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SHORT TERM ELECTRICITY LOAD FORECASTING FOR TUMAKURU CITY BASED ON ANN, LSTM AND RANDOM FOREST

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Abstract: Due to the ongoing integration of renewable energy sources (RES) into the energy mix and the transformation of the conventional electric grid into a more intelligent, flexible, and interactive system, electrical load forecasting is now a crucial part of smart grid planning and management. It is challenging to anticipate the electric load due to its high volatility and uncertainty, whether the load is applied to the distribution system or a single residence. The main idea behind the proposed methodology is to optimise the hyper-parameters of the neural network by using the statistical properties of each time series dataset, as well as to arrange the dataset to maximise the advantages of the ANN algorithm. One of the three models is long short term memory. Random Forest and Artificial Neural Network are contrasted. An evaluation of algorithms was done for the smart city Tumakuru in Karnataka.

Key words: Load forecasting, LSTM, Random forest, ANN, Renewable Energy, Classification.

I. Introduction

Load forecasting minimizes business costs, determines just energy evaluating, controls capacity scheduling, and guides long-term planning. It also improves utility companies' capacity to forecast and foresee electricity demands in order to keep supply and demand in balance. For energy providers and other power system stakeholders, these forecasts are crucial for participants and the power production, transmission, and distribution industries. Additionally, for different points in the planning horizon, exact projections of the geographic locations and magnitudes of the electric load are made. The primary criterion is employed to evaluate the model's predictions based on the lead-time horizon. For effective generation planning, it is essential to accurately estimate future load requirements. Additionally, it enhances the efficiency of the power system and makes administrative decisions easier going forward. Massive economic losses for the housing and power systems may be caused by inaccurate forecasts [1]. To help the electrical load supply chain run smoothly, researchers have used a variety of statistical, mathematical, and artificial intelligence-based methodologies for forecasting electrical load demand. In compared to other conventional approaches, Combining neural networks (NN) with various meta-heuristic optimization techniques algorithms were discovered to have good capability in managing complex nonlinear relationships and model complexity [2]. This research project's major objective is to use cutting-edge ANNs with LSTM and RF architectures to increase the precision of electrical load demand projections.

Artificial Neural Network (ANN)

A computational model is an artificial neural network (ANN). Its foundations are in the design and operation of biological brain networks. It operates similarly to how the brain analyses information. It has many interconnected processing units that cooperate to process information. They also produce significant outcomes from it.

Random Forest (RF)

For classification and regression problems, a random forest is a machine learning technique. It takes use of ensemble learning, which combines a number of classifiers to find solutions to complex problems. There are numerous varieties of decision trees in RF algorithms. Through bagging or bootstrap aggregation, the RF method constructs a "forest" that is trained. The use of an ensemble meta-algorithm improves the accuracy of machine learning algorithms. The outcome is decided by the algorithm based on the predictions made by the decision trees. The data from various trees are averaged or averaged out to produce forecasts. As the number of trees increases, the precision of the result increases.

Long Short Term Memory (LSTM)

Long Short Term Memory networks are referred to as the LSTM Network model. These particular neural networks are capable of comprehending long-term dependencies in general. Long-term dependencies were generally intended to cause problems, and LSTM models successfully address the issues in the majority of cases. The LSTM Network models typically include the ability to selectively remove or add data, which is controlled by a unique structure known as gates. Identifying the information that needs to be thrown out of the cell comes first in the processing of LSTMs. The choice of what additional data should be stored in the cell comes next, and the final decision is made regarding the output format. The status of the cells generally determines the output [3].

II. Related Works

A deep neural network is a more complicated version of a traditional artificial neural network (ANN), and it learns by employing an architecture that is intricate and has many hidden layers and neurons. The topological structure of NN with numerous layers in the network is referred to as "deep" in this regard. An artificial neural network (ANN) is just a multiple-layer perceptron with more layers than the normal ANN's three levels (MLP). A deep neural network uses fundamental parallel computing elements and is inspired by biological nervous systems to incorporate multiple nonlinear layers of processing. Back propagation, gradient descent, a considerable number of neurons, and hidden layers are the main components of deep learning typically [9]. The ability of neural networks to abstract is improved by their deep structure DNNs can currently be deployed in a number of ways thanks to the development of the Internet of things (IoT) and big data [4,5]. Furthermore, current research on DNN has showed considerable potential in other areas as voice recognition and computer vision. In the literature, there is substantially less research on using DNN for STLF (short-term load forecasting) [7]. A deep neural network is a more sophisticated version of a traditional artificial neural network (ANN), and it learns by typically using a framework of complicated design with numerous hidden layers and neurons. The topological structure of NN with numerous layers is referred to as having a "deep" topology. A deep neural network (DNN) is an ANN with more layers than the standard multiple-layer perceptron's three (DNN-MLP). A deep neural network combines multiple nonlinear layers of processing, using fundamental parallelism from biologically inspired nerve systems. Back propagation, gradient descent, a sizable number of neurons, and hidden layers has traditionally been the mainstays of deep learning [9].The neural networks' capacity for abstraction is increased by their deep structure. Currently, there are numerous approaches to implement DNNs thanks to the development of the Internet of things (IoT) and big data [4,5]. Recent research on DNN has also demonstrated considerable potential in other disciplines, including speech recognition and computer vision. However, the literature shows that significantly less effort has been done when applying DNN to STLF short-term load forecasting. DNNs enable complex meticulousness to be reached by identifying prominent elements that affect electricity utility leanings, and they can undoubtedly make a significant contribution to the recently released Smart grid as well as next-generation energy systems. Figure 1 depicts a typical DNN network topology with an input and output layer, several hidden layers, and neurons. As can be seen, this neural network is transformed into a deep neural network by a number of hidden layers. More layers will increase the results' accuracy [8, 18, 19].

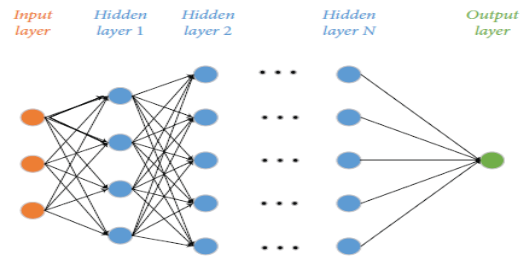


FIGURE 1: A typical deep neural network architecture.

Figure:1 Existing Neural network

III. Proposed Methodology

The meticulous examination of the load data and its dynamics is the primary need for an appropriate prediction model. Intelligent meters are used to collect enormous amounts of data on a daily basis, much of which is first referred to as raw data. To gain insights, big statistical analytics can be useful for smart grid energy management. Variation and the behaviour of the load data are important factors to take into account in order to get appropriate forecast results [11,12,13]. Data preparation, commonly referred to as data normalisation, is one of the first processes in the handling of data. Simple load shape analysis can be used to implement these solutions. The input data can be divided into various clusters based on characteristics, which can then be used to improve network performance [14,15,16,17,18,19]. The collection of data from several data systems, such as the equipment, client and indicting information, weather, and electrical load system, is the first step in the preprocessing of data. Thanks to power converters used by power grid firms, data management and smart electronics have advanced, and data-oriented applications have greatly increased attention in academia and business.. In addition to the load demand data, other parameters, such as metrological data and day type information, are also very important. [24].

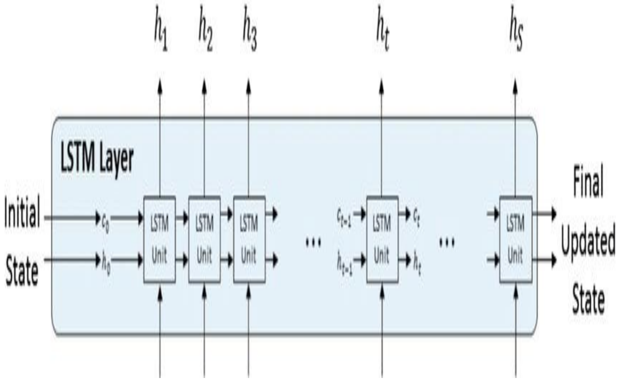


Figure:2 LSTM Model

A better version of recurrent neural networks called long short-term memory (LSTM) networks makes it simpler to recall previous material from memory. The problem of the lessening incline is resolved. Assumed the time suspensions are unpredictable, LSTM is a great tool for classifying, examining, and forecasting time series. Numerous smart systems, including smart grids, have demonstrated the effectiveness of LSTM-based intelligent forecast models [20,21,22,23,24].

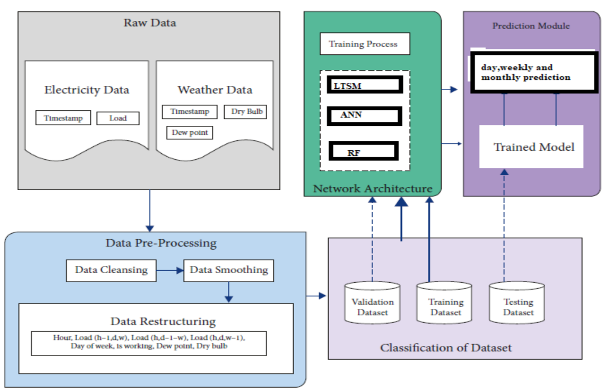


FIGURE 3: Modelling for load forecasting.

Figure:3 Load Forecasting Model

Block diagram

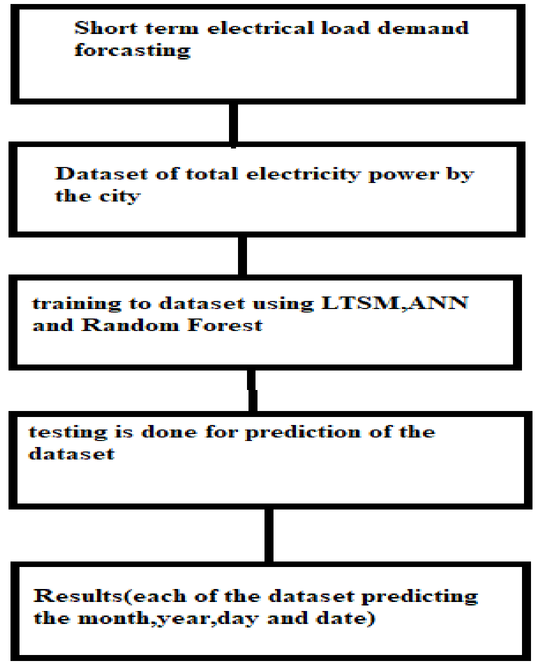


Figure:4 Block diagram of the Proposed model

Dataset

The dataset is taken for the electricity or power management of the city. There are eight attribute in the dataset they are year, month, date, day, hour, temperature, humidity and load where the dataset contain from 2014 to 2021 for the electricity consumption and 2022 January to July the dataset is used for the prediction of the electricity load in the city. The dataset is designed in this manner to predict the electricity load of the city.

Training

Training of the dataset is done using the LTSM, ANN and Random forest for each and every dataset is trained and getting the accuracy and loss graph of the dataset using the LTSM, ANN and Random forest.

Testing

Testing is done for dataset and prediction is done for only the 2022 January to July. Testing is done with all models.

Result

Result of the work is obtained using the prediction of the dataset in which the graphically representation of the total electricity consumed. The prediction is done on the day based, weekly based and monthly based.

IV. Experimental Setup

The historical load demand and the time for a 24-hour period are the two variables used in this technique to identify the input data. Through the use of past data, the network learnt how to provide input signals and desired outputs. The network generated an output signal for each input signal, and learning tried to reduce the sum of squares between desired and actual outputs. The input-output patterns were sent to the network frequently to enable learning. Epochs are single presentations of the full training set. Until the weights stabilised and the sum of squared errors converged to some minimum value or objective, the learning process was typically carried out epoch by epoch. The learning rate and momentum factor were the other variables. Both parameters were influenced by the system. The weight adjustments were made reliant on many input patterns as a result of the momentum factor. This parameter's usable range was between 0 and 1 [9].

Actual Identification of Input Data:

Two variables were used in this study: I the historical load demand, and [ii] time during a 24-hour period. To determine the profile of weekends, historical load demand data from Tumakuru city was used as a reference. Data was collected between January 1, 2014 and December 31, 2020. The work has been completed using MATLAB. Using Microsoft Excel 2007, the graph displayed below was created based on the data. The normalised root-mean-square error (NRMSE) and mean absolute percentage error (MAPE) are used in this study as performance evaluation indicators. Using the maximum and minimum load values, the NRMSE is normalised. The MAPE, which is frequently used in the field of forecasting energy load, is a percentage-based index that indicates forecasting accuracy level.

$$MAPE\% = \frac{1}{n}\sum_{i=1}^{n}\frac{ol_i - pl_i}{ol_i} \times 100$$

where n is the total number of hours predicted by system, oli is the observed load and pli the predicted load.

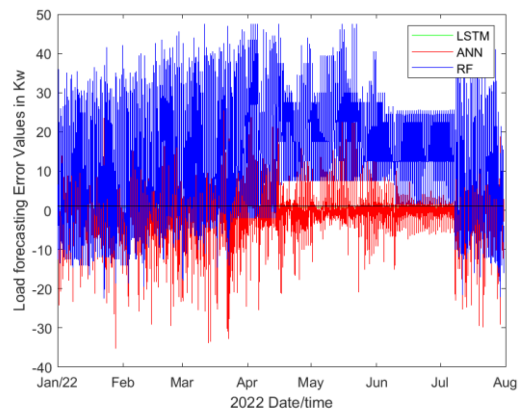
Results and Discussion

The predictions of electrical load demand made utilising benchmark combinational techniques that combine ANN, RF, and LSTM are shown in this section. Additionally, the simulation results and a conversation of the optional forecast model for a range of forecast situations are provided [25,26,27]. Additionally, the forecast performance is evaluated in conditions of high variable load demand one day, one week, and one month in advance to make sure the model does not over-fit. The data are gathered on an hourly sampling frequency and include electrical load as well as temperature and humidity, two climatic variables. Performance measurements like MSE and MAPE are used to assess then evaluate the effectiveness of several approaches.

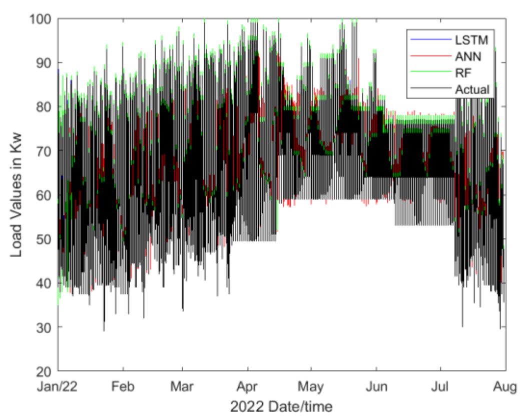
Table 1: Load prediction Error of MAPE, MAPE, MAE comparison table

Models	Absolute error (MAPE)	Daily peak (MAPE)	Absolute error (MSE)
ANN	0.73	0.79	0.47
LSTM	0.06	0.00	0.04
Random Forest	4.71	0.01	2.98

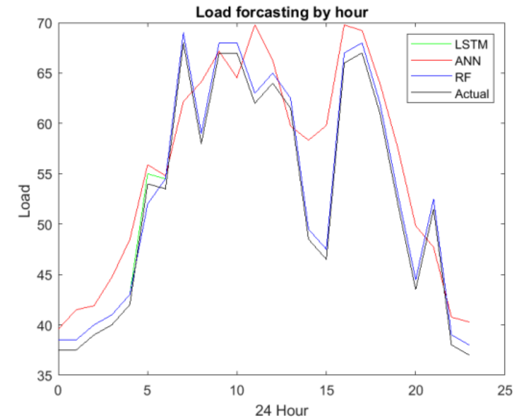
Graph 1: Represents the complete error prediction of the dataset using the different algorithms



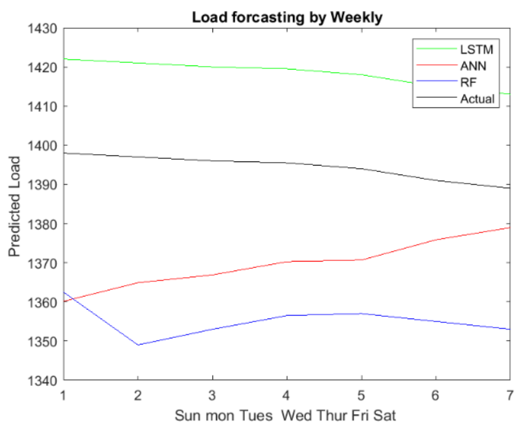
Graph 2: Represents the total electricity load prediction of the dataset



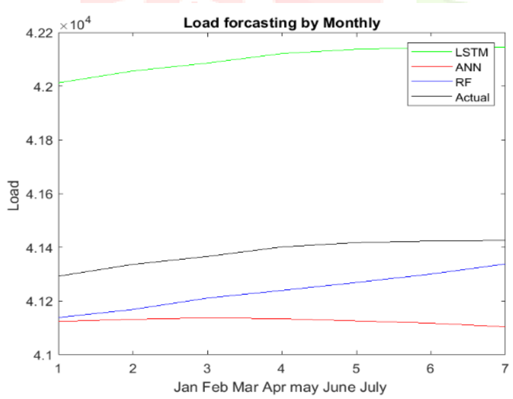
Graph 3: Represents the electricity load for the 24 hours



Graph 4: Represents the predicted load for the weekly Average



Graph 5 represents the predicted load for monthly average



V. Conclusion:

There are presently a number of feature descriptors that offer high-dimensional features to characterise the behaviour, but it takes in-depth analysis to determine how those features affect classification. Although there are methods for reducing an object's dimensions, their major objective is good reconstruction, which means that any potentially harmful data is lost in lesser-dimensional space. The three types of modeling—LSTM, ANN and RF—have all been used for one-day forecasting. Table 1 show that the LSTM model outperforms both the ANN and Random Forest models [10].

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