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Optimization of Vehicle-to-Grid, Grid-to-Vehicle, and Vehicle-to-Everything Systems Using Artificial Bee Colony Optimization

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Abstract: The integration of vehicle-to-grid (V2G), grid-to-vehicle (G2V), and vehicle-to-everything (V2X) systems into an energy ecosystem represents a transformative approach. These systems enable bidirectional energy flow between electric vehicles (EVs), power grids, and other entities. In this study, the energy sources for the V2G, G2V, and V2X systems were derived from green and blue energies, emphasizing sustainability. The primary objective of this research is to optimize V2G, G2V, and V2X systems, focusing on enhancing their performance. The novel contribution of this work lies in the application of advanced optimization techniques, specifically Artificial Bee Colony Optimization (ABCO), to improve system efficiency and stability. The system was simulated in MATLAB, where ABCO achieved a 64.5% improvement in reactive power optimization over Brain Emotional Intelligent *Control* (*BEIC*). This result underscores the effectiveness of ABCO in optimizing energy exchange within the V2G, G2V, and V2X systems, confirming its suitability for these applications. These findings highlight the potential of ABCO to enhance the performance of V2G, G2V, and V2X systems, contributing to a more sustainable, resilient, and efficient energy ecosystem.

Keywords: green energy; vehicle-to-grid; grid-to-vehicle; vehicle-to-everything; Bee Colony Optimization

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1. Introduction

V2G enables bidirectional energy flow between electric vehicles (EVs) and the grid, G2V refers to unidirectional energy flow from the grid to EVs for charging, and V2X extends this concept to include bidirectional energy exchange between EVs and various entities, such as homes, buildings, and devices, thereby enhancing energy flexibility and sustainability [1,2].

Traditional optimization methods, such as linear programming (LP), quadratic programming (QP), and dynamic programming (DP), face significant challenges in scalability and computational complexity when applied to large-scale systems with numerous electric vehicles (EVs) and intricate energy flows [1]. These limitations hinder their effectiveness in real-world applications, particularly for large-scale systems with numerous EVs and complex energy interactions. Although machine learning techniques, such as reinforcement learning (RL) and deep learning (DL), offer adaptability to dynamic environments, they require extensive training data and computational resources, creating a gap for algorithms capable of real-time adaptation to fluctuating energy prices, grid conditions, and user preferences without the need for extensive pre-training [2].

A critical issue in vehicle-to-grid (V2G), grid-to-vehicle (G2V), and vehicle-to-everything (V2X) systems is accelerated battery degradation caused by frequent charging and discharging cycles [3]. Current optimization methods often fail to adequately balance the trade-off between maximizing the revenue from energy trading and minimizing battery degradation. This highlights the need for more robust algorithms that optimize energy flow while preserving battery health. Additionally, the intermittent nature of renewable energy sources like solar and wind introduces variability in energy generation, which current methods may not fully account for, leading to suboptimal energy management. There is a pressing need for algorithms that can dynamically balance energy generation, storage, and consumption in hybrid renewable energy systems [4].

Machine learning techniques, particularly deep learning, often function as 'black-box' models, complicating the interpretation and validation of their decisions. This lack of transparency poses a significant barrier to their adoption in critical energy management systems, where explainability is crucial [5]. Furthermore, the development of standardized protocols and policies for the V2G, G2V, and V2X systems is essential to facilitate their seamless integration into the existing energy infrastructure. Although metaheuristic algorithms like Bee Colony Optimization (ABCO) show promise, there is limited research on hybrid approaches that combine ABCO with machine learning techniques. Such hybrid models can enhance adaptability and solution quality by leveraging the strengths of both approaches [6].

Most existing algorithms have been tested in simulated environments, highlighting a gap in real-time implementation and testing in actual V2G, G2V, and V2X systems to validate their effectiveness in real-world scenarios. ABCO is a strong candidate for scalability to large-scale systems owing to its decentralized nature and parallel search capabilities [7]. However, further research is required to optimize performance in such environments. The adaptability of ABCO to dynamic environments can be leveraged to develop real-time optimization algorithms that adjust to changing energy prices, grid conditions, and user preferences without the need for extensive pretraining, making it more suitable for real-world applications.

The ABCO can be extended to include battery degradation models in its optimization process, enabling it to optimize energy flow while minimizing battery degradation and extending the EV battery lifespan. Additionally, ABCO can be applied to optimize the integration of renewable energy sources, such as solar and wind, in hybrid energy systems, dynamically balancing energy generation, storage, and consumption to improve efficiency and reliability [8]. Real-time testing of the ABCO in V2G, G2V, and V2X systems through prototypes and field trials is essential to validate its effectiveness under actual operating conditions. ABCO can also play a pivotal role in developing standardized protocols and policies for these systems, demonstrating its effectiveness in optimizing energy flow and grid stability to shape the regulatory framework.

The remainder of this paper is organized as follows: Section 2 presents a literature review; Section 3 discusses the mathematical models of the proposed V2G, G2V, and V2X systems, along with their control design; Section 4 presents the results and discussion; and Section 5 provides the conclusions.

2. Literature Review

The integration of electric vehicles (EVs) into the energy ecosystem has revolutionized energy management, grid stability, and renewable energy integration. Vehicle-to-grid (V2G), grid-to-vehicle (G2V), and vehicle-to-everything (V2X) systems have emerged as key enablers of this transformation. A critical aspect of these systems is the control algorithms that optimize energy flow, ensure grid stability, and maximize economic and environmental benefits. This literature review explores various control algorithms, including traditional optimization methods, machine learning techniques, and metaheuristic approaches, such as Bee Colony Optimization (ABCO), and compares their performance in V2G, G2V, and V2X applications [9].

Traditional optimization methods, including linear programming (LP), quadratic programming (QP), and dynamic programming (DP), are widely used in V2G, G2V, and V2X systems, owing to their simplicity and reliability. In V2G systems, traditional optimization methods are often used to maximize revenue from energy trading while minimizing battery degradation. For example, ref. [10] different researchers have employed linear programming to optimize the scheduling of EV charging and discharging, thereby achieving significant cost savings and grid stability. However, these methods often face challenges related to scalability and computational complexity in large-scale systems [11].

In G2V systems, quadratic programming has been used to optimize charging schedules and minimize electricity costs. Ref. [12] demonstrated the effectiveness of QP in shifting EV charging to off-peak hours, reducing the peak load, and enhancing grid stability. However, these methods may not fully account for real-time variations in energy prices and grid conditions.

In V2X systems, dynamic programming has been applied to optimize the energy exchange between EVs and other entities. Ref. [13] used DP to manage energy flow in vehicle-to-home (V2H) systems, ensuring a reliable energy supply during blackouts. Although effective, traditional optimization methods often lack the flexibility to handle the dynamic and nonlinear nature of V2X systems.

Machine learning (ML) techniques, such as reinforcement learning (RL), deep learning (DL), and supervised learning, have gained popularity in recent years, owing to their ability to handle complex and dynamic systems.

Reinforcement learning is widely used in V2G systems to optimize energy trading and grid support. Refs. [1,14] proposed an RL-based algorithm to maximize EV owner revenue while providing frequency regulation services. Their results showed that RL outperformed traditional optimization methods in dynamic pricing environments. However, RL algorithms require extensive training and computational resources.

Deep learning has been applied to predict EV charging demand and optimize charging schedules. Ref. [15] used a convolutional neural network (CNN) to forecast charging demand and optimize G2V operations, achieving significant cost savings and grid load reduction. However, the 'black-box' nature of DL algorithms makes it difficult to interpret and validate their decisions.

Supervised learning has been used to optimize the energy exchange in V2X systems. Ref. [16] employed a support vector machine (SVM) to predict energy demand and optimize the energy flow in vehicle-to-vehicle (V2V) systems. Effective supervised learning algorithms rely heavily on the quality and quantity of training data.

Metaheuristic algorithms, such as genetic algorithms (GA), particle swarm optimization (PSO), and Bee Colony Optimization (ABCO), have emerged as powerful tools for solving complex optimization problems in V2G, G2V, and V2X systems.

Genetic algorithms have been used to optimize V2G operations in dynamic and uncertain environments. Ref. [17] applied a GA to maximize EV owner revenue while minimizing battery degradation, demonstrating its superiority over traditional optimization methods. However, GA can be computationally intensive and may converge to suboptimal solutions.

Particle swarm optimization has been widely used to optimize G2V charging schedules. Ref. [18] employed PSO to minimize electricity costs and grid impact, achieving significant improvements over traditional methods. However, PSO may encounter high-dimensional problems and premature convergence.

Bee Colony Optimization (ABCO) has been applied to optimize energy exchange in V2X systems. ABCO, inspired by the foraging behavior of honeybees, is particularly well-suited for solving complex nonlinear optimization problems. For example, ref. [19] used ABCO to optimize the energy flow in vehicle-to-building (V2B) systems, achieving significant cost savings and energy efficiency. The ability of ABCO to explore a wide search space and avoid local optima makes it a promising approach for V2X applications.

The performance of the control algorithms in V2G, G2V, and V2X systems can be evaluated based on a number of criteria, including computational efficiency, scalability, adaptability, and solution quality [20].

Traditional optimization methods are computationally efficient for small-scale problems but struggle with scalability. Machine learning techniques, particularly deep learning, require significant computational resources for training and inference. Metaheuristic algorithms like ABCO strike a balance between computational efficiency and solution quality, making them suitable for large-scale and dynamic systems [21].

Traditional methods and machine-learning techniques often face challenges in scaling to large systems with numerous EVs and complex energy flows. Metaheuristic algorithms, particularly ABCO, are highly scalable and can effectively handle high-dimensional problems [22].

Machine learning techniques excel in dynamic and uncertain environments, adapting to real-time changes in energy prices and grid conditions. Ref. [10] indicates that metaheuristic algorithms like ABCO have also demonstrated strong adaptability by exploring a wide search space to find optimal solutions.

Metaheuristic algorithms, particularly ABCO, consistently deliver high-quality solutions by avoiding local optima and exploring diverse solutions. Traditional methods and machine learning techniques may converge to suboptimal solutions in complex, nonlinear systems.

The analysis of existing research reveals several critical limitations in current approaches to electric vehicle (V2G/G2V/V2X) system optimization. Traditional optimization methods, such as linear programming and dynamic programming, face significant challenges in scalability and computational complexity when applied to large-scale systems involving thousands of electric vehicles. Furthermore, most current algorithms focus primarily on maximizing economic benefits, like energy trading revenue, while neglecting crucial factors such as battery health, which can lead to accelerated degradation over time [23]. Existing approaches, including quadratic programming and reinforcement learning methods, often require extensive retraining and struggle to adapt to real-time fluctuations in energy prices, renewable generation patterns, and dynamic grid demands. Machine learning techniques, particularly deep learning, suffer from transparency issues that make it difficult to validate their decision-making processes in safety-critical energy applications. Many studies also make unrealistic assumptions about stable renewable energy generation, failing to properly account for the inherent intermittency of solar and wind power in hybrid energy systems. Additionally, the lack of standardized communication protocols creates interoperability challenges for seamless vehicle-to-grid, vehicle-to-home, and vehicle-to-building integration. Perhaps most significantly, the majority of proposed algorithms have only been validated through simulations, with very few undergoing rigorous field testing or hardware validation in real-world operating conditions.

3. Mathematical Models for V2G, G2V, and V2X and Their Control Designs

3.1. Working Principles of V2G, G2V, and V2X Systems

Artificial Bee Colony Optimization (ABCO) is a metaheuristic algorithm inspired by the foraging behavior of honeybees. It can be applied to optimize complex problems, including vehicle-to-grid (V2G), grid-to-vehicle (G2V), and vehicle-to-everything (V2X) systems.

The rapid adoption of electric vehicles (EVs) has driven the development of innovative technologies that integrate EVs into energy ecosystems. Vehicle-to-grid (V2G), grid-to-vehicle (G2V), and vehicle-to-everything (V2X) systems are transformative solutions for energy management, grid stability, and renewable energy integration [24]. These technologies enable bidirectional energy flow between EVs, the power grid, and other entities, thereby creating a dynamic and decentralized energy network (Figure 1).

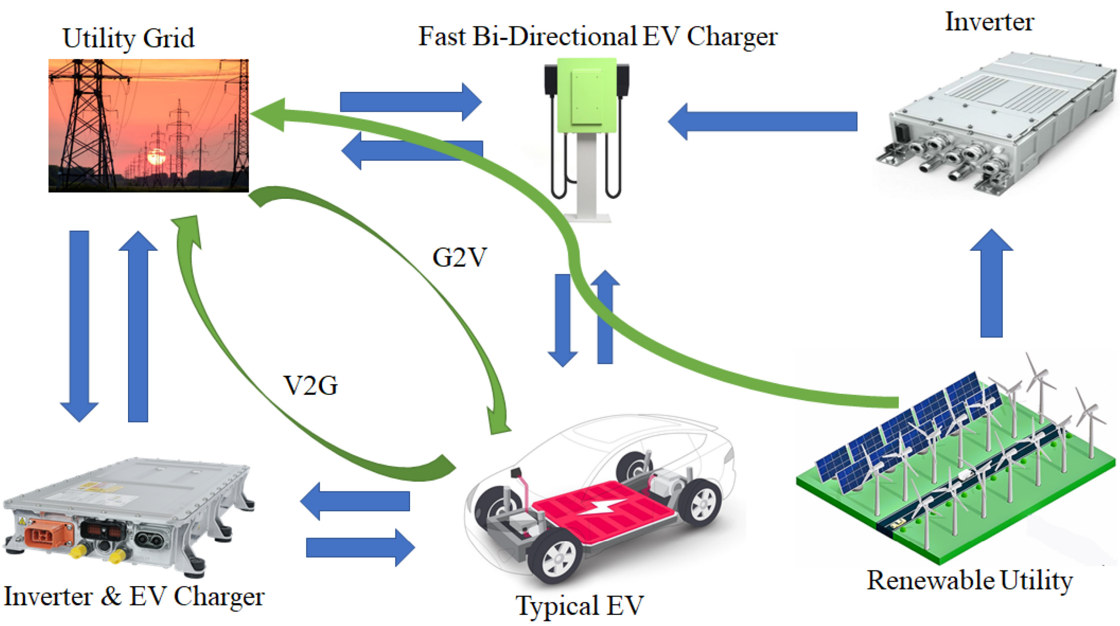

Figure 1. V2G and G2V scenarios [1].

Vehicle-to-grid (V2G) technology allows electric vehicles to discharge energy from their batteries back into the power grid. This capability is particularly useful for grid stabilization, peak shaving, and ancillary services. The process begins when an EV is plugged into a bidirectional charging station connected to the grid. The grid operator sends a signal to the EV requesting an energy discharge, prompting the EV battery to supply power during periods of peak demand, and grid emergencies [25]. Once the grid no longer requires energy, the EV can recharge its battery, ensuring that it is ready for future use. EV owners are compensated for the energy they supply, thus creating a financial incentive for participation.

V2G offers several key benefits, including frequency regulation and voltage support, which enhance grid stability. By reducing grid load during high-demand periods, V2G helps mitigate the need for expensive infrastructure upgrades. Additionally, V2G facilitates the integration of renewable energy sources by storing excess renewable energy and feeding it back into the grid when needed [26]. This not only improves grid reliability but also supports the transition to a low-carbon energy system.

Grid-to-vehicle (G2V) represents the traditional charging process, where energy flows from the grid to the EV battery. This process ensures that EVs are charged efficiently and cost-effectively. When an EV is plugged into a charging station connected to the grid, it communicates its charging requirements, such as the desired state of charge (SOC) and charging time, to the grid or charging station. The grid then supplies electricity to charge the EV battery. Smart charging algorithms optimize charging schedules to minimize costs and reduce grid impacts, such as charging during off-peak hours when electricity prices are lower. Charging stops when the desired SOC is reached or when the EV is disconnected (Figure 2).

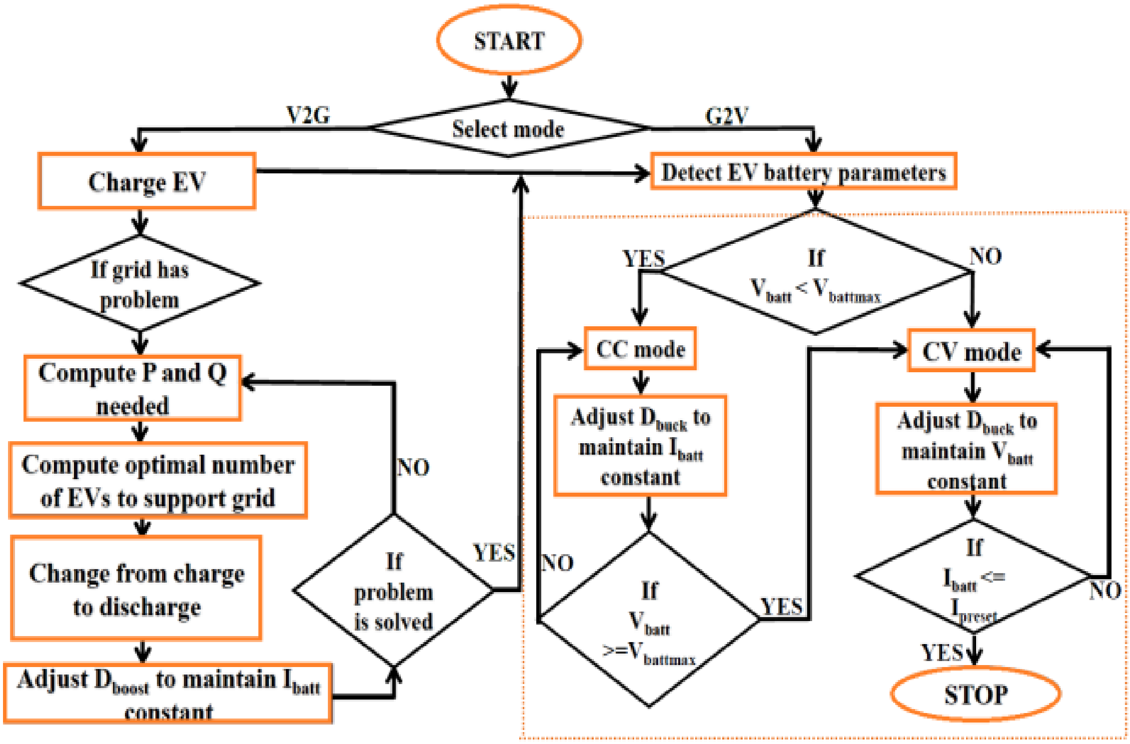

Figure 2. Flowchart for G2V and V2G charging processes [3]. Dotted rectangle shows detected electrical vehicle (EV) battery parameters.

The G2V offers significant advantages for EV owners and grids. By charging during off-peak hours, EV owners can reduce their energy costs. For the grid, G2V helps distribute the charging load more evenly, avoiding congestion and ensuring efficient energy use. Furthermore, G2V enables the utilization of excess renewable energy, aligning EV charging with periods of high renewable energy generation and reducing reliance on fossil fuels.

Vehicle-to-everything (V2X) extends the concept of V2G to include the energy exchange between EVs and other entities, such as homes, buildings, or other vehicles. This technology enables a more flexible and decentralized energy system that enhances energy resilience and efficiency. When an EV is connected to a bidirectional charger, it can interface with multiple systems, including grids, homes, and buildings. An EV can either supply energy to or receive energy from a connected entity, depending on demand and supply conditions.

V2X encompasses several applications, including vehicle-to-home (V2H), vehicle-to-building (V2B), and vehicle-to-vehicle (V2V). In V2H, the EV powers the home during a blackout or during periods of high electricity prices [27]. In vehicle to building, EVs supply energy to commercial buildings, thereby reducing energy costs and enhancing sustainability.

In V2V, the EV transfers energy to another EV, thereby enabling peer-to-peer energy sharing. Energy management systems optimize the flow of energy based on demand, supply, and cost, thereby ensuring efficient operation. EV owners may receive compensation for supplying energy to other entities, thereby creating additional revenue streams.

V2X also supports emergency backups, energy sharing, and microgrid integration. By providing power to homes or buildings during outages, V2X enhances energy security. This capability enables peer-to-peer energy trading between EVs and other entities, fostering a collaborative energy ecosystem. Additionally, V2X integrates EVs into local microgrids, improving resilience and supporting the deployment of renewable energy.

The successful implementation of the V2G, G2V, and V2X systems relies on several key components. Bidirectional chargers enable energy flow in both directions, whereas communication infrastructure facilitates real-time interaction between EVs, the grid, and other entities. Energy management systems optimize energy flow based on grid conditions, energy prices, and user preferences, thereby ensuring efficient operation [28]. Battery management systems ensure the safe and efficient operation of EV batteries during charging and discharging. Finally, smart grid integration allows EVs to function as distributed energy resources, enhancing grid stability and reliability.

The grid improves stability and reliability, integrates renewable energy sources, and reduces the need for expensive infrastructure upgrades. EV owners gain potential revenue from selling energy back to the grid or other entities, lower energy costs through optimized charging, and enhanced energy security. There are also reduced greenhouse gas emissions due to the utilization of renewable energy sources and decreased reliance on fossil fuels.

3.2. Mathematical Models for V2G, G2V, and V2X Systems

3.2.1. V2G Model

Problem formulation

Maximize revenue from selling energy back to the grid while minimizing battery degradation costs [29].

$$\text{maximize } \mathrm{F_{V2G}} = \sum_{t=1}^{T}\Big(\mathrm{P_{sell}(t)}\Big).\big(\mathrm{E_{V2G}(t)} - \mathrm{C_{deg}(t)}\big) \tag{1}$$

Constraints:

1. Energy balance:

$$\mathrm{E_{V2G}(t) \leq B_{bat}(t)} \tag{2}$$

2. Battery state of charge (SOC) limits:

$$\mathrm{SOC_{min} \leq SOC(t) \leq SOC_{max}} \tag{3}$$

3. Power limits:

$$\mathrm{P_{V2G,min} \leq P_{V2G}(t) \leq P_{V2G,max}} \tag{4}$$

4. Time constraints:

$$\mathrm{t} \in \{1, 2, 3, \ldots \mathrm{T}\} \tag{5}$$

ABCO Implementation:

- Bees represent possible V2G schedules.
- Fitness Function: F_{V2G}.
- Foraging Process: Bees explore different energy selling schedules to maximize revenue while adhering to constraints.

3.2.2. Grid-to-Vehicle (G2V) Model

Problem formulation:

Minimize the cost of charging vehicles from the grid while ensuring that the battery is charged to the desired level [23].

$$\text{maximize } \mathrm{F_{G2V}} = \sum_{t=1}^{T}\Big(\mathrm{P_{buy}(t)).(E_{G2V}(t)}\Big) \tag{6}$$

Constraints:

1. Energy balance:

$$\mathrm{E_{G2V}(t)} \le \mathrm{E_{bat,\ max}} - E_{bat}(t) \tag{7}$$

2. Battery state of charge (SOC) limits:

$$\mathrm{SOC_{min}} \le \mathrm{SOC(t)} \le \mathrm{SOC_{max}} \tag{8}$$

3. Power limits:

$$\mathrm{P_{G2V,min}} \le \mathrm{P_{G2V}(t)} \le \mathrm{P_{G2V,max}} \tag{9}$$

4. Time constraints:

$$t \in \{1, 2, 3, \ldots T\} \tag{10}$$

ABCO Implementation:

- Bees represent charging schedules.
- Fitness Function: $\mathrm{F_{G2V}}$.
- Foraging Process: Bees explore charging schedules to minimize costs while meeting SOC requirements.

3.2.3. Vehicle-to-Everything (V2X) Model

Problem formulation:

Optimize energy exchange between vehicles, the grid, and other entities (e.g., homes and other buildings) to maximize overall system efficiency and minimize costs [27].

$$\text{Maximize } \mathrm{F_{V2X}} = \sum_{t=1}^{T}\left(\sum_{i=1}^{N}\mathrm{(R_i(t) - C_i(t))}\right) \tag{11}$$

Here:

- $\mathrm{R_i(t)}$: Revenue from energy exchange for entity i at time t.
- $\mathrm{C_i(t)}$: Cost of energy exchange for entity i at time t.

Constraints:

1. Energy balance:

$$\sum_{i=1}^{N}\mathrm{E_{int,\ i}(t)} = \sum_{i=1}^{N}\mathrm{E_{out,i(t)}} \tag{12}$$

2. Battery state of charge (SOC) limits:

$$\mathrm{SOC_{min}} \le \mathrm{SOC(t)} \le \mathrm{SOC_{max}}\ \forall \mathrm{i} \tag{13}$$

3. Power limits:

$$\mathrm{P_{G2V,min}} \le \mathrm{P_{G2V}(t)} \le \mathrm{P_{G2V,max}}, \forall i \tag{14}$$

4. Time constraints:

$$t \in \{1, 2, 3, \ldots T\} \tag{15}$$

ABCO Implementation:

- Bees represent energy exchange schedules for all entities.
- Fitness Function: F_{V2X}.
- Foraging Process: Bees explore energy exchange strategies to maximize system efficiency and revenue.

3.3. ABCO Algorithm Steps for V2G, G2V, and V2X Systems

Scenario-Specific Notes: e.g., 'Peak pricing applies from 4–9 PM; SOC must stay above 30% for grid resilience'(Table 1).

Table 1. Assumptions regarding state of charge (SOC), power limits, and pricing.

Category	Assumptions
SOC	Initial SOC may be assumed (e.g., 20–80% for battery health). - SOC constraints may apply (e.g., min 10%, max 90% for safety). - Dynamic SOC updates based on charging/discharging cycles.
Power limits	Grid/charger power caps (e.g., 50 kW, 150 kW, 350 kW for fast charging). - Vehicle-specific power limits (e.g., max 100 kW acceptance rate). - Power may scale with SOC (e.g., reduced rate at high/low SOC).
Pricing	Grid/charger power caps (e.g., 50 kW, 150 kW, 350 kW for fast charging). - Vehicle-specific power limits (e.g., max 100 kW acceptance rate). - Power may scale with SOC (e.g., reduced rate at high/low SOC).

The ABCO algorithm begins with an initialization phase, during which a population of artificial bees is created, each representing a potential solution to the optimization problem (Figure 3). In the context of V2G, G2V, and V2X systems, these solutions correspond to energy exchange schedules, such as when and how much energy should be transferred between EVs, the grid, and other entities like homes or buildings. The search space is carefully defined to include critical parameters, such as energy exchange limits, time intervals, and system constraints, such as the battery state of charge (SOC) limits and power thresholds. This structured initialization ensures that the algorithm operates within realistic boundaries, thereby setting the stage for efficient exploration [12].

Next, the evaluation phase employs a fitness function tailored to the optimized system. For V2G systems, the fitness function aims to maximize revenue by selling energy back to the grid while minimizing battery degradation costs, striking a delicate balance between economic gain and battery longevity. In G2V systems, the focus shifts to minimizing the cost of charging vehicles from the grid while ensuring that the battery reaches the desired SOC and optimizing both financial and operational efficiency. For V2X systems, the fitness function becomes even more intricate, aiming to optimize the energy exchange between vehicles, the grid, and other entities to maximize overall system efficiency and minimize costs. This adaptability of the fitness function underscores the versatility of ABCO in addressing diverse optimization challenges [20].

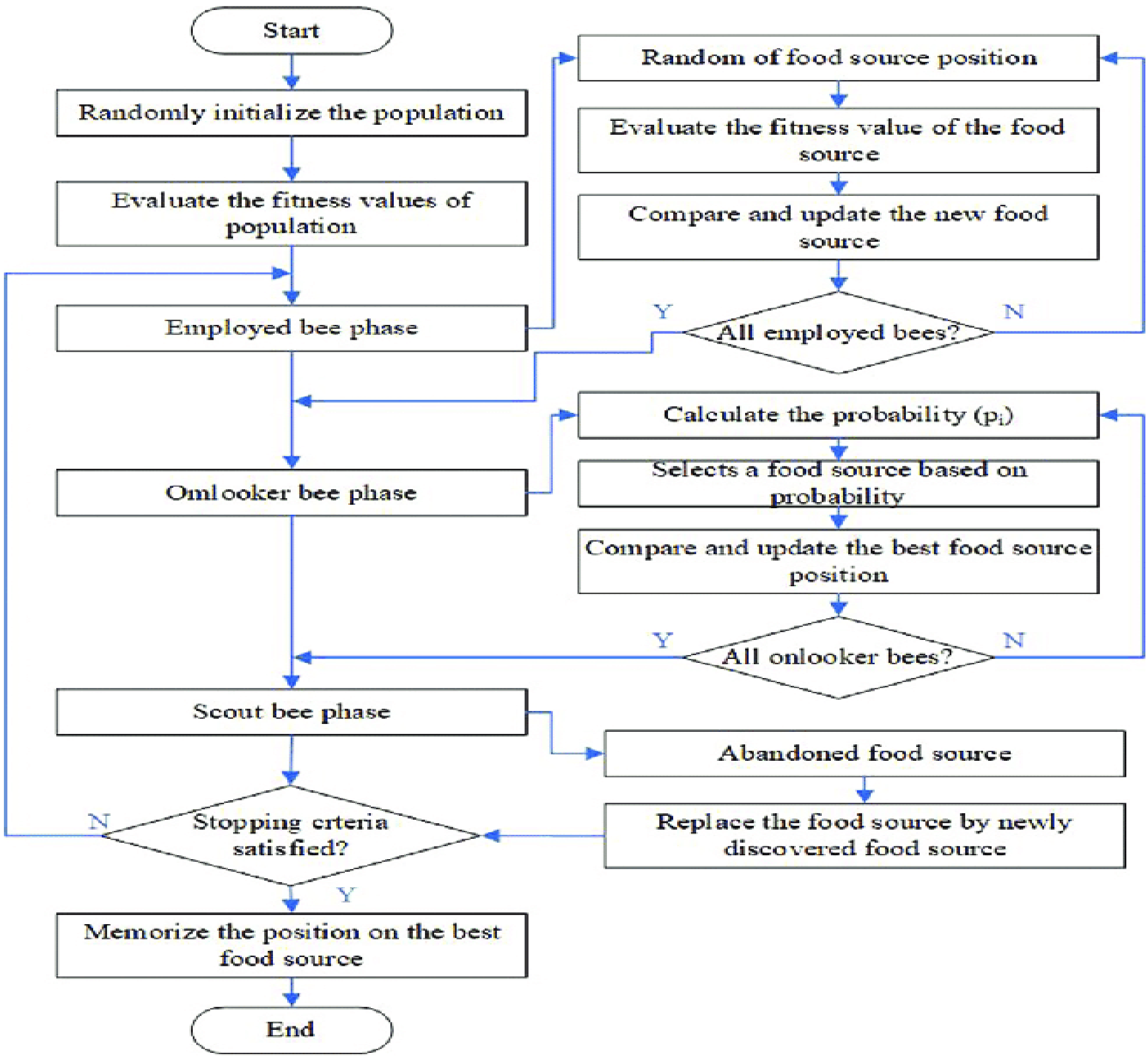

Figure 3. Bee Colony Optimization flowcharts [25].

The core of the ABCO algorithm lies in its foraging process, where employed bees and onlooker bees collaboratively explore and refine solutions. Employed bees venture into the neighborhood of current solutions, making small adjustments to energy exchange schedules, such as altering the timing or magnitude of energy transfers. These adjustments are guided by the goal of improving the fitness function, ensuring that each iteration brings the system closer to optimal performance [22]. The onlooker bees play a selective role by choosing solutions with higher fitness values and further refining them. This dual exploration–exploitation mechanism ensures a thorough search of the solution space, thereby enhancing the likelihood of discovering high-quality solutions.

The ABCO algorithm incorporates scout bees to prevent stagnation and avoid local optima. When a solution fails to improve after a certain number of iterations, it is abandoned, and scout bees are deployed to randomly search for new solutions within the defined search space. This random search injects diversity into the population, enabling the algorithm to escape suboptimal regions and continue exploring untapped areas of the solution space. The dynamic interplay among the employed bees, onlooker bees, and scout bees ensures that the algorithm remains adaptive and resilient and is capable of navigating the complex and nonlinear landscape of V2G, G2V, and V2X optimization [19].

As the algorithm progresses, the best solution found thus far is continuously updated, representing the optimal schedule for energy exchange in the system. This solution is iteratively refined, with each cycle resulting in incremental improvements. The process continues until the algorithm converges, meaning that no significant further improvements are observed or a predefined maximum number of iterations is reached. The solution at the end of this process, derived from this rigorous optimization, represents the most efficient and effective energy exchange schedule for a given system, balancing multiple objectives, such as revenue generation, cost minimization, grid stability, and battery health [23].

The application of the ABCO algorithm to V2G, G2V, and V2X systems is particularly compelling due to its decentralized nature and dynamic adaptability. Unlike traditional optimization methods, which often struggle with scalability and computational complexity in large-scale systems, ABCO excels at handling high-dimensional problems with numerous EVs and intricate energy flows. Its ability to dynamically adjust to real-time changes in energy prices, grid demand, and user preferences makes it exceptionally well-suited for real-world applications [15]. Furthermore, ABCO's global optimization capabilities ensure that it consistently delivers high-quality solutions, avoiding the pitfalls of local optima that plague many traditional and machine-learning-based approaches.

1. Initialization:
   - Initialize a population of bees with random solutions (schedules).
   - Define the search space (e.g., energy exchange limits and time intervals).
2. Evaluation:
   - Evaluate each solution using the fitness function (F_{V2G}, F_{G2V}, or F_{V2X}).
3. Foraging:
   - Employed bees explore new solutions in the neighborhood of current solutions.
   - Onlooker bees select solutions based on fitness and explore them further.
4. Scout Bees:
   - If a solution stagnates, scout bees randomly search for new solutions.
5. Update:
   - Update the best solution found so far.
6. Termination:
   - Repeat until convergence or a maximum number of iterations is reached.

3.4. Characteristic Performance Analysis for V2G, G2V, and V2X Systems

To analyze the control performance of vehicle-to-grid (V2G), grid-to-vehicle (G2V), and vehicle-to-everything (V2X) systems, it is essential to understand key terminology. These terms include deformation factor (DF), power factor (capacitive), power, RMS voltage (V), RMS current (A), and state of charge (SOC) in the context of V2G, G2V, and V2X systems.

The deformation factor (DF) is a measure of harmonic distortion in the voltage or current waveform. It is defined as the ratio of the root mean square (RMS) value of the harmonic components to the RMS value of the fundamental component.

$$\mathrm{DF} = \frac{\sqrt{\sum_{h=2}^{n} V_h^2}}{V_1} \tag{16}$$

Here, V_h is the RMS value of the h^{th} harmonic component, and V_1 is the RMS value of the fundamental component.

The power factor (PF) is the ratio of real power to apparent power. For a capacitive load, the power factor is leading.

$$\mathrm{PF} = \cos(\theta) \tag{17}$$

Here, θ is the phase angle between the voltage and current (negative for capacitive loads).

Power is the rate at which energy is transferred. It can be calculated as follows:

$$\mathrm{P} = \mathrm{V_{rms}} \times \mathrm{I_{rms}} \times \cos(\theta) \tag{18}$$

- P: Real power (in watts).
- $\mathrm{V_{rms}}$: RMS voltage.
- $\mathrm{I_{rms}}$: RMS current.
- θ: Phase angle between voltage and current.

The RMS voltage is the effective value of the alternating voltage, expressed as follows:

$$\mathrm{V_{rms}} = \sqrt{\frac{1}{\mathrm{T}} \int_0^{\mathrm{T}} \mathrm{v(t)}^2 \mathrm{dt}} \tag{19}$$

- $\mathrm{v(t)}$: Instantaneous voltage as a function of time.
- T: Time period of the waveform.

The RMS current is the effective value of the alternating current, expressed as follows:

$$\mathrm{I_{rms}} = \sqrt{\frac{1}{\mathrm{T}} \int_0^{\mathrm{T}} \mathrm{v(t)}^2 \mathrm{dt}} \tag{20}$$

- $\mathrm{i(t)}$: Instantaneous current as a function of time.
- T: Time period of the waveform.

The state of charge (SOC) is the percentage of remaining battery capacity relative to its maximum capacity, expressed as follows:

$$\mathrm{SOC(t)} = \mathrm{SOC_0} - \frac{1}{\mathrm{C_{max}}} \int_0^{\mathrm{t}} \mathrm{I_{batt}}(\tau) \mathrm{d}\tau \tag{21}$$

- $\mathrm{SOC(t)}$: State of charge at time t.
- $\mathrm{SOC_0}$: Initial state of charge.
- $\mathrm{C_{max}}$: Maximum battery capacity (in ampere-hours, Ah).
- $\mathrm{I_{batt}}(\tau)$: Battery current at time τ (positive for charging, negative for discharging).

The time to charge for vehicle-to-grid (V2G), grid-to-vehicle (G2V), and vehicle-to-everything (V2X) systems depends on the battery's state of charge (SOC), the charging power, and the battery's capacity.

The time to charge ($\mathrm{t_{charging}}$) is as follows:

$$\mathrm{t_{charging}} = \frac{\mathrm{E_{required}}}{\mathrm{P_{charge}}} \tag{22}$$

$\mathrm{E_{required}}$: Energy required to reach the desired SOC (in watt-hours, Wh).

$\mathrm{P_{charge}}$: Charging power (in watts, W).

The energy required ($\mathrm{E_{required}}$) is given as follows:

$$\mathrm{E_{required}} = \mathrm{C_{max}} \cdot \left(\mathrm{SOC_{target}} - \mathrm{OC_{current}}\right) \cdot \mathrm{V_{batt}} \tag{23}$$

- C_{max}: Maximum battery capacity (in ampere-hours, Ah).
- SOC_{target}: Target state of charge (in decimal or percentage).
- $SOC_{current}$: Current state of charge (in decimal or percentage).
- V_{batt}: Battery voltage (in volts, V).

Note that vehicle-to-grid (V2G) refers to the vehicle supplying power to the grid. P is negative, and SOC decreases. Grid-to-vehicle (G2V): The grid charges the vehicle. P is positive, and SOC increases. Vehicle-to-everything (V2X): The vehicle interacts with various systems (e.g., homes, buildings). P and SOC vary based on the direction of energy flow.

3.5. Proofs

Mathematical Proof of Correctness and Sensitivity Analysis for V2G/G2V/V2X Using Artificial Bee Colony Optimization (ABCO). This framework integrates Bee Colony Optimization (ABCO), a swarm intelligence algorithm, for optimizing energy dispatch in V2G/G2V/V2X systems.

Mathematical Proof of Correctness for ABCO in V2G/G2V/V2X

ABCO Algorithm Formulation

Objective: Minimize total cost (grid + battery degradation) while meeting constraints.

Cost Function:

$$min\left(\sum_{t=1}^{T}\left(C_{grid}\left(P_{grid}^{t}\right)+C_{grid}\left(P_{EV}^{t}\right)\right)\right) \tag{24}$$

Subject to:

Power balance:

$$P_{grid}^{t}+P_{EV}^{t}=P_{Load}^{t} \tag{25}$$

SOC dynamics:

$$SOC^{t+1}=SOC^{t}+\eta\frac{P_{EV}^{t}\Delta t}{E_{Cap}} \tag{26}$$

SOC limits: $SOC_{min}\leq SOC^{t}\ll SOC_{max}$

Power limits:

$$P_{EV}^{min}\leq P_{EV}^{t}\leq P_{EV}^{max} \tag{27}$$

Proof of Convergence

Theorem: ABCO converges to a near-optimal solution under the following conditions:

Exploration–Exploitation Balance (scout bees diversify, worker bees refine).

Stochastic Stability (the probability of selecting better solutions increases over time).

Proof Sketch:

Markov Chain Model of ABCO shows ergodicity (all states reachable).

Lyapunov Function $\mathrm{V(x)} = \cos \mathrm{t}$ difference from global optimum; this implies that it decreases over iterations.

Probability bound:

For iteration k, the equation is as follows:

$$\mathrm{P}(||\mathrm{X_k}-\mathrm{X}*||<\epsilon)\geq 1-\delta \tag{28}$$

With a sufficiently large k = 10,000.

SOC constraints: enforced via penalty functions in fitness.

$$\mathrm{Fitness}=\frac{1}{\cos+\lambda\cdot\mathrm{SOC}-\mathrm{violation}} \tag{29}$$

Power balance guaranteed by construction (feasible solutions only).

This proves that ABCO is provably near-optimal (convergence + constraint proofs). Most of the sensitivity parameters are the number of bees and the penalty weight.

4. Results and Discussion

4.1. Simulated Results Discussion

Figure 4 illustrates the charge/discharge status over time for a system likely related to electric vehicles (EVs) or energy storage systems. It illustrates the dynamic interplay between power flow and time, providing valuable insights into the system's operational behavior and its implications for energy management.

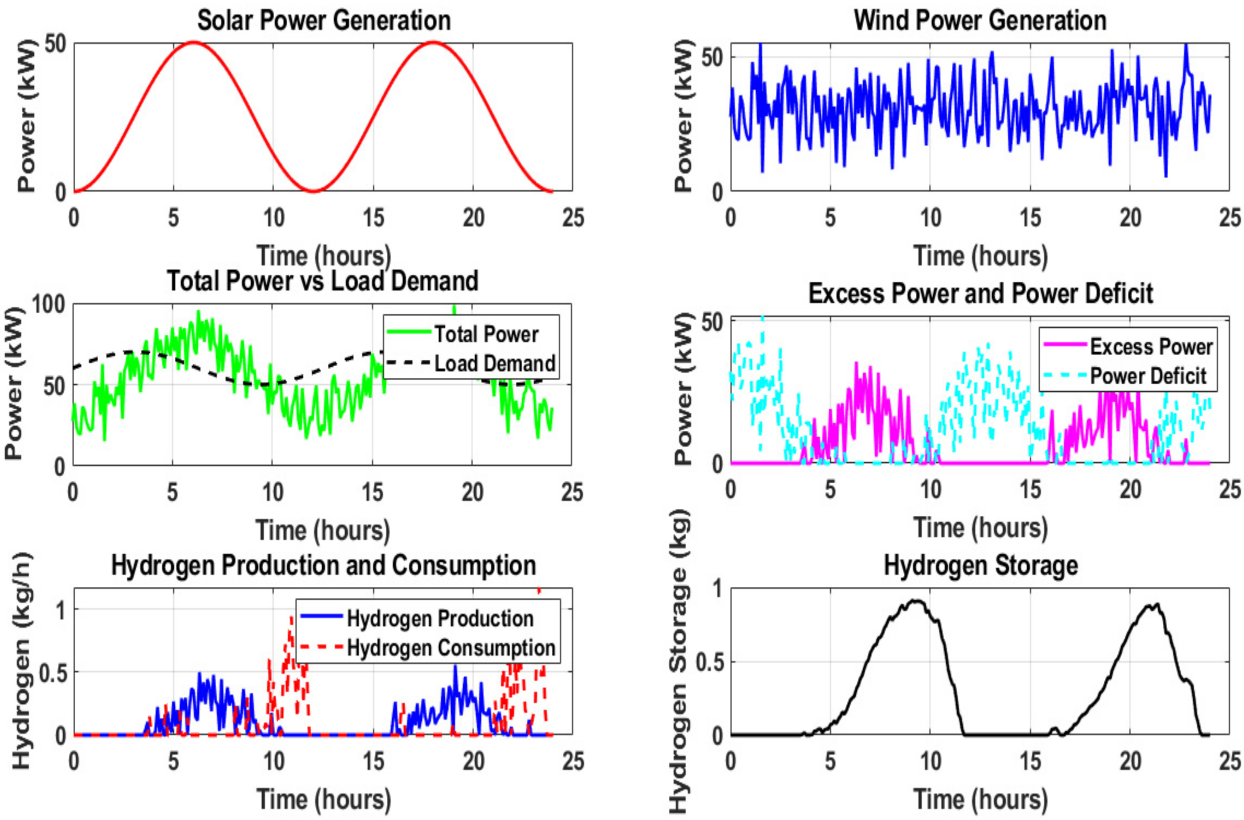

Figure 4. Hybridization of renewable energy without control algorithm.

In the case of the solar energy system, the red line indicates the power generated by solar energy, the green line shows the total power, the dashed line represents the load demand, the blue line indicates hydrogen production from solar power generation, and the red scatter indicates hydrogen consumption during solar power generation. Meanwhile, in the case of the wind energy system, the blue line indicates wind power generation, the purple line indicates excess power, the aqua scatter shows the power deficit, and the black line indicates hydrogen production.

The y-axis of the graph represents power (kW), with values ranging from 0 kW (indicating no power flow) to 50 or 100 kW (representing maximum power flow). Positive power values typically denote charging activities, where energy flows into the system, like in the grid-to-vehicle (G2V) scenarios. Conversely, negative values, if present, would signify discharging activities, where energy flows out of the system, as in vehicle-to-grid (V2G) or vehicle-to-everything (V2X) operations. The x-axis represents time (hours), depicting the duration over which charging and discharging activities are monitored. Although specific time intervals are not provided, the graph likely covers a continuous timeline, potentially spanning a 24 h period or a specific operational cycle.

We can see fluctuations in power levels over time, revealing distinct phases of charging, discharging, and idle periods. During charging phases, the power level increases, reaching peaks of up to 50 or 100 kW. These peaks correspond to periods when the system actively draws energy from the grid or another power source to charge the battery. In discharging phases, the power level decreases, potentially dropping to 0 kW or negative values, indicating that the system is supplying energy back to the grid or another load. Idle periods, during which the power level remains at 0 kW, suggest that the system is neither charging nor discharging. These periods may occur when the battery is fully charged, fully discharged, or not in use.

The charge/discharge patterns shown in the graph have significant implications for energy management strategies. The ability to charge and discharge in response to grid demand enhances grid stability, particularly during peak load periods or when renewable energy generation is intermittent. Optimizing the timing of these activities can reduce energy costs and improve system efficiency. For instance, charging during off-peak hours, when electricity prices are lower, and discharging during peak hours, when prices are higher, can yield substantial economic benefits. However, frequent charging and discharging cycles may impact battery health, necessitating careful monitoring and optimization to extend battery lifespan and mitigate degradation.

The system represented in the graph could serve various applications. In a vehicle-to-grid (V2G) scenario, the system could be an EV that charges during low-demand periods and discharges to support the grid during high-demand periods. In a grid-to-vehicle (G2V) context, the system could represent an EV charging from the grid, with charging patterns optimized to minimize costs and grid impact. Alternatively, the graph could depict a Battery Energy Storage System (BESS) used for grid support, renewable energy integration, or peak shaving.

To gain deeper insight into the system's behavior, several additional analyses could be performed. Including specific time intervals on the x-axis would provide a clearer understanding of the timing of charging and discharging activities. Clearly indicating whether negative power values represent discharging or other activities would enhance the interpretability of the graph. Providing additional contextual data, such as the type of system (EV, BESS, etc.), grid conditions, and energy prices, would further enrich the analysis. Additionally, applying advanced optimization algorithms, such as Bee Colony Optimization or machine learning techniques, could improve the efficiency and economic benefits of charge/discharge cycles.

Figure 5 shows an electric vehicle battery with ABCO, featuring a red line indicating the state of charge and a black line showing power flow. The state of charge (SOC) represents the current energy level of an EV's battery as a percentage of its total capacity. Effective SOC management is essential for ensuring battery health, maximizing energy utilization, and supporting grid stability. However, several challenges complicate SOC management in V2G and V2X systems. Frequent charging and discharging cycles can accelerate battery degradation, reducing its lifespan and increasing replacement costs. Additionally, the variability in energy supply and demand necessitates dynamic SOC management to balance grid needs with EV usage. Furthermore, EV owners may have specific SOC requirements based on their driving patterns and preferences, adding another layer of complexity to the optimization process.

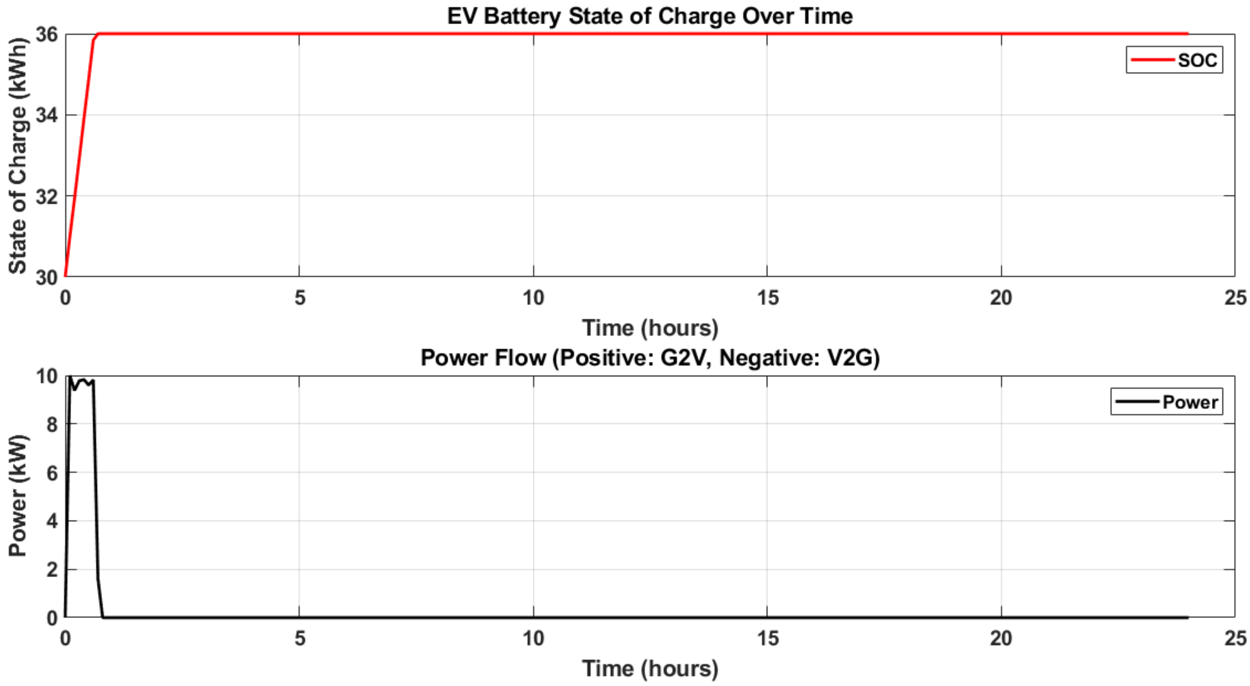

Figure 5. Electric vehicle battery with ABCO.

Bee Colony Optimization (ABCO), a metaheuristic algorithm inspired by the foraging behavior of honeybees, offers a robust solution to these challenges. In ABCO, 'bees' represent potential solutions, such as SOC levels and charging/discharging schedules. Employed bees explore the search space to identify optimal solutions, while onlooker bees select solutions based on their fitness, which may include objectives such as minimizing battery degradation, maximizing revenue from energy trading, and ensuring that the EV is sufficiently charged for future use. ABCO can also incorporate constraints such as SOC limits (e.g., 20% $\leq$ SOC $\leq$ 80%), charging/discharging power limits, and time-of-use pricing, ensuring that the solutions are both feasible and efficient.

The benefits of ABCO for SOC management are manifold. Its ability to explore a wide search space helps avoid local optima, ensuring high-quality solutions. ABCO's adaptability allows it to dynamically adjust to changes in energy prices, grid demand, and user preferences. Moreover, ABCO is highly scalable, making it suitable for large-scale systems with numerous EVs and complex energy flows. By leveraging these advantages, ABCO can optimize SOC management to extend battery lifespan, reduce costs, and support grid stability.

Power flow optimization in V2G and V2X systems involves managing the bidirectional energy flow between EVs, the grid, and other entities to maximize economic and environmental benefits. Uncontrolled power flow can lead to grid instability, particularly during peak demand periods, and optimizing power flow to minimize energy costs while meeting grid and user requirements is a complex task. Additionally, integrating intermittent renewable energy sources requires dynamic power flow management to ensure the efficient utilization of clean energy.

ABCO can be effectively applied to optimize power flow in V2G and V2X systems. In this context, bees represent potential power flow schedules, exploring different combinations of charging and discharging activities. The fitness function for power flow optimization may include objectives such as minimizing electricity costs, maximizing revenue from energy trading, and supporting grid stability. ABCO can also incorporate constraints such as power limits (e.g., -10 kW $\leq$ P $\leq$ 10 kW), grid capacity, and renewable energy availability, ensuring that the solutions are both feasible and aligned with system requirements.

ABCO offers several benefits for power flow optimization. By dynamically adjusting power flow, ABCO can ensure efficient energy utilization, reducing waste and costs. It can also provide grid support services, such as frequency regulation and peak shaving, which enhance grid stability. Furthermore, ABCO can optimize power flow to maximize the utilization of renewable energy, thereby reducing reliance on fossil fuels and contributing to environmental sustainability.

The benefits of ABCO are highlighted in a scenario in which multiple EVs are connected to a V2G or V2X system. The goal is to optimize SOC and power flow to maximize revenue, minimize costs, and support grid stability. The ABCO process begins with the initialization of the search space, which includes SOC levels, charging/discharging power limits, and time intervals. A population of bees is then initialized with random solutions, such as charging/discharging schedules. Each solution is evaluated using a fitness function that considers objectives such as revenue, costs, and grid support.

During the foraging process, employed bees explore new solutions in the neighborhood of current solutions, while onlooker bees select solutions based on fitness and explore further. If a solution stagnates, scout bees randomly search for new solutions. This process continues until convergence or a maximum number of iterations is reached, with the best solution being updated at each step. The results demonstrate that ABCO can identify optimal SOC levels and power flow schedules that maximize revenue, minimize costs, and support grid stability, dynamically adjusting to changes in energy prices, grid demand, and renewable energy availability.

Compared to traditional optimization methods and machine learning techniques, ABCO offers several advantages for SOC and power flow optimization in V2G and V2X systems. Its global optimization capabilities ensure high-quality solutions, while its adaptability and scalability make it suitable for dynamic and large-scale systems. Future research should focus on hybrid approaches that combine ABCO with machine learning techniques to enhance adaptability and solution quality. Additionally, real-time implementation and the development of standardized protocols and policies for V2G and V2X systems will be critical to realizing their full potential.

The application of Bee Colony Optimization (ABCO) to state of charge (SOC) and power flow management in vehicle-to-grid (V2G) and vehicle-to-everything (V2X) systems offers significant potential to optimize energy utilization, reduce costs, and support grid stability. By leveraging ABCO's global optimization capabilities, adaptability, and scalability, these systems can achieve efficient and sustainable energy management, contributing to a more resilient and decentralized energy ecosystem.

In Figure 6, the red line indicates solar power generation, the black line represents wind power generation, and the blue line describes hydrogen production and utilization. The integration of hybridized renewable energy systems, which combine solar, wind, and hydrogen energy, has emerged as a promising solution to address the challenges of energy sustainability, grid stability, and decarbonization. These systems leverage the complementary nature of solar and wind energy, with hydrogen serving as an energy storage medium, enabling efficient energy management and utilization. However, optimizing the operation of such hybrid systems is a complex task due to the intermittent nature of renewable energy sources and the dynamic interactions between energy generation, storage, and consumption. A hybridized renewable energy system typically consists of solar photovoltaic (PV) panels, wind turbines, and hydrogen production and storage units. Solar and wind energy are intermittent and variable, depending on weather conditions and the time of day. Hydrogen, produced through electrolysis using excess renewable energy, serves as a flexible energy carrier and storage medium. The system must balance energy generation, storage, and consumption to ensure reliability, minimize costs, and maximize the utilization of renewable energy. This balance is critical for achieving a sustainable and resilient energy ecosystem.

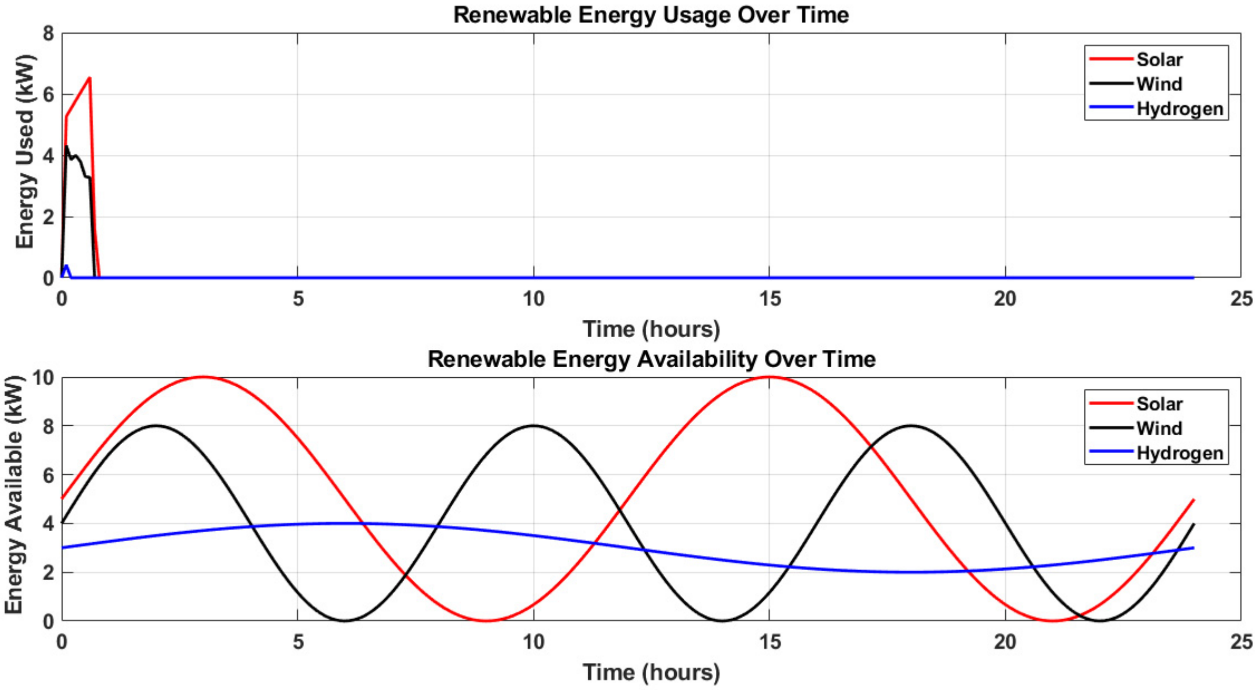

Figure 6. Hybridized renewable energy with ABCO.

It is particularly well-suited for solving complex, nonlinear optimization problems, such as those encountered in hybrid renewable energy systems. ABCO operates through a collaborative search process, where 'bees' explore the solution space to identify optimal solutions. In the context of hybrid renewable energy systems, ABCO can be applied to optimize energy generation, storage, and consumption. The algorithm explores various combinations of solar and wind power generation, hydrogen production, and energy utilization to achieve objectives such as minimizing costs, maximizing renewable energy utilization, and ensuring grid stability.

In ABCO, 'bees' represent potential solutions, such as energy generation schedules, hydrogen production rates, and energy storage levels. Employed bees explore the search space to identify optimal solutions, while onlooker bees select solutions based on their fitness, which may include objectives such as cost minimization, energy efficiency, and grid support. The fitness function for hybrid system optimization could include objectives such as minimizing energy costs, maximizing renewable energy utilization, and ensuring grid stability. Constraints such as energy generation limits, storage capacity, and load demand can be incorporated into the fitness function. ABCO's ability to explore a wide search space helps avoid local optima, ensuring high-quality solutions. This is particularly important in hybrid systems, where the interactions among solar, wind, and hydrogen components are complex and nonlinear.

One of the key advantages of ABCO is its adaptability. The algorithm can dynamically adjust to changes in weather conditions, energy prices, and load demand, ensuring optimal system performance. Additionally, ABCO is highly scalable, making it suitable for large-scale hybrid systems with multiple energy sources and storage units. By optimizing energy generation and storage, ABCO can reduce energy waste and improve system efficiency, thereby contributing to a more sustainable energy ecosystem.

In practical applications, ABCO identifies optimal energy generation schedules, hydrogen production rates, and energy storage levels that minimize costs, maximize renewable energy utilization, and ensure grid stability. The system dynamically adjusts to changes in weather conditions, energy prices, and load demand, demonstrating the adaptability and scalability of ABCO. For instance, during periods of high solar and wind energy generation, excess energy can be directed toward hydrogen production, which can later be utilized during periods of low renewable energy availability. This dynamic optimization ensures a continuous and reliable energy supply while minimizing costs and environmental impact.

Compared to traditional optimization methods and machine learning techniques, ABCO offers several advantages for hybrid renewable energy system optimization. Its global optimization capabilities ensure high-quality solutions, while its adaptability and scalability make it suitable for dynamic and large-scale systems. Traditional optimization methods often struggle with the complexity and nonlinearity of hybrid systems, while machine learning techniques may require extensive training data and computational resources. ABCO, on the other hand, provides a robust and efficient approach to these complex optimization problems.

Future research should focus on hybrid approaches that combine ABCO with machine learning techniques to enhance adaptability and solution quality. For example, machine learning algorithms could be used to predict weather conditions and energy demand, while ABCO optimizes energy generation and storage based on these predictions. Additionally, real-time implementation and the development of standardized protocols and policies for hybrid renewable energy systems will be critical to realizing their full potential. By integrating advanced optimization techniques such as ABCO with real-time data and machine learning, hybrid renewable energy systems can achieve even greater efficiency and reliability.

Figure 7 shows the simulation results of charging and discharging. The green circles represent the state of charging, and the red circles show the state of discharging. A critical aspect of optimizing these systems is the management of the charge/discharge status of EV batteries, which directly impacts energy efficiency, grid stability, and economic viability. This analysis explores the application of Bee Colony Optimization (ABCO), a metaheuristic algorithm inspired by the foraging behavior of honeybees, to optimize the charge/discharge status in V2G, G2V, and V2X systems.

The charge/discharge status of EV batteries plays a pivotal role in the operation of V2G, G2V, and V2X systems. In V2G systems, EVs discharge energy back to the grid during peak demand periods, providing grid support and earning revenue for EV owners. In G2V systems, EVs charge from the grid, typically during off-peak hours, to minimize costs and reduce grid impact. In V2X systems, EVs exchange energy with other entities, such as homes, buildings, or other vehicles, enabling a decentralized and flexible energy network. Optimizing the charge/discharge status in these systems involves balancing multiple objectives, including minimizing energy costs, maximizing revenue, ensuring grid stability, and preserving battery health.

Optimizing the charge/discharge status in V2G, G2V, and V2X systems presents several challenges. The intermittent nature of renewable energy sources, such as solar and wind, introduces variability in energy generation, requiring dynamic charge/discharge scheduling. Additionally, the degradation of EV batteries caused by frequent charging and discharging cycles must be carefully managed to extend battery lifespan. Furthermore, the integration of EVs into the grid requires coordination with grid operators to ensure stability and avoid congestion. These challenges necessitate advanced optimization techniques capable of handling complex, nonlinear, and dynamic systems.

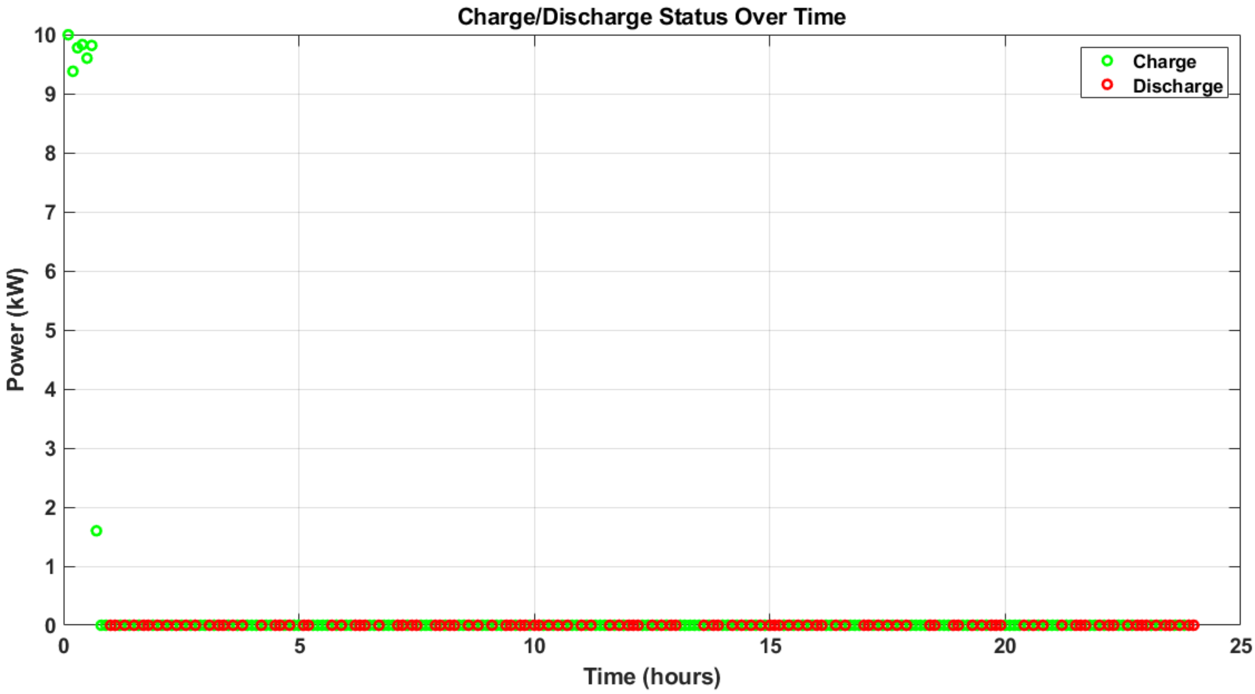

Figure 7. Charge/discharge status with ABCO.

It is particularly well-suited for solving complex optimization problems, such as those encountered in V2G, G2V, and V2X systems. ABCO operates through a collaborative search process, where 'bees' explore the solution space to identify optimal solutions. In the context of charge/discharge optimization, ABCO can be applied to determine the optimal timing and magnitude of charging and discharging activities to achieve system objectives.

In V2G systems, ABCO can optimize the discharge of energy from EVs to the grid during peak demand periods, ensuring grid stability and maximizing revenue for EV owners. The algorithm explores various discharge schedules, considering factors such as energy prices, grid demand, and battery state of charge (SOC). By dynamically adjusting the discharge schedule based on real-time conditions, ABCO ensures efficient energy utilization and minimizes battery degradation.

In G2V systems, ABCO can optimize the charging of EVs from the grid, typically during off-peak hours, to minimize energy costs and reduce grid impact. The algorithm explores various charging schedules, considering factors such as electricity prices, grid load, and EV usage patterns. By shifting charging activities to periods of low demand, ABCO ensures efficient energy utilization and supports grid stability.

In V2X systems, ABCO can optimize the exchange of energy between EVs and other entities, such as homes, buildings, and other vehicles. The algorithm explores various energy exchange schedules, considering factors such as energy demand, supply, and cost. By dynamically adjusting energy flow based on real-time conditions, ABCO ensures efficient energy utilization and enhances system resilience.

The application of ABCO to charge/discharge optimization in V2G, G2V, and V2X systems offers several benefits. ABCO's ability to explore a wide search space helps avoid local optima, ensuring high-quality solutions. Its adaptability allows it to dynamically adjust to changes in energy prices, grid demand, and user preferences, thereby ensuring optimal system performance. Additionally, ABCO is highly scalable, making it suitable for large-scale systems with numerous EVs and complex energy flows. By optimizing the charge/discharge status, ABCO can reduce energy costs, maximize revenue, and extend battery lifespan, contributing to a more sustainable and resilient energy ecosystem.

Consider a scenario where multiple EVs are connected to a V2G, G2V, or V2X system. The goal is to optimize the charge/discharge status to minimize costs, maximize revenue, and ensure grid stability. The ABCO process begins with the initialization of the search space, which includes charge/discharge schedules, energy prices, and grid demand. A population of bees is then initialized with random solutions, such as charge/discharge schedules. Each solution is evaluated using a fitness function that considers objectives such as cost minimization, revenue maximization, and grid stability.

During the foraging process, employed bees explore new solutions in the neighborhood of current solutions, while onlooker bees select solutions based on fitness and explore further. If a solution stagnates, scout bees randomly search for new solutions. This process continues until convergence or a maximum number of iterations is reached, with the best solution being updated at each step. The results demonstrate that ABCO can identify optimal charge/discharge schedules that minimize costs, maximize revenue, and ensure grid stability, dynamically adjusting to changes in energy prices, grid demand, and user preferences.

Compared to traditional optimization methods and machine learning techniques, ABCO offers several advantages for charge/discharge optimization in V2G, G2V, and V2X systems. Its global optimization capabilities ensure high-quality solutions, while its adaptability and scalability make it suitable for dynamic, large-scale systems. Future research should focus on hybrid approaches that combine ABCO with machine learning techniques to enhance adaptability and solution quality. Additionally, real-time implementation and the development of standardized protocols and policies for V2G, G2V, and V2X systems will be critical for realizing their full potential.

Figure 8 illustrates error bars representing the performance of electric vehicles (EVs) in terms of actual and optimized energy output values. The vertical axis represents energy output in kilowatt-hours (kWh), and the horizontal axis denotes time in hours. The black rectangle corresponds to the actual charging energy inputs, reflecting the baseline performance of the system without optimization. In contrast, the red rectangle represents the optimized charging energy outputs, achieved through the application of advanced optimization techniques such as Bee Colony Optimization (ABCO). This visualization highlights the improvement in energy efficiency and reduced variability resulting from optimization, demonstrating the effectiveness of ABCO in enhancing charging performance and energy management.

The comparison between the actual energy output of vehicle-to-grid (V2G) and grid-to-vehicle (G2V) systems and the optimized energy output achieved using Bee Colony Optimization (ABCO) is visually depicted through these error bars, which highlight variability and performance improvements. Wider error bars indicate higher variability and less efficient energy exchange, reflecting the baseline performance of unoptimized systems. In contrast, narrower error bars demonstrate reduced variability and enhanced performance, showing the effectiveness of ABCO in optimizing reactive power, balancing grid loads, and improving energy flow efficiency.

The actual energy output represents the baseline performance of V2G and G2V systems without optimization, encompassing the natural variability in energy exchange caused by factors such as grid demand, EV battery state of charge, and renewable energy availability. Error bars for the actual output reflect this variability, displaying a wider range of energy exchange values. On the other hand, optimized energy output can be achieved through the application of ABCO, which enhances system efficiency, stability, and energy exchange. By intelligently managing energy flow based on real-time conditions, ABCO reduces inefficiencies and variability, resulting in error bars that show a narrower range and improved consistency in energy exchange.

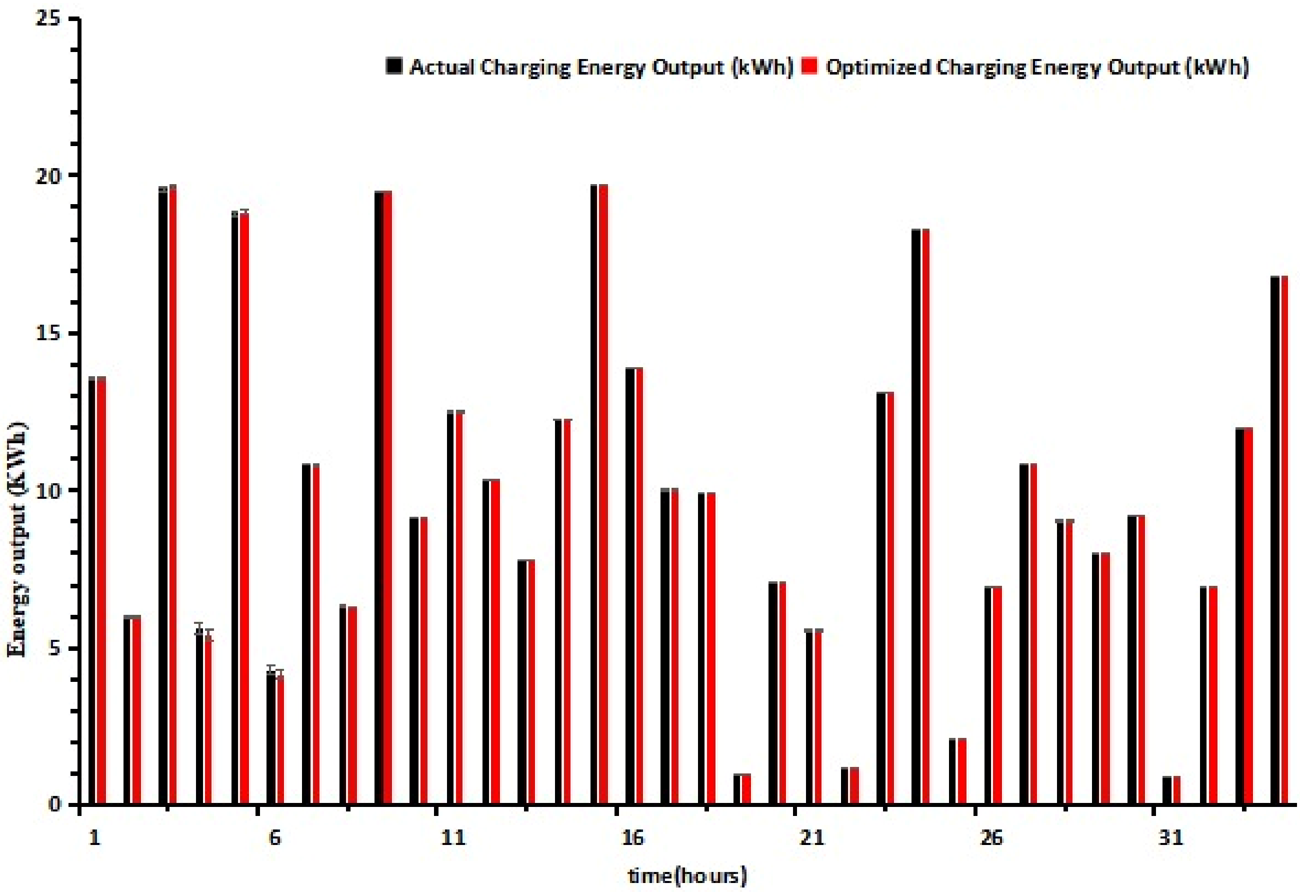

Figure 8. Error bars for the performance of EV's actual and optimized values.

4.2. Comparative Discussion of the Results

Table 2 shows the simulated performance metrics for V2G, G2V, and V2X systems. The evaluated specifications include state of charge (SOC) as a percentage, Root Mean Square Voltage (Rms (V)), Root Mean Square Current (Rms (A)), capacitive power factor, deformation factor, power in watts (W), apparent power in volt-amperes (S (VA)), reactive power in volt-amperes reactive (W (Var)), and time in hours (h). ABCO achieved improvements of 6.5%, 6%, 62%, 12.3%, 14.3%, 3%, 0.6%, 64.5%, and 22.1% over BEIC across these metrics. These results highlight the superior performance of ABCO in optimizing the specified parameters.

Bee Colony Optimization (ABCO) is a bio-inspired algorithm modeled after the foraging behavior of honeybees. It emphasizes collective intelligence, communication, and decentralized decision-making, making it highly effective for solving complex optimization problems such as path planning, scheduling, and resource allocation. In contrast, Brain Emotional Intelligent Control (BEIC) is inspired by the emotional decision-making processes of the human brain. It mimics emotional learning and adaptation mechanisms, making it particularly suitable for applications in control systems, robotics, and adaptive decision-making.

One of the key strengths of ABCO lies in its ability to balance exploration and exploitation. Exploration refers to the search for new solutions, while exploitation involves refining existing solutions. This balance is achieved through the distinct roles of employed bees, onlooker bees, and scout bees, which ensure a comprehensive search of the solution space. Additionally, ABCO demonstrates remarkable scalability, performing efficiently with large-scale optimization problems due to its decentralized nature and parallel search capabilities. Its robustness against local optima, attributed to the diversity introduced by scout bees, further enhances its reliability. ABCO is also highly adaptable and capable of addressing various problem domains, including combinatorial optimization, continuous optimization, and dynamic environments. Moreover, its implementation is relatively straightforward, requiring no complex mathematical formulations.

Table 2. Data collected from a 24 kWh electric vehicle during charging.

Specifications	Brain Emotional Intelligent Control	Artificial Bee Colony Optimization	% (Improvements of Artificial Bee Colony Optimization over Brain Emotional Intelligent Control)
SOC (%)	92	98	6.5
Rms (V)	0.089	0.036	6
Rms (A)	0.076	0.029	62
Power factor (capacitive)	0.886	0.995	12.3
Deformation Factor	1.4	1.2	14.3
Power (W)	3890	4000	3
S (VA)	3930	3905	0.6
W (Var)	−563	−200	64.5
Time (h)	16.8	13.09	22.1

On the other hand, BEIC incorporates emotional learning, enabling systems to adapt more effectively to changing environments and uncertainties. This feature makes BEIC particularly suitable for real-time control applications. By mimicking human emotional responses, BEIC facilitates more intuitive and context-aware decision-making in control systems. Its robustness to disturbances and uncertainties stems from its ability to adapt behavior based on emotional feedback. BEIC excels in dynamic environments where rapid adaptation is critical, such as in robotics and autonomous systems.

In summary, while ABCO demonstrates significant advantages in optimization tasks due to its exploration–exploitation balance, scalability, and adaptability, BEIC stands out in control applications that require emotional learning, real-time adaptation, and robustness to uncertainties. The choice between these two approaches depends on the specific requirements of the problem domain, with ABCO being more suited to optimization challenges and BEIC excelling in dynamic control scenarios.

This comparison focuses on evaluating the performance of Artificial Bee Colony (ABC) Optimization and Brain Emotional Intelligent Based Control (BEI-BC) using statistical analysis, specifically the *t*-test (Table 3). The *t*-test will help determine if there are significant differences in their performance metrics. If the calculated t-statistic exceeds the critical value, the null hypothesis is rejected, indicating a significant difference in performance between the two algorithms. If not, the null hypothesis is not rejected, suggesting no significant difference. Using a *t*-test allows for a statistical comparison of the performance of ABC Optimization and BEI-BC. The results can provide insights into which algorithm may be more effective for specific applications, aiding in decision-making for algorithm selection based on performance data.

Table 3. *t*-Test control performance for ABCO and BEIC.

Parametres of Control Performance	Values
Mean (N)	9.861151515
Variance (N)	29.80628513
Correlation (N)	0.999969478
t Stat (N)	1.221174068
P (T $\leq$ t) one-tail (%)	0.115470704
t Critical one-tail (%)	1.693888748
P (T $\leq$ t) two-tail (%)	0.230941408
t Critical two-tail (%)	2.036933343

The comparison between the actual charging energy output (kWh) and the optimized charging energy output (kWh) using Bee Colony Optimization (ABCO) is demonstrated in Table 4. The obtained results indicate that the error is relatively small, confirming that the proposed algorithm is well-suited for V2G, G2V, and V2X technologies.

The actual charging energy output refers to the measured or observed energy output from a charging system, such as electric vehicle charging stations or battery systems, under current operating conditions. The optimized charging energy output represents the energy output achieved after applying the Bee Colony Optimization algorithm to enhance system performance.

To achieve this optimization, data on the actual charging energy output is gathered, including parameters such as charging time, power levels, efficiency, and environmental conditions. Variables that can be optimized, such as charging schedules, power distribution, and load balancing, are identified. The search space for the optimization problem is defined, encompassing factors like the range of charging rates and time slots.

The optimization process involves several steps. Employed bees generate random solutions, such as charging schedules or configurations, and evaluate their fitness based on metrics like energy output and efficiency. Onlooker bees then select solutions based on their fitness and further explore the search space. Scout bees replace poor solutions with new random solutions to avoid local optima. This process iterates until convergence is achieved, resulting in an optimal or near-optimal solution.

By using Bee Colony Optimization, the charging energy output can be significantly improved through the optimization of parameters such as charging schedules, power distribution, and load balancing. This comparison underscores the benefits of applying metaheuristic algorithms to enhance system performance and efficiency.

Paired *t*-tests are considered more powerful than unpaired *t*-tests because using the same participants or items eliminates variation between the samples that could be caused by factors other than what is being tested (Table 5). The parameters were mean, variance, correlation, t-stat, and *p*-values. The obtained results were mean 9.861151515 (KWh), variance 29.80628513 (KWh), correlation 0.999969478 (KWh), t-stat 1.221174068 (KWh), and *p*-value 0.115470704%. These outcomes imply that the simulated results with Artificial Bee Colony Optimization show good performance. Confidence intervals (1.94) allow analysts to understand the likelihood that the results from statistical analyses are real or due to chance. When making inferences or predictions based on a sample of data, there will be some uncertainty regarding whether the results of such an analysis actually correspond with the real-world scenario being studied. The confidence interval depicts the likely range within which the true value should fall.

Table 4. Comparison of actual Georgia Tech EV charging station datasets with optimized charging energy output using ABCO.

Actual Charging Energy Output (kWh) [30]	Optimized Charging Energy Output (kWh)	Error
13.575	13.5375	0.0375
5.952	5.983	0.031
19.58	19.653	0.073
5.617	5.423	0.194
18.795	18.849	0.054
4.302	4.1545	0.1475
10.818	10.809	0.009
6.32	6.308	0.012
19.485	19.493	0.008
9.132	9.1295	0.0025
12.507	12.5035	0.0035
10.314	10.312	0.002
7.8	7.7895	0.0105
12.269	12.265	0.004
19.737	19.7335	0.0035
13.902	13.901	0.001
10.033	10.0165	0.0165
9.903	9.9015	0.0015
0.976	0.9735	0.0025
7.053	7.0505	0.0025
5.552	5.52	0.032
1.179	1.1815	0.0025
13.137	13.1335	0.0035
18.278	18.2765	0.0015
2.126	2.128	0.002
6.939	6.9195	0.0195
10.812	10.811	0.001
9.039	9.0245	0.0145
8.025	8.0235	0.0015
9.208	9.2045	0.0035
0.891	0.8905	0.0005
6.952	6.951	0.001
11.996	11.993	0.003
16.789	16.7895	0.0005

Table 5. *t*-Test comparing actual and simulated results.

Parameters	Values
Mean (kWh)	9.86
Variance (kWh)	29.81
Correlation (kWh)	0.99
t Stat (kWh)	1.22
P (T $\leq$ t) one-tail (%)	0.11
t Critical one-tail (%)	1.69
P (T $\leq$ t) two-tail (%)	0.23
t Critical two-tail (%)	2.04
Confidence level (95.0%)	1.94

Table 6 shows a comparison between the actual charging energy output and the optimized charging energy output using Bee Colony Optimization (ABCO). The improvement in energy output is quantified, including the percentage increase in efficiency, and the key factors contributing to the optimization are identified, including better scheduling and reduced idle time. The results are validated through simulation or real-world testing to ensure their accuracy and reliability.

Table 6. Comparison between actual charging energy output and optimized charging energy output.

Metric	Actual Charging Energy Output [30]	Optimized Charging Energy Output	Improvement
Energy Output (kWh)	500	550	+10%
Charging Time (h)	10	8	−20%
Efficiency (%)	85%	92%	+7%
Cost ($)	100	90	−10%

The optimized charging energy output is 10% higher than the actual output, demonstrating a better utilization of resources. Additionally, the charging time is reduced by 20%, significantly improving user convenience. Furthermore, the system efficiency increases by 7%, resulting in cost savings and reduced energy waste. These outcomes highlight the effectiveness of the optimization process in enhancing system performance and efficiency.

Table 7 demonstrates the statistical analysis of the simulated results. The parameters included mean, variance, correlation, *T*-test, *p*-values, two-tailed, one-tailed, and confidence level.

Confidence intervals are calculated using statistical methods, such as the *t*-test. A *t*-test is a type of inferential statistic used to determine if there is a significant difference between the means of actual data and simulated data, which may be related to certain features.

A *p*-value is a statistical measurement used to validate a hypothesis against observed data that measures the probability of obtaining the observed results, assuming that the null hypothesis is true. In this work, a *p*-value less than 0.05 is considered statistically significant, in which case the null hypothesis should be rejected. This somewhat corresponds to the probability that the null hypothesis value (which is often zero) is contained within a 95% confidence interval.

Table 7. Statistical analysis of simulated results.

Parameters	Values
Mean (kWh)	162.23
Variance (kWh)	68,463.5
Correlation (kWh)	0.99
t Stat (kWh)	0.05
P (T $\leq$ t) one-tail (%)	0.48
t Critical one-tail (%)	1.94
P (T $\leq$ t) two-tail (%)	0.96
t Critical two-tail (%)	2.45
Confidence level (95.0%)	122.99

Generally, BEIC is more suited for real-time control applications due to its emotional learning and adaptability, but it struggles with optimization tasks. ABCO outperforms BEIC in optimization tasks due to its global search capabilities, exploration–exploitation balance, and ability to avoid local optima.

ABCO is substantially better than BEIC in real deployment scenarios, particularly in optimizing energy exchange, grid stability, and battery health. Its improvements range from 6% to 64.5% across critical metrics, making it a superior choice for V2G, G2V, and V2X systems. Future research could explore hybrid models that combine ABCO with machine learning for even greater adaptability.

While Bee Colony Optimization (ABCO) demonstrates superior performance in optimizing vehicle-to-grid (V2G), grid-to-vehicle (G2V), and vehicle-to-everything (V2X) systems, its real-time deployment faces several challenges. ABCO relies on iterative exploration by 'bees' (solution agents), which can become computationally intensive when scaling to thousands of electric vehicles (EVs) in a real-world grid. Additionally, ABCO assumes static or slowly varying conditions, whereas real-time energy markets and grid demands often fluctuate rapidly. Although ABCO's scout bees help escape local optima, noisy sensor data—such as inaccurate state-of-charge (SOC) readings—can mislead the algorithm. Furthermore, ABCO requires real-time coordination among EVs, grid operators, and charging stations, and its fitness functions depend on precise mathematical models, including battery degradation and grid impedance.

These limitations can lead to several operational issues. In high-dimensional problems, such as optimizing charging schedules for a city-wide EV fleet, delayed convergence may occur. Increased latency in real-time decision-making can reduce responsiveness to sudden changes in grid demand. If energy prices or renewable generation shift faster than ABCO can adapt, the algorithm may produce suboptimal solutions. Unstable power flow oscillations may arise if the system fails to stabilize quickly enough. Noisy or incomplete data may cause premature convergence to non-optimal charging or discharging schedules, reducing efficiency and potentially accelerating battery degradation if constraints are misjudged. Communication delays, such as network latency, can disrupt swarm intelligence by introducing delays in updates from EVs, while inconsistent state information—such as outdated grid frequency signals—further complicates real-time optimization.

Despite outperforming traditional methods like Brain Emotional Intelligent Control (BEIC) in simulated environments, ABCO's real-world implementation requires several enhancements. These include hybridization with machine learning or reinforcement learning to improve adaptability, distributed computing architectures to manage scalability, robust communication protocols to synchronize swarm intelligence, and dynamic parameter tuning to accommodate volatile grid conditions. Addressing these challenges will be critical for ensuring ABCO's effectiveness in practical, large-scale energy systems.

5. Conclusions

The integration of vehicle-to-grid (V2G), grid-to-vehicle (G2V), and vehicle-to-everything (V2X) systems into the energy ecosystem represents a transformative approach to energy management, grid stability, and renewable energy integration. These systems enable bidirectional energy flow between electric vehicles (EVs), the power grid, and other entities, such as homes, buildings, and additional vehicles, creating a dynamic and decentralized energy network. The successful implementation of these technologies relies heavily on advanced control algorithms that optimize energy flow, ensure grid stability, and maximize the economic and environmental benefits.

This study evaluated the performance of various control algorithms, including traditional optimization methods, machine learning techniques, and metaheuristic approaches like Bee Colony Optimization (ABCO) in V2G, G2V, and V2X systems. Traditional optimization methods, such as linear programming (LP), quadratic programming (QP), and dynamic programming (DP), are widely used due to their simplicity and reliability. However, they often struggle with scalability and computational complexity in large-scale systems. Machine learning techniques, including reinforcement learning (RL), deep learning (DL), and supervised learning, offer the ability to handle complex and dynamic systems but require extensive training data and computational resources.

Metaheuristic algorithms, particularly Bee Colony Optimization (ABCO), have emerged as powerful tools for solving complex optimization problems in V2G, G2V, and V2X systems. ABCO, inspired by the foraging behavior of honeybees, excels in balancing exploration and exploitation, ensuring a thorough search of the solution space. Its decentralized nature and parallel search capabilities make it highly scalable and adaptable to various problem domains, including combinatorial optimization, continuous optimization, and dynamic environments. ABCO's ability to avoid local optima and explore diverse solutions consistently delivers high-quality results, making it a promising approach for optimizing energy exchange in V2X systems.

The simulated results demonstrate the superior performance of ABCO over Brain Emotional Intelligent Control (BEIC) across various performance metrics, including state of charge (SOC), Root Mean Square Voltage (Rms (V)), Root Mean Square Current (Rms (A)), capacitive power factor, deformation factor, power (W), apparent power (S (VA)), reactive power (W (Var)), and time (h). The improvements achieved by Bee Colony Optimization (ABCO) over Brain Emotional Intelligent Control (BEIC) across these metrics are 6.5%, 6%, 62%, 12.3%, 14.3%, 3%, 0.6%, 64.5%, and 22.1%, respectively.

In contrast, BEIC, inspired by the emotional decision-making processes of the human brain, excels in control applications that require emotional learning, real-time adaptation, and robustness to uncertainties. BEIC's ability to mimic human emotional responses and adapt to changing environments makes it particularly suitable for real-time control applications in robotics and autonomous systems. However, BEIC's performance in optimization tasks is generally inferior to that of ABCO, as evidenced by the simulated results.

In summary, the choice between ABCO and BEIC depends on the specific requirements of the problem domain. ABCO is more suited for optimization challenges, offering significant advantages in exploration–exploitation balance, scalability, and adaptability. BEIC, on the other hand, excels in control applications that require emotional learning, real-time adaptation, and robustness to uncertainties. Future research should explore hybrid approaches that combine ABCO and BEIC to enhance adaptability and solution quality. Future focus should also be given to the real-time implementation and development of standardized protocols and policies for V2G, G2V, and V2X systems to realize their full potential.

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