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Convolution Neural Network based Short-Term Load Forecasting

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ABSTRACT

Load forecasting (LF) is an important process in forecasting future load for sustainable power system operations and control. Due to deregulation of electrical markets, load forecasting has attracted many researchers and hence accurate load forecasting is very much needed. LF is categorised based on time horizons. Neural network based Convolution Neural Network (CNN) is used to forecast short-term load for Tumakuru, a city in Karnataka, India. RMSE and MAPE are performance metrics with temperature and humidity as two weather factors.

Keywords: *Load forecasting, Short-term load forecasting, Convolution Neural Network, Weather factors, Performance metrics.*

1. INTRODUCTION

The connection of variable loads, such as electric vehicles and the integration of renewable energy sources, two prerequisites of the Net Zero by 2050 project for "greener" power grids, have a significant impact on the stability and effectiveness of power networks. Instantaneous and constant load situation poses a significant challenge to power plant operation and management in general, including economic dispatch [1], demand side management [2], price forecasting [3,4], maintenance scheduling and the formulation of an effective bidding strategy in power system markets [5], along with the financial viability of electrical companies themselves, are increasingly relying on accurate load predictions [6].

1.1 Categories of load forecasting

Forecasting the load on a power system may be separated into four categories based on time horizon. Very Short-term load forecasting (VSTLF) is the time between a few seconds and a few minutes. Short-term load forecasting (STLF) is over a period of one hour to one week. Medium-term load forecasting (MTLF) is forecasting window ranges from one month to one year. Long-term load forecasting (LTLF) is the forecasting with a time horizon of one to 10 years [7].

1.2 Factors influencing load forecasting

The accuracy of forecast is affected by a number of different factors. Time, duration, climate and economic factors influence an accurate forecast. LF seems to be significantly influenced by temperature, humidity, moisture, cloud cover and other environmental variables and among these factors, temperature is the prime factor [8].

1.3 Traditional methodologies

For STLF include time series models, regression models, and Kalman filtering-based procedures [9, 10]. Artificial intelligence and deep learning approaches, include Artificial Neural Networks (ANNs) [11], such as Multilayer Perceptrons (MLPs) [12], Radial Basis Function Neural Networks (RBFNNs) [13], Convolutional Neural Networks (CNNs) [14], Recurrent Neural Networks (RNNs) [15], Support Vector Machines (SVMs) [16], Decision Trees (DT) or Random Forests (RF) [17], and Fuzzy-Neural models, offering high accuracy and effective convergence time for the STLF problem. In deep learning approaches, the demand for even more accurate predictions has led researchers to develop hybrid forecasting models, which integrate a clustering algorithm for the pre-processing of data before it is used to train the neural network. Typically, clustering methods are implemented in order to create clusters of the load data, which is first pre-processed using an enhanced min-max scaling method [12].The short-term load forecasting coupled with a clustering strategy, has been extensively studied using methods based on RNNs, Long Short-Term Memory (LSTM), CNNs, SVMs [18], ANNs, Simple Exponential Smoothing (SES) and Group Method of Data Handling (GMDH) algorithms [19].

2. CONVOLUTION NEURAL NETWORK (CNN):

It is a type of ANN and the capacity of CNNs to identify local patterns in contiguous data that is arranged as an array, such as picture pixels or measured values from a time series, is its key characteristic. In [20], a classifying model based on CNN is developed for transient stability assessment, outdoing other machine learning methods. A CNN represents a neural network that employs the convolution operation for feature extraction in at least one of its layers [21].

The following equation can be used to describe the convolution procedure when using a one-dimensional input.

$$\boldsymbol{S}\ (\boldsymbol{i}) = (\boldsymbol{I} * \boldsymbol{K})(\boldsymbol{i}) = \sum_{\boldsymbol{n}=\boldsymbol{1}}^{\infty} \boldsymbol{I}(\boldsymbol{i}+\boldsymbol{n})\boldsymbol{X}\ \boldsymbol{K}(\boldsymbol{n}) - (1)$$

where * represents the convolution operator, while I and K are the 1D input and the kernel, respectively. The output of the convolution operation is the feature map S.

In addition to the convolution operation, CNNs define the pooling operation, which extracts the maximum or average value of adjacent elements from a feature map, thus achieving a down-sampling of the initial feature maps.

The neural network is guaranteed to have sparse connectivity since the parameters of the kernel are multiplied by each value of the input array. This results in a large decrease in the number of parameters that must be updated during training, which accelerates convergence. Moreover, because the input array's components share the kernel's weights, the neural network can learn and recognise features regardless of where they appear in the input [22]. Hence, a CNN might learn the patterns of power usage and produce effective solutions to the STLF problem. One-dimensional inputs, such as a sequence of previous consumption data, proven to be an effective approach for solving load forecasting issues using CNNs [23]. The applications outlined in the literature also use two-dimensional CNNs, focusing on the relationship between the same times from other days [24], arriving at good accuracy. Given that 1D CNNs have less complexity than 2D CNNs, the model suggested in this work is based on 1D CNNs.

3. IMPLEMENTATION OF CNN MODEL

The proposed load forecasting model employs several data types, including electrical load consumption, temperature, humidity and time. A CNN model is developed in this paper for one-day, one-week, weekdays and weekend load prediction with four weather seasons of the year-winter, summer, monsoon and post-monsoon. The electrical load forecasting is done for Tumakuru, a city in Karnataka, India. The model is trained with the years 2014 to 2021 data and tested for the year 2022.

4. PERFORMANCE INDICTORS:

Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) are the most commonly used metrics. MAPE is the prime indicator.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}$$

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right|$$

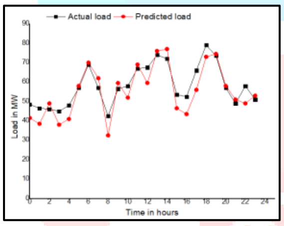
Where, y_i = actual load, $\hat{y}_i$ = forecasted load, n = no. of training data

5. RESULTS:

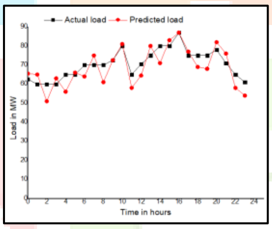
The graphs show time in hours to electrical load in megawatts for four seasons of a year- winter (January, February), summer (March, April, May), monsoon (June, July, August, September) and post-monsoon (November, December) and two weather factors (temperature and humidity) considered and not considered.

5.1 One day graph (24 hours)

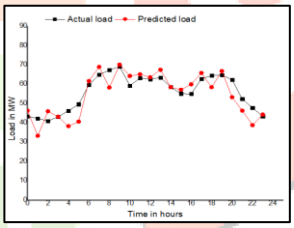
5.1.1 Without weather factors for four seasons of a year 2022.



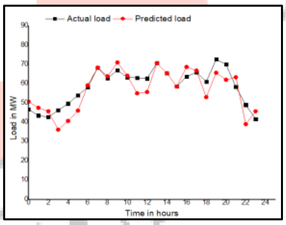
Winter



Summer

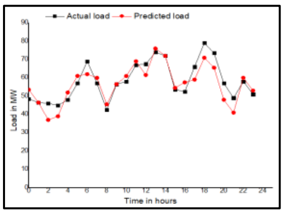


Monsoon

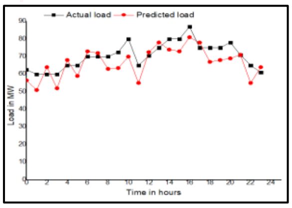


Post-monsoon

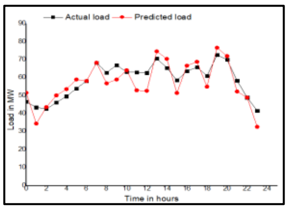
5.1.2 With weather factors for four seasons of a year 2022.



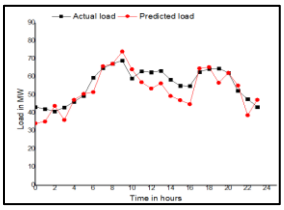
Winter



Summer



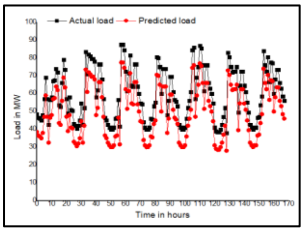
Monsoon

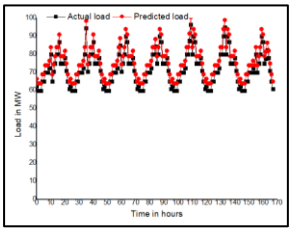


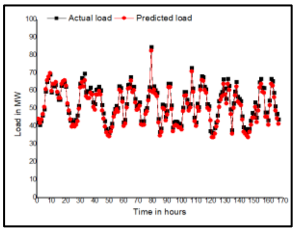
Post-monsoon

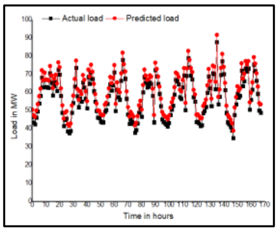
5.2 One Week graph (168 hours)

5.2.1 Without weather factors for four seasons of a year 2022.



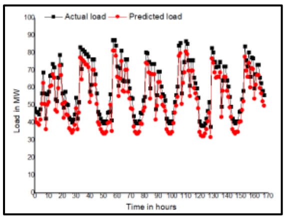


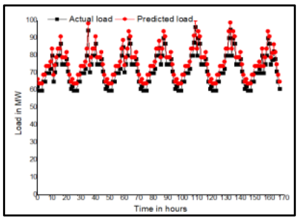


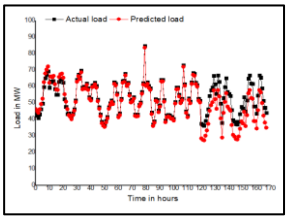


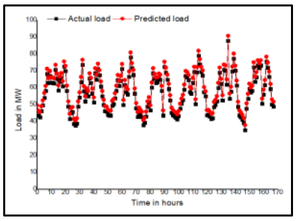
Winter **Summer** **Monsoon** **Post-monsoon**

5.2.2 With weather factors for four seasons of a year 2022.





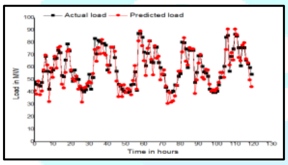
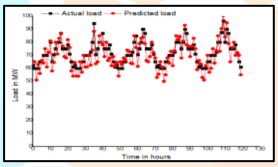
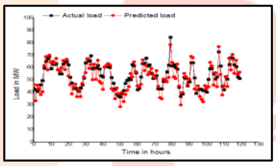
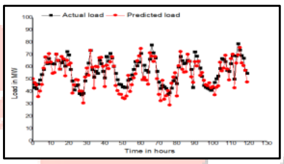




Winter **Summer** **Monsoon** **Post-monsoon**

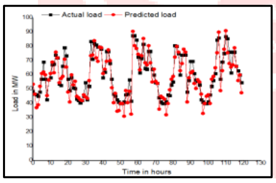
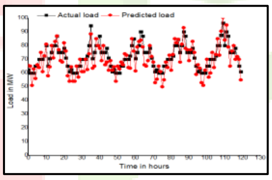
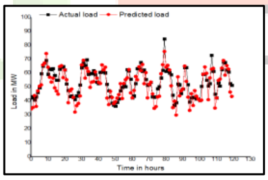
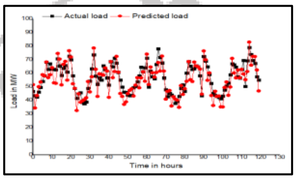
5.2 Weekdays graph (Monday to Friday – 120 hours)

5.3.1 Without considering weather factors for four seasons of a year 2022.

Winter **Summer** **Monsoon** **Post-monsoon**

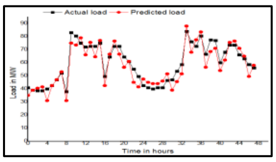
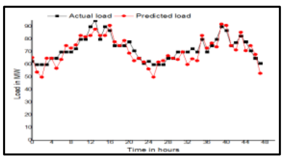
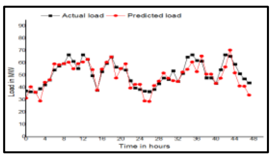
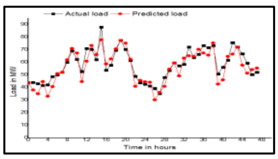
5.3. 2 With weather factors for four seasons of a year 2022.

Winter **Summer** **Monsoon** **Post-monsoon**

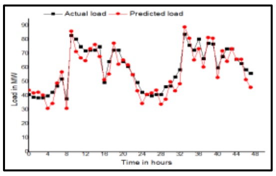
5.4 Weekend graph (Saturday and Sunday – 48 hours) - comparison

5.4.1 Without weather factors for four seasons of a year 2022.

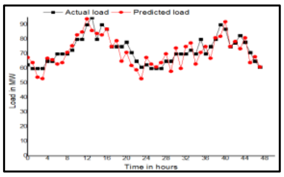





Winter **Summer** **Monsoon** **Post-monsoon**

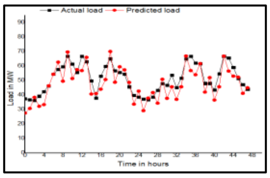
5.4.2 With weather factor for four seasons of a year 2022.



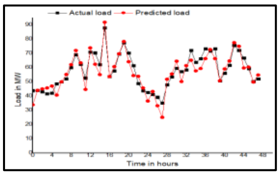
Winter



Summer



Monsoon



Post-monsoon

Table 1 shows without weather factors and with weather factors with performance metrics- RMSE and MAPE for four seasons. **Legend:** W–winter, S- summer, M-monsoon and PM-post-monsoon.

Table 1: Performance metrics for weather seasons of a year 2022 with weather factors.

Weather Factors	without considering weather factors								with considering weather factors							
Metrics	RMSE				MAPE				RMSE				MAPE			
Season	W	S	M	PM	W	S	M	PM	W	S	M	PM	W	S	M	PM
One day	10	4	1.1	4	17.7	5.7	1.9	7	6	4	3	3	10.6	5.7	5.5	5.3
One week	10	4	2.2	4	17.7	5.6	4.2	7.2	6	4	5	3	10.6	5.6	7.0	5.4
Weekdays	10	4	2	4	17.7	5.6	3.7	7.3	6	4	1.6	3	10.6	5.6	2.6	5.4
Weekend	10	4	2.7	4	17.9	5.6	5.3	7.1	6	4	9	3	10.7	5.6	18.2	5.3
Average	10	4	2	4	17.7	5.6	3.8	7.2	6	4	4.6	3	10.6	5.6	8.3	5.4

6. CONCLUSION:

The RMSE and MAPE for all the four weather seasons of a year 2022 is shown in table 1. From table 1, average MAPE without considering weather factors is 8.6% and average MAPE with considering weather factors is 7.5%. From this, it is evident that weather factors are important in short-term load forecasting for improving accuracy of forecasting.

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