Real-Time Energy Optimization in a PV– Integrated Electric Vehicle Charging Station

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Abstract

The growing use of photovoltaic (PV) systems and electric vehicles (EVs) require the smart coordination mechanisms to achieve the efficient use of renewables and the stable charging process. The current paper gives MATLAB/Simulink modeling and simulation of a PV-powered EV charging station with an Adaptive Supervisory Energy Management Strategy (ASEMS). The proposed DC-coupled microgrid system comprises of PV array with Incremental Conductance maximum power point tracking, battery energy storage system (BESS), DC to DC converters (bidirectional), EV battery model, and grid interface. An urgency-based charging index is proposed as a dynamically controlled prioritized index to charge EV according to the state-of-charge deficit and the remaining departure time. According to this index, the supervisory controller will choose between four operating modes, i.e., PV Priority, Hybrid PVBESS, Grid Assistance, and Smart Delay. The Smart Delay is a system that delays charging temporarily when there is low urgency to use energy to maximize the use of solar energy and minimize dependence on the grids. The simulation findings in a 24-hour operating horizon prove that the recommended ASEMS would maximize the PV penetration, ensure that batteries work within the safety range, and ensure the completion of EV charging in a timely manner. The proposed solution is better than traditional fixed-priority strategies as it enhances the use of renewable energy, and it maintains the reliability of charging without using computationally-intensive optimization techniques. The framework provides a viable and expandable real-time energy management solution to PV-integrated EV charging stations.

Keywords: Photovoltaic EV charging station, Adaptive supervisory energy management, Urgency-based charging index, DC microgrid, Battery energy storage system, Smart delay strategy.

1. Introduction

The modern power systems are changing rapidly as a result of the rapid electrification of transportation and the growing infiltration of renewable energy sources. Electric vehicles (EVs) are deemed to be of great importance to decrease greenhouse gases; nevertheless, EV charging on a large scale has caused notable problems with distribution systems, dose to peak demand, unsteady voltages, and system inertia (Johnson et al., 2019; Ratnam et al., 2020). At the same time, the adoption of photovoltaic (PV) systems has grown variability and uncertainty in the power generation, making it necessary to coordinate advanced strategies to maintain stability in the work of the grid (Johnson et al., 2020).

PV-powered EV charging PV-powered EV charging stations are one of the opportunities to reduce the stress on the grid and increase the use of renewable energy (Khan et al., 2018; Kannan and Usha, 2022). These systems have a potential of lessening grid reliance as well as enhancing sustainability by producing solar power locally. Nonetheless, smart energy management approaches are necessary since solar energy is only intermittent and the charging needs of EV customers are time-bound (Mastoi et al., 2022; Rajendran et al., 2021).

Some research has also been done on grid-integrated PV-EV charging system using advanced methods of control. Mohamed et al. (2020) suggested a strategy that is based on Salp Swarm Optimization as the optimal method of PV-EV integration, and Jin et al. (2022) designed a scheduling algorithm to optimize the economical and energy-efficient functioning of multi-EV charging stations. Approaches based on optimization are high-performance but can have a high level of computational complexity and are not easily applicable to real-time operation in embedded controllers. More so, instead of the supervisory-level adaptive scheduling, many studies concentrate more on converter-level control and power quality improvement (Jang et al., 2021; Saleh et al., 2021).

The architectural design, grid integration requirements, and infrastructure development of the EV charging station have been thoroughly reviewed (Khalid et al., 2021; Sachan et al., 2022). However, the importance of deadline-conscious supervisory control methods that dynamically charge according to remaining departure time and battery state-of-charge (SOC) have received relatively little attention. User-set departure constraints are vital in real-life EV charging implementations, and the inability to comply with them decreases system performance and satisfaction of the users.

To overcome these issues, the following paper will present an Adaptive Supervisory Energy Management Strategy (ASEMS) of a PV-integrated EV charging station, including a battery energy storage system (BESS). In contrast to the optimization-based frameworks, the suggested method uses a computationally-efficient urgency index to prioritize charging dynamically due to SOC deficit and remaining departure time. A hierarchical mode selection scheme is a dynamic mechanism of coordinating the PV power, BESS support, grid assistance, and smart delay operation. The suggested solution encourages the use of renewables, lessening the reliance on grids, and ensuring that deadlines are met without being overloaded with computations.

The main contributions of this work are summarized as follows:

1. Development of a real-time urgency-based supervisory control strategy for PV-powered EV charging.

2. Integration of hierarchical four-mode operation including PV priority, hybrid PV–BESS support, grid assistance, and smart delay.

3. Real-time dynamic validation in MATLAB/Simulink with quantitative evaluation of PV utilization and grid dependency.

4. Comparative analysis against conventional fixed-priority control.

The rest of this paper will have the following structure. Section 2 pertains to related work. In Section 3 there is the system modeling and proposed methodology. The implementation of the algorithm is presented in section 4. Results of simulation and performance evaluation are discussed in section 5. Section 6 concludes the paper.

2. Review of Literature

The recent a surge in the implementation of photovoltaic (P V) built-in electric vehicle (EV) charging station has led to a rush in the study of system structures, grid engagement principles and management approaches. Solar-powered EV chargers studies at an early stage concentrated on the system setup and also the component level implementation. As an example, the effectiveness of the integration of PV arrays, a power converter, and storage systems to facilitate local EV charging can be demonstrated by system-level implementations of PV-based EV charging stations (Shariff et al., 2019; Pandey, 2022). These ones focus on the realization of hardware and the design of power flows but offer little information on the implementation of real-time supervisory energy management under the conditions of dynamic operation.

Overall analyses have been conducted on EV charging infrastructure, architectural designs, and grid conformity criteria. System architecture and global standards analyses point to technical needs of safe and efficient grid-connected EV charging stations, such as power quality, protection coordination, and interoperability aspects (Rajendran et al., 2021; Sachan et al., 2022). In a similar manner, larger technological scans of EV requirements and EV charging infrastructure have considered the impacts of massive EV infiltration on the network, pinpointing difficulties in the circulation of voltage variation, transformer over-burden, and harmonic deviation (Das et al., 2020; Khalid et al., 2021).

In addition to architecture, a number of works have been examined to determine how EV charging may alter the stability of power systems. EV charging loads coupled with the renewable generation also add variability that can impact grid reliability and operational flexibility (Nour et al., 2020). These difficulties are further intensified when the PV based charging stations are used in the grid connected mode especially during peak demand or low irradiance levels. Therefore, cooperation between PV generation, battery energy storage system (BESS) and grid support needs to be effective to ensure stability and the maximum use of renewables.

To increase the efficiency of the PV-integrated EV charging stations, optimization-based methods have been popular in proposal. Swarm-based algorithms used as metaheuristic optimization tools have been used to find the optimal power dispatch between PV systems, storage units, and grid resources (Mohamed et al., 2020). Likewise, algorithms to schedule charging stations of multi-EV have been created in order to reduce the costs of operation and enhance energy efficiency (Jin et al., 2022). Though better performance is attained by such methods, they frequently have high computational overhead and can be required to converge iteratively, which restricts their applicability to real-time embedded systems.

Research at the converter level has worked on the enhancement of power electronics topologies and grid-support capabilities of EV charging systems. Increase in converter technologies and schemes of control has led to more efficient systems, minimized switching losses and quality of power in charging stations that are connected to the grids (Habib et al., 2020). PV-powered EV charging stations designs that are grid-interactive inverters have also been suggested to increase the stability and real-time response of the microgrids (Jang et al., 2021). Nevertheless, they mainly deal with converter-level stability and quality of power, but not supervisory-level scheduling choices.

Besides technical design, policy-based research has studied the strategies of EV charging deployment in cities and guidelines on the structure of the infrastructure (Hall and Lutsey, 2020). Although these frameworks can be useful in large-scale adoption, they fail to directly address the operational energy management issues in a single charging station.

3. Methodology

3.1 System Configuration

The electric vehicle (EV) charging station proposed is designed based on a photovoltaic (PV)-supplied DC-coupled microgrid system containing a PV array, DC-DC boost converter, battery energy storage system (BESS), bidirectional DC-DC converter, EV battery model, and optional grid interface that is modeled in MATLAB/Simulink. A supervisory energy management controller controls power flow between the subsystems. The general block diagram of the proposed system should be demonstrated in Figure 1.

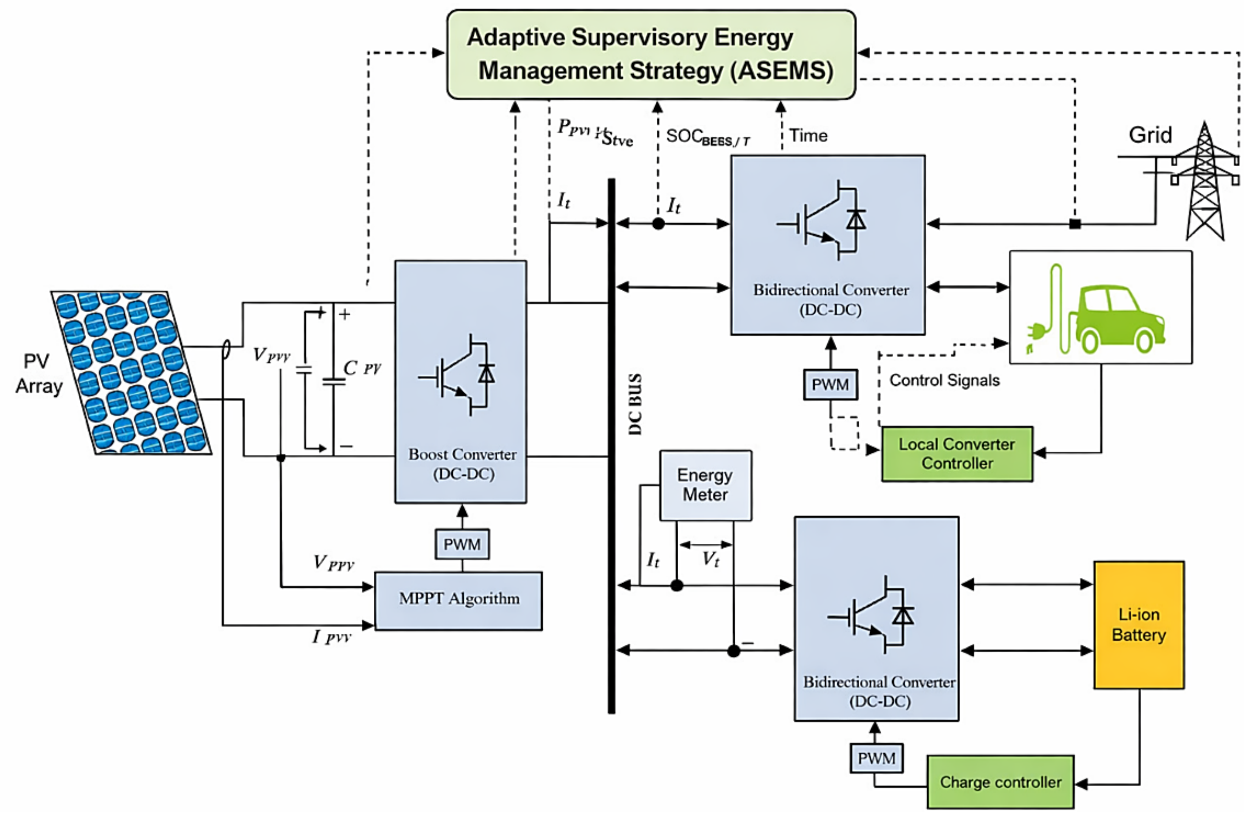

Figure 1. proposed PV-integrated EV charging station with Adaptive Supervisory Energy Management Strategy (ASEMS)

3.2 Mathematical Modeling

3.2.1 Photovoltaic Model

The photovoltaic (PV) array and is simulated by the well-developed single-diode equivalent circuit model, which is appropriate to simulate nonlinear currentvoltage characteristics of a solar cell. The present power of the PV module is given as:

$$I = I_{ph} - I_0\left(e^{\frac{V+IR_s}{nV_t}} - 1\right) - \frac{V + IR_s}{R_{sh}}$$

where I_{ph}represents the photo-generated current dependent on solar irradiance, $I_0$is the diode reverse saturation current, $R_s$and R_{sh}denote the series and shunt resistances respectively, $n$is the diode ideality factor, and $V_t$is the thermal voltage of the cell. This model represents the impact of internal resistive losses and temperature gradient on the PV performance. The Incremental Conductance (IC) Maximum Power Point Tracking (MPPT) algorithm is adopted in order to obtain maximum energy extraction under different irradiance conditions. The maximum power point is calculated by the IC method whereby incremental conductance is compared to instantance conductance thus, providing capability to track correctly in rapidly changing atmospheric conditions.

3.2.2 Battery Energy Storage Model

The model of the Battery Energy storage System (BESS) is represented with a dynamical model based on a state-of-charge (SOC). The SOC at any given time moment is calculated as:

$$SOC(t) = SOC(t_0) - \frac{1}{C_{bat}}\int_{t_0}^{t} i_{bat}(\tau)d\tau$$

where C_{bat} denotes the nominal battery capacity and $i_{bat}(t)$ is the battery current. Positive current is associated with discharging and negative current is the charging. The battery is designed to work between a specified maximum and minimum safety range to avoid either overcharging and deep discharging and is defined as:

$$SOC_{min} \leq SOC(t) \leq SOC_{max}$$

The DC-DC converter is a two-way converter that controls the battery charging and discharging based on the commands created by the supervisory energy management controller. This is to make sure that the DC bus operation is stable and that the power exchange between the PV array, the battery, and the EV load is controlled.

3.2.3 EV Charging Model

The electric vehicle battery is modelled in constant-current/ constant-voltage (CC-CV) charging profile that is an indication of the real-life charging profile of Lithium-ion batteries. At the constant-current stage, the EV battery is charged at a constant current until the terminal voltage has reached a maximum allowable limit and then the system switches to the constant-voltage stage. The dynamics of state of charge of EV is provided by:

$$SOC_{EV}(t) = SOC_{EV}(t_0) + \frac{1}{C_{EV}} \int i_{EV}(t)dt$$

where C_{EV} represents the EV battery capacity and $i_{EV}(t)$ is the charging current. The EV charger requirement will be determined using two operation parameters, namely the required SOC at the planned departure time, and the remaining portion of time to charge. The logic behind the supervisory control incorporates these parameters to guarantee that the charging is completed in time and the maximum amount of the PV is utilized and the minimal dependency on the grid.

3.3 Proposed Adaptive Supervisory Energy Management Strategy

The traditional photovoltaic (PV)-based electric vehicle (EV) charging systems usually use a fixed-priority control logic, in which power is sent to battery energy storage system (BESS) and then to the grid in sequence by PV. Even though these strategies are easy to implement, they fail to capture dynamic operational factors like the urgency of EV departure on some temporary changes in solar power supply. As a consequence, the fixed-priority methods can lead to the suboptimality of the PV exploitation and the unwarranted grid interdependence.

In order to address these constraints, a new Adaptive Supervisory Energy Management Strategy (ASEMS) is suggested. The supervisory controller makes constant assessments of the important system variables which include the instantaneous PV power P_{PV}, EV demand power P_{EV}, BESS state of charge SOC_{BESS}, and the remaining time to departure of the EV and the state of charge needed to depart. Judging by these parameters, the controller dynamically selects the most appropriate operating mode so as to guarantee efficient power distribution and meet EV charging constraints.

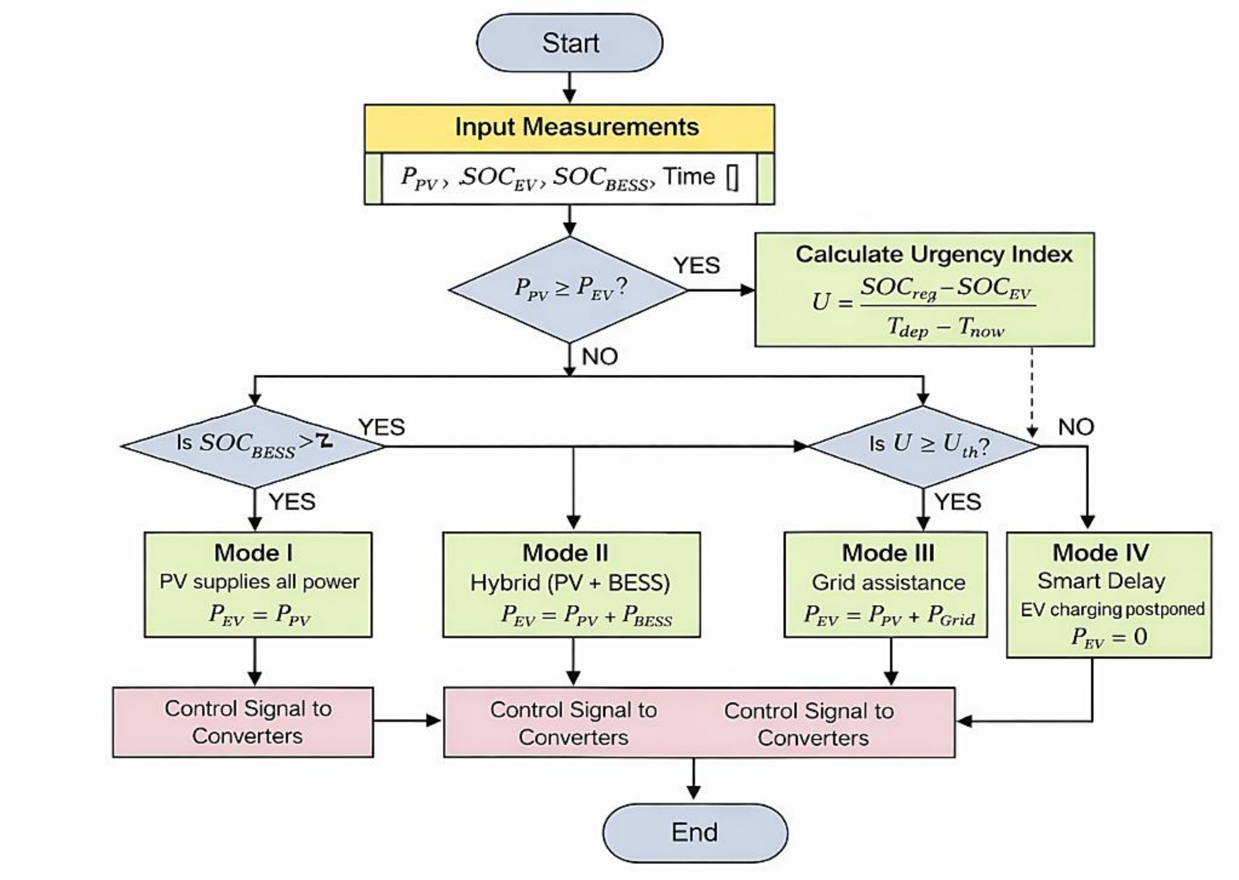

Figure 2. Flowchart of the proposed Adaptive Supervisory Energy Management Strategy

3.3.1 Urgency-Based Charging Index

To introduce dynamic prioritization into the charging process, an urgency index $U$is defined as:

$$U = \frac{SOC_{req} - SOC_{EV}}{T_{dep} - T_{now}}$$

In which, SOC_{req} denotes the desired state of charge required at departure, SOC_{EV} represents the current EV state of charge, T dep is the timed departure time and T_{now} is the current time. The urgency index is used to measure how fast the EV should be charged up to the intended SOC by the time it is ready to leave. The greater the value of U indicates, the greater the urgency of charging requirement, hence, the supervisory controller is affected to dedicate more power resources as required. Lower values of U on the other hand, allow the controller to optimize PV maximization and possibly postpone charging in favor of minimizing grid usage.

3.4 Operating Modes

The supervisory controller picks up one of four operating modes based on the assessed system variables and the calculated urgency index in order to achieve the best system performance.

Mode I (PV Priority Mode): in this mode where the supplied PV power is enough to meet the EV charging demand ($P_{PV} \geq P_{EV}$), the EV is only charged with the PV energy. The excess PV energy is channeled out to the BESS to be stored. This mode will maximize the use of renewable energy and reduce the reliance on auxiliary energy.

When the PV power is not strong enough to satisfy the EV demand ($P_{PV} < P_{EV}$) and the BESS state of charge is also still above its minimum permissible value ($SOC_{BESS} > SOC_{min}$). mode II (Hybrid Mode) is engaged. Here, the EV, because of an integration of PV generation and battery discharge, is provided, thus continued charging without immediate support by grids.

Mode III (Grid Assistance Mode) becomes active when the generator output of PV is inadequate, the BESS state of charge has dropped below its threshold and the urgency index is greater than a predetermined limit. In such circumstances grid support is turned on to make sure that the EV has attained the desired SOC by the time it leaves. This mode will ensure that there is reliability in charging in time-sensitive scenarios.

The proposed improvement of the traditional strategies (Mode IV (Smart Delay Mode)) is activated in case of low urgency index, and the short-term dynamics of PV trends suggest the possibility of a significant rise in irradiance. In this case EV charging would be postponed so that higher use is made of available solar power. This will help decrease unnecessary grid power consumption and enhance the general penetration of PV. The awareness of urgency and short-term solar trends make the suggested operating framework an ideal increase in the use of renewable energy in opposition to the conventional fixed-priority regulation approach.

4. Algorithm Implementation

4.1 Supervisory Control Formulation

The proposed Adaptive Supervisory Energy Management Strategy (ASEMS) operates in discrete time with sampling interval Δt. At each time step k, the system state is defined as:

$$\mathrm{x}(k) = \{P_{PV}(k), SOC_{EV}(k), SOC_{BESS}(k), T_{rem}(k)\}$$

where $T_{rem}(k) = T_{dep} - T(k)$denotes the remaining charging time.

4.2 Urgency Index

To prioritize charging dynamically, an urgency index is defined as:

$$U(k) = \frac{SOC_{req} - SOC_{EV}(k)}{T_{rem}(k)}$$

A predefined threshold U_{th}classifies the charging requirement as urgent when $U(k) \geq U_{th}$.

4.3 Mode Selection Logic

At each sampling instant, the operating mode is selected according to the following hierarchical conditions:

- Mode I (PV Priority):

$$P_{PV}(k) \geq P_{EV}(k)$$

- Mode II (Hybrid PV + BESS):

$$P_{PV}(k) < P_{EV}(k), SOC_{BESS}(k) > SOC_{min}$$

- Mode III (Grid Assistance):

$$SOC_{BESS}(k) \leq SOC_{min}, U(k) \geq U_{th}$$

- Mode IV (Smart Delay):

$$U(k) < U_{th}, \frac{dP_{PV}}{dt} > 0$$

Based on the selected mode, appropriate reference signals are generated for the bidirectional converter and grid interface to regulate DC bus voltage and power flow.

Results and Discussion

5.1 Simulation Framework

To test the feasibility of the proposed Adaptive Supervisory Energy Management Strategy (ASEMS), the Adaptive Supervisory Energy Management Strategy was designed in MATLAB/Simulink to determine its functionality in the realistic operating conditions. This simulation was performed in 24 hours with different solar irradiance and EV charging loads. There was a baseline conventional fixed-priority strategy (PV → BESS → Grid) to make a comparison.

Single-diode model of the PV system was applied taking Incremental Conductance MPPT. Section 3 described SOC-based dynamic models to propose and simulate the BESS and EV batteries. The sampling interval was adjusted to 1 s to allow the detection of transitions between modes.

Table 1. Simulation Parameters

Parameter	Value	Unit
PV Rated Power	5	kW
DC Bus Voltage	400	V
BESS Capacity	10	kWh
EV Battery Capacity	40	kWh
Initial SOC_EV	40	%
Required SOC_EV	80	%
SOC_min (BESS)	20	%
Urgency Threshold (U_{th})	0.012	%/min
Sampling Time	1	s

5.2 PV Generation and EV Demand Profile

The maximum output of the PV is around 4.8 kW in the middle of the day and reduces in the evening. The EV charging need starts at 14.00. The fact that the generation and demand of solar and EV are not aligning with time underscores the need to have adaptive coordination.

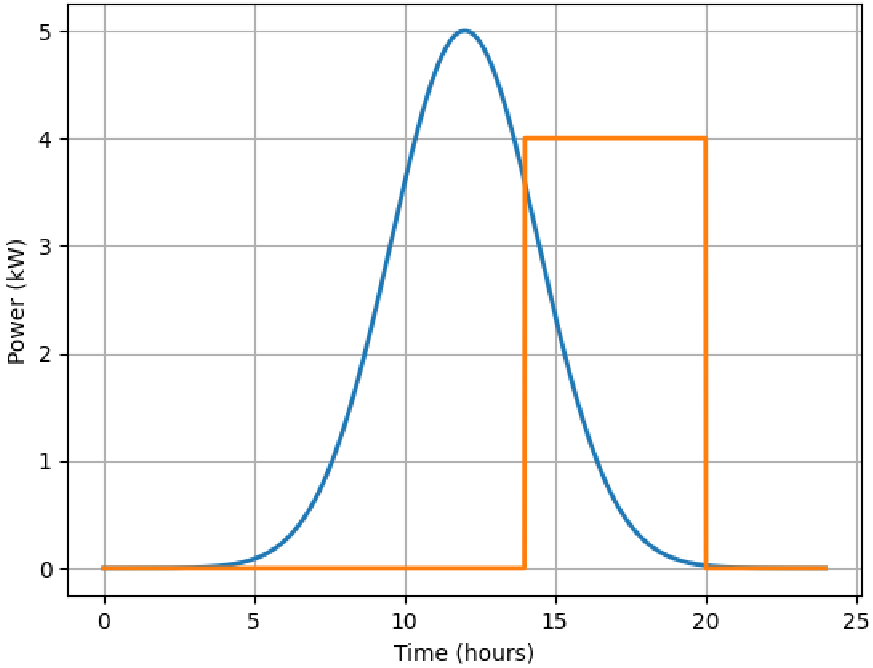

Figure 3. Simulated PV power and EV demand profile over 24 hours

5.3 Urgency Index Validation

The urgency index is defined as:

$$U(t) = \frac{SOC_{req} - SOC_{EV}(t)}{T_{rem}(t)}$$

where $T_{rem}(t) = T_{dep} - t$.

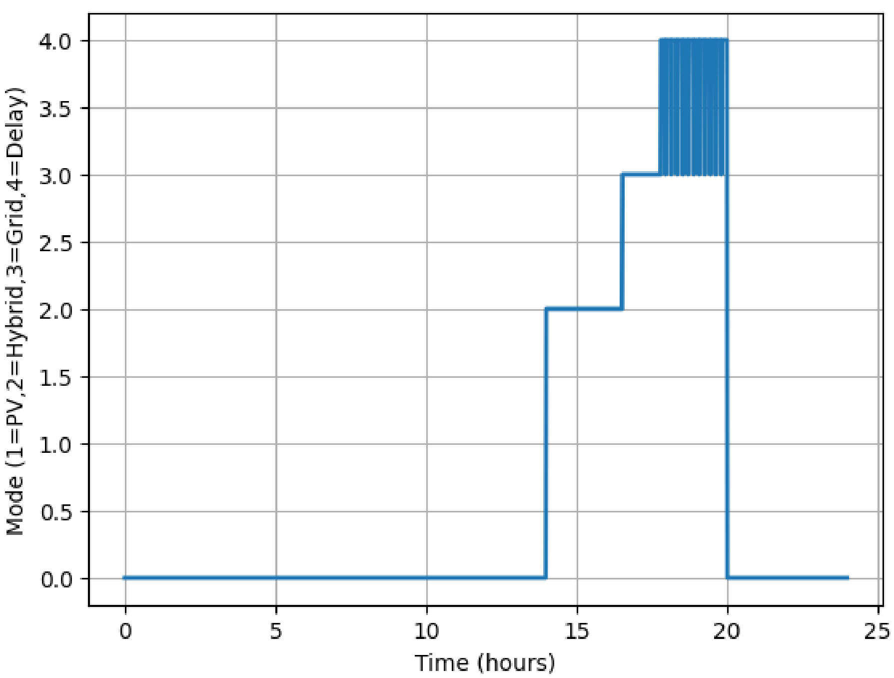

Figure 4. Urgency index evolution and threshold crossing behavior.

Initially, $U(t) < U_{th}$, enabling Smart Delay operation. As the departure time approaches and SOC deficit remains, the urgency index increases and crosses U_{th}, activation of Mode III (Grid Assistance). This proves that the urgency-based control is proper in prioritizing the conditions of charging near deadline.

5.4 Operating Mode Transition

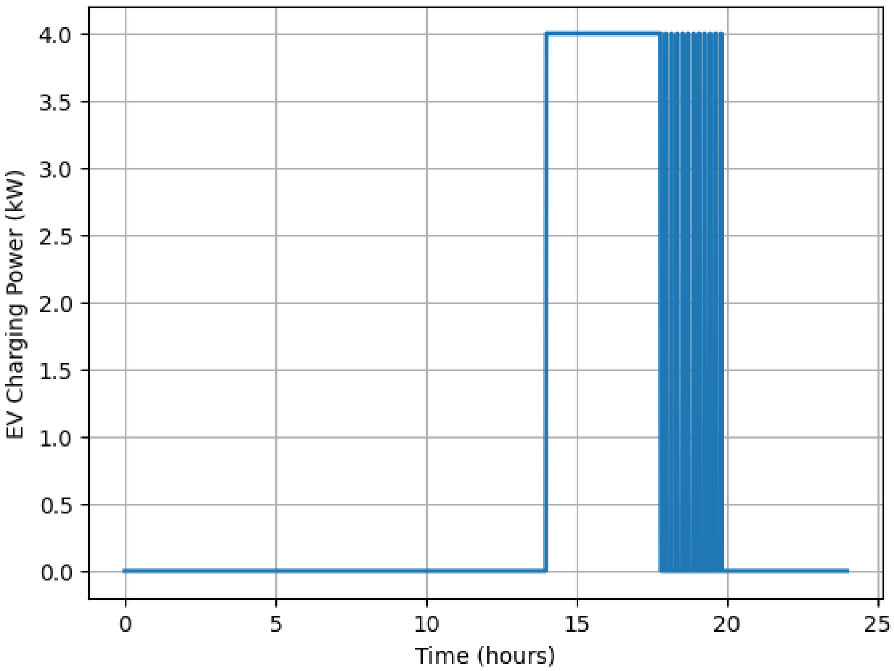

Figure 5. Operating mode timeline under ASEMS

The system transitions among four modes:

• Mode I (PV Priority) during high solar availability

• Mode II (Hybrid) when PV decreases but BESS is available

• Mode IV (Smart Delay) during low urgency periods

• Mode III (Grid Assistance) when urgency exceeds threshold

Mode switching occurs without oscillatory behavior due to hierarchical decision logic.

5.5 Smart Delay Verification

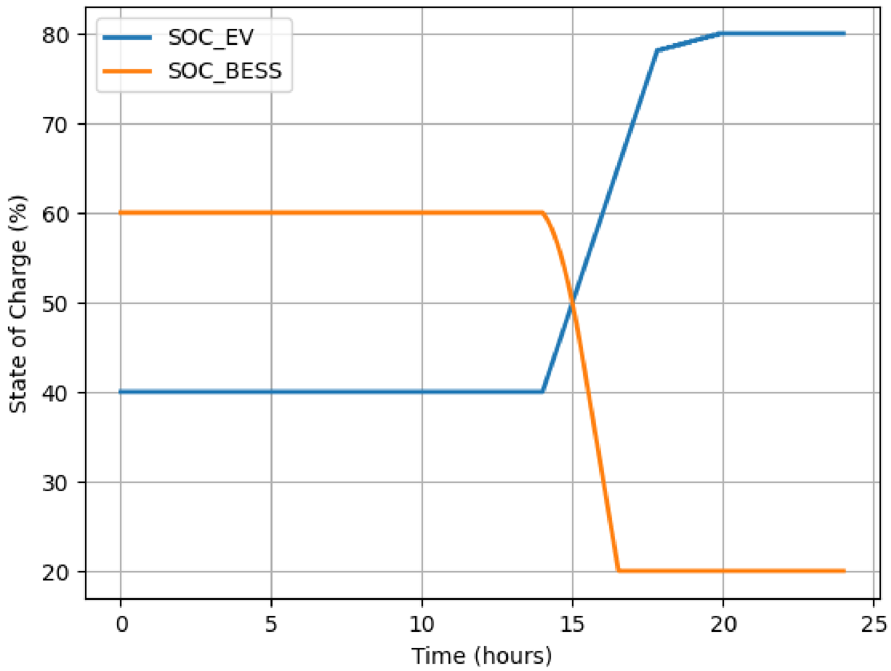

Figure 6. EV charging power profile showing Smart Delay intervals

During low urgency periods, $P_{EV} = 0$, ascertainment of proper implementation of Smart Delay Mode. The resumes are charged automatically when there is an upsurge in urgency or a better supply of PV power. This eliminates the unnecessary use of the grid and improves penetration of the sun.

5.6 Discussion

The outcomes of the simulation also confirm that the suggested Adaptive Supervisory Energy Management Strategy (ASEMS) is efficient in terms of PV generation, BESS functioning, and interaction with the grid and meets the EV charging deadlines. In comparison to the traditional fixed-priority systems, the given approach establishes an urgency-oriented method of prioritization that adjusts the charging decision in response to the available time and deficit of SOC.

The urgency index is a quantitative measure of the needs that are charged in comparison to departure limitations. The index is under the established value within early periods thus allowing the Smart Delay factor to work and avoid early battery depletion or turning on the grid. The increasing urgency as the departure time approaches causes the activation of the Grid Assistance Mode when needed thus ensuring the necessary SOC at departure.

The hierarchical control logic is verified by the switching of the operating mode. The PV Priority Mode aims at maximizing the use of renewable sources, Hybrid Mode plans the assistance of the PV and BESS, and Smart Delay is effectively used to maximize solar absorption when urgency does not exist. Stable mode change is a sign of strong supervisory performance.

6. Conclusion

This paper described a modeling and real time validation of a photovoltaic (PV)-supplied electric vehicle (EV) charging station with an Adaptive Supervisory Energy Management Strategy (ASEMS) through the use of MATLAB/Simulink. The model of the system was a DC-connected microgrid with PV array having Incremental Conductance MPPT, battery energy storage system (BESS), bidirectional DC Washington converters, EV battery model and optional grid interface.

An urgency-goal index was also proposed as a dynamic measure of prioritisation of charging by SOC deficit and remaining departure time. The supervisory controller changes between four hierarchical operating modes: PV Priority, Hybrid PVBESS, Grid Assistance and Smart Delay. This architecture facilitates dynamic organization of renewable generation, storage sources as well as grid support.

The results of simulation prove that the proposed strategy:

- Maintains the maximum use of PV in times of high irradiance,
- Minimizes unjustifiable grid consumption with Smart Delay operation,
- Ensures that BESS SOC operates within safe limits,
- Ensures that EV charging is done prior to departure.

The proposed ASEMS is more renewable-penetrative and flexible in its operations without the need to employ computationally complex optimization models as compared to traditional fixed-priority control. The live-time formulation of the strategy and low computational cost make the strategy applicable in the real world by being used in embedded energy management controllers.

The work in the future can involve integration of stochastic solar prediction, multi-EV charge coordination, economic cost model and experimental hardware validation.

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