Short Term Residential Load Forecasting Using Temporal Weather Based Embedding Stacked LSTMs

Srinivasa Raghavan Vangipuram, and Giridhar A. V., *Senior Member, IEEE*

***Abstract*—Resource management is crucial to balance human needs with sustainability, prevent overuse, and preserve natural resources like water, forests, and minerals for future generations. Managing electricity at the root of human usage can be a crucial first step, helping us move toward better resource management and reducing the strain on natural resources. Superior forecasting approaches are needed to determine usage patterns. Accurate predictions can serve as key input to the Home Energy Management Systems (HEMS) mechanisms in optimizing electricity operation, reducing energy waste, and increasing resource utilization. Neural network-based methods are being developed to forecast electricity usage in residential buildings by learning behavioral patterns over time. These approaches leverage historical data to identify trends and predict future consumption, offering a promising direction for more accurate forecasting methods. Although still evolving, they provide a foundation for optimizing energy management by anticipating demand and enabling more efficient resource allocation. However, these approaches primarily rely on historical patterns to predict future electricity usage, often overlooking the impact of daily weather conditions. In this paper, we explore a method that incorporates weather information to enhance electricity usage predictions. We propose a simple Stacked LSTM-based neural network that integrates historical usage data and weather information as learned inputs for more effective electricity usage prediction. Our approach demonstrates improved prediction performance compared to methods that do not account for weather factors and the CNN-SLSTM model. For the BR04 hourly test dataset, our proposed model achieves a 56% and 67% reduction in RMSE compared to the SLSTM with weather and CNN_SLSTM models, respectively.**

Link to graphical and video abstracts, and to code: https://latamt.ieeer9.org/index.php/transactions/article/view/9316

***Index Terms*—Building Energy Management system, Electricity Load, short-term Forecasting, Neural Networks, Time Series Embeddings**

I. Introduction

ELECTRICITY is fundamental to the advancement of a nation's economic activities, agriculture, transportation, and various other sectors. Accurate forecasting of electricity demand is crucial for optimizing energy management systems (EMS) such as Distributed Energy Resource Management Systems (DERMS) [1], Home Energy Management Systems (HEMS) [2], and Demand Response programs. These systems rely on precise forecasts to enhance electricity planning, operation, and scheduling, ensuring reliability, efficiency, and cost-effectiveness for consumers. According to an IEA report [3], India's residential energy consumption increased from 31% to 39% of global averages between 2000 and 2019, emphasizing the growing penetration of grid-connected consumers and the significant need for Demand Side Management (DSM) [4] to mitigate grid imbalances and optimize energy utilization.

Electricity demand forecasting is categorized into Short-Term (minutes to weeks), Mid-Term (months to years), and Long-Term (beyond a year) forecasting [5]. Residential electricity consumption is influenced by various factors, including seasonality, time of use, occupant behavior, appliance efficiency, and environmental conditions. Short-Term Electricity Load Forecasting (STELF) is particularly beneficial for residential consumers by enabling load management based on renewable energy availability, optimizing electricity usage during low-tariff periods, and minimizing overall energy wastage. To achieve high forecasting accuracy, models must integrate key influencing factors, such as environmental conditions [6] and historical consumption patterns [7]. Mid-Term Electricity Load Forecasting (MTELF) [8], [9] supports power generation planning and resource allocation, While Long-Term Electricity Load Forecasting (LTELF) assists in addressing electricity demand by sectors such as residential, commercial, and industrial, it also helps in navigating the evolving energy landscape.

Traditional forecasting approaches have relied on statistical models such as Autoregressive Integrated Moving Average (ARIMA), Seasonal ARIMA (SARIMA), Exponential Smoothing (ETS), and Simple Moving Average (SMA). However, with the increasing availability of high-resolution data and advancements in computational power, there has been a shift toward machine learning (ML) and deep learning (DL) models. Methods such as Support Vector Regression (SVR) [11], Feedforward Neural Networks, Radial Basis Function Neural Networks (RBFN) [12], K-Nearest Neighbors (KNN) [13], Random Forests (RF), and Decision Trees have demonstrated improved forecasting accuracy. These advancements have resulted in hybrid and ensemble models that leverage multiple methodologies for increased forecasting accuracy.

Deep learning techniques such as Convolutional Neural Networks (CNN) [27], Recurrent Neural Networks (RNN) [19], Long Short-Term Memory Networks (LSTM) [28], Gated Recurrent Units (GRU) [29], transformer architectures [6] and ensemble-based models [8], [33], [22] have been exten-

The associate editor coordinating the review of this manuscript and approving it for publication was Giner Alor-Hernández (*Corresponding author: Srinivasa Raghavan Vangipuram*).

Srinivasa Raghavan Vangipuram, and Giridhar A. V. are with the Department of Electrical Engineering, National Institute of Technology, Warangal, India (e-mails: vs21eerer18@student.nitw.ac.in, and giridhar@nitw.ac.in).

TABLE I
SUMMARY OF EXISTING ELECTRICITY LOAD FORECASTING MODELS

Ref No	Methodology	Forecast Type	Predicted Parameter	Electrical parameters	Weather Parameters	Time Resolution	Forecasting Timeframe	Compared Models	Evaluation Metrics
[14]	CNN+LSTM	ST	ELC	Yes	No	Half-hourly	Week & Month-ahead	LSTM, RBFN, XGBoost	RMSE, MAE, MAPE, R^2
[15]	ETS + Recurrent Dilated LSTM	Mid Term	ELC	Yes	No	Monthly	Monthly	K-NN, LSTM, ARIMA, MLP	MAPE, APE
[16]	LSTM + Rolling Horizon Optimization	ST (Residential)	EG&D	Yes	No	Hourly	Hourly	Offline optimization model	RMSE
[17]	VAE-BiLSTM	MT (City)	Energy Demand	Yes	Yes	Hourly	Seasonal	LSTM, SVR	RMSE, MSE, MAPE
[18]	LSTM and LSTM Seq2Seq	ST (Residential)	ELC	Yes	No	Hourly	Hourly	LSTM, LSTMseq2seq	RMSE
[19]	Pooling Deep RNN	ST (Residential)	ELC	Yes	No	Half-hourly	Half-hourly	ARIMA, SVR, 3-layer Deep-RNN	RMSE, NRMSE, MAE
[20]	Parallel Deep LSTM-CNN	ST	ELC	Yes	No	Hourly	Hourly	LSTM-CNN, ARIMA, DNN, SVR, ETS	RMSE, MAPE, R^2
[21]	CNN-LSTM, K-NN	ST (Residential)	ELC	Yes	No	Half-hourly	Hourly	LSTM without Cluster	MAPE
[22]	BiLSTM-CNN-GWO	ST (Building)	ELC	Yes	No	Hourly	Hourly	LSTM, BiLSTM, CNN-LSTM, APSO-BiLSTM, GWO-BiLSTM	MSE, RMSE, MAPE, MAE
[23]	CNN-LSTM	LT	Peak Load	Yes	Yes	5-minute	3 Years ahead	CNN, LSTM	MAE, MAPE
[24]	CNN-(LSTM+AE)	ST (Residential & Commercial)	ELC	Yes	No	Hourly	Hourly and Daily	CNN, LSTM, CNN+LSTM	MSE, MAE, RMSE, MAPE
[25]	BiLSTM	ST (Country)	EG&D	Yes	Yes	Day	Daily Demand		RMSE, MSLE, MSE
[26]	DCNN-LSTM-AE-Attention	ST (Residential)	ELC	Yes	No	15-minute	15-min and Hourly	LSTM, CNN-LSTM, LSTM-AE	MSE, RMSE, MAPE, MAE
[43]	TAB-LSTM (Transfer Learning)	ST (Building)	ELC	Yes	Yes	Day	Daily	TAB-RF, LSTM, GA-RBF	RMSE, MAE, MAPE

ST: Short term, MT: Mid term, LT: Long term, ELC: Electricity Load Consumption, EG&D: Electricity Generation and Demand, AE: AutoEncoder, ETS: Exponential Smoothing, VAE: Variable AE, GWO: Grey-Wolf Optimization, TAB-LSTM: TrAdaBoost-LSTM, MLP: Multilayer Perceptron, APSO: Adaptive Particle Swarm Optimization, RMSE: Root Mean Square Error, MAE: Mean Absolute Error, MAPE: Mean Absolute Percentage Error, MSE: Mean Squared Error, NRMSE: Normalized Root Mean Square Error, MSLE: Mean Squared Logarithmic Error, R^2: Coefficient of determination

sively applied in energy forecasting. Hybrid models integrating LSTM with CNN [7], [20], [22], [21], [14], [8], [23], [24], [26] or BiLSTM with support vector regression (SVR), Bayesian algorithms, and genetic algorithms [37] have been explored to extract key data features for accurate forecasting. These approaches have been used for forecasting usages on various consumer categories like single households [18], multiple households [19], a small and medium enterprises, industries, and a region or country [25].

Early RNN-based models [19] were effective in capturing short-term consumption trends but struggled with vanishing gradient issues, limiting their ability to model long-term dependencies. To address these challenges, LSTM [18], [34] was introduced, leveraging gating mechanisms that enable efficient long-term memory retention. LSTM-based models have since been widely applied in residential electricity load forecasting, often combined with Autoencoders [24], stacked autoencoders [36], and attention mechanisms [24], [26] to extract meaningful temporal patterns.

The analysis compares forecasting methodologies across various parameters, including electrical and weather data, within specified timeframes. Table I presents a comparative analysis of forecasting models, detailing methodologies, input data time resolutions, timeframes, comparative models, and evaluation metrics. In [17], climatic parameters such as temperature, humidity, precipitation, wind speed, cloud cover, and solar radiation are included as input variables for seasonal predictions. In contrast, [23] considers only temperature for long-range forecasting. In this study, we incorporate all weather parameters except cloud cover and solar radiation, as these are more relevant for PV generation forecasting. Additionally, we include wind direction for short-term prediction and apply embeddings to enhance performance.

Recent studies [39] highlight the use of embeddings in time-series forecasting. Wei et al. [40] proposed a Graph Neural Network (GNN) model with trained temporal embeddings to capture recurrent patterns in residential load data. Alves et al. [31] applied time series embeddings to improve the wind direction nowcast in the aviation sector. Traditional approaches employ additional neural networks like CNN [21], [14], [8], [23] and SVR [37] to extract impactful features before feeding them into LSTMs, increasing computational complexity. Embedding-based methods offer a structured representation of input parameters, effectively capturing spatial and temporal dependencies while reducing memory usage. Unlike autoencoders [24] and one-hot encoding [21], embeddings effectively capture both spatial and temporal patterns while reducing memory usage and model complexity. They provide a continuous, high-quality representation of data that reflects real-world relationships between concepts. Incorporating weather data as an input to neural networks improves electricity forecasting. Using embedding representations for weather data enhances the model's flexibility in handling inputs, allowing it to better capture the influence of environmental conditions on electricity usage.

We propose a novel model that integrates a Stacked LSTM with time series embeddings for various time-related features, including year, date, month, hour, and minute, while also incorporating weather parameters to enhance building-level short-term energy load forecasting accuracy. By utilizing separate embeddings for each time-related feature and integrating weather conditions such as temperature, relative humidity, and precipitation, the model creates robust memory representations that capture key temporal and environmental trends in climate data. The model's efficacy is evaluated across multiple forecasting intervals (3-minute, 15-minute, and hourly) using diverse Indian individual household datasets. To verify the efficacy of our approach, we compare the approach with other methods with/without weather parameters as direct input and explore various other design choices for the network and CNN-SLSTM model.

The key contributions of this work are:

- We introduce a novel Stacked LSTM framework incorporating weather embeddings to improve short-term electricity forecasting.
- We perform ablation studies to evaluate different network architectures and the impact of weather parameters.
- The proposed method is validated using data sets from Indian residential smart meter datasets, demonstrating its effectiveness across multiple forecasting intervals.

The remainder of the paper is organized as follows: Section II presents the proposed methodology, Section III details the implementation, Section IV analyzes experimental results, and Section V concludes the study.

II. Background

Basic concepts of the techniques are discussed as follows.

A. Long Short Term Memory (LSTM)

Sepp Hochreiter et al. [28] proposed LSTM to overcome the conventional RNN's disadvantages of capturing long term dependency due to vanishing gradient issue. Figure 1 represents the LSTM cell, it contains multiple learnable weights that work to create the LSTM cell's memory and output state. The LSTM may forget or add information to the cell's memory state using gated representation. There are three gates representing input, output and forget gate. The forget gate (f_t), as stated in the equation (1), applies the sigmoid function to the present input and the hidden state to determine their contributions to the future state of the LSTM cell. It is critical in resolving the long-term dependency issue. The input gate determines the important of current timestep input using learnable weights on the input and hidden state representation, as indicated in equations (2,3,4). (i_t), ($\hat{C}_t$) and (C_t) represents the input gate, present cell state and updated cell state respectively. As stated in equations (5,6), the output gate (O_t) applies learnable weights to the input and hidden state to activation, which in turn regulates the computation of the cell's next hidden state (h_t) and the current output.

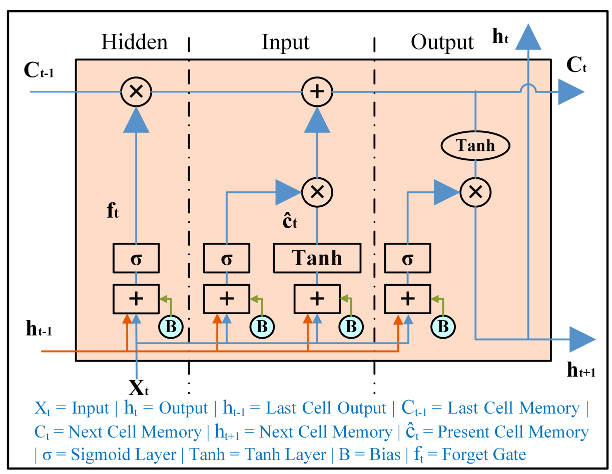


Fig. 1. LSTM cell.

$$
\begin{aligned}
f_t &= \sigma(W_f.[h_{t-1}, X_t] + b_f) &(1)\\
i_t &= \sigma(W_i.[h_{t-1}, X_t] + b_i) &(2)\\
\hat{C}_t &= \tanh(W_i.[h_{t-1}, X_t] + b_c) &(3)\\
C_t &= f_t * C_{t-1} + i_t * \hat{C}_t &(4)\\
O_t &= \sigma(W_O.[h_{t-1}, X_t] + b_o) &(5)\\
h_t &= O_t * tanh(C_t) &(6)
\end{aligned}
$$

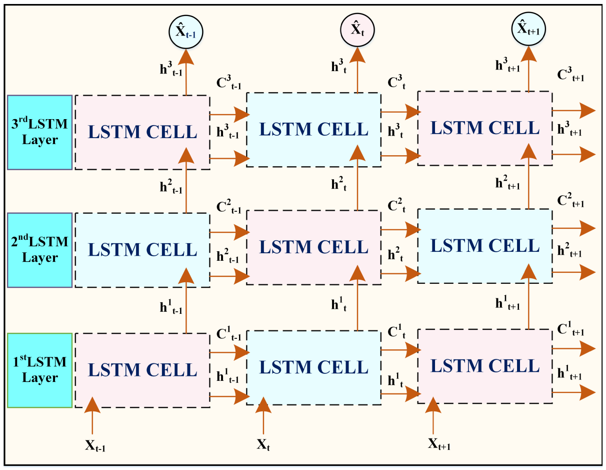


Fig. 2. Stacked LSTM layers structure.

(X_t) stands for input variable at time t. W_f, b_f, W_i, b_i, b_c, W_o and b_o are the weights (W) and biased (b) values of respective gates. (h_{t-1}) and (C_{t-1}) represent the hidden and cell states of previous time step (t-1). $(\hat{X}_t)$ represents the output of a stacked LSTM network at t interval.

B. Stacked LSTM

A stacked LSTM [10] architecture consists of multiple LSTM layers placed on top of each other, where the output of one layer serves as the input for the next, enabling the model to capture complex hierarchical patterns in sequential data. This architecture enhances the model's ability to learn both low-level and high-level features, making it more effective at handling tasks such as natural language processing, time series forecasting, and speech recognition. The primary benefit of using a stacked LSTM is its improved capacity to model intricate dependencies within sequences, leading to better performance on tasks that require an understanding of long-term relationships and patterns. Fig. 2 provides the overview of Stacked LSTMs.

For n^{th} layer in the Stacked LSTM:

$$h_t^{(n)}, C_t^{(n)} = LSTM^{(n)}(h_t^{(n-1)}, h_{t-1}^{(n)}, C_{t-1}^{(n)}) \tag{7}$$

C. Time Series Embeddings

Time series embeddings [30] capture essential patterns in sequential data by transforming them into low-dimensional vectors. These embeddings are useful in applications such as anomaly detection, price or demand prediction, and categorical time series analysis. By embedding time-based features, models can better understand seasonal trends, leading to improved forecasting accuracy. Additionally, embedding weather data and temporal features enhances the analysis of how weather conditions impact power consumption.

Embeddings are helpful when there's an intricate correlation between various factors, as they allow prediction models to remember and encode essential trends over time. Accurate power consumption prediction relies on understanding past patterns but handling historical data can be challenging. Additionally, human behavior, influenced by weather, adds unpredictability to power usage.

One way to tackle these challenges is using past weather data to predict electricity usage. Extreme temperatures, whether hot or cold, usually require more electricity for heating or cooling. Looking at how weather has affected electricity use in the past can help us understand future consumption patterns.

It's important to use past climate data and real-time weather conditions to predict power usage accurately. Instead of relying on raw daily data, embeddings can capture patterns over time. By combining historical consumption data with current weather data, this approach improves forecasting by considering long-term trends and immediate effects, leading to better power usage predictions.

D. CNN + SLSTM

CNNs [32], introduced in 2015, are widely used in image analysis and computer vision applications. The core component of a CNN is convolution, where kernels, strides, padding, and pooling methods extract features from input data. Typically, variations of the ReLU activation function are used in CNNs. Recently, CNN models have been applied to time series data analysis. However, CNNs alone often struggle with accurate future predictions. To address this limitation, they are integrated with LSTM [28] networks. While CNNs effectively extract important features from time series data, LSTMs are well-suited for sequential learning and future outcome prediction. However, LSTMs have a drawback in selecting the most relevant features from the available data. By combining CNN with LSTM, their respective weaknesses are mitigated: CNN selects the necessary features, and LSTM predicts the future outcome based on them.

For experimentation, the CNN model consists of three convolutional layers with batch normalization, followed by an integration with a four-layer LSTM network.

III. METHODOLOGY DESCRIPTION

This study aims to predict short-term electricity consumption for individual households. A Stacked LSTM model with time series embeddings is proposed to make predictions at 3-minute, 15-minute, and hourly intervals. The model uses past consumption data and environmental factors to forecast future usage. In this section, describes the overall approach, dataset and evaluation.

A. Proposed Method

1) Overall Approach: We train an LSTM model for predicting household's current electricity consumption $\hat{x}_t$ (predicted values) to be closer to the real observed values x_t at a given time step t. The input representation w_t is created by combining weather data with embeddings and other relevant factors for the model at every time step 't' and is expressed as:

Algorithm 1 Training for Residential Power Consumption Prediction

Input: The algorithm takes various input parameters, including temp = temperature (C), wet = wet bulb temperature (C), hum = relative humidity (%), perc = precipitation (mm/hour), wind = wind speed at 10 meters (m/s), wind_dir = wind direction at 10 meters (degrees), Avg_Volt = Average Voltage, Avg_Curr = Average Current, freq = Frequency, and utilizes the Adam optimizer to update the parameters of the model.

```
for Epochs in 1, 2, ..., 30 do
    for i in iterations do
        Get data points for T time steps: temperature, wet, perc, hum, wind, wind_dir, Avg_Volt, Avg_Curr, freq.
        Embed year (y): y_emb = Embs(year_t)                                    ▷ Embedding layers
        Embed date (d): d_emb = Embs(date_t)
        Embed month (m): m_emb = Embs(month_t)
        Embed hours (h): h_emb = Embs(hours_t)
        Embed minutes (mi): mi_emb = Embs(minutes_t)
        Create feature vector Y1: Y1 = [temp, wet, perc, hum, wind, wind_dir, Avg_Volt, Avg_Curr, freq]
        Apply dropout: Z = dropout(y_emb, d_emb, m_emb, h_emb, mi_emb)          ▷ Dropout rate = 0.4
        Concatenate embeddings with feature vector: Y = [Z, Y1]                 ▷ Combining embeddings and features
        Pass Y through Stacked LSTM network to get predictions.
        Calculate L2 loss: L2 loss = (1/m) Σ_{l=1}^{m} (real(l) − prediction(l))^2
        Backpropagation the loss and update model weights using Adam optimizer.
    end for
end for
Save the trained model and loss data.
Calculate and plot between predictions vs actual values.
```

$$\mathbf{w_t} = [\mathrm{emb}(\mathrm{year}_t), \mathrm{emb}(\mathrm{month}_t), \mathrm{emb}(\mathrm{date}_t), \mathrm{emb}(\mathrm{hour}_t), \mathrm{emb}(\mathrm{minute}_t), \mathrm{temperature}_t, \mathrm{humidity}_t, \mathrm{precipitation}_t, \mathrm{wind\ speed}_t, \mathrm{wind\ direction}_t, \mathrm{avg\_current}_t, \mathrm{frequency}_t, \mathrm{avg\_voltage}_t] \tag{8}$$

Given the input representation to models it is trained to predict $\hat{X}$ value to be closer to real value X represented as:

$$\mathbf{X} = [x_0, x_1, ..., x_{N-1}] \tag{9}$$

$$\hat{\mathbf{X}} = [\hat{x}_0, \hat{x}_1, ..., \hat{x}_{N-1}] \tag{10}$$

The model weights are updated using back-propagation during training so that predicted values are closer to observed values, and the Adam optimizer helps reduce the difference between actual and predicted values. Adam does this by adjusting learning rates based on the average and variance of gradients.

2) Model Architecture and Design Choices: The overall network design is divided into two main parts: the Input Representation Block (see Fig. 3) and the Prediction Network (see Fig. 4). The Input Representation Block converts discrete factors like year, month, and hour into 128-dimensional vectors and combines these with other factors such as temperature and humidity. This representation is then used by the Prediction Network, which consists of stacked LSTM layers and a fully connected (FC) layer to make predictions about current consumption. Stacked LSTM of 4 layers and input hidden layer having 256 dimensions is configured and dropout of 0.4 on embedding representation is used in the input block for preventing overfitting.

The Input Representation Block and Prediction Network is trained using the Adam optimizer. During inference, the model predicts the value at the 6th time step based on the previous 5 time steps of input data, which covers 15 minutes.

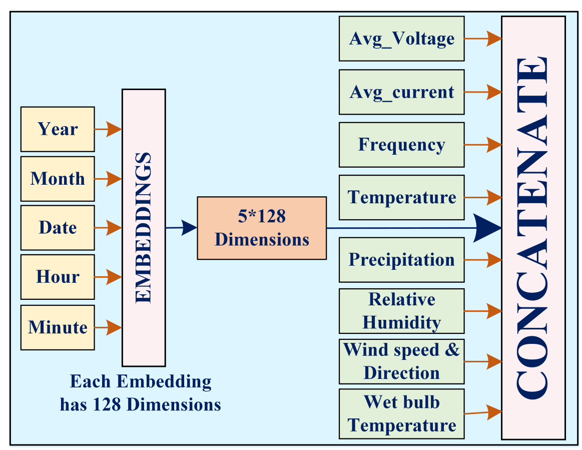


Fig. 3. Input representation block of proposed stacked LSTM with embedding initialization model.

This provides the temporal information needed for accurate predictions. The model follows a systematic training approach as detailed in Algorithm 1. L_2 loss is used as the loss function and process the data in batches during training.

$$L_2\ loss = \frac{1}{m}\sum_{l=1}^{m}(real(X) - predict(\hat{X}))^2 \tag{11}$$

The proposed methodology reduces computational complexity compared to the CNN-LSTM model [7], [20], [22], which requires multiple convolutional layers to extract impactful features, leading to higher computational demands. Additionally, the SVR-BiLSTM [37] model suffers from higher complexity and lower scalability when processing temporal aspects. By leveraging embeddings, a single LSTM neural network archi-

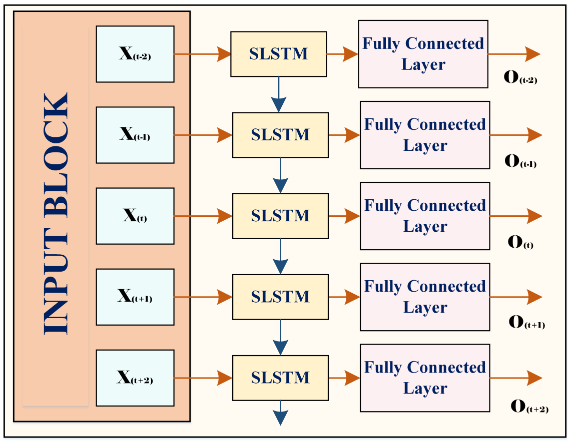


Fig. 4. Prediction network block of proposed stacked LSTM with embedding initialization model.

tecture is sufficient to understand temporal patterns and predict future outcomes with reduced complexity.

B. Dataset and Evaluations of Proposed Methodology

In this section, a detailed overview of the data used and the evaluation metrics chosen for the experiments is provided. PyTorch Framework is used for the entire implementations.

1) Data Description: For the analysis, a minimum of 80% data coverage of each meter within the specified time period was required. Due to some data being unavailable, Data from meters BR04, BR06, BR08, BR09, MH10, and MH11 is selected from the "High-Frequency Smart Meter Data from Two Districts in India (Mathura and Bareilly)" dataset [44] as described in Table II. 70% of the data was used for training and 30% for testing. The meters recorded data every 3 minutes, including total consumption, average current, average voltage, and frequency. This detailed data helps analyze trends and accurately predict different periods.

TABLE II
SMARTMETER DATA PER HOUSEHOLD

Meter ID	Time Period	Data points	Consumption(kWh)
BR04	Aug 2019 - Jun 2021	324000	6942.728
BR06	Aug 2019 - Jun 2021	325440	10444.302
BR08	Aug 2019 - Jan 2021	261120	3752.443
BR09	Oct 2019 - Feb 2021	234015	1529.38
MH10	May 2019 - Jan 2021	281280	9757.93
MH11	May 2019 - Jan 2021	268801	6964.495

Meteorological data from NASA's POWER project [45], providing hourly temperature, humidity, precipitation, wind speed, and direction at a 10-meter elevation, was integrated into the analysis. This data enhances the information from the smart meters, helping us train and evaluate the model more effectively. NASA's POWER project supports research in renewable energy and sustainable buildings, making this comprehensive weather data a valuable addition for our electricity forecasting.

2) Evaluation Metrics: Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) are used to evaluate the model's performance. RMSE [41] measures the standard deviation between actual and predicted values, focusing more on

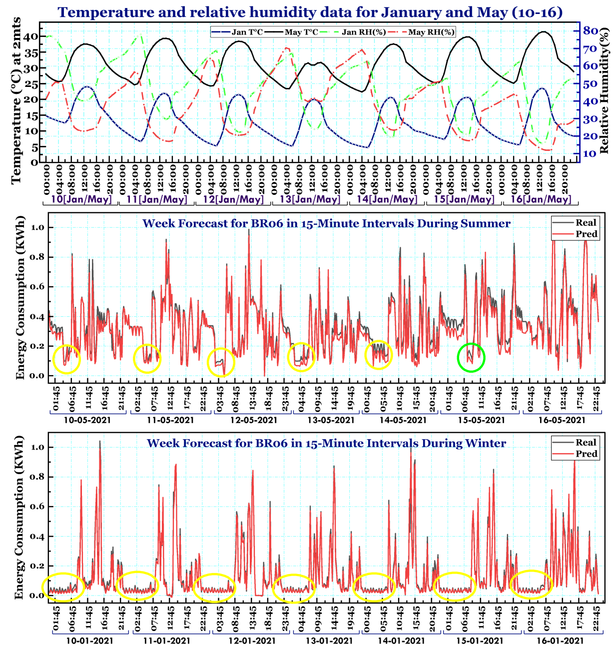


Fig. 5. The proposed SLSTM with time embeddings model predictions on week forecast for BR06 in 15-minute intervals during summer and winter month.

larger errors (Equation (12)). MAE [42] calculates the average absolute difference between the predicted $(\hat{X}_i)$ and actual (X_i) values, treating all errors equally (Equation (13)). Together, these metrics provide a detailed view of how well the model performs.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{X}_i - X_i)^2} \tag{12}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|(\hat{X}_i - X_i)| \tag{13}$$

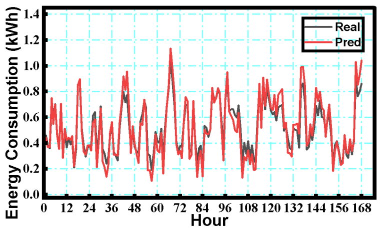
IV. RESULTS AND DISCUSSION

To demonstrate the model's effectiveness, it was tested on six household smart meters (BR04, BR06, BR08, BR09, MH10, and MH11). Detailed data collected every 3 minutes provides a deeper understanding of consumption patterns and provides more information of accurate forecasting for each household.

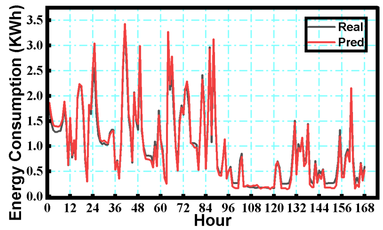
A. Consumption Forecasting

During the survey period, the average daily consumption for each household (as shown in Table II) was approximately 10 kWh (BR04), 15 kWh (BR06), 7 kWh (BR08), 3 kWh (BR09), 15 kWh (MH10), and 11 kWh (MH11), respectively. BR08 and BR09 meters have a lower average consumption compared to the other households. Despite these differences, the proposed methodology effectively predicts consumption values for both high and low-consumption households.

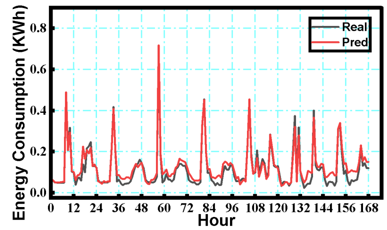
To analyze the effect of weather conditions on consumption patterns, we incorporated hourly temperature and humidity



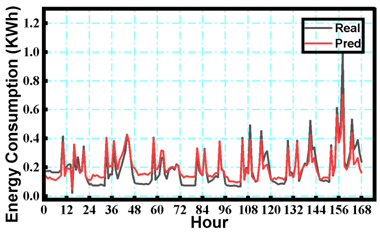
(a) BR04



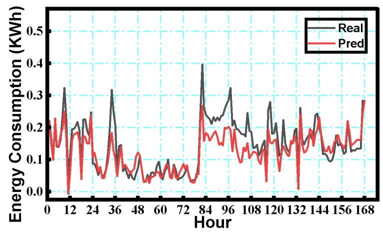
(b) BR06



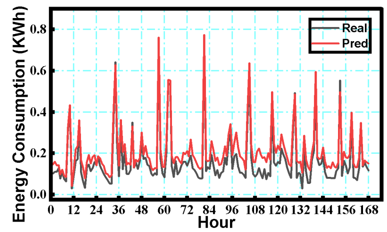
(c) BR08



(d) BR09



(e) MH10



(f) MH11

Fig. 6. Hourly forecast between real and prediction for an entire week by the proposed SLSTM_EMB+W model on different home meters.

levels sourced from [45]. Fig. 6 illustrates the model's performance at 15-minute intervals for the Bareilly meter BR06 across different seasons. The analysis highlights the impact of temporal weather parameters on residential electricity consumption, as shown in Fig. 5. Summer consumption patterns are more volatile due to higher cooling needs, while winter exhibits more stability. A noticeable dip in consumption between 2:00-5:30 AM, marked by yellow circles, aligns with lower ambient temperatures and behavioural patterns like sleep and wake-up times. Green circles indicate shifts in morning routines on summer weekends.

On January (10^{th} and 16^{th}), and May (15^{th} and 16^{th}), weekend daytime consumption deviates from weekday patterns. Similar routines are observed during winter nights, with consumption drops corresponding to constant loads like refrigeration. The model effectively captures these temporal patterns using embeddings, achieving RMSE and MAE values of 0.04065, 0.03124 for summer and 0.01937, 0.01045 for winter, over a one-week interval.

In Fig. 6, depicts the proposed model's performance on each household's test data at hourly intervals over a week. The figure illustrates the model's ability to capture consumption trends and patterns, likely due to the incorporation of time-based weather information within the embeddings.

B. LSTM vs Stacked LSTM

To evaluate the model's effectiveness, we tested it on six household smart meters (BR04, BR06, BR08, BR09, MH10, and MH11). The detailed 3-minute interval data offers deeper insights into consumption patterns, enabling more accurate forecasting for each household.

To simplify the comparison, we did not use embedding representations for weather parameters, focusing solely on the impact of the model's design. These variants utilized historical consumption data for forecasting at 3-minute, 15-minute, and hourly intervals. This comparison highlights the contribution of weather parameters to the model's performance.

TABLE III
COMPARISON BETWEEN LSTM WITH & WITHOUT WEATHER PARAMETERS ON DIFFERENT METERS

Meter	Interval	MAE		RMSE	
		WW	W	WW	W
BR04	3min	0.02073	0.01367	0.03037	0.02222
	15min	0.09738	0.06626	0.14383	0.10804
	60min	0.36747	0.25644	0.55167	0.41980
BR06	3min	0.01442	0.02333	0.02036	0.02931
	15min	0.06749	0.11488	0.09416	0.14334
	60min	0.25208	0.45410	0.35099	0.56338
BR08	3min	0.02347	0.01420	0.02948	0.01959
	15min	0.11437	0.06788	0.14243	0.09348
	60min	0.44631	0.25320	0.54973	0.35372
BR09	3min	0.01874	0.01183	0.02606	0.01584
	15min	0.09175	0.05700	0.12573	0.07504
	60min	0.35967	0.21883	0.48817	0.28224
MH10	3min	0.02530	0.02066	0.03316	0.02827
	15min	0.12436	0.10198	0.16126	0.13804
	60min	0.48782	0.40516	0.62416	0.53776
MH11	3min	0.01953	0.01358	0.03144	0.02125
	15min	0.09458	0.06603	0.15228	0.10328
	60min	0.36521	0.25739	0.58818	0.40282

WW: Without Weather, W: Weather Parameters

For MH10's test data, the SLSTM model without weather parameters achieved an RMSE of 0.17733 and an MAE of 0.11424 for hourly predictions, significantly outperforming the LSTM model without weather parameters, which had RMSE and MAE values of 0.62416 and 0.48782, respectively. With weather parameters, the SLSTM model achieved an RMSE of 0.13318 and an MAE of 0.10411, excelling compared to the LSTM model with weather, which had RMSE and MAE values of 0.53776 and 0.40516, respectively. By leveraging embeddings on weather parameters, the model's performance further improved, achieving RMSE and MAE values of 0.04728 and 0.03704, respectively, outperforming all other configurations.

Performance metrics, MAE and RMSE of LSTM and SLSTM models, are provided in Tables III and IV. For BR06, the SLSTM model with weather parameters achieved an RMSE of 0.00791 and an MAE of 0.00538 at a 3-min interval.

TABLE IV
COMPARISON OF SLSTM MODELS WITH AND WITHOUT WEATHER PARAMETERS

Meter	Interval	MAE		RMSE	
		WW	W	WW	W
BR04	3min	0.00685	0.00575	0.00884	0.00791
	15min	0.03341	0.02791	0.04271	0.03813
	60min	0.13086	0.10851	0.16596	0.14851
BR06	3min	0.00693	0.00538	0.01037	0.00791
	15min	0.03304	0.02530	0.04705	0.03512
	60min	0.12462	0.09485	0.16726	0.12772
BR08	3min	0.00355	0.00364	0.00552	0.00558
	15min	0.01617	0.01693	0.02472	0.02510
	60min	0.05714	0.06296	0.08252	0.08479
BR09	3min	0.00473	0.00477	0.00583	0.00593
	15min	0.02285	0.02337	0.02772	0.02853
	60min	0.08801	0.09157	0.10383	0.10948
MH10	3min	0.00597	0.00544	0.00924	0.00701
	15min	0.02917	0.02647	0.04515	0.03398
	60min	0.11424	0.10411	0.17733	0.13318
MH11	3min	0.00738	0.00298	0.00996	0.00409
	15min	0.03623	0.01360	0.04882	0.01820
	60min	0.14206	0.04729	0.19132	0.06312

WW: Without Weather, W: Weather Parameters

TABLE V
COMPARISON OF CNN_SLSTM WITH THE PROPOSED SLSTM WITH EMBEDDINGS ON WEATHER PARAMETERS (EMB+W)

Meter	Interval	CNN_SLSTM		SLSTM_EMB+W	
		MAE	RMSE	MAE	RMSE
BR04	3min	0.00865	0.01242	0.00310	0.00419
	15min	0.03963	0.05624	0.01394	0.01781
	60min	0.14162	0.20021	0.05068	0.06439
BR06	3min	0.01231	0.01737	0.00416	0.00632
	15min	0.05719	0.07899	0.01822	0.02517
	60min	0.21439	0.28977	0.06601	0.08738
BR08	3min	0.00178	0.00308	0.00148	0.00207
	15min	0.00777	0.01270	0.00593	0.00784
	60min	0.02864	0.04309	0.02080	0.02669
BR09	3min	0.00376	0.00522	0.00288	0.00345
	15min	0.01835	0.02426	0.01392	0.01613
	60min	0.07100	0.08657	0.05423	0.06160
MH10	3min	0.00316	0.00521	0.00220	0.00293
	15min	0.01441	0.02149	0.00976	0.01270
	60min	0.05217	0.07394	0.03704	0.04728
MH11	3min	0.00289	0.00459	0.00256	0.00334
	15min	0.01306	0.01958	0.01198	0.01465
	60min	0.04675	0.06577	0.04490	0.05359

EMB+W: Embeddings on weather Parameters

In contrast, the LSTM model with weather parameters had RMSE and MAE values of 0.02931 and 0.02333, respectively. At the 15-min interval, the BR04 SLSTM model with weather parameters recorded an RMSE of 0.03813 and an MAE of 0.02791. Based on RMSE and MAE values in different time intervals, the SLSTM consistently outperformed the LSTM.

C. Importance of Weather Embeddings

Additional model variants with different input representations were trained to investigate the impact of embedding representations for weather parameters. As discussed in Subsection IV-B, one variant relied solely on previous consumption data, while another incorporated weather parameters as direct inputs for the LSTM and SLSTM models.

The proposed approach leveraged embeddings to learn representations of weather parameters, resulting in improved performance across all meters. Models incorporating weather data outperformed those without it, and performance further improved with embeddings, as they captured complex patterns that enhanced prediction accuracy. This superior representation effectively reduced the model's prediction burden.

The performance metric values of CNN+SLSTM and the proposed SLSTM with Embeddings on weather parameters model are provided in Table V. For BR04's test data, the proposed model achieved an RMSE of 0.06439 and an MAE of 0.05068 for hourly predictions, outperforming the CNN+SLSTM values of 0.20021 and 0.14162 respectively, LSTM and SLSTM models, with or without weather parameters (see Tables III and IV). This represents a 56% reduction in RMSE compared to the SLSTM model with weather parameters. Similarly, the proposed model delivered the best results for all other meters across different forecast horizons. While LSTM and SLSTM models performed better with weather parameters than without it, incorporating time-based embeddings for weather parameters in the proposed model further captured temporal patterns, resulting in lower errors and improved forecasting accuracy. The error, defined as the difference between actual and predicted values for all models at an hourly interval in the BR06 test dataset, is depicted in Fig. 7 as a scatter plot. The majority of values for the SLSTM_EMB+W model fall within the range of ± 0.2, compared to ± 0.5 for the SLSTM+W and -0.5 to 1 for the CNN_SLSTM model.

In Fig. 8, RMSE and MAE values for the 3-minute, 15-minute, and hourly predictions of the proposed SLSTM with time embeddings and weather parameters model on the test data are shown for each meter. The evaluation metrics confirm the significant impact of the weather parameters on household electricity consumption. The proposed stacked LSTM model with embeddings, using both temporal and environmental data, performs well in making accurate forecasts and understanding how weather conditions affect energy use. This approach highlights the value of incorporating weather parameters into electricity consumption forecasts. The model's strong performance across different consumption levels suggests it could be further developed and scaled for larger communities.

V. CONCLUSION AND FUTURE SCOPE

A simple and effective model for short-term electricity load forecasting in individual households using a Stacked Long Short-Term Memory (SLSTM) architecture is proposed. The model utilizes embeddings for time-related features and environmental factors to predict power consumption at 3-minute, 15-minute, and hourly intervals. It is evaluated by analyzing seasonal consumption variations in 15-minute intervals over a week. By incorporating voltage fluctuations, weather data, and separate embeddings for each feature, the model accurately predicts how these factors influence household energy consumption.

The model forecasts consumption by analyzing the previous five timestamps, using 15 minutes of data to predict the next

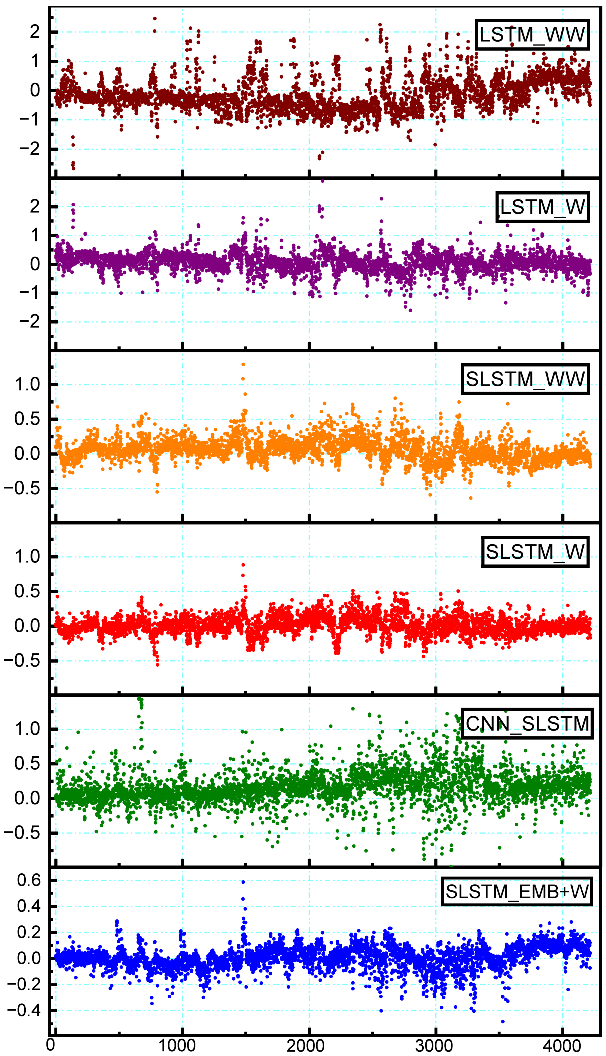


Fig. 7. Error variations of various models on the BR06 meter test dataset at an hourly resolution. X-axis represent data points and Y-axis represent error values in kWh.

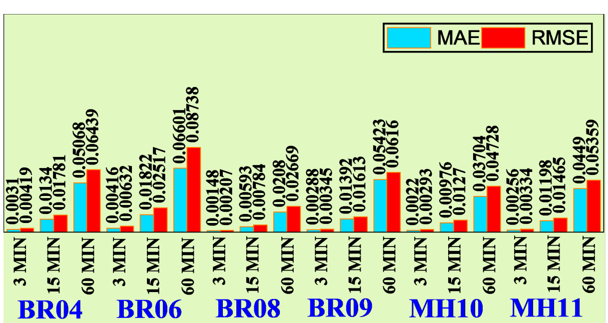


Fig. 8. MAE and RMSE values of proposed SLSTM, considering EMB+W predictions on various metric for different intervals of test data.

interval. RMSE and MAE values indicate that the SLSTM model with time embeddings consistently outperforms others across different time intervals, emphasizing the importance of time-related embeddings and weather information. For BR04 dataset, our proposed model achieves a 56% and 67% reduction in RMSE compared to the SLSTM with the weather and CNN_SLSTM model. The majority of error, defined as difference between actual and predicted values for the proposed SLSTM_EMB+W model fall within the range of ± 0.2, compared to ± 0.5 for the SLSTM+W and -0.5 to 1 for the CNN_SLSTM model. However, factors such as occupancy status, building type, and equipment details are not considered in this study.

This model has significant potential for improving residential energy management. Accurate forecasts can optimize resource allocation and reduce electricity costs for consumers. Future directions include incorporating behavioral and social factors to enhance prediction accuracy. The inclusion of weather parameters in prediction models may help manage residential HVAC equipment more efficiently. Additionally, the model will be extended to forecast electricity prices, the generation capacity of solar and wind energy, and the battery status of both EVs and backup batteries within the smart building's Energy Management System.

REFERENCES

[1] L. Strezoski, "Distributed energy resource management systems (DERMS): State of the art and how to move forward", WIREs Energy and Environment, vol. 12, no. 1, 2022. https://doi.org/10.1002/wene.460

[2] Mahapatra, B., Nayyar, A. Home energy management system (HEMS): concept, architecture, infrastructure, challenges and energy management schemes. Energy Syst 13, 643–669 (2022). https://doi.org/10.1007/s12667-019-00364-w

[3] International Energy Agency (IEA), Key indicators in India as a percentage of global averages, 2000 and 2019 [Online]. Paris, France: IEA, 2022. Available: https://www.iea.org/data-and-statistics/charts/key-indicators-in-india-as-a-percentage-of-global-averages-2000-and-2019.

[4] A. Garulli, S. Paoletti and A. Vicino, "Models and Techniques for Electric Load Forecasting in the Presence of Demand Response," in IEEE Transactions on Control Systems Technology, vol. 23, no. 3, pp. 1087-1097, May 2015, doi: 10.1109/TCST.2014.2361807.

[5] S. Khuntia, J. Rueda, & M. Meijden, "Forecasting the load of electrical power systems in mid- and long-term horizons: a review", IET Generation, Transmission &Amp; Distribution, vol. 10, no. 16, p. 3971-3977, 2016. https://doi.org/10.1049/iet-gtd.2016.0340

[6] J. Yuan, S. -Z. Chen, S. S. Yu, G. Zhang, Z. Chen and Y. Zhang, "A Kernel-Based Real-Time Adaptive Dynamic Programming Method for Economic Household Energy Systems," in IEEE Transactions on Industrial Informatics, vol. 19, no. 3, pp. 2374-2384, March 2023, doi: 10.1109/TII.2022.3181034.

[7] Zulfiqar Ahmad Khan, Amin Ullah, Ijaz Ul Haq, Mohamed Hamdy, Gerardo Maria Mauro, Khan Muhammad, Mohammad Hijji, Sung Wook Baik, Efficient Short-Term Electricity Load Forecasting for Effective Energy Management, Sustainable Energy Technologies and Assessments, Volume 53, Part A, 2022, 102337, ISSN 2213-1388, https://doi.org/10.1016/j.seta.2022.102337.

[8] D. Hadjout, J.F. Torres, A. Troncoso, A. Sebaa, F. Martínez-Álvarez, Electricity consumption forecasting based on ensemble deep learning with application to the Algerian market, Energy, Volume 243, 2022, 123060, ISSN 0360-5442, https://doi.org/10.1016/j.energy.2021.123060.

[9] Son H, Kim C. A Deep Learning Approach to Forecasting Monthly Demand for Residential–Sector Electricity. Sustainability. 2020; 12(8):3103. https://doi.org/10.3390/su12083103.

[10] Sourabh Shastri, Kuljeet Singh, Sachin Kumar, Paramjit Kour, Vibhakar Mansotra, Time series forecasting of Covid-19 using deep learning models: India-USA comparative case study, Chaos, Solitons & Fractals, Volume 140, 2020, 110227, ISSN 0960-0779, https://doi.org/10.1016/j.chaos.2020.110227.

[11] Moradzadeh A, Mansour-Saatloo A, Mohammadi-Ivatloo B, Anvari-Moghaddam A. Performance Evaluation of Two Machine Learning Techniques in Heating and Cooling Loads Forecasting of Residential Buildings. Applied Sciences. 2020; 10(11):3829. https://doi.org/10.3390/app10113829.

[12] M. Q. Raza, N. Mithulananthan, J. Li and K. Y. Lee, "Multivariate Ensemble Forecast Framework for Demand Prediction of Anomalous Days," in IEEE Transactions on Sustainable Energy, vol. 11, no. 1, pp. 27-36, Jan. 2020, doi: 10.1109/TSTE.2018.2883393.

[13] R. Zhang, Y. Xu, Z. Y. Dong, W. Kong and K. P. Wong, "A composite k-nearest neighbor model for day-ahead load forecasting with limited temperature forecasts," 2016 IEEE Power and Energy Society General Meeting (PESGM), Boston, MA, USA, 2016, pp. 1-5, doi: 10.1109/PESGM.2016.7741097.

[14] S. H. Rafi, Nahid-Al-Masood, S. R. Deeba and E. Hossain, "A Short-Term Load Forecasting Method Using Integrated CNN and LSTM Network," in IEEE Access, vol. 9, pp. 32436-32448, 2021, doi: 10.1109/ACCESS.2021.3060654.

[15] G. Dudek, P. Pełka and S. Smyl, "A Hybrid Residual Dilated LSTM and Exponential Smoothing Model for Midterm Electric Load Forecasting," in IEEE Transactions on Neural Networks and Learning Systems, vol. 33, no. 7, pp. 2879-2891, July 2022, doi: 10.1109/TNNLS.2020.3046629.

[16] Sara Abedi, Soongeol Kwon, Rolling-horizon optimization integrated with recurrent neural network-driven forecasting for residential battery energy storage operations, International Journal of Electrical Power & Energy Systems, Volume 145, 2023, 108589, ISSN 0142-0615, https://doi.org/10.1016/j.ijepes.2022.108589.

[17] Arash Moradzadeh, Hamed Moayyed, Kazem Zare, Behnam Mohammadi-Ivatloo, Short-term electricity demand forecasting via variational autoencoders and batch training-based bidirectional long short-term memory, Sustainable Energy Technologies and Assessments, Volume 52, Part C, 2022, 102209, ISSN 2213-1388, https://doi.org/10.1016/j.seta.2022.102209.

[18] D. L. Marino, K. Amarasinghe and M. Manic, "Building energy load forecasting using Deep Neural Networks," IECON 2016 - 42nd Annual Conference of the IEEE Industrial Electronics Society, Florence, Italy, 2016, pp. 7046-7051, doi: 10.1109/IECON.2016.7793413.

[19] H. Shi, M. Xu and R. Li, "Deep Learning for Household Load Forecasting—A Novel Pooling Deep RNN," in IEEE Transactions on Smart Grid, vol. 9, no. 5, pp. 5271-5280, Sept. 2018, doi: 10.1109/TSG.2017.2686012.

[20] B. Farsi, M. Amayri, N. Bouguila and U. Eicker, "On Short-Term Load Forecasting Using Machine Learning Techniques and a Novel Parallel Deep LSTM-CNN Approach," in IEEE Access, vol. 9, pp. 31191-31212, 2021, doi: 10.1109/ACCESS.2021.3060290.

[21] M. Alhussein, K. Aurangzeb and S. I. Haider, "Hybrid CNN-LSTM Model for Short-Term Individual Household Load Forecasting," in IEEE Access, vol. 8, pp. 180544-180557, 2020, doi: 10.1109/ACCESS.2020.3028281.

[22] Charan Sekhar, Ratna Dahiya, Robust framework based on hybrid deep learning approach for short term load forecasting of building electricity demand, Energy, Volume 268, 2023, 126660, ISSN 0360-5442, https://doi.org/10.1016/j.energy.2023.126660.

[23] O. Rubasinghe, X. Zhang, T. K. Chau, Y. H. Chow, T. Fernando and H. H. -C. Iu, "A Novel Sequence to Sequence Data Modelling Based CNN-LSTM Algorithm for Three Years Ahead Monthly Peak Load Forecasting," in IEEE Transactions on Power Systems, vol. 39, no. 1, pp. 1932-1947, Jan. 2024, doi: 10.1109/TPWRS.2023.3271325.

[24] Khan ZA, Hussain T, Ullah A, Rho S, Lee M, Baik SW. Towards Efficient Electricity Forecasting in Residential and Commercial Buildings: A Novel Hybrid CNN with a LSTM-AE based Framework. Sensors. 2020; 20(5):1399. https://doi.org/10.3390/s20051399

[25] Xiaolei Liu, Zi Lin, Impact of Covid-19 pandemic on electricity demand in the UK based on multivariate time series forecasting with Bidirectional Long Short Term Memory, Energy, Volume 227, 2021, 120455, ISSN 0360-5442, https://doi.org/10.1016/j.energy.2021.120455.

[26] Ji X, Huang H, Chen D, Yin K, Zuo Y, Chen Z, Bai R. A Hybrid Residential Short-Term Load Forecasting Method Using Attention Mechanism and Deep Learning. Buildings. 2023; 13(1):72. https://doi.org/10.3390/buildings13010072

[27] K. Amarasinghe, D. L. Marino and M. Manic, "Deep neural networks for energy load forecasting," 2017 IEEE 26th International Symposium on Industrial Electronics (ISIE), Edinburgh, UK, 2017, pp. 1483-1488, doi: 10.1109/ISIE.2017.8001465.

[28] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," in Neural Computation, vol. 9, no. 8, pp. 1735-1780, 15 Nov. 1997, doi: 10.1162/neco.1997.9.8.1735.

[29] Kyunghyun Cho, Bart van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. 2014. Learning Phrase Representations using RNN Encoder–Decoder for Statistical Machine Translation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1724–1734, Doha, Qatar. Association for Computational Linguistics, doi: 10.3115/v1/D14-1179.

[30] Chang, C., Chan, C. T., Wang, W. Y., Peng, W. C., & Chen, T. F. (2024, May). TimeDRL: Disentangled Representation Learning for Multivariate Time-Series. In 2024 IEEE 40th International Conference on Data Engineering (ICDE) (pp. 625-638). IEEE.

[31] Alves, D., Mendonça, F., Mostafa, S.S. et al. Time-Series Embeddings from Language Models: A Tool for Wind Direction Nowcasting. J Meteorol Res 38, 558–569 (2024). https://doi.org/10.1007/s13351-024-3151-9

[32] Y. LeCun et al., "Handwritten digit recognition with a back-propagation network", Proc. Int. Conf. Adv. Neural Inf. Process. Syst., vol. 2, pp. 399-402, 1989.

[33] Mustaqeem, M. Ishaq and S. Kwon, "Short-Term Energy Forecasting Framework Using an Ensemble Deep Learning Approach," in IEEE Access, vol. 9, pp. 94262-94271, 2021, doi: 10.1109/ACCESS.2021.3093053.

[34] W. Kong, Z. Y. Dong, Y. Jia, D. J. Hill, Y. Xu and Y. Zhang, "Short-Term Residential Load Forecasting Based on LSTM Recurrent Neural Network," in IEEE Transactions on Smart Grid, vol. 10, no. 1, pp. 841-851, Jan. 2019, doi: 10.1109/TSG.2017.2753802.

[35] Fan Liang, Austin Yu, William G. Hatcher, Wei Yu, Chao Lu, Deep Learning-Based Power Usage Forecast Modeling and Evaluation, Procedia Computer Science, Volume 154, 2019, Pages 102-108, ISSN 1877-0509, https://doi.org/10.1016/j.procs.2019.06.016.

[36] Zahra Fazlipour, Elaheh Mashhour, Mahmood Joorabian, A deep model for short-term load forecasting applying a stacked autoencoder based on LSTM supported by a multi-stage attention mechanism, Applied Energy, Volume 327, 2022, 120063, ISSN 0306-2619, https://doi.org/10.1016/j.apenergy.2022.120063.

[37] X. Lin, R. Zamora, C. A. Baguley and A. K. Srivastava, "A Hybrid Short-Term Load Forecasting Approach for Individual Residential Customer," in IEEE Transactions on Power Delivery, vol. 38, no. 1, pp. 26-37, Feb. 2023, doi: 10.1109/TPWRD.2022.3178822.

[38] C. S. Lai et al., "Multi-View Neural Network Ensemble for Short and Mid-Term Load Forecasting," in IEEE Transactions on Power Systems, vol. 36, no. 4, pp. 2992-3003, July 2021, doi: 10.1109/TPWRS.2020.3042389.

[39] Tjøstheim, Dag and Jullum, Martin and Løland, Anders, Some recent trends in embeddings of time series and dynamic networks, Journal of Time Series Analysis, vol. 44, no. 5-6, pp. 686-709, 2023, https://doi.org/10.1111/jtsa.12677.

[40] Chuyuan Wei, Dechang Pi, Mingtian Ping, Haopeng Zhang, Short-term load forecasting using spatial-temporal embedding graph neural network, Electric Power Systems Research, Volume 225, 2023, 109873, ISSN 0378-7796, https://doi.org/10.1016/j.epsr.2023.109873.

[41] Rob J. Hyndman, Anne B. Koehler, Another look at measures of forecast accuracy, International Journal of Forecasting, Volume 22, Issue 4, 2006, Pages 679-688, ISSN 0169-2070, https://doi.org/10.1016/j.ijforecast.2006.03.001.

[42] Sammut, Claude, and Geoffrey I. Webb. "Mean absolute error." Encyclopedia of Machine Learning 652 (2010).

[43] Meng Zhou, Junqi Yu, Fukang Sun, Meng Wang, Forecasting of short term electric power consumption for different types buildings using improved transfer learning: A case study of primary school in China, Journal of Building Engineering, Volume 78, 2023, 107618, ISSN 2352-7102, https://doi.org/10.1016/j.jobe.2023.107618.

[44] Agrawal, Shalu; Mani, Sunil; Ganesan, Karthik; Jain, Abhishek, 2021, "High frequency smart meter data from two districts in India (Mathura and Bareilly)", https://doi.org/10.7910/DVN/GOCHJH, Harvard Dataverse, V2.

[45] National Aeronautics and Space Administration (NASA) POWER [Power Prediction of Worldwide Energy Resources]. Retrieved from https://power.larc.nasa.gov/data-access-viewer/

Vangipuram Srinivasa Raghavan received a Bachelors (B.Tech) degree in Electrical and Electronics Engineering from GITAM University, Visakhapatnam,in 2016, and an Masters (M.Tech) degree in Renewable Energy from MANIT-Bhopal in 2021. He is currently pursuing the Ph.D. degree with the Department of Electrical Engineering, NIT Warangal. His research interests include Machine Learning and Deep Learning application in power systems, and Home Energy management systems.

Giridhar A. V. (Senior Member, IEEE) received the Doctorate degree from IIT Madras in 2011. He joined the National Institute of Technology, Warangal, India, in 2012, where he is currently an Associate Professor with the Department of Electrical Engineering. He is also working on SPARC Project as a Co PI. Also, he had done consultancy services to state power utility. He has published more than fifteen articles in journals and conferences. His research area includes high voltage engineering, smart homes, and Deep Learning.