Multi-objective economic emission dispatch of thermal power-electric vehicles considering user’s revenue

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Abstract
In recent years, the rapid development of electric vehicles has increased the load power system and brought new challenges to the safe and stable operation of the grid. Although the vehicle-to-grid technology can reduce the load that electric vehicles put on the grid, without any incentives, electric vehicle owners are more inclined not to use vehicle-to-grid services. In this paper, therefore, a new dynamic economic emission model based on electric vehicles (DEED_EV) is proposed to maximize the electric vehicle user’s revenue, as well as minimize the fuel cost and emission of the thermal power unit. In the DEED_EV model, the stochastic of electric vehicles user’s travel and wear of the battery, as well as some constraints such as electric vehicles charging/discharging rate and status, electric vehicles remain power, electric vehicles travel power capacity, ramp limits, up and down reserves, and the system balance are considered. To solve the DEED_EV model, a multi-objective evolutionary algorithm based on decomposition with a step-by-step constraint handling strategy is developed. Different test cases based on the 10-unit are simulated to verify the proposed model and method. The results show that the DEED_EV model not only encourages more electric vehicles to plug into the grid but also reduces the fuel cost and emission of the thermal power unit. Besides, the electric vehicles in the DEED_EV completely realizes the peak shaving and valley filling of the load.

Keywords Dynamic power system dispatching · Electric vehicles · Multi-objective optimization · User’s revenue

1 Introduction
Green, energy-saving, and environmentally-friendly electric vehicles (EVs) have developed rapidly over the past decade, thanks to people’s concern about low-carbon life and the environment (Amjad et al. 2010; Farahani 2017; Lu et al. 2017). Various countries have also introduced policies to promote automobile manufacturers to develop superior EVs and encourage users to purchase EVs, which has increased the market share of EVs year by year. According to the “Global EV Outlook 2021” published by International Energy Agency (IEA) (Admin 2021), the global stock of EVs exceeded 10 million in 2020, a 43% increase over 2019. Despite a drop in global car sales due to the Covid-19 pandemic, about 3 million EVs were sold globally in 2020. China had about 4.5 million EVs on the road by the end of 2020, the largest number in the world. It is estimated that the global EV fleet (excluding two/three-wheelers) will reach 230 million in 2030. The expanding number of EVs will continue to reduce greenhouse gas (GHG) emissions. In 2030, the global EV fleet is estimated to reduce GHG emissions by more than one-third compared to an equivalent internal combustion engine vehicles fleet. Although the development of EVs brings benefits to the environment, the use of larger-scale EVs will add additional load to the power grid, thereby affecting the safe and stable operation of the power grid. It is worth mentioning that the battery of the EV could be also used as the energy
storage unit to store electrical energy. Moreover, EVs can be also used as a reserve energy storage unit to ensure the load demand of the system when the power supply of the generator unit is insufficient or fails. Kempton and Letendre (1997) proposed the vehicle-to-grid (V2G) technology, which allows EVs to interact with the power grid by a charging and discharging mode. Vehicles equipped with V2G services can be plugged into the grid, when they are parked at the charging station and plugged into the grid, and they can be charged or discharged (Peng et al. 2012). Therefore, the problem of EVs based on V2G services plugging into the power grid has become hot research.

Reasonable scheduling of generating units in the thermal power plant can improve the efficiency of power generation, reduce redundant power, as well as decrease the use of fossil fuels and reduce pollution emissions. The economic emission dispatch (EED) problem (Azizipanah-Abarghooei et al. 2012; Nourianfar and Abdi 2019; Xiong et al. 2012; Guo et al. 2012; Li et al. 2021; Niknam et al. 2012). Many studies about DEED problems have been published over the past decades (Arul et al. 2015; Hu et al. 2022; Mason et al. 2017; Zhang et al. 2015). However, due to the different load demand in each interval, and the ramp limits of the unit, a dynamic EED (DEED) model that is more suitable for the actual dispatch scenario was proposed (Basu 2008; Guo et al. 2012; Li et al. 2021; Niknam et al. 2012). The above literature has verified from various aspects that large-scale EVs were plugged into the grid can peak shaving and valley filling for the load. However, they failed to consider the user’s revenue of EVs or battery wear cost when EVs are plugged into the grid. The user’s revenue and battery wear cost determine whether users agree to take part in the V2G service. Usually, the repeated charge and discharge of the EV will cause wear of the battery. Consequently, without any incentives, it is difficult for users to actively participate in the V2G service. Therefore, in this paper, a novel DEED model based on EVs (DEED_EV) is proposed, which considers the maximization of user benefit and the minimization of fuel cost and pollution emission of the thermal unit. The purpose of the proposed DEED_EV model is to explore the optimal dispatching scheme considering three objectives simultaneously. In addition, the stochastic of the EV user’s travel, and wear of the battery are considered. Some constraints such as EVs charging/discharging rate and status, EVs remain power, EVs travel power capacity, units output power and ramp limits, up and down reserves, and the system balance are included in the DEED_EV model. The framework of the DEED_EV model is illustrated in Fig. 1. From Fig. 1, the framework of the proposed DEED_EV model is divided into two components. One is the thermal power plant, and the other is the EV aggregator fleets, and they interact through the dispatch center or agency. In the power grid component, it is mainly to reduce the total fuel cost and emission by controlling the output power of the thermal power unit under the premise of ensuring load demand. However, in the EV fleets component, the charging and discharging behavior of EVs is determined according to the stochastic of the user’s travel and the peak and valley state of the load.

The proposed DEED_EV is a non-convex, high-dimensional MOP with strong coupling constraints. It is hard to be solved by the conventional mathematical programming approach. In addition, the pre-handling of the constraints could reduce the calculation time and can quickly make the solutions enter the space domain to search. Therefore, according to the constraints of different components, a step-by-step adjustment constraint handling method is proposed. Firstly, the charging and discharging power in EV components is dynamically adjusted. Secondly, the output power of the thermal unit in the power grid components is adjusted to meet the power balance. Finally, the penalty function method (Qiao and Liu 2020)
is used to weigh the objective functions to get the new objective functions.

The multi-objective evolutionary algorithm based on decomposition (MOEA/D) is developed by Zhang and Li (2007) to solve the unconstraint MOPs. Because of its superior performance in solving MOPs, MOEA/D has been applied in many fields (Gopu and Venkataraman 2019; Wang et al. 2021; Xie et al. 2022; Xu et al. 2021b; Zhu et al. 2019). In this paper, the MOEA/D with a step-by-step constraint handling method (MOEA/D-SS) is developed to solve the proposed DEED_EV problem. And four test cases based on the 10-unit system are used to verify the proposed DEED_EV model and the MOEA/D-SS method. Besides, compared with the vector evaluated particle swarm optimization (VEPSO) (Greeff and Engelbrecht 2008), multi-objective different evolution algorithm with self-adaptive parameter and local search operators based on non-dominant sorting (SaMODE_LS) (Qiao and Liu 2020), non-dominant sorting multi-objective different evolution algorithm with self-adaptive parameter (NSDESa) (Qiao et al. 2021) and dynamic NSGA-II (dNSGA-II) (Kalyanmoy et al. 2007), the performance of the MOEA/D-SS in optimizing the proposed DEED_EV with complex constraints is verified. The results show that the proposed DEED_EV model can not only reduce the fuel cost and emission of the thermal power unit but also maximize the revenue of EV users. Besides, the EV charging and discharging modes of EV obtained from the proposed model are the best compared to other modes. Moreover, the EVs in the proposed model fully realize the peak shaving and valley filling of the load. Finally, the impact of battery capital cost and electricity price on the DEED_EV model is analyzed, respectively.

The rest of this paper is organized as follows. The proposed DEED_EV model is formulated in Sect. 2. Section 3 is the pre-handling of constraints and the implementation of MOEA/D-SS in DEED_EV. The experimental and discussion are given in Sect. 4. Finally, Sect. 5 is the conclusion.

2 Problem formulation

2.1 The stochastic model of electric vehicles

Generally, according to different usage scenarios, the uses of EVs include commercial vehicles, taxis, private vehicles, commuter vehicles, etc. Because commercial vehicles can travel at any moment, and taxis are driving almost all day. Therefore, they could not participate in V2G services and only exist in the grid as loads. However, private vehicles and commute vehicles are commonly used for daily commuting between home and the workplace. Consequently, when their owners are working or resting, they can participate in V2G services, cut the peak and fill the valley for the grid load. In this paper, the model of EVs is mainly private and commuter vehicles. For simplicity, suppose that an EV commutes only once a day; that is, there are two periods of driving, namely the periods to go to work and home. In these periods, EVs could not plug into the grid. Due to different work schedules, the commuting time of EV users is random. Let the time from home to workplace be the arrival time, and the time from workplace to home be the departure time. Based on the US National Household Travel Survey (NHTS 2017), the stochastic of EVs arrival time and departure time can be modeled with a normal distribution (Lu et al. 2018; Mohiti et al. 2019), respectively.

\[ F_a(t) = \frac{1}{\sigma_a \sqrt{2\pi}} e^{-\frac{(t - \mu_a)^2}{2\sigma_a^2}}, \quad 0 < t \leq 24 \]  

\[ F_d(t) = \frac{1}{\sigma_d \sqrt{2\pi}} e^{-\frac{(t - \mu_d)^2}{2\sigma_d^2}}, \quad 0 < t \leq 24 \]
where \( \sigma_a \) and \( \sigma_d \) are the variances of the arrival time and departure time, \( \mu_a \) and \( \mu_d \) are the means of the arrival time and departure time, respectively.

### 2.2 Battery wear model

The heart that drives an EV is the battery component. The battery lifetime determines the key factor for whether the user intends to buy an EV, and it also directly affects the user’s time limit for using the EV. More importantly, it is also a key factor that determines EV users’ participation in V2G services. Therefore, it is necessary to study the battery wear when EVs participate in grid V2G services. At present, there are three battery technologies, lead-acid, nickel-metal hydride, and lithium-ion, that are used most in the market (Zhou et al. 2011). These technologies have different advantages in capability, safety, life, and cost. In the same case, lithium-ion technology is widely used by automobile manufacturers because of its high-power density (Gonzalez-Castellanos et al. 2020). For simplicity, the EVs are driven by lithium-lion in this paper. The service life of the battery will degrade with calendar aging and cycling, which is mainly caused by irreversible electrochemical side reactions. This will result in a reduction in battery capacity, and the battery needs to be replaced to ensure the normal users of the EV when reduced to the standard threshold. Calendar life represents the expected life of the battery, while cycle life is usually expressed by the number of charge/discharge cycles (Wang et al. 2016).

In this paper, the revenues of a charge and discharge cycle of EV users are considered, so only the battery wear caused by the cycle is analyzed.

The cycle life of the battery is related to ambient temperature and discharge of depth (DoD). However, the researchers have shown that compared to other technology, the effect of ambient temperature on lithium-ion is less obvious (Zhou et al. 2011). In this paper, the ambient temperature is reasonably ignored, and only the impact of DoD on battery wear is analyzed. The DoD refers to the absolute discharge relative to the rated battery capacity, denoted by \( D_{od} \), which is related to the state of charge (SoC). The relationship between battery cycle life and \( D_{od} \) is defined as follows.

\[
\ln(L) = -0.795\ln(D_{od}) + 6.5425 \tag{3}
\]

where \( L \) is the number of battery cycles under \( D_{od} \). (3) can be transformed into

\[
L = 694D_{od}^{0.795} \tag{4}
\]

The \( D_{od} \) can be calculated by SoC. Therefore, during discharge, \( D_{od} \) at time \( t \) within a cycle is defined as Eq. (5), which is illustrated in Fig. 2a.

\[
D_{od} = \text{SoC}(t - 1) - \text{SoC}(t), \quad 0 < t \leq 24 \tag{5}
\]

where SoC (0) = 1 means that the initial SoC is 100%. Figure 2(b) shows that the battery cycle life goes down with increasing \( D_{od} \). When each \( D_{od} \) of the battery is 20%, the cycle life of the battery is approximately 2494. However, when the battery is fully discharged (\( D_{od} \) is 100%) each time, its cycle life is only 694. Therefore, the appropriate \( D_{od} \) of the battery can ensure that EVs have a long service life.

### 2.3 Modeling of dynamic economic emission dispatch with electric vehicles

In this subsection, the DEED_EV model is proposed to minimize the fuel cost and the population emission of the thermal power units as well as maximize the revenues of the EVs user. In the proposed DEED_EV model, the EVs battery wear cost and the user’s travel stochastic are included. And some constraints such as system power balance, EVs remain power, users travel, ramp rates and spinning reserve are considered.

#### 2.3.1 Objective functions

1. **Fuel cost**

   The fuel cost of thermal power units is defined in the form of a quadratic function (Han et al. 2001; Qiao and Liu 2020).

   Minimize \( F_C = \sum_{i=1}^{T} \sum_{t=1}^{N} (a_i + b_i P_{it} + c_i P_{it}^2) \) \tag{6}

   where \( T \) and \( N \) are the dispatching period and number of units, respectively. \( a_i, b_i \) and \( c_i \) are the coefficients of the \( i \)th unit, and \( P_{it} \) is the dispatchable power of the \( i \)th unit at time \( t \).

2. **Emission**

   The emission of thermal power units is defined as the sum of the quadratic function and exponential function (Qu et al. 2018).

   Minimize \( F_M = \sum_{i=1}^{T} \sum_{t=1}^{N} [(\alpha_i + \beta_i P_{it} + \gamma_i P_{it}^2 + \zeta_i \exp(\varphi_i P_{it})] \) \tag{7}

   where \( \alpha_i, \beta_i, \gamma_i, \zeta_i \) and \( \varphi_i \) are the emission coefficients of the \( i \)th unit.

3. **EVs users’ revenues**

   When EVs participated in V2G services, certain revenues will be generated. And the higher the revenue, the
Fig. 2 Definitions of the $D_{od}$ and cycle life. a) The relationship between $D_{od}$ and SOC, and b) The relationship between $D_{od}$ and the cycle of life.

more incentives users will add their EVs to the V2G services. The user’s revenue is defined as follows.

Maximum $F_R = \sum_{t=1}^{T} \sum_{i=1}^{N_{ev}} (P_{Ch,i}^{t} \pi_t - P_{Dch,i}^{t} \pi_t)\pi_{bd}$

where the first term is the income from EVs discharge. The second term is the cost of charging EVs. The last term is the cost of battery wear caused by the discharge. $N_{ev}$ is the number of EVs. $P_{Ch,i}$ and $P_{Dch,i}$ are the discharging and charging of the $i$th EVs at time $t$, respectively. $\pi_t$ is the electricity price at time $t$. $\pi_{bd}$ is the battery wear cost which can be calculated as follows.

$\pi_{bd} = \frac{C_{ev}}{E_{cap}D_{od}}$

where $C_{ev}$ is the battery capital cost in $/kWh. E_{cap}$ is the battery capacity.

2.3.2 Constraints

The DEED_EV problem is subjected to some technology constraints which are described as follows.

1) Constraints of EVs

$0 \leq P_{Ch}^{t} \leq P_{Ch}^{t} u_{Ch}^{t}, \quad t \in \lfloor t_{arr}, t_{dep} \rfloor$ (10)

$0 \leq P_{Dch}^{t} \leq P_{Dch}^{t} u_{Dch}^{t}, \quad t \in \lfloor t_{arr}, t_{dep} \rfloor$ (11)

$u_{Ch}^{t} + u_{Dch}^{t} = 1, \quad t \in \lfloor t_{arr}, t_{dep} \rfloor$ (12)

$u_{Ch}^{t} + u_{Dch}^{t} = 0, \quad t \not\in \lfloor t_{arr}, t_{dep} \rfloor$ (13)

$R_t = R_{t-1} + \lambda_c P_{Ch,t} \Delta t - \frac{1}{\lambda_D} P_{Dch,t} \Delta t - S_{Trip,t}$ (14)

$SoC_{E_{cap}} \leq R_t \leq SoC_{E_{cap}}$ (15)

$\sum_{t=1}^{T} S_{Trip,t} = \sum_{t=1}^{T} \lambda_c P_{Ch,t} \Delta t - \sum_{t=1}^{T} \lambda_D P_{Dch,t} \Delta t$ (16)

where $P_{Ch}$ and $P_{Dch}$ are the maximum charging and discharging of the EV at time $t$. $u_{Ch}$ and $u_{Dch}$ are binary variables representing the charging and discharging state of the battery. $t_{arr}$ and $t_{dep}$ represent the arrival time and departure time. $SoC$ and $SoC$ are the minimum and maximum SoC. $R_t$ is the remaining power of the EVs at time $t$. $\lambda_c$ and $\lambda_D$ are the charging and discharging efficiencies. $\Delta t$ is the dispatch interval and set to 1 in this paper. $S_{Trip,t}$ is the power consumed in driving EVs at time $t$, and $S_{Trip,t} = \Delta P_{L_d}$, where $\Delta P_{L_d}$ is the average power consumption of EV driving and $L_d$ is the driving distance. Equations (10) and (11) are the charging and discharging constraints of EVs, which indicates that EVs could not be overcharged and over-discharged. Equation (12) indicates that charging and discharging could not be performed simultaneously. Equation (13) represents not participating in V2G when EV is driving. The remaining power calculation and constraint are Eqs. (14) and (15), respectively. Equation (16) represents the travel constraint of EVs, which ensures that EVs have sufficient travel power.

2) Constraints of power system

$P_{SL,t} \leq P_{L,t} \leq P_{UL,t}$ (17)

$\sum_{i=1}^{N} P_{i,t} + \sum_{j=1}^{N_{ev}} P_{Dch,j} = P_{D,t} + \sum_{i=1}^{N} P_{i,t}$ (18)

$P_{L,t} = \sum_{i=1}^{N} P_{i,t} + \sum_{j=1}^{N} P_{Dch,j}$ (19)
where \( P_{Li} \) and \( P_{Di} \) are the minimum and maximum power of the \( i \)th unit, respectively. \( P_{Di} \) is the load demand. \( P_{Li} \) is the system loss at time \( t \), which is calculated by Eq. (19), and \( B_{ij} \), \( B_{ip} \), and \( B_{00} \) are the coefficients. \( U_{Ri} \) and \( D_{Ri} \) are the increase and decrease rates at time \( t \). \( Su R_{t} \) is the up spinning reserve at time \( t \). \( \vartheta_{u} \) and \( \vartheta_{d} \) are the reserve coefficients of EVs, respectively. Equation (17) is the output limit of the thermal power unit. Equation (18) is the power balance constraint of the system. Equation (20) is the up and down ramp constraints, which indicates that the power change in adjacent intervals could not exceed the set threshold. The system’s up and down reserve constraints are defined as Eqs. (21) and (22), which means that the generator is conked or the power supply is interrupted, and the system can respond quickly to maintain the continuity of the grid power supply.

### 3 Implementation of MOEA/D-SS for dynamic economic emission dispatch with electric vehicles

#### 3.1 Constraint handling method

The proposed DEED_EV model has three objective functions, which are to minimize fuel cost and emission of the thermal power unit and maximize the user’s revenue. To optimize these three objective functions at the same time, the function of the user’s revenue Eq. (8) is transformed into the form of minimum \( F^{E}=1/F_{R} \). Therefore, the optimization of the DEED_EV problem could be transformed into the following form:

\[
\begin{align*}
\{ & P_{i,t} - P_{i,t-1} \leq U_{Ri}\Delta t \\
& P_{i,t-1} - P_{i,t} \leq D_{Ri}\Delta t \\
& \sum_{i=1}^{N} \min \left( \min \left( P_{i,t}, P_{i,t+1} + U_{Ri}\Delta t \right) - P_{i,t}, U_{Ri}/6 \right) \\
& \geq \vartheta_{u} \sum_{i=1}^{N} \left( P_{Dch,i}^{e} + P_{Ch,i}^{e} \right) \\
& \sum_{i=1}^{N} \min \left( P_{i,t} - \max \left( P_{i,t}, P_{i,t-1} - D_{Ri}\Delta t \right), D_{Ri}/6 \right) \\
& \geq \vartheta_{d} \sum_{i=1}^{N} \left( P_{Dch,i}^{e} + P_{Ch,i}^{e} \right)
\end{align*}
\]  

(20)

### 3.2 Constraint handling method

There are many constraints in the proposed DEED_EV model, and these constraints are highly coupled. Therefore, if the constraints are not processed in advance, infeasible solutions will be generated, which will lead to difficulty in optimization and a waste of calculation time. The constraint handling method with the step-by-step adjustment is adopted in this paper, and the detailed processes are given as follows.

When EVs participate in V2G services, they must always be plugged into the grid except for the driving, and there should be enough power for the users to travel. Therefore, the travel constraint (16) in constraints of EVs should be adjusted first. The detailed adjustment process for EVs constraints is shown in Algorithm 1. Lines 1 and 2 are operations before constraints adjustment. Lines 3–14 are step-by-step adjustment operations. When the adjustment of \( P_{Ch,t}^{e} \) and \( P_{Dch,t}^{e} \) is completed (lines 8 and 9), judge whether it is out of bounds (lines 10 and 11). Finally, when the \( k \) and \( |vilo_{ev}^{k}| \) meet the preset threshold (\( K_{ev} \) and \( e_{ev} \)), the adjustment is terminated (lines 5–7). After performing Algorithm 1, new \( P_{Ch,t}^{e} \) and \( |vilo_{ev}^{k}| \) will be output, and then Eq. (14) constraint violation \( vilo_{R} \) will be calculated.

#### Algorithm 1: EVs Constraint Handling Procedure

**Input:**
- \( F_{Ch}, P_{Dch} \): Charging and discharging of EVs;
- \( K_{ev}, e_{ev} \): Maximum adjustment and the threshold value of EVs;

**Output:**
- Adjusted \( P_{Ch}, P_{Dch} \) and \( |vilo_{ev}^{k}| \).

1. \( k \leftarrow 0; \)
2. \( vilo_{ev}^{k} \leftarrow \sum_{i=1}^{K} S_{op, i} - \left( \sum_{i=1}^{K} A_{i} P_{Ch,i}^{e} \Delta t - \sum_{i=1}^{K} A_{i} P_{Dch,i}^{e} \Delta t \right) \) \( (24); \)
3. while \( k < K_{ev} \) do
4.   repeat
5.     if \( k > K_{ev} \) or \( |vilo_{ev}^{k}| \leq e_{ev} \) then
6.       break; % End constraint adjustment
7.     end if
8.     \( P_{Ch} = P_{Ch} + vilo_{ev}^{k}/T; \)
9.     \( P_{Dch} = P_{Dch} - vilo_{ev}^{k}/T; \)
10.    \( P_{Ch} = \min \left( P_{Ch}, P_{Ch}^{\text{max}} \right); \)
11.    \( P_{Dch} = \min \left( P_{Dch}, P_{Dch}^{\text{max}} \right); \)
12.    Update vilo_{ev}^{k}, according to (24);
13.    \( k \leftarrow k + 1; \)
14. end while.

When the EVs constraint handling is completed, new \( P_{Ch,t}^{e} \) and \( P_{Dch,t}^{e} \) are added to the constraint handling of the power system. The constraint handling procedure of the power system is shown in Algorithm 2, in which the loss \( P_{Li}^{e} \) is calculated first (line 2), and then the value \( vilo_{R}^{k} \) to be adjusted is obtained (line 3). Through iterative adjustment (lines 4–24), the dynamic update of \( P_{Li}^{e} \) (lines 9–20) is realized. However, when the adjustment is completed
After performing Algorithm 2, new $P_{t,i}$ and $|vilo_p^k|$ will be output, and then calculate Eqs. (21) and (22) constraint violations $vilo_u$ and $vilo_d$. Therefore, the proposed DEED_EV model total constraint violations $vilo = \text{vilo}_{ev}^t + |\text{vilo}_u| + |\text{vilo}_d| + |\text{vilo}_d| + |\text{vilo}_d|$. The multi-objective problem with constraint (23) is transformed into an unconstrained optimization problem (26) through the penalty function method (Ding et al. 2015). It is obvious that when $vilo = 0$ all objective functions are minimum, and the corresponding solutions are the feasible solutions.

Minimize $F_j = F_Q + s \cdot \text{vilo}, \ j, Q = C, M, R \quad (26)$

where $s$ is the penalty coefficient.

### 3.2 Implementation of MOEA/D-SS in DEED_EV

MOEA/D has been proved to have a very significant effect in solving unconstrained MOPs. In order to optimize the proposed DEED_EV model with strong constraints, MOEA/D-SS is developed by combining the step-by-step constraint handling method with MOEA/D. In MOEA/D-SS, the decomposition method of Tchebycheff is adopted to decompose the MOP into a series of subproblems and optimize the subproblems to obtain the final solutions.
Different from the method of generating weight vectors for two objectives, here, the Latin hypercube sample method is used to generate weight vectors for three objectives. The specific procedure of implementation of MOEA/D-SS in DEED_EV is shown in Algorithm 3. Lines 1–8 are the initialization process of MOEA/D-SS, and its detailed iterative operations are lines 9–19. Besides, the flowchart of the proposed MOEA/D-SS to optimize the DEED_EV problem is shown in Fig. 3. $g_{\text{e}^\text{max}}$ and $g_{\text{e}^\text{n}}$ represent the maximum number of iterations and the number of iterations.

The computational complexity of MOEA/D-SS is analyzed as follows. The major computational costs of Algorithm 1 are to calculate $P_{\text{Dch},i}^{t}$ and $P_{\text{Ch},i}^{t}$ by Eq. (16). Therefore, the total computational complexity of Algorithm 1 is $O(K_{c} \log N)$. In the same way, the computational costs of Algorithm 2 are to calculate $P_{i}^{t}$ and $P_{L,i}^{t}$ by Eqs. (18) and (19), and its computational complexity is $O(K_{p} \log N)$ and $O(2K_{p} \log N)$, respectively. The total computational complexity of Algorithm 2 is $O(K_{p} \log N)$. The computational costs of MOEA/D are to generate $Np$ trial

**Algorithm 3: MOEA/D-SS Implemented in DEED_EV**

**Input:**
- DEED_EV problem parameters and a termination criterion;
- $Np$: Population size;
- $\lambda_{1}^{1}, \lambda_{2}^{2}, \ldots, \lambda_{Np}^{Np}$: $Np$ weight vectors;
- $T$: The number of weight vectors in the neighborhood of $\lambda_{1}^{1}, \lambda_{2}^{2}, \ldots, \lambda_{N}^{N}$;
- DE: Parameters: Scaling factor ($F$) and crossover rate ($CR$);

**Output:**
- Dispatch solutions (final $[P_{1}^{1}, \ldots, P_{Np}^{Np}]^{T}$ and $[F_{C}(P^{1}), F_{M}(P^{1}), F_{R}(P^{1})]^{T}$);

1: **Initialize:**
   - Generate $Np \times m$ ($m$: Number of objective functions) weight vectors by Latin hypercube sample method;
   - Calculate the Euclidean distances between any two weight vectors;
   - Find out $T$ closest weight vectors from $Np \times m$ weight vectors, for each $i = 1, 2, \ldots, Np$, set neighboring $B(i) = (i_{1}, \ldots, i_{T})$; therefore, $\lambda_{\hat{i}}^{i}, \lambda_{\hat{i}}^{i}, \ldots, \lambda_{\hat{i}}^{i}$ are the $T$ closest weight vectors to $\lambda^{i}$;
2:   - Random generation of initial population $P_{1}^{1}, \ldots, P_{Np}^{Np}$; Initialize the reference point $z = (z_{1}, \ldots, z_{m})^{T}$;
3:   - Repair $P^{t}$ according to Algorithms 1 and 2;
4:   - Compute objective functions: $F_{j}(P^{t}), j = C, M, R$;
5:   - Update $z$: if $z_{j} < F_{j}(P^{t})$, then set $z_{j} = F_{j}(P^{t})$;
6: **Iterations:**
   - **while** (termination criteria are not satisfied) **do**
   - Evolve by DE operators;
   - for $i = 1$ to $Np$ **do**
   - Randomly select three indexes $r_{1}, r_{2}, r_{3}$ inequal $i$ from $B(i)$; and then obtain a new $P^{t}$ from $P^{n}, P^{n}$, $P^{n}$ by using DE operator DE/rand/1;
   - Repair new $P^{t}$ by the variable boundary ($P_{lB}, P_{rB}, P_{C}, P_{Dch}$), and further change its diversity by mutation operator in genetic operations;
   - Perform lines 6–8 in initialization to update $P^{t}$ and $z$;
   - Update of neighboring solutions, for each $l \in B(i)$, if $g^{\text{p}}(P^{t} | \lambda^{i}, z) \leq g^{\text{p}}(P^{t} | \lambda^{i}, z)$, then set $P^{t} = P^{t}$, where $g^{\text{p}}$ represents Tchebycheff method, and minimize $g^{\text{p}}(P^{t} | \lambda^{i}, z) = \max_{1 \leq j \leq m} \{\lambda_{j}^{i} - F_{j}(P^{t}) - z_{j}\}$;
   - **end for**
   - If the termination criteria are satisfied, then stop and output $[P_{1}^{1}, P_{2}^{1}, \ldots, P_{Np}^{Np}]^{T}$, and $[F_{C}(P^{1}), F_{M}(P^{1}), F_{R}(P^{1})]^{T}$, $i = 1, 2, \ldots, Np$ . Otherwise, go to line 10;

   **end while:**
4 Experimental results and discussion

In this section, four test cases based on the 10-unit system are used to demonstrate the availability of the proposed DEED_EV model and the performance of the MOEA/D-SS. The thermal power unit parameters and load demand are given in (Qiao and Liu 2020) and (Basu 2014). Assuming that all EVs in the model are the same type, and all times are participated in V2G service dispatching except the driving periods. In addition, let each EV have an SoC of 100% before the start of the first commute time, that is, the EV is full power before daily use. Therefore, SoC(1) = 100%, and the SoC(2) = 1 - \frac{L_d}{L_{max}}. L_{max} is the maximum driving distance when SoC is 100%. The EV parameters are listed in Table 1. Due to the \( P_{Ch} \) and \( P_{Dch} \) are 0.2\( E_{cap} \), the \( D_{od} \) is 0.8 of each EV. \( R_u \) and \( R_d \) are set to 0.1\( P_{D,t} \), and one dispatch is 24 h. \( K_{ev} \) and \( K_P \) are both set to 10, \( s \) is set to 100. \( C_{ev} \) and \( C_P \) are set to 1e - 6. \( \mu_e \) and \( \mu_d \) are set to 8 and 18, respectively. \( \sigma_e \) and \( \sigma_d \) are set to 1. The load demand \( P_{D,t} \) (Qiao and Liu 2020) and electricity price \( \pi \) (Zakariazadeh et al. 2014) are shown in Fig. 4. All tests are performed in MATLAB 2019a environment on a PC with Core i5-6500 CPU, 8G RAM. In each case, the iteration is set to 3000, and the \( N_p \) is set to 300. Each algorithm runs independently 31 times and records the corresponding results.

4.1 Case 1

In this case, the 10-unit system with 50,000 EVs is simulated to verify the proposed MOEA/D-SS. In order to further demonstrate the performance of MOEA/D-SS, the VEPSO (Greeff and Engelbrecht 2008), SaMODE_LS (Qiao and Liu 2020), NSDESa (Qiao et al. 2021), and dNSGA-II (Kalyanmoy et al. 2007) are compared with it.
The median value of the minimum values of each objective function obtained by all algorithms is listed in Table 2. The minimum value of the objective function obtained by each algorithm is the extreme solution of the objective function, and the corresponding row indicates the values of other objective functions under this value. Besides, in this paper, the best values are highlighted in bold. It can be seen from Table 2, in terms of the median value, dispatching solutions obtained by SaMODE_LS and NSDESa can maximize users’ revenue. However, in terms of the cost and emission of the objective function, the median value of the optimal value obtained by the proposed MOEA/D-SS is the best compared with those of other algorithms. Besides, although dNSGA-II (3.8288E + 05) obtained those users’ revenue 18.65% higher than MOEA/D-SS (3.2271E + 05). However, the cost and the emission decreased by 5.75% and 9.82%, respectively, compared with MOEA/D-SS. Therefore, for the median indicator, the performance of the proposed MOEA/D-SS is better than those of other algorithms.

### Table 2 The median solution of all algorithms

| Indicator | Methods   | Cost ($)       | Emission (lb) | Revenue ($)    |
|-----------|-----------|----------------|---------------|----------------|
| Median    | VEPSO     | 2.4401E + 06   | 3.0897E + 05  | 2.6348E + 05   |
|           | dNSGA-II  | 2.4961E + 06   | 2.8999E + 05  | 2.8034E + 05   |
|           | NSDESa    | 2.5355E + 06   | 3.0582E + 05  | 3.0841E + 05   |
|           | dNSGA-II  | 2.4325E + 06   | 2.8922E + 05  | 2.6103E + 05   |
|           | NSDESa    | 2.4727E + 06   | 2.8299E + 05  | 2.5343E + 05   |
|           | SaMODE_LS | 2.5389E + 06   | 3.1148E + 05  | 3.8288E + 05   |
|           | MOEA/D-SS | 2.3970E + 06   | 2.762E + 05   | 4.6433E + 05   |

### Table 3 The evaluation indicators of the objective functions obtained by all algorithms

| Indicators | Methods   | Cost ($)       | Emission (lb) | Revenue ($)    |
|------------|-----------|----------------|---------------|----------------|
| Best       | VEPSO     | 2.4705E + 06   | 2.8684E + 05  | 3.4110E + 05   |
|            | dNSGA-II  | 2.4559E + 06   | 2.8144E + 05  | 4.1790E + 05   |
|            | NSDESa    | 2.4003E + 06   | 2.7784E + 05  | 4.6770E + 05   |
|            | SaMODE_LS | 2.3828E + 06   | 2.7484E + 05  | 4.9607E + 05   |
|            | MOEA/D-SS | 2.3807E + 06   | 2.7090E + 05  | 3.5203E + 05   |
| Worst      | VEPSO     | 2.4817E + 06   | 2.9249E + 05  | 2.7751E + 05   |
|            | dNSGA-II  | 2.4143E + 06   | 2.9154E + 05  | 3.2932E + 05   |
|            | NSDESa    | 2.4347E + 06   | 2.8401E + 05  | 4.2707E + 05   |
|            | SaMODE_LS | 2.4305E + 06   | 2.8257E + 05  | 4.5074E + 05   |
|            | MOEA/D-SS | 2.4065E + 06   | 2.7465E + 05  | 2.7350E + 05   |
| Avr        | VEPSO     | 2.4430E + 06   | 2.9071E + 05  | 3.0533E + 05   |
|            | dNSGA-II  | 2.4328E + 06   | 2.8473E + 05  | 3.8664E + 05   |
|            | NSDESa    | 2.4384E + 06   | 2.8506E + 05  | 3.7636E + 05   |
|            | SaMODE_LS | 2.4534E + 06   | 2.8017E + 05  | 4.4575E + 05   |
|            | MOEA/D-SS | 2.3928E + 06   | 2.7307E + 05  | 3.1601E + 05   |
| Std        | VEPSO     | 1.9246E + 04   | 3.2579E + 03  | 2.0707E + 04   |
|            | dNSGA-II  | 1.1691E + 04   | 3.3955E + 03  | 2.6531E + 04   |
|            | NSDESa    | 7.5046E + 03   | 1.5181E + 03  | 1.0885E + 04   |
|            | SaMODE_LS | 1.1397E + 04   | 1.7471E + 03  | 1.1272E + 04   |
|            | MOEA/D-SS | 6.2493E + 03   | 8.9455E + 02  | 2.2732E + 04   |
algorithms and only slightly worse than those of SaMO-
DE_LS and NSDESa in terms of user’s revenue.

The evaluation indicators such as the best and worst of
the objective functions, as well as the average (Avr) and
standard deviation (Std) of the best value, are listed in
Table 3. From Table 3, compared with VEPSO, dNSGA-II,
and NSDESa, the corresponding objective function value
of the dispatch solutions obtained by SaMODE_LS is the
best among all indicators. However, in the best, worst, and
Avr indicators corresponding to objective functions cost
emission, the proposed MOEA/D-SS is superior to
SaMODE_LS. Besides, among the three objective func-
tions, MOEA/D-SS only performs worse than SaMO-
DE_LS on objective function user revenue. The same
conclusion above can be also drawn from the best com-
promise solution, and the best compromises obtained by
five algorithms are shown in Table 4.

The Pareto front of MOEA/D-SS and the best compro-
mise of the five methods are illustrated in Fig. 5. It is
obvious that those results obtained by MOEA/D-SS are superior to those of other methods. Consequently, the
MOEA/D-SS’s performance is better than that of VEPSO
and dNSGA-II’s and, in terms of the objective functions of
the cost and emission, is better than NSDESa and
SaMODE_LS. The best compromise solutions obtained by
MOEA/D-SS are given in Table 5, and the negative in the
V2G item indicates EV charging. Besides, constraints
checking for the compromise solution are shown in Fig. 6,
which shows that the dispatch solution obtained by MOEA/
D-SS satisfies the power balance.

4.2 Case 2

The different charging and discharging control behavior
are studied in this case. In case 1, the charging and dis-
charging modes are smartly selected, and the system
intelligently selects the charging or discharging time
according to the load. The charging and discharging time
are fixed according to different peak loads. In the fixed
scenario, let the EVs perform discharge operation during
the peak periods of the load, that is, the periods included
in A and B in Fig. 4. Then charge it during periods other than
A and B. The median of results is listed in Table 6. It is
obvious that the results in the smart scenario are better than
in the fixed scenario. In particular, the user’s revenue
objective, when the EV chooses the charging and dis-
charging time according to the system intelligence, the
user’s revenue in the best compromise is increased by
48.1%, compared to the fixed scenario, and the best
extreme is increased by 45.6%. Therefore, in V2G services,
EVs choose smart charging and discharging modes, which
not only can improve the user’s income, but also reduce the
fuel cost and pollution emission of the thermal power unit.

The arrival time of EVs at the workplace and the cor-
responding number of EVs can be calculated according to
(1). The distribution of the first commute time and the
number of 50,000 EVs are shown in Fig. 7. It can be seen
from Fig. 7 that the travel time to work is between 04:00
and 12:00 and reaches a peak at 08:00. Besides, assume
that EVs participating in V2G services complete a charge
and discharge cycle within a period, and it is ensured that
the SoC is 100% when using the EV for the first time each
day. Figure 8 illustrates the SoC curves for two charging
and discharging scenarios with different travel times. The
solid black line in Fig. 8 represents the total SoC (tSoC) of
all EVs in a period. The tSoC of the two scenarios can meet
the changing trends of discharging during the peak load
and charging in the valley. The difference is that in the
smart scenario in Fig. 8a, the EVs have only one moment
in a period, the SoC is 100%, that is, the moment before
travel. However, in the fixed scenario in Fig. 8b, because
the charge and discharge time is fixed, it will appear that
when the SoC is 100%, it has not yet reached another state
(charging or discharging state). This results in multiple
moments where the SoC is 100% in a period. Consequently,
the user’s revenue in the fixed scenario is less than in the
smart scenario. These prove that the proposed DEED_EV

| Methods   | Cost ($)    | Emission (lb) | Revenue ($) |
|-----------|-------------|---------------|-------------|
| VEPSO     | 2.4450E + 06| 2.9075E + 05  | 3.1840E + 05|
| dNSGA-II  | 2.4276E + 06| 2.8430E + 05  | 3.0568E + 05|
| NSDESa    | 2.4268E + 06| 2.8351E + 05  | 3.6657E + 05|
| SaMODE_LS | 2.4416E + 06| 2.8218E + 05  | 4.0368E + 05|
| MOEA/D-SS | 2.4145E + 06| 2.7913E + 05  | 3.2883E + 05|

Fig. 5 The MOEA/D-SS Pareto front and five algorithms best compromise
The model, which generates the EVs charging and discharging scheme, can improve the user’s revenue.

The most important role of EVs plugging into the power grid with V2G is to cut the peak and fill the valley of the system load. Figure 9 shows the profiles of load change when the system is plugged into the EVs in two scenarios. The gray areas represent the load reduced during peak load and the increase during the low valley, respectively. It can be seen from Fig. 9 that both scenarios can play the role of peak shaving and valley filling. In addition, in the smart scenario in Fig. 9a, the discharge power of EVs has reduced the load value in the peak areas of 08:00–15:00 and 19:00–22:00, respectively. These areas exactly match the peak areas (A and B) defined in Fig. 4. However, in the fixed scenario in Fig. 9b, the discharge power of EVs has reduced the load value in the peak areas of 08:00–14:00 and 17:00–22:00, respectively. But the 17:00–22:00 area contains part of the valley area, that is, the 17:00–19:00 area. Therefore, the peak shaving and valley filling performance of EVs in the fixed scenario is weaker than that of the smart scenario. This also proves that the proposed DEED_EV model can not only reduce the cost and emission of the thermal power unit but also have high peak shaving and valley filling performance.

Table 5 The best compromise solutions obtained by MOEA/D-SS

| t  | $P_1$  | $P_2$  | $P_3$  | $P_4$  | $P_5$  | $P_6$  | $P_7$  | $P_8$  | $P_{10}$ | V2G    | $P_L$  | $P_D$  |
|----|--------|--------|--------|--------|--------|--------|--------|--------|----------|--------|--------|--------|
| 1  | 151.75 | 136.62 | 111.60 | 111.12 | 166.74 | 122.60 | 116.64 | 76.43  | 53.19    | -135.64| 24.91  | 1036   |
| 2  | 151.97 | 142.83 | 146.15 | 140.11 | 208.01 | 129.81 | 119.42 | 79.27  | 53.76    | -187.45| 30.39  | 1110   |
| 3  | 155.01 | 157.67 | 172.89 | 169.83 | 223.23 | 128.23 | 119.26 | 79.11  | 53.96    | -126.30| 34.62  | 1258   |
| 4  | 164.59 | 181.59 | 194.92 | 219.35 | 242.72 | 160.00 | 130.00 | 119.91 | 55.00    | -100.80| 41.27  | 1406   |
| 5  | 169.45 | 176.65 | 202.20 | 211.40 | 237.05 | 158.56 | 129.05 | 118.78 | 54.66    | -9.70  | 40.34  | 1480   |
| 6  | 218.56 | 229.74 | 230.81 | 224.88 | 223.91 | 159.59 | 129.89 | 120.00 | 55.00    | 5.32   | 48.93  | 1628   |
| 7  | 234.06 | 254.71 | 260.48 | 260.29 | 243.00 | 159.90 | 129.65 | 119.87 | 55.00    | -38.20| 56.72  | 1702   |
| 8  | 252.00 | 274.16 | 287.36 | 283.05 | 242.80 | 159.85 | 129.72 | 119.78 | 54.80    | -44.66| 62.59  | 1776   |
| 9  | 260.44 | 283.73 | 303.72 | 281.86 | 242.13 | 159.17 | 129.10 | 119.20 | 54.05    | 76.14  | 64.74  | 1924   |
| 10 | 279.64 | 285.45 | 305.07 | 299.05 | 243.00 | 159.99 | 130.00 | 119.95 | 55.00    | 132.81| 67.94  | 2022   |
| 11 | 284.24 | 310.80 | 306.61 | 299.81 | 242.48 | 159.89 | 129.88 | 119.86 | 54.79    | 188.17| 70.42  | 2106   |
| 12 | 291.31 | 309.90 | 325.82 | 300.00 | 243.00 | 160.00 | 130.00 | 120.00 | 55.00    | 184.34| 72.38  | 2127   |
| 13 | 279.08 | 308.29 | 309.95 | 299.82 | 242.89 | 159.90 | 129.81 | 119.86 | 54.55    | 158.00| 70.04  | 2072   |
| 14 | 257.97 | 284.71 | 302.84 | 299.33 | 242.58 | 159.79 | 129.81 | 119.80 | 54.80    | 58.57 | 65.94  | 1924   |
| 15 | 219.42 | 268.89 | 270.48 | 291.27 | 243.00 | 160.00 | 130.00 | 119.98 | 55.00    | -2.76 | 59.27  | 1776   |
| 16 | 197.93 | 219.67 | 255.21 | 255.82 | 242.95 | 159.94 | 129.99 | 119.94 | 54.99    | -111.26| 51.18  | 1554   |
| 17 | 195.77 | 207.08 | 236.68 | 242.82 | 159.64 | 129.83 | 119.79 | 79.47  | 54.70    | -108.99| 46.45  | 1480   |
| 18 | 237.30 | 237.72 | 244.87 | 224.67 | 225.54 | 160.00 | 130.00 | 120.00 | 55.00    | -35.36| 51.73  | 1628   |
| 19 | 235.66 | 268.00 | 271.71 | 275.94 | 242.92 | 159.82 | 129.82 | 119.82 | 54.81    | -2.74 | 59.45  | 1776   |
| 20 | 254.60 | 281.87 | 298.57 | 299.69 | 242.87 | 159.85 | 129.98 | 119.98 | 54.98    | 115.01| 65.26  | 1972   |
| 21 | 237.35 | 265.51 | 291.68 | 294.31 | 242.89 | 160.00 | 129.95 | 119.98 | 54.89    | 109.46| 61.88  | 1924   |
| 22 | 208.33 | 230.17 | 252.37 | 237.98 | 242.97 | 159.96 | 129.94 | 119.96 | 54.97    | -37.23| 51.40  | 1628   |
| 23 | 162.63 | 167.18 | 195.37 | 167.79 | 242.44 | 160.00 | 130.00 | 120.00 | 55.00    | -110.63| 37.77  | 1332   |
| 24 | 150.49 | 136.15 | 131.60 | 141.38 | 176.52 | 157.39 | 129.17 | 118.31 | 79.19    | -62.96| 28.02  | 1184   |
4.3 Case 3

The battery capital cost $C_{ev}$ is one of the factors that users should consider when buying an EV. Therefore, different $C_{ev}$ from 200 to 800 is studied in this case. Table 7 lists the average values including three objective functions, EVs battery wear cost caused by V2G, and the battery wear cost of normal driving. And the change trends are shown in Fig. 10. It can be seen from Table 7 and Fig. 10 that the cost and emission of the thermal power unit have only slight changes when $C_{ev}$ increases. Since the battery wears cost and drive wear cost are positively related to $C_{ev}$. Therefore, when $C_{ev}$ increases, its corresponding battery wears cost and drive wear cost also increase. However, the user’s revenue changes with $C_{ev}$ are not monotonous. In Fig. 10, the user’s revenue reaches the highest peak when $C_{ev}$ is 500. In addition, as can be seen in Table 7, the use’s revenue is much higher than wear cost and drive wear cost. Consequently, the wear of the battery in the proposed DEED_EV model is negligible for EVs plugged into V2G services. And the user can choose an EV with appropriate battery capital cost to ensure the best revenue when it is plugged into the grid.

4.4 Case 4

In the proposed DEED_EV model, the time-of-use electricity price is used to calculate the charging cost and

| Scenario | Best extreme | | Best compromise | | |
| --- | --- | --- | --- | --- |
| Cost ($) | Emission (lb) | Revenue ($) | Cost ($) | Emission (lb) | Revenue ($) |
| Fixed | 2.4348E + 06 | 2.8080E + 05 | 2.2169E + 05 | 2.4465E + 06 | 2.8388E + 05 | 2.2206E + 05 |
| Smart | 2.3916E + 06 | 2.7323E + 05 | 3.2271E + 05 | 2.4145E + 06 | 2.7913E + 05 | 3.2883E + 05 |

Fig. 7 The distribution of the arrival time and the number of EVs

Fig. 8 SoC curves for different arrival times. a Smart scenario, and b fixed scenario
discharging income. The time-of-use electricity price is shown in Fig. 4, in which the minimum $\text{Min}_p$ is 17$/\text{MW}$ and the maximum $\text{Max}_p$ is 572$/\text{MW}$. In this case, the effect on the DEED_EV model is analyzed when the electricity prices are $0.1p_t$, $0.5p_t$, $1p_t$, $2p_t$, $\text{Min}_p$, and $\text{Max}_p$, respectively. The average values are listed in Table 8. The user’s revenue is the highest when the electricity price is $2p_t$. But when the electricity price is fixed at $\text{Min}_p$ (17$/\text{MW}$) and $\text{Max}_p$ (572$/\text{MW}$), respectively, instead of the time-of-use price. The user’s revenue only is 315.6996$ at $\text{Min}_p$ and 6.6830E$^{-03}$ at $\text{Max}_p$, which is much lower than that of the time-of-use price.

In the cost objective, when the electricity price is $1p_t$, compared with $0.1p_t$, $0.5p_t$, and $2p_t$, the fuel cost of the thermal power unit is reduced by 0.021%, 0.076%, 0.088%, and only increased by 0.001% compared to $1.5p_t$. Besides, the fuel cost of the thermal power unit corresponding to the time-use-of electricity price is better than fixed prices $\text{Min}_p$ and $\text{Max}_p$. In the emission objective, the different emission of the thermal power unit in time-of-use prices is only reflected after the percentile. In addition, the emission in fixed prices $\text{Min}_p$ and $\text{Max}_p$ is increased by 6.34% and 3.00%, respectively, compared to $1p_t$. Therefore, compared with the fixed price, the time-use-of price enables the EVs to get higher revenue by participating in the V2G services. Moreover, the higher the time-of-use price, the more the user’s revenue.

5 Conclusions

In this paper, to promote the enthusiasm of users to participate in V2G services, considering the maximization of EV user’s revenue, a new dynamic economic emission dispatch model with EVs (DEED_EV) is proposed for the minimum fuel cost and emission of the thermal power unit. In the DEED_EV, the travel randomness and battery wear of EVs users are considered. To quickly get the solutions into the decision space, a multi-objective method MOEA/D with a step-by-step constraint handling method (MOEA/D-SS) is developed. To verify the proposed model and method, four test cases based on the 10-unit are simulated, as well as the VEPSO, SaMODE_LS, NSDESa, and dNSGA-II are compared to MOEA/D-SS. The results show that the performance of MOEA/D-SS is better than VEPSO, SaMODE_LS, NSDESa, and dNSGA-II. In
addition, the DEED_EV model not only reduced the fuel cost and emission but also increased the revenue of EV users. Furthermore, the smart charging and discharging mode from the DEED_EV model is the best compared to the fixed mode, and the EVs fully realize the peak shaving and valley filling of the load. Moreover, the effect of battery capital cost on the DEED_EV is analyzed. The results show that the user’s revenue is the highest when the battery capital cost is $500/kW. Finally, only by adopting a reasonable time-of-use electricity pricing strategy EV users can obtain higher revenues, thereby incentivizing more EV owners to add their EVs to V2G services. However, there are two major limitations in this study that can be addressed in future research. First, the study focused on a complete charging and discharging process of EVs in a dispatch cycle; that is, SoC changes from 100 to 0% and

(a) The objective functions of cost and emission
(b) The profile of revenue for EVs users
(c) Cost of battery wear caused by charging/discharging and normal driving

Fig. 10 The changing trend of objective function under different battery capital costs

| Electricity price | 0.1\(\pi_t\) | 0.5\(\pi_t\) | \(\pi_t\) | 1.5\(\pi_t\) | 2\(\pi_t\) | Min\(\pi_t\) | Max\(\pi_t\) |
|-------------------|-------------|-------------|---------|-------------|---------|----------|----------|
| Cost ($)          | 2.3933E + 06 | 2.3946E + 06 | 2.3928E + 06 | 2.3926E + 06 | 2.3949E + 06 | 2.4029E + 06 | 2.3997E + 06 |
| Emission (lb)     | 2.7296E + 05 | 2.7326E + 05 | 2.7307E + 05 | 2.7378E + 05 | 2.7379E + 05 | 2.7539E + 05 | 2.7417E + 05 |
| Revenue ($)       | 3.1030E + 04 | 1.5513E + 05 | 3.1601E + 05 | 4.5787E + 05 | 5.9859E + 05 | 315.6996 | 6.6830E + 03 |
then to 100%, but based on the psychological effect on users, they may not choose the V2G service when the power is still sufficient. Second, the study only considers thermal power units. With the development of low-carbon energy sources, renewable energy power will become the main power supply in the future. Therefore, in our future work, we will deeply study the influence of different SoCs of EVs, as well as the flexible interactive dispatching mechanism between renewable energy and EVs.

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**Data Availability** Enquiries about data availability should be directed to the authors.

**Declarations**

**Conflict of interests** The authors declare no potential conflict of interests.

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