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Research paper

Swarm Intelligence-driven Multi-objective Optimization for Microgrid Energy Management and Trading considering DERs and EVs integration: Case Studies from Green Energy Park, Morocco

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ABSTRACT

The objective of this study is to develop and validate a comprehensive multi-objective optimization approach for energy management and trading in microgrids, with a particular focus on the integration of Distributed Energy Resources (DERs) and Electric Vehicles (EVs). As the demand for sustainable and smart energy solutions increases, the development of robust Energy Management Systems (EMS) that optimize energy flows while ensuring efficiency, reliability, cost-effectiveness, and sustainability becomes crucial. In this work, we propose an advanced EMS that employs an enhanced Particle Swarm Optimization (PSO) technique to address the complexities of optimal energy scheduling, cost minimization, revenue maximization, battery health preservation, and EV users satisfaction. Additionally, our EMS incorporates demand response (DR) mechanisms while considering dynamic pricing strategies to enhance operational efficiency and adaptability. This methodology is rigorously validated through a case study at the Green Energy Park (GEP) in Morocco, serving as a practical testbed for real-world applications. The results of this study demonstrate that the proposed EMS strategy can reduce net costs by up to 42 % compared to a baseline scenario while simultaneously optimizing renewable energy utilization and enhancing EV users' satisfaction. The findings elucidate significant trade-offs and provide insights into the multi-dimensional decision-making processes essential for effective microgrid management. This research contributes to advancing the development of sustainable energy systems and offers a robust framework for future investigations focused on microgrid optimization.

Nomenclature

ACRONYMS			
AC	Alternative Current	FL	Flexible Loads
ATP	Arrival-time-based Priority	G2V	Grid-to-Vehicle
ASAPSO	PSO with Adaptive Simulated Annealing	GEP	Green Energy Park
BESS	Battery Energy Storage System	GSA	Gravitational Search Algorithm

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BPSO	Binary Particle Swarm Optimization	kW	Kilowatts
CBMO	Converged Barnacles Mating Optimizer	kWp	Kilowatts-peak
CMDP	Constrained Markov Decision Process	MAD	Moroccan Dirhams
CCP	Chance-Constrained Programming	MOPSO	Multi-objective Particle Swarm Optimization

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CL	Critical Loads	MPC	Model Predictive Control
CPP	Critical Peak Pricing	NSGA	Non-dominated Sorting Genetic Algorithm
DC	Direct Current	MOEA	Multi-objective Evolutionary Algorithm
DERs	Distributed Energy Resources	PSO	Particle Swarm Optimization
DSM	Demand-Side Management	RTP	Real-time Pricing
EDM	Energy Demand Management	SBP	SOC Based Priority
EMS	Energy Management System	SOC	State-of-Charge
ESS	Energy Storage System	ToU	Time-of-Use
EVs	Electrical Vehicles	V2G	Vehicle-to-Grid

1. Introduction

This first section presents the need for efficient energy management in microgrids, emphasizing the integration of Distributed Energy Resources (DERs) and Electric Vehicles (EVs). It highlights the challenges of optimizing energy flows, managing battery health, and adapting to dynamic energy demands. The research proposes a novel Energy Management System (EMS) designed to address these challenges using advanced optimization techniques. The introduction also outlines the study's objectives and summarizes the paper's structure.

1.1. Background and motivations

As the global energy landscape transitions towards sustainability and decentralization, the demand for efficient energy management within microgrids has become increasingly urgent. EMS play a crucial role in optimizing the integration of DERs to ensure reliable, cost-effective, and sustainable operations in modern energy systems [1]. Microgrids, which can operate both in grid-connected and islanded modes, offer a practical solution to the challenges posed by the variability of renewable energy sources, such as solar and wind, and the unpredictable nature of loads, such as EVs [2]. By integrating DERs, microgrids can enhance the stability and resilience of energy systems. EMS in these systems manages load balancing, energy storage dispatch, and the overall coordination of energy networks to achieve key objectives such as cost reduction, improved grid quality, and maximized utilization of renewable energy resources [3].

1.2. Problem statement

The variable charging behaviors of EVs, coupled with fluctuating renewable energy generation, necessitate the development of robust EMS that can optimize the microgrid power flows. The integration of DERs and EVs into the power grid creates complex interactions between energy supply, demand, and storage, which need to be dynamically managed to ensure not supply reliability, economic dispatch and environmental sustainability.

1.3. Research objectives and methodology

The motivation for this research stems from the need to address the challenges of integrating DERs and EVs while maximizing the benefits of renewable energy sources. By developing a flexible, scalable EMS for grid-connected microgrids, this paper aims to contribute to the decarbonization of the energy sector and enhance the overall efficiency and reliability of the power grid.

The main objective of this research is the development of an advanced EMS designed specifically for grid-connected microgrids, integrating DERs and EVs. Unlike some existing approaches, this work offers several key contributions:

- The proposed EMS can handle various optimization targets, including minimizing grid import costs, optimizing net energy costs through feed-in tariffs, reducing battery degradation, and enhancing EV user satisfaction. Each of these targets has been simulated under real-world conditions, showing the EMS's flexibility in adapting to multiple operational objectives.
- Our approach leverages real-time and forecasting data for both energy demand and supply management. This capability allows the EMS to make proactive decisions, enhancing operational efficiency.
- By incorporating demand response (DR) mechanisms, our EMS can dynamically adjust demand schedules and optimize energy dispatch in response to both dynamic tariffs and renewable generation availability to maximize the use of renewable energy, avoid grid congestion, and optimize cost savings for end-users.
- Our EMS has the ability to optimize energy trading between the microgrid components and the grid, strategically exporting energy during high-tariff periods.
- The proposed EMS incorporates strategies to minimize battery degradation by smoothing the battery's charge and discharge cycles.
- Our comprehensive real-world case study incorporates six different scenarios, including a baseline (no optimization) as a reference, demonstrating the EMS's adaptability and effectiveness across diverse operational goals. The findings provide valuable insights into the multi-dimensional decision-making process required for smart microgrid management.

1.4. Outlines of the paper

The structure of this paper is organized as follows: Section 2 provides a comprehensive literature review and discusses related works, highlighting existing EMS in microgrids and identifying research gaps addressed by this study. Section 3 presents the methodological framework, detailing the architecture and design of the EMS for grid-connected microgrids. Section 4 describes the microgrid model, including the load, power grid, and DERs such as PV, BESS, and EVs. Section 5 formulates the multi-objective optimization problem, focusing on minimizing grid import costs, maximizing renewable energy utilization, reducing battery degradation, and ensuring EV user satisfaction. Section 6 outlines the EMS algorithm design, emphasizing the enhanced Particle Swarm Optimization (PSO) technique for real-time, dynamic energy management. Section 7 presents a case study of the Green Energy Park (GEP) microgrid, where the EMS is validated under six different scenarios, demonstrating its effectiveness and adaptability. Finally, Section 8 summarizes the key findings and contributions of this research while suggesting potential future directions.

2. Literature review

A comprehensive analysis by Abbasi et al. [3] underscores the importance of EMS in managing the unpredictability of renewable energy generation and fluctuating demand, particularly in microgrids. Effective EMS solutions often involve advanced control strategies and real-time decision-making processes. Several approaches have been proposed to improve EMS in both grid-connected and islanded microgrids, including demand response (DR) mechanisms, energy storage system (ESS) control, and distributed generation management [4]. These strategies have proven to enhance the operational efficiency of microgrids by enabling flexible and dynamic responses to changing energy needs.

Despite these advancements, significant challenges remain in the development of reliable, cost-effective, and scalable EMS strategies that can be applied across diverse microgrid configurations. Various EMS control strategies, including centralized, decentralized, and distributed approaches, have been introduced in recent years, each offering distinct advantages and limitations depending on the scale and architecture of the microgrid [5]. Centralized EMS configurations rely on a central unit to manage all DERs and energy flows, optimizing performance across the entire system [6]. However, this requires a sophisticated communication infrastructure, which may not be feasible for larger, more geographically distributed systems. In contrast, decentralized and distributed control methods allow local controllers to manage individual subsystems, improving flexibility and scalability [7]. However, these methods often struggle to achieve coordinated, system-wide optimization, particularly in the face of fluctuating grid conditions [8].

The implementation of EMS in larger or more complex microgrids can be prohibitively expensive due to the high costs associated with communication, computational infrastructure, and ongoing maintenance. Additionally, issues such as load forecasting, peak shaving, and real-time energy dispatch remain areas for further refinement, as EMS must contend with the inherent variability of renewable energy sources and dynamic demand patterns [9]. As the global shift towards decentralized energy systems continues, addressing the challenges of scalability and cost-effectiveness in EMS will be critical to ensuring that these strategies can be deployed effectively across a wide range of microgrid applications [3].

The integration of EVs into microgrids offers new opportunities to enhance EMS performance. The synergy between EV integration and EMS represents a significant advancement in microgrid optimization, allowing for more efficient use of renewable energy resources while reducing reliance on conventional energy sources [10].

Furthermore, switching from combustion engines toward EVs has gained significant interest as a viable solution, mainly driven by its promise to enhance energy security and reduce greenhouse gas emissions for future energy systems [11]. Furthermore, EVs can contribute to the bidirectional flow of power to the grid [12]. This in turn has a stabilizing impact on the grid, although the full potential of this strategy is not exploited when used to compensate for fluctuations [13].

EVs can be incorporated into the operational strategies of microgrids, as essential components of distributed energy. Consequently, many researchers are interested in developing optimal strategies for managing the charging and discharging behavior of electric vehicles as part of microgrid scheduling. The authors of the article [14] have carried out a literature review of recent technical and economic aspects of electric vehicle charging management taking into account V2G. Another review study is presented in [15], exploring the issues, solutions, and challenges involved in integrating electric vehicles into energy demand management (EDM). In particular, it discusses how to optimize this integration (EV-DSM) and to improve its efficiency. Authors in [16] analyze the interaction between microgrids and the electrification of transport. They outline the management strategies and challenges associated with microgrid and electric vehicle (EV) technologies.

Therefore, a growing number of researchers are investigating multiple strategies for the optimal scheduling of microgrids involving EVs. In the referenced study [17], the V2G scheduling problem is conceptualized as a Constrained Markov Decision Process (CMDP) to optimize the overall operational costs of the microgrid. Considering the electric vehicles as mobile storage, the study also envisages limiting the duration of the planned cycles to encourage active participation by EV users. The authors in [18], have developed a programmable model for a fleet of EVs, using the Minkowski sum, aimed at minimizing the random access of an EV to power system operation. In [19], an optimal energy scheduling method using multiple agents has been developed for microgrids. This approach aims to reduce the total costs associated with domestic energy consumption and electric vehicle charging, taking into account both market tariffs and battery degradation costs. In [20], the research presents an optimal scheduling model using chance-constraint programming (CCP). Under various renewable energy uncertainties, the model integrates the charging properties of electric vehicles, demand response and carbon emissions. In [21], a stochastic operation model has been developed for a microgrid integrating renewable energies and EVs, using an uncentered transformation-based approach to optimize operating costs. The problem is solved with the Converged Barnacles Mating Optimizer (CBMO) algorithm, demonstrating its effectiveness in energy resource management.

Most of research studies have considered multiple objective functions for optimizing microgrid dispatching results. Authors in [22], present a comprehensive review of multi-objective optimization algorithms applied to a hybrid AC/DC microgrid powered by renewable energies. Moreover, the authors in [23] propose a multi-objective optimization method for hybrid renewable energy systems for electric vehicle (EV) charging stations. The approach takes into account economic aspects, reliability and seasonal fluctuations of both energy consumption and production. The performance of four algorithms, MOPSO, NSGA-II, NSGA-III and MOEA/D, has been analyzed. In [24], the authors have designed a multi-objective optimization model aimed at improving the economic and environmental performance of a microgrid comprising electric vehicles. This model was solved using the ASAPSO (Particle Swarm Optimization with Adaptive Simulated Annealing) algorithm. By regulating the charging and discharging cycles of the electric vehicles, the model reduced the operating costs and environmental impact of the microgrid, thus improving its sustainability and economic efficiency. In this research [25], a multi-objective optimization algorithm coupled with the fuzzy membership function method is used to optimize the management of a microgrid integrating electric vehicles and a transferable load. The simulations in this study also demonstrate that the orderly management of electric vehicle charging and discharging, as well as the integration of transferable load, significantly improve the cost, efficiency, and security of the microgrid's economic operations. In [26], the work develops a model for optimal energy scheduling within microgrids integrating electric vehicles, employing an enhanced variant multi-objective particle swarm optimization (EV-MOPSO). The model aims to meet the economic objectives of EV users, by minimizing battery charging and degradation costs, as well as reducing overall microgrid operating costs over the long term. In [27], an energy management model for microgrids has been introduced, using multi-objective optimization that incorporates plug-in EVs. The model controls battery charge levels to avoid overcharging and uses an improved gray wolf algorithm to optimize the balance between capacity exploitation and exploration. The objective is to reduce fuel costs, operating expenses, and environmental impact. In [28], they developed a goal-programming-based multi-objective optimization problem. This model takes into account the degradation of energy storage systems, including batteries and electric vehicles, as well as load and renewable energy management. To solve this model, the weighted sum and priority approach methods are applied.

As the number of EVs increases, the temporal and spatial aspects become more complex, adding to the complexity of the model. Consequently, the use of advanced optimization algorithms becomes essential for solving large-scale, complex problems [29]. Intelligent optimization algorithms are largely used in microgrid programming. In [30], a particle swarm optimization (PSO) has been introduced to solve the EV charging and discharging strategies optimization problem, to minimize operating costs. By exploiting EV energy data and real-time microgrid pricing, this approach significantly reduced operational costs and load on microgrids. In [31], a model for optimized management of electric vehicle charging and power distribution in microgrids has been developed. A hybrid scheme, combining the GSA and PSO algorithms and named MGSAPSO, was proposed to improve load distribution. Its effectiveness has been confirmed by analyses of different vehicle and load scenarios. In [32], an optimized electric vehicle charging scheduling algorithm is developed using particle swarm optimization (PSO) to minimize costs while respecting charging station constraints. Compared with conventional methods such as ATP (arrival-time-based priority) and SBP (SOC-based priority) algorithms, this approach, tested in a microgrid scenario, proves more effective in reducing energy consumption and charging costs. In [33], an optimal scheduling method for household microgrids using a multi-objective particle swarm algorithm is proposed. This model, involving variable electricity tariffs and the mobility behavior of electric vehicle users, aims to reduce daily electricity costs and stabilize energy supply. The findings show that this strategy is effective in reducing household energy costs. Authors in [34–47,48,49] explored various methodologies and approaches for Microgrids energy management and EVs integration.

3. Methodological framework

3.1. Research scope

This section defines the scope of our research, focusing on the design and development of an EMS for a grid-connected microgrid that integrates DERs, Battery Energy Storage System BESS, Electric Vehicles EVs and other critical loads. As depicted in Fig. 1, the EMS's main function is to orchestrate the microgrid's energy flows efficiently among the different components, ensuring reliability, cost-effectiveness, and sustainability [50].

From a systemic perspective, the EMS functions as the central control unit within the microgrid, interacting with various components and utilizing both real-time and forecasted data to perform optimization, scheduling, and control tasks. As shown in Fig. 2, the EMS is designed to operate seamlessly within this environment, ensuring efficient energy management across all microgrid systems and components.

To perform the decision-making process, the EMS executes the following core functions: Forecasting, Optimization, Scheduling, and Control, as illustrated in Fig. 3. These functions ensure the efficient operation of the microgrid by managing the energy flows between generation, storage, and consumption based on historical, real-time and forecast data.

However, the scope of this paper is limited to the optimization and scheduling functions. Our research focuses on developing and evaluating the optimization strategies that maximize economic and technical objectives, while ensuring a cost-effective energy dispatch and a well-managed interaction with the grid. Forecasting and Control functionalities, though critical for the overall performance, fall outside the scope of this study and are assumed to be provided by external systems.

3.2. Proposed microgrid EMS architecture

As illustrated in Fig. 4, the EMS communicates directly with the microgrid's monitoring system, enabling real-time data acquisition from a range of sensors, meters, and data sources. These data streams provide critical information on several key parameters and form the foundation for the EMS's decision-making processes.

The EMS operates with a day-ahead forecasting and scheduling horizon, typically using a timestep of 5 to 15 min. This level of granularity enables the system to respond dynamically to changes in energy supply, demand, and market prices, maintaining optimal performance throughout the day. To manage real-time disturbances and uncertainties, the control horizon can be governed by a Model Predictive Control (MPC) framework. MPC allows the EMS to make continuous adjustments to its control strategy, using the latest data to mitigate the impact of unexpected events and ensuring that the microgrid remains efficient and stable under varying conditions.

Additionally, the microgrid is assumed to maintain a grid-connected status, enabling energy imports and exports as needed, based on dynamic pricing and the availability of local resources. The integration of DERs such as solar PV systems and BESS is central to the EMS's operation, with the potential for future integration of additional renewable energy sources. EVs are treated as flexible loads within this framework, with potential for bidirectional energy flow. However, in this study, EVs are primarily modeled as unidirectional flexible batteries, focusing on their role as energy consumers. The EMS also accounts for user preferences, particularly regarding EV charging profiles, to ensure that user satisfaction is balanced with overall system optimization.

4. Microgrid modeling

This section defines the power flows among the microgrid components and provides the corresponding models, including loads, power grid, DERs such as PV, BESS, and EVs.

4.1. Power flows

After defining the various components of the microgrid and the core functions of the EMS, Fig. 5 visually illustrates the real-time power exchanges among the system's agents. The figure uses arrows to represent the direction of power flow:

- Bidirectional arrows: Indicate that power can flow in both directions between components.
- Unidirectional arrows: Indicate that power flows in only one direction.

The power transmitted between the different components at any given time slot t is denoted by $\boldsymbol{P_t^{x2y}}$, where x and y represent the source and destination of the power, respectively. The specific power exchanges within the microgrid are defined as follows:

- P_t^{p2l}: Power transmitted from the PV system to the Loads at time slot t (in kW).
- P_t^{p2b}: Power transmitted from the PV system to the BESS at time slot t (in kW).
- P_t^{p2g}: Power transmitted from the PV system to the Grid at time slot t (in kW).
- P_t^{b2l}: Power transmitted from the BESS to the Loads at time slot t (in kW).
- P_t^{b2g}: Power transmitted from the BESS to the Grid at time slot t (in kW).
- P_t^{g2l}: Power transmitted from the Grid to the Loads at time slot (in kW).

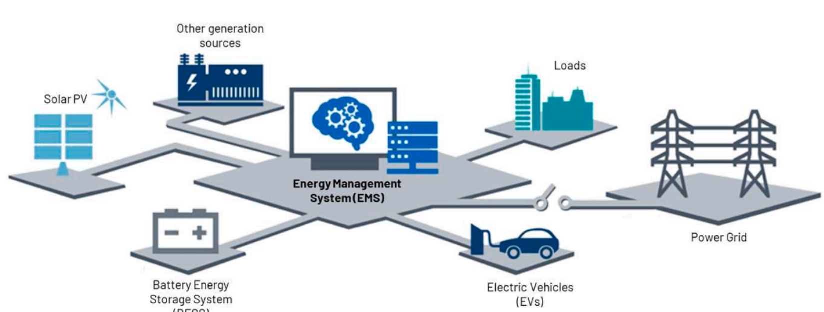

Fig. 1. Schematic overview of a microgrid EMS.

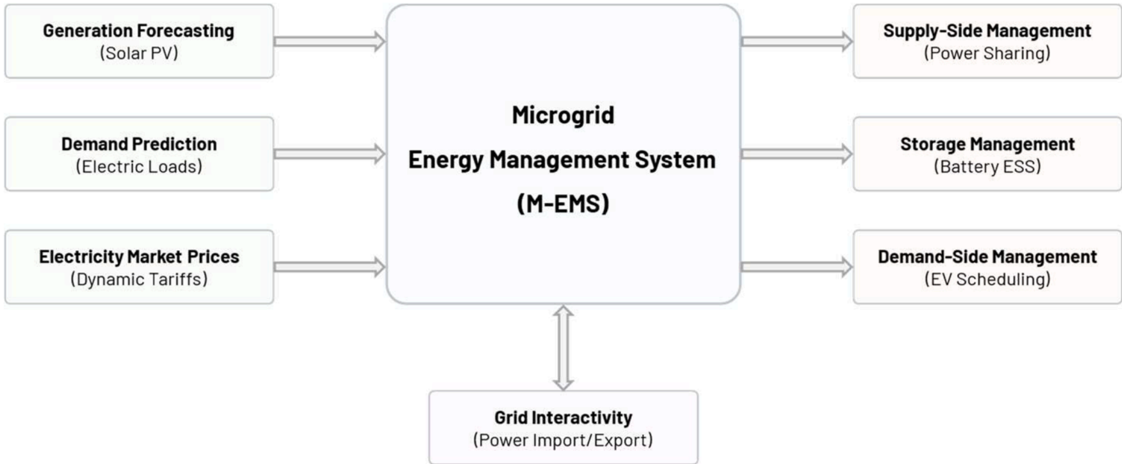

Fig. 2. A systemic representation of a microgrid EMS.

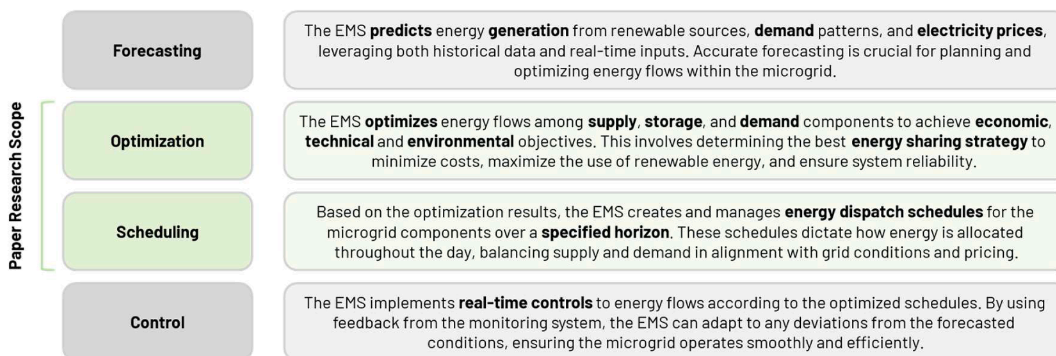

Fig. 3. EMS core functions and the paper's research scope.

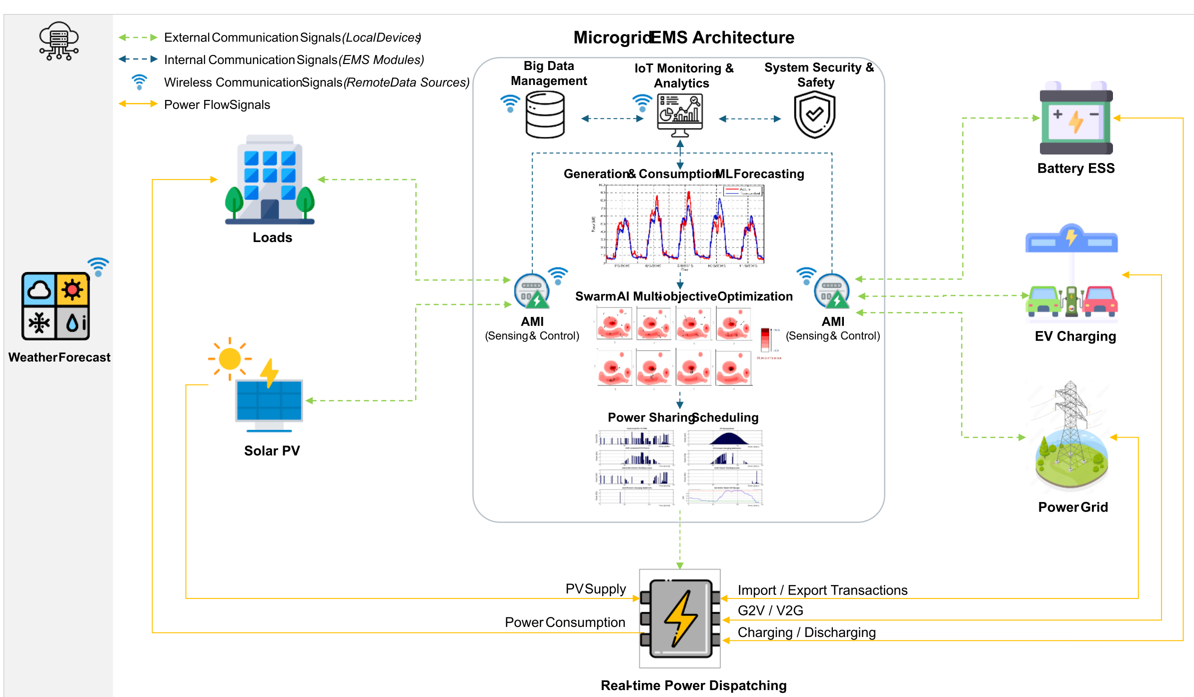

Fig. 4. Proposed microgrid EMS architecture.

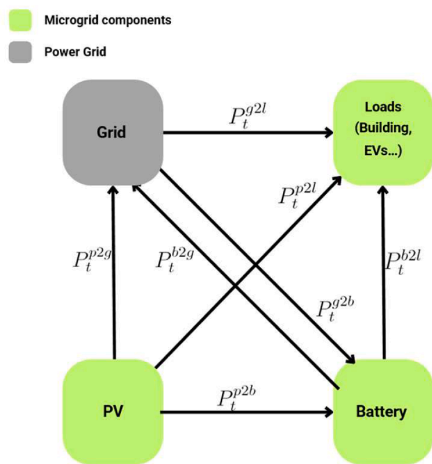

Fig. 5. Power exchange among the microgrid components.

- P_t^{g2b}: Power transmitted from the Grid to the BESS at time slot t (in kW).

The balance of active powers in the microgrid will be set as a constraint for the optimization problem that is expressed as follows:

The total power generated by the PV system at time t (P_t^{PV}) must be equal to the sum of the power dispatched to the loads, the battery, and the grid:

$$P_t^{p2l} + P_t^{p2b} + P_t^{p2g} = P_t^{PV} \tag{1}$$

The total load demand at time t (P_t^{Load}) must be satisfied by the power supplied from the PV system, the battery, and the grid:

$$P_t^{p2l} + P_t^{b2l} + P_t^{g2l} = P_t^{EV} + P_t^{CL} = P_t^{Load} \tag{2}$$

Where:

- P_t^{PV} : The PV production during time slot t, measured in kW.
- P_t^{CL} : The total power of the critical load during time slot t in kW.
- P_t^{EV} : The total power of the flexible loads (EVs) during time slot t in kW.
- P_t^{Load} : The total load power during time slot t in kW.

4.2. Solar PV supply

In our microgrid model, the solar PV power, denominated P_t^{PV}, corresponds to a forecast data model (dataset), and is considered as an input for the optimization model. The EMS should ensure a dispatch strategy of solar energy that improves metrics such as self-consumption and self-sufficiency. To minimize operational costs, including grid dependence and battery degradation, and maximize profits through grid feed-in tariffs, solar PV should be prioritized as the primary energy source in the load supply as its generated energy is free at the point of use.

From a long-term financial perspective, maximizing the use of solar energy is essential for quickly amortizing the solar PV system investment and increasing its profitability. By efficiently deploying solar PV energy to meet local demand and feeding excess energy back into the grid, the EMS not only reduces the daily electricity expenses and generates revenues, but also shortens the payback period and enhances the financial viability of the microgrid [51].

The solar PV predicted data is assumed to be generated by a Forecasting module utilizing a machine learning or a physical model (Fig. 6) [52]. This model is trained on historical generation data and weather forecasts to predict the expected PV power output. The forecasting horizon is set to 24 h ahead, with a time resolution that can range between 5 and 15 min. This granularity ensures that the EMS has accurate short-term predictions for efficient decision-making in scheduling and optimization processes, allowing it to better manage the variability of solar energy generation.

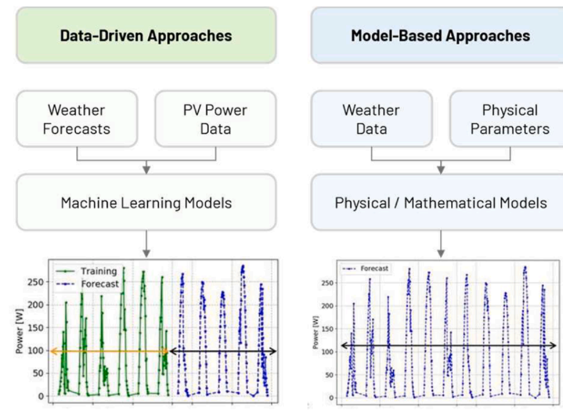

Fig. 6. Solar PV short-term forecasting approaches.

4.3. Loads

Electric loads in a microgrid system can be classified into two main categories: Critical Loads (CL) and Flexible Loads (FL) [53].

CL require a continuous and uninterrupted power supply, with no possibility for shedding or shifting across different timeslots. These loads are essential for maintaining core functions and are thus treated as fixed input datasets for the optimization problem, denominated P_t^{CL}. For instance, in our model, the main microgrid's loads—such as servers, HAVC systems, machinery, essential electronics, lighting, and security systems—are categorized as Critical Loads, given their non-negotiable demand for constant power.

FL, inversely, provide opportunities for optimization due to their inherent flexibility in terms of consumption time, duration, or power rate. These loads can be shifted or modulated to align better with the availability of renewable energy sources, fluctuations in grid tariffs, and the state of energy storage systems. In our model, electric vehicles (EVs) are considered Flexible Loads, as their charging schedules can be adjusted within a specified time window without compromising user requirements (Fig. 7).

Our optimization model will be designed to shift EV charging activities across the tolerable time window. This involves aligning the flexible demand with periods of high solar PV generation, low grid tariffs, or favorable energy storage conditions. By doing so, the model aims to maximize the use of renewable energy, minimize costs associated with grid energy purchases, and reduce the strain on battery storage

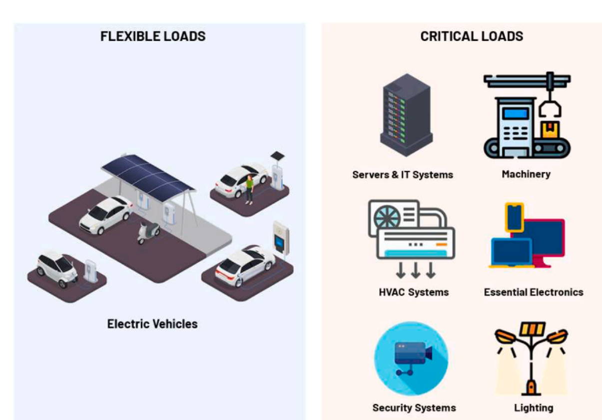

Fig. 7. Load classification in the proposed microgrid.

systems. Moreover, the model will incorporate user-defined preferences, such as the acceptable delay in charging completion and the desired final state of charge (SOC) for the EV. For example, if an EV user specifies a maximum allowable delay of 2h and a final SOC of 80 %, the model will optimize charging to meet these criteria while considering the availability of solar energy, the current grid conditions and the battery storage system state.

4.4. Main power grid

The grid in a microgrid system functions as a bidirectional energy source, enabling both the delivery of power to the microgrid (energy import) and the absorption of excess power generated by the microgrid (energy export). This bidirectional flow is governed by dynamic pricing, which reflects the fluctuations in electricity markets. Such fluctuations are managed through various pricing schemes, including Time-of-Use (ToU), Critical Peak Pricing (CPP), and Real-Time Pricing (RTP) [54] (Fig. 8).

Time-of-Use (ToU) pricing sets different rates for electricity depending on the time of day, encouraging energy consumption during off-peak periods when rates are lower. Critical Peak Pricing (CPP) imposes higher rates during periods of extreme demand, incentivizing reduced consumption during these times. Real-Time Pricing (RTP) offers prices that fluctuate in real-time based on current market conditions, providing the most responsive pricing scheme. These pricing mechanisms are essential components of Demand Response (DR) and Demand-Side Management (DSM) programs, which aim to influence and optimize energy consumption patterns by shifting or reducing energy usage in response to price signals [55].

In grid-connected microgrids, the ability to connect to or disconnect from the main grid is a crucial feature, allowing the microgrid to adapt to real-time conditions such as renewable energy availability, energy storage levels, and current grid prices. This flexibility enables the microgrid to import energy when prices are low and export energy when prices are high, optimizing financial performance. In addition to importing and exporting energy, the microgrid's energy storage system (ESS) can also participate in dynamic energy transactions. The ESS can be charged from the grid during periods of low electricity prices, storing energy that can later be used to meet the microgrid's demand or be sold back to the grid when prices rise. This capability allows the ESS to act as a financial buffer, taking advantage of price differentials to maximize economic returns [56].

From the supply side, our optimization model is designed to manage these complex interactions by minimizing the costs associated with energy imports, maximizing the profits from energy exports, and optimizing the transactions between the battery ESS and the power grid, all while considering the dynamic tariff rates under RTP, denominated c_t^{grid}. For instance, during periods of low grid prices, the model may prioritize charging the ESS from the grid to store inexpensive energy for later use. Conversely, when grid prices are high, the model might favor discharging the ESS to export energy to the grid, thereby generating revenue.

From the demand side, the model integrates a Demand-Response (DR) and a Demand-Side Management (DSM) strategies, adjusting the microgrid's energy consumption patterns in response to pricing signals or grid conditions, while shifting the operation of Flexible Loads to times when energy is cheapest or when the grid is incentivized to absorb excess power, further enhancing the microgrid's economic efficiency.

4.5. EV battery model

In a microgrid system, EVs have the potential to interact bidirectionally with the grid through Grid-to-Vehicle (G2V) and Vehicle-to-Grid (V2G) mechanisms. These interactions allow EVs to not only absorb energy from the grid but also to discharge energy back into the grid when needed. However, in our model, EVs are treated solely as flexible batteries that absorb energy, without engaging in bidirectional energy flow.

In this context, we define the state of charge (SOC) of EV batteries as a function of several key factors: the charging power, the duration of the charging period, and the EV battery's capacity. The SOC evolution is modeled by considering the binary operation status of the EVs—whether they are charging or not, to determine when and how much energy is being absorbed by the EVs at any given time.

The state of charge (SOC) of the vehicle's battery is calculated as follows [57]:

$$SOC_{t+1}^{EV} = SOC_t^{EV} + P_t^{EV} \cdot \frac{\Delta t}{C_{EV}} \tag{3}$$

Where:

- SOC_{t+1}^{EV} : State-of-Charge of the EV battery during time slot '$t+1$'.
- SOC_t^{EV} : State-of-Charge of the EV battery during time slot 't'.
- C_{EV} : The nominal capacity of the EV battery in kWh.
- P_t^{EV} : The charging power of the EV battery during time slot t in kW.
- Δt : The time slot in h.

With the charging station power being P^{EV}, P_t^{EV} is obtained by:

$$P_t^{EV} = P^{EV} \cdot S_t^{EV} \tag{4}$$

Where S_t^{EV} is a binary number, representing the decision variable to charge or not during the time slot t, represented by 1 for "*charging*" or 0 for "*not charging*".

To ensure that the charging process aligns with the technical limitations of the system and the specific needs of the users, we incorporate operational constraints and user preferences through a set of inequalities. For instance, the EV battery protection is a major concern and is manifested by maintaining the State of Charge (SOC) within a safety range, as follows:

$$SOC_{min}^{EV} \leq SOC_t^{EV} \leq SOC_{max}^{EV} \tag{5}$$

Where:

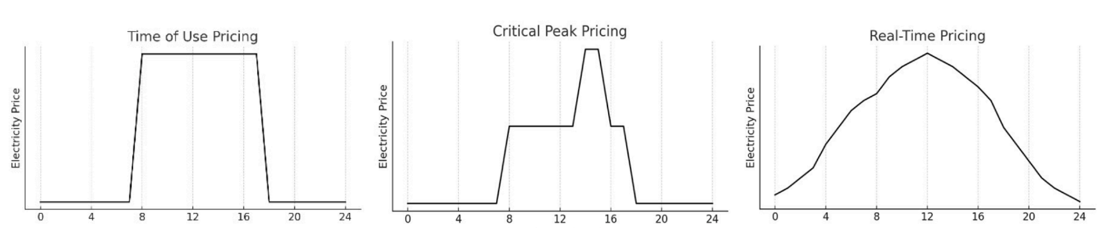

Fig. 8. Dynamic grid pricing schemes.

- SOC_{min}^{EV} : refers to the minimal EV State-of-Charge.
- SOC_{max}^{EV} : refers to the maximal EV State-of-Charge.

Furthermore, to meet user satisfaction, the SOC of the EV after charging $SOC_{end+delay}^{EV}$ must be greater than or equal to the predefined value SOC_{final}^{EV} set by the user. This constraint is represented by:

$$SOC_{final}^{EV} \leq SOC_{end+delay}^{EV} \leq SOC_{max}^{EV} \tag{6}$$

Where:

- $SOC_{end+delay}^{EV}$: The State-of-Charge of the EV at the end of the charging process, including any additional delay.
- SOC_{final}^{EV} : The target State-of-Charge for the EV at the end of the charging process, as specified by the user.

4.6. Battery energy storage system (BESS)

4.6.1. BESS model

In microgrids, the primary function of a BESS is to manage real-time imbalances, called also mismatch, between supply and demand, thereby ensuring the regulation of frequency and voltage which is crucial for maintaining system stability [58]. Beyond this foundational role, BESS is also used to enhance microgrid autonomy and self-sufficiency by reducing reliance on the main grid. Furthermore, it serves as a backup system during power outages and blackouts, providing a reliable and secure energy supply when external power sources are unavailable [59]. In addition to these core functions, BESS can perform advanced applications such as providing ancillary services and participating in electricity markets. These services include frequency regulation, voltage support, and reserve power, all of which contribute to the overall efficiency and reliability of the broader energy system. By participating in electricity markets, BESS can also generate revenue, enhancing the economic performance of the microgrid [60].

In our model, the status of the BESS is characterized by its State-of-charge (SOC), which is directly influenced by the energy it absorbs (charging) and releases (discharging) over time. The power dispatch strategy within the microgrid is designed to manage the SOC, charging power, and discharging power, while adhering to operational constraints and physical limitations of the battery system. This includes, among others, ensuring that the SOC remains within safe limits and that charging and discharging rates do not exceed the battery's capacity or degrade its performance.

The charging and discharging of the battery determine the State of Charge (SOC) of the battery for each time slot as follows [61]:

$$SOC_{t+1}^{BESS} = SOC_{t}^{BESS} + P_{t}^{BESS,ch}.\ \frac{\Delta t\ \eta^{BESS,\ ch}}{C_{BESS}} \tag{7}$$

$$SOC_{t+1}^{BESS} = SOC_{t}^{BESS} - P_{t}^{BESS,\ dis}.\ \frac{\Delta t\ \eta^{BESS,\ dich}}{C_{BESS}} \tag{8}$$

Where:

- SOC_{t}^{BESS} : State-of-charge of the BESS at time slot t.
- SOC_{t+1}^{BESS} : State-of-charge of the BESS at time slot $t+1$.
- $P_{t}^{BESS,ch}$: Power charging the BESS at time slot t in kW.
- $P_{t}^{BESS,Dis}$: Power discharged from the BESS at time slot t in kW.
- $\eta^{BESS,\ ch}$: BESS charging efficiency.
- $\eta^{BESS,\ dich}$: BESS discharging efficiency.
- C_{BESS} : Battery energy capacity in kWh.
- Δt : The time slot in h.

4.6.2. BESS constraints

To prevent overcharging and excessive discharging of the battery, the SOC should always be maintained within a specified range as follows [61]:

$$SOC_{min}^{BESS} \leq SOC_{t}^{BESS} \leq SOC_{max}^{BESS} \tag{9}$$

A safety measure is necessary regarding the charging and discharging powers, which must not exceed their respective maximum capacities. As illustrated in Fig. 5, on one hand, the microgrid battery is charged by the PV P_t^{p2b} and the grid P_t^{g2b}, and on the other hand, it supplies energy to the loads P_t^{b2l} and the grid P_t^{b2g}. Therefore, these safety constraints are expressed as follows:

$$0 \leq P_{t}^{BESS,\ ch} = P_{t}^{p2b} + P_{t}^{g2b} \leq P_{max}^{BESS,\ ch} \tag{10}$$

$$0 \leq P_{t}^{BESS,\ dich} = P_{t}^{b2l} + P_{t}^{b2g} \leq P_{max}^{BESS,\ dis} \tag{11}$$

Where:

- $P_{max}^{BESS,\ ch}$: The maximum power that can be absorbed by the BESS during charging.
- $P_{max}^{BESS,\ dis}$: The maximum power that can be delivered by the BESS during discharging.

Simultaneous charging and discharging operations are not possible for the battery. This implies that the battery cannot supply energy while undergoing charging. This could be expressed as follows:

$$P_{t}^{BESS,ch}.\ P_{t}^{BESS,\ dis} = 0 \tag{12}$$

4.6.3. BESS-grid transactions and real-time battery costs

In our approach, the optimization model should maximize profitability by strategically timing energy transactions with the main grid, taking advantage of dynamic pricing. As described in the previous section, this involves charging the BESS when grid prices are low and discharging when prices are high, thereby capitalizing on market opportunities to generate revenue.

Since the BESS can engage in energy transactions with the main grid under dynamic pricing conditions, the energy stored within the BESS is consequently subject to a variable cost. This variability arises from the fluctuating prices at which the energy was initially purchased or stored. As a result, the real-time dispatching strategy within the microgrid must continuously evaluate and compare the instantaneous costs associated with both grid-supplied energy and the energy stored in the BESS. This comparison is crucial when deciding how to meet the demand, particularly during periods when solar PV generation is absent or insufficient to fully satisfy the load.

c_t^{BESS} denotes the price of the energy stored in the microgrid's BESS at time t. It is calculated during the battery charging as follows [61]:

$$c_{t+1}^{BESS} = \frac{c_t^{BESS}.E_t^{BESS} + P_t^{g2b}.\ \Delta t\ .\ c_t^{grid}}{E_{t+1}^{BESS}} \tag{13}$$

Where:

$$E_{t+1}^{BESS} = E_t^{BESS} + \left(P_t^{g2b} + P_t^{p2b}\right)\ .\Delta t\ .\ \eta^{BESS,\ ch} \tag{14}$$

Where E_t^{BESS} refers to the energy in kWh stored in the microgrid battery at time t.

To control the power exchange among the BESS and the main grid while ensuring a cost-effective interaction, we introduce the following threshold parameters to be fine-tuned for an enhanced economic dispatch:

- $c^{BESS,\ sell}$: The threshold above which the energy stored in the microgrid's BESS can be sold to the grid to generate revenue.
- $c^{BESS,\ buy}$: The threshold below which the microgrid battery is allowed to purchase energy from the grid to charge.

These thresholds are calculated by the following formulas:

$$c^{BESS,\ sell} = \beta^{sell}.max\left\{c_1^{grid},\ c_2^{grid}, \ldots, c_{N_{slot}}^{grid}\right\} \tag{15}$$

$$c^{BESS,\ buy} = \beta^{buy}.min\left\{c_1^{grid},\ c_2^{grid}, \ldots, c_{N_{slot}}^{grid}\right\} \tag{16}$$

Where:

- β^{sell}: Controls the possibility of selling the energy stored in the microgrid's BESS to the grid. It can range from 0 to 1. The smaller it is, the greater the possibility.
- β^{buy}: Controls the ability to purchase energy from the grid to charge the microgrid's BESS. It can range from 0 to 1. The bigger it is, the greater the possibility.

4.6.4. *Battery degradation costs*

To ensure a cost-effective performance for both the short and long terms, our optimization model considers minimizing degradation costs associated with battery usage. This involves optimizing the frequency and depth of charge-discharge cycles to extend the battery's lifespan and reduce maintenance expenses.

Battery degradation is affected by various parameters, and its associated equivalent costs could be expressed as follows [62]:

$$c_{deg}^{BESS} = \frac{C_{invest\_BESS}}{DOD\ .\ N_{cycles}\ .\ C_{BESS}\ .\ \eta_{BESS}} \tag{17}$$

- C_{invest_BESS}: is the investment cost of the BESS (MAD).
- C_{BESS}: is the capacity of the BESS (kWh).
- DOD: is the depth of discharge of the BESS.
- N_{cycles}: is the number of charge/discharge cycles of the BESS.
- η_{BESS}: denotes the average charging/discharging efficiency of the BESS.

5. Multi-objective optimization problem formulation

5.1. *Optimization problem description*

The optimal operation of microgrids involves balancing multiple, often competing, objectives across technical, economic, and environmental dimensions. These include ensuring system reliability, achieving cost-effectiveness, and minimizing environmental impact, all while meeting energy demand and maintaining user satisfaction and comfort. Simultaneously optimizing all these aspects can be challenging due to their conflicting nature, making multi-objective optimization necessary to find an acceptable trade-off [63] (Fig. 9).

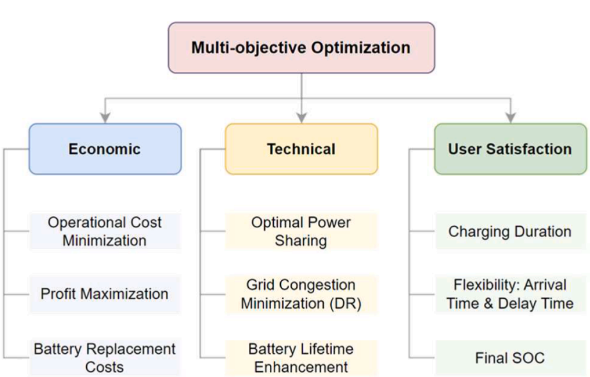

Fig. 9. Microgrid multi-objective optimization targets.

In this section, we formulate a multi-objective optimization problem that targets several key objectives:

- **O1. Reducing Operational Costs:** This includes minimizing costs associated with grid imports and battery degradation. By optimizing when and how much energy is imported from the grid or stored in the BESS, the model aims to lower overall energy expenses while preserving the longevity of the battery system.
- **O2. Maximizing Profitability:** The model seeks to enhance the financial performance of the microgrid by maximizing revenue from grid feed-in of surplus solar PV energy and BESS-to-grid trading. By strategically dispatching energy when grid prices are favorable, the microgrid can capitalize on dynamic pricing to boost profits.
- **O3. Optimizing EV users' satisfaction:** The optimization also focuses on managing the charging schedule of electric vehicles (EVs) to maximize user satisfaction. This involves aligning charging times with user preferences, such as desired state of charge (SOC) levels and acceptable delays, while also considering the availability of renewable energy and grid tariffs.

While the primary focus of this optimization is on economic and operational efficiency, environmental performance is implicitly optimized as well. By prioritizing the reduction of operational costs, the model naturally increases the use of low-carbon energy sources within the microgrid, such as solar and wind energies. Additionally, the efficient use of batteries, which is a byproduct of cost optimization, helps to extend the lifetime of the BESS, further contributing to environmental sustainability.

Reliability, another critical aspect, is inherently maintained by the optimization process. The algorithm ensures that at every time slot, the available energy sources are optimally dispatched to meet the required demand, thus avoiding any load shortages. This guarantees that the microgrid remains reliable, providing a continuous and stable energy supply without compromising user comfort or system integrity.

5.2. *Cost function*

Using day-ahead forecasting algorithms of demand and generation, as well as electricity tariffs, it is possible to minimize the overall cost of electricity through the optimal planning of *i)* power dispatching among PV, battery, power grid, and loads (supply-side management) and *ii)* EV charging scheduling (demand-side management).

This cost should naturally encompass the total expense of purchasing electricity from the grid (short-term expenses) expressed by F_{cost1}, but needs also to consider the cost associated with the degradation of the microgrid battery energy storage system (long-term expenses) expressed by F_{cost2}, as well as the overall revenue from electricity sales to the grid (revenue generation through feed-in) expressed by F_{cost3}. Consequently, the net overall cost of electricity over the planning horizon is formulated as follows [61]:

$$\begin{cases} F_{cost1} = \sum_{t=1}^{N_{slot}} \left[\left(P_t^{g2l} + P_t^{g2b}\right)\ .\ \Delta t\ .c_t^{grid,\ buy}\right] \\ F_{cost2} = \sum_{t=1}^{N_{slot}} \left[\left(P_t^{p2b} + P_t^{g2b} + P_t^{b2g} + P_t^{b2l}\right)\ .\ \Delta t\ .c_{deg}^{BESS}\right] \\ F_{cost3} = -\sum_{t=1}^{N_{slot}} \left[\left(P_t^{p2g} + P_t^{b2g}\right)\ .\ \Delta t\ .c_t^{grid,\ sell}\right] \end{cases} \tag{18}$$

$$F_{cost} = F_{cost1} + F_{cost2} + F_{cost3}$$

Where:

- $c_t^{grid,\ buy}$: The grid electricity tariff during time slot t, in which the EMS purchases electricity from the grid (MAD/kWh).
- $c_t^{grid,\ sell}$: The electricity price during time slot t, in which the EMS sells electricity to the grid (MAD/kWh).
- c_{deg}^{BESS}: The equivalent cost of battery degradation (MAD/kWh).

5.3. EV user satisfaction function

The user's satisfaction level with EV charging depends on the time at which the charging process concludes. The user is more content when, after connecting the electric vehicle, it continues to charge until the predetermined battery SOC level is reached. In practice, the user may tolerate a certain delay in completing the charge, making the EV more flexible in terms of charging. However, this tolerance is limited; if the delay becomes too significant, the user will be less satisfied. The user satisfaction indicator $U_{EV,j}$ for an EV_j could therefore be determined as follows [61]:

$$U_{EV,j} = \frac{d_{EV,j}}{N_{slot} - \left(t_{end,j} + t_{delay,j}\right)} \times 100$$

Where:

$$d_{EV,j} = \begin{cases} 0, \ if \ t_{plug,j} \leq t_{fSOC,j} \leq t_{end,j} + t_{delay,j} \\ t_{fSoc,j} - \left(t_{end,j} + t_{delay,j}\right), \ if \ t_{fSOC,j} > t_{end,j} + t_{delay,j} \end{cases} \tag{19}$$

j represents the numerical identifier for electric vehicles; EV_j.

- $t_{plug,j}$: The time slot for the EV_j to be plugged-in.
- $t_{end,j}$: The time slot in which the charging period ends for EV_j.
- $t_{delay,j}$: The maximum tolerated time to complete the charging for EV_j.
- $t_{fSOC,j}$: The time slot in which the SOC achieves the value desired by the EV_j's user.
- $t_{end,j}$: The last time slot in the scheduling horizon for EV_j.

$$F_{satisfaction} = \frac{1}{N_{EV}} \times \sum_{j=1}^{N_{EV}} U_{EV,j} \tag{20}$$

N_{EV} stands for the total number of EVs involved in the scheduling process (Fig. 10).

5.4. Multi-objective function

The multi-objective optimization model of the EMS could be expressed as follows:

$$\begin{cases} min \ F_{cost} \\ \min F_{satisfaction} \\ constraints \ to \ (5), (6), \ (9) - (12) \end{cases} \tag{21}$$

The above multi-objective model can be transformed into a single-objective model through the following weighting method:

$$\min F_{total} = \alpha \ F_{cost} + (1 - \alpha) \ F_{satisfaction} \tag{22}$$

Where α is the user's preference factor, ranging from 0 to 1, through which a user can easily strike a trade-off between electricity cost and satisfaction level. By employing the penalty function method, model (22) is transformed into an unconstrained and single-objective optimization model, simplifying the task:

$$\boldsymbol{min \ F_{final}} = F_{total} + P. \ F_{viol} \tag{23}$$

Where:

- F_{final}: designates the final objective function.
- P: A very large positive number.
- F_{viol} : The overall value of the violation.

$$F_{viol} = \sum_{i=1}^{N_{EV}} \frac{\left(F_{viol,\ 1}^{EV,j} + F_{viol,2}^{EV,j}\right)}{N_{EV}}$$

$$F_{viol,\ 1}^{EV,j} = \sum_{i=1}^{N_{slot}} max\left(0, \ SOC_{max}^{EV,j} - SOC_t^{EV,j}, \ SOC_t^{EV,j} - SOC_{min}^{EV,j}\right)$$

$$F_{viol,\ 2}^{EV,j} = max\left(0, \ SOC_{t_{end}+\ t_{delay}}^{EV,j} - SOC_{max}^{EV,j}, \ SOC_{final}^{EV,j} - SOC_{t_{end}+\ t_{delay}}^{EV,j}\right) \tag{24}$$

Where:

- $F_{viol,\ 1}^{EV,j}$: The value of the violation for constraint (5) for the EV_j.
- $F_{viol,\ 2}^{EV,j}$: The value of the violation for constraint (6) for the EV_j
- F_{viol} : Takes into account only constraints (5) and (6), while other constraints are addressed by different methods.

6. EMS algorithm design

6.1. Particle swarm optimization (PSO) algorithm

Swarm Intelligence (SI) algorithms are inspired by the collective behavior of decentralized, self-organized systems, typically composed of a population of agents that interact locally with one another and their

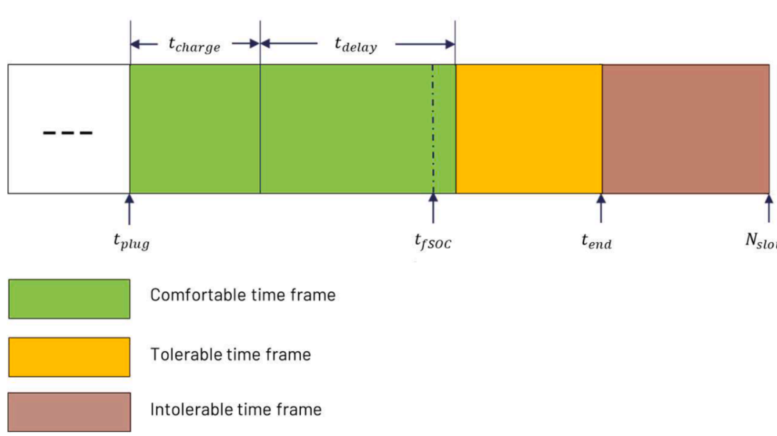

Fig. 10. Illustration of EV users' satisfaction zones.

environment [62]. Particle Swarm Optimization (PSO), a well-known method within the SI discipline, leverages this collective intelligence to solve optimization problems. The fundamental principle of PSO is to explore the solution space by iteratively testing multiple candidate solutions, referred to as Particles.

Each particle i represents a potential solution to the optimization problem and has a position x_i in a search space. The particles move with a velocity v_i through the search space according to a set of rules governed by both random factors and the experiences of the particles. The movement is guided by two critical factors: Learning (cognitive factor) and Communication (social factor).

The learning or cognitive component reflects how each particle relies on its own best-known position, called p^i_{best} (the best position visited by particle i). The communication or social component enables each particle to take into account the best position found by the entire population, referred to as g_{best} (the best global position visited by all the swarm).

The swarm velocities and positions are updated according to the following rules:

$$\begin{cases} v_i(k+1)=\omega(k)\,v_i(k)+c_1\,r_1\left[p^i_{best}(k)-x_i(k)\right]+c_2\,r_2\left[g_{best}(k)-x_i(k)\right] \\ x_i(k+1)=x_i(k)+v_i(k+1) \end{cases} \tag{25}$$

Where:

- $v_i(k+1), v_i(k)$: designate the velocities of particle i in iterations $k+1$ and k.
- $x_i(k+1), x_i(k)$: designate the positions of particle i in iterations $k+1$ and k.
- $\omega(k)$: designates the inertia weight of the particles for iteration k.
- c_1 and c_2 : are, respectively, cognitive, and social learning factors.
- r_1 and r_2: are two stochastic aleatory variables within the interval [0,1].
- p^i_{best} and g_{best} : are, respectively, the best personal position of particle i and the best global position of the entire population.

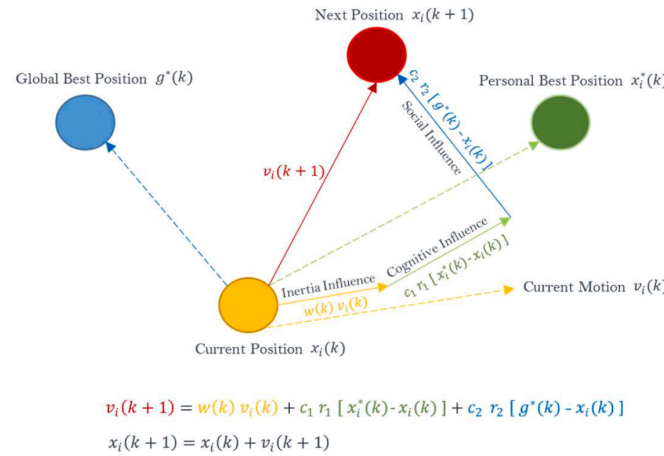

Fig. 12. A geometric presentation of PSO optimization process.

Fig. 11 illustrates the generic PSO optimization flowchart. On the other hand, Fig. 12 offers a geometric representation of the algorithm's convergence. It visually demonstrates how the particles (represented as points in the search space) move iteratively toward the optimal solution.

6.2. Binary particle swarm optimization (BPSO)

The Binary Particle Swarm Optimization (BPSO) algorithm is an adaptation of the standard PSO designed for binary optimization problems, where each particle makes binary decisions, such as choosing between "yes" or "no" or "true" or "false." Similar to the continuous version of PSO, BPSO updates both personal best positions p^i_{best} and global best positions g_{best} during each iteration. However, the key distinction lies in how velocities are interpreted and updated.

In BPSO, particle velocities are treated as probabilities that a particular bit will change from 0 to 1. These velocities, unlike in the real-valued PSO, are constrained to the range [0, 1] to represent these probabilities accurately. To achieve this, a transformation function,

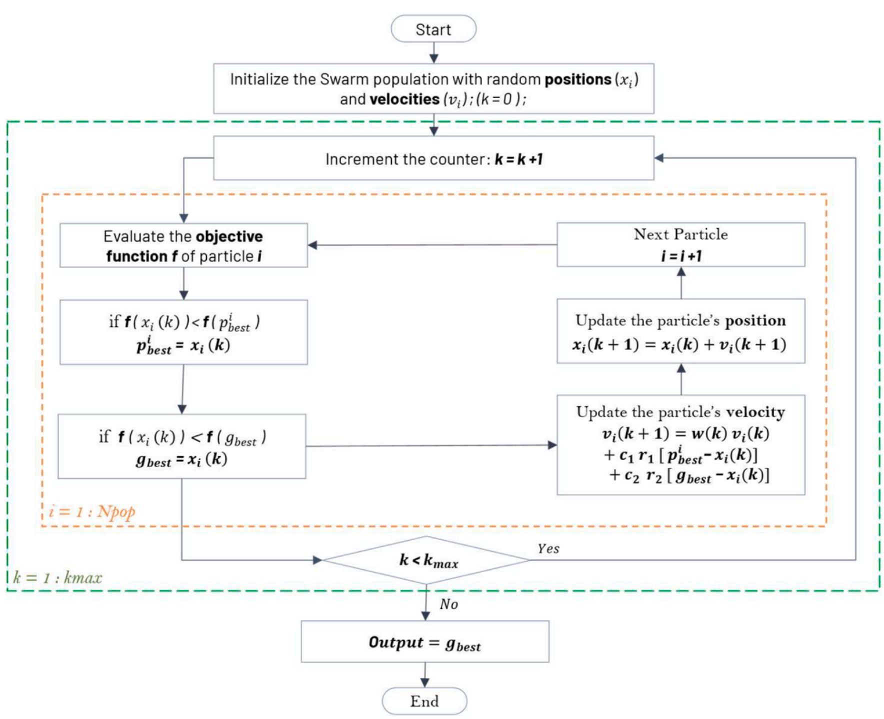

Fig. 11. A generic flowchart of PSO algorithm.

called Sigmoïde, is employed to convert the calculated real-valued velocities into a probability range. Consequently, the velocities in BPSO are calculated as follows [64]:

$$v_i'(k) = Sigmo\ddot{i}de\ (v_i(k)) = \frac{1}{1 + \exp\ (-v_i(k))} \tag{26}$$

Thus, the particle position update is performed according to Eq. (27):

$$x_i\ (k) = \begin{cases} 1\ if\ r_3 < Sigmo\ddot{i}de\ (v_i(k)) \\ 0\ else \end{cases} \tag{27}$$

Where r_3 is a stochastic number ranging randomly within the interval [0

6.3. Proposed EMS algorithm

In this section, we present an EMS optimization algorithm that was developed based on PSO (Fig. 14), with a position vector representing the decision variables defined as follows:

$$X^i = \begin{bmatrix} S_{EV,1} \\ \dots \\ S_{EV,N_{EV}} \end{bmatrix} \text{ Where } \begin{cases} S_{EV,1} = \left[S^{EV,1}_{t_{plug}},\ S^{EV,1}_{t_{plug}+1},\ \dots,\ S^{EV,1}_{t_{plug}+delay}\right] \\ \dots \\ S_{EV,N_{EV}} = \left[S^{EV,N_{EV}}_{t_{plug}},\ S^{EV,N_{EV}}_{t_{plug}+1},\ \dots,\ S^{EV,N_{EV}}_{t_{plug}+delay}\right] \end{cases} \tag{28}$$

Where $S_{EV,j}$, denoting the charging status vector of vehicle j, is a binary vector of dimension $\dim(S_{EV,j}) = t_{end,j} + t_{delay,j} - t_{plug,j} + 1$. Thus, the decision/position matrix's dimension of particle i is $\dim(X^i) = N_{EV} \times max[dim\ (S_{EV,1}),\ \dots,\ dim\ (S_{EV,N_{EV}})]$. The dimension of this vector is variable because it is linked to the time slots when the EVs are plugged-in and when they are unplugged (including delay times).

To address the challenges of multi-objective optimization in microgrid energy management, the following enhancements were introduced to the traditional Particle Swarm Optimization (PSO) framework:

- **Dynamic Inertia Weight Adjustment**: A dynamic mechanism was implemented to balance exploration and exploitation. Higher inertia weight promotes exploration at the start, while a decreasing weight focuses on convergence near optimal solutions. This prevents premature convergence and ensures a well-distributed Pareto front, balancing conflicting objectives like cost minimization and renewable energy utilization.
- **Multi-Objective Weighted Aggregation**: Weights assigned to objectives (e.g., cost, battery health preservation, renewable utilization) dynamically adapt to system priorities during optimization. This allows the framework to effectively manage varying real-time operational priorities, such as renewable usage during high generation or cost savings during peak hours.
- **Penalty Function for Constraint Handling**: A penalty-based mechanism was integrated into the fitness function to address violations of constraints, such as battery SOC limits, EV charging schedules, and grid import/export limits. This ensures feasible and practical solutions for real-world microgrid operations.
- **Enhanced Solution Diversity**: Particle initialization and velocity updates were modified to improve solution space diversity, avoiding local optima and ensuring robust exploration during the optimization process.
- **Parameter Tuning**: Algorithm parameters (e.g., population size, maximum iterations, acceleration coefficients) were fine-tuned to match the specific characteristics of the studied microgrid, including its DERs and EV integration patterns. This tailoring enhances the PSO algorithm's efficiency and accuracy in addressing the unique features of the studied microgrid.

Step 1. Acquire the electricity price, the predicted profile of the microgrid load, and the forecasted PV generation throughout the scheduling horizon.
Step 2. Set EV users preference parameters, such as the preference factor α, $t_{plug,j}, t_{end,j},\ t_{delay,j}\ SOC^{EV,j}_{final}$ for each EV_j.
Step 3. Define the PSO parameters, such as the population size N_{pop}, the maximum number of iterations k, the maximum inertia ω_{max}, the minimum inertia ω_{min}, and the learning factors c_1, c_2.
Step 4. Initialize the particle population:

1. Initialize the position vector X^i, the velocity vector V^i, and the best personal position vector P^i_{best} for the N_{pop} particles.
2. Calculate the power sharing vectors $\boldsymbol{P}^{x2y} = [P^{g2l};\ P^{g2b};\ P^{p2l};\ P^{p2b};\ P^{p2g};\ P^{b2g};\ P^{b2l}]$ according to the electricity price (purchase and feed-in), the available PV power, BESS state, load level, among others. The power sharing vectors are of dimension N_{slot} each which designates the number of time slots in the planning horizon. For instance, $P^{g2l} = \left[p^{g2l}_1, \dots, p^{g2l}_{N_{slot}}\right]$. The procedure for calculating these vectors is shown in Fig. 13.
3. Evaluate the objective function according to (23).
4. Initialize the vector of the best global position g_{best}.

Step 5. Calculate the inertia weight at the iteration k according to the formula:

$$\omega(k) = \omega_{max} - k \times \frac{(\omega_{max} - \omega_{min})}{k_{max}} \tag{29}$$

Step 6. Perform the following steps for each particle in the population:

1. Update the velocity vector V^i according to (25).
2. Update the position vector X^i according to (27).
3. Calculate the corresponding power-sharing vector P^{x2y} for each particle.
4. Evaluate the objective function according to (23).
5. Update the personal best position vector as follows:

$$p^i_{best}(k+1) = \begin{cases} x_i\ (k+1)\ if\ F_{final}[x_i\ (k+1)] < F_{final}\left[p^i_{best}(k+1)\right] \\ p^i_{best}(k)\ else \end{cases} \tag{30}$$

6. Update the global best position vector as follows:

$$g_{best}(k+1) = arg\left\{min_{1 \le i \le N_{pop}}\ F_{final}\left[p^i_{best}(k+1)\right]\ \right\},\ k\ \in [0,\ k_{max}] \tag{31}$$

Step 7. Increment the iteration counter k by 1. Check if the k has reached the k_{max}. If it is the case, continue to step 8; If not, proceed to step 5.

Step 8. Calculate the electricity cost function, the user satisfaction function, and the microgrid indicators as follows:

1. Extract the vector from the best overall position (optimal EV charging profile).
2. Calculate the optimal power-sharing vectors P^{x2y}.
3. Calculate the cost and the user satisfaction functions according to (16) and (18), respectively. Check if the simulation counter has reached the maximum N_{Sim} number. If yes, go back to step 4; Otherwise, continue to step 9.

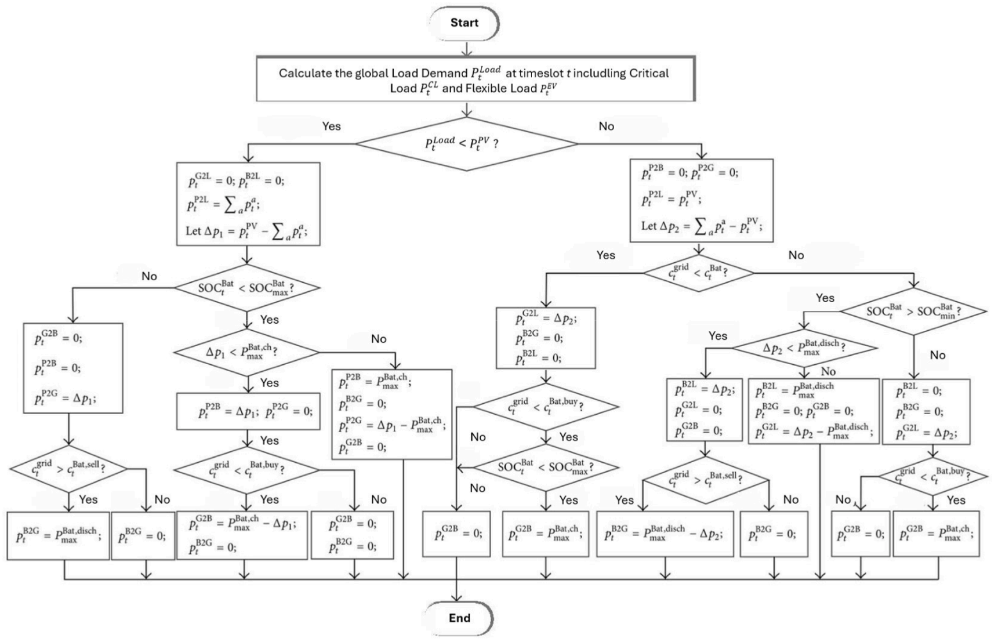

Fig. 13. Proposed real-time power-sharing control strategy.

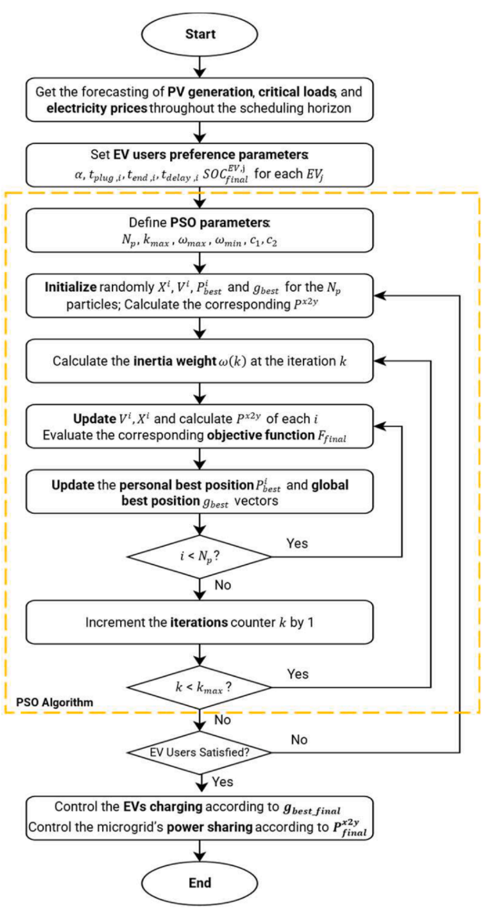

Fig. 14. Proposed microgrid EMS's algorithm flowchart.

Step 9. Control the EVs charging operations according to the vector of the best final global position of particles g_{best_final}. In each time slot, the power-sharing between loads, battery, renewable generation, and the power grid is determined by the method described in Fig. 13 (power dispatch strategy).

7. Case study: Green Energy Park

7.1. Living-lab description

The Green Energy Park (GEP), located in the Green City of Benguerir, Morocco, serves as a cutting-edge platform dedicated to R&D, innovation, demonstration, testing, and training in the realm of green technologies. To evaluate realistic scenarios for the developed EMS algorithm, we considered GEP as a testbed platform.

In terms of power infrastructure, as illustrated in Fig. 15, GEP provides an ideal test environment for our EMS as it consists of a grid-connected microgrid featuring a 250 kWp PV power plant and a 100 kWh Battery Energy Storage System (BESS). The microgrid supports critical indoor loads ranging from 20 to 200 kW. Additionally, the platform is equipped with an EV charging infrastructure, comprising three charging stations with a capacity of 22 kW each.

7.2. Input data and algorithm parameters

To validate the effectiveness of the proposed optimization algorithm, this section provides a detailed description of the simulations conducted. The algorithm was implemented within the MATLAB environment.

The scheduling horizon for the simulations spans 24 h, divided into 10 min timeslots, meaning that $N_{slot} = 144$ and $\Delta t = 0.16\ h$ (10 mins). The following section presents the input data and microgrid parameters used in the simulations, including energy generation and consumption profiles of a typical day (Fig. 16), electricity prices (Fig. 17), BESS and

Fig. 15. A panoramic view of Green Energy Park.

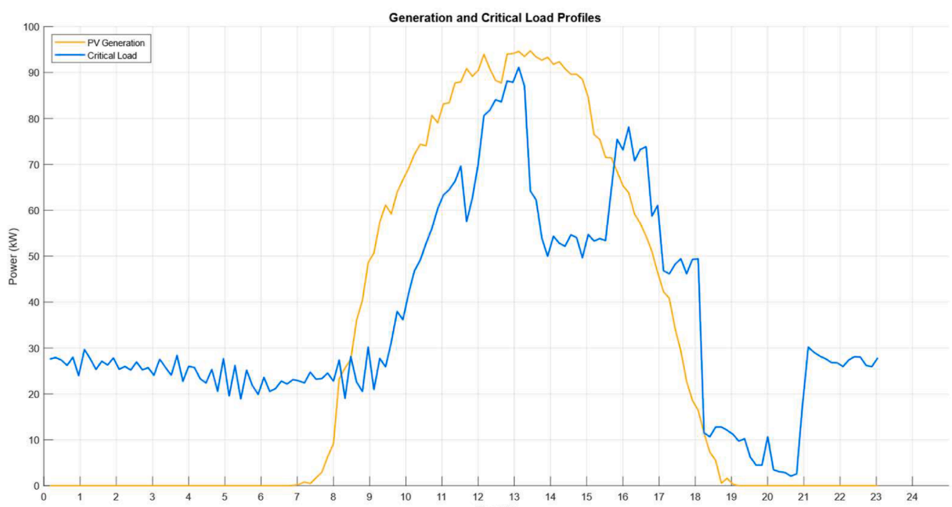

Fig. 16. Microgrid's generation and consumption profiles of a typical day.

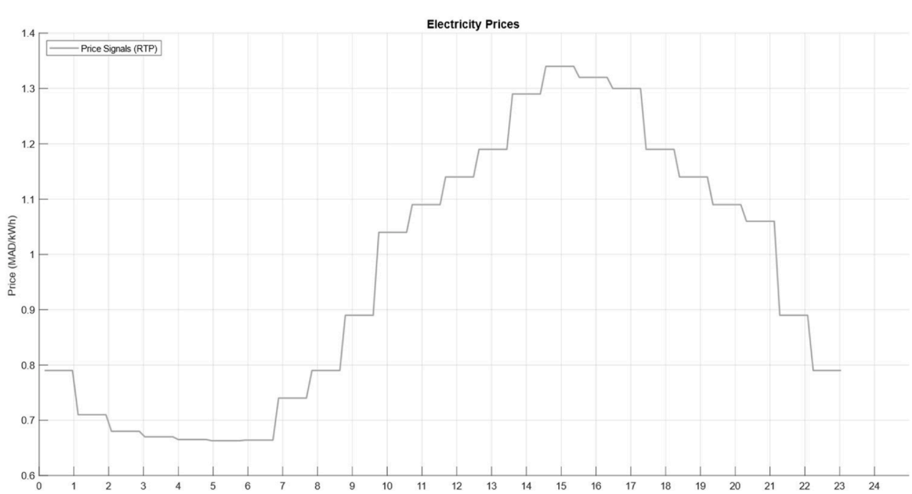

Fig. 17. Electricity prices under RTP scheme.

Table 1
Microgrid parameters.

Parameter	Value	Unit
P_t^{PV}	Timeseries (Fig. 16)	kW
P_t^{CL}	Timeseries (Fig. 16)	kW
c_t^{grid}	Timeseries (Fig. 17)	MAD/kWh
C_{BESS}	100	kWh
$\eta^{BESS,\ ch}$	0.92	–
$\eta^{BESS,\ dich}$	0.92	–
$P_{max}^{BESS,\ ch}$	100	kW
$P_{max}^{BESS,\ dich}$	100	kW
c^{sell}	1.2	MAD/kWh
c^{buy}	0.7	MAD/kWh
SOC_{max}^{BESS}	1	–
SOC_{min}^{BESS}	0.15	–
SOC_0^{BESS}	0.5	–
N_{EV}	2	–
P^{EV}	22	kW
C_{EV}	[77.4 68.5]	kWh

Table 2
EV users' preferences.

Parameter	Value(s)	Unit
SOC_{max}^{EV}	[1 1]	–
SOC_{min}^{EV}	[0.2 0.2]	–
SOC_{final}^{EV}	[0.95 1]	–
SOC_0^{EV}	[0.4 0.3]	–
t_{delay}	[6 7]	h
t_{end}	[19 18]	h
t_{plug}	[8.5 9]	h

Table 3
PSO parameters.

Parameter	Value(s)
N_{sim}	10
N_{pop}	100
k_{max}	300
ω_{min}	0.9
ω_{max}	0.6
c_1	2
c_2	2

EVs parameters (Table 1), EV users' preferences (Table 2), and the PSO parameters (Table 3).

This setup ensures that the results reflect real-world operating conditions of the microgrid, allowing for a robust analysis of how the algorithm handles dynamic changes in energy supply, demand, and pricing.

7.3. Results and discussion

7.3.1. Scenarios description

To evaluate the developed optimization algorithm's performance and effectiveness, various scenarios have been simulated, each considering different assumptions and optimization objectives, as illustrated in Table 4. The corresponding results of these simulations are presented and analyzed in the following sections.

7.3.2. Simulation results

Fig. 18 provides the results of power dispatching using a basic rule-based strategy (scenario 0). This baseline scenario serves as a reference for comparison with the following optimization scenarios. The dispatching follows pre-set rules for energy distribution among generation, storage, and load without any dynamic adjustments.

Additionally, Fig. 19 illustrates the charging power profiles of the electric vehicles (EVs) along with their corresponding state of charge (SOC) evolution, assuming no flexibility in charging. In this scenario, EVs charge continuously starting from the plug-in time, without consideration for time-varying grid tariffs, renewable energy availability or BESS status.

Fig. 20 presents the optimization process of the PSO algorithm, considering 10 distinct swarm families ($N_{sim} = 10$), with each family consisting of a 100-particle population ($N_{pop} = 100$) exploring the search space for 300 iterations ($k_{max} = 300$). This process 0visualizes the convergence behavior and the search for the optimal solution over the defined iterations.

For Scenario 1, Figs. 21 and 22 display the microgrid power dispatching and the EV scheduling strategies, respectively. In Figs. 23 and 24, the load supply and the PV generation dispatching are shown, demonstrating how energy resources are allocated across the microgrid over time.

In Fig. 25, the charging and discharging cycles of the BESS are illustrated, along with the corresponding SOC fluctuations over time, while Fig. 26 displays the time-varying grid and battery energy prices. Fig. 27 provides a comparative analysis between the scenario 1 and the baseline scenario, focusing on the contribution of each energy source in meeting the demand. Table 5 gives the numerical results summary for all simulation scenarios.

7.3.3. Discussion & findings

a. *Analysis of Scenario 0 (baseline)*

In Scenario 0, the microgrid operates without any optimization, relying on a static, priority-based control strategy. The PV system directly supplies the load during the day, and any excess energy is stored in the BESS, which discharges throughout the night until the grid takes

Table 4
Simulation scenarios under various assumptions and optimization targets.

	Optimization Targets				Assumptions		
	Grid Import Cost Minimization	Feed-in Revenues Maximization	BESS Degradation Minimization	EV Users' Satisfaction Maximization	Optimization Algorithm?	EV Charging Flexibility?	Grid Feed-in?
Scenario 0 (Baseline)	–	–	–	–	No	No	No
Scenario 1 (F_{cost1})	✓	–	–	–	Yes	Yes	Yes
Scenario 2 (F_{cost1} + F_{cost2})	✓	✓	-	-			
Scenario 3 (F_{cost3})	–	–	✓	–			
Scenario 4 ($F_{satisfaction}$)	–	–	–	✓			
Scenario 5 (F_{Total})	✓	✓	✓	✓			

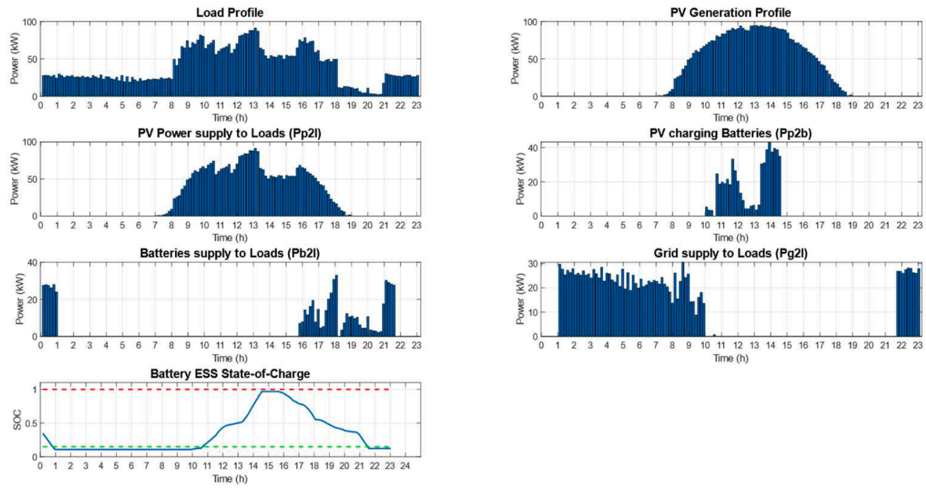

Fig. 18. Power dispatching results for scenario 0.

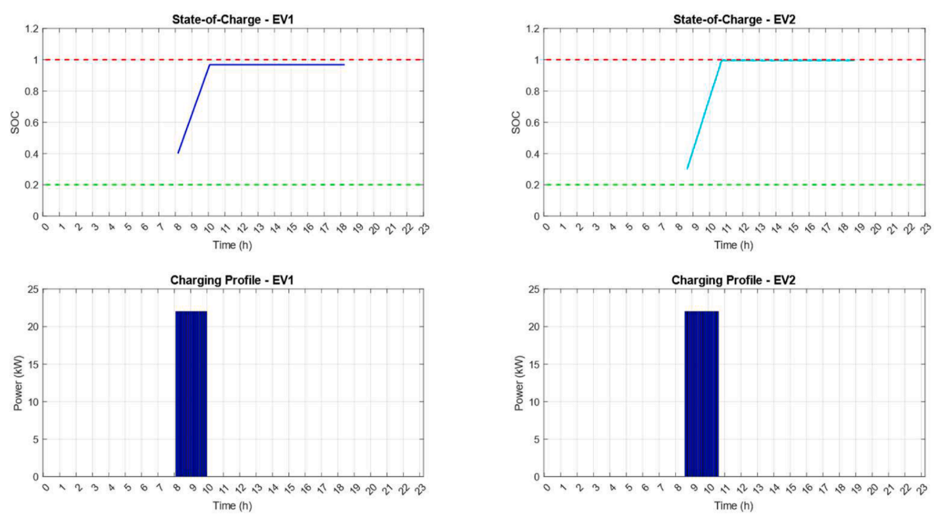

Fig. 19. EV charging profile for scenario 0.

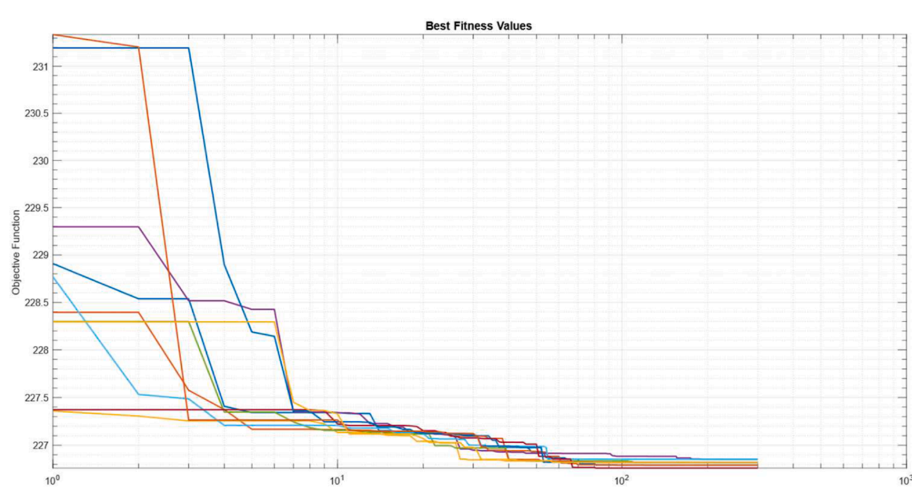

Fig. 20. PSO optimization process for scenario 1.

over to meet the remaining demand (Fig. 18). There is no dynamic energy management, as the scenario does not account for time-varying electricity prices or demand response (DR) mechanisms. In Fig. 19, it is clear that the EVs do not exhibit any flexibility in their charging behavior. The charging process initiates immediately upon the EVs being plugged in.

This baseline scenario demonstrates the need for intelligent optimization to minimize operational costs while ensuring user satisfaction.

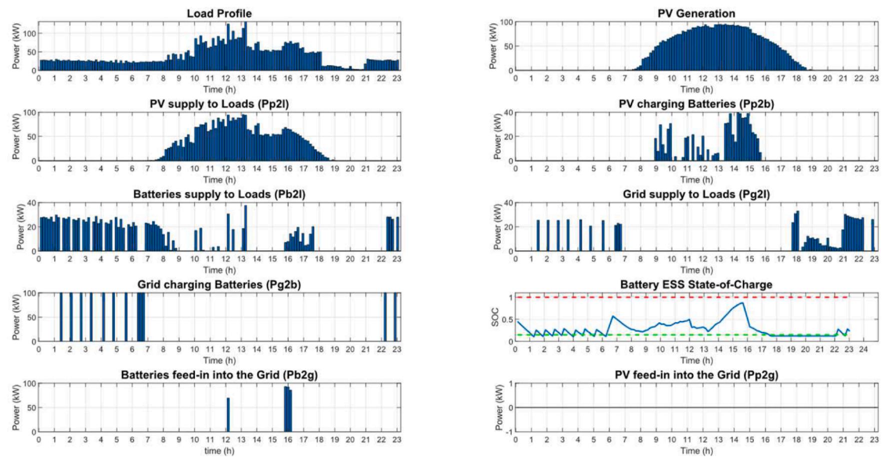

Fig. 21. Power dispatching results for scenario 1.

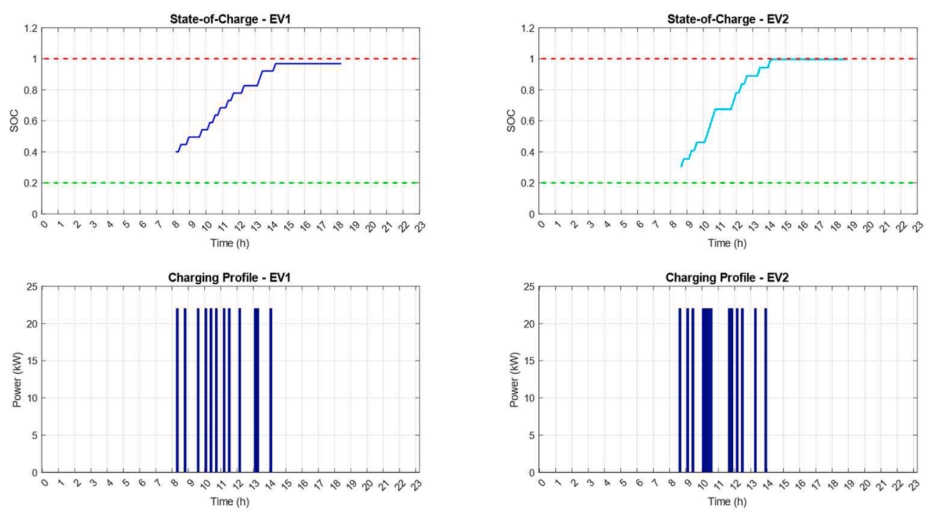

Fig. 22. EV charging profile for scenario 1.

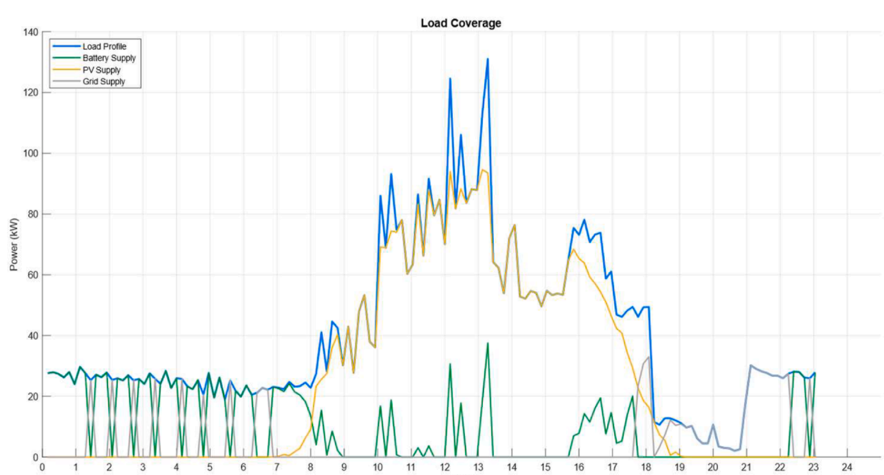

Fig. 23. Load coverage for scenario 1.

b. *Analysis of Scenario 1 (optimizing grid import costs)*

It is clear in Fig. 20 how the EMS effectively reduces grid energy import by prioritizing the use of local DERs (reduced by over 42 % compared to Scenario 0). Beyond this, the EMS anticipates periods of higher electricity prices by purchasing and storing energy in the BESS during low-tariff time slots, which is later used during high-tariff periods to optimize cost savings. This strategy ensures minimal reliance on expensive grid energy during peak pricing.

Additionally, Fig. 21 highlights how the EMS harnesses the flexibility

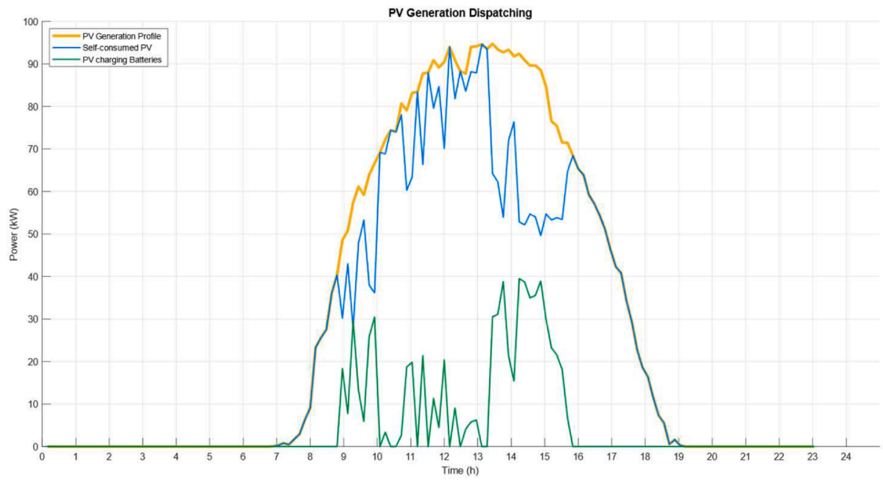

Fig. 24. PV generation dispatching for scenario 1.

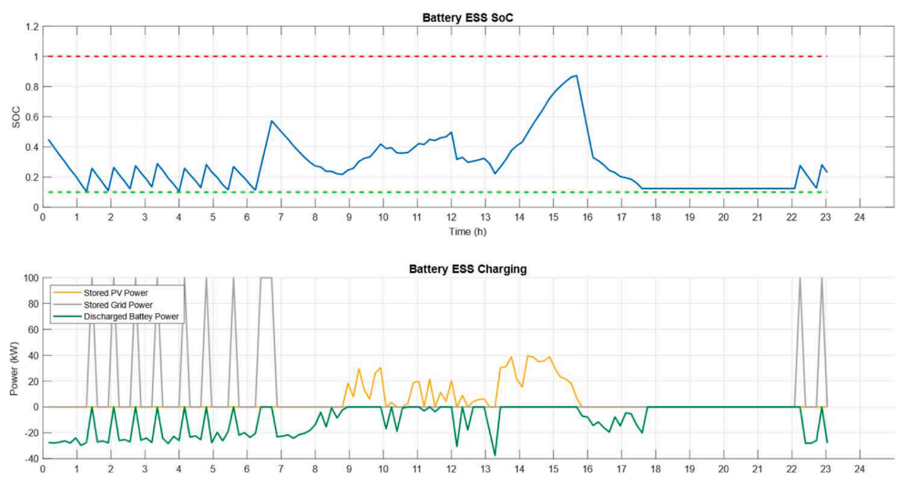

Fig. 25. BESS charging, discharging and SOC profiles for scenario 1.

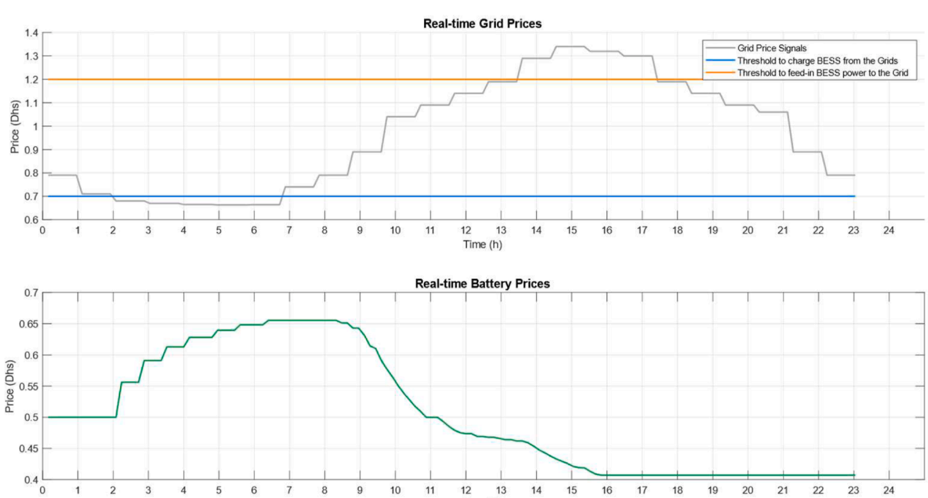

Fig. 26. Real-time grid and BESS prices for scenario 1.

of EV charging by dynamically shifting EV charging throughout the time horizon based on the availability of PV power, the status of the BESS, and the fluctuations in electricity prices. This flexibility maximizes the use of renewable energy while ensuring that charging operations occur during optimal price periods, thus saving costs.

Figs. 22, 23, and 24 provide a more detailed analysis of real-time energy flows and interactions among the different microgrid components. These figures validate that the EMS successfully adheres to the

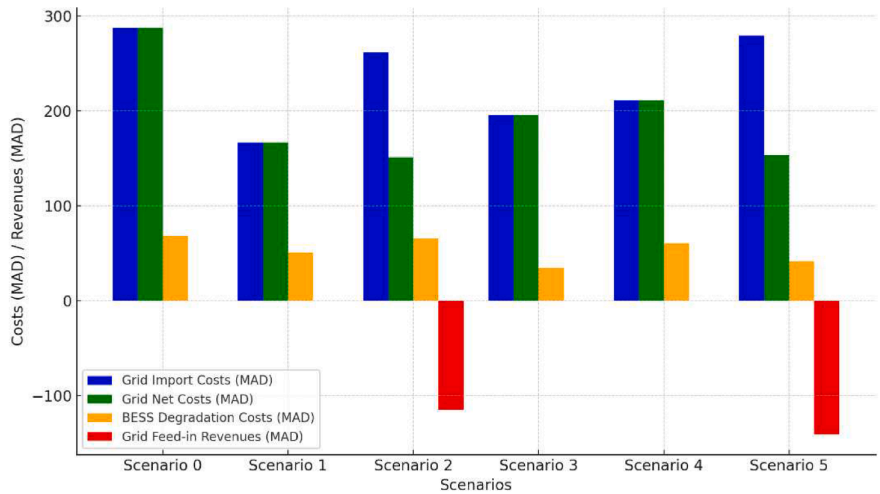

Fig. 27. Comparison of costs and grid feed-in revenues across scenarios.

Table 5
Numerical results summary for simulation scenarios.

Objective Function	**Scenario 0** - Baseline	**Scenario 1** -Optimizing Grid Import Costs	**Scenario 2** - Optimizing Net Costs	**Scenario 3** -Optimizing BESS Degradation Costs	**Scenario 4** - Optimizing EV Users' Satisfaction	**Scenario 5** - Multi-objective Optimization (Trade-off)
Grid Import Costs (MAD)	287.0177	166.4483	261.2200	195.7608	211.2578	279.133
Grid Feed-in Revenues (MAD)	0	0	−115.1427	0	0	−140.8204
Grid Net Costs (MAD)	287.0177	166.4483	151.0471	195.7608	211.2578	153.3126
BESS Degradation Costs (MAD)	68.5630	50.6616	65.321	34.4674	60.5630	41.5681
EV Users' Satisfaction Level (%)	100 %	73.47 %	71.39 %	72.47 %	97.14 %	89.79 %

defined constraints related to real-time power balance (constraints 1 and 2) and BESS operations (constraints 9, 10, 11, and 12), ensuring system stability and efficiency.

Fig. 25 illustrates the evolution of the stored energy price within the BESS over time. We can interpret this behavior because when the BESS is charged using grid energy, its associated energy cost rises due to the purchased electricity. However, as the BESS begins to charge using solar PV energy, the price of stored energy decreases, given that solar energy is considered free.

c. *Analysis of Scenario 2 (optimizing net costs)*

Scenario 2 optimizes the Net Costs, incorporating both grid import costs and feed-in revenues. A significant advantage in this scenario is the introduction of energy trading with the grid. By enabling the EMS to charge the BESS during low-price periods and feed surplus energy back to the grid when prices are high, net costs drop to 151.05 MAD.

Feed-in revenues play a crucial role here, contributing −115.14 MAD, which offsets the grid import costs, making this scenario one of the most financially beneficial. Despite these gains, BESS degradation costs remain high (65.32 MAD), indicating that the system prioritizes short-term financial returns without considering long-term battery health. EV user satisfaction drops slightly to 71.39 %, reflecting some trade-offs between cost optimization and charging convenience.

d. *Analysis Scenario 3 (optimizing BESS degradation costs)*

As this scenario targets the minimization of BESS degradation costs, the EMS adopts a conservative dispatch strategy, reducing the frequency of charge and discharge cycles to extend the battery's lifespan. The results show a significant reduction in BESS degradation costs to 34.47 MAD, the lowest across all scenarios.

However, this focus on preserving the battery comes at a cost: grid import costs increase slightly to 195.76 MAD, as the system avoids aggressive use of the BESS for arbitrage opportunities. While this strategy effectively reduces operational wear and tear on the battery, it does not fully capitalize on potential cost-saving measures. EV satisfaction remains relatively high at 72.47 %, indicating that the EMS balances battery health with user needs effectively.

e. *Analysis of Scenario 4 (optimizing EV users' satisfaction)*

This scenario prioritizes EV User Satisfaction, focusing on optimizing charging time and ensuring that vehicles reach their desired state of charge (SOC) efficiently. By implementing demand-response mechanisms, the EMS schedules EV charging sessions to align with favorable grid and microgrid conditions, minimizing delays while preventing load peaks.

The result is a high EV satisfaction level of 97.14 %, just below the baseline. Grid import costs are controlled at 211.26 MAD, demonstrating that the system can still operate efficiently despite prioritizing user satisfaction. However, this scenario does not generate feed-in revenues or significantly reduce BESS degradation costs, suggesting that the focus on user satisfaction may compromise some opportunities for cost savings or revenue generation.

f. *Analysis of Scenario 5 (finding a trade-off – multi-objective optimization)*

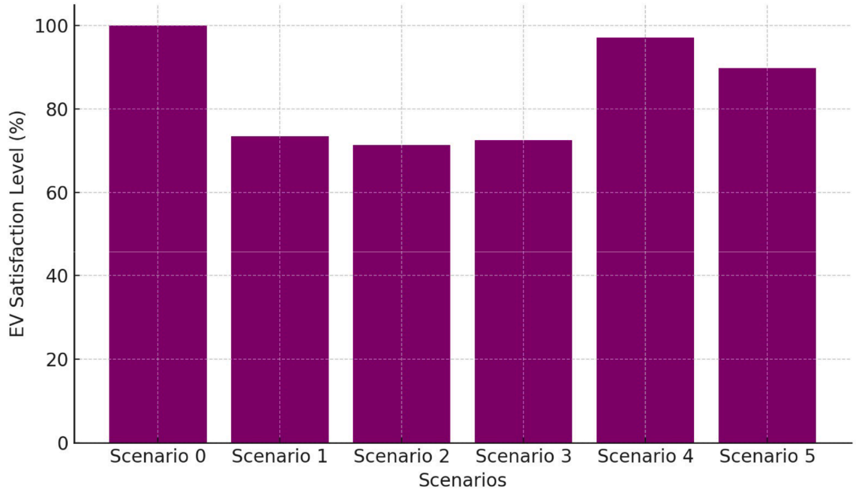

Fig. 28. EV users' satisfaction levels across scenarios.

This scenario presents a multi-objective optimization, aiming to balance grid import costs, feed-in revenues, BESS degradation, and EV user satisfaction. This scenario achieves the best overall performance across all KPIs. Grid import costs are moderate at 279.13 MAD, while feed-in revenues of −140.82 MAD contribute significantly to offsetting net costs, resulting in a total grid net cost of 153.31 MAD.

BESS degradation costs are also controlled (41.57 MAD), reflecting a balanced use of the battery to optimize both short-term financial returns and long-term health. EV user satisfaction is 89.79 %, reflecting a good balance between cost-saving and user experience. This trade-off scenario effectively demonstrates the EMS's ability to optimize multiple objectives simultaneously, providing a comprehensive solution for real-world applications.

g. *Main Findings*

From the scenario analysis section, and according to Figs. 27 and 28, several key insights and findings emerge:

- Scenario 1 shows that optimizing for grid import costs leads to a significant reduction in energy expenditures, cutting grid reliance by over 42 % compared to the baseline. However, this comes at the expense of slightly lower EV satisfaction and continued BESS degradation.
- Scenario 2 leverages energy trading with the grid, producing a strategy that optimizes net costs by feeding excess PV energy into the grid. However, the introduction of feed-in tariffs can lead to negative feed-in revenues. Although this scenario offers short-term financial gains, long-term costs increase due to higher BESS degradation.
- Scenario 3 proves effective in minimizing BESS degradation, showing the trade-off between energy cost and BESS longevity. The reduction in battery cycling operations greatly extends the life of the battery but at the expense of slightly higher grid import costs and limited revenue opportunities.
- In Scenario 4, optimizing for EV user satisfaction improves the overall user experience by reducing charging delays and ensuring high SOC upon departure. This comes at a cost, as grid import increases and battery wear accelerates, suggesting that prioritizing user satisfaction may impact energy efficiency.
- Scenario 5 demonstrates that a multi-objective optimization approach provides the best trade-offs, balancing grid import costs, BESS health, and EV satisfaction. This approach ensures that no single objective dominates the others, leading to an overall efficient, cost-effective, and user-friendly solution for microgrid operations.

The simulation results suggest that microgrid optimization should consider a multi-objective approach to ensure the best trade-offs between cost, BESS health, and EV user satisfaction. Each scenario provides insights into how specific optimization goals affect the overall performance of the system, and a balanced approach offers the most efficient and sustainable solution for long-term operations.

8. Conclusion & future works

This paper demonstrated the effectiveness of a multi-objective Energy Management System (EMS) for microgrids, integrating Distributed Energy Resources (DERs), Battery Energy Storage Systems (BESS), and Electric Vehicles (EVs). Using the Green Energy Park in Morocco as a testbed, the research highlights the ability of the proposed system to optimize key objectives, including net cost minimization, battery degradation control, renewable energy maximization, and user satisfaction.

Through scenario analysis, the paper shows that the EMS can significantly reduce operational costs (up to 42 %) by optimizing the power flows between the microgrid and the main grid. Scenarios focused on net cost reduction, EV user satisfaction, and battery health preservation revealed valuable trade-offs. For instance, while prioritizing cost reduction reduces grid dependence, it leads to higher battery degradation, and enhancing user satisfaction tends to increase grid imports and reduce efficiency. The multi-objective approach, however, offers a balanced solution, demonstrating that a holistic optimization strategy provides the best performance across different objectives.

The case study results validate the EMS's adaptability and real-world applicability, demonstrating the potential of such systems in managing decentralized energy systems efficiently while balancing economic, technical,0 and environmental factors.

Future research should focus on integrating additional renewable energy sources, such as wind turbines and hydrogen plants, and developing real-time adaptive optimization to handle fluctuations in energy supply and demand. Incorporating Vehicle-to-Grid (V2G) capabilities will enable bidirectional energy flows, allowing EVs to contribute energy back to the grid. Long-term battery lifecycle management strategies are needed to optimize battery health and reduce replacement costs. Additionally, exploring decentralized control methods will enhance scalability for larger or interconnected microgrid systems. Strengthening cybersecurity measures and testing the EMS in different geographical contexts will further improve system robustness and adaptability.

CRediT authorship contribution statement

Abdelilah Rochd: Writing – original draft, Visualization, Methodology, Investigation, Conceptualization. **Abdelhadi Raihani:** Supervision, Methodology, Conceptualization. **Oumaima Mahir:** Writing – original draft, Investigation. **Mohammed Kissaoui:** Writing – review & editing, Supervision, Conceptualization. **Mohamed Laamim:** Validation, Software. **Abir Lahmer:** Writing – review & editing, Data curation. **Bouthaina El-Barkouki:** Writing – review & editing, Validation. **Mouna El-Qasery:** Writing – review & editing, Visualization. **HongJian Sun:** Writing – review & editing, Supervision. **Josep M. Guerrero:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Abdelilah ROCHD reports financial support, administrative support, equipment, drugs, or supplies, and statistical analysis were provided by Green Energy Park. Abdelilah ROCHD reports a relationship with Green Energy Park that includes: employment. Other 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.

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Data availability

Data will be made available on request.

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