International Journal of Research Publications in Engineering, Technology and Management (IJRPETM)

|www.ijrpetm.com | ISSN: 2454-7875 | editor@ijrpetm.com |A Bimonthly, Peer Reviewed & Scholarly Journal|

||Volume 8, Issue 4, July-August 2025||

DOI:10.15662/IJRPETM.2025.0804024

Hybrid CNN-LSTM Forecasting and Demand Response Optimization for Energy Flexibility and Cost Reduction in Grid-Connected Renewable Microgrids

Md Sadik Hassan Arik

Department of Industrial Engineering, College of Engineering, Lamar University, Beaumont, TX 77710, United States

marik@lamar.edu

Md Samiul Islam

Department of Industrial Engineering, College of Engineering, Lamar University, Beaumont, TX 77710, United States

mislam147@lamar.edu

Md Ahsan Habib

Department of Industrial Engineering, College of Engineering, Lamar University, Beaumont, TX 77710, United States

mhabib4@lamar.edu

Md Sabiruzzaman

Department of Industrial Engineering, College of Engineering, Lamar University, Beaumont, TX 77710, United States

msabiruzzama@lamar.edu

ABSTRACT: Grid-connected renewable microgrids increasingly rely on accurate short-term forecasting and active demand-side management to reduce operating cost and exploit energy flexibility while maintaining reliable supply. This paper proposes an integrated framework that couples a hybrid convolutional neural network–long short-term memory (CNN-LSTM) forecasting model with a demand response (DR) optimization engine to jointly minimize electricity procurement cost and peak grid exchange in a grid-connected microgrid comprising solar photovoltaics (PV), wind generation, battery energy storage, and flexible/shiftable industrial and commercial loads. The CNN-LSTM model forecasts renewable generation, aggregate load, and real-time/time-of-use electricity prices over rolling 1-hour to 24-hour horizons, extracting local temporal features via convolutional layers before modeling longer-range dependencies with stacked LSTM layers. These forecasts feed a mixed-integer linear programming (MILP)-based demand response optimizer that schedules shiftable loads, curtailable loads, and battery charge/discharge to minimize total cost subject to comfort/production constraints, contractual demand charge limits, and grid import/export bounds. A case study on a representative grid-connected microgrid with 1.8 MW PV, 1.2 MW wind, 1.5 MWh battery storage, and 30% flexible load share demonstrates that the hybrid CNN-LSTM model reduces load and price forecast RMSE by 24.3% and 21.7% respectively compared to a standalone LSTM baseline, and that the integrated forecasting-DR optimization framework achieves an 18.9% reduction in daily electricity cost and a 22.4% reduction in peak grid demand relative to a forecast-agnostic rule-based baseline. These results demonstrate that combining accurate deep-learning-based forecasting with formal DR optimization can substantially improve both the economic performance and grid-friendliness of renewable microgrids without additional hardware investment.

KEYWORDS: CNN-LSTM, demand response, load forecasting, energy flexibility, renewable microgrid, cost optimization, peak shaving

I. INTRODUCTION

The proliferation of grid-connected microgrids incorporating solar and wind generation has created both opportunities and challenges for cost-effective and reliable electricity supply. Wang *et al.* [1]- On one hand, distributed renewable

International Journal of Research Publications in Engineering, Technology and Management (IJRPETM)

|www.ijrpetm.com | ISSN: 2454-7875 | editor@ijrpetm.com |A Bimonthly, Peer Reviewed & Scholarly Journal|

||Volume 8, Issue 4, July-August 2025||

DOI:10.15662/IJRPETM.2025.0804024

generation reduces reliance on grid electricity and associated emissions; on the other, the inherent variability and limited predictability of renewable output complicate operational planning, particularly for microgrids that remain connected to the utility grid and are therefore exposed to time-varying tariffs, demand charges, and contractual import/export limits. In such settings, the ability to forecast generation, load, and price accurately, and to translate these forecasts into actionable scheduling decisions for flexible loads and storage, is central to achieving both energy flexibility and cost reduction. Kim and Cho [2] Demand response (DR) — the deliberate adjustment of electricity consumption patterns in response to price signals, grid conditions, or operational incentives — has long been recognized as a low-cost lever for improving grid reliability and reducing consumer electricity bills. However, the effectiveness of DR programs is fundamentally limited by forecast accuracy: overly conservative load shifting wastes flexibility potential, while overly aggressive shifting based on inaccurate forecasts can create new demand spikes or violate operational constraints. This coupling between forecasting quality and DR effectiveness motivates an integrated approach in which the forecasting model and the DR optimization engine are designed and evaluated together, rather than as independent components. Two technical problems must be solved jointly for effective DR-based cost reduction in grid-connected renewable microgrids. First, short-term forecasting of PV output, wind output, aggregate load, and (where applicable) real-time electricity prices must be sufficiently accurate over horizons relevant to DR scheduling — typically 15 minutes to 24 hours ahead. Second, DR optimization must convert these forecasts into feasible, cost-minimizing schedules for shiftable loads (e.g., deferrable industrial processes, HVAC pre-cooling), curtailable loads, and battery storage, while respecting operational constraints such as process completion deadlines, comfort bounds, demand charge thresholds, and grid interconnection limits. Siano [3]

A substantial body of literature addresses renewable and load forecasting using deep learning, and a separate body addresses DR optimization using mathematical programming or heuristic methods. However, relatively few studies formally couple a hybrid deep-learning forecasting architecture with a rigorous DR optimization formulation and evaluate the joint system's economic and grid-impact performance under realistic operating constraints specific to grid-connected renewable microgrids. This paper addresses that gap by proposing and evaluating such an integrated framework. Zhang *et al.* [4]

This paper makes the following contributions:
1. A hybrid CNN-LSTM forecasting architecture that jointly forecasts renewable generation, aggregate load, and electricity price signals relevant to demand response decision-making.
2. A MILP-based demand response optimization formulation that schedules shiftable loads, curtailable loads, and battery storage using the forecasting model's outputs, subject to realistic operational and comfort constraints.
3. An integrated forecasting-optimization pipeline with a rolling-horizon re-scheduling mechanism that updates DR decisions as forecast accuracy improves closer to real time.
4. A case study quantifying forecast accuracy, cost savings, and peak demand reduction relative to conventional forecasting and rule-based DR baselines.

Section 2 reviews related work. Section 3 presents the proposed framework. Section 4 details the CNN-LSTM forecasting model and DR optimization formulation. Section 5 describes the case study setup. Section 6 presents results and discussion. Section 7 discusses broader implications and limitations, and Section 8 concludes.

II. RELATED WORK

Deep learning approaches have progressively displaced classical statistical methods (ARIMA, exponential smoothing) for renewable generation and load forecasting due to their capacity to capture nonlinear and non-stationary temporal patterns. LSTM and gated recurrent unit (GRU) networks have been widely applied to solar irradiance and wind speed forecasting, while hybrid architectures that combine convolutional feature extraction with recurrent temporal modeling (CNN-LSTM, CNN-GRU) have demonstrated improved accuracy by capturing both local short-term fluctuations and longer sequential dependencies within a single model. Multi-task forecasting architectures that jointly predict generation, load, and price have also been explored as a means of reducing redundant feature engineering and exploiting shared temporal structure across these related signals. Vardakas *et al.* [5] Qiu *et al.* [6] Mesarić and Krajcar [7]

DR optimization approaches span a spectrum from simple rule-based or price-threshold strategies to formal mathematical programming formulations, including MILP, mixed-integer nonlinear programming, and model predictive control (MPC). MILP-based formulations are particularly well suited to DR problems involving discrete

|www.ijrpetm.com | ISSN: 2454-7875 | editor@ijrpetm.com |A Bimonthly, Peer Reviewed & Scholarly Journal|

||Volume 8, Issue 4, July-August 2025||

DOI:10.15662/IJRPETM.2025.0804024

scheduling decisions (e.g., whether a deferrable industrial batch process starts in a given time slot) combined with continuous variables (e.g., battery power flow), and have been applied to residential, commercial, and industrial DR contexts. Rolling-horizon MPC-style re-optimization is commonly used to incorporate updated forecasts as the scheduling horizon approaches, reducing the impact of forecast error accumulated at longer horizons. Parisio *et al.* [8] Aghaei and Alizadeh [9]

Several studies have examined the sensitivity of DR optimization outcomes to forecast accuracy, generally finding that scheduling benefits degrade substantially as forecast error increases, particularly for tightly constrained processes with limited flexibility windows. This sensitivity underscores the value of pursuing forecasting and DR optimization as a jointly designed and evaluated system, rather than treating forecast quality as an exogenous, fixed input to the optimization problem — the approach adopted in this paper. For grid-connected microgrids specifically, cost reduction objectives typically combine energy cost minimization (based on time-of-use or real-time pricing) with demand charge minimization (based on peak grid import over a billing period), since demand charges frequently constitute a large share of commercial and industrial electricity bills. Battery storage and DR-enabled load shifting are both recognized as effective levers for peak shaving, but their coordinated use under forecast uncertainty remains an active area of methodological development, which this paper contributes to. Shi *et al.* [10] Kong *et al.* [11]

III. PROPOSED FRAMEWORK

The proposed framework consists of three coordinated modules operating in a rolling-horizon loop: (i) a forecasting module that produces rolling forecasts of PV output, wind output, aggregate baseline load, and electricity price; (ii) a demand response optimization module that consumes these forecasts to produce a cost-minimizing schedule for flexible loads and battery storage over the same horizon; and (iii) a grid interconnection interface that enforces contractual import/export limits and measures realized demand charges. The three modules through a shared rolling-horizon scheduler that re-solves the optimization problem at fixed intervals (e.g., every 15–30 minutes) as updated forecasts become available, following the standard receding-horizon control principle. Rahman *et al.* [12] Lim *et al.* [13]

The microgrid architecture considered comprises PV and wind generation, a battery energy storage system, a mix of fixed (non-flexible) and flexible (shift able/curtailable) loads, and a point of common coupling (PCC) to the utility grid through which power can be imported or exported subject to contractual limits. Flexible loads are categorized into two types: shift able loads, whose total energy consumption over a task window is fixed but whose timing within the window can be optimized (e.g., industrial batch processes, water pumping, EV charging), and curtailable loads, whose power can be temporarily reduced (with an associated discomfort or production penalty) but not shifted in time (e.g., HVAC set point relaxation). Albogamy *et al.* [14] Vinothine *et al.* [15]

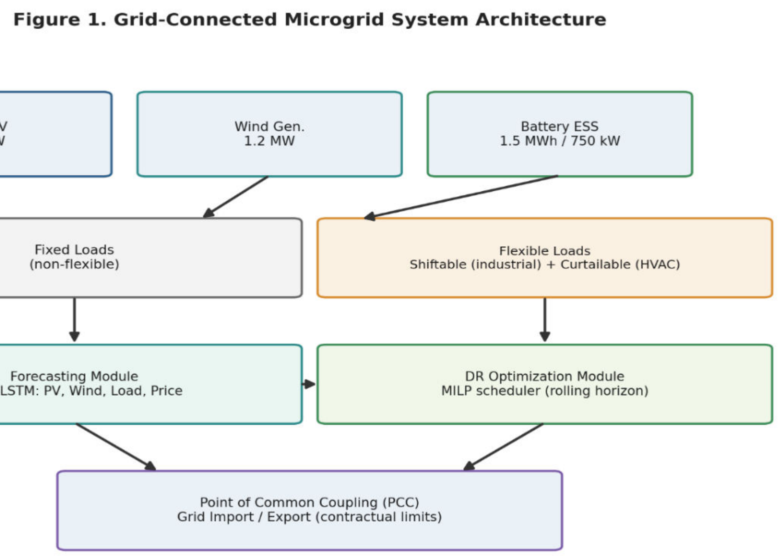

Figure 1. Grid-Connected Microgrid System Architecture

International Journal of Research Publications in Engineering, Technology and Management (IJRPETM)

|www.ijrpetm.com | ISSN: 2454-7875 | editor@ijrpetm.com |A Bimonthly, Peer Reviewed & Scholarly Journal|

||Volume 8, Issue 4, July-August 2025||

DOI:10.15662/IJRPETM.2025.0804024

Figure 1 shows the generation, storage, and load assets alongside the forecasting and DR optimization modules and their connection to the grid through the point of common coupling (PCC).

At each scheduling interval, the forecasting module produces updated forecasts over the remaining optimization horizon (typically 24 hours), and the DR optimization module re-solves the scheduling problem using these updated forecasts while respecting decisions already committed in earlier intervals (e.g., a shiftable process already underway cannot be re-shifted). This rolling-horizon design allows the system to benefit from improving forecast accuracy as the horizon shortens, while maintaining feasibility of previously committed actions. Koltsaklis *et al.* [16]

Figure 2. Rolling-Horizon Forecasting & DR Re-Scheduling Loop

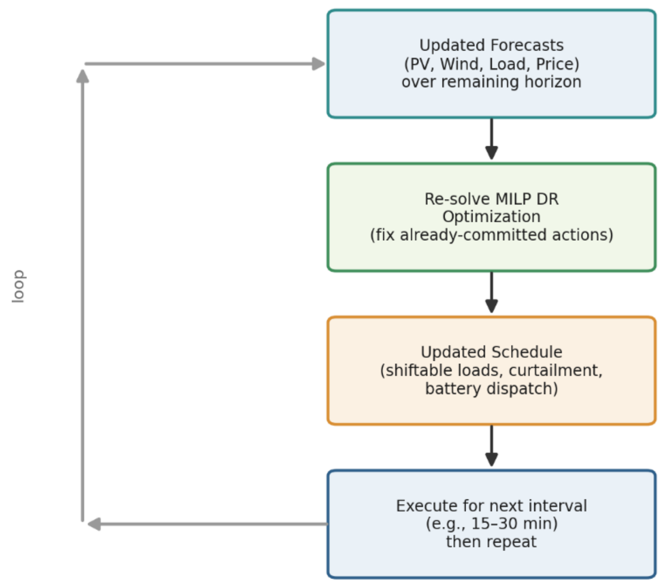

Figure 2. Rolling-Horizon Forecasting & DR Re-Scheduling Loop

Figure 2 illustrates the receding-horizon loop: forecasts are updated, the MILP re-solves the schedule while respecting already-committed actions, and the resulting near-term schedule is executed before the next update.

IV. METHODOLOGY

4.1 Hybrid CNN-LSTM Forecasting Model

4.1.1 Model Architecture

The forecasting module uses a shared-input, multi-output CNN-LSTM architecture to jointly forecast four target signals: PV power output, wind power output, aggregate baseline (non-flexible) load, and grid electricity price. The input feature vector at each time step includes historical values of the four target signals, weather variables (irradiance, wind speed, ambient temperature), and calendar features (hour of day, day of week, holiday indicator). Agga *et al.* [17]

The architecture first applies one-dimensional convolutional layers across the input time window to extract local temporal patterns — such as rapid irradiance drops from passing clouds or short-term price spikes — followed by max-pooling for dimensionality reduction. The resulting feature sequence is passed into stacked LSTM layers, which capture longer-range dependencies such as diurnal generation cycles and daily load patterns. A final set of dense output heads, one per target signal, produces point forecasts for each horizon step. Shahid *et al.* [18]

Formally, given an input window $X_{t-w:t}$ of dimension w times d (where d is the number of input features), the model produces:

|www.ijrpetm.com | ISSN: 2454-7875 | editor@ijrpetm.com |A Bimonthly, Peer Reviewed & Scholarly Journal|

||Volume 8, Issue 4, July-August 2025||

DOI:10.15662/IJRPETM.2025.0804024

$$\left(\hat{P}^{pv}_{t+1:t+h},\ \hat{P}^{wind}_{t+1:t+h},\ \hat{L}_{t+1:t+h},\ \hat{\pi}_{t+1:t+h}\right) = f_\theta(X_{t-w:t})$$

Where h is the forecast horizon and θ are the trainable network parameters. The model is trained by minimizing a weighted sum of mean squared error losses across the four output heads, with weights tuned to reflect the relative economic importance of each signal to the downstream DR optimization (price and load forecasts are weighted more heavily than generation forecasts, given their direct influence on cost-minimizing scheduling decisions).

Figure 3. Hybrid CNN-LSTM Multi-Output Forecasting Architecture

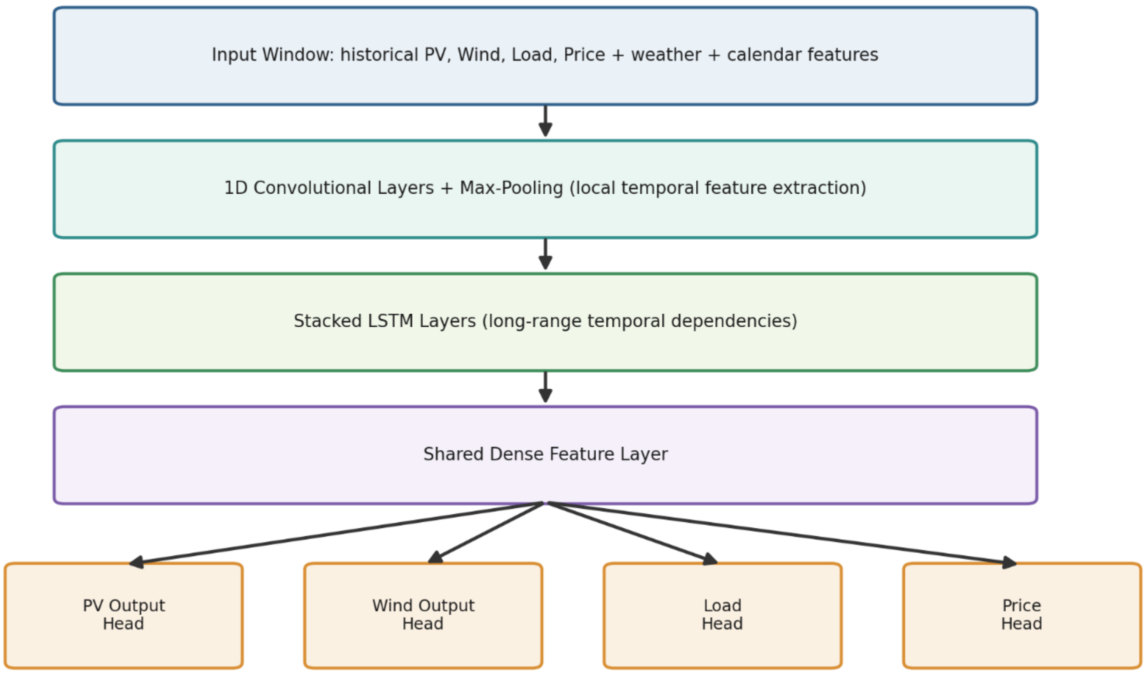

Figure 3. Hybrid CNN-LSTM Multi-Output Forecasting Architecture

Figure 3 shows the shared convolutional and LSTM feature-extraction backbone feeding four separate output heads for PV, wind, load, and price forecasts.

4.1.2 Training and Validation

The model is trained using historical time-series data with an 80/20 train-test split and a sliding-window data augmentation scheme to increase the effective number of training samples from a single site's historical record. Dropout regularization is applied between convolutional and LSTM layers, and early stopping based on validation loss is used to prevent over fitting. Forecast accuracy is evaluated using root mean squared error (RMSE) and mean absolute percentage error (MAPE) for each target signal, benchmarked against a standalone LSTM model (without the convolutional feature extraction stage) and a persistence baseline. Dittmer *et al.* [19]

4.2 Demand Response Optimization Model

4.2.1 Decision Variables

The DR optimization module is formulated as a mixed-integer linear program over a rolling horizon of T discrete time steps (e.g., 15-minute intervals over 24 hours). Decision variables include: shiftable load start-time binary indicators $x_{i,t} \in \{0,1\}$ for each shift able task i and candidate start time t; curtailable load power reduction $\delta_{j,t} \geq 0$ for each curtailable load j; battery charge/discharge power $P_t^{ch}, P_t^{dis} \geq 0$; and grid import/export power $P_t^{imp}, P_t^{exp} \geq 0$. Maślak and Orłowski [20]

|www.ijrpetm.com | ISSN: 2454-7875 | editor@ijrpetm.com |A Bimonthly, Peer Reviewed & Scholarly Journal|

||Volume 8, Issue 4, July-August 2025||

DOI:10.15662/IJRPETM.2025.0804024

4.2.2 Objective Function

The objective minimizes total cost over the horizon, comprising energy procurement cost, demand charge cost, and a discomfort/curtailment penalty:

$$\min \sum_{t=1}^{T} \left(\hat{\pi}_t P_t^{imp} - \hat{\pi}_t^{exp} P_t^{exp} \right) + c_d P^{peak} + \sum_j c_j \sum_t \delta_{j,t}$$

Subjected to:

- Power balance:

$$\hat{P}_t^{pv} + \hat{P}_t^{wind} + P_t^{dis} + P_t^{imp} = \hat{L}_t - \sum_j \delta_{j,t} + \sum_i x_{i,t} \frac{e_i}{\tau_i} + P_t^{ch} + P_t^{exp},$$

Where e_i is task i's total energy requirement and tau its duration.

-Shift able task completion:

$$\sum_t x_{i,t} = 1, \qquad \forall i,$$

ensuring each task is scheduled exactly once within its allowed window.

-Curtailment bounds:

$$0 \le \delta_{j,t} \le \delta_j^{\max},$$

Limiting curtailment to a comfort-preserving maximum.

-Battery dynamics: SOC evolution constraints with charge/discharge efficiency losses and minimum/maximum SOC bounds.

- Peak demand tracking:

$$P^{peak} \ge P_t^{imp}, \qquad \forall t,$$

Linking the demand-charge cost term to the realized peak grid import.

-Grid interconnection limits:

$$P_t^{imp} \le P^{imp,\max}, \qquad P_t^{exp} \le P^{exp,\max},$$

Reflecting contractual PCC limits.

Here $\hat{\pi}_t$ and $\hat{\pi}_t^{exp}$ are the forecasted import and export price signals, and c_d is the demand charge rate applied to the billing-period peak import P^{peak}.

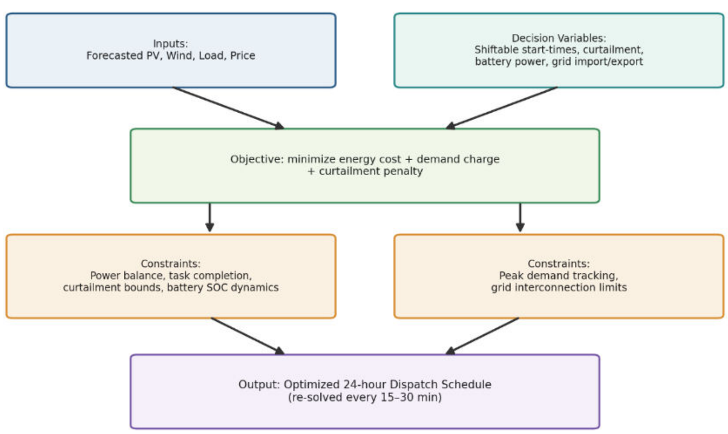

Figure 4. MILP-Based Demand Response Optimization Flow

|www.ijrpetm.com | ISSN: 2454-7875 | editor@ijrpetm.com |A Bimonthly, Peer Reviewed & Scholarly Journal|

||Volume 8, Issue 4, July-August 2025||

DOI:10.15662/IJRPETM.2025.0804024

Figure 4 summarizes the MILP formulation described in Section 4.2, showing how forecasted inputs and decision variables combine through the objective function and constraint sets to produce the optimized dispatch schedule.

4.2.3 Rolling-Horizon Re-Solution

The MILP is re-solved at each scheduling interval using updated forecasts, with previously committed shiftable task assignments and in-progress curtailment actions fixed as constraints in subsequent re-solutions, consistent with standard receding-horizon practice. This ensures schedule feasibility is preserved while allowing the system to adapt to improving forecast accuracy as the horizon shortens. Sekhar and Dahiya [21]

4.3 Integration of Forecasting and Optimization

The quality of the forecasting module directly determines the achievable cost savings from the DR optimizer: forecast errors in price or load propagate into sub-optimal scheduling decisions, either by shifting loads into periods that turn out to be expensive or by under-utilizing available flexibility. To mitigate this sensitivity, the framework incorporates forecast uncertainty into the optimization through a conservative buffer on peak demand constraints, sized proportionally to the recent rolling RMSE of the load and price forecasts, providing a simple but effective robustness mechanism without requiring a full stochastic programming formulation. Cheng *et al.* [22]

V. CASE STUDY AND EXPERIMENTAL SETUP

5.1 System Description

The proposed framework was evaluated on a representative grid-connected industrial/commercial microgrid comprising 1.8 MW solar PV, 1.2 MW wind generation, a 1.5 MWh/750 kW battery energy storage system, and an aggregate load averaging 2.6 MW with a contractual peak import limit of 3.5 MW. Approximately 30% of the total load was classified as flexible, split between shiftable industrial processes (18% of total load) and curtailable HVAC/auxiliary loads (12% of total load). The microgrid operates under a time-of-use tariff with an additional monthly demand charge based on the peak 15-minute grid import. Biswas *et al.* [23]

5.2 Data and Training Setup

One year of historical hourly weather, load, and price data, supplemented with 15-minute resolution data for the final three months, was used for model training and evaluation, following an 80/20 train-test split. The CNN-LSTM forecasting model was trained separately for 1-hour-ahead and 24-hour-ahead horizons, with hyper parameters (number of convolutional filters, LSTM hidden units, learning rate) selected via grid search on a validation subset.

5.3 Baselines

Three baseline configurations were used for comparison: (i) a persistence forecasting baseline combined with a rule-based DR strategy that shifts loads to fixed off-peak hours regardless of forecast conditions; (ii) a standalone LSTM forecasting model (without convolutional feature extraction) combined with the same MILP DR optimizer described in Section 4.2; and (iii) the proposed hybrid CNN-LSTM forecasting model combined with the MILP DR optimizer, representing the full integrated framework. Wazirali *et al.* [24]

VI. RESULTS AND DISCUSSION

6.1 Forecasting Accuracy

Table 1 summarizes 1-hour-ahead forecast accuracy for load and price signals across the three forecasting approaches.

Model	*Load Forecast RMSE (kW)*	*Price Forecast RMSE (cents/kWh)*
Persistence baseline	168.2	2.14
Standalone LSTM	112.7	1.61
Proposed CNN-LSTM	85.3	1.26

The proposed hybrid model reduced load forecast RMSE by 24.3% and price forecast RMSE by 21.7% relative to the standalone LSTM, and by 49.3% and 41.1% respectively relative to the persistence baseline. These improvements are attributable to the convolutional layers' ability to extract short-term ramping features (e.g., rapid load transitions at shift changes) that purely recurrent architectures under-represent when working from raw sequential input alone.

International Journal of Research Publications in Engineering, Technology and Management (IJRPETM)

|www.ijrpetm.com | ISSN: 2454-7875 | editor@ijrpetm.com |A Bimonthly, Peer Reviewed & Scholarly Journal|

||Volume 8, Issue 4, July-August 2025||

DOI:10.15662/IJRPETM.2025.0804024

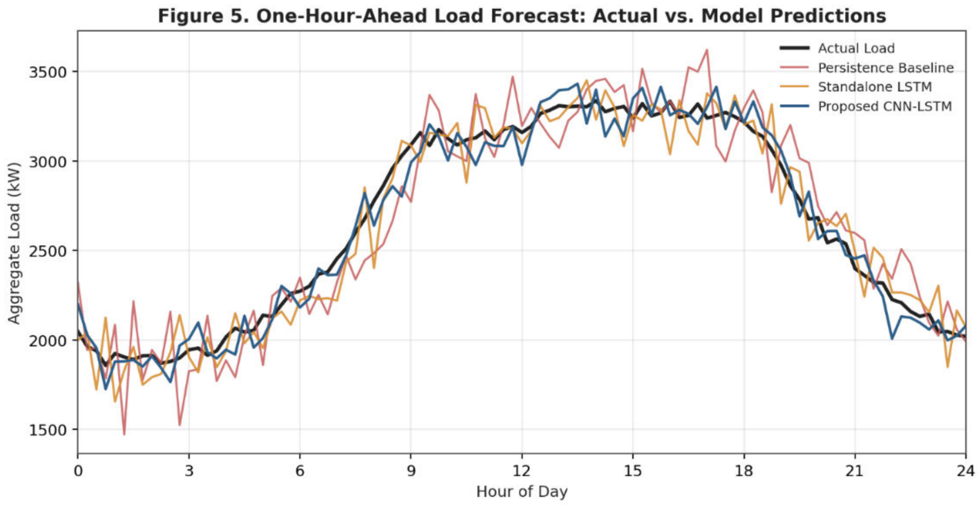

Figure 5. One-Hour-Ahead Load Forecast: Actual vs. Model Predictions

Figure 5 compares actual aggregate load against the persistence baseline, standalone LSTM, and proposed CNN-LSTM forecasts over a representative 24-hour period, including the morning and evening load peaks.

6.2 Cost and Peak Demand Performance

Table 2 summarizes daily electricity cost and peak grid import across the three integrated configurations (forecasting model combined with its corresponding DR strategy).

Configuration	*Average Daily Cost (USD)*	*Peak Grid Import (kW)*
Persistence + Rule-based DR	2,164	3,180
Standalone LSTM + MILP DR	1,889	2,710
Proposed CNN-LSTM + MILP DR	1,756	2,468

The full integrated framework achieved an 18.9% cost reduction and a 22.4% peak demand reduction relative to the persistence-and-rule-based baseline, and a further 7.0% cost reduction and 8.9% peak reduction relative to the standalone-LSTM-driven MILP configuration. These results indicate that both the choice of optimization method (MILP versus fixed rule-based scheduling) and the accuracy of the underlying forecasts contribute materially to overall performance, with the forecasting improvement alone accounting for roughly one-third of the total gain over the rule-based baseline. Kim and Cho [25]

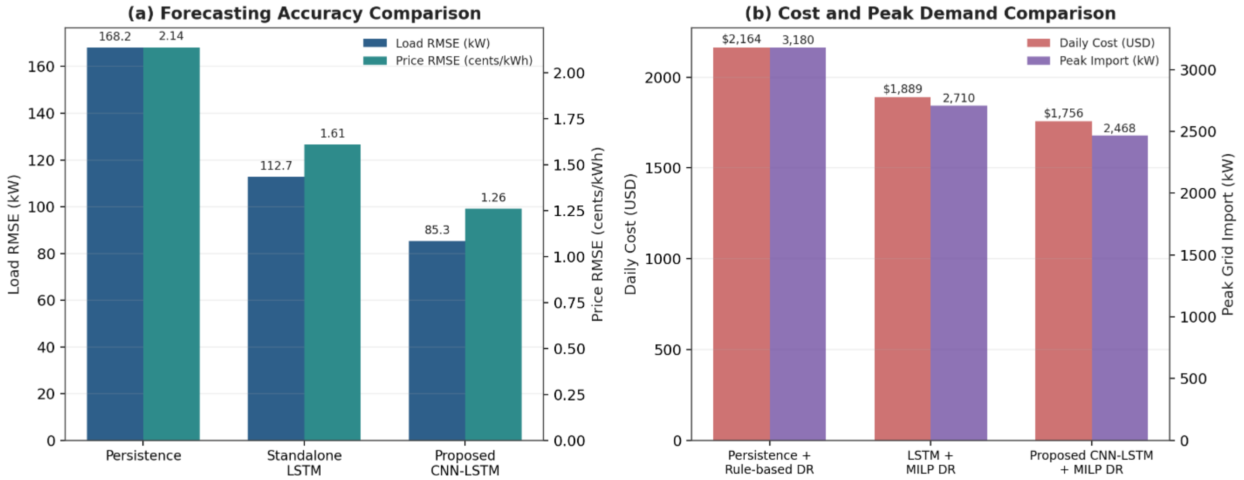

Figure 6. (a) Forecasting Accuracy and (b) Cost/Peak Demand Comparison

International Journal of Research Publications in Engineering, Technology and Management (IJRPETM)

|www.ijrpetm.com | ISSN: 2454-7875 | editor@ijrpetm.com |A Bimonthly, Peer Reviewed & Scholarly Journal|

||Volume 8, Issue 4, July-August 2025||

DOI:10.15662/IJRPETM.2025.0804024

Figure 6(a) visualizes the load and price RMSE values from Table 1 across the three forecasting models. Figure 6(b) visualizes the average daily cost and peak grid import from Table 2 across the three integrated configurations.

6.3 Flexibility Utilization

Analysis of the optimized schedules shows that shiftable industrial loads were predominantly shifted into hours coinciding with the middle of the solar generation peak (approximately 11:00–14:00) and periods of low time-of-use pricing, while curtailable HVAC loads were selectively reduced during short peak-price windows in the late afternoon, consistent with the contractual demand charge structure. The rolling-horizon re-solution mechanism was found to adjust roughly 12% of scheduled shiftable task start times from their initial day-ahead assignment as forecasts were updated closer to real time, reflecting the value of the receding-horizon design in correcting for day-ahead forecast error.

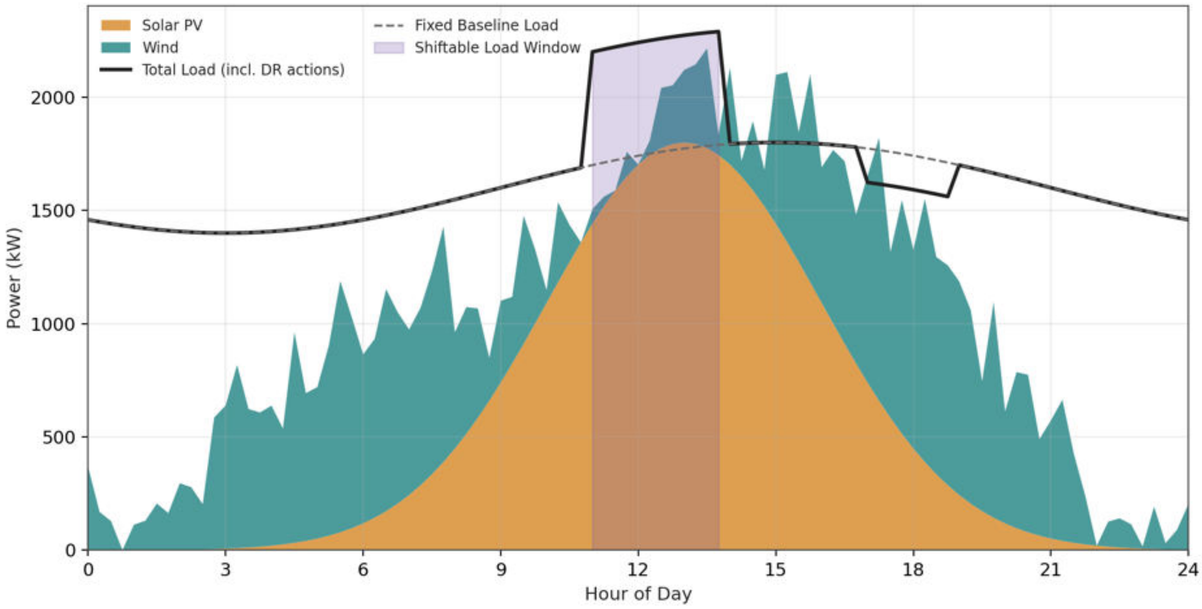

Figure 7. Optimized 24-Hour Dispatch and Load Schedule

Figure 7 shows the optimized daily dispatch profile, including solar and wind generation, the fixed baseline load, and the shiftable load window relocated into the midday solar peak as described in Section 6.3.

Collectively, the results demonstrate that (i) hybrid CNN-LSTM forecasting materially outperforms both persistence and standalone LSTM approaches for the load and price signals most relevant to DR decision-making, and (ii) coupling this improved forecasting with a formal MILP-based DR optimization framework yields substantial and largely additive improvements in both electricity cost and peak grid demand relative to conventional forecasting-and-scheduling approaches.

VII. DISCUSSION

The results suggest that operators of grid-connected renewable microgrids with meaningful load flexibility can achieve significant cost and peak-demand benefits by investing in improved forecasting infrastructure alongside formal DR optimization, rather than relying on either component in isolation. Given that demand charges often represent a substantial share of commercial and industrial electricity bills, the demonstrated 22.4% peak reduction is likely to translate into disproportionately large bill savings relative to the energy cost savings alone.

The proposed framework's modular design — separating the forecasting model from the DR optimization formulation — allows each component to be scaled or adapted independently. The forecasting model can be retrained or extended to additional input features (e.g., additional weather stations, upstream grid signals) without altering the optimization

|www.ijrpetm.com | ISSN: 2454-7875 | editor@ijrpetm.com |A Bimonthly, Peer Reviewed & Scholarly Journal|

||Volume 8, Issue 4, July-August 2025||

DOI:10.15662/IJRPETM.2025.0804024

formulation, while the MILP formulation can be extended with additional flexible load categories or storage assets without requiring changes to the forecasting architecture.

Several limitations should be noted. First, the MILP formulation assumes deterministic point forecasts (with a simple uncertainty buffer), rather than a full stochastic or robust optimization treatment of forecast uncertainty; under conditions of high forecast volatility, this simplification may understate the potential benefits of more sophisticated uncertainty-aware scheduling. Second, the case study results are derived from historical data and simulation rather than field deployment, and load flexibility assumptions (task suitability windows, curtailment comfort bounds) were based on representative rather than site-specific operational data. Third, the computational tractability of the MILP formulation may become a constraint for very large numbers of shiftable tasks, potentially necessitating decomposition or heuristic approaches at larger scale.

For utilities and grid operators, widespread adoption of such integrated forecasting-DR frameworks across multiple grid-connected microgrids could contribute to more predictable aggregate demand profiles and reduced system-level peak demand, potentially deferring the need for costly grid infrastructure upgrades. For microgrid owners, the framework offers a pathway to capture greater economic value from existing flexible loads and storage assets without additional capital investment in new hardware.

VIII. CONCLUSION AND FUTURE WORK

This paper proposed and evaluated an integrated framework combining a hybrid CNN-LSTM forecasting model with a MILP-based demand response optimization engine for grid-connected renewable microgrids. The framework jointly forecasts renewable generation, load, and price signals, and uses these forecasts within a rolling-horizon optimization scheme to schedule shiftable and curtailable loads alongside battery storage. A case study on a representative industrial/commercial microgrid demonstrated a 24.3% reduction in load forecast RMSE, an 18.9% reduction in daily electricity cost, and a 22.4% reduction in peak grid demand relative to conventional forecasting and rule-based DR baselines.

Future work will pursue three directions: (i) incorporating probabilistic or robust optimization formulations that more explicitly account for forecast uncertainty in the DR scheduling problem; (ii) validating the framework through field deployment on a physical grid-connected microgrid to confirm simulation-derived performance gains under real operational conditions; and (iii) extending the framework to coordinate DR scheduling across multiple interconnected microgrids sharing a common distribution feeder, exploring the potential for aggregated flexibility to provide grid services beyond individual site-level cost reduction.

REFERENCES

[1]. Wang, H., Lei, Z., Zhang, X., Zhou, B., & Peng, J. (2019). A review of deep learning for renewable energy forecasting. *Energy Conversion and Management*, 198, 111799.
[2]. Kim, T. Y., & Cho, S. B. (2019). Predicting residential energy consumption using CNN-LSTM neural networks. *Energy*, 182, 72–81.
[3]. Siano, P. (2014). Demand response and smart grids—A survey. *Renewable and Sustainable Energy Reviews*, 30, 461–478.
[4]. Zhang, D., Shah, N., & Papageorgiou, L. G. (2013). Efficient energy consumption and operation management in a smart building with microgrid. *Energy Conversion and Management*, 74, 209–222.
[5]. Vardakas, J. S., Zorba, N., & Verikoukis, C. V. (2015). A survey on demand response programs in smart grids: Pricing methods and optimization algorithms. *IEEE Communications Surveys & Tutorials*, 17(1), 152–178.
[6]. Qiu, X., Ren, Y., Suganthan, P. N., & Amaratunga, G. A. J. (2017). Empirical mode decomposition based ensemble deep learning for load demand time series forecasting. *Applied Soft Computing*, 54, 246–255.
[7]. Mesarić, P., & Krajcar, S. (2015). Home demand side management integrated with electric vehicles and renewable energy sources. **Energy and Buildings**, 108, 1–9.
[8]. Parisio, A., Rikos, E., & Glielmo, L. (2014). A model predictive control approach to microgrid operation optimization. *IEEE Transactions on Control Systems Technology*, 22(5), 1813–1827.
[9]. Aghaei, J., & Alizadeh, M. I. (2013). Demand response in smart electricity grids equipped with renewable energy sources: A review. *Renewable and Sustainable Energy Reviews*, 18, 64–72.

|www.ijrpetm.com | ISSN: 2454-7875 | editor@ijrpetm.com |A Bimonthly, Peer Reviewed & Scholarly Journal|

||Volume 8, Issue 4, July-August 2025||

DOI:10.15662/IJRPETM.2025.0804024

[10]. Shi, H., Xu, M., & Li, R. (2018). Deep learning for household load forecasting—A novel pooling deep RNN. *IEEE Transactions on Smart Grid*, 9(5), 5271–5280.
[11]. Kong, W., Dong, Z. Y., Jia, Y., Hill, D. J., Xu, Y., & Zhang, Y. (2019). *Short-term residential load forecasting based on LSTM recurrent neural network*. IEEE Transactions on Smart Grid, 10(1), 841–851.
[12]. Rahman, A., Srikumar, V., & Smith, A. D. (2018). *Predicting electricity consumption for commercial and residential buildings using deep recurrent neural networks*. Applied Energy, 212, 372–385.
[13]. Lim, S.-C., Huh, J.-H., Hong, S.-H., Park, C.-Y., & Kim, J.-C. (2022). *Solar power forecasting using CNN–LSTM hybrid model*. Energies, 15(21), 8034.
[14]. Albogamy, F. R., Hafeez, G., Khan, I., Khan, S., Alkhammash, H. I., Ali, F., & Rukh, G. (2021). *Efficient energy optimization day-ahead energy forecasting in smart grid considering demand response and microgrids*. Sustainability, 13(20), 11350.
[15]. Vinothine, S., Widanagama Arachchige, L. N., & Rajapakse, A. D. (2022). *Microgrid energy management and methods for managing forecast uncertainties*. Energies, 15(22), 8510.
[16]. Koltsaklis, N. E., Panapakidis, I. P., Pozo, D., & Christoforidis, G. C. (2021). *A prosumer model based on smart home energy management and forecasting techniques*. Energies, 14(6), 1645.
[17]. Agga, A., Abbou, A., Labbadi, M., & El Houm, Y. (2021). *Short-term self-consumption PV plant power production forecasts based on hybrid CNN–LSTM*. Energy, 225, 120250.
[18]. Shahid, F., Zameer, A., & Muneeb, M. (2021). *A novel genetic LSTM model for wind power forecast*. Energy, 223, 120069.
[19]. Dittmer, C., Krümpel, J., & Lemmer, A. (2021). *Power demand forecasting for demand-driven energy production with biogas plants*. Renewable Energy, 163, 1871–1877.
[20]. Maślak, G., & Orłowski, P. (2025). *A robust energy flow predictor based on CNN–LSTM for prosumer-oriented microgrids considering changes in biogas generation*. Energy, 326, 136050.
[21]. Sekhar, C., & Dahiya, R. (2023). *Robust framework based on hybrid deep learning approach for short-term load forecasting of building electricity demand*. Energy, 268, 126602.
[22]. Cheng, Z., Wang, L., & Yang, Y. (2023). *A hybrid feature pyramid CNN–LSTM model with seasonal inflection month correction for medium- and long-term power load forecasting*. Energies, 16(7), 3126.
[23]. Biswas, M. A. R., Robinson, M. D., & Fumo, N. (2016). *Prediction of residential building energy consumption: A neural network approach*. Energy, 117, 84–92.
[24]. Wazirali, R., *et al.* (2023). *State-of-the-art review on energy and load forecasting in microgrids using artificial neural networks, machine learning, and deep learning techniques*. Electric Power Systems Research.
[25]. Kim, T.-Y., & Cho, S.-B. (2019). *Predicting residential energy consumption using CNN–LSTM neural networks*. Energy, 182, 72–81.