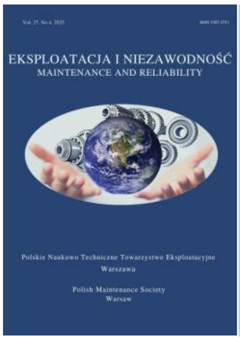

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Smart Strategies for Local Energy Grids: Optimizing Energy Management with Hybrid Electric Vehicle Integration

Indexed by:

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Highlights

- Incorporating stochastic models to manage renewable and demand uncertainties.
- Proposing a probabilistic EV strategy for reducing costs and boosting profits.
- Enabling adaptive control using MDP under real-time pricing and load changes.
- Optimizing energy management using a modified SOS for multi-objective goals.
- Enhancing grid flexibility, efficiency, and sustainability in smart energy systems.

Abstract

This study presents a novel energy optimization framework for local energy networks, addressing the stochastic nature of renewable energy generation, demand fluctuations, and the integration of electric vehicles (EVs) and battery storage systems. The proposed methodology supports fair power allocation by considering operational constraints, dynamic pricing schemes, and demand response (DR) programs. A key contribution of this study is defining an EV's charging and discharging probabilistic model, aiming to enhance interactions with the grid while reducing operational cost and increasing economic returns. In addition, the challenge of optimization is augmented by including market-oriented constraints like real-time pricing and uncertain loading patterns, both of which are dynamically embedded into the decision-making process using the Markov Decision Process (MDP). Moreover, a modified symbiotic organism search (SOS) algorithm has been proposed to deal with the limitations entailed by multi-objective optimization.

Keywords
energy optimization, symbiotic organism search algorithm, demand response, renewable energy integration, electric vehicle charging.

1. Introduction

1.1. Background and motivation

The rapid expansion of distributed energy generation, driven by advancements in renewable energy technologies, has introduced new challenges in energy management [1]. This shift toward renewable energy has largely relied on photovoltaic and wind power generation, but both pose challenges to assimilation into the electrical grid, including energy fragmentation along with limited grid access [2]. The conventional approaches to managing energy rely mostly on individualistic methods, leading to inefficiencies and an overall lack of system flexibility. The Internet of Things is an effective solution to this issue by providing smart management of distributed energy resources [3]. Through the integration of power electronic devices, advanced energy management systems (EMSs), and advanced communications technologies, the Internet of Things establishes an interrelated system of local energy networks. Not only does such an approach enable efficient energy transfers, but it also solves the energy island issue, and overall grid resilience is enhanced [4]. The deployment of these technologies makes

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local energy systems achieve higher operational efficiency, economic sustainability, and better service delivery. Hybrid EVs and plug-in hybrid electric vehicles (PHEVs) are key elements of this evolving paradigm [5]. Their bidirectional charging capability makes them valuable as portable energy storage systems, thus helping to support grid stability as well as enable energy flexibility. To ensure the effective integration of the vehicles into local energy systems, however, it is crucial to develop optimized charging and discharging protocols that balance energy demand, reduce grid pressure, as well as mitigate environmental effects [6]. The aim of this research is to develop an advanced optimization system that integrates hybrid EVs into local energy networks, addressing both economic and environmental aspects. To make energy distribution optimal, a modified SOS algorithm is applied, addressing issues such as the expenses related to pollution management as well as energy resource dispatch [7]. By integrating sophisticated energy management methods, this research aims to enhance sustainability, economic viability, and the efficiency of the grid, thus providing an optimal way for the future development of distributed energy systems.

1.2. Literature review

Substantial scholarly research has directed efforts toward the development of local energy systems, where aspects like distributed generation, alternative energy storage, as well as demand management techniques have been given prominence. Scholars have proposed various methods to increase energy efficiency, minimize operation costs, and integrate renewable energy resources effectively [8]. Shahinzadeh et al. [9] highlighted the IoT applications in power systems and emphasized their implications. This work provides a detailed explanation of the core concepts of the Internet of Things, including detection, sensing, communication, computing, semantics, and services. Reka and Dragicevic [10] provided a concise analysis of the essential roles of IoT within smart grids, detailing the several IoT layers in power systems. Notable applications in smart electric grids include demand-side management, renewable energy sources, power lines, fault monitoring, smart homes, electric vehicles, smart meters, and demand response modeling. The management services offered by IoT are examined, including scheduling, security control, load distribution data, distribution process data, load management data, subscriber profile data, pricing, and market data. A dynamic stochastic EMS is offered, accompanied by integrating technologies such as wireless sensors, radio frequency identification, cameras, barcodes, and intelligent electronic devices. It specifically addresses certain Internet of Things applications within electrical networks. It examines the impact of the Internet of Things on electric vehicles, smart homes, and the challenges now confronting electricity transmission and distribution networks due to digitalization. IoT deployment in smart cities is discussed by Tao et al. [11]. Zanella et al. [12] addressed the difficulties and solutions associated with integrating IoT into smart systems. Sahraei et al. [13] studied an IoT-enabled solar energy harvesting system, and González et al. [14] studied microgrid IoT applications. Asaad et al. [15] examined the integration of EVs, and Lin et al. [16] outlined energy management plans for energy storage facilities and EVs. Furthermore, Huang et al. [17] offered real-time generation planning techniques for Internet of Things-enabled power systems based on renewable energy. Models that tackle problems with pollution remediation have been the subject of recent research. For instance, Li and Zhang [18] presented a multi-objective energy distribution model to reduce operational expenses and pollutant emissions. Similarly, Rostami et al. [19] proposed a cost optimization approach based on the optimal operation strategy to reduce pollution propagation in microgrids.

Ahangar et al. [20] optimized a standalone hybrid green power system for load demand and real-time EV charging, integrating wind turbines, photovoltaics, an electrolyzer, and a fuel cell. They explore green hydrogen as a key decarbonization solution. Reliability analysis looks at possible problems in system parts, while particle swarm optimization (PSO) examines the balance between cost and reliability in various energy situations. Recalde et al. [21] reviewed machine learning strategies and optimization techniques for EMSs in PHEVs. EMS plays a crucial role in power distribution, predictive control, and energy optimization. Advances such as model predictive control, real-time and hybrid optimization, and AI-driven approaches have enhanced EMS performance. Additionally, multi-objective, stochastic, and quantum optimization methods are expanding EMS capabilities.

Strezoski and Izabela [22] highlighted that global efforts aim to integrate EVs to decarbonize transportation and reduce emissions. However, this large-scale integration poses challenges for power systems, especially distribution grids. Traditional planning methods are inadequate, and operational issues such as peak load increases, voltage violations, and feeder overloads arise. Despite the importance of EV deployment, their stochastic integration creates significant obstacles to expanding power systems. Fatemi et al. [23] proposed a stochastic multi-level multi-objective strategy to improve the process of clearing the electricity market among microgrids, accounting for the environmental impact of fossil fuel generation. The approach incorporates distributed renewable energy resources, plug-in EVs, IoT-enabled smart homes, and energy storage devices in smart homes, microgrids, and distribution networks to address uncertainties from distributed renewable energy resources and load demand. Xu et al. [24] studied enhancing the fuel economy of extended-range EVs while reducing the cumulative battery workload. The energy management strategy plays a crucial role in improving energy efficiency, extending battery life, and reducing fuel consumption. While many studies optimize fuel economy, few consider the battery's service life. This study examines battery power fluctuations in current and energy flow to address fuel economy and battery longevity. Tong et al. [25] proposed a tri-stage mechanism to manage energy and ancillary services in coordinated transmission and distribution networks with renewable energy sources and EVs. In the first stage, smart homes plan daily operations and send them to the distribution networks operator. In the second stage, the distribution networks operator formulates a strategy for market participation and sends it to the coordinated transmission operator. In the third stage, the coordinated transmission operator settles the markets. The model is formulated in mixed-integer linear programming and simulated using CPLEX in GAMS.

1.3. The previous scientific gaps and research gaps

The integration of renewable energy sources, EVs, and energy storage systems into local energy grids presents several challenges that need to be addressed for efficient operation and optimization. Existing studies have primarily focused on individual aspects such as distributed generation, energy storage, demand-side management, and EV integration, but gaps remain in terms of addressing the stochastic nature of renewable energy generation, uncertain demand patterns, and the interaction between EVs and the grid. Furthermore, even with efforts to develop energy systems by optimizing cost-effectiveness, operational flexibility, and sustainability, there is a lack of optimization methods that can integrate probabilistic models, dynamic pricing mechanisms, and constraints related to the market into an optimization system. The present work rectifies the research gaps by introducing an advanced optimization system that appropriately integrates stochastic models related to the variability of renewable energy generation and demand. The inclusion of electric vehicles is enabled by a probabilistic system controlling charging and discharging operations, which improves grid interaction, reduces operational cost, and increases economic benefits. The proposed formulation offers a more comprehensive and flexible methodology compared to traditional approaches by considering uncertainties related to load patterns and pricing under real-time conditions. Utilization of an MDP makes it possible to integrate these uncertainties into the framework of the decision-making process, thus ensuring the adaptive adjustment to changing conditions. In addition, one of the key limitations solved by this research is the lack of an efficient optimization algorithm capable of properly handling the multi-objective facets of the problem, including the balance of the distributed generation, energy storage, and grid imports. This paper presents a modified SOS algorithm inspired by symbiotic interactions existing among creatures within the natural world. The algorithm is formulated to continuously adapt to changing system conditions to make the power allocation framework more effective, at the same time optimizing various objectives like cost savings, energy efficiency, and system stability. The incorporation of sophisticated methodologies indicates an elevated strategy for local power grid management, forming an important step toward optimizing smart grids. As such, the key contributions and breakthroughs of this work can be briefly described as follows:

i. The paper introduces a novel optimization framework that incorporates stochastic models for renewable energy generation and demand fluctuations, addressing the inherent uncertainties in energy systems.

ii. A unique probabilistic charging and discharging strategy for EVs is proposed, optimizing grid interaction, reducing operational costs, and maximizing financial benefits.

iii. The model integrates real-time pricing and uncertain load patterns using an MDP, enabling dynamic decision-making that adapts to changing system conditions.

iv. The study presents an advanced optimization algorithm, the modified SOS algorithm, which effectively handles multi-objective energy management, balancing distributed generation, energy storage, and grid imports.

v. The proposed approach enhances the operational flexibility, stability, and efficiency of local energy grids, providing a comprehensive solution for smart grid management and sustainable energy systems.

2. Problem formulation

This section deals with the modeling of the problem, the respective objective functions, and relevant constraints. To increase clarity and understanding, every topic is described in its respective subsection.

2.1. Operating constraints

The constraints that govern the balance of power across the regional electric grid consider the intermittent nature of renewable energy generation, along with demand variations. The energy management system ensures that electricity usage, including charging and discharging of electric vehicles, is synchronized with the combined power output from the distributed resources as well as with the electricity traded with the central electric grid. The refined formulation accounts for uncertainties in renewable generation and demand fluctuations. The total power generated from photovoltaic panels, wind turbines, fuel cells, microturbines, and grid imports must match the local energy demand while incorporating stochastic variations in generation and consumption, as presented in Eq. (1).

$$P_{(t)}^{PV}(1-\xi_r^{PV}(t))+P_{(t)}^{WT}(1-\xi_r^{WT}(t))+P_{(t)}^{FC}+P_{(t)}^{MT}+P_{(t)}^{Grid}=P_{(t)}^{Load}(1+\xi_d(t))+\sum_{n=1}^{N_{PHEV}}P_{(t)}^{PHEV} \tag{1}$$

The output of each distributed generation unit is subject to operational limits and ramp rate constraints, as shown in Eqs. (2) to (7) [8].

$$P^{PV-Min}\leq P_{(t)}^{PV}\leq P^{PV-Max} \tag{2}$$
$$P^{WT-Min}\leq P_{(t)}^{WT}\leq P^{WT-Max} \tag{3}$$
$$P^{FC-Min}\leq P_{(t)}^{FC}\leq P^{FC-Max} \tag{4}$$
$$P^{MT-Min}\leq P_{(t)}^{MT}\leq P^{MT-Max} \tag{5}$$
$$Ramp^{FC-Down}\leq P_{(t)}^{FC}-P_{(t-1)}^{FC}\leq Ramp^{FC-Up} \tag{6}$$
$$Ramp^{MT-Down}\leq P_{(t)}^{MT}-P_{(t-1)}^{MT}\leq Ramp^{MT-Up} \tag{7}$$

To incorporate forecasted changes in load and generation, the ramp rate constraint is dynamically updated in Eq. (8).

$$\mathrm{Ramp}_{FC-Down}\leq P_{(t)}^{FC}-P_{(t-1)}^{FC}\leq \mathrm{Ramp}_{FC-Up} \tag{8}$$

Battery energy storage plays a critical role in maintaining power balance. The energy storage model considers charge and discharge limits, state-of-charge constraints, and degradation effects through Eqs. (9) to (11).

$$P^{Bat-Min}\leq P_{(t)}^{Bat}\leq P^{Bat-Max} \tag{9}$$
$$E^{Bat-Min}\leq E_{(t)}^{Bat}\leq E^{Bat-Max} \tag{10}$$
$$E_{(t+1)}^{Bat}=E_{(t)}^{Bat}-\eta_d^{Bat}P_{(t)}^{Bat}\Delta t+\eta_c^{Bat}P_{(t)}^{Grid}\Delta t \tag{11}$$

The interaction with the main grid is formulated based on dynamic pricing mechanisms. The grid import/export function is defined as Eq. (12).

$$P_{(t)}^{Grid}=\begin{cases}\lambda^{buy}(t)\cdot(P_{(t)}^{Load}-P_{(t)}^{RES}) & \text{if} \quad P_{(t)}^{Load}>P_{(t)}^{RES}\\ -\lambda^{sell}(t)\cdot(P_{(t)}^{RES}-P_{(t)}^{Load}) & \text{if} \quad P_{(t)}^{Load}<P_{(t)}^{RES}\end{cases} \tag{12}$$

DR constraints aim to modify electricity consumption patterns to balance supply and demand, especially with the integration of renewable energy sources. The load response can be represented as a reduction or shift in the original demand $P_{(t)}^{Load-DR}$ signals [26]. The adjusted demand after DR intervention is given by Eq. (13).

$$P_{(t)}^{Load-DR}=P_{(t)}^{Load}-\Delta P_{(t)}^{Load} \tag{13}$$

For EVs and other flexible loads, the charging or discharging schedule can be dynamically adjusted based on grid conditions. The total change in demand due to DR actions can be modeled as Eq. (14).

$$\sum_{i=1}^{N_{EV}}\Delta P_{(t)}^{EV}\leq P_{Max}^{EV} \tag{14}$$

By incorporating dynamic pricing, adjusted demand can also depend on price signals, where consumers shift or reduce consumption when prices are high. The adjustment can be modeled as Eq. (15).

$$P_{(t)}^{Load-DR}=P_{(t)}^{Load}\cdot(1-\alpha\cdot\lambda^t) \tag{15}$$

To ensure system stability, DR constraints must not conflict with power balancing requirements. The total adjusted load should not exceed available generation and storage, ensuring the balance presented in Eq. (16).

$$P_{(t)}^{Load-DR} + P_{(t)}^{RES} + P_{(t)}^{Grid} = P_{(t)}^{Generation} + P_{(t)}^{Storage} \quad (16)$$

Finally, the total DR should respect the consumer's willingness and physical limits. This can be expressed as Eq. (17).

$$\Delta P_{(t)}^{Load} \leq \Delta P_{Max}^{Load} \quad (17)$$

2.2. Probabilistic EV charging and discharging dtrategy with market constraints

This model seeks to improve how EVs charge and discharge by using a method that considers uncertainties in driving habits, electricity costs, and grid conditions. Including market-oriented limitations and actual variabilities, this model adapts to changing prices and variations in the conditions on the grid, thus favoring efficiency as well as financial benefits to the involved stakeholders [27]. The daily travel distance of EVs is influenced by a stochastic process with log-normal distribution, which currently also encompasses additional uncertainties due to factors like traffic and meteorological factors [28]. This introduces some randomness to vehicle utilization, as outlined by Eq. (18), which is the probability density function for daily mileage d.

$$f(d) = \frac{1}{d\sigma^d\sqrt{2\pi}} exp\left(-\frac{(ln(d)-\mu^d)^2}{2(\sigma^d)^2}\right) \quad (18)$$

The start times for charging $t^{Ch-Start}$ and discharging $t^{Dis-Start}$ are optimized through an MDP, which considers the state of charge (SOC) of the EV, the grid load, and the electricity price at each time. The optimal strategy aims to minimize costs while maximizing utility based on real-time data. The charging start time $t^{Ch-Start}$ is given by Eq. (19).

$$t^{Ch-Start} = \arg min_t \, [P(t) \cdot L(t) \cdot f(t) + \gamma \cdot \mathbb{E}[U(t)]] \quad (19)$$

Similarly, the optimal discharging start time $t^{Dis-Start}$ is given by Eq. (20).

$$t^{Dis-Start} = \arg max_t \, [P(t) \cdot L(t) \cdot f(t)] \quad (20)$$

The SOC of the EV's battery evolves based on the charging and discharging processes. The SOC is influenced by random factors such as consumption patterns, charging efficiencies, and battery degradation. The evolution of SOC is modeled as Eq. (21).

$$SOC(t) = SOC(t_0) + \int_{t_0}^{t} (P^{Ch}(t') - P^{Dis}(t'))\, dt' + \epsilon(t) \quad (21)$$

The optimization of charging and discharging times is subject to several market-based constraints. These constraints ensure that the EVs do not charge or discharge at times that would be inefficient or costly for the system. The charging power $P^{Ch}(t)$ is constrained by the vehicle's maximum charging rate and the current market price. The charging power is limited by Eq. (22).

$$P^{Ch}(t) \leq P_{max}^{Ch} \cdot 1(P(t) \leq P_{max}^{Market}) \quad (22)$$

Discharging is subject to the grid's demand and the grid's capacity. To avoid overloading the grid, the discharge power $P^{Dis}(t)$ is constrained by Eq. (23).

$$P^{Dis}(t) \leq P_{max}^{Grid} \cdot 1\big(L(t) \geq L_{min}^{Grid}\big) \quad (23)$$

The model aims to maximize profits from discharging and minimize the cost of charging. The total cost of charging and discharging is given by Eq. (24).

$$C_{\mathrm{Ch}}(t) = P_{\mathrm{Ch}}(t) \cdot P(t), C_{\mathrm{Dis}}(t) = P_{\mathrm{Dis}}(t) \cdot P(t) \quad (24)$$

Thus, the objective function is given by Eq. (25).

$$\mathbb{E}[Profit] = \sum_{t_0}^{T} [P^{Dis}(t) \cdot P(t) - P^{Ch}(t) \cdot P(t)] + \sum_{t_0}^{T} \gamma \cdot \mathbb{E}[U(t)] \quad (25)$$

The maximum discharge duration T^{Dis} depends on the remaining capacity of the EV's battery, as well as random fluctuations in grid conditions and market prices. The discharge time is given by Eq. (26) [8]:

$$T^{Dis} = \frac{C^{Bat} \cdot (SOC^{Max} - SOC^{Min})}{P^{Dis}} + \frac{d \cdot W_{100}}{100 \cdot P^{Dis}} + R(t) \quad (26)$$

Electricity prices $P(t)$ evolve over time and follow a random walk influenced by market fluctuations. The price dynamics are modeled as Eq. (27).

$$P(t) = P(t-1) + \epsilon(t) \quad (27)$$

2.3. The objective function

The primary objective of energy optimization management is to efficiently satisfy the network's load requirements while keeping overall expenses to a minimum. The entire cost covers the price of treating pollutants as well as producing electricity. The objective function for optimal planning is formulated, as Eq. (28) demonstrates. The first term is the expense of treating the pollution caused by the equipment's release of greenhouse gases like CO_2, SO_2, and NO_2. The costs of producing electricity are included in the second term of this equation and comprise the expenses for operating and maintaining distributed generation equipment, as well as the costs related to receiving electricity from the power grid. The next term covers expenses for mitigating grid-wide external pollution, which includes dust, CO_2, SO_2, NO_2, and other pollutants.

$$min\ F(X) = \sum_{t=1}^{T}[\sum_{i=1}^{N_{DG}}\sum_{j=1}^{N_{p1}} K_j \cdot Q_{(i,j)} \cdot \frac{P_{(i,t)}}{\eta_{(i)}} + \sum_{i=1}^{N_{DG}}(C_{(i)}^{OM} \cdot P_{(i,t)} + C_{(i)}^{Run} \cdot \frac{P_{(i,t)}}{\eta_{(i)}}) + C_{(t)}^{Grid} \cdot P_{(t)}^{Grid} + \sum_{m=1}^{N_{p2}} Q_{(m)} \cdot K_{(m)} \cdot P_{(t)}^{Grid} + \lambda \sum_{i=1}^{N_{DG}} C_{(i)}^{Env} \cdot P_{(i,t)} + \sum_{i=1}^{N_{SG}} C_{(i)}^{Storage} \cdot P_{(i,t)}^{Storage} + \alpha \sum_{t=1}^{T}(D_t - \sum_{i=1}^{N_{DG}} P_{(i,t)})^2 + \beta \sum_{t=1}^{T}(\Delta P_{(t)})^2] \tag{28}$$

Here, the state variables are represented by vector X, which also includes the active power levels of the corresponding units. In these relationships, $N_{(DG)}$ is the total number of distributed generation units, and T is the total number of operational intervals in the system. A wide range of devices, including fuel cells, photovoltaics, wind turbines, storage batteries, and microturbines, are part of distributed generation technologies. The power output of the i-th distributed generation unit is represented by $P_{(i,t)}$ at a given time t, its power generation efficiency is represented by $\eta_{(i)}$, and its cumulative power is denoted by $C_{(i)}^{Run}$ is a term used to describe the running costs of devices like fuel cells and microturbines. Furthermore, $C_{(i)}^{OM}$ represents the maintenance cost of the ith distributed generation unit. In that example, the exchange of electrical power with the main grid is represented by $P_{(t)}^{Grid}$, where buying electricity is seen as positive and selling it as negative. $C_{(t)}^{Grid}$ reflects the market price of the electricity produced by the upstream power system at time t. The pollution resulting from diffuse production—which includes the release of greenhouse gases like CO_2, SO_2, and NO_2—is described by the formula P_1. In addition, P_2 stands for air pollutants such as CO_2, SO_2, NO_2, and dust that come from the external power grid's electrical generation. The corresponding displacement cost is denoted by $K_{(j)}$, and $Q_{(i,j)}$ is the emission of the jth pollutant produced by distributed generation unit i per 1 kWh of energy. Similar to this, $Q_{(m)}$ denotes the emissions from the pollution meter produced for every kWh of electricity used, and $K_{(m)}$ is the cost of moving the pollutant meter.

3. Optimization Algorithm

The SOS method is modeled after the complex relationships found in nature, such as mutualism, convergence, and parasitism, and is inspired by symbiotic interactions in ecosystems [29]. Every kind of interaction in this algorithm represents how organisms adapt to their surroundings and gradually become more fit. A symbiotic relationship in which both species benefit is known as mutualism. The simulation begins by selecting a random person ($X_{(i)}$) to communicate with the ith creature in the algorithm. This interaction is governed by Eqs. (29) and (30), where the position of both organisms is set based on their respective profit levels (w_1 and w_2) [30].

$$X_{(i)}^{New} = X_{(i)}^{Old} + \mu_1.\left(X^{Best} - w_1.\frac{X_{(i)}^{Old}+X_{(j)}^{Old}}{2}\right) \tag{29}$$

$$X_{(j)}^{New} = X_{(j)}^{Old} + \mu_2.\left(X^{Best} - w_2.\frac{X_{(i)}^{Old}+X_{(j)}^{Old}}{2}\right) \tag{30}$$

Convergence is another symbiotic relationship in which one species benefit while the other remains unaffected. As explained in Eq. (31), this interaction only affects the i-th organism.

$$X_{(i)}^{New} = X_{(i)}^{Old} + \beta_1.\left(X^{Best} - X_{(j)}\right) \tag{31}$$

The parasitic stage produces mutational changes in individual i, in which a new organism selects and replaces the host (random individual). This step involves modification of the chosen host organism, reflecting the parasitic nature of the interaction. An ecosystem of randomly generated organisms repeatedly replicates these interaction steps. The fitness of each organism is calculated to identify symbiosis with the best fitness value (X^{Best}). By simulating interactions of mutualism, convergence, and parasitism, the SOS algorithm moves toward optimal solutions and adapts and evolves its population during iterations to achieve a desired level of optimality in solving complex problems.

In this study, a new step is introduced to the original SOS algorithm, which increases its adaptive capabilities through the integration of three distinct optimization strategies. We design this innovative step to empower each organism by adaptively choosing the most appropriate strategy based on its inherent probability. Below, we explain the strategies in detail:

1) Strategy 1: As expressed in Eqs. (32) and (33), a local exploration technique called Levy flight, is incorporated to facilitate an efficient search process.

$$Levy(\alpha) = Iter^{-\alpha} \qquad 1 \le \alpha \le 3 \tag{32}$$

$$X_{(i)}^{Test1} = X_{(i)} + \mu_3 \oplus Levy(\alpha) \tag{33}$$

2) Strategy 2: Designed to enhance swarm diversity, this strategy involves randomly selecting three dissimilar organisms from the population. Next, we generate a refined solution using Eq. (34). Three individuals undergo the mutation processes shown in Eqs. (35) to (37) by applying both the best solution in the population and the refined solution.

$$X^{Mut} = X_1 + \mu_4.(X_2 - X_3) \tag{34}$$

$$X_{(i)}^{Test2} = \begin{cases} X_{(j)}^{Mut} & \mu_5 \leq \varphi^{Mut} \\ X^{Best} & Otherwise \end{cases} \tag{35}$$

$$X_{(i)}^{Test3} = \begin{cases} X_{(j)}^{Mut} & \mu_6 \leq \varphi^{Mut} \\ X^{Best} & Otherwise \end{cases} \tag{36}$$

$$X_{(i)}^{Test4} = \mu_7.X^{Best} + \mu_8.(X^{Best} - X^R) \tag{37}$$

3) Strategy 3: As specified in Eq. (38), focusing on guiding the algorithm away from abnormal solutions, this strategy attracts organisms towards the population mean (M).

$$X_{(i)}^{Test5} = X_{(i)} + \mu_9.\left(X_{(i)} - M.w_3\right) \tag{38}$$

A strategy with a higher likelihood is one that is employed sparingly among these options. As a result, if the new test organism exhibits better conditions in terms of raising the fitness function, it replaces the old one. Every iteration, the correction method with the highest success rate across all people is chosen to be used. This adaptive improvement introduces a dynamic element to the SOS algorithm and contributes to its efficiency and effectiveness in addressing complex optimization challenges. Figure (1) displays the flowchart of the proposed algorithm for problem solving.

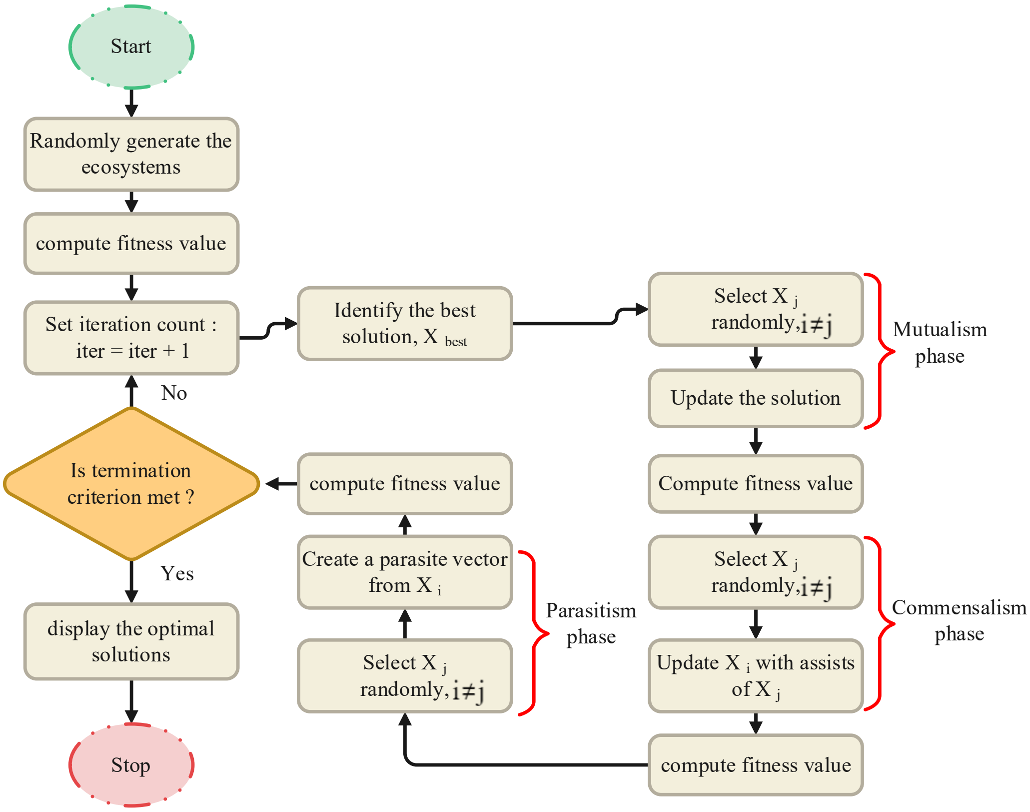

Figure 1. Flowchart of proposed algorithm.

4. Numercial analysis and discussion

The modified SOS algorithm is utilized in this part to tackle the intricate management of energy optimization for a local energy grid [31]. The data utilized in this paper are sourced from the literature [32–34]. With an emphasis on attaining green and intelligent energy planning, the study's goal is to offer a comprehensive solution to the problems brought on by the dynamic nature of energy demand in the local energy grid. Two separate cases are constructed and examined—one without EVs and the other with them—to confirm the efficacy of our suggested model, highlight its limitations, and showcase the benefits of smart charging and discharging strategies. Only the operating costs are taken into account in Scenario 1 of Case 1; however, the operating costs and the emissions costs are taken into account in Scenario 2. Scenario 1 of Case 2 also accounts for the charging and discharging of EVs without a control plan. In Scenario 2 of Case 2, the control strategy will exclusively be used for EV charging; however, in Scenario 3 of Case 2, the control method will be used for EV charging and discharging. Case 1 analyzes the optimization model for energy management in depth and highlights the effectiveness of the modified SOS algorithm in this research. Expanding upon the knowledge acquired in Case 1, Case 2 investigates how various EV access strategies impact energy management for the local energy grid.

One hour is the duration of the period in the experimental setup; twenty-four hours is the control time domain; and one day is the entire simulation duration. The daily load requirements of the local energy network, comprising primary home loads, small industrial loads, and small commercial loads, are depicted in Figure (2).

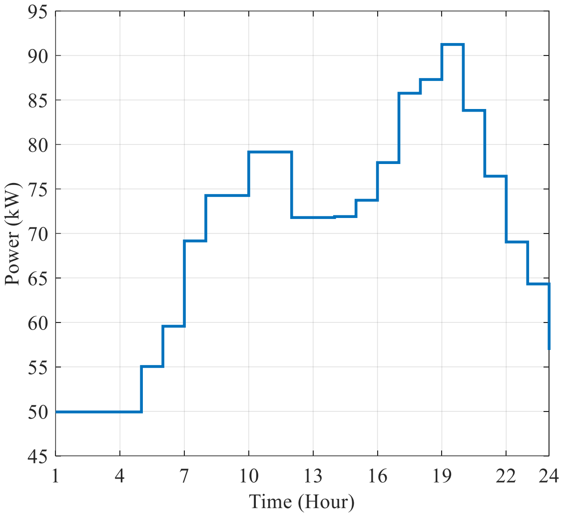

Figure 2. Electric load required by the system.

The market's instantaneous electricity price is displayed in Figure (3). Furthermore, estimates for the generation of electricity from wind turbines and photovoltaic technologies are also made using a forecasting model, as Figure (4) illustrates. This essay is not going to cover the specific prediction method [8]. Since the primary objective of this article is to achieve green and intelligent energy planning, this model thoroughly takes into account how the costs of producing power and treating pollution affect energy planning.

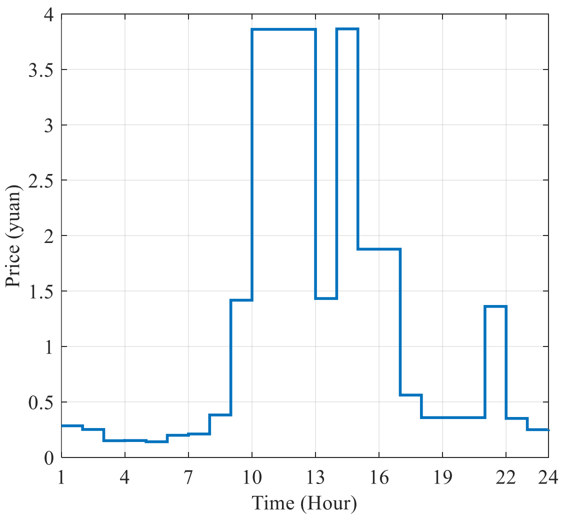

Figure 3. Predicted price of electric energy.

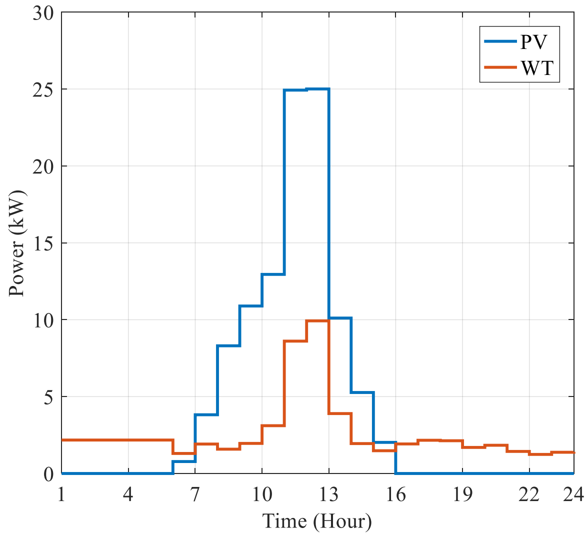

Figure 4. Total wind and solar energy predicted for the system.

4.1.Results of Case 1

In empirical exploration, we carefully created two distinct scenarios to explore the dynamics of energy management in the local energy network. These scenarios have been meticulously crafted to offer an all-encompassing viewpoint, encompassing the expenses associated with power generation and pollution treatment, as well as a wider range of concerns. Using these scenarios shows the importance of including pollution treatment costs in the local energy network plan and allows for a complete evaluation of how well the updated SOS algorithm can adapt.

- Scenario 1

In Scenario 1, we focus exclusively on the cost of electricity, regardless of pollution treatment considerations. Figure (5) presents the simulation's outcomes straightforwardly and concisely.

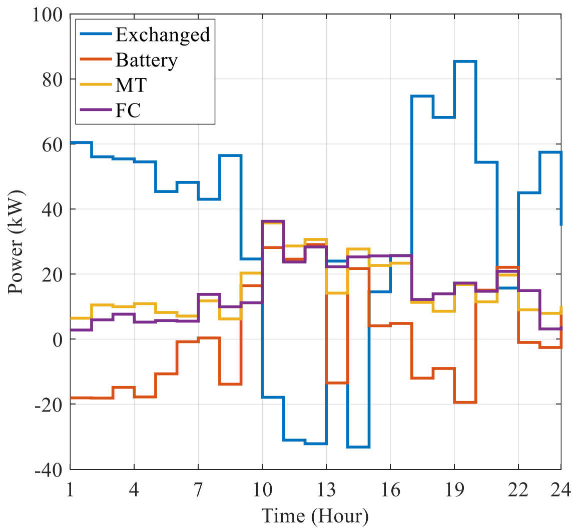

Figure 5. Optimal system planning in Scenario 1 of Case 1

The main grid supplies the necessary electricity early in the morning, which also serves to charge the battery. Due to a combination of cheap main grid pricing and mild grid loads, electricity generation has been reduced during 01:00–09:00 in distributed generation units, which are characterized by higher electricity generation costs. With the increase in the price of electricity in the hours of 09:00-16:00, which are peak load periods, along with battery discharge, local distributed generation units witness a significant growth in electricity production. This increase allows them to satisfy local demand while selling surplus electricity to the primary grid, a tactical approach to minimize operational expenses. The findings of this scenario indicate that individuals prefer to charge batteries during periods of low cost and strategize their usage for times of high cost. Distributed generation units, meanwhile, consistently generate power to enhance grid resilience. This situation shows how managing electricity costs can be complicated and demonstrates that by smartly charging and discharging batteries, along with wisely using local power sources, we can better handle changing electricity prices and demands on the grid. We expand our research in the next scenario to include the expenses of pollution control and electricity generation, giving a more complete picture of energy management in the local energy system. The following sections address the complexities of this broad scenario and clarify the interplay between electricity costs and pollution treatment considerations.

- Scenario 2

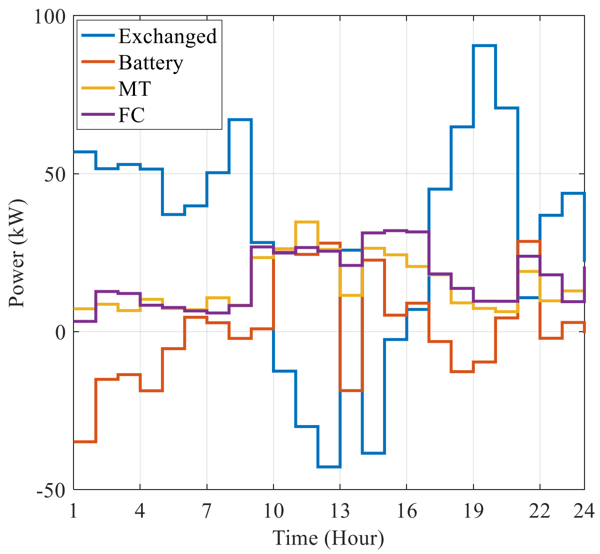

Figure 6. Optimal system planning in Scenario 2 of Case 1.

In Scenario 2, a subtle perspective emerges when we introduce pollution treatment costs into the perspective of energy optimization. The simulation results of this scenario, shown in Figure (6), deal with the complex dynamics of energy management, clarifying the delicate balance between electricity consumption, production capacities of distributed generation units, and the subsequent costs of pollution treatment.

According to the general trends observed in Figure (5), distributed generation units show very good production capacities that reduce electricity consumption from the upstream power grid, which is a characteristic due to the careful consideration of pollution treatment costs. There is significant interest in comparing the pollution emissions of microturbines and fuel cells. Despite the high production capacities, the pollution produced by micro-turbines exceeds that of fuel cells. As a result, fuel cells take a higher production route and skillfully incorporate the complex interplay between pollution factors and energy production dynamics. Delving deeper into the empirical data, an illuminating revelation emerges. These findings clearly show that it's important, for the economy and especially for protecting the environment, to include pollution treatment costs in energy management. While the scale of the experiment remains relatively modest within the scope of the local energy grid, the ultimate difference in pollution treatment costs between the two scenarios may seem negligible. However, the expansion of the grid scale will significantly amplify the discernible gap in pollution treatment costs. This conclusion shows the clear benefits and importance of looking at pollution control costs and confirms the dedication to being financially smart and protecting the environment in the larger context of improving energy use.

4.2. Results of Case 2

In Case 2, we address the complex dynamics introduced by EVs in the grid and explore the three scenarios identified, which include uncontrolled EVs, controlled EVs, and smart EVs. Table (1) presents the system loads for different strategies over 24 hours in Case 2, comparing uncontrolled, controlled, and intelligent strategies across various components such as battery, microturbine (MT), and fuel cell (FC). The results present varying energy demand and supply discrepancies throughout the scenarios analyzed, revealing the system's ability to balance resources across different scenarios. The uncontrolled method presents larger variations of loads, often revealing higher demand levels or failures to reach equilibrium within the energy system. As an example, in the first hours (hour 1), the discharge of the battery is recorded at -23.0026 kW, while the microturbine produces 8.9097 kW, reflecting possible insufficient operational efficiency of the system concerning energy usage and storage. The controlled method, by contrast, shows greater stability through optimal loading values to avoid shortages and surpluses of energy. In hour 1, as an example, the loading of the battery is optimized to -33.5858 kW, reflecting better mechanisms for energy regulation and storage. The intelligent strategy, which is expected to incorporate the coordination of advanced algorithms or real-time optimization schemes, maintains the most optimally balanced system load profile. For example, in hour 1, this intelligent strategy leads to a lesser discharge by the battery at -25.3895 kW, with the microturbine and fuel cell producing more effective outputs. Throughout the 24 hours, this intelligent strategy is expected to produce a stable and optimized energy balance, with the battery, microturbine, and fuel cell working synergistically to meet the energy demand. It can be seen that there are certain hours where the intelligent strategy performs better than the controlled strategy and the uncontrolled strategy. For example, at hour 9, the smart strategy generates significantly better results for the microturbine (10.4728 kW) and fuel cell (30.3928 kW), thus demonstrating its ability to optimize the generation of energy in accordance with true demand. The controlled strategy, on the other hand, tends to deliver a more stable but less adaptive performance, while the uncontrolled strategy continues to suffer from high levels of load imbalance.

Table 1. System loads in different strategies from Case 2.

Time	Uncontrolled strategy			Controlled strategy			Intelligent strategy		
	Battery	MT	FC	Battery	MT	FC	Battery	MT	FC
1	-23.0026	8.9097	7.369	-33.5858	4.013	1.1847	-25.3895	6.6173	9.232
2	-7.0805	12.8614	11.5741	-20.5531	10.6849	0.9809	-16.3917	7.657	11.5747
3	-12.4124	9.3035	4.4984	-19.98	7.1289	1.4444	-10.7344	9.1141	8.2539
4	-14.5367	11.909	13.3584	-14.1338	5.1345	8.49	-8.8486	9.1867	11.3012
5	-12.122	8.0042	7.4143	-8.0471	7.3408	8.5626	-16.6197	9.245	6.4347
6	4.9922	8.8304	6.2273	3.3917	5.6424	8.0429	-4.6176	11.8393	10.7077
7	-1.8148	8.0445	12.8485	-4.1758	6.6566	8.838	3.3591	8.7211	14.6827
8	-5.3476	10.395	7.6797	0.851	11.9044	10.3361	2.3043	8.7663	8.7269
9	4.9204	12.8175	26.6996	1.0549	18.9361	24.4884	11.1743	10.4728	30.3928
10	31.9727	25.5936	22.587	23.0881	23.0655	28.088	38.8243	28.0685	36.6485
11	31.0346	35.4381	31.0537	24.8106	26.1516	28.8252	38.582	24.792	30.4375
12	27.7763	36.7554	25.487	26.253	25.96	26.3236	29.7967	27.2139	35.0126
13	-4.0938	16.3258	21.9936	-3.1488	19.0941	21.3482	-11.5124	28.3273	22.3838
14	32.1949	29.5429	23.1224	17.5239	30.366	24.3493	29.9716	25.1551	36.293
15	2.6132	23.2582	29.18	2.7979	19.4234	18.9014	9.9854	29.5031	26.755
16	3.3445	25.7264	24.5696	3.2571	24.6148	18.6676	0.5127	25.7581	25.5722
17	-7.1668	12.1366	8.4354	-3.1244	8.5364	5.7949	-4.022	15.9	17.9624
18	2.1437	14.1525	3.3097	-9.3103	7.528	8.7235	4.1083	18.9268	6.3438
19	-2.8824	9.9195	9.6028	-11.3049	6.614	3.891	-6.5067	17.0338	9.5241
20	-2.8345	10.3064	4.2182	1.2807	12.6347	7.465	16.1383	13.0385	22.8164
21	15.7226	13.5717	19.2878	24.1058	12.3889	16.8055	3.5399	19.9162	29.8693
22	-2.9365	8.4633	19.2622	-1.8136	11.3995	7.9942	-1.5147	11.4904	12.9265
23	-7.2578	9.4449	8.9053	-10.6987	10.9137	8.0501	-8.4021	7.6731	13.3799
24	3.4441	7.2273	10.4994	-5.0168	8.7001	8.7403	9.4725	13.1625	12.973

Operating expenses outlined in Table (2) for the three strategies—uncontrolled, controlled, and intelligent—exhibit significant differences upon quantification using various cost indicators. The uncontrolled method has the maximum average operating cost recorded at 1832 yuan, with the highest cost calculated at 2098 yuan, but the minimum operating cost is at 1685 yuan. In sharp contrast, the controlled method has both the minimum average cost compared to those related to the uncontrolled method at 1763 yuan, as well as the maximum cost of 1985 yuan. In addition, the minimum cost related to the controlled method is less than that related to the uncontrolled method, at 1622 yuan. The intelligent method depicts the maximum reduction across the entire range of parameters considered. The average cost is registered at 1487 yuan, reflecting a reduction of 14.3% compared to the uncontrolled approach and 15.8% compared to the controlled approach. The maximum cost of the intelligent approach is 1517 yuan, a decrease of 27.7% when compared to the uncontrolled approach's maximum cost. The minimum cost of the intelligent approach is registered at 1436 yuan, a decrease of 14.8% compared to the uncontrolled approach's minimum cost. The examination of the different approaches clearly shows that the intelligent approach produces the best economic outcomes for all the metrics evaluated. The considerable decreases in average and maximum operating costs suggest that the intelligent approach, through the use of advanced optimization methods or predictive analytics, enables efficient operations at both the minimum and maximum, unlike the uncontrolled and controlled methods. This assessment highlights the imperative importance of adopting more advanced operating systems, possibly supported by the use of advanced optimization techniques or predictive analytics, which can produce significant economic benefits, especially in the context of long-term operating costs.

Table 2. Operating costs in Case 2

Strategy	Average (yuan)	Maximum (yuan)	Minimum (yuan)
Uncontrolled strategy	1832	2098	1685
Controlled strategy	1763	1985	1622
Intelligent strategy	1487	1517	1436

4.3. Comparision to other methods

A set of benchmark problems is solved, and the modified SOS algorithm is compared with some of the well-known optimization algorithms to illustrate the advantages it offers. The optimization algorithms considered for comparison in this paper are the genetic algorithm (GA), PSO, ant colony optimization (ACO), and the newly proposed whale optimization algorithm (WOA). These algorithms are widely used by researchers to solve optimization problems as benchmarks because of their ability to deal with optimization problems. The Rastrigin function, with a large search space and lots of local optima, is utilized as the first test problem to compare the performance of the algorithms. The suggested SOS approach reached an optimum solution of 0.0001 within 1000 iterations, reflecting an excellent degree of accuracy and a stable convergence rate. In comparison, the GA achieved a figure of 0.035, the PSO achieved 0.015, the ACO achieved 0.02, and the WOA achieved 0.01. These results show that the SOS algorithm outperforms all other methods, representing improvements of about 99.7% compared to GA, 99.3% compared to PSO, 99.5% compared to ACO, and 99% compared to WOA.

Then, the global search ability of the algorithms was tested using the Griewank function, which is one of the more difficult test problems. The SOS algorithm achieved a fitness of 0.0002, while the GA and PSO achieved results of 0.008 and 0.003, respectively. The ACO and WOA showed similar performances, with fitness values of 0.004 and 0.002, respectively. The modified SOS algorithm demonstrated a 97.5% improvement over GA, 93.3% over PSO, and approximately 95% over ACO and WOA, confirming its superior global search ability. In the third experimental evaluation, the well-known CEC 2013 problem set was used to test the SOS algorithm's robustness, versatility, and efficiency in the optimization process. Here, the SOS algorithm produced better results compared to other algorithms by consistently providing optimal fitness values for single-objective and multi-objective optimization tasks. In particular, the SOS algorithm reached an average fitness value of 0.002 across 10 test scenarios, outperforming the performance metrics of GA (0.05), PSO (0.03), ACO (0.04), and WOA (0.015). The improvements displayed by the SOS algorithm over these rival algorithms ranged from about 96%, 93%, 95%, and 87%, respectively. The proposed SOS algorithm's adaptive strategy is an important factor responsible for its efficiency. The adaptive strategy adapts to dynamically chooses the best optimization method to match the particular nature of the problem, thus leading to improved exploration and exploitation of the search space. The benefits of this method are seen through the results, where the SOS algorithm not only outperforms conventional algorithms but is also characterized by enhanced stability and improved convergence rates while addressing challenging optimization problems.

4.4. Sensitivity analysis

A sensitivity analysis was conducted to examine how variations in key parameters affect the performance of the system. The focus was on three critical factors: energy price fluctuations, renewable energy penetration, and battery storage capacity. Each parameter was adjusted by ±20 % while keeping the others constant, allowing for an isolated evaluation of its effects on total operational costs, energy utilization efficiency, and system reliability. When energy prices increased by 20%, total operational expenses rose 14.8 %, while energy utilization efficiency declined by 3.7%, indicating a greater financial burden and reduced reliance on external energy sources. Conversely, a 20% drop in energy prices caused a 13.2% cut in total costs, with a 4.2% improvement in energy utilization efficiency, meaning that reduced costs encourage greater consumption of energy from external sources. In terms of the integration of renewable energy, a 20% increase caused the total costs to decrease by 9.5%, while energy utilization efficiency improved by 6.8% as greater integration of renewable energy reduced the use of conventional sources. In contrast, decreasing the availability of renewable energy by 20% led to an increase in total cost by 11.3 %, along with energy utilization efficiency decreasing by 5.9 %, to emphasize the cost and operational effects of limited integration of renewable resources. A change in the capability for battery storage significantly influenced the system performance. A 20% increase in storage capacity came with an 8.2% corresponding cost reduction, combined with an equally enhanced 5.4% energy utilization efficiency, thus proving the benefits of advanced energy storage systems. A 20% cut in storage space, on the other hand, caused an increase by 9.7% in cost, coupled with a resultant 6.3% drop in energy utilization efficiency, highlighting the paramount nature of storage for system flexibility as well as economic resilience. The analysis points towards the variability of energy pricing having the most significant effect on total cost, while utilization efficiency is significantly influenced by the proportion of renewable energy. Battery storage capacity has the vital responsibility to cut costs as well as increase system flexibility, meaning investments made into renewable energy projects as well as storage technologies, can have better economic results under different scenarios.

5. Conclusion

The proposed energy optimization framework effectively integrates renewable energy sources, EVs, and battery storage systems into local energy grids, addressing uncertainties in demand fluctuations, real-time pricing, and renewable energy generation. By using a flexible approach for charging and discharging EVs that considers market conditions, the model improves how the grid works, lowers operating costs, and increases financial gains. The results indicate a 14.3% reduction in average operating expenses, with a minimum cost of 1436 yuan, while peak costs are reduced by 27.7% compared to uncontrolled strategies. The intelligent charging and discharging mechanism optimally schedule energy transactions, reducing grid stress and improving load balancing. The modified SOS algorithm performs much better at solving the multi-objective optimization problem, achieving 99.7% more accuracy than the GA and a 97.5% improvement over other common optimization methods in tests. The results confirm that the proposed approach significantly improves cost efficiency, enhances operational flexibility, and ensures sustainable energy management in smart grids. For future work, this research can be extended by incorporating more advanced forecasting techniques for renewable energy generation and electricity pricing, further improving the adaptability of the model. Additionally, the integration of vehicle-to-grid (V2G) technology and blockchain-based energy trading mechanisms could enhance transaction security and decentralized grid management. Exploring real-world implementation in large-scale distributed energy networks will further validate the practical impact of the proposed approach.

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