018 will have an increase in prices then a decrease at the end of the year.

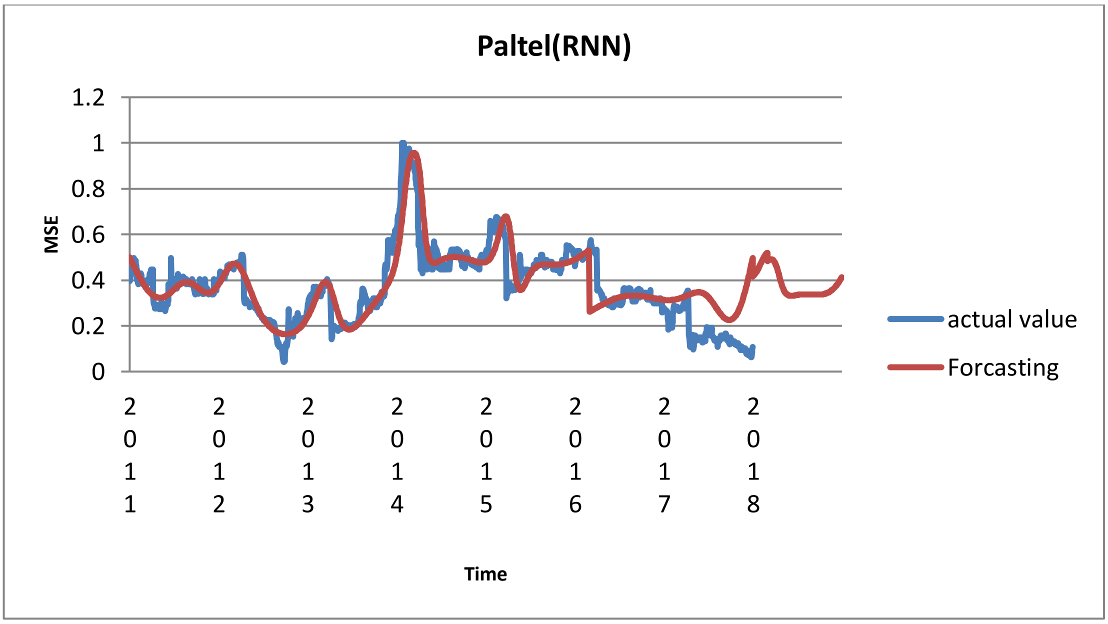

Figure 4. 14: Real and predicted Paltel Company values for the next year using (RNNs-LM) model.

The prediction of the next year using the three methods as depicted in Figures [4.10], [4.12] and [4.14] give the same prediction behavior with the stable political situation, which indicates that Paltel Company stock prices will increase and then decrease at the beginning of the second half for the upcoming predicted year of 2018 to reach the stable prices that will be less than the mean of Paltel stock prices for the past seven years, which equals 0.369.

4.2.3 Bank of Palestine

We calculated the average mean values of eight years from (2010-2017) for Bank of Palestine to predict the daily closed price for the next year (2018).

4.2.3.1MLPNNs-GAs

In this experiment, we applied the first model (MLPNNs-GAs) to the data set of the Bank of Palestine Company. As shown in table 4.12 increase the number of neurons until 40 neurons make an excellent improvement in the performance of MSE. After that testing error becomes worst. The best performance for testing and train have been obtaining at 40 neurons (MSE train= 0.0009, MSE test=0.0021). Actual data and outputs of the training phase for Bank of Palestine using MLPNNs-GAs model are shown in Figure [4.15].

Table 4. 12: Results of Bank of Palestine company MSE for MLPNNs-GAs model.

Number of Neurons	Mse-Train	Mse-Test
5	0.0063	0.006
10	0.003	.0046
15	0.0019	.0042
20	0.0013	0.0027
25	0.0012	0.0025
30	.0011.00	0.0023
35	0.001	0.0022
40	0.0009	0.0021
45	0.0009	0.0022
50	0.0009	0.0022

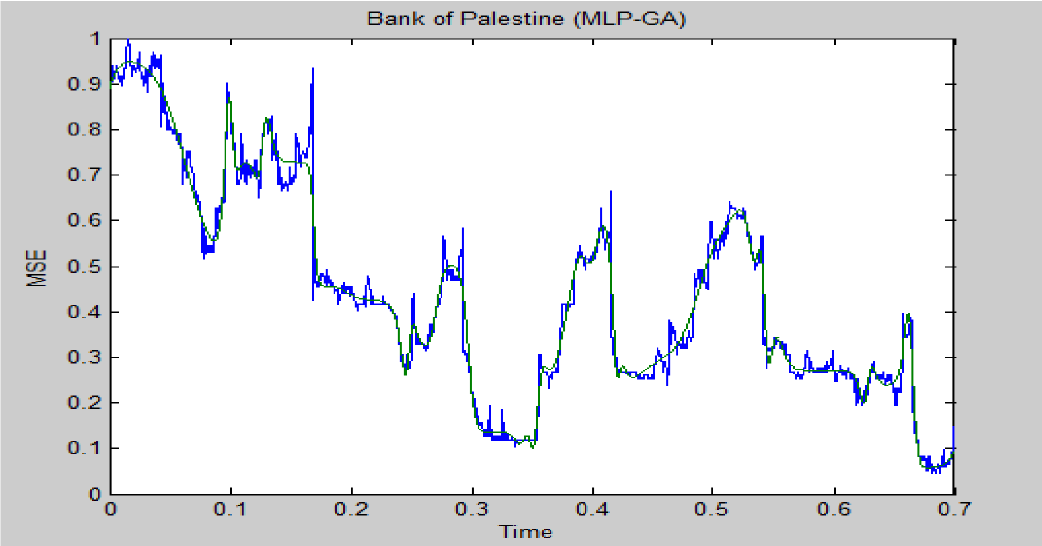

Figure 4. 15: Real and predicted Bank of Palestine Company values using (MLPNNs-GAs) model.

Figure 4.15 illustrates that the predicted Bank of Palestine Company stock prices are nearly close to the actual stock prices. The prediction of the next year 2018 is described clarified in figure [4.16], which indicates that Bank of Palestine stock prices will increase at the beginning of the upcoming year and converge the stable prices that will be greater than the mean of Bank of Palestine stock prices for the past eight years that equals 0.345, then decrease in its stock prices and go up again at the end of the year.

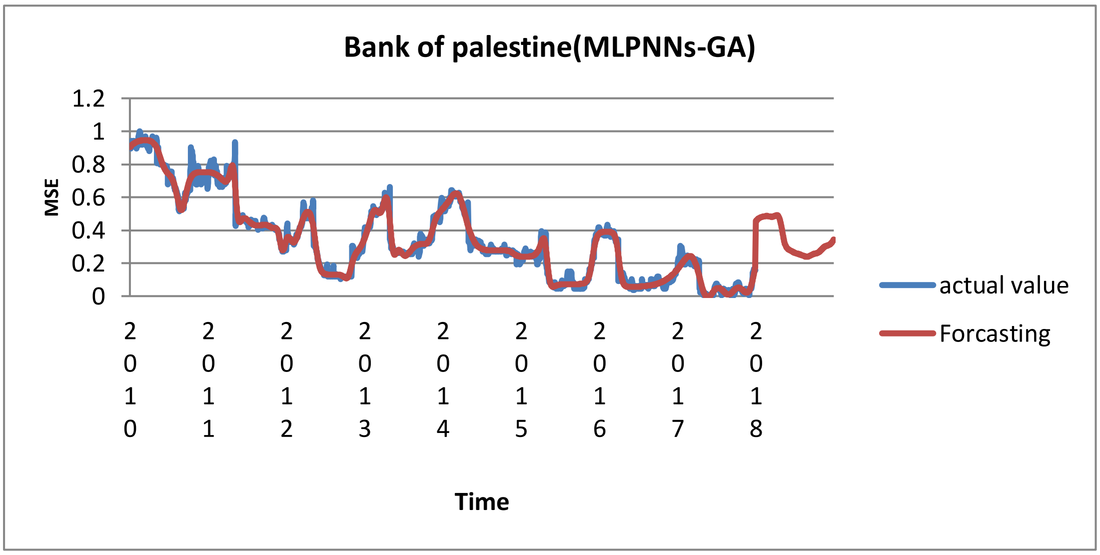

Figure 4. 16: Real and predicted Bank of Palestine Company values for the next year using (MLPNNs-GAs) model.

4.2.3.2MLPNNs-LM

MLPNNs-LM model in the second experiment is applied to the Bank of Palestine Company. Table4.13 shows that in the MLPNNs–LM increment number of neurons make a variation in the MSE. And the best error for training and testing obtained with 45 neurons (MSE train= 0.001, MSE test=0.0023). Actual data and outputs of the training phase for the Bank of Palestine Company are presented in figure [4.17].

Table 4. 13: Results of Bank of Palestine company MSE for MLPNNs-LM model

Number of Neurons	Mse-Train	Mse-Test
5	0.0129	0.013
10	0.0046	0.0049
15	0.0029	0.0035
20	0.0011	0.0024
25	0.0012	0.00265
30	0.0011	0.0025
35	0.001	0.00241
40	0.0011	0.0025
45	0.001	0.0023
50	0.00092	0.0023

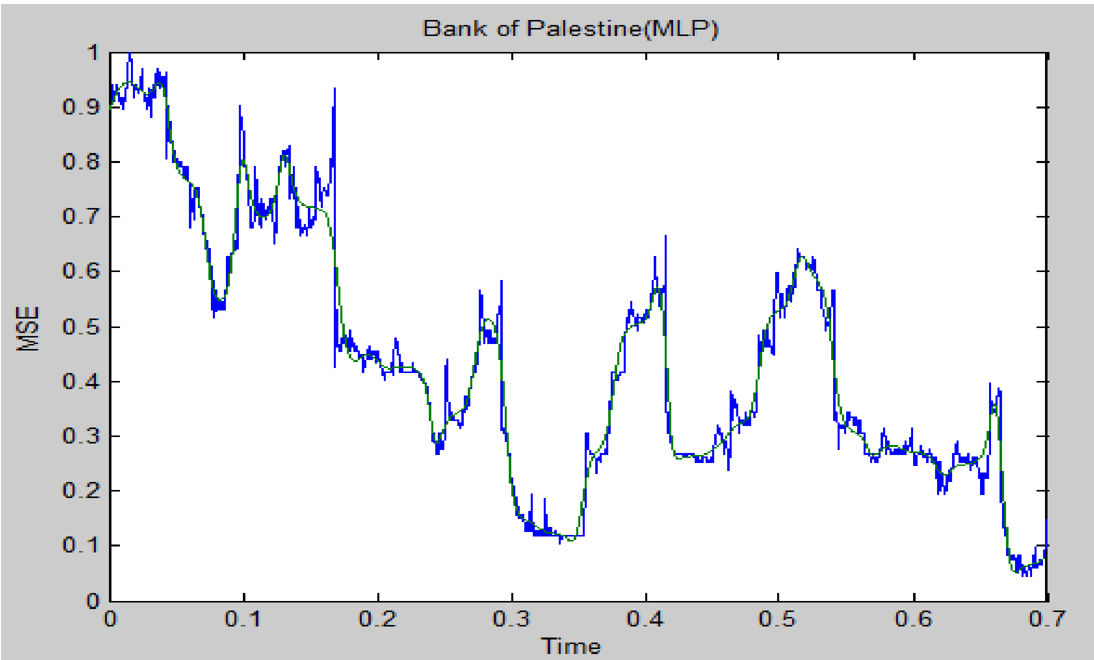

Figure 4. 17: Real and predicted Bank of Palestine Company values using (MLPNNs-LM) model.

As we notice in figure 4.17, the results are closer to the results obtained from the previous applied model (MLPNNs-GAs), in which there is convergence between the real and predicted values of Bank of Palestine Company. The prediction of the next year is represented in figure [4.18], which also has the same behavior of MLPNNs-GAs model for the prediction of Bank of Palestine stock prices.

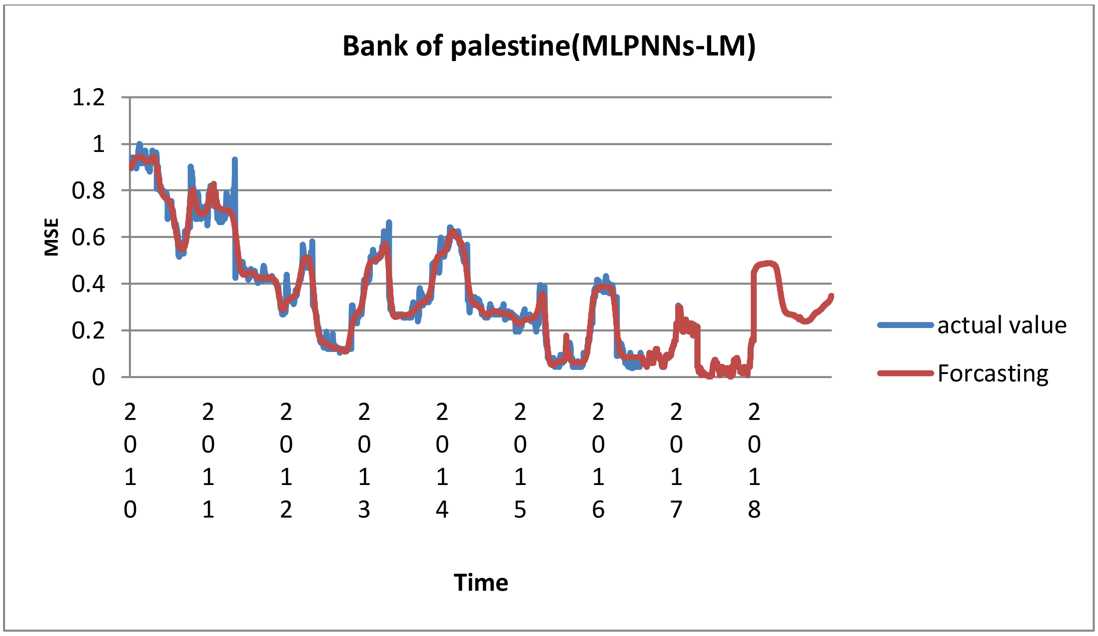

Figure 4. 18: Real and predicted Bank of Palestine Company values for the next year using (MLPNNs-LM) model.

4.2.3.3 RNNs-LM

In this experiment example we used the RNNs-LM Model applied to the data set of the Bank of Palestine Company. As shown in table 4.14 behavior of MSE performances have variation when increase neuron numbers. And the best error for training and testing obtained with 50 neurons (MSE train= 0.00106, MSE test=0.001066). Real data and outputs of the training phase for the Bank of Palestine Company using RNNs-LM model are depicted in figure [4.19].

Table 4. 14: Results of Bank of Palestine company MSE for RNNs-LM Model

Number of Neurons	Mse-Train	Mse-Test
5	0.011	0.0129
10	0.003	0.00322
15	0.002	0.0021
20	0.011	0.01
25	0.0112	0.0133
30	0.00199	0.0022
35	0.006	0.00617
40	0.00307	0.003071
45	0.01232	0.01295
50	0.00106	0.001066

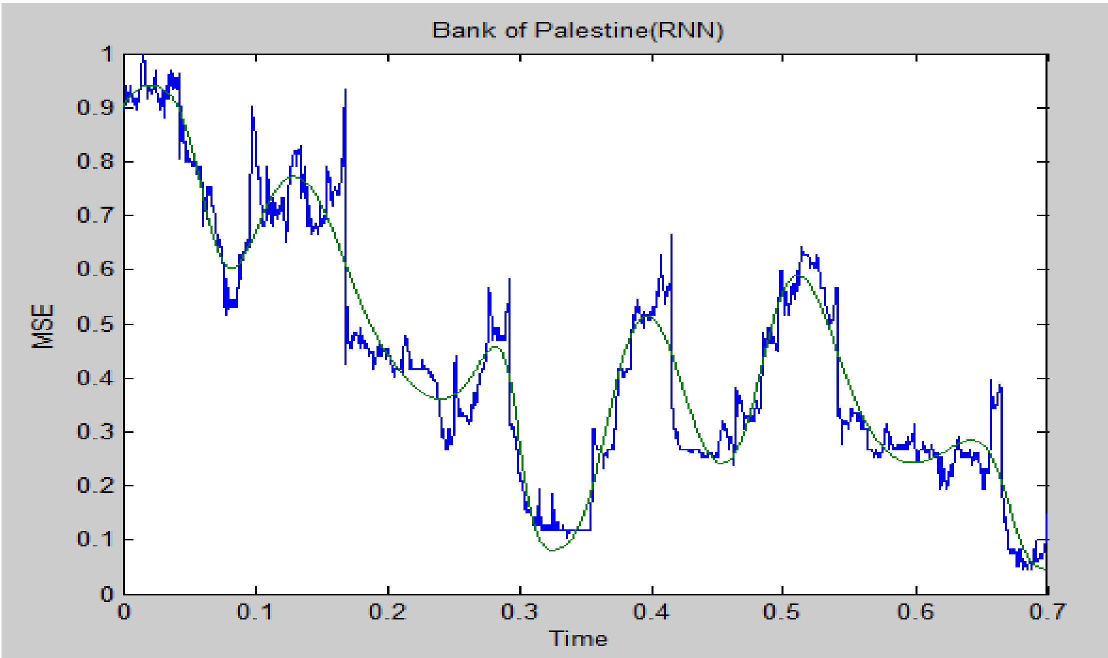

Figure 4. 19: Real and predicted Bank of Palestine Company values using (RNNs-LM) model.

It's clear that there is a slight convergence in the real and predicted values of Bank of Palestine, and the prediction of the next year (2018) using RNNs-LM model is depicted in figure [4.20] which indicates an increase in the stock prices in the first half of 2018, then a decrease in its stock prices and going up again at the end of the year.

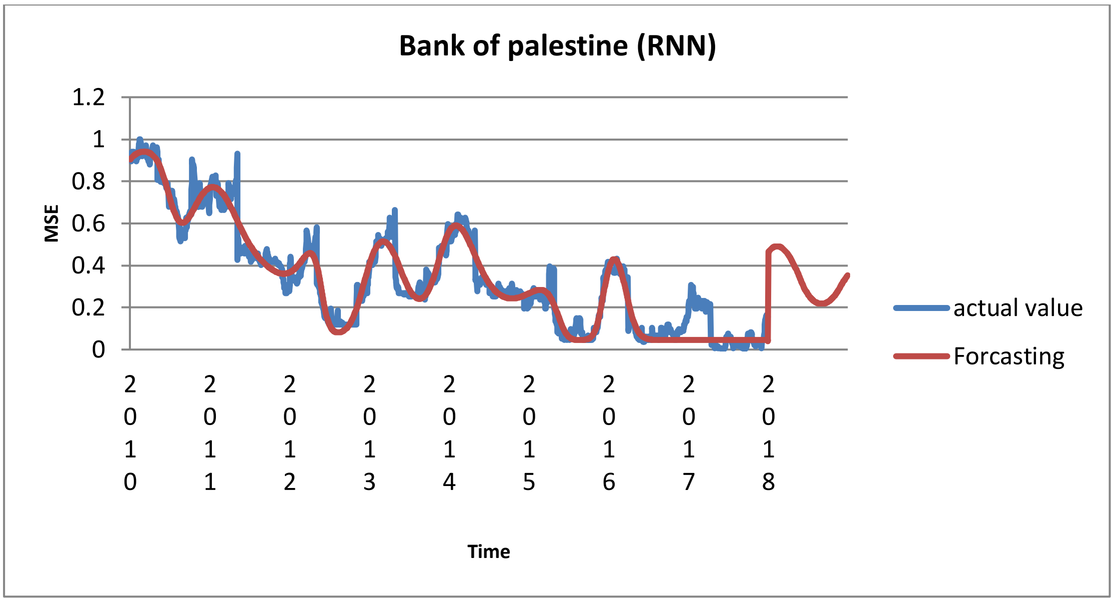

Figure 4. 20: Real and predicted Bank of Palestine Company values for the next year using (RNNs-LM) model.

As depicted in Figures (4.16, 4.18 and 4.20) for Bank of Palestine Company using the three methods MLPNNs-GAs, MLPNNs-LM and RNNs-LM, all of these methods give nearly the same perdition for the next year of 2018. The forecast results indicate that we will have an increase in its stock prices at the beginning of upcoming year to converge stable prices that will be greater than the mean of Bank of Palestine stock prices for the past eight years, and then the stock prices will decrease and go up again at the end of the year. Convergences of prediction using these methods make investors take these results into consideration when they make investment decisions.

4.2.4 Al-Quds Index

Al-Quds Index and its predictions are applicable to the whole Palestine Exchange. This, in turn, helps the investors make their investment options. To predict Al-Quds Index weekly closed price for the next year (2018), we will calculate the average mean values of eight years duration from (2010-2017).

4.2.4.1MLPNNs-GAs

This experiment includes applying the first model (MLPNNs-GAs) to Al-Quds Index. As shown in the table below 4.15 increasing the number of neurons gives enhancement in the performance function. And best performance (minimum testing and training MSE) at 50 neurons. (MSE train= 0.0011, MSE test=0.0021). Figure [4.21] illustrates actual data and outputs of the training phase for Al-Quds-Index using MLPNNs-GAs model.

Table 4. 15: Results of AlQuds Index MSE for MLPNNs-GAs model.

Number of Neurons	Mse-Train	Mse-Test
5	0.0041	0.0171
10	0.0021	0.0027
15	0.0018	0.0026
20	0.0018	0.00257
25	0.0015	0.00251
30	0.0014	0.232
35	0.0013	0.00231
40	0.0013	0.0023
45	0.0011	0.00224
50	0.0011	0.0021

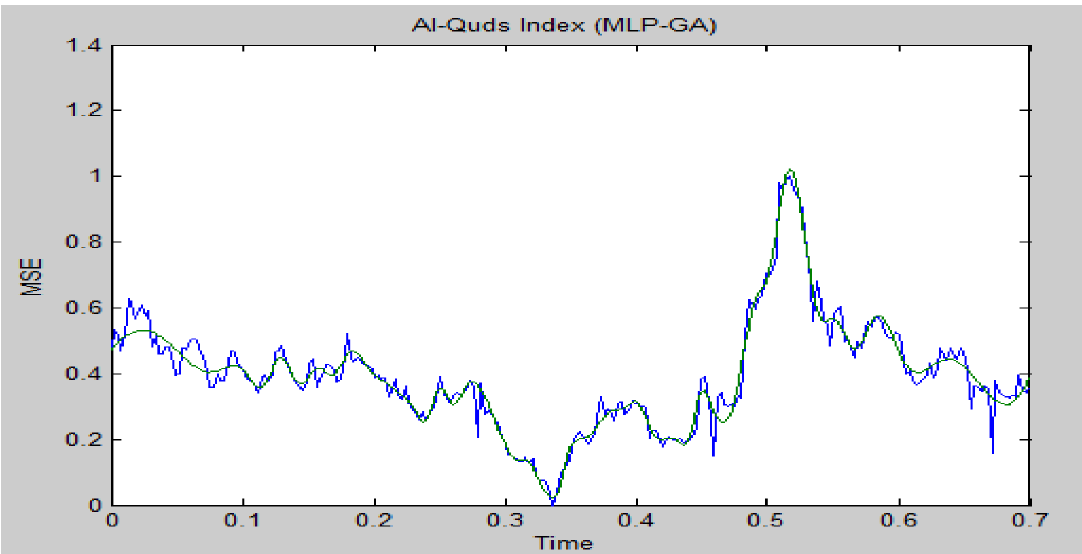

Figure 4. 21: Real and predicted Al-Quds- Index values using (MLPNNs-GAs) model.

In figure [4.21], it is clear that the actual and predicted Al-Quds- Index values are close to each other, and this proves that MLPNNs-GAs model is suitable for the prediction of stock prices. Figure [4.22] illustrates the prediction of the next year (2018) for Al-Quds- Index using this model. As shown, the stock prices in Al-Quds- Index decrease in the beginning of 2018, then stabilize around the mean of Al-Quds- Index stock prices for the past 8 years that equal 0.456 and increase at the end of the year.

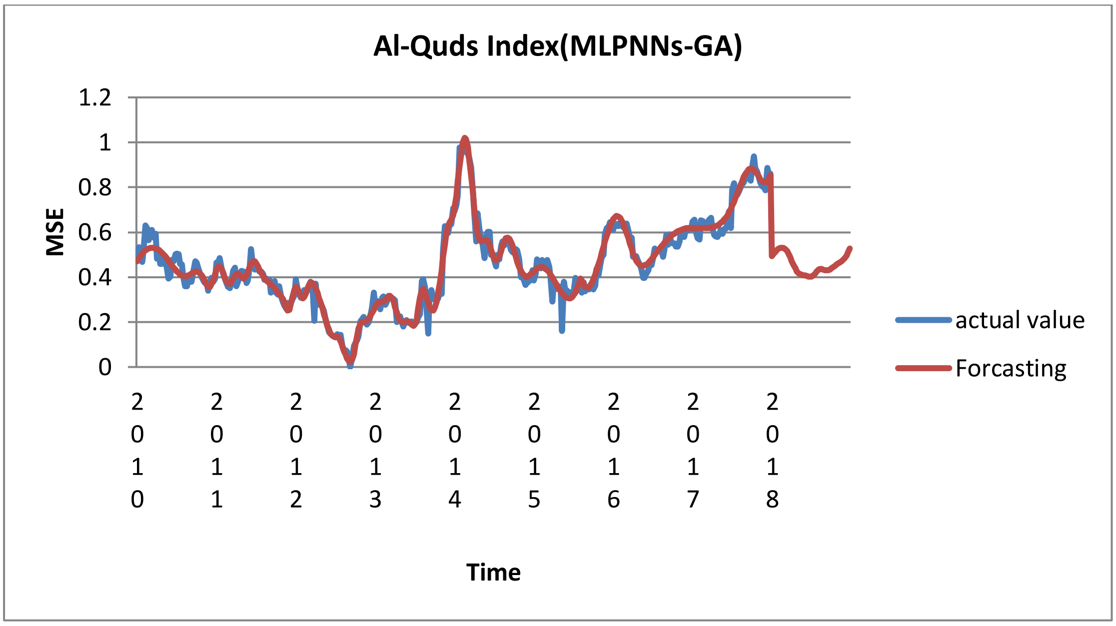

Figure 4. 22: Real and predicted Al-Quds- Index values for the next year using (MLPNNs-GAs) model.

4.2.4.2MLPNNs-LM

The experiment was conducted to apply (MLPNNs-LM) model to Al-Quds Index. As shown in table 4.16 increasing the number of neurons gives fluctuation in the behavior of the performance function. best performance at 20 neurons. (MSE train= 0.0021, MSE test=0.0022). Figure [4.23] illustrate the actual data and outputs of the training phase for Al-Quds-Index using MLPNN-LM model. The prediction of the next year (2018) is explained in figure [4.24].

Table4. 16: Results of AlQuds Index MSE for MLPNN-LM model.

Number of Neurons	Mse-Train	Mse-Test
5	0.0113	0.022
10	0.0042	0.0063
15	0.004	0.0043
20	0.0021	0.0022
25	0.0015	0.0022
30	0.0014	0.0025
35	0.0016	0.0023
40	0.0017	0.003
45	0.0011	0.0023
50	0.0011	0.0022

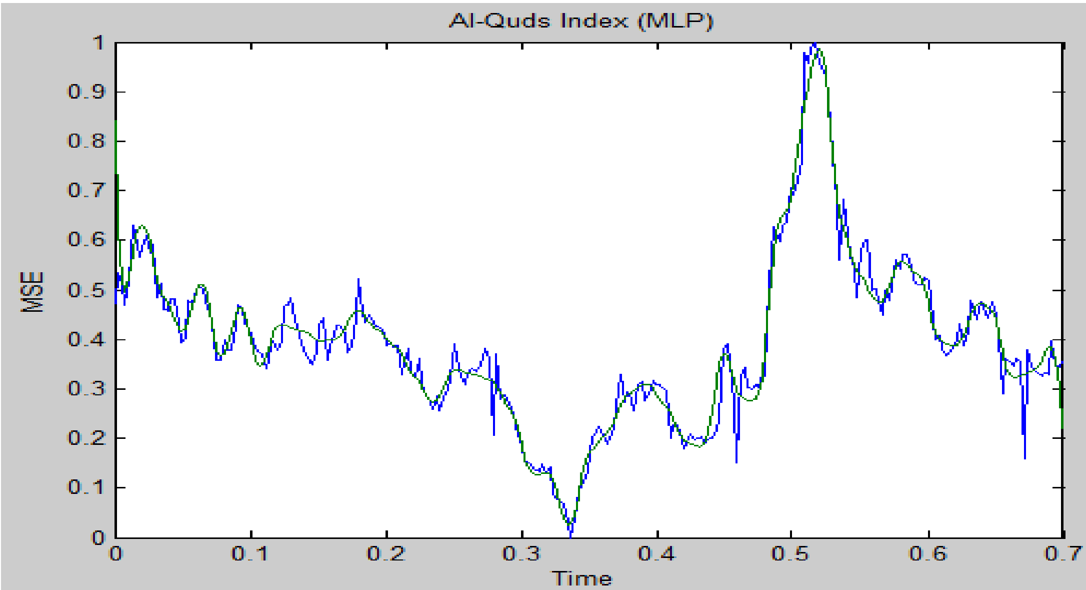

Figure 4. 23: Real and predicted Al-Quds-Index values using (MLPNNs-LM) model.

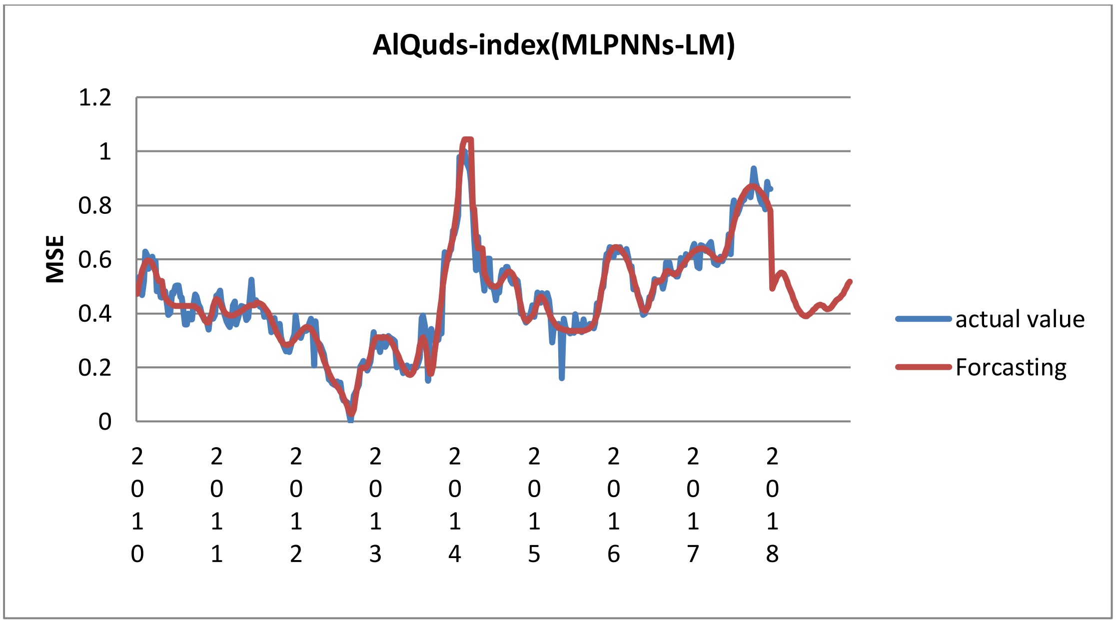

Figure 4. 24: Real and predicted Al-Quds Index values for the next year using (MLPNNs-LM) model

As shown in figure 4.23, the results obtained from the previous applied model, which is MLPNNs-Gas, were convergent regarding the actual and predicted values of Al-Quds-Index, and so were they for the stock prices for the next year (2018).

4.2.4.3RNNs-LM

The third model (RNN-LM) was also applied to Al-Quds Index. As illustrate in table 4.17 best training and testing MSE when 20 neurons (MSE train= 0.00379, MSE test=0.00384, there's a fluctuation in the performance when an increasing number of neurons and fluctuation in the performance after 20 neurons become worse. The actual data and outputs of the training phase for Al-Quds Index using RNNs-LM model is explained in figure [4.25].

Table 4. 17: Results of AlQuds Index MSE for RNN-LM model.

Number of Neurons	Mse-Train	Mse-Test
5	0.0166	0.018
10	0.00804	0.0092
15	0.00485	0.0049
20	0.00379	0.00384
25	0.00565	0.0066
30	0.00455	0.00456
35	0.00424	0.00433
40	0.0159	0.1593
45	0.00473	0.00478
50	0.00473	0.00477

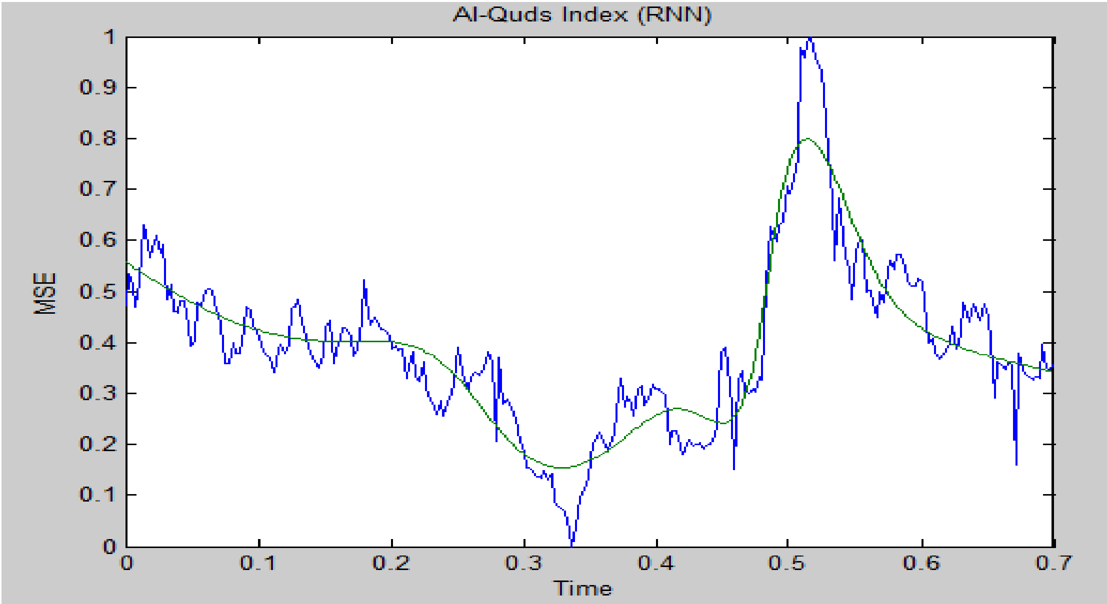

Figure 4. 25: Real and predicted Al-Quds-Index values using (RNNs-LM) model.

It's clear that there is a slight convergence between the real and predicted values of Al-Quds-Index. The prediction of the next year (2018) using RNNs-LM model is explained in figure [4.26], which indicates the decrease of the stock prices in the first half of 2018, then increases at the end of the prediction year (2018)

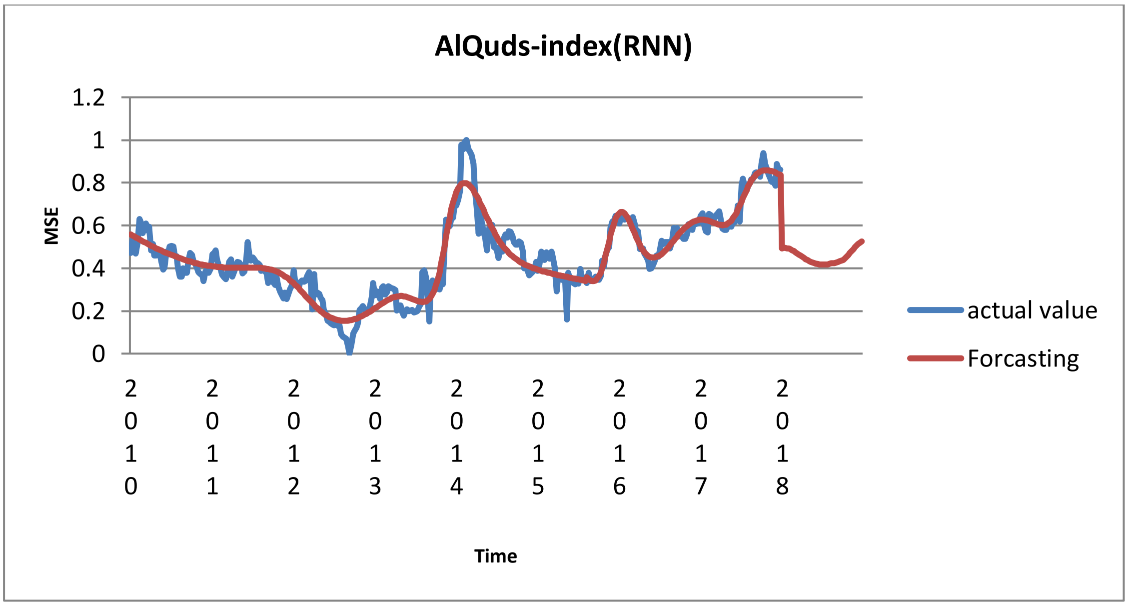

Figure 4. 26: Real and predicted Al-Quds- Index values for the next year using (RNNs-LM) model.

Investor can bear profits when choosing a good stock for investing in addition to invest at the right time. The prediction using the three methods as depicted in Figures [4.22],[4.24] and [4.26] indicates that Al-Quds index is going to slightly decrease through the next year 2018 and increase at the end of the prediction year 2018 under normal conditions, and this is a good indication for investors to invest in registered companies in Palestinian Exchange.

4.3 Comparison

In this section, we compares between the behavior of MSE errors for all the applied models for each dataset (Padico Company, Paltel Company, Bank of Palestine Company and Al-Quds index) as illustrated in Figures [4.27], [4.28], [4.29] and [4.30]. Also we compares between the behavior of the actual data and the predicted data for all the applied models to the mentioned companies and Index.

4.3.1MSE-Test Errors comparison

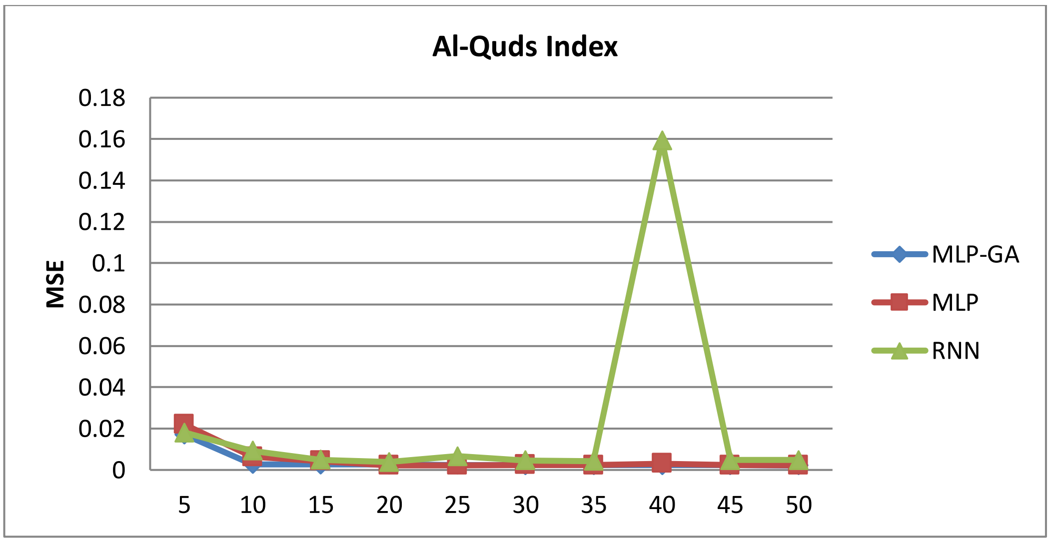

Figure 4. 27: MSE-Test Errors behavior for the three applied Models (Al-Quds-Index).

As we notice in the figure [4.27] above, the best testing of MSE for Al-Quds-index (when the number of neurons equals 50 with MLPNN-LMs and MSE test=0.0022, 20 with RNNs-LM and MSE test=0.00384, 50 with MLPNNs-GAs and MSE test=0.0011).

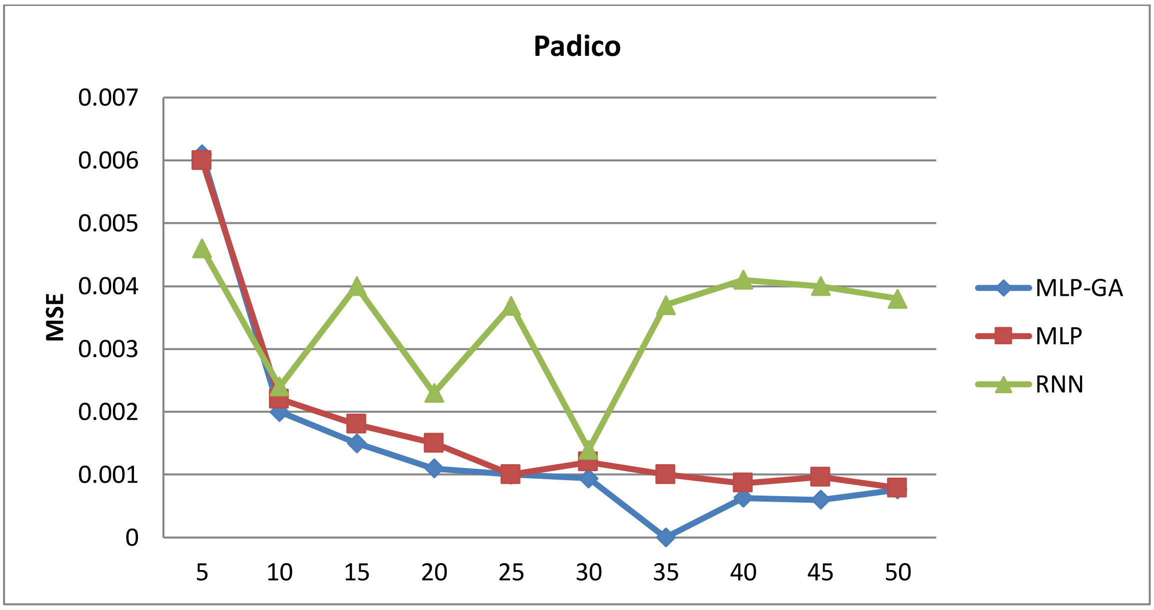

Figure 4. 28: MSE-Test Errors behavior for the three applied Models (Padico).

As shown, the best prediction results for Padico (when the number of neurons equals 50 with MLPNN-LMs and MSE test= 0.00079, 30 neurons with RNNs-LM and MSE test=0.0014, 50 with MLPNNs-GAs and MSE test=0.00064).

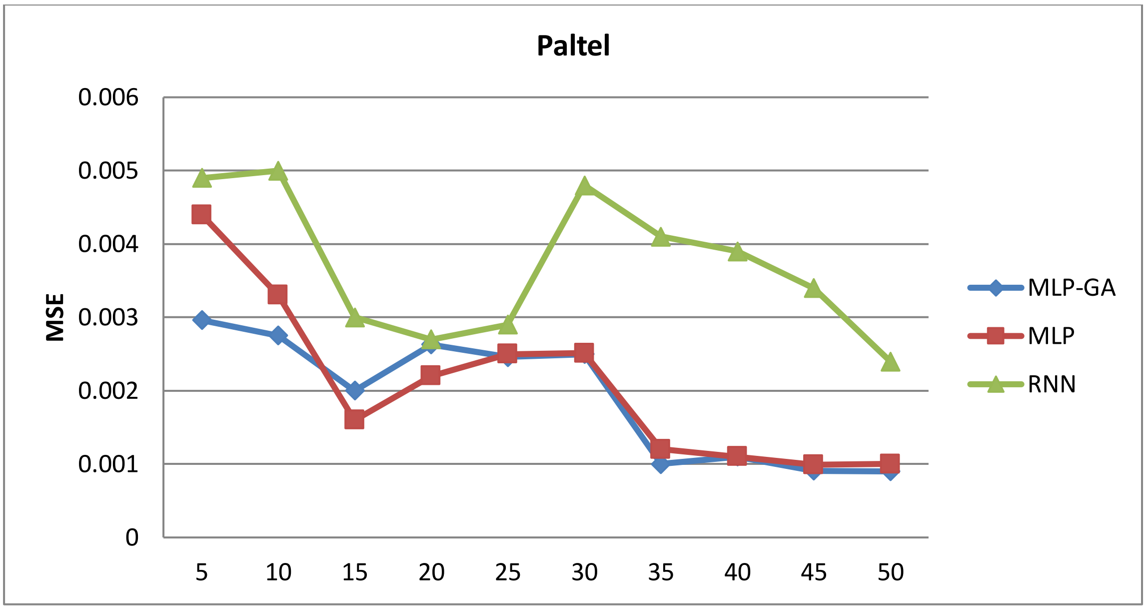

Figure 4. 29: MSE-Test Errors behavior for the three applied Models (Paltel).

Figure [4. 29] show that the best prediction results for Paltel (where the number of neuron equals 45 with MLPNN-LMs and MSE test=0.000991, 50 with RNNs-LM and MSE test=0.0024, 50 with MLPNNs-GAs and MSE test=0.0009).

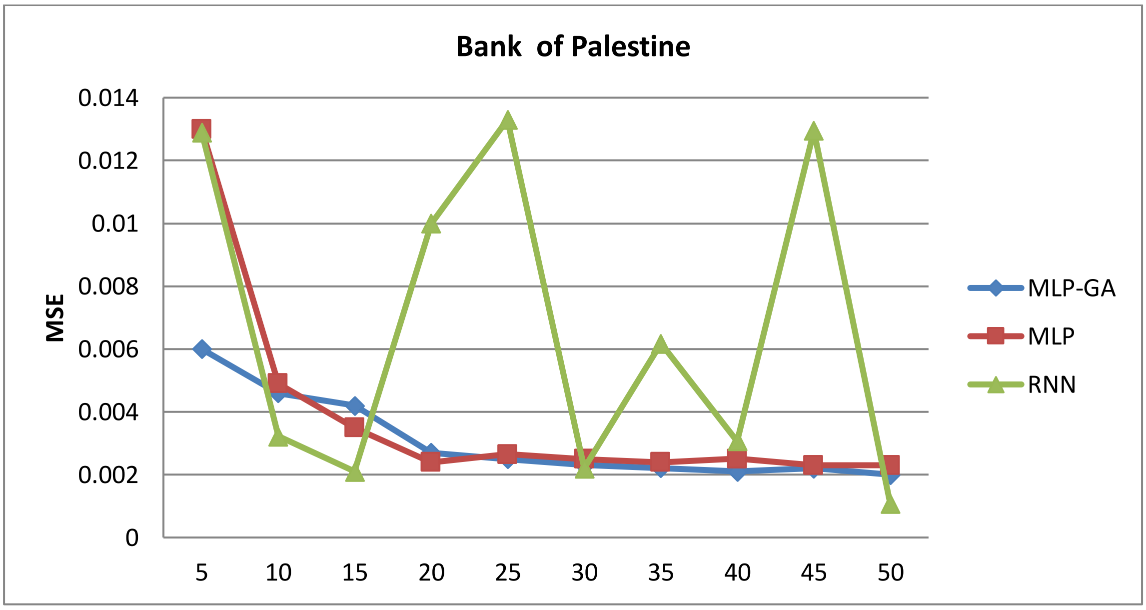

Figure 4. 30: MSE-Test Errors behavior for the three applied Models (Bank of Palestine).

As shown in the figure above [4.30], the best prediction results for Bank of Palestine (when the number of neurons equals 50 with MLPNN-LMs and MSE test=0.0023, 50 with RNNs-LM and MSE test=0.001066, 50 with MLPNNs-GAs and MSE test=0.002).

As shown in the illustrate figures (4.27, 4.28, 4.29 and 4.30). For all companies, we have noticed that there's a fluctuation in the behavior of MSE errors using RNNs-LM model, where the behavior of each one of the datasets that we have applied our models on as follows, Al-Quds index behavior of MLPNNs is close to the behavior of MLPNNs-GAs models, Padico behavior using MLPNNs-GAs have outperformed the behavior of MLPNNs as shown in the results, the Bank of Palestine behavior using MLPNNs-GAs have outperformed the behavior that results using MLPNNs except when it applied with 15 hidden neurons and in Paltel the behavior of MLPNNs-GAs was better than MLPNNs except when it applied with 15 and 20 hidden neurons.

4.3.2 Actual data and predicted data comparison

We have applied denormalization in order to recovering the original dataset. So, this function reverse the process of normalization using the same equation that we have used for normalization according to d instead of d_i. Where the original maximum and minimum values (min(d) and max(d)) are needed. The trend of the predicted closing price values of the stocks with the actual stock price values, were applied using the applied models in this thesis for each of the companies/index dataset (i.e. Padico stock, Paltel stock, Bank of Palestine stock and Al-Quds index) are illustrated in figures [4.31], [4.32], [4.33] and [4.34].

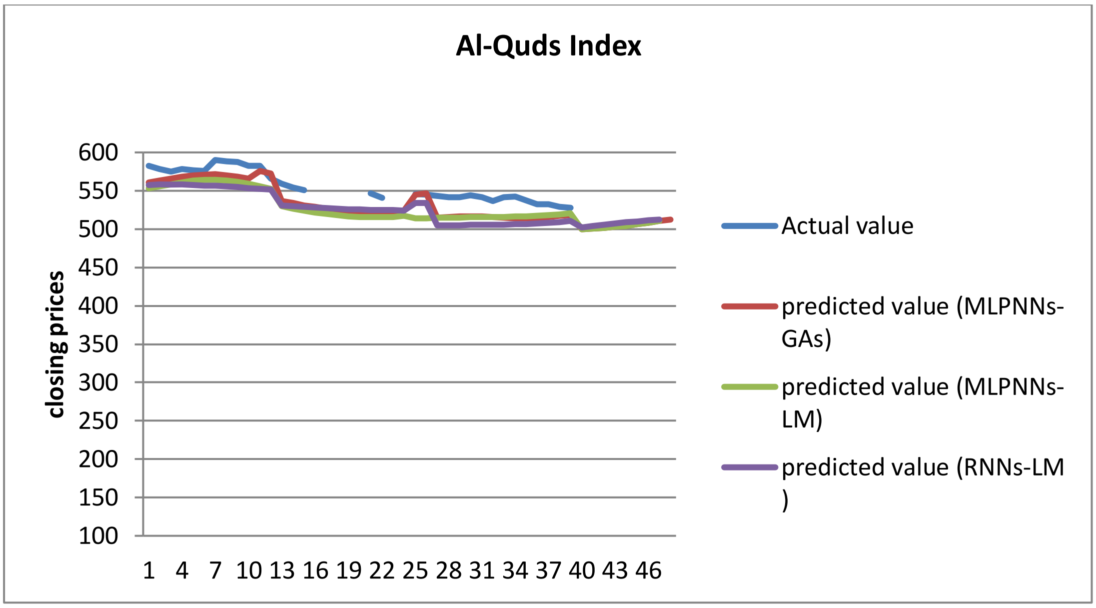

Figure 4. 31: predicted Al-Quds- Index values for 2018 of the three applied models against actual.

As shown in the figure [4.31] above, all of the three applied models MLPNNs-GAs, MLPNNs-LM and RNNs-LM give nearly the same prediction for the next year of 2018, where the behavior of the prediction of 2018 is close to the actual behavior (i.e. the actual index prices). The MLPNNs-GAs model has the nearest behavior to the actual one. In addition, we didn't get all the actual data.

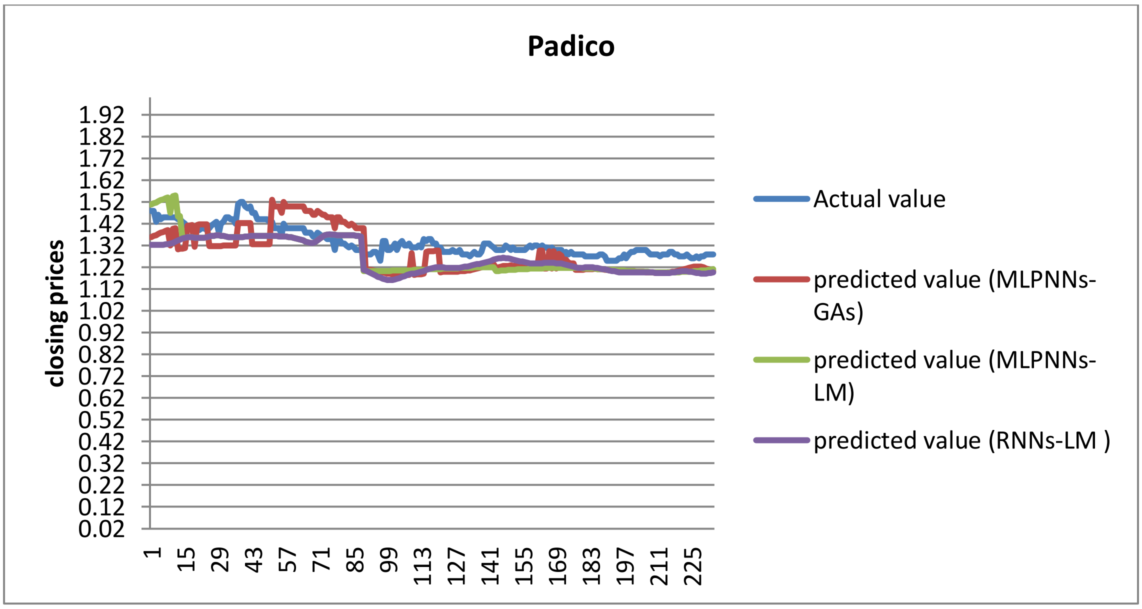

Figure 4. 32: Predicted Padico company values for 2018 of the three applied models against actual.

As shown in figure [4.32], it's clear that the actual and predicted values of Padico stock using the three applied models MLPNNs-GAs, MLPNNs-LM, and RNNs-LM are nearly close.

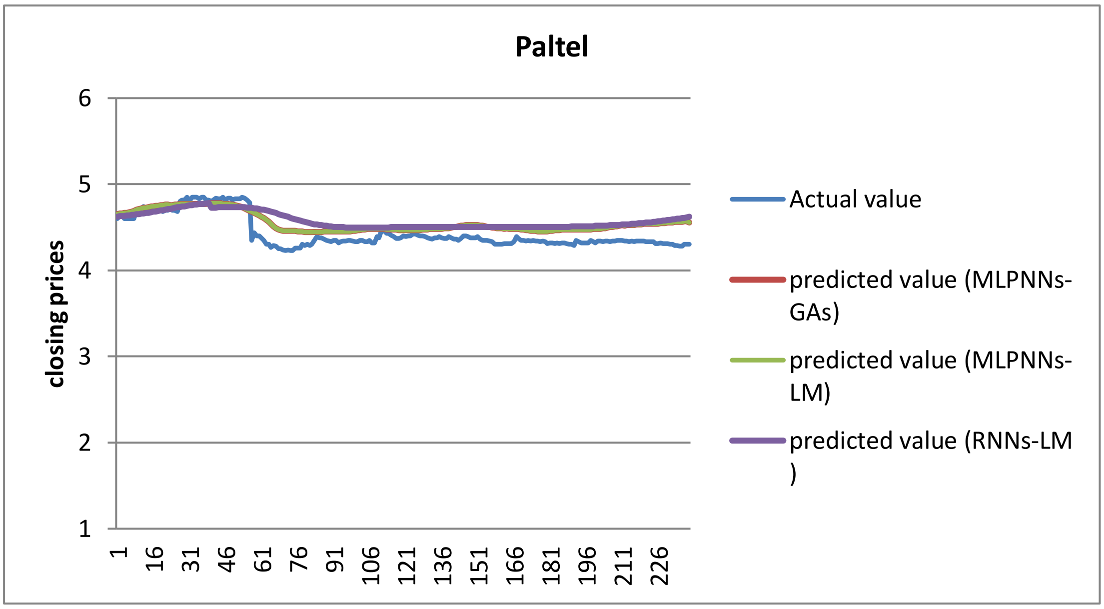

Figure 4. 33: Predicted Paltel Company values for 2018 of the three applied models against actual.

For the Paltel Company, all of the three applied models MLPNNs-GAs, MLPNNs-LM, and RNNs-LM give nearly the same prediction for the next year of 2018, where the behavior of this prediction is nearly close to the actual one.

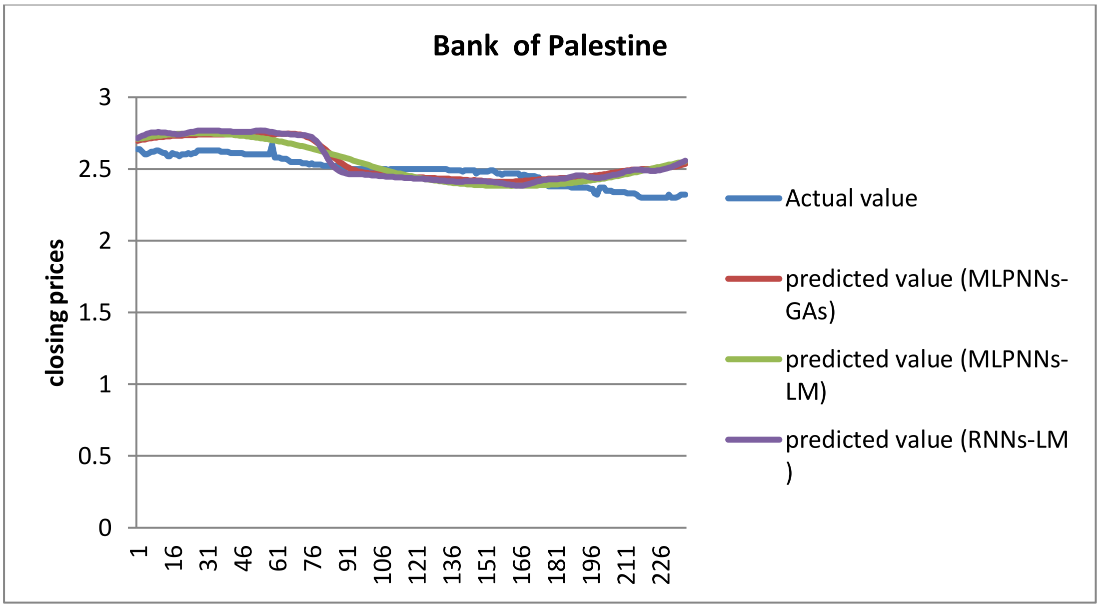

Figure 4. 34: predicted Bank of Palestine values for 2018 of the three applied models against actual.

It's clear that the actual and predicted values gained of applying the three models MLPNNs -GAs, MLPNNs-LM, and RNNs-LM are close to each other.

4.5 Summary

For all datasets, our findings revealed that all applied models (MLPNNs -GAs, MLPNNs-LM and RNNs-LM) can achieve good forecast results that close to the actual values. And the performance of the proposed hybrid model (MLPNNs-GAs) outperformed the MLPNNs-LM and RNNs-LM models in forecasting the closed price. This is because this model is characterized by selecting GA the best initial parameters to the NNs, whereas the MLPNNs-LM model came up with much better accuracy than RNNs-LM. In the case of RNN-LM model, this depends on the previous information for forecasting the future instances, and the patterns in dynamical stock system will not always be the same.

Chapter Five: Conclusion and Future Works

5.1 Conclusion

The application of the artificial intelligent prediction techniques to the stock market prices is a subject of growing interest in the financial community. Strictly speaking, contrary to the traditional approach of punctual prediction of the level of prices, this current approach of prediction has more evident benefits. That is, the direction of the movement of the stock market index indicates the development of effective trading strategies, which may come up with better results than those based on the specific projection of the price level, and therefore become more significance and profitable for the investors in leading their investments and consequently leads to the growth and prosperity of the national economy.

This thesis presented a hybrid model to predict the stock market closing prices. Specifically, this study analyzed the ability of intelligent hybrid systems that depend on using the artificial neural networks (MLPNNs-LM) with other evolutionary algorithms (GAs) to predict the daily Palestine Exchange stock prices depending on the patterns of the historical datasets. In this work, genetic algorithms (GAs) are used for optimization in order to select optimal initial weights for NNs. This thesis also aims to illustrate two types of artificial neural networks models and study their architectures; namely, MLPNNs and RNNs. Then we will separately apply each model in term of MSE values to show the best model that produces the best results for forecasting the Palestinian Stock Exchange.

Datasets are gathered from the main index, which is Al-Quds Index of the Palestinian Stock Exchange, Paltel, Padico and Bank of Palestine during the period of 2010 to 2017. Datasets for the training purposes were also determined to include 70% of the original data and the 30% of original data in testing.

The predicted closing price is given for the next year: daily for Paltel, Padico, and Bank of Palestine, and weekly for Al-Quds Index.

The best prediction results after applying the models to the above-mentioned companies and Index were as follows: Padico (where a number of neuron equal 50 with MLPNN-LMs and MSE test= 0.00079, 30 neurons with RNNs-LM and MSE test=0.0014, 50 with MLPNNs-GAs and MSE test=0.00064). Secondly, Paltel (where a number of neuron equal 45 with MLPNN-LMs and MSE test=0.000991, 50with RNNs-LM and MSE test=0.0024, 50 with MLPNNs-GAs and MSE test=0.0009). Thirdly, Bank of Palestine (when a number of neuron equal50 with MLPNN-LMs and MSE test=0.0023, 50 with RNNs-LM and MSE test=0.001066, 50 with MLPNNs-GAs and MSE test=0.002). Finally, Al-Quds-index (when a number of neuron equal 50 with MLPNN-LMs and MSE test, 20 with RNNs-LM and MSE test=0.00384, 50 with MLPNNs-GAs and MSE test=0.0011). Note that the characteristics of the hybrid model (MLPNNs-GAs) for four applied datasets are illustrated in chapter four, which include a number of generations, number of population. And genetic algorithms function (crossover, mutation and selection) that improves performance of (MLPNNs-GAs) model and therefore give best prediction results.

For each datasets results of (MLPNNs-GAs) model outperform the MLPNNs-LM and RNNs-LM models, where MLPNNs-LM model outperforms RNNs-LM model. Therefore, the main experimental results achieved can give some very significant conclusions of this thesis, which show how forecasting the Palestinian Stock Market price could be achieved by using the hybrid model (MLPNNs-GAs). Based on the comparison of the performance for all models applied with the same changing number of neurons, we conclude that this model can be used as a better alternative method for forecasting the stock price movement in Palestine.

5.2 Future Works

In this thesis, for the first time, the Palestinian Stock Exchange behavior has been applied using the proposed hybrid model (MLPNNs-GAs). The results that we have gained will be given to the Palestinian Stock Exchange to achieve the goal of the researcher's thesis. In the future, the researcher is intending to apply the proposed model on additional Palestinian stock Exchange companies to classify them using different classification methods. Also, the researcher aims to use different intelligent systems that depend on the use of the artificial neural networks such as MLPNNs and RBFNNs with any one of the optimization algorithms such as (Particle swarm optimization and a Neuro-Fuzzy system) to enhance the performance of the researcher's model.

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الملخص

إن الهدف الرئيس لسوق الأوراق المالية هو توفير بيئة آمنة للتداول من أجل تحقيق خدمات أفضل للمستثمرين والحفاظ على استثماراتهم. فسوق الأوراق المالية في أي بلد يلعب دورًا مهمًا في التنمية الاقتصادية الوطنية والناتج المحلي الإجمالي، ويعني وجود سوق أسهم نشط وجودَ اقتصاد قوي ناشئ. وبالتالي، فإن عملية التنبؤ بعوائد سوق الأوراق المالية ذات أهمية عالية.

تساعد هذه التوقعات، إن تحققت، المستثمرين في صياغة استراتيجياتهم الاستثمارية على أسس قوية وعلمية. وبالتالي، فقد ساعدت هذه المفاهيم إلى جانب الأساليب الرياضية في ظهور تنبؤات الاقتصاد القياسي لقياس عدم اليقين من خلال المعايير السببية متعددة المتغيرات بدعم من التوزيع العشوائي للسوق. ويمكن التنبؤ بمتغيرات السوق مثل سعر السهم وأسعار الفائدة وأسعار الصرف والتضخم وما إلى ذلك باستخدام أساليب ذكية تتيح للمستثمرين استثمار أموالهم بطريقة أكثر أمانًا وموثوقية.

في هذه الأطروحة، قدم الباحث نموذجًا هجينًا محسنًا يجمع بين الشبكات العصبية المدركة متعددة الطبقات مع الخوارزميات الجينية (**MLPNNs-GAs**) للتنبؤ بوضع بورصة فلسطين لمؤشر القدس كمؤشر رئيس. بالإضافة إلى ذلك، سيتم استخدام بورصة فلسطين لثلاث شركات فلسطينية كبيره (**Paltel**، **Padico**، **Bank of Palestine**) للتنبؤ بأسعار أسهمها. الفكرة الأساسية، في هذا البحث، للجمع بين الشبكات العصبية الاصطناعية (**ANNs**) مع **GAS**، هي أن خصائص البيانات في أسعار الأسهم متقلبة وغير خطية. وكما نعلم دون فرض علاقة معينة في البيانات فإن **ANNs** لديها القدرة على تعلم العلاقات غير الملاحظة فيها. تستخدم الخوارزميات الجينية (**GAs**) لتحسين الأوزان لل **NNs**، وسوف تختار **GAs** أفضل الأوزان من أجل تحسين الأداء والحصول على الحد الأدنى لمتوسط قيمة الخطأ (**MSE**) المتوقع. وقد تم تطبيق عملية **GAs** باستخدام أفضل طرق الجمع بين الخطوات الرئيسية لـ **GAs**. علاوة على ذلك، طبقنا نموذجين آخرين لمنهجيات الشبكات العصبية المختلفة ؛ الشبكات العصبية المدركة متعددة الطبقات المدربة باستخدام الانتشار الخلفي لـ **Levenberg-Marquardt (MLPNNs-LM)** والشبكات العصبية المتكررة **RNNs-LM** المدربة باستخدام الانتشار الخلفي **Levenberg-Marquardt** أيضًا. وتمت مقارنة أداء النماذج الثلاثة المطبقة باستخدام معيار **MSE**.

أظهرت النتائج التجريبية التي تم الحصول عليها من نموذج **MLPNNs-GAs** المقترح ونماذج **NNs** الأخرى المطبقة، مع نفس عدد معلمات التعلم أن أداء (**MLPNNs-Gas**) يتفوق على أداء كل من **MLPNNs-LM** و **RNNs-LM** في التنبؤ بسعر الاغلاق لكل واحد من مجموعات البيانات الأربعة التي تمثل سوق الأوراق المالية ل **(Padico**، **Paltel**، **Bank Palestine**، ومؤشر القدس)، في حين أن نموذج **MLPNNs-LM** ينتج دقة أفضل من **RNNs-LM.**