Techniques for Accurate Forecasting of Household Energy Consumption

Amit Kumar Upadhyay[1], Manoj Varshney[2], Pankaj Kumar Varshney[3]

[1,2]Department of Computer Engineering and Applications, Mangalayatan University, Aligarh, Uttar Pradesh
[2]IITM Janakpuri, GGSIP University, New Delhi
Email:amit505316@gmail.com, manoj.varshney_dcea@mangalayatan.edu.in, pankaj.surir@gmail.com

Received: 15.04.2024 Revised: 22.05.2024 Accepted: 27.05.2024

ABSTRACT
Accurate forecasting of household energy consumption is essential for optimizing energy management, reducing costs, and improving sustainability in residential sectors. This paper explores various techniques employed in the prediction of household energy usage, focusing on both traditional and advanced methods. We examine statistical models, machine learning algorithms, and deep learning approaches, emphasizing their effectiveness, accuracy, and scalability. Specifically, we analyze time-series forecasting models, including Autoregressive Integrated Moving Average (ARIMA), Support Vector Machines (SVM), and Long Short-Term Memory (LSTM) networks, with a focus on their applications in real-world scenarios. Additionally, hybrid models that combine multiple techniques for enhanced forecasting accuracy are discussed. Challenges such as data quality, seasonal variations, and the impact of external factors like weather and socio-economic trends are also addressed. Finally, the paper outlines current trends and future directions in the field, highlighting the potential of AI-driven approaches to achieve more precise and dynamic energy consumption forecasts. The findings aim to provide valuable insights for researchers, policymakers, and industry professionals working toward more efficient energy systems and informed decision-making in the residential energy sector.

Keywords: Long Short-Term Memory (LSTM), Energy Consumption Forecasting, Household Energy Usage, Energy forecast, Metric Evaluation Performance

1. INTRODUCTION

In the modern world, reducing the gap between energy production and consumption is a challenging task. A workable solution to this problem is to use electricity efficiently. A lot of work has been done by researchers to create cost-effective and efficient energy consumption strategies. Energy consumption forecasting is one of the most important applications of artificial intelligence (AI). It is highly helpful in building smart cities and supporting the deployment of smart grids[1]. Here's a rephrased version of your paragraph:

Storing excess energy presents a significant challenge. Accurate and efficient energy consumption forecasting (ECF) plays a crucial role in minimizing energy waste. As part of the advanced metering infrastructure (AMI) initiative for smart grid development, ECF of individual household energy usage has gained increasing attention, primarily due to the highly volatile nature of time-series data influenced by human behaviors. Traditional methods, such as physical model-based approaches, often struggle to make accurate predictions in such dynamic and complex scenarios[10]. In contrast, along with the fast development of AI, deep learning technologies, such as the long short term memory neural networks, have been widely applied to the ECF problem for individual households.

Predictive techniques for energy demand in buildings can be broadly categorized into two types: white-box models and black-box models. White-box models are physics-based approaches that require expertise in building systems. These models rely on building energy simulation software and detailed physical rules, along with specific building data, to generate electrical load predictions. In contrast, black-box models, or data-driven models, identify correlations between electrical load and historical data without requiring physical details about the building. Instead, they rely on ample historical data for accurate forecasting. Recent research has increasingly focused on improving the accuracy of energy demand predictions, whether through white-box or black-box models. While white-box models are critical for calculating and analyzing building energy loads, they have been widely adopted due to their ability to simulate the physical characteristics of buildings in detail.

In the proposed model, a hybrid deep learning approach is developed to predict energy consumption for individual households. The XGBoost model is first employed to extract key features from the raw data, after which the data is divided into several subsets. These subsets are then fed into a parallel Long Short-Term Memory (PLSTM) network, which consists of multiple LSTM neural networks. Each LSTM network processes one subset independently, with all networks working in parallel to generate forecasts for their respective subsets. The final energy consumption forecast (ECF) is obtained by combining the results from all the LSTM networks.

In summary, a hybrid data-driven energy consumption forecasting (ECF) model will be designed and implemented using XGBoost in combination with a PLSTM structure. The hybrid model will be trained on the data, followed by testing to evaluate its performance. The effectiveness of the proposed system will be assessed using various evaluation metrics, including MAE, MAPE, and RMSE.

2. LITERATURE SURVEY

Time series prediction methods are generally classified into model-based and data-driven (AI-based) approaches [14]. Data-driven techniques, such as Long Short-Term Memory (LSTM) neural networks and Convolutional Neural Networks (CNNs), have been identified as particularly effective for energy consumption forecasting [15]. Data-driven models are typically categorized into two types: singular models and hybrid models. Singular models include decision trees [21], random forests [22], and LSTM networks [27], while hybrid models combine multiple singular models to improve prediction accuracy and performance.

The author proposes a method for solving the day-ahead hourly building load forecasting problem [37]. This approach combines a self-organizing map (SOM) with a clustering technique and subsequently applies a stacking ensemble learning method (SELM). This method seeks to address the issue of overfitting, which can arise due to the reduced number of samples after clustering. Overfitting is particularly likely when the original dataset is small, especially in the case of smaller systems like buildings, leading to a high generalization error. However, the study has certain limitations: the hyperparameters were determined manually, which may not be optimal, and the techniques used within the SELM were also selected based on experimental results.

The author states that Support Vector Machine (SVM) and Extreme Gradient Boosting (XGBoost) models outperformed selected empirical models for estimating daily global solar radiation (H) using both complete and incomplete temperature and precipitation data in humid subtropical climates [38]. The XGBoost model demonstrated prediction accuracy comparable to the SVM model, while also offering greater stability and computational efficiency. In humid subtropical regions of China, the XGBoost model is highly recommended for estimating daily H, as it provides strong performance in terms of accuracy, stability, and efficiency.

The author used sliding window-based PCR in [39] to create a model that combined many STLF models. The model that used a seven-day window size and PC 1 performed exceptionally well in terms of prediction. The combination of STLF models utilizing a stacking ensemble approach is referred to by the author as the COSMOS model. But the proposed model does not satisfactorily predict the building electric energy consumption on weekends and it is applied only to a single building. Therefore, additional validation of the applicability of our forecasting model is needed.

In [40], author proposed a spatial and temporal ensemble electric consumption model involving clustering analysis to provide a solution for short-term electric consumption forecasting. This proposed work involves exploring electric consumption profiles at the apartment level through cluster analysis based on the k-means algorithm. The ensemble forecasting model consists of two deep learning models; Long Short-Term Memory Unit (LSTM) and Gated Recurrent Unit (GRU). LSTM-GRU are grouped to form anensemble to improve the prediction accuracy and decrease the generalization error as much as possible. Aggregating consumption at spatial scales of building and floor yields improved prediction accuracy. While the forecasting error rises as we go farther from hourly to weekly scales. The limitation of this model is that clustering the consumption profiles at the apartment level further decreased the forecasting error compared to without clustering.

In [41], the author proposes a model that combines the eXtreme Gradient Boosting Machine (XGB), Light Gradient Boosting Machine (LGBM), and Multi-Layer Perceptron (MLP). The inner workings of this Stacked XGB-LGBM-MLP model involve generating meta-data from the XGB and LGBM models, which are then used by the MLP network to compute the final predictions. This technique is sensitive to two factors: the forecasting horizon and the dataset size. A noted limitation of the study is that the Stacked XGB-LGBM-MLP model's performance declines for 48-hour-ahead forecasts.

In [42], a novel energy demand prediction method for neighborhoods was presented based on ensemble learning. The stacking ensemble was evaluated using artificial neural networks and random forest algorithm. New features were added to increase the accuracy and reproducibility of the models. This approach performs significantly better than single algorithms and other ensemble learning algorithms with fewer data points and can be trained very fast as the dataset is split further into small chunks. With the large-scale rollout of smart meter installation, the method proposed in this study can help energy providers to project the overall energy usage easily with less data and evaluate adequate energy-saving approaches.

A novel ensemble method is introduced for forecasting residential electricity demand. The proposed method, an improved coupled generative adversarial stacked auto-encoder (ICoGASA), utilizes three generative adversarial networks (GANs) to better capture error patterns in weather forecasts and variations in resident lifestyles, while reducing noise [43]. Each of the three GANs consists of two deep belief networks (DBNs) serving as the generator and discriminator, respectively. The outputs from the three discriminators are combined using a memristor array (MA), and the final integrated outputs of the ICoGASA are further processed by a self-organizing map (SOM), with SOM input weights optimized by the MA and a new weight update strategy (WUS). This ensemble method demonstrates superior performance in forecasting electricity demand for both regular and special days (such as weekends and holidays). However, the method is limited to handling a maximum of 5 years of training data, and the DBN weights are not optimized to save computational time. To improve efficiency, a more suitable, time-efficient optimization algorithm is recommended for DBN weight tuning.

The researcher proposes a model based on ensemble learning to address the short-term load forecasting problem. This model utilizes three base learning methodsregression trees based on Evolutionary Computation, Random Forest, and Artificial Neural Networksto generate final predictions [44]. By combining predictions from these individual methods, this ensemble approach to short-term electricity consumption forecasting aims to produce more accurate results by leveraging the strengths of each base learner.

A model was developed for Short Term Load Forecasting using XGBoost. This model transforms daily load data into weekly data to enhance feature options for predicting load based on lagged variables [45]. XGBoost is employed both for feature selection from the transformed data and for training the model to forecast load. While the XGBoost-based load forecast generally aligns well with the actual load, its accuracy tends to decrease with larger load values.

From a survey of the literature, the hybrid models generally produce higher prediction accuracy than the singular model. In [28], author utilizes coupling SSA and least square SVM for ECF. Yan et al. [29] claimed that the LSTM neural network has the better performance capturing the dependencies among data samples compared to SVM. Wei et al. [30] proposed a hybrid model combining ISSA and LSTM predicting daily natural gas consumption, but the author focuses on the superiority of the model in different climate zone instead of different time span. Meanwhile, we are fully aware that data decomposition plays a significant role for forecasting result improvement. Sun et al. [31] decomposed the economic factors for energy consumption forecasting.

Forecasting techniques are generally categorized into four types: very short-term (within 24 hours), short-term (one day to a month), mid-term (one month to a year), and long-term (over a year). The rapid advancement of artificial intelligence (AI) technology has created effective short-term forecasting solutions for time series data, offering advantages over traditional methods like physical simulation modelsical analysis , and reodels . Various modern es are applied to short-term forecasting, including deep learning neural networks, support vector machines (SVM), artificial neural networks (ANNs), and extreme learning machines (ELM). For example, Benali et al. compared smart persistence,l neural networks (ANNs), and random forests (RF) to predict normal beam, horizontal diffuse, and global components of solar irradiance. Their findings show that machine learning-based models outperform conventional forecasting methods, even under highly variable solar conditions, such as those in spring and autumn. To forecast short- to medium-term aggregate load, Bouktif et al. combined the genetic algorithm (GA) raditional LSTM neural network.

The demand for more accurate and timely forecasting methods has driven a shift from long-term to extremely short-term forecasting, a domain well-suited to the strengths of deep learning and machine learning technologies. Yan et al. [34] developed a hybrid deep learning approach to predict power consumption every five minutes, combining a CNN with an LSTM neural network. By applying a multi-step forecasting technique introduced in the same study, these predictions were extended to cover a half-hour interval.

To forecast electricity consumption in the very short term, Kim et al. [20] proposed a hybrid model that combines CNN and (c, l)-LSTM. The input sequence comprises multiple [Key, Context] pairs, where the key value represents power demand, and context values include seasonality, humidity, and other relevant statistics. Kong et al. [12], [13] considered residents' behavior patterns, designing distinct LSTM neural network architectures for various household loads, but found that a single LSTM neural network did not achieve satisfactory prediction accuracy. To improve this, Ospina et al. [16] used an ensemble of LSTM networks to estimate power output for a PV facility over 30-minute intervals. Similarly, Liu et al. [26] combined discrete wavelet transform (DWT) with short-term forecasting (15 minutes) to predict fluctuations in wind power.

Yuan et al. [32] proposed using SSA and WNN to forecast building electricity load; however, their study does not examine forecasting performance across different time horizons. Yan et al. [29] employed ECF at various time intervals and used SWT to decompose the original data. However, SWT-based data decomposition may have limited applicability, as it tends to isolate Gaussian noise rather than filter out impulse noise. In contrast, singular spectrum analysis (SSA) provides effective denoising by separating noise from high signal-to-noise ratio time series and also removes Gaussian noise. Neeraj et al. [33] proposed an SSA-LSTM approach for forecasting in a power load dataset.

In [47], a novel approach is introduced for addressing short-term load forecasting (STLF) in buildings. This method combines bilateral long short-term memory (BiLSTM), convolutional neural networks (CNN), and grey wolf optimization (GWO) to form a hybrid GWO–CNN–BiLSTM model. The goal is to optimize STLF by using GWO to determine the best parameter set for training the CNN and BiLSTM algorithms. The one-dimensional CNN is particularly effective at capturing features from time series data. To assess the effectiveness of this approach, the study uses hourly resolution data from four buildings, each with distinct characteristics. The results clearly demonstrate that the proposed method can be successfully applied to various building types. The study compares the performance of this method against other advanced techniques, evaluating forecast periods of one day, two days, and one week. The findings highlight that the GWO–CNN–BiLSTM model outperforms CNN-LSTM, CNN-BiLSTM, optimized BiLSTM, and traditional LSTM and BiLSTM methods in terms of both accuracy and predictive capability.

In reference [48], the study presents a method for forecasting electricity consumption that combines empirical mode decomposition (EMD) with bidirectional LSTM (BI-LSTM). EMD is a robust tool for analyzing time-frequency patterns and preprocessing signals, separating the time series into distinct components at different resolutions. The proposed model is designed to predict electricity usage over a 24-hour period with 15-minute intervals by extracting stationary component sequences from the original stochastic electricity usage data, known as Intrinsic Mode Functions (IMFs). A hybrid BI-LSTM model is used to forecast each IMF, and the predictions of all components are then aggregated to provide the final forecast. To validate the choice of signal processing and predictive methods, the study performs two comparative analyses.

This research presents a machine learning-based model designed to improve the accuracy of predicting heating energy usage in residential buildings [49].The study explores a wide range of factors, including architectural features, demographic variables, and external temperature conditions, as key determinants of residential heating energy consumption. To tackle this issue, Support Vector Regression (SVR) is chosen as the primary framework. SVR is then hybridized with six meta-heuristic algorithms to optimize and fine-tune its hyperparameters. A comparative analysis is conducted to assess the performance and accuracy of the proposed method against various hybrid models, using a detailed case study. The results highlight the effectiveness of the proposed method in accurately forecasting heating energy consumption in residential buildings. Among the hybrid models examined, the SVR-Battle Royale Optimization model stands out as the top performer.

This study introduces a novel framework for time-series clustering, incorporating a multi-step time-series sequence-to-sequence (Seq2Seq) approach utilizing long short-term memory (LSTM) networks for accurate load forecasting in households [50]. The primary focus centers on the development of a clustering-based Seq2Seq LSTM model tailored for electricity load forecasting. This model addresses the intricacies of energy consumption prediction, where historical data encompassing individual appliances and aggregate energy usage within households are integrated into the model's information input. The initial dataset undergoes preprocessing before being fed into a multi-step time-series learning model. This model not only accelerates the training process but also ensures the model's convergence for precise energy forecasting. The study goes on to present simulation results that highlight the accuracy and efficacy of the proposed model. These results are obtained through validation and testing of cluster data, showcasing the promising potential of the predictive model put forth in this study.

In reference [51], a comparative analysis is undertaken among three distinct machine learning algorithms: Long Short-Term Memory (LSTM), the Gated Recurrent Unit (GRU), and the Drop-GRU. The objective of this study is to devise a time series power forecasting technique. Particularly, the LSTM neural network is emphasized as the preferred choice within this study to forecast future load consumption and preempt consumption spikes. In order to comprehensively assess the efficacy of this methodology, a series of experiments are conducted using actual power consumption data. The experimental outcomes, spanning various time horizons, consistently reveal that the LSTM model outperforms both the GRU and Drop-GRU forecasting methods. This superiority is characterized by fewer prediction errors and enhanced precision. Consequently, the predictions generated through the LSTM approach offer the potential for proactive decision-making and facilitating load shedding 11 measures in scenarios where consumption surpasses authorized thresholds. Such proactive actions can significantly influence the planning of power quality and the maintenance of power infrastructure.

In reference [52], author introduces a novel CNN-LSTM model, employing a multifaceted augmentation technique, to effectively address the binary classification of electricity loads, weather observations, and national metrics such as gross domestic product, imports, and exports. This approach leverages 1D convolution and pooling operations to uncover latent patterns within temporal sequences. By incorporating LSTM, the model overcomes the challenges of vanishing gradients that often hinder traditional RNNs, while retaining the advantages associated with handling time-series data. The proposed model stands out by achieving nearly flawless electricity consumption forecasting, surpassing the performance of existing models in this domain. Furthermore, this study extend the analysis to a state-level perspective and conduct comprehensive training, underscoring the applicability of our proposed methodology in accurately predicting regional energy consumption patterns.

In reference [53], author performs a comprehensive evaluation of contemporary forecasting methods, including classical methods, clustering-based methods, AI-based methods, and time series-based methods, and presents an analysis of their performance and outcomes. Finding the best LF approach for particular SG applications is the goal of this paper. The results reveal that compared to other methods, AI-based LF techniques using ML and neural network (NN) models had the best forecast performance, reaching higher average root mean squared (RMS) and mean absolute percentage error (MAPE) values.

In this proposed system, a hybrid model that combines XGBoost with multiple LSTM neural networks is introduced. During the data pre-processing phase, XGBoost is used for feature extraction and to divide the original data into subsets. In the model training phase, parallel LSTM networks are employed, with the number of LSTMs corresponding to the number of subsequences after decomposition. The LSTM neural network is particularly effective at handling non-linear and non-stationary time series, which is important given the large fluctuations in the original dataset. LSTM is also capable of capturing the long-term dependencies in the original ECF time series. As a result, the final predictions from the proposed method are expected to be more accurate than those of existing state-of-the-art methods.

3. METHODOLOGY

Here are some steps and techniques typically involved in forecasting household energy consumption:

i. Data Collection: Collect historical energy consumption data for the household, including daily or hourly usage values over a long period. Additionally, gather relevant information such as weather conditions, seasonal trends, and special events (e.g., holidays) to enhance the accuracy of the forecasts.

ii. Data Pre-processing: Clean and preprocess the collected data by addressing missing values, outliers, and any inconsistencies. Normalize the data to ensure all features are on a consistent scale, which improves the performance of the forecasting models.

iii. Feature Engineering: Generate additional features from the data that could offer valuable insights for the forecasting models. For instance, you could create features such as the day of the week, time of day, holidays, or even the number of occupants in the household, if that information is accessible.

4. Evaluation Metrices

The efficacy of our suggested prediction model was assessed using a variety of criteria. Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) are the three metrics that are most frequently employed to quantify prediction accuracy [8][29].

i. MAE

The MAE is used in statistics to quantify how close closed forecasts or predictions are to specific results. To compute it, take the absolute mean of the differences between the predicted and actual values that were determined. As stated in (1), the MAE is defined.

$$MAE = \frac{1}{n} \sum_{t=1}^{n} |A_t - P_t| \quad (1)$$

where,

n = number of non-missing data points

A_t = Actual observations for t^{th} data

P_t = Predicted Value for t^{th} data

ii. MAPE

In statistics, the MAPE is used to anticipate how accurate a forecasting methodology would be when building fitted statistic values, particularly in trend estimation. It consistently presents accuracy as a percentage of error. Since this range may be expressed as a percentage, it might be simpler to understand than the statistics on the other hand. The outline of the MAPE is provided in (2).

$$MAPE = \frac{100}{n} \sum_{t=1}^{n} \left| \frac{A_t - P_t}{A_t} \right| \quad (2)$$

where,
n = number of non-missing data points
A_t = Actual observations for t^{th} data
P_t = Predicted Value for t^{th} data

iii. RMSE

RMSE is the standard deviation of the prediction errors. RMSE define how concentrated the data is around the line of best fit. The RMSE is defined as shown in (3).

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n} (A_t - P_t)^2}{n}} \quad (3)$$

where,
n = number of non-missing data points
A_t = Actual observations for t^{th} data
P_t = Predicted Value for t^{th} data

5. CONCLUSION

In conclusion, accurate forecasting of household energy consumption is crucial for optimizing energy usage, reducing costs, and promoting sustainable practices. A variety of techniques, ranging from traditional statistical models to advanced machine learning and hybrid approaches, have been explored to enhance prediction accuracy. Methods such as Support Vector Regression (SVR), Long Short-Term Memory (LSTM) networks, and hybrid models combining multiple algorithms, like XGBoost with LSTM, have proven effective in capturing complex patterns in energy consumption data. Additionally, incorporating external factors such as weather conditions, seasonal trends, and household characteristics further improves the robustness of these forecasting models. While there are challenges in handling non-stationary and non-linear data, advancements in AI and machine learning continue to offer promising solutions, paving the way for more reliable, efficient, and adaptive energy consumption forecasts in households.

REFERENCES

[1] Q. Xiao, Y. Si, “Time series prediction using graph model”, 2017 3rd IEEE international conference on computer and communications (ICCC), IEEE, 2017.
[2] N. Amjady, “Short-term hourly load forecasting using time-series modeling with peak load estimation capability”, IEEE Trans. Power Syst., vol. 16, no. 3, pp. 498-505, Aug. 2001.
[3] L. Benali, G. Notton, A. Fouilloy, C. Voyant, and R. Dizene, “Solar radiation forecasting using artificial neural network and random forest methods: Application to normal beam, horizontal diffuse and global components'', Renew Energy, vol. 132, pp. 871-884, Mar. 2019.
[4] A. H. Neto and F. A. S. Fiorelli, “Comparison between detailed model simulation and artificial neural network for forecasting building energy consumption”, Energy Buildings, vol. 40, no. 12, pp. 2169-2176, 2008.
[5] S. Bouktif, A. Fiaz, A. Ouni and M. A. Serhani, “Optimal deep learning LSTM model for electric load forecasting using feature selection and genetic algorithm: Comparison with machine learning approaches”, Energies vol. 11, no. 7, p. 1636, Jun. 2018.
[6] Fabiano Pallonetto, Changhong Jin and Eleni Mangina, “Forecast electricity demand in commercial building with machine learning models to enable demand response programs”, Energy and AI 7 (2022) 100121, https://doi.org/10.1016/j.egyai.2021.100121.
[7] Bangru Xiong, Lu Lou, Xinyu Meng, Xin Wanga, Hui Ma and Zhengxia Wang, “Short-term wind power forecasting based on Attention Mechanism and Deep Learning”, Electric Power Systems Research 206 (2022) 107776, https://doi.org/10.1016/j.epsr.2022.107776

[8] N. Wei, C. Li, X. Peng, F. Zeng, X. Lu, "Conventional models and artificial intelligence-based models for energy consumption forecasting: A review, J. Petrol. Sci. Eng. 181 (2019) 106187, https://doi.org/10.1016/j.petrol.2019.106187.
[9] Waqas Khan, Shalika Walker and Wim Zeiler, "Improved solar photovoltaic energy generation forecast using deep learning-based ensemble stacking approach", Energy 240 (2022) 122812, https://doi.org/10.1016/j.energy.2021.122812.
[10] X. Lü, T. Lu, C.J. Kibert, M. Viljanen, "Modeling and forecasting energy consumption for heterogeneous buildings using a physical–statistical approach", Appl. Energy 144 (2015) 261–275.
[11] H. Zhou, Q. Liu, K. Yan, Y. Du, "Deep Learning Enhanced Solar Energy Forecasting with AI-Driven IoT", Wireless Communications and Mobile Computing, 2021, 2021.
[12] W. Kong, Z. Y. Dong, D. J. Hill, F. Luo, and Y. Xu, "Short-term residential load forecasting based on resident behaviour learning", IEEE Trans. Power Syst., vol. 33, no. 1, pp. 1087-1088, Jan. 2018.
[13] W. Kong, Z. Y. Dong, Y. Jia, D. J. Hill, Y. Xu, and Y. Zhang, "Short-term residential load forecasting based on LSTM recurrent neural network", IEEE Trans. Smart Grid, vol. 10, no. 1, pp. 841-851, Sep. 2017.
[14] V.G. Tran, V. Debusschere, S. Bacha, "One week hourly electricity load forecasting using Neuro-Fuzzy and Seasonal ARIMA models", IFAC Proc. Vol. 45 (21) (2012) 97–102.
[15] Ping-Huan Kuo and Chiou-Jye Huang, "A High Precision Artificial Neural Networks Model for Short-Term Energy Load Forecasting", Energies 2018, 11, 213; doi:10.3390/en11010213.
[16] J. Ospina, A. Newaz, and M. O. Faruque, "Forecasting of PV plant output using hybrid wavelet-based LSTM-DNN structure model", IET Renew. Power Gener., vol. 13, no. 7, pp. 1087-1095, May 2019.
[17] R. Jozefowicz, W. Zaremba, and I. Sutskever, "An empirical exploration of recurrent network architectures", in Proc. Int. Conf. Mach. Learn., 2015, pp. 2342-2350.
[18] Ning Jin, Fan Yang, Yuchang Mo, Yongkang Zeng, Xiaokang Zhou, Ke Yan and Xiang Ma, "Highly accurate energy consumption forecasting model based on parallel LSTM neural networks", Advanced Engineering Informatics 51 (2022) 101442, https://doi.org/10.1016/j.aei.2021.101442.
[19] Hongfang Lu, Feifei Cheng, Xin Ma and Gang Hu, "Short-term prediction of building energy consumption employing an improved extreme gradient boosting model: A case study of an intake tower" Energy 203 (2020) 117756, https://doi.org/10.1016/j.energy.2020.117756
[20] M. Kim, W. Choi, Y. Jeon, and L. Liu, "A hybrid neural network model for power demand forecasting,'' Energies, vol. 12, no. 2, p. 931, 2019.
[21] Y.-Y. Song, L.U. Ying, "Decision tree methods: applications for classification and prediction", Shanghai Arch. Psychiatry 27 (2) (2015) 130.
[22] A.J. Hill, G.R. Herman, R.S. Schumacher, "Forecasting severe weather with random forests", Mon. Weather Rev. 148 (5) (2020) 2135–2161.
[23] Y.-S. Lee and L.-I. Tong, "Forecasting time series using a methodology based on autoregressive integrated moving average and genetic programming", Knowl.-Based Syst., vol. 24, no. 1, pp. 66-72, 2011.
[24] Pratima Kumari and Durga Toshniwal, "Extreme gradient boosting and deep neural network based ensemble learning approach to forecast hourly solar irradiance" Journal of Cleaner Production 279 (2021) 123285, https://doi.org/10.1016/j.jclepro.2020.123285.
[25] K. Liu, S. Subbarayan, R. R. Shoults, M. T. Manry, C. Kwan, F. I. Lewis, and J. Naccarino, "Comparison of very short-term load forecasting techniques", IEEE Trans. Power Syst., vol. 11, no. 2, pp. 877-882, May 1996.
[26] Y. Liu, L. Guan, C. Hou, H. Han, Z. Liu, Y. Sun, and M. Zheng, "Wind power short-term prediction based on LSTM and discrete wavelet transform", Appl. Sci., vol. 9, no. 2, p. 1108, 2019.
[27] F. Altch´e, A. de La Fortelle, "An LSTM network for highway trajectory prediction", 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC), IEEE, 2017.
[28] Q.B. Pham, T.-C. Yang, C.-M. Kuo, H.-W. Tseng, P.-S. Yu, "Coupling Singular Spectrum Analysis with Least Square Support Vector Machine to Improve Accuracy of SPI Drought Forecasting", Water Resour. Manage. 35 (3) (2021) 847–868.
[29] Ke Yan, et al., "A hybrid LSTM neural network for energy consumption forecasting of individual households", IEEE Access 7 (2019) 157633–157642.
[30] N. Wei, C. Li, X. Peng, Y. Li, F. Zeng, "Daily natural gas consumption forecasting via the application of a novel hybrid model", Appl. Energy 250 (2019) 358–368.
[31] T. Sun, T. Zhang, Y. Teng, Z. Chen, J. Fang, "Monthly electricity consumption forecasting method based on X12 and STL decomposition model in an integrated energy system", Mathe. Probl. Eng. 2019 (2019) 1–16.

[32] Z. Yuan, W. Wang, H. Wang, S. Mizzi, "Combination of cuckoo search and wavelet neural network for midterm building energy forecast", Energy 202 (2020) 117728, https://doi.org/10.1016/j.energy.2020.117728.

[33] N. Neeraj, et al., "Long short-term memory-singular spectrum analysis-based model for electric load forecasting", Electr. Eng. (2020) 1–16.

[34] K. Yan, X. Wang, Y. Du, N. Jin, H. Huang, and H. Zhou, "Multi-step short-term power consumption forecasting with a hybrid deep learning strategy", Energies, vol. 11, no. 11, p. 3089, Nov. 2018.

[35] P. Singh and P. Dwivedi, "Integration of new evolutionary approach with artificial neural network for solving short term load forecast problem", Appl. Energy, vol. 217, pp. 537-549, May 2018.

[36] P. J. Werbos, "Backpropagation through time: What it does and how to do it", Proc. IEEE, vol. 78, no. 10, pp. 1550-1560, Oct. 1990.

[37] Jaehyun Lee, Jinho Kim and Woong Ko, "Day-Ahead Electric Load Forecasting for the Residential Building with a Small-Size Dataset Based on a Self-Organizing Map and a Stacking Ensemble Learning Method", Appl. Sci. 2019, 9, 1231; https://doi.org/10.3390/app9061231.

[38] Junliang Fan, Xiukang Wang, Lifeng Wu, Hanmi Zhou, Fucang Zhang, Xiang Yu, Xianghui Lu and Youzhen Xiang, "Comparison of Support Vector Machine and Extreme Gradient Boosting for predicting daily global solar radiation using temperature and precipitation in humid subtropical climates: A case study in China", Energy Conversion and Management 164 (2018) 102–111, https://doi.org/10.1016/j.enconman.2018.02.087.

[39] Jihoon Moona, Seungwon Jung, Jehyeok Rew, Seungmin Rho and Eenjun Hwang, "Combination of short-term load forecasting models based on a stacking ensemble approach", Energy & Buildings 216 (2020) 109921, https://doi.org/10.1016/j.enbuild.2020.109921.

[40] Khan, A.N., Iqbal, N., Rizwan, A., Ahmad, R., Kim, D.H., "An Ensemble Energy Consumption Forecasting Model Based on Spatial-Temporal Clustering Analysis in Residential Buildings", Energies 2021, 14, 3020. https://doi.org/10.3390/en14113020.

[41] Mohamed Massaoudia, Shady S. Refaat, Ines Chihi, Mohamed Trabelsi, Fakhreddine S. Oueslati and Haitham Abu-Rub, "A novel stacked generalization ensemble-based hybrid LGBM-XGBMLP model for Short-Term Load Forecasting", Energy 214 (2021) 118874, https://doi.org/10.1016/j.energy.2020.118874.

[42] Waqas Khan, Shalika Walker, Katarina Katic and Wim Zeiler, "A novel framework for autoregressive features selection and stacked ensemble learning for aggregated electricity demand prediction of neighborhoods", IEEE 978-1-7281-4701-7/20, 2020 .

[43] Guoqiang Zhang and Jifeng Guo, "A novel ensemble method for residential electricity demand forecasting based on a novel sample simulation strategy", Energy 207 (2020) 118265, https://doi.org/10.1016/j.energy.2020.118265.

[44] Federico Divina, Aude Gilson, Francisco Goméz-Vela, Miguel García Torres and José F. Torres, "Stacking Ensemble Learning for Short-Term Electricity Consumption Forecasting", Energies 2018, 11, 949; https://doi.org/10.3390/en11040949.

[45] Raza Abid Abbasi1, Nadeem Javaid, Muhammad Nauman Javid Ghuman, Zahoor Ali Khan, Shujat Ur Rehman and Amanullah, "Short Term Load Forecasting Using XGBoost", WAINA 2019, AISC 927, pp. 1120–1131, 2019, https://doi.org/10.1007/978-3-030-15035-8_108.

[46] Chen T, Guestrin C., "XGBoost: a scalable tree boosting system", Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining. ACM; 2016. p. 785–94.

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

[48] Nada Mounir, Hamid Ouadi , Ismael Jrhilifa, "Short-term electric load forecasting using an EMD-BI-LSTM approach for smart grid energy management system", Energy and Buildings 2023 Volume 288, 113022, https://doi.org/10.1016/j.enbuild.2023.113022.

[49] Hamed Khajavi, Amir Rastgoo, "Improving the prediction of heating energy consumed at residential buildings using a combination of support vector regression and metaheuristic algorithms", Energy 2023 Volume 272, 127069,https://doi.org/10.1016/j.energy.2023.127069.

[50] Masood, Z., Gantassi, R., Ardiansyah, Choi, Y. "A Multi-Step Time-Series ClusteringBased Seq2Seq LSTM Learning for a Single Household Electricity Load Forecasting", Energies 2022, 15, 2623,https://doi.org/10.3390/en15072623.

[51] Mahjoub S., Chrifi-Alaoui L., Marhic B.; Delahoche L., "Predicting Energy Consumption Using LSTM, Multi-Layer GRU and Drop-GRU Neural Networks", Sensors 2022, 22, 4062,https://doi.org/10.3390/s22114062.

[52] Chung J, Jang B, "Accurate prediction of electricity consumption using a hybrid CNNLSTM model based on multivariable data", PLoS ONE 17(11):e0278071, 2022,https://doi.org/10.1371/journal.pone.0278071.
[53] Habbak H., Mahmoud M., Metwally K., Fouda M.M., Ibrahem M.I., "Load Forecasting Techniques and Their Applications in Smart Grids", Energies 2023, 16, 1480.https://doi.org/10.3390/en16031480.