International Journal of Research and Innovation in Multidisciplinary (www.ijrim.com)
||Volume 3, Issue 8, August 2026 || Impact Factor: 5.2 |

A Deep Learning based Technique for Residential Electrical Load Forecasting in Smart Home

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***Abstract*— The increasing variation in residential electricity consumption has created a need for accurate electrical load forecasting to support efficient energy management and reliable operation of smart-home power systems. This paper proposes a deep learning-based technique combining Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) for residential electrical load forecasting. The proposed approach utilizes historical household electricity consumption data to learn temporal patterns and nonlinear variations in residential load demand. The RNN component captures sequential relationships in the electrical load profile, while the LSTM component effectively learns long-term dependencies and reduces the limitations associated with conventional recurrent networks. The proposed model is evaluated for short-term residential load forecasting using suitable performance measures such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The forecasting results demonstrate the capability of the RNN-LSTM approach to accurately track variations in household electricity demand and improve prediction reliability. Accurate load forecasting can support peak-load management, demand response, appliance scheduling, battery energy storage operation, rooftop photovoltaic integration, and smart-home energy management. The proposed technique provides an effective electrical load forecasting framework for improving energy utilization and supporting reliable operation of future smart residential distribution systems.**

Keywords: Smart Meter, Electricity Theft, CNN, Deep Learning, Smart Grid.

I. INTRODUCTION

The rapid increase in residential electricity consumption has made residential electrical load forecasting an important requirement for efficient energy management and reliable operation of modern power systems. In a smart home, electricity demand varies continuously according to appliance operation, occupancy, time of day, weather conditions, consumer activities, and seasonal patterns. Accurate forecasting of this demand enables better understanding of future load requirements and helps maintain a proper balance between electricity demand and available power resources [1]. Unlike conventional aggregated load forecasting, residential-level forecasting deals with highly variable and irregular consumption patterns because individual households have different appliance combinations and usage behaviors [2].

The development of smart-home technologies and advanced metering infrastructure has provided high-resolution electricity consumption data that can be used to analyze household load characteristics. Smart meters can record electrical consumption at different time intervals and provide detailed information about daily, weekly, and seasonal demand profiles. Such data are useful for identifying consumption trends, peak-demand periods, and variations in household electrical loads, thereby creating a strong foundation for accurate residential load forecasting [3]. The availability of historical load data also allows forecasting models to learn the temporal relationship between previous and future electricity consumption.

Residential electrical loads are strongly influenced by several external and internal factors. Weather parameters such as temperature, humidity, and solar radiation can significantly affect electricity demand because of heating, cooling, and ventilation requirements. Similarly, occupancy and consumer behavior influence the operating schedule of domestic appliances and consequently change the household load profile. Considering these electrical, environmental, and behavioral factors can improve the representation of actual residential demand and enhance forecasting performance [4].

Accurate residential load forecasting is particularly important for smart-home energy management systems (HEMS). Forecasted electricity demand can be used to schedule flexible appliances during suitable periods, reduce unnecessary consumption, and avoid high-demand operating conditions [5]. It can also assist consumers in monitoring their electricity usage and making better energy-management decisions. From the utility perspective, reliable household load forecasts can support demand-side management and improve coordination between residential consumers and the distribution network [6].

The increasing penetration of renewable energy and distributed energy resources has further increased the importance of residential load forecasting. Rooftop photovoltaic generation, battery energy storage systems, and other local energy resources can significantly change the net electricity demand of a household. Since renewable generation is variable and battery operation depends on charging and discharging requirements, accurate prediction of residential demand is necessary for effective coordination of local generation and consumption [7]. Similarly, the growing adoption of electric vehicles can introduce additional and sometimes unpredictable charging loads into

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residential networks, creating new challenges for household demand prediction [8].

Residential load forecasting also plays an important role in peak-load management and distribution-system operation. Residential demand generally increases during specific periods when multiple appliances are operated simultaneously[9]. Accurate prediction of these peak-demand periods can help utilities plan appropriate demand-response strategies and reduce stress on distribution transformers and feeders. Forecasting future load conditions can also support efficient power scheduling and improve the utilization of available electrical infrastructure [10].

II. METHODOLOGY

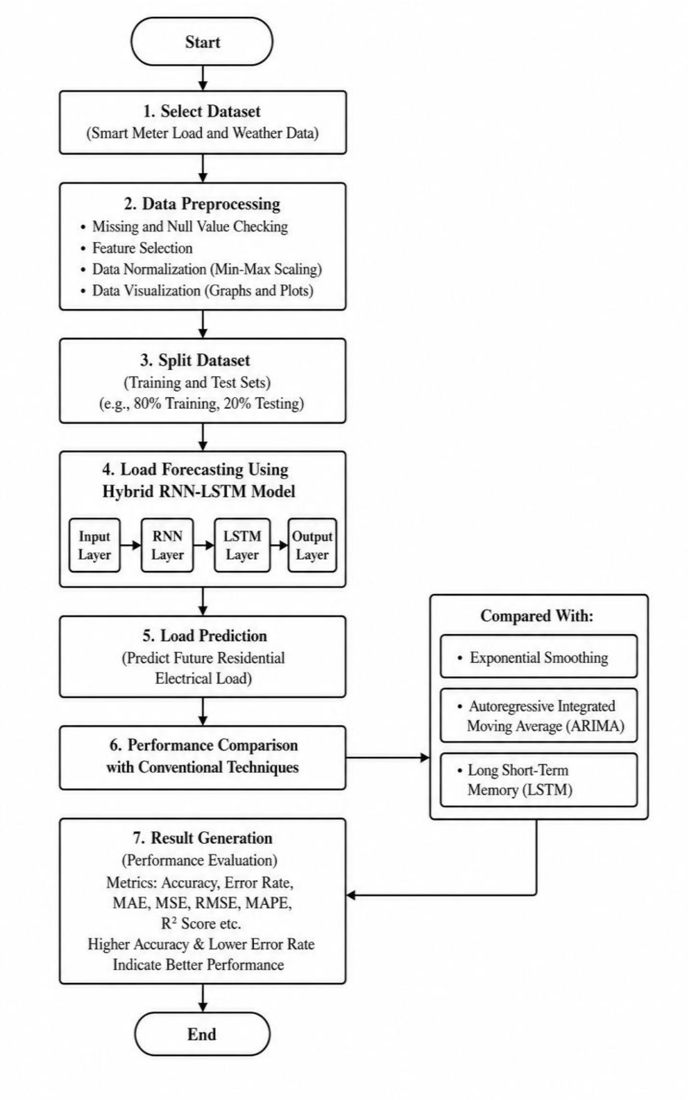


Figure 1: Flow chart

Step 1. Dataset Selection

In the first step, a suitable residential electrical load dataset is selected for developing and evaluating the forecasting model. The dataset contains time-series electricity consumption recorded through smart meters along with relevant parameters such as date, time, temperature, humidity, and other available weather information. Historical electrical load is considered the primary variable for forecasting future residential demand. The time-series nature of the dataset allows the model to learn variations in household electricity consumption over different hours and days.

Step 2. Data Preprocessing

The collected residential load data is first examined for missing values, null values, duplicate records, abnormal observations, and inconsistent measurements. Missing or invalid observations are appropriately handled so that they do not negatively affect model training. After cleaning, important features influencing residential electrical demand are selected. Typical features include previous load values, hour, day, month, temperature, and humidity. The selected features are then normalized to bring them into a common numerical range. Min-Max normalization can be expressed as:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

where X is the original value, X_{min} and X_{max} are the minimum and maximum values, respectively. Data visualization is also performed using load-profile graphs to understand daily consumption patterns, peak demand, and variations in residential electricity usage.

Step 3. Dataset Splitting

After preprocessing, the dataset is divided into training and testing sets. For example, 80% of the observations can be used for training and the remaining 20% for testing. The training data is used to learn the relationship between historical electrical load and future demand, while the test data evaluates the model using previously unseen observations. For time-series forecasting, the chronological order of the observations is maintained to avoid information leakage from future data into the training process.

Step 4. Hybrid RNN–LSTM Model Development

The main forecasting stage uses a hybrid Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) architecture. The input layer receives sequential residential electrical load data and associated input features. The RNN layer processes the sequence and learns short-term temporal relationships between successive load observations. A basic RNN can be represented as:

$$h_t = f(W_x X_t + W_h h_{t-1} + b)$$

where X_t is the input at time t, h_t is the current hidden state, h_{t-1} is the previous hidden state, W_x and W_h are weight matrices, and b is the bias.

The output of the RNN layer is provided to the LSTM layer. LSTM is used to learn longer-term dependencies in residential load sequences and overcome the difficulty of conventional RNNs in retaining information over long sequences. The LSTM controls information flow through input, forget, and output gates. Its cell-state operation can generally be represented by:

$$C_t = f_t C_{t-1} + i_t \tilde{C}_t$$

where $C_t$represents the current cell state, $f_t$is the forget gate, $i_t$is the input gate, and $\tilde{C}_t$represents the candidate cell state. Finally, the LSTM output is passed to the output layer to generate the predicted residential electrical load.

Step 5. Residential Electrical Load Prediction

After training, the hybrid RNN–LSTM model is applied to the test sequence to predict future residential electrical demand. The model uses previously observed load values and selected input parameters to estimate the load for the next forecasting interval. The predicted values are then compared with the actual measured electrical load. The difference between actual and predicted demand represents the forecasting error and indicates how effectively the model tracks residential load variations.

Step 6. Comparison with Other Forecasting Techniques

To determine the effectiveness of the proposed hybrid model, its forecasting performance is compared with other established techniques. In the proposed framework, Exponential Smoothing, ARIMA, and standalone LSTM are considered comparison methods. Exponential Smoothing is useful for identifying trends in load data, while ARIMA models statistical relationships within time-series observations. Standalone LSTM provides a deep-learning baseline for evaluating whether the combination of RNN and LSTM provides additional forecasting capability. The comparison is performed using the same test data and evaluation conditions.

Step 7. Performance Evaluation and Result Generation

The final step evaluates the forecasting performance using appropriate statistical error measures. Mean Absolute Error (MAE) measures the average magnitude of forecasting errors:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i |$$

where $y_i$is the actual electrical load and $\hat{y}_i$is the predicted load. Similarly, Root Mean Square Error (RMSE) gives greater importance to larger forecasting errors:

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

Other measures such as MSE, MAPE, error rate, and R^2can also be used for comprehensive evaluation. Lower MAE, MSE, RMSE, and MAPE values indicate better forecasting performance, while a higher R^2value indicates a stronger agreement between actual and predicted residential electrical load. The final results are presented through tables and graphs to demonstrate the effectiveness of the hybrid RNN–LSTM model for smart-home electrical load forecasting.

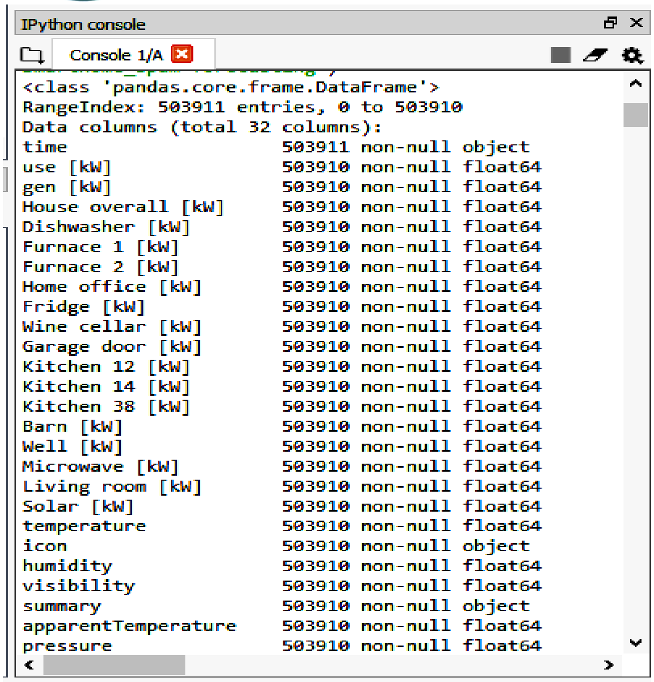
III. SIMULATION RESULTS

The simulation results are performed using the python software.

	A	B	C	D	E	F	G	H	I	J	K	L
1	time	use [kW]	gen [kW]	House ov	Dishwash	Furnace 1	Furnace 2	Home offi	Fridge [kV	Wine cell	Garage dc	Kitchen 1
2	1.45E+09	0.932833	0.003483	0.932833	3.33E-05	0.0207	0.061917	0.442633	0.12415	0.006983	0.013083	0.000417
3	1.45E+09	0.934333	0.003467	0.934333	0	0.020717	0.063817	0.444067	0.124	0.006983	0.013117	0.000417
4	1.45E+09	0.931817	0.003467	0.931817	1.67E-05	0.0207	0.062317	0.446067	0.123533	0.006983	0.013083	0.000433
5	1.45E+09	1.02205	0.003483	1.02205	1.67E-05	0.1069	0.068517	0.446583	0.123133	0.006983	0.013	0.000433
6	1.45E+09	1.1394	0.003467	1.1394	0.000133	0.236933	0.063983	0.446533	0.12285	0.00685	0.012783	0.00045
7	1.45E+09	1.391867	0.003433	1.391867	0.000283	0.50325	0.063667	0.447033	0.1223	0.006717	0.012433	0.000483
8	1.45E+09	1.366217	0.00345	1.366217	0.000283	0.4994	0.063717	0.443267	0.12205	0.006733	0.012417	0.000517
9	1.45E+09	1.4319	0.003417	1.4319	0.00025	0.477867	0.178633	0.444283	0.1218	0.006783	0.01255	0.000483
10	1.45E+09	1.6273	0.003417	1.6273	0.000183	0.44765	0.3657	0.441467	0.121617	0.00695	0.012717	0.000467
11	1.45E+09	1.735383	0.003417	1.735383	1.67E-05	0.17155	0.6825	0.438733	0.121633	0.007233	0.01335	0.000367
12	1.45E+09	1.585083	0.003417	1.585083	5.00E-05	0.0221	0.678733	0.4402	0.12145	0.007433	0.013583	0.00035
13	1.45E+09	1.510317	0.003433	1.510317	3.33E-05	0.021967	0.620667	0.43695	0.12125	0.007317	0.013533	0.000333

Figure 2: Dataset

The figure 2 is showing the dataset, which is taken from the Kaggle machine learning website.



```
IPython console
Console 1/A
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 503911 entries, 0 to 503910
Data columns (total 32 columns):
time                    503911 non-null object
use [kW]                503910 non-null float64
gen [kW]                503910 non-null float64
House overall [kW]      503910 non-null float64
Dishwasher [kW]         503910 non-null float64
Furnace 1 [kW]          503910 non-null float64
Furnace 2 [kW]          503910 non-null float64
Home office [kW]        503910 non-null float64
Fridge [kW]             503910 non-null float64
Wine cellar [kW]        503910 non-null float64
Garage door [kW]        503910 non-null float64
Kitchen 12 [kW]         503910 non-null float64
Kitchen 14 [kW]         503910 non-null float64
Kitchen 38 [kW]         503910 non-null float64
Barn [kW]               503910 non-null float64
Well [kW]               503910 non-null float64
Microwave [kW]          503910 non-null float64
Living room [kW]        503910 non-null float64
Solar [kW]              503910 non-null float64
temperature             503910 non-null float64
icon                    503910 non-null object
humidity                503910 non-null float64
visibility              503910 non-null float64
summary                 503910 non-null object
apparentTemperature     503910 non-null float64
pressure                503910 non-null float64
```

Figure 3: Process Initialization

Figure 3 is presenting the python console, here the dataset various smart home devices shows the power and rating of various devices.

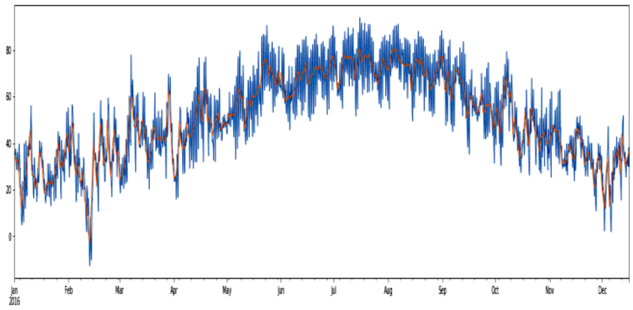


Figure 4: Smart home device with month

Figure 4 is presenting various smart home devices total count with the month format. The month consider from the Jan to Dec.

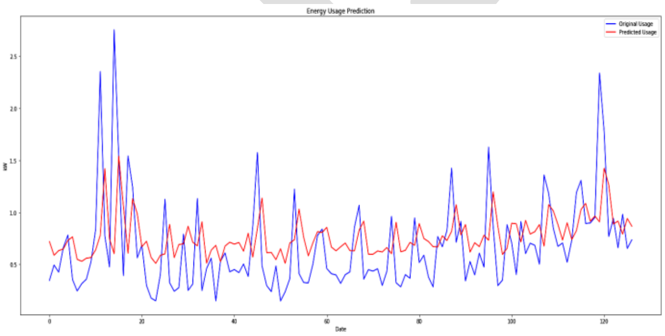


Figure 5: Energy Prediction

Figure is 5 is showing energy prediction. The original and predicted energy is shown in the graphical form.

Table 1: Result Comparison

Sr. No.	Parameters	Previous Work [1]	Proposed Work
1	Technique	Attention based CNN-Bi-LSTM	Deep Learning (RNN-LSTM)
2	Accuracy	91.8%	95.72 %
3	Classification Error	8.2 %	4.28 %

IV. CONCLUSION

The increasing variation in residential electricity demand highlights the need for accurate forecasting in smart-home energy management and modern power systems. Residential electrical load forecasting supports peak-load management, demand response, energy scheduling, and efficient utilization of electrical resources. The study focused on developing a Deep Learning-based RNN-LSTM technique for accurate residential electrical load prediction. The methodology included dataset selection, data preprocessing, feature selection, normalization, and training-testing data division. The proposed RNN-LSTM model achieved an accuracy of 95.72%, compared with 91.80% for the previous Attention-based CNN-BiLSTM approach. The classification error was reduced from 8.20% to 4.28%, demonstrating improved forecasting performance. These results indicate that the proposed approach can effectively capture variations in residential electrical demand. The improved forecasting capability can support smart-home load scheduling, peak-demand reduction, and demand-side management. Overall, the proposed RNN-LSTM technique provides a promising approach for reliable residential electrical load forecasting and future smart-grid applications.

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