MERAMAL PERMINTAAN PRODUK MENGUNAKAN RANGKAIAN NEURAL BUATAN (ANN)

(PRODUCT DEMAND FORECASTING USING ARTIFICIAL NEURAL NETWORK (ANN))

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Adapt - Allow a neural network to adapt.

adaptParam - defines the parameters and values of the current adapt function.

Global - Define global variable.

Init - Initialize a neural network.

initFcn - initialization function

Initlay - Layer-by-layer network initialization function.

initnw - Nguyen-Widrow layer initialization function.

Mse - Mean squared error performance function.

Net - Network

Newff - Create a feed-forward backpropagation network.

Newp - Create a perceptron.

Postreg - Postprocess network response w. linear regression analysis.

Premnmx - Normalize data for maximum of 1 and minimum of -1.

Purelin - Hard limit transfer function.

Sim - Simulate a neural network.

Tramnmx - Transform data with pre-calculated minimum and max.

Train - Train a neural network.

Trainlm - Levenberg-Marquardt back-propagation.

trainParam - training parameters

trainFcn - training function

Tansig - Hyperbolic tangent sigmoid transfer function.

ABSTRACT

This thesis is to forecast the product demand using Artificial Neural Networks (ANN). This thesis helps readers to understand Artificial Neural Network (ANN). Question about what is ANN, how ANN work and how to used ANN to predict and simulate the data to forecast the product demand can be found in this thesis. General use of ANN in other fields also include in this thesis.

This thesis also includes the literature review from many journals by researchers in forecasting which proves that ANN is really suitable for forecasting because of its accuracy.

By using the Neural Network Toolbox in the Math lab, Feedforward Back propagation Neural Network is chosen for forecast and simulates the data to complete this project. The data used for training ANN are is the actual data from the production line. After the training, the forecast data compared well with the actual data.

ABSTRAK

Tesis ini adalah mengenai membuat ramalan untuk permintaan produk menggunakan rangkaian neural buatan (ANN). Tesis ini membantu pembaca untuk memahami serba sedikit tentang rangkaian neural buatan (ANN). Persolan tentang apakah ANN, bagaimanan ANN berkerja dan bagimana untuk menggunakan ANN untuk menganggar dan membuat simulasi data untuk meramal permintaan produk boleh didapati di dalam tesis ini. Penggunaan umum ANN dalam bidang lain juga diterangkan serba sedikit didalam repot ini.

Taksiran daripada penulisan jurnal oleh penyelidik-penyelidik terdahulu juga dimasukkan di dalam tesis ini sebagai pembuktian bahawa rankaian neural buatan ini amat sesuai digunakan dalam membuat ramalan kerana ketepatannya.

Dengan menggunakan kotak peralatan rankaian neural di dalam Mathlab, rangkaian buatan “Feedforward Backpropagation” dipilih untuk meramal dan membuat simulasi data bagi menyiapkan projek ini. Data yang digunakan untuk latihan rangakaian buatan ini adalah data sebenar hasil baris pengeluaran. Selepas latihan, nilai ramalan yang terhasil di bandingkan dengan nilai sebenar pengeluaran.

CHAPTER 1
INTRODUCTION

1.1 FORECASTING

Demand products and services is one of the most fundamental tasks that a business must perform. It is a proactive process of determining what products are needed where, when, and in what quantities. Besides try to improve the products itself and make more promotion for widen the market, forecast the demand for the product for the next production are very important to make sure the company will not produce products that customer less demand.

Effective demand forecasting will help the business reach its goals. From the customer’s perspective, their needs will be satisfied by having goods available when they want them. You're obviously in trouble if you don't have the inventory your customers expect you to have. And if you've bought too much of an item, your money is tied up and can't be invested in the other products that allow you to take advantage of new sales opportunities.

Various methods such as moving average, exponential smoothing, regression, trend line analysis et cetera are use for forecasting. Company should refers to an approach to forecasting that develops forecasts by various techniques, then picks the forecast that was produced by the best of these techniques, where best is determined by some measure of forecast error. It is not easy to forecast the demand product, a very good method much be choose to make sure the forecast really can forecast the demand without higher failure.

For this thesis, Artificial Neural Networks (ANN) is being used as a method to make the products demand forecasting and was training by Math lab software.

1.2 ARTIFICIAL NEURAL NETWORKS (ANN)

1.2.1 Artificial Neural Networks.

Artificial Neural Networks is one of the new tools in Artificial Intelligence (AI). It is a relatively crude electronic models based on the neural structure of the brain.

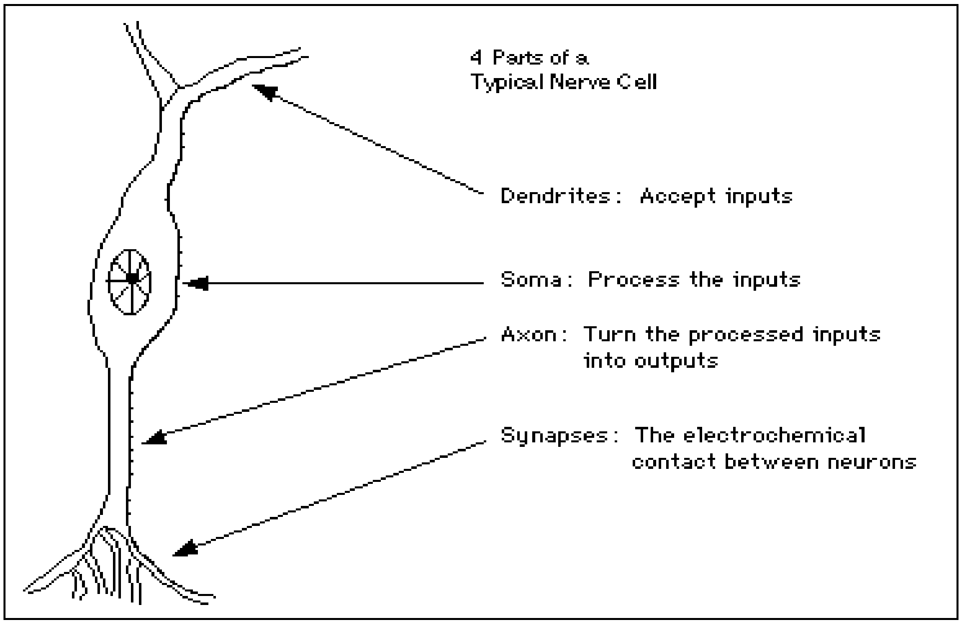


Figure 1.2.1: A Simple Neuron

Dendrites are hair-like extensions of the soma which act like input channels. These input channels receive their input through the synapses of other neurons. The soma then processes these incoming signals over time. The soma then turns that processed value into an output which is sent out to other neurons through the axon and the synapses.

A neural network is, in essence, an attempt to simulate the brain. Neural network theory revolves around the idea that certain key properties of biological neurons can be extracted and applied to simulations, thus creating a simulated (and very much simplified) brain. The first important thing to understand then is that the components of an artificial neural network are an attempt to recreate the computing potential of the brain. The second important thing to understand, however, is that no one has ever claimed to simulate anything as complex as an actual brain. Whereas the human brain is estimated to have something on the order of ten to a hundred billion neurons, a typical artificial neural network (ANN) is not likely to have more than 1,000 artificial neurons.

1.3 MATHLAB SOFTWARE

Math lab is derived from term “matrix laboratory”. It provides an interactive development tool for scientific and engineering problems and more generally for those areas where significant numeric computations have to be performed. Math lab provides the users with:

- Easy manipulation of matrix structures
- A vast number of powerful inbuilt routines which is constantly growing and developing
- Powerful two- and three-dimensional graphing facilities
- A scripting system which allows users to develop and modify the software for their own needs.

1.3 OBJECTIVES

The objectives of this thesis are:

i. To understand the concept of Artificial Neural Network (ANN)
ii. Use the ANN to forecast the product demand forecasting for production planning.
iii. Training the data.
iv. Check the accuracy of the forecast.

1.4 SCOPE

Forecasting is very important for production planning to make sure the company will produce the products that are demand by the customer. For this project MATHLAB software was used to write the program for forecasting using ANN. From the software I used neural network toolbox to build the program. This program can be used for short term forecasting. Feed Forward Back-propagation was choosing to complete the programmed. This program can be use to forecast the data that was not given as the input in the program. The data that was given as an input were used as the training data for ANN to study the relationship between the input and output data. The data is the actual production line that was given by Dr. Shahrul.

CHAPTER 2
LITERATURE REVIEW

2.1 Human Brain

Human brain was studied for along time ago. The first step toward artificial neural network came in 1943 when Warren McCulloch, a neurophysiologist, a mathematician, Walter Pitts, wrote a paper on how neurons might work. They modeled a simple neural network with electrical circuits. The human nervous system consists of billions of neurons of various types and lengths relevant to their location in the body (Schalkoff, 1997).Because the biological neuron is the basic building block of the nervous system, its operation will be briefly discussed for understanding artificial neuron signal transfer between two biological neurons total receiving area of the dendrites of a typical neuron is approximately 0.25 mm (Zupan and Gasteiger, 1993).

In 1982, several events caused a renewed interest. John Hopfield of Caltech presented a paper to the national Academy of Science. Hopfield's approach was not simply a model brains but to create useful devices.

2.2 Artificial Neural Network (ANN)

Artificial neural networks (ANNs) as presented by I.A Basherr and M.Hajmeer (2000), is a relatively new computational tools that have found extensive utilization in solving many complex real-world problems. The attractiveness of ANNs comes from their remarkable information processing characteristics pertinent mainly to nonlinearity, high parallelism, fault and noise tolerance, and learning and generalization capabilities. ANNs are compared to both expert systems and statistical regression and their advantages and limitations are outlined. A bird's eye review of the various types of ANNs and the related learning rules is presented, with special emphasis on back-propagation (BP) ANNs theory and design.

Artificial models possessing such characteristics are desirable because:

i. Nonlinearity allows better fit to the data.
ii. Noise-insensitivity provides accurate prediction in the logical presence of uncertain data and measurement errors.
iii. High parallelism implies fast processing and hardware failure-tolerance.
iv. Learning and adaptively allow the system to update (modify) its internal structure in response to changing environment.
v. Generalization enables application of the model to unlearned data. The main objective of ANN-based computing (neurocomputing) is to develop mathematical algorithms that will enable ANNs to learn by mimicking information processing and knowledge acquisition in the human brain.

The Organization of Behavior was written in 1949 by Donald Hebb to reinforce the concept of neurons and how they work. In the book, it points out the advantages of using neural network and its strength while applying the network. According to Hecht and Nielsen, (1990) and Schalkoff, (1997), ANNs are computational modeling tools that have recently emerged and found extensive acceptance in many disciplines for modeling complex real-world problems. ANNs may be defined as structures comprised of densely interconnected adaptive simple processing elements (called artificial neurons or nodes) that are capable of performing massively parallel computations for data processing and knowledge representation.

ANN is like the brain; consist of connected processing elements called neurons. The information contained in such a network is stored in the weight coefficients of the interneuron connections. Neural networks are able to learn to associate a vector of input variables with a vector of output variables. (P. Koprinkova and M. Petrova, 1999)

Although ANNs are drastic abstractions of the biological counterparts, the idea of ANNs is not to replicate the operation of the biological systems but to make use of what is known ANNs may about the functionality of the biological networks for solving complex problems. The attractiveness of ANNs comes from the remarkable information processing characteristics of the biological system such as nonlinearity, high parallelism, robustness, fault and failure tolerance, learning, ability to handle imprecise and fuzzy information, and their capability to generalize (Jain et al., 1996).

Recent research activities in ANNs have shown that ANNs have powerful pattern classification and pattern recognition capabilities. Inspired by biological systems, particularly by research into the human brain, ANNs are able to learn from and generalize from experience. Currently, ANNs are being used for a wide variety of tasks in many different fields of business, industry and science (Widrow et al., 1994). Thus ANNs are well suited for problems whose solutions require knowledge that is difficult to specify but for which there are enough data or observations. In this sense they can be treated as one of the multivariate nonlinear nonparametric statistical methods (White, 1989; Ripley, 1993; Cheng and Titterington, 1994).

In 1958, Rosenblatt introduced the mechanics of the single artificial neuron and introduced the 'Perceptron' to solve problems in the area of character recognition (Hecht-Nielsen, 1990). Basic findings from the biological neuron operation enabled early researchers (e.g., McCulloh and Pitts, 1943) to model the operation of simple artificial neurons.

(White, 1990) expressed that if wishing the output more precise, feedforward networks with a single hidden layer and trained by least-squares are statistically consistent estimators of arbitrary square-integrable regression functions under certain practically-satisfiable assumptions regarding sampling, target noise, number of hidden units, size of weights, and form of hidden-unit activation function. Such networks can also be trained as statistically consistent estimators of derivatives of regression functions (White and Gallant, 1992) and quantiles of the conditional noise distribution (White, 1992a).

Feedforward networks with a single hidden layer using threshold or sigmoid activation functions are universally consistent estimators of binary classifications (Faragó and Lugosi, 1993; Lugosi and Zeger 1995; Devroye, Györfi, and Lugosi, 1996) under similar assumptions. Note that these results are stronger than the universal approximation theorems that merely show the existence of weights for arbitrarily accurate approximations, without demonstrating that such weights can be obtained by learning.

Rudolph, et. Al, (1995) introduces Location-Independent Transformations (LITs) as a general strategy for parallel implementation of feedforward networks that use dynamic topologies. A LIT creates a set of location-independent nodes, where each node computes is part of the network output independent of other nodes, using local information. This type of transformation allows efficient support for adding and deleting nodes dynamically during learning. He deals the LITs for localist ANNs--localist in the sense that ultimately one node is responsible for each output. In particular, this paper presents LITs for two ANNs:

i. the single-layer competitive learning network,
ii. The counter propagation network, which combines elements of supervised learning with competitive learning. The complexity of both learning and execution algorithms for both ANNs is linear in the number of inputs and logarithmic in the number of nodes in the original network.

Javier (1996), shows how the alternative algorithms can be obtained within the framework of ordered partial derivatives. Feedforward multilayer neural networks (FMNN) able to approximate arbitrary continuous nonlinear mappings to any desired degree has lead to their wide spread popularity as a powerful tool in a huge variety of engineering applications during the last ten years. Two alternatives for feedforward propagating algorithms are derived in this work which is mathematically equivalent to the back-propagation (BP).

Different of function *f* can be computed with an extended back-propagation algorithm or with a direct method. The model is powerful enough to describe classic architectures such as multilayer perceptrons or wavelet networks and simple enough to allow the derivation of an extended back-propagation algorithm. (Cédric, et.al, 1996).

Fastest training is usually obtained if MacQueen's on-line algorithm is used for the first pass and off-line k-means algorithms are applied on subsequent passes (Bottou and Bengio, 1995). However, these training methods do not necessarily converge to a global optimum of the error function. The chance of finding a global optimum can be improved by using rational initialization. Multiple random initializations or various time-consuming training methods intended for global optimization (Ismail and Kamel, 1989; Zeger, Vaisy, and Gersho, 1992).

2.3 Application of ANN in Forecasting System.

O.A. Alsayegh, (2003) presents the development of an artificial neural network (ANN)-based short-term load forecasting system for the Power Control Center of the Ministry of Electricity and Water (MEW), Kuwait. The proposed seasonal ANN (SANN) consists of 12 independent networks. Every three networks are assigned to a season, namely, winter, transition from winter to summer, summer, and transition from summer to winter. Each of the three networks (in each group) is trained with weather-related data, historical electric load-related data, and social event-related data for particular time durations. The results show that the proposed configuration of the ANN forecasters (SANNs) is able to bring down the average percentage error from 5.6% (produced by the MEW regression-based forecasting system) to 1.9%.

Gwo-Ching and Ta-Peng, (2003) used the integrated evolving fuzzy neural network and simulated annealing (AIFNN) for load forecasting method. They combined both methods to obtain both advantages, and so improve the shortcoming of the traditional ANN training where the weights and biases are always trapped into a local optimum. The more accurate load curve forecast can be achieved by the AIFNN approach.

Istook, et.al, (2002) present the Windowed momentum algorithm, which increases speedup over standard momentum. Windowed momentum is designed to use a fixed width history of recent weight updates for each connection in a neural network. By using this additional information, Windowed momentum gives significant speed-up over a set of applications with same or improved accuracy.

Excellent prediction of a method for electric load forecasting in buildings based on a feedback ANN. The main virtue of this system is its simplicity, which is based on the fact that the developed tool is very simple and the resources for its application are tiny and available at modern automation systems. In particular, in order to apply it to a STLF system, only simple methods for atmospheric temperature and electric power measurement are required. The numbers of neurons that compose the hidden layer of the ANN, the optimal size of the data window and the parameters of the algorithm of training have not been deeply analyzed. The experimental works carried out suggest that these values should be carefully studied, but anyway, as it is expounded; many neurons were not needed to get satisfactory results. (Pedro, et.al, 2004)

Gianluigi, (2003) forecast exercise on 30 time series, ranging on several fields, from economy to ecology. The statistical approach to artificial neural networks modeling developed by the author is compared to linear modeling and to other three well-known neural network modeling procedures: Information Criterion Pruning (ICP), Cross-Validation Pruning (CVP) and Bayesian Regularization Pruning (BRP). The findings are that:

i. The linear models outperform the artificial neural network models
ii. Albeit selecting and estimating much more parsimonious models, the statistical approach stands up well in comparison to other more sophisticated ANN models.

Artificial neural networks (ANN) are used for prediction of pesticide occurrence in rural domestic wells from the available limited information. According to G.B. Sahoo, et.al (2005), among the three ANN models (a feed-forward back propagation [BP], a radial basis function [RBF] and an adaptive neural network-based fuzzy inference system [ANFIS]) employed for this investigation, the BP neural network was found to be superior to RBF and ANFIS type networks for the detection of pesticide occurrences in wells. For improved model prediction efficiency, optimization of network structure (e.g., number of hidden layers and number of nodes in each hidden layer) and spread (the width of the radial basis function) are important for BP and RBF type of network, respectively. A four layer BP network with a 3:2 neurons ratio of the first hidden layer to the second hidden layer produced better prediction performance efficiencies in terms of the pesticide detection efficiency (*E*f), the root mean square error (RMSE), and the correlation coefficient (*R*) and the overall *E*f of the BP neural network was found greater than 85%. Sensitivity analysis was performed to measure the relative importance of one input parameter over the other in pesticide occurrence in wells. It was shown in terms of the prediction efficiencies (*E*f, RMSE, and *R*) of a four-layer BP neural network that the time of sample collection (TSC; month of the year), the depths of wells, and pesticide travel times (PTT) were more important parameters in the prediction of the pesticide occurrences in rural domestic wells.

Alex, et.al. (1993) presents a new Artificial Neural Network (ANN) based model for the calculation of short-term load forecasts. The ANN model consistently outperforms the regression model in terms of both average errors over a long period of time and number of “large” errors. They conclude that neural networks have matured enough to be successfully applied in many power system applications. Due to their great flexibility and adaptability, neural networks appear promising fur rapid development of products in these areas.

Features and desired outputs that related to the system should be study to avoid problem before neural network load forecasting systems can be successfully applied to inflow forecasting. By using Karhunen-Loeve transform (KLT), they compress the larges input and output vectors. They are using KLT because; Neural Networks with large input and output are difficult to train. (Chandrashekar and Michael, 1995)

Ben, et.al, (2004), presents that the use of the experimental design combined with the ANN proved to be effective for optimization of CE Pharmaceutical product determination of Huperzine A in aqueous media and in a biological fluid. The method was optimized and validated with regard to specificity linearity, range, limit of detection quantization and precision. Lower limit of detection was reached.

Ioannis, et.al. (2005) stated that a proper design of the architecture of ANN models can provide a robust tool in water resources modeling and forecasting. Seven different types of network architectures and training algorithms are investigated and compared in terms of model prediction efficiency and accuracy. The different experiment results show that accurate predictions can be achieved with a standard feedforward neural network trained with the Levenberg–Marquardt algorithm providing the best results for up to 18 months forecasts.

ANN was used in physiological model to predict the energy cost to different prolonged manual lifting tasks for the different lifting heights commonly encountered in industry. The physiological models developed in this study maintain the advantages of the existing regression models and overcome some of their deficiencies. (Mona, 1999).

Bahman and Hiroshi, (2002) wrote a paper title Up to year 2020 Load Forecasting Using Neural Nets. They described about a total system load forecast reflecting current and future trends is carried out for nine power companies in Japan. Two ANNs, a three-layered back-propagation and a recurrent neural network, were designed and tested for the purpose. Predictions were done for target years 1999, 2000, 2005, 2010, 2015, and 2020, respectively. There are different from the short-term load forecasting, long-term load forecasting is mainly affected by economical factors rather than weather conditions. Their paper focuses on economical data that seem to influence long-term electric load demands. The data used are: actual yearly, incremental growth rate from the previous year, and both together (actual and incremental growth rate from the previous year)

Michael, et.al, (2005) demonstrate the effectiveness of an artificial neural network (ANN) model in mapping gait measurements onto COM motion in the frontal plane. They used data from 40 subjects of varied age and balance impairment was entered into a 3-layer feed-forward model with back-propagated error correction. Bootstrap re-sampling was used to enhance the generalization accuracy of the model, using 20 re-sampling trials. The ANN model required minimal processing time (5 epochs, with 20 hidden units) and accurately mapped COM motion (R-values up to 0.89). As training proportion and number of hidden units increased, so did model accuracy. Overall, this model appears to be effective as a mapping tool for estimating balance control during locomotion. With easily obtained gait measures as input and a simple, computationally efficient architecture, the model may prove useful in clinical scenarios where electromyography equipment exists.

The idea of using ANNs for forecasting is not new. The first application dates back to 1964. Hu (1964), in his thesis, uses the Widrow's adaptive linear network to weather forecasting. Due to the lack of a training algorithm for general multi-layer networks at the time, the research was quite limited. It is not until 1986 when the back propagation was introduced (Rumelhart et al., 1986) that there had been much development in the use of ANNs for forecasting. Werbos (1974), (1988) first formulates the back propagation and finds that ANNs trained with back propagation outperform the traditional statistical methods such as regression and Box-Jenkins approaches. Lapedes and Farber (1987) conduct a simulated study and conclude that ANNs can be used for modeling and forecasting nonlinear time series.Weigend et al. (1990), (1992); Cottrell et al. (1995) address the issue of network structure for forecasting real-world time series. Tang et al. (1991), Sharda and Patil (1992), and Tang and Fishwick (1993), among others, report results of several forecasting comparisons between Box-Jenkins and ANN models. In a recent forecasting competition organized by Weigend and Gershenfeld (1993) through the Santa Fe Institute, winners of each set of data used ANN models (Gershenfeld and Weigend, 1993).

Guoqiang, et.al (1998), in their journal summarized that the unique characteristics of ANNs adapt ability, nonlinearity, and arbitrary function mapping ability make them quite suitable and useful for forecasting tasks. Overall, ANNs give performance in forecasting. A considerable amount of research has been done in this area. The findings are inconclusive as to whether and when ANNs are better than classical methods. There are many factors that can affect the performance of ANNs. However, there are no systematic investigations of these issues. The shotgun (trial-and-error) methodology for specific problems is typically adopted by most researchers.

Nowrouz, et.al, (1996) was compare ARIMA and neural network price forecasting performance by using feedforward neural network which can account for nonlinear relationships. Data used was monthly live cattle and wheat prices from 1950 through 1990. The experiment was repeated seven times for successive three year periods. This involved using a walk forward or sliding window approach from 1970 through 1990 which generated out of sample results. The neural network models achieved a 27 percent and 56 percent lower mean squared error than AR&IA model. The absolute mean error and mean absolute percent error were also lower for the neural network models. The neural network models were able to capture a significant number of turning points for both wheat and cattle, while the ARIMA model was only able to do so for wheat. Since this forecasting method is not complex problem and uses only past prices, it can be applied to other forecasting problems such as stocks and other financial prices.

From the literatures review we can see that ANN have been used for forecasting in variety tasks in many different fields of business, industry and science from several years ago with high accuracy.

CHAPTER 3
METHODOLOGY

Artificial neural networks are, as their name indicates, computational networks which attempt to simulate, in gross manner, the networks of nerve cell (neurons) of the biological (human or animal) central nervous system. The simulation borrows from the neurophysiologic knowledge of biological neurons and of networks of such biological neurons. It’s different from the conventional (digital or analog) computing machines that serve to place, enhance or speed-up human brain computation without regard to organization of the computing elements and of their networking.

3.1 MATHLAB NEURAL NETWORKS TOOLBOX.

To carry out this work Math lab is used to write a program to test and simulate based on Artificial Neural Network (ANN). Neural Network Toolbox (NNT) in Math lab simply a summary of established procedures that are known to work well. It is a very useful tool for education and research, a tool that will help users find what works and what doesn’t, and a tool that will help develop and extend the field of neural networks. From the NNT, FeedForward Back-propagation Neural Network had been chosen to complete the program.

3.2 BACK-PROPAGATION NEURAL NETWORKS.

Back-propagation (BP) is one of the most widely used neural network paradigms, which have been applied successfully in application studies. BP can be applied to any problem that requires pattern mapping. Given an input pattern, the network produces an associated output pattern. Its learning and update procedure is intuitively appealing, because it is based on a relatively simple concept: the network is supplied with both a set of patterns to be learned and the desired system response for each pattern.

The typical back-propagation network has an input layer, an output layer, and at least one hidden layer. There is no theoretical limit on the number of hidden layers but typically there is just one or two. Some work has been done which indicates that a minimum of four layers (three hidden layers plus an output layer) are required to solve problems of any complexity. Each layer is fully connected to the succeeding layer, as shown in Figure 3.2.1. I used 4 layers of neural network for this program. The first layer, the input nodes, receives the input data (also called the middle layer or the hidden layer). The results of the first layer are passed to the next layer. This process is repeated for each layer until an output is generated.

The advantages of using such a network center on some of their properties, too. Firstly, they automatically generalize their knowledge enabling them to recognize patterns, which they have had seen. Secondly, they are robust enough to recognize patterns, which have been obscured by noise. Lastly, once they have been trained on the initial set of patterns, their recognition of similar patterns is accomplished very quickly.

BP training has also two more key advantages for applications, which other network paradigms do not possess. The first advantage is that BP training is mathematically designed to minimize the mean squared aggregate error across all training patterns. The other advantage is that it is a supervised training technique. This means that the network designer can dictate the exact results he or she wants the network to achieve, and the network's performance can always be measured against those results. Supervised training is predictable, easy to use, and thus it is the prime favorite for our long-term load forecasting study.

3.2.1Feedforward back-propagation

Feedforward back-propagation have one-way connections from input to output layers. They are most commonly used for prediction, pattern recognition, and nonlinear function fitting. Supported feed-forward networks include feed-forward back-propagation, cascade-forward back-propagation, feed-forward input-delay back-propagation, linear, and perceptron networks.

Feedforward back-propagation architecture was developed in the early 1970¹s by several independent sources (Werbor; Parker; Rumelhart, Hinton and Williams). This independent co-development was the result of a proliferation of articles and talks at various conferences which stimulated the entire industry. Currently, this synergistically developed back-propagation architecture is the most popular, effective, and easy to earn model for complex, multi-layered networks. This network is used more than all other combined. It is used in many different types of applications. This architecture has spawned a large class of network types with many different topologies and training methods.

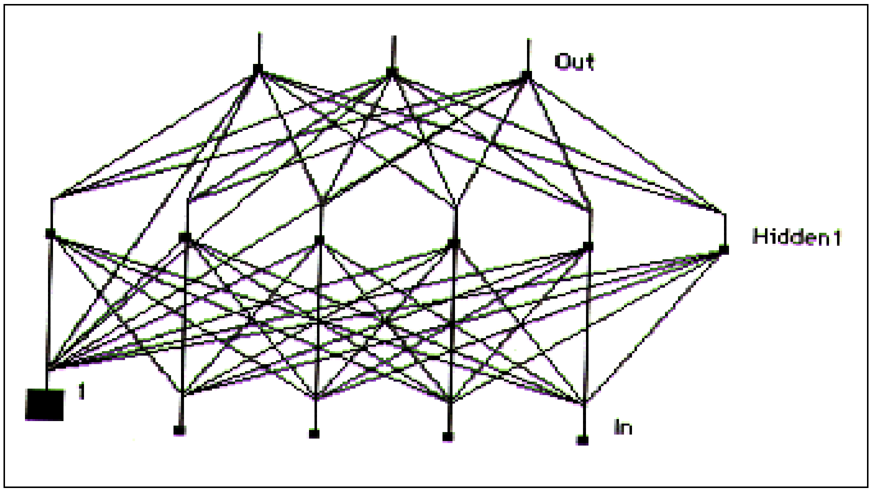
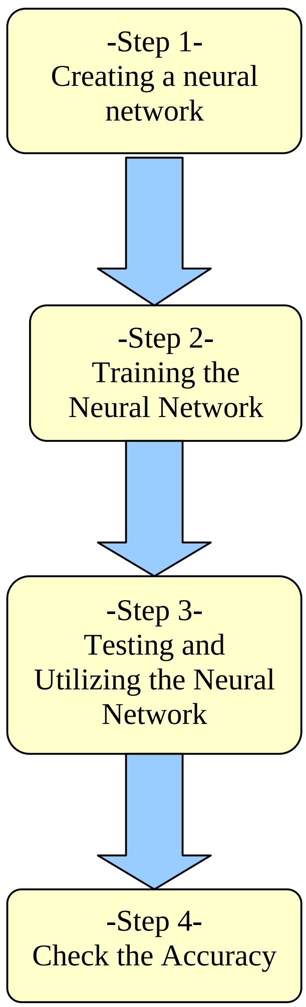


Figure 3.2.1: An Example Feedforward Back-propagation Network

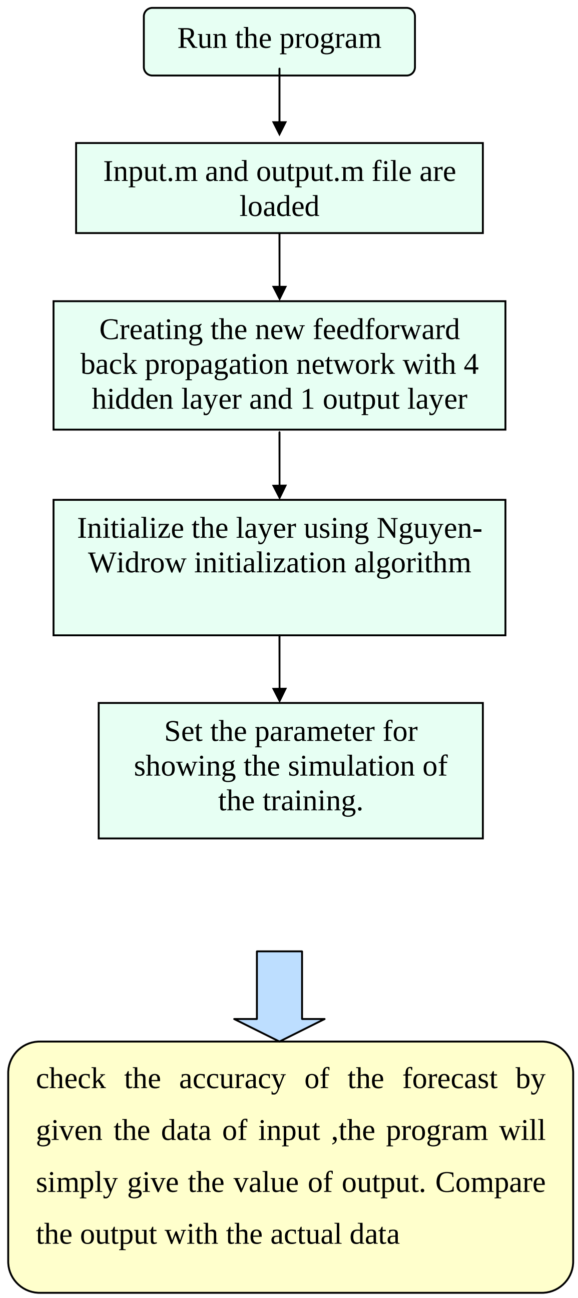
There are limitations to the feedforward, back-propagation architecture. Back-propagation requires lots of supervised training, with lots of input-output examples. Additionally, the internal mapping procedures are not well understood, and there is no guarantee that the system will converge to an acceptable solution. At times, the learning gets stuck in a local minimum, limiting the best solution. This occurs when the network systems finds an error that is lower than the surrounding possibilities but does not finally get to the smallest possible error. Many learning applications add a term to the computations to bump or jog the weights past shallow barriers and find the actual minimum rather than a temporary error pocket.

The purpose of this project is applying the ANN to forecast the product demand for production line and to check the accuracy of the forecast. Math lab programming was used for this forecasting. I had taken 300 production data for this project. Input data is the days and the output data is the actual production line data. From the 1 to 300 data, 290 from them are used to train the program and 10 are chosen randomly from the data to be used as a test input to check the accuracy of the forecast. The results from this test are compared with production the actual data and were given in the Table 1 and the forecast test in Table 2.

Figure 3.3 : The flow chart for solving the project problem.



3.4: Math lab Program Flow Chart



Training parameters that have set for this program is:

1) To show every 1000 training parameters
2) The maximum epochs is 20000
3) The training parameter goal is (1e-2)/2 or 0.005

Training will stops when any of these conditions occurs:

1) The maximum number of epochs (repetitions) is reached.
2) The maximum amount of time has been exceeded.
3) Performance has been minimized to the goal.
4) The performance gradient falls below mingrad.
5) Validation performance has increased more than max fail time since the last time it decreased (when using validation).

CHAPTER 4
RESULT AND DISCUSSION

4.1 RESULT

To achieve the main purpose of the project, to forecast the product demand for production line the math lab programming are built. With this program, ANN will train the given data of input and input to get the associate between these variables. Over of 300 data, 10 of them are chosen randomly as a test to check the accuracy of the networks.

The graph of the training with trainlm as shown in figure 4.1 will appear after we run the program.

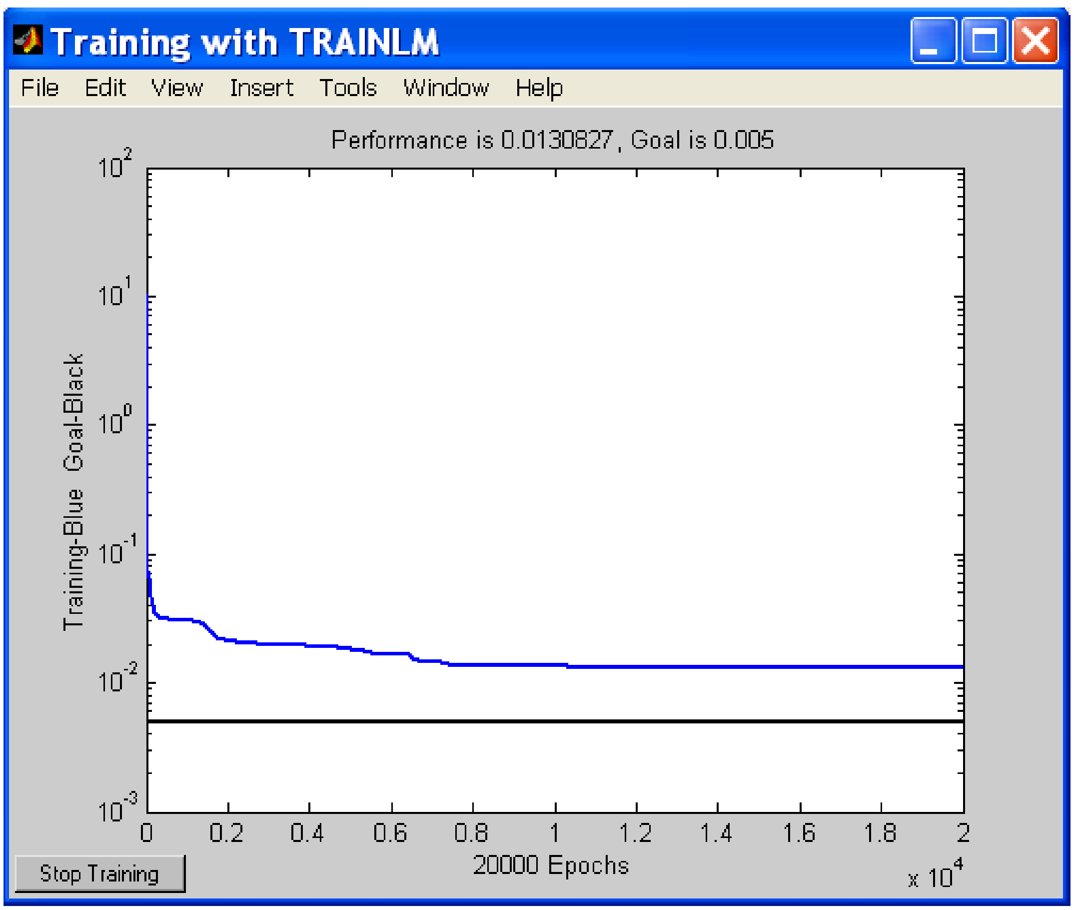


Figure 4.1: Training with Trainlm Graph.

From the figure 4.1 shows that the goal parameter that have used is 0.005 and the performance is 0.0130827. The training stopped at the maximum epochs as stated in the parameter setting, 20000. After the training was stopped, a new type of graph appeared. It is the best linear fit graph as shown below.

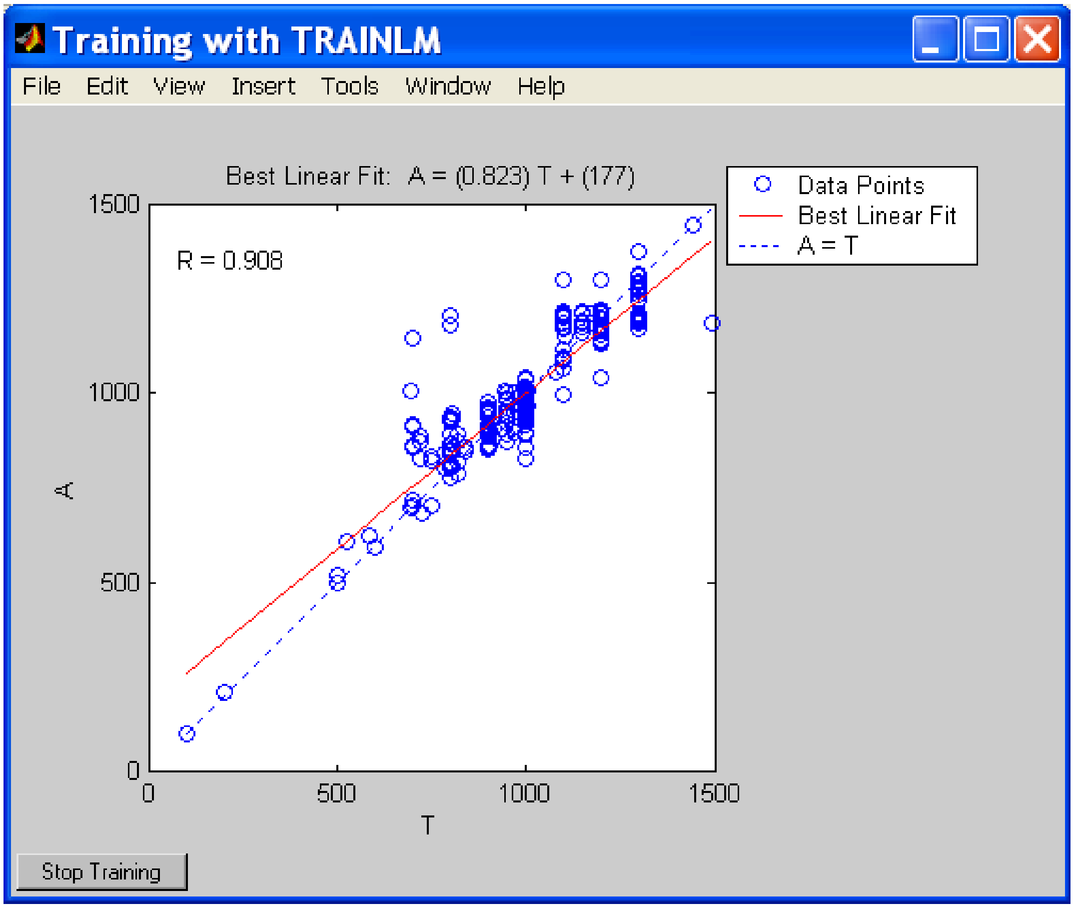


Figure 4.2: The Best Linear Fit Graph

From this graph it shows that the value of the best correlation R is equal to 0.908 and best linear fit of training is 0.823T+177.

The training is finish after the best linear fit graph appeared and the test for the networks can be done. For the beginning I had test the networks with give the input that was included in the training and the 50 over 290 results from that test is shows in the table 1. The purpose of this test is to show the accuracy of the training.

Table 1: Result of the networks test with the data given in the program.

Day	Actual Data	Forecast	% of Error
1	900	933	3.67
2	1000	954	4.6
3	1000	953	4.7
4	954	952	0.21
5	920	951	3.37
6	1000	950	5
7	1000	950	5
8	950	949	0.11
9	1000	960	4
10	905	933	3.09
11	900	926	2.89
12	950	918	4.42
13	900	908	0.88
14	950	905	4.7
16	900	861	4.33
17	784	820	4.6
18	750	780	4
19	800	815	1.89
20	1000	960	4
21	720	750	4.17
22	1000	958	4.2
23	1000	998	0.2
24	1000	1017	1.7
25	1000	1011	1.1

Day	Actual Data	Forecast	%Error
26	1000	996	0.4
27	1000	975	2.5
28	1000	1000	0
29	1443	1443	0
30	900	916	1.78
31	900	894	0.67
32	900	899	0.11
33	900	901	0.11
34	700	703	0.43
35	900	894	0.67
36	902	920	2
37	900	886	1.56
38	822	819	0.36
39	1003	1005	0.2
40	1000	1003	0.3
41	1000	992	0.8
42	500	521	4.2
43	1000	963	3.7
44	1000	1038	3.8
46	1000	973	2.7
47	950	964	1.47
48	1000	979	2.1
49	1000	1007	0.7
50	1000	1019	1.9

From the table we can see that the forecast data are near to the actual data which are gives as the output in the program. These values are really near to the given data with the percent of error only 0 to 4.42%. All the data have less than 5% of error.

From the 300 data, input of 15, 45, 75, 105, 135, 165, 195, 225 and 285 are not given in the program and were used as the test new input. After the test the result is shows as in the Table 2.

Table 2: Result of test new input.

Day	**Actual data**	**Forecast Using ANN**	**% Error**
15	850	879	3.41
45	1000	1006	0.6
75	1200	1206	0.5
105	1300	1239	4.69
135	1100	1109	0.82
165	1000	956	4.4
195	900	863	4.11
225	1000	1000	0
255	900	902	0.22
285	1300	1245	4.23

From the table, it shows that the outputs are really near to the actual production line data. The percentages of error are less than 5%. Because of the accuracy of the result, this Math lab program can be used to predict the product demand.