

Cost-effective and emission-aware dispatch strategy for a smart EV charging parking lot

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ABSTRACT

The growing adoption of electric vehicles (EVs) necessitates intelligent charging strategies to alleviate grid congestion and control rising operational costs. This study introduces an IoT-enabled centralized energy management framework for a PV-BESS-EV integrated smart parking system, leveraging real-time data on carbon emissions, grid pricing, and solar irradiance. A key innovation is its bi-objective optimization model, which simultaneously minimizes both cost and carbon footprint, setting it apart from traditional single-objective approaches. The study evaluates teaching-learning-based optimization (TLBO) and particle swarm optimization (PSO) for addressing the system's nonlinear challenges. Results indicate that TLBO offers faster convergence and greater robustness, leading to improved load flattening, enhanced PV utilization, and stable battery energy storage system (BESS) state of charge (SoC). Overall, the framework provides a scalable solution that effectively balances economic and environmental objectives for modern grid-integrated EV charging systems.

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1. INTRODUCTION

The global shift toward sustainable energy has accelerated electric vehicle (EV) adoption as an alternative to fossil-fuel mobility, with regulators worldwide incentivizing EVs through subsidies, policy frameworks, and expanded charging infrastructure. However, large-scale EV integration creates significant grid challenges, particularly in urban areas where simultaneous charging causes peak demand surges and grid instability [1]. Although advances in photovoltaic technology have improved sustainable power generation [2], exploiting these sources within a smart grid requires intelligent dispatch algorithms to synchronize variable renewable generation with fluctuating EV demand, since uncoordinated charging risks transformer overloading, voltage instability, and increased reliance on high-emission grid power.

A practical solution involves smart EV charging parking lots integrating photovoltaic (PV) panels and battery energy storage systems (BESS), which reduce grid dependency and improve system resilience [3]. Nevertheless, solar variability, shifting EV usage patterns, and dynamic electricity pricing demand intelligent, real-time dispatch algorithms [4]. Incorporating carbon intensity signals into dispatch decisions enables emission-aware scheduling, while cost-conscious optimization ensures financial sustainability under dynamic pricing, necessitating a bi-objective framework that simultaneously minimizes cost and emissions while respecting power balancing, BESS SoC limits, and PV utilization constraints.

Although existing literature addresses EV charging optimization and vehicle-to-grid (V2G) scheduling through mathematical and metaheuristic methods, most works target either cost or emissions independently, and few employ comparative algorithmic analyses for constrained, nonlinear dispatch problems. To address these gaps, this study proposes the cost-effective and emission-aware dispatch strategy (CEEADS) for smart EV parking lots, managed by an IoT-enabled centralized controller monitoring PV generation, BESS status, grid conditions, and EV charging needs. Two metaheuristic algorithms, particle swarm optimization (PSO) and teaching-learning-based optimization (TLBO) are implemented and comparatively evaluated. PSO offers rapid convergence, while TLBO provides strong exploration with fewer parameter requirements. The key contributions include a bi-objective optimization model balancing cost reduction and carbon footprint minimization, supported by real-time IoT sensing of irradiance, grid pricing, and emission data distinguishing CEEADS from conventional single-objective approaches.

2. LITERATURE REVIEW

Researchers have extensively studied integrating EVs with renewable energy and storage technologies, developing ways to optimize charging and discharging schedules that account for both cost and pollution.

2.1. EV charging strategies

EV charging techniques fall into two categories: uncoordinated and coordinated approaches. Early research focused on uncoordinated charging, which frequently causes higher peak load and system instability, while coordinated strategies such as time-of-use scheduling, load flattening, and demand response have shown promise for lowering operating costs and peak demand. Advanced techniques use stochastic modelling of EV arrival/departure times and SoC needs to dynamically optimize charging patterns.

2.1.1. Uncoordinated charging

In uncoordinated charging, EVs draw maximum power immediately upon connection, frequently causing peak demand surges, voltage instability, and elevated power costs; studies show this can raise peak demand by up to 30% in metropolitan networks with high EV adoption [5], [6]. Key consequences include:

- i) Increased peak load: uncoordinated charging (UCC) typically coincides with residential peak hours (6–9 PM), causing rapid aggregate demand spikes.
- ii) Grid instability and component stress: Synchronized peak loads trigger voltage dips and thermal overloading on critical components like service transformers, accelerating ageing and failure.
- iii) High power losses: The elevated peak current draw intensifies ohmic losses (I^2R) across distribution networks.

2.1.2. Coordinated charging

Coordinated or smart charging employs an EMS or aggregator to synchronize EV charging rates with grid capacity and local generation, managing bidirectional power flow. The literature identifies three key strategies [6]:

- i) Time-of-use (TOU) scheduling: Shifts charging to lower-tariff off-peak periods [6], though this static method neglects real-time renewable availability, reducing PV utilization.
- ii) Load flattening approaches: Convex optimization and model predictive control distribute demand evenly for grid stability [7], but lack flexibility for time-varying carbon emission signals.
- iii) Stochastic and probabilistic scheduling: Probabilistic distributions model unpredictable EV arrival and departure patterns, improving system resilience under real-world uncertainty [8].

While these methods address cost or grid stability, they often operate in isolation from environmental objectives. The proposed CEEADS framework overcomes this by integrating real-time IoT-based emission signals with metaheuristic optimization, ensuring a balanced dispatch that minimizes both cost and carbon footprint simultaneously.

2.1.3. Vehicle-to-grid (V2G) enabled charging

V2G enables EVs to discharge power back into the grid or a micro-grid, providing ancillary services like peak shaving and frequency management while increasing renewable energy utilization. Recent research has investigated coordinated V2G scheduling in conjunction with PV-BESS systems, suggesting potential savings in both operating costs and carbon emissions [7]. While many studies focus on TOU-based or unidirectional charging, adding stochastic EV behavior and V2G capabilities has received little attention. There is still a research vacuum in developing real-time adaptive dispatch techniques that include cost, emissions, and EV customer preferences.

2.2. PV-BESS integration

Integrating photovoltaic (PV) systems with battery energy storage systems (BESS) is fundamental to overcoming solar intermittency and ensuring reliable EV charging within the CEEADS framework. This combination buffers surplus solar energy during peak irradiance for dispatch during high-demand or low-solar periods, enhancing renewable self-consumption and reducing charging carbon intensity [9]. The BESS also stabilizes voltage fluctuations and prevents grid overloading by time-shifting solar energy to align with EV arrival patterns [10], while its bidirectional capability enables effective V2G and G2V participation, maximizing economic and environmental benefits [4], [11] and minimizing dependence on high-emission grid power [12]. Despite these established benefits, many previous studies assume deterministic PV output while ignoring real-time changes a gap this work addresses by merging PV-BESS operations with real-time IoT-based monitoring for adaptive, emission-aware dispatch.

2.3. Carbon-aware dispatch

Emission-aware energy management has gained popularity as a result of strict environmental restrictions and the goal for net-zero carbon emissions [13], [14]. Carbon-aware dispatch methods prioritize renewable energy use, reduce fossil fuel consumption, and take into account real-time emissions from grid electricity. According to studies, including emission-aware objectives in EV charging frameworks reduces the overall carbon impact substantially [15].

2.4. Metaheuristic optimization methods

Metaheuristic algorithms such as particle swarm optimization (PSO), genetic algorithm (GA), and teaching-learning-based optimization (TLBO) are widely used to solve complex, non-linear energy management problems. While effective, traditional methods like PSO often suffer from premature convergence and require extensive parameter tuning, limiting reliability in dynamic, real-time environments. This work instead adopts TLBO, which is parameter-less, reduces computational sensitivity, and uses a two-phase search mechanism to avoid the local-optima traps common in GA combining IoT-enabled control, renewable energy, and metaheuristic optimization to produce cost-effective and emission-free EV charging solutions in smart parking lots [16], [17].

3. SYSTEM ARCHITECTURE AND PROBLEM FORMULATION

The suggested cost-effective and emission-aware dispatch strategy (CEEADS) framework outlines an intelligent, IoT-enabled architecture for regulating energy flow in a PV-BESS-EV-based smart parking lot, providing optimal power allocation, cost minimization, and pollution reduction by dynamically coordinating renewable generation, energy storage, and car charging operations. As shown in Figure 1, the architecture has four major subsystems: i) Renewable energy and grid interface: PV arrays supply energy to EVs and BESS. The grid supplements power during low solar generation or peak demand, ensuring reliability and sustainability; ii) Battery energy storage system (BESS): The battery energy storage system (BESS) stores surplus PV energy and releases it as needed. Bidirectional converters ensure excellent state of charge (SoC) and grid stability; iii) Electric vehicle (EV) cluster: Multiple EVs with different SoC, arrival/departure timings, and charging preferences may charge from PV/BESS or discharge via V2G. Wireless charging and IR-based vehicle detection help to automate the procedure; and iv) IoT-enabled energy management system (EMS): The IoT-enabled energy management system (EMS) collects real-time data (e.g., solar, grid price, carbon intensity, EV SoC) and uses particle swarm optimization (PSO) and teaching-learning-based optimization (TLBO) to accomplish cost and emission targets. The integrated IoT layer, which includes ESP32 controllers, cloud platforms (ThingSpeak/Blynk), and RFID access, enables unified monitoring, adaptive decision-making, and efficient resource utilization.

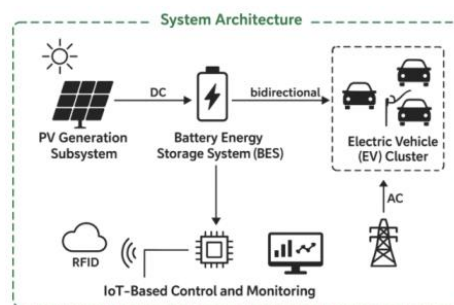


Figure 1. System architecture of the proposed system

3.1. System subsystems

3.1.1. PV generation unit

The PV subsystem is the principal renewable energy source, turning solar irradiance into direct current power for EVs and BESS, with modules coupled in series-parallel and controlled by DC-DC converters using maximum power point tracking (MPPT) for best performance. IoT sensors track sun irradiance and module temperature in real time, and the EMS dynamically adjusts charging and storage based on available PV energy, reducing grid reliance. Surplus energy is charged to the BESS, while PSO and TLBO arrange dispatch during low irradiance or high grid-pricing periods [18]. Real-time visualization on ThingSpeak/Blynk promotes transparency and predictive maintenance, and the EMS's predictive modelling handles seasonal and diurnal irradiation fluctuations for more effective dispatch planning.

3.1.2. Battery energy storage system (BESS)

The BESS acts as an energy buffer, storing excess PV energy for later use. Bidirectional DC-DC converters regulate charging/discharging while maintaining voltage and current balance, with SoC continuously monitored via IoT sensors. The EMS optimizes BESS operation using PSO and TLBO, considering grid pricing, PV output, EV demand, and carbon intensity to minimize cost and emissions, with constraints such as SoC limits, efficiency, and degradation applied to extend battery life. Overall, the BESS enhances load balancing, peak shaving, and renewable utilization, addressing key issues: i) Intermittency: Ensures reliable EV supply despite solar variability; ii) Peak demand: Reduces grid dependence and prevents overloading by discharging during peaks; and iii) Grid stability and cost: Stores energy during off-peak and supplies during peak periods, reducing costs and smoothing the load profile.

3.1.3. Electric vehicle (EV) cluster

The EV cluster includes multiple vehicles with varying SoC, arrival/departure times, and user preferences. Each EV supports G2V and V2G operations for both charging and discharging. IoT sensors monitor EV status, enabling the EMS to schedule charging based on PV output, BESS SoC, grid pricing, and CO₂ intensity. PSO and TLBO optimize schedules considering SoC limits, deadlines, and battery degradation. Wireless charging with IR-based detection and RFID ensures automated and secure operation, while dashboards provide real-time insights into charging, energy use, and cost.

3.1.4. IoT-based control and monitoring

The IoT layer is the digital backbone of the CEEADS platform, enabling real-time sensing, communication, and control across all subsystems. Sensors capture key operating data — PV output, solar irradiance, BESS SoC, EV status, grid pricing, and carbon intensity — transferred to a cloud-based EMS over Wi-Fi, Zigbee, or MQTT. The EMS uses PSO and TLBO to identify the best energy dispatch between PV, BESS, EVs, and the grid, while constantly reacting to environmental and operational changes, with control instructions prioritizing PV energy during high-generation periods and triggering BESS or V2G at low irradiance or peak grid costs [19].

3.2. Power flow model

At any given time, the total power balance is expressed as (1).

$$P_{PV}(t) + P_{BESS}^{dis}(t) + P_{EV}^{dis}(t) + P_{grid}^{import}(t) = P_{EV}^{ch}(t) + P_{BESS}^{ch}(t) + P_{load}(t) + P_{grid}^{export}(t) \quad (1)$$

Where P_{PV} : PV power generation, $P_{BESS}^{ch}/P_{BESS}^{dis}$: charging/discharging power of BESS, P_{EV}^{ch}/P_{EV}^{dis} : charging/discharging power of EVs (in V2G mode), and $P_{grid}^{import}/P_{grid}^{export}$: power imported from/exported to the grid.

3.3. Optimization objectives

A bi-objective optimization problem is presented (2).

- Cost minimization objective

$$\text{Minimize } C_{total} = \sum_t [C_{grid}(t) \cdot P_{grid}^{import}(t) - R_{V2G}(t) \cdot P_{EV}^{dis}(t)] \quad (2)$$

where $C_{grid}(t)$ is the grid electricity price and $R_{V2G}(t)$ is the revenue gained through V2G services.

- Emission minimization objective

$$\text{Minimize } E_{total} = \sum_t [EF_{grid}(t) \cdot P_{grid}^{import}(t) - EF_{PV} \cdot P_{PV}(t)] \quad (3)$$

where $EF_{grid}(t)$ is the time-varying emission factor of grid electricity. These objectives are normalized and combined using a weighted sum approach:

$$\text{Minimize } J = w_1 \cdot \frac{C_{total}}{C_{ref}} + w_2 \cdot \frac{E_{total}}{E_{ref}} \quad (4)$$

where w_1 and w_2 are the weighting factors for the cost and emission objectives, respectively, and C_{ref} and E_{ref} are normalization constants (baseline grid-only case).

3.4. Optimization algorithms

Two metaheuristic methods are utilized for comparative performance evaluation.

- Particle swarm optimization (PSO) utilizes the social behavior of bird flocks to efficiently explore the search space and discover near-optimal dispatch schedules with rapid convergence [20].
- Teaching-learning-based optimization (TLBO) operates in two phases: "teaching phase" (global exploration) and "learning phase" (local exploitation), resulting in strong convergence with fewer control parameters.

Both algorithms are examined under similar simulation settings to provide fair performance comparisons in terms of convergence time, solution stability, and optimal cost-emission trade-offs.

4. OPTIMIZATION FRAMEWORK

The cost-effective and emission-aware dispatch strategy (CEEADS) combines metaheuristic optimization with an IoT-based energy management system (EMS) to enable intelligent energy management in a PV-BESS-EV smart parking system. It primarily targets EV charging scheduling by leveraging photovoltaic (PV) generation and battery energy storage system (BESS) support. The problem is formulated as a bi-objective optimization aimed at minimizing both operating costs (including grid energy consumption and vehicle-to-grid (V2G) interactions) and carbon emissions [21]. Due to the problem's nonlinear and constrained characteristics, particle swarm optimization (PSO) and teaching-learning-based optimization (TLBO) are employed and compared to obtain near-optimal solutions [22].

4.1. Objective function

The basic aim of the optimization challenge is to minimize total operating costs and related carbon emissions while adhering to system and operational restrictions. The weighted objective function J is stated as (5).

$$\text{Minimize } J = w_1 \left(\frac{C_{grid} - R_{V2G}}{C_{ref}} \right) + w_2 \left(\frac{E_{grid}}{E_{ref}} \right) \quad (5)$$

Where C_{grid} = cost of energy purchased from the grid (₹/kWh), R_{V2G} = revenue from vehicle-to-grid (V2G) energy discharge (₹/kWh), E_{grid} = grid energy-related emissions (kg CO₂/kWh), w_1, w_2 = weighting factors for cost and emission objectives, respectively, and C_{ref}, E_{ref} = Normalization constants (baseline grid-only case).

4.2. Constraints

To ensure viable and safe functioning, the optimization process follows a number of technical and operational limitations.

- Power balance constraint

$$P_{PV} + P_{BESS}^{dis} + P_{EV}^{dis} + P_{grid}^{import} = P_{EV}^{ch} + P_{BESS}^{ch} + P_{load} + P_{grid}^{export} \quad (6)$$

Battery state of charge (SoC) limits $SOC_{min} \leq SOC_t \leq SOC_{max}$. EV energy requirement [23].

$$\sum_{t=t_{arr}}^{t_{dep}} P_{EV}^{ch}(t) \cdot \Delta t \geq E_{EV,req} \quad (7)$$

- Grid power directionality:

$$P_{grid}^{imp} \cdot P_{grid}^{exp} = 0 \quad (8)$$

- Power capacity limits

$$|P_{BESS}| \leq P_{BESS,max}, |P_{EV}| \leq P_{EV,max} \quad (9)$$

These limitations work together to provide energy balance, prevent overcharging and discharging, and keep the grid stable.

4.3. Particle swarm optimization (PSO)

Kennedy and Eberhart [20] suggested particle swarm optimization, which is inspired by the social behavior of bird flocks and schooling fish. In PSO, each possible solution to the optimization issue is represented as a "particle" in the search space. The particles travel repeatedly around the solution space, altering their position and velocity based on their personal and swarm experience:

- Personal best (pbest) refers to the optimal solution discovered by an individual particle.
- Global best (gbest): The optimal solution identified by all particles in the swarm.

The location and velocity of each particle are updated as in (10) and (11).

$$v_i^{(t+1)} = w \cdot v_i^{(t)} + c_1 r_1 (pbest_i - x_i^{(t)}) + c_2 r_2 (gbest - x_i^{(t)}) \quad (10)$$

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \quad (11)$$

Where $x_i^{(t)}$ and $v_i^{(t)}$ are the velocity and position of particle i at iteration t ; w is the inertia weight controlling exploration vs. exploitation; c_1, c_2 are cognitive and social acceleration coefficients; and r_1, r_2 are random numbers in $[0,1]$. The PSO effectively explores the search space by combining individual learning and social cooperation, making it ideal for fast convergence in dispatch scheduling problems with numerous constraints including power balancing, PV utilization, and BESS state of charge (SoC).

4.4. Teaching-learning-based optimization (TLBO)

Rao *et al.* [19] presented teaching-learning-based optimization, which is inspired by the teaching and learning processes in the classroom. It functions in two major stages.

- Teaching phase (global exploration)

The "teacher" is the most effective solution in the population. Other students (candidate solutions) advance their knowledge by getting closer to the teacher's solution, imitating knowledge transfer. The update rule is (12).

$$X_{new} = X_{old} + r(X_{teacher} - T_F \cdot X_{mean}) \quad (12)$$

Where X_{old} and X_{new} are the learner's current and updated positions; $X_{teacher}$ is the teacher's position; X_{mean} is the mean of all learners' positions; T_F is the teaching factor (usually 1 or 2); and r is a random number in $[0,1]$.

- Learning phase (local exploitation)

Learners communicate with one another to share information and improve local search skills. Each learner modifies its solution based on a comparison with another randomly selected student, as expressed in (13).

$$X_{new}^i = X_{old}^i + r(X_i - X_j), \text{ if } f(X_i) < f(X_j) \quad (13)$$

TLBO does not require algorithm-specific parameters like PSO (e.g., inertia weight and acceleration coefficients), making it easier to build and more resilient for limited optimization issues like EV charging dispatch.

5. SIMULATION RESULT

The performance of the proposed cost-effective and emission-aware dispatch strategy (CEEADS) was assessed using MATLAB/Simulink simulations under realistic operating conditions, comparing two metaheuristic algorithms PSO and TLBO for energy dispatch in a PV-BESS-EV smart parking lot, focusing on operational cost, emissions, and system stability.

5.1. Simulation setup

The simulation ran on an Intel Core i5 CPU with MATLAB R2021a. The PV generation and grid pricing profiles were estimated using a typical 24-hour urban demand and irradiation pattern. Grid energy

emission factors were considered time-varying to match real-time carbon intensity. Table 1 summarizes the key system parameters. Both PSO and TLBO were run 30 times independently to verify robustness and convergence consistency. To achieve fair comparisons, each algorithm employed similar population sizes and iteration limitations [24].

5.2. Robustness and convergence analysis

Figure 2 shows a box plot comparing the weighted fitness function for PSO and TLBO. The TLBO method has lower mean and standard deviation values, indicating greater resilience and consistency over repeated runs [25]. Figure 3 shows the convergence characteristics. TLBO achieves faster convergence and stabilizes earlier than PSO because of its adaptive teacher-learner phase structure, which encourages guided exploration and appropriate use of the search space.

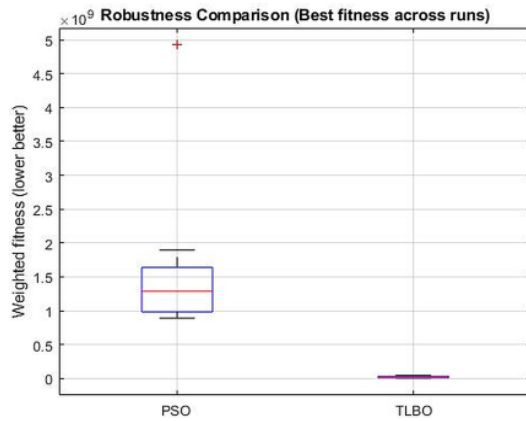


Figure 2. Robustness comparison of PSO and TLBO (box plot)

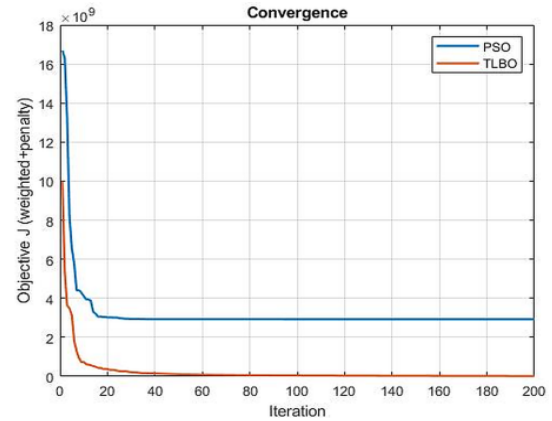


Figure 3. Convergence curves for PSO and TLBO algorithms

5.3. Power dispatch and grid interaction

Figures 4 and 5 illustrate power distribution for PSO and TLBO, demonstrating that TLBO enhances PV utilization and decreases grid dependence through improved BESS coordination. Figure 6 shows the state of charge (SoC) trajectories, where TLBO enables smoother transitions and reduces battery stress. Figures 7 and 8 depict load patterns, with TLBO achieving a more uniform load curve. Figure 9 confirms that TLBO more effectively flattens demand and minimizes peak surges by optimizing PV utilization and BESS discharge.

5.4. Comparative performance metrics

Table 2 provides a quantitative summary of the two algorithms' comparative performance. The findings show that TLBO regularly beats PSO on all assessment measures, resulting in lower operational costs, lower emissions, and better renewable energy utilization. The TLBO algorithm effectively adapts to variable renewable generation and dynamic grid pricing through a deterministic update mechanism that prevents premature convergence and ensures consistent results [11]. The CEEADS framework, combined with IoT monitoring and TLBO optimization, delivers an efficient and balanced solution for smart EV charging [19]: increased PV utilization reduces grid dependency and emissions, while robust convergence guarantees reliable real-time operation, presenting a scalable and sustainable approach for next-generation EV infrastructure [21], [23].

Table 1. System parameters used for simulation

Parameter	Symbol	Value
PV rated power	$P_{PV,max}$	25 kW
BESS capacity	E_{BESS}	50 kWh
BESS efficiency	η_{BESS}	95%
EV cluster size	N_{EV}	10
Grid maximum power	$P_{grid,max}$	20 kW
Simulation duration	T	24 hours
Optimization algorithms	-	PSO and TLBO

Table 2. Comparative performance evaluation of PSO and TLBO

Metric	PSO	TLBO	Improvement (%)
Total operational cost (₹)	1520	1385	8.9
Total carbon emissions (kg CO ₂)	47.2	42.8	9.3
PV utilization (%)	78.4	86.7	10.6
Mean fitness value	0.284	0.257	9.5
Standard deviation	0.041	0.023	-43.9

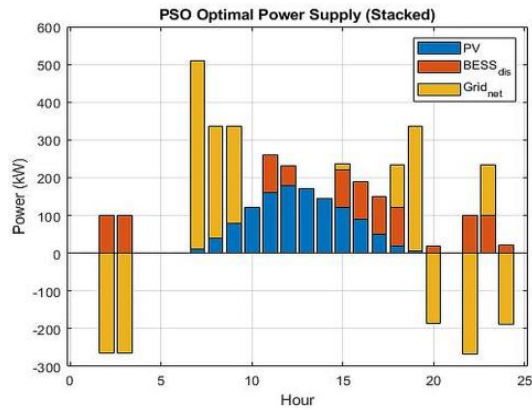


Figure 4. PSO-based optimal power supply (stacked bar)

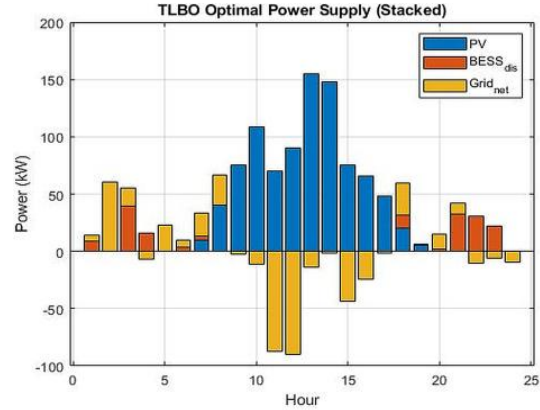


Figure 5. TLBO-based optimal power supply (stacked bar)

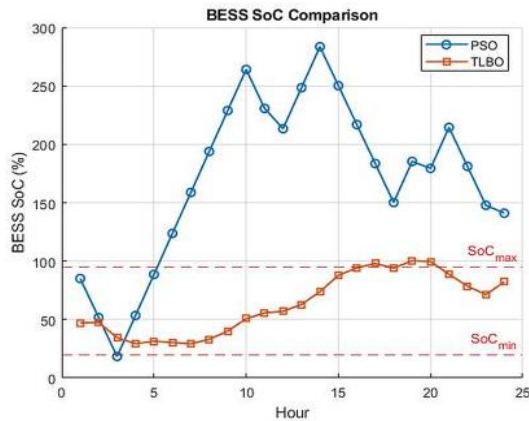


Figure 6. Comparison of BESS SoC for PSO and TLBO

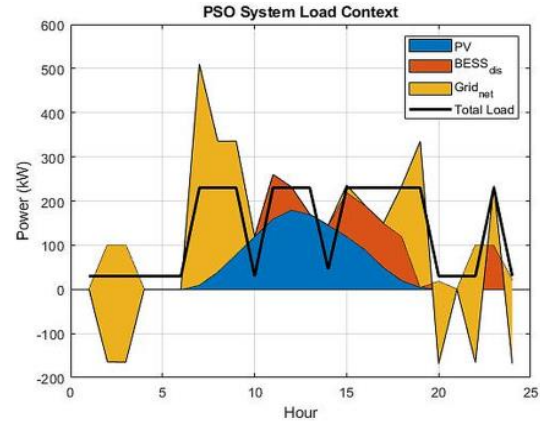


Figure 7. PSO system load context (stacked area + total load)

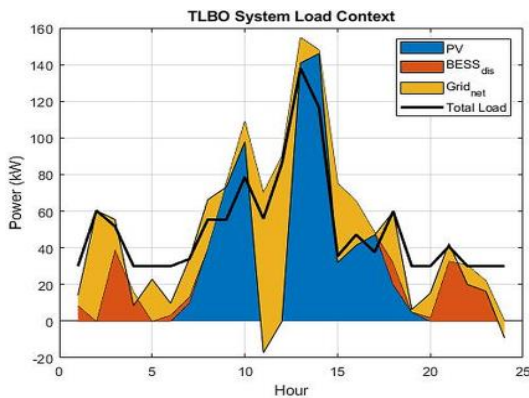


Figure 8. TLBO system load context (stacked area + total load)

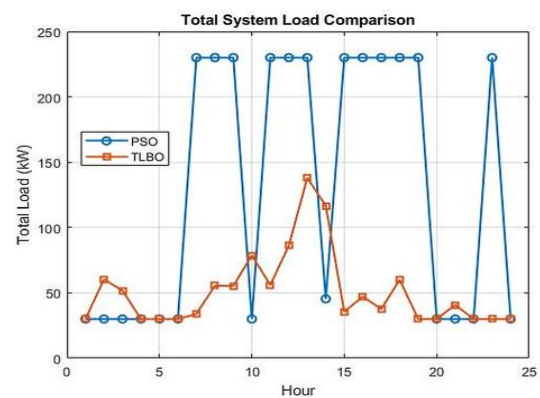


Figure 9. Total system load comparison (PSO vs. TLBO)

6. CONCLUSION

This study developed and validated the cost-effective and emission-aware dispatch strategy (CEEADS) for a smart EV parking system integrating photovoltaic (PV) generation and a battery energy storage system (BESS) under IoT-based control using MATLAB. The bi-objective optimization model enhances both economic and environmental performance, achieving an 8.9% reduction in operating costs (from ₹1520 to ₹1385) and a 9.3% decrease in carbon emissions compared to uncoordinated charging methods. The

teaching-learning-based optimization (TLBO) algorithm outperformed particle swarm optimization (PSO), delivering a 9.5% improvement in mean fitness and a 43.9% reduction in standard deviation, reflecting greater reliability and higher PV utilization reaching up to 86.7%.

The study's novelty lies in its dynamic adaptation to real-time grid conditions via IoT-integrated data, distinguishing it from traditional static models. This framework significantly enhances renewable energy usage while reducing grid dependency. Future research could explore incorporating AI-driven solar forecasting and hardware-in-the-loop (HIL) validation to support large-scale deployment.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [OKR], upon reasonable request.

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