Discrete Stochastic Control for Energy Management With Photovoltaic Electric Vehicle Charging Station

Suwaiba MATEEN, Ahteshamul HAQUE, Varaha Satya Bharath KURUKURU, and Mohammed Ali KHAN

***Abstract*—This paper develops an intelligent energy management system for optimal operation of grid connected solar powered electric vehicle (EV) charging station at workplace. The optimal operation is achieved by controlling the power flow between the photovoltaic (PV) system, energy storage unit, EV charging station (EVCS) and the grid. The proposed controller is developed considering the PV availability, grid loading and the EV charging load data. This information is modelled using Markov decision process (MDP) to develop a control strategy that eliminates the conventional problem of immediate recharging of energy storage unit after each EV charging by setting a target state of charge (SOC) level. This maximizes the use of PV power for EV charging and minimizes the impact on the grid. To test the operation of the proposed controller, a charging station powered by a 5 kW PV system with 35 kW energy storage unit connected to grid is developed through numerical simulations and experiment. The experiments were carried out for three different conditions under varying irradiance profile and load profile for multiple days. The results estimated the EV load and PV power and optimized the energy storage unit SOC between 0.3–1. Further, the energy management strategy minimized the impact of energy exchange between the grid and charging station by a factor of 2.**

***Index Terms*—Bidirectional inverter, electric vehicle charging station, energy management system, photovoltaic power, state of charge.**

I. Introduction

THE varying charging requirements of electric vehicles (EV's) and nonlinear photovoltaic (PV) power generation in the operation of a grid connected PV powered EV charging stations (EVCS), pose a challenge for the utility [1]. Conventionally, methods to handle these challenges deal with upgrading the distribution infrastructure [2], [3], but they proved to be economical during the operation process. To overcome this, the approaches for allowing high penetration of EVCS and PV power generation into the present distribution infrastructure is achieved by developing PV powered EVCS equipped with a battery unit [4]. These systems provide reliable power supply for EV charging while maintaining or improving PV system value, and utility system reliability.

Generally, an increased electricity generation connected to the low-voltage grid, such as PV power generation, requires flexible voltage regulation on both the transmission and distribution grid [5], [6]. Furthermore, the future electricity system will require not only flexible power generation, but flexible power usage as well. This way, excessive current loads on the local grid can be prevented. One way of achieving this would be by adjusting the electricity price on an hourly basis. This would encourage increased electricity usage when prices are low resulting in variations for peak and off peak demands [7]. In addition, reduced charging powers and assigning EV's with a unique starting time were proposed as flexible solutions to reduce grid loads caused by charging currents [8], [9]. However, this prohibited the possibilities for fast charging and resulted in irregular charging patterns especially during peak hours [10]. Further, a wide literature is available on the lenient charging patterns [11] for solar powered EVCS with energy storage devices [12]–[15]. Most of these studies are aimed at immediate recharging of the battery unit after each EV charging event [16]. To overcome this, an intelligent controller needs to be developed considering the impact of nonlinear PV power generation and EV charging load profiles to reduce the impact of energy exchange on the grid.

In [17], a charging strategy for PV based battery switch station is developed by considering the self-consumption and service availability of the PV energy. The developed approach defines the evaluation indices for operating performance and develops the charging method by including the battery swapping service and power distribution model. In [18], an optimal power management technique for PV-battery powered EVCS is developed using particle swarm optimization and dynamic programming to continuously minimize the operation cost. Further in [19], a fleet of grid connected charging stations are controlled with an approximate dynamic programming method to achieve minimum cost requirements by considering the user preferences. In [20], the high energy costs of storage while overcoming the intermittency effects of home PV systems are minimized by developing an efficient energy management approach utilized the EV batteries. The developed strategy aids in reducing the unexpected peak power demand by implementing vehicle-to-grid (V2G) and

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improves the stability of the grid during peak load. In [21], a grid connected PV based residential EV charger is developed to cater the needs of household loads, EV and the grid. The charger operates autonomously with PV array to power the households by providing uninterruptable charging. Similarly in [22], a multimode control strategy is developed to coordinate between PV array, battery, and diesel generator based charging station to provide continuous charging and uninterruptible supply to the household loads. Further, a cooperative energy management strategy for PV-energy storage system based EVCS is developed using multiagent deep reinforcement learning approach [23]. The developed approach estimates the scheduling solutions of multiple EVs to achieve desirable performance and reduced cost operations.

From the above literature, it is desired to identify that the uncertain behaviors of EV users, and various boundary conditions pertaining to intermittent nature of PV may significantly affect the optimal charging strategy. In order to address this problem, the EV user behavior and the PV power generation needs to be predicted. However, this problem is regarded as an multi stage decision making process where the present state of the system is dependent on all the previous states and actions. In light of these issues, this paper aims at estimating the feasibility of including real-time weather and load information with an energy management system for a PV-EVCS with energy storage system (ESS). The major contributions of this research are:

- It develops an intelligent EMS for PV assisted EV charging station by utilizing the PV power forecasting, and demand side energy management data.
- The Markov decision process (MDP) framework is adapted to provide flexibility while developing the EMS for handling the real-time dynamics of the PV assisted EV charging station.
- The proposed approach when implemented with an optimal SOC operation of Buffer battery-based PV assisted EV charging station minimizes the peak demand on the local grid during EV charging event and maximize the use of PV power generation.
- Estimates the power generation, EV charging demand, and optimal SOC based on the historical generation, charging patterns, and optimized SOC with the proposed EMS.

The novelty of the proposed approach lies in maximizing the PV power generation for EV charging and minimizing the impact on utility especially during peak loading on the grid. Further, the proposed approach doesn't require the information related to EV arrival and departure times to achieve the energy management process. It also provides flexibility for the EVCS aggregator and distributed generation companies in forecasting and planning their daily power consumption and generation activities. More details on these aspects are discussed in the remaining sections of the paper as: In Section II, the design considerations, and the requirements for developing the intelligent EMS for the PV powered EVCS in the grid connected environment are identified. The development of the proposed energy management system is discussed in Section III, and in Section IV, the implementation of the developed EMS with the PV powered EVCS is analyzed with both simulation and experiments. The conclusion of the research is discussed in Section V.

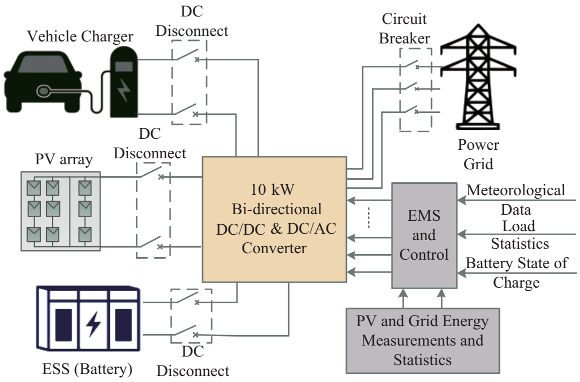

Fig. 1. Grid connected architecture of the PV powered EVCS with battery unit.

II. System Design and Requirements

A. Design Considerations

The effect of EV charging and the PV power generation on the utilities is analyzed by simulating a grid connected PV-EVCS with an energy storage system (battery unit). The maximum power point tracking (MPPT) for the PV is achieved with the perturbation and observation (P&O) algorithm controlling a boost converter at the PV array output terminals. Further, the design process of the system is achieved by considering two different situations of charging the battery unit from the grid. In the first situation, the battery charging occurs immediately after an EV is charged at the charging station. For the second situation, during an off-peak period, the battery is charged up to an optimal SOC value. Apart from the above, the events of no PV generation, no EV charging, and multiple EV charging are also included during the design process. Further, to control the operation of the converters and to direct the power flow between PV, EV, battery, and the utility, an intelligent energy management system (EMS) is proposed as shown in Fig. 1. The proposed EMS should be capable of predicting the availability of PV power based on the meteorological data and also estimates the EV charging demand considering the previous charging patterns at a given station. These estimated PV power and EV charging measurements are further used in estimating the optimal SOC for charging the battery unit during off-peak periods.

B. PV Power Forecasting

The solar power forecasting data is required for resourceful management of the PV generation while operated with the grid connected PV powered EVCS. Multiple complex forecasting algorithms have been proposed for the irradiance estimating and electrical grid management [24]–[27]. The PV generation can be estimated by adding up the solar insolation (actual) over a time step and multiplying it with the area of the panel along with PV conversion efficiency. The mathematical representation is as follow:

$$E_{\mathrm{PV}}^{P} = A\eta \int (1 - c)\, G\,(d, t)\mathrm{d}t \tag{1}$$

where, the daily solar PV generation is represented by E_{PV}^{P} (Wh/m^2), the panel area is denoted by A (m^2), the panel conversion efficiency is denoted by η, the cloud cover is represented by c and the solar insolation over the clear day is represented by $G(d, t)$ (W/m^2). The 2-D array is represented by $G(d, t)$ which is indexed by day of the year and time of the day.

C. EV Charging Demand Estimation

The load estimation of EV charging is required to maximize the utilization of solar PV, SOC optimization for energy storage, limiting the power spikes caused by EV charging during the peak operation hours of the utility, and enhancing the economics and efficiency of the charging station. Various algorithms have been discussed [27]–[29] for forecasting of electric load/demand by exploiting statistical data on load, weather and multiple factor impacting electrical utility industry. The inconsistency in demand is depended on the weather, mostly ambient temperature. Whereas the traditional EV forecasting methods which focuses on the charging habits and driving pattern many are not suitable for prediction of EV changing load requirement. As a result, for forecasting the accumulated EV charging and electrical demand on a certain day, a historical data of the charger in use is exploited.

$$E_{\mathrm{EV}}^{P} = at + b \tag{2}$$

where, the projected EV charging for a time (t) is denoted by E_{EV}^{P} (Wh/m^2), the slope and the intercept for the fitted model (t = 0) are represented by a and b, respectively. The historical charging data is used to determine the best fit of a and b at each time instance.

The estimation of battery SOC also plays an important role along with statistical load and meteorological data. Assuming that most of the charging take place in the early morning when the output of PV is minimal, during that instance the battery should be able to meet the demand predicted by the EVCS. The target SOC of the battery at the start of the day can be mathematically represented as:

$$SOC^{P} = SOC_{\mathrm{mean}} + \frac{k\Delta E_{\mathrm{ESS}}^{P}}{E_{\mathrm{ESS}}} \tag{3}$$

where, the projected SOC at the start of the day is represented as $SOC^{P} \Rightarrow \left[SOC_{\max} \geqslant SOC^{P} \geqslant \left(SOC_{\min} + \frac{E_{\mathrm{EV}}^{P}}{E_{\mathrm{ESS}}} \right) \right]$ with maximum state of charge (%), the minimum state of charge (%) and mean state of charge (%) represented as $SOC_{\max}$, $SOC_{\min}$ and SOC_{mean}, respectively. Considering that the charging takes place in the morning, the correction factor k accounts for the losses in the battery and other electronic components (k > 1). Further, $\Delta E_{\mathrm{ESS}}^{P} = E_{\mathrm{EV}}^{P} - E_{\mathrm{PV}}^{P}$ is the estimated energy deficit, where E_{ESS}(kWh) corresponds to the total capacity of the battery unit.

III. Energy Management System

The EMS aims at minimizing the peak load demand on the grid and maximize the PV generation for EV charging. The control strategy is implemented through MDP [30] for identifying the operation of the system and projecting the future requirements of the charging station, and battery. The MDP is a framework for modelling a sequence of decisions based on the state of a variable or group of variables. The state denoted S, evolves stochastically over time. At each time-step t an action a is selected, resulting in a reward being given, its value depending on the current state and the chosen action. These actions also have an impact on how the state evolves. The Markov Assumption is used, meaning that the state at the next time-step depends only on the state and action taken at the current time-step. The transition model denoted T, is the name given to the probability model that describes how the state changes over time. It specifies the conditional probability of moving into a state at the next time step, given the current state and the action taken. The formula below shows the transition probability for any pair of state values s_i and s_j:

$$T(s_j \mid s_i, a) = \Pr(\mathcal{S}^{t+1} = s_j \mid \mathcal{S}^{t} = s_i, \mathcal{A}^{t} = a) \tag{4}$$

It is to be noted that the S_t denotes the state at time t while lower case s_i denotes one of the possible values the state can take. Further, $\mathcal{A}$ denotes the action. The state variable can be continuous or discrete. In the latter case, the transition model is often summarised in matrix form, with the probability of moving from s_i to s_j appearing in the i_{th} row, j_{th} column. The horizon h of an MDP defines how many time-steps the decision sequence contains. It can have a finite value or the MDP can be "infinite-horizon". The infinite horizon is frequently used as it means that the transition and reward models can be considered stationary and so do not change over time. This research only considered the infinite-horizon case, so little more will be said regarding finite-horizon cases. The reward model $R(s, a)$ defines what reward is given for taking an action when the state is a certain value. The reward at time t is therefore a function of the state and action at time t. The reward for a decision sequence $r_{0:h}$ is simply the sum of the rewards r_t at each time-step up till the horizon. For infinite-horizon MDPs, where there is an infinite number of decisions in the sequence, a discount factor γ is introduced to make the accumulated reward finite, as shown below:

$$r_{0:\infty} = \sum_{t=0}^{h=\infty} \gamma^{t} r_{t} \tag{5}$$

Here, the value of discount factor ranges between 0−1 and indicates how important future rewards are with respect to the current state.

The aim of such an MDP is to determine a strategy to get the largest reward over the whole sequence. The concept of strategy is formalised as a policy. A policy $\pi_t(s)$ selects an action to take at time t based only on the current state s, based on Markov Assumption. For an infinite horizon, the transition and reward models are stationary (not a function of time) so the policies considered will also be stationary: the policy $\pi(s)$ will be the same for all time-steps. Another important concept in MDPs is the value function. The value function is defined as the expected utility U of executing the policy p when the state is s. For an infinite horizon, the value $U^{\pi}(s)$ of executing the policy π given the current state s is calculated using the following formula:

$$U^{\pi}(s) = R(s,\pi(s)) + r\sum s'T(s'\,|\,s,\pi(s))U^{\pi}(s') \tag{6}$$

where $R(s,\pi(s))$ is the immediate reward gained by taking the action $\pi(s)$ (the action recommended by the policy p given the current state s). $\sum s'T(s'\,|\,s,\pi(s))U^{\pi}(s')$ is the expected reward to be gained at the next time step by executing the policy, where s' is the next state. The expectation is taken with respect to transition probabilities given the current state.

The term utility is used here (and not reward) as the future rewards are scaled by the discount factor, meaning that the rewards are regarded with decreasing importance the further into the future t4hey are obtained. The aim of an MDP is to find an optimal policy π^*, ie. a policy that maximises the value function:

$$\pi^* = \arg_{\pi} \max U^{\pi}(s) \tag{7}$$

The optimal policy is usually obtained using dynamic programming. One of the most common algorithms used is value iteration. The value iteration aims to find the optimal value function and then extract the respective optimal policy after. The optimal value function U^* satisfies the Bellman equation:

$$U^*(s) = \max_{a}(R(s,a) + \gamma\sum s'T(s'\,|\,s,a)\backslash U^*(s')) \tag{8}$$

Algorithm 1: Control algorithm for Grid-tied and standalone operation with the PV power EVCS

Step1	Identify the operating mode of the DG system and the charging station									
	Grid Connected Operation					Standalone Operation				
Step 2	$P_{EVSE} < 0$		$P_{EVSE} > 0$			$P_{EVSE} < 0$		$P_{EVSE} > 0$		
Step 3	$P_{PV} < 0$	$P_{PV} > 0$	$P_{PV} < 0$	$P_{PV} > 0$		$P_{PV} < 0$	$P_{PV} > 0$	$P_{PV} < 0$	$P_{PV} > 0$	
				$P_{PV} < P_{EVSE}$	$P_{PV} > P_{EVSE}$				$P_{PV} < P_{EVSE}$	$P_{PV} > P_{EVSE}$
Step 4	(4.1)	(4.2)	(4.3)	(4.4)	(4.5)	(4.6)	(4.7)	(4.8)	(4.9)	(4.10)

Grid Connected Operation	(4.1)	**if** $SOC \geqslant SOC_{opt}$, **then** $P_{Bat} = 0$, **else** charge the battery from the grid: ($P_{Bat} = -P_{cmd} = -P_{Grid}$).
	(4.2)	**if** $SOC \geqslant SOC_{max}$, **then** the PV system operates in a grid feeding mode: $P_{Bat} = 0$, $P_{Grid} = P_{PV}$, **else** PV system charges the battery and the remaining power is fed into the grid $P_{Bat} = -\min(P_{PV}, P_{Bat,max,Chg}, V_{Bat} \times I_{Bat,max})$, and $P_{Grid} = P_{PV} + P_{Bat}$.
	(4.3)	**if** $SOC > SOC_{min}$, **then** Battery charges the EVs, and the deficiency is provided by the grid: $P_{Bat} = \min(P_{EVSE}, P_{Bat,max,dischg}, V_{Bat} \times I_{Bat,max})$, $P_{Grid} = P_{EVSE} - P_{Bat}$, **else** Grid power charges the EVs $P_{Bat} = 0$, and $P_{Grid} = P_{EVSE}$.
	(4.4)	**if** $SOC > SOC_{min}$, **then** PV, Battery, and grid charges the EVs $P_{Bat} = \min(P_{EVSE} - P_{PV}, V_{Bat} \times I_{Bat,max}, P_{Bat,max,Chg})$, $P_{Grid} = P_{PV} - P_{EVSE} - P_{Bat}$, **else** PV and grid charge the EVs: $P_{Bat} = 0$, and $P_{Grid} = P_{EVSE} - P_{PV}$.
	(4.5)	**if** $SOC \geqslant SOC_{opt}$, **then** PV system charges the EVs and the remaining power is fed into the grid: $P_{Bat} = 0$, and $P_{Grid} = P_{PV} - P_{EVSE}$, **else** PV charges the EVs and the battery: $P_{Bat} = -\min(P_{PV} - P_{EVSE}, V_{Bat} \times I_{Bat,max}, -P_{Bat,max,Chg})$, and $P_{Grid} = P_{EVSE} - P_{PV} - P_{Bat}$.
Standalone Operation	(4.6)	**for** $P_{PV} < 0$, $P_{Bat} = 0$
	(4.7)	**if** $SOC \geqslant SOC_{max}$, **then** $P_{Bat} = 0$, **else** PV charges the battery: $P_{Bat} = -P_{PV}$.
	(4.8)	**if** $SOC > SOC_{min}$, **then** Battery charges the EVs: $P_{Bat} = \min(P_{EVSE}, P_{Bat,max,dischg}, V_{Bat} \times I_{Bat,max})$, **else** $P_{Bat} = 0$.
	(4.9)	**if** $SOC > SOC_{min}$, **then** PV, and Battery charges the EVs: $P_{Bat} = -\min(P_{PV} - P_{EVSE}, V_{Bat} \times I_{Bat,max}, -P_{Bat,max,Chg})$, **else** $P_{Bat} = 0$.
	(4.10)	**if** $SOC \geqslant SOC_{opt}$, **then** PV charges EVs: $P_{Bat} = 0$, **else** PV charges EVs and Battery: $P_{Bat} = -\min(P_{PV} - P_{EVSE}, V_{Bat} \times I_{Bat,max}, -P_{Bat,max,Chg})$.

*P_{EVSE} is the power of the electric vehicle supply equipment

Value iteration starts with an estimate of U^* then updates this estimation iteratively through the equation above, until convergence is reached. As a part of the proposed intelligent controller, the MDP achieves power management and transition between the operations in grid connected (nominal state) and standalone (below nominal state) modes on basis of state of charging station, grid, battery SOC and availability of the PV power at discrete time intervals [31]. Based on the operating state of the PV powered EVCS in the grid connected environment, two different control modes are developed as shown in the Algorithm 1. In the grid connected operation, the EV can be charged from any of the available sources [32], and for the standalone operation, the EV can be charged either with the available PV power or from the battery unit.

Further, considering the boundary constraints caused by the stochastic behavior of the EVs, their effect on the optimization model can be minimized with the MDP process. The constraints mainly include initial SOC of EVs, estimated SOC, charging plugin time, charging plug out time, and the charging point selected. Hence to achieve intelligent energy management approach the optimization model developed Algorithm 1 must be solved by estimating the boundary conditions. Further, the boundary conditions change with the time period as they are affected by the current environment conditions. This will vary the behavior of EV user resulting in the need for updated predictions at each time step. Hence, the boundary conditions are formulated as a time series representation $(q_0, q_1, ..., q_T)$, and characterized as temporal relation using 5-tuples $\{S, \mathcal{A}, R, \pi, J\}$ of MDP with $S = (s_1, ..., s_t, ..., s_T)$ as the state space which describes the environment, $\mathcal{A} = (a_1, ..., a_t, ..., a_T)$ as the action space which describes the agents decision to the environment, $R = (r_1, ..., r_t, ..., r_T)$ is the reward associated to the state action pair, $\pi = (\pi_1, ..., \pi_t, ..., \pi_T)$ represents the policy that maps the state action pairs, and the $J = (J_1, ..., J_t, ..., J_T)$ is the return which is to be maximized with the optimal policy. These variables are defined as:

$$s_t = S = (W^\nu, \Gamma^\nu, T^\nu_{\text{in}}, T^\nu_{\text{out}}, D^\nu, d), \nu = 1, ..., t, \tag{9}$$

where W^ν corresponds to the weather information including humidity, temperature, cloudiness, and air quality index during past period ν, Γ^ν represents the traffic information effecting the boundary conditions of past time $(T_{\text{in}}/T_{\text{out}})$ and initial SOC (SOC_{ini}), D^ν is the charging station load level at i^{th} charging point, and vector d = (season, month, holiday) is an integer set representing days in an year.

$$a_t \in \mathcal{A} = \{q^f_{t+1}, ..., q^f_\delta, ..., q^f_T\} \tag{10}$$

where q^f_δ corresponds to the boundary condition prediction at time period $\delta = \{t+1, ..., T\}$.

$$\pi(a_t|s_t) = \mathcal{P}(a_t|s_t)|: S \times \mathcal{A} \rightarrow [0, 1] \tag{11}$$

where $\mathcal{P}(a_t|s_t)$ corresponds to conditional probability under the state and action spaces.

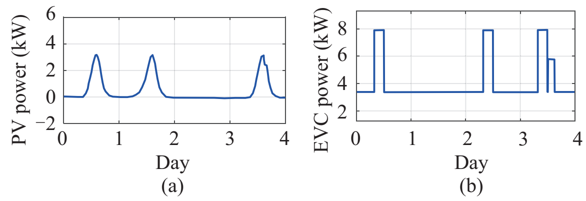

Fig. 2. Input data (a) Available PV power generation. (b) EV charging demand.

TABLE I
PARAMETERS OF THE GRID CONNECTED PV POWERED EVCS

Parameter	Rating
PV Array	250 – 600V_{DC}/10 kW
Bidirectional DC/DC and DC/AC converter	10 kW
Vehicle charger	7.2 kW
Battery	275 – 400V_{DC}/35 kWh
Utility grid	220 V/110 V

TABLE II
HYPERPARAMETERS OF MARKOV DECISION PROCESS

Hyperparameter	Value
Soft update coefficient	0.005
Interpolation factor	0.9
Learning rate	1e−4
Discount factor (ranging between 0−1)	0.99
Replay buffer size	1000000
Minibatch size	100
Episodes	1000
Time steps per episode	1e+6
Reset steps per episode	100
Max time steps	2e+6

IV. RESULTS AND DISCUSSION

A. Simulation

The simulation analysis demonstrates the operation of the developed EMS with the grid connected PV based EVCS. The available PV power generation and the EV charging demand of a charging station for 4 days is shown in Fig. 2. The parameters of the simulated system are shown in Table I, and the hyperparameters for learning with the stochastic approach are shown in Table II. The hyperparameters for training the environment are empirically optimized such that there exists a direct mapping between the agent and the observations to the control. The operational window of battery SOC is limited between 0.4−1.0. As most of the EVs have an onboard charger of capacity 6.6 kW or a 3.3/3.6 kW, the time taken by the EV to charge its battery from 0.5 SOC is assumed to be 2−2.5 hours for a 6.6 kW charger and 4 hours for 3.3 kW charger for the simulation analysis. Further, the developed EMS implements two approaches with the grid connected PV powered EVCS, one for immediately charging the battery to a prescribed

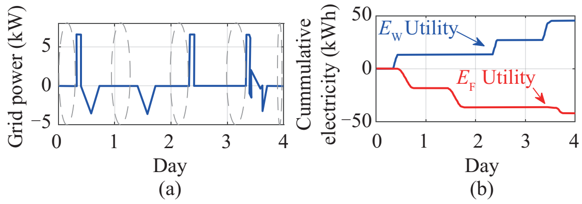

Fig. 3. Grid connected PV powered EVCS without battery (a) Grid power. (b) Cumulative electricity between the utility and the charging system.

level within 1−2 hours after each EV charging event, and the other approach is for charging the battery to an optimal SOC value during the off-peak hours from midnight to 7 am. For the second approach, the optimal SOC is estimated using the projections of PV power generation and EV load demand.

The training of the MDP framework is done in MATLAB/Simulink environment with the data related to an EVCS operating in a grid connected system. The estimated target for the algorithms is regulation of power flow between the PV, EV and the grid with reference to the load requirement and battery SOC. As the measured data from the system is a continuous data, it is accommodated with the discrete control unit by defining the action and observation space are defined as a tuple of discrete values. This introduces a structure in to the action space and the agent decides which action to take to perform the actor representation with input observations and output actions. The measured error is reliant on estimated characteristics and setpoint characteristics which keeps updating as per the reward generation. Later, the actions are evaluated and higher action values will be actually executed to perform optimal control action and conduct policy search. The objective of algorithm is to regulate the impact of peak loading on the grid. The algorithm learns each task for 1e+6 time steps and provides the average return for each time step.

B. Simulation Results

To begin with, the aspects of PV powered EVCS without the battery system are simulated, and the corresponding grid power and cumulative electricity are plotted as shown in Fig. 3. The circled areas in the grid power chart represent the off-peak periods.

The results in Fig. 3 showed the grid power (Fig. 3(a)) and cumulative electricity (Fig. 3(b)) for the PV powered EVCS without battery unit. The positive amplitude in the Fig. 3(a) indicates the energy consumption from the grid and negative dip indicates the energy fed into the grid. Similarly, the blue curve in Fig. 3(b) indicates the cumulative electricity consumption from the grid (E_W Utility), and the red curve indicates the cumulative electricity fed into the grid (E_F Utility).

Further, to analyze the system behavior for the approaches implemented by the EMS, the grid power, and the cumulative electricity exchange between the utility grid and the charging system are plotted as shown in Fig. 4.

From the results in Fig. 4, it is identified that, after each EV charging event, the battery unit is charged up to the SOC of 1. It also indicates the impact of the EMS approach, as the charging occurs during the on-peak, and partial-peak periods.

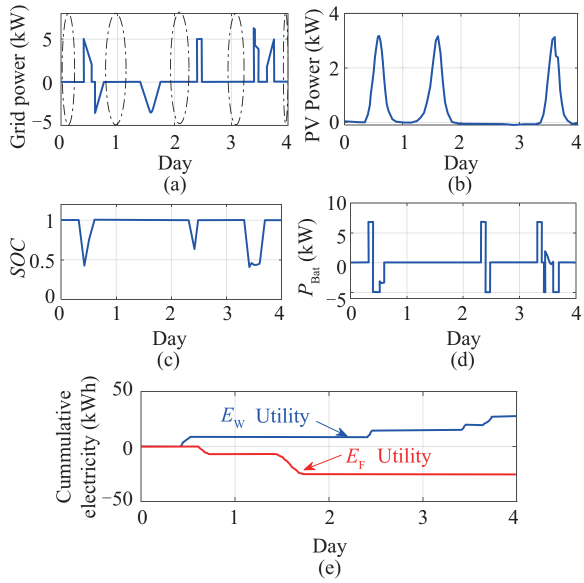

Fig. 4. Grid connected PV powered EVCS with fixed buffer battery SOC (a) Grid power. (b) Available PV power generation. (c) Battery SOC. (d) Battery power. (e) Cumulative electricity between the utility and the charging system.

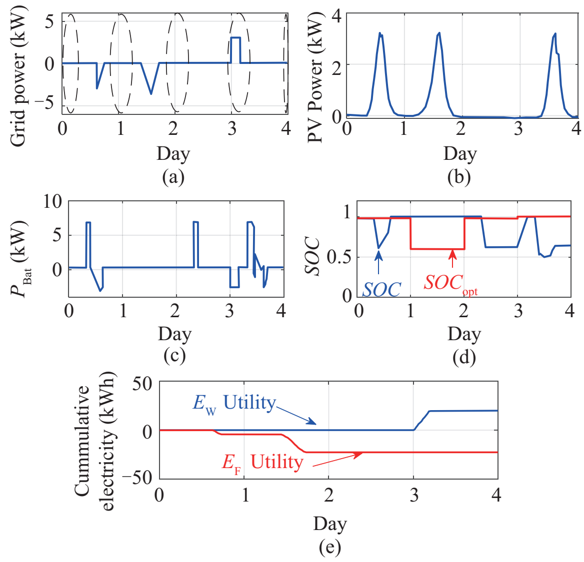

Fig. 5. Grid connected PV powered EVCS with battery unit and intelligent EMS (a) Grid power. (b) Available PV power generation. (c) Battery SOC. (d) Battery power. (e) Cumulative electricity between the utility and the charging system.

By comparing the outcomes of PV powered EVCS with fixed battery unit with the outcomes of PV powered EVCS without battery unit, it can be observed that the power demand spikes on the utility were only slightly reduced. Besides, the energy exchange between the utility and the charging system were also reduced by a factor of 2.

Furthermore, the action of developed EMS while implementing the approach related to optimal soc for a grid connected PV powered EVCS is shown in Fig. 5. In this condition, the actual battery SOC is compared with the target SOC of the battery to understand the charging needs for the battery during

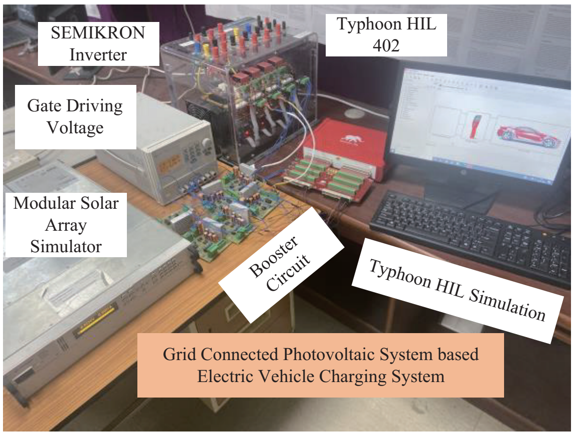

Fig. 6. Experimental setup for grid connected PV based EVCS.

the off-peak periods. Compared to Fig. 3, the power demand for battery charging was shifted away from the on-peak to the off-peak time period, and the power demand peak was reduced by a factor of 2. This approach resulted in a better energy management.

C. Experiment

The real-time experimental setup for a grid connected PV powered EVCS with a battery storage and the bi-directional inverter is developed as shown in Fig. 6. The PV simulator realizes the operation of the 5 kW PV array operating under six different mission profiles. The output of the PV simulator is provided as input at the DC link terminal of the inverter and simultaneously fed into the typhoon HIL through the analogue inputs. These analogue inputs identify the measured DC link voltage variations.

Further, the grid characteristics, EV charging characteristics and Battery operation are simulated in the typhoon HIL and integrated with the measurement from the PV simulator and in the inverter terminal voltage. Here the typhoon HIL 402 setup provides an interconnection between the PV simulator, and Semikron inverter in the hardware, and the bidirectional converter developed in the simulation. The interconnection diagram for the hardware and simulation interface through the typhoon HIL are shown in Fig. 7. The details of battery development and charger development used in the experimental analysis are provided in [33], [34]. This integration setup is used to generate the data for developing the power management control through Model-sim and Quartus programming. The Model-sim platform replicates the driving cycles and charging discharging pattern of the EV through and Quartus programming software is used to achieve the control strategy which is implemented in typhoon HIL simulation through Python programming language.

The controller manages the power flow between the different components and optimizes the battery storage according to the estimated PV electricity and the projected EV load. The test operation of the system demonstrated that the controller can successfully extract weather information, estimate PV electricity, project EV charging load, and optimize the battery

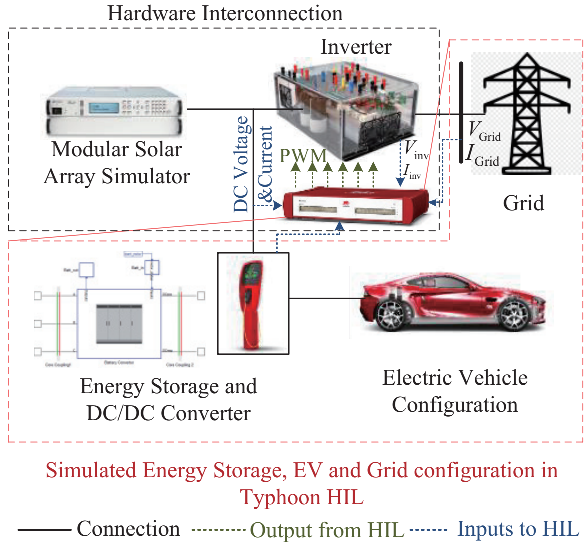

Fig. 7. Connection between Hardware components and Typhoon HIL simulation.

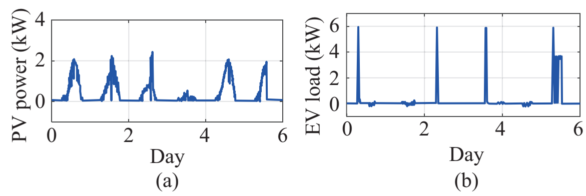

Fig. 8. Measured data (a) PV power. (b) EV charging load.

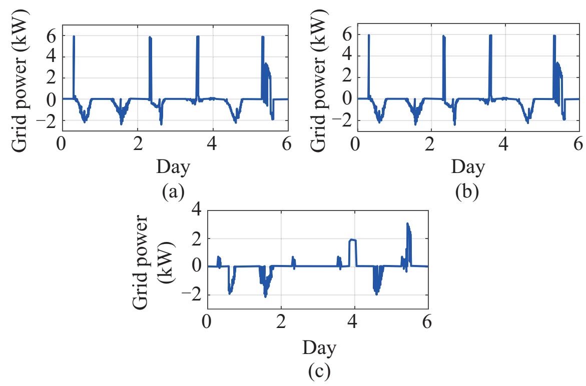

Fig. 9. Grid power of the system (a) Charging system without battery unit. (b) Charging system with fixed SOC battery unit. (c) Charging system with battery unit.

target SOC between 0.3−1. For a low SOC, the battery unit is recharged during off peak hours, and the charging station is operated without the intelligent controller. The measured PV power for different mission profiles and the adapted EV charging load are shown in Fig. 8.

D. Experiment Results

The operation of charging station with and without the battery unit and its impact on grid power utilization with the system is shown in Fig. 9. From the results it is observed that the charging station with battery unit has a significant reduction

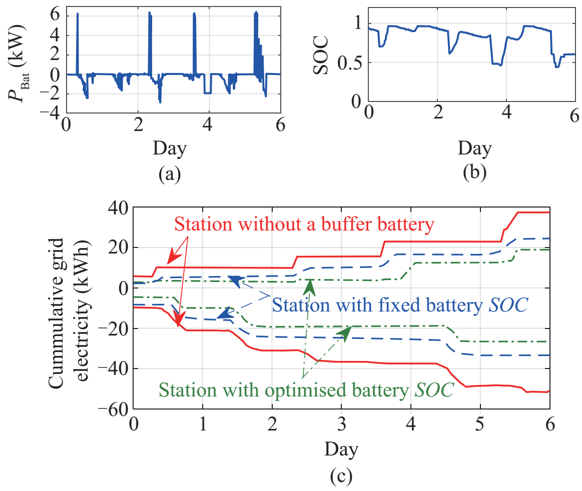

Fig. 10. Battery and grid characteristics (a) Battery power. (b) Battery SOC. and (c) Cumulative electricity for charging station with and without battery.

in peak power demand when compared with the charging station without battery unit. Further, the charge, discharge pattern of the battery with respect to the battery power and SOC, and the cumulative electricity for charging station with and without battery unit are shown in Fig. 10. The curves in red indicate the energy withdrawn and energy fed into the grid with the charging station without buffer battery system. Further, the curves in blue indicate the energy withdrawn and energy fed into the grid with the charging station with fixed buffer battery SOC. Similarly, the curves in green indicate the energy withdrawn and energy fed into the grid with the charging station with optimized buffer battery SOC. Comparing the energy exchange in both the charging scenarios with the grid, the charging station with battery unit has a reduced energy exchange factor of 2.

The scenarios in Fig. 10(a–c) correspond to operation of PV based EV charging without a buffer battery, PV based EV charging with fixed buffer battery SOC, and PV based EV charging with optimized buffer battery SOC respectively. The total energy withdrawn from the grid for the complete period during scenario (a) is 38 kWh, scenario (b) is 24 kWh, and scenario (c) is 18 kWh. Similarly, the total energy fed into the grid during the complete period in scenario (a) is 52 kWh, scenario (b) is 33 kWh, and scenario (c) is 27 kWh. Further, the energy shift from on- to off-peak hours from scenario (b) to scenario (c) is optimised by a factor of 0.8 and the stations peak power demand and energy exchange with the grid is lowered by a factor of 1.5 reducing the burden on the grid.

Further, the data is collected to achieve EV charging load projection, by operating the charging station continuously without optimizing the battery unit. Once the data is collected, the system is operated with the intelligent energy management system. In addition, the estimated PV generation calculated from the simulated models and actual the actual PV generation measured from the PV simulator output are shown in Fig. 11 (a). It is observed that, the estimated PV generation for the data sheet information is higher by 14% −17% than the actual PV generation data. This is mainly due to effect of varying mission profile.

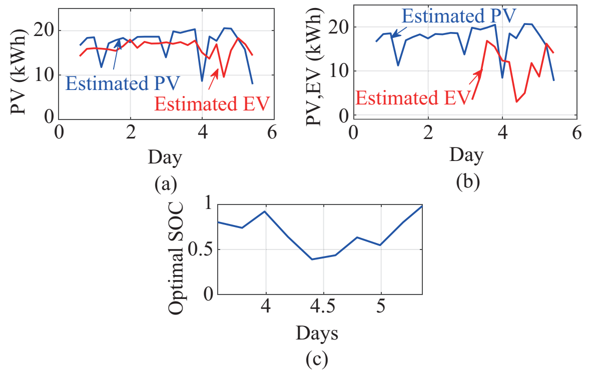

Fig. 11. PV and EV characteristics for optimal SOC estimation (a) Estimated and measured PV power generation. (b) Estimated PV power and EV charging load. (c) Optimized SOC target.

TABLE III
COMPARISON BETWEEN CONVENTIONAL AND PROPOSED EVCS TECHNOLOGIES

Parameter	Traditional charging strategies [4][8]	Without buffer battery	With fixed buffer battery SOC [12], [13], [17]–[19]	Proposed optimization method
Grid Impact	High	High	Medium	Low
Energy management strategy	No	No	Yes	Yes
PV and Load estimation	No	No	No	Yes
Cost	Low	Medium	High (battery cost)	High (battery cost)

Similarly, the estimated PV and EV charging load are shown in Fig. 11(b). From both the estimated EV and PV scenarios, the battery SOC target is optimized and charges during the off-peak hours for SOC less than the target SOC. The project EV load, estimated PV generation and optimized SOC are shown in Fig. 11(b) and (c). The results of the developed optimization approach with the charging strategies available in the literature are compared in Table III.

From the result it is identified that the intelligent controller along with optimized battery soc target can almost eliminate the peak power demand of the charging station on the utility grid.

V. CONCLUSION

An intelligent energy management system for optimal operation of grid connected solar powered electric vehicle charging station is developed. The controller is developed by adapting Markov decision process with the mission profile data of PV availability, grid loading, and the EV charging load data and achieved optimal operation by controlling the power flow between the photovoltaic (PV) system, energy storage unit, EVCS and the grid. The introduction of varying irradiance data and EV load profile eliminated the conventional problem of immediate recharging of energy storage unit after each EV charging by setting a target SOC level. This maximized the utilization of PV power for charging of EV charging and minimized the impact of energy exchange on the grid. Further, numerical simulations and experiments were carried out and the operation of the proposed controller is tested. Three different experiment scenarios are carried out as follows: charging station without energy storage unit, charging station with energy storage unit, and charging station with energy storage unit controlled by intelligent controller for varying irradiance profile and load profile for multiple days. The results showed an estimation of EV load and PV power and optimized the energy storage unit SOC between 0.3−1. These projections and optimizations minimized the impact of energy exchange between the grid and charging station by a factor of 2.

This work can be further extended by considering the preferred charging rate of the EV, and time of stay at charging station, along with the EV battery soc while designing the controller. Besides, the ancillary services of EVs like vehicle to grid can also considered while designing the developed approach.

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