# A Review on Deep Learning and Hybrid Model for Forecasting Residential and Commercial Buildings Energy Consumption

Siti Sarah Mat Isa
*Centre for Electrical Engineering Studies,*
*Universiti Teknologi MARA,*
*Cawangan Pulau Pinang,*
Permatang Pauh, Malaysia
sitisarah6195@uitm.edu.my

Ahmad Asri Abd Samat*
*Centre for Electrical Engineering Studies,*
*Universiti Teknologi MARA,*
*Cawangan Pulau Pinang,*
Permatang Pauh, Malaysia
ahmadasri759@uitm.edu.my

Nur Hazahsha Shamsudin
*Faculty of Electrical Technology and Engineering,*
*Universiti Teknikal Malaysia,*
Durian Tunggal, Malaysia
nurhazahsha@utem.edu.my

Mohd Najib Mohd Hussain
*Centre for Electrical Engineering Studies,*
*Universiti Teknologi MARA,*
*Cawangan Pulau Pinang,*
Permatang Pauh, Malaysia
najibmh@uitm.edu.my

Siti Salwa Mat Isa
*Centre for Electrical Engineering Studies,*
*Universiti Teknologi MARA,*
*Cawangan Pulau Pinang,*
Permatang Pauh, Malaysia
salwaisa@uitm.edu.my

Abdul Malek Saidina Omar
*Centre for Electrical Engineering Studies,*
*Universiti Teknologi MARA,*
*Cawangan Pulau Pinang,*
Permatang Pauh, Malaysia
amalek218@uitm.edu.my

2024 5th International Conference on Artificial Intelligence and Data Sciences (AiDAS) | 979-8-3315-2855-3/24/$31.00 ©2024 IEEE | DOI: 10.1109/AIDAS63860.2024.10729959

***Abstract*—The population growth and urbanization have a significant impact on the current rise in electricity demand. Therefore, it is essential to embrace a proactive approach to determine the future energy requirements to consistently meet user needs. The prediction of energy usage within buildings holds great importance in the realm of effective resource management, as it directly impacts both the economy and the environment. The conventional approach, which relied heavily on historical data and economic indicators, is now being replaced by more advanced methodologies like Machine Learning (ML) and Artificial Intelligence (AI). These modern techniques integrate a wider range of data sources such as weather patterns, occupancy, and seasonal variations to enhance the precision of energy consumption forecasts. This paper offers an extensive review of literature pertaining to energy consumption prediction through Deep Learning (DL) and hybrid model, a combination of various forecasting methods applied in real-world situations. The study considered different types of forecasting approaches, two building categories, time frame, findings, and future recommendation. The insights provided in this review are anticipated to guide future research endeavors and identify potential research gaps, particularly in the domain of energy consumption forecasting for buildings.**

***Keywords*—*energy consumption, forecasting, predicting, deep learning, hybrid model***

## I. INTRODUCTION

Globally, energy is very important for economic growth and development. The progressive energy demand increases from year to year. Most countries face this significant world challenge and will be expected to grow by more than half by 2040. There are two reasons for this rise; human population and dependency on electricity for every task we do [1]. Electricity is now a key role, accounting for more than one-third of the energy consumed in buildings. The electricity use is related to more individuals owning appliances for heating, cooking, and air conditioning. Buildings have consumed significantly more energy each year for the last 10 years, totalling 133 EJ in 2022 [2]. In addition, urbanization, expanding economies, growth of residentials, commercial, and manufacturing buildings are also contributed to the world's rising energy consumption [3]. Over the past few years, many great efforts have been made to preserve the existing power system, especially the energy consumption that shows a varied form. This causes an impact on the imbalance of electricity demand and supply [4].

Therefore, finding strategies to reduce energy usage in buildings is quite challenging. For instance, create a policy that focus on energy efficiency rule for buildings, implement an adoption of new renewable energy programs and introduce to energy management systems [5]. Artificial Neural Networks (ANN) and Machine Learning algorithms are two examples of automation and optimization approaches that can further improve energy efficiency by enabling precise management of building systems and forecasting patterns of energy consumption [6], [7]. ML methods can offer improved accuracy and adaptability when solving complex optimization problems [8].

For instance, studies that have demonstrated to the importance of using ANN to forecast energy consumption were conducted by [9], [10]. A recent study presented a new method for predicting heating, ventilation, and air conditioning (HVAC) energy consumption using a Deep Neural Network (DNN) optimized by the Particle Swarm Optimization (PSO) algorithm, demonstrating better performance than traditional models. The utilization of ANN for short-term electricity consumption forecasting has yielded promising outcomes, emphasizing the practicality of using ANN to optimize energy market operations and modernize networks [11].

Literally, energy consumption forecasting methods can be categorized into three parts, data-driven, engineering and statistical [12]. Deep Learning (DL) techniques and ML methodologies are examples of data-driven methods [13].

In 2023, the results analysed by Sarab Shaman Swibe et.al [14] showed that DL performed best accuracy than ANN. Moreover, Noman Khan et. al [15] discovered the proposed hybrid model which was Dilated Depthwise Separable Convolutional Neural Network (DDSCNN) and Bidirectional

Gated Recurrent Unit (BGRU) outperforms traditional ANN. Therefore, this paper will review DL and hybrid models for residential buildings.

## II. Deep Learning

Deep learning, a powerful branch of machine learning, utilizes ANN with multiple layers to significantly impact AI. First proposed in 2006, this approach leverages the depth of these networks to learn complex features from data. By connecting numerous processing units (neurons) that transform and combine information, deep learning enables machines to achieve advanced learning goals [16], [17]. Additionally, Aditya Dubey et. al [18] explained that deep learning, similar to how the human brain works, is very good at handling a lot of information and different kinds of data that is not organized. This makes it essential for many real-world applications such as computer vision, understanding natural language, healthcare, weather forecasting, computer security, and navigation. Furthermore, Payan Chhabra et. al [19] explored the growth of DL research, where these techniques are surpassing traditional machine learning by leveraging layers of data analysis.

In 2020, Hossein Abbasimehra et. al [20] proposed a new method for forecasting demand using multi-layered Long Short-Term Memory (LSTM) networks. This method automatically finds the best model by testing different LSTM settings on a specific dataset. It can capture complex patterns in time series data, even when the data itself keeps changing over time. The researchers compared their method to other forecasting techniques, including Autoregressive Integrated Moving Average (ARIMA), exponential smoothing, and neural networks. Their results showed that the multi-layered LSTM method was the most accurate for the furniture company data they examined. Furthermore, Ewa Chodakowska et.al [21] emphasized that the response of ARIMA models to random disturbances can be rather weak, impairing their capacity to reliably predict electrical load time series. However, research [22] also found that LSTM indicated high accuracy in predicting electricity consumption trends, can significantly improve LSTM's ability to anticipate energy use.

In 2022, Fj Vincent Atabay et. al [23] compared different forecasting models for a house in Houston. They tested traditional AutoRegressive Integrated Moving Average with eXogenous (ARIMAX) and Seasonal Autoregressive Integrated Moving Average and exogenous (SARIMAX) models, alongside deep learning models based on Recurrent Neural Network (RNNs) ie. LSTM, Gated Recurrent Unit (GRU) and Bidirectional. They included factors like daily electricity use, day type (weekday, weekend, etc.) and weather data. The GRU model came out on top. It had the lowest errors (measured by Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) when compared to the other models on the testing data. In other words, the GRU model provided the most accurate forecasts for daily electricity use in the house.

In the same year, Anuj V Abraham et. al [24] proposed LSTM and Convolution Neural Network (CNN) to analyses 14 years of hourly electricity usage data (from Kaggle) to predict future demand. LSTMs were better suited than CNNs for tasks like predicting energy as this method can handle sequences of data. Unlike CNNs, LSTMs consider past information when making predictions, which is crucial for understanding how energy consumption changes over time. This makes LSTMs more accurate for forecasting energy demand.

## III. Hybrid Model

Hybrid metaheuristic techniques are a significant method for optimization to enhance the results. By combining with other optimization techniques such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Artificial Bee Colony (ABC) or other. This technique has been implemented in various fields such as for forecasting parameters of the photovoltaic cells and panels [25], electricity load demand [26], Maritime Inventory Routing Problem [27] and other sectors.

DL is a subset of Machine Learning (ML) which consist of a single architecture. Meanwhile, combination two or more of DL known as multimodal hybrid deep learning model. Both methods have been applied extensively and have their own characteristics and advantages depending on the dataset, complexity, and likely training process. However, in this paper, we emphasize the combination of two or more DL techniques known as hybrid model. Example of studies that has been conducted using these method are [28], [29], [30] and others. Overall, energy consumption forecasting empowers smarter decision-making, leading to a more sustainable and secure energy future.

In 2019, Tae-Young Kim et. al [31] introduced short term energy consumption for residential, using four methods; Conditional Restricted Boltzmann Machine (CRBM), Factored Conditional Restricted Boltzmann Machine (FCRBM), LSTM-based Sequence-to-Sequence (Seq2Seq) and CNN-LSTM. Real energy consumption data were taken from homes, considering various housing characteristics, used a sliding window technique every hour. According to the findings of the study, CNN-LSTM attained the best performance of 0.37 MSE compared to the other methods. Furthermore, the researchers had set target for future recommendation to work with a larger dataset that includes a wider variety of residential properties and energy usage trends. In future, they aim to explore into using transformer models or attention mechanisms to enhance the model's capacity to recognize more complex designs for better accuracy and efficiency.

The following year, in 2020, Zulfiqar Ahmad Khan et. al [32] proposed hybrid CNN with LSTM-AE. From the paper, preprocessing was done on the input dataset to get rid of duplication, outlier, or missing values. Normalization was then used to improve prediction accuracy. In the suggested model, spatial features were extracted from the input data by integrating CNN layers, and these features were subsequently fed into an LSTM-AE model. The encoder function of LSTM-AE autoencoders learned significant features and encoded them into a feature vector for representation learning in unsupervised inputs. As the result, the proposed model demonstrated its efficacy in energy consumption forecasting for residential and commercial buildings by outperforming in terms of mean square error (MSE), mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE) over the University of California (UCI) residential building.

In [33] Noman Khan et. al presented hybrid model for residential and commercial building energy forecasting, named CNN-LSTM, Diffusion - convolutional neural network

(DCNN-LSTM), CNN-BiLSTM, DB-Net (DCNN-BiLSTM). The authors utilised 2,049,280 one minute time frame of IHEPC dataset from the residential building located in France in 2006 to 2010. After the optimization, the results showed significant performance with MSE = 0.0029, RMSE 0.0538, MAE 0.0298 and MAPE 0.5629 for minutely time frame. In this research, the authors conducted four variation time series; minutely, hourly, daily and weekly. Surprisingly, DB-Net marked the best results four all-time series.

Another study that applied CNN – LSTM were Mosbah Aouadal et. al [34]. The analysis was about a comparison between two methods; CNN and an attention-based Sequence-to-Sequence network (CNN-Seq2Seq-Att) and CNN – LSTM. This research examined 2,075,259 for a household in Sceaux, France, from 2006 to 2010. This data set had multiple time series variables to predict the total Global Active Power (GAP) consumption. The time variables consist of day, month, hour, and a flag for specifying the day of the week. Other variables include voltage levels, previous GAP measurements, Global Reactive Power (GRP) measurements, and three sub-metering energy sensor measurements for multiple household appliances. Sub-metering 1, 2, and 3 correspond to the energy consumed by kitchen appliances, laundry room appliances, and heating and cooling appliances, respectively. As the results, CNN-Seq2Seq-Att demonstrated a 9.6% in MSE and 5.94 improvement in MAE over the CNN-LSTM. The authors enthusiast to examine the pricing dynamics of electricity and study energy resources to maximize impact and utilization, such as solar panels and wind turbines for future research.

In 2023, Davi Guimaraes da Silva et. al [35] investigated between Bidirectional long short-term memory (BLSTM) and LSTM models for short-term forecasts of electricity consumption. They tested the models on data from various locations, including households, universities, and entire cities. The analysis showed that BLSTM models were consistently more accurate than LSTM. This suggests that BLSTM's ability to analyse data in both directions led to better performance in electricity consumption forecasting. This research proposed a new way to forecast demand using a special kind of neural network called a multi-layer LSTM.

A lot of studies were done to determine the best effective technique for estimating a building's energy consumption. Thus, Table 1 and Table 2 presents some previous findings emphasizing and hybrid model for residential and commercial building.

## IV. Method Evaluation

It is essential to assess energy consumption forecasts to verify the accuracy of the model's predictions. Evaluation is necessary to determine whether the model is accurately representing usage patterns. An energy consumption prediction model's performance can be assessed in several ways: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). High precision in predicting is shown by lower MAPE and RMSE values [4]. A study conducted by [36], discovered that with lower RMSE and relative error percentage, prediction of energy consumption are more accurate. Hence, these are several typical measures and equations

1. Mean Absolute Error (MAE) calculates the difference between predicted and actual values for each point in a scatter plot. It is calculated by averaging the absolute errors between expected to and actual effort. n is the number of observation dataset.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_{predict,i} - y_{actual,i}\right| \quad (1)$$

2. Mean Squared Error (MSE) is the squared variation between estimated and actual values. MSE evaluates the quality of a predictor. Methods having error levels near zero are considered the best estimating technique.

$$MSE = \frac{\sum_{i=1}^{n}\left(y_{predict,i} - y_{actual,i}\right)^2}{n} \quad (2)$$

3. Root Mean Squared Error (RMSE) is used for calculating the difference between predicted actual values. This is performed by taking the square root of the Mean Square Error (MSE).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(y_{predict,i} - y_{actual,i}\right)^2}{n}} \quad (3)$$

4. Mean Absolute Percentage Error (MAPE) expresses the average error between predicted and actual values as a percentage.

$$MAPE\ (\%) = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_{predict,i} - y_{actual,i}}{y_{actual,i}}\right| \times 100 \quad (4)$$

## V. Discussion

Accuracy and efficiency can vary significantly between different forecasting methods for energy consumption as certain models in ML can be enhanced for quicker processing, while certain can be adjusted for higher precision. Other than that reason, we examined and identified several elements that must be considered to forecast future energy consumption. For instance:

### *A. Larger Dataset*

A larger dataset contains more previous examples of these elements interacting, which helps the forecasting model find and capture these complicated relationships. As referred to Razak Olu-Ajayi et. al [37] agreed that to improve performance, future research should concentrate on larger data sets and investigate the applicability of alternative ensemble algorithms for forecasting building energy usage [31], [37], [45].

### *B. Time Frame*

There are three types of load forecasting: Medium Term Load Forecasting (MTLF), Long term Load Forecasting (LTLF), and Short Term (STLF). Numerous factors influence the prediction for each of these time frame [38], [39].

1. Short Term predicts the hourly load for the next week, rely on historical data, weather forecasts, occupancy schedule and simpler model.
2. Medium Term is more than a week to few months, incorporate with economic factor, more complex for

TABLE 1 CHARACTERISTICS OF DL FOR RESIDENTIAL AND COMMERCIAL BUILDING ENERGY CONSUMPTION

| Ref | Method | Building Type | Time Frame | Findings | Future Work Recommendation |
|---|---|---|---|---|---|
| [42] | LSTM | Residential | Short Term | LSTM, achieved a very small Mean Absolute Percentage Error (MAPE) of 3.14%, which means their predictions were very close to actual usage. | Capture even more complex patterns over time within energy consumption data. |
| [37] | Deep Neural Network (DNN), ANN, Gradient Boosting (GB), Support Vector Machines (SVM), Random Forest (RF), K Nearest Neighbors (KNN) | Residential | Medium Term | DNN emerged the most efficient model for predicting annual energy consumption with RMSE = 1.19. | DNN and other deep learning models might perform even better for predicting building energy consumption if trained on much larger datasets, exceeding 40,000 data points. |
| [43] | DNN, Support Vector Regressor (SVR,) RF | Commercial | Short Term | DNN model outperformed SVR and RF models by a large margin, demonstrating clear advantages in its performance. | Developed techniques lead to new method that could significantly improve how to predict energy use in commercial buildings and offices. |
| [44] | Holt-Winters, SARIMA, Dynamic Linear Model, Trend, and Seasonal components (TBATS), Neural Network Autoregression (NNAR), Multilayer Perceptron (MLP) | Commercial | Medium Term | MLP demonstrated the best performance. | Explore other univariate models like RNN and LSTM.<br><br>Investigate hierarchical time-series forecasting strategy for comparison. This approach would involve looking a at different levels of detail, like individual floors, zones within the building, and the entire building.<br><br>Explore multivariate models that might influence energy use, such as temperature, occupancy levels, and even weather forecasts. |

TABLE 2 CHARACTERISTICS OF HYBRID MODEL FOR RESIDENTIAL AND COMMERCIAL BUILDING ENERGY CONSUMPTION

| Ref | Method | Building Type | Time Frame | Findings | Future Work Recommendation |
|---|---|---|---|---|---|
| [45] | CNN-LSTM, ConvLSTM,CNN-LSTM, CNN-BiLSTM, CNN-GRU, BiLSTM, CNN-BiGRU CNN-BiGRU (PSO) | Residential | Short Term | CNN-BiGRU optimized with PSO MAE = 29.32 for MAPE = 3.11 % , RMSE = 44.28% fixed train-test split method MAE = 21.90, MAP = 2.32% RMSE = 28.19% | Explore on constructing an intelligent demand response system<br><br>Working with a larger dataset collected from smart meters |
| [46] | Stationary Wavelet transform (SWT), Bidirectional Nested LSTM (MC-BiNLSTM), SWT – MC-BiLSTM, | Residential | Short term | SWT – MC-BiLSTM outperformed, higher accuracy and efficiency, lowest error rates | Investigate the proposed method using a range of IoT energy consumption statistics<br><br>Examine to incorporate outside variables into the forecasting model, such as the weather, occupancy trends, or energy costs.<br><br>Investigate hybrid models that integrate alternative forecasting methods algorithms with the suggested MC-BiNLSTM framework. |
| [47] | Bi -GRU<br>Bi -LSTM | Commercial | Short Term | Bi-GRU outperformed errors < 1, indicating followed by Bi – LSTM, and other DL methods | Working with a larger dataset, explore on refining the cooling load prediction. |
| [48] | Multivariate Multilayered LSTM (M – LSTM), Bi – LSTM | Commercial | Short Term | M-LSTM, gained the lowest MAE values of 0.75, 335 0.49, and 0.66 for 3 commercial buildings. | Working on different architectural configurations or hyperparameters.<br><br>working on several commercial building types or in various geographic regions. |

seasonal variations.

3. Long Term is next year's energy consumption, consider for many uncertainties such as macro-economy trends, population and demographic shifts.

### C. Leverage local pattern

Yavuz Eren et. al [40] emphasized that forecasting the electricity demand of different user groups is a complex task. This difficulty arises from two main factors; behaviour of building occupants is inherently unpredictable and external influences like weather patterns, local events, nationwide activities, and even holidays significantly impact energy consumption [31]. Behnam Farsi et. al [38] also highlighted several crucial factors that must be factored into any forecasting model such as trend, seasonality, noise and stationary.

### D. Type of Building

Even though specific details are not significantly available, Zhifeng Lin et. al [41] addressed that different building types exhibit distinct consumption patterns and characteristics. For instance, commercial buildings demonstrate notable regional variations in energy consumption because business practices and operational patterns differ across geographic locations.

## VI. Conclusion

This study has reviewed several methods for predicting energy consumption in both residential and commercial buildings. While the research provides a general overview of prediction techniques, it places a particular emphasis on Deep Learning (DL) and hybrid approaches, which are becoming increasingly important in forecasting. The findings suggest that hybrid models outperform other methods in terms of both accuracy and efficiency. Additionally, focusing on specific building types, such as residential housing, with shorter time frames and larger datasets can further improve forecasting results. To strengthen the understanding in this area, additional literature reviews would be beneficial. Particularly valuable would be a focus on data sources and classification methods employed in energy consumption forecasting. A deeper exploration of these aspects could provide valuable insights for future research.

## Acknowledgment

The authors would like to express their gratitude Electrical Engineering Studies, College of Engineering, Universiti Teknologi MARA, Cawangan Pulau Pinang (UiTMCPP) for providing the funding and support for this publication.

## References

[1] A. H. Azman, N. N. A. Tukimat, M. A. Malek, and R. Faizah Che, “Analysis of Malaysia electricity demand and generation by 2040,” IOP Conf. Ser. Earth Environ. Sci., vol. 880, no. 1, 2021, doi: 10.1088/1755-1315/880/1/012050.

[2] “World Energy Outlook 2023,” International Energy Agency. Accessed: Apr. 30, 2024. [Online]. Available: https://iea.blob.core.windows.net/assets/86ede39e-4436-42d7-ba2a-edf61467e070/WorldEnergyOutlook2023.pdf

[3] S. El Gindi, “Investigation of the Performance of Zero Energy Homes in Hot Climates,” IOP Conf. Ser. Earth Environ. Sci., vol. 1283, no. 1, 2024, doi: 10.1088/1755-1315/1283/1/012012.

[4] A. Naz et al., “Electricity Consumption Forecasting Using Gated-FCN with Ensemble Strategy,” IEEE Access, vol. 9, pp. 131365–131381, 2021, doi: 10.1109/ACCESS.2021.3112666.

[5] L. B. F Tahrour, F Djeffal, “Journal of Renewable Energies,” J. Renew. Energies, vol. 24, pp. 179–187, 2021.

[6] B. Chegari, M. Tabaa, E. Simeu, F. Moutaouakkil, and H. Medromi, “Multi-objective optimization of building energy performance and indoor thermal comfort by combining artificial neural networks and metaheuristic algorithms,” Energy Build., vol. 239, p. 110839, 2021, doi: https://doi.org/10.1016/j.enbuild.2021.110839.

[7] C. Robinson et al., “Machine learning approaches for estimating commercial building energy consumption,” Appl. Energy, vol. 208, pp. 889–904, 2017, doi: https://doi.org/10.1016/j.apenergy.2017.09.060.

[8] S. Akyol, “A new hybrid method based on Aquila optimizer and tangent search algorithm for global optimization,” J. Ambient Intell. Humaniz. Comput., vol. 14, no. 6, pp. 8045–8065, 2023, doi: 10.1007/s12652-022-04347-1.

[9] G. Oğcu, O. F. Demirel, and S. Zaim, “Forecasting Electricity Consumption with Neural Networks and Support Vector Regression,” Procedia - Soc. Behav. Sci., vol. 58, pp. 1576–1585, 2012, doi: 10.1016/j.sbspro.2012.09.1144.

[10] S. S. Md Ramli, M. Nizam Ibrahim, A. Mohamad, K. Daud, A. M. Saidina Omar, and N. Darina Ahmad, “Review of Artificial Neural Network Approaches for Predicting Building Energy Consumption,” 2023 IEEE 3rd Int. Conf. Power Eng. Appl. Shap. Sustain. Through Power Eng. Innov. ICPEA 2023, no. March, pp. 328–333, 2023, doi: 10.1109/ICPEA56918.2023.10093183.

[11] L. Du, X. Li, K. Wang, and Y. Li, “Prediction of HVAC Energy Consumption Using PSO Optimized Deep Neural Network,” Proc. 2023 IEEE 12th Data Driven Control Learn. Syst. Conf. DDCLS 2023, pp. 52–57, 2023, doi: 10.1109/DDCLS58216.2023.10165860.

[12] N. Somu, G. Raman M R, and K. Ramamritham, “A deep learning framework for building energy consumption forecast,” Renew. Sustain. Energy Rev., vol. 137, p. 110591, 2021, doi: https://doi.org/10.1016/j.rser.2020.110591.

[13] T. Ahmad, H. Zhang, and B. Yan, “A review on renewable energy and electricity requirement forecasting models for smart grid and buildings,” Sustain. Cities Soc., vol. 55, no. April 2019, p. 102052, 2020, doi: 10.1016/j.scs.2020.102052.

[14] S. S. Swide and A. F. Marhoon, “Energy Demand Prediction Based on Deep Learning Techniques,” Iraqi J. Electr. Electron. Eng., vol. 19, no. 2, pp. 83–89, 2023, doi: 10.37917/ijeee.19.2.10.

[15] N. Khan, S. U. Khan, and S. W. Baik, “Deep dive into hybrid networks: A comparative study and novel architecture for efficient power prediction,” Renew. Sustain. Energy Rev., vol. 182, no. May, p. 113364, 2023, doi: 10.1016/j.rser.2023.113364.

[16] X. Du, Y. Cai, S. Wang, and L. Zhang, “Overview of deep learning,” Proc. - 2016 31st Youth Acad. Annu. Conf. Chinese Assoc. Autom. YAC 2016, vol. 376, no. Sschd, pp. 159–164, 2017, doi: 10.1109/YAC.2016.7804882.

[17] J. Gupta, S. Pathak, and G. Kumar, “Deep Learning (CNN) and Transfer Learning: A Review,” J. Phys. Conf. Ser., vol. 2273, no. 1, pp. 0–10, 2022, doi: 10.1088/1742-6596/2273/1/012029.

[18] A. Dubey and A. Rasool, “Usage of deep learning in recent applications,” Arch. Mater. Sci. Eng., vol. 115, no. 2, pp. 46–57, 2022, doi: 10.5604/01.3001.0016.0752.

[19] P. Chhabra and S. Goyal, “A Thorough Review on Deep Learning Neural Network,” 2023 Int. Conf. Artif. Intell. Smart Commun. AISC 2023, pp. 220–226, 2023, doi: 10.1109/AISC56616.2023.10085166.

[20] H. Abbasimehr, M. Shabani, and M. Yousefi, “An optimized model using LSTM network for demand forecasting,” Comput. Ind. Eng., vol. 143, no. July 2019, p. 106435, 2020, doi: 10.1016/j.cie.2020.106435.

[21] E. Chodakowska, “ARIMA Models in Electrical Load Forecasting and Their,” vol. 14, no. 23, p. 7952, 2021.

[22] H. J. S and M. M. Raju, “A Study on Deep Learning,” Int. J. Res. Appl. Sci. Eng. Technol., vol. 10, no. 11, pp. 961–964, 2022, doi: 10.22214/ijraset.2022.47486.

[23] F. V. Atabay, R. M. Pagkalinawan, S. D. Pajarillo, A. R. Villanueva, and J. V. Taylar, “Multivariate Time Series Forecasting using ARIMAX, SARIMAX, and RNN-based Deep Learning Models on Electricity Consumption,” 3rd Int. Informatics Softw. Eng. Conf. IISEC 2022, pp. 1–6, 2022, doi: 10.1109/IISEC56263.2022.9998301.

[24] A. V. Abraham, P. Sasidharan, S. J. S. Tejas, M. Manohara, R. Muthu, and R. C. Naidu, “Predicting Energy Consumption Using LSTM and CNN Deep Learning Algorithm,” 2022 7th Int. Conf. Environ. Friendly Energies Appl. Renew. Sustain. Energy Syst. Hybrid Transp. Syst.

Energy Transition, Energy Secur. EFEA 2022 - Proc., pp. 1–6, 2022, doi: 10.1109/EFEA56675.2022.10063818.

[25] D. T. Cotfas, P. A. Cotfas, M. P. Oproiu, and P. A. Ostafe, "Analytical versus Metaheuristic Methods to Extract the Photovoltaic Cells and Panel Parameters," Int. J. Photoenergy, vol. 2021, no. i, 2021, doi: 10.1155/2021/3608138.

[26] B. U. Islam, M. Rasheed, and S. F. Ahmed, "Review of Short-Term Load Forecasting for Smart Grids Using Deep Neural Networks and Metaheuristic Methods," Math. Probl. Eng., vol. 2022, 2022, doi: 10.1155/2022/4049685.

[27] A. Adhi, N. Siswanto, and B. Santosa, "Hybrid Metaheuristic for Solving Maritime Inventory Routing Problem in Bulk Product Transportation," Int. J. Intell. Eng. Syst., vol. 16, no. 2, pp. 361–374, 2023, doi: 10.22266/IJIES2023.0430.29.

[28] R. Ihsan, S. K. Khurshid, M. Shoaib, S. Ali, S. Mahnoor, and S. M. Hamza, "A technique to forecast Pakistan's news using deep hybrid learning model," Int. J. Inf. Technol., pp. 1–22, 2024, doi: 10.1007/s41870-024-01781-6.

[29] X. Wang and W. Ma, "A hybrid deep learning model with an optimal strategy based on improved VMD and transformer for short-term photovoltaic power forecasting," Energy, vol. 295, p. 131071, 2024, doi: https://doi.org/10.1016/j.energy.2024.131071.

[30] N. Ahmed, M. Assadi, and Q. Zhang, "Investigating the impact of borehole field data's input parameters on the forecasting accuracy of multivariate hybrid deep learning models for heating and cooling," Energy Build., vol. 301, p. 113706, 2023, doi: https://doi.org/10.1016/j.enbuild.2023.113706.

[31] T. Y. Kim and S. B. Cho, "Predicting residential energy consumption using CNN-LSTM neural networks," Energy, vol. 182, pp. 72–81, 2019, doi: 10.1016/j.energy.2019.05.230.

[32] Z. A. Khan, T. Hussain, A. Ullah, S. Rho, M. Lee, and S. W. Baik, "Towards efficient electricity forecasting in residential and commercial buildings: A novel hybrid CNN with a LSTM-AE based framework," Sensors (Switzerland), vol. 20, no. 5, pp. 1–16, 2020, doi: 10.3390/s20051399.

[33] N. Khan, I. U. Haq, S. U. Khan, S. Rho, M. Y. Lee, and S. W. Baik, "DB-Net: A novel dilated CNN based multi-step forecasting model for power consumption in integrated local energy systems," Int. J. Electr. Power Energy Syst., vol. 133, no. July 2020, p. 107023, 2021, doi: 10.1016/j.ijepes.2021.107023.

[34] M. Aouad, H. Hajj, K. Shaban, R. A. Jabr, and W. El-Hajj, "A CNN-Sequence-to-Sequence network with attention for residential short-term load forecasting," Electr. Power Syst. Res., vol. 211, no. February, p. 108152, 2022, doi: 10.1016/j.epsr.2022.108152.

[35] D. G. da Silva and A. A. de M. Meneses, "Comparing Long Short-Term Memory (LSTM) and bidirectional LSTM deep neural networks for power consumption prediction," Energy Reports, vol. 10, no. September, pp. 3315–3334, 2023, doi: 10.1016/j.egyr.2023.09.175.

[36] R. Yashaswini and S. Vinay, "Improved Energy Consumption Prediction using XGBoost with Hyperparameter tuning," 4th Int. Conf. Emerg. Res. Electron. Comput. Sci. Technol. ICERECT 2022, no. 3, pp. 1–3, 2022, doi: 10.1109/ICERECT56837.2022.10060356.

[37] R. Olu-Ajayi, H. Alaka, I. Sulaimon, F. Sunmola, and S. Ajayi, "Building energy consumption prediction for residential buildings using deep learning and other machine learning techniques," J. Build. Eng., vol. 45, no. October 2021, p. 103406, 2022, doi: 10.1016/j.jobe.2021.103406.

[38] 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," IEEE Access, vol. 9, pp. 31191–31212, 2021, doi: 10.1109/ACCESS.2021.3060290.

[39] N. Tsalikidis, A. Mystakidis, C. Tjortjis, P. Koukaras, and D. Ioannidis, Energy load forecasting: one-step ahead hybrid model utilizing ensembling, vol. 106, no. 1. Springer Vienna, 2024. doi: 10.1007/s00607-023-01217-2.

[40] Y. Eren and İ. Küçükdemiral, "A comprehensive review on deep learning approaches for short-term load forecasting," Renew. Sustain. Energy Rev., vol. 189, no. April 2023, 2024, doi: 10.1016/j.rser.2023.114031.

[41] Z. Lin, L. Cheng, and G. Huang, "Electricity consumption prediction based on LSTM with attention mechanism," IEEJ Trans. Electr. Electron. Eng., vol. 15, no. 4, pp. 556–562, 2020, doi: 10.1002/tee.23088.

[42] D. Vasenin, M. Pasetti, S. Rinaldi, P. Golovinski, and N. Savvin, "Long-Term Electrical Energy Forecasting of the Residential Sector Using the LSTM Model: The Italian Use Case," 2023 Int. Conf. Futur. Energy Solut. FES 2023, pp. 1–6, 2023, doi: 10.1109/FES57669.2023.10182653.

[43] R. Panigrahi, N. R. Patne, S. Pemmada, and A. D. Manchalwar, "Prediction of Electric Energy Consumption for Demand Response using Deep Learning," 2022 Int. Conf. Intell. Controll. Comput. Smart Power, ICICCSP 2022, pp. 1–6, 2022, doi: 10.1109/ICICCSP53532.2022.9862353.

[44] F. L. C. da Silva, K. da Costa, P. C. Rodrigues, R. Salas, and J. L. López-Gonzales, "Statistical and Artificial Neural Networks Models for Electricity Consumption Forecasting in the Brazilian Industrial Sector," Energies, vol. 15, no. 2, pp. 1–12, 2022, doi: 10.3390/en15020588.

[45] A. Irankhah, M. H. Yaghmaee, and S. Ershadi-Nasab, "Optimized short-term load forecasting in residential buildings based on deep learning methods for different time horizons," J. Build. Eng., vol. 84, no. August 2023, pp. 1–18, 2024, doi: 10.1016/j.jobe.2024.108505.

[46] K. Yan, X. Zhou, and J. Chen, "Collaborative deep learning framework on IoT data with bidirectional NLSTM neural networks for energy consumption forecasting," J. Parallel Distrib. Comput., vol. 163, pp. 248–255, 2022, doi: 10.1016/j.jpdc.2022.01.012.

[47] R. Lv, Z. Yuan, B. Lei, J. Zheng, and X. Luo, "Building thermal load prediction using deep learning method considering time-shifting correlation in feature variables," J. Build. Eng., vol. 61, no. May, p. 105316, 2022, doi: 10.1016/j.jobe.2022.105316.

[48] T. N. Dinh, G. S. Thirunavukkarasu, M. Seyedmahmoudian, S. Mekhilef, and A. Stojcevski, "Predicting Commercial Building Energy Consumption Using a Multivariate Multilayered Long-Short Term Memory Time-Series Model," Appl. Sci., vol. 13, no. 13, pp. 1–15, 2023, doi: 10.3390/app13137775.