International Journal of Informatics and Communication Technology (IJ-ICT)
Vol. 14, No. 2, August 2025, pp. 708~716
ISSN: 2252-8776, DOI: 10.11591/ijict.v14i2.pp708-716

Load forecasting of electrical parameters: an effective approach towards optimization of electric load

Debani Prasad Mishra[1], Rudranarayan Pradhan[2], Ananya Priyadarshini[1], Subha Ranjan Das[3], Surender Reddy Salkuti[4]
[1]Department of Electrical and Electronics Engineering, IIIT Bhubaneswar, Odisha, India
[2]Department of Electrical Engineering, OUTR Bhubaneswar, Odisha, India
[3]School of Computer Science and Engineering, XIM University, Bhubaneswar, India
[4]Department of Railroad and Electrical Engineering, Woosong University, Daejeon, Republic of Korea

Article Info

Article history:

Received Jun 1, 2024
Revised Dec 17, 2024
Accepted Jan 19, 2025

Keywords:

Load forecasting
Machine learning
Optimization
Renewable energy
Sustainable energy

ABSTRACT

The increasing need for energy and the increasing cost of electricity have prompted the development of smart energy optimization systems that can help consumers reduce their electricity consumption and minimize costs. These systems are developed on the concept of a "smart grid" which is a digitalized and intelligent energy network that provides help in the efficient distribution of energy. Load forecasting plays a crucial role in the precise prediction of uncontrollable electrical load. Long-term load analysis predicts a load of more than one year and helps in the planning of power systems whereas short-term and medium-term load forecasting helps in the supply and distribution of load, maintenance of load system, ensuring safety, continuous electricity generation, and cost management. Machine learning (ML) focuses on the development of smart energy optimization systems by enabling intuitive decision-making and reciprocation to sudden variations in consumer energy demands. This study focuses on the consumption of consumer electricity and provides a solution regarding the optimized methods that will predict future consumption based on previous data and help in reducing costs and preserving renewable energy. This research promotes sustainable energy usage. The use of ML models enables intelligent decision-making and accurate predictions, making the system an effective tool for managing electricity consumption.

Corresponding Author:

Surender Reddy Salkuti
Department of Railroad and Electrical Engineering, Woosong University
Jayang-Dong, Dong-Gu, Daejeon 34606, Republic of Korea
Email: surender@wsu.ac.kr

1. INTRODUCTION

A smart grid (SG) is a futuristic energy infrastructure, showcased as an advanced technique to meet high-priority demands that creates and improves the quality of the modern human lifestyle [1]. The importance of SG technology cannot be overstated, especially in today's world where energy is a critical component of increasing economy and social growth [2]. A SG enables utilities to observe and manage the distribution of energy, allowing for optimal allocation and utilization of resources [3]. In a SG, machine learning (ML) algorithms are used to analyze huge data generated by the grid, permitting the identification of patterns and anomalies [4]. Additionally, ML can be used to identify areas of the grid that are at risk of failure or outage, enabling proactive maintenance and reducing downtime. Effective management of the SG requires a combination of human expertise and advanced technological solutions, including ML [5]-[7].

A comparison is provided between every ML algorithm for load forecasting and the predicted trend is analyzed with the real trend. The comparison proved that the enhanced decision tree classifier (EDTC) model is more accurate and precise and has low loss. The accuracy of the model was 99.07% which is higher than the other algorithms [8]. The possible benefits of using ML techniques for SG analysis, including improving energy efficiency, reducing energy consumption, and optimizing energy management are demonstrated. The highlights consist of the challenges associated with implementing ML techniques for SG analysis and provides recommendations for overcoming these challenges [9]. The focus is on the energy usage reduction in the residential area by comparison of several highly accurate forecast algorithms. The result shows a comparison between general regression neural network (GRNN) and edited nearest neighbour (ENN) models and also shows the electricity cost prediction [10].

This study introduces a novel multidirectional long short-term memory (MLSTM) model for predicting the stability of SG, surpassing traditional models like gated recurrent unit (GRU), long short-term memory (LSTM), and recurrent neural network (RNN) in accuracy, precision, and loss metrics. Tested on the ML repository's SG dataset, the MLSTM achieved significantly higher performance, suggesting future exploration in context-aware models for dynamic power management [11]. Estimation of the electricity generation in Cyprus is done by implementing four models' artificial neural network (ANN), adaptive neuro neutrosophic inference system (ANNIS), support vector machine (SVM), and multiple linear regression (MLR) as long-term and short-term analysis. This research aims at better load prediction for electricity load. In the evaluation, SVM stands out of all the models used for the long-term whereas ANN is better in the short-term analysis [12]. For estimating the load forecasting of short-term electrical loads and mainly in load profiles of day-ahead forecasting which are of schools, industries, supermarkets, and residential data the methods used are support vector regression (SVR), linear regression (LR), multi layer perception (MLP), LSTM, random forest (RF), autoregressive integrated moving average (ARIMA), and K-nearest neighbour (KNN). Among all the methods, KNN was found to be the most suitable which is followed by SVR, LR, and ARIMA [13]. Two models were applied and tested for the data of electric load taken from a grocery store and library, then compared with the existing forecasting models. The logistic mixture vector autoregressive model (LMVAR) outperforms all the models [14]. A hybrid model, combining variational mode decomposition, SVR, self-recurrent mechanisms, chaotic mapping, and Cuckoo search algorithm improvements, outperforms other forecasting models. This shows efficacy in fields like stock price forecasting, offering advanced data analysis, enhanced accuracy, and effective boundary handling. Future work aims to integrate these techniques with other algorithms for broader applications [15]. The proposed statistical load forecasting (SLF) assesses risks in load demand profiles verified with international organization for standardization (ISO)-New England data, this outperforms benchmarks by providing precise prediction intervals and risk evaluations for smarter grid operations [16]. The empirical mode decomposition-support vector regression-backpropagation in neural network (EMD-SVR-BPNN) model enhances load forecasting accuracy and fitting, effectively addressing data volatility and trend issues for power system stability [17].

A short-term load forecasting method was coined for Memorial University of Newfoundland using 19 regression models, with gaussian process regression (GPR) models identified as the most effective due to their nonparametric, kernel-based approach. GPR excels in pattern recognition and extrapolation from small datasets, making rational quadratic and exponential GPR algorithms ideal for forecasting [18]. A relevance vector machine (RVM) based technique for short-term electricity load forecasting, integrating wavelet transform and feature selection this outperforms traditional methods by effectively handling noisy data and providing probabilistic predictions. When tested with New York independent system operator (NYISO) and ISO New England data, this shows potential for practical application and future pricing strategy optimization [19]. Demonstrated effectiveness on benchmarks and real-world data shows significant forecasting improvement, highlighting its importance for sustainable development [20]. The RF-moment generating function (MGF) response surface methodology (RSM) hybrid model combines RF and mean generating function for short-term load forecasting, significantly maximizing accuracy by optimizing input variables and using response surface methodology, especially in fluctuating data peaks and valleys [21]. The deep forest regression, designed for short-term power system load forecasting, outperforms traditional algorithms with its dual-procedure structure, minimizing mean absolute percentage error. It simplifies hyper-parameter settings, promising enhancements for mid and long-term forecasting through improved iterations [22]. The C# open source managed operating system (COSMOS) scheme combines deep neural network (DNN) models using a stacking approach for improved short-term building electric consumption forecasting and integrating models with varied hidden layers, tested on actual data, COSMOS outperforms traditional forecasting methods, offering a novel, accurate prediction tool for energy management systems [23]-[25].

2. RESEARCH METHOD

The dataset consists of power consumption records collected from various households over three years. The dataset was sourced from Kaggle's dataset repository, specifically from the "Household_power_consumption" dataset provided by Ahmed [26]. The dataset is freely available for download and accessible for further analysis and research. Sub-metering allows for a detailed breakdown of energy consumption in different areas or specific appliances within a household or building [27]. Data cleaning is an important step in ensuring the integrity and accuracy of the dataset. In this study, the data-cleaning process involved handling missing values, correcting inconsistencies, and addressing outliers. Techniques such as imputation and outlier detection were employed to mitigate the impact of missing or erroneous data points. Feature selection focuses on finding out the most relevant and explanatory variables for the analysis. In the context of household power consumption, features like "global active power", "global reactive power", "voltage", and "global intensity" were selected based on their significance in capturing energy consumption patterns. Other features that were not deemed relevant to the research objectives were excluded to reduce noise and improve the efficiency of subsequent analyses. For the evaluation of the performance of models and to ensure their generalizability, the dataset was partitioned into two sets namely training and testing sets. The commonly used train-test split ratio of 80:20 was employed, ensuring that the models are trained on a sufficiently large portion of the data while still having unseen instances for evaluation. All the Training data was then used to train the used models to undergo evaluation to assess their performance in predicting suitable values.

The models included RF regressor, vector regressor, and Seasonal autoregressive integrated moving average eith exogenous factors (SARIMAX). These models leveraged various features such as active power, reactive power, voltage, and intensity to forecast power consumption accurately. RF regressor is an efficient learning algorithm that uses ensemble learning to create a model that can predict a target value from a set of features [28]. A vector autoregressive (VAR) [29] model that used to predict multiple time series simultaneously. SARIMAX with exogenous variables, is an advanced statistical model used for forecasting time series data. It extends the ARIMA model by incorporating seasonality and external variables, determining to identify complex patterns and relationships within the data [30].

Figure 1 provides a detailed view of the minute trends of voltage over one year. It can be useful for analyzing patterns and identifying any significant changes or anomalies in the voltage over time. Figure 2 presents a detailed view of the hourly trends of voltage over three years. It can be useful for analyzing patterns and identifying any significant changes or anomalies in the voltage over time.

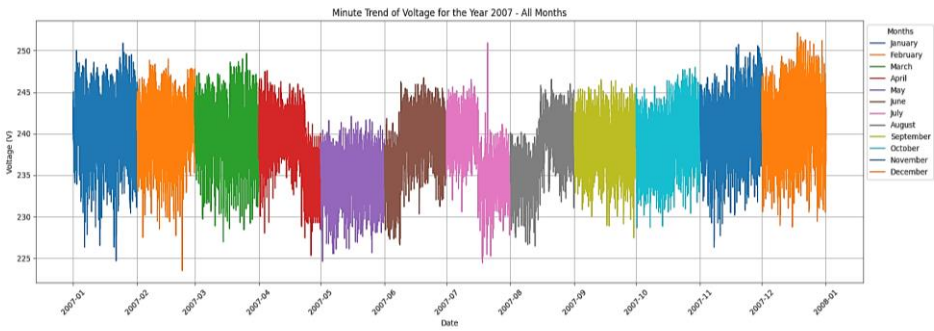

Figure 1. Minute trend of voltaage for the year 2007 for all the months

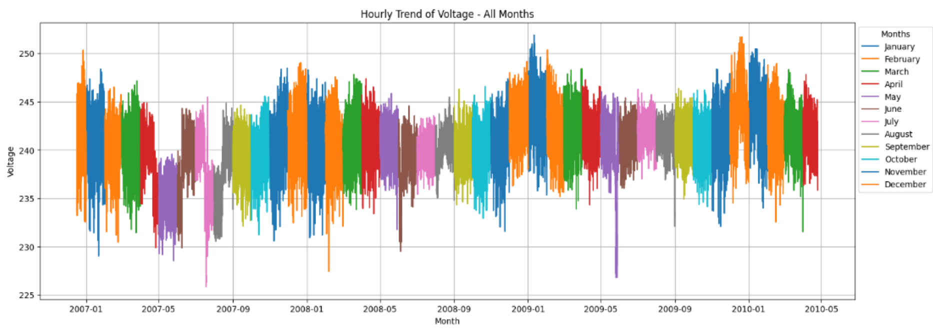

Figure 2. Hourly trend of voltage over all the months for all years

3. RESULTS AND DISCUSSION

3.1. Analysis of graphs

The developed system includes several graphs to analyze the pattern of power consumption in a household. This includes the representation of all the parameters like 'global_active_power', 'global_reactive_power', and their distribution among months. Focusing on the 'voltage' parameter, to know the frequent changes and to identify changes; the time series graph for 'voltage' was plotted but the minute was unable to capture any trend then with the hourly conversion of the dataset again graph was plotted with the same parameter. In the new graph, we observed that a similar pattern of voltage fluctuation is carried out rather most likely in the month of summer. To know the daily usage pattern of a household then a specific date was randomly chosen, i.e., '2007-03-01' and there was a significant change for a fixed interval of time i.e., '04:00-6:00' and '15:00-17:00'. To study the pattern of seasonality the dataset was passed through for seasonal decomposition that delivered the trend, seasonality, and residuals on weekly terms.

3.2. Inference

The initial phase of our research focused on leveraging ML models, including RF and DT regressors, to predict various components of household electricity consumption. Following this, we extended our analysis through the implementation of VAR and SARIMAX models, which are particularly well-suited for capturing the temporal dependencies and seasonal trends prevalent in time series data related to energy usage. Further detailed analysis is done for each method and the results obtained have been discussed.

3.2.1. Random forest regressor results

This model was trained to predict several key metrics related to household power consumption, including global_active_power, global_reactive_power, voltage, global_intensity, sub_metering_1, sub_metering_2, and sub_metering_3. The performance of these models varied across these different targets: global_active_power: the model achieved exceptionally high accuracy, with a mean squared error (MSE) of approximately 0.00026 and an R^2 score close to 1 (0.9997), indicating nearly perfect predictions. global_reactive_power and voltage: these predictions were moderately accurate, with R^2 scores of 0.564 and 0.671, respectively. The errors were larger compared to global_active_power but still indicated a good level of prediction accuracy. Global_intensity: similar to global_active_power, the model performed extremely well, with an MSE of 0.0051 and an R^2 score of 0.9997. Sub_metering_1, sub_metering_2, and sub_metering_3: the predictions for these targets were highly accurate, with R^2 scores ranging from 0.898 for Sub_metering_1 to 0.983 for sub_metering_3, showcasing the model's ability to accurately predict energy consumption in various categories.

Subsequently, the decision tree (DT) regressor model was employed, offering a simpler, yet often effective, alternative for regression tasks. However, the performance of the DT regressor was notably inferior in this context, as evidenced by a higher MSE of 36.73, a significantly lower R-squared value of 0.07, and an increased root mean square error (RMSE) of 6.06. The diminished R-squared value particularly highlights the model's limited capability in accounting for the variance observed in the target metrics, underscoring a substantial reduction in predictive accuracy compared to the RF regressor.

3.2.2. SARIMAX results

The application of a SARIMAX model for forecasting household 'global_active_power' consumption has shown promising results, with satisfactory accuracy as evidenced by the MSE and RMSE metrics. After preprocessing, which involved resampling to hourly frequencies and handling missing values, we focused on forecasting the 'global_active_power' using its previous hour's value ('Lag_1') as an exogenous variable. The dataset was split into 80% of train and 20% of test sets to evaluate the model's performance on unreviewed data. A SARIMAX model with the configuration (1, 1, 1) x (1, 1, 1, 24) was chosen, indicating the use of first-order autoregression, differencing, and moving average processes, along with their seasonal counterparts and a 24-hour seasonal period.

The efficiency of the SARIMAX model was evaluated using MSE and RMSE metrics on the test set. The model achieved an MSE of 0.363 and an RMSE of 0.603. These metrics indicate the model's accuracy in forecasting 'global_active_power' consumption. Figure 3 presents a comparison of actual 'global_active_power' values against the forecasted values and visually represents the model's performance. The forecast values are also compared with actual values. The forecast closely follows the actual data trends, demonstrating the model's effectiveness in capturing the consumption pattern and predicting future values.

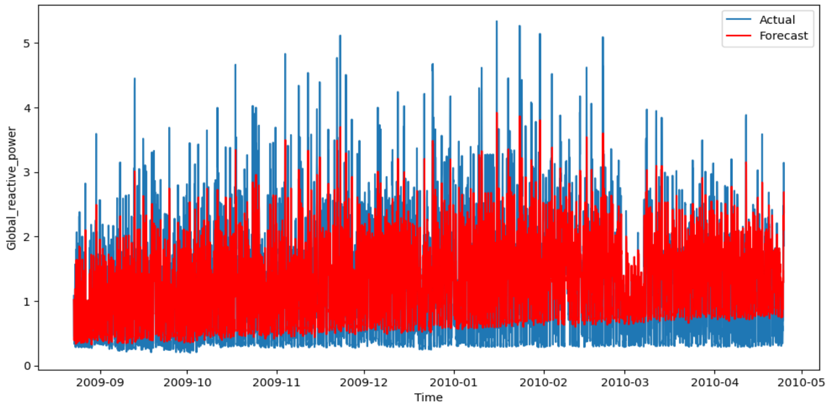

Figure 3. Actual vs forecast values for the SARIMAX model

When comparing VAR and SARIMAX models for energy consumption forecasting, we got VAR values MSE 1.092 and RMSE 1.045; each shows unique strengths. VAR's ability to model interdependencies among variables works well for certain metrics, like 'global_active_power,' but struggles with more complex or seasonal trends seen in 'sub_metering_3' and 'sub_metering_4'. Conversely, SARIMAX excels in handling datasets with clear seasonal patterns and external impacts, thanks to its incorporation of seasonality and exogenous variables. While VAR offers deep insights into variable interrelations, SARIMAX's adaptability makes it superior for complex, seasonally affected data. Choosing the right model depends on the dataset's specific traits, considering that leveraging both could yield the most comprehensive understanding of energy consumption dynamics. Figure 4 shows a minute-wise trend of voltage for all the years. It highlights January, April, and July voltages in red, green, and blue respectively. The graph indicates significant variations in voltage during these periods, providing insights into power stability over time and also helping in the forecasting of future trends.

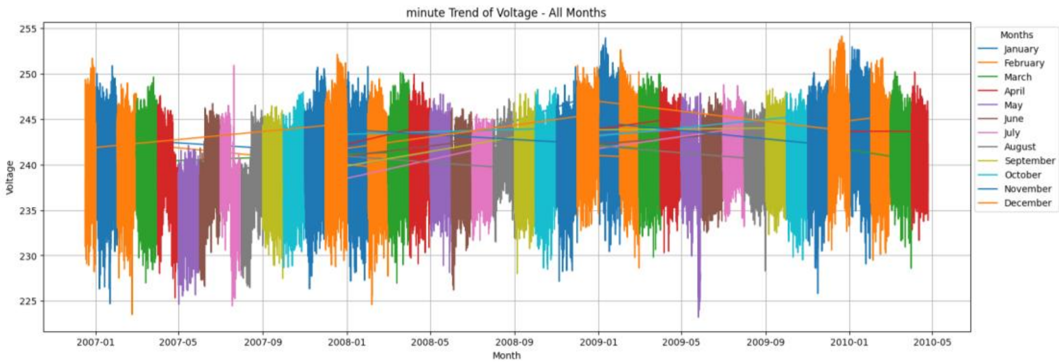

Figure 4. Voltage trend for the months of January, April, and July for all years

The research findings have significant implications for energy management and reducing household power consumption. By accurately predicting expected power consumption, households can proactively take necessary steps to decrease energy usage and optimize resource allocation. The predictive modeling approach enables the identification of energy-saving opportunities and empowers households to implement targeted measures for reducing power consumption. This dataset of a household suggests reducing the use of appliances during those two hours of peak session. The appliances can be replaced with more energy-efficient appliances, use of solar energy can also reduce power usage.

Table 1 presents the values obtained after testing various models such as decision forest (DF), RF, and VAR. It compares different parameters like global active power, global reactive power, voltage, global intensity, sub-metering 1, sub-metering 2, sub-metering 3, and sub-metering 4. Table 2 presents the MSE, RMSE, and R^2 score values for global active power, global reactive power, voltage, global intensity, sub-metering 1, sub-metering 2, sub-metering 3, and sub-metering 4 under the operation of SARIMAX model.

DT provided a straightforward, interpretable model but were outperformed in terms of accuracy by the more complex RFs. The latter showed a significant improvement in predictive accuracy, as evidenced by lower MSE and higher R-squared values, underscoring the value of ensemble learning in capturing the intricate patterns of energy consumption. Expanding our analysis to time series models, the VAR model captured the linear interdependencies among multiple time series but showed variability in performance across different metrics. It was particularly challenged by metrics demonstrating complex patterns or seasonal trends, where its predictive accuracy, as measured by MSE and RMSE, varied significantly.

Table 1. Comparison of DF, RF, and VAR models

Variable	Model	MSE	RMSE	MAE	R^2 score
Global active power	DF	0.000585	0.024198	0.014	0.999324
Global active power	RF	0.000574	0.023973	0.014	0.999337
Global active power	VAR	1.092	1.045010	0.805	-
Global reactive power	DF	0.003824	0.061796	0.039	0.112670
Global reactive power	RF	0.003815	0.061752	0.039	0.114825
Global reactive power	VAR	0.014	0.117615	0.089	-
Voltage	DF	6.359017	2.514952	1.766	0.352550
Voltage	RF	6.488995	2.546218	1.789	0.339316
Voltage	VAR	12.162	3.487420	2.763	-
Global intensity	DF	0.011127	0.105594	0.068	0.999267
Global intensity	RF	0.011338	0.106485	0.068	0.999253
Global intensity	VAR	19.115	4.372051	3.331	-
Sub metering 1	DF	10682.528	103.362360	27.006	0.800698
Sub metering 1	RF	11203.703	105.904540	27.538	0.790975
Sub metering 1	VAR	39.654	6.297160	2.127	-
Sub metering 2	DF	12800.620	113.143162	35.526	0.802282
Sub metering 2	RF	11460.213	107.084791	34.536	0.822986
Sub metering 2	VAR	30.836	5.552991	1.895	-
Sub metering 3	DF	9596.198	97.960208	34.015	0.951974
Sub metering 3	RF	8745.824	93.554123	32.926	0.956230
Sub metering 3	VAR	84.554	9.195301	8.336	-
sub metering 4	DF	13011.987	114.034235	41.016	0.949388
sub metering 4	RF	11876.662	108.974627	39.570	0.953804
sub metering 4	VAR	76.739	8.760105	6.455	-

Table 2. Comparison of SARIMAX model

Variable	MSE	RMSE	R^2 score
Global active power	0.363479	0.602894	0.525965
Global reactive power	0.011565	0.107556	-
Voltage	7.674620	2.771110	-
Global intensity	6.473471	2.544107	0.515130
Sub metering 1	11.952510	3.457551	0.078765

4. CONCLUSION

This research highlights the significance of smart energy optimization in reducing electricity consumption and minimizing costs. In our comprehensive analysis of energy consumption data, we employed a variety of modeling techniques, including DT, RF, VAR, and SARIMAX, each offering unique insights into forecasting energy consumption metrics. In addition to employing various modeling techniques for forecasting energy consumption, we generated a series of graphs to visually explore and understand the patterns and behaviors of the energy consumption parameters. These visual analyses played a crucial role in comprehending the underlying trends, seasonal variations, and anomalies within the data, providing invaluable insights that informed our modeling strategies. Our investigation reveals the nuanced performance of these models across different parameters of energy usage, highlighting their potential applications and limitations. In conclusion, our exploration underscores the importance of the selection of appropriate modeling methods based on the characteristics of the dataset and the forecasting objectives. While ensemble methods like RFs offer superior accuracy in complex datasets, time series models like SARIMAX provide invaluable precision in data with seasonal influences and external factors. The integration of these modeling techniques, aligned with the dataset's unique attributes, can empower us to make informed decisions, optimize energy consumption, and contribute to sustainable energy management practices.

ACKNOWLEDGEMENTS
This research work was supported by the "Woosong University's Academic Research Funding–2025".

FUNDING INFORMATION
This research work was supported by "Woosong University's Academic Research Funding - 2025".

AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Debani Prasad Mishra	✓	✓		✓	✓	✓	✓	✓		✓		✓	✓	
Rudranarayan Pradhan	✓	✓		✓			✓	✓		✓		✓	✓	
Ananya Priyadarshini		✓	✓		✓	✓		✓	✓	✓	✓			
Subha Ranjan Das		✓	✓		✓	✓		✓	✓		✓			
Surender Reddy Salkuti				✓		✓	✓			✓		✓	✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT
The authors state no conflict of interest.

DATA AVAILABILITY
The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

REFERENCES

[1] V. C. Güngör *et al.*, "Smart grid technologies: communication technologies and standards," *IEEE Transactions on Industrial Informatics*, vol. 7, no. 4, pp. 529–539, Nov. 2011, doi: 10.1109/TII.2011.2166794.

[2] W. Tian, "A review of smart grids and their future challenges," *MATEC Web of Conferences*, vol. 173, p. 02025, Jun. 2018, doi: 10.1051/matecconf/201817302025.

[3] Archana, R. Shankar, and S. Singh, "Development of smart grid for the power sector in India," *Cleaner Energy Systems*, vol. 2, p. 100011, Jul. 2022, doi: 10.1016/j.cles.2022.100011.

[4] I. H. Sarker, "Machine learning: algorithms, real-world applications and research directions," *SN Computer Science*, vol. 2, no. 3, p. 160, May 2021, doi: 10.1007/s42979-021-00592-x.

[5] R. S. Kumar, S. Saravanan, P. Pandiyan, and R. Tiwari, "Impact of artificial intelligence techniques in distributed smart grid monitoring system," in *Smart Energy and Electric Power Systems: Current Trends and New Intelligent Perspectives*, Elsevier, 2022, pp. 79–104.

[6] F. Lezama, T. Pinto, Z. Vale, G. Santos, and S. Widergren, "From the smart grid to the local electricity market," in *Local Electricity Markets*, Elsevier, 2021, pp. 63–76.

[7] K. Berk, A. Hoffmann, and A. Müller, "Probabilistic forecasting of industrial electricity load with regime switching behavior," *International Journal of Forecasting*, vol. 34, no. 2, pp. 147–162, Apr. 2018, doi: 10.1016/j.ijforecast.2017.09.006.

[8] T. Alquthami, M. Zulfiqar, M. Kamran, A. H. Milyani, and M. B. Rasheed, "A performance comparison of machine learning algorithms for load forecasting in smart grid," *IEEE Access*, vol. 10, pp. 48419–48433, 2022, doi: 10.1109/ACCESS.2022.3171270.

[9] A. S. Kushwaha, M. S. Naruka, and P. Tripathi, "Artificial intelligence based analysis of smart grid by using machine learning techniques in an electrical power system," *Neuro Quantology*, vol. 20, no. 6, pp. 7411–7419, 2022, doi: 10.14704/nq.2022.20.6.NQ22742.

[10] N. Koltsaklis, I. Panapakidis, G. Christoforidis, and J. Knápek, "Smart home energy management processes support through machine learning algorithms," *Energy Reports*, vol. 8, pp. 1–6, Jun. 2022, doi: 10.1016/j.egyr.2022.01.033.

[11] M. Alazab, S. Khan, S. S. R. Krishnan, Q. V. Pham, M. P. K. Reddy, and T. R. Gadekallu, "A multidirectional LSTM model for predicting the stability of a smart grid," *IEEE Access*, vol. 8, pp. 85454–85463, 2020, doi: 10.1109/ACCESS.2020.2991067.

[12] D. Solyali, "A comparative analysis of machine learning approaches for short-/long-term electricity load forecasting in Cyprus," *Sustainability (Switzerland)*, vol. 12, no. 9, p. 3612, Apr. 2020, doi: 10.3390/SU12093612.

[13] A. Groß, A. Lenders, F. Schwenker, D. A. Braun, and D. Fischer, "Comparison of short-term electrical load forecasting methods for different building types," *Energy Informatics*, vol. 4, no. S3, p. 13, Sep. 2021, doi: 10.1186/s42162-021-00172-6.

[14] D. Jeong, C. Park, and Y. M. Ko, "Short-term electric load forecasting for buildings using logistic mixture vector autoregressive model with curve registration," *Applied Energy*, vol. 282, p. 116249, Jan. 2021, doi: 10.1016/j.apenergy.2020.116249.
[15] Z. Zhang, W. C. Hong, and J. Li, "Electric load forecasting by hybrid self-recurrent support vector regression model with variational mode decomposition and improved Cuckoo search algorithm," *IEEE Access*, vol. 8, pp. 14642–14658, 2020, doi: 10.1109/aCCESS.2020.2966712.
[16] H. Aprillia, H. T. Yang, and C. M. Huang, "Statistical load forecasting using optimal quantile regression random forest and risk assessment Index," *IEEE Transactions on Smart Grid*, vol. 12, no. 2, pp. 1467–1480, Mar. 2021, doi: 10.1109/TSG.2020.3034194.
[17] G. F. Fan, Y. H. Guo, J. M. Zheng, and W. C. Hong, "A generalized regression model based on hybrid empirical mode decomposition and support vector regression with back-propagation neural network for mid-short-term load forecasting," *Journal of Forecasting*, vol. 39, no. 5, pp. 737–756, Aug. 2020, doi: 10.1002/for.2655.
[18] M. Madhukumar, A. Sebastian, X. Liang, M. Jamil, and M. N. S. K. Shabbir, "Regression model-based short-term load forecasting for university campus load," *IEEE Access*, vol. 10, pp. 8891–8905, 2022, doi: 10.1109/ACCESS.2022.3144206.
[19] J. Ding, M. Wang, Z. Ping, D. Fu, and V. S. Vassiliadis, "An integrated method based on relevance vector machine for short-term load forecasting," *European Journal of Operational Research*, vol. 287, no. 2, pp. 497–510, Dec. 2020, doi: 10.1016/j.ejor.2020.04.007.
[20] Z. Wang, X. Zhou, J. Tian, and T. Huang, "Hierarchical parameter optimization based support vector regression for power load forecasting," *Sustainable Cities and Society*, vol. 71, p. 102937, Aug. 2021, doi: 10.1016/j.scs.2021.102937.
[21] G. F. Fan, L. Z. Zhang, M. Yu, W. C. Hong, and S. Q. Dong, "Applications of random forest in multivariable response surface for short-term load forecasting," *International Journal of Electrical Power and Energy Systems*, vol. 139, p. 108073, Jul. 2022, doi: 10.1016/j.ijepes.2022.108073.
[22] L. Yin, Z. Sun, F. Gao, and H. Liu, "Deep forest regression for short-term load forecasting of power systems," *IEEE Access*, vol. 8, pp. 49090–49099, 2020, doi: 10.1109/ACCESS.2020.2979686.
[23] J. Moon, S. Jung, J. Rew, S. Rho, and E. Hwang, "Combination of short-term load forecasting models based on a stacking ensemble approach," *Energy and Buildings*, vol. 216, p. 109921, Jun. 2020, doi: 10.1016/j.enbuild.2020.109921.
[24] S. R. Salkuti, P. Ray, and S. Pagidipala, "Overview of next generation smart grids," in *Lecture Notes in Electrical Engineering*, vol. 824, 2022, pp. 1–28.
[25] J. V. Kumar, H. Sesham, and S. R. Salkuti, "Smart energy management model for electric vehicles," in *Green Energy and Technology*, vol. Part F2899, 2024, pp. 193–209.
[26] A. A. Ahmed, "Household Power consumption," *Kaggle*, 2022. https://www.kaggle.com/datasets/ahmedashrafahmed/household-power-consumption?resource=download (accessed Nov. 24, 2022).
[27] L. Krishnan, A. Kuppusamy, and S. S. Akadiri, "Prediction of electrical power consumption in the household: fresh evidence from machine learning approach," *Energy Efficiency*, vol. 16, no. 7, p. 77, Oct. 2023, doi: 10.1007/s12053-023-10155-z.
[28] P. S. Yu, T. C. Yang, S. Y. Chen, C. M. Kuo, and H. W. Tseng, "Comparison of random forests and support vector machine for real-time radar-derived rainfall forecasting," *Journal of Hydrology*, vol. 552, pp. 92–104, Sep. 2017, doi: 10.1016/j.jhydrol.2017.06.020.
[29] J. M. B. Haslbeck, L. F. Bringmann, and L. J. Waldorp, "A tutorial on estimating time-varying vector autoregressive models," *Multivariate Behavioral Research*, vol. 56, no. 1, pp. 120–149, Jan. 2020, doi: 10.1080/00273171.2020.1743630.
[30] W. K. Adu, P. Appiahene, and S. Afrifa, "VAR, ARIMAX and ARIMA models for nowcasting unemployment rate in Ghana using Google trends," *Journal of Electrical Systems and Information Technology*, vol. 10, no. 1, p. 12, Feb. 2023, doi: 10.1186/s43067-023-00078-1.

BIOGRAPHIES OF AUTHORS

Debani Prasad Mishra received the B.Tech. in electrical engineering from the Biju Patnaik University of Technology, Odisha, India, in 2006 and the M.Tech. in power systems from IIT, Delhi, India in 2010. He has been awarded the Ph.D. degree in power systems from Veer Surendra Sai University of Technology, Odisha, India, in 2019. He is currently serving as assistant professor in the Department of Electrical Engineering, International Institute of Information Technology Bhubaneswar, Odisha. His research interests include soft computing techniques application in power system, signal processing and power quality. He can be contacted at email: debani@iiit-bh.ac.in.

Rudranarayan Pradhan received the M.Tech. degree in power system engineering from VSSUT, Burla, Sambalpur, India, in 2009 and a Ph.D. degree in power system engineering from the Department of Electrical Engineering, Indian Institute of Technology Roorkee, Roorkee, India, in the year 2024. Since 2013, he has been an assistant professor at the School of Electrical Sciences, Odisha University of Technology and Research Bhubaneswar, India. His research interests include power system protection, microgrid protection, advanced relying techniques, advances in smart grid techniques, signal processing applications for power system relaying, and issues of renewables integration with the existing power system. He can be contacted at email: rudranarayan@outr.ac.in.

Ananya Priyadarshini is a student of the Electrical and Electronics Engineering Department of International Institute of Information Technology Bhubaneswar. Her research interests are analysis and statistics to problems from energy and environment. She focuses on the development of new techniques and applications of existing methodologies to data generation, prediction and analysis. She can be contacted at email: ananya191001@gmail.com.

Subha Ranjan Das is a student of School of Computer Science and Engineering of XIM University, Bhubaneswar, India. His research interests are data analysis, machine learning, and automation of problems from the environment. He focuses on developing new methodologies, techniques and applications to synthesis of data and also analyze and predict from current data. He can be contacted at email: subhadas201201@gmail.com.

Surender Reddy Salkuti received Ph.D. degree in electrical engineering from the Indian Institute of Technology, New Delhi, India, in 2013. He was a postdoctoral researcher at Howard University, Washington, DC, USA, from 2013 to 2014. He is currently an associate professor at the Department of Railroad and Electrical Engineering, Woosong University, Daejeon, South Korea. His current research interests include market clearing, including renewable energy sources, demand response, and smart grid development with the integration of wind and solar photovoltaic energy sources. He can be contacted at email: surender@wsu.ac.kr.