
Research article

Behavior-aware optimal sizing and energy management of hybrid microgrids with Vehicle-to-Grid integration via Quokka Swarm Optimization

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Abstract: The integration of renewable energy sources (RESs) and electric vehicles (EVs) in grid-connected microgrids offers significant potential for improving energy flexibility, renewable-energy utilization, and supply reliability. However, many existing studies assume continuous EV availability or full user participation, which may overestimate the actual flexibility provided by EV fleets. To address this limitation, this study proposes a unified behavior-aware framework for a grid-connected photovoltaic–wind turbine–battery energy storage system electric vehicle (PV-WT-BESS-EV) microgrid, combining quokka swarm optimization (QSO) for optimal component sizing with a rule-based energy management system (RB-EMS). The framework incorporates EV availability, state-of-charge constraints, user willingness, mobility patterns, V2G/G2V operation, and time-of-use pricing. The system was evaluated over 8760 h using measured 2024 meteorological data and the actual hourly load profile of Al-Ramadi General Teaching Hospital, Iraq. Results showed that incorporating driver behavior reduces both V2G and G2V energy exchange by 50.88%, while battery discharge and charging increase by 1.47% and 1.48%, respectively. Grid import increases by only 0.52%, whereas exported energy decreases by 3.41%, and the cost of energy increases by 1.78%, while maintaining LPSP = 0. Optimal sizing changes from 116 WT, 1331 PV, and 937 battery units to 98 WT, 1335 PV, and 958 battery units. Statistical comparison over five independent runs showed that QSO achieves the lowest mean fitness and standard deviation, outperforming PSO, POA, and GA

in convergence consistency and robustness. Sensitivity analysis further confirmed the robustness of the proposed framework under variations in EV fleet size, electricity pricing, and user behavioral composition. Increased EV penetration enhances V2G/G2V energy exchange, while tariff and behavioral variations primarily affect grid interaction and EV flexibility without compromising system reliability. Overall, the proposed framework provides a realistic and robust approach for jointly evaluating microgrid sizing and operation under practical EV behavioral constraints.

Keywords: hybrid microgrid; Vehicle-to-Grid; electric vehicle behavior; rule-based; energy management system; Quokka Swarm Optimization; Time-of-Use pricing

1. Introduction

The rapid process of urbanization has greatly raised the world's energy demand and environmental pressure. Even though cities cover only about 3% of the earth's surface, they use around 75% of the world's energy and are responsible for about 80% of global CO₂ emissions [1]. In countries such as Iraq, where an unreliable power supply and continued reliance on diesel generators is still a common situation, using diesel generators remains a costly option, together with the associated environmental pollution. As a result, a global shift toward renewable energy sources, such as solar and wind energy, has taken place as a result of sustainable policies. However, the current state of grid-connected systems that are intermittent and have high initial costs only meets demand to a certain extent, and thus acts as a limiting solution in areas with weak grids. Renewable energy systems (RES) have now appeared as a solution by combining a variety of generation and storage technologies. These systems improve reliability, flexibility, and the ability to integrate renewable energy, making them useful for both grid-connected and stand-alone uses [2]. Since the energy management system (EMS) will have to manage real-time power generation, storage, electric vehicle (EV) charging and discharging, and the connection to the grid, various operational difficulties may reduce reliability (because of the intermittent nature of renewables) and increase reliance on the main grid [3]. The inclusion of electric vehicles adds even more complexity to EMS operation because of the uncertainties regarding vehicle availability and user involvement, so assuming constant availability and participation is unrealistic and could result in poor system performance. Furthermore, present EMS designs have only a limited incorporation of electricity pricing and are not economically efficient when operating in optimal market conditions. Therefore, conventional EMS methods may not be adequate for dealing at the same time with the intermittency of renewables, the uncertainty of electric vehicles, and the bidirectional interaction between EVs and the grid through Grid-to-Vehicle (G2V) charging and Vehicle-to-Grid (V2G) discharging in microgrids that have V2G capability.

Apart from the management of operational energy, the proper sizing of components is of great importance in deciding the performance and economic feasibility of hybrid microgrids. For this reason, metaheuristic optimization algorithms are commonly employed, including particle swarm optimization (PSO) [4], genetic algorithms (GA) [5], and other evolutionary techniques. Even though these methods are effective, they can have a number of drawbacks, such as premature convergence, sensitivity to the choice of parameters, and lower efficiency in the case of complex multi-objective optimization problems. Most of the current studies treat the integration of renewable energy, EV operation, and coordinated energy management as separate issues, usually making use of simplified

models that do not sufficiently reflect real system behavior. Furthermore, if the sizing of system components is carried out independently of the energy management strategy, this may result in solutions that are not optimal and are unable to guarantee acceptable performance under realistic operating conditions [6]. The availability of vehicles, the state of charge (SOC), financial incentives, and user acceptance are key factors that affect system participation and flexibility. Probabilistic models, Monte Carlo simulations, Markov chains, and machine learning have all been applied to model charging patterns and mobility [7]. Yet, they generally do not account for real-time user decisions and variations in behavior. A number of studies ignore user willingness and SOC constraints [8] or depend on complicated predictive models, considering driver behavior as a general input rather than incorporating it into the decisions made by the EMS. Moreover, the absence of a priority based on SOC when charging and discharging lowers the operational effectiveness of V2G systems. Recent studies have pointed out the role of V2G systems in improving the flexibility of microgrids by providing services such as peak shaving, frequency regulation, and energy arbitrage, with dynamic pricing providing support [9]. However, challenges still exist, including infrastructure costs, power quality problems, grid instability caused by uncoordinated charging, and behavioral uncertainty. Many EMS frameworks continue to assume static pricing and complete EV participation, thus reducing the level of realism [10].

To contextualize these operational and sizing challenges, recent studies have explored various energy management and optimization approaches for renewable microgrids with EV integration. Amghar et al. [11] developed an energy management framework for a residential (PV), (BESS) microgrid with bidirectional EVs using a hybrid PSO-sequential quadratic programming (SQP) optimization approach. The model incorporated stochastic EV availability, mobility requirements, SOC constraints, battery degradation, and time-varying electricity tariffs. The proposed method coordinated battery, EV, and grid power exchange while maintaining vehicle readiness. Results showed 42.70% lower grid purchases, 34.20% lower daily energy costs, and 78.40% PV self-consumption, with an average EV SOC of 82.40%. The hybrid method also achieved a 0.90% optimality gap compared with benchmark methods. El Ganaoui Mourlan et al. [12] proposed a rule-based EMS for a PV-wind turbine (WT), (BESS) microgrid with V2G-enabled EVs. The EMS coordinated energy flow based on renewable availability, EV SOC and availability, user demand, travel requirements, and time-varying electricity prices. Weekday and weekend vehicle-use scenarios were considered, while target SOC was determined according to travelled distance. Compared with a reference V2G strategy without price consideration, the enhanced EMS prioritized renewable energy and low-price grid periods, achieving 12.24% electricity-cost savings and 11.26% lower energy consumption. Pezzati et al. [13] proposed a scalable energy management model for integrating V2G into renewable energy communities (RECs) using a hybrid control framework combining MILP-based day-ahead optimization with local rule-based controllers. The model coordinated EV and BESS charging according to user requirements, flexibility, SOC, electricity prices, PV forecasts, and battery-aging penalties. A six-month case study, using historical demand data and charging sessions generated from real-world events, was evaluated under uncontrolled, V1G, and V2G scenarios. Results showed that V2G improved energy sharing and grid interaction, achieving a 15.50% reduction in consumption ramps and a 90% increase in shared power within the REC.

Cheng et al. [14] developed a multi-objective scheduling framework for a PV-redox flow battery (RFB)-EV flexible microgrid using an enhanced dynamic weight slime mould algorithm (DW-SMA). The framework incorporated three EV participation types (fixed-rate charging, flexible charging, and bidirectional charging/discharging), together with flexible loads and grid

interaction. The modified algorithm employed dynamic weight adaptation to improve convergence and scheduling performance. Simulation results showed up to 58% lower daily operating cost, 18.30% lower grid-energy dependence, and 25.70% higher EV discharge utilization with RFB integration. DW-SMA also converged 27% faster and achieved a 14.60% lower objective value than the standard benchmark methods. Iqbal et al. [15] developed a comprehensive framework for EV-fleet integration into a smart campus microgrid, combining Monte Carlo stochastic simulation with energy-hub optimal dispatch. The model considered uncertain EV charging demand, charging-port availability, Level-2 and DC fast charging rates, plug-in duration, controlled charging, V2G operation, and Time-of-Use (ToU) pricing. The framework jointly evaluated charging-infrastructure requirements and operational strategies while accounting for variability in EV user behavior. Results demonstrated that controlled charging improved operational flexibility, load balancing, and system resilience, while V2G enabled EVs to operate as mobile storage and reduce the cycling burden on stationary ESS. The study further showed that V2G effectiveness depends strongly on sufficient charging infrastructure and EV connectivity. Table 1 compares representative and recent studies in terms of their main focus, behavioral representation, EMS integration, and remaining limitations.

Hemachandu et al. [16] proposed a hybrid energy-management framework for a PV-based EV charging system integrating BESS and V2G operation. The approach combined the pelican optimization algorithm (POA) for power flow and storage scheduling with a triple-memristor Hopfield neural network (TMHNN) for energy-demand forecasting. The proposed framework improved storage utilization and coordinated PV generation, battery operation, and EV charging while reducing energy cost and carbon emissions compared with several benchmark optimization and intelligent-control approaches. However, the study primarily focused on PV-based charging-station energy management, power-flow optimization, storage scheduling, and demand forecasting, while EV behavioral participation and optimal hybrid microgrid sizing were not explicitly incorporated within the proposed framework. Atheeswaran et al. [17] presented a comprehensive review of renewable energy-integrated EV systems covering charging infrastructure, V2G technologies, battery-management strategies, and AI-based energy-management approaches. The study highlighted the advantages of coordinated renewable generation, bidirectional EV operation, and smart EMS techniques. It also identified other challenges such as renewable variability, EV charging uncertainty, real-time control, scalability, communication standards, and practical validation. The review also highlighted the need for more integrated, scalable, and practically deployable energy-management strategies for renewable-powered EV systems.

Table 1. Summary of literature on behavioral participation in EV; representation and integration in EMS for V2G applications.

Ref./year	System/ main focus	Behavioral factors considered	EMS/optimization approach	Pricing consideration	Sizing	Main contribution	Key limitation
Sharifi et al., 2019 [18]	V2G fleet scheduling with wind integration	Arrival/departure, SOC requirements, owner flexibility, degradation concern, emergency needs	Aggregator-based MIQP with rolling-horizon optimization	Real-time price-responsive	×	Coordinated EV scheduling for cost reduction and wind utilization	Forecast dependency; computational burden; difficulty in ensuring user participation; no integrated microgrid sizing
Alsharif et al., 2023 [19]	Residential PV-WT-BESS-EV grid-connected microgrid	No explicit behavioral model; stochastic arrival/departure, SOC, and EV number	RB-EMS + SMCM; IALO sizing	Fixed grid buy/sell tariffs	√	Integrated sizing and EMS under stochastic EV integration	No explicit user-behavior modeling; fixed tariffs
Shi et al., 2022 [20]	V2G discharging price and EV user participation	Price-responsive willingness based on user characteristics	CDEP + PW model	Dynamic /price-responsive	×	Quantifies critical discharge price and user willingness considering battery degradation	No integrated microgrid EMS, charging-side behavioral coordination, or optimal system sizing
Guyen, 2024 [21]	Optimal sizing and EMS of grid-connected PV-WT-BESS-EV microgrid with V2G/G2V	EV availability profile, daily travel, SOC, and charging/discharging rates	Dynamic rule-based EMS + TFWO	Fixed grid purchase/feed-in tariffs	√	Optimal PV-WT-BESS sizing with EV integration and V2G/G2V operation	Predefined EV availability; fixed tariffs; no explicit behavioral participation or user-willingness model

Continued on next page

Ref./year	System/ main focus	Behavioral factors considered	EMS/optimization approach	Pricing consideration	Sizing	Main contribution	Key limitation
El Ganaoui Mourlan et al., 2025 [12]	V2G-based energy management of a PV-WT-battery-EV smart microgrid	EV availability, SOC, departure time, travel distance, emergency distance, and user charging demand	Rule-based EMS with V2G	Time-varying electricity price	× Predefined system size	Coordinates renewable generation, battery storage, EV charging/V2G, and grid use; achieved 12.24% cost savings	Uses predefined weekday/weekend EV-use scenarios; no optimal system sizing; no explicit stochastic behavioral willingness model
Pezzati et al., 2025 [13]	Scalable V2G energy management for renewable energy communities	Probabilistic arrivals, target SOC, parking duration, and user charging preferences	MILP day-ahead optimization + local rule-based control	Day-ahead market/zonal pricing	×	Scalable coordination of EVs and BESS with V1G/V2G; improves power sharing and reduces ramps	No optimal microgrid sizing; behavior represented mainly through charging preferences and probabilistic events rather than explicit psychological willingness
Cheng et al., 2026 [14]	Optimal scheduling of PV-storage-EV flexible microgrid with RFB	Three EV types: fixed-rate, flexible charging, and bidirectional charging/discharging	DW-SMA multi-objective scheduling	ToU pricing	×	Coordinates EV flexibility, RFB storage, flexible loads, and grid interaction	Behavior represented by predefined EV user types; no explicit stochastic willingness model or integrated microgrid sizing

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Ref./year	System/ main focus	Behavioral factors considered	EMS/optimization approach	Pricing consideration	Sizing	Main contribution	Key limitation
Amghar et al., 2026 [11]	Coordinated PV-BESS-EV residential microgrid with V2G	Stochastic EV availability, travel patterns, SOC targets, and mobility requirements	Hybrid PSO-SQP optimization	Time-varying tariffs	×	Coordinates EVs, BESS, PV, and grid while considering mobility and battery degradation	No explicit psychological /user-willingness model; focuses on 24-h operational scheduling rather than optimal system sizing
Hemachandru et al., 2025 [16]	PV-based EV charging with BESS and V2G support	EV charging demand considered through forecasting; no explicit user behavioral participation model	POA + TMHNN	Not specified	×	Optimizes power flow and storage scheduling while forecasting energy demand; reduces COE and carbon emissions	Focuses on PV-based charging, storage scheduling, and demand forecasting; no explicit behavioral participation or integrated hybrid microgrid sizing
Proposed Framework	Grid-connected hybrid PV-WT-BESS-EV microgrid with V2G/G2V	EV availability, willingness, travel patterns, SOC, charging preference, and price response	Behavior-aware RB-EMS + QSO sizing	Dynamic ToU pricing	√	Joint consideration of system sizing, EV behavior, and price-aware operation within one framework	Simulation-based validation; experimental/HIL validation remains for future work

Though technology has improved, the literature still reveals a disjointed approach of microgrid sizing, EV behavioral unpredictability, and operating energy management. Most of the current research follows one of two paths: either they improve microgrid component sizing depending on simplified or given operating assumptions or they create sophisticated EMS techniques without clearly relating operational decisions to the ideal component sizing. This means that the interplay between realistic EV operation and system setup is not fully captured. Existing methods also usually only partly or independently handle EV mobility, availability, user engagement, V2G operation, and energy pricing [22,23]. Even if recent research has more and more taken into account user-related elements and EV mobility, the simultaneous integration of best component sizing, behavior-aware rule-based energy management, user involvement, and time-of-use power pricing inside a single framework is still restricted [24]. This difference drives the suggested framework's combination of microgrid sizing, RB-EMS operation, realistic EV user behavior, and ToU pricing to produce more realistic and coordinated system design and operation.

To address these interconnected gaps, this study develops a unified framework in which system sizing and behavior-aware energy management are evaluated under consistent operating conditions. The proposed grid-connected hybrid microgrid integrates renewable energy sources (RES), battery storage, behavior-aware EV modeling, V2G/G2V operation, and ToU pricing. The key contributions are as follows: (i) optimal system sizing using the quokka swarm optimization (QSO) algorithm; (ii) development of a behavior-aware rule-based energy management system (RB-EMS) incorporating EV availability, SOC constraints, and user participation into charging and discharging decisions; (iii) integration of ToU pricing to support economic energy-management decisions; and (iv) benchmarking of QSO against PSO, GA, and POA under identical operating conditions. Accordingly, the proposed framework directly addresses the key limitations identified in Table 1 by replacing full-participation assumptions with behavior-aware EV modeling and integrating pricing, EMS operation, and optimal system sizing within a unified framework. This enables a more realistic assessment of the impact of EV behavioral uncertainty on both system configuration and operational performance.

2. Design and optimization of the proposed EMS

The proposed energy management system (EMS) is applied to a grid-connected hybrid microgrid consisting of RES, battery storage, and electric vehicles (EVs). EMS has a rule-based structure due to its native simplicity, low computational cost, and fast response time; moreover, a stochastic model captures EV behavioral uncertainty in availability and charging patterns. In order to improve system performance, the quokka swarm optimization (QSO) is applied and compared with PSO, GA, and POA algorithms coupling EMS. Therefore, the optimization minimizes COE, LPSP, and GCF simultaneously for dynamic electricity price in order to maximize energy export.

2.1. Fundamental concept and architecture of the proposed hybrid microgrid

Few examples exist of integrated renewable generation with EV-based V2G operation at a system level. The proposed hybrid microgrid including PV, WT, battery storage, and EVs with bidirectional power flow is shown in Figure 1. PV and WT serve as the main sources of generation, whereas grid connection provides reliability in supply. Battery charging and EV discharging are controlled by bidirectional DC-DC converters, which work in buck mode for charging and boost mode for discharging.

Wind power is transformed by an AC-DC converter, whereas EVs are interfaced with the grid via bidirectional AC-DC converters to provide services like voltage and frequency regulation [25].

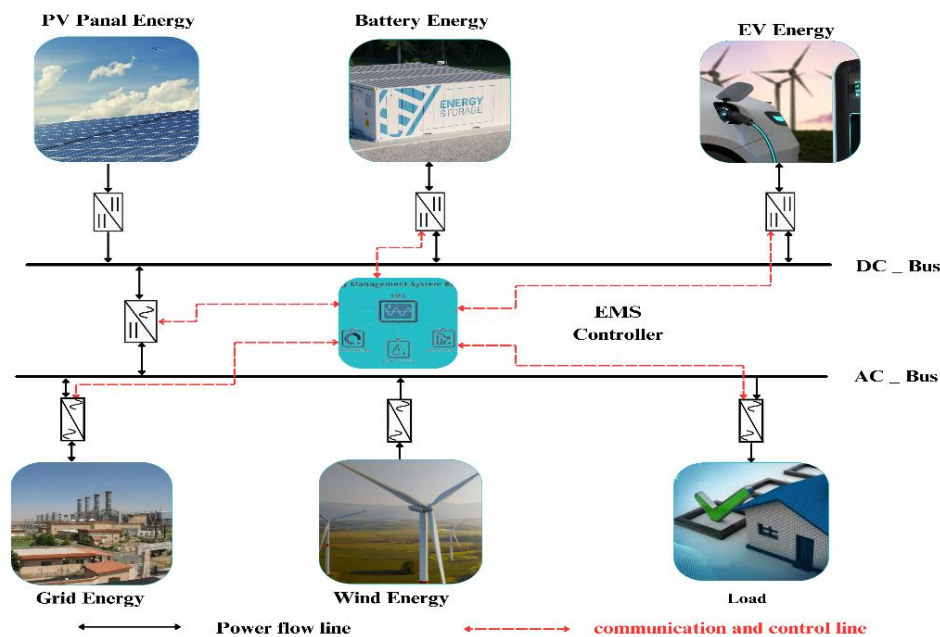


Figure 1. An energy management system (EMS) combined with integrated hybrid power sources.

A strong connection to the grid contributes to the overall system, providing reliability. Detailed mathematical models of each component are developed for simulation and long-term planning [26], resulting in an accurate representation of the system's behavior.

2.2. Models of microgrid components

In this section, the mathematical models of the main components of the proposed hybrid microgrid are presented, including the PV, WT, BESS, EVs, load demand, and utility grid. The chosen models offer a computationally effective characterization of the operational behavior and energy exchanges among the system parts. Using real hourly weather and electrical load data for January 1 to December 31, 2024 (8760 h), the entire system is simulated in MATLAB over one year. For Al-Ramadi City, the Upper Euphrates Centre for Sustainable Development Research at University of Anbar, Iraq, provided the meteorological inputs, which included solar irradiance, wind speed, and ambient temperature. Iraq has great renewable energy potential, especially in wind and solar resources, with a value of approximately 5.0–6.5 kWh/m²/day of solar irradiation and more than 3000 sunshine hours yearly. Because of its hot desert environment and strong solar availability, Western Iraq—including Al-Anbar—is especially ideal for solar energy uses [27,28]. The Iraqi Electricity Distribution Directorate, Al-Ramadi Branch, helped to provide Al-Ramadi General Teaching Hospital with its real hourly electrical load profile. These datasets show the demand patterns of a vital load in Al-Anbar Governorate and the local weather conditions. The following subsections describe the mathematical formulation of each component and its role within the proposed energy management framework.

2.2.1. Photovoltaic (PV) model

Photovoltaic (PV) systems are widely used due to their ability to directly convert solar energy into electrical power. In this study, a simplified and computationally efficient PV model is adopted to estimate power output under varying meteorological conditions [29]: The output power of the $P_{pv(t)}$ module at time (t) is given by Eqs (1) and (2):

$$P_{pv(t)} = P_{PV}^{rated} \times \frac{G(t)}{1000} \times [1 + \sigma_t (T_{amb} + 0.03125 \times G(t)) - T_c] \quad (1)$$

$$T_c = T_{amb} + G(t) \times \left(\frac{NOCT-20}{800} \right) \quad (2)$$

The photovoltaic output power at time t is denoted $P_{pv(t)}$ and given in watts (W), depending on the rated power $P_{PV}^{rated}(t)$, solar irradiance $G(t)$ (W/m²), and temperature-related effects. The influence of temperature is represented by the PV temperature coefficient σ_t , typically -3.7×10^{-3} (1/°C), and the ambient temperature T_{amb} ; PV cell temperature is assumed to be T_c equal to 25 °C, while the nominal operating cell temperature (NOCT), provided by the manufacturer, describes expected field operating conditions. Solar irradiance is 1000 W/m² under standard test conditions (STC) [30].

2.2.2. Wind turbine model

Wind turbines (WTs) are among the most widely utilized renewable energy sources (RESs) due to their potential to generate energy across day and night. The electrical power output of a WT depends significantly on the instantaneous wind speed $v(t)$ and the turbine's power curve, which characterizes its three main operating regions. The power $P_{WT}(t)$ is calculated by Eq (3) [31]:

$$P_{WT(t)} = P_r * \begin{cases} 0 & v(t) \leq v_{cut-in} \\ \frac{v(t) - v_{cut-in}}{v_r - v_{cut-out}} & v_{cut-in} < v_r \\ P_r & v_r < v(t) < v_{cut-out} \end{cases} \quad (3)$$

where v_{cut-in} (m/s) is the minimum wind speed required for the turbine to start generating power. v_r (m/s) is the rated wind speed at which the turbine delivers its rated power P_r (kW). $v_{cut-out}$ (m/s) is the maximum wind speed beyond which the turbine stops to avoid damage. P_r is the rated power of the WT (kW). $P_{WT,Total}(t)$ is the total power from all installed turbines at time t , and N_{WT} is the number of installed wind turbines, as given in Eq (4). Wind speed is typically measured at a reference height v_{ref} using an anemometer. To calculate the wind speed at the hub height h , Eq (5) is used [32]:

$$P_{WT,Total}(t) = P_{WT(t)} \times N_{WT} \quad (4)$$

$$v = v_{ref} \left(\frac{h}{h_{ref}} \right)^\gamma \quad (5)$$

where v (m/s) is the wind speed at the hub height h (m), v_{ref} (m/s) is the measured wind speed at the reference height h_{ref} . γ is the surface roughness exponent, typically ranging between 0.1 (flat terrain) and 0.25 (rough terrain). For this study, h is 30 m, and h_{ref} is 43.6 m [33].

2.2.3. Battery model

The battery system operates as a backup energy source for the microgrid. It provides continuity of supply in periods of low renewable generation. The battery stores the extra energy generated by the (PV) panels and WT when the generation is more than the load demand. Eqs (6), (7), and (8) show the maximum and minimum battery capacity [34]:

$$Eb_{max} = N_{bat} \times Bat_{Unit} \quad (6)$$

$$SOC_{(t)}^{BESS} = \frac{E_{bat(t)}}{Eb_{max}} \quad (7)$$

$$Eb_{min} = Eb_{max} \times (1 - DoD) \quad (8)$$

where N_{bat} stands for the number of battery units, and Bat_{Unit} shows the nominal capacity of every battery unit, which is fixed at 40 kWh; Eb_{max} signifies the total stored battery energy at time t (kWh), and Eb_{min} indicates the minimum allowed battery energy level. The depth of discharge (DoD) is assumed to be 80%. The battery energy is limited within set upper and lower boundaries to help preserve battery life and guarantee dependable system operation by avoiding overcharging and too much discharge. Eq (9) gives the net renewable power balance that decides whether the battery works in charging or releasing mode [35].

$$P_b(t) = (P_{PV}(t) + P_{WT}(t)) - \frac{P_{L(t)}}{\mu_{In}} \quad (9)$$

A high $P_b(t)$ shows extra renewable energy and charging of the battery. A negative number shows a power shortage and the battery discharges to assist the load. $P_{L(t)}$ is the load demand at time t , and μ_{In} is the inverter efficiency. Then, Eqs (10) and (11) [35] help to update the battery charging energy.

$$E_{bat(t)} = E_{bat(t-1)} + \mu_{ch(t)}^{BESS} \times E_{ch(t)}^{BESS} \quad (10)$$

$$E_{bat(t)} = E_{bat(t-1)} - \frac{E_{disch(t)}^{BESS}}{\mu_{disch}^{BESS}} \quad (11)$$

At hour t (kWh), $E_{bat(t)}$ is the battery energy. $E_{bat(t-1)}$ is the kWh of battery energy at the last hour. $E_{ch(t)}^{BESS}$ is the charging effectiveness. μ_{ch}^{BESS} is the amount of energy given to the battery at hour t (kWh). The battery energy is changed during discharging using the following formula: $E_{disch(t)}^{BESS}$: kWh of energy removed from the battery during hour t . μ_{disch}^{BESS} is the efficiency of discharging. The battery energy update is carried out following converter efficiency application to guarantee sensible modeling of power losses during charging and discharging. With a time, resolution of 1 h, the charging and discharging energies reflect hourly energy values (kWh).

2.2.4. Electric vehicle (EV) model

Electric vehicles (EVs) are active, mobile energy storage assets inside the microgrid that enable both grid-to-vehicle (G2V) charging and vehicle-to-grid (V2G) discharging. Estimating the range of

EVs and maximizing their performance depends on the knowledge of their energy use patterns. A definition-based formulation of the SOC^{EV} , which is commonly defined in the literature as the ratio of the remaining battery energy (or capacity) to its nominal capacity, is shown in Eq (12) [36].

$$SOC_{(t)i}^{EV} = \frac{E_{EVi(t)}}{EV_{max}} \quad (12)$$

$SOC_{(t)i}^{EV}$ is the battery energy level of EV i at time t (kWh). EV_{max} is the maximum EV battery capacity (kWh), 24 kWh. This relationship represents the minimum amount of energy that can remain in an electric vehicle's battery, which is equal to 20% of the battery's total capacity. The purpose of this limit is to prevent deep discharge, as over-discharging reduces battery life and impairs its performance. Therefore, the battery's energy is not allowed to drop below EV_{min} as shown in Eq (13) [37], so that the vehicle's charge remains within a safe level during charging and discharging operations in the V2G system. EV battery energy update is given in Eq (14) [38].

$$EV_{min} = 0.2 \times EV_{max} \quad (13)$$

$$E_{EVi(t+1)} = \frac{E_{EVi(t)} - EV_{drive\ i(t)} + \mu_{ch}^{EV} * P_{ch\ i(t)}^{EV} \times \Delta(t) - P_{disch\ i(t)}^{EV} \times \Delta(t)}{\mu_{disch}^{EV}} \quad (14)$$

where $E_{EVi(t+1)}$ is the electrical vehicle battery energy stored in EV i at hour $t + 1$ after all updates (kWh). $E_{EVi(t)}$ is the electrical vehicle battery energy stored in EV i at hour t (kWh). $EV_{drive\ i(t)}$ is the driving energy consumed by EV i during hour t (kWh). μ_{ch}^{EV} is the charging efficiency of the EV battery (typically 0.95). $P_{ch\ i(t)}^{EV}$ is the charging power supplied to EV i at hour t (kW). $P_{disch\ i(t)}^{EV}$ is the discharging (V2G) power drawn from EV i at hour t (kW). μ_{disch}^{EV} is the discharging efficiency of the EV battery (typically 0.95).

2.2.5. Utility grid model

The suggested hybrid microgrid depends on the utility grid for bidirectional energy exchange and a dependable source of energy. Particularly during times of low solar irradiance or wind availability, it serves as a complementary energy source when the available renewable generation, BESS, and EV resources are insufficient to meet load demand. At each time step (t), the net energy balance is determined using Eq (15). As expressed in Eq (16), under energy deficit situations, that is, when $E_{net}(t) < 0$, the utility grid provides the remaining energy demand after the BESS and EV discharging assets have been used [39]. Conversely, under energy surplus conditions, when $E_{net}(t) > 0$, the excess renewable energy remaining after satisfying the load demand and charging the BESS and available EVs is exported to the utility grid, as expressed in Eq (17) [40]. This bidirectional energy exchange enhances system flexibility and supports economic operation through appropriate energy purchasing and selling transactions with the main grid.

$$E_{net(t)} = E_{PV(t)} + E_{WT(t)} - E_{L(t)} \quad (15)$$

$$E_{net(t)} = E_{PV(t)} + E_{WT(t)} - E_{L(t)} \quad (16)$$

$$E_S^{grid}(t) = E_{PV(t)} + E_{WT(t)} - E_{L(t)} - E_{ch(t)}^{BESS} - E_{ch(t)}^{EV}, \quad E_{net}(t) > 0 \quad (17)$$

$E_{PV(t)}$ is the energy generated by the photovoltaic system at time t , in kWh, $E_{WT(t)}$ is the energy generated by the wind turbine system at time t , in kWh. $E_{L(t)}$ is the load energy demand at time t , in kWh. $E_{disch(t)}^{BESS}$ is the energy discharged from the battery energy storage system (BESS) at time t to support the load during an energy deficit, in kWh. $E_{disch(t)}^{EV}$ is the energy discharged from the available electric vehicles through vehicle-to-grid (V2G) operation at time t , in kWh. $E_{ch(t)}^{BESS}$ is the energy used to charge the battery energy storage system at time t during renewable energy surplus conditions, in kWh. $E_{ch(t)}^{EV}$ is the energy used to charge the available electric vehicles through grid-to-vehicle/charging operation at time t during surplus energy conditions, in kWh.

2.3. Rule-based energy management system (RB-EMS)

In this section, the proposed V2G-enabled microgrid is discussed in detail, with emphasis on the operational logic of the energy management system. Conventional EMS strategies may suffer from inefficient coordination among renewable generation, stationary battery storage, EVs, and the utility grid due to inappropriate dispatch priorities. For example, prioritizing V2G over stationary battery discharge may be constrained by EV availability and can increase supply risk (LPSP) and operational cost (COE). Likewise, prioritizing grid support before local storage reduces renewable-energy utilization and increases GCF. Similarly, giving priority to EV charging before stationary battery charging can improve V2G readiness but may reduce locally stored energy and increase grid reliance during periods of low renewable generation [41]. The suggested RB-EMS gives the stationary battery top priority during both charging and discharging procedures to solve these constraints; EV-based V2G and grid exchange are only engaged as needed. This hierarchy raises operational effectiveness, renewable-energy use, and system dependability. (η_{inv}): Inverter efficiency, representing the efficiency of converting DC input power into AC output power. Figure 2 illustrates the complete RB-EMS decision flow and the transitions among the four operating modes according to renewable-energy availability, storage status, EV conditions, and load demand.

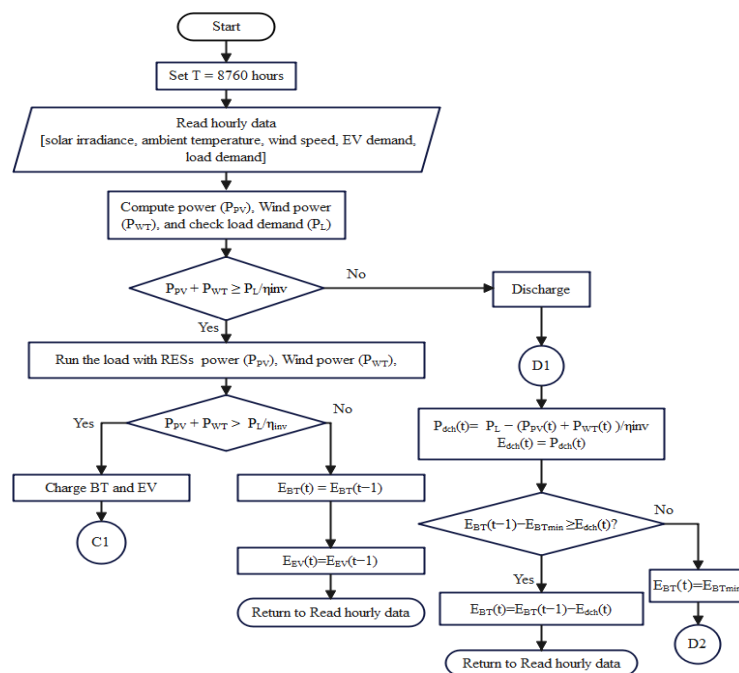


Figure 2. Operational flowchart of the proposed rule-based energy management system (RB-EMS).

Figure 3 illustrates surplus energy management and EV charging process in RB-EMS. This flowchart illustrates the management of surplus renewable energy after meeting the load demand. The excess energy $E_{ch}(t)$ is calculated from the difference between the total PV and wind generation and the load demand. C1 is the connector to the surplus-energy and charging process, where the BESS is charged first, followed by evaluation of EV charging and grid export. If the battery state is below its maximum capacity, the surplus is used to charge the battery. Otherwise, the system proceeds to evaluate EV participation. EV charging is performed only if operational, technical, economic, and behavioral participation conditions are satisfied. The surplus energy after EV charging is exported to the grid for economic benefit. If the participation EV conditions are not met, the surplus energy is directly exported to the grid.

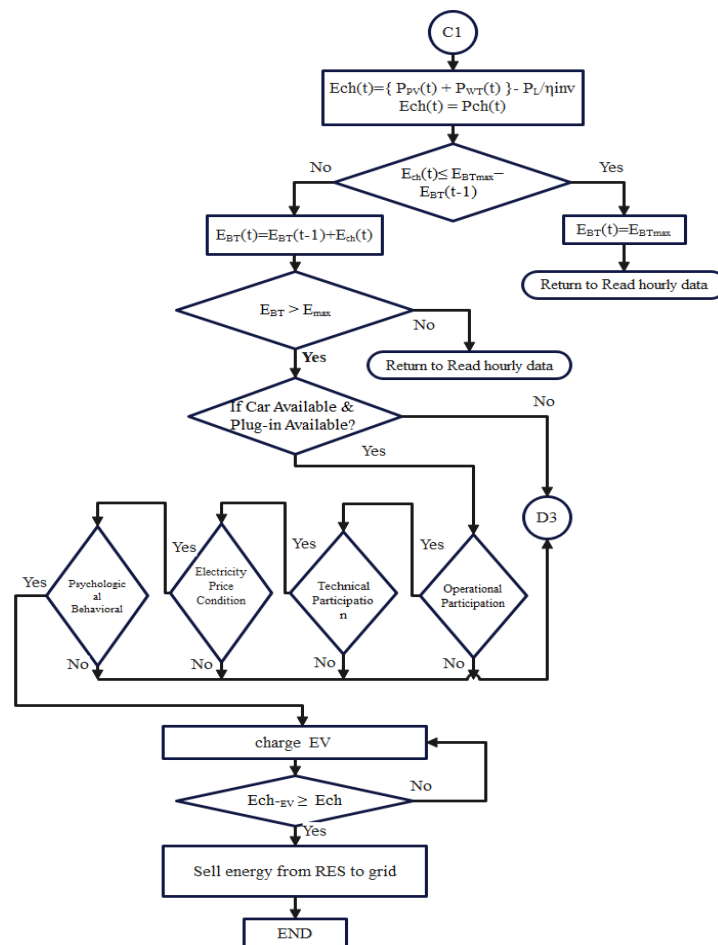


Figure 3. Flowchart of the surplus energy management and EV charging process in the RB-EMS.

Figure 4 illustrates the deficit energy management process of the proposed RB-EMS, where (a) represents the EV discharging decision process (D2), and (b) represents grid power purchase (D3). D1 denotes the connector to the initial deficit-management stage, where the power deficit is calculated, and BESS discharging is evaluated first. If the BESS cannot fully satisfy the deficit or reaches its minimum allowable energy level, the system proceeds to D2, which represents the EV/V2G discharging stage. At this stage, EV availability and the operational, technical, economic, and behavioral participation conditions are evaluated. If the required conditions are satisfied, eligible EVs are discharged through

V2G to support the load. Otherwise, the system proceeds to D3, which represents the utility-grid support stage, where the remaining energy deficit is supplied by the utility grid.

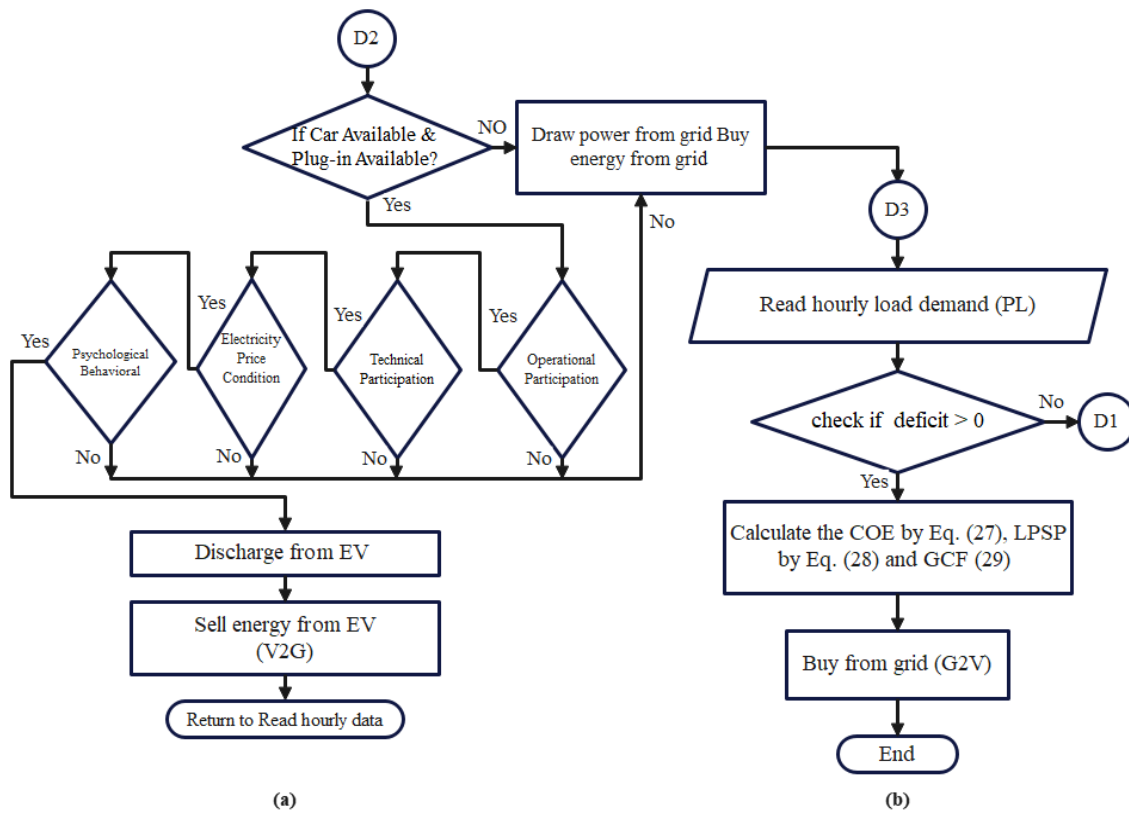


Figure 4. Flowcharts for the proposed RB-EMS in deficit conditions: (a) EV discharging decision process (D2), and (b) grid power purchase (D3).

2.4. Proposed decision factors influencing EV charging and discharging

Vehicle-to-Grid systems enable bidirectional energy exchange between EVs and the grid, enhancing flexibility and renewable integration [42]. However, EV participation is inherently uncertain due to variability in availability and user behavior, which affects EMS decision-making. Many existing approaches assume constant availability, leading to unrealistic results. Therefore, a behavior-aware framework that integrates operational, technical, economic, and behavioral factors is required for more realistic system modeling [7]. The adopted EV mobility and behavioral profiles were developed to reflect realistic charging characteristics reported in large-scale real-world EV datasets. Previous data-driven studies have demonstrated substantial heterogeneity among EV users in terms of connection time, connection duration, charging frequency, and daytime/overnight charging behavior. Accordingly, the EV fleet in this study is represented by three behavioral archetypes with different daily availability and participation patterns. Arrival and departure behavior determine hourly EV availability, while SOC and charger power limits determine the technical capability for G2V/V2G operation. Behavioral participation is then generated probabilistically according to the archetype-specific hourly willingness profile [43].

2.4.1. Operational participation factors for EV charging and discharging

An electric vehicle's ability to participate in V2G/G2V operations is governed by two essential operational conditions: the availability of a charging/discharging port and the absence of any sudden travel requirements. If no port is available or the vehicle is expected to leave unexpectedly, the EMS immediately excludes the EV from participating in charging or discharging. These constraints directly limit the opportunity for energy exchange, especially when port capacity is restricted. Accordingly, the proposed operational participation factor is formulated in Eqs (18) and (19).

$$(F_1^{Disch}) = P_{port}(t) \times (1 - P_{Travel}(t)) \quad (18)$$

$$(F_1^{ch}) = P_{port}(t) \times (1 - P_{Travel}(t)) \quad (19)$$

$P_{port}(t) \in [0,1]$ represents the availability of a charging F_1^{ch} or discharging F_1^{Disch} port, while $P_{Travel}(t) \in [0,1]$ indicates the likelihood of a sudden trip, where 0 means no expected travel, and 1 means the vehicle may be needed imminently. If either a port is unavailable or a sudden trip is expected, the participation factor becomes zero, preventing the EV from engaging in the discharge/charge process. The corresponding hourly probability profiles are defined according to the adopted EV availability and mobility patterns. For each EV (i) and each time step (t), a random number uniformly distributed over the interval $[0,1]$ is generated and compared with the corresponding predefined probability. The EV is considered to have access to a charging/discharging port when the generated random number falls within the specified port-availability probability; otherwise, the port is considered unavailable. Similarly, a travel event is assumed to occur when the generated random number falls within the specified travel probability. Through this stochastic sampling procedure, the probability values are converted into binary operational states, where 1 indicates that the corresponding participation condition is satisfied, while 0 indicates that the EV is temporarily unavailable for charging or discharging. This procedure is repeated for every EV and every simulation time step to generate the hourly operational participation status used by the EMS.2.4.2.

2.4.2. Technical participation factors for charging and discharging

EV owners often specify technical SOC^{EV} limits to safeguard battery health and mobility needs. While a maximum SOC threshold SOC_{Max}^{EV} (100%) stops charging to prevent overcharging and high SOC degradation, a minimum SOC^{EV} threshold SOC_{Min}^{EV} (normally around 20%) stops V2G discharging when the battery gets too low. Only when the SOC^{EV} drops below this threshold does charging start again. These user-defined limits, shown in technical involvement elements of Eqs (20) and (21), guarantee realistic EV behavioral participation.

$$(F_2^{disch}) = if \begin{cases} 1, & if SOC^{EV}(t) \geq SOC_{Min}^{EV} \\ 0, & if SOC^{EV}(t) < SOC_{Min}^{EV} \end{cases} \quad (20)$$

$$(F_2^{ch}) = if \begin{cases} 1, & if SOC^{EV}(t) \leq SOC_{Max}^{EV} \\ 0, & if SOC^{EV}(t) > SOC_{Max}^{EV} \end{cases} \quad (21)$$

where SOC^{EV} represents the real battery state of charge for EV. The suggested formula captures this behavior; the car stops discharging when the SOC^{EV} drops below the set limit (F_2 is 0) and can join V2G once more only when the SOC^{EV} rises above it (F_2 is 1). This helps EMS to function in line with how consumers really behave.

2.4.3. Pricing-based participation factors for EV charging and discharging

A major element affecting EV participation in G2V charging and V2G discharging is electricity cost. This study uses a ToU tariff with low, medium, and high three pricing levels. During low- and medium-price periods, grid import is permitted, while grid export is restricted, encouraging surplus renewable energy to be used for EV charging rather than being sold at a low price. During high-price periods, grid import is limited, and grid export is enabled, allowing local resources and EV discharging to reduce expensive grid purchases and support energy export. To improve operational flexibility, an OR-based decision rule is applied. EV discharging is activated when the average SOC_{avg}^{EV} of the eligible EV fleet exceeds 70% or when grid import is restricted. Similarly, EV charging is activated when the average SOC_{avg}^{EV} falls below 50% or when grid export is disabled. If local resources are insufficient to satisfy the load demand, limited grid import is still permitted to maintain system reliability and keep the LPSP close to zero. These pricing-based participation conditions are formulated in Eqs (22) and (23).

$$(F_3^{Disch}) = \begin{cases} 1, & \text{if } SOC_{avg}^{EV}(t) > 0.7 \text{ OR } P(t) \geq (P_{high}) \\ 0, & \text{otherwise} \end{cases} \quad (22)$$

$$(F_3^{ch}) = \begin{cases} 1, & \text{if } SOC_{avg}^{EV}(t) < 0.5 \text{ OR } P(t) \leq (P_{med}) \\ 0, & \text{otherwise} \end{cases} \quad (23)$$

where $(F_3^{Disch}), (F_3^{ch})$ represent the pricing-based participation factors for EV discharging and charging, respectively. A value of 1 enables the corresponding V2G/G2V operation, while a value of 0 disables it. SOC_{avg}^{EV} : state of charge of the EV fleet, $P(t)$ is the electricity price at time t , P_{high} is the high electricity price period, P_{med} is the medium electricity price period, and P_{Low} is the low electricity price period.

2.4.4. Behavioral participation factors for EV charging and discharging

Traditional V2G models often assume full EV participation once connected, neglecting user behavior. In practice, participation may be limited by user participation willingness factors such as user willingness or reluctance. To address this limitation, binary behavioral participation factors are introduced as strict conditions for both V2G discharging and G2V charging. EV participation is permitted only when the user is willing; otherwise, the corresponding charging or discharging action is completely blocked, regardless of technical or economic feasibility. The behavioral participation factor for EV operation, covering both discharging (V2G) and charging (G2V), is defined in Eq (24). A value of 1 indicates that the EV owner is willing to participate, whereas a value of 0 indicates unwillingness and therefore blocks the corresponding EV operation. This behavioral filtering prevents overestimation of actual EV participation and enables a more realistic and user-centered representation of EV involvement in G2V/V2G operation.

$$(F_4^{disch}) \text{ or } (F_4^{ch}) = \begin{cases} 1 & \text{if } user_{ready}(t) \\ 0 & \text{if } user_{not_ready}(t) \end{cases} \quad (24)$$

where F_4^{disch} is the binary behavioral participation factor for EV discharging (V2G) at time (t), and F_4^{ch} is the binary behavioral participation factor for EV charging (G2V) at time (t). For both factors, a value of 1 denotes user willingness to participate, while a value of 0 denotes unwillingness.

To capture heterogeneity among EV users, the fleet is represented by three driver archetypes: Default, Night Worker, and Evening Worker. Each archetype is assigned a distinct daily availability pattern and time-dependent participation profile to reflect differences in working schedules and charging preferences. The baseline patterns are further varied from day to day through stochastic temporal shifts and occasional short trips, preventing the use of identical deterministic schedules for all EVs. This representation is consistent with data-driven studies showing that EV users exhibit distinct daytime, overnight, and mixed charging patterns rather than a single uniform behavior. Accordingly, the proposed model provides a real-world-inspired stochastic representation of EV mobility and behavioral diversity while retaining computational simplicity for long-term microgrid simulation. After identifying EVs that satisfy the operational, technical, economic, and behavioral conditions, the eligible EVs are passed to the subsequent power allocation stage. The user willingness state is generated probabilistically at each time step by comparing the assigned participation probability with a uniformly distributed random number in the range $([0,1])$. If the generated random value is less than or equal to the participation probability, the user is considered willing to participate; otherwise, the EV is excluded from G2V/V2G operation [43]. To represent EV-user heterogeneity, the fleet is divided into three behavioral archetypes (Default, Night Worker, and Evening Worker), with nominal proportions of 50%, 30%, and 20%, respectively. Each archetype follows a distinct daily availability pattern and time-dependent participation behavior. To introduce realistic variability, the availability profiles are randomly shifted by ± 2 h, with a 10% dropout probability and occasional 1–3 h short trips. User willingness is generated probabilistically only when the EV is available.

The binary willingness factor describes the realized participation decision of an individual EV rather than presuming that driver behavior itself is predictable. Behavioral uncertainty is captured through a time-dependent participation probability linked with each driving archetype. Thus, the participation probability conveys ambiguity in user willingness, whereas the binary component converts this uncertainty into an active decision for the EMS. Importantly, willingness alone does not guarantee EV participation; G2V or V2G operation is permitted only when the EV simultaneously satisfies the necessary availability, mobility, SOC, and EMS operational parameters. This probabilistic-to-binary representation thus avoids the automatic consideration of all technically available EVs as controllable energy resources and allows for a more realistic estimate of the EV flexibility actually available to the microgrid, while preserving computational simplicity for annual simulation.

2.5. Benchmark algorithms

Quokka swarm optimization is used in this study as an optimization tool for solving the hybrid microgrid sizing problem. QSO's performance is compared to three well-known metaheuristic algorithms: the (PSO) [4], (GA) [5], and (POA) [6]. This comparison analysis allows the assessment of how well QSO optimizes the techno-economic and reliability objectives for the hybrid microgrid system.

2.6. Proposed optimization approach: Quokka swarm optimization (QSO)

We adopt the quokka swarm optimization algorithm [44], which is chosen as our main optimization approach because of its exploration-exploitation balance and high dimensional robustness. This algorithm loops between a global search and local exploration around the best-found solution, until convergence. QSO has demonstrated efficient performance in many power system applications like optimal location of distributed generator and EV charging stations to achieve improved voltage stability and loss reduction at faster convergence speed [45]. The developed QSO is synergistically interlocked with a behavior-aware (EMS) to make possible realistic, efficient operation of V2G-enabled microgrid. The QSO is defined in Eqs (25) and (26).

$$D^{new} = \frac{(T+H)}{(0.8*D^{old})} + \Delta_w \times rand \times \Delta_x \quad (25)$$

$$X^{new} = X^{old} + D^{new} \times N \quad (26)$$

D_{old} represents the drought factor within the range [0,1]. T and H denote the temperature and humidity ratios, varying within (0.2–0.44) and (0.3–0.65), respectively. Δ_w is the body weight difference between the leader and quokka i, while ΔX represents the positional difference. And rand is a uniformly distributed random number in [0,1]. X^{new} and X^{old} denote the updated and previous positions of the search agent, respectively. N represents the nitrogen ratio within [0,1] [44]. The overall procedure of QSO, including exploration, exploitation, and termination phases, is illustrated in Figure 5.

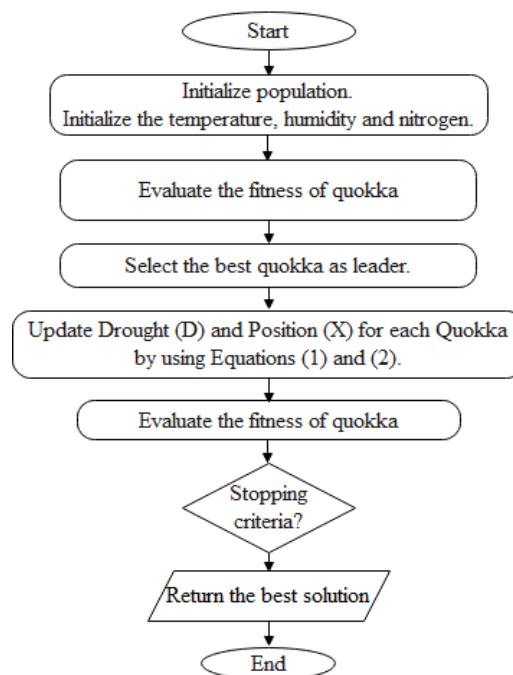


Figure 5. Flowchart of the quokka swarm optimization (QSO) algorithm.

2.7. Design variables and component parameters of the hybrid microgrid

Additionally, the designed variables (control parameters) are listed for the utilized components of

the microgrid and are tabulated in Table 2, including PV-WT-BT-EVCF-grid-converter economic parameters.

Table 2. Technical and economic parameters of the proposed hybrid microgrid components.

Components	Parameters	Value	Unit	Parameters	Value	Unit
PV system [46,47]	Lifetime	25	Years	Temperature coefficient (α_t)	-3.7×10^{-3}	1/°C
	Rate power at STC	325	W	Replacement cost	0	\$/year
	Operation and maintenance (O&M) cost	20	\$/year	Nominal operating cell temperature	45 ± 2	°C
	Initial cost	2.15	\$	Regulator cost	1500	\$
Wind turbine [48]	Lifetime	25	Years	Operation and maintenance (O&M) cost	50	\$/year
	Replacement cost	0	\$/year	Rated speed (V_r)	7.5	m/s
	Cut-in speed (V_{cut-in})	2.8	m/s	Blades diameter	15.8	m
	Cut-out speed (V_{cut-ut})	20	m/s	Hub height (h)	30	m
	Rated power of wind turbine	1000	W	Overall efficiency	26	%
	Regulator cost	1200	\$			
Battery storage [49,50]	Lifetime	10	Years	Replacement cost	280	\$/year
	SOC_{Min}^{BESS}	20	%	Hourly self-discharge	0.007	%/hour
	SOC_{Max}^{BESS}	100	%	O and M cost	5	\$/year
	Minimum charge current	14	A	Maximum DoD	80	%
	Maximum charge current	17	A	The initial cost of the battery	280	\$
Electric vehicle [51–53]	Battery capacity	40	KWh			
	Max/min capacity of EV battery	24/20	A	EV capacity	24	kWh
	SOC_{Max}^{EV}	100	%	SOC_{Min}^{EV}	20	%

2.8. Electricity pricing model

Due to the absence of an official V2G pricing framework in Iraq, validated Malaysian (ToU) tariffs were adopted as the benchmark [54]. The tariff is divided into off-peak, mid-peak, and peak periods, as summarized in Table 3.

Table 3. Adopted time-of-use tariff structure.

Period type	Time interval (hour)	Grid purchase price (\$/kWh)	Grid sell price (\$/kWh)
Valley (off-peak)	1–7, 22–24	0.067	0.0536
Mid-peak	8–10, 12–13, 17–21	0.085	0.068
Peak	11, 14–16	0.14	0.112

The grid selling price, including V2G transactions, is assumed to be 20% lower than the corresponding purchase price to reflect practical market conditions and transaction losses. This pricing structure is integrated into the EMS to encourage grid import during lower-price periods and V2G operation during peak-price periods.

2.9. Objective functions and optimization of the proposed microgrid

This section formulates the optimization problem used to determine the optimal sizes of the PV, WT, and battery systems. The objective functions consider economic performance and system reliability, while operational feasibility is ensured through the proposed RB-EMS. The numbers of PV panels, wind turbines, and battery units are treated as decision variables, and several optimization algorithms are applied and compared to identify the best system configuration.

2.9.1. Cost of energy

The cost of energy (COE) represents the average annualized cost of supplying one unit of electrical energy to the load and is used as the main economic objective of the proposed microgrid. It considers the annualized system cost together with the net cost of energy exchanged with the utility grid. The COE is calculated by Eq (27).

$$\text{COE} = \frac{ASC + C_{grid} - R_{grid}}{E_{served}(t)} \quad (27)$$

where ASC is the annualized system cost (\$/year), C_{grid} is the annual cost of electricity purchased from the utility grid, R_{grid} is the annual revenue obtained from electricity exported to the grid, and $E_{served}(t)$ is the total annual electrical energy supplied to the load (kWh/year). The annualized system cost includes the annualized capital, replacement, and operation and maintenance costs of the PV, WT, BESS, and inverter components [54].

2.9.2. Loss of power supply probability

In this work, we evaluate the reliability of the proposed microgrid using the loss of power supply probability (LPSP), which indicates the probability that the power available from all sources is not sufficient to meet the actual load. The LPSP value is between 0 and 1, where $\text{LPSP} = 0$ means that the load is supplied without interruption, and $\text{LPSP} = 1$ means that the demand cannot be met [55]. In this study, acquiring $\text{LPSP} = 0$ is of particular significance, because the Al-Ramadi General Teaching Hospital has critical load that needs continuous power supply. Therefore, LPSP is retained as a reliability indicator to verify that the optimized system can continuously satisfy the hospital load throughout the annual simulation using renewable generation, BESS, V2G-enabled EVs, and the utility grid as the final backup source, as in Eq (28) [32].

$$\text{LPSP}(\%) = \frac{\sum_{i=1}^N [P_l(t) - (P_{PV}(t) + P_{WT}(t) + \text{SOC}_{BESS}(t) + \text{SOC}_{EV}(t))]}{\sum_{i=1}^N P_l(t)} \quad (28)$$

where $\text{SoCBT}(t)$ denotes the state of charge of the stationary (deep-cycle) battery at time t , while

$SoCEV(t)$ represents the state of charge of the electric vehicle battery at the same time.

2.9.3. Grid contribution factor

The grid contribution factor (GCF) is an energy-based measure that indicates how much a hybrid microgrid depends on the utility grid to meet its electricity demand. A lower GCF means the microgrid can meet more of its demand using local renewable sources and storage such as PV, wind turbines, BESS, and V2G-enabled EVs, as shown in Eqs (29) and (30) [20,40]. The renewable energy fraction (REF) represents the portion of the total load that is supplied by renewable energy sources [32].

$$GCF = 1 - RFE \quad (29)$$

$$REF(\%) = \frac{\sum_{t=1}^{8760} (P_{pv} + P_{wt}) \times \Delta t}{\sum_{t=1}^{8760} (P_{pv} + P_{wt} + P_{grid-purchased})} \quad (30)$$

where $P_{gri-purchased}$ refers to the total amount of electricity imported from the utility grid over one year [40].

2.9.4. Energy sold to the grid

Energy sold to the grid (ESOLD) represents the total surplus electrical energy exported from the hybrid microgrid to the utility grid during the simulation period and is expressed in kWh. This metric reflects the system's ability to generate surplus energy beyond the local demand, particularly during periods of high renewable generation or low load demand, as given by Eq (31).

$$ESOLD = \sum_{t=1}^{8760} P_{export}(t) \times \Delta(t) \quad (31)$$

where $P_{export}(t)$ is the power exported to the utility grid at time step t (kW), Δt is the simulation interval (1 h), and T is the total number of simulation time steps (8760 h/year). A higher ESOLD indicates greater utilization of surplus energy for grid export. The corresponding export revenue is calculated separately using the applicable electricity selling price and is reported in monetary units (\$).

3. Results and discussions

This section shows the simulation findings of the hybrid microgrid combining PV-WT-BESS-EV with the grid that was suggested. Under the RB-EMS system, the study examines renewable energy use, economic performance, and system dependability. Key metrics like COE, LPSP, GCF, and energy sold to the grid (ESOLD) help to assess system performance. Four metaheuristic techniques (PSO, GA, POA, and QSO) were all tested under the same circumstances in a comparative study to check the validity of the suggested method. Mean and STD are statistical indicators used to assess optimization accuracy, convergence, and stability; behavior-free and behavior-aware EV settings are investigated to show how real-world user involvement affects V2G operation. Moreover, a sensitivity analysis is carried out to find how changes in important system parameters and operating circumstances affect optimal sizing and general microgrid performance. Hourly recorded observations help to determine the meteorological data; the load data comes from the actual building in Al-Anbar Governorate. The

analysis of the results shows QSO to be the best among all algorithms. Through a low STD value, the suggested framework seeks $LPSP = 0$ for better dependability, low COE, lower GCF, greater ESOLD, and good convergence stability.

Figure 6 shows the real hourly electrical load profile of the Al-Ramadi City hospital across a full year of 8760 hours. The load shows significant temporal fluctuation, therefore reflecting the actual operating conditions of the hospital instead of an assumed or manufactured demand curve. Generally ranging from about 600 to 900 kW during low-demand times, the electrical demand rises to more than 2.5–3.0 MW during high-demand times, with a maximum demand of about 3.3–3.4 MW. The yearly average load is around 1.575 MW. The changes throughout the year show hourly operational needs, seasonal demand, and changes in hospital activities. Using real load data gives a more realistic foundation for assessing the suggested microgrid's size, dependability, and energy-management performance.

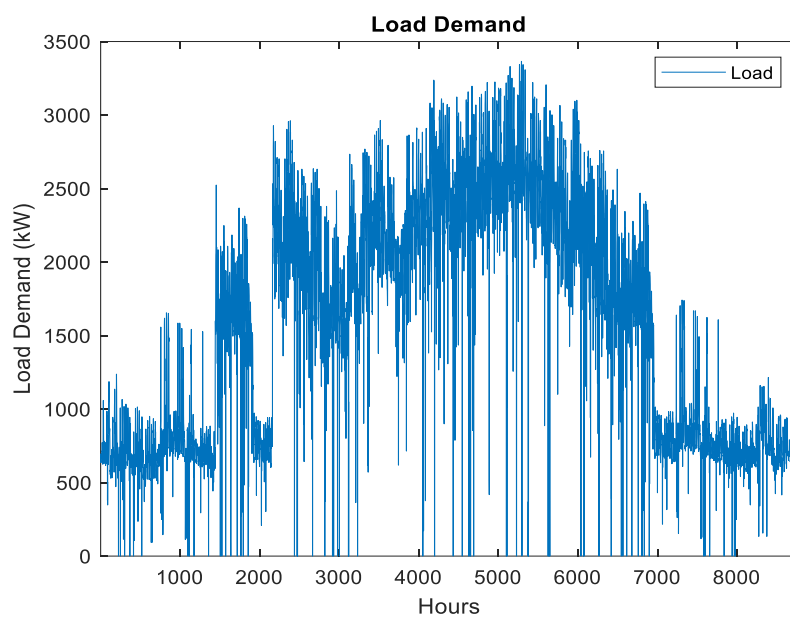


Figure 6. Measured annual hourly electrical load profile of Al-Ramadi hospital.

3.1. Comparative convergence performance of optimization algorithms

For a fair comparison, PSO, POA, GA, and QSO were tested under the same computational settings. Each algorithm was run independently five times with a population size of 25 and a maximum of 50 iterations per run. All algorithms were executed with the same objective function, decision-variable bounds, and simulation conditions (Figure 7). Each optimization algorithm was run independently five times under the same simulation conditions to ensure a statistically meaningful and fair comparison. For both cases, QSO rapidly converges to the area of lower fitness and maintains a stable solution for the remaining iterations. PSO and POA also approach similar final solutions, but require more iterations before reaching a stable region, whereas GA exhibits slower convergence and remains at higher fitness levels for a larger number of iterations. The convergence curves therefore indicate that QSO provides the fastest and most stable search behavior under both operating conditions.

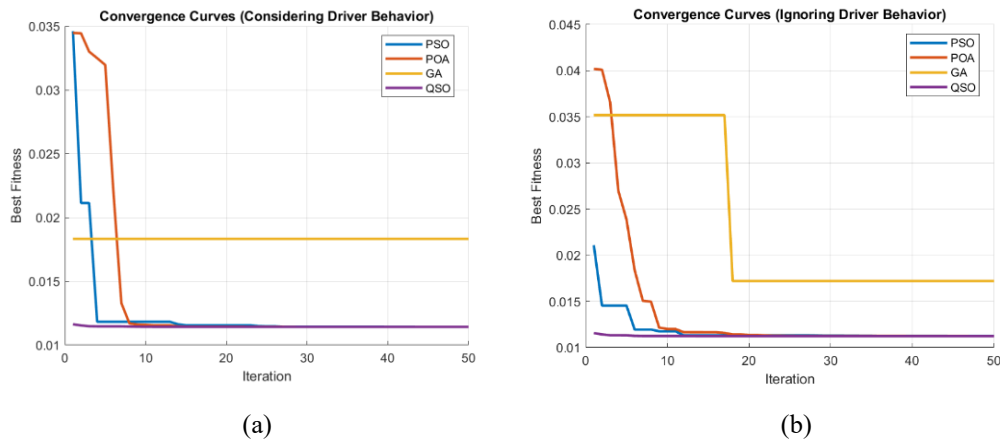


Figure 7. Convergence examination of PSO, POA, GA, and QSO under (a) behavior-aware and (b) behavior-free operating situations.

3.2. Statistical algorithmic performance

Figure 8 shows the statistical performance of PSO, POA, GA, and QSO under behavior-free and behavior-aware circumstances. In the behavior-free scenario, QSO had the lowest best fitness value of 0.011240, closely followed by POA (0.011241) and PSO (0.011243), whereas GA got a much higher value of 0.017207. Considering driver behavior, the same order was kept with best fit values for QSO, POA, PSO, and GA of 0.011427, 0.011428, 0.011429, and 0.018327, respectively. The mean fitness values followed a similar trend. QSO showed the lowest mean fitness in the behavior-free (0.011241) and behavior-aware (0.011428) circumstances, in contrast to POA (0.011249 and 0.011447), PSO (0.011318 and 0.011505), and GA (0.018485 and 0.029065).

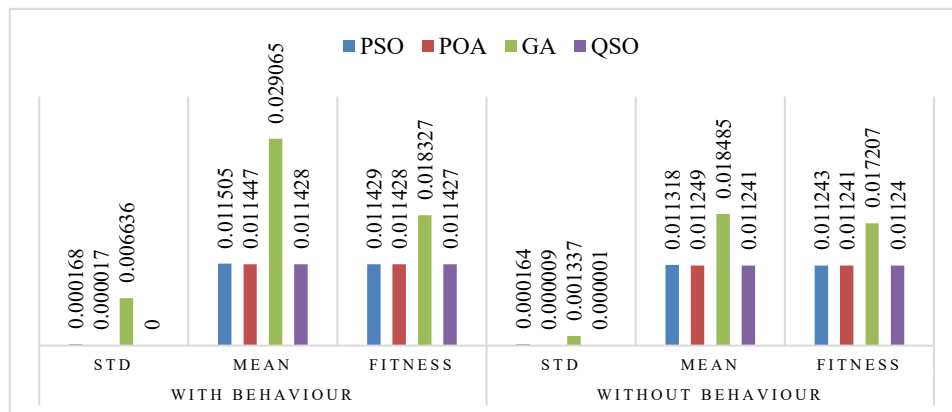


Figure 8. Statistical performance of PSO, POA, GA, and QSO under behavior-aware and behavior-free scenarios.

The consistency and repeatability of every optimization technique across separate runs is assessed using the standard deviation (STD). A reduced STD shows that the algorithm generates more consistent results with less variation across runs; a higher STD shows more variability and sensitivity to stochastic

initialization. In the behavior-free situation, QSO had the lowest standard deviation (0.000001), followed by POA (0.000009), PSO (0.000164), and GA (0.001337). With a standard deviation of 0.000000, behavior-aware operation saw virtually equivalent performance of QSO across the five separate runs; POA, PSO, and GA had 0.000017, 0.000168, and 0.006636, respectively. Under both behavior-free and behavior-aware situations, QSO showed the greatest weighted performance in terms of statistical stability, convergence uniformity, and solution quality. Though PSO and POA got rather similar best fitness levels, QSO consistently had the lowest mean fitness and least variation across the five separate runs. Choosing QSO as the main optimizing technique for the following energy-management and sensitivity analyses is justified by its excellent resilience and consistency.

3.3. Optimal sizing comparison under behavior-free and behavior-aware operation

The best sizing findings show that adding driver behavior affects the chosen system setup while maintaining the same general PV-WT-BESS structure. The best solution based on QSO under the behavior-free case comprises 116 wind turbine units, 1331 PV units, and 937 battery units. Taking into account how drivers behave, the best setup becomes 98 wind turbine units, 1335 PV units, and 958 battery units. Thus, the wind turbine capacity drops by around 15.50%, while the PV and battery capacity rise subtly by 0.30% and 2.20%, respectively. These developments show that sensible driving behavior influences the best distribution of microgrid parts, mostly because lower and erratic EV involvement changes the balance among renewable energy, fixed storage, and grid support. Driver behavior alters the contribution needed from certain parts to keep dependable and affordable functioning instead of altering the general system architecture. Figure 9 shows the best sizing trade-off under the two behavioral extremes.

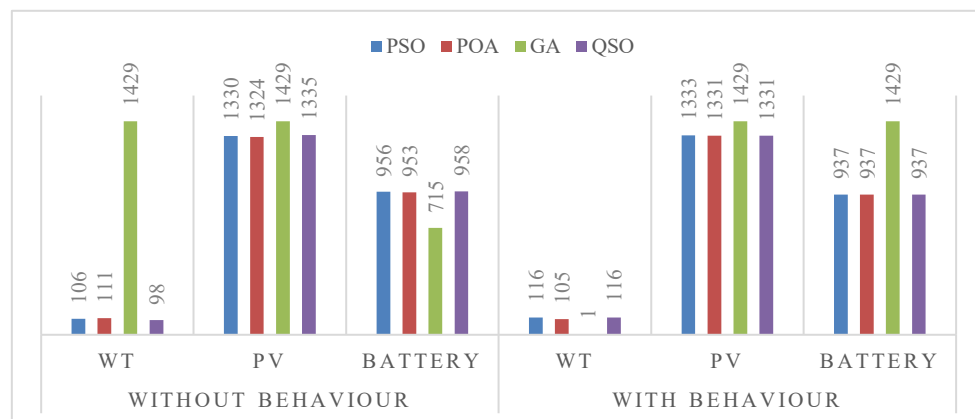


Figure 9. Comparison of optimal sizing for PSO, POA, GA, and QSO without and with driver behavior.

The sizing shift further highlights how behavioral restrictions influence the appropriate distribution of flexibility within the microgrid. The optimizer does not only make up for decreased EV participation by equally boosting all stationary components, as evidenced by the roughly 15.52% decrease in WT units and the small increases in PV and BESS capabilities. Rather, it reorganizes the generation-storage mix to support more stationary storage with zero LPSP. This emphasizes how

crucial it is to incorporate EV behavioral restrictions at the sizing stage instead of waiting until after component capabilities have been established.

The annual average SOC of the EV fleet over 8760 h is presented in Figure 10, where panel (a) represents the behavior-aware scenario, and panel (b) represents the behavior-free scenario. The average EV SOC is still near its maximum level over most of the year in both cases; significant drops happen during times of high EV use and V2G help. Under behavior-free operation, the minimum average SOC^{EV} approaches 47%–50%, therefore smoothing the SOC profile. Conversely, the behavior-aware example shows more variation and a somewhat deeper SOC decrease (44%–46%), particularly in the middle of the year. Time-varying vehicle availability, user willingness, mobility patterns, and EMS-controlled charging and discharging's combined effects drive this enhanced fluctuation. The average SOC's subsequent return toward 100% shows how well the EMS restores EV energy levels when there are possibilities for charging. Taken as a whole, the findings point to the fact that including driver behavior creates a more dynamic and realistic EV SOC profile than depending on unconstrained EV involvement.

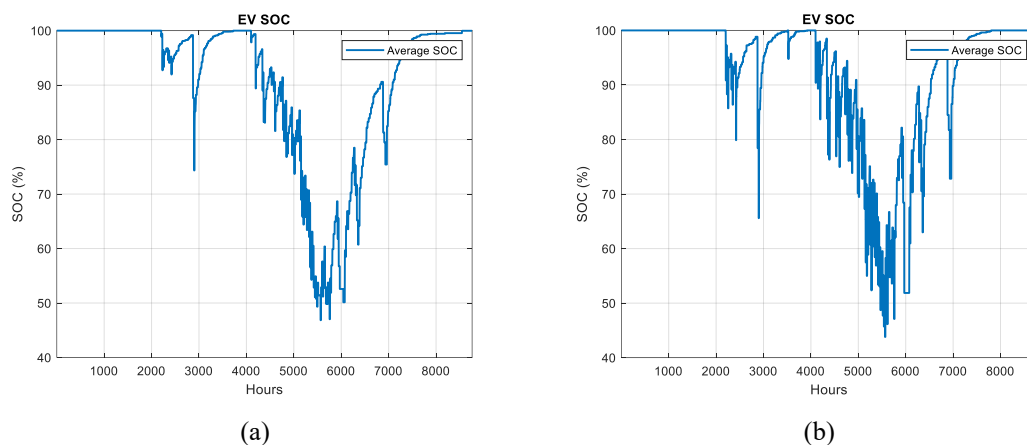


Figure 10. Annual average EV fleet SOC: (a) behavior-aware and (b) behavior-free scenarios.

The annual charging and discharging patterns of the EV fleet are compared in Figure 11, where panel (a) represents the behavior-aware scenario, and panel (b) represents the behavior-free scenario. Grid-to-vehicle (G2V) charging power, where EV batteries absorb energy, is represented by the positive red numbers; vehicle-to-grid (V2G) discharging power, where EVs return energy to the microgrid, is represented by the negative blue values. Because EV participation is limited by vehicle availability, user willingness, SOC restrictions, and EMS operating circumstances, charging and discharging events become less intense and more sporadic when driver behavior is taken into account. The highest G2V charging power in the behavior-aware scenario is roughly 410–420 kW, as opposed to roughly 950 kW when driver behavior is disregarded. This represents a 55%–60% decrease. Similarly, with behavior-aware operation, the maximum V2G discharge magnitude drops by around 45%–50%, from roughly 450–480 kW in the behavior-free scenario to about 240–250 kW. Additionally, the behavior-free example shows denser and more frequent charging and discharging activities, especially in the middle of the year, suggesting higher EV participation. The behavior-aware situation, on the other hand, has longer intervals with little to no energy exchange because of EV unavailability, SOC limitations, or participant reluctance. In general, the suggested behavior-aware

EMS offers a more accurate depiction of G2V and V2G operation throughout the year, whereas ignoring driver behavior may exaggerate the potential EV flexibility.

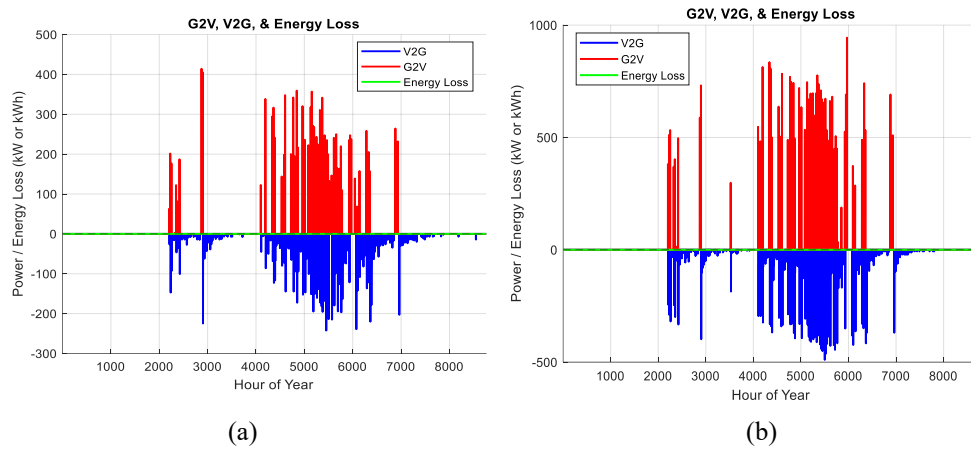


Figure 11. Annual G2V and V2G power profiles: (a) behavior-aware and (b) behavior-free scenarios.

Figure 12 shows the annual battery SOC profiles for the behavior-aware scenario (panel a) and the behavior-free scenario (panel b). The QSO sizing results indicate that the effect of driver behavior increases the required battery capacity from 937 to 958 units, which is an increase of 21 battery units (approximately 2.20%). For the battery unit capacity of 40 kWh, the total BESS capacity increases from approximately 37.48 MWh without driver behavior to 38.32 MWh with driver behavior. In the behavior-aware case, the total battery discharge increases to 6.860 from 6.760 GWh, and the total charging energy increases to 7.59 from 7.48 GWh, resulting in slightly increased battery utilization. The average battery SOC stays almost the same at 75.52% and 75.54% for the behavior-free and behavior-aware cases, respectively. Despite these changes, the final SOC increases slightly from 92.47% to 92.75%. These results show that the inclusion of driver behavior has a significant effect on the required storage capacity and annual battery energy throughput, whereas the overall SOC operating pattern is very similar.

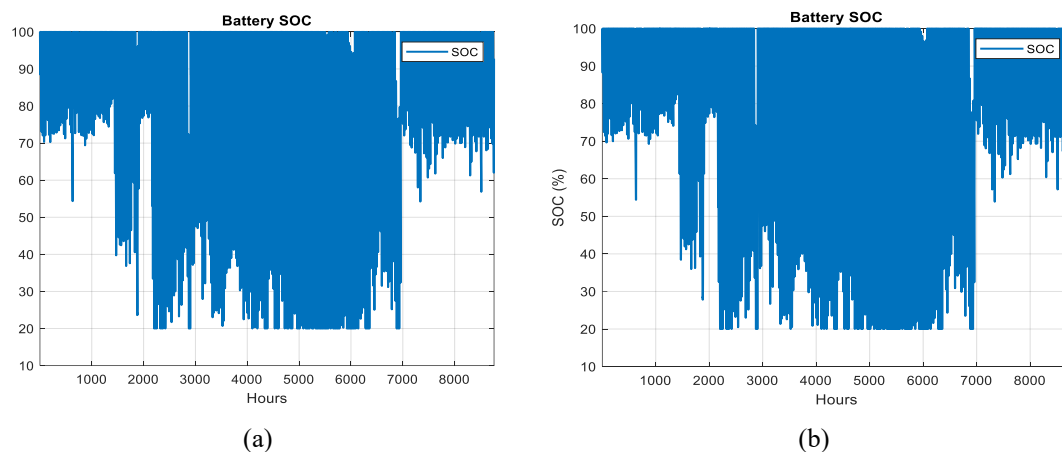


Figure 12. Yearly battery SOC profiles: (a) behavior-aware, and (b) behavior-free scenarios.

Figure 13 shows the annual charging and discharging profiles of BESS for the behavior-aware scenario (panel a) and behavior-free scenario (panel b). Positive values represent battery discharge, whereas negative values represent battery charging. In both cases, the BESS exhibits continuous energy exchange throughout the year, with higher charging and discharging activity during the middle portion of the year. The annual battery discharge increases from 6.76 to 6.86 GWh, considering the driver behavior, an increase of approximately 1.47%. The annual charging energy also increases from 7.48 to 7.59 GWh, an increase of approximately 1.48%. The small increase indicates that the stationary battery provides additional support when EV participation is more limited and sporadic. Although this increases the amount of BESS used in total, the overall charging and discharging patterns are similar in both cases, suggesting that driver behavior mainly influences the magnitude of BESS utilization, rather than fundamentally changing the annual operating pattern of BESS.

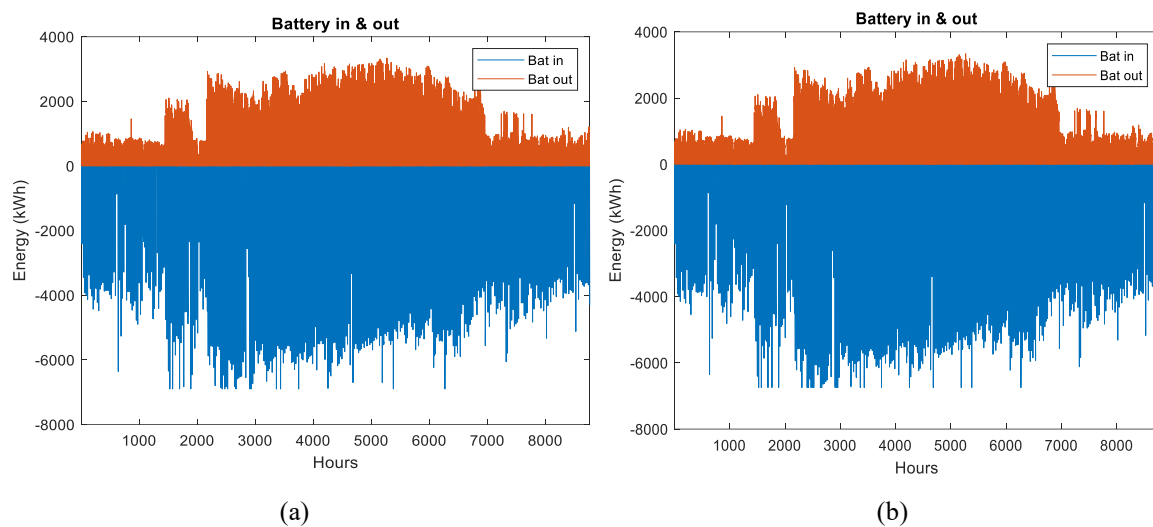


Figure 13. Annual charge and discharge profiles of the BESS for (a) behavior-aware and (b) behavior-free scenarios.

Figure 14 shows the 24-h power balance of the proposed microgrid, where panel (a) shows the behavior-aware case, and panel (b) shows the behavior-free case. In both cases, the solar generation is the main source during the day, and battery discharge is more important during low renewable generation times. The surplus solar energy is mainly used for battery charging and grid export. The load is continuously supplied by the coordinated contributions of the available energy sources. In the behavior-free case, a slightly higher power exchange is observed during the daytime period, especially in battery charging and grid export, indicating a higher flexibility of the EVs and less constrained energy participation. In contrast, the behavior-aware case exhibits a more moderate operating profile, since the availability of the EV and user participation restrict the contribution of the EV fleet. Despite the differences, the two cases show similar overall power balance patterns, demonstrating the capability of the proposed EMS of coordinating renewable generation, battery storage, EV interaction, and grid exchange over the daily operating cycle.

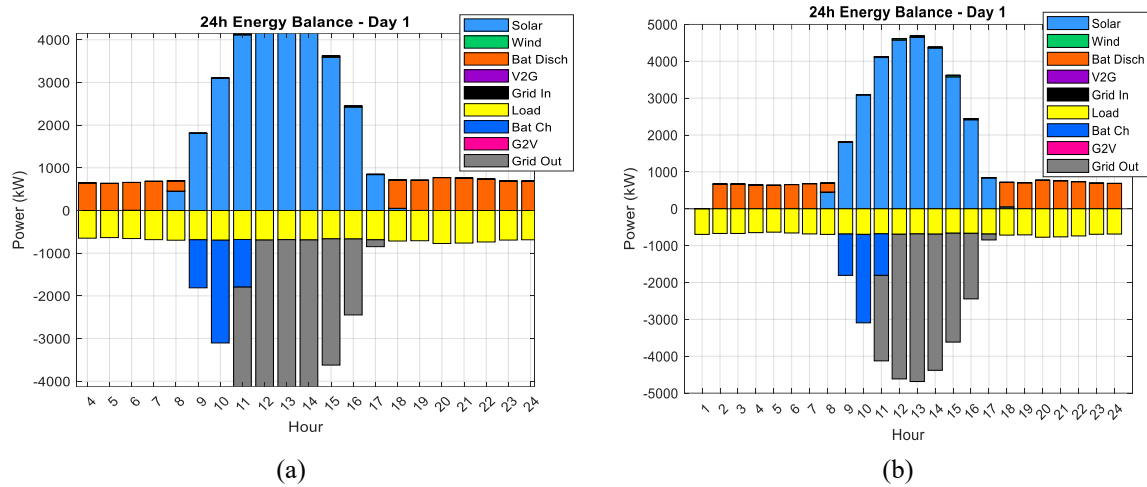


Figure 14. The power balance for a 24-h microgrid for the (a) behavior-aware case and (b) behavior-free case.

Figure 15 illustrates the operation of the EV, with panel (a) showing EV availability and panel (b) showing driver behavioral participation. Although several EVs may be physically available within the system, their actual participation in charging and discharging remains intermittent and does not always coincide with availability. This is because effective EV participation is determined by multiple conditions, including physical availability, technical feasibility, driver willingness, and electricity-price signals. In particular, the EMS permits G2V or V2G operation only when the required SOC^{EV} and operational constraints are satisfied, the driver is willing to participate, and the prevailing ToU price supports the corresponding charging or discharging action. Consequently, periods of high EV availability may still exhibit limited or no energy exchange. These results highlight the distinction between physical EV presence and effective V2G/G2V participation and avoid the unrealistic assumption of continuous EV involvement commonly adopted in deterministic models.

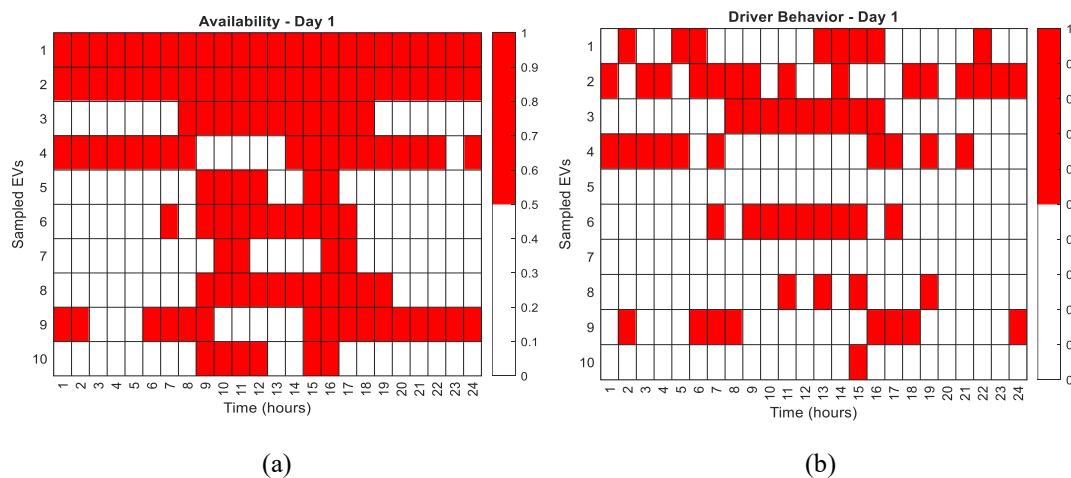


Figure 15. Maps for EVs on 1-day (a) availability and (b) driver behavior.

3.4. Impact of driver behavior on microgrid energy and economic performance

This section compares the performance of the microgrid in behavior-free and behavior-aware scenarios using the QSO algorithm and evaluates the impact of EV participation on energy flows, optimal sizing, algorithm behavior, economic performance, and overall system dynamics. The fleet consists of 250 EVs, which are used in all simulations. The fleet consists of 138 Default users, 74 Night Workers, and 38 Evening Workers. The same fleet composition is maintained in both behavior-free and behavior-aware cases to isolate the effect of driver behavior. The analysis is divided into five subsections to examine the main technical and economic impacts of driver behavior.

3.4.1. Energy flow comparison

Under behavior-aware operation, noticeable deviations are observed in the annual energy-flow results, as shown in Figure 16. Compared with the behavior-free case, wind generation decreases by 15.52%, from 1,530,905.02 to 1,293,350.79 kWh/year, whereas solar utilization increases slightly by 0.30%, from 18,430,994.96 to 18,486,384.88 kWh/year. To compensate for the reduced and more uncertain EV contribution, battery discharge increases by 1.47%, from 6,759,886.53 to 6,859,583.46 kWh/year, while battery charging rises by 1.48%, from 7,487,209.03 to 7,597,723.87 kWh/year.

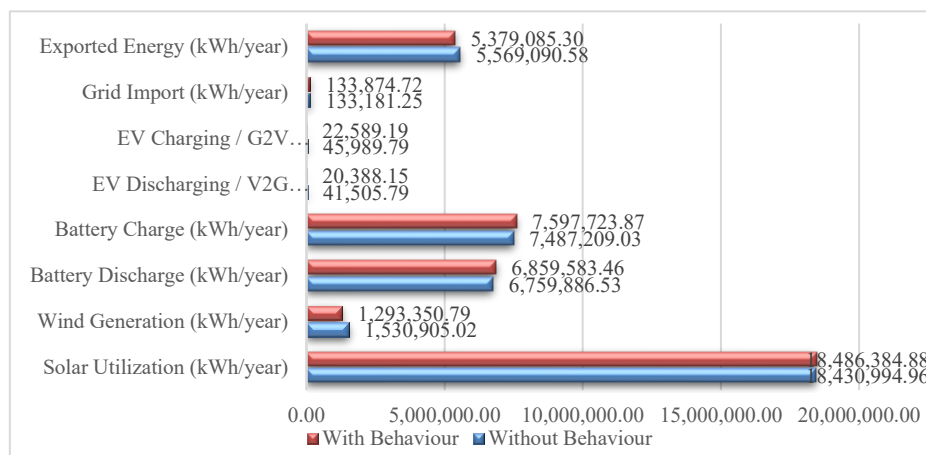


Figure 16. Energy flow comparison with and without driver behavior.

In contrast, EV discharging (V2G) and EV charging (G2V) decrease significantly by 50.88% and 50.88%, respectively, reflecting the impact of realistic driver availability and participation. Grid import increases only marginally by 0.52%, from 133,181.25 to 133,874.72 kWh/year, while exported energy decreases by 3.41%, from 5,569,090.58 to 5,379,085.30 kWh/year. Overall, these results indicate that incorporating driver behavior mainly reduces EV contribution and wind dependence, while the stationary battery and PV system compensate effectively to maintain reliable system operation. This conclusion demonstrates that the main consequence of driver behavior is not a worsening in system dependability but a fall in the useful flexibility of the EV fleet. Although the same number of EVs is included in both scenarios, behavioral and availability restrictions reduce the number of vehicles that can actually participate in charging and discharging at a given moment. Consequently,

part of the energy-balancing role expected from the EV fleet is moved to the stationary BESS and PV generation. This explains why V2G/G2V exchanges reduce by 50.88%, but BESS charging and discharging rise just marginally, and LPSP remains zero. Therefore, presuming full EV participation may greatly exaggerate the operational contribution of EVs without necessarily disclosing its effect on supply reliability.

3.4.2. Economic comparison

Figure 17 presents a multi-objective comparison of QSO, PSO, POA, and GA under behavior-free and behavior-aware operating scenarios. QSO, PSO, and POA exhibit closely comparable performance, with COE values of approximately 0.0145–0.0149 \$/kWh, very low GCF values, zero LPSP, and annual exported energy of approximately 5.38–5.60 GWh. Among these algorithms, the incorporation of driver behavior produces only modest changes in the main performance indicators. For QSO, COE increases by 1.78%, GCF increases by 0.81%, and ESOLD decreases by 3.41%. Similarly, PSO shows increases of 1.71% in COE and 1.02% in GCF, accompanied by a 3.17% reduction in ESOLD. POA shows a 2.27% increase in COE, while GCF decreases by 4.32%, and ESOLD decreases slightly by 0.41%. In contrast, GA exhibits markedly different behavior, with substantially higher COE values of 0.02449–0.02492 \$/kWh and a highly variable system configuration between the two operating scenarios. Under behavior-aware operation, GA produces exceptionally high exported energy of 24.61 GWh/year due to the oversized renewable configuration, indicating a less balanced sizing solution. Despite these variations, all algorithms maintain LPSP at zero. Overall, QSO provides a highly competitive and stable solution, achieving a favorable balance among cost, grid dependence, energy export, and system reliability while showing only limited sensitivity to behavioral constraints.

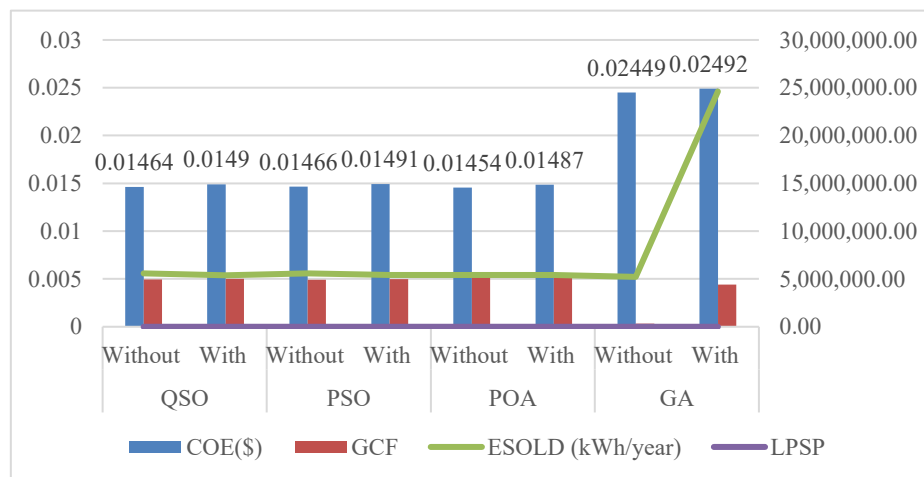


Figure 17. Impact of behavioral constraints on multi-objective optimization performance.

Figure 18 compares the economic performance of the QSO-based system under behavior-free and behavior-aware operating scenarios. Incorporating driver behavior slightly increases the cost of energy from 0.01464 to 0.01490 \$/kWh, corresponding to an increase of approximately 1.78%. At the same time, exported energy decreases from 5,569,090.58 to 5,379,085.30 kWh/year, representing a reduction of approximately 3.41%. Grid purchase cost increases marginally from 11,319.85

to 11,378.78 \$, while grid-sale revenue decreases from 404,991.50 to 393,120.44 \$. Consequently, the net grid revenue decreases from approximately 393,671.65 to 381,741.66 \$, corresponding to a reduction of approximately 3.03%. This decline is mainly attributed to the reduced EV participation under realistic driver Behavior, which limits V2G and G2V energy exchanges and slightly reduces the system's ability to benefit from time-varying electricity prices. As a result, the behavior-aware case exhibits slightly higher operating costs and lower export-related revenue, although the overall economic performance remains relatively stable.

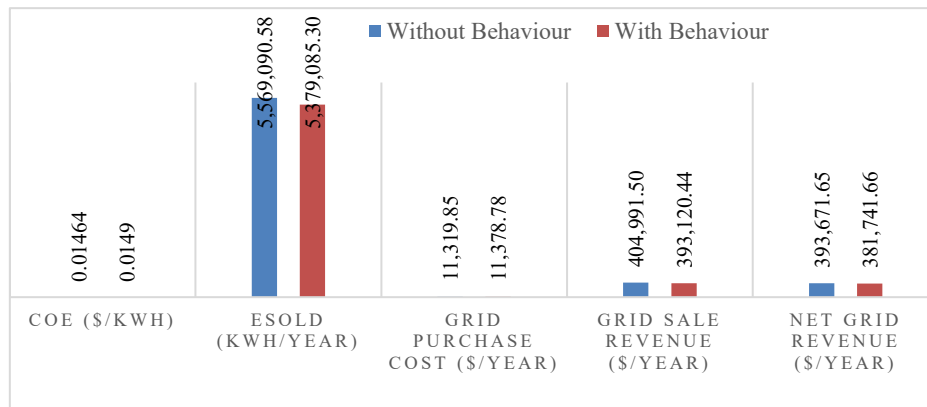


Figure 18. Impact of driver behavior on the economic performance of the microgrid.

It is important to note that the relatively small increase in COE, amounting to 1.78% in contrast to the 50.88% reduction in EV energy exchange, shows the microgrid to be economically resilient in the face of large reductions in EV flexibility. As a result, the stationary BESS and the renewable generation take on much of the operational impact of behavioral uncertainty and thus reduce its effect on the total energy cost.

3.5. Comparison of the proposed framework with recent studies

The proposed QSO-based behavior-aware EMS was compared with three recent hybrid microgrid optimization studies. The proposed framework achieved a COE of 0.014 \$/kWh, compared with 0.98, 0.08, and 0.148 \$/kWh reported in [56–58], respectively. Although these studies differ in system configuration and optimization objectives, the results indicate strong techno-economic performance. The proposed system also maintained LPSP = 0, whereas values of 5% and 2.23% were reported in [57,58], respectively, while [56] did not explicitly report LPSP. This is particularly important for the considered hospital microgrid, where continuous power supply is essential. The proposed framework also achieved GCF = 0.005 and ESOLD = 5,379,085.30 kWh, enabling direct assessment of grid dependency and renewable-energy export. In [56], authors reported that approximately 10%–23% of generated energy was exported to the grid, while comparable export values were not reported in [57] and [58]. A key distinction of the present work is the unified integration of optimal sizing, behavior-aware EV participation, V2G operation, ToU pricing, and rule-based energy management. To the best of the authors' knowledge, this is also the first application of QSO for optimal sizing of a behavior-aware V2G-enabled hybrid microgrid. Although direct numerical comparison is limited by differences in system configurations and operating conditions, the results show competitive economic and reliability

performance. The main distinction of the proposed framework is the integrated consideration of EV behavior, optimal sizing, V2G/G2V operation, and ToU-based energy management.

3.6. Sensitivity analysis

To further investigate the impact of the size of the EV fleet on the proposed microgrid, a comparative statistical analysis has been conducted for the 125-EV and 250-EV cases under behavior-aware and behavior-free operation. The analysis focuses on key technical and economic indicators, such as optimal component sizing, COE, GCF, V2G/G2V energy exchange, grid import/export, and system reliability. The percentage variation between the two fleet sizes was calculated to quantify the changes resulting from increasing EV penetration. Increasing the EV fleet from 125 to 250 vehicles produced clear changes in the microgrid operation. Under behavior-aware operation, the COE decreased slightly from 0.015 to 0.0149 \$/kWh (−0.73%), while GCF and grid import decreased by approximately 1.19% and 1.35%, respectively. The most significant change was observed in EV energy exchange, where V2G increased by 69.84%, and G2V increased by 69.82%. Meanwhile, grid export decreased slightly by 0.54%. The optimal system configuration also changed slightly, with wind turbines decreasing from 100 to 98 units and battery units from 961 to 958, while the PV size remained unchanged at 1335 units. Under behavior-free operation, increasing the fleet from 125 to 250 EVs resulted in a larger increase in EV energy exchange, with both V2G and G2V increasing by approximately 102.63%. At the same time, COE decreased by 1.68%, GCF decreased by 1.39%, and grid import decreased by approximately 1.34%. Grid export increased by 2.46%. The optimal configuration also shifted, with wind turbines increasing from 101 to 116 units, while PV units decreased slightly from 1336 to 1331, and battery units decreased from 955 to 937. Overall, increasing the EV fleet from 125 to 250 vehicles improved the energy flexibility of the microgrid, particularly through higher V2G and G2V participation, while slightly reducing COE and grid dependency. The effect was more pronounced in the behavior-free case, where EV energy exchange almost doubled.

The electricity grid purchase price changed from [0.067, 0.085, 0.140] to [0.050, 0.085, 0.170] \$/kWh and affected the optimal system configuration and grid interaction. In behavior-aware QSO operation, the number of wind turbines was reduced to 93 from 98, and PV units were reduced to 1321 from 1335, but the battery capacity remained practically unchanged at 958–959 units. Grid import increased by around 11.15%, and exported energy decreased by 4.58%, from 5.38 to 5.13 GWh/year. Meanwhile, V2G and G2V exchanges dropped by approximately 2.63%. These operational changes achieved only a slight increase in the COE from 0.01490 to 0.01494 \$/kWh with zero LPSP. Ignoring driver behavior, grid import increased significantly by approximately 35.8% and the COE dropped to 0.01429 \$/kWh; much higher V2G and G2V exchanges were observed. The overall results show that the variations of electricity prices mainly affect the grid interaction, energy trading, and the optimal sizing of renewables, while realistic driver behavior limits the available EV flexibility and has only a minor impact on the system reliability and overall energy cost.

The sensitivity of the proposed microgrid to EV-user behavior was evaluated by comparing the baseline archetype distribution of 50%/30%/20% (Default/Night Worker/Evening Worker) with 40%/30%/30% and 40%/20%/40%, respectively. Thus, the sensitivity cases modify only the proportion of EV users assigned to each behavioral archetype while maintaining their predefined availability patterns. The results based on the QSO show that changes in user composition have a small effect on system cost and sizing but a stronger effect on EV energy exchange. For the 40%/30%/30%

case, the COE was reduced from 0.01490 to 0.01480 \$/kWh, and V2G and G2V were increased by around 34%. For the 40%/20%/40% case, V2G and G2V increased approximately 82%, and the COE decreased only 2.21% (to 0.01457 \$/kWh). Optimal WT capacity was increased from 98 to 118 units with a slight reduction in PV and battery sizes. In all cases, LPSP was equal to zero, which means that system reliability was preserved despite the variations in the EV behavioral composition. The overall sensitivity analysis verifies the technical reliability and economic stability of the proposed framework for the considered variations in EV penetration, electricity pricing, and user behavioral composition. These factors modify the energy exchange patterns and grid interaction, but do not endanger system reliability or cause important deterioration of the overall economic performance, showing the robustness of the proposed approach under different operating conditions.

4. Conclusions

In this paper, a behavior-aware grid-connected PV-WT-BESS-EV microgrid integrated with a rule-based energy management system (RB-EMS) is proposed to account for realistic EV user participation. Unlike conventional approaches that assume continuous or complete EV availability, the proposed framework incorporates mobility, SOC limits, vehicle availability, and user willingness to provide a more realistic representation of EV participation in G2V and V2G operations. The optimization framework simultaneously minimizes the cost of energy (COE), loss of power supply probability (LPSP), and grid contribution factor (GCF), while maximizing the energy sold to the grid (ESOLD) under dynamic electricity pricing. The results demonstrate that incorporating driver behavior noticeably affects both optimal component sizing and system operation. Under the QSO-based solution, considering behavioral constraints reduces the required wind turbine units from 116 to 98, while PV units increase slightly from 1331 to 1335 and battery units from 937 to 958. More importantly, realistic behavioral constraints reduce both V2G and G2V energy exchanges by approximately 50.88%, demonstrating that neglecting driver behavior can considerably overestimate the flexibility available from the EV fleet. This reduction in EV participation is partially compensated by the stationary BESS, whose annual charging and discharging activities increase by approximately 1.48% and 1.47%, respectively. Despite these behavioral restrictions, the overall system performance remains stable. For the QSO-based configuration, COE increases only slightly from 0.01464 to 0.0149 \$/kWh, corresponding to approximately 1.78%, while annual ESOLD decreases by about 3.41%. Grid import increases only marginally, and LPSP remains zero under both operating scenarios, confirming that the proposed RB-EMS is able to maintain reliable supply to the critical hospital load despite reduced EV flexibility. From the optimization perspective, PSO and POA achieve closely comparable best objective values; however, QSO provides the strongest overall performance in terms of convergence speed, average solution quality, repeatability, and statistical stability over five independent runs. In contrast, GA exhibits higher fitness values, greater variability, and a less balanced sizing solution, particularly under behavior-aware operation. Within the analyzed sensitivity ranges, the suggested framework maintained stable technical and economic performance under fluctuations in EV fleet size, power pricing, and EV-user behavioral mix. Increasing the EV fleet from 125 to 250 vehicles enhanced V2G and G2V energy exchange by roughly 69.84% and 69.82%, respectively, under behavior-aware operation, while COE declined by 0.73% and LPSP remained zero. Variations in power pricing and behavioral composition mostly affected grid interaction and EV energy exchange, although system dependability was maintained for all tested situations. Overall, for the analyzed hospital microgrid,

integrating EV behavioral restrictions gave a more realistic assessment of available EV flexibility and demonstrated measurable implications on optimal component sizing, V2G/G2V energy exchange, grid interaction, and economic performance. The proposed QSO-based RB-EMS framework maintains a favorable balance among economic performance, renewable-energy utilization, grid dependence, energy export, and system reliability while avoiding unrealistic assumptions regarding EV availability and participation. Future work may extend the proposed framework through adaptive and learning-based EMS strategies, real-time communication and control infrastructure, cybersecurity and interoperability considerations, demand-response mechanisms, and user incentive models to further improve practical implementation under uncertain operating conditions.

Use of AI tools declaration

During the preparation of this manuscript, AI-based tools were used only to assist with the language improvement of several sentences. In addition, an AI-based tool was used to assist in creating the visual illustration for the graphical abstract.

Acknowledgments

This research was supported by the Ministry of Higher Education (MOHE) through the Fundamental Research Grant Scheme (FRGS/1/2021/TK0/UTM/02/19). The authors would like to express gratitude to Universiti Teknologi Malaysia (UTM) for providing comprehensive facilities. The authors would like to thank the Ministry of Higher Education and Scientific Research of Iraq and the University of Anbar. Lastly, thanks to colleagues who have either directly or indirectly contributed to the completion of this work.

Conflict of interest

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

Author contributions

Ahmed K. Abbas: Conceptualization, Methodology, Software, Formal Analysis, Investigation, Data Curation, Visualization, and Writing—Original Draft. Razman Ayop: Supervision, Validation, Project Administration, and Writing—Review & Editing. Chee Wei Tan, Yousif Al Mashhadany, Munir Ganbasha, Rozana Ali, Siti Mahfuza Saimon, and Nur Faizal Kasri: Validation, Investigation, Resources, and Writing—Review & Editing. All authors contributed to the interpretation of results, critically reviewed the manuscript, and approved the final version.

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