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Design and development of Residential Sector Load Prediction model during COVID-19 Pandemic using LSTM based RNN

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ABSTRACT

Covid-19 pandemic and resulting lockdown has created a wide impact on social life, including sudden rise in residential load demand. Utilities, for better load scheduling and economic operations, rely on different prediction models among which neural networks proved to be more appropriate. For such unforeseen situations, the non-availability of prior predictions elevated the utility challenges. Moreover, the stringency of lockdowns caused due to mutated COVID-19 virus, necessitates accurate lockdown load predictions. This paper proposes a Recurrent Neural Network based Long Short-Term Memory (RNN-LSTM) model, trained to produce such predictions for two areas of residential sector. The model uses real-time residential load data from the year 2020, with and without weather parameters. The correlation factor (R) of proposed method 0.9683 outperformed the ARIMA’s value 0.703. The model is evaluated with correlation factors of 0.9683 and 0.9235 without temp; 0.90361 and 0.913662 with temperature for Apurupa and Jyothi colonies respectively located in Hyderabad, India. In addition, the error metrics namely, Mean absolute percentage error (MAPE) and Mean absolute error (MAE) are 2.0464 and 138.576 for Apurupa colony; 0.015 and 201.648 for Jyothi colony respectively. However, the prediction error metrics increased slightly with temperature data. The proposed framework will assist utilities for effective load predictions during situations such as pandemic lockdown.

1. Introduction

Uninterrupted electrical power supply has become one of the basic needs of modern times and the greatest source of economic growth world-wide. India with ~US$ 3 trillion of GDP and 7% of average annual GDP growth, the power sector plays a crucial role for its sustained economic progress [1]. Indian power sector has most diversified generation resources and has undergone significant development since its independence to meet the energy demand of the consumers. The inter-connected power grid of India has an installed capacity of about 370 GW and a regular base load of 150 GW [2]. In general, factors like industrialization, technological developments, weather conditions and time affect the rise and fall of electricity demand. Also, diseases outbreak at times influences the same. Novel Corona virus (COVID-19), the global epidemic (as declared by WHO) that was first detected in Wuhan city, China [3] also had a menacing effect on living styles of world population including India. The spreading rate and terrific situations of COVID-19 enforced the Indian government to impose complete lockdown from 24th March 2020 till 7th June 2020 [2,4] in different phases (Table. 1). This adversely affected the growth of many sectors that includes economic, public health, industrialization, marketing etc., and the energy sector was no exception.

The lockdown restrictions imposed on social movement and travel made people stayed at home and industries were completely shut down. Also, most of the organizations adopted work from home policy. Even schools, colleges and almost all education training institutions started functioning online in fear of pandemic conditions. These societal changes influenced the variations in energy demand profile nationwide in 2020 as shown in Fig. 1 [5]. The Indian grid witnessed a demand reduction of 9.17% in March and 24% in April due to lockdown, and power generation based on coal got reduced by 26% within two weeks from the initiation of lockdown period [2, 5]. Also, the 9-minute call by the Indian government to turn off lights for 9 min on 5 April 2020 at 9 pm to mark the determination by the civil societies to fight against COVID-19, have caused instability in the power system due to sudden variation in the frequency with in short duration, but the situation was efficiently handled by the Indian utility [5].

During lockdown tenures, the load variation was in such a way that

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the industrial and commercial demand was reduced drastically and the residential demand increased significantly [3] due to work from home policy. Few studies [6–8] analyzed the impact of COVID-19 on energy consumption of different consumer categories among which, residential demand pattern has experienced huge variations due to change in lifestyle of people during lockdown. Fig. 2 depicts the hourly load variations on Apurupa colony domestic feeder during and prior to the lockdown. During lockdown, a significant rise in electricity demand of about 2.79% on the feeder was observed. Hence utilities find it difficult to manage such unexpected increase in residential load with no prior load prediction models available for lockdown tenures. This also affects the performance of electrical equipment such as distribution transformers and protection equipment in the corresponding substations.

In general, storage constraints of electrical energy in huge quantities, made utilities to generate and supply it on demand. The energy demand varies continuously throughout a day based on the time of the day, social and environmental factors [10], which utilities have to supply by maintaining safety and stable grid conditions. To achieve this, it is essential for the electrical utilities to predict the energy demand. The process of estimating electrical energy demand beforehand is called Load Forecasting (LF) or Load Prediction (LP). Usually, utilities with given historical data of load demand and weather conditions develops load forecasting that helps to make critical findings related to

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**Table 1**

| Phases of lockdown | Dates of lockdown | Period of lockdown (days) | Status of lockdown |
|--------------------|------------------|---------------------------|--------------------|
| Lockdown 1.0       | 24th March, 2020–14th April, 2020 | 22 | Complete lockdown |
| Lockdown 2.0       | 15th April 2020–3rd May, 2020 | 19 | Complete lockdown |
| Lockdown 3.0       | 4th May 2020–17th May 2020 | 14 | Relaxations provided for regions under Orange and Green zones. Industries and offices allowed to work with permitted strength |
| Lockdown 4.0       | 18th May, 2020–7th June, 2020 | 21 | Same relaxations as that of 3rd phase. |

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**Fig. 1.** Energy demand variation during 2019 and 2020 [9].

**Fig. 2.** Load variation on a domestic feeder.
production costs, planning, operation and maintenance which in turn improves the reliability of the power system [11]. However, there are no such predictions available with utilities before pandemic to understand the residential load variations. Utilities at times adopt load forecasting for short, medium and long terms. Short term LF refers to forecasting for an hour to a week, medium term LF intends from a week to a year and long term LF refers to forecasting of demand for more than a year [11, 12].

1.1. Literature review

Many significant literatures contributing towards development of various load forecasting models for the best estimations are available for normal(non-lockdown) conditions. The methods include both qualitative and quantitative approaches. Qualitative methods like Delphi method and curve fitting [13] are adopted when historical data is insufficient or unavailable [14,15], whereas, quantitative methods for load forecasting includes regression analysis [16–20], exponential smoothing models [21–23] and Box-Jenkins models [24–26]. These methods are based on mathematical and statistical formulations that can be applied on available load data for future load forecasting. In spite of their advantages, statistical methods have limitations like vague relation between the variables, error distribution verification, accuracy dependence on proper future condition representation, etc. [15,27]. To overcome such challenges, herein, the work is carried out using the modern methods of artificial intelligence that includes Neural Networks, Fuzzy logic and Support vector machine (SVM) for load predictions.

Y Li et.al., [28] proposed ForecastNet based short-term load forecasting with single parameter of past load data. Park et.al. [29] introduced an adaptable technique for electric load forecasting through artificial neural network (ANN), which combined time series and regression approach, and was able to perform non-linear modeling. Short term load forecast with feedforward neural network and SVM was proposed by Gajowniczek et.al [12]. GF Fan et.al., [30] proposed a hybrid load forecasting model for short term using random forest and mean generating function. Songpu et.al [31] proposed domestic load prediction of active and reactive power using ANN and obtained a regression of 0.728 and 0.9 respectively. Almeshaiei and Soltan [10] discussed load forecasting based on time series decomposition and segmentation method. Swaroop and Abdulkader [32] proposed back propagation based neural network for load forecasting. Multiple regression [33], SVM [34] and neural networks [35] are also used by the researchers to forecast residential energy usage. X Tang et.al., [36] proposed temporal convolution network based short-term load forecasting that uses maximum information coefficient for high quality input variable selections. Charlton and Singleton [20] proposed a
parametric model for electricity load forecasting based on multiple linear regression by considering temperature and day as functions. Wang et.al [37] analyzed the effect of preceding hours temperatures on load forecasting using big data analytics.

Very few literatures exist on load prediction models during lockdown. Wang and Ziyun [38] evaluates the load forecasting for energy markets amid Covid-19 using Auto Regressive Integrated Moving Average (ARIMA) and deep neural networks. The authors considered data of week-ends stay-at-home before Covid-19 for training and hence claimed enhanced efficiency. Gulati et.al [39] analysed the effect of Covid pandemic on electricity demand of different circles in the state of Haryana, India. The authors also proposed load forecasting using conventional machine learning methods and claimed superiority of ANN results. Lokhande et.al [4] in addition to analysis of Covid-19 effect on energy consumption, proposed a load forecasting model for industrial and commercial dominated urban utility using quick learning approach. Alavi et.al [40] presented the variations in sectorial load demand of Bangladesh and proposed nonlinear autoregressive neural network for 30 min ahead load prediction which proved to be inaccurate for longer predictions. Alasali et.al [41] proposed a stochastic ARIMA with Exogenous (ARIMAX) model of load prediction during pandemic.

In this paper, an AI based deep learning technique to predict short term residential load demand for lockdown conditions is proposed using real-time data collected from smart meters installed and manual log books from the utilities. The non-availability of past load data and corresponding prediction models during lockdown tenure motivated this investigation. The conditions and constraints were different during lockdown which made it difficult to use the concerned models developed using data of non-lockdown tenure. During the lockdown, in spite of great reduction of load on the grid [3], the utilities encountered problem in forecasting residential load due to non-availability of prior energy usage patterns.

The prevailing circumstances of recurrent waves of Covid-19 may enforce repeated national/ region wise lockdown, restricting the people to home, which may further lead to a rise in domestic sector energy consumption. Hence, there exists grave requirement for developing intelligent load prediction algorithms that aids regional or national utilities to manage load with optimized resources for future lockdown. The proposed prediction model aims at predicting load demand during lockdown period especially for residential sector, whose electricity profile gets affected due to the work from home / online classes due to pandemic. Contrary to the other predictions [4,40], the work uses
real-time load data collected from pure residential feeders during lockdown period. Because of lockdown conditions, no load demand variations were observed based on day of a week so, the data collected was not segregated into week days and week-ends for prediction. The proposed model is based on recurrent neural networks (RNNs) with Long-short term memory (LSTM) technique. The reason for adopting the method is the capacity of LSTM to learn through long-term dependencies [42] that make it to takeout patterns from large time-series data sets. The predictions were carried out with and without considering weather parameters. Finally, the prediction accuracies were compared.

The contributions of the paper include:

1. The proposed model uses real-time residential load data recorded and collected during lockdown, from smart meters that are installed as a part of smart grid mission implemented in the state.
2. The work uses an RNN based LSTM network for load prediction and the results are compared with ARIMA to highlight the superiority of proposed model.
3. The work includes prediction of load for pandemic conditions with and without considering weather conditions like temperature.
4. Load predictions are carried out for two different residential load circles/colonies namely Apurupa and Jyothi.
5. The proposed model is used for hourly load predictions and also for 7-day load predictions.
6. The work also compares the load prediction results with different data scaling techniques and compared the results with error metrics.

The rest of the paper is organized as follows: Section 2 explains about neural networks and deep learning, Section 3 presents the methodology, architecture, description and designing of the proposed model, datasets, software requirements, training and evaluation indices. Results and discussions are incorporated in Section 4, Conclusion in Section 5.

2. Neural networks and deep learning

A Neural Network (NN) is a system designed to simulate a model that performs a task or analyses information in the same way as human brain does. Neuron(s) in an NN is (are) a cell that process and transmits information through a structure called synapse to reach another cell [43]. A NN is typically a parallel distributed processor that can be implemented or simulated to obtain desired objective through a functional relationship between inputs and outputs [44,45]. NNs learns through a process called training and store the knowledge acquired to produce output for a given future input. They find more applications in

| S. No | List of dates                                | Input data size | Input training data set |
|-------|---------------------------------------------|-----------------|------------------------|
| 1     | 17th March 2020 – 23rd March 2020           | 7 × 24          | 168                    |
| 2     | 24th March 2020 – 30th March 2020           | 7 × 24          | 168                    |
| 3     | 31st March 2020 – 6th April 2020            | 7 × 24          | 168                    |
| 4     | 7th April 2020 – 13th April 2020            | 7 × 24          | 168                    |
| 5     | 14th April 2020 – 20th April 2020           | 7 × 24          | 168                    |
| 6     | 21st April 2020 – 27th April 2020           | 7 × 24          | 168                    |
| 7     | 28th April 2020 – 4th May 2020              | 7 × 24          | 168                    |
| 8     | 5th May 2020 – 11th May 2020                | 7 × 24          | 168                    |
| 9     | 12th May 2020 – 18th May 2020               | 7 × 24          | 168                    |
| 10    | 19th May 2020 – 25th May 2020               | 7 × 24          | 168                    |
| 11    | 26th May 2020 – 1st June 2020               | 7 × 24          | 168                    |
| 12    | 2nd June 2020 – 8th June 2020               | 7 × 24          | 168                    |
| 13    | 9th June 2020 – 15th June 2020              | 7 × 24          | 168                    |
|       | Total training data set                     |                 | 2184                   |
Deep learning, is a process by which multilayered neural network learns using vast data sets through repeated tasks for an improved output each time [47]. The dimensionality of raw data can be reduced by employing feature extraction process that involves complex procedures and requires domain knowledge. Apart from traditional learning algorithms, deep learning methods does not require the step of feature extraction as the layers implicitly learn data representation [48]. Deep learning algorithms includes the following:

1. Convolution neural networks (CNN)
2. Recurrent neural networks (RNN)
3. Long short-term memory (LSTM)

### 2.1. Convolution neural networks (CNN)

Convolution Neural Network (CNN), popularly called as ConvNet, has deep feed forward architecture (Fig. 3) with convolution, pooling and fully-connected layers [49]. In the convolution layer, the neurons output of each convolution unit is determined and optimized using back propagation algorithm [49]. In pooling layer, the outputs of neuron groups of a layer are combined to form a neuron of next layer, which results in significant dimensionality reduction. In fully-connected layer of CNN, local features are combined to form global features that are used to produce final output. CNN is mostly preferred for image pattern recognition where data sets have high local correlation [50].

### 2.2. Recurrent neural network (RNN)

Recurrent neural network (RNN) (Fig. 4) is a type of ANN that allows the information of past knowledge using a looped architecture called recurrent network. For making a decision, RNN contemplates the current input and produce outputs from the previous input that it has learned. Each repeating module of standard RNN has a single activation layer containing the function of hyperbolic tangent as shown in Fig. 5. RNN is used for applications that have data in sequential format like speech recognition and time series predictions. A simple RNN can be modelled using the following equations [51].

\[
h^{(i)} = \sigma(W_{ih}x + W_{hh}h^{(i-1)} + b_h)
\]  

### Table 3

| Number of hidden layers | Coefficient of determination (or) R Squared value |
|-------------------------|--------------------------------------------------|
| 2                       | 0.8591                                           |
| 3                       | 0.8031                                           |
| 4                       | 0.8689                                           |
| 5                       | 0.5224                                           |

### Table 4

List of selected prime parameters of the proposed model.

| S. No | Parameter                           | Parameter value                  |
|-------|-------------------------------------|----------------------------------|
| 1.    | LSTM cell size                      | 64,128,256,512                   |
| 2     | LSTM cells (No. of consecutive LSTM layers) | 4                                  |
| 3     | Optimizer                           | Adam                             |
| 4     | Activation function                 | Tangent hyperbolic (Tanh)        |
| 5     | Recurrent activation function       | Sigmoid                          |
| 6     | Dropout                             | (0%,10%,20%,30%)                 |

### Table 5

Error metrics of load predictions with Standard and MINMAX scalers (without temperature).

| Feature Scaling technique | Apurupa colony | Jyothi colony | MINMAX colony |
|---------------------------|----------------|---------------|---------------|
|                           | Standard | MAE | MAPE | Standard | MAE | MAPE | Standard | MAE | MAPE |
| Test-1                    | 0.98994 | 202.431 | 3.132 | 0.9668 | 404.280 | 6.468 | 0.9409 | 157.009 | 0.0122 | 0.0597 | 540.21 | 0.0425 |
| Test-2                    | 0.85925 | 182.580 | 3.0961 | 0.89045 | 375.7 | 6.333 | 0.8894 | 232.9 | 0.0179 | 0.7073 | 299.1 | 0.0228 |
| Test-3                    | 0.99888 | 78.730 | 0.875 | 0.9993 | 176.832 | 1.982 | 0.9176 | 225.401 | 0.0179 | 0.5781 | 506.17 | 0.036 |
| Test-4                    | 0.9961 | 154.511 | 2.123 | 0.9842 | 312.276 | 4.233 | 0.9616 | 144.41 | 0.0111 | 0.6311 | 460.61 | 0.0354 |
| Test-5                    | 0.99799 | 74.63 | 1.006 | 0.9688 | 387.679 | 5.18 | 0.908 | 278.52 | 0.0178 | 0.893 | 433.75 | 0.0273 |
| Average                   | 0.9683 | 138.576 | 2.0464 | 0.9434 | 331.353 | 4.8586 | 0.9235 | 207.648 | 0.0150 | 0.5738 | 447.92 | 0.0328 |
The gates of LSTM module that controls the interactions of different memory units generally contains a non-linear sigmoid function as recurrent activation. The input gate controls the state of memory cell modification as required with an input signal. The forget gate controls the memory cell state through self-recurrent tie and then adds it as input, hence resetting the cell. Output gate regulates the output of cell activations to other neurons \[56\]. Tangent hyperbolic is used as input activation function to create a new value of vector C and as output activation for updating cell state.

The gates of LSTM module are defined as:

\[
\begin{align*}
    i_t &= \sigma(W_{ix}x_t + W_{im}m_{t-1} + W_{ic}c_{t-1} + b_i) \\
    f_t &= \sigma(W_{fh}h_{t-1} + W_{fm}m_{t-1} + W_{fc}c_t + b_f) \\
    c_t &= f_t \odot c_{t-1} + i_t \odot g(W_{cx}x_t + W_{cm}m_{t-1} + b_c) \\
    o_t &= \sigma(W_{ox}x_t + W_{om}m_{t-1} + W_{oc}c_t + b_o)
\end{align*}
\]

where, \( W_{ih} \) is the weight matrix between the input and hidden layers, \( W_{hh} \) is the recurrent weight matrix between the hidden layers of adjacent time steps. \( b_h \) and \( b_y \) are biased vectors that allow each node to learn and offset.

2.3. Long short-term memory (LSTM)

Although RNNs are superior in working with sequence based data, they suffer from a disadvantage of losing past information for long time intervals due to gradient vanishing and explosion problems \[54,55\]. To overcome this, Hochreiter and Schmidhuber in 1997 \[54\] added a memory cell in hidden layer of RNN in place of artificial neurons and the resulted architecture is called Long Short Term Memory (LSTM). Similar to RNN, LSTM also have chain structure, but with different repeating module. Each LSTM repeating module (Fig. 6) contains one cell state vector C, a hidden state vector and three gates namely input, output and forget gates \[42\].

Fig. 10. Hourly load predictions of Apurupa colony from different tests (without temperature) (a) Test-1, (b) Test-2, (c) Test-3, (d) Test-4, (e) Test-5.
\[ m_t = o_t \odot h(c_t) \]  
(7)

\[ y_t = \sigma (W_{ym}m_t + b_y) \]  
(8)

Where, i, f, o and c are vectors of input, forget, output gates and cell activation respectively.

Weight matrices are indicated by W terms, for instance \( W_{ix} \) is the input weight matrix, \( W_{ic}, W_{fc}, W_{oc} \) are diagonal weight matrices, \( b_i, b_f, b_o, b_y \) are bias vectors of different gates and \( \sigma \) is logistic sigmoid function. \( \odot \) indicates element-wise product of vectors and \( \sigma \) are activation functions of input and output cells. \( \sigma \) is the activation function of network output.

2.4. Back-Propagation algorithm

In back-propagation algorithm, to obtain minimum error function value, the training progresses through two steps including forward and backward pass among different network layers. In the forward pass, the input nodes are stimulated with specific pattern and the effects proceed successively to layer by layer in order to produce output sets. Then the actual output is compared with desired output of input pattern to produce error signal. Corresponding to the error correction rule, the error is back-propagated by adjusting the weights so as to obtain optimal match between the predicted and real data.

3. Methodology

3.1. Description of proposed method

This section presents the description of proposed RNN-LSTM model of residential load prediction during lockdown. The process of designing a neural network based load forecasting model involves training and testing. Training is the procedure to make the network perform the assigned task and the testing is to validate the output. The proposed short term load forecasting model uses supervised back-propagation algorithm with RNN-LSTM architecture. The architecture improves the forecasting accuracy with scarce past data [58] collected during lockdown period which is of short duration. The hourly recorded residential load data during and after the lockdown is collected from local power utilities. The data of Apurupa colony is collected from the installed smart meters in the area that account nearly to 10,000 m and the data of Jyothi colony from the records (log books) maintained by the utilities. The data collected is pre-processed and suitably scaled and fed to the RNN-LSTM model. For scaling of data, Standard and MINMAX scalars are used.

Fig. 11. Hourly load predictions of Jyothi colony from different tests (without temperature) (a) Test-1, (b) Test-2, (c) Test-3, (d) Test-4, (e) Test-5.
initially and then adopted to Standard scalar since its results are superior. The model is trained for hourly and daily load predictions with and without temperature parameter for both the colonies. The results are validated and compared for acceptable range of accuracy.

3.2. Designing of proposed RNN-LSTM network model

This section presents the designing of proposed residential load prediction model based on RNN-LSTM architecture. Multi-layered perceptron network, the most commonly used NN for effective modeling of prediction tools is considered in the proposed model with fully connected layers. The NN model containing the functionalities of RNN and LSTM is shown in Fig. 7. The model is trained to obtain minimum error function value using back propagation method with the pre-processed data. During training, the gradient vanishing problem of RNN is addressed by including LSTM layers. Also, with dropout regularization in a fully connected network, weight matrix redundancies can be limited to achieve better performance [59]. The best suited value of dropout is found and applied in the proposed neural network. The trained RNN-LSTM model outputs the short-term load predictions in a fully connected network. The output predictions are evaluated through different error metrics and through correlation factor between real and predicted values.

3.3. Description of data set

Due to COVID-19 pandemic, the complete national lockdown was imposed in India on 21 March 2020, but as per the GO (Government Order) issued by the state Government of Telangana on 14th March,2020, the lockdown was initiated a week ahead of national lockdown i.e.,15th March 2020. The data used in this work was collected from two feeders that belongs to residential areas named “Apurupa” and “Jyothi” colonies in Hyderabad, Telangana, India. The input dataset consists of 24-hour daily load (active power) data for about 3 months 15 days (from 17 March 2020 to 30 June 2020) adding to a total of 2352 measurements of each area. The sample pattern of the real-time residential load variation during the period of lockdown is as shown in Fig. 8. Weather conditions like temperature, rainfall, humidity etc., and also type of days (week days and weekends) generally affects the consumer load demand [60,61]. Even though the load variation during pandemic period is mostly due to lockdown imposed and work from home policy adopted, [4] the temperature parameter is also considered for load prediction as it significantly effects residential power usage. The load data is categorized as training, validation and testing datasets. Neural network uses the training dataset to learn the traits from the input. Validation dataset is used to produce unbiased output to fit with the training dataset during network tuning. The testing dataset is meant for testing the response of the model. The output of the model is the load forecast for next 7 days.

3.4. Processing of load data

Data representation significantly affects the results of machine learning algorithms [35]. In the raw data sampled for each hour, collected from a residential feeder, contains missing data errors i.e., reading is not recorded for certain hours of a day. Ahead of using the
data for training such missing data errors are to be handled to minimize their influence on output predictions. This is done by taking average of two neighboring readings of missing data. Then the data is scaled and normalized so as to feed into the RNN model using two scaling techniques Standard scaler and MINMAX scaler given by the Eqs. (9) and (10) respectively [62, 63] and the results are compared.

\[
x_{ss} = \frac{(x_i - \bar{x})}{\sigma_x}
\]

\[
x_{mm} = \frac{(x_i - x_{\text{min}})}{(x_{\text{max}} - x_{\text{min}})}
\]

where, \(x\) is input data, \(\bar{x}\) is the mean, \(x_{\text{min}}\) is minimum value and \(x_{\text{max}}\) is maximum value of \(x\).

3.5. Network selection

In the designed network, input and output layers are fixed. It is important to select number of hidden layer with required number of neurons in each hidden layer for getting better results. To identify the best fit of hidden layers, different combinations were tested and the network that gives the best R-squared value was chosen. The network selected finally contains an input layer, 4 hidden layers and an output layer.

3.6. Network training and testing

The complete gathered data for training and testing accounts for a total of 106 days of each area. Out of which 91 days’ data (about 85.8%) is assigned for network training and validation and the remaining 15 day’s data is considered for network testing. Each training data set includes 7 days’ hourly data accounting to a total of 168 (7 × 24) inputs as represented in Table 2. On data split, the training, validation and testing sets are randomly selected for iterative training and testing of the proposed model to cross verify the achieved results for reliability.

3.8. Model evaluation indices

Typically, the performance indices of proposed load forecasting model use correlation coefficient (R) [64], Mean Square Error (MSE) [12, 65, 66], Mean Absolute Error (MAE) [67], and Mean Absolute Percentage Error (MAPE) [59, 68, 69]. The correlation coefficient (R) signifies the linear dependency between the predicted and real values and is given by Eq. (11). MSE is the measure of closeness of fitted line to data points and is given by Eq. (12). MAE [70] and MAPE are given by Eq. (13) and (14).

\[
R = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}
\]

\[
MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2
\]

\[
MAE = \frac{1}{N} \sum_{i=1}^{N} |y_i - \hat{y}_i|
\]

\[
MAPE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100
\]

where, \(x\) is input data, \(\bar{x}\) is the mean of \(x\) values, \(\hat{y}\) represents the actual value, \(\hat{y}\) represents predicted value, \(\bar{y}\) represents mean of predicted
4. Results and discussion

In this section the results of proposed RNN-LSTM model analysis are presented and are compared with a benchmark method of ARIMA to highlight the usefulness of the proposed method. Initially, real-time datasets, collected from a residential feeders of two different load circles namely Apurupa and Jyothi are briefly introduced followed by the explanation of chosen architecture and its justifications. The hourly load validations collected during lockdown period from a local power distribution authority, purely corresponds to a feeder serving residential areas. Corresponding temperature data of areas under consideration is also used as one of the input parameter. The load data is segregated into three parts with a purpose of training, validating and testing the developed model. Values of weights and bias during neural network training process necessitates for training data set and the network is regularly validated using validation dataset. Then, the predicted load results for future lockdown tenure with and without temperature considerations are presented along with model evaluations.

4.1. Load predictions with ARIMA

ARIMA being one of the popular and widely used statistical method for time series forecasting, an experiment is conducted with ARIMA model for load prediction to compare the performance of the proposed model. Load prediction of Apurupa colony with the ARIMA model is shown in Fig. 9. The R-squared value and the correlation factor of ARIMA model are obtained as 0.25709 and 0.703 respectively.

4.2. Load predictions with proposed RNN-LSTM method

The proposed RNN uses LSTM layers and the network model is tested for prediction accuracy by considering real-time data from two different residential feeders. The model is trained with training dataset in steps of 7 days each. With the feature shifting value for the input being 168,
The number of neurons during the training is considered to be 32, 64, 128, 256, 512 that gave satisfactory predictions compared with other combinations of neurons. LSTM is trained with different numbers of hidden layers for 20 iterations to choose the best fit for the model. After experimenting with different hidden layer combinations, the number of hidden layers are chosen to be 4 based on the coefficient of determination ($R^2$) value obtained (Table 3).

$$R^2 = 1 - \frac{\sum (y - \hat{y})^2}{\sum (y - \bar{y})^2}$$  \hspace{1cm} (15)

where, ‘$y$’ is the actual value, ‘$\hat{y}$’ represents forecasted value and ‘$\bar{y}$’ represents mean of forecasted values.

In addition to network architecture, different prime parameters of the proposed model are shown in Table 4 to get effective predictions. The model is trained and the residential load on the feeders are predicted on hourly and daily basis. The iterative training and testing of the proposed model was carried out with random combinations of collected data in five tests. As such in random, for Test-1, a dataset chosen for training was from March 17 to June 30 and for testing was 16 June to 30 June. The prediction reliabilities of the model are evaluated using $R$, MAE, and MAPE in each test. Moreover, the performance of the model with two different data scaling techniques was carried out and the results are compared in the Table 5.

### 4.2.1 Load predictions with past load data (without temperature)

The proposed RNN-LSTM model was initially trained with previous load data alone without considering any weather parameters, to produce the load predictions of Apurupa and Jyothi colonies. Fig. 10 and Fig. 11 shows the hourly load predictions of “Apurupa” and “Jyothi” load circles respectively for each test case i.e., Test-1 to Test-5. The results obtained are with Standard scaler.

Fig. 12 and Fig. 13 shows the next 7-day load predictions of each test case with MINMAX scaling of data for Apurupa and Jyothi load areas respectively.

Fig. 14 and Fig. 15 displays the seven-day load predictions of Jyothi colony with MINMAX and Standard data scaling.

Fig. 16 shows the Standard deviation (Eq. (16)) of the results obtained using MINMAX and Standard scalers respectively along with error bars.
Fig. 16. Standard deviations of the prediction results (a) Apurupa colony using MINMAX scaler (b) Apurupa colony using Standard scaler, (c) Jyothi colony using MINMAX (d) Jyothi colony using Standard scaler.

Fig. 17. Sample of hourly load predictions of Apurupa colony from different tests (with temperature) (a) Test-1, (b) Test-3, (c) Test-5.
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\[ SD = \sqrt{\frac{\sum_{i=1}^{N} (x_i - \bar{x})^2}{N-1}} \]  

(16)

Where \(x_i\) is data point, \(\bar{x}\) is the mean of data points and \(N\) is number of data points.

The detailed experimental values of correlation factor (R), MAE and MAPE of each test case with Standard and MINMAX scalers without considering temperature parameter are shown in Table 5.

It is observed that the average correlation factor (R) of 0.9683, MAE of 138.576 and MAPE of 2.0464% are obtained with Standard scaler. On the other hand, using MINMAX scaler, the correlation factor of the model achieved a value of 0.9434, MAE of 331.35 and MAPE of 4.8586.

4.2.2. Case-2: load predictions with temperature

The demand for electrical energy is greatly influenced by the atmospheric conditions like temperature, humidity, wind speed etc., [60, 73–75]. However, in the regions under consideration the influence of temperature is dominant compared to other weather parameters due to geographical conditions. So in this work, temperature is included as one of the input parameters. This section presents the load predictions of two areas under consideration by taking temperature as one of the input parameter to the neural network in addition to past load data. The required temperature data of the time period and areas under study is collected from [76]. Since the results with standard scaling is better compared to MINMAX in the previous case, while considering temperature the authors directly chose the standard scaled data for load predictions. Fig. 16 shows the samples of hourly load predictions of Apurupa colony including temperature data. Fig. 18 shows the hourly load predictions of Jyothi colony with temperature data for each case. Fig. 19 and Fig. 20 shows the load predictions for next seven days for Apurupa and Jyothi colonies respectively.

Table. 6 shows the error metrics of load predictions made by considering temperature data for both the residential areas. Fig. 21 shows the Standard deviations (Eq. (16)) [72] of load prediction results with temperature data obtained for Apurupa and Jyothi colonies.
4.3. Comparison of proposed model with ARIMA

The experiments conducted for the comparison of performance shows that the proposed model gave improved results compared to ARIMA model. (Table 7). The correlation factor obtained for hourly load prediction for Apurupa colony using ARIMA is 0.703 while with the proposed RNN-LSTM model is 0.9683. Since improved results are obtained with the proposed model, all other combination of data predictions were carried out with it.

Compared to traditional prediction model like ARIMA, the proposed model produces better results with good accuracies, and in particular with standard scaler data scaling. Table. 8 shows all the results of load predictions of both Apurupa and Jyothi colony with and without temperature parameter. However, temperature being one of the important weather factor that affects load consumption, the results manifest that the predictions obtained without considering temperature is more precise than with the consideration of temperature. The correlation coefficient (R) for Apurupa colony is 0.9683 for the case not considering the temperature and it decreases to 0.90361 with temperature consideration. Similarly, for Jyothi colony the value of R decreased from 0.9235 to 0.91366 with temperature data. Also it is observed that the error metrics MAE and MAPE are only slightly increased with the inclusion of temperature data during training [77]. However, the results achieved with the proposed RNN-LSTM model, will make it an effective tool for the utilities to predict the short-term residential loads under any future lockdown conditions.

5. Conclusion

COVID-19 pandemic had a strong impact on power consumption patterns among various consumer loads including residential sector. Lockdown, as a result of COVID pandemic, has restricted the mobility of social community that enforced unexpected increase of residential demand. This has challenged the utilities for effective managing and scheduling of loads because of lack of lockdown load estimations. The recurrent attacks of such unseen COVID-19 pandemic highlights the need for lockdown load predictions. This research proposed a RNN-LSTM based deep learning load prediction model for residential sector using real-time load data collected from local utilities. The architecture produces short term load predictions for two colonies named Apurupa and Jyothi.
Fig. 20. 7-day prediction results of Jyothi colony with temperature (a)Test-1, (b) Test-2, (c) Test-3, (d)Test-4, (e) Test-5.

Table 6
Error metrics of load predictions with temperature.

| Error metrics | Apurupa colony | Jyothi colony |
|---------------|----------------|---------------|
|               | Correlation coefficient (R) | MAE | MAPE   | Correlation coefficient (R) | MAE | MAPE   |
| Test-1        | 0.9441          | 64.160        | 1.0158 | 0.90851          | 114.071        | 0.897516 |
| Test-2        | 0.863088008     | 355.6039      | 5.875137 | 0.95798          | 199.226        | 1.5629 |
| Test-3        | 0.838118        | 119.0497      | 1.336217 | 0.90502          | 402.543        | 2.9725 |
| Test-4        | 0.918809        | 116.7093      | 1.559383 | 0.9339           | 197.357        | 1.51915 |
| Test-5        | 0.953951652     | 68.97382      | 0.897516 | 0.8629           | 448.115        | 2.88539 |
| Average       | 0.9036          | 144.899       | 2.1368  | 0.91366          | 272.2624       | 1.96612 |
The predictions were carried out with and without temperature data for each load area and with different data scaling methods. The prediction capabilities of proposed model were evaluated through correlation factor, MAE and MAPE for each case. The results obtained were compared with ARIMA model that gave 0.703 correlation and with the proposed model the value is 0.9683 for Apurupa colony. The model gave correlation factors of 0.9683 and 0.9235 without temperature and with temperature 0.90361 and 0.913662 for Apurupa and Jyothi colonies respectively. In addition, the error metrics MAPE and MAE are 2.0464 and 138.576 for Apurupa colony; 0.015 and 201.648 for Jyothi colony.

Table 7
Comparison of proposed method RNN-LSTM with ARIMA.

|                | ARIMA | RNN-LSTM |
|----------------|-------|----------|
|                |       | Apurupa colony | MINMAX scalar |
| Correlation coefficient | 0.703 | 0.9683 | 0.9434 |

Table 8
Comparison of prediction results of two colonies (with and without temperature data).

| Test No. | Feature Scaling technique | Apurupa colony | Jyothi colony |
|----------|---------------------------|----------------|---------------|
|          | Error metrics | Without Temperature | With Temperature | Without Temperature | With Temperature |
|          |             | R | MAE | MAPE | R | MAE | MAPE | R | MAE | MAPE |
| Test-1   | R           | 0.98994 | 202.431 | 3.132 | 0.9441 | 64.16 | 1.0158 | 0.9409 | 157.009 | 0.0122 | 0.90851 | 114.071 | 0.8907 |
| Test-2   | R           | 0.85925 | 182.58 | 3.0961 | 0.86308 | 355.603 | 5.8751 | 0.8894 | 232.9 | 0.0179 | 0.95798 | 192.226 | 1.5629 |
| Test-3   | R           | 0.9988 | 78.730 | 0.875 | 0.83811 | 119.049 | 1.33621 | 0.9176 | 225.401 | 0.0163 | 0.90502 | 402.543 | 2.9725 |
| Test-4   | R           | 0.9961 | 154.511 | 2.123 | 0.9188 | 116.709 | 1.5593 | 0.9616 | 144.41 | 0.0111 | 0.93982 | 197.597 | 1.51915 |
| Test-5   | R           | 0.9979 | 74.63 | 1.006 | 0.95395 | 68.9738 | 0.8975 | 0.908 | 278.52 | 0.0178 | 0.96293 | 448.115 | 2.88539 |
| Average  | R           | 0.9683 | 138.576 | 2.0464 | 0.90361 | 144.899 | 2.1368 | 0.9235 | 207.648 | 0.0150 | 0.913662 | 272.2624 | 1.96612 |

Fig. 21. Standard deviations of the prediction results with temperature (a) Apurupa colony, (b) Jyothi colony.

Fig. 22. Comparison of proposed method load prediction with ARIMA.

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In the context of the given text, the authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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