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Energy Management System of a Microgrid Using Deep Learning

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***Abstract*—The increasing adoption of microgrids with renewable energy systems, driven by environmental and socioeconomic factors, faces challenges such as renewable energy variability and dynamic load fluctuations, leading to increased grid consumption. This study addresses these challenges by proposing an advanced Energy Management System (EMS) integrated with a Deep Learning model for load forecasting. The objective is to enhance the efficiency and cost-effectiveness of microgrids by dynamically adjusting to forecasted load demands. The EMS utilizes Long Short-Term Memory (LSTM) networks to predict the load demand of a commercial building, allowing for optimized battery scheduling and reduced reliance on the utility grid. The study conducted a month-long simulation using real historical load and solar power data, comparing the proposed EMS with a standard EMS. Key findings indicate that the proposed EMS significantly reduces grid consumption, resulting in a 9.3% reduction in monthly electricity bills. Integrating deep learning in EMS demonstrates substantial improvements in handling dynamic conditions and optimizing energy usage. These findings imply that deep learning-based EMS can lead to significant cost savings and more efficient microgrid energy management, promoting the broader adoption of renewable energy solutions.**

Keywords—Energy Management System, Microgrid, Deep Learning, Load Forecasting, Long-Short-Term Memory

I. INTRODUCTION

Microgrids face substantial challenges, such as the intermittent nature of renewable energy and load fluctuations, which cause imbalances in the system. The energy demand of a building can fluctuate depending on factors such as the time of day, occupancy levels, and operational activities. These imbalances necessitate increased energy exchange with the grid to stabilize the system, which can be less economically favorable and lead to higher electricity bill costs due to peak-time energy purchases. This not only results in higher costs but also in inefficient utilization of local generation resources [1].

Energy Management Systems (EMS) are part of the microgrid controller. They play a critical role in ensuring that the power generated within microgrids meets the building's load demand. EMS involves decision-making processes to maximize the use of renewable energy, minimize consumption from the utility grid, and efficiently manage energy storage systems [2]. In general, three approaches to EMS have been explored in the past: Classical methods, Metaheuristic methods, and Artificial Intelligence methods.

Classical methods involve mathematically modeling specific variables and constraints to provide an optimal solution based on the given problem. An example of classical methods is linear programming, which makes optimal decisions in EMS considering cost, availability, and environmental impact. For example, this paper [3] proposed an optimization method based on linear programming to minimize operation costs and maximize solar energy's power. Despite their success, linear programming models are based on linear constraints, which means that they may not be able to capture the complexities of nonlinear systems.

Another method is a Metaheuristic approach, which involves random searching and generating potential solutions. It is widely used to address complex problems that classical methods cannot achieve. For example, Grisales-Noreña et al. [4] proposed a Proximal Policy Optimization algorithm and Artificial Neural Network (ANN) to schedule a day-ahead dispatch of Battery Energy Storage Systems (BESS) to reduce consumption costs from the utility grid, However, the proposed method does not consider the battery efficiency and self-discharge effect, which could impact the economic efficiency of the BSS operation. Additionally, the mathematical formulation of the EMS does not include the battery's maximum charging and discharging cycles, which could limit its lifespan.

Lastly, Artificial Intelligence methods such as Machine Learning and Deep Learning have seen a significant increase in the application of EMS. These methods can analyze the problem, identify patterns, and make optimal decisions. For example, Iringan Iii et al. [5] aimed to increase the consumption of solar PV and battery while decreasing reliance on the utility grid to reduce electricity costs by using machine learning to forecast solar and load. The study achieved an NRMSE of 0.398 and 0.409 for load and solar power forecasting, respectively. However, it does not explicitly state how much the electricity costs are reduced using the proposed methods. Additionally, there is a lack of consideration for weather conditions and solar irradiance, which can impact the accuracy of solar forecasting. Not to mention, using data from a location different from the microgrid system being studied may limit the generalizability of the results.

This paper proposes an advanced EMS integrated with deep learning to predict load fluctuations and adjust energy management strategies accordingly. The proposed EMS algorithms are based on [6], where the BESS will discharge

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during peak power by prioritizing charging before the expected peak power arrives. A deep learning Long Short-Term Memory (LSTM) model is proposed to predict the load demand of a commercial building. This paper primarily focuses on the performance of the proposed EMS, which utilizes load forecasting, rather than on the performance of the LSTM forecasting model itself. The performance of the proposed EMS was compared with that of a standard EMS of battery scheduling proposed by [7], where the battery prioritizes charging during non-peak hours and discharging during peak hours. The simulation used Python with real-life historical data from the United States.

II. METHODOLOGY

This section outlines the methodology employed in developing and implementing the proposed EMS for the microgrid, detailing the microgrid design, the EMS algorithms, and the deep learning techniques used for load forecasting.

A. Proposed Microgrid Design

The microgrid's proposed block diagram is shown in Fig. 1. The PV panel generates power from sunlight, stored in the Battery Energy Storage System (BESS). The BESS acts as the main supplier, providing power to the load. The utility grid supplies the remaining power if the power stored in the BESS does not fulfill the load demand. A Deep Learning Energy Management System (DL EMS) is integrated to analyze current power conditions and forecast load demand, deciding optimal strategies for charging and discharging the battery in the microgrid, thereby reducing power consumption from the utility grid.

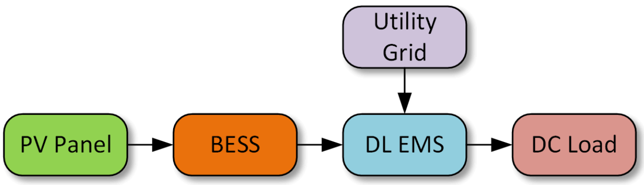

Fig. 1. PV-Battery system design

The power balance equation for EMS can be expressed in Eq. (1).

$$P_{load} = P_{grid} + P_{BESS} \tag{1}$$

This equation signifies that the total power consumed by the loads (P_{load}) must be equivalent to the power discharged from the battery (P_{BESS}) and grid (P_{grid}). The BESS must also adhere to a State-of-Charge (SOC) constraint to avoid overcharging and ensure the battery's lifetime. The constraint equation is shown in Eq. (2).

$$SOC_{min} < SOC < SOC_{max} \tag{2}$$

The PV and battery system design are based on the load demand of load demand for a commercial building obtained hourly from the U.S. Department of Energy [8]. The dataset represents a large office with fans, facilities, lighting, equipment, gas, heating, water systems, and appliances. The maximum energy per day is over 40000kWH. Therefore, the proposed PV panel power system capacity is 1MW with a battery energy storage capacity of 50MWh. The PV power is obtained hourly from the historical solar generation profiles for plant within the United States that is part of the Energy Information Administration [9]. For this simulation to mimic solar generation in Malaysia, the time resolution is modified to produce sunlight-generated power from 8 am to 6 pm.

B. Proposed Energy Management System Algorithms

Two algorithms proposed are EMS strategies and EMS with Load Forecasting algorithms. Fig. 2. is the EMS strategies based on Eq. (1) and (2). This algorithm determines whether to charge or discharge the battery or to supply power from the grid to the load. It also abides by the SOC constraints to avoid overcharge and over-discharge.

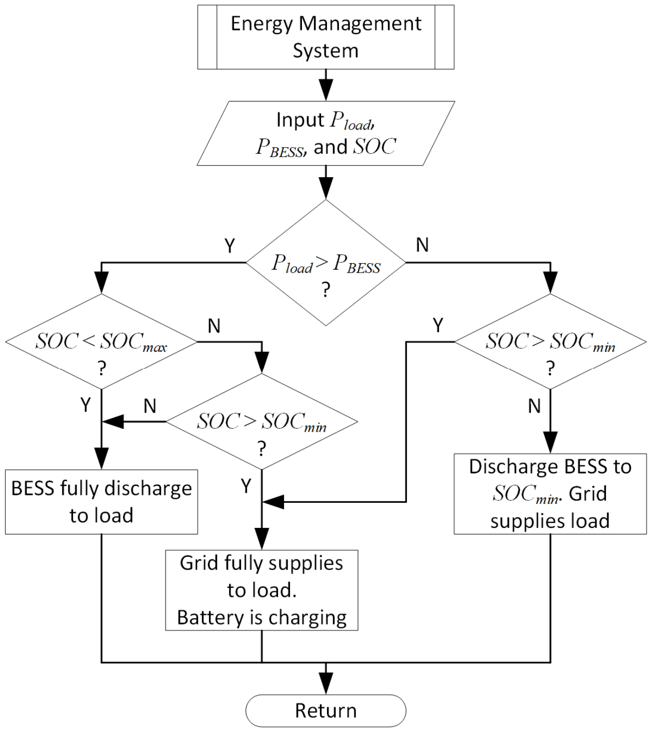

Fig. 2. EMS strategies

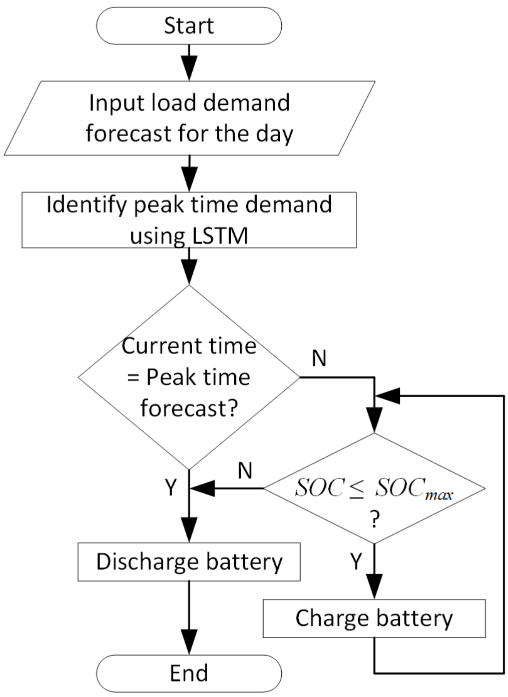

Fig. 3. Proposed EMS with LSTM load forecasting

Fig. 3. illustrates the proposed EMS integrating load forecasting. The system collects daily load forecasts and identifies the time of the highest predicted load. During peak periods, it prioritizes charging the battery before the next expected peak period. This approach ensures sufficient battery power to meet the load demand during peak times. The EMS also considers battery SOC constraints, charging the battery if the SOC is below SOC_{max} or discharging if it exceeds SOC_{min}, and stops charging when SOC reaches SOC_{max}.

C. Proposed Deep Learning Techniques for Load Forecasting

The proposed deep learning technique is LSTM for forecasting the demand load. LSTM is selected due to its widespread use in time series forecasting tasks. LSTM networks are designed to handle long-term dependencies better and mitigate the vanishing gradient problem, which is common in traditional Recurrent Neural Networks [10]. LSTM can effectively capture complex temporal patterns present in sequential data, making it particularly suitable for load forecasting where historical data points heavily influence future predictions. The steps of the load forecasting model are as follows: data collection and preparation, data preprocessing for deep learning, and application of the Long Short-Term Memory algorithm. Finally, the performance of the deep learning model is studied.

1) Data Collection

Fig. 4 illustrates the load demand pattern from March to May over two months. The graph shows significant fluctuations in load demand, with consistent peaks and troughs indicating higher demand on weekdays and reduced demand on weekends. The pronounced regularity suggests typical office building usage, with minimal weekend activity. The data highlights the variability and predictability of load demand, which is crucial for optimizing the EMS. The cyclical pattern underscores the importance of accurate load forecasting to ensure efficient energy distribution and minimize reliance on the grid during peak periods.

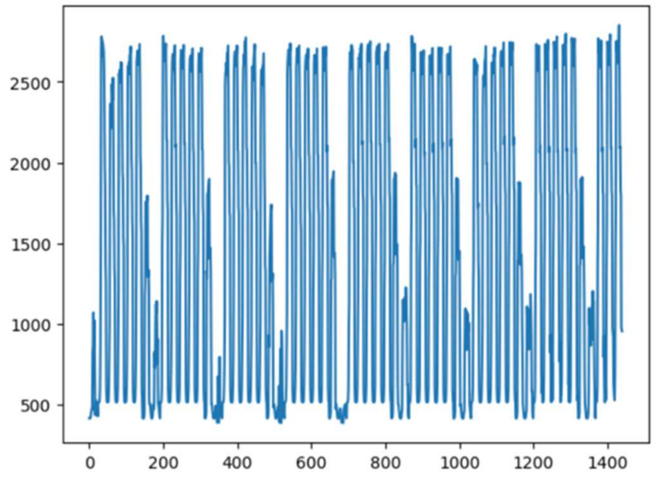

Fig. 4. Load demand for 2-month period

Fig. 5 illustrates the daily load demand profile, showing significant daily variations. The load demand peaks sharply around noon, reaching over 1000 kW, indicative of increased activity during working hours. This peak is followed by a gradual decline in the afternoon and a steep drop in the evening as work activities wind down. The lowest demand is observed during nighttime, reflecting minimal usage outside working hours. This pattern underscores the need for efficient load forecasting and management, particularly during peak hours, to optimize energy usage and reduce costs. The dataset was split into 70% for training and 30% for testing to validate the model's accuracy.

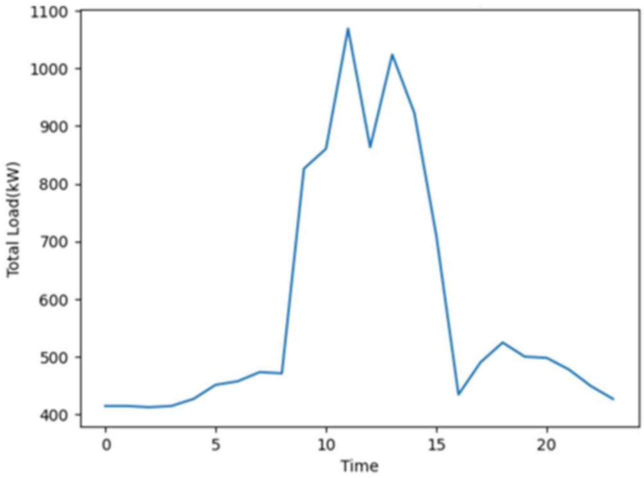

Fig. 5. Load demand for a day

2) Data Preprocessing

Data preprocessing is a crucial stage in training machine learning models. It involves transforming raw data into a format that machine learning algorithms can effectively use [11]. Various methods are available depending on the nature of the data. In this case, max-min normalization scales features between 0 and 1, as shown in Eq. (3). This ensures that all features contribute equally to the learning process and helps stabilize gradients during training.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{3}$$

3) LSTM Hyperparameters

The hyperparameters used to achieve the best results are detailed in Table 1. They were determined based on the findings in [11]. The tuning process was conducted multiple times to identify the optimal set of hyperparameters. Only the performance of the selected optimal hyperparameters will be studied.

TABLE I. LSTM HYPERPARAMETERS

Parameters	Value
Number epochs	2000
Learning rate	0.01
Hidden size	50
Number of layers	1
Number of classes	1
Optimizer	Adam

4) Performance Metrics

Three popular statistical metrics are used to evaluate the forecasting algorithms: the mean absolute error (MAE), the root mean square error (RMSE), and the mean absolute percentage error (MAPE).

$$MAE = \frac{1}{N}\sum_{k=1}^{N}|\hat{x}(k) - x(k)| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(\hat{x}(k) - x(k)\right)^2} \tag{4}$$

$$MAPE = \frac{1}{N}\sum_{k=1}^{N}\left|\frac{\hat{x}(k)-x(k)}{x(k)}\right| \times 100\% \qquad (6)$$

where $\hat{x}$ is the predicted value, x is the actual value and N is the number of samples.

D. Electricity Bill Calculation

The calculation of the electricity cost consumption of the microgrid must refer to the Time-Of-Use Tariff Rate. In this project, a commercial building is used as a DC load. The Tariff Rates are taken from the TNB website [12]. Table II shows the TNB Tariff Rate for C2 commercial buildings. Table III refers to the peak and off-peak periods.

TABLE II. TARIFF C2 MEDIUM VOLTAGE PEAK/OFF-PEAK COMMERCIAL TARIFF

Tariff category	Unit	Current rate
For each kilowatt of maximum demand per month during the peak period	RM/kW	45.10
For all kWh during the peak period	RM/kW	36.50
For all kWh during the off-peak period	RM/kW	22.40
Minimum monthly charge	RM	7.2

TABLE III. PEAK AND OFF-PEAK PERIOD [12]

Period	Time Range
Peak	08:00 – 22:00
Off-peak	22:00 – 08:00

Eq. (7) represents the formula used to calculate the total electricity cost for a commercial building within the microgrid setup based on the Time-Of-Use Tariff Rate. The total cost is derived by summing the costs incurred during peak and non-peak periods.

$$Total\ Cost = 36.5E_{peak} + 22.4E_{off-peak} \qquad (7)$$

where E_{peak} represents the total energy consumed during peak hours and $E_{off-peak}$ represents the total energy consumed during non-peak hours.

III. RESULTS AND ANALYSIS

This study's forecasting models and microgrid simulation were all modeled in Python using Jupyter Notebooks. The deep learning environment used was PyTorch. Additionally, other Python libraries were used for data processing and manipulation. The computations, such as fitting the models and evaluating the results, were made on a computer with a MacBook Air M1 having 8 GB RAM and running a MacOS Sonoma operating system.

A. Experiment on Load Forecasting

Figure 6 illustrates the load forecasting prediction for a large office over two months, comparing actual data with predicted data using an LSTM model. The graph shows a strong correlation between the actual and predicted values, indicating the model's effectiveness. Despite MAE of 53.23, MAPE of 5.51%, and RMSE of 105.82, which might seem high, the visual alignment suggests that the LSTM model reliably captures the load demand pattern. This close resemblance validates the model's predictive capability, highlighting its potential for accurate load forecasting in practical applications, thus ensuring efficient energy management.

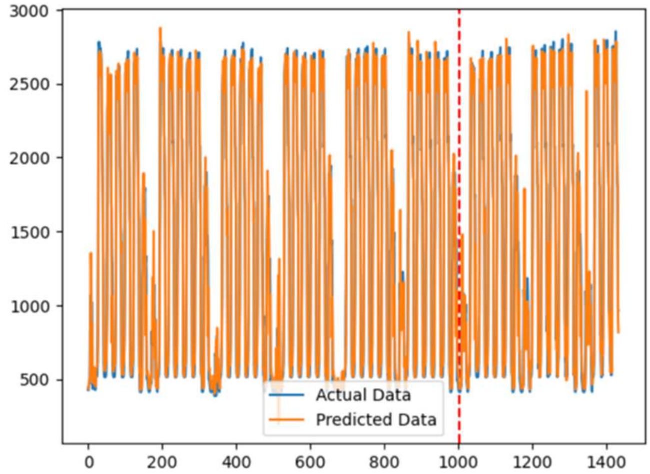

Fig. 6. Load forecasting result for 2 months

B. Microgrid Simulation Result

The simulation is conducted for 30 days using the real historical PV and load power data. Fig. 7 shows the power generated by the PV panel. The maximum power that it can charge is up to 9000kW. Fig. 8 shows the actual load and load forecast; it can be seen that the load forecast is nearly identical to the actual load. From the figure, the load demand is the highest during the weekday compared to the weekend. The office is closed during the weekend, reducing the load power.

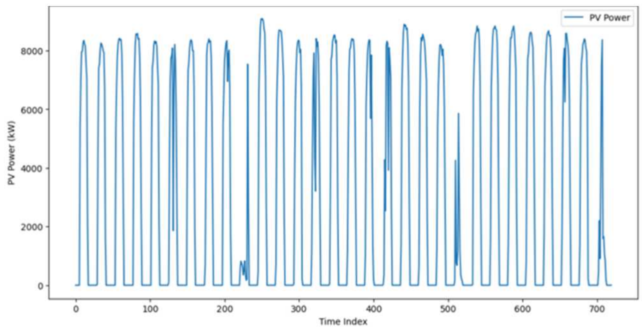

Fig. 7. PV power for 30 days

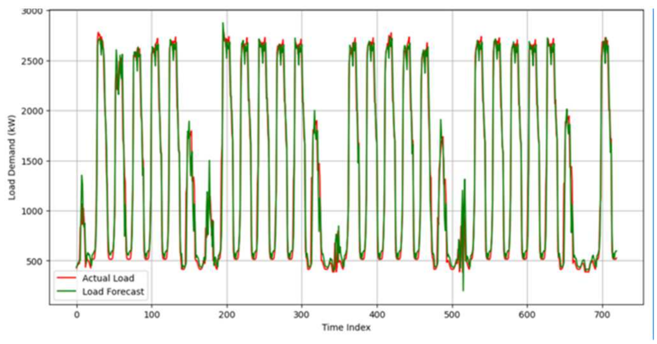

Fig. 8. Actual and forecast load demand power for 30 days

Fig. 9 and Fig. 10 present bar graphs illustrating the daily grid and battery supply for both EMS configurations: one with deep learning integration and the other without. The number at the top of the graph shows the percentage of battery supply for the day. There are noticeable variations in battery supply between the two EMS setups on certain days. For instance, on the third day, the proposed EMS has a self-consumption of 73%; meanwhile, the standard EMS is 61.4%. From that day onwards, the proposed EMS is higher than standard EMS except on certain days, such as on day 10, where the proposed EMS is 22.2%, while standard EMS is 57.4%. To further investigate these differences, the data for the day 3 and day 10 have been isolated and plotted.

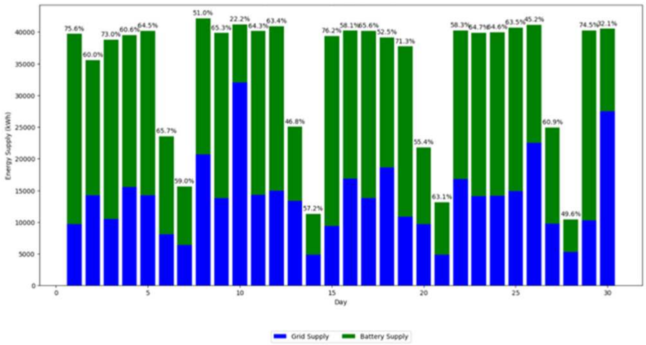

Fig. 9. Proposed EMS battery and grid supply

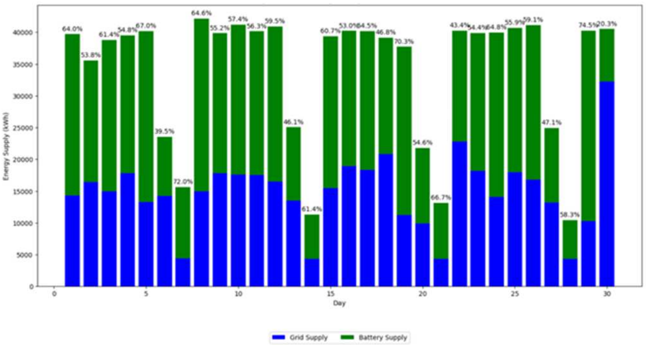

Fig. 10. Standard EMS battery and grid supply

1) Day 3 Analysis

On day 3, the peak time for peak load is 10 a.m. Therefore, the battery was supposed to be charging before 10 a.m. to anticipate the peak demand. Fig.11 illustrates the battery SOC results of the proposed EMS. In the proposed EMS strategy, the battery prioritizes charging before peak load demand periods. This approach ensures the battery maintains a sufficient charge level throughout the day to meet energy demands. As a result, the battery remains operational and capable of supplying power continuously throughout the day.

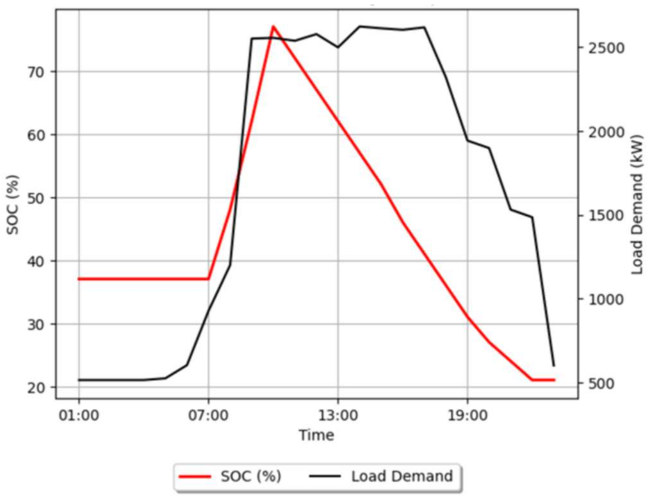

Fig. 11. Proposed EMS day 3

In contrast, the standard EMS in Fig. 12 operates differently. It immediately discharges battery power when peak load hours arrive, leading to an early depletion of battery reserves. At 5 p.m., the battery has already reached its minimum SOC and requires charging before it can be discharged again.

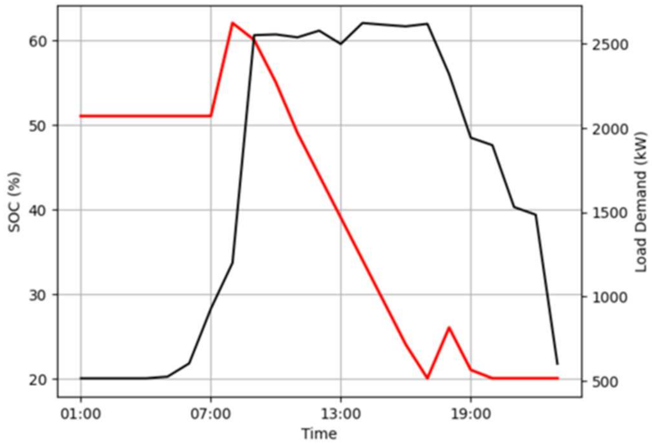

Fig. 12. Standard EMS day 3

2) Day 10 Analysis

On day 10, the peak time for the peak load forecast is at 4 p.m. Fig. 13 shows that the battery is charging before 4 p.m., and the load demand before that time is already high, even though it is not at its maximum. This is a limitation since the proposed EMS only considers the time of the maximum peak and not the threshold of maximum peak demand. Coincidentally, the PV power available is also low during the day, causing the SOC to increase very slowly.

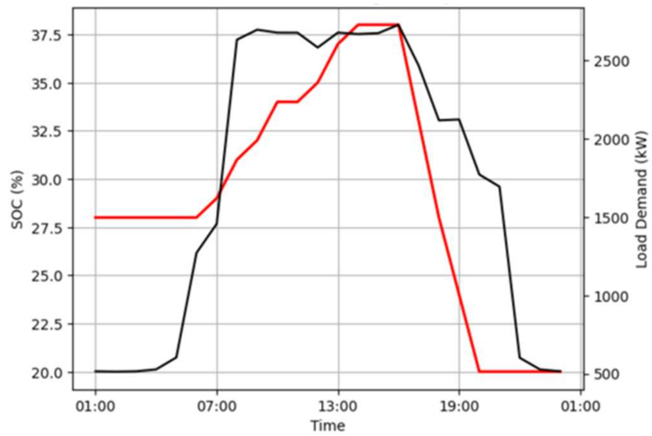

Fig. 13. Proposed EMS day 10

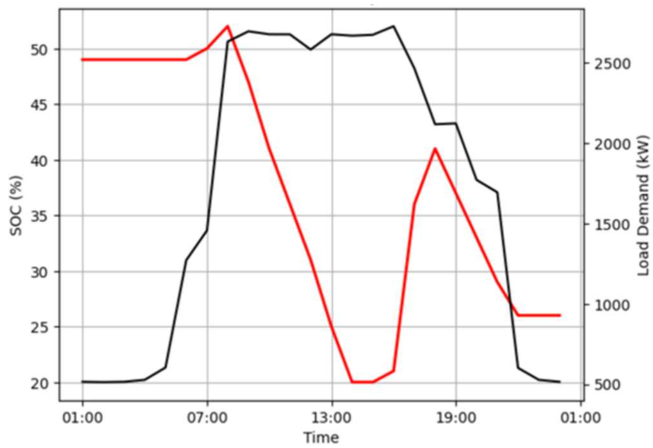

Fig. 14. Standard EMS day 10

In Fig. 14, the starting point of the battery's SOC is much higher compared to that in the proposed EMS. Therefore, there is enough power to supply until 2 PM before needing to recharge again.

To further analyze the results, an economic analysis was conducted to evaluate the total electricity bill for each day. Fig. 15. illustrates the comparison between the total costs of the proposed EMS and the standard EMS. The red circles highlight the days when the total cost of the proposed EMS exceeds that of the standard EMS. There is a total of 9 days where the proposed EMS incurs higher costs than the standard EMS. However, this result is acceptable because there are more days where the proposed EMS's costs are significantly lower, leading to overall savings.

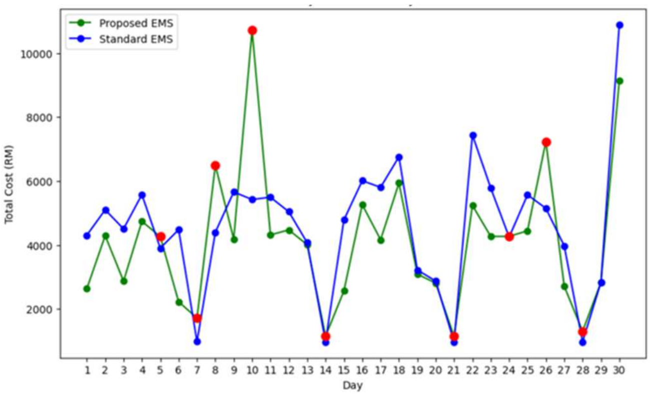

Fig. 15. Daily electricity cost for 30 days

TABLE IV. COMPARISON OF TOTAL COST FOR A MONTH

Hour	Proposed EMS	Standard EMS
Peak	RM83609.57	RM96289.45
Off-Peak	RM40967.67	RM40967.67
Total Cost	**RM124577.24**	**RM137257.12**

Table IV shows the daily costs for the proposed EMS and the standard EMS during peak and non-peak hours over a month. During non-peak hours, the costs are identical for both EMS because both systems prioritize battery charging during these times due to the lower electricity prices. However, during peak hours, the proposed EMS incurs significantly lower costs than the standard EMS, with a difference of RM12,679.88. Overall, the total monthly cost is calculated for both systems, demonstrating that the proposed EMS achieves a 9.23% reduction in total costs compared to the standard EMS.

The study demonstrates the superior performance of the proposed EMS with integrated deep learning for load forecasting in a microgrid setting. Over two months, the LSTM model has shown high accuracy, proving its practical applicability. The 30-day simulation reveals the proposed EMS significantly outperforms the standard EMS, particularly in reducing peak-hour costs through strategic battery management. Daily analyses highlight the EMS's ability to maintain optimal battery SOC, ensuring continuous power supply and reducing grid dependence. Economic analysis shows a 9.23% reduction in monthly costs compared to the standard EMS, validating the proposed EMS as a more effective solution for microgrid energy management and emphasizing its potential for broader adoption.

IV. CONCLUSION AND FUTURE WORK

In conclusion, this study presents a robust EMS for microgrids, enhanced with deep learning techniques to effectively address the variability in renewable energy and dynamic load fluctuations. The integration of LSTM networks for load forecasting has proven to significantly optimize energy usage and reduce costs, as demonstrated by the 9.23% reduction in monthly electricity bills compared to a standard EMS. The detailed simulations and economic analyses confirm the proposed EMS's superior performance in maintaining battery SOC and reducing reliance on grid power during peak periods. These findings underscore the potential of advanced deep-learning models in revolutionizing microgrid energy management. Future work should explore the integration of renewable energy forecasting and adaptive threshold-based discharge strategies to enhance the EMS's efficiency and applicability in diverse settings.

ACKNOWLEDGMENT

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REFERENCES

[1] M. Uddin, H. Mo, D. Dong, S. Elsawah, J. Zhu, and J. M. Guerrero, “Microgrids: A review, outstanding issues and future trends,” *Energy Strategy Rev.*, vol. 49, p. 101127, Sep. 2023.

[2] Y. Zahraoui *et al.*, “Energy Management System in Microgrids: A Comprehensive Review,” *Sustainability*, vol. 13, no. 19, Art. no. 19, Sep. 2021, doi: 10.3390/su131910492.

[3] A. Shufian and N. Mohammad, “Modeling and analysis of cost-effective energy management for integrated microgrids,” *Clean. Eng. Technol.*, vol. 8, p. 100508, Jun. 2022.

[4] L. F. Grisales-Noreña, O. D. Montoya, and C. A. Ramos-Paja, “An energy management system for optimal operation of BSS in DC distributed generation environments based on a parallel PSO algorithm,” *J. Energy Storage*, vol. 29, p. 101488, Jun. 2020.

[5] R. A. Iringan Iii, A. M. S. Janer, and L. A. R. Tria, “A Machine-learning Based Energy Management System for Microgrids with Distributed Energy Resources and Storage,” in *2022 25th International Conference on Electrical Machines and Systems (ICEMS)*, Chiang Mai, Thailand: IEEE, Nov. 2022, pp. 1–6.

[6] J. Koskela, A. Mutanen, and P. Järventausta, “Using Load Forecasting to Control Domestic Battery Energy Storage Systems,” *Energies*, vol. 13, no. 15, 2020, doi: 10.3390/en13153946.

[7] M. Moghimi, D. Leskarac, C. Bennett, J. Lu, and S. Stegen, “Rule-based Energy Management System in an Experimental Microgrid with the Presence of Time of Use Tariffs,” *MATEC Web Conf.*, vol. 70, p. 10011, 2016, doi: 10.1051/matecconf/20167010011.

[8] “Commercial and Residential Hourly Load Profiles for all TMY3 Locations in the United States.” National Renewable Energy Laboratory, Dec. 01, 2022. Accessed: May 17, 2024. [Online]. Available: https://catalog.data.gov/dataset/commercial-and-residential-hourly-load-profiles-for-all-tmy3-locations-in-the-united-state-bbc75

[9] C. Bracken, S. Underwood, A. Campbell, T. B. Thurber, and N. Voisin, “Hourly wind and solar generation profiles for every EIA 2020 plant in the CONUS.” Zenodo, May 05, 2023.

[10] I. H. Sarker, “Deep Learning: A Comprehensive Overview on Techniques, Taxonomy, Applications and Research Directions,” *SN Comput. Sci.*, vol. 2, no. 6, Art. no. 6, Nov. 2021.

[11] M. Abumohsen, A. Y. Owda, and M. Owda, “Electrical Load Forecasting Using LSTM, GRU, and RNN Algorithms,” *Energies*, vol. 16, no. 5, Art. no. 5, Jan. 2023, doi: 10.3390/en16052283.

[12] “TNB Better. Brighter.,” TNB Better. Brighter. Accessed: Jan. 17, 2024. [Online]. Available: https://www.tnb.com.my/commercial-industrial/pricing-tariffs1/