Solar Energy
And Sustainable Development
Refereed, biannual scientific journal issued by:
The Libyan Center for Solar Energy Research and Studies

Forecasting Energy Consumption on a Microgrid Using ARIMA-GRU Model

Lahoucine Oumiguil [1*], Ali Nejmi [2].

[1,2]Laboratory of Automatics, Energy Conversion and Microelectronics (LACEM), Faculty of Sciences and Technics, Sultan Moulay Slimane University, Campus Mghilla, Beni Mellal, Morocco.

E-*mail:* [1]lahoucine.oumiguil@usms.ma ,[2]ali.nejmi@gmail.com .

SPECIAL ISSUE ON:

The 1st International Conference on Sciences and Techniques for Renewable Energy and the Environment.

(STR2E 2025)

May 6-8, 2025 at FST-Al Hoceima-Morocco.

KEYWORDS

ARIMA; GRU; Deep learning; Energy consumption; Microgrid.

ABSTRACT

Accurate forecasting of energy consumption is crucial for the efficient management and control of modern energy grids, particularly amid the escalating integration of renewable energy sources. This study proposes a hybrid approach that combines the Autoregressive Integrated Moving Average (ARIMA) and the Gated Recurrent Unit neural network (GRU) to predict energy consumption in a microgrid setting. The proposed hybrid ARIMA-GRU model integrates ARIMA's residuals with GRU's non-linear modeling capabilities, enabling enhanced prediction accuracy while capturing both linear and non-linear dependencies in microgrid energy data. The model's performance is evaluated using real-world energy consumption data, achieving an RMSE of 38.28 kWh, MAE of 31.24 kWh, and MAPE of 10.29%. These results highlight the model's effectiveness in improving energy forecasting and providing practical insights for better energy management in microgrids.

*Corresponding author.

DOI: https://doi.org/10.51646/jsesd.v14iSTR2E.791

التنبؤ باستهلاك الطاقة في الشبكة الكهربائية الصغيرة باستخدام نموذج ARIMA-GRU

الحسين اوميكيل، علي نجمي.

ملخص: يُعد التنبؤ الدقيق باستهلاك الطاقة أمرًا بالغ الأهمية لإدارة شبكات الطاقة الحديثة والتحكم فيها بكفاءة، لا سيما في ظل تصاعد تكامل مصادر الطاقة المتجددة. تقترح هذه الدراسة نهجًا هجينًا يجمع بين المتوسط المتحرك المتكامل الانحداري الذاتي الانحداري (ARIMA) والشبكة العصبية للوحدة المتجددة المسندة (GRU) للتنبؤ باستهلاك الطاقة في بيئة الشبكات الصغيرة. يدمج نموذج GRU–ARIMA الهجين المقترح بين المتبقي من المتوسط المتحرك الانحداري التلقائي المتكامل (ARIMA) وقدرات النمذجة غير الخطية لوحدة GRU. يتيح هذا النموذج دقة تنبؤ محسّنة مع التقاط الترابطات الخطية وغير الخطية في بيانات طاقة الشبكة المصغرة. تم تقييم أداء النموذج باستخدام بيانات استهلاك الطاقة في العالم الحقيقي، محققًا متوسط خطأ جذر متوسط المربع (RMSE) قدره38 .28 كيلوواط ساعة، ومتوسط خطأ مطلق (MAE) قدره31 .24 كيلوواط ساعة، ومتوسط خطأ النسبة المئوية المطلقة (MAPE) قدره 10.29 %. تسلط هذه النتائج الضوء على فعالية النموذج في تحسين التنبؤ بالطاقة وتوفير رؤى عملية لتحسين إدارة الطاقة في الشبكات الصغيرة.

الكلمات المفتاحية –الكلمات المفتاحية: ARIMA ؛ GRU؛ التعلم العميق؛ استهلاك الطاقة؛ الشبكة الكهربائية الصغيرة.

1. INTRODUCTION

The growing complexity of power systems, driven by factors such as the integration of renewable energy sources, the rise of electric vehicles, and the need for flexible distribution grids, has made accurate energy consumption forecasting more critical than ever before[1]. Recent advancements in machine learning and deep learning techniques have exhibited encouraging outcomes in enhancing the precision of energy forecasting models, with techniques like Long Short-Term Memory (LSTM) and Gated Recurrent Unit networks (GRU) demonstrating superior performance with traditional statistical approaches[2].

Traditional statistical methods such as Autoregressive Integrated Moving Average (ARIMA) have been widely used for time series forecasting due to their simplicity and effectiveness in modeling linear relationships[3]. ARIMA has demonstrated notable success in various applications, including energy demand prediction[4]. However, its inability to capture non-linear patterns and its reliance on stationary data limit its effectiveness for more complex energy datasets[5]. In contrast, machine learning approaches, particularly Support Vector Machines (SVM) and neural networks, have gained traction for their ability to model non-linear dynamics and adapt to diverse data patterns[6]. Among these, deep learning algorithms such as LSTM and GRU have shown superior performance in capturing temporal dependencies and handling sequence data[7], [8].

The integration of traditional statistical techniques and modern machine learning approaches has emerged as a promising solution for energy forecasting challenges. Hybrid models that combine statistical and deep learning techniques, such as ARIMA-GRU or ARIMA-LSTM, leverage the strengths of both methodologies[9,10]. This synergistic approach leverages ARIMA's capability to capture linear trends and temporal patterns, while simultaneously harnessing the non-linear modeling capacity of deep learning models[11]. This hybrid framework has been demonstrated to enhance the accuracy of energy forecasts[12], particularly for complex and volatile energy consumption datasets, making it a highly suitable technique for microgrid energy forecasting applications[13].

Recent studies have highlighted the potential of hybrid models in addressing the challenges of energy forecasting[14]. For example, ARIMA-LSTM models have demonstrated improved performance over standalone models in predicting renewable energy outputs[15], while ARIMA-GRU hybrids have been noted for their computational efficiency and accuracy[16]. However, research specifically focused on using the ARIMA-GRU hybrid approach for energy consumption forecasting in microgrids remains limited, creating a gap that this study aims to address[17]. This paper proposes an ARIMA-GRU hybrid model for forecasting energy consumption in a microgrid. By combining ARIMA's ability to model linear trends with GRU's capacity to capture non-linear dependencies, the model aims to enhance prediction accuracy and reliability. The approach is validated using real-world energy consumption data and benchmarked against standalone models such as ARIMA, SVM, GRU, and LSTM, as well as other hybrid techniques like ARIMA-LSTM. The findings contribute to the growing knowledge on energy forecasting and provide practical insights for improving energy management in microgrids.

2. MATERIALS & METHODS

This study employs a hybrid ARIMA-GRU model to forecast energy consumption, leveraging the strengths of both linear statistical models and deep learning techniques. The ARIMA model is first applied to identify and predict the linear trends and temporal patterns in the time series data. The residuals, representing the nonlinear components not captured by ARIMA, are then modeled using a GRU neural network. The GRU model is trained on lagged sequences of the ARIMA residuals to learn complex temporal dependencies. Finally, The forecasts from the ARIMA and GRU models are integrated to produce the final prediction. This approach harnesses ARIMA's ability to model linear relationships and GRU's capacity to handle nonlinear patterns, providing a robust solution for energy consumption prediction. The model performance is evaluated using standard metrics, including Mean Absolute Error, Root Mean Squared Error, and Mean Absolute Percentage Error, which validate the reliability of the results. The methodology is illustrated in Figure 1 as a series of sequential phases. Table 1 encompasses the different abbreviations used in this paper.

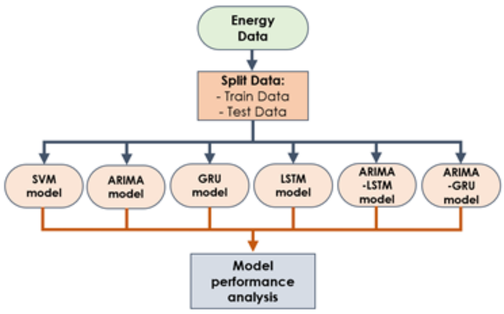

Figure 1. architecture of proposed method.

Table 1. Abbreviations meaning.

Abbreviations	Definition
ARIMA	Autoregressive Integrated Moving Average
GRU	Convolutional Neural Network
LSTM	Long-Short Term Memory
SVM	Support vector machine
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error

2.1. Long-Short Term Memory (LSTM)

Long short-term memory is a type of recurrent neural network that is well-suited for modeling sequential data. LSTM models are capable of learning long-term dependencies in the data and effectively capturing the temporal dynamics of energy consumption[18]. The architecture of the LSTM is illustrated in Figure 2.

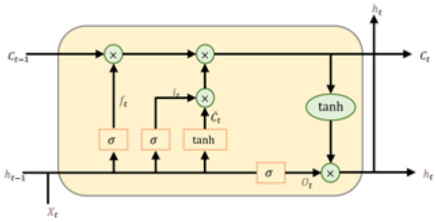

Figure 2. The architecture of LSTM.

The key components of an LSTM model are the memory cell, the forget gate, the input gate, and the output gate. The memory cell holds the state of the LSTM, which is updated at each time step based on the current input, the previous hidden state, and the previous cell state. The forget gate determines what information from the previous cell state should be retained, the input gate controls what new information from the current input and previous hidden state should be added to the cell state, and the output gate decides what parts of the cell state should be used to generate the current output. Equations (1, 2, 3, 4, 5, and 6) define the mathematical formulation of the LSTM model[19]:

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \quad (1)$$

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f) \quad (2)$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \quad (3)$$

$$\hat{C}_t = tanh(W_c x_t + U_c h_{t-1} + b_c) \quad (4)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \hat{C}_t \quad (5)$$

$$h_t = o_t \odot tanh(C_t) \quad (6)$$

In the equations above, i_t, f_t and o_t are the three gates, input, output and forget gates, respectively at the time t, The W_i, W_f and W_o: denotes the weight matrices from the input, forget and output gates to the input, respectively. The b_i, b_f and b_o are the bias of input, forget and output gate, respectively. The U_i, U_f and U_o denote the weight matrices from the input, forget and output gates to the hidden, respectively. σ is a logistic sigmoid function and $\odot$ denotes the Hadamard product of two vectors. x_t is a vector that is located in the input layer of the LSTM. h_t is an output vector of the hidden layer and is located in the LSTM unit at the time, t. C_t denotes the current cell state and $\hat{C}_t$ denotes the new candidate value for the next cell state. h_{t-1} denotes the previous state and is determined by the forget gate, f_t, by how much is passed to the next state. C_{t-1} denotes the update of the old cell state to the new cell state C_t.

2.2. Gated Recurrent Unit (GRU)

The Gated Recurrent Unit represents a type of recurrent neural network architecture that is a simplified version of the LSTM cell, as proposed by Chung et al[20]. The architecture of the GRU is depicted in Figure 3.

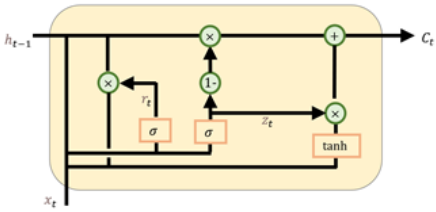

Figure 3. The architecture of GRU.

The GRU architecture includes two key gates that regulate the flow of information through the network. The reset gate determines the amount of past information to be retained, while the update gate controls the incorporation of new information into the cell state. The following equations (7, 8, 9, and 10) represent the formula of the GRU model[19]:

$$Z_t = \sigma(W_z \odot [h_{t-1}, z_t]) \qquad (7)$$

$$r_t = \sigma(W_r \odot [h_{t-1}, x_t]) \qquad (8)$$

$$\tilde{h}_t = tanh(W \odot [r_t \odot h_{t-1}, x_t] \qquad (9)$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \qquad (10)$$

The equations in the Gated Recurrent Unit model involve several mathematical components. The sigmoid activation function is represented by σ, while W_r and W_z denote the weight coefficients for the reset gate and update gate, respectively. The hidden state at the previous time step *t-1* is given by h_{t-1}, and x_t represents the input at the current time t. The candidate hidden state at time t is denoted by $\tilde{h}_t$, and the tanh activation function is represented by tanh. The weight coefficients are denoted by *W*, the Hadamard product is represented by ⊙, and ht is the hidden state at the current time t.

2.3. Autoregressive Integrated Moving Average (ARIMA)

The ARIMA model is a well-established time series forecasting technique commonly employed for predicting electrical load, which represents the amount of electrical energy demanded by consumers within a power system[21]. Accurate forecasting of electrical load is crucial for the efficient planning and operation of power systems. The ARIMA model integrates autoregressive and moving average components, enabling the capture of key temporal characteristics. The Autoregressive (AR) component leverages the dependence between an observed value and its past counterparts to generate predictions, which is particularly useful for forecasting upcoming energy consumption or potential demand peaks. The Integrated (I) component accounts for the necessary degree of differentiation required to achieve stationarity in the time series. Furthermore, the Moving Average (MA) component allows the model error to be defined as a linear combination of past error values, capturing the dependencies between observations and residual errors. The ARIMA (p,d,q) model, which utilizes the lag polynomial L is represented by the equation (11).

$$\left(1-\sum_{k-1}^{p}\varphi_k L^k\right)(1-L)^d=\theta\left(1-\sum_{j=1}^{a}\theta_j L^k\right)\varepsilon_t \qquad (11)$$

where the lag operator L^k represents past values in the series, φ_k denotes the parameters of the autoregressive (AR) component, and θ_j signifies the parameters of the moving average (MA) component, while ε_t represents the error terms. To determine the optimal parameters for the model, the Akaike Information Criterion (AIC) is commonly employed.
The Akaike Information Criterion (AIC) is a widely used metric for selecting the optimal parameters of an ARIMA model[21]. It balances model fit and complexity by maximizing the likelihood function while imposing a penalty for the number of estimated parameters. The mathematical expression for the AIC is as follows:

$$AIC=-2\log k+2m \qquad (12)$$

where the number of estimated model parameters is denoted by m, and k represents the maximized likelihood function for the model.

2.4. Support vector machine (SVM)

The Support Vector Machine (SVM) is a supervised machine learning algorithm widely used for classification and regression tasks. SVM works by finding the optimal hyperplane that separates data points of different classes with the maximum margin [22]. For linearly separable data, the algorithm constructs a hyperplane using support vectors, which are the closest data points to the hyperplane.
The decision boundary can be expressed as:

$$f(x)=sign(\omega.x+b) \qquad (13)$$

$$min\frac{1}{2}\|\omega\|^2 \qquad (14)$$

subject to the constraint:

$$y(\omega.x_i+b)\geq 1 \qquad (15)$$

where yi represents the class label of a data point xi .

2.5. Proposed ARIMA-GRU Model

The proposed approach combines the strengths of the ARIMA model and the GRU neural network to capture the linear and non-linear patterns in energy consumption data.
The ARIMA model is first used to fit the time series data and generate residuals, which represent the non-linear and seasonal components not captured by the linear ARIMA model.
The GRU network is then trained on the residuals to learn the remaining non-linear patterns. The final forecast is obtained by combining the ARIMA and GRU predictions, as shown in Figure 4. Table 2 resume all various layers and parameters of proposed approach, which were determined using grid search.

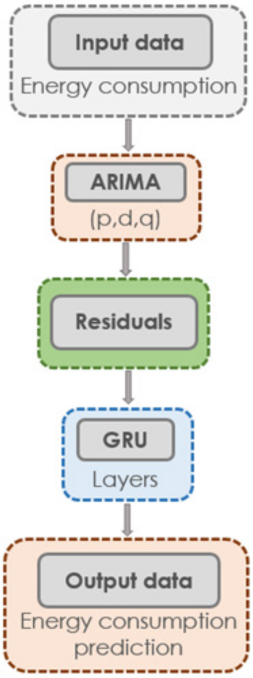

Figure 4. Proposed approach's architecture.

Table 2. Configuration of the various layers and parameters of ARIMA-GRU model.

Algorithm	Parameters	Values
ARIMA	P	12
	d	1
	q	21
GRU	GRU	50, activation='relu'
	GRU	50, activation='relu'
	Dense	1

2.6. Data description

The dataset used in this study was gathered from residential households within an energy community in Ireland as part of the StoreNet project[23]. It includes local weather parameters and detailed per-household power and energy measurements, encompassing active power consumption, photovoltaic generation, grid import and export, energy storage charging and discharging, as well as the state of charge of energy storage systems. The weather data is available at a 1-minute temporal resolution for the year 2020, while the energy consumption data has been aggregated to a daily resolution for forecasting daily energy consumption.

2.7. Evaluation metrics

The forecasting performance is evaluated using accuracy metrics including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics quantitatively evaluate the discrepancy between the predicted and actual values, as defined below:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|(y_i - f_i)\right| \qquad (16)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - f_i)^2} \qquad (17)$$

$$MAPE = \frac{1}{N}\sum_{i-1}^{N}\left|\frac{y_i - f_i}{y_i}\right| \times 100 \qquad (18)$$

where N represents the number of values and yi is the actual value, and fi is the forecasted value. MAE, RMSE, and MAPE are widely used in energy prediction due to their ability to capture prediction errors in various forms. RMSE is particularly sensitive to large errors, making it suitable for detecting peaks, while MAPE provides an intuitive percentage error that is easy to interpret. These metrics were chosen to reflect the challenges of energy data, including sudden peaks and seasonal variations[24]. The MAE is a commonly used statistical metric that calculates the average of the absolute differences between the predicted and actual values, offering insight into the model's performance. In contrast, the RMSE reflects the standard deviation of these differences, placing greater emphasis on larger errors due to its mathematical structure. Additionally, the MAPE metric provides a measure of prediction accuracy as a percentage by calculating the average of the absolute percentage differences between the forecasted and actual values. In general, a model with lower MAE, RMSE, MAPE values, indicate a more accurate predictive model [25].

3. RESULTS & DISCUSSION

Figure 5 provides a visual representation of the performance of different forecasting models, while Table 3 presents the numerical evaluation of their accuracy using RMSE, MAE, and MAPE." The results depicted in Figure 5 illustrate the comparative performance of the various models in predicting energy consumption. The standalone models, such as ARIMA and SVM, exhibited challenges in capturing the non-linear patterns in the data, leading to higher deviations from the actual trends. Conversely, the deep learning models, particularly the GRU, demonstrated a closer alignment with the observed data, outperforming the LSTM in tracking the rapid changes. The hybrid models, which combined the ARIMA and deep learning approaches, further improved the prediction accuracy by effectively integrating the strengths of linear and non-linear modeling. Notably, the ARIMA-GRU hybrid model provided the most accurate predictions, exhibiting minimal deviations and effectively capturing the variability in energy consumption, thus establishing it as the most robust approach for this forecasting task.

The comparisons shown in Table 3 reveal the performance of different models, as evaluated by RMSE, MAE, and MAPE. Among the standalone models, the ARIMA model exhibited the highest RMSE and MAE, along with a MAPE of 18.70%. This suggests that while the ARIMA approach is effective for modeling linear patterns, it struggled to capture the complex non-linear relationships inherent in the data. In contrast, the Support Vector Machine model demonstrated moderate performance, with an RMSE of 59.79kWh, MAE of 41.90kWh, and MAPE of 12.78%, but it was outperformed by the deep learning models.

The deep learning models, GRU and LSTM, displayed better adaptability to the complexities of the dataset. The GRU model achieved the lowest RMSE and MAE among the standalone models, along with a MAPE of 11.10%, outperforming the LSTM model, which reported an RMSE of 49.91kWh, MAE of 42.05kWh, and MAPE of 13.74%. This highlights the superior ability of the GRU model to capture long-term dependencies and temporal dynamics compared to the LSTM model in this context.

The hybrid models, which combine the ARIMA approach with deep learning architectures, provided notable improvements. The ARIMA-LSTM model achieved an RMSE of 44.30kWh, MAE of 33.59kWh, and MAPE of 12.35%, surpassing its standalone counterpart. However, The ARIMA-GRU model demonstrated the most favorable overall performance, as reflected in the lowest recorded values for RMSE, MAE, and MAPE. These results emphasize the effectiveness of hybrid models in leveraging the strengths of both statistical and deep learning techniques to enhance prediction accuracy.

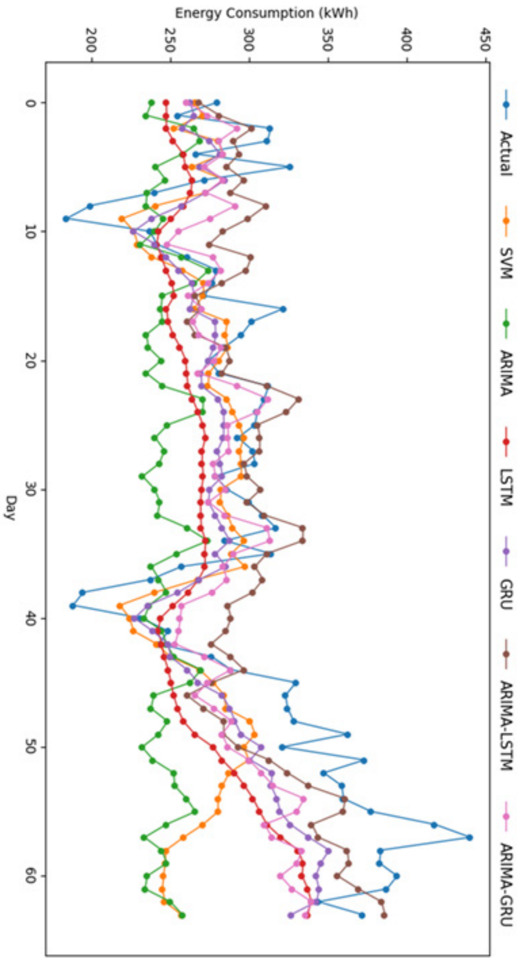

Figure 5. Daily energy consumption predictions.

Table 3. Comparison of the proposed model's performance with other models

Model	RMSE (kWh)	MAE (kWh)	MAPE (%)
SVM	59.79	41.90	12.78
ARIMA	76.25	60.68	18.70
GRU	43.50	32.10	11.10
LSTM	49.91	42.05	13.74
ARIMA-LSTM	44.30	33.59	12.35
ARIMA-GRU	38.28	31.24	10.29

Although the ARIMA-GRU model demonstrates overall superior performance, it struggles to capture sharp peaks in energy consumption accurately. This limitation may arise from the smoothing effects of both ARIMA and GRU during forecasting. Future enhancements could include incorporating external features such as real-time weather data or using attention

mechanisms to prioritize peak prediction.
In summary, the ARIMA-GRU hybrid model emerged as the most accurate for the forecasting task, demonstrating the potential of combining traditional time series models with advanced machine learning architectures to address complex forecasting challenges.

4. CONCLUSION

This study investigated the performance of various forecasting models, including standalone ARIMA, SVM, GRU, and LSTM, as well as hybrid ARIMA-LSTM and ARIMA-GRU, for predicting energy consumption. The results reveal that traditional time series models like ARIMA struggle to capture complex non-linear patterns, while deep learning models, particularly GRU, exhibit superior performance in tracking temporal dynamics and abrupt changes.
The hybrid models that integrate the strengths of statistical and deep learning methods have demonstrated superior performance compared to their individual counterparts. Notably, the ARIMA-GRU hybrid model emerges as the most accurate and robust approach, demonstrating the lowest RMSE, MAE, and MAPE.
These findings highlight the potential of integrating advanced machine learning architectures with traditional time series models to improve the precision and reliability of energy consumption forecasting. Future research should explore scalability across diverse datasets and environments. The integration of additional contextual variables, such as real-time weather and economic indicators, could further improve model accuracy. Additionally, optimizing computational efficiency without compromising accuracy remains a critical avenue for exploration.

REFERENCES

[1] N. M. Manousakis, P. S. Karagiannopoulos, G. J. Tsekouras, and F. D. Kanellos, "Integration of Renewable Energy and Electric Vehicles in Power Systems: A Review," Processes, vol. 11, no. 5, 2023, doi: 10.3390/pr11051544.

[2] M. Abumohsen, A. Y. Owda, and M. Owda, "Electrical Load Forecasting Using LSTM, GRU, and RNN Algorithms," Energies (Basel), vol. 16, no. 5, 2023, doi: 10.3390/en16052283.

[3] W. Liao, B. Bak-Jensen, J. R. Pillai, Z. Yang, and K. Liu, "Short-term power prediction for renewable energy using hybrid graph convolutional network and long short-term memory approach," Electric Power Systems Research, vol. 211, p. 108614, 2022, doi: https://doi.org/10.1016/j.epsr.2022.108614.

[4] B.-M. Hodge, A. Zeiler, D. Brooks, G. Blau, J. Pekny, and G. Reklatis, "Improved Wind Power Forecasting with ARIMA Models," in 21st European Symposium on Computer Aided Process Engineering, vol. 29, E. N. Pistikopoulos, M. C. Georgiadis, and A. C. Kokossis, Eds., in Computer Aided Chemical Engineering, vol. 29. , Elsevier, 2011, pp. 1789–1793. doi: https://doi.org/10.1016/B978-0-444-54298-4.50136-7.

[5] Y. E. Shao and Y.-S. Tsai, "Electricity Sales Forecasting Using Hybrid Autoregressive Integrated Moving Average and Soft Computing Approaches in the Absence of Explanatory Variables," Energies (Basel), vol. 11, no. 7, 2018, doi: 10.3390/en11071848.

[6] D. Koschwitz, J. Frisch, and C. van Treeck, "Data-driven heating and cooling load predictions for non-residential buildings based on support vector machine regression and NARX Recurrent Neural Network: A comparative study on district scale," Energy, vol. 165, pp. 134–142, 2018, doi: https://doi.org/10.1016/j.energy.2018.09.068.

[7] G. Lai, W.-C. Chang, Y. Yang, and H. Liu, "Modeling long-and short-term temporal patterns with deep neural networks," in The 41st international ACM SIGIR conference on research & development in information retrieval, 2018, pp. 95–104.

[8] Y. Hua, Z. Zhao, R. Li, X. Chen, Z. Liu, and H. Zhang, "Deep Learning with Long Short-Term Memory for Time Series Prediction," IEEE Communications Magazine, vol. 57, no. 6, pp. 114–119, 2019, doi: 10.1109/MCOM.2019.1800155.

[9] M. Dong and L. Grumbach, "A Hybrid Distribution Feeder Long-Term Load Forecasting Method Based on Sequence Prediction," IEEE Trans Smart Grid, vol. 11, no. 1, pp. 470–482, 2020, doi: 10.1109/TSG.2019.2924183.

[10] J. Lee and Y. Cho, "National-scale electricity peak load forecasting: Traditional, machine learning, or hybrid model?," Energy, vol. 239, p. 122366, 2022, doi: https://doi.org/10.1016/j.energy.2021.122366.

[11] H. Hewamalage, C. Bergmeir, and K. Bandara, "Recurrent Neural Networks for Time Series Forecasting: Current status and future directions," Int J Forecast, vol. 37, no. 1, pp. 388–427, 2021, doi: https://doi.org/10.1016/j.ijforecast.2020.06.008.

[12] H. Hamdoun, A. Sagheer, and H. Youness, "Energy time series forecasting-analytical and empirical assessment of conventional and machine learning models," Journal of Intelligent & Fuzzy Systems, vol. 40, pp. 12477–12502, 2021, doi: 10.3233/JIFS-201717.

[13] J. Wan, W. Hua, and B. Wang, "Compulsory Islanding Transition Strategy Based on Fuzzy Logic Control for a Renewable Microgrid System," Math Probl Eng, vol. 2021, no. 1, p. 9959222, 2021, doi: https://doi.org/10.1155/2021/9959222.

[14] X. Ma and D. Liu, "Comparative Study of Hybrid Models Based on a Series of Optimization Algorithms and Their Application in Energy System Forecasting," Energies (Basel), vol. 9, no. 8, 2016, doi: 10.3390/en9080640.

[15] Y. Wang, Y. Shen, S. Mao, G. Cao, and R. M. Nelms, "Adaptive Learning Hybrid Model for Solar Intensity Forecasting," IEEE Trans Industr Inform, vol. 14, no. 4, pp. 1635–1645, 2018, doi: 10.1109/TII.2017.2789289.

[16] M. Du, "Improving LSTM Neural Networks for Better Short-Term Wind Power Predictions," in 2019 IEEE 2nd International Conference on Renewable Energy and Power Engineering (REPE), 2019, pp. 105–109. doi: 10.1109/REPE48501.2019.9025143.

[17] S. Haben, S. Arora, G. Giasemidis, M. Voss, and D. Vukadinović Greetham, "Review of low voltage load forecasting: Methods, applications, and recommendations," Appl Energy, vol. 304, p. 117798, 2021, doi: https://doi.org/10.1016/j.apenergy.2021.117798.

[18] S. and O. S. Hoyer Michael and Eivazi, "Efficient LSTM Training with Eligibility Traces," in Artificial Neural Networks and Machine Learning – ICANN 2022, P. and J. C. and P. A. and A. M. Pimenidis Elias and Angelov, Ed., Cham: Springer Nature Switzerland, 2022, pp. 334–346.

[19] K. E. ArunKumar, D. V Kalaga, Ch. Mohan Sai Kumar, M. Kawaji, and T. M. Brenza, "Comparative analysis of Gated Recurrent Units (GRU), long Short-Term memory (LSTM) cells, autoregressive Integrated moving average (ARIMA), seasonal autoregressive Integrated moving average (SARIMA) for forecasting COVID-19 trends," Alexandria Engineering Journal, vol. 61, no. 10, pp. 7585–7603, 2022, doi: https://doi.org/10.1016/j.aej.2022.01.011.

[20] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, "Gated feedback recurrent neural networks," in International conference on machine learning, 2015, pp. 2067–2075.

[21] N. Guo, W. Chen, M. Wang, Z. Tian, and H. Jin, "Appling an Improved Method Based on ARIMA Model to Predict the Short-Term Electricity Consumption Transmitted by the Internet of Things (IoT)," Wirel Commun Mob Comput, vol. 2021, no. 1, p. 6610273, 2021, doi: https://doi.org/10.1155/2021/6610273.

[22] M. Awad and R. Khanna, "Support Vector Machines for Classification," in Efficient

Learning Machines, Berkeley, CA: Apress, 2015, pp. 39–66. doi: 10.1007/978-1-4302-5990-9_3.

[23] R. Trivedi, M. Bahloul, A. Saif, S. Patra, and S. Khadem, "Comprehensive Dataset on Electrical Load Profiles for Energy Community in Ireland," Sci Data, vol. 11, no. 1, p. 621, 2024, doi: 10.1038/s41597-024-03454-2.

[24] H. Yin, D. Jin, Y. H. Gu, C. J. Park, S. K. Han, and S. J. Yoo, "STL-ATTLSTM: Vegetable Price Forecasting Using STL and Attention Mechanism-Based LSTM," Agriculture, vol. 10, no. 12, 2020, doi: 10.3390/agriculture10120612.

[25] A. Youssfi, and Youssef El Y. Kadi, "A New Advanced Strategy for Controlling the Charging and Discharging of a Storage Unit in a Microgrid Using a Finite Control Set Predictive Model" Solar Energy and Sustainable Development Journal, 14(SI_MSMS2E), 38–52, 2024, https://doi.org/10.51646/jsesd.v14iSI_MSMS2E.404.