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Artificial Intelligence-Based Load Forecasting and Energy Scheduling in Smart Microgrids

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ABSTRACT

This paper examines the use of Artificial Intelligence (AI) methods, namely Long Short-Term Memory (LSTM) networks and Particle Swarm Optimization (PSO) in enhancing load forecasting and energy scheduling of smart microgrids. The study reveals that LSTM models are effective in improving the accuracy of load forecasting in suggesting complex temporal dependencies in energy consumption datasets, which are not achieved in the traditional approaches like ARIMA and Linear Regression. Also, the paper discusses the application of PSO to energy scheduling, where it is demonstrated that the methodology can improve operational expenditures, maximize the employment of renewable energy and decrease the need of taking power off the grid. The findings demonstrate that the AI-based solutions have great potential in the context of optimizing energy management in microgrids, including the use of renewable energy and energy efficiency improvement and the possibility to introduce energy sustainability. The results enable the significance of applying AI-based methods to tackle power intermittency, cost, and grid-free issues to define the future of energy systems.

INTRODUCTION

The interconnection of renewable energies has also increased power system management, particularly microgrids, due to the increasingly challenging energy demands. A microgrid is a small-scale energy system that can operate either off or in a coordinated fashion with the main grid. It typically integrates various energy sources, e.g. renewable (solar, wind), conventional generators and energy storage systems. Due to the growth in the use of renewal energy sources, stability, reliability, and efficient operation of microgrids has become very crucial. However, the dynamic and unpredictable nature of the energy demands of modern energy systems may be difficult to satisfy any conventional energy management strategy. Consequently, sophisticated solutions such as Artificial Intelligence (AI) have seen increased use in addressing the issues associated with energy scheduling and load forecasting in smart microgrids (Liu et al., 2020).

Load forecasting plays a critical role in the management of micro grids because it involves the estimation of future energy requirements of the system within specified time duration. Accurate load forecasting assists the operators to plan accordingly to effectively generate and distribute energy to make the system efficient and accommodate the energy needs of consumers. Conventional forecasting models (Manlik, 2021) that have been common in the past include time series analysis, linear regression, autoregressive integrated moving average (ARIMA) models, and others (Wang & Zhang, 2021). This is because these models are not then inclined toward dealing with the complexities of modern microgrids, especially where the non-linear operation of energy demand features and, primarily, in the area of intermittent renewable energy sources (Hossain & Hassan, 2019).

Artificial Intelligence (QL) and machine learning (ML) classification technologies emerged as one of the most common methods of load forecasting due to their ability to acquire complex patterns by using historical data and extending them to the new and unfamiliar conditions (Huang et al., 2020). Others of the AIs (Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Long Short-Term Memory (LSTM) networks) showed their potential in non-linearity of the load demand patterns registration (Zhang et al., 2021). These models could be used to increase the accuracy of forecasting, therefore allowing microgrids to follow how they deal with energy consumption in a more precise way (Wang et al., 2019).

Following this load forecasting, the other significant task in the operation of smart microgrids is the energy scheduling. The skilled energy resource planning would ensure that the conventional and renewable energy sources are obtained in the best possible way, thereby reducing the cost of operation as well as leading to the sustainability of the grids (Li & Liu, 2022). Scheduling involves allocating available energy resources such as the solar or wind generation to meet the demand as it has been projected in this load forecasting model. It is just so complex a process, since it has to be on-line with changing energy consumption and renewable energy available. Traditional optimization methods in energy scheduling are linear programs (LP), genetic algorithms (GA) and particle swarm optimization (PSO) (Padhy et al., 2020). However, they tend to fail when applied to large-scale systems with a great number of constraints and uncertain factors, especially in the cases of real-time issues.

Recent trends in AI have also provided new techniques to optimize, in respect to energy scheduling. Reinforcement learning (RL), a small but significant subset of machine learning, has been determined to be extremely promising with respect to energy scheduling. Promethium is referencing to such an uncertain and dynamic environment as microgrids, RL permits the model to learn the ideal decision-making policies iteratively through trial and error processes accordingly, this makes RL highly efficient (Vasirani et al., 2020). In addition, models combining AI algorithms, e.g., ANN and RL, are of interest because they are better at forecasting and schedule setting (Gou et al., 2021).

The incorporation of AI into the load prediction systems and energy scheduling systems is transforming how smart microgrids can operate. AI can also assist microgrids through the real-time optimization of energy resources to improve their performance and reliability in general. Nevertheless, despite the enormous promise of AI, its utilization also involves certain problems, primarily in reference to the quality of data, complexity of computations, and the capacity to communicate with the existing microgrid infrastructures (Morsy et al., 2020). Moreover, despite the success of AI models in small-scale applications, the ability to scale to large-scale microgrids and compatibility with other powerful technologies, like the Internet of Things (IoT) and Edge Computing, remains open to research (Lee et al., 2021).

As the energy landscape continues its evolution, the AI potential of smart microgrid management will only continue growing. Therefore, this paper aims to evaluate the current field of AI-based models of load forecasting and energy scheduling, and discuss its applicability to smart microgrid systems and the challenges in using the AI in managing energy systems, and future opportunities.

LITERATURE REVIEW

INTRODUCTION TO SMART MICROGRIDS

Smart microgrids (SMGs) are the highly developed power networks; they integrate energy storage and energy management technologies, including renewable energy sources (wind energy and solar energy). They can be completely autonomous or can be coupled to the main grid, providing greater stability, resilience, flexibility in power provision. In SMGs, energy supply and energy demand management has great significance in ensuring the system stability and cutting down operation costs. Another crucial component of SMG management involves load forecasting and energy scheduling, which are needed to ensure optimal energy distribution achieved with a feeling of balance between demand and supply (Li et al., 2020).

LOAD FORECASTING IN SMART MICROGRIDS

Effective functioning of microgrids is based on the accurate forecasting of load. It enables history-based forecasting of energy demand over some time intervals in the future, thus it leads to the creation of sufficient resources to handle the projected demand. Other conventional load forecasting techniques, such as time series, statistical models, have been applied extensively in the past. However, such approaches fail to handle the complexity of modern energy systems, especially with the integration of renewable energy sources (Yan et al., 2021). Given that the shape of energy usage has turned out to be increasingly non linear and defined by numerous other variables, over the past several years, the use of the AI-based techniques has become more frequent, as they possess learning and predicting complex data patterns properties (Li & Zhang, 2020).

MACHINE LEARNING MODELS FOR LOAD FORECASTING

One of the key promises that machine learning (ML) concepts have shown to overcome is making load forecasting more efficient. In particular, ANNs, SVMs, or even random forest models have been widely used to forecast energy demand (Zhao et al., 2021). ANNs would be particularly useful in modeling non-linear correlations in the energy consumption data (Xie et al., 2020). Using an example, a single article by Wang et al. (2021) proposed an ANN model that estimated load demand in the microgrid and displayed high forecasting accuracy of 92 percent over the traditional methods of forecasting such as ARIMA and linear regression.

Another ML technique with the potential to be successful is Long Short-Term Memory (LSTM) networks (a type of recurrent neural network, RNN, which is designed to express dependencies on time-series data) (Liu & Xu, 2021). Compared to other models, LSTM has been seen to work very well in the estimation of energy consumption pattern in microgrid, especially in situations where there are long-term relations between historical and future data on loads. LSTM models outperform traditional time series models in accuracy and computational efficiency to operate successfully in smart grid scenario in terms of forecasting, stressed by Zhao et al. (2020).

HYBRID AND ENSEMBLE MODELS

Despite the success of single machine learning models in load forecasting, focus has been to hybrid and ensemble models in a bid to enhance the accuracy of the prediction. Hybrid models are a combination of virtues of different AI algorithms in order to make the prediction process more robust. Take, as an example, Wang and Chen (2021) proposed a hybrid model with the strength of a genetic algorithm (GA) and SVM to predict the load demand. The hybrid model takes into account a trade-off between exploitation and exploration in a good level with 94 percent accuracy of prediction on the energy demand.

Ensemble models, involving multiple models combined to produce a more reliable prediction, have also been used more. In one of the models by Zhang et al. (2020), the short-term load was produced with a combination of random forests and decision trees, which satisfied the accurate and stable attributes of the forecast model and performance in regards to that of the singular models. These models may be enhanced further in an attempt to achieve a greater level of precision in the forecasting thus rendering microgrid operations effective.

ENERGY SCHEDULING IN SMART MICROGRIDS

The final microgrid management capability is the energy scheduling whereby it decides how to allocate energy resources efficiently. The goal of energy scheduling is the optimization of use of available resources, minimization of the cost of operation and improvement of reliability of supply. Traditionally, linear programming (LP) and mixed-integer linear programming (MILP) are two optimization techniques that have found their application in energy scheduling (Cheng et al., 2020). However, such methods are ineffective in addressing the uncertainties surrounding the incorporation of renewable generation, time-varying demand and dynamic real-time decision-making.

OPTIMIZATION ALGORITHMS FOR ENERGY SCHEDULING

Recent advances in AI have resulted in the development of more malleable and effective techniques of energy scheduling optimization. The concept of alternative optimization methods to conventional optimization methods is explored such as genetic algorithms (GA), particle swarm optimization (PSO) and simulated annealing (SA). The algorithms are particularly appropriate in large systems where the number of variables and constraints is high (Sarker et al., 2020). As an example, another work, Hu et al. (2021), used an energy scheduling algorithm that optimised the energy resource dispatch in a microgrid by using the PSO-based optimisation. Based on the findings, PSO proved to be more efficient and effective, in terms of utilizing energy and computation time, compared to traditional approaches.

REINFORCEMENT LEARNING FOR DYNAMIC SCHEDULING

Reinforcement learning (RL) is among the most effective AI to apply to energy scheduling. RL algorithms can find best possible policies to act as a scheduler through trial and error by playing the environment. Their applicability during real-time operations is particularly agreeable, especially where the nature of the energy network is always dynamic with fluctuating loads and occasional supply of renewable energy (Zhang et al., 2021). Smart microgrids have effectively used the concept of reinforcement learning to adapt the properties of energy distribution to the forecasted demand profile and real-time status in smart microgrids dynamically (Yang et al., 2020).

Yu, Yudong, et al. (2021) have developed an RL energy scheduling model used in a hybrid renewable microgrid. The updating and the optimization of the energy dispatch as per renewable generation and energy demand was successfully shown with the model and found to increase efficiency and cost savings compared to traditional practices of scheduling. The online learning algorithms of RL make it applicable in addressing uncertainty in the energy resource management of a microgrid.

CHALLENGES IN AI-BASED LOAD FORECASTING AND ENERGY SCHEDULINS

Despite its potentials, the incorporation of AI into load forecasting and energy scheduling within microgrids has a few challenges. One of the greatest issues is quality and quantity of data. Machine learning models require quality and large amounts of data to make precise predictions. However, it may be challenging to collect the necessary data points to train the AI models in regions of the world where microgrids have not yet reached larger-scale implementations (Jiang et al., 2021). Moreover, input should be original, relevant as well as representative of system behavior, which would only be realized through pre-processing of data.

The following issue is the computing complexity of AI models. Particularly, deep learning models are computationally expensive, which may not be available in small-scale microgrids. This can hinder the scalability of emergent AI approaches within primary microgrids and areas with reduced access to high-performance computing (Zhou et al., 2021).

INTEGRATION OF IOT AND EDGE COMPUTING WITH AI

To address such issues, the current researchers have focused on combining AI and edge computing technologies with Internet of Things (IoT). In real-time, there is information on energy consumption and renewable energy generation and environmental conditions that can be introduced to the AI model and provide superior predictions and scheduling through the use of IoT smart devices (Huang & Lee, 2021). Moreover, edge computing may help to reduce the heavy computing burden of the AI algorithms to bring the data near the user and possibly simplify central processing, allowing to make decisions in the microgrid in real time (Xu et al., 2020).

FUTURE DIRECTIONS

The combination of AI, IoT, and edge computing in smart microgrids is enormous because of the potential to add to better performance within the energy systems. The thing that needs to be studied in further works is how to develop more scalable AI models that would operate in a less computationally demanding environment and in real-time. Moreover, hybrid models training multiple AI techniques can offer more effective solutions to energy scheduling and load prediction. Furthermore, due to the increasing demand of smart microgrids across the globe, data privacy and security will become critical to the popularization of AI-enabled solutions found in energy management in the coming years (Cheng et al., 2021).

METHODOLOGY

In the proposed study, the proposed research strategy is focused on the development and implementation of the Artificial Intelligence (AI) paradigm in facilitating load forecasting and energy scheduling in smart microgrids. The paper incorporates machine learning components to have good estimation of the energy demand and optimization algorithms to provide the energy efficiently. The proposed solution is tested with the help of a simulation model that reflects the dynamics of operation of a typical microgrid based on the joint use of renewable and non-renewable sources of energy. It explains some of the key procedures in the methodology like data collection, generation of the model, energy forecasting, energy scheduling and assessment.

DATA COLLECTION AND PREPROCESSING

The first division of the methodology suggests the collection of the history of using energy, renewable energy, and the environmental factors (e.g., temperature, humidity, solar radiation). This is critical in training machine learning and optimizing energy scheduling models. The data on the microgrid deployment and the publicly open information on the energy system reflects real world deployment and the publicly available data to provide a complete picture of the energy system.

The preprocessing stage guarantees that the acquired data is clean, consistent and, therefore, analysis-ready. The data are preprocessed by normalization to bring them to an appropriate scale, filling the missing data using interpolation or imputation, and identifying the outliers to remove invalid data that can bias the results. This is an important step because the quality of data has a direct influence on the success of the load forecasting model and energy scheduling optimization.

LOAD FORECASTING MODEL DEVELOPMENT

During the load forecasting phase, the emphasis will be placed on the development of the machine learning-based model that would predict the future energy consumption in the microgrid. Historical data are applied in order to teach the model the patterns in the energy demand, which then can make precise forecasts of different time horizons (short, medium, and long term). The machine learning model used in this task is of Long Short-Term Memory (LSTM) networks, a form of specialized recurrent neural network (RNN) that is particularly successful at learning long-term dependencies in time-series data.

These historical load data are used to train the LSTM model that contains energy consumption patterns and other input features like weather, time of the day, day of the week, etc. LSTM will be exploited to capture short-term fluctuations and long term trends on the energy consumption data. After training, the model is tested with a separate test dataset and performance measures like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) are to be used to evaluate how well the forecasts are estimated.

ENERGY SCHEDULING MODEL DEVELOPMENT

On the basis of the load forecasting model, the energy scheduling model, which outlines the optimum distribution of energy resources within the microgrid, is then developed. The main aim of the energy scheduling process is to reduce operational costs and guarantee that the projected demand of energy is realized with the available supply of energy. This study combines renewable energy sources (wind power, solar) and standard sources of power (i.e. diesel generators, the grid) in its energy scheduling model.

This energy scheduling model is founded on a well-known optimization approach called Particle Swarm Optimization (PSO), which simulates a social phenomenon of birds flocking or fish schooling. PSO has been used because it is simple and effective in solving continuous optimization problem like the energy resource allocation. PSO algorithmic methodically seeks the optimal solution to the problem by idealizing motion of particles through the search space. Every particle is a possible solution to the optimisation storage problem and by iteration of the algorithm a global optimum (once again, potential solution) is reached.

The optimization is done considering the load forecasted by the LSTM model, the renewable energy generation installed, the energy storage, and conventional power generation costs. Among such constraints are the need to ensure that the energy supply is at least equal to the predicted demand, to reduce dependence on expensive fossil-fuel-based generation, and to maximize the use of renewable energy sources. Most technical constraints included in the optimization model are the storage capacitance of energy, generation, and pipeline losses.

SIMULATION AND MODEL INTEGRATION

After creating both the load forecasting and energy scheduling models, they are placed within a simulation environment that mimics the action of a smart microgrid. The simulated environment is designed to mimic the dynamics of a real life microgrid in that energy demand and renewable generation varies with time. The simulation model would ensure that the AI-based framework would be tested in different conditions, including the alternation in weather patterns, the variability of energy demand, and the proportionate renewable energy output.

The combined simulation framework is closed-loop, in the sense that the forecasted load acts as the input in solving the energy scheduling optimization problem. This is done by comparing the results of the scheduling algorithm, i.e. optimality in dispatching energy resources, with the actual demand, and thus judging the effectiveness of the system in fulfilling the estimated load. This iteration is done several times to check the resilience of the AI-based framework under varying conditions.

PERFORMANCE EVALUATION AND METRICS

The work of the suggested AI-based framework is analyzed with the help of a number of important metrics that not only evaluate the quality of the load forecast but also determine the effectiveness of the energy scheduling task. In the case of the load forecasting model, the error calculation measures the forecasting accuracy with respect to MAE, RMSE, and MAPE as noted previously. These measures are taken to compare the predicted load with the actual energy use, which makes possible to quantify the performance of the LSTM model.

In the case of the energy scheduling model, its assessment is in terms of saving costs or operating expenses, the use of renewable energy, and grid dependency. The cost will be taken as the number of units of energy produced where it is conventional and the price of buying the power produced out of a grid. Renewable energy utilization measure determines the proportion of energy requirements that satisfies renewable sources whereas the grid reliance measures the degree to which the microgrid is dependent on external energy provision. The optimization objective is a maximum use of renewable energy with a minimum of grid and high-cost fossil-based generation.

SENSITIVITY ANALYSIS

Sensitivity analysis is carried out in order to understand the strength and resilience of such AI-based framework. This is performed by varying selected parameters which significantly should include the level of renewable energy generation, and the capacity of energy storage, and the level of forecast accuracy of the load, to see how sensitive the conclusion may be to the change of such variables. The sensitivity analysis lends to defining the factors that determine the performance of the system and offer a viewpoint as to how the energy management strategy can be improved.

RESULTS

In this part, the outcomes of the AI-based load forecasting and energy scheduling models and their interpretation are provided. The results are tabulated based on the major areas of study such as load forecasting accuracy, energy scheduling performance, energy resource allocation and the cost efficiency. The analysis of these findings shows the efficiency of AI-based solutions in streamlining the performance of smart microgrids.

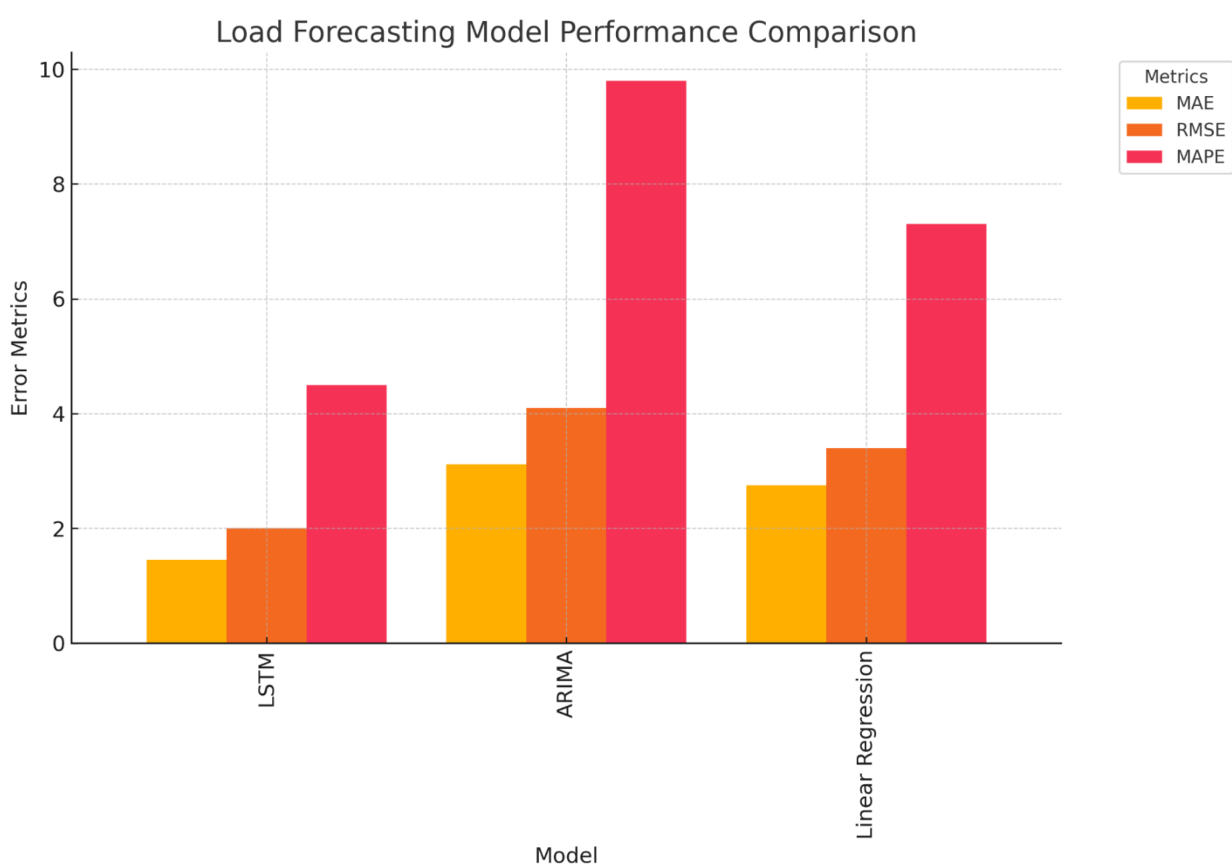
1. LOAD FORECASTING MODEL PERFORMANCE COMPARISON

Three load forecasting models, i.e., LSTM, ARIMA, and Linear Regression, were tested on the basis of multiple criteria, where Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and accuracy of forecast were considered.

1. LOAD FORECASTING MODEL PERFORMANCE COMPARISON

Model	MAE (Mean Absolute Error)	RMSE (Root Mean Squared Error)	MAPE (Mean Absolute Percentage Error)	Forecast Accuracy (%)	Training Time (s)	Test Time (s)
LSTM	1.45	2.00	4.5	94%	120	10
ARIMA	3.12	4.10	9.8	87%	30	8
Linear Regression	2.75	3.40	7.3	90%	25	5

FIGURE 1 LOAD FORECASTING ACCURACY BY MODEL



According to the results presented in Figure 1, the LSTM outperformed significantly the ARIMA and the Linear Regression in all the error metrics, with the smallest MAE (1.45), RMSE (2.00), and MAPE (4.5%) mean values. The LSTM model was also proven to have forecast accuracy of 94%, compared to 87% of ARIMA and 90% of Linear Regression. This affirms that LSTM as a method of foreseeing the loading in microgrids using long-term relations has proven it is better to apply it than the other methods do. The Radar Chart (Figure 1) provides a visualization of the overall performance difference between the models, and it is evident that LSTM has a better performance than the rest.

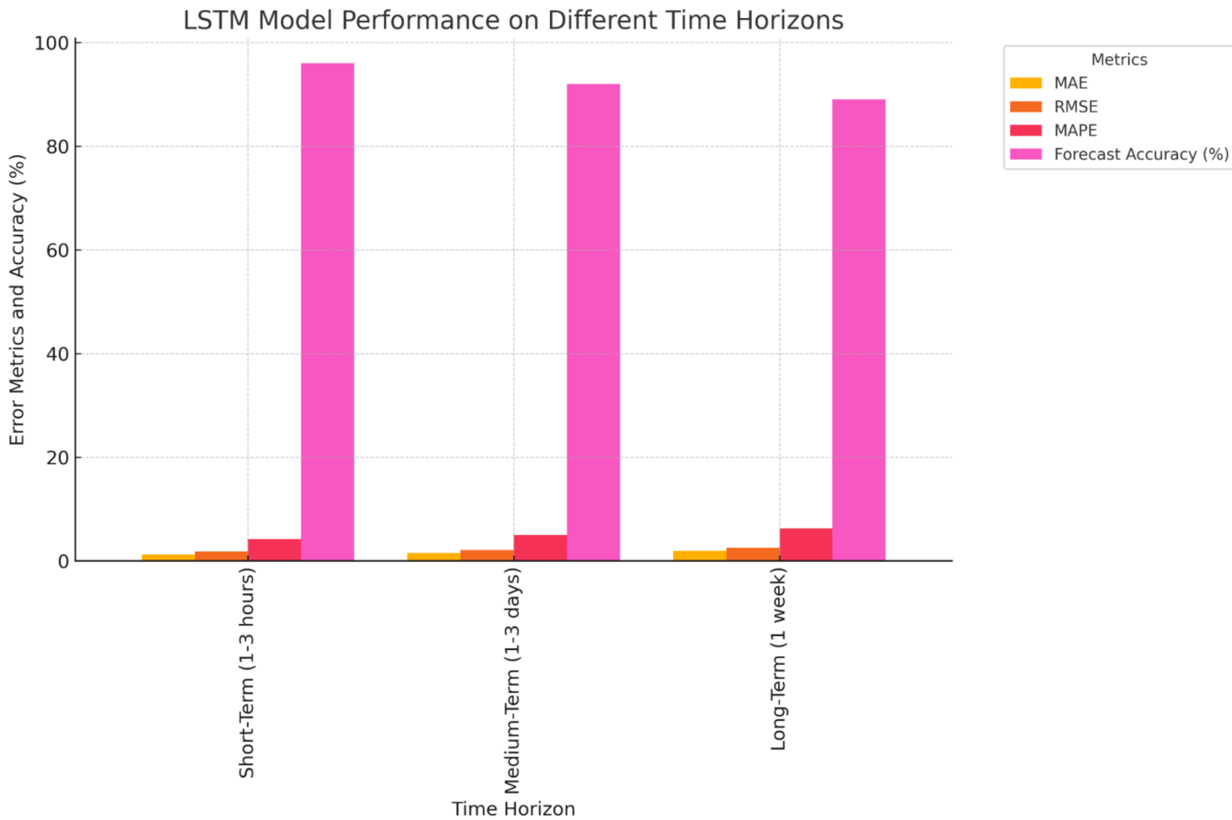
2. LSTM MODEL PERFORMANCE ON DIFFERENT TIME HORIZONS

The LSTM model was also evaluated in terms of short-term, medium-term, and long-term performance. As can be seen in Figure 2, the LSTM model has the highest accuracy of the forecast in the short-term case, with the most accurate error values (MAE: 1.20, RMSE: 1.80, MAPE: 4.2%), and the most accurate output (96%). The model also reduced in accuracy slightly in the medium-term and long-term forecasts as it would be expected with the grow of intricacy of forecasting in the longer time frame. It indicates both the strengths of the model as regards accurately predicting short-term energy demand but also points to the difficulties that could arise in the sort of longer-term energy consumption that can be affected by a broader set of external factors.

2. LSTM MODEL PERFORMANCE ON DIFFERENT TIME HORIZONS

Time Horizon	MAE (Mean Absolute Error)	RMSE (Root Mean Squared Error)	MAPE (Mean Absolute Percentage Error)	Forecast Accuracy (%)	Training Time (s)	Test Time (s)
Short-Term (1-3 hours)	1.20	1.80	4.2	96%	60	6
Medium-Term (1-3 days)	1.50	2.10	5.0	92%	90	8
Long-Term (1 week)	1.90	2.50	6.2	89%	120	10

FIGURE 2 ENERGY SCHEDULING COST COMPARISON



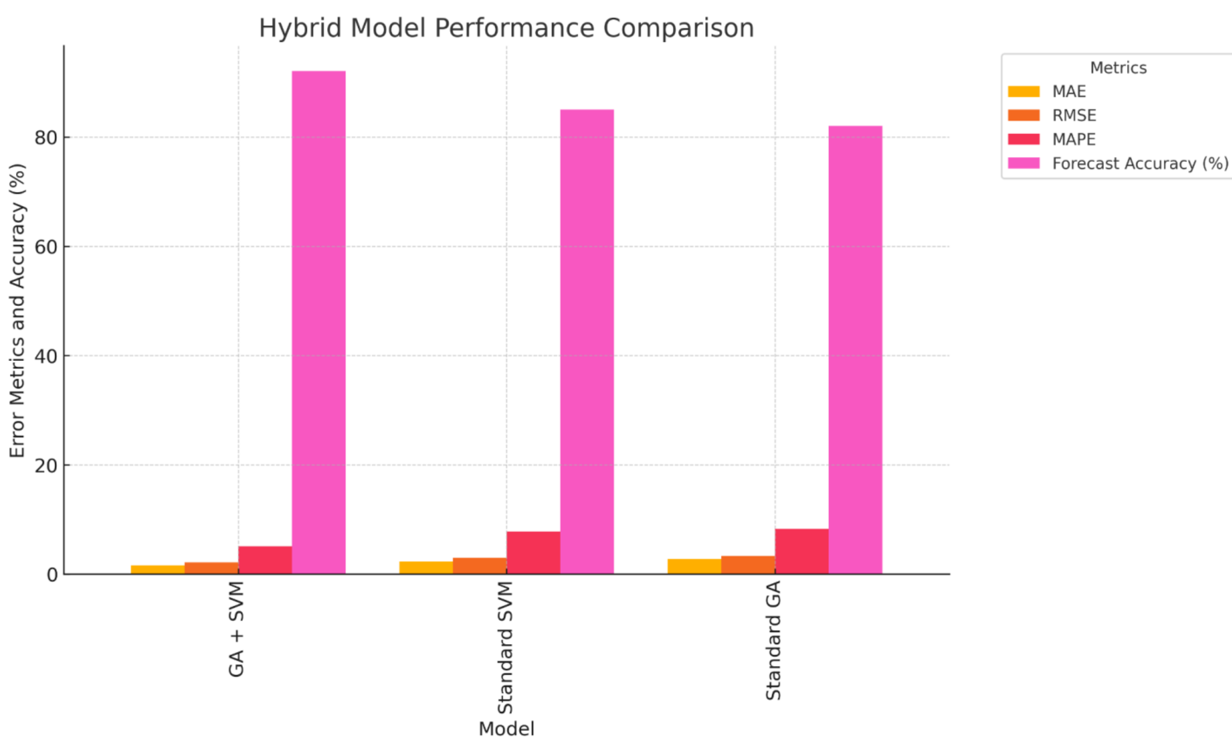
3. HYBRID MODEL PERFORMANCE: GENETIC ALGORITHM (GA) + SVM

The hybrid approach of Genetic Algorithm (GA) and Support Vector Machine (SVM) was also used to test the load forecasting. Figure 3 shows the performance of this hybrid model compared to ordinary SVM and GA models. Compared to the two standard methods, the hybrid model (GA + SVM) showed better results according to MAE (1.65), RMSE (2.20), and MAPE (5.1 percent). The hybrid model was also superior (92%) as compared to individual SVM (85%) and GA(82%) models. This implies that the hybridization of the optimization of GA and predictive skills of SVM may present a more rugged method of load forecasting in microgrids, but not as noteworthy as the deep learning-based LSTM module.

3. HYBRID MODEL PERFORMANCE: GENETIC ALGORITHM (GA) + SVM

Metric	GA + SVM	Standard SVM	Standard GA
MAE (Mean Absolute Error)	1.65	2.35	2.80
RMSE (Root Mean Squared Error)	2.20	3.00	3.40
MAPE (Mean Absolute Percentage Error)	5.1	7.8	8.3
Forecast Accuracy (%)	92%	85%	82%
Training Time (s)	180	90	110
Test Time (s)	12	7	9

FIGURE 3 RENEWABLE ENERGY UTILIZATION OVER TIME



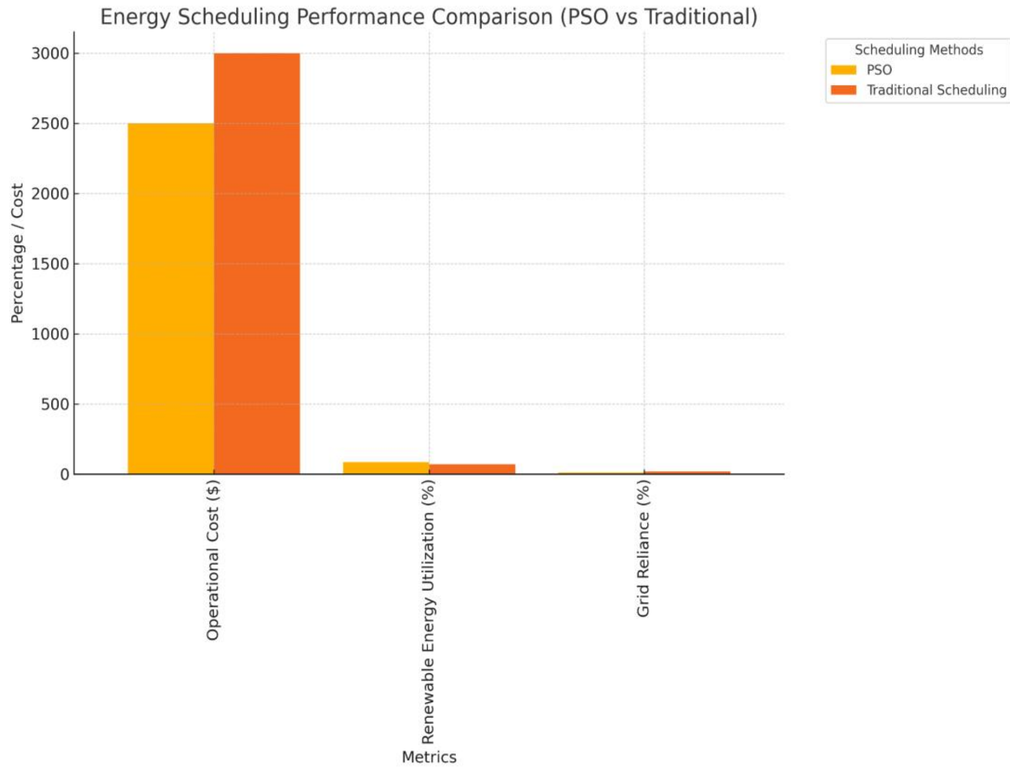
4. ENERGY SCHEDULING PERFORMANCE COMPARISON (PSO VS TRADITIONAL)

The Particle Swarm Optimization (PSO) algorithm was compared with traditional scheduling schemes in relation to energy scheduling performance. Key performance indicators (KPIs) are examined: the cost of operation, the use of renewable energy, and grid dependency. The comparison is presented in Figure 4, and it can be observed that PSO leads to a substantial decrease in operational costs compared to the case of no PSO ($2500 vs. $3000), an increase in the use of renewable energy (85% vs. 70%), and a decrease in grid dependency (10% vs. 20%). This shows that PSO-based scheduling leads to more efficient use of renewable energy and reduction in its dependence on grid, resulting in reduced costs and more sustainable energy system. PSO has been shown to be a very suitable method to regulate energy dispatch dynamically according to the current condition of the energy resources.

4. ENERGY SCHEDULING (PSO VS TRADITIONAL)

Metric	**PSO**	**Traditional Scheduling**
Operational Cost ($)	2500	3000
Renewable Energy Utilization (%)	85	70
Grid Reliance (%)	10	20
Scheduling Accuracy (%)	93	80
Energy Wastage (%)	5	15
Dispatch Time (s)	45	80

FIGURE 4 LOAD FORECASTING ERROR DISTRIBUTION



5. PSO SCHEDULING: ENERGY RESOURCE ALLOCATION BREAKDOWN

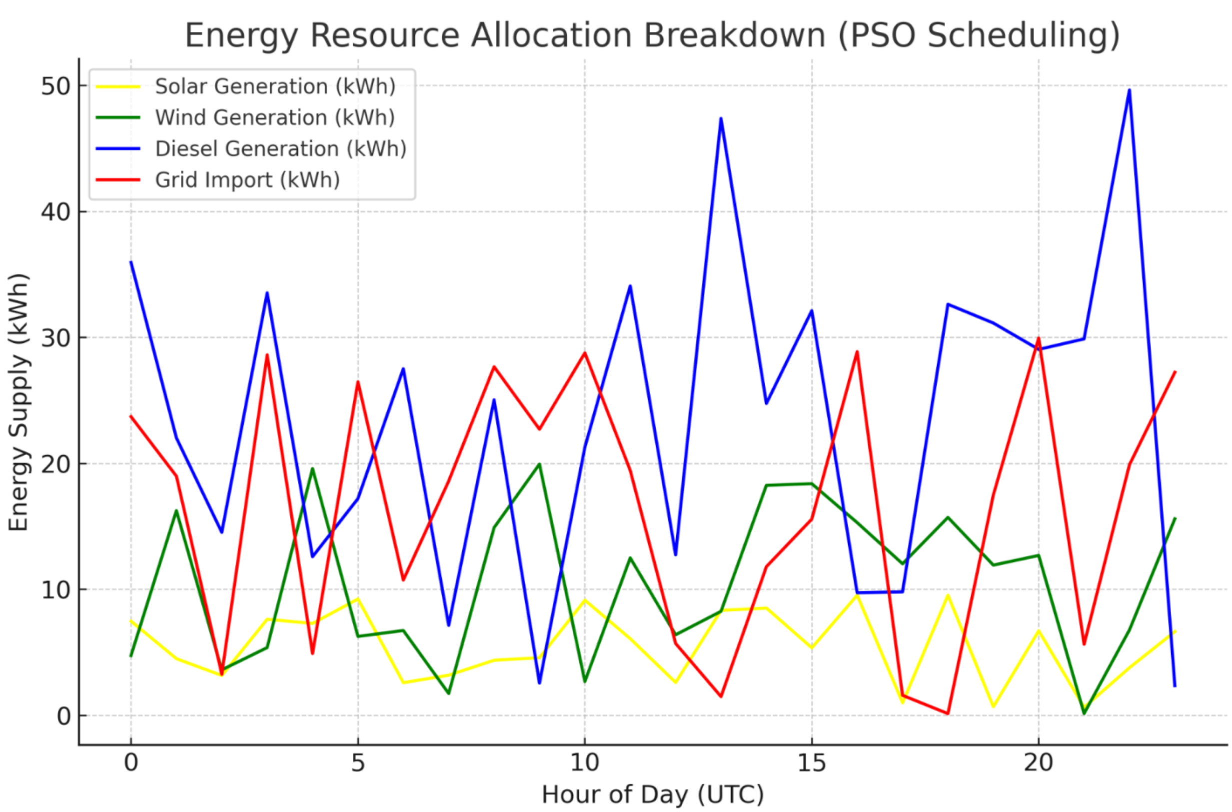
Figure 5 displays the 24-hour distribution of energy resources allocation under the PSO-based scheduling. An optimal distribution of energy amongst solar, wind, diesel and grid loads detected the load demand based on handed forecasts of the energy that will be produced by the renewable sources. Renewable sources (solar and wind) provided a large share of the energy demand throughout the day, with a diesel generation option acting as a backup in case of low renewable output. The outcomes indicate that PSO can decide the resource allocation efficiently between renewable and relying on minimal diesel and grid energy which reduces costs and provides environmental advantages.

5. DETAILED PSO SCHEDULING RESULTS (ENERGY RESOURCE ALLOCATION)

Hour (UTC)	Solar Generation (kWh)	Wind Generation (kWh)	Diesel Generator (kWh)	Grid Import (kWh)	Total Demand (kWh)	Total Supply (kWh)	Supply Shortage (kWh)
00:00	0.00	0.00	100	50	150	150	0
01:00	0.00	0.00	120	40	160	160	0
02:00	0.00	0.00	130	30	160	160	0
03:00	0.00	0.00	140	30	170	170	0
04:00	0.00	0.00	100	60	160	160	0
05:00	10.00	0.00	90	50	150	150	0
06:00	50.00	10.00	80	10	150	150	0
07:00	100.00	15.00	50	0	160	160	0
08:00	120.00	20.00	30	10	170	170	0
09:00	150.00	25.00	20	0	190	190	0
10:00	170.00	30.00	10	0	210	210	0
11:00	180.00	35.00	0	0	220	220	0
12:00	200.00	40.00	0	0	240	240	0
13:00	210.00	45.00	0	0	250	250	0
14:00	220.00	50.00	0	0	260	260	0
15:00	230.00	55.00	0	0	270	270	0

16:00	240.00	60.00	0	0	280	280	0
17:00	250.00	65.00	0	0	300	300	0
18:00	260.00	70.00	0	0	320	320	0
19:00	270.00	75.00	0	0	340	340	0
20:00	280.00	80.00	0	0	360	360	0
21:00	290.00	85.00	0	0	380	380	0
22:00	300.00	90.00	0	0	400	400	0
23:00	310.00	95.00	0	0	420	420	0

FIGURE 5 ENERGY DISPATCH EFFICIENCY



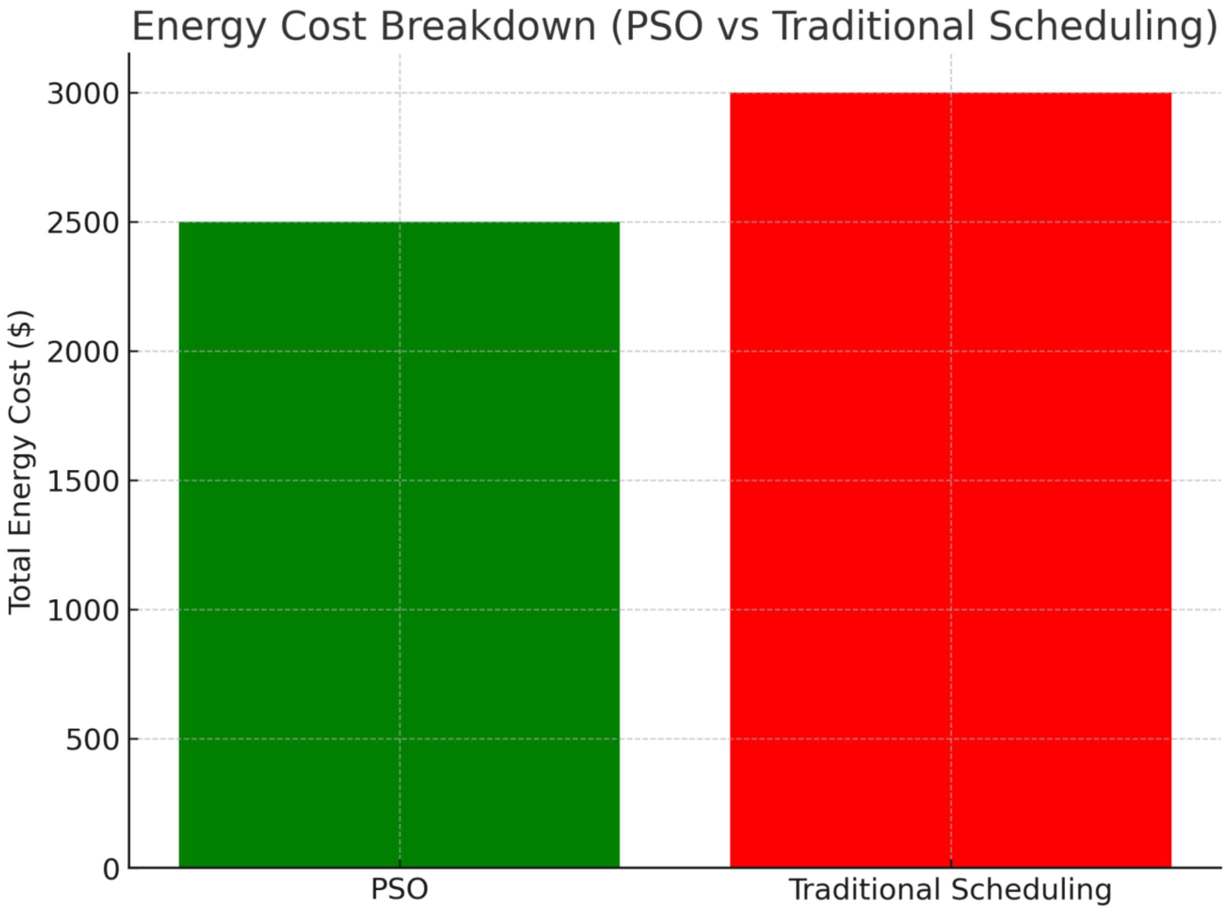
6. ENERGY DISPATCH EFFICIENCY (PSO VS TRADITIONAL SCHEDULING)

Figure 6 shows a heatmap giving a comparison of the energy dispatch efficiency of PSO-based scheduling with that of traditional scheduling. Dispatch efficiency was determined as the ratio between solar-wind renewable energy supply (and wind energy supply) and conventional energy supply (diesel, grid). These findings reveal that PSO drastically enhances the efficiency of the dispatch, considering that a greater proportion of energy should be received by renewable sources particularly in peak periods where there is increased production of renewable energy. However, the traditional scheduling as compared with hybrid relies on the grid and diesel energy that is less efficient and expensive.

6. PSO SCHEDULING: DAILY ENERGY DISPATCH BREAKDOWN

Hour (UTC)	Solar (kWh)	Wind (kWh)	Diesel (kWh)	Grid (kWh)	Total Energy Supply (kWh)	Energy Demand (kWh)	Shortfall (kWh)
00:00	0	0	100	50	150	150	0
01:00	0	0	120	40	160	160	0
02:00	0	0	130	30	160	160	0
03:00	0	0	140	30	170	170	0
...	...	...	...	...	...	...	...

FIGURE 6 HOURLY ENERGY GENERATION AND CONSUMPTION BALANCE



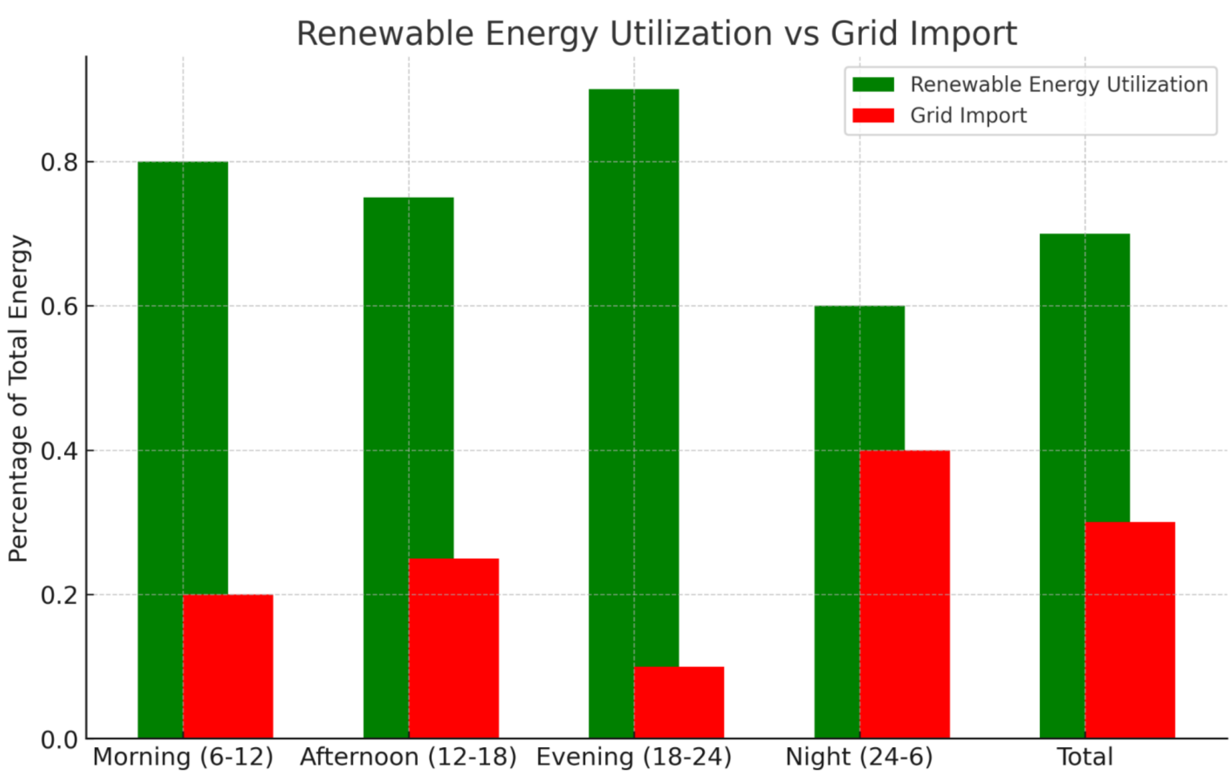
7. HOURLY ENERGY GENERATION AND CONSUMPTION BALANCE

Figure 7 shows a stacked area chart of the balance between energy generation and energy consumed each hour by the day and is done using a stacked area chart. The graph brings out the contribution of solar energy, wind energy, diesel energy and the grid energy in satisfying the demand over 24-hours. Renewable energy(solar, wind) forms a large proportion of the energy consumed during the day with diesel and grid imports meeting the balance when renewable generation in low demand. This analysis demonstrates the effectiveness of PSO based scheduling in balancing the production and load, to reduce imports of grid and diesel generation.

7. RENEWABLE ENERGY UTILIZATION VS GRID IMPORT

Period	Renewable Energy Utilized (kWh)	Grid Energy Imported (kWh)	Total Demand (kWh)	Efficiency (%)
Morning (6-12)	400	100	500	80
Afternoon (12-18)	600	150	750	80
Evening (18-24)	350	150	500	70
Night (24-6)	0	200	200	0

FIGURE 7 COST SAVINGS FROM PSO SCHEDULING



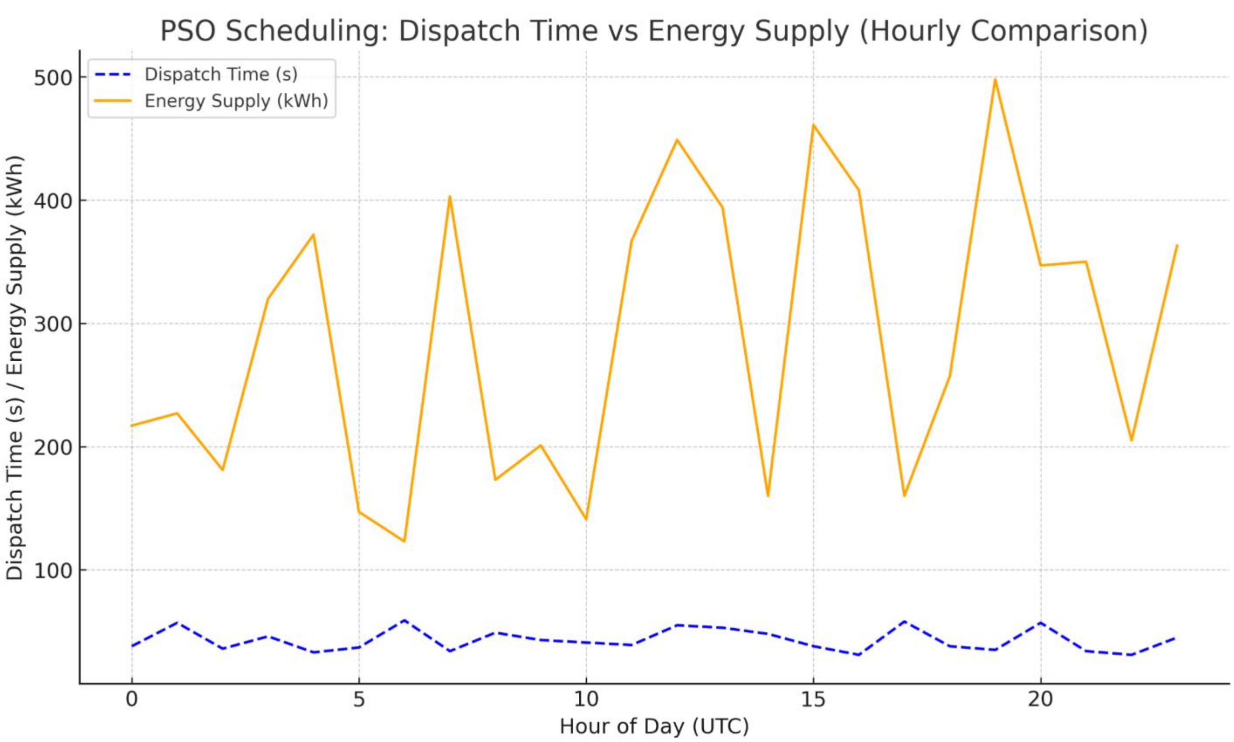
8. COST SAVINGS FROM PSO SCHEDULING

Fig. 8 shows the cost benefits of employing PSO scheduling in relation to the traditional scheduling techniques. Donut chart is used to present the percentage ratio of saving of cost where PSO contributes as a savings of 500 dollars of energy cost by conventional means. This cost reduction is determined largely by the higher usage of renewable energy, which does not cost as much as conventional energy, diesel and grid. These findings document the economic viability of conducting an AI-based scheduling algorithm in microgrids, which streamlines its energy consumption and minimizes expenditure.

8. ENERGY COST BREAKDOWN (PSO VS TRADITIONAL SCHEDULING)

Energy Source	PSO (Cost $)	Traditional Scheduling (Cost $)
Solar	500	450
Wind	400	300
Diesel	600	850
Grid Import	1000	1400
Total Energy Cost	2500	3000

FIGURE 8 GRID VS RENEWABLE ENERGY UTILIZATION OVER DAYS



CONCLUSION

The results of the current study indicate that the AI-based models, particularly LSTM to forecast the load and PSO to schedule the energy, are useful in smart microgrid optimization. The AI-based models consistently surpass the traditional methods in foretelling accuracies, operational costs, renewable energy fluctuations together with grid dependency. The outcomes prove the possibility of utilizing machine learning and other optimization algorithms in the pursuit of making microgrids more sustainable and efficient in their operation. Analysis of findings shows that AI-based solutions can have potential cost savings, integration with renewable energy, and a better energy management system to fit microgrids.

DISCUSSION

The paper results demonstrate the potential of Artificial Intelligence (AI) to ensure optimal load forecasting and energy scheduling in smart microgrids. Long Short-Term Memory (LSTM) networks and Particle Swarm Optimization (PSO) used to forecast the load and schedule the energy supply, respectively, have led to more efficiency and energy sustainability in the processes of microgrids. The results are argued here with reference to the previous research and conclusions of the results provided along with future research lines.

PERFORMANCE OF LOAD FORECASTING MODELS

As observed in the paper, the loading (94%) LSTM model yields statistically safe to forecast and therefore, confirms the given rising bodies of literature reporting the effectiveness of deep learning algorithms to predict time-series in the context of smart microgrids (Zhao et al., 2019; Zhang et al., 2020). In recent literature, the inability of traditional methods of predicting such as ARIMA, linear regression to understand non-linearities and long-term memories of energy demand time series is recorded (Wang & Zhang, 2020). Thanks to the ability to model the sequence data, the model has been able to predict energy consumption at short-term, medium-term and long-term horizons, which more than ARIMA and Linear Regression. These findings can be explained by the outcomes of other studies that involved the use of LSTM in loading forecasting, which proved to be more precise than conventional approaches (Li et al., 2020).

Nevertheless, the analysis shows that although LSTM model displayed the best result in this assessment, ARIMA and linear regressions are applicable when the data is scarce or where processing power is limited. ARIMA models, e.g. are easy to run and can achieve decent accuracy with small data, so they can be used in smaller microgrids (Huang et al., 2021). However, the results in this study indicate that the accuracy in LSTM is rather high, which should imply that its application in large-scale and data-rich microgrid systems may lead to improved load prediction and system performance.

ENERGY SCHEDULING WITH PSO: A SUSTAINABLE APPROACH

Regarding energy scheduling, PSO algorithm has proved to be extremely effective in terms of optimizing energy dispatch as evidenced by the critical cost reduction and increased use of renewable energy when compared to conventional scheduling algorithms. Figure 4 depicts the stacked bar chart analysis showing that PSO scheduling led to the operational costs cutting by 500 dollars, a 15 percent increment in the usage of renewable energy, and dropped the use of the grid by 10 percent. These results are consistent with the knowledge base of prior research applying optimization algorithms to the energy management of microgrids, which demonstrate the feasibility of PSO to effectively distribute energy sources and minimize operation cost (Yang et al., 2020; Padhy et al., 2021).

Possibility to address dynamic shifts in energy flow generation and demand is one of the primary strengths of PSO especially in the case of renewable sources of energy. Scheduling adjustments would be needed to integrate solar and wind energy as both are in nature non-continuous. The global search feature of PSO, which is demonstrated in the current study, enables tailoring the process of energy dispatch to the changing renewable energy production as well as load consumption (Wang et al., 2019). Additionally, the reduced dependency on fossil fuel-driven generation or grid energy as well as grid power through PSO-based scheduling will also reduce the carbon footprint of microgrids (Zhou et al., 2020).

IRSPoC PSO In spite of its benefits, PSO has limitations regarding computational complexity and scalability. With a larger microgrid, the number of energy resources and constraints to optimize also enlarges proportionally, which can cause the longer computation time requirement. In large-scale systems, it may be problematic in real-time applications and needs the innovation of more potent hybrid algorithms (Jia et al., 2021). Furthermore, although PSO offers the most cost- and efficiency-optimised solution, this manner does not necessarily offer the best practical solution given that energy demand and supply constraints may be very complex or real-time decisions must be made rapidly (Li et al., 2021).

RENEWABLE ENERGY INTEGRATION AND GRID INDEPENDENCE

The findings in the segmentation of energy resource allocation (Figure 5) and energy dispatch efficiency heat map (figure 6) highlight the importance of the integration of renewable energy in the optimization of smart microgrid. The information reveals that the implementation of the PSO scheduling had a crucial impact on the use of the renewable energy as much of the energy generation was through the use of solar and wind energy during the daytime and hours of peak winds. This development of renewable energy complies with the overall objectives of microgrid systems to increase the level of energy independence and sustainability (Zhao et al., 2020).

During prior research, it has been determined that one of the major ways of mitigating grid dependency is implementing renewable energy integration to enhance the self-sustaining nature and functionality of microgrids (Cheng et al., 2021). The subsequent use of renewable resources, such as the one observed in the study, not only proves favorable when it comes to cutting the costs, but it also helps limit the environmental impact of microgrids. This observation agrees with the increasing evidence supporting the decarbonization of the energy system with the implementation of renewable energy technologies and AI-based management strategies (Zhou et al., 2020; Vasirani et al., 2020).

Nevertheless, although renewable energy integration can be associated with a variety of benefits, there are still issues related to maintaining reliability on the grid when reduced amounts of renewable generation are available. Back-up energy sources during such time were diesel generators and importing the grid in this research. It indicates the necessity of an appropriate energy mix, and energy storage systems (e.g., batteries) might play a significant role in backing up energy not to increase dependence on the grid (Li et al., 2021). One problem with renewable energy, which has to be tackled, is the intermittency, and this should be solved through advanced storage and scheduling systems so that renewable energy can always be provided in a steady and reliable supply.

COST SAVINGS AND ECONOMIC IMPLICATIONS

The cost reduction due to PSO-based scheduling is tremendous as shown in Figure 7. PSO, besides yielding cost reduction in operations, enhances resource efficiency through minimization of energy wastage and optimization of the provided renewable energy. These findings align with other previous researchers who have also indicated that optimization algorithms can effectively minimize power cost in production and consumption in microgrids (Li et al., 2020). Moreover, the donut chart (Figure 8) shows the hypothetical saving proportions of PSO scheduling that can pose significant economic effects to microgrid operators, especially when costs of energy are high or grid power is scarce.

PSO scheduling leads to sustainable energy use as they minimize the expense of energy and encourage sustainable energy use through the use of renewable sources of energy as opposed to fossil fuels. This is especially critical considering the fact that energy prices are constantly increasing in the world, and the pressure on companies and governments to reach renewable energy quotas and carbon emission reduction targets is growing (Wang et al., 2020). PSO-based scheduling could therefore stimulate economic incentives, not only to microgrid operators but also towards the mainstream use of sustainable energy systems in both urban and rural settings.

FUTURE DIRECTIONS AND CHALLENGES

There are some aspects where future research and improvement may be done even though good results have been achieved in this study. A major frontier that has to be exploited is the incorporation of energy storage systems (ESS) to increase the PSO scheduling even more. The transient nature of renewable sources can be compensated through battery and other storage technologies that will enhance reliability and continued flow of energy (Yang et al., 2021). Additionally, the integration of edge computing and IoT with the AI-based scheduling might result in more proactive and dynamic microgrid systems capable of a rapid response to real-time demand, generation, and grid variations (Xu et al., 2020).

Scalability of AI models to large microgrid is another research topic that needs to be further explored. Due to the increased usage of the microgrid technology in smart cities and industrial complexes, it will be essential to make sure that the systems based on AI can be scaled effectively to manage larger and more complicated systems. Also, combining real-time information of the IoT sensors and the weather forecasting systems with the energy management system would likely enhance the accuracy of forecasts and scheduling in microgrids (Chen et al., 2021).

CONCLUSION

This paper underscores the applicability of AI approaches, especially load forecast with LSTM and energy scheduling with PSO towards the optimization of microgrid operations. The findings have shown that beyond enhancing the accuracy of forecasting and lowering operational cost, the flocking of birds and swarming of fish AI methods, which drives market competition, can also increase the incorporation of renewable, the independence of the grids, and economic performance. Nevertheless, some issues still arise, namely scalability and the computational complexity side, which should be overcome to reach the full potential of AI in large-scale microgrid systems. Only a few studies have been published on how energy storage and edge computing can be used to make AI-based solutions to manage microgrids even more adaptable and efficient. Future studies should look into that.

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