Dr. B. C. Roy Polytechnic

BCRP Journal of Innovative Research in Science and Technology (BJIRST)

A peer-reviewed open-access journal
ISSN: 2583-4290
Journal homepage: https://bcrpjournal.org/

BJIRST

Electrical Load Prediction using Recurrent Neural Networks (RNNs)

Santu Kundu
Dept. of Computer Science and Technology
Dr. B.C. Roy Polytechnic
Durgapur, India
santu.kundu@bcrec.ac.in

Saikat Chatterjee
Dept. of Computer Science and Technology
Dr. B.C. Roy Polytechnic
Durgapur, India
saikat.chatterjee@bcrec.ac.in

Sarada Mallik
Dept. of Computer Science and Technology
Dr. B.C. Roy Polytechnic
Durgapur, India
sarada.mallik@bcrec.ac.in

Abhishek Pal
Dept. of Computer Science and Technology
Dr. B.C. Roy Polytechnic
Durgapur, India
abhishek.pal@bcrec.ac.in

Rima Dutta
Dept. of Computer Science and Technology
Dr. B.C. Roy Polytechnic
Durgapur, India
rima.dutta@bcrec.ac.in

Prasanta Karmakar
Dept. of Computer Science and Technology
Dr. B.C. Roy Polytechnic
Durgapur, India
prasanta9064.pk@gmail.com

ABSTRACT

Accurate electrical load prediction is important for power system planning, energy trading, and grid stability. It is important from both a technical and a financial standpoint as it strengthens the power system performance, reliability, safety, and stability as well as lowers operating costs. Traditional statistical procedures such as ARIMA and regression models often do not satisfy to capture the complex temporal dependencies inherent in load demand. Recurrent Neural Networks (RNNs) provide a significant alternative by leveraging sequential learning to model short-term and long-term dependencies in time-series data. This paper analyses the use of RNN-based architectures in the field of electrical load forecasting. Experimental results demonstrate that RNNs outperform classical strategies, boosting fidelity and robustness under dynamic load variations.

Keywords—Electrical load forecasting, RNN, time series data, load variations, energy systems

1. INTRODUCTION

Forecasting electrical load is very important for making plans, scheduling, managing demand, and keeping contemporary power systems stable. Electrical load patterns have become more unpredictable and nonlinear because people are using more electricity, renewable energy is becoming more common, and consumer behaviour is changing quickly. Long-range dependencies, changing weather patterns, and complicated time-related factors that are common in modern load profiles are typically missed by traditional forecasting methods like ARIMA, regression-based models, and exponential smoothing. Consequently, these traditional methods often exhibit inferior performance in the face of quick fluctuations, seasonal influences, or peak load situations.

Although machine learning and artificial neural network (ANN) models have been widely used to solve these limitations, many existing studies fail to capture long-term temporal features or successfully deal with nonlinear variations. Traditional ANN models don't have explicit memory, which makes it hard for them to remember historical context, which is important for predicting changing electrical needs that are affected by daily, weekly, and seasonal patterns. This constraint underscores a critical research deficiency: the necessity for forecasting models that may acquire long-term temporal dependencies while ensuring stability and precision among dynamically evolving settings.

The goal of this study is to create and test recurrent-neural-network-based architectures for short-term electrical load forecasting and to see how well they operate compared to traditional statistical models and feedforward neural networks. The study seeks to ascertain if models, including simple RNNs, Long Short-Term Memory (LSTM) networks, and Gated Recurrent Units (GRUs), may yield more dependable and precise forecasts in the context of real-world peak load variations and weather-induced fluctuations. This research provides a thorough comparative analysis of traditional, ANN, and deep recurrent architectures, utilising weather features as supplementary predictors, and illustrates the enhanced efficacy of LSTM and GRU in capturing long-term temporal dependencies for load forecasting.

2. LITERATURE REVIEW

Artificial intelligence (AI), particularly machine learning and deep learning, is commonly employed to forecast energy demand and electricity usage. These advanced methods enable engineers and data scientists to analyze, explain, and explore temporal data patterns. Using the insights gained from intelligent consumers, deep learning models are used to manage the dynamic markets for electricity, heat, and hydrogen with high efficiency. In the face of a burgeoning population and escalating demand for resources, reliable forecasting is paramount for efficient utility management. The long-term aspect of this forecasting is particularly critical because it guides strategic and high-cost decisions, like building facilities, and avoids the risks associated with poor planning. The field of load forecasting includes two distinct families of techniques: engineering-based models, which use physical laws to project power consumption, and information-based techniques, which use statistical and AI methods. The effectiveness of these models is limited by their dependence on the availability and quality of the data used for training. Researchers have developed two types of forecasting methods: quantitative and qualitative. Analytical methods such as moving averages, deep learning, time series analysis, exponential smoothing and trend projection are used in stable situations with sufficient historical data. Conversely, qualitative techniques like the Delphi method and expert opinion are used when there are high uncertainty and historical data is limited or unavailable. Overcoming obstacles in load forecasting has been a focus for scholars globally, leading to the use of numerous models and techniques designed to enhance predictive accuracy. To discuss the aim to utilize time series forecasting alongside machine learning strategies to foretell energy loads for buildings and campuses and to enhance precision by factoring in atmospheric and environmental variables. Early load forecasting models were based on linear regression and autoregressive models (e.g., ARIMA). These methods offered a good approximation but lacked precision of highly volatile and nonlinear load data. The advent of machine learning introduced feed forward neural networks (FNNs) for load forecasting, which improved performance but still lacked temporal memory. RNNs, with feedback connections, addressed this restriction by preserving information across time steps. Variants such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs) further enhanced performance by mitigating the vanishing gradient problem [1, 2]. Researches demonstrate that RNN-based models outstrip in short-term load forecasting, especially under conditions of high variability due to weather, holidays, and consumer behavior [3].

3. METHODOLOGY

3.1. Dataset

The study utilizes open-source hourly electrical load datasets obtained from regional power grid operators, including organizations such as the New York ISO, PJM Interconnection, and various Indian State Load Dispatch Centers. These datasets provide historical hourly load demand values along with essential meteorological variables such as temperature and humidity, as well as calendar-based attributes including the hour of the day, day of the week, and public holiday indicators. The integration of these diverse features allows the model to account for the influence of weather fluctuations, consumer behavior, and temporal patterns that significantly affect electricity consumption.

3.2. Data Preprocessing

A structured preprocessing pipeline is employed to ensure that the input data is suitable for recurrent neural network training. All continuous variables, including load and weather attributes, are normalized to a range between 0 and 1 using min–max scaling to enhance computational stability and accelerate model convergence. Time-based features such as hour, weekday–weekend distinction, and holiday status are engineered and appended to the dataset to capture cyclical consumption trends. The dataset is then divided into three subsets following a 70:15:15 split, where the training set is used for model learning, the validation set for hyperparameter tuning, and the test set for evaluating the model on unseen data. This approach ensures that the forecasting model maintains generalization capability and avoids overfitting.

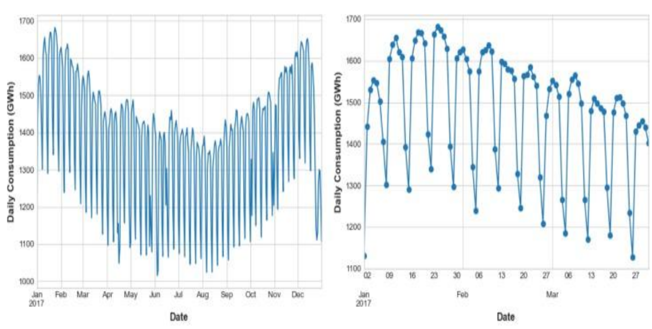
3.3. RNN Architecture

The forecasting framework is developed using recurrent neural network architectures, specifically simple RNN, Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) models. The input layer receives sequential hourly load values together with associated weather and temporal features, enabling the network to analyze multivariate time-series patterns. The hidden layers consist of stacked recurrent units, where LSTM and GRU models are employed to capture long-term dependencies and temporal dynamics that simple RNNs typically fail to learn due to vanishing gradients. Dropout regularization is incorporated between layers to reduce overfitting and improve generalization. The final output layer produces the next-hour load prediction based on the learned temporal relationships. The models are trained by minimizing the Mean Squared Error (MSE) loss function, and the Adam optimizer is used because of its adaptive learning-rate mechanism, which enhances convergence speed and stability when training deep recurrent neural networks.

TABLE 1 TIME SERIES FORECASTING

Forecasting Model	**Mean Absolute Error (MAE) (MW)**	**Root Mean Square Error (RMSE) (MW)**	**Mean Absolute Percentage Error (MAPE) (%)**	**R-squared (R2)**
ARIMA (Traditional)	15.5	22.8	3.55	0.905
Feedforward NN (FNN)	11.2	17.5	2.51	0.932
Simple RNN	8.9	14.1	2.08	0.950
Long Short-Term Memory (LSTM)	6.5	10.9	1.45	0.975
Gated Recurrent Unit (GRU)	7.1	11.8	1.62	0.969

4. EXPERIMENTAL FINDINGS



(a) Hourly Daily Consumption (b) In-depth Analysis

FIG. 1 HOURLY DAILY CONSUMPTION/ IN-DEPTH ANALYSIS

One must first assess the computational requirements and architectural complexity of the rnn model.

5. RESULTS AND DISCUSSIONS

Performance Metrics The models were evaluated using:

- Mean Absolute Error (MAE)
- Root Mean Squared Error (RMSE)
- Mean Absolute Percentage Error (MAPE) **RNNs vs. Traditional Models:** RNNs outperformed ARIMA and linear regression, decreasing RMSE by up to 20%.
- **LSTM/GRU vs. Vanilla RNN:** LSTMs and GRUs achieved top-notch performance due to effective treatment of long-term dependencies.
- **Impact of Weather Variables:** Incorporating weather characteristics enhanced forecast accuracy, especially during peak demand periods.
- **Short-term vs. Long-term Forecasting:** RNNs provided strong short-term (next 24 hours) predictions, though performance slightly declined for longer horizons.

  5.3. Visualization Predicted vs. Actual load curves showed strong alignment, with minimal deviation during peak hours. Error distribution showed reduced bias and variance compared to traditional models.

6. CONCLUSION

This research illustrates that recurrent neural network architectures, specifically LSTM and GRU, provide a robust and dependable methodology for electrical load forecasting. Their capacity to capture and learn intricate temporal relationships leads to markedly enhanced forecasting accuracy in comparison to traditional statistical models and feedforward neural networks. The experimental results demonstrate that gated recurrent units are exceptionally proficient at modelling nonlinear and weather-affected load patterns that define contemporary power systems.

Subsequent research may investigate hybrid methodologies that integrate RNNs with convolutional or attention methods to further improve feature extraction and long-term dependency modelling. Including data on renewable energy sources like solar and wind power may make it possible to make better predictions about the system. More research into probabilistic load forecasting can help us figure out how certain we are about things, which is useful for making decisions that take risks into account. Using forecasting models in real-time intelligent grid management systems is another interesting way to put them to use.

7. ACKNOWLEDGEMENT

The authors acknowledge the useful tools and resources provided by the open-source machine learning, which helped with model building, testing, and analysis.

REFERENCES

[1] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735–1780.

[2] Werbos, P. J. (1990). Backpropagation through time: What it does and how to do it. Proceedings of the IEEE, 78(10), 1550–1560.

[3] Kong, W., Dong, Z. Y., Jia, Y., Hill, D. J., Xu, Y., & Zhang, Y. (2017). Short-term residential load forecasting based on LSTM recurrent neural network. IEEE Transactions on Smart Grid, 10(1), 841–851.

[4] Hinton, G. E., & Salakhutdinov, R. R. (2006). Reducing the dimensionality of data with neural networks. Science, 313(5786), 504–507.

[5] Box, G. E. P., & Jenkins, G. M. (1976). Time Series Analysis: Forecasting and Control. Holden-Day.

[6] Hippert, H. S., Pedreira, C. E., & Souza, R. C. (2001). Neural networks for short-term load forecasting: A review and evaluation. IEEE Transactions on Power Systems, 16(1), 44–55.

[7] Taylor, J. W., & McSharry, P. E. (2007). Short-term load forecasting methods: An evaluation based on European data. IEEE Transactions on Power Systems, 22(4), 2213–2219.

[8] Amasyali, K., & El-Gohary, N. M. (2018). A review of data-driven building energy consumption prediction studies. Renewable and Sustainable Energy Reviews, 81, 1192–1205.

[9] Bhatnagar, R., & Srivastava, G. (2020). Time-series based energy forecasting using LSTM networks: A review. International Journal of Electrical Power & Energy Systems, 121, 106130.

[10] Hong, T., & Fan, S. (2016). Probabilistic electric load forecasting: A tutorial review. International Journal of Forecasting, 32(3), 914–938.

[11] Chae, Y. T., Horesh, R., Hur, J., & Lee, J. (2016). Artificial neural network model for forecasting sub-hourly electricity demand. Energy, 112, 1204–1212.

[12] Marino, D. L., Amarasinghe, K., & Manic, M. (2016). Building energy load forecasting using deep neural networks. In IECON 2016–IEEE Industrial Electronics Conference, 7046–7051.

[13] Sagheer, A., & Kotb, M. (2019). A deep LSTM neural network model for time series prediction. Applied Energy, 253, 113596.

[14] Parmezan, A. R. S., Souza, V. M. A., & Batista, G. E. A. P. A. (2019). Evaluation of forecasting models for building energy consumption: A comparative study. Energy and Buildings, 179, 103–113.

[15] Ahmad, T., & Chen, H. (2019). Short and medium-term load forecasting using time series and machine learning techniques. Energy, 175, 365–377.