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Multi-energy dispatching for uncertainty EV demand: A simulation approach

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Uncertainty and randomness in demand and supply bring significant challenges to the stable operation of the grid and the scheduling planning of multi-energy sources. To solve these challenges, we propose and analyze a multi-energy dispatching model which minimizes the total cost and enhances the efficiency of supplying power. Specifically, we design matching algorithms that simulate an appropriately scaled sequence of stochastic EV demand. We also analyze four different energy dispatching scenarios proving that the scheduling model and the multi-energy synergistic microgrid structure can bring higher efficiency and lower costs. Our main contribution is using a simulation approach to take EVs into account for demand-side uncertainty, which significantly improves the efficiency of grid dispatch.

KEYWORDS

uncertainty EV demand, simulation approach, multi-energy sources, microgrid, solar power

1 Introduction

Most electricity has been produced through fossil fuels (e.g., coal, natural gas, and oil) with depleting reserves and unstable prices. They emit large amounts of greenhouse gases, which are very unfriendly to the environment (Akram et al., 2018). In order to ensure reliable and environmentally friendly power generation, renewable energy sources are increasingly becoming alternatives to fossil fuels. However, as the inherent intermittency of renewable energy generation imposes significant forecast uncertainty on the supply side, it leaves a fundamental challenge for grid energy dispatching (Hosseini et al., 2020).

In terms of the demand side, according to data from China's Ministry of Public Security, as of the end of June 2022, the number of new energy vehicles in China has reached 10.1 million, of which EVs accounted for 80%. The growing number of EVs will produce new and unpredictable load conditions for the electrical networks (Buzna et al., 2021). However, affected by battery capacity and user behavior, the distribution of EV charging load has strong randomness (Huang et al., 2022), which cannot be ignored and will largely influence the energy dispatch decision from the demand side.

The decision maker must integrate regional renewable and traditional energy based on the above two uncertain factors. Therefore, the purpose of this paper is to propose a solution to dispatch microgrid energy. Considering the uncertainty of the arrival time and charging demand of EVs, this paper proposes a simulation model to optimize the interests of grid operators by modeling the uncertainty of various parts in the grid system and the demand for EVs. We brought the EV simulation data, the main grid load, and distributed solar power data into the optimization scheduling model. In order to improve the original load dispatching model, the satisfaction of the grid system with the uncertain charging demand of EVs is added to the objective function to measure the effectiveness of the dispatching model.

Compared with the existing research works on multi-energy microgrid dispatch, the significant contributions of this paper can be summarized as follows:

(1) We propose a multi-energy microgrid deployment method that considers supply and demand uncertainty. The microgrid system comprises distributed power sources, energy storage, and traditional energy sources. The numerical results show that our chosen deployment method has more robust reliability compared to microgrids with different energy structures.
(2) We propose a simulation-based optimal scheduling model. The model reconciles the uncertainty of EV access and charging with the uncertainty of distributed generation such as solar energy, considers critical factors such as carbon emissions and EV charging demand satisfaction, and converts the multi-objective scheduling problem into a single-objective decision. The optimal scheduling scheme is obtained using an exact solution method.

(3) Compared with existing research, our model not only effectively reduces the total cost of system operation but also improves the stability of the microgrid load and the satisfaction rate of EV random charging demand. The multi-energy synergistic microgrid structure has higher efficiency and lower cost under demand uncertainty providing solid practical guidance for grid energy dispatching.

This paper is structured as follows: The second section describes the relevant literature. Section 3 proposes the multi-energy microgrid energy optimal dispatch model considering the uncertain demand for EVs. Then, the simulation approach is introduced in Section 4. Section 5 is about the simulation results and discussion. The final part contains the conclusion, limitations, and future research.

2 Literature review

Our work considers the uncertainty on the demand side of multi-energy systems. With the massive popularity of EVs, multi-energy system scheduling and system optimization operations face new challenges (Xu et al., 2018). EVs, bring new uncertainty to the demand side (Xu et al., 2018), which is reflected in the time when EVs are connected and off the grid, the uncertainties of charging demand, and the uncertainties of batteries (Pan et al., 2018). Leou et al., 2015 applied Poisson distribution to the model to determine the average number of EVs starting charging within each time interval when building the load behavior model of electric vehicle charging stations, as Poisson distribution is appropriate for models waiting for an occurrence. The charging demand for electric vehicles is related to the state of charge and driving distance. Li et al., 2019 and Wang et al., 2020 believed it followed a normal distribution. In this paper, considering the uncertain demand side of the multi-energy system brought by EVs, Poisson distribution is used to simulate the uncertain arrival and departure law of EVs, and normal distribution is used to simulate charging demand. Compared with other relevant literature, for example, Pan et al., 2018 classified EVs with the same access time and departure time into one cluster and divided a large number of EVs into several clusters, the processing method in our paper is more accurate. Furthermore, the simulation method reduces the computational burden compared with the study by Mobasseri et al., 2022, where the refueling demand of fuel cell EVs was simulated *via* scenarios.

Our work is also related to the literature on multi-objective optimization. Hong et al., 2013 and Liu et al., 2022 took multiple objectives, such as the economy and environment of the system, into account and used a genetic algorithm to solve the optimization problem. However, the results obtained by the meta-heuristic are not optimal, and the calculation process is complicated. Inspired by Wu et al., 2016, with the dual objectives of charging demand and the total cost considered, we deal with the multi-objective decision problem synthesized into a single objective problem, simplifying the calculation and results more accurately. In addition, the sensitivity test of λ can provide a reference basis for decision-making. If λ is approaching 0, it means that the model focuses on meeting EV charging requirements; otherwise, more emphasis is put on reducing the cost.

Collaborative scheduling of supply and demand in multi-energy systems has excellent economic and environmental benefits. Pan et al., 2018 analyzed and compared the optimization results of different energy center structures and found that introducing the power to gas and gas storage equipment can improve the system operation. In order to illustrate the influence of the microgrid

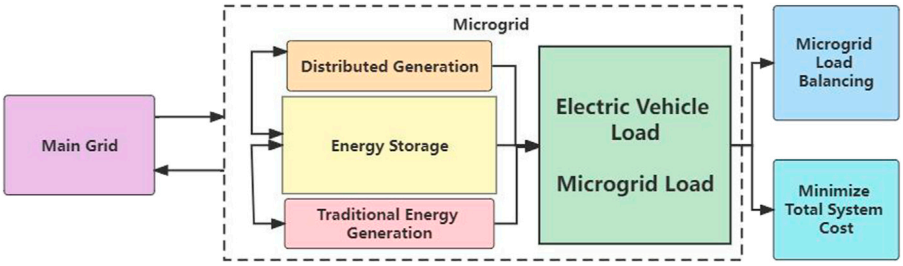

FIGURE 1
Power grid system structure.

structure on the scheduling scheme, this paper makes a more comprehensive and consistent comparison through several variables, including energy storage equipment, thermal power generation, and Evs orderly charging.

Table 1 compares this paper with other relevant literature.

3 Microgrid load optimal scheduling model

Considering the uncertainty of the arrival time and charging demand of EVs, this paper proposes a simulation model to optimize the interests of grid operators by modeling the uncertainty of various parts in the grid system and the demand for EVs.

3.1 Microgrid structure considering EVs' load

It is assumed that there are multiple distribution subsystems in the power grid that will supply power to the entire microgrid, including thermal power, solar power, main grid and energy storage, while the three factors of microgrid base load, EV load, and grid electricity sales consume electricity. The multi-energy grid structure described in this paper is shown in Figure 1.

3.2 Assumptions and notations

In this typical energy system, in order to simulate the actual dispatching scenario of the microgrid as much as possible, and at the same time simplify the model within the allowable range, we formulate the following assumptions.

(1) EVs are not used as energy storage devices but as consumers and do not provide energy to the microgrid.
(2) The charging demand of each EV is uncertain, and the arrival time is also uncertain.
(3) Energy storage equipment and distributed power supply all supply power or store energy as a whole.
(4) The cost of the microgrid system in this paper is mainly composed of the following parts: the operating cost and startup cost of various equipment in the microgrid, the transaction cost between the microgrid and the main grid, and the cost of carbon emissions disposal. The carbon emission of the microgrid is mainly carbon dioxide, which is generated by fuel combustion and grid operation. Here we only consider the cost of carbon dioxide disposal.

The key mathematical notations used in this paper are listed in Tables 2, 3, 4.

3.3 Objective functions

The goal of optimal scheduling of microgrid system load is to minimize the total system cost, which can be divided into the following parts.

(1) If demand for EVs cannot be met due to the grid itself, there is a penalty cost per unit of unmet electricity.

$$C_1 = \sum_{i\in I}\left(D_i^{EV} - \sum_{t\in T} P_{i,t}^{EV}\cdot \Delta t\right)\cdot \rho^u \tag{1}$$

(2) The operating cost of energy storage equipment, which will be incurred as long as there is power consumption.

$$C_2 = \sum_{t\in T}\rho^{ES}\cdot\left(P_{t,ch}^{ES} + P_{t,dch}^{ES}\right)\cdot\Delta t \tag{2}$$

(3) Cost of thermal power, including operating costs and fuel costs.

$$C_3 = \sum_{t\in T}\left(\rho^{TE} + \frac{\rho^G}{\eta^{TE}}\right)\cdot P_t^{TE}\cdot\Delta t \tag{3}$$

TABLE 1 Comparison of related literature.

Studies	Simulation method of EVs	Multi-objective	Converted into a single-objective decision	Comparisons
Mobasseri et al. (2022)	EVs demand is modelled *via* scenarios	×	/	×
Liu et al. (2022)	×	√	×	√
Wu et al. (2016)	×	√	√	×
Pan et al. (2018)	Dealt with by fuzzy theory	√	√	√
Hong et al. (2013)	×	√	×	×
This study	Simulated by Poisson distribution and normal distribution	√	√	√

TABLE 2 Variable collections.

Symbol	Description
I	EV collectionact
T	Total time set, with one unit time of 10 min

(4) Main network and micro-network transactions, microgrids generate additional revenue by selling excess electricity to the main grid.

$$C_4 = \sum_{t\in T}\left(\rho^{buy} \cdot P_t^{buy} - \rho^{sell} \cdot P_t^{sell}\right) \cdot \Delta t \tag{4}$$

(5) The start-up cost of thermal power equipment can be ignored if thermal power is not needed to supplement the electricity gap.

$$C_5 = z_{te} \cdot \rho^{TE} \tag{5}$$

(6) Costs caused by carbon emissions, only carbon dioxide emissions and disposal are considered here.

$$C_6 = \rho^{CO_2} \cdot Q \tag{6}$$

where Q represents the total amount of carbon emissions, which is calculated as follow.

$$Q = e_G \cdot \sum_{t\in T} \frac{P_t^{TE}}{\eta^{TE}} \cdot \Delta t + e_E \cdot \left(\sum_{t\in T}\sum_{i\in I} P_{i,t}^{EV} \cdot \Delta t + \sum_{t\in T} P_{t,ch}^{ES} \cdot \Delta t + \sum_{t\in T} P_t^{sell} \cdot \Delta t\right) \tag{7}$$

The multi-objective decision problem is synthesized into a single-objective problem and λ is used to adjust the relationship between the objectives. When λ is close to 1, the model focuses on satisfaction with EV charging demand, and when λ is close to 0, the model focuses on reducing microgrid operating costs.

$$\min C = \lambda \cdot C_1 + (1-\lambda) \cdot (C_2 + C_3 + C_4 + C_5 + C_6) \tag{8}$$

TABLE 3 Decision variables.

Symbol	Description	Unit
$P_{i,t}^{EV}$	Charging power of EV i at time t	kW
$P_{t,ch}^{ES}$	The charging power of the energy storage device at time t	kW
$P_{t,dch}^{ES}$	The discharging power of the energy storage device at time t	kW
P_t^{TE}	Energy supply of thermal power generation at time t	kW
P_t^{buy}	The microgrid buys power from the main grid at time t	kW
P_t^{sell}	The microgrid sells power to the main power grid at time t	kW
$z_{i,t}$	Whether the EV i charged at time t	Binary
$z_{t,ch}$	Whether the energy storage is charged at all the time t	Binary
$z_{t,dch}$	Whether the energy storage device discharges at time t	Binary
$z_{t,mb}$	Whether to buy electricity from the main grid at time t	Binary
$z_{t,ms}$	Whether to sell electricity to the main grid at all time t	Binary
z_{te}	Whether to use thermal power during a cycle	Binary

TABLE 4 Parameters.

Symbol	Description	Unit
P_t^{SE}	Solar energy supplies power at time$t$	kW
P_t^{load}	The basic load of the microgrid at time t	kW
r	Maximum climbing power of various power sources	kW
D_i^{EV}	Charging demand for EV i	kW·h
ρ^u	Unit penalty costs for failing to meet EV's charging demand	¥/(kW·h)
ρ^{ES}	Unit operating cost of energy storage	¥/(kW·h)
ρ^{TE}	Unit operating cost of thermal power equipment	¥/(kW·h)
ρ^G	Unit cost of fuel for thermal power generation	¥/(kW·h)
ρ^{buy}	Unit cost of purchasing electricity from the main grid	¥/(kW·h)
ρ^{sell}	The price that the microgrid sells electricity to the main grid	¥/(kW·h)
ρ^{CO_2}	Disposal cost of unit CO_2 emission	¥/kg
ρ^{start}	Thermal power start-up cost	¥
e_G	CO_2 emissions per unit of thermal power generation	kg/(kW·h)
e_E	CO_2 emissions per unit of electricity consumption in the grid	kg/(kW·h)
η^{TE}	Thermal power conversion efficiency	%
η_{ch}^{ES}	Charging efficiency of energy storage	%
η_{dch}^{ES}	Discharge efficiency of energy storage	%
$t_{i,arr}$	Arrival time of EV i	T
$t_{i,dep}$	Leaving time for EV i	T
$t_{i,full}$	The amount of time needed for EV i to be fully charged	T

3.4 Model constraints

3.4.1 System balance constraints

Constraint Eq. 9 describes the power balance of power consumption and supply in the microgrid system. System load imbalance will have a considerable impact on electricity safety.

$$P_t^{SE} + P_t^{TE} + P_t^{buy} + P_{t,dch}^{ES} = P_t^{load} + \sum_{i\in I} P_{i,t}^{EV} + P_t^{sell} + P_{t,ch}^{ES} \tag{9}$$

3.4.2 Related constraints of EVs

$$E_{i,t+1}^{EV} = E_{i,t}^{EV} + P_{i,t}^{EV} \cdot \eta_{ch}^{EV} \cdot \Delta t, \forall t \in \left[t_{i,start}, t_{i,end}\right) \tag{10}$$

$$0 \leq \sum_{t\in T_i} E_{i,t}^{EV} \leq D_i^{EV}, \forall i \in I \tag{11}$$

$$t_{i,arr} \leq t_{i,start}\ ,\ t_{i,end} \leq t_{i,dep}\ ,\ 0 \leq t_{i,end} - t_{i,start} \leq t_{i,full}, \forall i \in I \tag{12}$$

$$0 \leq P_{i,t}^{EV} \leq P_{i,max}^{EV} \cdot z_{i,t}^{EV}\ ,\ z_{i,t}^{EV} = \begin{cases} 1 & \forall t \in [t_{start}, t_{end}] \\ 0 & \forall t \notin [t_{start}, t_{end}] \end{cases} \tag{13}$$

$$\left|P_{i,t+1}^{EV} - P_{i,t}^{EV}\right| \leq r^{EV}, \forall i \in I, t \in \left[t_{i,start}, t_{i,end}\right) \tag{14}$$

Constraint Eq. 10 represents energy conservation in an EV charging state. Constraint Eq. 11 describes the charging capacity limit for EVs. Constraint Eq. 12 characterizes the quantitative relationship at critical moments, such as the arrival of EVs and the start of charging. Constraint Eq. 13 limits the charging power of each EV within a specific range, and the upper and lower limits of the charging power are both 0 when not charging. Constraint Eq. 14 describes the power grid climb power limit, which means the power change between two time periods cannot exceed a particular value.

3.4.3 Related constraints of energy storage equipment

$$E_{t+1}^{ES} = E_t^{ES} + P_{t,ch}^{ES} \cdot \eta_{ch}^{ES} \cdot \Delta t - \frac{P_{t,ch}^{ES} \cdot \Delta t}{\eta_{dch}^{ES}}, \forall t \in T \tag{15}$$

$$\begin{aligned} 0 \leq P_{t,ch}^{ES} \leq P_{ch,max}^{ES} \cdot z_{t,ch} \\ 0 \leq P_{t,dch}^{ES} \leq P_{dch,max}^{ES} \cdot z_{t,dch} \end{aligned} \tag{16}$$

$$z_{t,ch} + z_{t,dch} \leq 1, \forall t \in T \tag{17}$$

$$z_{t,ch} \in \{0,1\}, z_{t,dch} \in \{0,1\} \tag{18}$$

$$\begin{aligned} \left|P_{t+1,ch}^{ES} - P_{t,ch}^{ES}\right| \leq r_{ch}^{ES} \\ \left|P_{t+1,dch}^{ES} - P_{t,dch}^{ES}\right| \leq r_{dch}^{ES} \end{aligned} \tag{19}$$

Constraint Eq. 15 represents the energy conservation equation for stored energy. Constraint Eq. 16 limits the charging and discharging power of the energy storage. Constraint Eq. 17 describes that the charging and discharging processes of the energy storage cannot proceed simultaneously. Constraint Eq. 19 represents the climb power limit.

3.4.4 Related constraints on solar power generation

$$P^{SE}_{min} \le P^{SE}_t \le P^{SE}_{max}, \forall t \in T \tag{20}$$

$$\left|P^{SE}_{t+1} - P^{SE}_t\right| \le r^{SE} \tag{21}$$

Constraints Eqs. 20, 21 represent distributed energy (solar) power constraints and ramp power constraints.

3.4.5 Constraints related to main grid transactions

$$\begin{aligned} 0 &\le P^{buy}_t \le P^{buy}_{max} \cdot z_{t,mb} \\ 0 &\le P^{sell}_t \le P^{sell}_{max} \cdot z_{t,ms} \end{aligned} \tag{22}$$

$$z_{t,mb} + z_{t,ms} \le 1, \forall t \in T \tag{23}$$

$$z_{t,ms} \in \{0,1\}, z_{t,mb} \in \{0,1\} \tag{24}$$

$$\begin{aligned} \left|P^{sell}_{t+1} - P^{sell}_t\right| &\le r^{sell} \\ \left|P^{buy}_{t+1} - P^{buy}_t\right| &\le r^{buy} \end{aligned} \tag{25}$$

Constraint Eq. 22 limits the power limit of the microgrid to purchase and sell electricity from the main grid at each moment. Constraint Eq. 23 states that the power purchase and sale behavior of the microgrid cannot be carried out at the same time, and constraint Eq. 25 describes the climbing power of power purchase and sale.

3.4.6 Power supply constraints of thermal power generation

$$0 \le P^{TE}_t \le P^{TE}_{max} \tag{26}$$

$$z_{te} \in \{0,1\} \tag{27}$$

$$\left|P^{TE}_{t+1} - P^{TE}_t\right| \le r^{TE} \tag{28}$$

$$\sum_{t \in T} P^{TE}_t \cdot (1 - z_{te}) = 0 \tag{29}$$

Constraints Eqs. 26, 28 describe the power limits and ramp-up power limits for conventional energy generation.

4 Simulation

4.1 Simulation of uncertain arrival and departure times for EVs

In this model, uncertain variables are represented by simulation methods. Leou et al. (2015) proposed that the uncertain arrival law of EVs can be described by the arrival frequency per unit time, which can be simulated by Poisson distribution, as shown in Eq. 30.

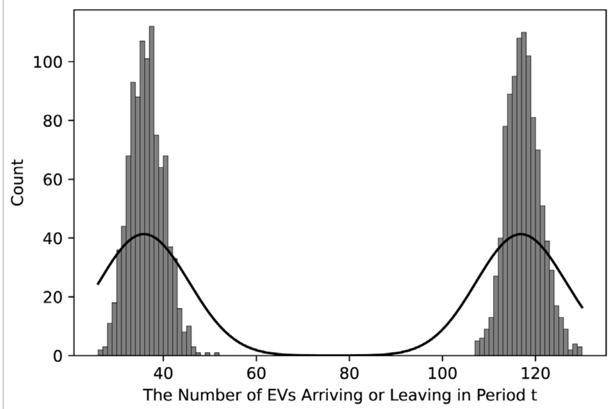

FIGURE 2
The Number of EVs Arriving or Leaving in Period t.

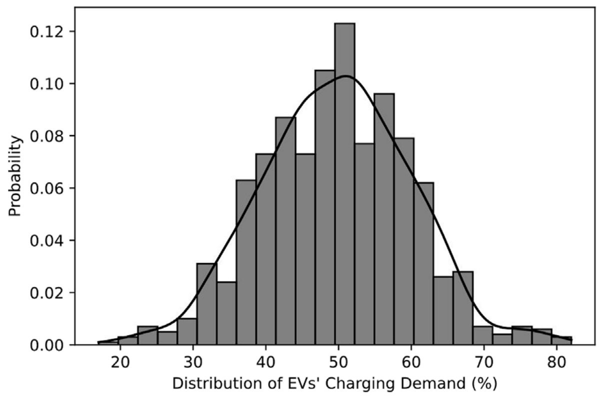

FIGURE 3
Distribution of EVs' charging demand (%).

$$P(X_t = k|\lambda_t) = \frac{\lambda_t^k}{k!} e^{-\lambda_t}, k = 0, 1, 2 \ldots \tag{30}$$

where λ_t is the average number of EV arrivals in unit time t, and X_t is the number of EV arrivals in unit time t.

The operating system used for this simulation is win10 × 64, and the programming language is Python 3.9. According to the actual situation, the departure and arrival peak times of private EVs in the city are 6:00–9:00 and 16:30–19:30. In this paper, a day is divided into 144 periods, each period is 10 min, and the origin of the coordinates is 12:00 noon to simulate the arrival and departure time of EVs, as shown in Figure 2.

TABLE 5 Typical baseload and solar powered power data.

Period	Base load (KW)	Solar energy (KW)
00:00–01:00	101	0
01:00–02:00	80	0
02:00–03:00	42	0
03:00–04:00	101	0
04:00–05:00	67	0
05:00–06:00	82	0
06:00–07:00	85	0
07:00–08:00	111	0
08:00–09:00	115	63
09:00–10:00	121	206
10:00–11:00	99	731
11:00–12:00	104	1286
12:00–13:00	122	1389
13:00–14:00	136	1259
14:00–15:00	138	1395
15:00–16:00	119	1040
16:00–17:00	139	603
17:00–18:00	157	300
18:00–19:00	102	0
19:00–20:00	127	0
20:00–21:00	135	0
21:00–22:00	97	0
22:00–23:00	90	0
23:00–24:00	110	0

4.2 Simulation of uncertain charging demand for EVs

Li et al., 2019 and Wang et al., 2020 proved that an EV's state of charge (SOC) is related to the driving distance, and a normal distribution can represent the driving distance. Its probability density is shown in Eq. 31. The relationship between this and the charging demand is shown in Eq. 32.

$$f_d(x) = \frac{1}{\sqrt{2\pi} \cdot x \cdot \sigma_d} \exp\left[-\frac{(\ln x - \mu_d)^2}{2\sigma_d^2} \right] \tag{31}$$

$$d_i^{EV} = 1 - SOC_i = \frac{d}{d_{\max}} \tag{32}$$

where d_i^{EV} is the percentage of the charging demand of the EV$i$to the total electricity, d is the actual driving distance of the EV, and $d_{\max}$ is the maximum driving distance of the EV.

The normal distribution $N(0.5, 0.1^2)$ is used to describe the proportion of the EVs' uncertain charging demand to its total power. The simulation results are shown in Figure 3.

5 Results and discussion

5.1 Scheduling results

The parameters and energy supply datasets of the microgrid system used in this study come from a set of typical datasets and parameter tables (Hong et al., 2013). The main grid load distributed solar power selected in this paper is shown in Table 5.

Gurobi Optimizer (Version 9.1.2) was used to solve the model. After inputting a set of actual parameters, the solution result is shown in Figure 4.

5.2 Analysis of scheduling results

Figure 4 depicts the grid maintaining power balance during one cycle of operation. The upper part describes the total power supply of the grid in each time interval, and the sources include solar power supply, energy storage discharge power, thermal power generation, and main grid power purchase power, and the lower part describes the power consumption of the grid in each time interval. Total power, including EV charging power, energy storage device discharging power, main grid electricity sales power, and basic load.

It can also be seen from Figure 4 that the charging peak period of EVs and the time of solar power generation hardly coincide, which is in line with common sense. During the daytime, solar energy is the main energy source, and the microgrid relies on energy storage and main grid transactions to maintain balance; at night, when EVs begin to charge, the microgrid mainly relies on thermal energy generation, energy storage discharge, and main grid transactions to maintain system balance.

Comparing the processing method of the multi-objective problem in this paper with the processing method in the related work (Pan et al., 2018) that also obtains the exact solution under the same example, the obtained time comparison is shown in Table 6.

Pan et al., 2018 introduced the membership function into the multi-objective optimization problem. Considering that the optimal value of the objective function we need is the cost of system operation, which has practical significance, this method will become relatively complicated in this scenario.

Adjust the value of λ to obtain the cost caused by unmet demand, total system cost, and demand satisfaction rate, as shown in Table 7.

It can be seen that the more decision-makers pay attention to the satisfaction rate of the microgrid for the uncertain demand of EVs, the lower the cost caused by the charging demand of EVs. However, at the same time, the total cost of the microgrid system will rise to a certain extent, which requires decision-makers to

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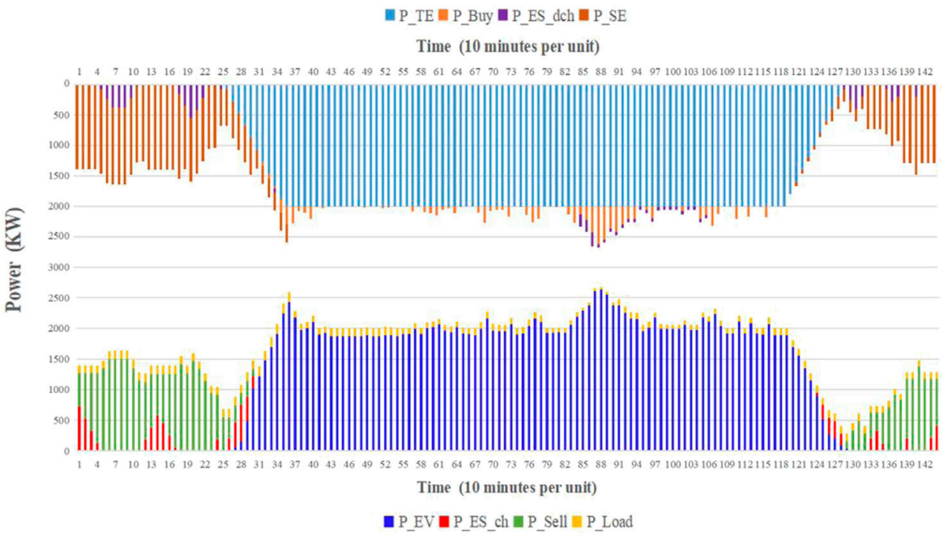

FIGURE 4
Multi-energy power distribution in each period.

TABLE 6 Comparison with related work.

	The method of this paper	The method of Pan et al. (2018)
Run time (seconds)	54.14	55.31

TABLE 7 Sensitivity analysis of cost weights.

Weight	0.10	0.30	0.50	0.70	0.90
C1	44,746	44,746	14,610	14,599	13,028
Total Cost (*10^7)	3.913	3.913	3.944	3.945	3.964
Demand Satisfaction Rate	75%	75%	91%	92%	95%

TABLE 8 Sensitivity analysis of energy storage.

Energy Storage (KW·h)	2000	3000	4000	5000	6000
C1	15,141	14,599	14,058	13,517	12,975
Total Cost (*107)	4.001	3.945	3.881	3.818	3.756
Demand Satisfaction Rate	91.5%	91.8%	92.1%	92.4%	92.8%

make a trade-off between satisfaction and cost to formulate a more economical and practical compliance scheduling scheme.

The energy storage system in the microgrid can absorb excess energy or release energy to compensate for the microgrid's lack of energy and plays a crucial role in maintaining the stable distribution of the microgrid load. With the upgrading of technology or the increase in the number of energy storage devices in the microgrid, the energy storage capacity in the microgrid will also increase accordingly. When changing the microgrid's energy storage capacity, set λ to 0.7, the impact on the dispatching results is shown in Table 8.

Table 8 proves that as the capacity of the energy storage system increases, both the demand satisfaction cost and the total cost of the system show a downward trend, and the demand satisfaction rate continues to rise. This shows that decision makers can improve the economic and social benefits of microgrid charging for EVs by increasing the energy storage upper limit of the energy storage system.

As EV technology advances, EV battery capacity will also increase. Sensitivity analysis of the model is carried out with the change of the battery capacity of the EV, and the results are shown in Table 9.

TABLE 9 Sensitivity analysis of EVs' battery capacity.

EVs' battery Capacity (KW·h)	60	70	80	90
C1	14,599	42,806	59,641	67,096
Total Cost (*10^7)	3.945	4.753	7.107	8.626
Demand Satisfaction Rate	91.8%	79.5%	72.0%	67.4%

Keeping the original electric vehicle arrival and demand distribution unchanged, and changing the number of electric

TABLE 10 Sensitivity analysis of total number of EVs.

Total number of EVs (*10^3)	1	1.25	1.5	2.0
C1	14,599	55,102	102,418	179,574
Total Cost (*10^7)	3.945	4.913	5.838	9.347
Demand Satisfaction Rate	91.8%	75.3%	62.2%	50.1%

TABLE 11 Comparison of cost, demand satisfaction rate and load variance for scenarios 2–4.

Scenarios	Scenario2	Scenario3	Scenario4
Total Cost (*10^7)	3.945	6.2806	4.204
Demand Satisfaction Rate	91.8%	65.0%	86.2%
Microgrid Load Variance (*10^5)	2.84	4.44	3.36

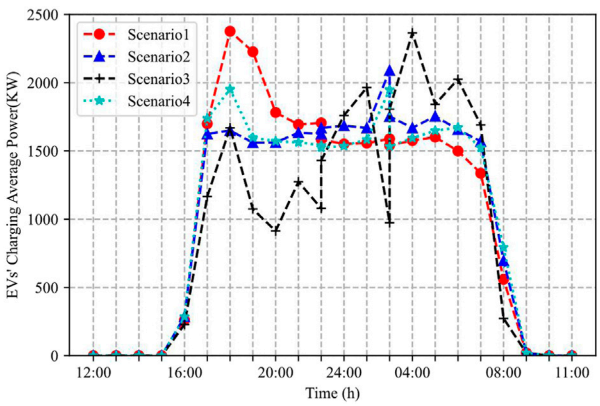

FIGURE 5
Average charging power of EVs in each time period under four scenarios.

vehicles connected to the system, the changes in related indicators are shown in Table 10.

The results in Tables 9, 10 show that holding other existing parameters constant, an increase in EV battery capacity and the total number of EVs leads to a decrease in charging satisfaction rates and an increase in total system cost. Decision makers need to increase the energy storage capacity of the microgrid or the energy supply capacity of thermal energy sources on time so that the microgrid system can adapt to this change and avoid significant changes in the total system cost and EV charging satisfaction needs.

5.3 Comparison of various microgrid configuration methods

In order to illustrate the influence of the microgrid structure on the dispatching scheme, this paper considers dispatching under two other microgrid configuration schemes. We designed four scenarios to compare the scheduling model under these three configuration schemes with the basic model under the EV disorder charging scenario. The four scenarios are described as follows.

Scenario 1: Basic model, that is, a microgrid scheduling model that considers the disordered charging of EVs under the constraints of total power.

Scenario 2: The microgrid structure includes distributed power, energy storage, and thermal energy generation, and EVs are charged in an orderly manner.

Scenario 3: The microgrid structure only includes distributed power and energy storage, and EVs are charged in an orderly manner.

Scenario 4: The microgrid structure includes distributed and thermal energy sources, and EVs are charged in an orderly manner.

Under the condition that the weight λ is taken as 0.7 and the other main parameters remain unchanged, the average charging power of EVs in each period in the four scenarios is shown in Figure 5.

Under the three scenarios of orderly charging of EVs, the charging demand at the peak period has been allocated more orderly manner. The disordered charging of EVs in Scenario 1 causes the microgrid to allocate a large amount of charging load during the afternoon-evening period. The curves of scenario 2 and scenario 4 are similar, the demand is evenly scheduled in each period, and the load fluctuation is slight. The curve of Scenario 3 is more volatile and tends to shift more charging demand to the early morning hours.

Next, the total cost, demand satisfaction rate, and microgrid load variance of the last three scenarios are compared, as shown in Table 11.

The cost, demand satisfaction rate, and load variance of scenario 2 are better than those of the other two scenarios. The indicators of scenario 4 are better than those of scenario 3 because there is no energy storage device in Scenario 4; excess or missing energy can be directly sold or supplemented through the primary grid, so there are additional benefits, and the load is relatively stable. In Scenario 3, no part is missing from thermal energy supplements, and the energy storage capacity can only be reasonably arranged. More costs will be invested in purchasing electricity from the primary grid.

Based on the above comparison results, our model not only effectively reduces the total cost of system operation but also improves the stability of the microgrid load and the satisfaction rate of random charging requirements for EVs. At the same time, it also shows that under uncertain demand, the multi-energy synergistic microgrid structure has higher efficiency and lower cost.

6 Conclusion

This paper proposes a multi-energy scheduling model for microgrids based on the simulation method, which uses Poisson distribution and normal distribution to simulate the time point when EVs connect or leave the microgrid and the charging demand of EVs. In order to improve the original load scheduling model, the degree of satisfaction of the grid system with the uncertain charging demand of EVs is added to the objective function to measure the effectiveness of the scheduling model. Using a set of actual data as parameters to solve the scheduling model, the demand satisfaction rate can reach more than 90%, and the total cost in one cycle is about 40 million. The sensitivity analysis is carried out on energy storage capacity, the EV battery capacity, and the cost weight in the target, which shows that the stability of the model is good. In addition, this paper compares the scheduling models in three different scenarios with the existing models, proving that this scheduling model and the multi-energy synergistic microgrid structure can bring higher efficiency and lower costs.

However, this article also has the following shortcomings. Firstly, there have been many V to G modes, namely Vehicle-to-grid, a two-way interactive technology from EVs to the grid that can realize two-way electric energy storage (Cai Li et al., 2020). Therefore, the impact of the access of EVs on the power grid is not only limited to increasing the power grid load but also may provide power to the power grid. However, our article does not consider the impact of this aspect and only treats EVs as electrical energy consumables. In future research, the V2G mode can also be considered in the model through the way that the grid directly dispatches each EV connected with other power generation units in a unified manner, and adopt an intelligent algorithm to control the V2G operation of each vehicle to restore the reality of EV access to a greater extent.

Second, in fact, in the process of modeling, we only considered the costs of punishment, pollution control, operation, thermal power generation, foremost microgrid transactions, and constraints such as system balance, EV energy storage equipment, and distributed power sources. However, many other costs and constraints were still not considered and should be included in subsequent studies.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

Author contributions

SY: Formal analysis, Writing—original draft, Conducting experiments and analyses, Revising the manuscript critically for important content and English writing. YD: Writing original draft, Building the research process and mathematical model, Revising the manuscript critically for important content. FZ: Writing original draft, Revising the manuscript critically for important content and English writing. ZQ: Resources, Writing—review. SJ: Resources, Methodology, Writing—review and; editing. QY: Writing original draft, Methodology. YX: Resources, Formal analysis, Supervision, Writing—review and; editing.

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Conflict of interest

Author SY is employed by Weiwojiangxin Tech. Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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