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A Simulation-Based Experiential Learning Framework for Smart Pricing and Hybrid Storage Optimization in PV-Integrated EV Charging Systems

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***Abstract*— The rapid development of photovoltaic (PV)-based electric vehicle (EV) charging systems with hybrid energy storage systems presents complicated operational and economic issues that are hard to communicate using conventional pedagogical strategies. In this research, an experiential learning framework that is introduced where students are able to learn about smart pricing and multi-objective optimization in EV charging systems. The framework proposed represents a PV-powered EV charger station in combination with a hybrid energy storage system (HESS) comprising of lithium-ion batteries and supercapacitors. A virtual learning environment is integrated with a dynamic electricity pricing system and a multi-objective optimization system based on Multi-Objective Oppositional Swordfish Optimization (MOOSFO). PV variability, temperature effects and EV charging demand are the parameters of the system that students interact with and observe how they affect the grid stability, cost and system performance. The framework is created as a virtual laboratory module whereby the learners will be able to experiment on the real-life problems like reduction of peak load, cost optimization, and energy management. Educational assessment shows better student knowledge of the integration of renewable energy, smart grid economics, and methods of optimization, as well as better analytical and problem-solving abilities. This research can be used in engineering education through offering a complex energy management problem to a student-centric interactive learning environment, which facilitates outcome-based education and interdisciplinary learning.**

***Keywords*— Electric Vehicle; Photovoltaic; Oppositional Swordfish Optimization; Cost optimization;**

I. INTRODUCTION

THE speed of the Electric Vehicles (EV) expansion is changing the face of the contemporary transportation industry by providing a sustainable and environmental friendly solution to the traditional internal combustion engine powered vehicles. The main reason behind this shift is the growing insecurities about air pollution, climate change, and the exhaustion of fossil fuel reserves. Besides their beneficial environmental contribution, EVs also have such advantages as high energy efficiency, lower cost of operation, less noise, and the ability to integrate Vehicle-to-Grid (V2G), meaning the possibility of exchanging energy between vehicles and the power grid. The large-scale deployment of EVs however presents huge challenges of power systems operation such as high peak loads, voltage variability, and grid congestion that can negatively impact on the reliability of the grid. Moreover, such practical challenges as the cost of charging, waiting time, availability of charging infrastructure, and battery degradation concern EV users. Thus, it is necessary to evolve smart and effective scheduling methods of charging and discharging EVs to get the best grid working and performance (Liikkanen, 2024).

Over the past few years, a number of studies have been devoted to the optimization of charging schedules of EVs with the help of sophisticated computational methods. The integration of V2G minimized the EV charging cost with the help of a metaheuristic-based scheduling method using Differential Evolution (DE), Particle Swarm Optimization (PSO), Whale Optimization Algorithm (WOA), and the Grey Wolf Optimizer (GWO) was proposed, and the results showed that WOA could be used to optimize the EV charging cost at a level of the best convergence results among the algorithms discussed (Shaheen, 2024). Equally, the hybrid energy management approach according to Groundwater Flow Optimization and Vascular Invasive Tumor Growth (GFO-VITG) was presented to PV-assisted EV charging systems with a considerable saving of up to 55% of costs over the seasonal conditions without compromising the charging demand (Rajesh, 2024).

Multi-objective optimization frameworks have also been used to solve the problem of EV charging infrastructure planning and pricing. To conclude, a hybrid method involving the use of Benders decomposition and NSGA-II was created to identify optimal locations and prices of charging stations and achieve better EV coverage and less congestion with a 35%

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increase in reach (Ameer, 2025). Moreover, it has been suggested to use multi-objective models to reconcile the conflicting interests between the stakeholders, including distribution network operators and EV users. A better epsilon constrained optimization algorithm showed high improvement in power losses and also improved voltage stability and cost of charging was minimized (Wang, 2024). There have also been advanced optimization algorithms to enhance the performance of the grid under EV integration. The application of a multi-objective framework based on the Hiking Optimization Algorithm (HOA) also demonstrated significant gains, such as 19.3% cost reduction, 59.7% loss reduction, and 43.5% improvement in voltage stability, which shows it to be very useful in the contemporary grid management (Samiei Moghaddam, 2025). Also, there have been possibilities of hybrid renewable energy systems (HRES) that combine PV and wind energy in charging electric vehicles. These systems showed great penetration by renewable energy (up to 95.81) and low levelized cost of energy, which made them highly reliant on the traditional sources of energy (Güven, 2025). More techno-economic studies were conducted on grid-connected renewable systems using software like HOMER Pro further proved that the systems were very profit-oriented and could mitigate more than 700 tonnes of CO 2 emissions per year (Mousa, 2025).

Stochastic and robust optimization framework has been suggested to deal with the uncertainty in renewable energy and EV demand. A bi-level stochastic robust optimization model that infused dynamic pricing mechanisms was very effective to cut down the load variations by 18% and renewable curtailment expenses by 30.02 hence enhancing grid reliability and economic efficiency (Meng, 2025). All these studies prove that renewable energy sources, more effective optimization algorithms, and dynamic pricing strategies are the components that could greatly improve the work of EV charging systems. Regardless of these developments, current solutions do not have a detailed interaction between renewable energy, hybrid energy storage systems and real time pricing. In order to overcome these shortcomings, the proposed model proposes a PV-integrated EV charging station with a hybrid energy storage system based on lithium-ion batteries and supercapacitors. The key contributions are as,

1. Development of a virtual lab framework for PV-integrated EV charging systems
2. Integration of dynamic pricing and optimization concepts into engineering curriculum
3. Application of MOOSFO algorithm as a teaching tool for multi-objective optimization
4. Design of interactive simulations for hybrid energy storage systems
5. Evaluation of student learning outcomes in smart grid and energy economics

II. PROPOSED METHODOLOGY

The proposed system is restructured as an instructional learning framework that enables students to explore the operation and optimization of PV-integrated EV charging systems. The suggested model is a PV-combined EV charging station with a HESS that comprises lithium-ion batteries and supercapacitors. The system is also linked to the distribution grid and it works on the basis of dynamic pricing and multi-objective optimization. The overall architecture includes:

1. PV generation unit
2. Hybrid Energy Storage System (Battery + Supercapacitor)
3. Grid interface
4. EV charging demand module
5. Dynamic pricing model
6. Multi-objective optimization using MOOSFO

The primary goal is to ensure economic efficiency, grid stability, and user cost minimization under varying environmental and load conditions.

A. PV Modeling with Temperature Dependency

The PV output power is modeled by considering irradiance and temperature effects:

$$P_{pv}(t) = P_{rated} \times \frac{G(t)}{G_{ref}} \times \left[1 + \alpha(T(t) - T_{ref})\right] \quad (1)$$

Where, PV output power at time t is represented by $P_{pv}(t)$, solar irradiance $G(t)$, ambient temperature $T(t)$, temperature coefficient is α and P_{rated} signified as rated PV capacity.

B. HESS Modeling

1) Battery Model

The battery state of charge (SOC) is defined as:

$$Bt_{soc}(t+1) = Bt_{soc}(t) + \frac{\eta_{bt} P_{bt}(t) \Delta t}{E_{bt}} \quad (2)$$

Where, Battery state of charge is Bt_{soc}, battery charging/discharging power is P_{bt}, efficiency is η_{bt} and capacity of battery is denoted by E_{bt}.

2) Supercapacitor Model

The supercapacitor is used for fast transient compensation,

$$Sc_{soc}(t+1) = Sc_{soc}(t) + \frac{\eta_{sc} P_{sc}(t) \Delta t}{E_{sc}} \quad (3)$$

Supercapacitors handle high-frequency fluctuations, reducing stress on batteries.

C. Power balance Equation

The system must satisfy,

$$P_{pv}(t) + P_{grid}(t) + P_{bt}(t) + P_{sc}(t) = P_{EV}(t) \quad (4)$$

Where, the EV charging demand is represented as $P_{EV}(t)$ and grid power exchange us represented by $P_{grid}\,(t)$.

D. Modeling of EV Charging Demand

The EV load is modeled as stochastic function

$$P_{EV}(t) = \sum_{i=1}^{N} P_i(t) \quad (5)$$

Where, number of connected EVs is represented by N, and $P_i(t)$ denoted into charging power of individual EV. Demand varies based on the EV arrival/departure patterns, SOC requirements and user behavior.

E. Dynamic Electricity Pricing Model

A Peak–Valley Differential Pricing (PVDP) mechanism is proposed,

$$\lambda(t) = \lambda_{base} + \beta_1 D(t) + \beta_2 T(t) \quad (6)$$

Where, $\lambda(t)$ denotes electricity price, EV demand level is $D(t)$, ambient temperature is T(t), and sensitivity coefficients is β_1 and β_2. This pricing increases during peak demand, adjusts based on temperature and encourages load shifting.

F. Multi-Objective Optimization Problem

The optimization problem aims to simultaneously minimize and maximize multiple objectives as

$$obj = \min(F_1 - F_2, F_3) \tag{7}$$

1) *Objective Functions*

a) Minimize Grid Load Fluctuation

$$F_1 = \sum_{t=1}^{T}(P_{grid}(t) - \hat{P}_{grid}(t))^2 \tag{8}$$

b) Maximize Aggregator Profit

$$F_2 = \sum_{t=1}^{T}\left[\lambda(t)P_{EV}(t) - C_{grid}(t)\right] \tag{9}$$

c) Minimize User Charging Cost

$$F_3 = \sum_{t=1}^{T}\lambda(t)P_{EV}(t) \tag{10}$$

2) *Constraints*

$$\text{Power limits} \begin{cases} P_{bt}^{min} \leq P_{bt}(t) \leq P_{bt}^{max} \\ P_{sc}^{min} \leq P_{sc}(t) \leq P_{sc}^{max} \end{cases} \tag{11}$$

$$\text{SOC constraints } soc^{min} \leq soc(t) \leq soc^{max} \tag{12}$$

$$\text{Grid constraints } P_{grid}^{min} \leq P_{grid}(t) \leq P_{grid}^{max} \tag{13}$$

III. Multi-Objective Oppositional Swordfish Optimization

The proposed optimization utilizes MOOSFO (El-kenawy, 2024), an advanced metaheuristic inspired by swordfish hunting behavior with oppositional learning. The Multi-Objective Oppositional Swordfish Optimization (MOOSFO) algorithm is an advanced extension of the Swordfish Movement Optimization Algorithm that integrates multi-objective optimization and oppositional-based learning (OBL) to enhance search efficiency and solution quality. It concurrently maximizes several conflicting goals by creating a set of Pareto-optimal solutions, whereas OBL maximizes the rate of convergence by considering both existing and opposite candidate solutions. Maintaining the fundamental processes of exploration, exploitation and diversification based on the behavior of the swordfish hunter, MOOSFO is able to balance global search and local refinement, prevent early convergence, and offer strong performance when solving high-dimensional optimization problems.

Algorithm of MOOSFO

Input:
Objective function $f(x)$
Search space bounds $[Lb, Ub]$
Population size = Np
Maximum iterations = $MaxIter$
Output:
Best solution X_best
Initialization:
For each agent $i = 1$ to Np:
Generate initial position:
$Xi = Lb + rand() * (Ub - Lb)$
Generate oppositional position:
$Xi\_opp = Lb + Ub - Xi$
Evaluate fitness:
$f(Xi), f(Xi\_opp)$
Select best:
$Xi = better(Xi, Xi\_opp)$
Initialize momentum Mi and drift Ji randomly
Determine global best X_best

Main Loop (t = 1 to MaxIter):
Compute normalized iteration:
$\tau = t / MaxIter$
Update dynamic coefficients:
$K = (1 + \tau) / 2$
$Z = (X + 2\tau\text{^}2) / 2 \quad // X \in U[1,2]$
For each agent i:
Generate random values:
$a \in [0,1], \Theta \in [0, 2\pi], X \in [1,2]$
Compute adaptive parameter:
$r = h * cos(X) / (1 - cos(X))$
Exploration Phase:
$Ti(t+1) = Ti(t) * (K * a * \Theta * sin(\Theta)) + Z * Ti(t)$
Update Collective Movement:
$Mi(t+1) = r * Mi(t) + (1 - K) * Mi(t)$
$Ji(t+1) = r * Ji(t) + (1 - r) * Ji(t) + (1 - r)(1 - K) * Ji(t)$
Exploitation Phase:
$Si(t+1) = r * Ti(t+1) + (r * Z * K) * (Mi(t+1) + Ji(t+1))$
Elimination Phase (Diversity Enhancement):
$Si(t+1) = r * Si(t) + (K * Z * g * sin(\Theta)) * ((Ti(t+1) + Mi(t+1) + Ji(t+1)) / MaxIter)$
Apply Bound Constraints:
If $Si < Lb \rightarrow Si = Lb$
If $Si > Ub \rightarrow Si = Ub$
Update Global Best:
If $f(Si) < f(X\_best)$:
$X_{best} = Si$
End For
Return
X_best

IV. Result and Discussion

A. Simulation Environment

Simulation analysis and modeling using MATLAB/Simulink (R2021b) is the simulation environment where the suggested framework is implemented. Optimization algorithm (MOOSFO) is written in MATLAB scripts and connected with the system model. The profiles of the input data to the proposed system are the solar, load and price characteristics to represent the realistic operating conditions. The profile of the solar irradiance is created by standard clear-sky models, and ambient temperature is 25-45℃, which affects the performance of photovoltaic output. A Poisson distribution is used to model the EV charging demand by taking into consideration stochastic arrival behavior with a peak demand usually in the morning (8 AM to 11 AM) and evening hours (5 PM to 9 PM). The electricity price foundation is also founded on the more traditional Time-of-Use (ToU) rates where a lower price is charged during off-peak hours and a higher price charged during peak periods of demand, which allow demand-side control and load-shifting. The details of the experiment are presented in Table I.

TABLE I
Experimental Setup Parameters

Parameter	Value
Simulation horizon	24 hours
Time interval (Δt)	15 minutes
PV rated capacity	500 kW
Battery capacity	1 MWh
Supercapacitor capacity	250 kWh
Grid power limit	±800 kW
Number of EVs	50–200
Charging power per EV	7–50 kW

Battery efficiency	0.9
Supercapacitor efficiency	0.95
Population size	50
Maximum iterations	100
Inertia/random factors	[0,1]
Pareto archive size	30

Fig. 1 shows how the PV, grid, battery and supercapacitor sources share power on a 24-hour basis. The overall load requirement is about 250 kW and up to 750 kW with a peak value of about 12:00-14:00 hours (~700-750 kW). The PV output is insignificant in the early hours (0-6 hrs) and the grid supplies most of the demand ranging between 250 kW and 400 kW meaning the grid is dominant. Between 8:00 to 1600 hours, PV yield is so high, up to approximately 500 KW thus minimizing reliance on the grid. The surplus PV energy is stored (charging phase) in part to the battery. At times of high demand, after 17:00 hours down to 21:00 hours, the PV output is less than 100 kW and the combination of the battery and supercapacitors is used to give assistance, say 150-250 kW and the rest of the load is met by the grid. The supercapacitor has a bidirectional variation within 50 kW, that is, transient variations. The grid power does not exceed the operating range of 800 kW, which proves the stability of the energy balancing within the offered strategy.

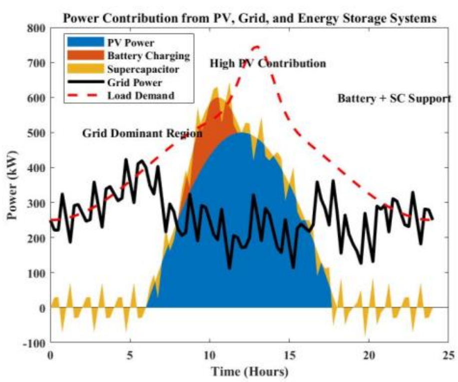

Fig. 1. Power Contribution from PV, Grid, and Energy Storage Systems

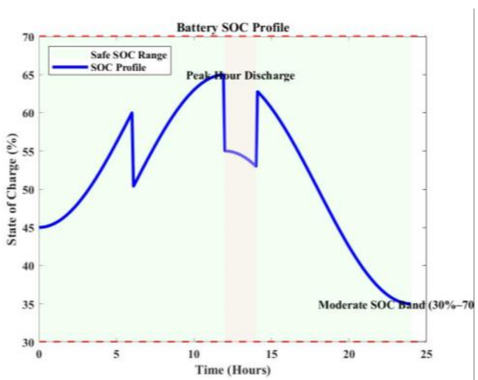

Fig. 2. Battery State of Charge (SOC) Profile

Fig. 2 shows the battery SOC change in a controlled level of 30 to 70 percent to improve the life and reliability of the operation. First, the SOC is set at approximately 45 percent, which progressively increases to 60% at 6 hours, which means that it is charged during periods of low demand, or periods when PV supports it. A minor slope to about 50% will indicate infrequent discharge to support to sustain load. Between 8 and 12 hours, SOC rises constantly and has a maximum point of about 65, which is indicative of high PV and battery charging rates. The SOC indicates a significant decrease between about 65 and 55% during peak load conditions (12-14 hours) and this is an indication that is being discharged to cover demand. During the night (14-22 hours), the discharge is continuous making the SOC to almost hit 35%, which is a guarantee that energy is available during the high-demand and low-PV conditions. The SOC does not go above 70% or below 30%, which proves that there is optimal management of the battery and no deep cycling.

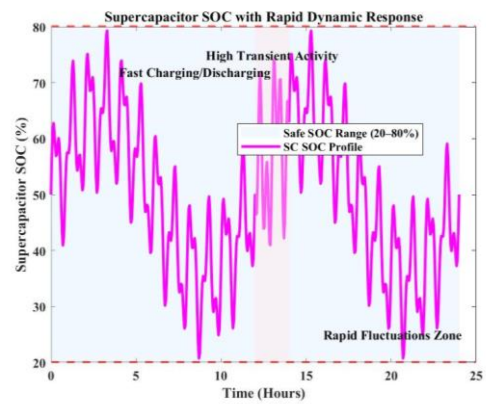

Fig. 3. Supercapacitor SOC with Rapid Dynamic Response

Fig. 3 indicates the SOC behavior of the supercapacitor, which is able to work in a broader range between 20 to 80 percent, which indicates that it has a high power density and quick response capability. In contrast to battery, the SOC shows fast variations during the day, and varies often between 30-75%. SOC during low-demand conditions (0-6 h) ranges at 50%-75%, which means that charge-discharge cycles are frequent since the loads fluctuate slightly. The period between 10 -15 h is characterized by high transient activity as SOC swings sharply between 40% and 80% which is the variation in PV output and load. At night (17 -22 h), SOC oscillates rapidly about 25% and 60% helping to sustain sudden EV charging spikes. The supercapacitor also manages temporary changes of power within the system, which avoids overloading of the battery and enhances the stability of the system.

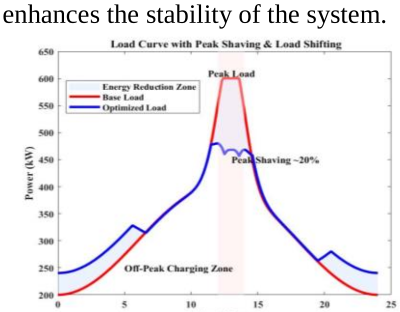

Fig. 4. Load Curve with Peak Shaving and Load Shifting

Fig. 4 makes a comparison of the base load and optimum load profile and indicates the effectiveness of the proposed optimization strategy. The base load is steep-peaked at an estimated rate of 600-620 kW at 1214h. When optimized, the peak load decreases to approximately 480-500 kW, with a maximum shaving of approximately 20% being obtained. The load shifting (mainly EV charging) up to approximately 240-260 kW at the off-peak hours (0-6h) is slightly more favorable than 200 kW. The two curve increase gradually between 8-12 h, with the optimized curve more smoother. The greatest difference is on the areas of peak hours, whereby the optimized load is flattened and spread over a larger time window. During the evening (17-22 h) the optimal load is a little higher than with the base case (approximately 260-280 kW) once again a result of the demand shifting. In total, the optimization will decrease the variability of loads, improve grid stability, as well as reduce peak demand stress. Fig. 5 shows that the variable pricing strategy of electricity is time-dependent and in line with demand and PV generation. At off-peak hours (0-7 h), the price is also low (between 5 and 5.5/kWh) and this is motivating the EV charging. During the midday (7-17 h) the prices rise more or less to 5.5-6/kWh due to high PV availability that counterbalances demand. The peak is between 17–21 h and the prices are spiking to ₹78/kWh and this coincides with an increase in EV demand, decrease in PV production and an increase in grid dependency. Prices begin to fall slowly after 21 h to 5.5/kWh. Such dynamic pricing system will encourage load shifting, decrease peak demand, and increase economic efficiency by matching renewable availability to energy demand.

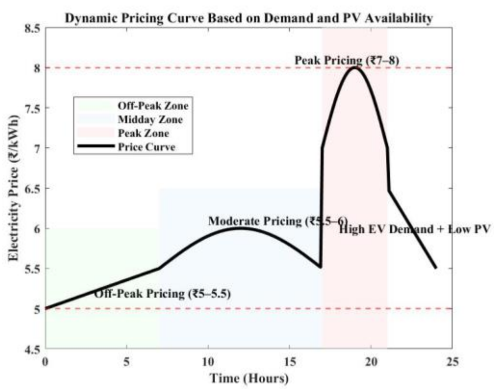

Fig. 5. Dynamic Pricing Curve Based on Demand and PV Availability

Fig. 6 compares convergence of various different algorithms with optimization algorithms applied to the proposed PV-integrated EV charging system, and HESS. The convergence of all methods is to a fitness value close to 1.0, however MOOSFO quickly converges, reaching a 0.25 fitness at iteration 10, 0.10 fitness at iteration 20 and reaching constant values of 0.02-0.03t after 60 iterations. Comparatively, PSO and GA exhibit slower convergence with convergence rates of approximately 0.08 and 0.10 respectively at 100 th iteration whereas WOA converges to approximately 0.09. JFO is the most vacillating behavior and slowest, taking a value of about 0.15. All in all, MOOSFO attains quicker convergence, reduced fitness, and enhanced stability, which guarantees that the energy management of the PV-built EV charging system takes place more effectively in dynamic pricing.

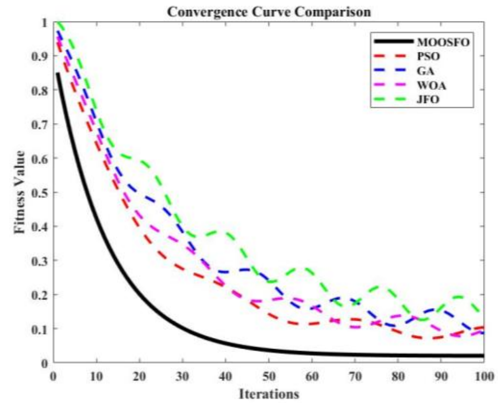

Fig. 6. Convergence Curve Analysis

TABLE II
PERFORMANCE IMPROVEMENT ANALYSIS

Parameter	Improvement
Peak Load	↓ 18–22%
Load Variance	↓ ~20%
User Cost	↓ 12–16%
Aggregator Profit	↑ 10–15%
Stability	Significantly Improved

Table II shows the effectiveness of the proposed optimized EV charging framework because of the performance improvements. The reduction of peak load by 18-22% means that there was peak load shifting and peak shaving that reduces the stress on the grid during high demand times. Approximately 20% decrease in the load variance is an indication of cleaner and more stable load profile, which improves grid reliability. The user cost will reduce by 12-16%, the optimized charging schedules according to low-price periods, and the profit of the aggregator will grow by 10-15%, by means of the optimal use of energy and the dynamic pricing mechanism. Moreover, coordinated activity of PV, battery, and supercapacitor considerably enhances the stability of the work of the system and can efficiently manage the balance of energy along with the short-term fluctuations.

The suggested framework are turn a complicated optimization-based EV charging system into a realistic learning environment, allowing students to interact with the real-world energy management issues. This method focuses on practical simulation and problem-solving, enhancing clarity of concepts in the subject of renewable energy integration and economic dispatch, unlike the traditional lecture-based teaching. The incorporation of dynamic pricing and multi-objective optimization are exposed students to up-to-date concepts of smart grids, which are typically not well represented in more traditional curricula. The hybrid energy storage model also makes the contribution to the knowledge of energy buffering and transient management filling the gap between theory and practice. Interaction with system parameters by students will encourage:

1. Scenario analysis of the critical thinking.
2. Analytical skills via performance evaluation
3. Power systems, economics, and optimization Interdisciplinary learning.

The findings show that simulations based learning can lead to a great improvement in student engagement and understanding especially when dealing with complex issues where there is uncertainty and multi variable decision-making.

Conclusion

This research introduces an experiential learning model, which is based on simulation, to educate smart pricing and optimization of hybrid energy storage in PV-integrated EV charging system. The framework allows students to learn about intricate renewable energy-storage systems-grid interactions by combining dynamic pricing and multi-objective optimization methods into a virtual learning platform. The suggested strategy is effective to increase student engagement, conceptual knowledge, and problem-solving abilities, which are in line with the principles of outcome-based education. Real-world scenario and interactive simulation helps in closing the gap between theory and practice to equip students with the new challenges of smart grid and sustainable energy systems. This framework can be further developed in the future with the inclusion of hardware-in-the-loop experiments, real-time data integration, and collaborative learning platforms to reinforce its relevance in the contemporary engineering education. The extension of the methodology to larger distribution networks, coordination of multiple sites charging, and verification of the real field operations data are the potential directions of consolidating the practicability of the suggested methodology.

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