Short Term Load Forecasting of Residential and Commercial Consumers of Karnataka Electricity Board using CFNN

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ABSTRACT- Electricity use and its access are correlated in the economic development of any country. Economically, electricity cannot be stored, and for stability of an electrical network a balance between generation and consumption is necessary. Electricity demand depends on various factors like temperature, everyday activities, time of day, days of the week days/Holidays. These parameters have led to price volatility and huge spikes in electricity prices. The research work proposes a short term Load prediction Model for LT2 (residential consumers), LT3 (Commercial Consumers) of Karnataka State Electricity Board using Cascaded Feed Forward Neural Network (CFNN). MATLAB software is utilized to design and test the forecasting model for predicting the power consumption. Furthermore, a shallow feed forward neural network-based prediction model is constructed and evaluated for performance comparison. The Performance metrics include Mean Absolute Percentage Error (MAPE) and Mean Squared Error (MSE). The suggested STLF CFNN prediction model outperformed shallow feed forward networks on both performance metrics with prediction errors of less than 1%.

Keywords: Absolute error, Demand Side Management, Mean Square Error, Power Consumption, Shallow ANN.

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1. INTRODUCTION

Electricity consumption varies on short and medium time frames based on various factors like climate, region and sector (residential, industrial, commercial). Residential loads consume most of electricity generated. To meet the varying demand of power, the utilities adjust to changing demand by supplying additional or less generation. The added generation during peak periods, places a burden on the utilities in terms of financial as well as environmental costs. Energy demand management activities aim in bringing supply and demand to a close optimum value reducing the burden on the utilities for additional infrastructure investment and also help end users get benefits for reducing their peak power consumption. Consumers are encouraged to use less energy during demand hours with Demand Side Management (DSM) or move their loads to off-peak times like nights and weekends. Consumer participation is the key factor for the success of an effective DSM. The customers are either paid incentives or reduction in electricity prices for modifying their energy consumption pattern during the peak hours which in turn help in flattening of the load curve. Electricity load and price prediction/ forecasting is an important parameter in the effective implementation of DSM which help consumers plan to manage their loads during off peak hours based on prices forecasted to them hourly, day ahead, weekly or monthly basis without causing much discomfort to them. Utilities can plan their activities based on the demand, either to purchase or sell power, resulting in flattening of load curve.

In order to achieve forecasting precision in power systems, various models have been used, including regression, statistical, and state space approaches. Artificial neural networks are the most common machine learning (ML) approaches in electricity price prediction and load forecasting because of their potential to process data that is not linear. ML methods tend to significantly outperform other statistical methods. The simplest version of a neural network is the feed forward network, which is mostly used for supervised learning when the input to be learned is not sequential or time dependent. In this paper a Cascaded Feed Forward Network (CFNN) an extension of the feed forward network that includes a connection from the input to each subsequent layer is demonstrated to forecast the load of LT2(residential consumers) and LT3(Commercial Consumers) of Karnataka State Electricity Board. A performance analysis of the proposed system is measured and collated to that of a shallow ANN network and based on the findings of the study, the accuracy of prediction of the suggested system is found to be greater than the existing system.

2. RELATED WORKS

The area of power load forecasting [1] is well-developed, with several methodologies offered over the years. Traditionally, they've focused on forecasting system demand that can range from tens to hundreds of megawatts. [2–3] provides a brief survey of the load forecasting process based on short term, while [4] and [5] include more traditional assessments. In recent decades, various approaches for anticipating electric load demand have been developed. The autoregressive integrated moving average (ARIMA) method [6], fuzzy logic [7], and the neuro-fuzzy method [8] are among the most prominent time series investigations. Load forecasting on a household-by-household basis is difficult due to the high system volatility caused by dynamic processes involving many different components. The type of device being used, the type of user, the type of economy, day time, week day, holidays, the weather condition, a geographic location, and other factors can all influence the quantity of power consumed by normal residential loads, which range between 1 and 3 kWh. The authors of [9] looked at six alternative methods for predicting a load equivalent to a single transformer that are commonly employed in large-scale energy networks. For two situations with different number of houses, ANNs, AR, ARMA, autoregressive integrated moving average, fuzzy logic, and wavelet NNs were investigated for following day and following week energy prediction. The authors of [10] implemented a neural network (NN)-based topology for constructing forecasting periods to evaluate potential forecast uncertainty. The authors of [11] developed a price forecasting model based on DL techniques, DNN as a conventional MLP extension, hybrid LSTM-DNN structure, hybrid GRU-DNN structure, and CNN model. The methodology that has been proposed is compared with 27 benchmark methods. The proposed DL model was found to improve prediction accuracy. The researchers of [12] built a next day peak load prediction model based on deep bidirectional long short-term memory-based sequence to sequence (Bi-LSTM S2S) regression method. The performance was compared with shallow Bi-LSTM S2S, shallow LSTM S2S, deep LSTM S2S, Levenberg-Marquardt back propagation artificial neural networks (LMBP-ANN), and medium Gaussian support vector regression (MG-SVR) and the proposed outperformed in terms of Mean absolute percentage error (MAPE) and Root Mean Squared Error (RMSE) error.

3. RESEARCH GAP AND CONTRIBUTIONS

In the light of the above literature review three major research gaps has been identified. The first being no research work has evaluated the performance of Shallow feed forward network or Cascaded feed Forward network to the best of our knowledge for predicting the non-linear power consumption data for both residential and commercial loads together. Secondly either the Electricity load or Price is forecasted individually for power markets or small residential loads. Lastly, no research is being conducted to investigate the problem of predicting peak demand in countries that are developing wherein the power system is underdeveloped and there are no devices such as smart meters that can store huge quantities of previous data. This study has made the following research contributions in light of the three research gaps listed above:

1. CFNN model has been effectively developed, implemented, and tested for predicting residential and commercial power consumption one week ahead.
2. The proposed method was successfully assessed for prediction accuracy by comparing it with Shallow feed forward network.
3. It has given a solution for demand response management in the Karnataka, India and similar developing countries.
4. The proposed methodology is suitable for limited data and does not require huge data for training.

4. RESEARCH METHODOLOGY

A model for predicting electricity usage of LT2 (residential load) comprising of 100 houses and LT3 (commercial) load comprising of 100 shops is proposed in this research.

4.1 Power Prediction Model

The electricity power prediction model comprises of
1. Data Set Collection
2. Prediction of Load using CFNN
3. Performance Evaluation

4.1.1 Data Set Collection

The power consumption data of 100 houses LT2 (residential consumers) and 100 shops LT3 (commercial consumers) of Karnataka State Electricity Board was collected based on sample of smart meter data obtained during the month of February 2020 from Mysore, Karnataka. The proposed model was trained with two data sets, one comprising the monthly power consumption data of 100 houses and another comprising of power consumption data of 100 shops.

4.1.2 Load Prediction using Multilayer Cascade Feed Forward Neural Network

Time series data that does not require residential presumptions can be modelled using Neural Network (NN) a nonparametric model [13]. Several studies have indicated that this model outperforms parametric methods in terms of prediction accuracy. When NN is used on time series prediction models, the results are more accurate and stable, and are less subject to data fluctuations. Feed Forward Neural Network (FFNN) model, is the major category of NNs and Cascaded Forward Neural Network (CFNN) is one of the NN model's classes besides the FFNN. The sole distinction between these two classes is that each input layer is connected to each hidden layer neuron and each output layer neuron. This method has the advantage of sustaining the nonlinear connection between the input-output layers yet retaining the linear connection intact. The input-output link formed in a perceptron is a direct relationship, whereas the input-output connection in an FFNN is an indirect relationship. The connection takes on a nonlinear structure through an active function in the buried layer. The accuracy of prediction increases with number of concealed layers connecting the input and output layer. In the proposed system, a CFNN structure comprising of five hidden layers is used which reduces the mean squared error of less than 10^{-4}. The structure is developed using the latest version of MATLAB and is as indicated in *Figure 1*. Using cascaded feed forward artificial neural networks, the suggested method produces accurate short-term load estimates. A week-ahead energy consumption projection for 100 houses and 100 shops is generated by a fully-connected ANN with five concealed layers and sigmoid as the function of activation in the concealed nodes. In the output node, an activation function that is linear is utilised. The neural network's architecture [14] is such that it is trained in open-loop with actual load data to build node weights before being used in closed-loop to construct the prediction using the anticipated forecast load as input. When compared to Shallow ANN models, the results reveal an improvement in forecasting. The proposed model's flowchart is shown in *Figure 2*. *Table 1* summarizes the CFNN architecture. The dataset division is done using divider and function that divides the data randomly with training, testing and validation ratio of 80%, 10%, and 10% respectively. The five hidden layers use log sigmoid function as the activation function where in the output node the activation function used is linear. The training of multilayer CFNN architecture is done using Levenberg-Marquardt algorithm. The Levenberg-Marquardt algorithm is very fast in training neural networks specially designed for sum of squared error functions as it works using loss functions that have the shape of sums of squared errors. Parameters of the Levenberg-Marquardt algorithm used to train the model are listed in *Table 2*.

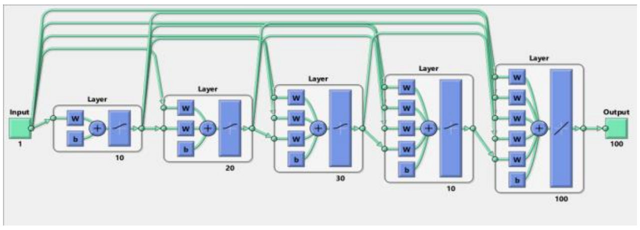

Figure 1: Multilayer CFNN Structure for Energy Prediction

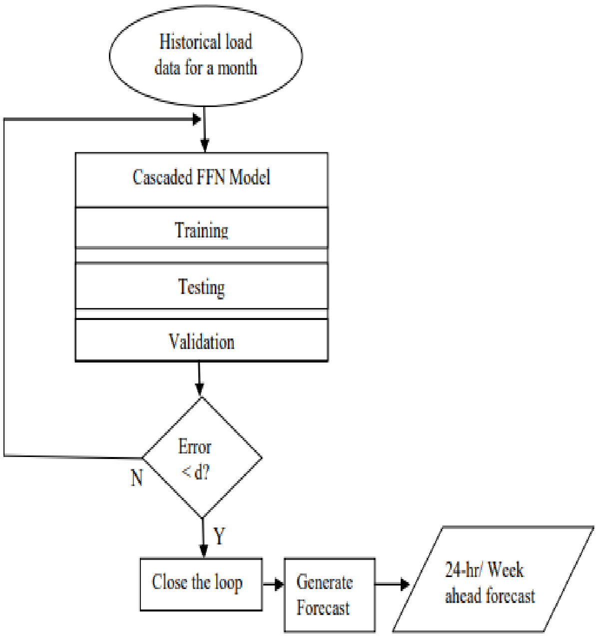

Figure 2: Flow chart of proposed CFNN

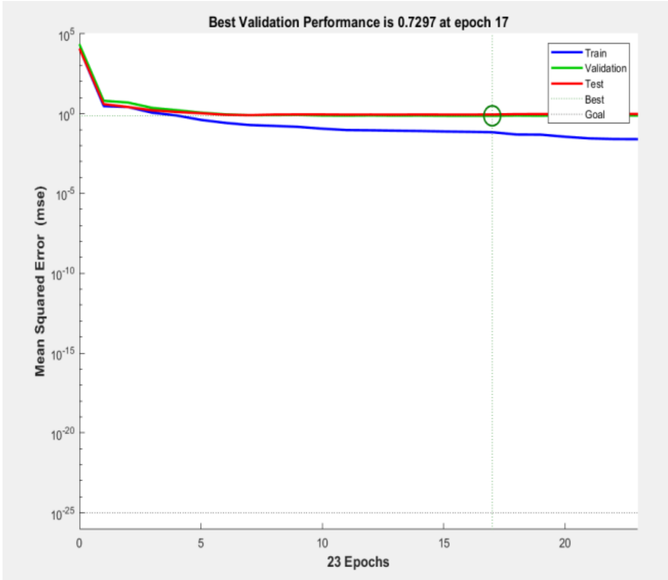

Figure 3: Validation performance Plot

Table 1: CFNN Architecture

Input Node	1
Hidden layers	5
Output Nodes	100
Interconnection	Cascaded
Activation Function	Sigmoid Function $S(t) = \frac{1}{1+e^{-t}}$
Learning algorithm	Levenberg Marquardt

Table 2: Levenberg-Marquardt Parameters

net.trainParam.epochs	15000	Highest number of epochs required for training
net.trainparam.goal	$1e^{-25}$	Performance target
Net.trainparam.lr	0.1	Rate of Learning
net.trainParam.max_fail	6	Highest validation failures
net.trainParam.min_grad	$1e^{-7}$	Least performance gradient
net.trainParam.mu	0.001	Initial mu
net.trainParam.epochs	15000	Highest number of epochs required for training
net.trainparam.goal	$1e^{-25}$	Performance target
Net.trainparam.lr	0.1	Rate of Learning
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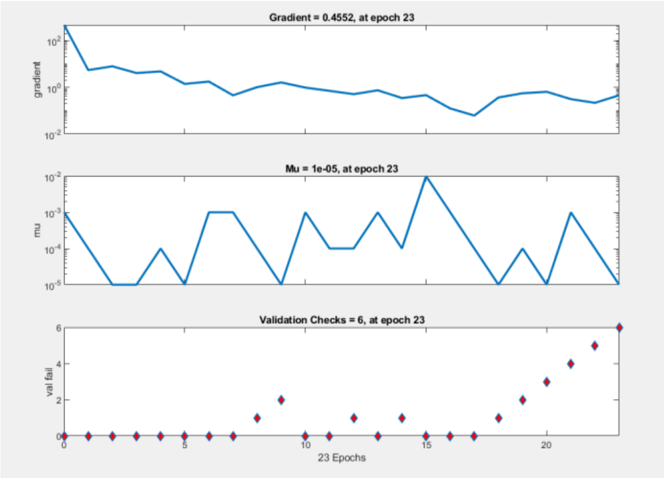

Figure 4: Validation checks and gradient error variations for Home Energy Prediction

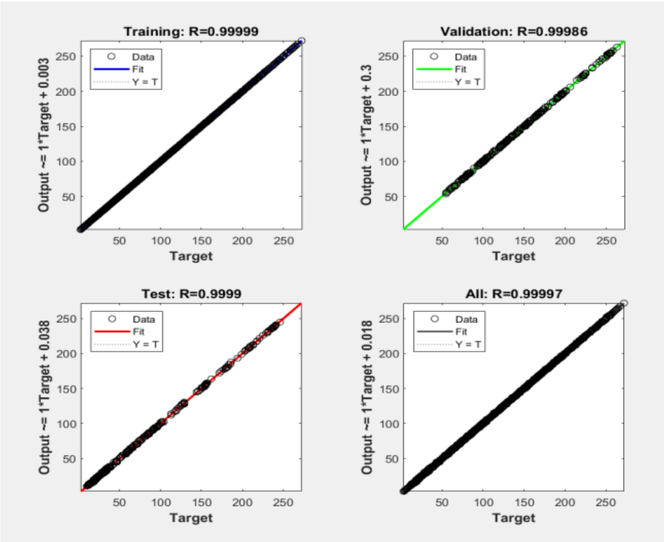

Figure 5: Training, validation, test, and total data scatter plot

The above model is assessed for accuracy of prediction by calculating absolute percentage error given by *equation 2*. *Table 3* lists the absolute percentage error for 10 houses on a particular day of the week.

Table 3: Absolute Error Percentage for day 31 for 10 houses

House	Actual	Forecast	Absolute Percentage Error
H1	105	105	0
H 2	232	231.6	0.172414
H 3	263	261.1	0.722433
H 4	169	167.8	0.710059
H 5	203	204	0.492611
H 6	139	138.5	0.359712
H 7	105	105	0
H 8	261	258.8	0.842912
H 9	249	247.9	0.441767
H 10	158	158.5	0.316456

It is observed from the *table* that accuracy of prediction is very high and the Absolute Percentage Error is less than 1%.

4.2 Shop Energy Prediction

The same CFNN architecture was used to anticipate the energy usage of 100 different stores (LT3 consumers). A 30-day energy consumption pattern of 100 shops was used to train the system. Using the cascaded feed forward structure, a simulation model was created and validated to anticipate the energy consumption of 100 stores. *Table 4* shows the absolute percentage error for ten establishments, and the Absolute Percentage Error observed is less than 1%.

Table 4: Absolute Error Percentage for day 31 for 10 shops

Shop	Actual	Forecast	Absolute Percentage Error
S1	1262	1262.00	0
S2	942	938.60	0.360934
S3	1063	1062.00	0.094073
S4	943	942.80	0.021209
S5	1317	1315.00	0.15186
S6	1220	1216.00	0.327869
S7	702	703.60	0.22792
S8	777	775.10	0.24453
S9	794	795.00	0.125945
S10	808	808.40	0.049505

Figure 6 indicates validation performance plot. The best validation performance was observed at epoch 14 with MSE of 1.8343 for validation period. *Figure 7* shows the gradient error as well as the validity tests. At epoch 20, the gradient error is 1.9482, and there are 6 validation checks. *Figure 8*. Depicts a scatter plot of experimental data for training, validation, and testing. The values of R during the training, validation, and testing periods are 1, 0.9999, and 0.9964, respectively, as seen in this graph.

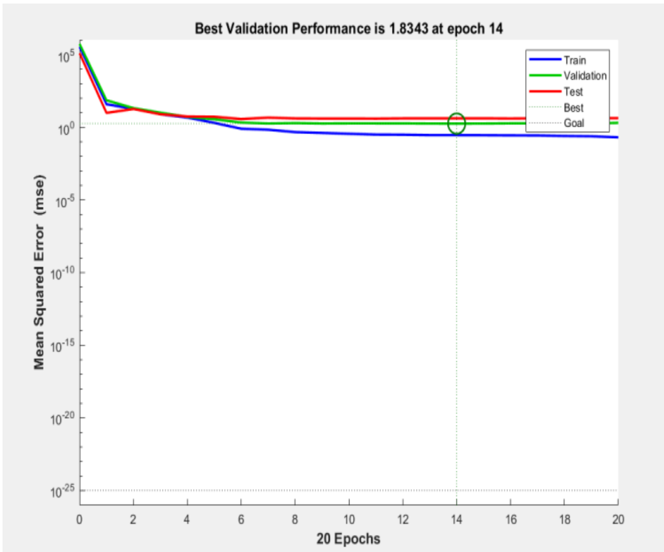

Figure 6: Validation performance Plot

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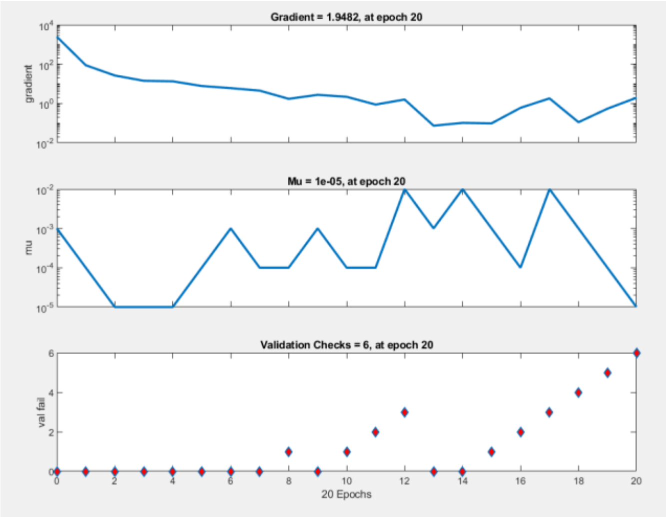

Figure 7: Validation checks and gradient error variations for Shop Energy Prediction

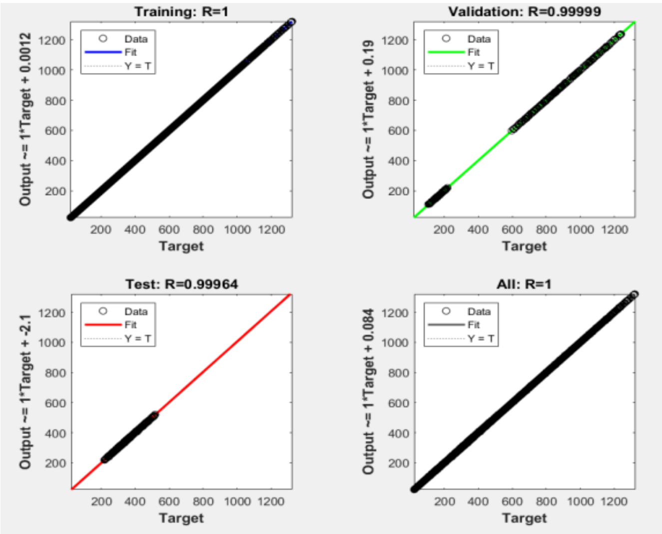

Figure 8: Training, validation, test, and total data scatter plot

The proposed CFNN structure was successfully trained and tested for load forecasting for 100 residential premises and 100 shops. The proposed model was compared to a Shallow Multilayer Feed Forward Network in terms of performance. The Multilayer Shallow FFNN architecture used for comparison is shown in *Table 5*. The architecture of a Multilayer Shallow FFNN for home energy prediction is shown in *Figure 9*.

Table 5: Shallow Multilayer FFNN

Input Node	1
Hidden layers	3
Output Nodes	100
Interconnection	Forward
Activation Function	Sigmoid Function $S(t) = \frac{1}{1+e^{-t}}$
Learning algorithm	Levenberg Marquardt

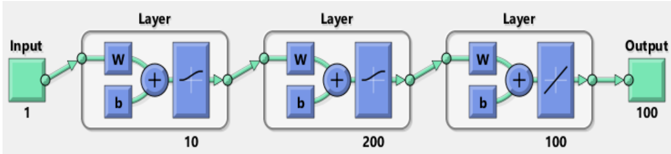

Figure 9: Structure of Multilayer Shallow ANN

The Prediction accuracy of multilayer Shallow FFNN with that of the proposed system was calculated and tabulated as in *Table 6* for 10 residential loads for performance comparison. The performance metrics MAPE of Multilayer Shallow FFNN Structure was observed to be 0.650428 and that of proposed CFNN is 0.1429. It was observed that Accuracy of prediction was improved by 50% in the suggested method. The performance of the suggested CFNN model was compared with shallow FFNN based on three metrics as shown in *Table 7*. The proposed method outperforms shallow FFNN in respect of training and prediction error.

Table 6: Performance Comparison of proposed system CFNN with Multilayer Shallow FFNN for home energy prediction for 10 houses

	Multi-layer Shallow FFNN			Proposed System (Multilayer Cascaded Feed Forward NN)	
House	Actual	Forecast	Absolute Error %	Forecast	Absolute Error %
H1	80	80.56	0.7	80.1	0.125
H2	185	186.5	0.810811	185.8	0.432432
H3	209	210.2	0.574163	209.2	0.095694
H4	134	135.2	0.895522	134.3	0.223881
H5	163	164	0.613497	162.9	0.06135
H6	112	113.1	0.982143	112.9	0.803571
H7	89	89.19	0.213483	88.81	0.21348
H8	210	211.8	0.857143	210.7	0.333333
H9	201	202.2	0.597015	201	0
H10	129	129.4	0.310078	128.6	0.31008
Mean Absolute Percentage Error			0.650428		0.1429

Table 7: Comparison of Performance of Used Models

Technique/Structure	MAPE	MSE	R	
			Training	Validation
Shallow FFNN	0.650428	5.8667	0.99985	0.99874
CFNN	0.1429	0.7297	0.99999	0.99986

5. CONCLUSION

Forecasting electricity demand has a substantial impact on energy supply prices and security. For a secure and reliable energy system, accurate forecasting models are required. A novel implementation of a non-linear auto regressive multilayer cascaded feed forward neural network has been presented. In this study, a model for energy load forecasting is proposed. The suggested method's main goal is to improve predicting accuracy. Within the framework of the existing tariff structure, the suggested model was simulated and evaluated for Karnataka Electricity Board LT2 and LT3 consumers. The model aims in the prediction of power consumed, and this will be known to the consumer well in advance, allowing for the modification of load patterns to reduce electricity costs. The consumers will be able to choose a suitable time period for saving money on power. Reduction of maximum load during peak hours will reduce the requirement for increased generation capacity and, to some extent, help alleviate power congestion. Reduced energy expenses in turn reward the consumers for energy saving. The results show that the proposed strategy achieves higher prediction accuracy of 99.85%. Multilayer cascaded feed forward network outperformed multilayer shallow feed forward network with MAPE error of less than 1%. With load forecasting, power plants are committed to supplying power, the more accurate the prediction, the more money and energy are saved. In the future hourly load prediction can be done using deep learning models for individual devices and model can be trained for load prediction of industrial consumers.

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