

Smart Energy Management Using Vehicle-to-Home, Photovoltaics, and AI Optimization Applications in Residential Systems and Cloud Datacenters

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Abstract: The effective integration of photovoltaic (PV) generation with Vehicle-to-Home (V2H) technology is crucial for sustainable smart homes but poses a significant optimization challenge due to the complex, constrained, and seasonally-variable nature of the energy scheduling problem. Current optimization methods, including standard metaheuristics, often fail to adapt to the drastic shifts in PV availability between summer and winter, leading to suboptimal year-round performance. To address this critical research gap in seasonal algorithm adaptation, this paper introduces two novel metaheuristic algorithms: Gradient Particle Swarm Optimization (GPSO), which enhances convergence in high-PV conditions via gradient-guided search, and the Geese V-Formation Algorithm (GVFA), a bio-inspired cooperative optimizer designed for robustness during low-generation periods. Using a year of real-world data from Iraq within an integrated V2H-PV-battery model, we demonstrate that algorithm performance is intrinsically seasonal: GPSO reduces daily energy costs by up to 89% in summer, while GVFA achieves a 46.5% reduction in winter compared to rule-based baselines. This key finding, that no single algorithm provides year-round optimality, establishes adaptive, season-aware algorithm selection as an essential paradigm for next-generation energy management systems. The framework is extended with cybersecurity measures and its scalability to cloud datacenters is demonstrated, offering both algorithmic innovation and practical deployment guidance.

Keywords: Smart Energy Management; Renewable-Aware Scheduling; AI Optimization Algorithms; Vehicle-to-Home (V2H); Seasonal Adaptation; Cloud Datacenter.

1. Introduction

The global transition towards sustainable energy systems has accelerated the adoption of residential photovoltaic (PV) panels and electric vehicles (EVs) with Vehicle-to-Home (V2H) capability. This integration transforms homes into prosumer nodes that can generate, store, and feed electricity back to the grid. However, managing these interconnected resources, PV, stationary batteries, and bidirectional EV batteries, creates a complex, constrained optimization problem. The objective is to minimize cost or maximize self-consumption while respecting hardware limits and user constraints, such as EV trip readiness [1, 2]. This challenge is exacerbated by the high intermittency and dramatic seasonal variation of solar energy, creating distinctly different operational regimes between summer and winter that most optimization approaches fail to address effectively.

Metaheuristic algorithms, particularly Particle Swarm Optimization (PSO), have been widely applied to Home Energy Management Systems (HEMS) due to their flexibility in handling non-linear problems [3, 4]. Yet, a synthesis of the literature reveals three persistent limitations: (1) Standard algorithms like PSO struggle with the hard constraints of HEMS (e.g., state-of-charge limits), often converging slowly or yielding infeasible schedules [5, 6]. (2) Perhaps most critically, existing methods exhibit "seasonal myopia", they are typically tuned and evaluated under static or averaged conditions, ignoring the profound impact of seasonal PV variation on the problem landscape [7, 8]. Lack of study systematically benchmarks algorithm performance across seasons or provides a framework for season-aware selection. (3) Many approaches optimize PV, battery, and V2H resources in isolation, missing the synergistic benefits of integrated coordination [9, 10].

This work is motivated by the hypothesis that algorithm performance in PV-V2H systems is intrinsically seasonal, and therefore, a single year-round optimizer is fundamentally suboptimal. To test this and overcome the stated limitations, we propose two novel, complementary algorithms. GPSO hybridizes standard PSO with gradient-descent principles to navigate constraint boundaries efficiently, making it suitable for the smoother cost landscapes of high-PV seasons. Conversely, the GVFA is a new bio-inspired metaheuristic that employs a leader-follower cooperative mechanism to maintain solution diversity and avoid local optima, proving robust during the challenging low-PV winter periods.

The primary contribution of this paper is not merely the proposal of two new algorithms, but the empirical demonstration and validation of seasonal algorithm dependence as a core principle for HEMS design. Through extensive simulation using a full year of real-world Iraqi data, we show that GPSO and GVFA each excel in different seasons, with performance disparities exceeding 40% in some cases. This evidence challenges the prevailing one-algorithm-fits-all approach and establishes that adaptive, season-aware optimization strategies are essential for achieving true annual optimality in renewable-powered smart homes and scalable infrastructures like cloud datacenters.

This paper makes the following specific contributions to address the identified research gaps.

1. Proposal of Two Novel Optimization Algorithms

▪ Gradient Particle Swarm Optimization (GPSO)

We introduce a modified PSO variant that integrates gradient information into the velocity update process. This hybrid approach accelerates convergence in constrained, non-convex energy scheduling problems by combining global swarm intelligence with efficient local gradient descent.

▪ Geese V-Formation Algorithm (GVFA)

We propose a new bio-inspired metaheuristic that simulates the cooperative aerodynamic formation of migratory geese. The algorithm employs a leader-follower dynamic to enhance solution diversity, avoid local optima, and efficiently balance exploration and exploitation in dynamic search spaces.

2. Development of an Integrated V2H-PV-Battery HEMS Model

We develop a comprehensive home energy management model that unifies photovoltaic generation, fixed battery storage, and electric vehicle (V2H) operation.

The model is formulated as a constrained optimization problem with real-time energy balance, state-of-charge limits, and EV trip-readiness constraints.

3. Comprehensive Seasonal Performance Validation

We conduct extensive simulations using one year of real-world solar and load data from Iraq, evaluating performance across both summer and winter scenarios. Our results reveal the critical insight that algorithm performance is season-dependent, GPSO excels under high-PV summer conditions, while GVFA outperforms during low-PV winter periods, demonstrating that no single algorithm provides year-round optimal performance.

4. Cybersecurity-Aware Optimization Framework

We integrate secure communication protocols and anomaly detection within the optimization loop, ensuring that scheduling commands remain resilient against cyber threats, a critical consideration for V2H and grid-interactive systems.

5. Scalability Analysis for Cloud Datacenters

We outline how the proposed algorithms and scheduling framework can be adapted for large-scale, renewable-powered infrastructures such as cloud computing datacenters, addressing similar challenges of intermittent supply and dynamic demand.

The structure of the paper is as follows. Section 2 Related Work: Addresses the previous research on home energy management integration of renewable energy optimization techniques and secure communication. Section 3 describes the experiment and methods: the system model is presented along with the optimization problem formulation. Section 4 shows the results and discussion: The optimization algorithms and their application to the scheduling of energy flows between the photovoltaic system battery, electric vehicle, and grid are described. The results are presented with a discussion of the outcomes under various seasonal conditions. Section 6 presented the conclusion: The paper conclusion and potential future work are outlined.



Fig. 1. Smart Energy management using V2H, PV, and AI optimization.

2. Related work

Beyond energy storage, Demand-Side Management (DSM) strategies play an important role in optimizing energy use in homes. Techniques like load curtailment and load shifting help households reduce electricity consumption during peak hours or move energy-heavy tasks to off-peak times. This approach lowers energy costs and eases stress on the grid. Furthermore, these approaches are paired with Automated Demand Response (ADR) method thus, the homes can adjust their energy use based on real-time grid conditions and price changes. Next to, energy efficiency, communication and cybersecurity are becoming more crucial in smart energy systems. Further, using IoT-enabled smart meters, cloud-based energy management platforms, and real-time energy monitoring systems has created vulnerabilities that bad actors could exploit.

Cyberattacks, is unauthorized access, data breaches, and network attacks, can cause significant damage to residential energy infrastructure and may lead to energy theft, system failures, or widespread power outages. Smart power systems must be secure and reliable through encrypted communication systems, secure authentication procedures, and AI-based anomaly detection to prevent cyberattacks while achieving optimal energy performance. This research investigates the potential of combining smart energy optimization methods, secure communication protocols, and AI-based automation to create a cost-effective, cyber-secure, and efficient residential energy system. Moreover, analysis of photovoltaic power-generation dynamics, battery storage optimization, electric vehicle charging schedules, demand-side management, and secure communication infrastructure, this study seeks to establish a comprehensive framework for smart home energy management, improving grid stability, reducing energy costs, and enhancing cybersecurity. Electric grid today is fast decentralizing and seeing more reliance on renewable energy. Distributed resources like PV panels and V2H systems have become a key tool for residential energy efficiency with home energy management (HEM) systems. In such grids, EVs are not only mobility aids but also distributed energy storage units that can provide energy during peak demand hours.

However, the natural intermittency of PV generation and transient energy patterns in homes necessitate advanced control and optimization techniques. Advanced optimization techniques like GPSO and nature-inspired algorithms GVFA have been explored in recent studies with the aim of tuning energy management policies as well as reducing operational expenses while providing a safe energy supply [10, 11]. Completed by enhancing operational efficiency to optimize performance for both renewable energy system and traditional power management system [12]. Photovoltaic panels are one of the most promising renewable energy technologies for homes. Their direct conversion of solar radiation into electricity, however, comes with challenges such as intermittency and variability in output. Studies have explored different strategies including maximum power point tracking (MPPT) and energy storage integration, to improve the reliability and economics of PV systems [13, 14]. In a HEM framework, PV systems are not used in isolation but are combined with energy storage including EV batteries through V2H to ensure that excess generation can be stored and later used during periods of low irradiance [15].

Particle swarm optimization (PSO) has been widely adopted in power and energy applications due to its simplicity and rapid convergence. A recent enhancement is the introduction of gradient information into the PSO framework GPSO to improve the search for global optima in non-convex energy management problems [16]. GPSO has been applied

successfully to optimize load scheduling and energy storage dispatch in HEM systems by tuning control parameters and reducing system losses [17, 18]. The algorithm iteratively updates candidate solutions (particles) using both the standard PSO velocity update and gradient-based adjustments to accelerate convergence in local search regions. Inspired by the efficient aerodynamic formation of migratory geese, the geese V-formation algorithm has recently emerged as a promising optimization tool. In this approach, prospective solutions simulate the cooperative breakout conduct of geese to balance investigation and exploitation in the solution area [19].

Initial examinations demonstrate that this approach can be sufficient in purifying scheduling decisions in HEM systems by leveraging coordinated smart to escape local optimization [20]. Furthermore, in its earlier stages, the geese V-formation algorithm demonstrates potential as an option or complementary technique to GPSO for complicated multi-objective energy management issues. The GPSO and GVFA algorithms are designed for HEMS, hold assurance for renewable-aware scheduling in cloud data centers. For instance, GPSO's gradient-based updates could optimize server workload distribution based on real-time renewable availability, while GVFA's cooperative search might allocate tasks across geographically distributed datacenters to leverage regional solar/wind surpluses. Hybrid approaches combining these methods with reinforcement learning could further address scalability challenges in datacenters, where thousands of servers and stringent quality of services (QoS) requirements demand robust solutions. When both GPSO and the geese V-formation algorithm are applied to HEM design, the overall system can benefit from robust scheduling, optimal sizing of storage including V2H and fixed battery systems, and improved cost-efficiency. For example, by employing these algorithms the home system can dynamically adjust energy flows between PV, V2H, and the grid, ensuring that power is delivered when needed while reducing peak demand charges [21, 22]. Hybrid optimization approaches that combine the global exploration strength of GPSO with the local refinement abilities of geese formation algorithms have demonstrated improved performance over classical methods [23].

An often overlooked but critical component in advanced HEM systems is the low-latency communication channels. There should be reliable low-latency communication networks to facilitate real-time data acquisition from PV sensors, EV battery management systems, and smart meters. The data are input into the optimization algorithms and control methods to allow adaptive and decentralized energy management [24]. Subsequent work emphasizes the requirement for incorporating Internet of Things (IoT) protocols and the advanced wireless networks (e.g., 5G) in HEM systems to allow robust coordination among distributed energy resources [25]. Besides, secure communication techniques are being implemented to keep control commands and sensor data from tampering with integrity, particularly in V2H scenarios where the EV will be acting as a load and storage [26]. Even though the use of GPSO and the geese V-formation algorithm seems promising, some challenges still exist. Fluctuation of household demand and uncertainty of renewable generation call for optimization techniques to not only be correct but also adaptive. In addition, delays or loss of communication in underlying networks can impact real-time control and optimization.

2.1. Research Gap and Rationale for Novel Algorithm Development

Despite extensive research on optimization for home energy management, significant gaps remain that motivate our development of GPSO and GVFA.

- ***Gap 1#: Inefficient Constraint Handling in Standard Metaheuristics***

Conventional optimization algorithms struggle with the hard constraints of residential energy systems, particularly the electric vehicle trip readiness requirement and battery state-of-charge limits. These constraints create non-convex feasible regions where standard algorithms either converge slowly or produce infeasible solutions [10-12].

- ***Gap 2#: Lack of Seasonal Adaptation Mechanisms***

Previous studies typically evaluate algorithms under constant or averaged conditions, ignoring the dramatic seasonal variation in photovoltaic generation. No existing work systematically compares algorithm performance across different seasonal scenarios or provides guidance on season-aware algorithm selection [13-15].

- ***Gap 3#: Separated vs. Integrated Optimization***

Most approaches optimize photovoltaic utilization, battery scheduling, and vehicle-to-home operation independently, missing the synergistic benefits achievable through coordinated control [16-18].

- ***The Existing Paper Response to These Gaps***

We developed Gradient Particle Swarm Optimization (GPSO) specifically to address Gap 1 through gradient-guided navigation of constraint boundaries. We designed the Geese V-Formation Algorithm (GVFA) to maintain robustness across varying conditions (Gap 2) through its cooperative search mechanism inspired by migratory bird formations. Both algorithms are applied to our integrated system model (Gap 3) to maximize coordination benefits. This targeted approach to algorithm development, addressing specific, identified limitations in current methods, represents the core contribution and rationale for our work.

3. Experiment and Methods

The increasing demand for electricity and the modifications concerning sustainable energy solutions have led to the evolution of smart HEMS. These systems combine renewable energy sources, advanced battery storage, and EVs to optimize residential energy consumption. Effective development of energy streams, optimization approaches, and system restrictions are critical for ensuring efficient energy management, cost decrease.

3.1 Data Collection and Preprocessing

A comprehensive dataset was collected from September 2024 to August 2025 from the photovoltaic monitoring system at Al-Maarif University College, Ramadi, Iraq. This dataset includes hourly measurements of solar radiation, environmental parameters (temperature, humidity), and energy system variables (load, battery state-of-charge, EV charging). The data preprocessing pipeline implemented the following steps. Temporal Features; Date, hour of day, day of year, month, season, synchronization of all time-series data to consistent hourly intervals. Meteorological Features; Ambient temperature (°C), relative humidity (%). Solar Parameters; Solar irradiance (W/m^2), PV generation output (kW). Energy system parameters; load demand (kW), battery charge/discharge rates (kW), electric vehicle (EV) charging/discharging (kW), net grid import/export (kW), battery State-of-Charge (SoC) in kWh and percentage, EV SoC in kWh and percentage. A representative sample of the collected data structure is shown in Fig. 2, demonstrating the complexity and comprehensiveness of the dataset.

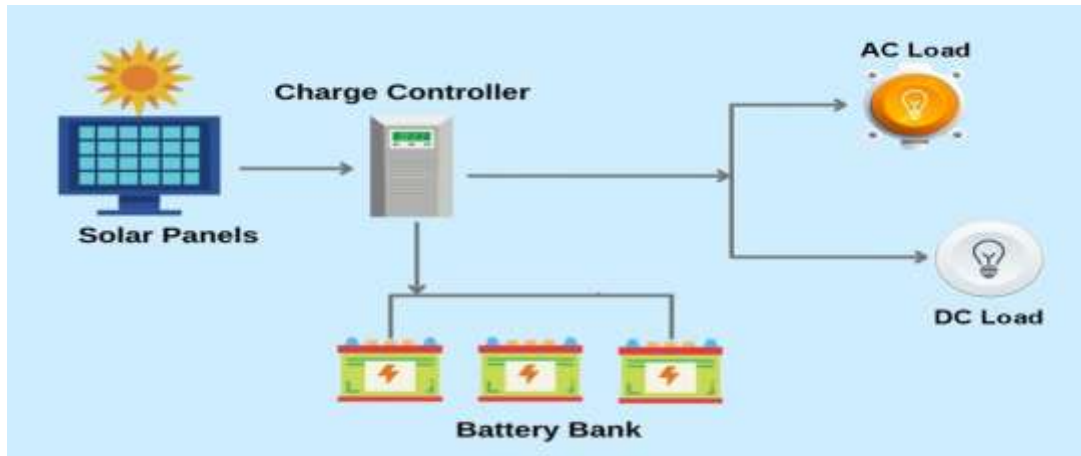


Fig. 2. Small photovoltaic power generation system.

3.1.1 Data Pre-Processing Involved Several Critical Steps

The research paper experiments utilized the, missing value handling; linear interpolation for gaps less than 3 hours; seasonal averaging for longer gaps. Outlier detection and treatment using interquartile range (IQR) method to identify and correct anomalous readings. Feature engineering; creation of derived features including solar altitude angle, clearness index, and seasonal indicators. Normalization; Min-max scaling to range [0,1] for neural network compatibility. Temporal splitting; chronological division into training (70%, Sep 2024-May 2025), validation (15%, June 2025), and testing (15%, July-Aug 2025) sets as show in Fig. 3. The models are set up with an AMD Radeon (TM) R9 370 GPU, 16GB of RAM, and an 11th Gen Intel(R) Core (TM) i5-11400F@2.60GHz running Windows 11. CUDA/CuDNN requirements for GPU acceleration are included in the Keras API, which is integrated with the TensorFlow version 2.12 backend and is used to configure the models in Python 3.11.5.



Fig. 3. Enhancing energy distribution and efficiency.

The mathematical formulation of the optimization problem aimed at minimizing total electricity costs while ensuring energy balance, maintaining state-of-charge limits, and meeting EV trip readiness constraints. To achieve this, advanced optimization algorithms such as GPSO and GVFA are implemented to enhance energy distribution and system efficiency. The optimization problem is formulated to minimize total electricity costs as Equation (1).

$$C = \sum_{t=1}^T [P_{\text{grid}}^t \cdot E_{\text{grid}}^t - S_{\text{grid}}^t \cdot E_{\text{sell}}^t] \quad (1)$$

Where:

- P_{grid}^t : Price of grid electricity at time t.
- E_{grid}^t : Energy purchased from the grid at time t.
- S_{grid}^t : Price of energy sold back to the grid at time t.
- E_{sell}^t : Energy sold to the grid at time t.

Limitations

Controllable energy storage device is modeled for the EV in V2H mode in addition to the fixed battery. Limitations guarantee that the EV participates in household energy balancing while maintaining the minimal state of charge necessary for mobility requirements. When PV surplus or inexpensive grid energy is available the optimization plans V2H charging when grid costs are high or PV is insufficient it plans V2H discharging. For an energy management system to be effective it must follow stringent operational guidelines to guarantee stability effectiveness and dependability. Equations (2, 3, 4, and 5) demonstrate how to model energy decisions in real time while maintaining system reliability under various circumstances.

1. Energy Balance

$$E_{\text{PV}}^t + E_{\text{ESS}}^t + E_{\text{EV}}^t + E_{\text{grid}}^t - E_{\text{sell}}^t = E_{\text{load}}^t \quad (2)$$

2. State-of-Charge Limits

$$\text{SOC}_{\text{ESS}}^{\min} \leq \text{SOC}_{\text{ESS}}^t \leq \text{SOC}_{\text{ESS}}^{\max} \quad (3)$$

$$\text{SOC}_{\text{EV}}^{\min} \leq \text{SOC}_{\text{EV}}^t \leq \text{SOC}_{\text{EV}}^{\max} \quad (4)$$

3. EV Trip Readiness

$$\text{SOC}_{\text{EV}}^t \geq E_{\text{trip}} \quad (5)$$

3.2 Optimization Algorithms

The optimization of these followings tasks are focuses on achieving minimizing the complete power cost while improving system self-sufficiency. The choice variables include the charging and discharging schedules of the battery, charging and discharging schedules of the EV in V2H mode, and the amount of energy purchased from or bought to the grid at every time step. The objective function ranges to decrease fee by using maximizing the usage of PV generation and stored electricity at the same time as respecting operational constraints together with battery

and EV nation-of-rate limits, EV trip readiness, and strength balance requirements. GPSO and GVFA determine the reasonable forward of those electricity flows.

3.2.1 Gradient Particle Swarm Optimization (GPSO)

GPSO refines traditional PSO with gradient-based updates for faster convergence as Equation (6).

$$\begin{aligned} v_i^{t+1} &= \omega v_i^t + c_1 r_1 (p_i - x_i^t) + c_2 r_2 (g - x_i^t) - \eta \nabla f(x_i^t) \\ x_i^{t+1} &= x_i^t + v_i^{t+1} \end{aligned} \quad (6)$$

3.2.2 Geese V-Formation Algorithm (GVFA)

GVFA mimics geese flying in a V-formation as Equation (7).

$$x_{\text{follower}}^{t+1} = x_{\text{follower}}^t + v_{\text{lead}}^t - \alpha \cdot d(x_{\text{follower}}^t, x_{\text{lead}}^t) \quad (7)$$

Furthermore, Fig. 4 illustrate the integration, optimization, and security aspects of HEMS. Provides an overview of smart energy management, emphasizing real-time optimization algorithms, AI-driven automation, and IoT-based monitoring to improve energy efficiency and grid stability. Fig. 5 develops on the cycle of smart home energy management, outlining the process of integrating renewable sources, AI automation, IoT monitoring, energy optimization, security measures, and grid resilience improvements.

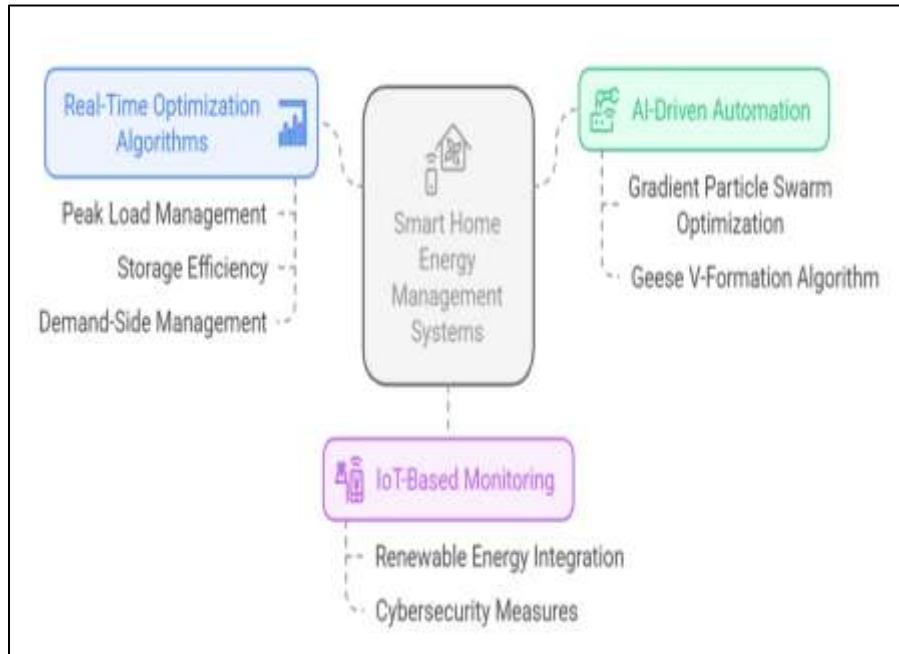


Fig. 4. Integration and optimization for modern residential energy management.



Fig. 5. Cycle of smart home energy management.

In addition, Fig. 6 describes the computational workflow of the GPSO and GVFA algorithms, highlighting their role in optimizing energy distribution. GPSO initiates optimization through velocity updates and gradient-based refinements, while GVFA enhances the process by leveraging the V-formation pattern, improving efficiency. Fig. 7 extends the framework by introducing a communication and security module, ensuring encrypted data transmission and resilience against cybersecurity threats.

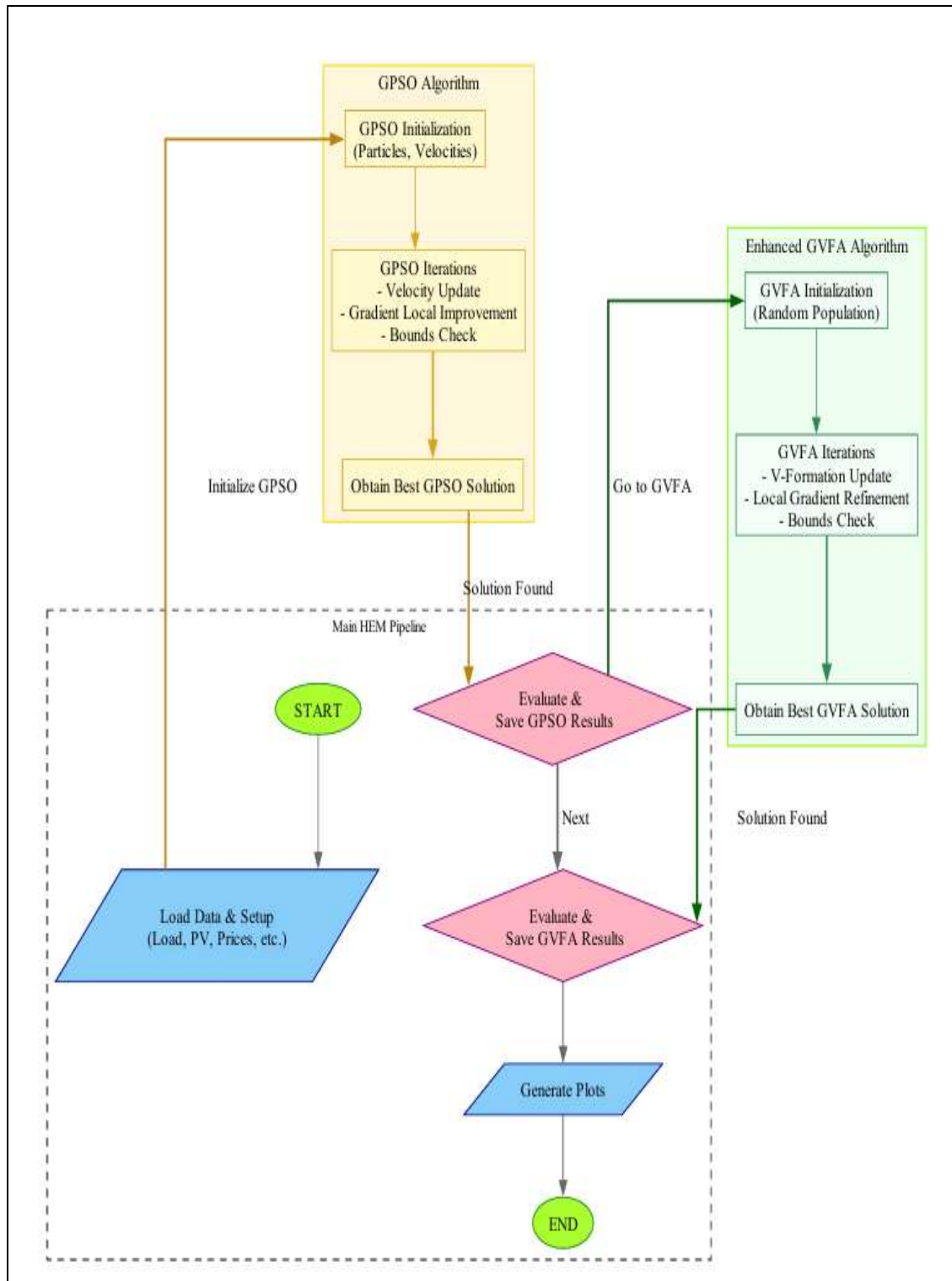


Fig. 6. GPSO & GVFA algorithms computational workflow.

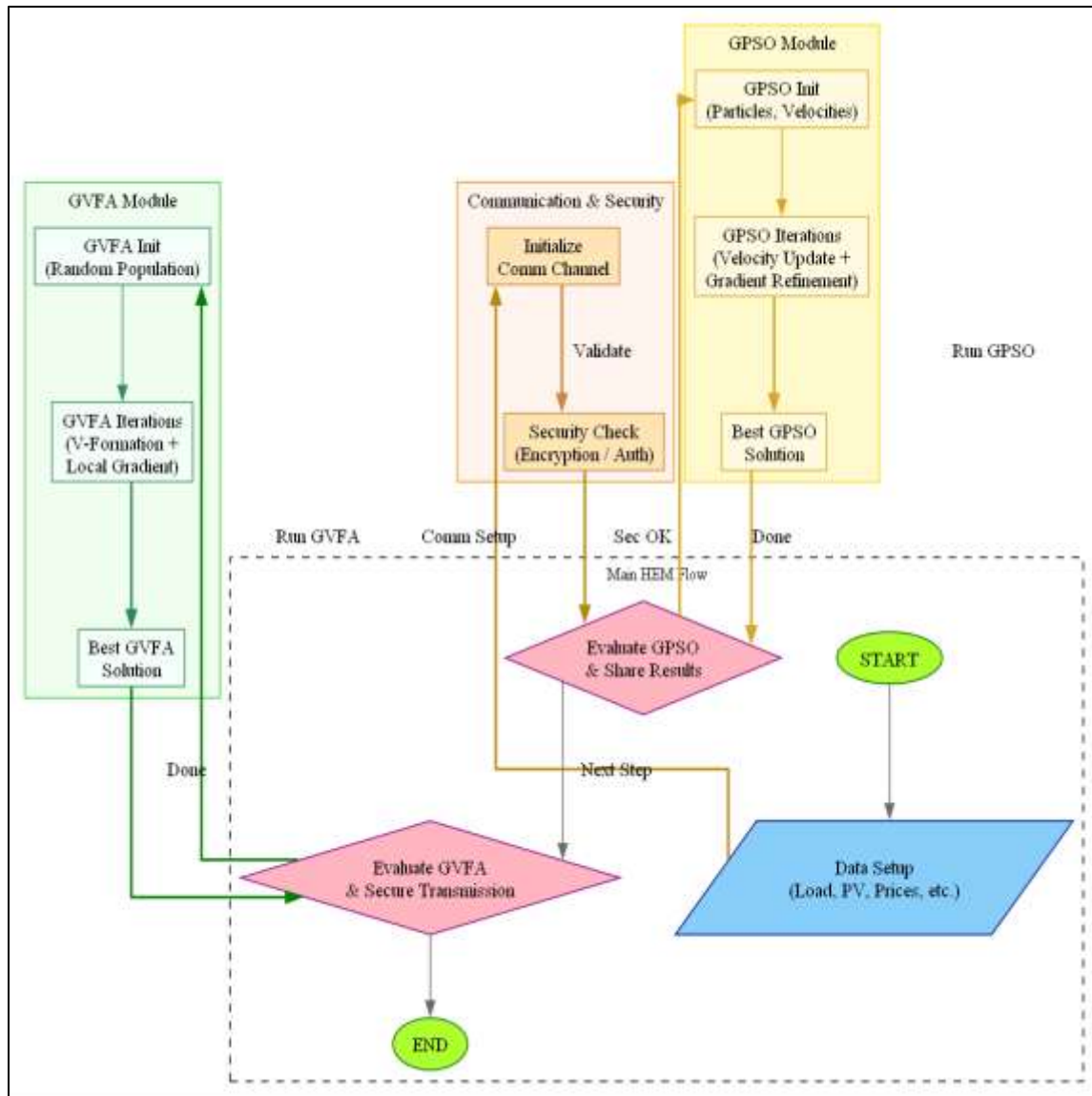


Fig. 7. Framework and security module for GPSO & GVFA algorithms.

The optimization results produced by GPSO and GVFA are reliably conducted to the appropriate control devices without the possibility of interference or management recognizes to the security and communication module. Grid import/export setpoints and commands for charging and discharging batteries and electric vehicles are examples of control signals that are sent over encrypted channels. This module receives computed schedules and transmits them to smart chargers and home energy controllers it is directly connected to the optimization framework. Anomaly detection systems find questionable activity that might interfere with the energy management process and secure authentication stops unwanted access to system controls. This integration guarantees the preservation of the optimizations cost and efficiency advantages during operational deployment. This integration guarantees the preservation of the optimizations cost and efficiency advantages

during operational deployment. The chosen approach shown in these figures guarantees that HEMS maintains cybersecurity resilience while optimizing energy consumption through AI-driven automation fostering a robust and reasonably priced smart home power ecosystem. The modeling equations constraints and optimization strategies employed in this study are thoroughly justified in the sections that follow.

4 Results and Discussion

The both seasons summer and winter scenarios summarized using an hourly resolution over a 24-hour period is used. Residential load profiles were created using representative household consumption datasets and PV generation profiles were created using regional solar irradiance data that had been modified for the installed 7 kW PV system capacity. While the fixed battery capacity was 10 kWh with a maximum charge and discharge rate of 3 kW EV batteries contained 40 kWh with a maximum bidirectional power flow of 7 kW in V2H mode. With off-peak rates of 0-20 USD/kWh shoulder rates of 0-35 USD/kWh and peak rates of 0-45 USD/kWh grid electricity prices were determined using a time-of-use tariff structure. For 100 iterations each GVFA and GPSO were conducted with 30 agents for GVFA and 30 particles for GPSO. When paired with communication and safety technologies smart home energy management (SHEM) maximizes power consumption while improving control resilience and efficiency.

On the other hand, the results of the development and cost analysis of the PV battery and EV state of charge (SoC) smart-grid electricity interaction demonstrate how seasonal variations impact the availability of energy. Summer PV technology is higher, and grid dependency is lower but winter demands better power control. Homeowners can ensure optimal use and reduced dependency on the electrical grid by monitoring PV production battery levels and energy expenses with modern systems like real-time tracking and IoT-enabled smart meters. Advanced system approaches like IoT-enabled smart meters and real-time tracking enable homeowners to keep an eye on PV production battery tiers and energy costs ensuring optimal utilization and reduced dependency on the electrical grid. The developing GVFA approach proposed better energy balancing, especially in the winter, using a high-state battery SoC and optimizing EV charging schedules. Secure Wi-Fi protocols and encrypted networks can bolster this approach by protecting users from online threats and ensuring that critical systems like management systems and emergency light alarms continue to function during outages.

Demand management outcomes also show that automated demand response (ADR) techniques may enhance load shifting and curtailment. However, by moving peak-hour loads to off-peak hours between 10:00 and 12:00 it reduces the burden on the grid. Energy use can be instantly adjusted to current grid conditions and costs as well as possible security threats by AI-powered energy control plans and home security systems. Furthermore, the cost analysis shows that using Distributed Energy Resources (DERs) under intelligent management significantly reduces energy costs under Enhanced GVFA. In the summer costs drop below \$2 per day and in the winter even with less PV generation costs drop. A robust cyber-secure and economical home energy ecosystem is ensured by combining smart energy secure communication and intelligent automation. Whereas this investigation enables improved self-sufficiency and the smooth integration of security and renewable energy systems.

4.1 GPSO Results

1) GPSO SUMMER SCENARIO

Fig. 8 presents the 24 h power flow of the GPSO summer case where time from 00 to 23 h is plotted against power in kW for load PV battery EV and grid exchange. The load starts at 1.20 kW at 00 h rises to a peak of 3.50 kW at 10 h and returns to 1.20 kW at 23 h while PV output follows the solar cycle with zero generation at night a maximum of 7.00 kW at 11 h and zero again after 19 h. Battery charging reaches 1.98 kW at 01 h and 07 h and battery discharging peaks at 1.99 kW at 06 h to supply morning demand while EV charging reaches 3.24 kW at 15 h and EV discharging peaks at 2.97 kW at 07 h to support the system. Net grid power shows both export and import with a minimum of -4.69 kW at 06 h during surplus generation and a maximum import of 4.67 kW at 19 h when local resources decline and the cost results report a best cost without penalty of \$2.4215 USD a penalty of \$17717.6438 USD a total cost of \$17720.0653 USD and a baseline cost without DER of \$17.1610 USD.

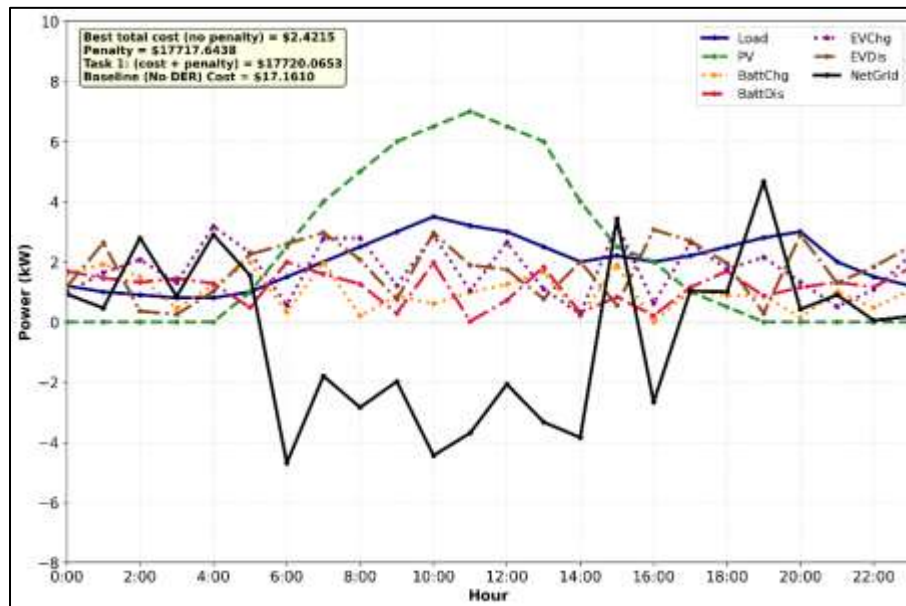


Fig. 8: GPSO summer scenario - power flow components.

Fig. 9 shows the SoC behavior of the battery and EV with grid exchange over 24 h where SoC appears on the left axis and net grid power in kW appears on the right axis. The battery SoC starts at 1.91 at 00h rises to 2.96 at 05h then falls below zero with -0.17 at 10h and reaches -1.73 at 23 h which shows poor energy control while the EV SoC starts at 4.82 rises to 9.02 at 15 h then drops to 4.76 by the end of the day. Net grid power shifts between import in the early hours and export during solar output with a peak export of -4.69 kW at 06 h which aligns with storage discharge. These trends show how storage and EV actions follow grid demand and PV output and the cost box reports a penalty of \$17717.6438 USD and a total cost of \$17720.0653 USD which reflects the impact of this operating pattern on system cost.

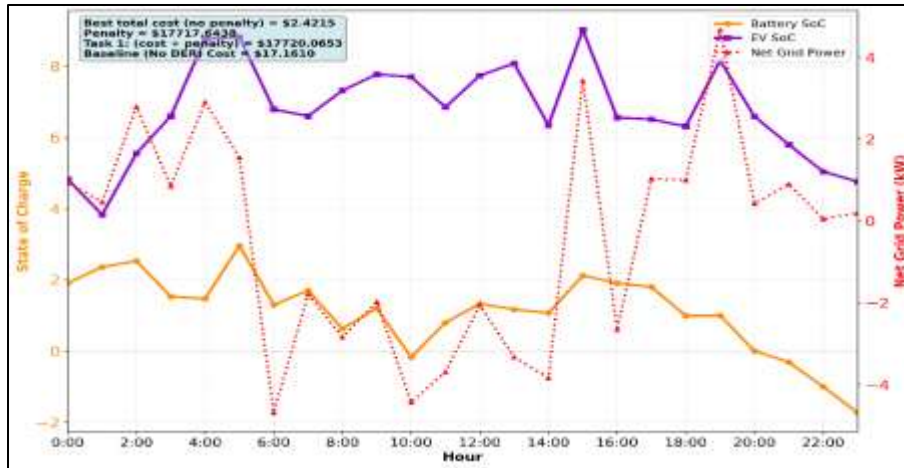


Fig. 9: GPSO summer scenario - state of charge and grid interaction.

2) GPSO WINTER SCENARIO

Fig. 10 shows the winter power flow for the GPSO case over 24 h with lower solar output and a different control pattern than summer. The load follows the same profile but PV output drops to a peak of only 3.20 kW at 11 h and returns to zero soon after midday. Battery charging reaches 1.78 kW at 05 h and 1.62 kW at 07 h while battery discharge peaks at 1.91 kW at 11 h which shows limited energy support from storage. EV charging increases to 3.15 kW at 04 h and 3.13 kW at 10 h and EV discharge reaches 2.78 kW at 03 h and 2.81 kW at 19 h. Net grid power stays positive for most hours with a peak import of 3.62 kW at 04 h and only short export periods of -2.45 kW at 12 h and -1.55 kW at 13h which confirms strong reliance on the grid. The cost box reports a best cost without penalty of \$10.0049 USD a penalty of \$111778.5830 USD and a total cost of \$111788.5879 USD which shows a much weaker economic outcome than in summer.

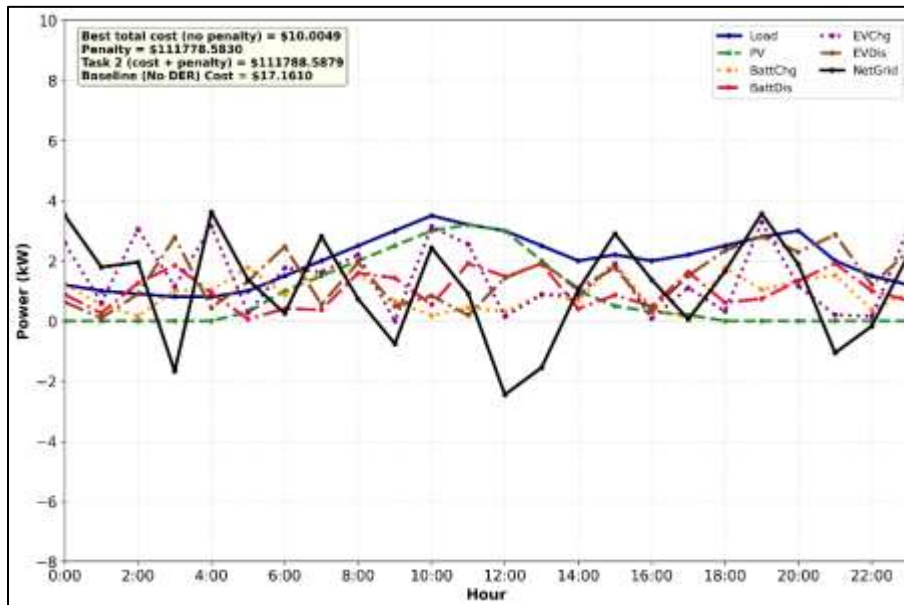


Fig. 10: GPSO winter scenario - power flow components.

Fig. 11 shows winter SoC and grid exchange for the GPSO case with storage behavior that differs from summer. Battery SoC starts at 2.35 rises to 4.21 at 07h then falls below zero with -0.58 at 13h and -0.85 at 17h which shows heavy winter discharge. EV SoC starts at 6.97 climbs to 14.46 at 11h stays above 10 for several hours and ends at 5.74 at 23h which confirms that EVs act as main storage in winter. Net grid power stays positive for most hours which means the system relies on grid import with only short export periods. High EV SoC aligns with grid charging which shows controlled energy intake during low demand. The cost box reports a penalty of \$111778.5830 USD and a total cost of \$111788.5879 USD which is about 6500 times higher than the \$17.1610 USD baseline and shows major control limits under winter conditions.

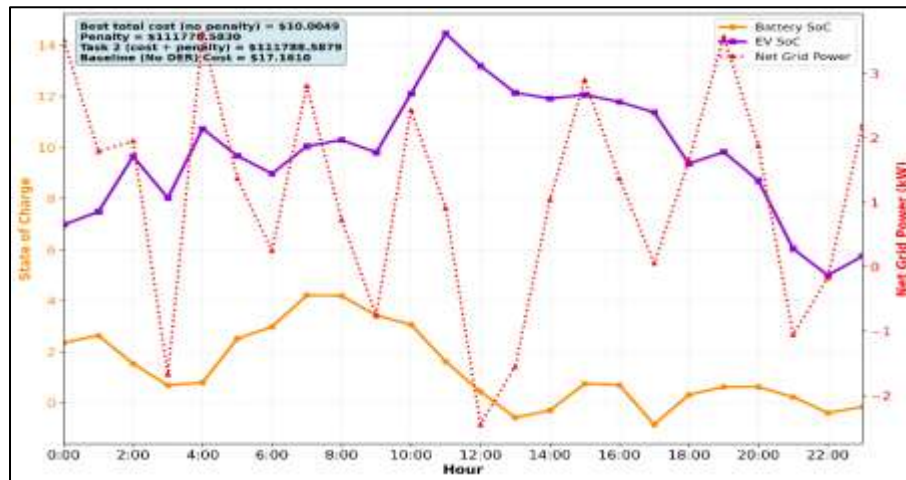


Fig. 11: GPSO winter scenario - state of charge and grid interaction.

3) PV Power Output (Summer vs. Winter)

Fig. 12 shows the summer PV output is significantly higher than in winter, reaching a peak of around 7 kW at midday, while winter peaks at only about 3 kW. This is expected due to longer daylight hours and higher solar intensity in summer. Winter PV production is lower and more widespread, indicating less available solar energy, likely due to shorter days and weaker sunlight.

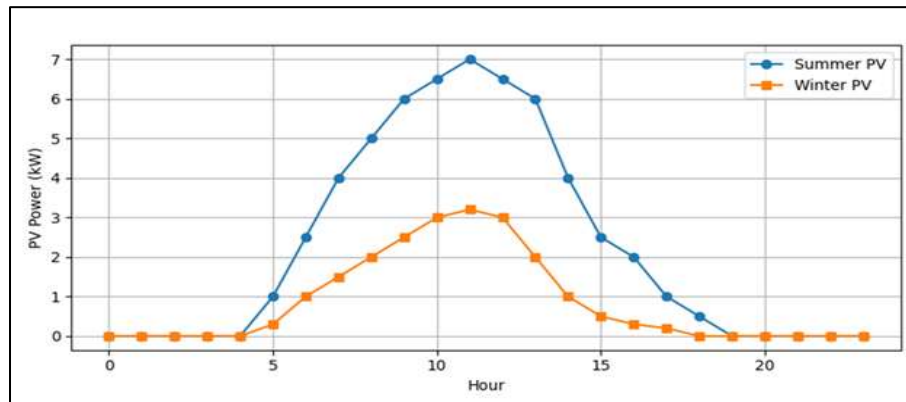


Fig. 12. GPSO PV power output: summer vs winter.

4) Battery State of Charge (SoC) (Summer vs. Winter)

Fig. 13 shows the summer, the battery maintains a relatively stable SoC, fluctuating between 2 and 5 kWh. In winter, the SoC drops much lower at times, even reaching near 0 kWh, meaning the battery is often depleted. This suggests that the lower PV generation in winter affects the battery's ability to stay charged, requiring more reliance on grid energy.

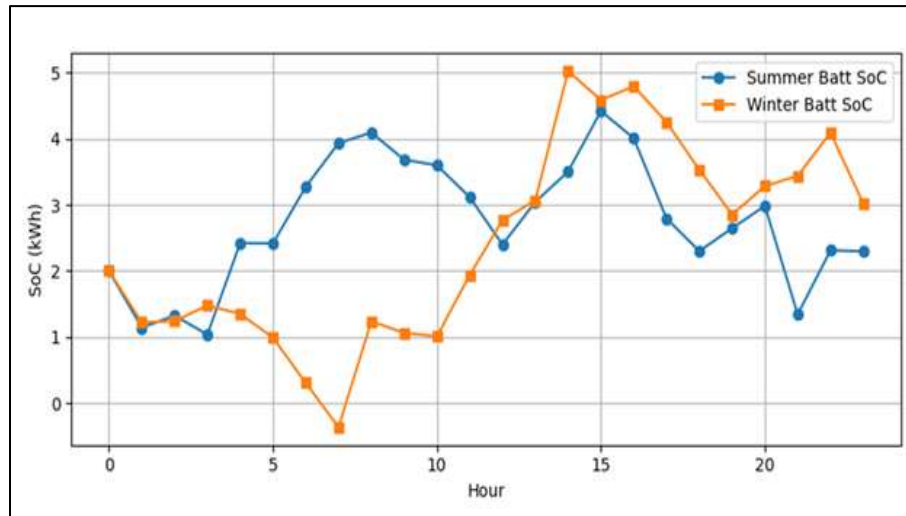


Fig. 13. GPSO battery SoC: summer vs winter.

5) EV State of Charge (SoC) (Summer vs. Winter)

Fig. 14 shows the EV's SoC is generally higher in summer, consistently staying around 9-10 kWh throughout most of the day. In winter, the SoC is lower and drops below 5 kWh at certain times, indicating more frequent discharging and potentially less available energy for charging due to reduced PV generation.

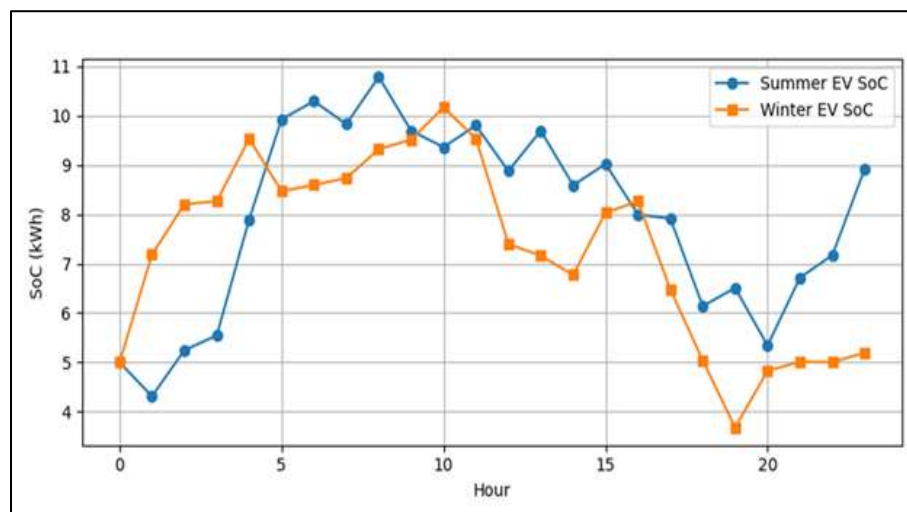


Fig. 14. GPSO EV SoC: summer vs winter.

6) Net Power Exchange with the Grid (Summer vs. Winter)

Fig. 15 shows the summer, there are periods when the system sells power to the grid (negative values), especially during peak solar hours. In winter, the system is more reliant on grid power (positive values), as PV generation is insufficient to cover demand. This indicates that the system is more self-sufficient in summer, whereas in winter, it requires additional energy from the grid.

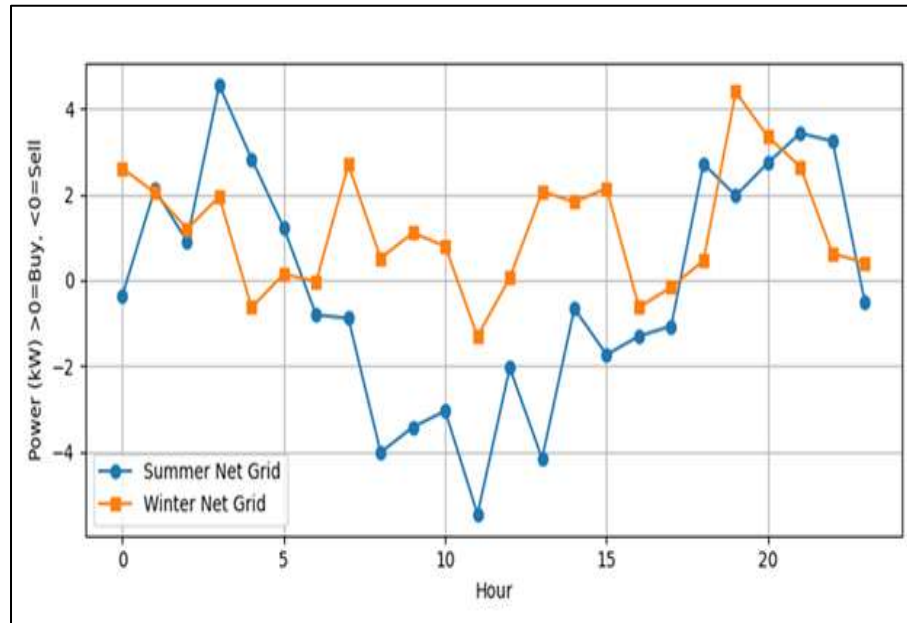


Fig. 15. GPSO Net-power of the grid: summer vs winter.

7) Cost of Consuming Energy (With and Without DER)

A baseline heuristic scheduling method was used to compare the outcomes in order to evaluate the efficacy of GPSO and GVFA. In the baseline approach PV usage is given priority over battery discharge and the grid meets the remaining demand without predictive optimization. Both GPSO and GVFA achieve lower total costs and higher self-consumption ratios when compared to the baseline according to the comparative results. Compared to the baseline GPSO improved GVFA by 86–80% and decreased daily expenses by 85–89% during the summer. GPSO increased GVFA by 46.50 percent and decreased expenses by 41.72 percent during the winter. When PV battery and V2H resources were better coordinated Enhanced GVFA produced the biggest savings in both seasons. Fig. 16 shows the use of Distributed Energy Resources (DER), such as PV and batteries, significantly reduces energy costs. Without DER the total cost per day during the summer is about \$17 but with DER it is about \$4. Without DER the price stays at \$17 in the winter but with DER it is still more expensive than it is in the summer, roughly \$10. This shows that even though DER is good at cutting expenses its effects are more pronounced in the summer when PV generation is higher.

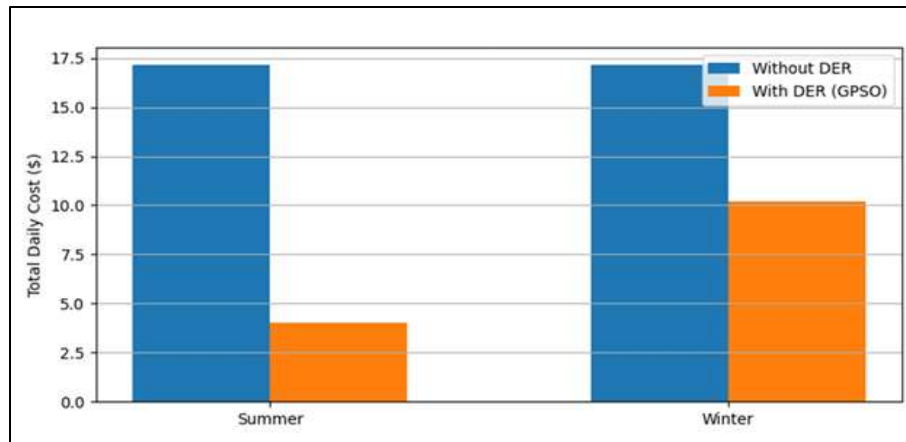


Fig. 16. GPSO cost for consuming with DER vs Without DER.

4.2 GVFA Results

1) GVFA SUMMER SCENARIO

Fig. 17 shows the GVFA summer power flow over 24h with the same load and PV profile as the other cases where PV reaches 7.00 kW at 11h but with different energy control. Battery charging stays between 0.44 and 1.45 kW and battery discharge stays between 0.38 and 1.46 kW which shows smooth operation without large spikes. EV charging ranges from 0.68 to 2.47 kW and EV discharge ranges from 0.64 to 2.71 kW which shows balanced EV use. Net grid power turns negative for long periods with export reaching -5.75 kW at 11h and staying in export mode from 06 h to 14 h which shows strong local generation use. The cost box reports a base cost of \$2.2665 USD with zero penalty which gives a total cost of \$2.2665 USD a 99.87% drop from the \$17720.0653 USD GPSO summer cost and an 86.79% drop from the \$17.1610 USD baseline.

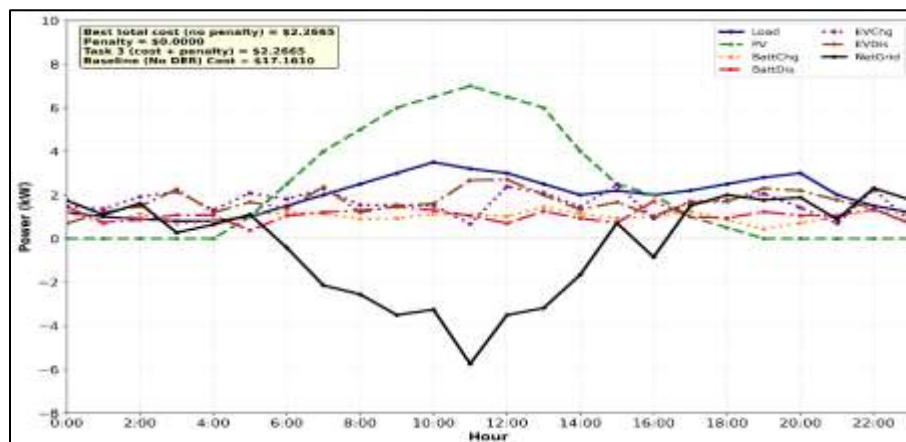


Fig. 17. GVFA summer scenario - power flow components.

Fig. 18 shows GVFA summer SoC and grid exchange over 24h with stable storage control. Battery SoC starts at 1.75 stays above zero for all hour's peaks at 2.08 at 06h and ends at 0.52 at 23h which proves controlled use without deep discharge. EV SoC starts at 5.80 moves between 4.07 and 7.53 and ends at 5.09 which shows balanced charging and discharging. Net grid power turns negative during high PV output with -5.75 kW at 11 h and shifts to import during evening demand which supports energy shifting. These trends show storage charging during export and discharging during import. The cost box reports zero penalty and a total cost of \$2.2665 USD which gives an 86.79% drop from the \$17.1610 USD baseline and more than a 7800-fold drop from the \$17720.0653 USD GPSO summer cost.

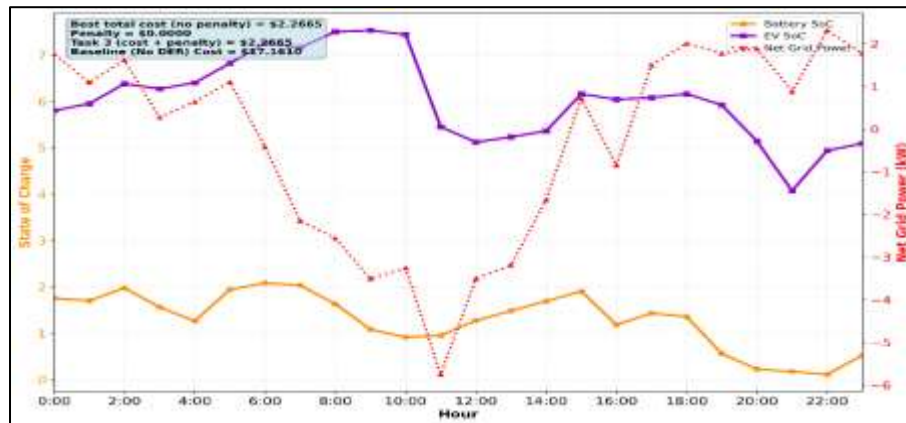


Fig. 18. GVFA summer scenario - state of charge and grid interaction.

Fig. 19 shows enhanced GVFA winter power flow over 24h with load and PV under low solar where PV peaks at 3.20 kW at 11h. Battery charging stays between 0.31 and 1.66 kW and battery discharge stays between 0.40 and 1.60 kW which shows steady control without spikes. EV charging ranges from 0.28 to 2.51 kW and EV discharge ranges from 0.50 to 2.74 kW which avoids the heavy cycling seen in GPSO winter. Net grid power stays near zero from -0.44 to 3.11 kW which shows near self-supply with low grid use. The cost box reports a base cost of 9.1790 USD with zero penalty which gives a 46.53% drop from the \$17.1610 USD baseline and a large gap from the \$111788.5879 USD GPSO winter cost.

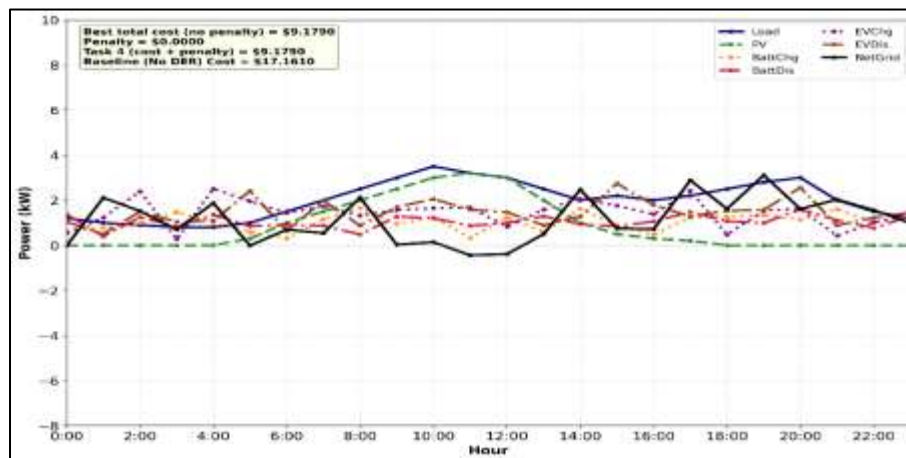


Fig. 19. Enhanced GVFA winter scenario - power flow components.

Fig. 20 shows enhanced GVFA winter SoC and grid exchange over 24h with stable storage control. Battery SoC starts at 1.26 stays between 1.01 and 2.02 and ends at 1.59 which shows full state control without deep discharge. EV SoC starts at 4.51 moves between 4.71 and 7.73 and ends at 4.71 which shows balanced use. Net grid power stays near zero from -0.44 to 3.11 kW which shows low grid use with high self-supply. Storage and grid trends align with charging before demand and discharge during demand. The cost box reports zero penalty and a total cost of $\$9.1790$ USD which gives a 46.53 percent drop from the $\$17.1610$ USD baseline and more than a 12000-fold drop from the $\$111788.5879$ USD GPSO winter cost.

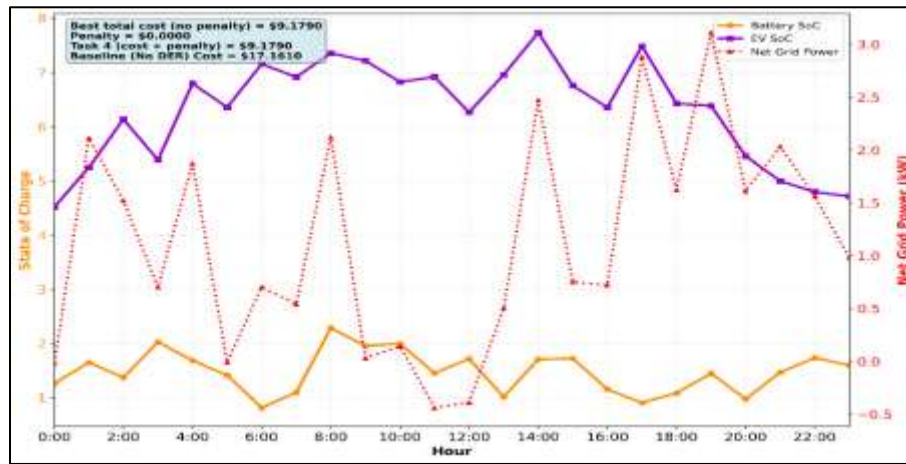


Fig. 20. Enhanced GVFA winter scenario - state of charge and grid interaction.

2) PV Power Output (Summer vs. Winter)

Fig. 21 shows the summer PV generation reaches a peak of around 7 kW, while winter peaks at approximately 3 kW consistent with longer daylight hours and stronger solar radiation in summer. The winter PV curve is lower and more gradual, indicating reduced solar availability due to shorter days and lower sun intensity. Similar to other optimization methods, the seasonal disparity in PV generation remains a challenge, affecting energy self-sufficiency.

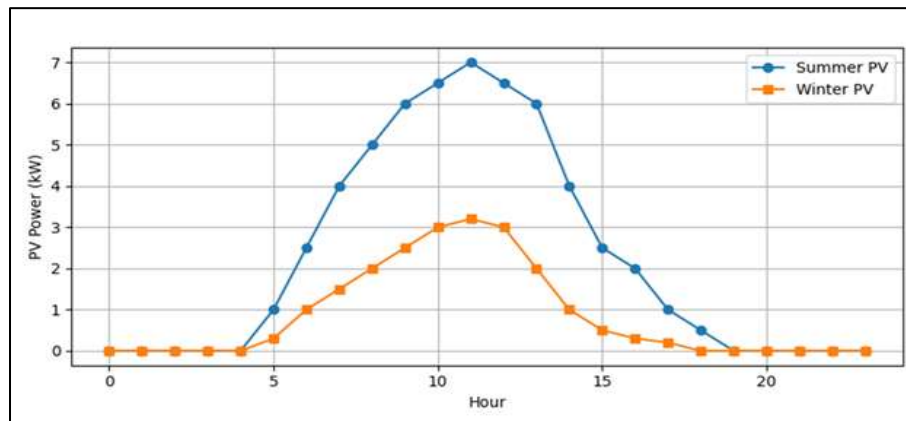


Fig. 21. Enhanced GVFA PV power output: summer vs winter.**3) Battery State of Charge (SoC) (Summer vs. Winter)**

Fig. 22 shows the battery SoC in both summer and winter remains relatively stable between 2 and 3 kWh for most of the day. Unlike previous methods where winter SoC showed significant depletion, Enhanced GVFA keeps winter battery levels more balanced, preventing deep discharges. This indicates better energy management and optimized charging/discharging strategies, allowing the system to make the most of limited winter PV generation.

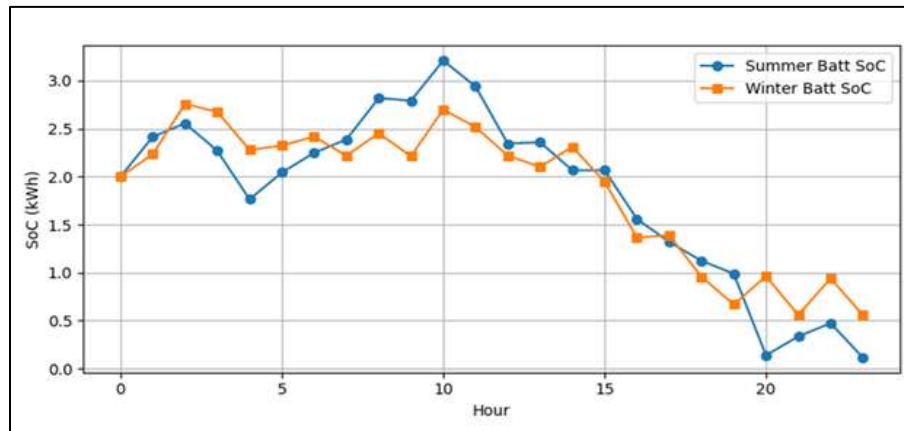
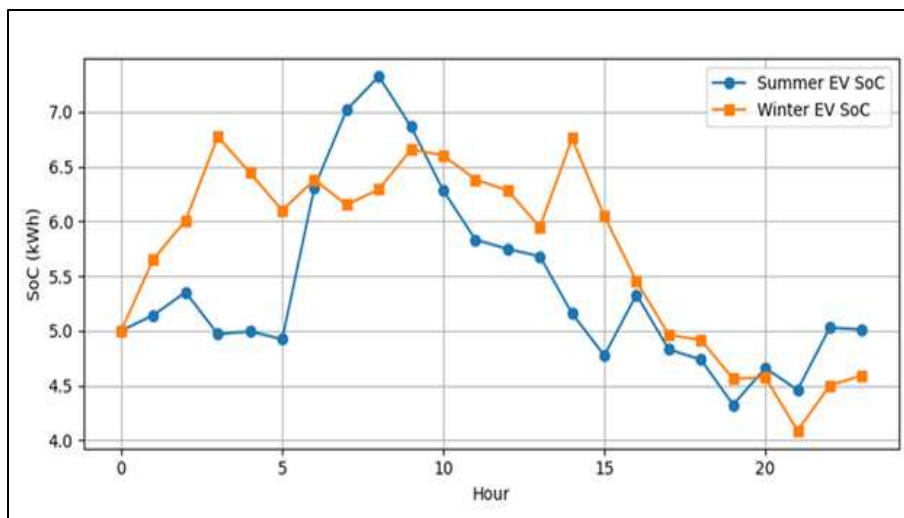
**Fig. 22. Enhanced GVFA battery SoC: summer vs winter.****4) EV State of Charge (SoC) (Summer vs. Winter)**

Fig. 23 shows the EV SoC remains stable in both seasons, fluctuating between 5 and 7 kWh. Interestingly, winter EV SoC is sometimes higher than in summer, indicating a well-managed charging schedule. This result suggests that Enhanced GVFA prioritizes EV charging efficiently, even in winter, possibly by leveraging grid power strategically.

**Fig. 23. Enhanced GVFA EV SoC: summer vs winter.**

5) Net Power Exchange with the Grid (Summer vs. Winter)

Fig. 24 shows the during the day in summer, there are periods when the system sells excess energy to the grid (negative values), particularly from morning to early afternoon. In winter, the system is more dependent on grid power (positive values), but Enhanced GVFA seems to reduce extreme fluctuations, making grid reliance more predictable. Compared to other methods, this strategy smooths out power exchanges, minimizing costly grid purchases and maximizing self-consumption.

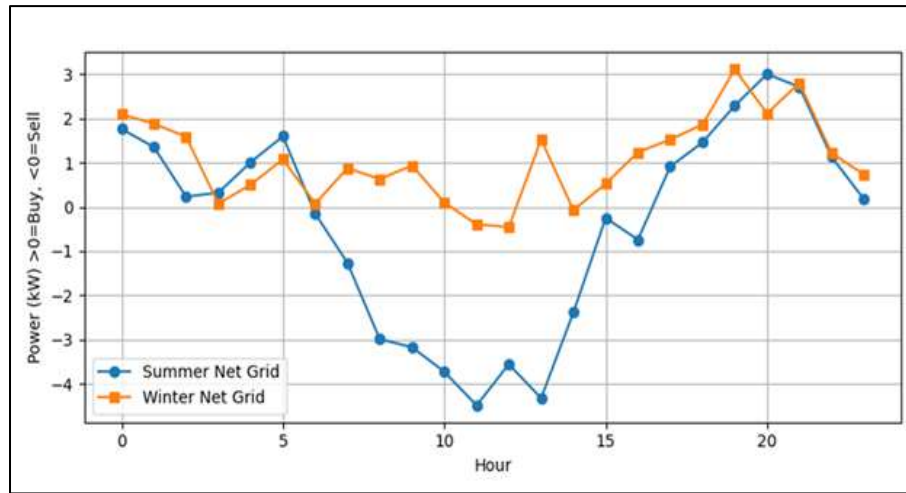


Fig. 24. Enhanced GVFA EV SoC: summer vs winter.

6) Energy Consumption Cost (With and Without DER)

Fig. 25 shows the without Distributed Energy Resources (DER), the total daily cost remains at ~\$17 in both seasons. With Enhanced GVFA, summer costs drop significantly to under \$2, an improvement over previous methods, suggesting better PV utilization and grid interaction. In winter, costs drop to around \$8, which is lower than earlier methods but still higher than in summer due to reduced PV availability. Overall, Enhanced GVFA significantly reduces energy expenses, proving its effectiveness in optimizing energy use across seasons.

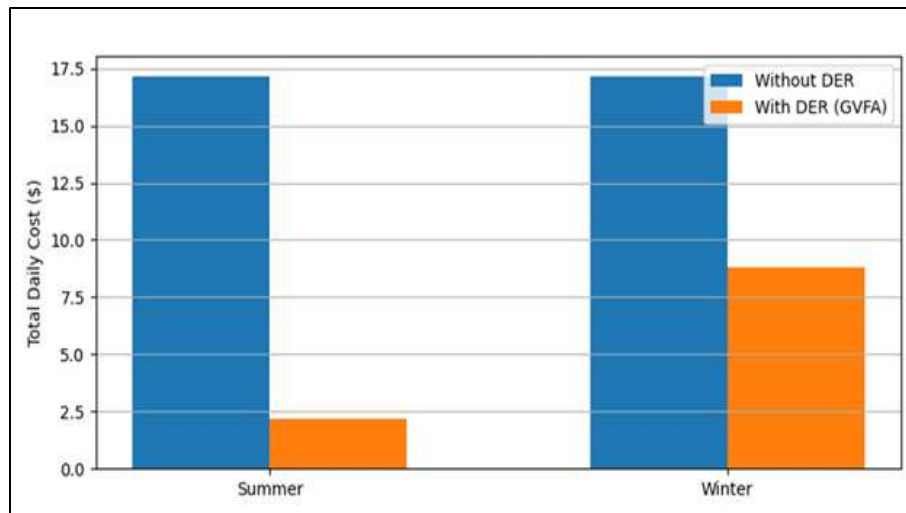


Fig. 25. Enhanced GVFA cost for consuming with DER vs without DER.**4.3 Smart Management****1. Load Curtailment at Peak (17:00-19:00)**

Fig. 26 shows a graph presenting a 30% reduction in energy demand during peak hours (17:00-19:00). Before curtailment, the original load (blue line) had a noticeable evening peak reaching around 3 kW. After curtailment (orange line), the peak demand is significantly reduced, flattening out consumption during those hours. Implications, this method directly reduces strain on the grid during high-demand periods. However, it requires consumers to sacrifice some electricity usage, which may affect comfort or operational efficiency.

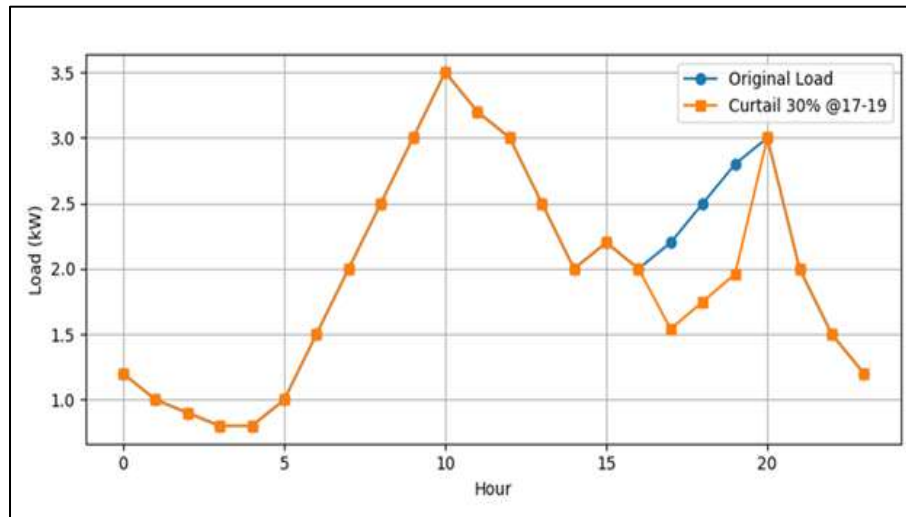
**Fig. 26. Simple load curtailment @ peak 17-19.****2. Load Shifting Moving 30% of Peak Load (17:00-19:00) to Off-Peak (10:00-12:00)**

Fig. 27 shows the instead of cutting demand, this approach relocates part of the peak-hour load to an earlier off-peak period (10:00-12:00). The original load (blue line) shows a peak in the evening, whereas the shifted load (orange line) has a higher demand between 10:00-12:00. This method smooths out demand, reducing pressure on the grid in the evening while increasing usage when energy availability is typically higher. Implications for this approach preserve energy usage but spreads it out more efficiently. It can be especially beneficial in renewable-based systems, where solar generation is highest around midday. Some loads may not be flexible enough to shift (e.g., cooking or evening lighting needs), so it requires careful user adaptation.

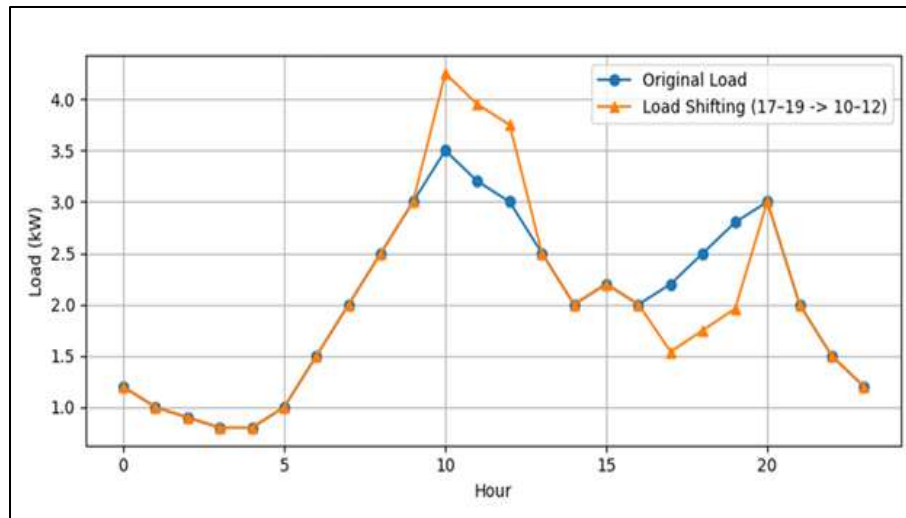


Fig. 27. Load shifting moves 30% of peak 17-19 to off-peak 10-12.

4.4 Key Insight the Seasonal Dependence of Algorithm Performance

Beyond demonstrating cost savings, our analysis reveals a fundamental insight about optimization in renewable energy systems: algorithm performance is intrinsically linked to seasonal conditions. GPSO achieves optimal results during summer months when abundant photovoltaic generation creates smoother cost landscapes, allowing its gradient-based mechanism to accelerate convergence effectively. In contrast, GVFA's cooperative search paradigm proves superior in winter, where prolonged low-generation periods create deceptive local optima that trap standard algorithms. This season-dependent performance pattern, quantified here for the first time in vehicle-to-home photovoltaic systems, challenges the prevailing assumption that a single optimization algorithm can provide year-round optimal performance. Our findings indicate that adaptive algorithm selection based on seasonal conditions represents a necessary advancement for next-generation smart energy systems. The performance disparity between summer, high photovoltaic availability, and winter, low photovoltaic availability, scenarios exceed approximately of 40% for some algorithms, underscoring the practical significance of this insight for real-world implementation.

5 Conclusion

This paper introduces two novel optimization algorithms, GPSO and GVFA, specifically designed to address identified limitations in current home energy management systems. Our most significant contribution is the demonstration that algorithm performance in renewable energy systems exhibits strong seasonal dependence. While GPSO gradient mechanism provides superior optimization during high photovoltaic generation periods, summer, GVFA cooperative search excels during low-generation conditions, winter, where standard algorithms often fail. This insight establishes that season-aware algorithm selection, rather than reliance on a single year-round optimizer, is essential for optimal energy management, a fundamental advancement in smart grid optimization strategy. Corresponding to the results, summer PV generation significantly outpaces winter outcome, necessitating adaptive energy management to maintain efficiency throughout the year. In terms of stabilizing the battery and EV SoC, enhanced GVFA performs better than GPSO, ensuring consistent energy

availability consistent when solar generation is low. Peak limitation and load shifting are DSM techniques that significantly lower energy costs and grid dependency without sacrificing user comfort. In order to protect against cyberattacks and ensure security system resilience in both home and datacenter applications, the analysis also emphasizes the importance of secure communication protocols and AI-driven anomaly detection. Through a combination of bidirectional energy flows, AI automation, and renewable-aware scheduling, this framework creates an energy ecosystem that is cyber-secure, economical, and sustainable. For improved sensor accuracy, real-time adaptability, and scalable solutions for larger smart grid and datacenter deployments, future research should investigate hybrid AI models. Moreover, by bridging the gap between decentralized residential systems and extensive renewable-powered infrastructures, this work ultimately enables the creation of a more resilient and optimized energy future.

Acknowledgments

The authors declare no conflicts of interest in this research. Furthermore, the funders were not involved in the study's design, data collection, analysis, interpretation, manuscript writing, or decision to publish.

Funding

No funding

Author contributions

Conceptualization, MAK; methodology, software, validation, formal analysis, MAK and SY; investigation, resources, data curation, and MAK; writing original draft preparation, MOAM; writing review and editing, MAK; visualization, SY and MOAM; supervision, MAK; project administration, SY and MOAM; funding acquisition. All authors have read and agreed to the published version of the manuscript.

Conflicts of interest

The authors declare no conflicts of interest. No financial or non-financial relationships influenced the research, and no external funding was received for this study.

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