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AN INNOVATIVE METHOD TO FORECASTING THE LOAD WITH THE HELP OF MULTILAYER PERCEPTRON NEURAL NETWORK

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ABSTRACT

Load forecasting have been a significant area of research as well as it has been a critical problem in planning and operation of electric power generation. In order to predict electrical load, the technique load forecasting is immensely used in global world. In addition, for power system planning the integration of short term load forecasting has been significant. Based on electric generating company, it is significant for them to analyse the market load demand in order to produce accurate power specifically in the deregulated market. This research paper have used half-hourly load data that have been gathered for short-term load forecasting in order to develop an more accurate model for New South Wales, Australia. The use of MATLAB tool box with the integration of multilayer feed forward neural network has been used. The training has been provided with the use of Levenberg-Marquardt back propagation in order to evaluate the result as well as performance of the model during testing, training and validation. The effectiveness of Mean Absolute Percentage Error has been also considered in the paper. The result illustrated that this method is highly an accurate and simple with minimum error as well as can be used for short term load forecasting.

Keywords: load forecasting, short-term load forecasting, artificial neural network, multilayer feed forward, levenberg marquardt back propagation algorithm, mean absolute percentage error.

INTRODUCTION

In today's world, energy is the most consumable thing. In addition, chemical energy in the form of batteries, electricity, wind energy, LPG as well as solar energy is all part of the energy that is being utilized extensively in the global world [1]. The aim is to offer an uninterrupted supply to the consumers of electricity as well as in order to attain such goal it is necessary to evaluate future demand power and present demand for power. This is the reason behind the need of appropriate technique which can be significantly attained through the integration of load forecasting in order to analyse the actual capability to generate power as well as the actual demand of consumers.

Load forecasting is a significant technique that aims to analyse the loads for the foreseen future. Furthermore, it assists to determine both future and present demand of the load. The applications of load forecasting integrate infrastructure development, energy purchasing, and generation, contract evaluation as well as load switching. It has been analysed that actual load forecasting has been a complicated and difficult task in nature [2]. Firstly, the load that would be predicted depends on the load of the previous week and the previous day. Secondly, the load series is complex in nature.

In contrary, the significance of load forecasting at present days scenario has been always essential in relation to operations and planning along with increasing energy prices at peak situations, demand, and supply fluctuation as well changes in weather conditions [3]. Furthermore, short term load forecasting has been immensely essential in order to analyse the load flow as well as to formulate effective decisions that would assist to prevent overloading. Based on successful implementations of such decisions in real time, can certainly lead to the enhancement of reliability of the network as well as mitigates the uncertain happening including blackouts and failure. Hence, it is significant to consider each factor in order to estimate accurate load. In addition, it is significant to consider influencing factors for load forecasting including historical data, time factor, Types of consumer as well as weather [4].

There are three kinds of the load forecast. One of the kinds is long term load forecasting that predicts electric load for the duration of 3 years to 50 years [5]. The second kind is medium term load forecasting that assists to schedule fuel supplies as well as unit maintenance efficiently for the duration of one week to a year. The third kind is short term load forecasting that provides essential information in order to effectively manage the system in regular operations. Its duration ranges from one hour to one week [6]. Furthermore, there several techniques for load forecasting such as time series, a regression method, fuzzy logic as well as the Delphi method and many others. However, the effectiveness of the artificial neural network has been appreciated as it solves non linear relationship between influencing factors such as humidity, a temperature that is attained through past data and load [7].

This research paper depicts significant information about multilayer perceptron neural network with significant evaluation. Furthermore, the data would be collected based on short term load forecasting that would assist to develop a model of New South Wales, Australia. Second part related work based on the historical case study of Australia for analysing the basic information. Third part would depict the concept of Artificial Neural Network and its applications in load forecasting in a detailed manner. Fourth part highlights the methodology based on multilayer feed forward neural network. Fifth part depicts the results that have been analysed after conducting the methodology. Sixth part discusses the appropriateness of multilayer feed forward neural network compared to traditional models for short term load forecasting. Sixth and seventh part depicts the future scope of the research for additional development and conclusion based on the research.

RELATED WORK

The research conducted as a case study for South Australia based on Application of Artificial Neural Network for seasonal rainfall. Forecasting depicts the combined lagged effects of the climate predictors for South Australian seasonal spring rainfall forecasts through the use of linear method multiple regressions [8]. Furthermore, the researchers compared Artificial Neural Network as a non linear method to analyse the inevitability of spring rainfall through the use of lagged DMI-ENSO-SAM combinations of climate. The results that have been gathered by the researchers illustrate Artificial Neural Network to be an effective model for pattern clustering, recognition, and classification. In addition, it resulted in a high degree of accuracy. The study depicted the enhancement of the generalization ability of the critical relationship between climate predictors and rainfall through the use of multivariate non-linear Artificial Neural Network modelling approach for the prediction of seasonal rainfall in South Australia. Furthermore, the occurrence of error has been reduced for rainfall forecasting.

The utilization of multiple regression technique in the study combined with predictors offered 0.56 correlations at maximum level which states the enhancement in the model by 44% compared to the models using single predictor based on linear relationship. The correlations that have been attained through the Artificial Neural Network approach also enhanced by 46% compared to the multiple regression models. Hence, it has been concluded that the Artificial Neural Network model output with the predictors has been the significant model to forecast South Australia's season rainfall in comparison to other available models.

For Artificial Neural Network training, the use of back propagation has been immensely used by scholarly [9]. Every multilayer feed forward neural network have been implemented to solve a few critical problems by training them through supervised learning with the integration of highly popular algorithm represented as error back propagation [10]. Furthermore, it is a supervised learning technique that requires dataset of output from a number of inputs in order to formulate training set. On the other hand, it can lead to inaccuracy but would provide advantages in analysing the problem by deriving better conclusions [11]. It is a technique that consists of two aspects in its learning cycle. The first aspect is to formulate the input pattern and the second is to adjust the output by altering the weights of the network [12].

Mean absolute percentage error is also well known as a mean absolute percentage deviation that measures the accuracy of forecasts through statistical approach such as trend estimation [13]. In addition, it assists to forecast performance evaluation by offering better accuracy of forecasting results and expressed as a percentage [14]. It can be calculated by

$$\text{MAPE} = \frac{1}{n}\sum_{k=1}^{n} \left| (A_t - F_t)/ A_t \right| * 100\ [\%] \qquad (1)$$

Equation (1) is the formula of Mean absolute percentage error where; n represents number of forecasted values to calculate error, k is index, A_t is the actual load and F_t is the forecasted load. The concept of Mean absolute percentage error is merely convincing and simple however it has significant drawbacks based on practical or real life application [15]. Firstly, it cannot be utilized if the values are zero which sometimes happened in demand data. Secondly, the percentage error can never exceed 100% when the forecasts are low and there are no upper limits when the forecasts are relatively high. Thirdly, it systematically chooses the method of lower forecasts which is a critical issue based on the accuracy of actual value [16].

THEORY

Based on threshold logic including algorithms and mathematics, Watter Pitts and Warren Mcculloh in the year 1943 created a computational model. Furthermore, this model forecasted the way for the research based on neural network which can be significantly split into two distinct approaches. On one hand, one approach considered the application of neural networks based on artificial intelligence and on the other hand the second approach focuses on the biological processes in the brain. Combining both the approach has led to the initiation of artificial neural network. In addition, these approaches and work has led to ling finite automata and nerve networks for initiating such an innovation in the field of technology and science. The machine learning was initiated in the year 1980s with conceptual and strategically research of scholarly. The first trigger towards back propagation was initiated by Werbos in the year 1975 for training multi layer networks in an efficient manner. The conventional networks based on artificial neural networks were developed in the year 2011 that included deep learning feed forward networks.

An Artificial Neural Network is a significant processing paradigm of information which is enthused similar to the biological nervous system like the brain processes the data. The major aspect of this approach is the significant structure of the processing system for information [17]. In order to solve critical problems, the Artificial Neural Network is integrated with several highly interconnected neurons or processing elements working together as a whole. In addition, an Artificial Neural Network learns similarly like the people learn [18]. The specific application of Artificial Neural Network is for data classification or pattern recognition in relation to the learning process. Based on a biological system, learning integrates adjustment in relation to the synaptic connection that is present between the neurons [19]. In addition, the significance of an Artificial Neural Network is contextual and adaptive information, nonlinearity as well as fault tolerance [20].

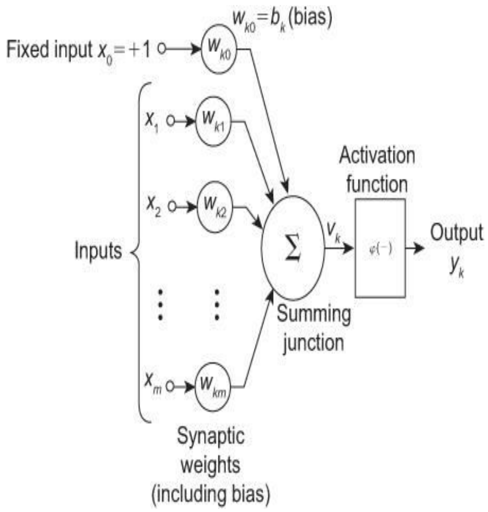

Figure-1. Artificial neuron model and its three basic elements.

Based on Figure-1, it can be stated that the corresponding weights W_{k0}, W_{k1}...., W_{km} and X_1, X_2..., X_n is the characterized strength or weight that are linked through the synapses [21]. Here the knowledge that has been acquired by the neural network based on the training data is represented by weights [22]. It significantly impacts the output of the network. For summing the input signals based on the weighted synapses of a neuron, an adder has been used.

$$V_k = \sum (W_{kj} X_j + b_k) \quad (2)$$

Where, j= [l, m] and k= [l, r]. 'r' represents a number of neurons and 'm' represents the number of input. The result of the equation 'v' would forward the input to the activation function [23]. The activation function can be denoted as $y_k = \Phi(x)$ which has a significant role in the schema of the neuron [24]. In addition, the activation function formulates output based on the summed up input signals in relation to the neurons.

METHODOLOGY

The methodology is a significant aspect of data mining. It assists to formulate specific assumptions and discussions that would enhance the aim of the research [25]. For the proposed research, the use of multilayer feed forward neural network has been integrated. This network architecture is formulated with the use of multiple layers. Furthermore other than just output and input layers, it also integrates hidden layers or intermediary layers. The intermediary computations are conducted by these hidden layers prior to directing the input towards the output layer. The neurons in the input layers are attached to the neurons of the hidden layers and consist of input hidden layer weights. On the other hand, the hidden output layer weights are also considered as the neurons of the hidden layers are links to the neurons of the output layers.

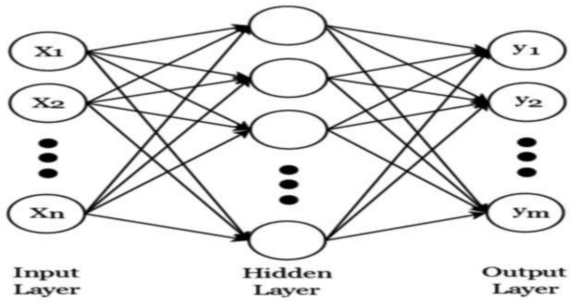

Figure-2. Basic structure of multilayer feed forward network.

In this research paper, half-hourly load data has been gathered for short-term load forecasting of New South Wales, Australia from 01 January, 2014 to 1 November, 2015. In addition, to developed forecasting model an experimental study is performed on load from 01 August, 2014 to 31 October, 2015. The trained network is tested for forecasting the data from 22 October, 2015 to 28 October, 2015. In the MATLAB tool box, multilayer feed forward neural network would be trained with Levenberg-Marquardt back propagation as well as to analyse the performance and result of the model by checking during testing, training, and validation. The main objective of this research study is to develop a more accurate model for New South Wales, Australia with a minimum error with the integration of a multilayer perceptron neural network. In addition, the use of such an approach would enable to compare traditional model based on the accuracy of load predictions.

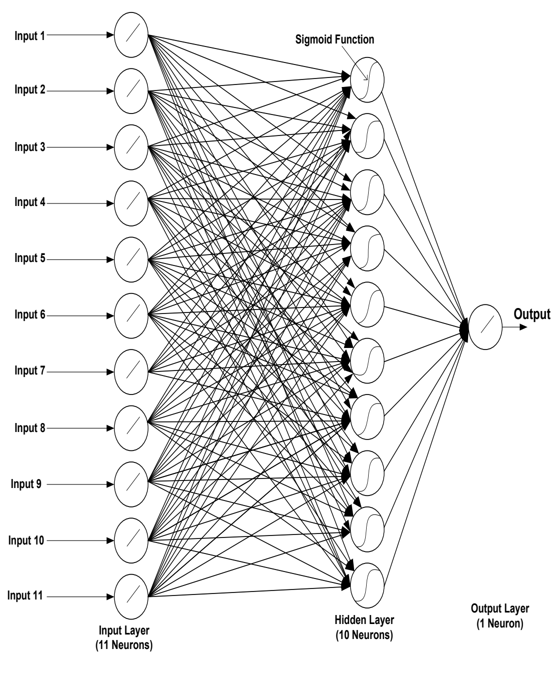

Figure-3. Multilayer feed forward neural network has 11 input layers (N_i), 10 hidden layers (N_h) & 1 output layer (N_o).

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For the training pattern neural network, the multilayer feed forward forecasting model has been developed specifically in this simulation process. It requires the proper sequence for the training of the data. Before developing the network, the arrangement of load data has been checked, as training patterns are developed on the basis of the application. To predict the load data 11 input layers (N_i), 10 hidden layers (N_h) and 1 output layer (N_o) has been taken. Data is normalized between 0 and 1, by applying min-max normalization. Here, for load forecasting development total number of input neurons Ni = 11 and there values as L(t-1), L(t-2), L(t-336), L(t-672), L(t-1008), L(t-1334), L(t-1680), L(t-2016), L(t-2352), h(t) and D(t). Where, L denotes load, t is the half-hour on which load is to be predicted and the value inside the braces is an index at which load value is considered as an input, h is the half hour type and last input D denotes type of the day Sunday, Monday, etc. Hidden neurons N_h = 10 and output neuron N_O = 1 has been considered for conducting the research successfully. Hidden layer is employed with sigmoid activation function for non-linear processing, whereas input and output layers are linearly activated.

SIMULATION RESULTS

In order to attain significant results, MATLAB tools have been used with the integration of Levenberg-Marquardt back propagation for analysing the performance during checking, testing and validating. After conducting the study on half-hourly data for New South Wales, Australia, the graph illustrated in Figure 4 depicts the forecasted load and actual load based on half hourly load data that has been gathered through short term load forecasting.

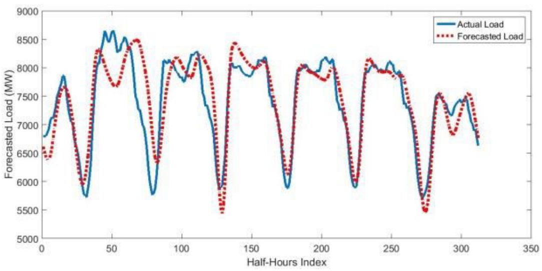

Figure-4. Graph between actual load and forecasted load.

In Figure-4 the blue line shows the actual load and the red dotted line shows the forecasted load which shows the performance of the model using a multilayer feed forward neural network.

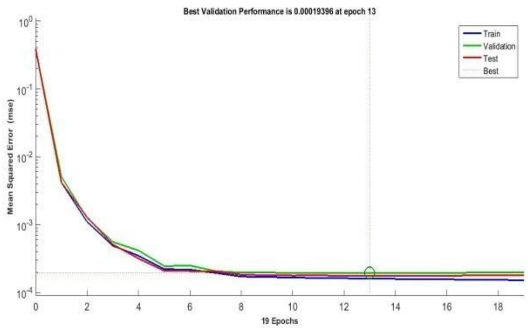

Figure-5. Best validation performances.

In Figure-5 the graph depicts the best validation performance of the model which is 0.00019396 at epoch 13. In addition, the graph plotted depicts the performance through mean square root and epochs. The graph clearly highlights the best performance at 13 epochs. The blue line represents training, the green line represents validation, the red line represents testing and the dotted line represents the best performance which has been significantly plotted.

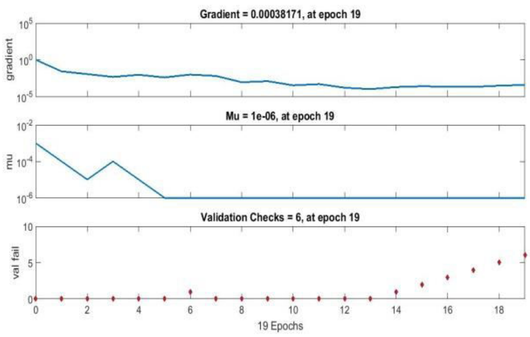

Figure-6. Training state of the developed model.

In Figure-6 the graph depicts the training state of the developed model that depicts the gradient of 0.00038171 at epoch 19, Mu of 1e-06 at epoch 19 and validation checks of 6 at epoch 19.

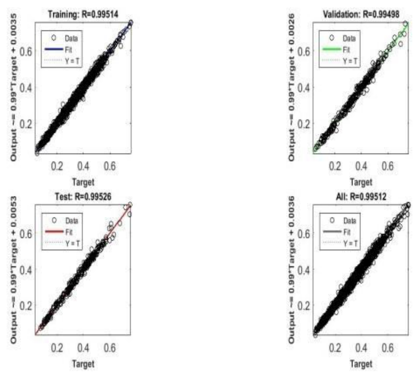

Figure-7. Regression during training, validation, and testing.

In Figure-7 the graph based on the regression analysis using Levenberg-Marquardt back propagation depicts that the mean square root was under tolerable level. Furthermore, the level of accuracy is relatively high with a minimized error. The Levenberg-Marquardt back propagation tool, as well as MATLAB software, is used for implementing multilayer architecture. In addition, it depicts significant consistency. It has been observed that regression during training is 0.99514, during validation is 0.99498 and during testing is 0.99526.

DISCUSSIONS

Based on the attained result, it has been observed that the proposed technique for load forecasting with the integration of multilayer feed forward neural network have been significant. In addition, the data that has been gathered using short term load forecasting on half-hourly load data basis have been also credible for fulfilling the objective of the research which could not be achieved in traditional models. The validation performance that has been analysed in the results depicts its best performance with minimum error and a high degree of accuracy which contrast to the traditional models where there are significant numbers of errors. The traditional models are highly inaccurate and complex in nature [26]. The Artificial Neural Network with the integration of MATLAB software and back propagation depicted significant results. Based on training, the use of Levenberg-Marquardt back propagation has been made in order to reduce the error and make the model highly accurate which resulted in highly accurate load data. Load forecasting has been complex and complicated in nature as it incurs load fluctuations due to influencing factors [27]. Based on the New South Wales, Australia, the need for highly accurate load forecasting techniques is significant due to climatic conditions as well as the demand of the consumers. The proposed model is highly validated, trained as well as tested for delivering more an accurate load data with minimum errors. Furthermore, after conducting this research study the main objective to develop such a model that would offer more an accurate load data for New South Wales have been significantly achieved.

In addition, the results also depicted the difference between actual and forecasted load through the graph that states that there is a minimum chance of occurrence of an error as the proposed model is highly credible to depict load data accurately. The use of 11 input layers, 10 hidden layers, and 1 output layer have been also significant as it assisted to depict the load data with a higher degree of accuracy. Hidden layer is employed with sigmoid activation function for non linear processing whereas input and output layers are linearly activated. The validation performance that has been attained also depicts that at epochs 13; the proposed model is highly accurate based on load forecasting. In addition, the training and testing performance are also credible which fulfils the objective of the research. Lastly, the regression model depicted the level of accuracy explicitly. Hence, the proposed model in this paper is highly credible and viable for fulfilling the objective to develop highly an accurate model for New South Wales, Australia compared to the traditional model of load forecasting. In addition, based on the literature it has been identified that this proposed model has not been developed yet that would deliver accurate results with minimum errors based on a very simple structure [28]. Hence, the significance of the proposed model has been attained in this research paper that offers accuracy in load data compared to other traditional complex models.

FUTURE SCOPE

In this research paper, the primary objective was to develop more an accurate model for New South Wales, Australia for efficient load forecasting. Based on such research objective, the validation, testing, and training of performance and results have been significantly achieved. In addition, it depicts the higher degree of accurateness in the model for forecasting as well as minimized errors. In the future, there is a wider area for developing more accurate models that would not depict any error in the neural networks.

CONCLUSIONS

Conclusively, in this research paper, an Artificial Neural Network in relation to the short term load forecasting model has been presented. In addition, multilayer feed forward neural network with 11 input neurons in the input layer, 10 hidden neurons in the hidden layer & 1 output has been significantly used for conducting the research successfully. The electricity demand (MWHrs.) of New South Wales, Australia is predicted from 22 October, 2015 to 28 October, 2015. It has been analysed that this method is relatively more accurate and simple with minimum error. Furthermore, the results that have been attained illustrates that Artificial Neural Network model with the enhanced structure would be highly credible and viable for analysing good forecasts with minimum error. In fact, this neural network could be a significant and essential tool for forecasting short term load. The load forecasting model developed with MATLAB tool box multilayer feed forward neural network which is trained with Levenberg-Marquardt back propagation is significant. The integration of such network architecture, simulation of test results, as well as training of the neural network, was significantly achieved with an elevated degree of accuracy.

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