# A CIMB Stock Price Prediction Case Study with Feedforward Neural Network and Recurrent Neural Network

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***Abstract*—Artificial Neural Network (ANN) is one of the popular techniques used in stock market price prediction. ANN is able to learn from data pattern and continuously improves the result without prior information about the model. The two popular variants of ANN architecture widely used are Feedforward Neural Network (FFNN) and Recurrent Neural Network (RNN). The literature shows that the performance of these two ANN variants is studied dependent. Hence, this paper aims to compare the performance of FFNN and RNN in predicting the closing price of CIMB stock which is traded on the Kuala Lumpur Stock Exchange (KLSE). This paper describes the design of FFNN and RNN and discusses the performances of both ANNs.**

***Index Terms*—Artificial Neural Network; Feedforward Neural Network; Recurrent Neural Network; Stock Prediction.**

## I. INTRODUCTION

The stock market is one of the most significant indicators that reflect the health of the economy of a country. This is because the listed stocks in the stock market represent the company's growth in the country. Hence, the performance of the stock market indicates the performance of these companies, which in turn reflect the country's economy. The average performances of these stocks are shown by the stock market index. This index reveals the performance of the stock market either increasing, stable or decreasing. Investors are always looking for ways to increase their wealth by having a greater understanding of how the market works and access to tools that can be used to predict the trend of the market price accurately. Due to this lucrative return, many researchers have devoted their works to predicting the stock market price based on stock market parameters such as stock closing price, stock market index, the increase, and decrease trend.

The conventional techniques used to forecast stock market are the Efficient Market Hypothesis (EMH) and the random walk theory. The EMH states the market is efficient and so all available information directly reflects the market price [1][2]. The EMH is categorised into three types namely weak, semi-strong and strong reflecting the availability of different level of information [3]. The random walk theory states that the market price is unpredictable due to the randomness of stock price fluctuations [4][5]. However, these two theories do not demotivate the continuous endeavour of researchers in devising techniques and methods to predict the stock market. The two early manual approaches to predict the stock market price are fundamental analysis and technical analysis. The fundamental analysis is based on the analysis of the essential information about the company such as financial statements [6-7]. Some of these financial statements include the annual report, balance sheet, cash flow and others [8-9]. This technique is used for long-term analysis. However, it is not suitable for the short-term prediction that needs to reflect the changes immediately. To solve this issue, the technical analysis approach is used to predict immediate changes in the stock market. This approach uses numerical values such as historical data and technical indicators to predict the stock market price [9-10]. The primary tool for this approach is chart diagram [11]. Chart diagram is used to investigate the breakeven point and change point of the stock price trend. However, this approach is dependent on the stock analyst's experience and knowledge.

The advancement of computational hardware and capabilities has influenced the shift from manual prediction techniques to computing techniques, which involve mathematical models. Traditional time-series forecasting techniques such as Moving Average (MA), Autoregressive Integrated Moving Average (ARIMA), and Box-Jenkins are used to predict the stock market [12-13]. However, these linear forecasting techniques are unable to capture the nonlinear characteristics of the stock market.

In order to capture these nonlinear traits of the stock market, researchers devised the nonlinear parametric models such as autoregressive conditional heteroskedasticity and general autoregressive heteroskedasticity to predict the nonlinearity in the function [14]. However, these parametric nonlinear models require the prior nonlinear model to be established. One of the drawbacks of this approach is that it might take time to find out the correct prior model. Another drawback is the consequences of previous drawback (wrong estimation of priori model) will cause the prediction performance to deteriorate drastically.

In order to overcome the limitations of the parametric nonlinear model, machine learning is introduced. Machine learning is a non-parametric computational approach that learns from experience during the computation process and incrementally improves the system performance (prediction result) [15-16]. There are many types of machine learning algorithms such as decision tree learning, data mining algorithms, Support Vector Machines and ANN [17]. Among these algorithms, ANN has been widely used in solving problems in a wide range of applications including robotics [18], computer games [19], and image processing [20].

ANN is a bio-inspired algorithm which mimics the mechanism of the human brain [21-22]. The basic building block for ANN is an artificial neuron, also known as a simple processing unit, whereby each neuron will perform a simple computation in parallel [22]. The artificial neuron is an oversimplified simulation of human brain neuron. An ANN is formed from several components which are organised in layers. These components are the input neurons, output neurons, hidden neurons, activation function, bias and weight [23]. The input neuron receives a signal from the external sources. The hidden neuron performs the computation to obtain the net input by multiplying the connection weight with the input signal that is connected to it plus a bias value. This net input is then passed to a transfer function to produce an output signal. The output neuron performs the same computation as the hidden neuron and produces the output value. The ANN can be organised in different topologies referred to as ANN architectures. There are many different types of ANN architectures such as Feedforward Neural Network (FFNN) and Recurrent Neural Network (RNN) [24].

In this paper, the performances of FFNN and RNN in forecasting the CIMB stock closing price are compared and analysed. The CIMB stock was selected due to its price fluctuation. The CIMB Group is a financial institution in Malaysia, which had grown to become one of the most powerful banking powerhouses in ASEAN and is listed on Kuala Lumpur Stock Exchange. Most of the previous studies used past closing prices to predict the future closing price. In this study, besides the CIMB's closing price, external parameters such as KLCI index, interest rate, and currency exchange rates were used to improve the accuracy of prediction. Experiments were carried out, and the results were analysed to determine which ANN architecture delivers better stock prediction accuracy.

The remainder of the paper is structured in the following manner. Section 2 reviews important studies related to this topic. Section 3 explains the experimental setup and the configuration of FFNN and RNN while the simulation prototypes are described in Section 4. Section 5 discusses the results, and finally, Section 6 concludes.

## II. LITERATURE REVIEW

FFNN is the most commonly used approach to stock market forecasting problem. Sutheebanjard and Premchaiswadi forecasted the movement of the index of the stock exchange of Thailand (SET) using FFNN with backpropagation learning [25]. They used the feedforward network structure of 7-4-1 to forecast the SET index. The inputs for the neural network were SET index, Dow Jones index, Strait Times index, Nikkei index, Hang Seng index, domestic Minimum Loan Rate (MLR) and domestic gold prices. The dataset used was from 2 July 2004 to 30 December 2004 (124 days). This study used 53 days' data for the training set and 71 days' data for the testing set.

The mean square error (MSE) and Mean Absolute Percentage Error (MAPE) were used to evaluate the performance of the FFNN. The result obtained proved that FFNN was able to achieve a promising error rate. Dong et al. [26] forecasted the closing value of the Shanghai Stock Exchange Composite Index (SHCOMP) using FFNN with backpropagation learning. They used the feedforward network structure of 5-5-1 to forecast the SHCOMP index. The inputs for the neural network were closing, opening, volume, highest and lowest value of SHCOMP Index. The data set used from 2 November 2007 to 11 July 2008. This study used 70% of the data for training, 15% data for validation and 15% data for testing. The mean square error (MSE), absolute error and hit rate were used to evaluate the performance of the FFNN. The result showed that FFNN was able to achieve a promising error rate. Jabin forecasted Net Asset Value (NAV) of SBI mutual fund using FFNN with backpropagation learning [27]. The dataset used in this investigation was from 1st of April 2012 to 4th of April 2014. There were four inputs which were used to predict the fifth NAV value of day 5. The number of the hidden neuron was 2n+1 based on the rule of thumb. The mean square error (MSE) and the Sum Squared Error (SSE) were used to evaluate the performance of the FFNN.

The result showed that FFNN has the ability to extract and discover useful information from a large set of data. Dematos et al. predicted the exchange rate between the Japanese Yen and US dollar using feedforward and RNN and using ARIMA model as a benchmark for the performance comparison [28]. The result showed that both ANN architectures performed better than the ARIMA model. Besides, the result also showed that the performance of FFNN was better than RNN. Agrawal et al. used four different techniques to predict the users' activity in a cognitive radio network [29]. The four techniques were multilayer perceptron, RNN, linear kernel support vector machine and Gaussian kernel support vector machine. The result showed that multiplayer perceptron performed better than the other three models in the activity prediction. Another similar study, Singh and Kansal attempted to predict the cognitive radio spectrum [30]. The result of the study showed that the perceptron neural network performed better than RNN in this prediction task. Imran et al. showed that FFNN performed better than RNN and radial basis function network in predicting the best available channel for user [31].

RNN (RNN) is another popular architecture used in stock market forecasting problem. Iqbal et al. forecasted the Pakistan State Oil using RNN. The RNN model used in this study was the Layered Recurrent Neural Network (LRNN) [32]. The study used Levenberg-Marquardt as the learning method in the LRNN. The data division is 60% for training, 20% for validation and 20% for testing. Mean squared error was used to evaluate the performance of LRNN. The result showed that LRNN outperformed FFNN. Grigoryan forecasted the closing price of Tallink stock using RNN. The RNN model used in this study was NARX [33]. The dataset was retrieved from the Nasqad OMX Baltic stock exchange. The duration of the sample was from 12 March 2012 to 30 December 2014 with a total of 700 daily observations. In this study, PCA was used to select 10 of 36 inputs which include daily opening price, closing price, highest price, lowest price, traded volume, turnover and 30 technical indicators.

The result of the study showed that NARX performed well in forecasting the closing price of the stock. [34] Wang forecasted the closing price of the Shanghai stock index using RNN with NARX model [34]. The dataset used was from 1999 to 2011 with a total of 5118 trading days. 70% of the data was used for training, 15% for validation and 15% for testing. The NARX was used to predict the 5th-day closing price using the previous four days' data and some technical indicators. The NARX's inputs include previous four-day closing price, moving average convergence divergence, price rate of change, acceleration between times, momentum between times and relative strength index total of the nine inputs. LMA was used as the training algorithm for the NARX. The result of this study showed that NARX performed better than FFNN. Mitrea, Lee, and Wu showed that the forecasting result of Panasonic Refrigeration Devices Company inventory database with Nonlinear Autoregressive network with exogenous inputs (NARX) RNN was better than FFNN, moving average (MA) and autoregressive integrated moving average (ARIMA) [35].

Singh and Tripathy predicted the electricity load/price model of New South Wales (NSW) Australia [36]. This study showed that RNN produced better forecasting model than FFNN and radial basis function neural network. Mittal and Saxena also showed the similar result in electricity load forecasting [37]. The result of the study showed that RNN performed better than FFNN in forecasting the load of the electricity.

Based on the literature. FFNN and RNN both performed well in different distinct studies. Hence, there is no superior ANN architecture for forecasting studies. This is the motivation for comparing the performances of FFNN and RNN in this study using a particular set of parameters in order to determine the better architecture.

## III. Experimental Setup

This section describes the experimental setup for the parameter configuration used to conduct the experiments. There are many parameters in the ANN which are configurable. These parameters are described in this section.

The data collected for this research includes the stock information (opening price, closing price, highest price, lowest price and volume trade) and the market reflected information such as interest rate, KLCI, and currency exchange rates (USD, EUR, and SGD). The stock information and KLCI were retrieved from Yahoo Finance while the interest rate was extracted from the central bank of Malaysia. The currency exchange rate was obtained from Oanda forex website. The dataset for all the parameters was retrieved from January 2000 to June 2015.

The input data for the ANN are opening price, closing price, highest price, lowest price, volume trade interest rate, KLCI, USD, EUR, and SGD. The preprocessed steps of the data include finding the missing value and outlier and data normalisation. If there is a missing value, this missing value is derived by averaging the previous and next day's values. The outlier of each parameter dataset is determined by using the mathematic equation of interquartile range, (IQR) = Q3 – Q1. The outlier is the value that is then less Q1 – (1.5 * IQR) and a value greater than Q3 + (1.5*IQR). Finally, each of the parameter data set is normalised and denormalised using the following equations:

$$x_n = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

$$x = x_n(x_{max} - x_{min}) + x_{min} \quad (2)$$

where: $x_n$ is the normalised value,
$x_{min}$ is the minimum value in the data set and
$x_{max}$ is the maximum value in the dataset.

The output of the neural network is the prediction of the 6th-day stock closing price from the previous five days' data. The arrangement of data into time series is made up of 4000 data points for computation. This amount of data should be sufficient for the training (70%), validation (15%) and testing sets (15%) [38]. The training iteration is known as an epoch. The number of epoch used in this research is 1000.

However, early termination is possible to avoid the ANN memorising the pattern instead of learning during the training process. A two-layer neuron network architecture is used in this experiment. The ANN used in this research comprises one input layer, one hidden layer, and one output layer. It is proved that a hidden layer with enough hidden neurons can approximate any continuous function [39-40]. The number of hidden neurons in the hidden layer is selected based on a rule of thumb, which is the number of input neuron plus the number of output neuron divided by two [41-42].

The training algorithm used in this study is the Levenberg-Marquardt algorithm (LMA) which was introduced by [43] and later extended by [44]. It is also known as the damped least squares (DLS) method. This algorithm helps in solving non-linear square problems by finding the minimum point of a function. The LMA is also used to train a backpropagation neural network. The Levenberg-Marquardt is an algorithm that interpolates between the methods of gradient descent and Gauss-Newton algorithm. The hyperbolic tangent is used as the activation function which fulfils the requirement for the backpropagation algorithm.

Mean Square Error (MSE) is used to evaluate the performance of the ANN in predicting the closing price of the stock. The significance of the input parameters towards the prediction result has been tested in the previous experiment [45]. In this paper, the performances of FFNN and RNN are investigated and compared. Table 1 shows the summary of the experimental setting for this study.

Table 1
Experiment Parameters

| Parameter | Value |
|---|---|
| Input Value | Closing price, opening price, highest price, lowest price, volume trade, KLCI, interest rates, currency exchange rates (USD, EUR, and SGD) |
| No. of Historical Day | 5 |
| Output Value | 6th-day closing price |
| ANN Architecture | 2-layer FFNN / 2-layer RNN |
| No. Hidden Neurons | (input neurons + output neurons) / 2 |
| Epoch | 1000 |
| Activation Function | tansig |
| Training Data Set | 70% |
| Testing Data Set | 15% |
| Validation Data Set | 15% |
| Training Algorithm | Levenberg-Marquardt Algorithm |
| Evaluation Function | MSE |
| No. of Run Per Experiment | 10 |

## IV. Simulation

A simulation prototype was built using MATLAB [46]. The simulation prototype allows for flexibility of parameter configuration in the experimental setup and reduces the effort of rewriting codes for different experiments, thereby, making it desirable for future experiments.

In the interface, it allows the user to set various parameters from the input parameter to the neural network setting and also the directory location of the result to be saved. The interface consists of 4 main panels: the data panel, network panel, training method panel and result panel as shown in the Appendix. The data panel contains all the input parameters selection that can be chosen in the experiment. These parameters include the closing price, the stock information (opening price, highest price, lowest price, and volume trade), KLCI index, the interest rate and foreign currency exchange rates (USD, EUR, and SGD). There is also an option for the user to choose all or some of the data points.

The network panel consists of the parameter configuration for a neural network which are the number of neurons to be used, the partition ratio of the training, validation and testing data set and the transfer function. In this experiment, two different neural networks are selected to test the prediction performance which is the FFNN and RNN. The RNN model used in this research is NARX. The RNN is slightly different from FFNN in that its input layer consists of input that is feedback from the output layer. The training panel specifies the learning algorithm (LMA) and configuration setting for the algorithm which consists of the training epoch, performance goal, maximum validation failures, minimum performance gradient, the initial mu value, the mu decrease factor, the mu increase factor, the maximum mu value and the maximum time to train in seconds. The last panel is the result panel that can be used by the user to choose the performance functions, the different plot function, the directory to store the result and the number of experiments to be run in each test.

## V. RESULT AND DISCUSSIONS

A series of experiments were carried out to investigate the performance of FFNN and RNN in predicting the CIMB stock closing price. Table 2 shows the prediction accuracy for FFNN. The result shows that FFNN achieved more than 90% accuracy in the majority of the prediction. FFNN also performs well in forecasting the CIMB stock market price by achieving a low MSE value and high prediction accuracy value.

Table 2
FFNN Prediction Accuracy

| **Prediction Accuracy** | **Data Points** | **Percentage of Data Points (%)** |
|---|---|---|
| 100% | 2321 | 58.10 |
| 90% | 1669 | 41.78 |
| 80% | 4 | 0.10 |
| 70% | 0 | 0.00 |
| 60% | 0 | 0.00 |
| 50% | 0 | 0.00 |
| 40% | 0 | 0.00 |
| 30% | 0 | 0.00 |
| 20% | 0 | 0.00 |
| 10% | 0 | 0.00 |
| 0% | 1 | 0.03 |
| Total Data Points: | 3995 | Total Percentage: 100.00 |

Table 3 shows the prediction accuracy for RNN. The result in Table 3, shows that the performance of RNN is quite similar to FFNN in that the 43.28% of its data point achieved a prediction accuracy of 90%.

In order to differentiate and distinguish the performances of the two neural network architectures, Table 4 shows the comparison between the prediction accuracy of FFNN and RNN in terms of lowest MSE, average MSE, prediction accuracy of 100% and prediction accuracy greater than 90%.

Table 3
RNN Prediction Accuracy

| Prediction Accuracy | Data Points | Percentage of Data Points (%) |
|---|---|---|
| 100% | 2258 | 56.52 |
| 90% | 1729 | 43.28 |
| 80% | 7 | 0.18 |
| 70% | 0 | 0.00 |
| 60% | 0 | 0.00 |
| 50% | 0 | 0.00 |
| 40% | 0 | 0.00 |
| 30% | 0 | 0.00 |
| 20% | 0 | 0.00 |
| 10% | 1 | 0.03 |
| 0% | 0 | 0.00 |
| Total Data Points: | 3995 | Total Percentage: 100.00 |

Table 4
RNN Prediction Accuracy

| | FFNN | RNN |
|---|---|---|
| Lowest MSE | **0.0211** | 0.0222 |
| Average MSE | **0.0301** | 0.0314 |
| Prediction Accuracy 100% | **58.1** | 56.52 |
| Prediction Accuracy > 90% | **99.87** | 99.8 |

Based on Table 4, it can be concluded that FFNN performs better than RNN in predicting the CIMB closing price as it recorded a lower lowest MSE, a lower average MSE, a higher prediction accuracy of 100% and a higher prediction accuracy greater than 90%. The result also showed the prediction result is dependent on the type of network architecture adopted in forecasting stock closing price.

## VI. CONCLUSION

This paper describes the application of FFNN and RNN in predicting the CIMB stock closing price. The results showed that both FFNN and RNN performed well by achieving more than 90% prediction accuracy. Moreover, the FFNN performed slightly better than the RNN in terms of performance evaluation criteria. The most important evaluation criteria were the percentage of 100% prediction accuracy which showed that FFNN has a higher hit rate that RNN. Hence, in terms of profit value, FFNN can achieve higher profit value than RNN. This paper compared the performance FFNN and RNN in predicting CIMB stock closing price. For future work, it would be useful to investigate the prediction accuracy for the aggregation of several neural networks and compare it to a single neural network.

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## APPENDIX

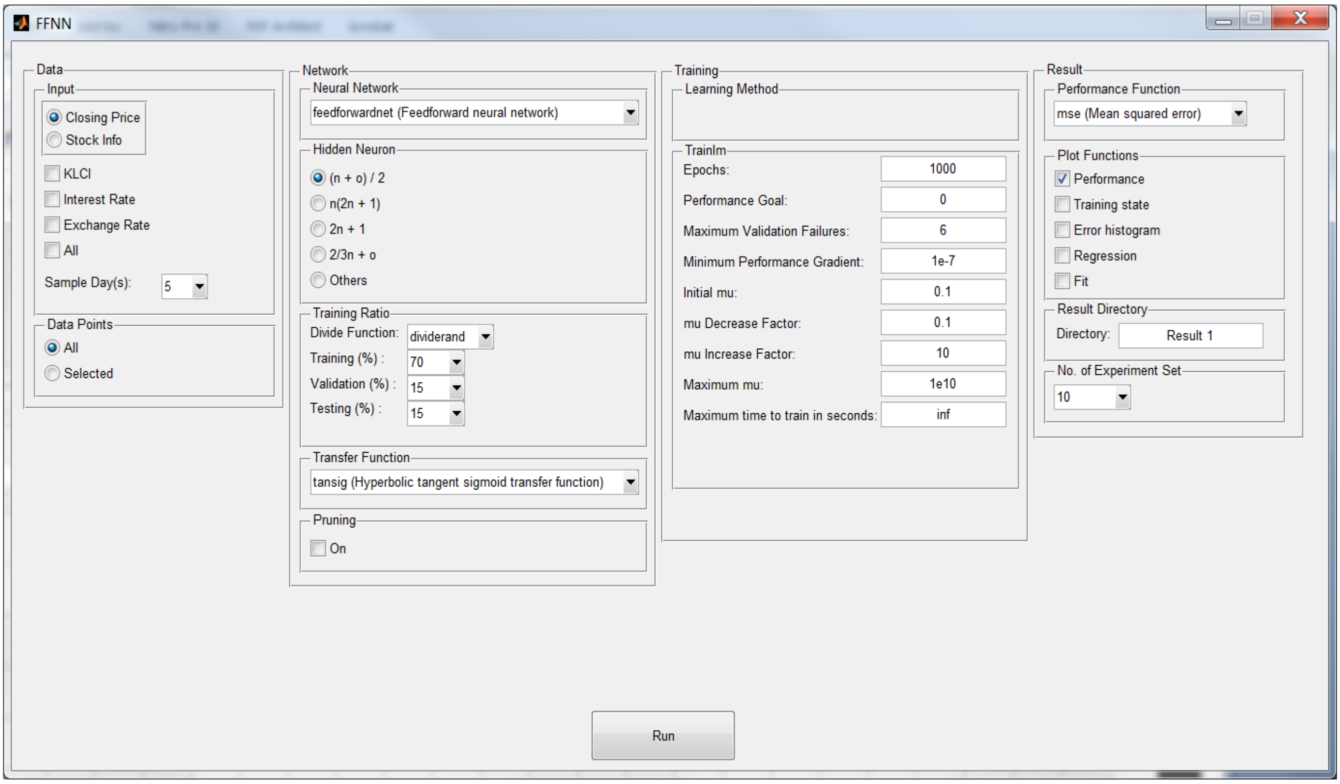


Figure 1: FFNN Simulation Interface

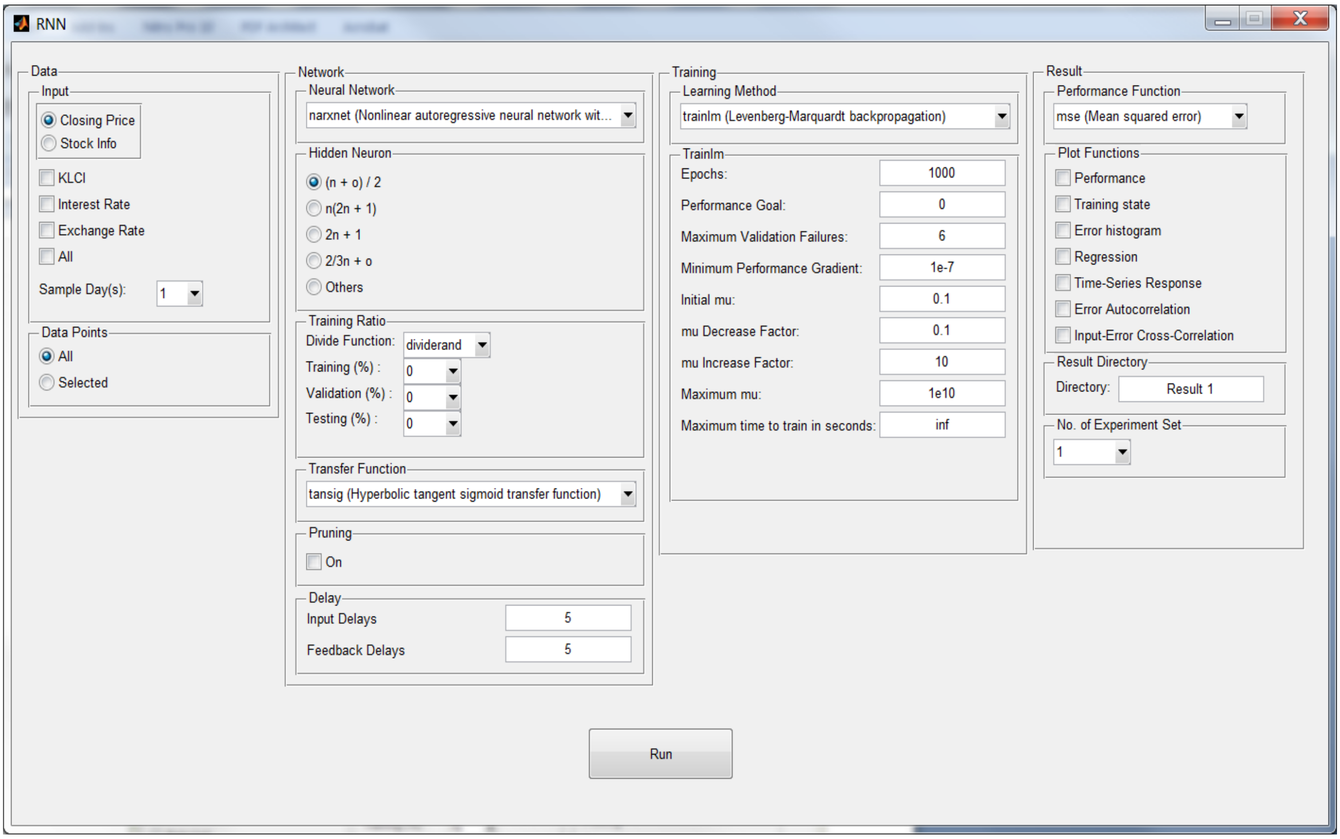


Figure 2: RNN Simulation Interface