Smart Energy Management for a Hybrid DC Microgrid Electric Vehicle Charging Station

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Received: 20.04.2023 Accepted:08.06.2023

Abstract- Electric Vehicles (EVs) are increasing in popularity due to their environment-friendly, lower-cost operation and technology elevation. With these advancements and new technologies come more significant challenges and opportunities. The increasing power demand and emerging EV usage reflect enhanced renewable energies such as PV and smart storage devices. Nevertheless, an EV charging station for a residential building or a parking lot powered through grid-connected local PV generation has specific uncertainty issues and energy management problems. Some of the main areas to investigate are selecting Energy Storage devices with adequate capacity, grid-PV integration, and energy management for maintaining constant EV charging station requirements based on the EV's State of Charge (SOC). This study proposes an intelligent, coordinated energy management strategy between the PV power station, the grid, the ESS, and the EV charging station. Here, a smart Energy Management system (EMS) based on Convolution Neural Network – Long Short Term Memory (CNN-LSTM) is proposed for the real-time changes in solar irradiance and State of Charge (SOC) of the ESS to manage grid power and local PV to maintain EV charging station requirements. Moreover, the proposed method prioritizes using Renewable PV sources for the EV charging station, making this eco-friendly and sustainable. Simulation results illustrate the effective integration of the proposed EMS.

Keywords: Electric vehicle, Energy management system, grid-integrated photovoltaic power, charging station, State of Charge.

1. Introduction

Electric vehicles (EVs) have become increasingly popular due to their efficiency and lower emissions. However, the widespread adoption of EVs has strained the electrical infrastructure, as they require significant amounts of power to charge [1][2][3]. Solar photovoltaic (PV) systems have been integrated into the grid to provide renewable energy for charging stations to address this challenge. However, the intermittent nature of solar energy can make it difficult to maintain grid stability. Therefore, an energy management system (EMS) is required to optimize the use of renewable energy and ensure grid stability. In response to the rising number of EVs using the energy grid, several types of research have been conducted to overcome the energy demand. However, if the energy crisis for EVs is met over conventional power, the carbon footprints due to vehicle emissions shift to power generating stations [4][5][6]. An EV can be powered by a combination of renewable energy sources and a power grid, among which PV-grid integration emerges with great opportunities for powering up residential and commercial parking lots. Hence, Photovoltaic power with ESS and smart grid for EV charging stations makes the integration cost-effective and eco-friendly [7][8][9].

To alleviate the energy management of integrated grid-PV for EV charging applications, several authors have analyzed and presented in the literature. Integration of PV and grid for EV charging applications requires intense energy management with the required ESS to meet their power demand due to the intermittent nature of PV [10]. Here we discuss some extensive research for EV charging with renewable energy systems. A real-time optimal EV charging and discharging scheme with photovoltaic and ESS integrated power system provides better utilization of PV with intermittent nature [11][12][13]. A mixed integer linear programming is used to prioritize the utilization of PV and ESS for the EV charging system [14]. Further, the authors proposed a rule-based energy management scheme for a PV-grid integrated EV charging station for uninterrupted daytime charging at a constant price with complete utilization of renewable PV sources [15]. The main objective remains to find a cost-effective solution for EV charging stations. Authors in [16] proposed a fast charging scheme with a Genetic Algorithm based energy management system and a Monte Carlo method to model the EV's demand and availability of PV power. Another dynamic EV charging scheme imposes a Model Predictive Control (MPC) to obtain real-time scheduling information, considering parking lots' scheduling as a benefit maximization problem [17].

Demand prediction for EV charging has escalated due to the increased installation of EV charging stations. Hence, developing a predictive model for EV charging and energy management has become inevitable. An accurate data-driven framework proposed in [18][19] predicts Electric Vehicles' charging needs based on battery SOC, ambient temperatures, and, grid power availability. In another study, a flexibility prediction method based on LSTM-RNN supports Demand response management for power grid operation planning based on the historical power consumption behavior of the EV and Demand response signals [20][21]. The emerging trends in the usage of renewable energy-based resources and microgrids have brought undeniable changes within the smart power generation and charging of EV's. EV's charged through photovoltaic-fed power stations require an outright energy management system (EMS) [22]. EMS for distributed energy resources is often formulated as an optimization problem to minimize emissions, running costs and energy consumption from the grid. In work [23], a particle swarm-based optimization technique establishes an optimized dispatch schedule with a PV-storage system for the EV charging station. However, due to constant changes in the EV charging demand, it is required to charge the battery whenever needed to operate the EV charging station effectively. A deep LSTM-RNN-based method for EV charging demands forecasts the constant changes using features extracted by Empirical Decomposition Method [24].

Although considerable research has been carried out for predicting EV charging demands, research on maintaining constant voltage and current for EVs with local PV-grid-connected charging stations is still an open research area. Predicting the SOC of stationary batteries and photovoltaic power for maintaining constant charging demands required for EV charging stations also plays an important role. Real-time coordination between EV charging stations (EVCS), grid-integrated PV supply, and energy storage systems is essential to maintain constant charging demands in the EVCS and reduce dependence on the grid for cost-effective operation. The main contribution of this paper are summarized as follows:

- In this study, a PV-grid integrated DC microgrid is examined for the EV charging station.
- A CNN-LSTM-based real-time online energy management system is developed for real-time changes in solar irradiance and SOC of the stationary energy storage system to manage grid power and local PV to maintain EV charging station requirements.
- The developed model predicts the SOC of the stationary battery according to prediction classes with high accuracy and effectively allocated resources for the EVCS requirements.

The organization of this paper is as follows. Section 2 gives the preliminaries of the system under study and its Modelling and control. Subsequently, Section 3 of the CNN-LSTM-based EMS is detailed. Section 4 discusses in detail the simulation results. Finally, Section 5 gives the overall conclusion on the performance of the proposed method.

2. Preliminaries

2.1 System Understudy

The EVCS, as shown in Figure 1 for the residential and commercial parking lot powered through a 2 kW Rooftop PV-Grid tied power source, consists of suitable Lithium-Ion ESS backup. The EVCS works with renewable PV power as long as possible, and the charging station connects with the grid to utilize conventional power in case of PV power unavailability.

The 2 kW PV system is integrated with a DC-DC boost converter linked to the common DC bus through a DC link voltage. It functions through an Adaptive Neuro-Fuzzy Inference System-based MPPT algorithm for maximum power extraction. The grid links to the DC bus through a bidirectional Voltage Source Converter (VSC) with voltage and current control loops. The voltage control loop maintains desired DC link voltage and the current loop assists the voltage control loop in providing the desired reference current. The ESS links to the DC bus through buck-boost converter control to handle bidirectional power flow since it acts as a buffer system to mitigate grid congestion. The EV battery-discharging mode is not considered. Hence it consists of a DC-DC converter with only buck operation to maintain DC bus voltage with a unidirectional power flow. The VSC connected with the grid considers a dq0 reference frame to decouple active and reactive power control taking the direct axis component of current, $i_{d,ref}$, for the outer voltage control loop. Various conditions are studied based on PV radiation, SOC of ESS battery, and grid power availability. For the proposed system, the test is carried out for two scenarios with EV and without EV under three different cases.

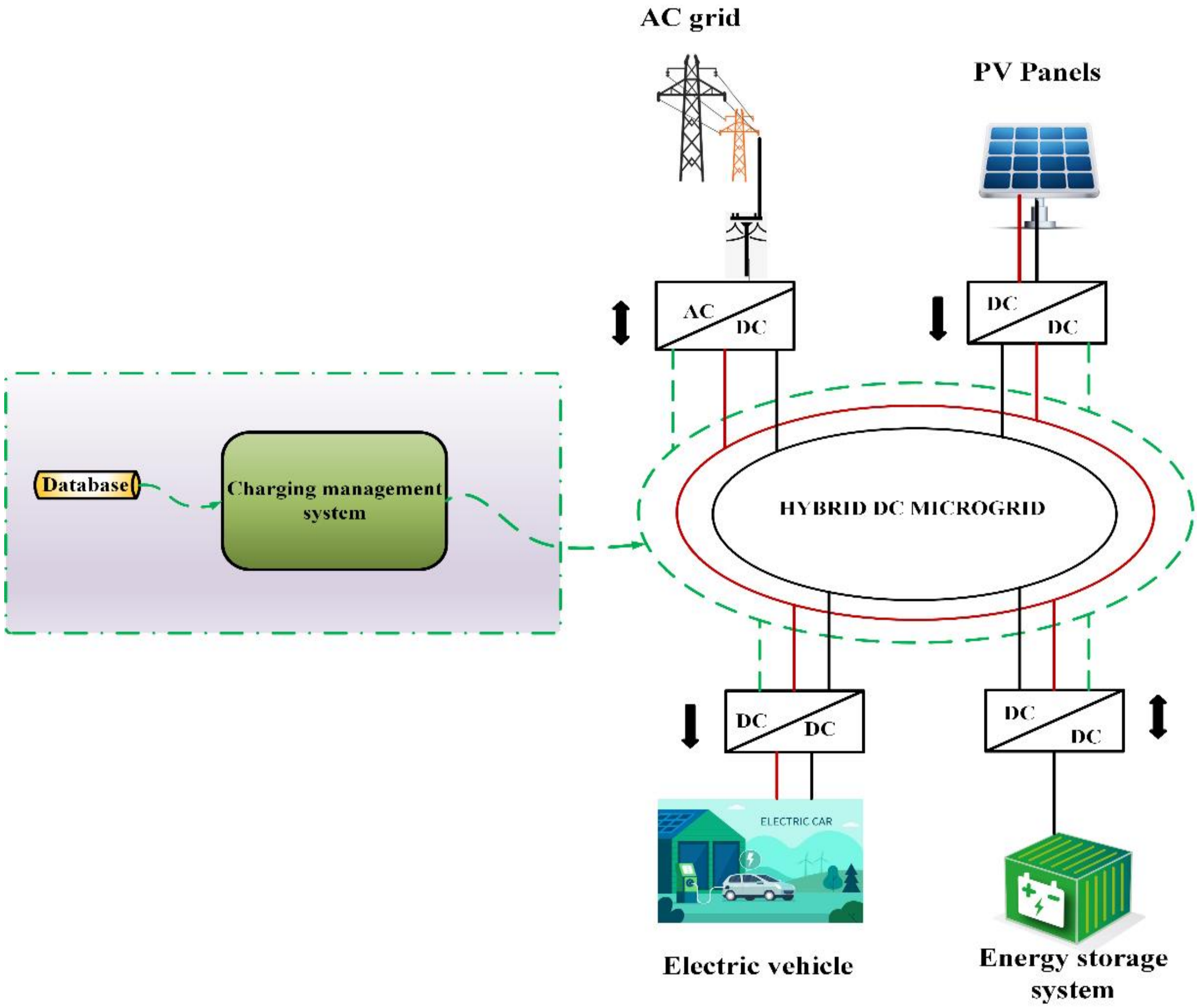


Fig. 1. Proposed charging management system

Case 1: PV stationary battery's (ESS) SOC = 90% with variation in PV radiation. The EVCS utilizes maximum PV power through stored battery power in this case.

Case 2: PV stationary battery's (ESS) SOC = 40% with variation in PV radiation. In this case, the EVCS utilizes available battery power and conventional grid power.

Case 3: PV stationary battery's (ESS) SOC = 10% with variation in PV radiation. In this case, the ESS battery enters charging mode, and the EVCS utilizes maximum power from the conventional grid.

2.2 Modelling and Control

A. PV Model and Boost Converter Control

The proposed PV model is a 2 kW solar PV array with eight series modules and one parallel string. The PV module data is provided in Table 1.

Table 1. PV Module Data

Open circuit voltage V_{oc} (V)	37.3
Short circuit current I_{sc} (A)	8.66
The voltage at maximum power point V_{mp} (V)	30.7
Current at maximum power point I_{mp} (A)	8.18

The mathematical equation of the PV output current I_{pv} is denoted using the following equation (*1*), which is generally represented as a single diode with one controllable current source, one resistance in series R_s and another resistance in parallel R_{sh}.

$$I_{pv} = I_{ph0}\left(1 + K_0(T - 300)\right)K_1T^3 \exp\left(q\left(\frac{V_{pv}+R_sI_{pv}}{NK_bT_{pv}} - \frac{V_g}{K_bT}\right)\right) - \left(\frac{V_{pv}+R_sI_{pv}}{R_{sh}}\right) \quad (1)$$

Since PV is intermittent in nature, an ANFIS-MPPT is implemented for varying irradiance and temperature to optimize maximum power extraction, as seen in Figure 2.

The fuzzy controller implements a zero-order Sugeno fuzzy model taking solar irradiance and temperature as inputs, and the maximum voltage generated at a given instant is considered as output and fed to the duty cycle generator. The reference voltage generated by the ANFIS output is compared with the actual V_{pv} to produce the duty cycle for the PV boost converter.

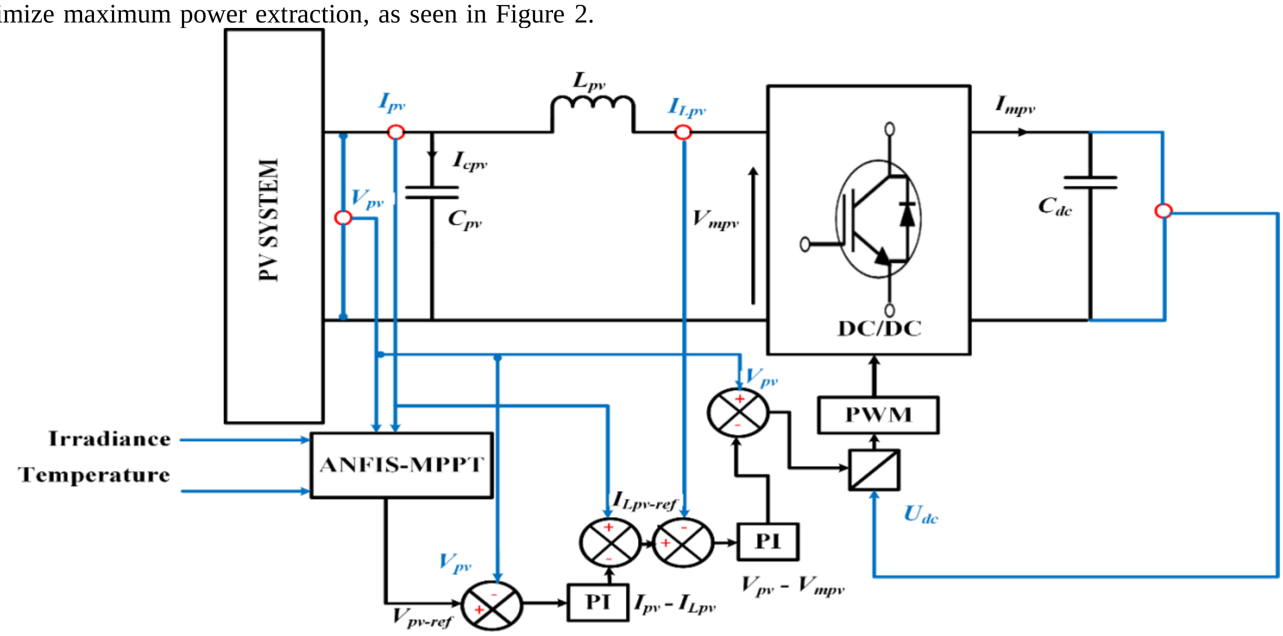


Fig. 2. Boost Converter Control

B. Energy Storage System Model and Buck-Boost Converter Control

The influence of intermittent PV sources in the hybrid charging system makes ESS crucial in effectively integrating renewable PV sources. Among various dominating batteries, Lithium-ion battery is the most choice of interest. ESS not only improves demand continuity at any instant but also decreases the dependency on conventional grid usage. The mathematical model of a Lithium-ion battery is given by equation *(2)* below:

$$V_{BAT} = E_T + R_{iBAT}I_{ch} \quad (2)$$

In the above equation, V_{BAT} represents the output voltage of the battery, E_T represents the internal voltage of the battery, R_{iBAT} refers to the internal battery resistance, and I_{ch} refers the charging current. ESS connects to the system via a bidirectional DC/DC converter; hence, it must work on both charge and discharge modes, as in Figure 3. Therefore, based on the reference power flow direction, the DC/DC converter works on a buck or boost operation for bidirectional power flow.

Proper charging and discharging control is required to ensure safe battery life. So, the battery management system maintains fair SOC between 10% and 90% to avoid excessive charge or deep discharge of the battery. SOC reflects the state of the battery and is represented by equation *(3)* below:

$$SOC = SOC_{int}\left[1 - \frac{1}{Q}\int_0^T i.dT\right] \quad (3)$$

Here in this equation, SOC is the State of Charge of the battery; SOC_{int} is the initial state of the battery; Q represents the total charging capacity of the battery and i represents the charging current. It is often represented in percentage to indicate the charge level at a particular instant.

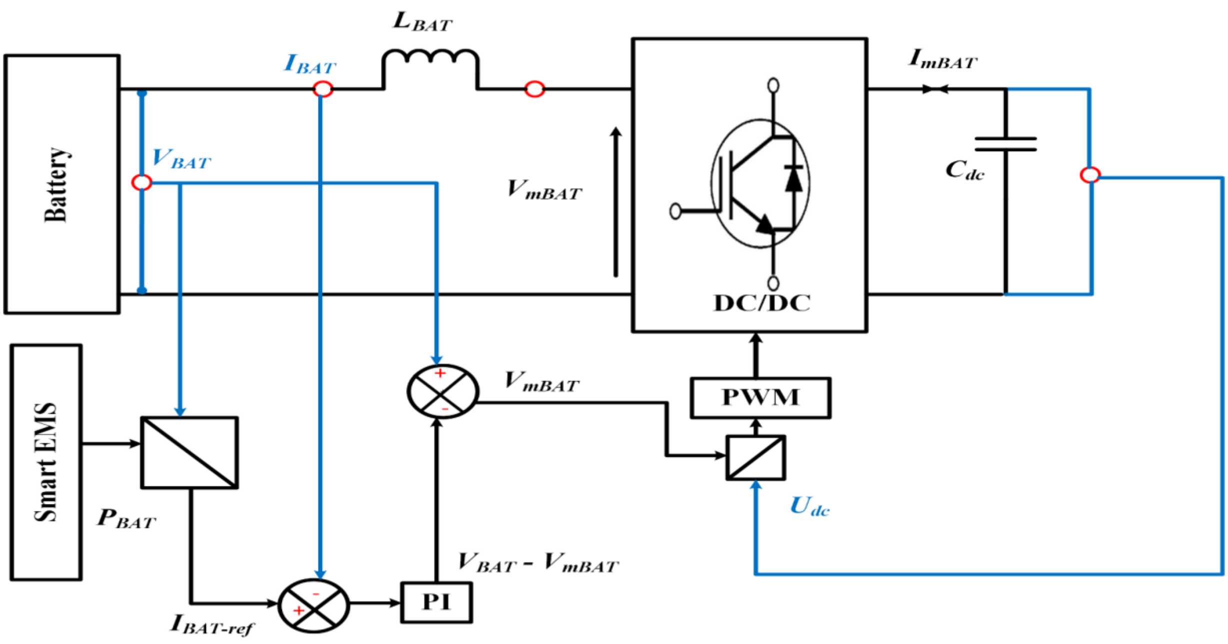


Fig. 3. Buck-Boost Converter Control

C. AC Grid

A single-phase AC grid with a single-phase inverter via an LCL filter is considered for this study, as seen in Figure 4. The grid inverter is bidirectional, such that it can supply and receive power from the system. The inverter control is modeled in the $dq0$ reference frame, where the generated reference current obtained through the smart charging system is converted $i_{dq0,}$ and the actual inverter current is compared and processed via a PID controller. The difference is then converted to $\alpha\beta0$; the α quantity is then considered to generate a pulse for the inverter to control the desired current flow.

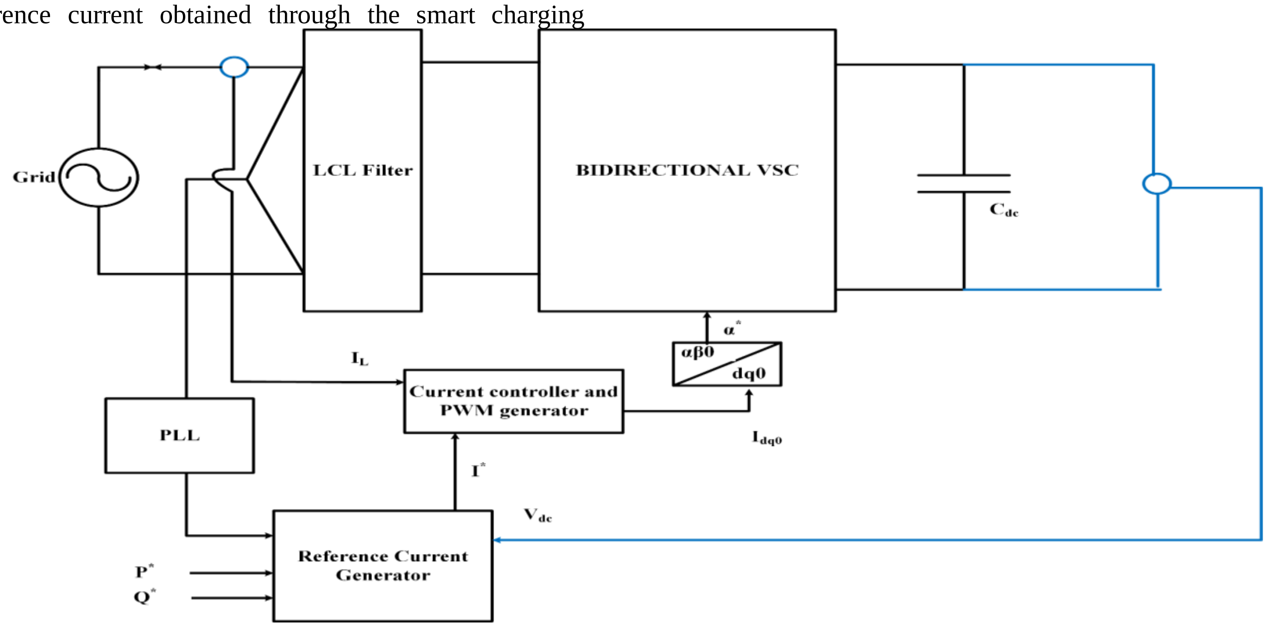


Fig. 4. Grid inverter control

3. Smart Energy Management

To design and develop smart energy management for the hybrid charging station, a CNN-LSTM-based SOC prediction for the electric vehicle charging demand. This section presents the feature extraction process for the SOC prediction according to the changes in the PV irradiance and solar battery SOC.

3.1 Feature Extraction for SOC Prediction for Energy Management in EV Charging Station

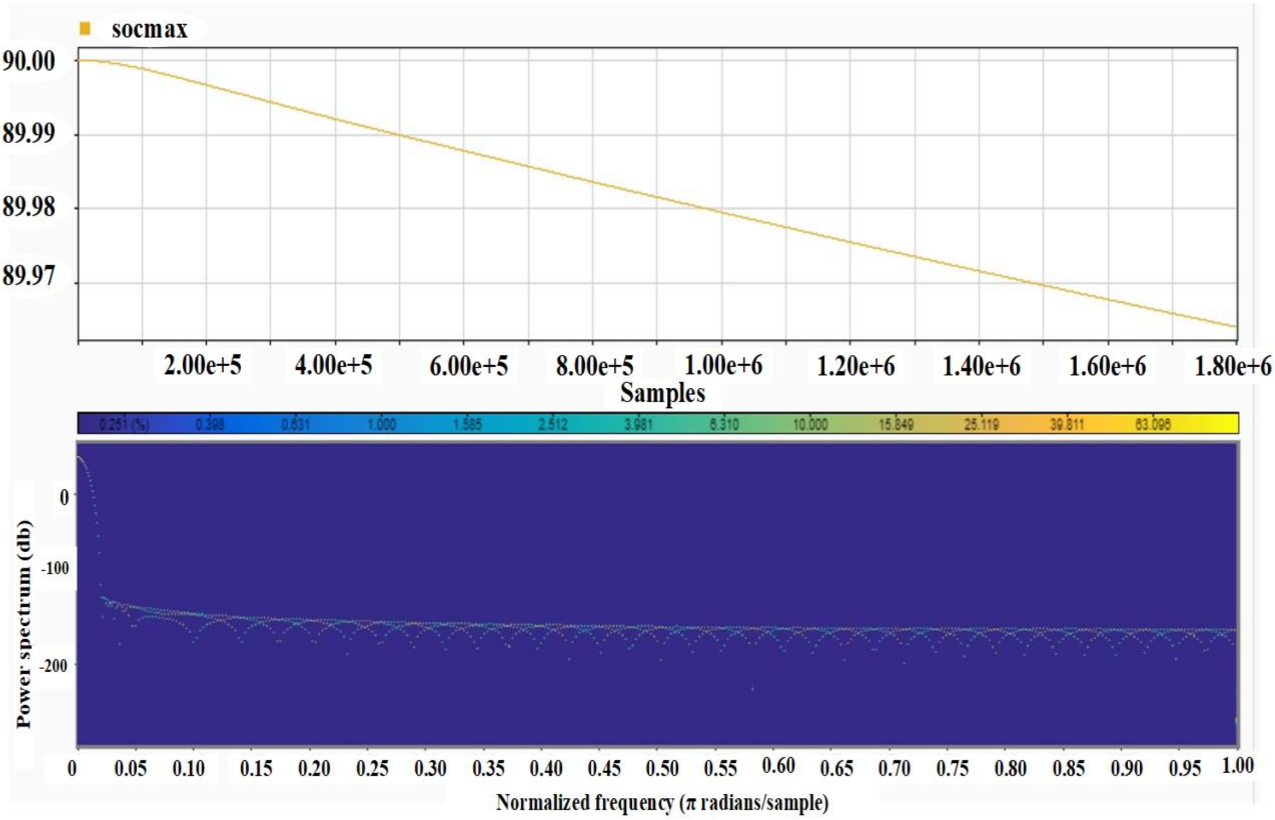
This work developed a combined CNN-LSTM architecture to automatically classify the state's battery SOC for smart energy management in an EV charging station. The CNN extracts complex features from images, and the LSTM is used as a classifier. As the emergence of

EV is very recent, we collect labeled data with images of three classes of SOC's of the PV-integrated stationary battery with varying solar irradiance for two cases with EV and without EV as described in Table 2.

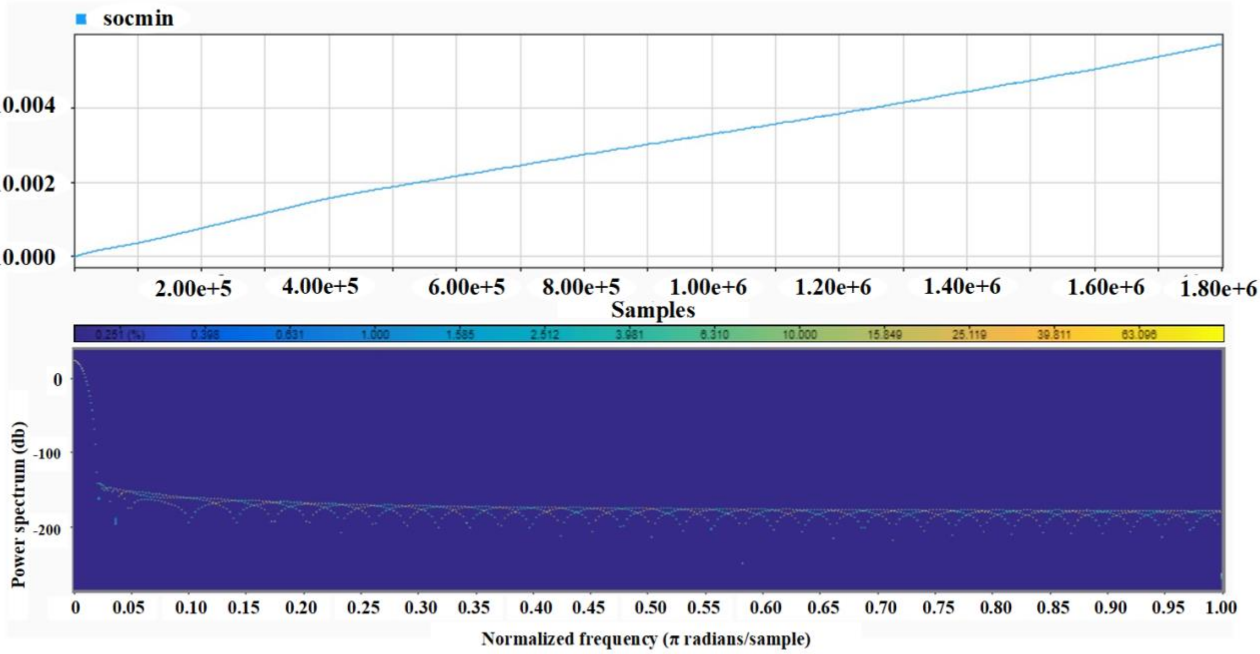
Figure 5(a), (b), and (c) shows the feature extraction for 2D image data collection to sort three different classes of battery states for the case with EV. Similarly, we perform the image data collection for the case without EV.

Table 2. Dataset Collection

Data/Cases	Classes			
	Class 1	**Class 2**	**Class 3**	**Overall**
	$SOC_{bat} >= SOC_{max}$	$SOC_{bat} <= SOC_{min}$	$SOC_{bat} = SOC_{opt}$	
With EV	150	150	120	420
Without EV	150	150	80	380
Total cases	300	300	200	800



(a)



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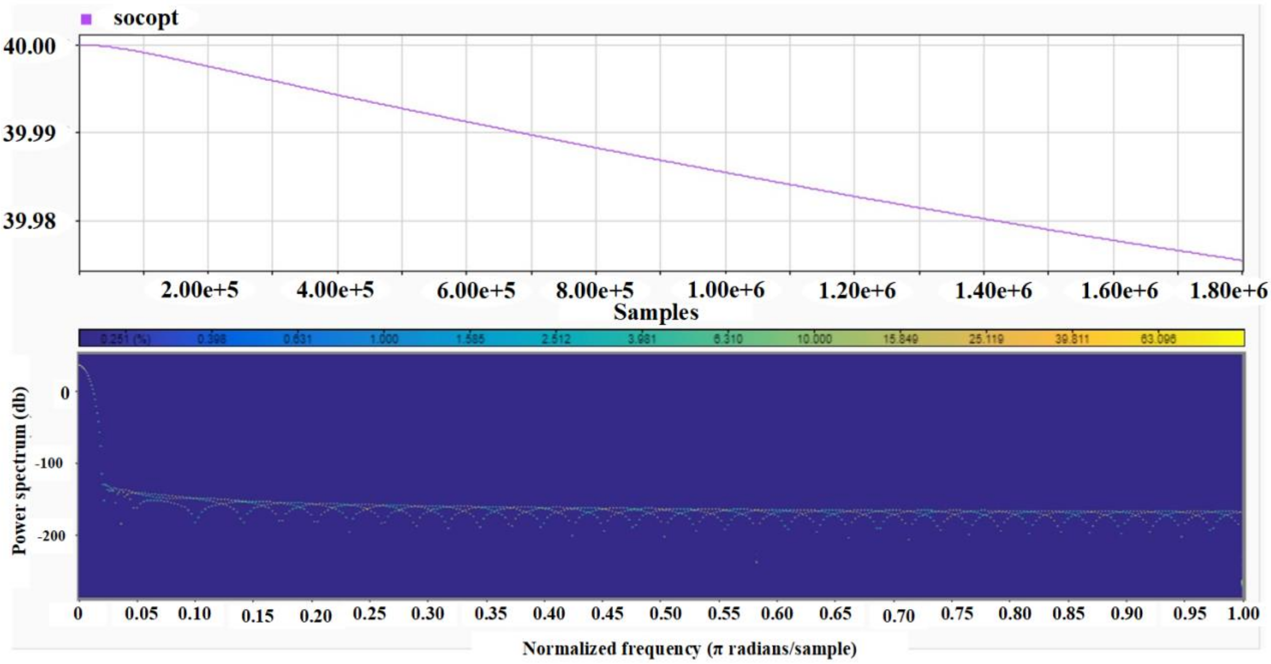


(c)

Fig. 5. (a) Class 1 $SOC_{bat} >= SOC_{max}$ (b) Class 2 $SOC_{bat} <= SOC_{min}$ (c) Class 3 $SOC_{bat} = SOC_{opt}$ for case with EV

3.2 CNN-LSTM Architecture

The images are resized to a resolution of 224 x 224 pixels to fit the 2D convolution layer of the CNN's. There are 20 layers, with 12 convolution layers, five pooling layers, one fully connected layer, 1 LSTM layer, and one output layer with a Softmax function, as seen in Figure 6. The convolution layer is set with a 3 x 3-kernel size for feature extraction with a ReLU-activated function to increase the non-linearity in feature maps. The max-pooling layer has a 2 x 2 kernel size and reduces the dimensions of the input image, followed by a 25% dropout rate. Towards the last part, the LSTM layer extracts time information from the function map of the convolution layers. After time characteristics extraction from the LSTM layer, the architecture sorts the images of the different classes through a fully connected layer to predict whether they belong under the three classes of battery SOC.

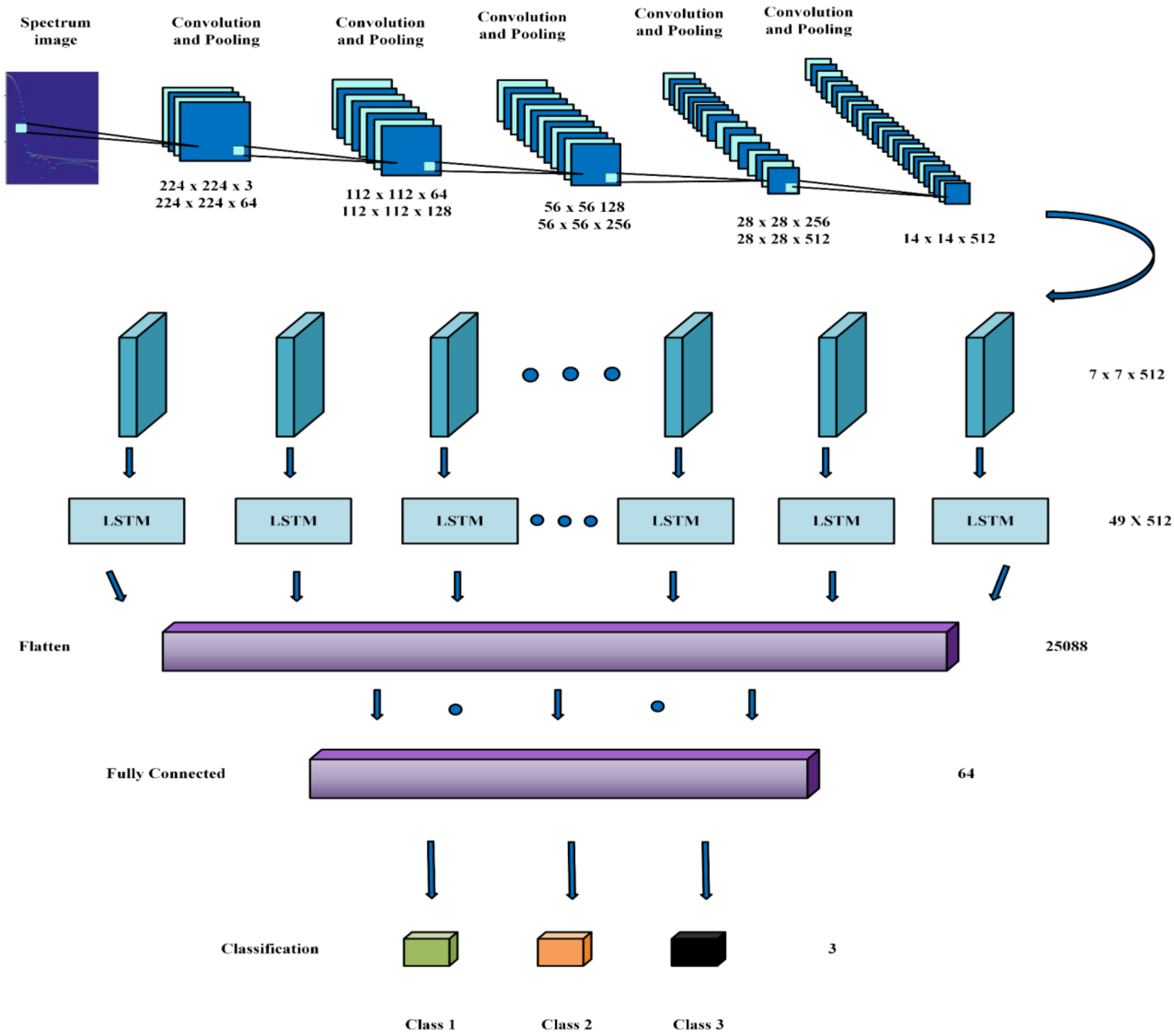


Fig. 6. Illustration of CNN-LSTM architecture

3.3 Performance Metrics

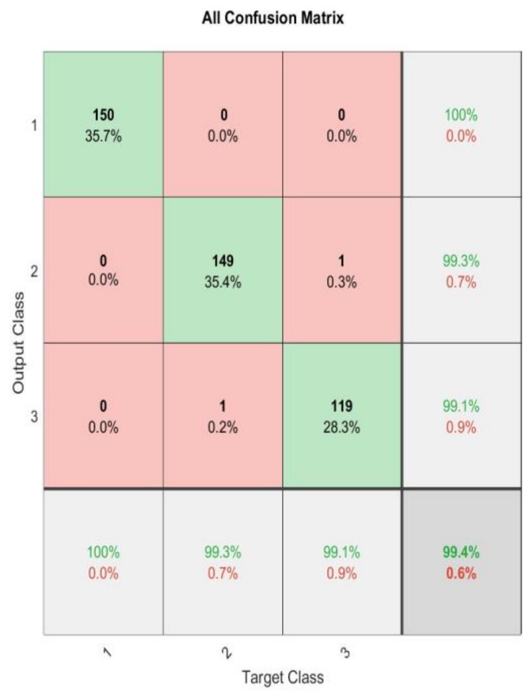
The performance of the proposed system is evaluated through assessment metrics like accuracy, precision, sensitivity, recall, and F1-score. Figures 7(a) and 7(b) show the confusion matrix of the proposed method for the case with EV and without EV for three different classes of battery states, and the figure shows the training accuracy plot for the two cases. The case with EV has a classification accuracy of 99.4%, and the case without EV has an accuracy of 99.1 %, as seen in Figure 8. Among the 420 data taken with EV, 418 data are correctly predicted and sorted in each class, while for 380 data without EV, 377 data are correctly predicted and sorted.

The performance metrics represent a True Positive (TP) value that denotes the correctly predicted class 1 cases, and a False Positive (FP) value denotes the class 2 and class 3 cases that are misclassified as class 1. Likely, True Negative (TN) indicates whether classes two and class 3 are correctly classified, and False Negative (FN) indicates whether class 1 is misclassified as class 2 and class 3.

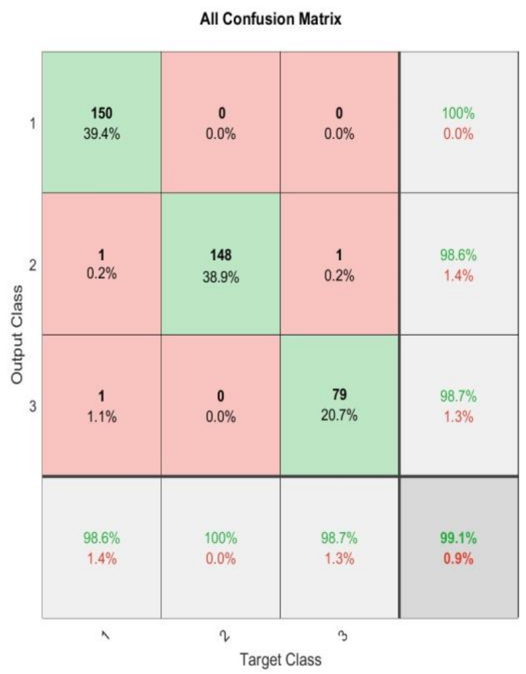
Table 3. Performance Metrics Formulae

S.No	Performance metrics	Formulae
1	Accuracy	$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$
2	Sensitivity	$Sensitivity = \frac{TP}{Actual\ Positive}$
3	Precision	$Precison = \frac{TP}{TP+FP}$
4	Recall	$Recall = \frac{TP}{TP+FN}$
5	F1-score	$F1-score = 2 * \frac{Precision * Recall}{Precison + Recall}$

Table 3 shows the performance metrics to be evaluated for the two cases with EV and without EV with three classes: Class 1 - $SOC_{bat} >= SOC_{max}$, Class 2 - $SOC_{bat} <= SOC_{min}$ and Class 3 - $SOC_{bat} = SOC_{opt}$ and Table 4 shows the performance evaluation for the individual classes in terms of accuracy, sensitivity, Precision, Recall, and F1-score. A comparative analysis of the existing SOC prediction approaches and the proposed method can be seen in Table 5.

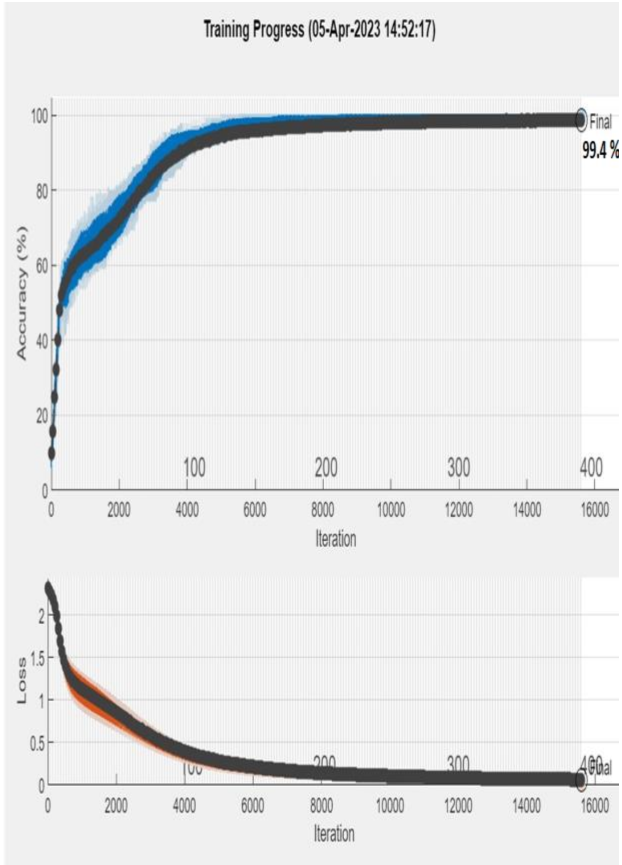


(a)

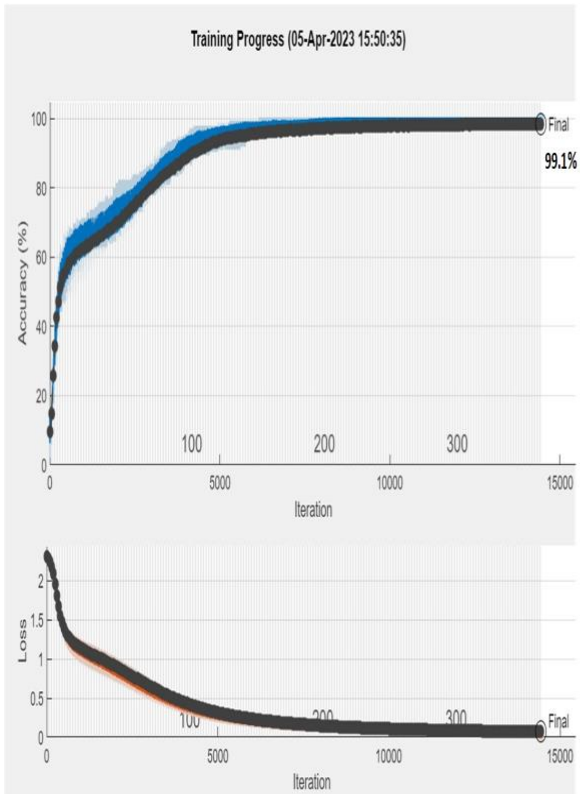


(b)

Fig. 7. Confusion matrix (a) With EV (b) Without EV



(a)



(b)

Fig. 8. Training accuracy plot (a) With EV (b) Without EV

Table 4. Performance Evaluation of Classification for Cases with EV and without EV

Class Label	Case	Accuracy	Sensitivity	Precision	Recall	F1-score	FN	FP
Class 1	With EV	100	100	100	100	100	0	0
Class 2		99.5	99.3	99.3	99.3	99.3	1	1
Class 3		99.5	99.1	99.1	99.1	99.1	1	1
Class 1	Without EV	99.4	100	98.6	100	99.2	0	2
Class 2		99.4	98.6	100	98.6	99.2	2	0
Class 3		99.4	98.7	98.7	98.7	98.7	1	1

Table 5. Comparison with the State-of-the art Techniques

SOC Prediction approaches		Training efficiency % Mean	Computational Time (s)	Prediction Accuracy %
Bayesian optimization technique with ML [25]		89.48	14.87	90.73
Probabilistic prediction [26]		91.45	15.04	93.26
LSTM Model [27]		93.51	11.60	95.03
Deep learning model [28]		96.44	9.15	96.91
EMD-AOA-DLSTM neural predictor [21]		98.62	7.4	97.14
Proposed CNN-LSTM SOC predictor	**With EV**	**99.4**	**6.4**	**99.4**
	Without EV	**99.1**	**6.8**	**99.1**

4. Simulation Results and Discussions

Combined CNN-LSTM adaptive energy management is tested on a hybrid DC microgrid-based residential EVCS. The time domain simulation is conducted in MATLAB/Simulink R2021b environment on an AMD Ryzen 5 3500U core processor of 8GB physical memory with a 64-bit operating system. The image classifier block converts the signals from battery SOC to spectrum images from the Deep Learning toolbox that loads a pre-trained network and performs prediction for image classification based on the trained CNN-LSTM model. The classified label is then converted to generate the reference signal to modify the reference current to perform the energy management within the hybrid DC microgrid-based EV charging station. Figure 9 shows the control flowchart for energy management with EV charging and without EV charging in the hybrid DC microgrid-based residential EV charging station. The energy management control strategy is tested for three cases under two different scenarios, i.e., with EV and without EV.

Case (i) PV stationary Battery SOC_{BAT} 90% *with EV*

Figure 10 shows the case with EV and PV stationary battery SOC_{BAT} 90%. When EV is plugged into the charging station, PV stored in stationary PV battery discharges to charge the EV battery. Excess power generated in the PV is fed to the grid. Figure 10(f) shows EV under charging mode. The below equation *(4)* represents the power flow within the charging station.

$$P_{Grid} = P_{PV} - P_{EV} \quad (4)$$

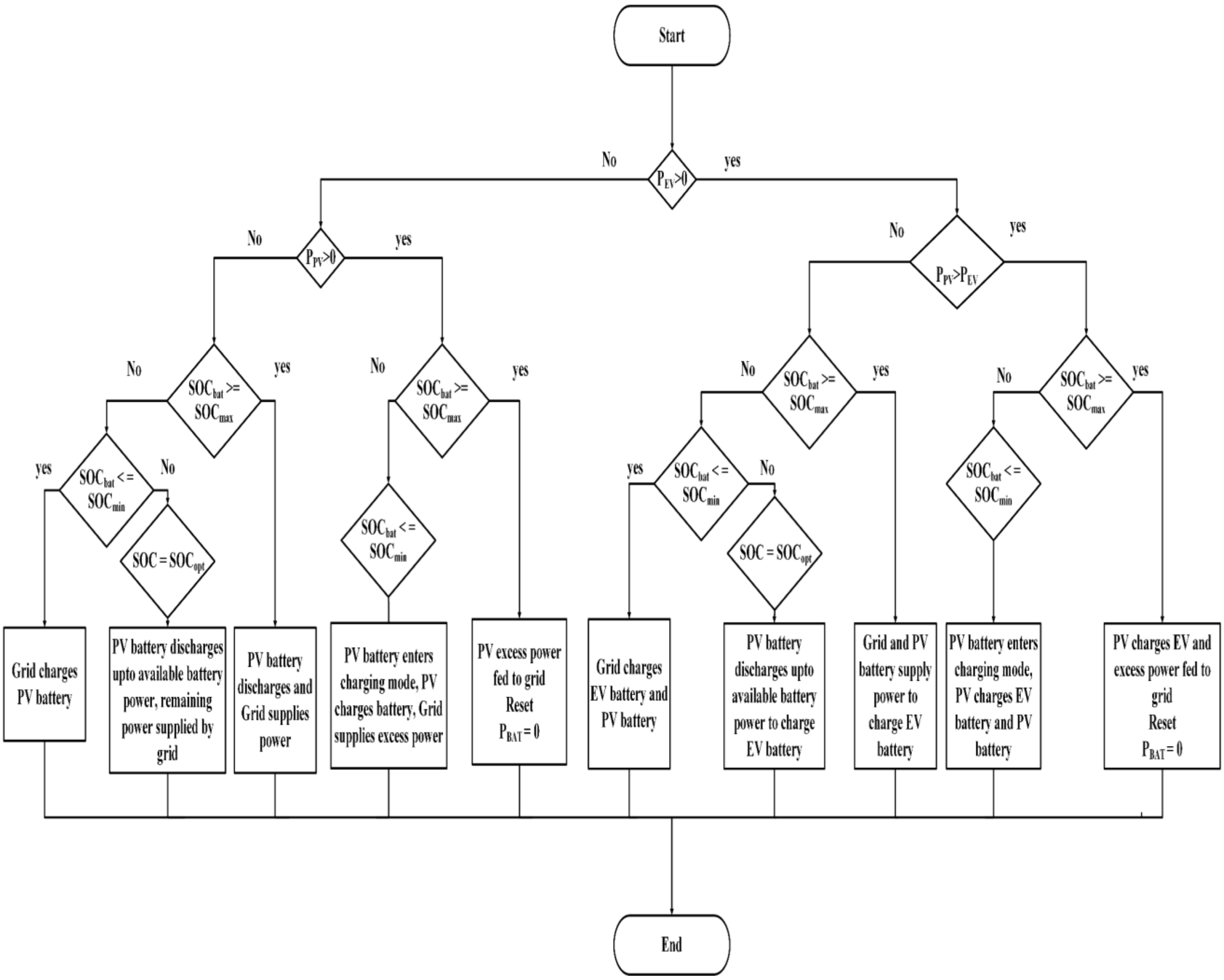
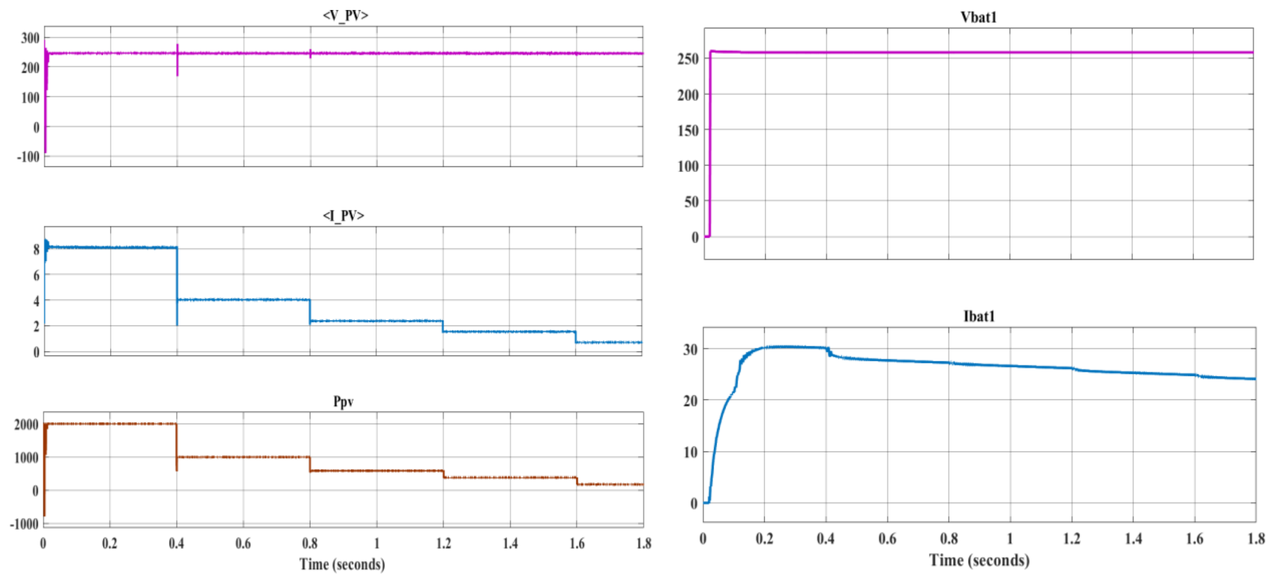
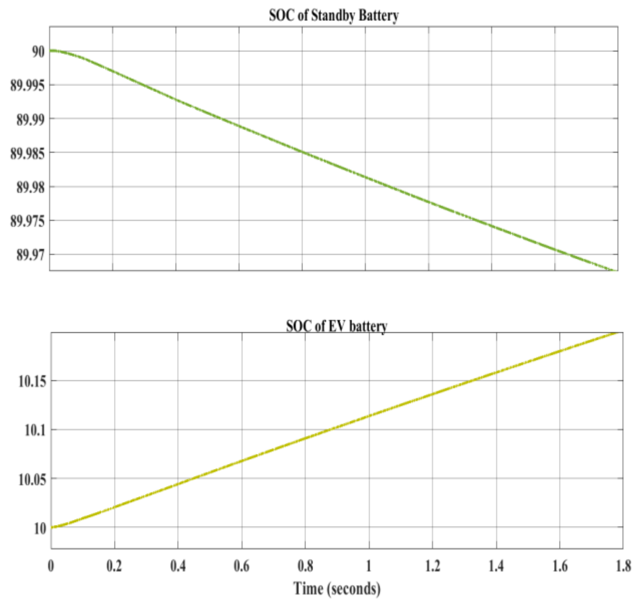
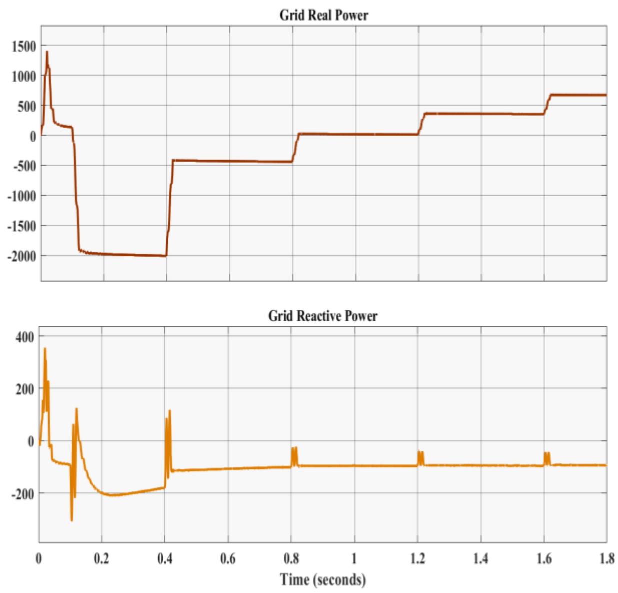


Fig. 9. Control Architecture

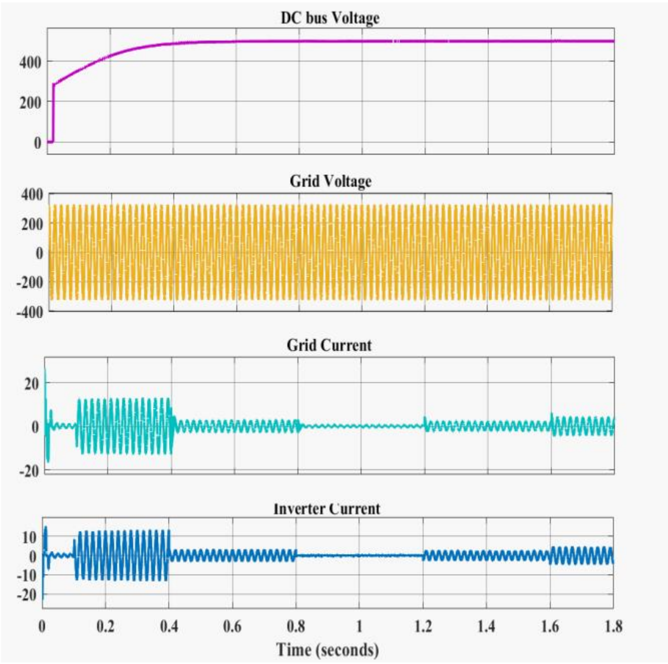


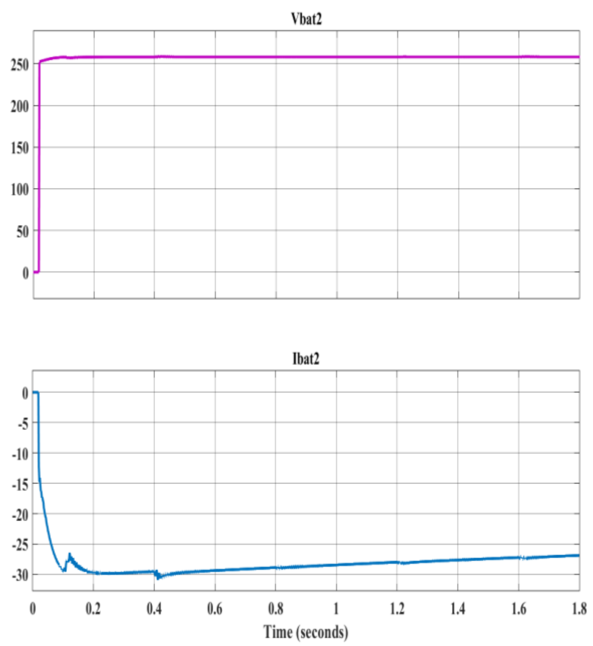
(a) (b)





(c) (d)





(e) (f)

Fig. 10. Case with EV for PV Stationary Battery $SOC_{bat} = 90\%$ (a) PV parameters (b) Standby PV battery parameters (c) SOC of standby PV battery and EV battery (d) Grid real and reactive power (e) Grid side parameters (f) EV battery charging parameters

Case (ii) PV Stationary Battery SOC_{BAT} 10% *with EV*

Figure 11 shows the case with EV and stationary PV batterySOC_{BAT} 10%. When EV is plugged into the charging station, the PV battery enters charging mode. PV supplies power to charge stationary PV batteries, while Grid provides power to charge EV batteries. The below equations *(5)* and *(6)* denotes the power flow within the charging station. Figure 11(e) EV battery still under charging mode.

$$P_{Grid} = P_{PV} - P_{BAT} \tag{5}$$

$$P_{Grid} = P_{EV} \tag{6}$$

Fig. 11. Case with EV for PV Stationary Battery $SOC_{bat} = 10\%$ (a) SOC of standby PV battery and EV battery (b) Grid real and reactive power (c) Grid side parameters (d) Standby PV battery parameters (e) EV battery charging parameters

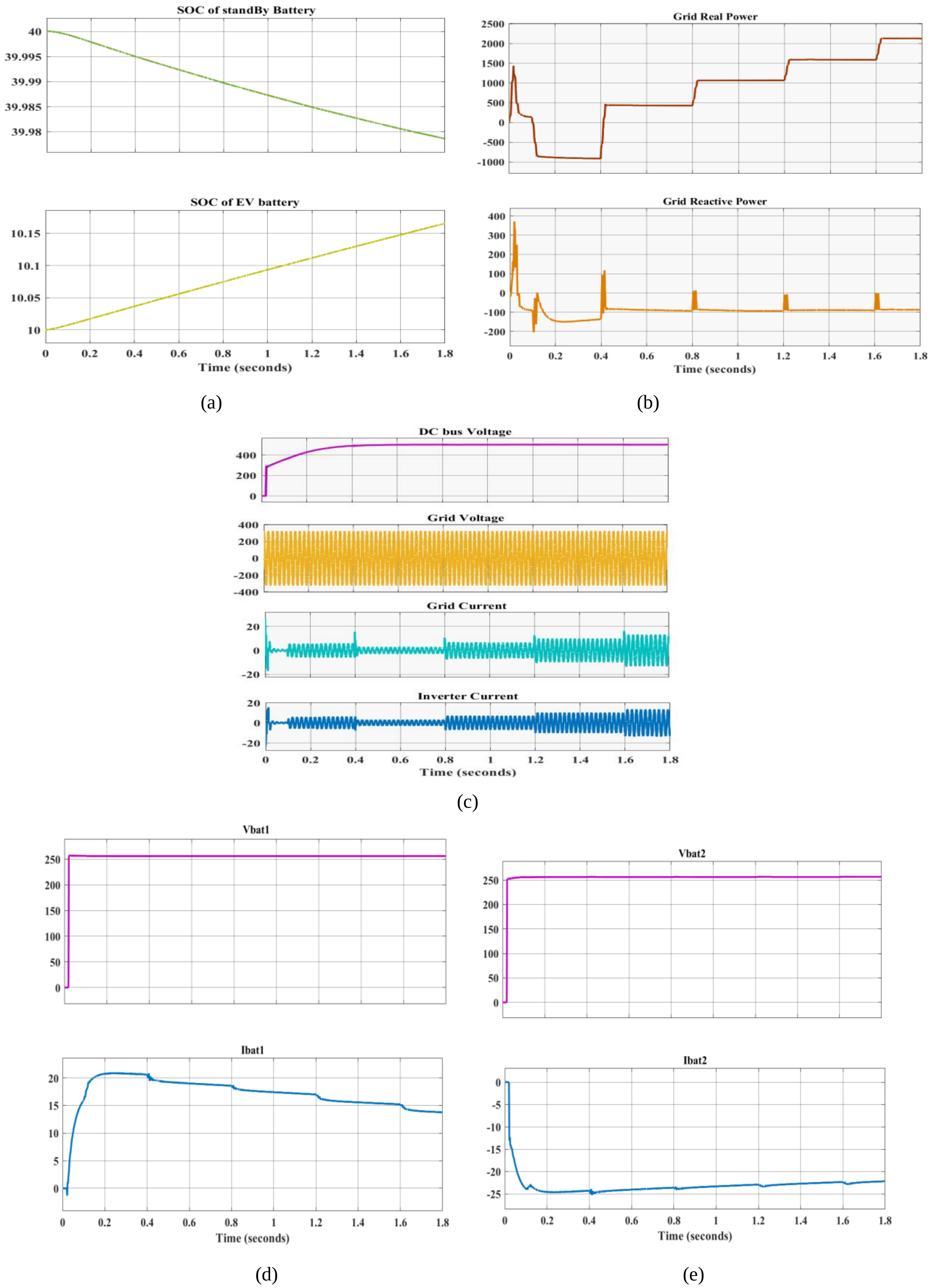
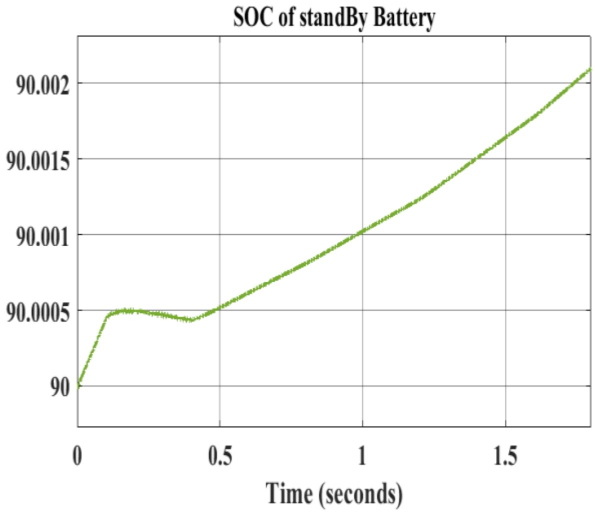


Figure 12. Case with EV for PV Stationary Battery $SOC_{bat} = 40\%$ (a) SOC of standby PV battery and EV battery (b) Grid real and reactive power (c) Grid side parameters (d) Standby PV battery parameters (e) EV battery charging parameters

Case (iii) PV Stationary Battery SOC_{BAT} 40% with EV

Figure 12 shows the case with EV and stationary PV battery SOC_{BAT} 40%. Figure 12(a) shows that the stationary PV battery discharges to charge the EV battery, and PV supplies the remaining power to the grid. When $SOC_{BAT} < SOC_{min}$, the grid supplies power to charge the EV battery while PV charges the stationary battery. Figure 12(e) shows the EV battery still in charging mode.



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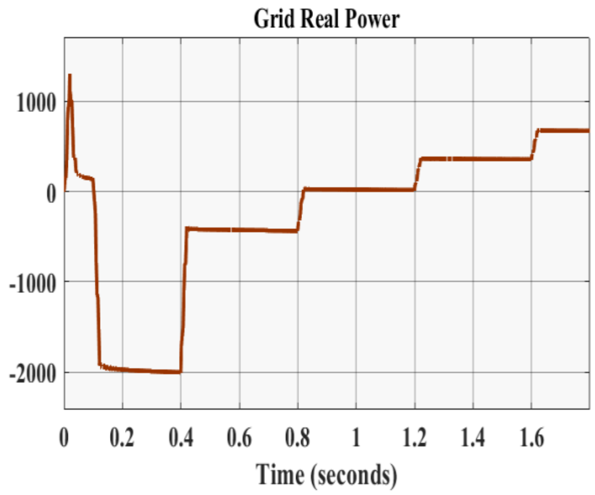

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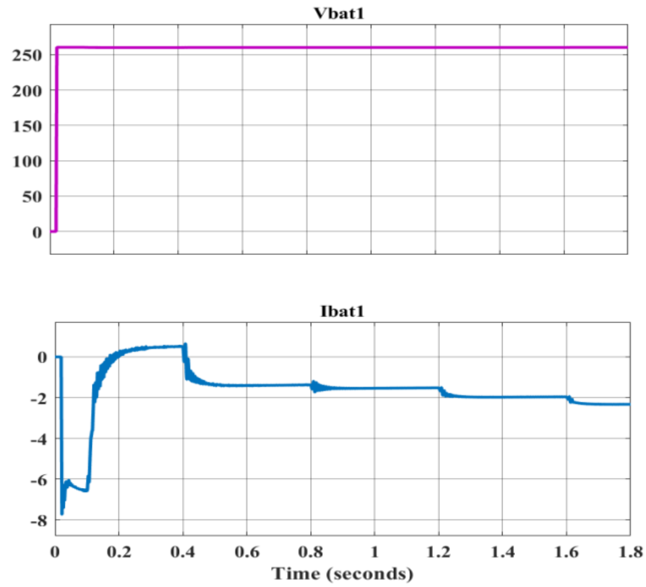

(c)

Fig. 13. Case without EV (a) SOC of PV standby battery (b) Grid real power (c) Standby PV battery parameters

Case (iv) PV stationary battery SOC_{BAT} 90% without EV

Figure 13 shows the case without EV. From Figure 13(a), the stationary PV battery can be seen in charging mode when $SOC_{BAT} > SOC_{max}$, excess PV power is supplied to the grid. The below equation denotes the power flow within the charging station when there is no arrival of the EV.

$$P_{Grid} = P_{PV} - P_{BAT} \tag{7}$$

Similarly, the other two cases (v) and (vi) without EV for SOC_{BAT} 40% and SOC_{BAT} 10% are tested on the Hybrid DC microgrid based EVCS which shows that without EV the stationary PV battery enters Charging mode and the excess power is shared among the various sources. Table 6 shows the power-sharing within the hybrid DC microgrid-based EVCS and their inferences.

Table 6. Power Sharing Within The Hybrid DC Microgrid-based EV Charging Station

Cases	***States of Stationary PV Battery***		
	$SOC_{BAT} = 90\%$	$SOC_{BAT} = 40\%$	$SOC_{BAT} = 10\%$
	Grid Real Power Flow (W)		
With EV	-2200, -500, +0, +400, +700	-1000, +500, +1000, +1500, 2000	+600, +1200, +1500, +1800, 2000
Comments	The grid takes power from solar PV and stationary PV batteries. Stored PV power is supplied to charge the EV battery as PV irradiance decreases. Grid supplies power to DC bus to charge EV battery.	Battery and PV supply power to the grid until minimum SOC. PV recharges the stationary battery, and Grid feeds power to charge the EV and PV batteries.	PV battery enters charging mode. PV recharges the stationary battery. Grid feeds power to charge EV battery and PV battery
Without EV	-2200, -600, +0, +600, +800	-900, +450, +900, +1400, +1900	+500, +1200, +1400, +1600, +1900
Comments	The SOC of Stationary PV battery in charging mode. PV charges the battery and supplies excess power to the grid. As solar irradiance decreases, Grid feeds the PV battery.	The SOC of Stationary PV battery in charging mode. PV charges the battery and supplies excess power to the grid.	The SOC of stationary PV battery in charging mode. As solar irradiance decreases, Grid feeds to charge PV battery

5. Conclusion

The proposed smart energy management could be integrated with A Hybrid DC microgrid-based EV charging station. For a residential charging system with one large Energy storage system and multiple charging outlets, the power flow control strategy could be executed through the CNN-LSTM-based classification model. The overall classification accuracy shows 99.4% for scenarios with EV and 99.1% for without EV under different cases tested, and the individual classification for each of the cases also has an accuracy of approximately 99%. The developed model predicts the SOC of the stationary battery according to prediction classes with high accuracy and effectively allocated resources for the EVCS requirements.

The simulation results justify that the classification for the different cases with EVs and without EVs has been performed, and the energy management within the hybrid charging station solves the energy demand for the EV and also enhances the optimized use of Grid and PV sources. The smart coordination between the PV source, the grid, and the ESS maintains the EV charging station requirements. Moreover, in the absence of EVs, the coordinated control strategy between the power sources resolves energy demand and effectively shares power, enhancing the utilization of PV.

Acknowledgements

I sincerely thank the Institute, the Department of Electrical and Electronics Engineering and the supervisor in helping me complete this research article.

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