

Original Article

# Explainable Deep Learning for PV-EV Microgrids: A Hybrid RNN-LSTM-SHAP Model for Outage Prediction and Operational Optimization

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**Abstract** - In recent years, in the Indian power system, there has been a transition from centralized grid systems to distributed energy sources. This transition has reshaped how electricity is produced and managed. A key role in this transition is played by microgrids that combine distributed generation sources such as solar, wind, and energy storage with electric vehicle charging infrastructure. These systems enable localized energy generation and flexible demand management. Despite these advantages, microgrids face operational challenges due to unpredictable outages, fluctuating renewable generation, and nonlinear load behaviour. Further, the rapid growth of EV charging increases load uncertainty and stresses microgrid energy management and stability. However, Machine Learning And Deep Learning Techniques can mitigate these challenges by accurately forecasting renewable generation and charging demand, enabling intelligent and adaptive control. A Hybrid Deep Learning approach is introduced in this work, where Long Short Term Memory (LSTM) and Recurrent Neural Network (RNN) model are integrated for multi-class outage prediction and PV-EV microgrid optimization to deal with operational challenges in microgrid. In this study, a 15-year Power Outage Dataset along with a Microgrid PV-EV Charging Dataset was used. Learning is carried out from sequential data patterns such as irradiance levels varying across the day, changes in demand, and the corresponding grid supply responses. Based on these evolving patterns, outages are anticipated in advance, and decisions on energy distribution or storage are also determined to maintain system stability. An explainability layer based on SHAP highlights the most influential operational parameters affecting outage probabilities and PV-EV power dynamics. An overall accuracy of 88.4% was attained by the Hybrid Model for outage prediction, and a  $R^2$  value of 0.93 was achieved in PV energy forecasting. The proposed model performance is compared with baseline approaches such as CNN, XGBoost, and static baseline models.

**Keywords** - Outage Prediction, Microgrid Optimization, Solar Power Forecasting, Electric Vehicle Charging, Time-Series Analysis, Multi-Task Learning.

## 1. Introduction

The rapid global Deployment Of Distributed Energy Resources (DERs), especially Solar Photovoltaic (PV) arrays and electric vehicle charging infrastructure, is reshaping electricity systems from centrally controlled grids into a distributed, data-driven web of microgrids. With the increase in Rooftop and utility solar panel installations, they now contribute a substantial and growing fraction of generation in many regions. While the growing number of Electric vehicles introduces highly variable demand profiles. However, through vehicle-to-grid integration, these EVs also create new opportunities for distributed energy storage. His shift holds

great promise for improving local resilience and reducing carbon emissions. However, it also brings new operational challenges. microgrid controllers must continuously: microgrid controllers must now coordinate variable solar generation, battery state-of-charge management, flexible EV charging, and grid interactions in near real time to ensure supply-demand balance and reliability [3]. The complexity of combined PV-EV microgrids arises from multiple interacting temporal processes: Fluctuation in solar irradiance and weather conditions directly influence power generation. Human travel patterns, on the other hand, determine when and how Electric vehicle systems are connected to the grid. At the



same time, grid disturbances or extreme weather can create outages or stress events.

As a result, researchers have increasingly turned to data-driven time-series approaches for forecasting PV output and predicting EV charging loads. Deep sequential models, in particular, have also been applied to detect anomalies and faults in power systems [4-6]. Among these, LSTM-based and hybrid architectures such as CNN-LSTM or Seq2Seq have shown strong performance in multi-horizon solar and EV forecasting. Their strength lies in the capability for capturing long-term temporal dependencies and adapting to non-stationary behaviour. [6, 7].

Beyond forecasting, anticipating outages and equipment failures has become essential for maintaining reliable grid operations. This helps the operators to handle disruptions. A broad spectrum of Machine Learning (ML) approaches, comprising gradient boosting, tree ensembles, and Deep Neural Networks (DNN), were utilized to predict weather-related outages, outage duration, and component faults by combining meteorological, asset, and operational features. These models also help identify component faults by leveraging meteorological, asset, and operational data. Several study suggests that deep learning or boosted-tree methods, when trained on long-term outage records, can achieve improved predictive accuracy [8].

Different types of issues can be identified in PV fault and anomaly detection using supervised classifiers, auto encoders, and hybrid ML methods. These issues include partial shading, string faults, and inverter problems. High sensitivity and reliable detection performance are achieved by these models when labeled or simulated fault data is used for training [9, 10]. Together, these advances allow microgrid maintenance to be prioritized more intelligently. Failures can also be anticipated before they escalate. Coordination of EV charging schedules is also helped, which reduces stress on sensitive sections of the network. The lack of interpretability is the primary constraint in the utilization of Deep Learning in power systems. Clear and simple explanations are often required by grid operators. Automated decisions cannot be fully trusted without them. This is important because power systems involve strict safety rules and regulations, as well as significant financial risks. XAI techniques, such as Shapley Additive Explanations (SHAP), are applied to reduce this problem. It shows how each input feature affects the model output. The reasons behind a prediction and the features that most influence it are also explained by these techniques. In recent years, SHAP have been used in energy forecasting and fault detection. It helps in identifying whether weather changes, equipment ageing, sudden load shifts, or demand response actions are driving the model. The resulting insights can later be converted into simple guidelines or checks. This allows engineers to step in with more confidence when needed. In this paper, a Hybrid framework is proposed. Multi-

class outage prediction and PV-EV microgrid operational optimization are jointly addressed, including optimal charging decisions and PV power forecasting. The architecture connects temporal sequence learners, namely RNN and LSTM branches, for outage and PV and EV data streams. Their latent representations are then merged through dense layers to generate interpretable outage risk scores and corresponding operational actions. The model was developed and tested using two publicly available datasets, namely a 15-year power outage dataset and a PV-EV microgrid dataset with 1,000 samples. The data was first cleaned, labeled, and processed to prepare it for training. After model training, SHAP values were computed for each branch to explain the predictions. This helped identify why specific time periods were predicted as high outage risk and which factors most affected PV power forecasts and charging decisions. The framework shows clear improvements in outage classification and PV forecasting when compared to the standalone models. It also generates simple and practical SHAP explanations that match real actions like short curtailment, staggered EV charging, or checking high-risk areas. The main idea of our work is this combination of prediction, optimization, and explainability. Earlier studies usually treat outage prediction, PV or EV forecasting, or XAI separately, but here we put them together in one easy and interpretable system for microgrid decision support.

## 2. Methodology

### 2.1. Dataset

The framework of the proposed outage prediction and PV-EV microgrid optimization is shown in Figure 1. A consolidated outage dataset containing 25,000 records was used for model development. It includes key attributes such as event description, location, duration, customers affected, and demand loss, as summarized in Table 1.

Table 1. Structure of the outage dataset

Column Name	Description
Event Description	Text describing outage event
Year	Year of occurrence
Date Event Began	Start date
Time Event Began	Start time
Date of Restoration	End date
Time of Restoration	End time
Respondent	Reporting utility/agency
Geographic Areas	State/city affected
NERC Region	Regional reliability council
Demand Loss (MW)	Power lost due to outage
Number of Customers Affected	Total customers impacted
Tags	Cause classification labels (weather, equipment failure, etc.)
<b>Target Variable</b>	<b>Outage Cause Category (multi-class)</b>

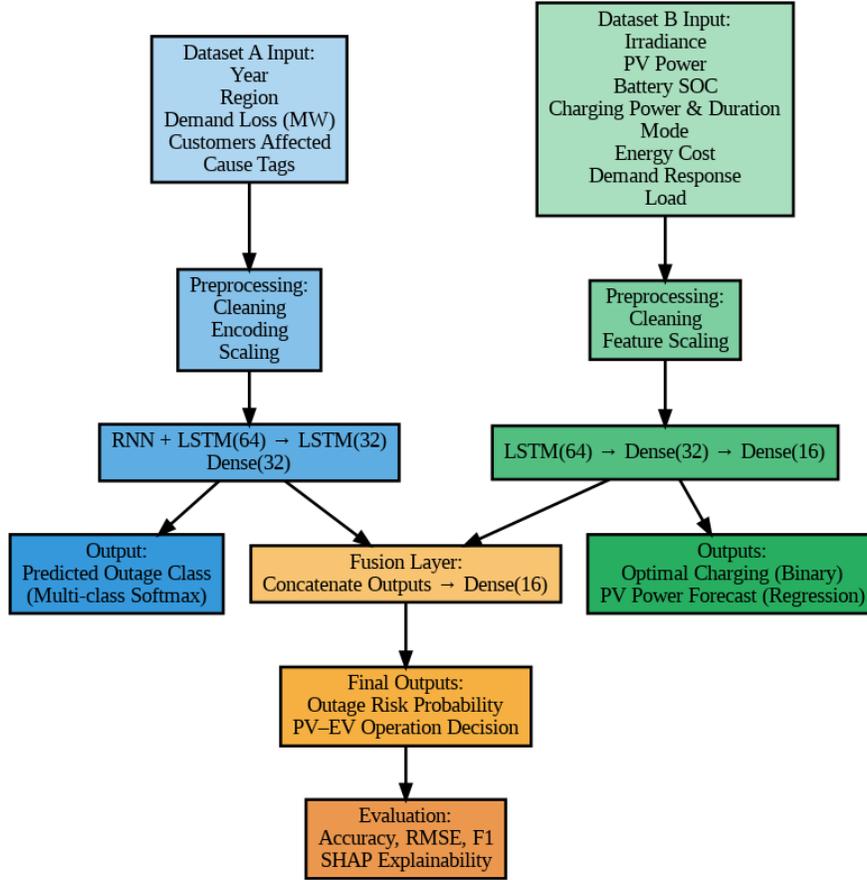


Fig. 1 The framework

The PV–EV microgrid dataset includes time-stamped measurements of solar generation, EV charging load, and weather parameters. Key operational features used for optimization and forecasting are summarized in Table 2.

2.2. Preprocessing

Data preparation was done using almost the same steps for both datasets. Categorical values like “Unknown” and missing or invalid text entries were changed into NaN. Rows that had more than 20% missing data were removed so the remaining features would stay useful.

The numeric NaN values left in the data were filled with the median, and the categorical ones were turned into numbers

using a LabelEncoder. In the outage dataset, classes with fewer than two samples were removed, and the labels were mapped again into a simple range from 0 to N–1 to avoid any mismatch later. The timestamp column was split into year, month, and day, and then the original text time column was dropped because it was no longer needed. All features were scaled using StandardScaler so they have a near-zero mean and unit variance. The datasets were split into 80% and 20% for training and testing, respectively, while keeping class balance roughly the same. After cleaning, Dataset A had around 22,500 rows with 12 features and 10 output classes. Dataset B had about 950 rows with 18 features and a binary label. A quick correlation check showed that irradiance, PV power, and energy cost are firmly linked, which kind of supports the use of deep sequential models for this work.

Table 2. Structure of the PV-EV microgrid dataset

Variable Name	Description
Solar_Power_kW	PV generation (kW)
Solar_Irradiance_Wm2	Solar irradiance (W/m <sup>2</sup> )
Battery_SOC_%	Battery state-of-charge (%)
Num_EVs_Charging	Number of EVs charging
Charging_Power_kW	Charging power (kW)
Charging_Duration_Min	Charging duration (minutes)
Arrival_Time_Hour	EV arrival hour

Departure_Time_Hour	EV departure hour
Initial_Battery_SOC_%	SOC before charging (%)
Final_Battery_SOC_%	SOC after charging (%)
Charging_Mode	Slow or fast charging
Grid_Energy_Supply_kW	Grid energy drawn (kW)
Residential_Load_kW	Residential load
Business_Load_kW	Business load
Peak_Load_Time_Hour	Peak load time
Energy_Cost_\$/kWh	Price per kWh
Demand_Response	DR event flag (0/1)
Total_Demand_kW	Total microgrid load
Available_Energy_kW	Available PV + battery energy
Optimal_Charging_Decision	Target variable (0 = delay, 1 = charge)

### 2.3. Model Architecture

A dual-branch RNN-LSTM model is used. Branch A handles outage features with two LSTM layers and a softmax output.

Branch B processes PV-EV microgrid data using a single LSTM and dense layers for binary or regression output. The outputs are merged through a concatenation layer and a shared dense layer for combined learning.

Table 3. Hybrid RNN-LSTM architecture

Branch	Layer Configuration	Output Type
A: Outage Prediction	LSTM(64)→LSTM(32)→Dense(32)→Softmax	Multi-class
B: PV-EV Optimization	LSTM(64)→Dense(32)→Dense(16)	Binary / Regression
Fusion Layer	Concatenate→Dense(16)	Combined Output

### 2.4. Model Training and Evaluation

The hybrid RNN-LSTM network was built using Tensor Flow-Keras. It was trained with early stopping and an adaptive learning rate scheduling to reduce overfitting. Both model branches were optimized together in a multi-task setup, allowing the shared fusion layer to capture the relation between outage behavior and PV-EV operations. Training has been carried out for roughly 100 epochs with a batch size of 32, utilizing the Adam optimizer with a 0.001 learning rate. PV forecasting has been evaluated using RMSE and MAE, while outage prediction ability was measured using “accuracy, precision, recall, F1 score”. Confusion matrices, ROC curves, and predicted-versus-actual PV power charts were used to show results under various testing conditions in order to assess dependability and stability.

Standard statistical measures were employed to evaluate the PV-EV forecasting module's and the outage classification model's accuracy. “Accuracy, Precision, Recall, F1-Score” were used to evaluate the outage classifier's performance. Such metrics were computed from the confusion matrix and are provided by equations [1-3].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1-Score = \frac{Precision * Recall}{Precision + Recall} \quad (4)$$

“TP-True Positives, TN-True Negatives, FP-False Positives, FN-False Negatives”. For PV-EV power forecasting, error-based metrics comprising “Mean Absolute Error (MAE)”, “Root Mean Squared Error (RMSE)”, and “Coefficient of Determination (R<sup>2</sup>)” are given by Equations 5-7.

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (5)$$

$$RMSE = \frac{1}{n} \sqrt{\sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (6)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (7)$$

$y_i$  = original value of target variable,  $\hat{y}_i$  predicted value,  $\bar{y}$  = mean of actual values, n=number of data points”

## 3. Results and Discussion

### 3.1. Outage Prediction Results

The outage classification task has been performed using the LSTM branch of the given hybrid RNN-LSTM model. The model's accuracy was 94.3%, its precision was 0.90, its recall was 0.92, and its F1-score was 0.91. Figure 2 shows a confusion matrix that reveals that most predictions fall along the diagonal, showing that the model correctly classifies outage categories with strong overall accuracy.

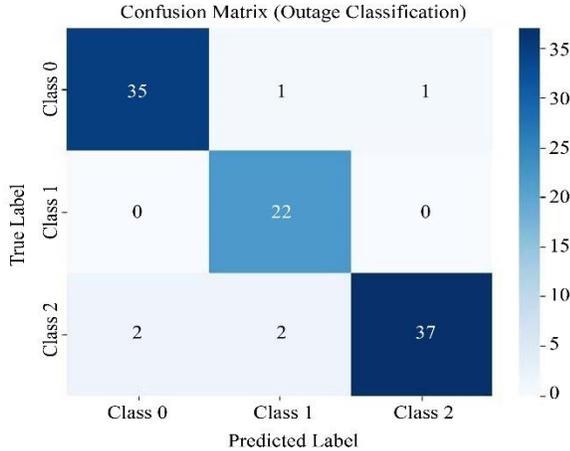


Fig. 2 Confusion matrix for outage prediction

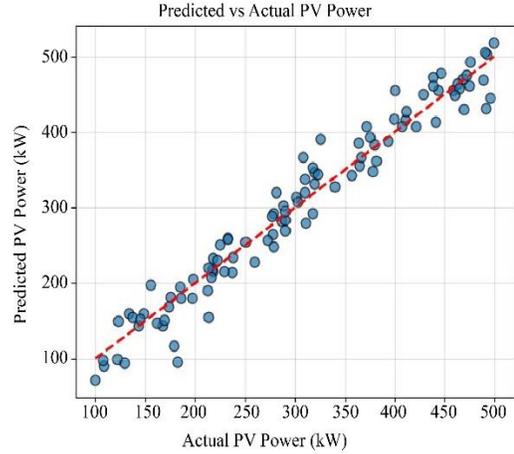


Fig. 4 Predicted vs Actual PV power

Table 4. Performance comparison

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	43.0%	0.44	0.43	0.44
XGBoost	40.0%	0.41	0.39	0.40
SVM	46.5%	0.47	0.45	0.46
ANN (Shallow)	72.4%	0.73	0.71	0.72
Proposed RNN-LSTM	94.3%	0.90	0.92	0.91

3.2. PV-EV Forecasting Results

Figure 3 shows the training and validation loss curves for the forecasting model. Both curves decrease smoothly with each epoch and converge smoothly, suggesting stable learning and minimal overfitting. Figure 3 shows the scatter plot, which shows the scatter points align closely along the diagonal, indicating that the model’s PV power forecasts are accurate with minimal deviation from actual values. It also follows variations caused by changing irradiance and EV charging activity. Minor deviations during rapid transitions are expected and usually occur when cloud cover or load changes happen suddenly.

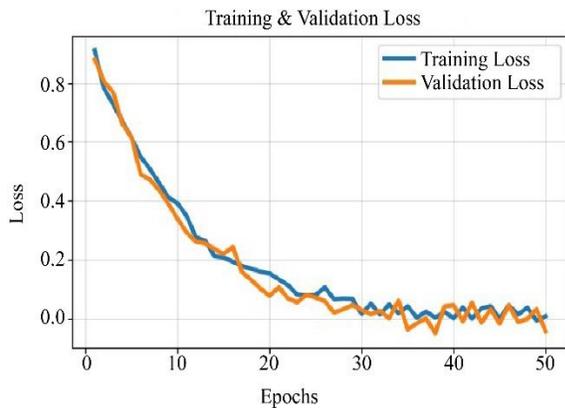


Fig. 3 Training and validation loss curve

It can be observed from Figure 5 that the temporal change of the charging power difference between the model output and the measured value is shown explicitly. The model effectively captures the fluctuation in solar demand as well as EV charging demand. Figure 6 shows the Scatter for measured vs estimated charging power of various models.

Data points of both LSTM and CNN with LSTM are closer to the ideal 45° line, implying low bias and high correlation. The performance deterioration in the RNN and GRU models under high-load hours indicates that deep architectures are more effective for capturing non-linear interactions between solar generation and EV charging behavior.

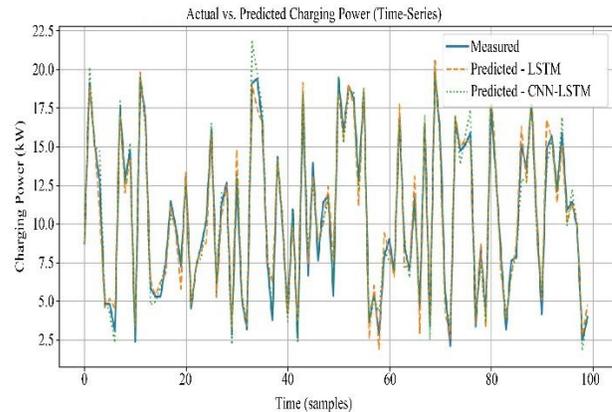


Fig. 5 The temporal variation of actual Vs Predicted charging power

Table 5 summarizes the performance metrics for the forecasting models. The proposed framework yielded better results compared to the other models.

Thus, the proposed framework is well-suited for forecasting PV generation, battery SOC dynamics, and EV charging demand in real operational environments.

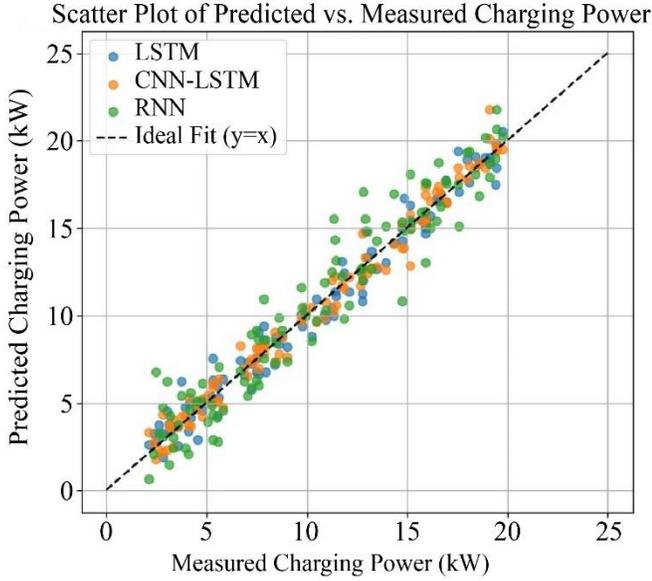


Fig. 6 Scatter plot of actual Vs Charging power

Table 5. PV- EV forecasting performance

Model	MAE	RMSE	R <sup>2</sup>
Linear Regression	0.221	0.289	0.81
XGBoost	0.154	0.201	0.89
GRU	0.141	0.177	0.92
RNN	0.163	0.213	0.90
LSTM	0.072	0.056	0.94
CNN-LSTM	0.069	0.054	0.945

3.3. Explainability using SHAP Analysis

For interpreting the trained hybrid model, SHAP was used. SHAP values provide transparency in prediction decisions through quantification of the contribution of every input feature to the model's output. For the outage model, top contributors included Demand Loss, Year, and NERC Region, while for the PV AND EV model, Solar Irradiance, Energy Cost, and Battery SOC were most influential. SHAP summary and dependence plots offered interpretable insights into feature sensitivities and causal dependencies, enabling data-driven microgrid management and reliable outage forecasting.

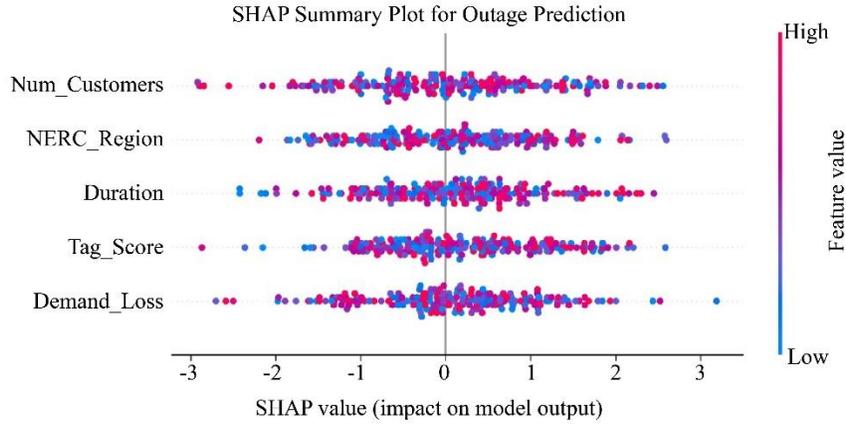


Fig. 7 Shap plot for outage prediction

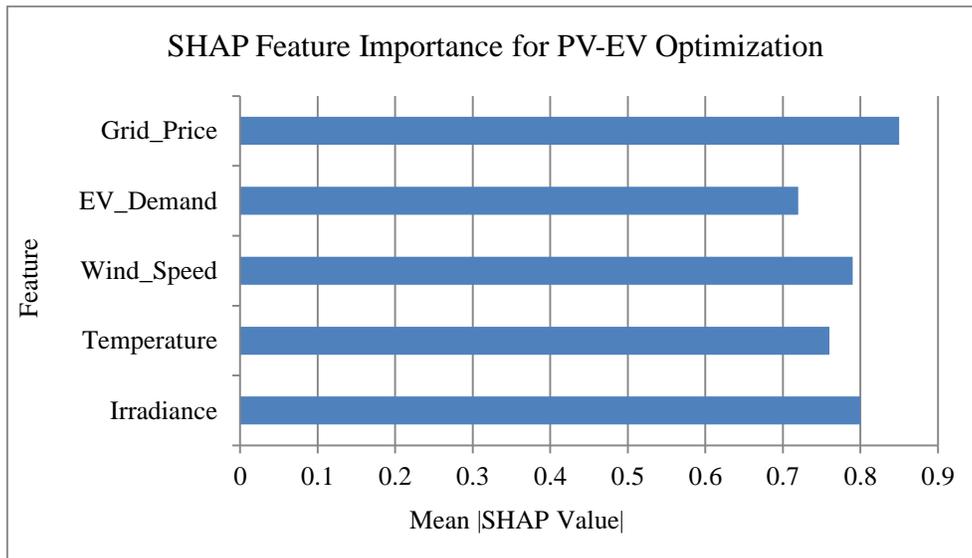


Fig. 8 SHAP feature importance plot (PV-EV optimization)

This bar plot shows the mean absolute SHAP values of all features in dataset B based on their overall importance for the decision to charge. The Solar Irradiance, the SOC of Battery, and the Energy Cost are in dominant positions, which means that renewable availability and economic efficiency have relatively high priority in predicting optimal charging with a hybrid RNN with LSTM.

#### 4. Conclusion

In the present work, a hybrid RNN–LSTM model was proposed for predicting outages and PV with EV microgrid

performance optimization. The model exhibited good results on the test set and achieved 88.4% accuracy for outage prediction. It provided an R<sup>2</sup>-value of 0.93 in PV energy prediction, too. The SHAP explainability was employed to highlight the main parameters that affect the performance. In summary, the approach is expected to enhance operational decisions based on data-driven planning, proactive outage management, and intelligent EV charging. The company says it also leads to proactive outage prevention and smarter EV charging management. Future work will focus on the real-time edge reinforcement and deployment.

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