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An Optimal Neural Network for Hourly and Daily Energy Consumption Prediction in Buildings

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ABSTRACT

In this work, hourly and daily energy consumption prediction has been carried out using multi-layer feed forward neural network. The network designed in the proposed architecture has three layers, namely input layer, hidden layer, and output layer. The input layer had eight neurons, output layer had one neuron, and the number of neurons in the hidden layer was varied to find an optimal number for accurate prediction. Different parameters of the neural network were varied repeatedly, and the prediction accuracy was observed for each combination of different parameters to find an optimized combination of different parameters. For hourly energy consumption prediction, a total of six weeks data (September 1 to October 12, 2004) of 10 residential buildings has been used whereas for daily energy consumption prediction, a total of 52 weeks data (January 2004 to December 2004) of 30 residential buildings has been used. To evaluate the performance of the proposed approach, different performance evaluation measurements were applied.

KEYWORDS

Daily Consumption Prediction, Energy Consumption, Feed Forward Neural Network, Hourly Consumption Prediction, Residential Buildings

INTRODUCTION

The energy prediction models can bring a considerable amount of improvement in overall energy savings and reduction in environmental impacts. In 2013, almost 57% of total energy was consumed by the residential and tertiary sector in the Metropolitan City of Turin (Pavone, 2014). A higher accurate energy consumption prediction is a very complicated and difficult to formulate the task but indeed very important and therefore is the focus of many researchers. There are many parameters that have a direct influence on energy consumption of residential buildings. The important of these are the structure of the building, the external weather conditions, the behaviour of residents, and the usage

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of home appliances and so on. Over the last many years, different mathematical models for energy consumption prediction have been proposed in the literature. In order to find the future demands of energy, the energy consumption prediction at various scales is very important. The accurate energy consumption prediction also plays a key role in efficient production, distribution, selling, operation, planning and management in the energy management system. Power generation systems can be made more reliable if with the accurate energy consumption prediction. Further, if efficient energy consumption is carried out, the economy, fuel utilization, and other sectors dependent on energy management systems can be managed in a better way.

The energy consumption prediction can be divided into, short term, medium term, and long-term categories based on the time in which the energy has been utilized. Different techniques have been proposed in the literature for the energy consumption prediction with various evaluation criteria, parameters and the varying degree of accuracies (Wahid and Kim, 2016). Likewise, the application of different types of AI techniques for energy consumption and other types of predictions was highlighted by Wahid et al. (2017), Shah and Ghazali (2011) and Shah et al. (2012).

A linear regression model was developed by Catlina et al. (2008) for the monthly energy consumption prediction of residential buildings in some areas of France. The authors have considered different parameters for an accurate prediction. The parameters considered were the compactness of buildings, the ratio of opaque and glass surfaces, the thermal diffusion of roof and walls and time constant of buildings. A maximum deviation of 5.1% between the actual and calculated consumption was observed whereas the average deviation observed in the simulation was 2%. The authors have concluded that the energy consumption can be optimized by considering the design of the building in terms of the strong relationship between the building compactness and the heat consumption. Some other parameters e.g. thermal inertia has also noticeable impact. Although, the authors have obtained a reasonable accuracy but still there is much room for improvement. The less accuracy is due to the fact that the authors have not considered the internal patterns of the consumption.

Different types of features have been explored by Zhou and Zhu (2013) that have a relationship with the energy consumption in residential buildings. The study was focused on residential buildings located in some parts of China and different seasons e.g. summer, winter and environmental conditions were considered in the study. The study was conducted for the annual energy consumption regression model was developed for simulation. The thermal diffusion of walls and the outdoor temperature were considered as independent variables. A maximum deviation of 15% was observed between the actual and calculated energy consumption values. Here, again the authors have focused more on the external parameters and have not considered the internal parameters representing valuable pattern in the energy consumption and hence the accuracy the found can further be improved. To emphasize on the importance of renewable energy systems and awareness of dangers by carbon dioxide, Wang and Liu (2017) proposed an energy optimization model based on particles swarm optimization (PSO) for efficient energy management in wireless sensor networks.

In another study conducted by Panwar et al. (2015), equality constraints like load balance and inequality constraints like system reserve and bounds like power generation, up/down time and ramp rate limits, finally shapes into a complex optimization problem were carried out using binary fireworks algorithm. Similarly, in continuation with the applications of artificial intelligence techniques, PSO was applied by Lin et al. (2014) for optimal design of power electric circuit that will facilitate in minimum power consumption. For long-term energy consumption prediction, Bianco et al. (2009) studied the effect of some demographic and economic variables for development of the prediction model and the Italian energy consumption historical data from 1970 to 2007 was considered in the study. In this study, the authors used some different types of independent variables e.g. gross domestic product (GDP), the electricity cost and the GDP per person. The consumption was divided into two categories namely domestic consumption and non-domestic consumption. It has been observed in the analysis that the cost of electricity has low influence on the energy consumption variability. On the other hand, the GDP and the GDP per person has a strong influence in energy consumption variations.

A similar study was conducted by Zaid and Pat (2003) for long-term energy consumption prediction considering the energy consumption of New Zealand with keeping in consideration the same parameters. The authors considered data from 1965 to 1999 and the conclusion was that the energy cost has the strongest influence in energy consumption variations. Similarly, Braun et al. (2014) have developed an energy prediction model based on regression considering some supermarket energy consumption data in the North of England. The authors have considered humidity and temperature. The historical data from 1961 to 1990 has been used for forecasting energy consumption in 2030 wherein it has been concluded that the electrical energy consumption will increase by 2.1% and thermal energy will decrease by 13%. Here the temporal information about energy consumption has not been considered which results in better prediction accuracy as compared to the parameters considered by the authors.

An evaluation of energy consumption in residential buildings was performed by Kavousian et al. (2013). Total of 1682 residential buildings located in the US were analysed in the study. The aim of the study was the evaluation of yearly energy consumption and the identification of days of minimum and maximum power consumption. Different types of home appliances were considered for energy consumption evaluation. Various architectures of Artificial Neural Network have been used for different types of modelling for many years in different disciplines, including medicine, mathematics, economics, engineering, meteorology, psychology, hydrology, neurology and other areas Sozen and Akcayol (2004). All these authors have not been successful in getting a more optimal design of neural network that may lead to better accuracy by considering various training functions, hidden layer functions and output layer functions. They have got much popularity since their first inception in 1943 McCulloch and Pitts (1943) due to their strong capability for the solving prediction problems with variables having stochastic nature, unknown or non-linear variations, or less controlled environment is required for their determination Moustris et al. (2004). Due to their flexibility and less assumption-dependency, the physical processing between their input and output is not needed Morid et al. (2007). This property makes neural networks more suitable for any kind of forecasting. Artificial neural networks learn from the variations in the historical data and make prediction based on these variations. In order to perform prediction, neural networks create an input-output mapping system. For training and testing of any model of neural network, inputs and their corresponding output are necessary (Azahim, 2012). There are many other artificial intelligence techniques that can be applied in various fields e.g. Garg (2015), Garg (2015), Garg (2016) and Patwal et al., (2018).

In all the work carried out by researchers, the energy consumption prediction has been performed in which different external parameters have been considered. For example, some authors considered the external temperature affecting the prediction performance whereas other authors focused on the internal building conditions to carry out the prediction. Some authors considered the occupants' behaviour whereas some other authors considered seasonal conditions as affecting the prediction accuracy. Yet, some of the authors argued that the building physical shapes have direct impact on the power consumption thus affecting the power consumption forecasting whereas many authors also suggested that building manufacturing materials have effect on the energy consumption leading to affect the prediction performance when considered. The major focus of our work is to consider the patterns present inside the energy consumption parameters recorded at a specific time. As compared to other external parameters, these patterns are extremely informative about the energy consumed which leads to better prediction accuracy. The second major drawback associated with the previously proposed approaches is all the authors have considered a specific combination of neural network parameters e.g. network training functions, input layer functions, output layer functions and the number of neurons in hidden layer. They don't provide any guidelines for using these parameters in various combinations to enable future researchers to consider them according to the results obtained. In our work, we have performed extensive experimentation to suggest the way how changing the network training function, hidden layer function, output layer functions and the number of neurons in the hidden layer which will provide comprehensive guidelines for future researchers.

In this paper we have proposed a Feed Forward Neural Network for Time-Series Energy Consumption Prediction. The rest of the paper is organized as: Proposed Nural Network architecture is discussed in section II, the results and discussion has been presented in section III, and finally the conclusion is presented in section IV.

Neural Network Architecture for Daily Energy Prediction

The interconnection among different neurons in the artificial neural network (ANN) is known as ANN architecture. Multi-layer perceptron (MLP) is considered to be one of the most practical and commonly used architectures of the artificial neural network (Wahid and Kim, 2017). In multi-layer perceptron, each neuron has connections with other neurons with different weights that represent the influence of neurons' inputs to other connected neurons. Every input to the neural network is given some weight and then all the weighted inputs are summed up to transmit them to the hidden layer for transformation using some specific activation function. Then the output of the hidden layer is entered as inputs to the output layer where they are transformed to output. in The proposed model can be seen in Figure 1. Equation (1) gives the output of multi-layer perceptron.

$$O_{jk} = A_k\left(\sum_{i=1}^{Nk} W_{ijk} A_k + \beta_{jk}\right) \tag{1}$$

Where O_{jk} = Output of neuron j from layer k β_{jk} = Bias weight of neuron j from layer k W_{ijk} = Kink Weights A_k = nonlinear activation transfer function which may take different forms e.g. binary sigmoid, Gaussian function, identity function, bipolar sigmoid and linear functions (Wahid et al. 2017).

Multi-layer perceptron uses back-propagation as learning algorithm e.g. SCG (Scaled Conjugate Gradient), LM (Levenberg Marquardt,), GDX (Gradient Decent with variable learning back propagation) and RP (Resilient back propagation) learning algorithms (Wahid et al. 2018). In order to develop an optimized multi-layer perceptron, different steps have been taken as shown. First of all the whole data set was randomly divided into 70% training and 30% testing data set. In the first step of NN architecture, we set the network training function as a scaled conjugate gradient (SCG), both the hidden layer function and output layer function as tangent sigmoid (Tansig) and the number of neurons in the hidden layer as 5. The designed neural network was trained for 70% of the whole data and tested for 30% of the whole data set. The performance of this architecture was evaluated using mean absolute error (MAE), means squared error (MSE) and root mean squared error (RMSE). These performance parameters (table 1) have been computed using equations 2, 3 and 4, respectively

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Ai - Pi\right)^2 \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Ai - Pi\right)^2} \tag{3}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Ai - Pi\right| \tag{4}$$

Where n, A and P represent a total number of observations, actual value and the predicted value, respectively. After the initial architecture of NN, the design was repeatedly changed using trial and error mechanism. First, the number of neurons in the hidden layer was changed with an increment of 5 until there was no significant improvement in the performance of the network. For the most of the designed NN architecture, no significant improvement was observed after the hidden layer neuron number reached above 60. So, for all the NN architectures, the number of hidden layer neurons was 5-60 neurons. During training and testing for a different number of neurons in the hidden layer, the other parameters remained unchanged. When the network was trained and tested for the maximum number of neurons, then the output layer function was changed and the network was trained and tested for different output layer functions. In the output layer, three main functions namely tangent sigmoid (Tansig), logarithmic sigmoid (Logsig) and linear functions were considered. After the network was trained for all the output layer functions, the hidden layer functions were changed. In the hidden layer, all the functions considered in the output layer were considered in the hidden layer. After the network was trained and tested for all the output layer and hidden layer functions, the network was trained and tested for different types of network training function e.g. traingscg, traincgp and trainlm.

EXPERIMENTAL RESULTS AND DISCUSSION

All simulations have been performed on Intel (R) Core (TM) 2 Quad CPU A9550 @ 2.83GHz with MATLAB installed on it. For hourly energy consumption prediction, the data consists of 10080 samples (10 buildings X 6 weeks X 7 days X 24 hours) [23] whereas for daily energy consumption prediction, we have only historical daily consumed energy data of 30 apartments' 50 weeks' data (30 Apartments x 52 Weeks x 7 Days (Total of 10920 samples)). The input parameters for hourly energy consumption prediction are building number, day, hour, previous hour consumption, the mean, the variance, the skewness and the kurtosis of the entire day hourly consumption. The building number ranges from 1 to 10, the day has values from 1 to 42, a total of 42 days data for ten buildings. The hour has values from 1 to 24, past consumption has real values of energy consumption during the last hour. The mean shows the average of 24 hours hourly consumption. The variance shows variations in 24 hours hourly consumption. The Skewness shows the asymmetry in 24 hours hourly consumption and Kurtosis shows peakedness or frequency of extreme 24 hours hourly consumption. The output parameter of the model is next hour energy consumption. The input parameters for daily energy consumption prediction are apartment number, week number, day, previous consumption, mean, variance, skewness and kurtosis. The apartment number takes values from 1 to 30 and this is important because different apartments have different daily energy consumption variations over the whole year. The week number takes values from 1 to 52 and this is important because different apartments have different daily energy consumption variations over different weeks. The day takes values from 1 to 7 and this is important because different apartments have different daily energy consumption variations over different weeks. Previous consumption takes real value of energy consumed over the previous day, and it has an effect on next day energy consumption. The mean of daily consumed energy over the whole week and it has an effect on every day energy consumption in a week. The variance represents the variations in daily energy consumption and it has an overall effect on every day energy consumption in a week. The Skewness represents the asymmetry in daily energy consumption and it has an overall effect on every day energy consumption in a week. The Kurtosis represents peakedness or frequency of extreme daily power consumption over the whole week, and it has an overall effect on every day energy consumption in a week. Figure 2 shows the architecture of MLP used for hourly and daily energy consumption prediction.

X1, X2, X3, X4, X5, X6, X7 and X8 represent building number, day of consumption, hour of consumption, previous hour consumption, the mean of 24 hours hourly consumption, variance of 24 hours hourly consumption, skewness of 24 hours hourly consumption and kurtosis of 24 hours hourly consumption for hourly energy consumption prediction whereas apartment number, week, day, previously daily consumed energy, and mean of 7 days of the weekly consumption, variance of 7 days of the weekly consumption, Skewness of the 7 days of the weekly consumption and Kurtosis of 7 days of the weekly consumption, respectively for daily energy consumption prediction. N1, N2, N3,…,N21 show the number of neurons in the hidden layer of the multi-layer perceptron. In the final

Figure 1. Proposed Model

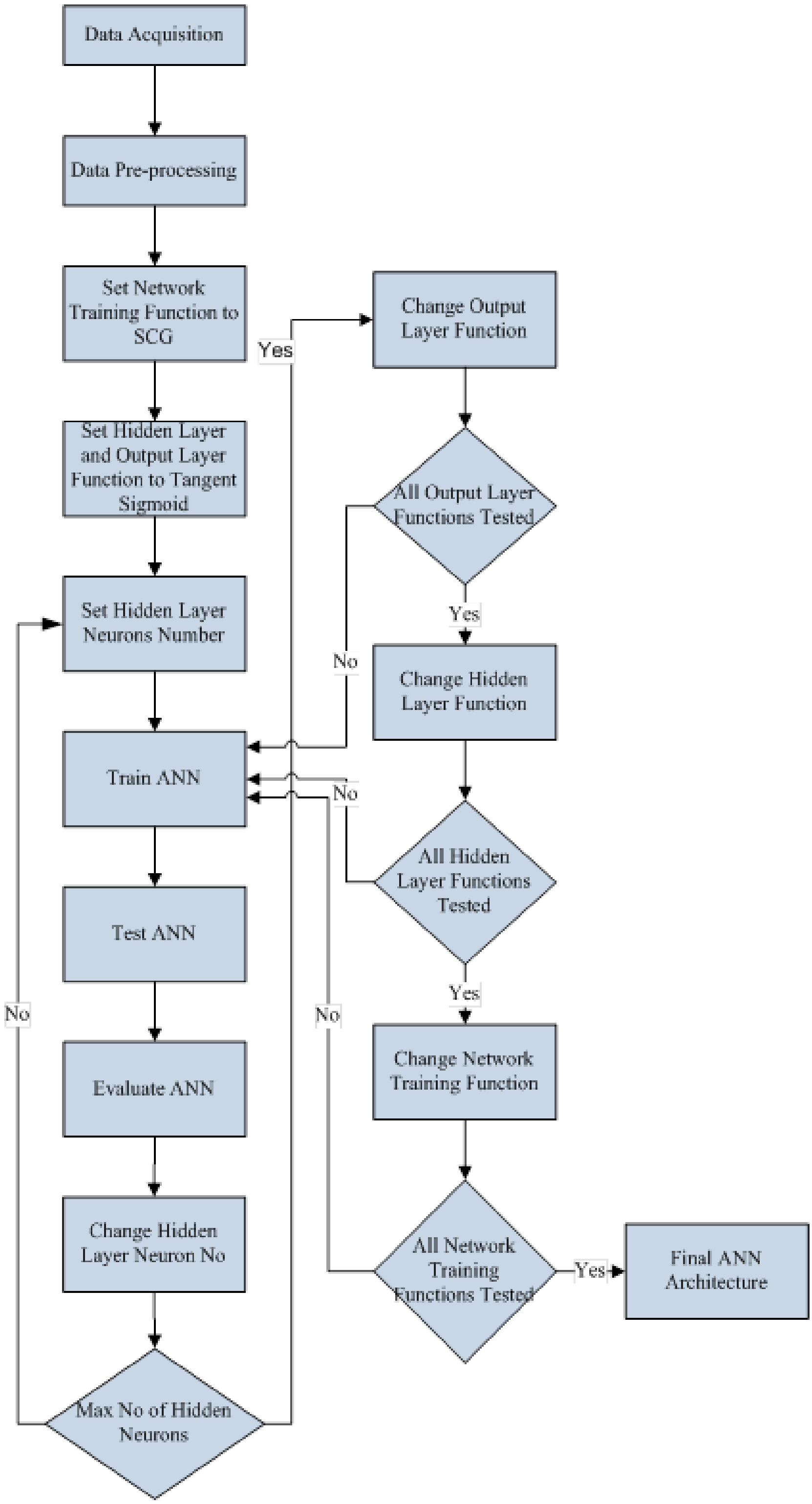
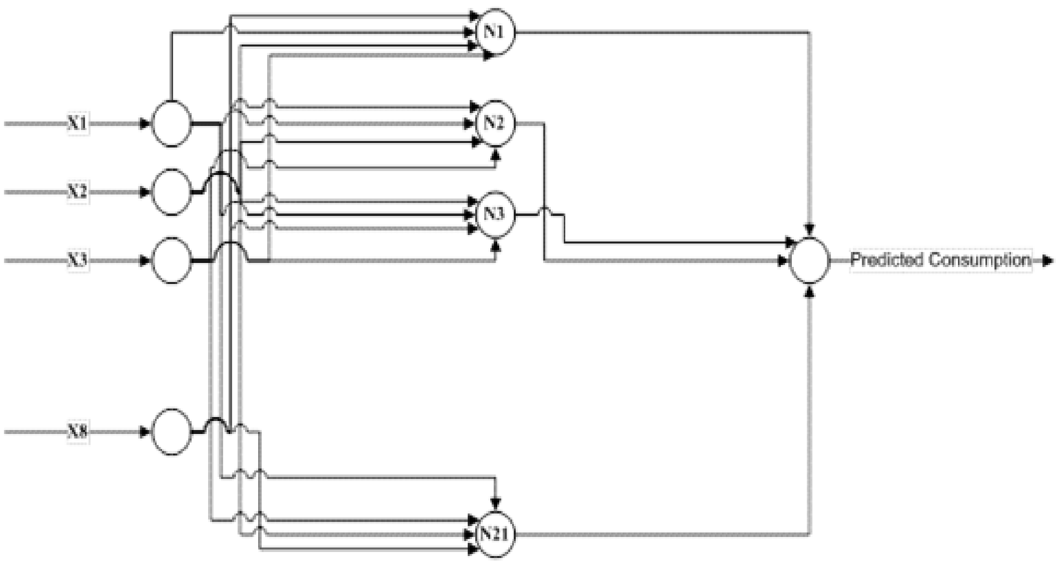


Table 1. Performance parameters measurements

Performance Parameters	Hourly Prediction			Daily Prediction		
	Best Value	Average Value	Worst Value	Best Value	Average Value	Worst Value
MSE	0.0425	0.0758	0.1326	3.5163	5.6485	11.5420
MAE	0.0253	0.0563	0.0987	1.9836	2.8794	3.8620
RMSE	0.2061	0.2753	0.3641	1.8758	2.3759	3.3973

Figure 2. MLP inputs/outputs

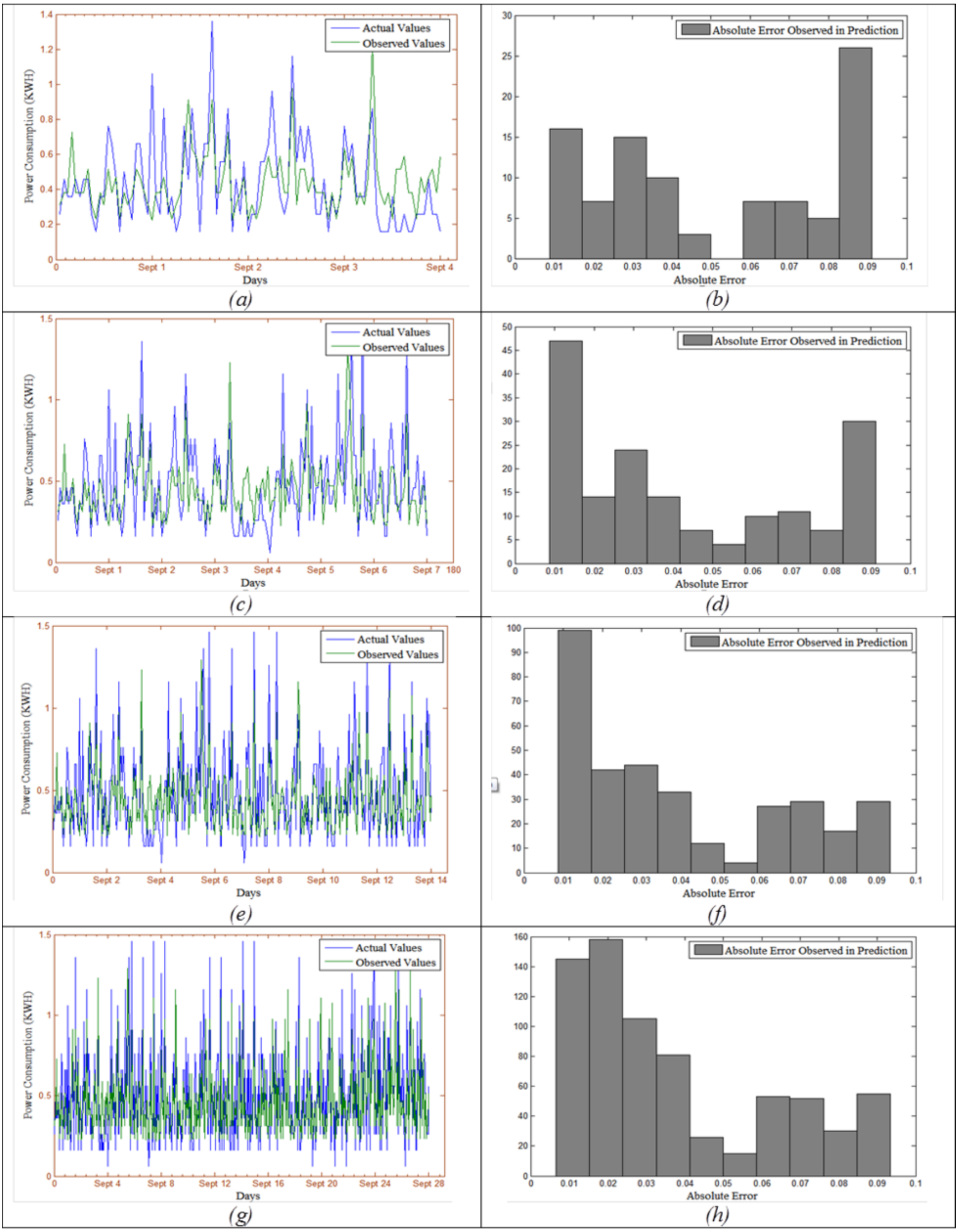


designed multi-layer perceptron, it was concluded that using scaled conjugate gradient (trainscg) as a network training function, tangent sigmoid (Tansig) as a hidden layer transfer function and linear function as output transfer function gave the best performance in terms of minimum prediction error. In the input layer, there were 8 neurons, in the hidden layer, there were 25 neurons and in the output layer, the number of neurons was one. The network was run for epochs from 150-300 epochs. The graphical representation of prediction results for the final model is presented in the following section. The actual and predicted values of energy consumption of different apartments during different time frames and the absolute error calculated are shown in different graphs (figure 3 & 4) in this section.

COMPARISON AND STATISTICAL ANALYSIS

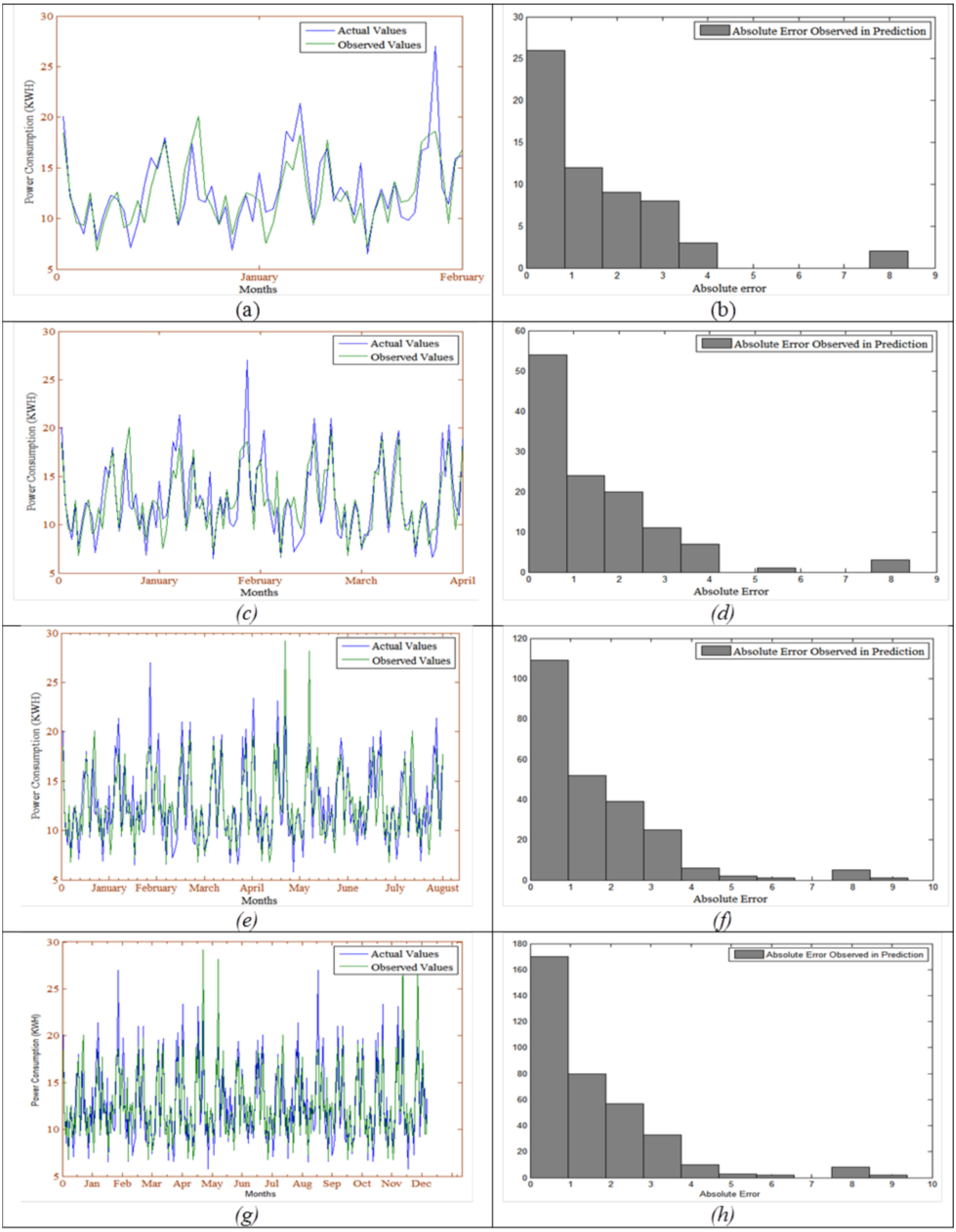
There are many techniques, approaches and methodologies for various types of energy consumption prediction with keeping different dimensions under consideration. In this section, a comprehensive comparison of the proposed approach with few of the techniques is given. Wahid Kim (2017) proposed a design of multi-layer perceptron for hourly power forecasting. The authors have given a detailed description of the multi-layer perceptron design with various types of network training functions, hidden layer functions and output layer functions. The drawback with their approach is that the authors have not got higher accuracy because of not considering the informative features in the data. Similarly, in another work, Wahid and Kim (2016) suggested a K-nearest model for classifying

Figure 3. Hourly Energy Consumption Prediction Absolute Error Observed (a), (c), (e), (g) Prediction during different days (b), (d), (f), (h) Absolute Error Observed



different residential apartments into two categories based on their daily energy consumption. In a similar work, Wahid and Kim (2016) proposed random forest classifier for daily energy consumption prediction. The approach is based on the classification of low power and high power consumption

Figure 4. Daily Energy Consumption Prediction Absolute Error Observed (a), (c), (e), (g) Prediction during different months (b), (d), (f), (h) Absolute Error Observed



residential apartments. The problems with both the K-nearest neighbor and random forest is that the prediction is based on classification of residential buildings according to their daily basis power consumption and the results show that the prediction error with each day prediction has not been given. Likewise, Wahid et al., (2017) gave a detailed usage of few artificial intelligence techniques for daily energy consumption prediction. The prediction accuracy for these techniques shows that the proposed approaches have not been successful in getting better results. A complete comparative analysis of the proposed approach with all these methods is given in *Table 2*.

CONCLUSIONS AND FUTURE DIRECTIONS

In this study, we have carried out a simple and easy approach for hourly and daily energy consumption prediction using multi-layer perceptron. The first and major focus of the work is to find informative pattern in the consumption of energy on hourly and daily basis. The distinction of the proposed approach is the identification of internal parameters of the power consumption instead of external environmental parameters considered in most of the works carried out previously. The informative features found in the energy consumption patterns leads to accurate energy consumption prediction which is considered to be a challenge for the researchers' due to high energy demands and less production. Therefore, this work will be proved extremely helpful for the energy producers, suppliers and consumers to estimate the future energy demands. Keeping in considerations the experimental results obtained and the facts and figures highlighted, the energy sector can take decisive measures to fulfill future energy demands. The second aim of this work is to find an optimal combination of neural network various parameters which will help the researchers to apply it to different applications by considering various results associated with different combinations. Extensive experimentation has been carried out with complex combinations of training algorithms, hidden layer transfer functions and output layer transfer functions. A very complex relationship among the training functions of different models, hidden layer transfer functions, output layer transfer functions and the number of neurons in the hidden layer can be observed. Both for hourly and daily energy consumption prediction, a final

Table 2.Comparative Analysis

Authors	Approach	Methodology	Accuracy	MSE RMSE MAE
Wahid and Kim (2017)	Daily Energy Consumption Prediction based on regression	Data retrieval Data processing Prediction Modal Validation Performance Evaluation	Not Given	0.0837 0.2893, 0.1988
Wahid and Kim (2016)	Daily Energy Consumption Prediction based on classification	Data Collection Data pre-processing Predictor training Predictor testing Predictor validation Performance Evaluation	10-Fold Cross Validation (94.6154)	Not Given
Wahid et al., (2017)	Daily Energy Consumption Prediction based on classification	Data Collection Feature Extraction Prediction Performance Evaluation	10-Fold Cross Validation 95.7692	Not Given
Proposed Approach	Hourly and Daily Energy Consumption Prediction based on regression	Data Specification Feature extraction Neural Network Architecture Development Neural Network Training Neural Network Testing Network Evaluation	Not Given	0.0425, 0.2061, 0.0253 (Hourly) 3.5163, 1.8758, 1.9836 (Daily)

model was chosen in which we have used Scaled Conjugate Gradient as a network training function, tangent sigmoid as a hidden layer transfer function, linear function in the output layer with 25 neurons in the hidden layer. After trials and errors on different types of training algorithms (trainscg, traincgp, trainlm), hidden layer transfer functions, output layer transfer functions (tansig, logsig, linear) and a different number of neurons in the hidden layer, different architectures of multi-layer perceptron were trained and tested. Our method of testing different combinations of training functions, hidden layer functions, output layer functions and a number of neurons in the hidden layer produce small prediction errors, therefore, this method can be applied for different types of predictions with keeping in consideration the best result obtained for the final model. Our next target is to minimize the energy consumption and maximize the user satisfaction and comfort inside the residential building using artificial intelligence, swarm intelligence and optimization algorithm which is left as our future directions. Furthermore, the application of the developed architecture of neural network to some other types of forecasting including weather forecasting and natural disaster prediction is another direction for our future work.

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