International Journal on Emerging Technologies **11**(2): 378-384(2020)

ISSN No. (Print): 0975-8364
ISSN No. (Online): 2249-3255

A Review of Short Term Load Forecasting using Deep Learning

Siva Sankari Subbiah[1] and Jayakumar Chinnappan[2]
[1]Assistant Professor, Department of Information Technology,
Kingston Engineering Colege, Anna University, Vellore (Tamilnadu), India.
[2]Professor, Department ofComputer Science and Engineering,
Sri Venkateswara College of Engineering, Pennalur (Tamilnadu), India.

(Corresponding author: Siva Sankari Subbiah)
(Received 28 December 2019, Revised 25 February 2020, Accepted 26 February 2020)
(Published by Research Trend, Website: www.researchtrend.net)

ABSTRACT: The deep learning is a powerful tool for the short term load forecasting. The accurate load forecasting is an inevitable task in power system for the proper planning of the electricity generation, making adjustments in the electricity generation and fixing tariff pricing of electricity depends on the market demand. An inaccurate prediction creates complications in managing the generation, distribution and consumption of power which in turn may leads to increase the operation and management cost, power supply reliability and affects the economic rationality of the power dispatching in the whole society. The optimal decision must be taken in power system for its proper functioning. The deep learning produces an accurate forecasting results with less computational cost. It can effectively model the sequence dependencies exist in the time series load data and feature extraction by adding the number of hidden layers and keeping the long sequences of past decisions made in the network. The present paper discusses the need for short term load forecasting, significance and review of deep learning in short term load forecasting.

Keywords: Convolutional neural network, Deep neural network, Gated recurrent unit, Long short term memory, Recurrent neural network

Abbreviations: RNN, recurrent neural network; LSTM, Long short term memory; CNN, Convolutional neural network; NARX, nonlinear autoregressive network with exogenous inputs; RBM, restricted Boltzmann machine; CRBM, conditional restricted Boltzmann machine; FCRBM, Factored conditional restricted Boltzmann machine; BR, Bayesian regularization; LSTM S2S, Long short term memory sequence to sequence; GRU, gated recurrent unit; DBN, Deep belief network.

I. INTRODUCTION

The forecasting of an electricity load represents the forecasting of the future electricity load behaviors in advance. The load values varies from time to time. The load has the characteristics such as demand factor, load factor, diversity factor, utilization factor and power factor. The load is broadly classified into five categories based on the application. They are domestic load, commercial load, industrial load, agricultural load and other loads like bulk supplies and street lights. Among these the usage of commercial and an agricultural loads vary depends on the seasonal variations. The requirements and the consumption of the industrial load varies with the variation of the weather. Most of the power is utilized by the power plant. The load forecasting is broadly classified into three types namely long term, medium term and short term load forecasting based on the time horizon [42, 46] and shown in Fig. 1. The short term load forecasting predicts the future electricity load for the time horizon ranges from one hour to one week. It has a prominent role in power system operations such as proper planning, scheduling, allocation and maintenance. It is also important for implementation of power grid and its maintenance [14, 26]. The required electricity cannot be generated by the power system for a longer period due to the inconvenient nature of storing the electricity. So the decision must be taken in power system for managing the generation, distribution and consumption of power efficiently [13].

In the developed countries, the residential and commercial buildings utilize 40%-50% of the total generated power. The major energy consumers are buildings where nearly 20%-30% of the total load produced are utilized. The power generation and the distribution in the power grid should be efficient for reducing the power wastage. But, it cannot be achieved easily due to the uncertainty of electricity, arrival of new customers to the vacant location, weather changes, seasonal changes, changes in the usage of power by an existing customers, national policy, time factors, electricity price, industrial structure, usage of electrical devices and economic fluctuations. An underestimation and over estimation of an electricity load may create an economical loss and wastage of energy respectively. Thus, an inaccurate prediction of power may leads to increase the operational cost and management cost [59].

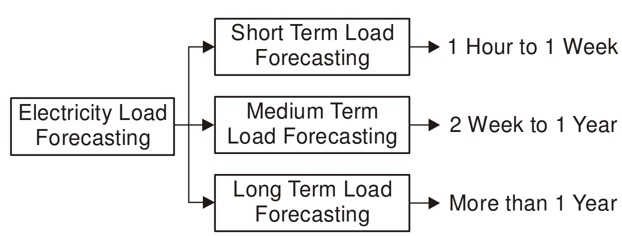

Fig. 1. Types of Load Forecasting.

The short term load forecasting can be done at different levels like hourly, daily and weekly basis. Especially, the daily peak load prediction is important in power system dispatching centers [5, 46]. The reliability of the power system is inevitable in the economic world. The methodologies utilized by various researchers for the electricity load forecasting includes statistical methods, time series based methods and artificial intelligence based methods [24, 50]. The statistical methods do not have the ability to produce an accurate forecasting by considering various factors compared to artificial intelligence methods. After the development of artificial intelligence methods, the process of forecasting becomes an easy task. The neural network is applied on variety of domains like signal processing, image classification, image captioning, natural language processing, medical diagnosis, precision medicine, automatic detection of breast cancer, time series data prediction, precision medicine and speech recognition due to its dominant capability of handling and modelling the non-linearity of data.

The neural network behaves like a human neural system and forecasts accurately compared to statistical methods. It is a fully connected network with the weighted directed connections between neurons in one layer of network to next layer. But, it faces some complications while processing big datasets. The predictions using large dataset requires multiple layers of complicated neural network. Due to multiple layers of the neural network, the gradient decent problems will be created on the network. The machine learning algorithms cannot converge due to the too small gradient (vanishing gradient) and too large gradient (exploding gradient) [19, 41, 45].

The weather data has much impact in the short term load forecasting. The short term load forecasting of the particular day or an hour depends on the past load values and the weather values. So the dataset consists of both load and weather values are utilized for deep learning prediction. Not all the features contribute equally in the deep learning. So, feature selection methodologies also can be utilized as a preprocessing technique which helps to reduce the complexity of the deep learning model and also for improving the learning accuracy [27, 44]. The optimization techniques also can be applied to improve the forecasting results [20-22]. The deep learning network overcomes the complications of machine learning methodologies. It can handle effectively the time series datasets and analyses the sequence dependencies exist in the time series load data. It differs from the machine learning methodologies by executing the feature engineering on itself without any external inputs. It scans the given large dataset and automatically searches for finding the correlated features. After that, it combines the features and performs the faster learning. It produces accurate prediction compared to machine learning methodologies.

II. RELATED WORKS

Marino *et al.*, (2016) utilized long short term memory for forecasting the power consumption at residential house [30]. Deep neural network utilized with restricted Boltzmann machine for forecasting the load from natural gas [31]. Shi *et al.,* (2017) designed a pooling based deep recurrent neural network with restricted Boltzmann machine for forecasting the residential and enterprise load [47]. Hafeez *et al.*, (2018) predicted the short term electricity load for smart grid applications using conditional restricted Boltzmann machine and stacked factored conditional restricted Boltzmann machine methodologies [15]. Also forecasted the load using deep neural network with the parallel CNN and RNN on hourly load data [16]. Mohammad *et al.*, (2018) proposed deep RNN in [32] for forecasting load using load and weather data.

In addition to this, the review of load forecasting done by various researchers shows that the deep learning methodologies such as LSTM-RNN [4, 17, 25, 34, 51, 52, 57, 61], DBN [58], ensemble deep learning with deep belief network and empirical mode decomposition [39], stacked LSTM [7, 55], LSTM encoder predictor [35], enhanced RNN [56], NARX [61], enhanced CNN [1, 12, 53], CNN [23], GRU [37], deep residual network with an ensemble [6] and Jordan recurrent neural network [38] are better utilized for the load forecasting than machine learning methodologies. The summary of related work is given in Table 1.

Table 1: Summary of Related Research Work.

S.No.	Author	Dataset	Methodology	Remarks
1.	Kuo and Huang (2018) [28]	USA District Public Consumption dataset and electric load dataset	Deep Energy with Convolutional Neural Network	Produce an accurate demand and load forecasting than SVM, random forest, decision tree, multilayer per ceptron, Deep Energy, MAPE: 9.7% , CV-RMSE : 11.7%
2.	Marino *et al.*, (2016) [30]	Individual household electric power consumption dataset from UCI repository	Long Short Term Memory based Sequence to Sequence (LSTM S2S)	Good for both hourly and minute data
3.	Merkel *et al.*, (2018) [31]	Load data from Natural gas operation around US	Deep neural network with RBM	Deep neural network outperforms linear regression and ANN
4.	Shi *et al.*, (2017) [47]	Irish residential customers dataset and small & medium enterprise dataset	Pooling based deep recurrent neural network (PDRNN)	PDRNN outperforms ARIMA, SVR and classical deep RNN. RMSE : 0.4505, MAE : 0.2510, NRMSE : 0.0912
5.	Hafeez *et al.*, (2018) [15]	Hourly load demand and weather data of US utility from Kaggle repository	Stacked FCRBM and CRBM	FCRBM is accurate and robust compared to ANN and CNN FCRBM - MAPE:0.3% CRBM – MAPE:1.2%

6.	Easley *et al.*, (2018) [11]	North central region load data from Electric Reliabilty Council of Texas (ERCOT) and weather data from National Oceanic and Atmospheric Administration (NOAA)	Deep neural network with NARX, Bayesian Regularization (BR) and Livenberg Marquardt	Produces better accuracy than Scaled Conjugant Gradient by considering the weather conditions and seasons
7.	He (2017) [16]	Hourly load of North China city	Deep neural network with parallel CNNRNN	Achieves better result than linear regression, SVR, DNN, CNN-RNN. MAPE : 1.40% and MAE: 104.24
8.	Mohammad *et al.*, (2018) [32]	Load data from New York Independent System Operator (NYISO) and weather data from National Climatic Data Center	Deep recurrent neural network	Deep RNN with tanh achieved better accuracy than deep RNN with sigmoid, deepRNN with ReLU, deep forward neural network (deep FNN) with sigmoid, deepFNN with tanh and deep FNN with ReLU
9.	Kong *et al.*, (2017) [25]	Different customers household smart meter data of New South Wales	Long Short Term Memory-Recurrent neural network	LSTM-RNN produces reduced MAPE compared to BPNN, KNN, ELM and Input Selection with Hybrid Forecasting (IS-HF) MAPE: 8.18%

III. IMPORTANCE OF DEEP LEARNING IN SHORT TERM LOAD FORECASTING

The deep learning is a type of machine learning that uses multilayered hierarchical artificial neural network for handling the complicated problems in all applications like image recognition, fraud detection, drug discovery, healthcare, object detection, time series analysis, natural language processing, speech recognition, recommendation system, toxicity prediction, etc and deliver accurate results [2, 8, 18, 40]. The deep learning has the ability of constructing the new features without the human intervention. Not like the machine learning methods, the deep learning solves the problems in an end-to-end manner without decomposing the problems into multiple smaller problems and then combining the results for making conclusions [29]. It is more suitable for processing large data sets that may comprise of structured or unstructured data. Within a short span of time, the deep learning models perform thousands of operations and repetitive tasks on large datasets. The deep neural network plays a dominant role in the time series analysis. It can effectively handle the sequence dependencies of time series data. It has the capability of learning the hidden features from the input data without demanding the manual extraction of features.

IV. DEEP LEARNING APPROACHES

The deep learning models follow deep neural networks. The working of the deep learning methodologies consists of two main phases namely training phase and inferring phase. In the training phase, it takes large volume of data, labels that data and identifies the intrinsic matching characteristics of those data. In the inferring phase, when the network receives an identical data, it analyzes these characteristics, find the matching characteristics from the already gained knowledge, produces correct results and remembers them for the future processing. The deep neural network is utilized for both classification and prediction process. It performs effectively the classification through transfer learning, training from scratch data and extracting features. The simple neural network consists of only input layer, only one output layer and one hidden layer in between the input and output layers. The deep neural network consists of only one I nput and output layers as the simple neural network but, it consists of a number of hidden layers in between input and output layers. It handles the complicated problems by using the multi-layered network easily.

A. Activation Function

In deep neural network, the activation function performs the non-linear transformation on the input provided at the node and pass it to the next layer of neurons in the neural network [43]. There may be a several types of activation functions utilized in deep learning such as binary step function, linear function, sigmoid function, tanh function, ReLu function, Leaky Relu function, ParameterisedReLu function, Exponent Linear Unit function, Softmax and Swish function.

The performance of the deep neural network depends on the selection of the right activation function for right problem. The binary step function is better for binary classification but not suitable for multi class problems and the linear activation function fails to handle the complex patterns. The sigmoid function is a non-linear activation function whose value ranges between 0 and 1. It is better for classification problems. The tanh activation function is similar to the sigmoid function but its value ranges between -1 and 1. The ReLu is the most popular activation function. It is utilized by most of the applications now a days and it is general to all problems. It is used in the hidden layers of the network and it suffers if the network consists of dead neurons. This problem can be effectively handled by its three variant activation functions namely Leaky ReLu, ParametirizedReLu and Exponent Linear ReLu. The soft max is the activation function that can be utilized for handling binary and also multiclass problems. It is a combination of number of sigmoid functions. The Swish activation function was invented by the popular Google. It is better than ReLu in providing the computational efficiency and performance for deep models.

B. Methodologies

Recurrent Neural Network: The recurrent neural network is a special kind of neural network that deals the sequence data effectively compared to machine learning models. It utilizes inputs and outputs of any length of variable size sequence and maps the inputs to outputs. The sequence information plays a major role in many applications in deciding the next information. It takes the past information and hidden state information as input for finding the future information. It consists of multiple hidden layers and in each hidden unit, it holds the previous state information [3]. The general structure of the recurrent neural network is shown in Fig. 2.

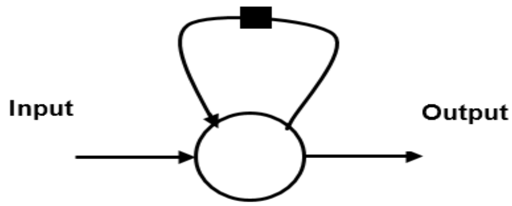

Fig. 2. Structure of Recurrent Neural Network.

The RNN receives the input and generates the output at the hidden layer by the activation function. The current state information is calculated as follows

$$h_t = f(h_{t-1}, x_t) \tag{1}$$

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t) \tag{2}$$

where 'h_t' represents hidden state information at time period 't', tanh represents the hyperbolic tangent activation function, 'W_{hh}' represents the weight at the recurrent neuron, 'h_{t-1}' represents the hidden state information at the time 'period t-1', 'W_{xh}' represents the weight at the input neuron and 'x_t' represents the input at the time period 't'. After calculating the current state information, the output state will be

$$y_t = W_{hy}h_t \tag{3}$$

It is utilized in many applications such as text mining, opinion mining, sentiment analysis, time series forecasting, natural language processing and financial forecasting [48].

Long Short Term Memory: The long short term memory (LSTM) is a type of recurrent neural network (RNN) which is designed to solve the limitations of simple RNN such as short term memory, vanishing gradient and exploding gradient. Now a days, one of the important problem in the data science is the sequence prediction. Even though, the RNN can be utilized for solving the sequence problem, it faces the complications due to its short term memory. It cannot remember the longer sequences. In some time series applications like stock market the stock price at the time 't' not only depends on the stock price at the time period 't-1'. The stock price at time period 't' depends on the previous values of long sequence [10, 33, 49]. So, the simple RNN fails in some applications for providing accurate results.

The LSTM has the capability to remember the longer sequences by using three types of gates in each neuron namely forget gate, input gate and output gate [60]. The forget gate is used to find which information should be discarded, the input gate helps to update the cell state and the output gate decides the next hidden state information [36]. The LSTM cell uses sigmoid and tanh activation functions. The LSTM is utilized in many applications like handwriting recognition, grammar learning, robot control, speech recognition and time series prediction. The electricity load is a non-linear, sequential time series data that can be effectively predicted using LSTM compared to simple RNN [9].

Convolutional Neural Network: The convolutional neural network is an alternate to RNN for modeling and forecasting the short term load. It is the noise resistant model that can extract deep features that is independent from time. The one dimensional convolutional network considers the time series data with multiple features as a grid with 'n' length (instances) and 'm' width (features). The kernels in the convolutional network always has same width with varying length [58]. At each time, the kernel moves in only one direction from the first time series instance to the end of the time series and performs the convolution. The multi scale convolutional neural network supports multi scalability. It consists of three stages namely transformation, local convolution and full convolution. In the first phase, transformation phase, different transformations are applied on three different branches of original time series samples where the first transformation maps the identity, the second transform performs smoothing and the third transformation performs the down-sampling using various down-sampling coefficients. In the second phase, local convolution phase, the one dimensional convolution is applied on time series samples with varying filter sizes. In this phase, each branch is considered as an independent time series and also processed independently. In the third phase, full convolution phase, the results of the different local convolutions on three branches are merged and utilized as an input vector to the fully connected layers of CNN [52]. The CNN works well with the residential load forecasting where there is a lack of sequence information in the load pattern.

Gated Recurrent Unit: The gated recurrent unit is a kind of LSTM which is also designed to solve the vanishing gradient problem of simple recurrent neural network. The design of gated recurrent unit (GRU) is same as that of LSTM, but it uses only two gates namely update gate and reset gate. The GRU keeps the long sequence of information for a longer period without removing any information. The update gate helps to eliminate the vanishing gradient problem by passing almost all information from the past. The reset gate is utilized to decide the amount of information to be forget from the past [54, 60]. It provides an improved accuracy of forecasting by carefully training the network.

V. PERFORMANCE METRICS

The performance of the prediction model can be measured in many ways such as by calculating Mean Absolute Error (MAE), Mean Square Error (MSE), Root Mean Square Error (RMSE), Percentage Error (PE), Mean Percentage Error (MPE), Mean Absolute Percentage Error (MAPE) and Symmetric Mean Absolute Percentage Error (SMAPE) by using Eqns. (4), (5), (6), (7), (8), (9) and (10) respectively.

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|Y_t - F_t| \tag{4}$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(Y_t - F_t)^2 \tag{5}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=0}^{n}(Y_t - F_t)^2} \tag{6}$$

$$PE = \left(\left(\frac{Y_t - F_t}{Y_t}\right)\right) * 100 \quad (7)$$

$$MPE = \frac{1}{n}\sum_{n=1}^{t}\frac{(Y_t - F_t)}{Y_t} * 100 \quad (8)$$

$$MAPE = \frac{1}{n}\sum_{n=0}^{n}|PE| \quad (9)$$

$$SMAPE = \frac{abs(Y_t - F_t)}{((abs(Y_t) + (abs(F_t))} \quad (10)$$

where 'Y_t' is an actual observation at the time period 't' and 'F_t' is the forecast for the same time period 't'.

VI. CONCLUSION

The deep neural network has a dominant role in the short term load forecasting and produces accurate results than other methodologies. The machine learning methodologies works well and produces good forecasting results. But, it may suffer from vanishing gradient and exploding gradient problems when the dataset is too large and the network has multiple hidden layers. The deep learning methodologies such as recurrent neural network (RNN), Long short term memory (LSTM), Convolutional neural network (CNN), nonlinear autoregressive network with exogenous inputs (NARX), restricted Boltzmann machine (RBM), Factored conditional restricted Boltzmann machine (FCRBM), Bayesian Regularization (BR), Long short term memory sequence to sequence (LSTM S2S) achieved better results in forecasting the short term electricity load. The deep neural network handles well the complex sequence dependencies exist in the time series load data. It differs from the machine learning methodologies by executing the feature engineering on itself without any external inputs. It scans the given large dataset and automatically searches for finding the correlated features. After that, it combines the features and performs the faster learning. It produces accurate prediction compared to other methodologies.

VII. FUTURE SCOPE

In future, the performance of the short term load forecasting can be improved by using the deep learning methodologies with feature selection, hybridization, optimization, ensemble learning and transfer learning concepts.

ACKNOWLEDGEMENTS

The authors would like to acknowledge the contributions made by anonymous reviewers whose valuable comments and insightful suggestions resulted in the improvement of the paper's preliminary version.

Conflict of Interest. The authors declare that there is no conflict of interest of any kind on this research work.

REFERENCES

[1]. Acharya, S. K., Wi, Y. M., & Lee, J. (2019). Short-Term Load Forecasting for a Single Household Based on Convolution Neural Networks Using Data Augmentation. *Energies*, *12*(18), 1-19.

[2]. Adhithiyan, M., & Karmel, A. (2019). Novel Approach of Deep Learning in Toxicity Prediction. *International Journal of Recent Technology and Engineering (IJRTE),* 7(5S4), 698-704.

[3]. Agila, N., & Senthil Kumar, P. (2020). An Efficient Crop Identification Using Deep Learning. *International Journal of Scientific & Technology Research*, *9*(1), 2805-2808.

[4]. Agrawal, M., Khan, A. U., & Shukla, P. K. (2019). Stock Indices Price Prediction Based on Technical Indicators using Deep Learning Model. *International Journal on Emerging Technologies*, *10*(2), 186-194.

[5]. Amjady, N. (2001). Short-term hourly load forecasting using time-series modeling with peak load estimation capability. *IEEE Transactions on power systems*, *16*(3), 498-505.

[6]. Chen, K., Chen, K., Wang, Q., He, Z., Hu, J., & He, J. (2018). Short-term load forecasting with deep residual networks. *IEEE Transactions on Smart Grid*, *10*(4), 3943-3952.

[7]. Cheng, Y., Xu, C., Mashima, D., Thing, V. L., & Wu, Y. (2017). PowerLSTM: power demand forecasting using long short-term memory neural network. In *International Conference on Advanced Data Mining and Applications, Springer, Cham,* 727-740.

[8]. Diviya, M., Malathi, G., & Karmel, A. (2019) Regression Based Model for Prediction of Heart Disease Recumbent. *International Journal of Recent Technology and Engineering, 8*(4), 6639-6642.

[9]. Dou, Y., Zhang, X., Wu, Z., & Zhang, H. (2018). Application of Deep Learning Method in Short-term Load Forecasting of Characteristic Enterprises. In *Proceedings of the 2018 Artificial Intelligence and Cloud Computing Conference,* 35-40.

[10]. Durairaj, M., & Krishna Mohan, B. H. (2019). A Review of Two Decades of Deep Learning Hybrids for Financial Time Series Prediction. *International Journal on Emerging Technologies*, *10*(3), 324-331.

[11]. Easley, M., Haney, L., Paul, J., Fowler, K., & Wu, H. (2018). Deep neural networks for short-term load forecasting in ERCOT system. In *2018 IEEE Texas Power and Energy Conference (TPEC),* College Station, TX, 1-6.

[12]. Faisal, H. M., Javaid, N., Sarfraz, B., Baqi, A., Bilal, M., Haider, I., & Shuja, S. M. (2019). Prediction of Building Energy Consumption Using Enhance Convolutional Neural Network. In *Workshops of the International Conference on Advanced Information Networking and Applications, Springer, Cham,* 1157-1168.

[13]. Fallah, S. N., Ganjkhani, M., Shamshirband, S., & Chau, K. W. (2019). Computational intelligence on short-term load forecasting: A methodological overview. *Energies*, *12*(3), 393.

[14]. Haben, S., Giasemidis, G., Ziel, F., & Arora, S. (2019). Short term load forecasting and the effect of temperature at the low voltage level. *International Journal of Forecasting*, *35*(4), 1469-1484.

[15]. Hafeez, G., Javaid, N., Ullah, S., Iqbal, Z., Khan, M., & Rehman, A. U. (2018). Short term load forecasting based on deep learning for smart grid applications. In *International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing, Springer, Cham,* 276-288.

[16]. He, W. (2017). Load forecasting via deep neural networks. *Procedia Computer Science*, *122*, 308-314.

[17]. Hossen, T., Nair, A. S., Chinnathambi, R. A., & Ranganathan, P. (2018). Residential load forecasting using deep neural networks (DNN). In *2018 North American Power Symposium (NAPS), IEEE,* 1-5.

[18]. Karmel, A. (2017). Multi-Level Privacy Preservation and Transmission of Medical Records Using Cryptographic Technique. *International Journal of Applied Engineering Research*, *12*(17), 6735-6740.
[19]. Karmel, A., Adhithiyan, M., & Senthil Kumar, P. (2018). Machine Learning Based Approach for Pothole Detection. *International Journal of Civil Engineering and Technology (IJCIET),* 9(5), 882–888.
[20]. Karmel, A., & Jayakumar, C. (2014). Analysis on Optimization of Energy Consumption in Mobile Ad Hoc Networks. In *Intelligent Computing, Networking, and Informatics, Springer, New Delhi*, 481-489.
[21]. Karmel, A., & Jayakumar, C. (2015). Recurrent Ant Colony Optimization for Optimal Path Convergence in Mobile Ad Hoc Networks. *KSII Transactions on Internet & Information Systems*, *9*(9), 3496-3514.
[22]. Karmel, A., Vijayakumar, V., & Kapilan, R. (2019). Ant-based efficient energy and balanced load routing approach for optimal path convergence in MANET. *Wireless Networks*, 1-13.
[23]. Khan, S., Javaid, N., Chand, A., Khan, A. B. M., Rashid, F., & Afridi, I. U. (2019). Electricity load forecasting for each day of week using deep CNN. In *Workshops of the International Conference on Advanced Information Networking and Applications,Springer, Cham*, 1107-1119.
[24]. Kiruthika, V. G., Arutchuda, V., & Senthil Kumar, P. (2014). Highest humidity prediction using data mining techniques. *International Journal of Applied Engineering Research (IJAER), 9*(16), 3259–3264.
[25]. Kong, W., Dong, Z. Y., Jia, Y., Hill, D. J., Xu, Y., & Zhang, Y. (2017). Short-term residential load forecasting based on LSTM recurrent neural network. *IEEE Transactions on Smart Grid*, *10*(1), 841-851.
[26]. Kouhi, S., Keynia, F., & Ravadanegh, S. N. (2014). A new short-term load forecast method based on neuro-evolutionary algorithm and chaotic feature selection. *International Journal of Electrical Power & Energy Systems*, *62*, 862-867.
[27]. Kumar, P. S., & Lopez, D. (2016). A review on feature selection methods for high dimensional data. *International Journal of Engineering and Technology*, *8*(2), 669-672.
[28]. Kuo, P. H., & Huang, C. J. (2018). A high precision artificial neural networks model for short-term energy load forecasting. *Energies*, *11*(1), 1-13.
[29]. Laxmi Lydia, E., Moses, G. J., Sharmili, N., Shankar, K., & Maseleno, A. (2019). Image Classification using Deep Neural Networks for Malaria Disease Detection. *International Journal on Emerging Technologies*, *10*(4), 66-70.
[30]. Marino, D. L., Amarasinghe, K., & Manic, M. (2016). Building energy load forecasting using deep neural networks. In *IECON 2016-42nd Annual Conference of the IEEE Industrial Electronics Society, IEEE,* 7046-7051.
[31]. Merkel, G. D., Povinelli, R. J., & Brown, R. H. (2018). Short-term load forecasting of natural gas with deep neural network regression. *Energies*, *11*(8).
[32]. Mohammad, F., Lee, K. B., & Kim, Y. (2018). *Short Term Load Forecasting Using Deep Neural Networks,* 1-5.
[33]. Muzaffar, S., & Afshari, A. (2019). Short-term load forecasts using LSTM networks. *Energy Procedia*, *158*, 2922-2927.
[34]. Palanivel, S., Ramya, S., Sekar, K. R., & Manivannan, D. (2019). Prediction of Currency Exchange Rate using Short Term Memory Networks. *International Journal on Emerging Technologies*, 10(2), 362-364.
[35]. Pasini, K., Khouadjia, M., Same, A., Ganansia, F., & Oukhellou, L. (2019). LSTM encoder-predictor for short-term train load forecasting.ECML/PKDD - The European Conference on Machine Learning and Principles and Practice of Knowledge Discovery in Databases. 1-17.
[36]. Pramono, S. H., Rohmatillah, M., Maulana, E., Hasanah, R. N., & Hario, F. (2019). Deep Learning-Based Short-Term Load Forecasting for Supporting Demand Response Program in Hybrid Energy System. *Energies*, *12*(17), 3359.
[37]. PreamSudha, V., & Vijaya, M. S., (2020). Gated Recurrent Neural Network for Autism Spectrum Disorder Gene Prediction. *International Journal on Emerging Technologies*, *11*(1), 136-141.
[38]. Putri, T. E., Firdaus, A. A., & Sabilla, W. I. (2018). Short-Term Forecasting of Electricity Consumption Revenue on Java-Bali Electricity System using Jordan Recurrent Neural Network. *Journal of Information Systems Engineering and Business Intelligence*, *4*(2), 96-105.
[39]. Qiu, X., Ren, Y., Suganthan, P. N., & Amaratunga, G. A. (2017). Empirical mode decomposition based ensemble deep learning for load demand time series forecasting. *Applied Soft Computing*, *54*, 246-255.
[40]. Ravi, L., Subramaniyaswamy, V., Vijayakumar, V., Chen, S., Karmel, A., & Devarajan, M. (2019). Hybrid location-based recommender system for mobility and travel planning. *Mobile Networks and Applications*, *24*(4), 1226-1239.
[41]. Raza, M. Q., & Khosravi, A. (2015). A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings. *Renewable and Sustainable Energy Reviews*, *50*, 1352-1372.
[42]. S. K. P. (2017). A Review of Soft Computing Techniques in Short-Term Load Forecasting. *International Journal of Applied Engineering Research (IJAER)*, *12*(18), 7202–7206.
[43]. Senthil K. P., & Lopez, D. (2016). Forecasting of wind speed using feature selection and neural networks. *International Journal of Renewable Energy Research*, *6*, 833-837.
[44]. Senthil K. P., & Lopez, D. (2015). Feature selection used for wind speed forecasting with data driven approaches. *Journal of Engineering Science and Technology Review*, *8*(5), 124-127.
[45]. Senthil, K. P. (2019). Improved Prediction of Wind Speed using Machine Learning. *EAI Endorsed Transactions on Energy Web*, *6*(23), 1-7.
[46]. Shabbir, M. N. S. K., Ali, M. Z., Chowdhury, M. S. A., & Liang, X. (2018). A probabilistic approach for peak load demand forecasting. In *2018 IEEE Canadian Conference on Electrical & Computer Engineering (CCECE),* 1-4.
[47]. Shi, H., Xu, M., & Li, R. (2017). Deep learning for household load forecasting—A novel pooling deep RNN. *IEEE Transactions on Smart Grid*, *9*(5), 5271-5280.
[48]. Sivasankari, S., & Baggiya Lakshmi, T. (2016). Operational Analysis of Various Text Mining Tools In

Bigdata, *International Journal Of Pharmacy & Technology (IJPT), 8*(2), 4087-4091.
[49]. Sugumar, R., Rengarajan, A., & Jayakumar, C. (2015). A technique to stock market prediction using fuzzy clustering and artificial neural networks. *Computing and Informatics*, *33*(5), 992-1024.
[50]. Swaroop, G., Senthil Kumar, P., & Muthamil Selvan, T. (2014). An efficient model for share market prediction using data mining techniques. *International Journal of Applied Engineering Research (IJAER),* 9(17), 3807–3812.
[51]. Tang, D., Li, C., Ji, X., Chen, Z., & Di, F. (2019). Power Load Forecasting Using a Refined LSTM. In *Proceedings of the 2019 11th International Conference on Machine Learning and Computing.*104-108.
[52]. Tian, C., Ma, J., Zhang, C., & Zhan, P. (2018). A deep neural network model for short-term load forecast based on long short-term memory network and convolutional neural network. *Energies*, *11*(12), 3493.
[53]. Umamaheswari, J., & Akila, A. (2019). An efficient speaker recognition using improved Convolution Neural Networks. *International Journal on Emerging Technologies*, *10*(3), 379-383.
[54]. Wu, W., Liao, W., Miao, J., & Du, G. (2019). Using Gated Recurrent Unit Network to Forecast Short-Term Load Considering Impact of Electricity Price. *Energy Procedia*, *158*, 3369-3374.
[55]. Yuan, C., Xiu, T., & Lou, T. (2019). Probabilistic Long-term Load Forecasting Based on Stacked LSTM. In *Proceedings of the 2019 4th International Conference on Mathematics and Artificial Intelligence,* 80-84.
[56]. Zahid, M., Ahmed, F., Javaid, N., Abbasi, R. A., Kazmi, Z., Syeda, H., & Ilahi, M. (2019). Electricity price and load forecasting using enhanced convolutional neural network and enhanced support vector regression in smart grids. *Electronics*, *8*(2), 122.
[57]. Zhang, C., & Fang, J. (2019). Application research of several LSTM variants in power quality time series data prediction. In *Proceedings of the 2nd International Conference on Artificial Intelligence and Pattern Recognition,* 171-175.
[58]. Zhang, X., Wang, R., Zhang, T., Liu, Y., & Zha, Y. (2018). Short-Term load forecasting using a novel deep learning framework. *Energies*, *11*(6), 1554.
[59]. Zhang, Y., Wang, J., & Lu, H. (2019). Research and application of a novel combined model based on multiobjective optimization for multistep-ahead electric load forecasting. *Energies*, *12*(10), 1931.
[60]. Zheng, J., Chen, X., Yu, K., Gan, L., Wang, Y., & Wang, K. (2018). Short-term Power Load Forecasting of Residential Community Based on GRU Neural Network. In *2018 International Conference on Power System Technology (POWERCON), IEEE,* 4862-4868.
[61]. Zheng, Z., Hainan, C. H. E. N., & Xiaowei, L. U. O. (2019). Spatial granularity analysis on electricity consumption prediction using LSTM recurrent neural network. *Energy Procedia*, *158*, 2713-2718.

How to cite this article: Subbiah, S. S. and Chinnappan, J. (2020). A Review of Short Term Load Forecasting using Deep Learning. *International Journal on Emerging Technologies*, *11*(2): 378–384.