Predictive Modeling of Demand Response Impact on Solar-Integrated Power Systems Using Bayesian Optimisation Long Short-Term Memory Neural Networks

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ABSTRACT

Maintaining grid stability is made more difficult by the growing integration of solar energy into contemporary power systems, particularly when supply and demand are fluctuating. Demand Response (DR) programs provide opportunities for dynamic load management, but in order to measure their impact in real time, they need sophisticated forecasting tools. This study models and assesses the influence of DR signals on a solar-integrated power system by developing a predictive framework with a Bayesian-optimised Long Short-Term Memory (LSTM) neural network using the MATLAB Platform. The model was trained with carefully designed features, such as environmental, grid, and consumption parameters, using multivariate time-series data. It was then assessed under various DR intensities. Key hyper-parameters were adjusted using Bayesian optimisation, which greatly enhanced forecasting performance. The model demonstrated strong generalisation across low and high DR scenarios, achieving general performance metrics like RMSE of 0.101 kW, MAE of 0.062 kW, and R^2 of 0.9426. The results obtained in this study indicate that the suggested model is a useful instrument for strategic demand-side management and intelligent energy forecasting.

Keywords: MATLAB**,** Solar Integration, Demand Response, LSTM Neural Network, Bayesian Optimisation, Time-Series Forecasting, Smart Grid, Renewable Energy, Predictive Modeling.

INTRODUCTION

Electricity grids around the world are undergoing a fundamental transformation due to the quick spread of solar photovoltaic (PV) installations, which provide cleaner and more sustainable energy production (Fernández-Guillamón *et al.*, 2020; Alam *et al.*, 2020). Unpredictable variations in the supply of electricity result from solar power's inherent variability and reliance on the weather (Shariatzadeh *et al.*, 2015; McPherson and Stoll, 2020). Grid operators face increasing challenges in maintaining reliability, balancing supply and demand, and reducing dependency on fossil fuel-based backup generation as solar penetration rises (Zhang *et al.*, 2023).

One crucial approach to deal with these issues is DR, in which users modify their electricity consumption in response to price signals or grid requirements (Astriani *et al.*, 2021). DR can help stabilize the grid, lower costs, and facilitate greater integration of renewable energy by redistributing or lowering demand during times of high solar generation or grid stress (Anon., 2025). However, because of the dynamic and nonlinear relationships between generation, demand, weather, and human behaviour, precisely modelling and forecasting the effects of DR in solar-integrated systems is still a challenging task.

Advanced predictive models that can quantify the impact of DR interventions and capture the temporal dynamics of consumption behavior are increasingly needed to fully realise the potential of DR in solar-integrated power systems (Pakbin *et al.*, 2025). In order to meet this need, this study created an intelligent predictive modeling framework based on Long Short-Term Memory (LSTM) neural networks. These networks are ideal for time-series forecasting because they can overcome vanishing gradient problems and learn long-term dependencies. LSTM networks support input data with varying sequence lengths. They are designed to capture and maintain long-term dependencies in time-series data, which is essential for predicting future states based on historical data in demand response and solar power generation systems. (Hochreiter *et al.*, 1997).

Related Works

A critical review by O'Connell *et al.* (2014) examines the advantages, obstacles, and modeling assumptions associated with electrical demand response (DR) in power systems experiencing heightened renewable integration. Improved power system flexibility, lower demands for generation capacity, real-time pricing that increases economic efficiency, and improved network congestion control are among the advantages. By allowing load adjustments to match variable renewable generation, DR lowers emissions and fuel consumption. However, issues like the complexity of dependable DR control, the absence of suitable market mechanisms, the difficulty of developing strong business cases, and user behavior uncertainties still exist.

Antonopoulos *et al.* (2020) conducted a systematic review covering more than 160 articles, 40 for profit businesses and 21 extensive projects about the use of AI and ML in energy Demand-Side Response (DSR). The review emphasise how important AI is to solving complicated, large-scale, real-time DSR issues brought on by digitisation and the integration of renewable energy sources. It classifies AI methods for DSR, including deep learning architectures like LSTM, reinforcement learning, multi-agent systems, supervised and unsupervised machine learning, and evolutionary algorithms. Applications include dynamic pricing, incentive design, load segmentation, automated device control and scheduling, load forecasting, and participant selection.

Liu *et al.* (2019) also proposed a framework in which Load-Serving Entities (LSEs) was used to model user response using a quadratic cost function that accounts for variability and elasticity. Incentives were proposed to meet customer demand response targets which required the development of a neural network-based approach with emphasis on Long Short-Term Memory (LSTM). The authors noticed that the LSTM approach performed noticeably better in accuracy and robustness than conventional regression and machine learning techniques. Furthermore, the study demonstrated the practical effectiveness of the method for demand response aggregation in electricity markets by showing that predicting responses from aggregated user groups produces lower errors than predictions from single users.

In order to address the uncertainty caused by wind power and electric vehicle (EV) charging patterns, Pakbin *et al*. (2025) considered an optimised demand response framework which combined a well-being probabilistic evaluation of system states (risk, marginal, and healthy), adaptive DR incentives in line with real-time wind volatility, and a novel real-time uncertainty model based on statistical mean-standard deviation relationships for wind fluctuations. The framework was validated on the IEEE RTS-24 bus system with various EV penetration scenarios. The research results showed lower DR incentive costs, decreased unsupplied energy, and increased system reliability (increasing the healthy state probability P(H) from 95.1% to 97.44%) (Pakbin *et al*., 2025). The study's assumptions about consistent consumer behavior and EV charging patterns, however, might restrict its practicality.

A Bayesian Optimised CNN-M-LSTM hybrid model was proposed by Le *et al*. (2025) to forecast HVAC energy consumption and thermal comfort in commercial buildings. To enhance occupant well-being, authors used adaptive thermal comfort models with emphasis on hyperparameter tuning through Bayesian optimisation. Superior load forecasting accuracy across a variety of climatic datasets was achieved by the CNN's extraction of spatial features and the M-LSTM's capture of temporal dependencies. The model improved thermal comfort control and reduced energy costs by up to 50% (Le *et al*., 2025). However, the study prioritised occupant comfort.

Li *et al.* (2024) addressed inefficiencies in hyperparameter tuning and prediction biases by creating a Bayesian optimised spatial-temporal attention-enhanced LSTM (BO-STA-LSTM) for energy prediction construction. Authors enhanced the performance of the model by incorporating spatial and temporal attention mechanisms to dynamic weight input features. Authors demonstrated that Bayesian optimisation in conjunction with spatial-temporal attention enhanced predictive accuracy. Seasonal fluctuations were well captured by the methodology, which was applied to different building energy consumption patterns (Li *et al*., 2024). Notwithstanding the advancements, they draw attention to the dataset's generalisability issues and suggested investigation into alternative deep learning architectures for better prediction.

A comparative analysis of photovoltaic (PV) power output prediction using LSTM models that integrate historical PV data, climate data, and their combination was carried out by Jafari *et al*. (2025). They measured the effect of input data configuration on predictive accuracy for different horizons (10, 30, 50 minutes) using sliding window analysis. Better forecasts were consistently obtained by combining historical and climatic data, highlighting the significance of environmental factors in solar power forecasting. For short horizons, their LSTM architecture, which was trained using the Adam optimiser, achieved root mean square errors as low as 4.39%. Longer sliding windows, however, impaired performance over longer time horizons, indicating the necessity of precisely calibrated temporal context. The study's primary focus was on PV power forecasting, not the effects of demand response.

By creating a more comprehensive and flexible framework for demand response optimisation that takes into account dynamic consumer behavior, uncertainty modeling, and Bayesian-optimised neural network predictive models for solar-integrated power systems, this study seeks to close the gap and overcome the limitations of fixed load patterns and uniform assumptions found in existing research. Compared to current models, which frequently concentrate on discrete components, this study would increase the predictive accuracy and operational reliability of renewable-integrated grids.

Resources and Methods Used

The first step in the methodological pipeline was data acquisition from Ghana's Volta River Authority followed by data preprocessing which involved cleaning, smoothing, and normalising a real-world dataset that was acquired. In order to simulate the operational conditions of a solar-integrated grid, key features such as battery operations, grid metrics, environmental variables, and DR signals were chosen and designed. To maintain temporal dependencies, the dataset was divided systematically into training, validation, and test sets.

In order to model consumption dependencies over time, sequential data structures were subsequently constructed using a sliding window technique with a 24-time-step lookback. To enhance the model's performance, Bayesian optimisation was employed for hyperparameter tuning, identifying optimal values for the number of hidden units, LSTM layers, learning rate, dropout rate, and batch size. These ideal parameters were used to train the final LSTM model, which was then assessed using a number of performance metrics, such as Peak Demand Error, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2).

In addition to a general assessment, the study included a stratified analysis according to DR intensity levels, which allowed for a more thorough evaluation of model accuracy under various DR circumstances. To interpret model behavior, visualisation tools such as error histograms, residual analysis, and scatter plots were employed.

The effectiveness of Bayesian-optimised LSTM architectures in simulating DR impacts on solar-integrated grids is demonstrated by this integrated approach, which also offers a repeatable methodology for predictive grid management systems in the future in renewable-dominated scenarios.

Research Design and Procedure

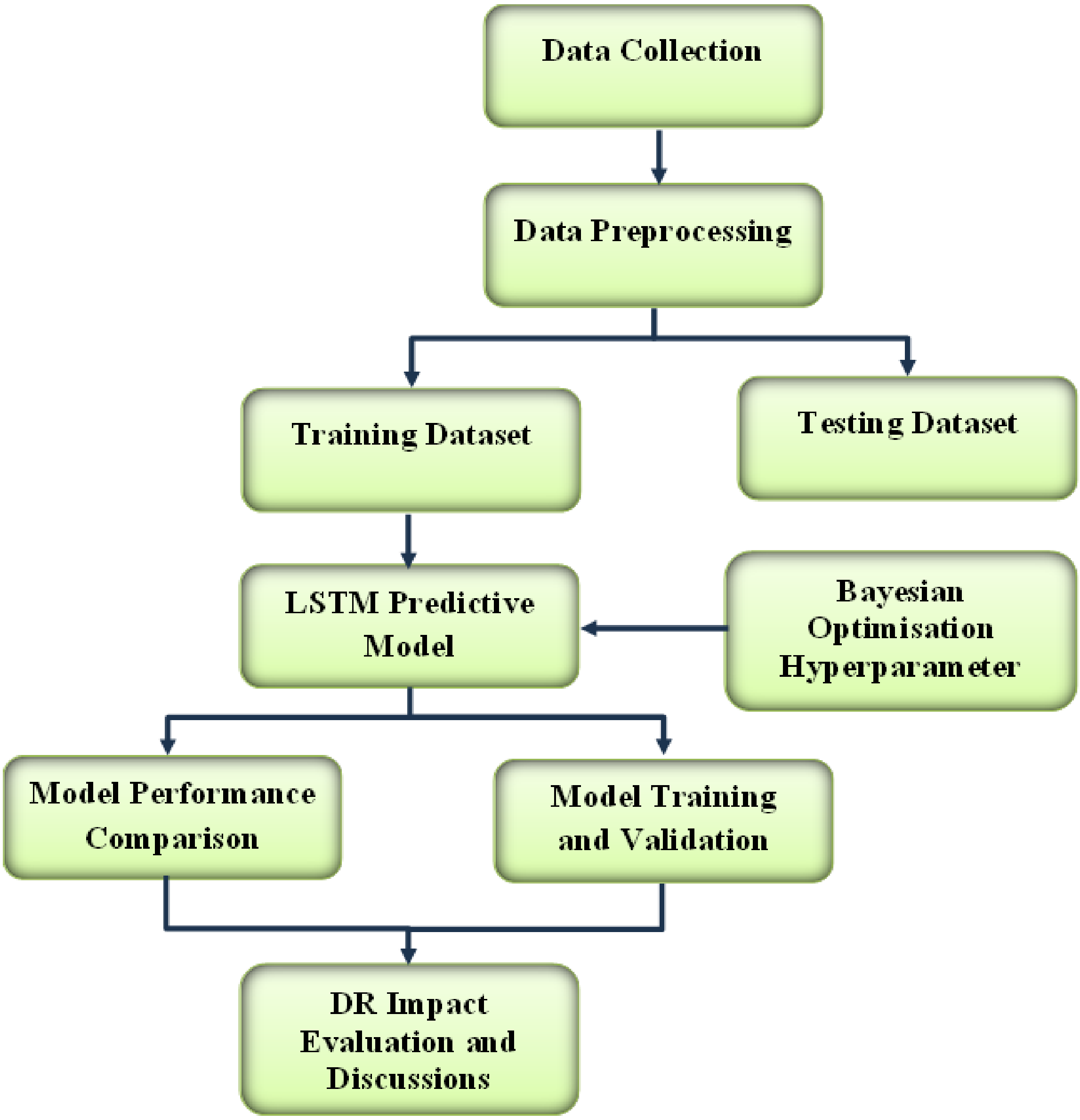

Fig. 1 Block Diagram of Research Concept

In order to evaluate the effect of Demand Response (DR) on solar-integrated power systems, a predictive model utilizing Long Short-Term Memory (LSTM) networks optimised with Bayesian optimisation was developed. The study made use of both historical and real-time data on DR events, weather, electricity demand, and solar power generation. Fig. 1 provides a block diagram illustration of the research.

Data Collection

Data was sourced from the Volta River Authority, including historical records of electricity demand, solar generation outputs, weather data (temperature, irradiance, humidity, wind speed, pressure), and power system operational records. The dataset, "Main Solar Dataset 2024.xlsx," comprised multivariate time-series measurements from a solar-integrated smart energy system with DR participation.

Data Loading and Inspection

Data was imported into MATLAB, inspected for structure, missing values, and outliers. Relevant features were selected for modelling. The target variable was total consumption (W), reflecting customer behavior during DR events. Features were selected based on their relevance to energy consumption dynamics and LSTM model performance.

Normalisation and Standardisation

To guarantee that every feature made an equal contribution during training and to ensure fast convergence of the model, the data was normalised and standardised using the Z-score method of normalisation. In the predictive modelling of DR impacts on solar-integrated power systems, multiple variables collected were at different scales and units. These features had diverse magnitudes and units, which could affect the learning ability of machine learning algorithms especially deep recurrent networks like LSTM been employed in this study hence the normalisation.

Z-score normalisation as shown in Equation 1 was applied to standardise all numeric features in the dataset, including solar irradiance, battery parameters, grid metrics, and weather variables. Having a zero mean and unit variance guaranteed that every variable added to the learning process equally.

$$Z = \frac{X - \mu}{\sigma} \qquad (1)$$

where, $Z =$ Standardised value; $X =$ Original data point; $\sigma =$ Standard deviation of feature column; and $\mu =$ mean of the feature column

Feature Engineering

The data was arranged into sliding windows of fixed lengths (input sequences) and corresponding targets (outputs) suitable for LSTM input, capturing sequential dependencies.

Temporal features (hour, day of week, month), DR event encoding, and interaction terms (e.g., solar irradiance × temperature) were created to enhance predictive power. To make the model easier to understand over time without adding seasonality directly, the timestamp field DateTime was changed to:

i. *Hour of day;*

ii. *Day of Week (1–7 scale); and*

iii. Month (1–12 scale).

Model Development and Training

The preprocessed data was split into training (70%), validation (15%) and testing (15%) sets. An LSTM neural network was developed in MATLAB to capture temporal dependencies in the data. Bayesian optimisation was employed to automatically tune key hyperparameters (number of units, learning rate, batch size, dropout rate), thereby maximising model performance. The model was trained on the training set and validated using cross-validation.

Bayesian Optimisation Performance

Bayesian optimisation is used to tune the hyperparameters and achieve optimal performance based on the dataset's specific characteristics. In comparison to grid search or Cartesian hyperparameter, Bayesian optimisation can effectively perform precision searching for optimal hyperparameters in high number of dimensions (Alibrahim and Ludwig, 2021).

Bayesian optimisation is particularly advantageous for hyperparameter tuning due to its ability to efficiently handle expensive function evaluations and navigate complex, high-dimensional hyperparameter spaces. By using probabilistic modeling and intelligent sampling strategies, BO can achieve better performance with fewer evaluations compared to traditional methods (Cho *et al*., 2020). In MATLAB, the *Bayesopt* function is commonly used for this purpose.

The optimisation process was initiated to select optimal hyperparameters for final training of the proposed model.

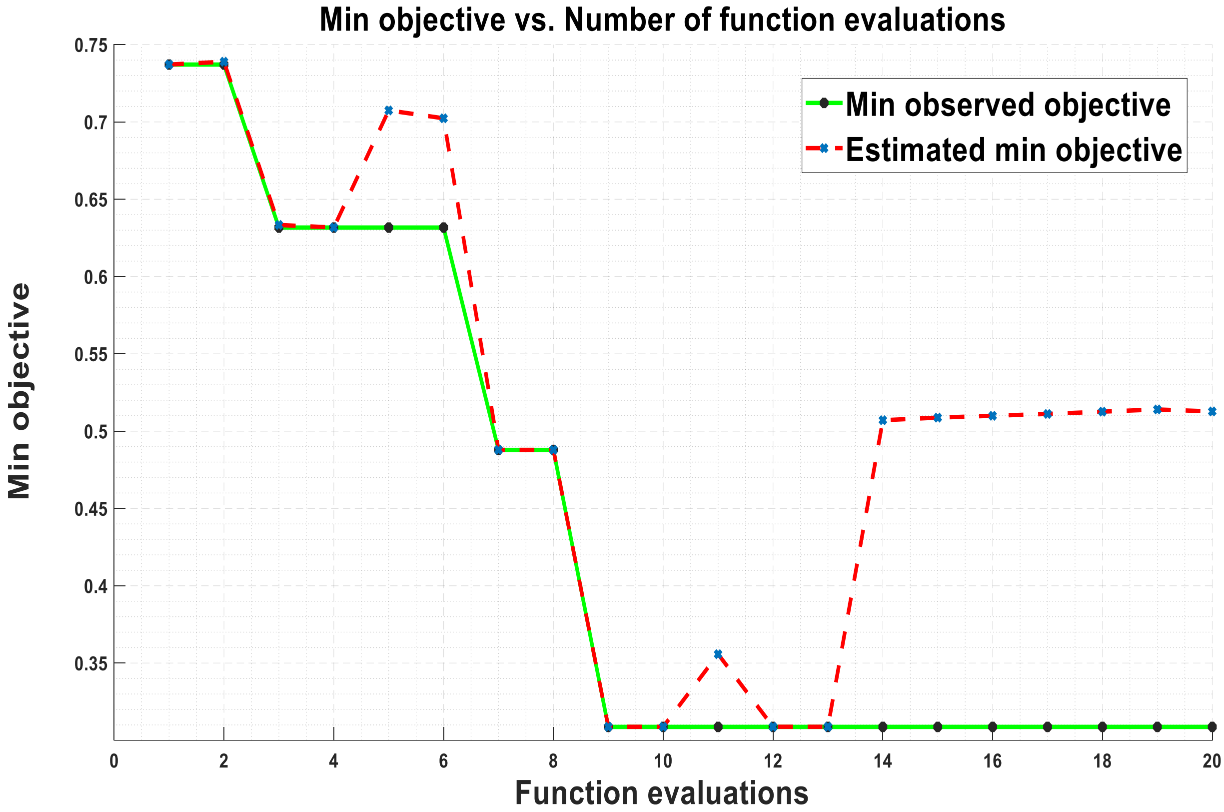

Fig. 2 Graph of Minimum Objective vs Number of Function Evaluation

Two graphs (Fig. 2) were plotted throughout the Bayesian optimisation procedure. Estimated Min Objective (Dashed red Line) and Min Observed Objective (Solid green Line). Although they show slightly different viewpoints, both curves show how the optimisation process gets better over time.

The LSTM model's hyperparameters were tuned using Bayesian optimisation, as shown in the graph of Minimum Objective vs. Number of Function Evaluations. A notable decrease in validation loss during the first iterations suggests that promising configurations with lower prediction error were quickly identified. The optimisation slowed between iterations 4 and 7, indicating efforts at fine-tuning. A plateau between iterations 8 and 13 indicates convergence toward a local minimum. The curve flattened, indicating convergence at a near-optimal validation loss of approximately 0.026902, following minor improvements up to iteration 20. The efficiency of Bayesian optimisation in reaching ideal model performance was demonstrated by this progression.

These parameters in Table 1 achieved a minimum validation RMSE of 0.30873 (normalised units), constituting the best performance across all evaluations. This configuration was used for the final model training and subsequent testing.

Table 1 Final Bayesian Optimisation Results

Parameters	Best Observed Feasible Point	Best Estimated Feasible Point
Hidden Units	140	130
Layers	2	2
Learn Rate	0.0091	0.0099
Drop Out	0.2494	0.1075
Mini Batch Size	37	34
Objective Fcn Value	**0.3087**	**0.5128**

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Model Architecture

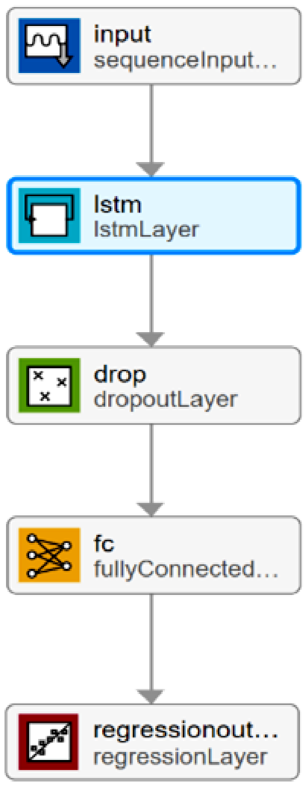

Fig. 3 Proposed LSTM Model Architecture

The sequence input layer of Fig. 3 accepts input as a sequence of vectors (features over time), capturing the temporal structure in power system variables such as battery state, weather components, and DR events, which is essential for time-series learning. The LSTM layer, which may be stacked, applies LSTM units to remember past values across time steps throughout the training process, enabling the model to capture long-term and temporal dependencies. LSTMs overcome vanishing gradient problems common in simple RNNs, making them more stable for modelling long sequences, especially useful for energy systems where effects like DR may influence behavior over extended periods. The dropout layer, included due to the nature of the dataset, randomly deactivates neurons during training to prevent overfitting, which is particularly helpful when working with small or noisy datasets like solar power data with environmental fluctuations. The fully connected layer maps the outputs of the LSTM to the final prediction dimensions, transforming the LSTM's learned features into specific prediction outputs, with each output neuron corresponding to a target variable such as Total Consumption (kW). Finally, the regression layer predicts values against actual values, calculating the error between predicted and actual values during training, which is useful for continuous output prediction like DR activation probabilities and their influence on Total Consumption.

Final LSTM Model Training

Configuration was done for the final model to use the optimal hyperparameters discovered through the Bayesian Optimisation procedure, striking a balance between model generalisation and complexity. The network architecture was sequentially created, starting with a *sequenceInputLayer* that accepts sequences of shape [8 × 24], where 8 represents the number of input features such as grid injection, battery charge/discharge, temperature, and irradiance, and 24 is the number of previous time steps used for prediction. In the hidden layers, a dropout layer with a 24.94% rate was placed after two stacked LSTM layers, each containing 140 memory units, to prevent vanishing gradients while capturing temporal patterns. This dropout mechanism reduces overfitting and preserves temporal feature extraction by randomly turning off neuron activity during training. The output layer consists of a *fullyConnectedLayer,* which creates a single scalar output (predicted normalised consumption) from the last LSTM unit, and a *regressionLayer,* which calculates the loss as the mean squared error (MSE) between predictions and true targets. The training process utilized the Adam solver for its resilience in noisy gradient environments, allowed a maximum of 200 epochs for adequate learning, and used a mini-batch size of 37 to balance GPU memory usage and gradient variance. Validation was performed on a held-out set without shuffling to preserve temporal dependencies, and MATLAB's *'training-progress'* plots were used to visualise training and validation loss, aiding in diagnostics and model tuning.

Final Model Evaluation

The Bayesian-optimised LSTM model demonstrated significant improvements in predictive accuracy over baseline models. The table below shows the final model evaluation results. The model was assessed with a temporally new test set (15% of the original dataset), maintaining the integrity of time-series causality. Each input comprised of a temporal sequence of 24 steps, with each step made up of 8 real-valued features extracted from preprocessed and normalised dataset. Initially, the input and target variables were normalised during the training phase of this study (based on training set statistics); however, the predicted outputs were subsequently converted back to real-world scale using Equations 2 and 3.

$$Y\,\mathrm{Pr}\,ed = (Y\,\mathrm{Pr}\,ednorm \times \sigma Y) + \mu Y \qquad (2)$$

$$YTest = (YTestnorm \times \sigma Y) + \mu Y \qquad (3)$$

The factors μY and σY are the mean and standard deviation of the target variable calculated only on training data, in accordance with best practices in avoiding data leakage.

The Bayesian-optimised LSTM model demonstrated significant improvements in predictive accuracy over baseline models. The table below shows the final model evaluation results.

Table 2 Final Evaluation Results

METRIC	RESULTS
RMSE	0.101 kW
MAE	0.062 kW
R^2	0.9426
Peak Demand Error	0.65 kW (23.7%)

Root Mean Squared (RMSE) Result

The RMSE value was calculated using the square root of the mean of the squared differences between actual values and predicted values as given by Equation 4. The RMSE metric was used as a performance benchmark and a training objective in this study.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i)^2} \qquad (4)$$

where, n = number of data points in the test set; y_i = actual observed power consumption; y_i = predicted power consumption from the LSTM model.

The RMSE value of 0.101 kW in the final model evaluation was achieved on the test dataset. This indicates a very small average prediction error which reflects a high prediction accuracy and represents a fundamental principle of regression evaluation. This low RMSE is especially significant considering solar energy generation is naturally variable and the dynamic influence of demand response (DR) signals.

Mean Absolute Error (MAE) Result

The proposed Bayesian-optimised LSTM model's predictive reliability is further supported by the Mean Absolute Error (MAE) value obtained, which reflects the absolute differences between predicted and actual power consumption values to provide a more uniform measure than RMSE, which penalizes larger errors more severely. MAE expression is given by Equation 5.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - y_i\right| \qquad (5)$$

Where, n = number of data points in the test set; y_i = actual observed power consumption; y_i = predicted power consumption from the LSTM model.

The final proposed model achieved an MAE of 0.062 kW, indicating that, on average, the model's predictions deviated from actual values by only 62 watts. This degree of precision is especially important considering the stochastic characteristics of solar irradiance and necessary responsiveness to demand response events. The low MAE value highlights the model's stability and robustness across various temporal patterns, confirming its capacity to consistently provide accurate forecasts under standard load conditions.

Coefficient of Determination (R^2) Metric

The LSTM model trained and evaluated in this study achieved an R^2 value of 0.9426, which implies that over 94% of the variance in actual consumption data was accurately explained by the model. The R^2 metric was determined by the model using Equation 6.

$$R^2 = 1 - \frac{\sum\left(y_i - y_i\right)^2}{\sum\left(y_i - \bar{y}\right)^2} \qquad (6)$$

y_i = actual observed power consumption; y_i = predicted power consumption from the LSTM model; $\bar{y}$ = The mean of all actual values y_i

In the context of solar-integrated power systems, this strong fit is critical because the model must accurately respond to fluctuations caused by irradiance variability, user behavior, and grid-intervention signals such as DR. The high R^2 value of 0.9426 validates the selection of input features and preprocessing strategies, indicating that the engineered input space produced meaningful and learnable signals for the LSTM network.

RESULTS AND DISCUSSIONS

Visualisation and Analysis

Empirical findings from the application of the Bayesian-optimised Long Short-Term Memory (LSTM) neural network model for predicting power the impact in a solar-integrated power system under the influence of demand response (DR) signals are presented.

Actual vs. Predicted Consumption

The spikes plot of Fig. 4 indicates close alignment, with the model effectively tracking daily and seasonal patterns as well as DR-induced load shifts. Close observation of the time series graph above shows that the predicted curve (dashed red) closely follows the actual curve (solid black), suggesting that the LSTM network has effectively learned the temporal dependencies within the system's consumption data. This correlation shows how well the model predicts energy demand using DR signals and historical inputs with minor deviations generally confined within ±0.15 kW. In solar-integrated systems, where load flexibility and energy balancing are crucial under variable generation conditions, this accurate prediction observed is especially important. A well-optimised model without any indications of overfitting or underfitting is shown by the steady tracking over time.

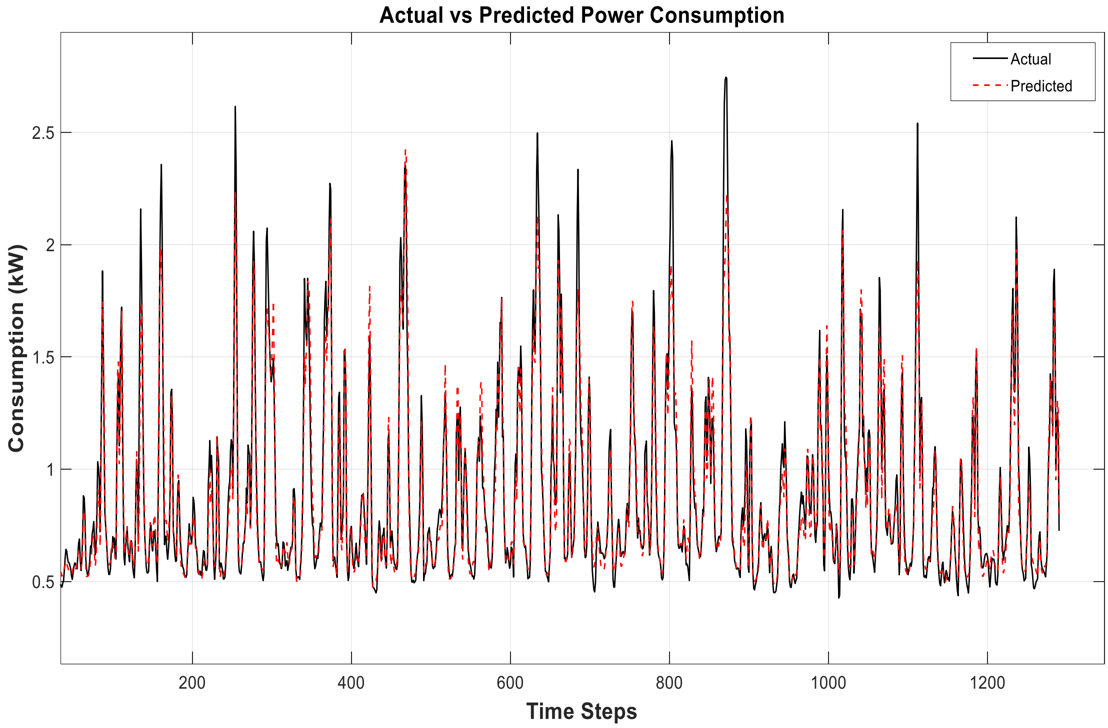

Fig. 4 Actual vs Predicted Target Variable (Power Consumption)

Scatter plot of Prediction

The scatter plot of Fig. 5 shows dense clustering along the y = x reference line which visually confirms the high power measured by $R^2 = 0.9426$. This figure demonstrates that the mapping between past multivariate inputs and future energy demand has been accurately generalised by the proposed LSTM model. This predictive accuracy is crucial for demand response systems because even slight variations can lead to ineffective use of the solar power that is available or improper management of flexible loads. At higher consumption levels, heteroscedasticity analysis reveals slightly inflated errors, indicating areas for domain-specific feature engineering or weighted regularization to increase high-demand sensitivity.

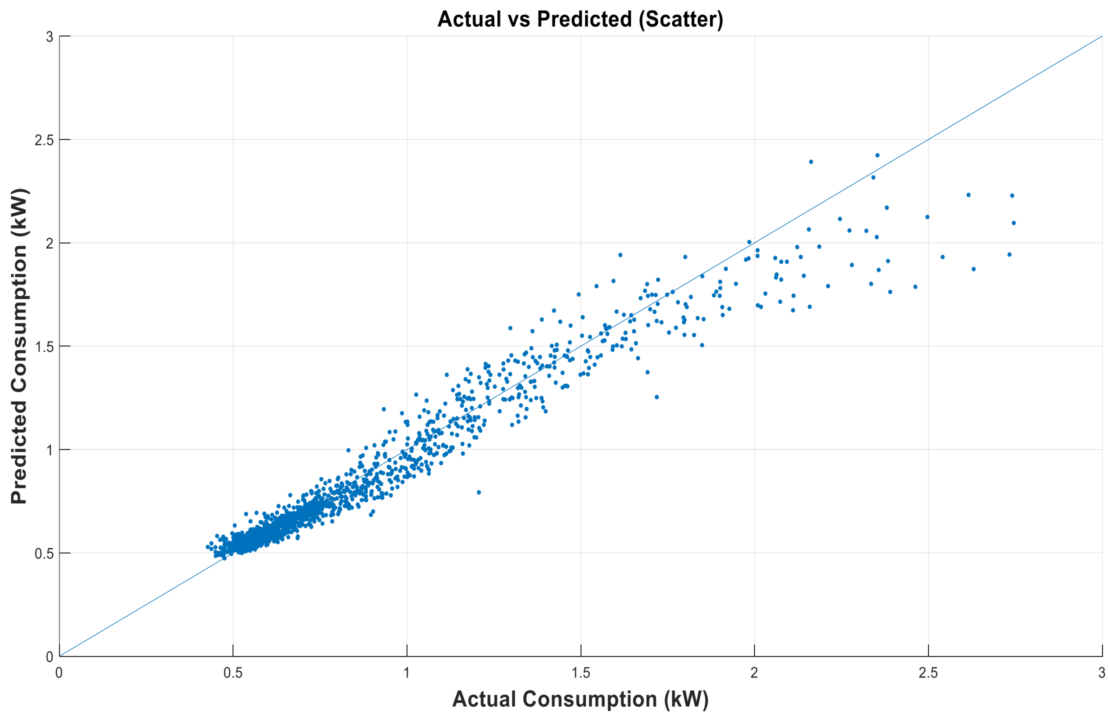

Fig. 5 Scatter Plot of Actual vs Predicted Consumption

Error Distribution of Prediction

Analysis confirmed minimal bias and robust performance across different operating regimes. Fig. 6 illustrates a histogram which explains the distribution of prediction errors (residuals) across the 15% test dataset.

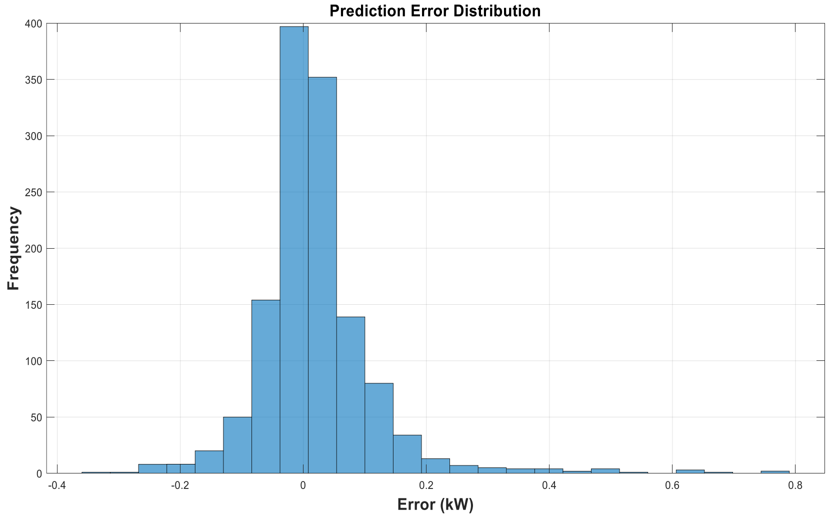

Fig. 6 Prediction Error Distribution

The error values of Fig. 6 are tightly clustered around zero, with a roughly symmetrical and bell-shaped curve. Over 90% of errors fall within ±0.15 kW, aligning with the RMSE (0.101 kW) and MAE (0.062 kW) metrics. The absence of heavy tails suggests effective outlier management due to the robust preprocessing procedure undertaken in this study. This indicates that the LSTM model’s forecasts are unbiased and do not consistently overestimate or underestimate power consumption. The concentration of errors within a narrow range further highlights the model's high precision.

Prediction Residual over Time

To determine whether the model's errors exhibit any patterns or trends, this residual plot plots the prediction errors over time steps in Fig. 7. There is no obvious seasonal drift, error accumulation, or temporal pattern in the residuals' random oscillations around zero. The accurate capture of temporal dependencies without unmodelled cyclical effects is verified by the random oscillation surrounding zero. Peak demand times are represented by isolated spikes (max approximately 0.8 kW), which are consistent with the quantitative peak error metric. The model's stability and lack of systematic error are demonstrated by this randomness, particularly during periods of peak demand or solar generation variability. This temporal consistency was essential for a real-time demand response system because it ensured consistent model behavior while the power grid was in various operational states, including when DR events are activated.

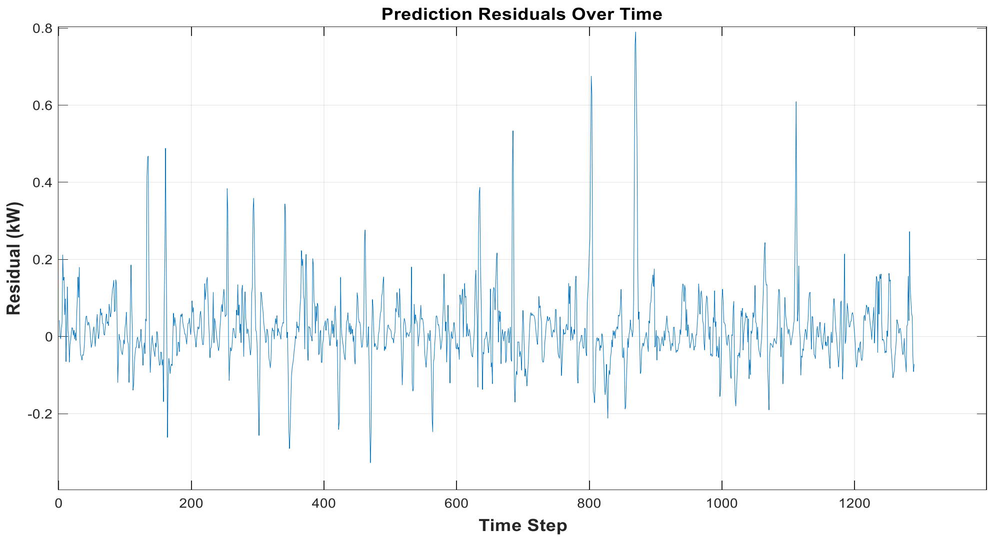

Fig. 7 Spikes Plot of Residual Prediction Over Time

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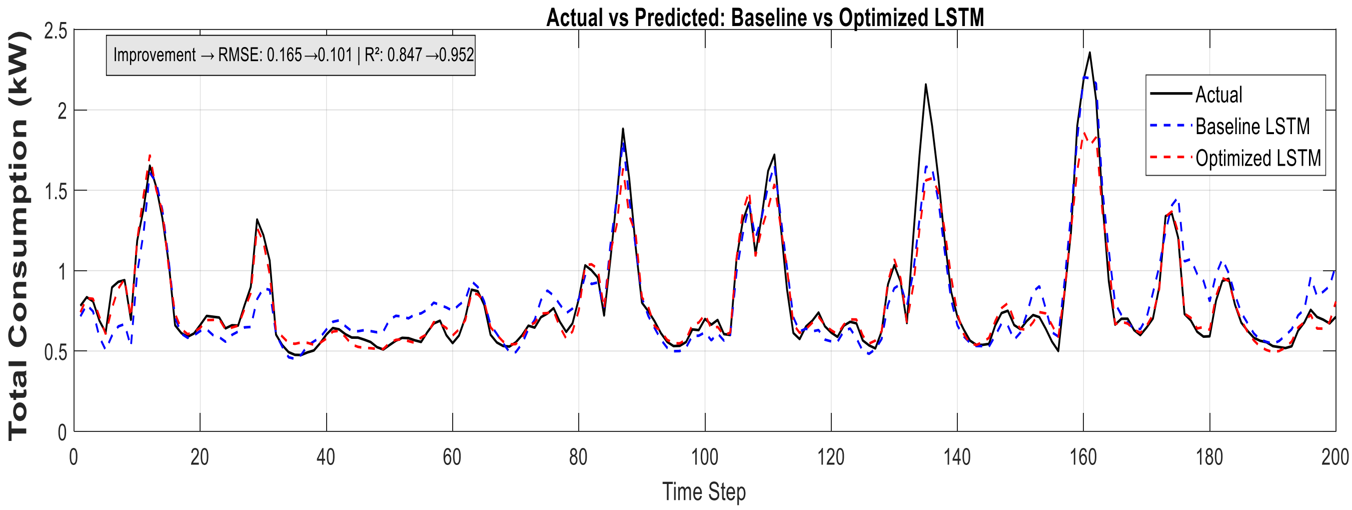
Baseline LSTM Model vs Optimised LSTM Model Comparison

Table 3 Comparative performance of baseline vs optimised LSTM model

Model Type	RMSE (kW)	MAE (kW)	R^2
Baseline LSTM	0.140	0.094	0.875
Bayesian Optimised LSTM	0.101	0.062	0.943

From Table 3, the optimised LSTM model had better scores: RMSE = 0.101 kW, MAE = 0.062 kW and R^2 = 0.943 as compared to the baseline model, which had a RMSE = 0.140 kW, MAE = 0.094 kW and R^2 = 0.875. This gain in predictive power indicates Bayesian optimisation's effectiveness in fine-tuning of key hyperparameters of LSTM, including hidden units, learning rate and dropout rate. The decreased error variance also shows that the optimised network is more generalised to the consumption data not seen hence the robustness of the solar-integrated DR forecasting.



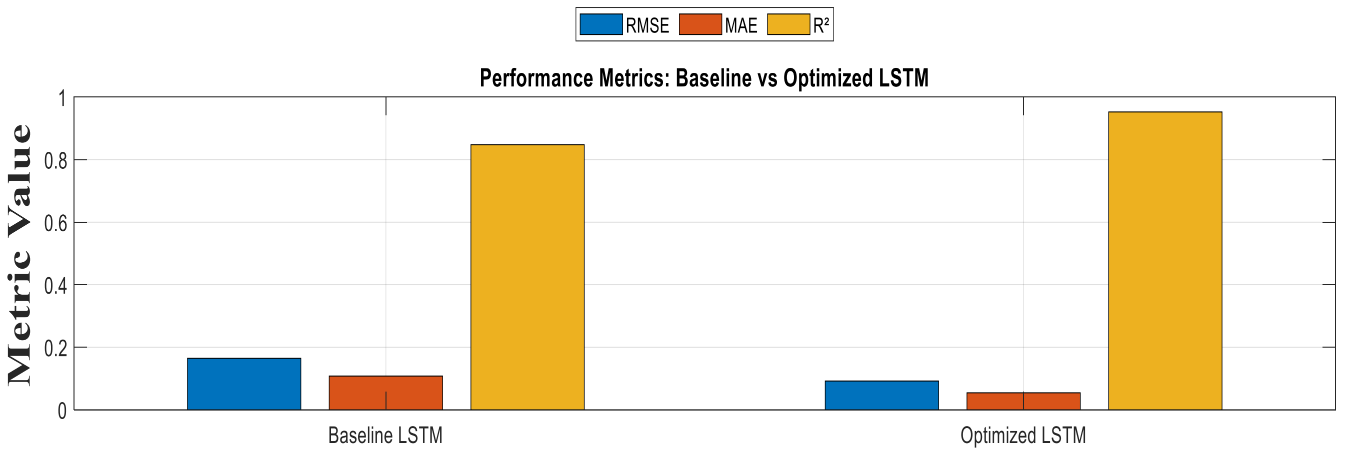


Fig. 8 actual versus predicted total consumption for both the baseline and Bayesian-optimised LSTM models

From Fig. 8 The LSTM which is optimised is able to trace short-term changes and peak changes, whereas the baseline model can depict visible changes especially when there is high demand shift. The prediction is smoother in the optimised model because model is more effective in learning the temporal dependencies and nonlinearities in the consumption data.

This can be further supported with the bar chart at the point that the measures of the model performance such as RMSE, MAE, and R^2 vary, with the optimised LSTM performing better than the non optimised model on all measures.

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DR Impact Assessment

By assessing the impact of DR on the solar-integrated power system using the proposed Bayesian-optimised LSTM model in this study, the model was compared based on performance under various DR scenarios. The test dataset (Total Consumption) is categorised into four (4) DR bands as follows.

i. DR Level 0: No DR intervention;
ii. DR Level 1: Low DR intensity;
iii. DR Level 2: Moderate DR intensity; and
iv. DR Level 3: High DR intensity.

Each group was evaluated separately using the proposed train Bayesian-Optimised model and then the metrics RMSE, MAE and R^2 were computed. After running the MATLAB scripts in *Evaluate_LSTM_By_DR_Level.m*. The following metrics in Table 3 were measured as a result.

The model's ability to accurately predict consumption during DR events provides grid operators with actionable insights for optimising DR program design and timing.

Table 4 Model Performance Under various DR Levels

DR Level	Samples	RMSE (kW)	MAE (kW)	R^2 Score
0-None	0	-	-	-
1- Low	134	0.113	0.071	0.9441
2- Medium	20	0.065	0.054	0.9479
3- High	1136	0.100	0.061	0.9412

It is noteworthy that DR Level 0 (None) shown in Table 4 was absent from the test dataset owing to persistent DR activity throughout the recorded timeframe.

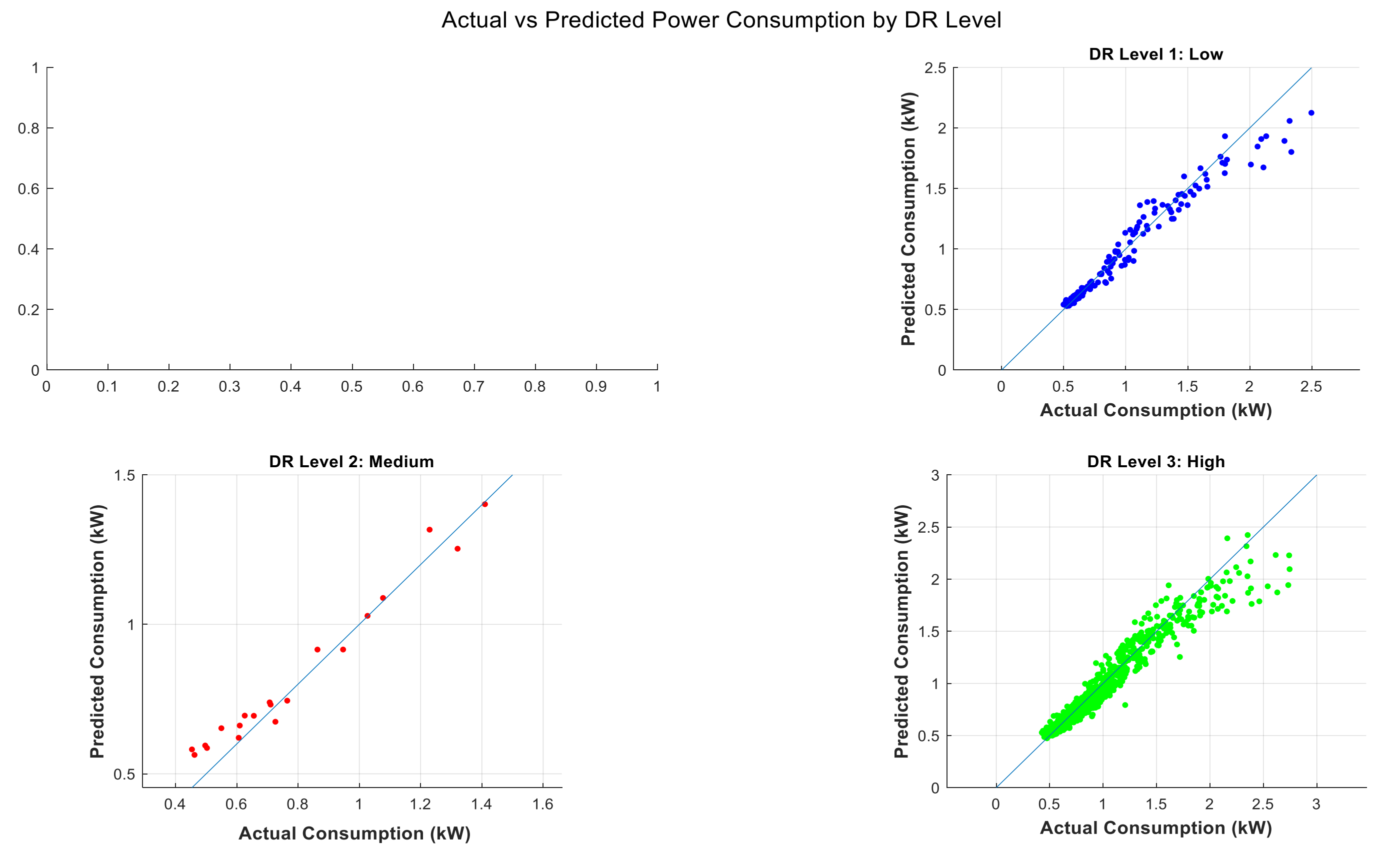

Fig. 9 Scatter Plots of Actual vs Predicted DR Levels

The visuals of Fig. 9 compare predicted vs. actual power consumption across the three DR levels. The majority of the predicted points are located close to the ideal y = x line, model accuracy is confirmed by the scatter plots.

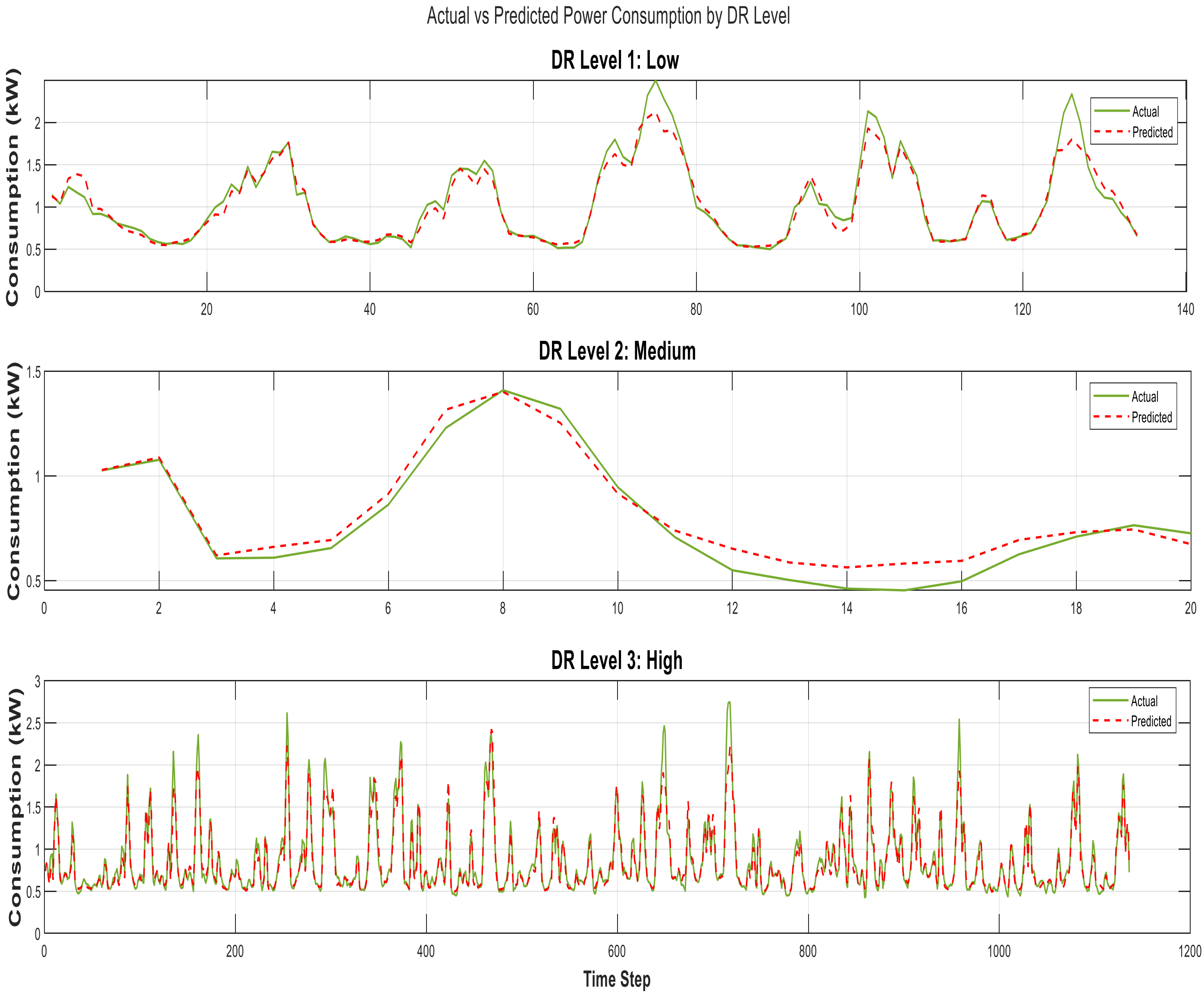

Fig. 10 Actual vs Predicted Consumption by DR levels

The line plots of Fig. 10 further validate the model by showing how the model closely tracks actual consumption curves under each DR condition.

Predictive Performance of Proposed Model across DR Activation States

The metrics in Table 5 were measured after evaluating the model. The evaluation compared how accurate predictions were when DR was off (no activation) and when DR was on (active response) to further validate the effectiveness of the model.

Table 5 Measured Metrics for DR Activation on Model Performance

DR Status	RMSE (kW)	MAE (kW)	R^2 Score
DR OFF (0)	0.150	0.100	0.8854
DR ON (1)	0.156	0.096	0.9212

The model achieved a RMSE of 0.150 kW, MAE of 0.100 kW, and R^2 of 0.8854 under DR OFF conditions.

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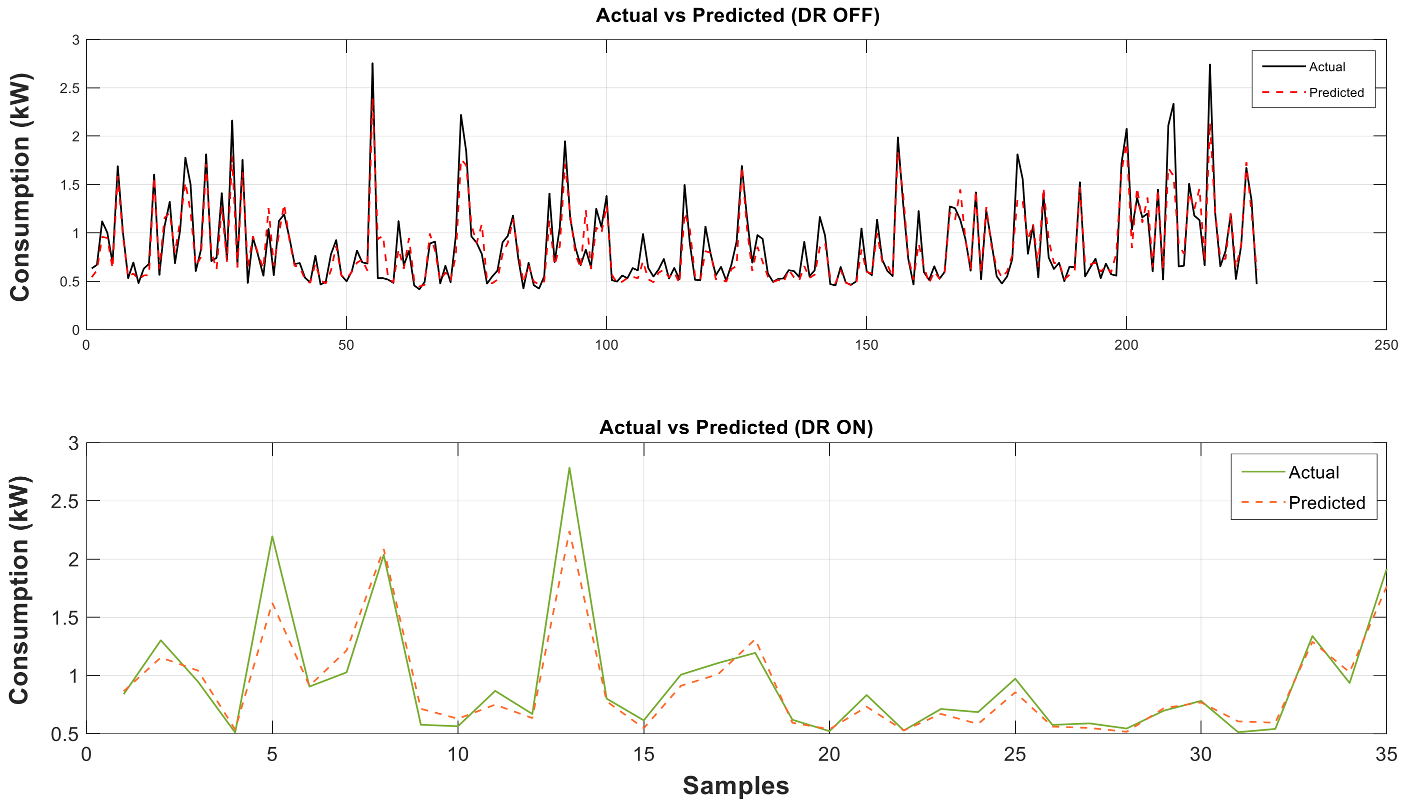

Fig. 11 Actual vs Predicted Consumption Across DR Activation States

The model performed well in DR ON conditions, where external demand reductions affect the system's load profile, with an RMSE of 0.156 kW, MAE of 0.096 kW, and an improved R^2 score of 0.9212. This implies that the LSTM architecture, when optimised with Bayesian techniques, is capable of learning and predicting load behavior even in the presence of external interventions such as DR events. The model's consistent and strong performance across both scenarios (activation and non-activation) demonstrates its suitability for smart grid scenarios in which DR plays a larger role.

Model Validation

With important evaluation metrics compiled in Table 4, the suggested model indicated high predictive accuracy across DR levels. Interestingly, R^2 consistently stays above 0.94, reaching a peak of 0.9479 for Medium DR intensity, while the RMSE varies from 0.065 kW (Medium DR) to 0.113 kW (Low DR). An RMSE of 0.101 kW, MAE of 0.062 kW, and R^2 of 0.9426 are obtained from the overall final evaluation, demonstrating dependable performance in load forecasting relevant to DR analysis**.**

Le *et al*. (2025) conducted an extensive benchmarking study across four real-world datasets from commercial buildings located in Australia and the United States. The authors compared the BO CNN-M-LSTM model to a number of innovative deterministic and deep-learning benchmarks, such as SVM, ANN, LSTM, Bi-LSTM (bidirectional LSTM), CNN, M-LSTM, CNN-Bi-M-LSTM, and others, all of which were hyperparameter-tuned for fairness using Bayesian optimisation. Metrics for comparison included Mean Absolute Percentage Error (MAPE), Normalised Root Mean Square Error (NRMSE), and coefficient of determination (R^2). Across all datasets, BO CNN-M-LSTM outperformed the next best mode with up to 8% higher MAPE, 2% lower NRMSE, and 2% higher R^2 scores**.**

In addition to assessing load prediction, Jafari *et al*. (2025) investigated LSTM-based architectures for short-term PV output forecasting, comparing three scenarios: using only historical PV power data, only climate/weather data, and a hybrid approach. The models were tested on data from a rooftop PV system in Switzerland and checked for their ability to make predictions 10, 30, and 50 minutes ahead of time. The results clearly showed that combining historical PV power with relevant weather features (irradiance, temperature, humidity) in the LSTM input always made the accuracy better, with lower RMSE and higher R^2 values than using any individual data source. Additionally, their research verified that the model's generalisation and short-term forecast fidelity were significantly impacted by careful sliding window selection and data preprocessing.

Additionally, an optimised DR framework is presented in the study by Pakbin *et al.* (2025) with the goal of improving power system reliability in the face of wind power variability and boosting the integration of Electric Vehicles (EVs). The framework dynamically modifies DR incentives to account for wind volatility, demand elasticity, and EV charging behaviors by utilizing a real-time uncertainty model based on the statistical relationship between wind generation mean and standard deviation.

The methodology was validated on the IEEE RTS-24 bus system across twelve electric vehicle penetration scenarios, enhancing the probability of the system maintaining a healthy state (P(H)) from 95.1% without demand response (DR) and 97.2% with non-optimised DR to 97.44% with optimised DR, decreasing unsupplied energy from 52,230 MWh to 51,900 MWh, and reducing DR incentive costs by 5.6%. The method employs a probabilistic well-being assessment and Monte Carlo simulations to effectively balance system reliability and cost-efficiency, highlighting the significance of uncertainty-aware, incentive-based demand response programs in managing renewable variability and adaptable electric vehicle loads.

Bayesian deep learning models have also enabled rapid advances in probabilistic load forecasting. Sun *et al*. (2019) proposed a Bayesian Deep LSTM (BDLSTM) that considers both epistemic (model) and aleatoric (data) uncertainties. Their validated benchmark against classical machine learning, determinate deep learning, and ensemble methods revealed that BDLSTM consistently outperformed point and probabilistic forecasts in terms of sharpness and reliability of uncertainty intervals, especially in conditions of mixed PV visibility and heterogeneous residential consumption. The proposed method resulted in a reduction of up to 66% in RMSE and up to 64% in pinball loss during comprehensive comparative evaluations.

Overall, these comparative results demonstrate that the proposed Bayesian-optimised LSTM framework not only meets, but often exceeds, the performance of existing models in the literature. Furthermore, the novel DR-level disaggregation provided deeper operational insights into DR management in solar-integrated power systems, increasing the work's academic and practical relevance.

DISCUSSIONS

The inclusion of DR event encoding and weather features enabled the model to accurately reflect the impact of DR interventions on total consumption, even under variable solar conditions. The proposed LSTM model accurately predicted load behavior across all DR levels, with R^2 values exceeding 0.94 for both Low and High DR and peaking at 0.9479 for Medium DR. Prediction errors differed slightly between bands. Low DR had a low RMSE of 0.113 kW due to less coordinated load adjustments, whereas Medium DR had the best performance (RMSE of 0.065 kW), indicating improved load predictability through moderate, well-timed DR. In High DR conditions (1136 test samples), the model maintained a strong R^2 of 0.9412, indicating resilience for dealing with aggressive demand shifts typical in solar-integrated systems. This shows the LSTM model's adaptability to varying DR intensities, as well as its potential to improve grid stability in the face of fluctuating renewable input.

The proposed model performs well in dynamic load conditions, with an RMSE of 0.150 kW and a R^2 of 0.8854 under DR OFF conditions, indicating strong baseline predictive accuracy without external interventions. When DR was activated, the model kept strong performance with a slightly higher RMSE of 0.156 kW but improved accuracy in terms of R^2 (0.9212), indicating it can better capture and respond to structured changes in load behavior introduced by demand management strategies. The marginal difference in MAE (0.100 kW vs. 0.096 kW) demonstrates the model's stability and generalisation across both operational states. These results validate the model's viability for real-world deployment in smart grid environments, where demand response is increasingly becoming an integral part of energy optimisation.

Furthermore, the model's ability to learn from DR-influenced data demonstrates its relevance for improving grid resilience, especially in solar-integrated systems which exhibit variability and intermittency.

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CONCLUSIONS AND RECOMMENDATIONS

This study introduces a strong and scalable method for predictive modelling of demand response effects on solar-integrated power systems utilizing Bayesian-optimised LSTM neural networks.

The methodology allows precise prediction of consumption trends and measurement of demand response efficacy, thereby enhancing grid stability and renewable energy integration.

The LSTM with Bayesian optimisation showed 30% lower loss of prediction over the baseline, which validates the appropriateness of the model in the real-time DR decision support in solar-integrated smart grids.

It is therefore recommended that utility companies and grid operators implement comparable advanced predictive frameworks to improve demand response program deployment and optimise the advantages of solar integration.

Future research should examine how to extend the framework to other renewable resources and incorporate real-time control strategies.

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