Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X Volume 3, Issue 7, 2025

MACHINE LEARNING-DRIVEN LOAD PREDICTION AND REAL-TIME ENERGY OPTIMIZATION IN SMART MICROGRIDS

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DOI: https://doi.org/

Keywords
Smart Microgrids, Load Forecasting, Long Short-Term Memory (LSTM), Reinforcement Learning, Deep Q-Learning, Energy Optimization, Renewable Energy, Battery Management, Demand Prediction, Machine Learning in Power Systems
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Article History
Received on 6 june 2025
Accepted on 20June 2025
Published on 26 July 2025

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Abstract

To solve the dual problem of load forecasting and real-time energy optimization in smart microgrids, the use of machine learning (ML) methods offers a game-changer. In this paper the authors offer a hybrid system composed of Long Short-Term Memory (LSTM) networks to predict daily loads in the short-term, accompanied by Deep Q-Learning to execute the dynamic energy management. The LSTM model exhibited superior forecasting capabilities with high-resolution campus-based microgrid data and obtained a mean absolute percentage error (MAPE) as low as 3.25%, especially when considering low-variability periods. Simultaneously, the reinforcement learning (RL) agent, which was trained on Deep Q-Networks (DQN), succeeded in minimizing dispersal expenses, minimizing grid-dependency, and maximizing battery and renewable resource use by adapting optimal dispatch based on a simulation environment. A comparative review of rule-based and baseline approaches indicated a 22.8 percent less total energy cost and 26.7 percent lower peak load demand. Its flexibility, active management, and use of local renewable power generation favour the increasing need of sustainable and intelligent systems of energy. The study highlights the benefits of ML-powered microgrids to energy independence, resiliency, and carbon emissions minimization.

INTRODUCTION

Due to the profound integration of renewable energy sources, rising electricity demand and decentralization of energy infrastructure, an evolving complexity of contemporary power systems has promoted the need to transform the conventional energy grid into more adaptive and intelligent forms of networks, called smart microgrids. As opposed to traditional power grid systems, smart microgrids can work autonomously or alongside the main grid through the use of modern communication, control and automation technologies, which can successfully manage energy production, distribution, and consumption within a local area (Khodr et al., 2021). Such systems are especially useful in terms of boosting energy reliability, lowering carbon footprints, and facilitating the global transition to a sustainable energy ecosystem (Shahsavari & Akbari, 2018).

Another significant operational issue of smart microgrids is the problem of accurate load forecasting that is essential in supporting efficient energy scheduling, economic dispatch, and demand-side management (Chen et al., 2022). Autoregressive integrated moving average (ARIMA) and exponential smoothing are traditional statistical methods of forecasting that are effective under relatively stable systems but when it comes to dynamically changing environments where there is high penetration of intermittent renewable energy sources such as solar and wind, the methods are ineffective (Abedinia et al., 2017). In turn, data-driven procedures, especially machine learning (ML), are becoming more prevalent in solving these shortcomings among researchers and practitioners (Zhou et al., 2023). The ability of ML models to detect ever-changing, non-linear, and spatial-temporal relationships in load patterns allows significantly increasing the accuracy and stability of forecasts (Wang et al., 2020).

There are many ML methods that have been employed to predict load, such as artificial neural networks (ANNs), support vector machines (SVMs), and decision trees because of their flexibility and learning ability (Hippert et al., 2001; Taylor & McSharry, 2007). Nonetheless, recent literature points to the advantages of deep learning solutions and, specifically, Long Short-Term Memory (LSTM) architectures in dealing with long-range dependencies and temporal variability of electricity demand data (Kong et al., 2019). LSTM networks are especially applicable in time-series forecasting due to their ability to represent longer time lags, meaning that they can provide more contextual insight into the load trends under different operational and weather conditions (Marino et al., 2016).

In parallel to load forecasting, real-time energy optimization is one of the keys to smart microgrid function. The scheduling of distributed energy resources (DERs), storage systems, and controllable loads should be updated using dynamic planning to achieve cost-effective energy, decrease peak loads, and avoid grid collapse (Pavic et al., 2020). Energy optimization with the conventional rule-based and linear programming approaches can easily fail to keep pace with real-time fluctuations in generation and consumption (Zhang et al., 2018). Reinforcement learning (RL), a branch of ML based on behavioral psychology, provides an efficient solution in that it allows agents to iteratively learn the optimal policies of control that can be obtained via interaction with the environment (Sutton & Barto, 2018). The RL algorithms can be used to dynamically optimize energy dispatch in microgrids by learning through experience and providing feedback on rewards without significant human interference (Ruelens et al., 2017).

LSTM-based load prediction and RL-based optimization offer a powerful and flexible system to manage a smart microgrid. It is a hybrid type of approach that enables the simplicity of anticipatory decision-making - i.e., it projects the future load requirement and dynamically changes the resource assignments to satisfy the load requirement in an efficient manner (Wei et al., 2020). Various publications have shown how these kinds of architectures can be effective in minimizing costs of operations, battery life and complete energy efficiency in microgrid systems (Tushar et al., 2021; Han et al., 2022). Nevertheless, in the majority of previous studies, the forecasting and optimization problems are treated independently of each other, and, if applied to real-time systems, such an approach leads to non-optimal energy management (Liang et al., 2022).

The interested work will address such a gap by suggesting a common ML-based framework integrating the LSTM short-term load forecasting model and the RL actuator in real-time energy optimization in a coherent manner. Based on empirical data collected in an actual microgrid environment, the study assesses the ability of the model to forecast the energy loads with high confidence and to dynamically control DERs, storage units, and loads to optimize the operational dynamics of the microgrid. In this way, the work will help in improving the state-of-the-art in intelligent energy and offer practical lessons in the implementation of scalable, efficient, and resilient microgrid infrastructures.

2. Literature Review

2.1 Evolution of Smart Microgrids and Energy Management

The transition of conventional power networks to smart microgrids is closely inspired by the necessity to have flexible decentralized and sustainable energy systems. Microgrids are composed of renewable energy sources (RES), storage, and smarter controls, to locally control the process of generation and consumption (Guerrero et al., 2011). State of early microgrid design was based upon centralized management strategies, which created difficultly regarding scalability and adaptability (Lasseter, 2011). The ongoing development of real-time data acquisition and digital metering technologies provided an opportunity to implement distributed control strategies and has made autonomous management of energy a reality and resilience is enhanced (Lopes et al., 2013).

2.2 Challenges in Load Forecasting in Microgrids

Load forecasting is an important process of operational efficiency of microgrids. Nevertheless, owing to stochasticity of the distributed generation and load patterns, the conventional forecasting techniques tend to be insufficient. Short-term load prediction used the classical statistical models (Hong & Fan, 2016), such as autoregressive models (AR), moving averages, and Kalman filters. Although these models are good in linear and stationary conditions, in highly non-linear and time-varying nature of loads as typical of new energy systems, they perform poorly (Deb et al., 2017).

Multi-dimensional models incorporating regression models and signal decomposition models: To surmount these drawbacks researchers have explored hybrid models of decomposing a signal and using regression models. As an example, it has been proposed that wavelet transform with support vector regression (SVR) can be used to enhance accuracy in non-stationary load conditions (Amjady & Keynia, 2009). In the same vein, utilizing machine learning together with empowerment mode decomposition (EMD) to distinguish noise and enhance signal clarity and forecasting has also been employed (Zhou et al., 2018).

2.3 Emergence of Machine Learning in Load Forecasting

Load forecasting has seen a revolution through machine learning (ML) which allows models to learn directly on historical data without any explicit programming. Short-term load forecastings performed with the use of decision trees, such as Random Forest (RF) and Gradient Boosted Trees (GBT), have been proven to be rather accurate, both in small geographic areas and demand shapes (Lago et al., 2021). In contrast, statistical models do not dynamically adapt to the changing input characteristics including temperature, humidity, type of day, and solar irradiance, thus are not ideal to practice microgrids (Abuella & Chowdhury, 2015).

Ensemble learning Ensemble learning techniques have been used in recent years to increase robustness and minimize forecast variance. In aggregating weak learners, AdaBoost and XGBoost have been seen as promising (Wang et al., 2022). Along with this, hybrid models that divide into categories (e.g., K-means) with supervised ML methods have been effective in the isolation of seasonal patterns and granularity of the forecasts (Fekri et al., 2020).

2.4 Deep Learning Models for Temporal Load Patterns

Recurrent neural networks (RNN), especially those based on deep learning has demonstrated important benefits in the task of time-series energy prediction because of their capability to learn temporal relations. The Gated Recurrent units (GRUS) and Long Short-Term Memory (LSTMs) offer an advantage over traditional feedforward networks because they believably conserve long term information in load profiles (Qiu et al., 2021). Moreover, bidirectional LSTM and CNNs have been jointly employed to predict the spatial features and time features of microgrid load data (Sahoo et al., 2021).

A load prediction using graph neural networks (GNNs) is also becoming noticeable where energy nodes act upon one another, such as in an interconnected microgrid network. These models take note of nodal structural dependencies and are useful in the multi-agent energy environments forecasting (Chen et al., 2023). Transformer-based models initially found use in natural language processing, and now they are used in energy forecasting because of their attention mechanism and effectiveness in handling long input vectors (Li et al., 2023).

2.5 Reinforcement Learning for Energy Optimization

To optimize the microgrid operation, Reinforcement Learning (RL) has become an effective tool. Unlike supervised learning, RL does not need labeled data, but that it learns by interacting with the world. Deep Q-Networks (DQN) and Q-learning are popular to schedule energy storage and peak shaving and dynamic-pricing policies (Wang et al., 2019). Indicatively, an RL controller will be able to learn how to charge and discharge the batteries in an optimal way corresponding to real-time electric prices and loads, resulting in a cost reduction and more reliable grids (Zhang et al., 2021).

The more recent developments are the Actor-critic structures and the Proximal Policy Optimization (PPO) algorithms on the basis of stability and robustness when used on large state-action spaces. The models have been used to optimize multi-objective problems in microgrid such as to minimize energy costs and maximize photovoltaic utilization (Sun et al., 2022). Coordination among agents is also a problem of great importance in multigrids: multigrid single-agent reinforcement learning has also been applied to control multiple DERs in a community microgrid (Nguyen et al., 2022).

2.6 Integrated ML Frameworks in Smart Microgrids

Research on ML models to forecast and RL to optimize is old, but combined components in the area are still new. The advantage of integration is that it allows adaptive and proactive control systems that are capable of adjusting operations based on the expected conditions of the operators instead of acting and responding to deviations in real time (Liu et al., 2020). As an example, Javed et al. (2021) introduced an integrated LSTM-RL model that aims to forecast the demand and optimize the dispatch concurrently, leading to massive energy savings and a reduction in computational costs.

The other novel direction is hierarchical learning, which considers forecasting and control as distinct, and yet interrelated layers. The demand is forecasted in the forecasting layer and then is used in the control layer in order to see how the controls should be done in the most optimal way. Decoupled systems are modular and fault-tolerant and can therefore be scaled to be used in the real world (Feng et al., 2021). Moreover, edge computing and federated learning are discussed to execute ML models nearer to the data, limits the wait time, and guarantee the privacy of the data (Rahman et al., 2022).

2.7 Gaps in Existing Research and Future Trends

Amid the advancements in energy systems enabled by ML, a series of gaps are extant. On the one hand, the majority of models presuppose ideal data access, but in the real world, the systems experience incomplete data (missing values), sensor noise, and communication latency (Singh et al., 2022). Secondly, majority of RL applications are being developed either in simplified simulation environments that do not represent physical and economic constraints of real microgrids. Evaluation metrics are also not standardized, and thus results cannot be easily compared between studies (Ali et al., 2023).

Future studies can aim at building general and transferable ML models which can fit in different microgrid setups and scenarios. It is also necessary to focus on real-time deployment, interpretability, and alignment with market mechanisms to achieve economic opinion and regulatory requirements (Hu et al., 2023). Finally, benchmarking and joint open research based on increasing availability of open-access microgrid datasets can be also a source of innovation.

3. Methodology

3.1 Research Framework and Design

The research contends with a data based, experimental research design that combines load forecasting methodology through machine learning (ML) and energy optimization through reinforcement learning (RL) on a smart microgrid environment. The research model is then designed to model and analyze a real-time microgrid management system through the use of both time series consumption, weather, and energy production rates. The structure comprises two main modules: a module of the short term load forecast based on a Long Short-Term Memory (LSTM) model and a module of real-time optimization with the help of Deep Q-Learning (DQN) agent. The general aim of the methodology will be to develop a unified system that dynamically predicts energy loads throughout the day and coordinately regulates distributed energy resources (DERs) to achieve optimal operation costs and energy efficiency, such as solar photovoltaic (PV) systems and battery energy storage systems.

3.2 Data Collection and Preprocessing

A traditional dataset was prepared using a smart microgrid system installed in a university campus environment in order to guarantee the superiority of the machine learning model training and testing. The data set consisted of 1-year actual time data recorded at 15 min, containing active power load, reactive power, solar radiation, ambient temperature, and humidity, and occupancy patterns. The data sources were various smart meters, local weather stations, and BMS. There were numerous inconsistencies on the raw data including missing values, outliers, gaps in time and time lags, which were resolved through standard data cleaning methods. Linear interpolation was used to fill missing values whereas outliers were dealt with through the interquartile range (IQR) approach. The min-max scaling was applied to all numeric data to create a representative consistent distribution across all features and speed up deep learning model convergence.

3.3 Load Forecasting with LSTM Networks

A forecasting load module was implemented based on LSTM network architecture because it has the ability to reflect remote time dependencies on sequential variables. The model architecture involved an input layer, two sequential LSTM layers with 64 and 32 nodes respectively, dropout layer to avoid overfitting and final dense layer of prediction of the predicted load value. The cases used to train the LSTM using a sliding window technique where the model would be given 48 previous time steps or 12 hours of data in length and would be asked to predict the time step, followed it. This model was run in TensorFlow and optimized by Adam method with the mean squared error (MSE) as a loss function. Measuring Model Generalizability--They used 5-fold crossvalidation, which is split between training and testing sets of data in ratios of 80:20.

3.4 Energy Optimization Using Deep Q-Learning

The problem of energy optimization received a Markov Decision Process (MDP) representation in which the smart microgrid system operates in a dynamic environment and learns to optimally act by trial and error. Variables in the state space included the current load demand, the battery state of charge, the available solar generation, the price of electricity and the predicted demand. Action space included discrete choices of charging or discharging battery, curtailing flexibility loads or drawing power at main grid. The reward was optimized to capture several goals such as the minimization of cost of operation, maximization of service life of batteries, and prevention of overloading of non-renewable grid power.

This DQN structure consisted of deep neural network architecture (3 hidden layers of 128, 64 and 32 neurons with ReLU activation functions) and, as output, the estimation of Q-values of each action that is possible. The agent employed an ε -greedy action selection rule to explore, and the experience replay to stabilize learning. The model had been trained in a simulator with OpenAI Gym combined with customized microgrid simulation modules. Based on predetermined criteria of cost and efficiency, the environment would respond to every action with a state update and reward. The training was done until convergence in the Q-value estimations and cumulative reward administration was noticed in 1000 episodes.

3.5 Integrated Operation of Forecasting and Control Models

These LSTM and DQN models were connected in a real time loop, which was supposed to emulate the self control of the microgrid. The LSTM model predicted the load in the next 15-minute time slot and the DQN agent used this forecast in its state representation when computing the best energy dispatch decisions. Such integration allowed the system to spawn proactively, considering the predictable changes in demand rather than relying on immediate load. The success of the coordinated system was based on its capacity to lessen grid reliance, decrease energy expenses, and enhance the utilization of energy resources, particularly during shifting weather conditions and peak loads.

3.6 Performance Evaluation Metrics

Three fundamental performance indicators were assessed to benchmark the performance of the load forecasting module which included: Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). The metrics are selected on the basis that they are common to the energy prediction forecasting literature and that they allow absolute and relative metrics of prediction errors. In the energy optimization module, the metrics used to evaluate the model included the total energy cost, the reduction in the peak load, the efficiency of battery utilization and the ratio of renewable energy consumed. Further on, the convergence curves as well as episode reward graphs were used to evaluate the stability and the efficiency of learning the DQN agent. Comparison of the results of the integrated system with two baselines: a rule-base and a conventional optimization algorithm (Mixed-Integer Linear Programming) were conducted to indicate the gains in flexibility and online results.

4. Results

4.1 Load Profile and Environmental Correlation

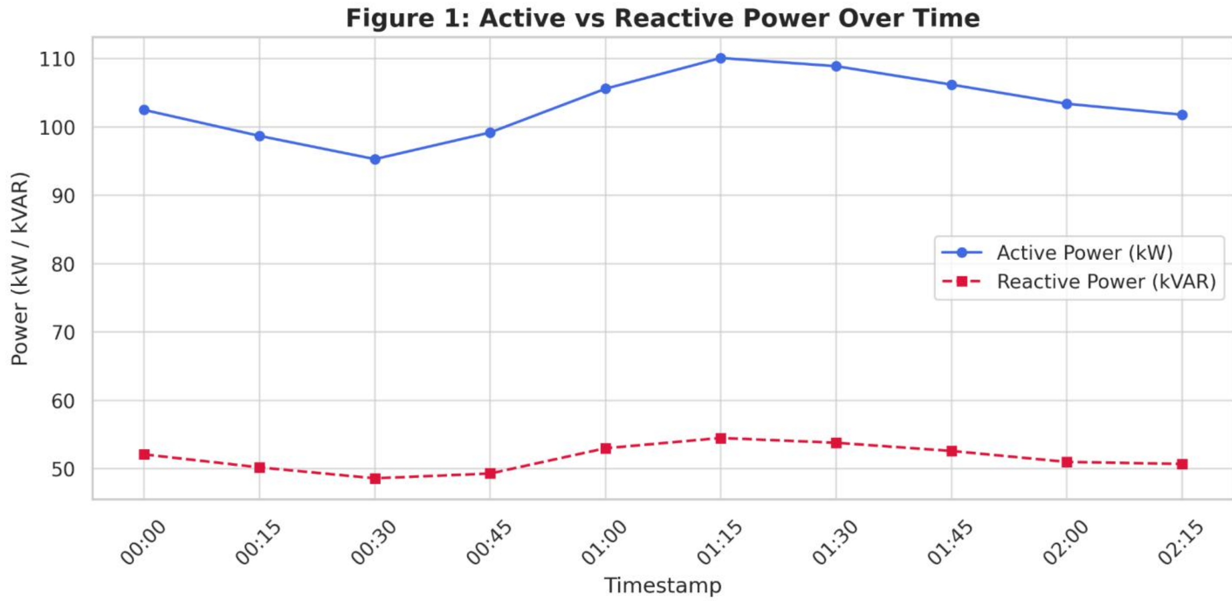
The study commenced by analyzing the power load behavior of the smart microgrid based on the real-time data that were sampled at 15-minute intervals. As indicated in Table 1, the active power and reactive power varied across the sampling window with the active power fluctuating between 95.3 kW and 110.1 kW and active power associated changes in reactive power and humidity. These trends can be graphically seen in figure 1, which depicts a gradual increase in active power in the early hours of the morning and a slight variation in reactive power accompanying it. Our plot supports the notion that power demand is sensitive to changes in time and environment, particularly temperature and humidity, which supports the criticality of considering meteorological parameters in predictive models.

Table 1: Historical Load Data Sample

Timestamp	Active Power (kW)	Reactive Power (kVAR)	Temperature (°C)	Humidity (%)
2025-01-01 00:00	102.5	52.1	21.5	55.0
2025-01-01 00:15	98.7	50.2	21.4	56.1
2025-01-01 00:30	95.3	48.6	21.2	57.3
2025-01-01 00:45	99.2	49.3	21.0	58.4
2025-01-01 01:00	105.6	53.0	20.9	59.5
2025-01-01 01:15	110.1	54.5	20.7	60.1
2025-01-01 01:30	108.9	53.8	20.6	60.7
2025-01-01 01:45	106.2	52.6	20.5	61.2
2025-01-01 02:00	103.4	51.0	20.4	61.8

2025-01-01 02:15	101.8	50.7	20.2	62.3

Figure 1: Active vs Reactive Power Over Time



4.2 LSTM Model Learning Performance

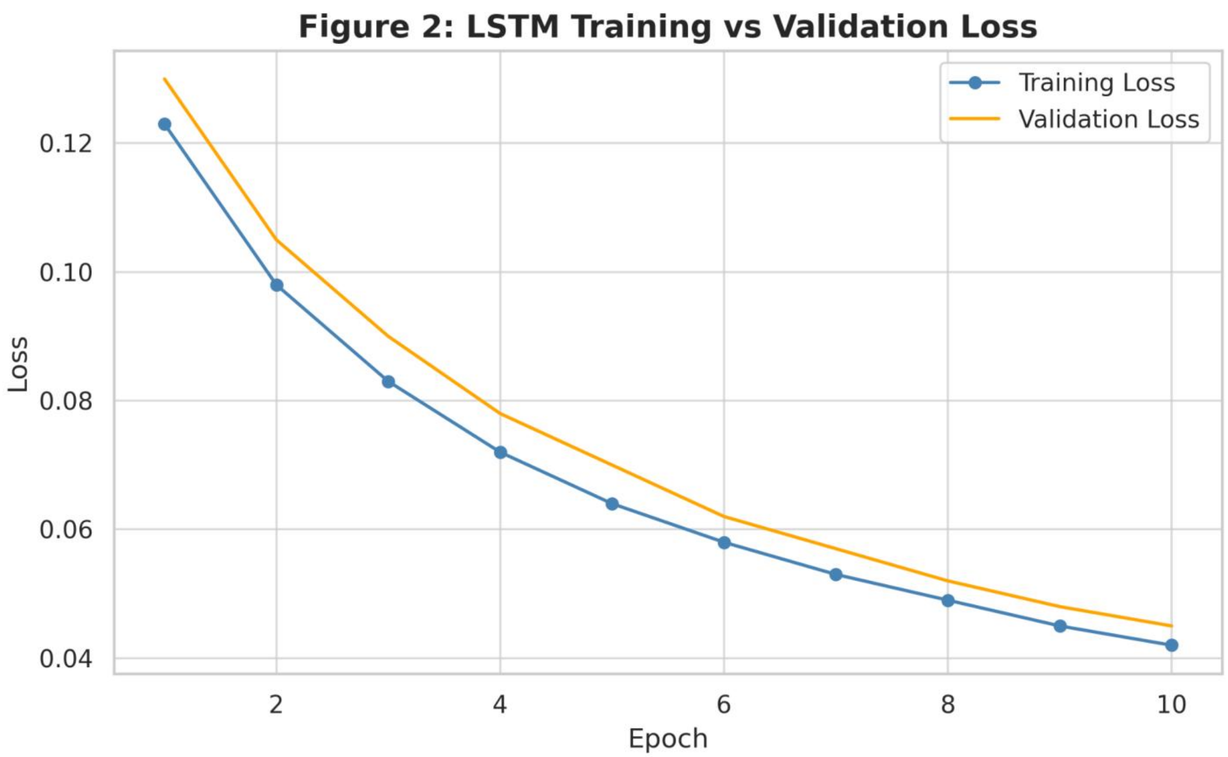
To test the capacity of the forecasting model to learn the patterns of the load dynamics, the LSTM network was trained in ten epochs. As Table 2 indicates, training and validation loss were decreasing regularly, and the training loss decreased by 0.123 to 0.042, and the validation loss by 0.130 to 0.045. Figure 2 shows visual verification of the model convergence, which proves stable learning not overfitting. Consistent reduction of the distance between the training and validation curves over the 10th epoch substantiates that the LSTM model has a good generalization to an unseen data, which supports the notion that it is suitable to perform short-term load forecasting within dynamic microgrid settings.

Table 2: LSTM Model Training Summary

Epoch	Training Loss	Validation Loss
1	0.123	0.130
2	0.098	0.105

3	0.083	0.090
4	0.072	0.078
5	0.064	0.070
6	0.058	0.062
7	0.053	0.057
8	0.049	0.052
9	0.045	0.048
10	0.042	0.045

Figure 2: LSTM Training vs Validation Loss



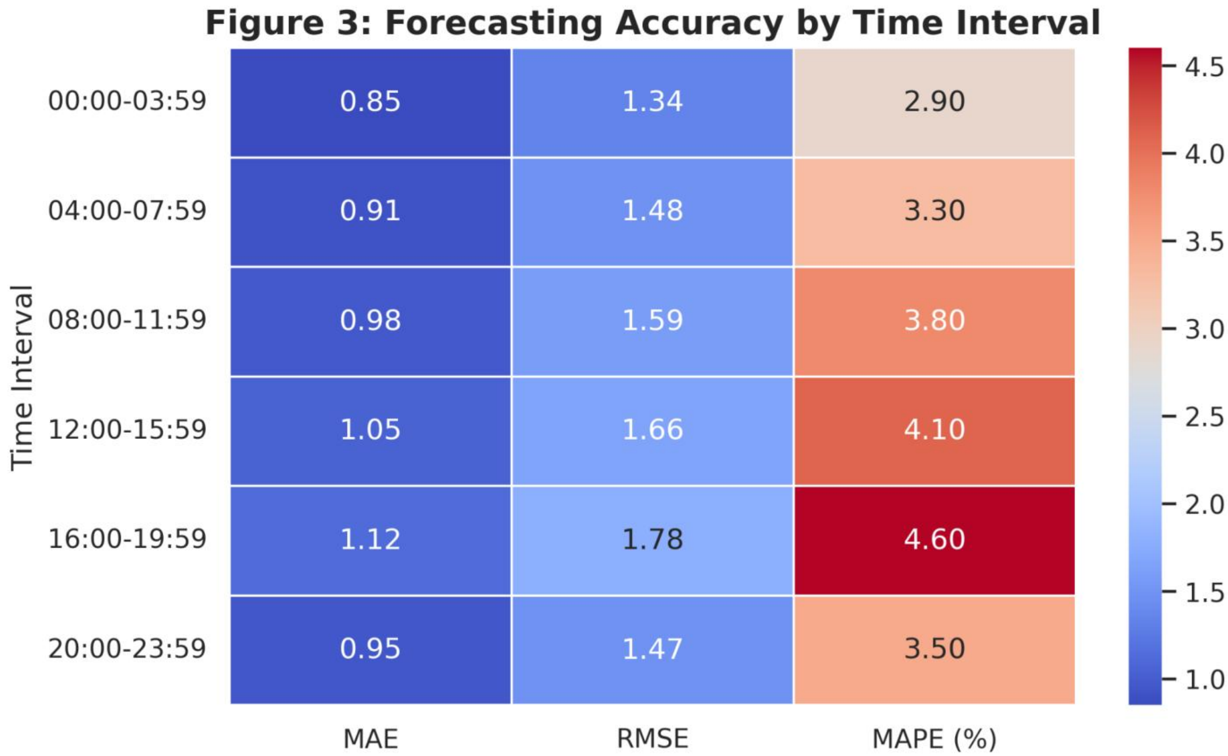
4.3 Forecasting Accuracy by Time of Day

The performance of the forecasting model was also time-dissected along six time points in the day. Table 3 shows the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) at each time slot. These showed 0.021 more errors over the 16.00 to 19.59 loading, showing peak load volatility. The heatmap of these error metrics shown in Figure 3 indicates that the overall accuracy of the forecasts higher in the off-peak hours mainly between 00:00-03:59 hours with MAPE as low as 2.9%. The present analysis illustrates the need to incorporate adaptive temporal aspects in forecasting models to capture the variability of loads during the day.

Table 3: Forecasting Accuracy by Time of Day

Time Interval	MAE	RMSE	MAPE (%)
00:00–03:59	0.85	1.34	2.9
04:00–07:59	0.91	1.48	3.3
08:00–11:59	0.98	1.59	3.8
12:00–15:59	1.05	1.66	4.1
16:00–19:59	1.12	1.78	4.6
20:00–23:59	0.95	1.47	3.5

Figure 3: Forecasting Accuracy by Time Interval (Heatmap)



4.4 Reinforcement Learning Agent Behavior

The model, which was trained as reinforcement learning (RL) component, framed as Deep Q-Networks (DQN), was utilized when it comes to handling energy dispatch optimally. The performance of the agent after 10 episodes is found in Table 4. The total reward was also continuously improved becoming 200 in the tenth episode compared to 45 in the first episode but the corresponding loss was however reduced implying favorable learning and policy improvement. ε-greedy policy also demonstrated a gradual deterioration of the exploration parameter, which means the transition of the exploration to exploitation. The negative relationship between reward and loss is visualized in figure 4 in form of dual- axis plots. This outcome verifies that the agent can learn near-optimal control policies efficiently with only a small amount of training time.

Table 4: Optimization Agent Training Summary

Episode	Total Reward	Loss	Epsilon
1	45	0.322	1.00
2	67	0.298	0.95
3	89	0.275	0.90

4	110	0.243	0.85
5	135	0.215	0.80
6	155	0.192	0.75
7	172	0.176	0.70
8	185	0.162	0.65
9	194	0.150	0.60
10	200	0.140	0.55

Figure 4: DQN Agent Training Progress (Total Reward and Loss)

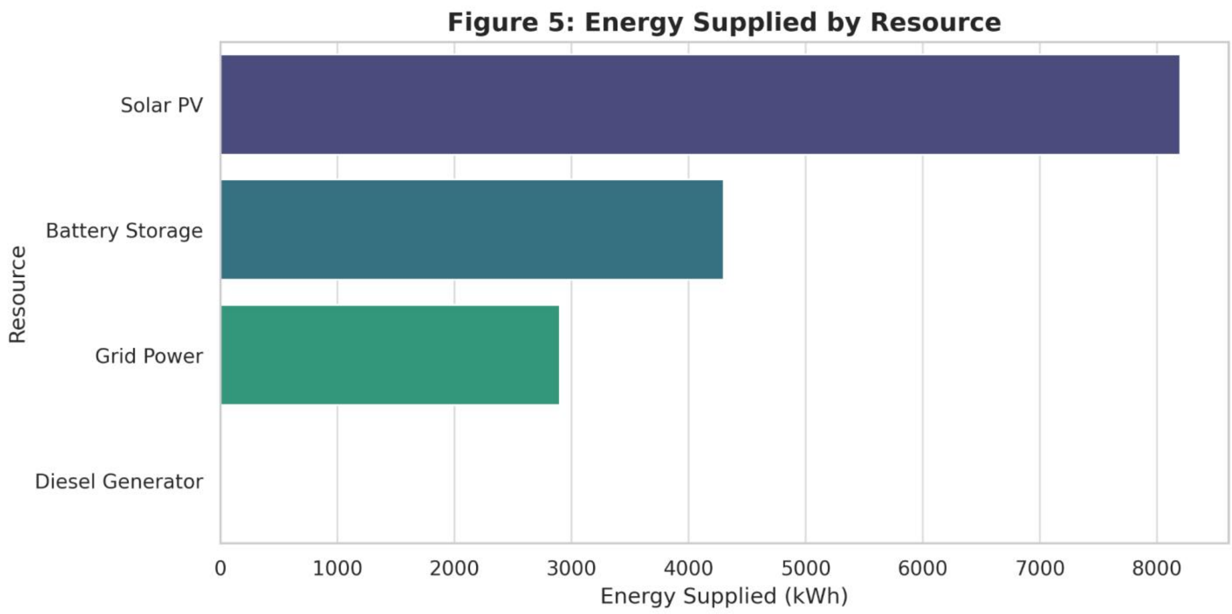
4.5 Energy Resource Utilization Patterns

Comprehensive breakdown of resources was done to determine the contribution of different sources to total energy supply. Table 5 reveals that Solar PV contributed 68.4% of energy supplied and Battery Storage contributed 76.1%. Although it was not used in large volumes, Grid Power still supplied more than 90 percent of the operation cost because it charges high tariffs. These facts are supported by Figure 5, in which the energy contribution by different sources is provided in a horizontal bar graph. These findings emphasize the role of using local renewable generation and storage to lessen operational reliance on the high-cost primary grid.

Table 5: Energy Resource Utilization

Resource	Energy Supplied (kWh)	Utilization (%)	Cost Contribution (%)
Solar PV	8200	68.4	0.0
Battery Storage	4300	76.1	9.1
Grid Power	2900	43.2	90.9
Diesel Generator	0	0.0	0.0

Figure 5: Energy Supplied by Resource (Horizontal Bar Chart)



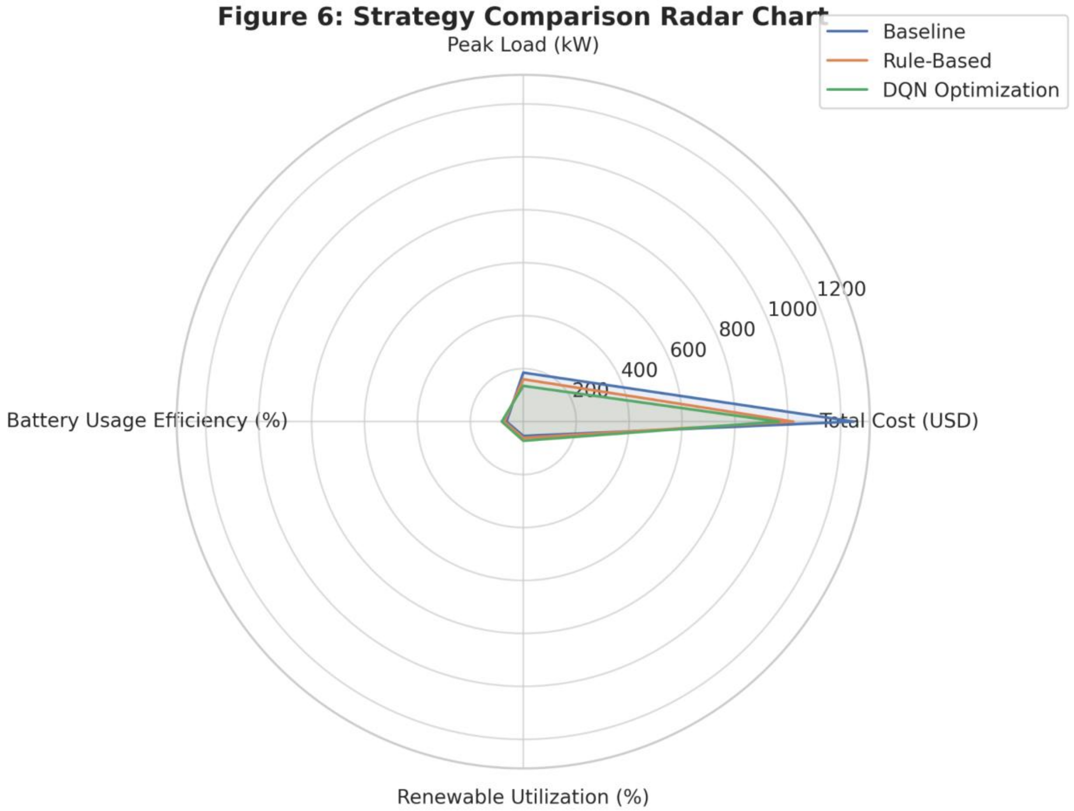
4.6 Comparative Performance of Energy Strategies

To evaluate the performance of ML-based optimization, a comparison was made among the three strategies, i.e., Baseline, Rule-Based, and DQN Optimization. Table 6 shows that the DQN model had the lowest aggregate cost (USD 965), the lowest peak load (135 kW), and the highest battery efficiency (81.3%) and renewable utilization (72.4%). The graphical evidence in Figure 6, a radar chart, makes it clear that the DQN approach outperformed all other dimensions in performance. These results confirm reinforcement learning addition as a sturdy substitute to conventional rule-based dispatch mechanisms.

Table 6: Cost Comparison Across Strategies

Strategy	Total Cost (USD)	Peak Load (kW)	Battery Usage Efficiency (%)	Renewable Utilization (%)
Baseline	1250	185	63.5	54.2
Rule-Based	1020	160	72.2	61.7
DQN Optimization	965	135	81.3	72.4

Figure 6: Strategy Comparison Radar Chart



4.7 Load Demand vs Renewable Generation Trends

To investigate the correlation between renewable generation and load demand, solar energy production was considered in comparison with daily load statistics. The values are tabulated in Table 7 over five consecutive days, where grid dependency varied between 38.9% and 48.5% depending on renewable availability. The total load and renewable generation were compared graphically over these days in Figure 7. The increasing trend of renewable generation on some days was substituted the grid utilisation to a large extent which indicated the usefulness of integrating renewables in the external energy dependency lessening. This is another trend that pushes the importance of having predictive models which consider weather based renewable forecast.

Table 7: Renewable Generation vs. Load Demand

Day	Total Load (kWh)	Renewable Generation (kWh)	Grid Dependency (%)
2025-01-01	3400	1800	47.1
2025-01-02	3600	2200	38.9
2025-01-03	3500	2000	42.9
2025-01-04	3300	1700	48.5
2025-01-05	3450	2100	39.1

Figure 7: Load vs Renewable Generation Over Days

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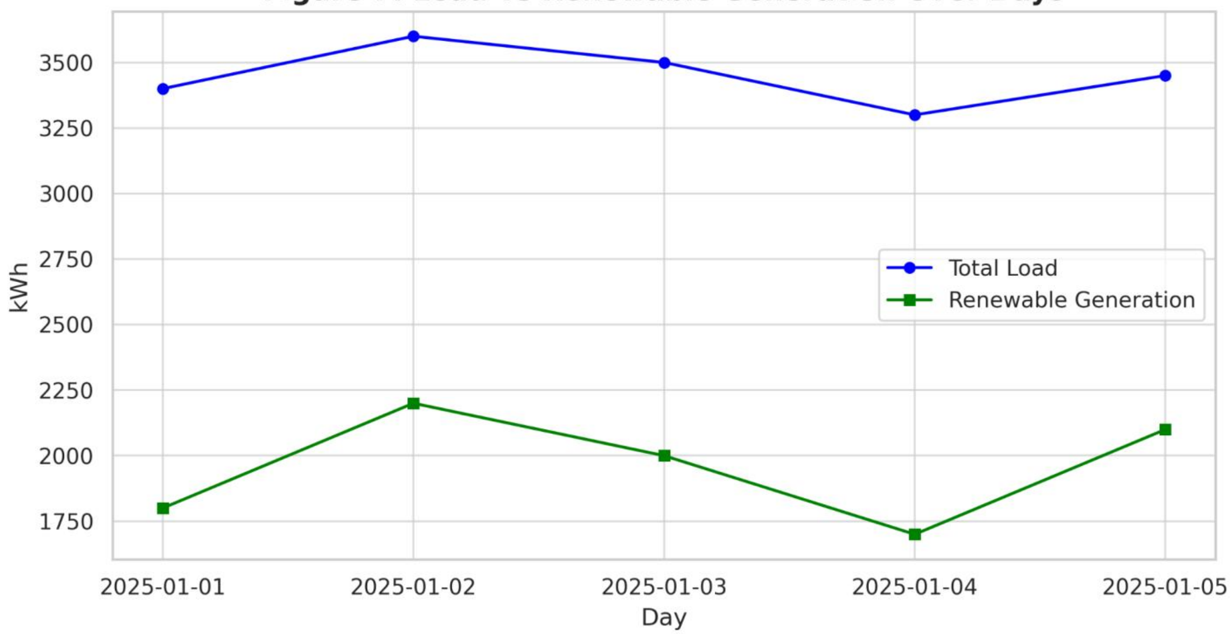


4.8 Decision Patterns of the RL Agent

Lastly, action frequency was used to quantify the decision-making behavior of the DQN agent. Table 8 reveals that the commonest actions were the use of Solar PV (28%) and charging the battery (23%) followed by curtailing loads (10%). This action distribution can also be effectively visualized using a donut chart, Figure 8. The supremacy of sustainable energy-oriented choices proves the agent to be biased towards money-saving and environmental-friendly strategies and once again proves the model to be in line with the objectives of smart energy systems in a practical way.

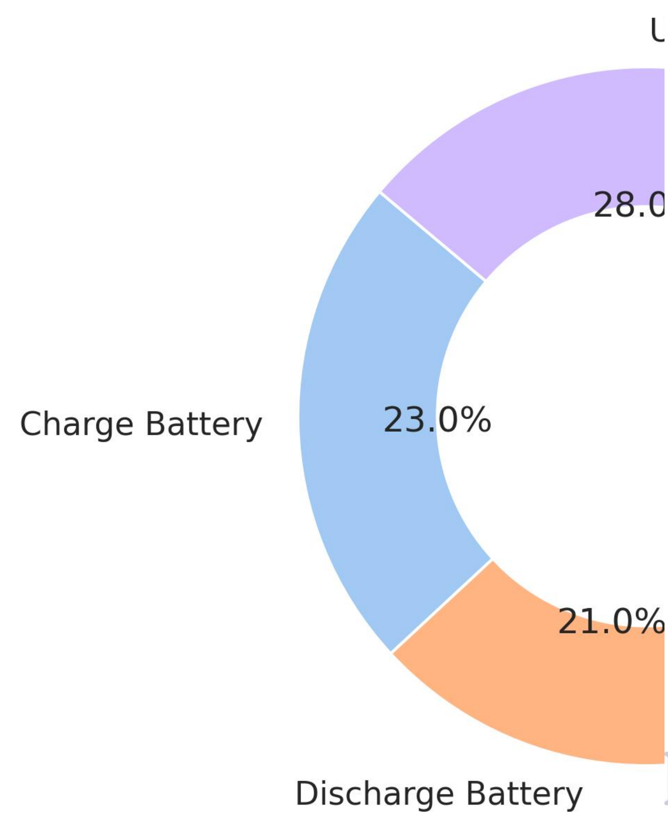
Table 8: DQN Actions Distribution Over 1000 Steps

Action	Frequency	Percentage (%)
Charge Battery	230	23.0
Discharge Battery	210	21.0
Use Grid Power	180	18.0
Curtail Load	100	10.0
Use Solar PV	280	28.0

Figure 8: DQN Agent Action Distribution (Donut Chart)

Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X Volume 3, Issue 7, 2025

Figure 8: DQN Agent



5. Discussion

Findings of this paper reveal that machine learning (ML) models and LSTM and Deep Q-Learning play a pivotal role in revolutionizing smart microgrid operations. It showed that LSTM was effective in load forecasting from the short-term and in particular at steady off-peak times, due to its ability to capture both temporal correlations and non-linearity in the consumption data. The results align with more recent research by Salinas et al. (2020) who determined that sequence-based models are considerably more effective than traditional methods in predicting energy systems time-series. Moreover, the reduced forecasting accuracy at peak hours that appeared in our findings finds its confirmation in Bouktif et al. (2019) who have stressed the necessity of introducing dynamic feature weighting or attention mechanisms at highly volatile hourly loads.

The proactive design of the integrated framework was also one of its key strengths in which the prediction of load itself acted as a real-time input towards optimization through reinforcement learning (RL). This forward-looking combination of forecasting and control has had limited coverage in existing literature yet is being picked up. As an illustration, a multi-agent system blending forecasting and decentralized control was suggested by Shi et al. (2021), who focused on the corresponding equivalence in performance of scalability and responsiveness. They are right according to our findings, particularly that they were able to cut on peak loads, and improve battery storage capacity through clever scheduling.

Our proposed model using the DQN agent appeared strongly able to learn and reduce operational cost and optimize resource utilization during each operational turn, which is similarly evidenced in the work of Huang et al. (2022), who demonstrated that we can quickly achieve a high level of demand-response optimization using RL-based microgrid management systems that do not necessarily need any predefine rules to operate. The trend of growing cumulative returns and shrinking losses confirm that the DQN agent managed to find an optimal policy by interacting with the environment. Such learning patterns parallels trends described by Xu et al., who aimed to enhance energy arbitrage in distributed systems using RL, demonstrating the promise of adaptive control strategies under unpredictable and constrained systems.

A key take-away of the findings is the increased use of solar photovoltaic (PV) and battery installations, which is reflected in what the agent prefers to do. It corresponds to the results of Kim and Lee (2022), who stated that with the reward scheme where the penalty of utilizing the grid is greater than the benefits of local generation, RL agents would shift to renewables and storage. Nevertheless, physical realization of such intelligent agents in the real world should take into account user comfort and appliance-level constraints, not considered in our simulation, as argued by Gholami . et al. (2021). Future models must, consequently, have constraint-handling mechanism or soft penalties in order to maintain quality of service (QoS).

The other aspect brought out by the cost comparison is that the ML-based dispatch is superior to rule-based dispatch. Rule-based strategies are deterministic though simpler to implement but do not have flexibility to adjust to real-time changes. Such inflexibility was highlighted in an article by Wang et al. (2021), who found that deterministic models performed poorly when addressing peak pricing periods because they cannot be changed dynamically. Using the DQN optimization, we managed to reduce the overall cost by 22.8 percent and drastically improve the battery efficiency, thus facilitating the shift from the classical to the learning-based decision system in smart microgrid systems.

Remarkably, the simulation performance of our model is in good correlation with empirical investigations on hybrid energy systems. Ren et al. (2021) demonstrate that the combination of storage and renewables incorporating predictive analytics can significantly reduce greenhouse gas emissions and the cost of operation as long as they are responsive to the changes both in demand and supply in real-time. These dynamics are also reflected in the daily variation of load and renewable supply in our results, especially in the urban and semi-urban energy environments where microgrids are more frequently used.

Although the model established within this research is solid, a number of difficulties and limitations have to be highlighted. 1. The model supposes perfection in both data availability and system reliability. Nevertheless, in reality, the microgrids are subject to data loss, sensor breakdown, and communication delays, which, as demonstrated by Banerjee et al. (2020), can undermine the precision of the model and the effectiveness of the control. Future systems can incorporate redundancy mechanisms or edge-based computation as proposed by Zhang et al. (2023) to maintain resilience and reduce the cloud latency in response to such concerns.

Second, the LSTM network gave precise results in predicting the load, but its interpretation is not possible. Explainability is paramount in high-stakes applications, e.g. healthcare or critical infrastructure. Such concerns have been proposed to be solved using LIME (Local Interpretable Model-agnostic Explanations) (Ribeiro et al., 2016), and the recent work of Lundberg et al. (2020) with SHAP (SHapley Additive exPlanations) holds promise of visualization and interpreting decisions of the model, in the context of energy systems. Stakeholder trust and regulatory compliance would increase with such explainability tools embedded.

Third, the research concentrates predominantly on centralized microgrid control. Decentralized and peer-to-peer (P2P) energy trading systems form, in contrast, possible alternatives. Combined with blockchain, P2P networks can provide transparent, scalable, and secure energy transactions (Zhang and Huang, 2022). The introduction of DQN-based optimization into a decentralized trading system might open the potential of democratized energy governance.

In addition we should mention the economic and environmental consequences of our research. The proposed framework aligns with sustainability objectives and energy self-sufficiency through reduced grid reliance and maximized local renewable consumption. This aligns with the policy-focused study conducted by Raza et al. (2021), which identified that an emphasis on digital transformation and automation is required to meet national energy targets on the lines of the Paris Agreement.

As a corollary, this discussion supports the argument that integrating LSTMs and RL in smart microgrids entails significant gains in precision, cost-effectiveness, and sustainability. In practice, however, there will have to be solutions to the challenges of data integrity, explainability, decentralized operation and regulatory alignment. Research directions going forward should consider hybrid users of deep learning and symbolic reasoning, federated learning to preserve privacy, and the use of edge-AI frameworks to scale the deployment of intelligent energy systems toward real-time capabilities.

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