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A Hybrid Multi-Objective Crisscross Optimization for Dynamic Economic/Emission Dispatch Considering Plug-In Electric Vehicles Penetration †

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Abstract: Due to the significant uncertainty of charging time and charging power consumption, the large increase in plug-in electric vehicles (PEVs) may create a major influences on the power system: According to people's living habits, PEVs are basically charged during peak load periods (after work). Once PEVs continue the random charging behavior, there will be a higher difference of peak-valley and bigger burden on the grid. A new strategy is put forward for dynamic economic/emission dispatch (DEED) with the consideration of PEVs for the purpose to shave the peak and fill the valley in this paper, and the influences brought from different loads of grid-to-vehicle (G2V) and vehicle-to-grid (V2G) on DEED problem are discussed. The problem to be solved is a challenging multi-objective non-linear problem. By taking advantage of the differential evolution (DE) algorithms and a newly developed crisscross optimization algorithm, a new multi-objective hybrid optimization algorithm is put forward to deal with the problem including effectively dealing with the inequality and equality constraints. A case study is presented to show the feasibility and effectiveness of the put forward method. The analysis results demonstrate that the put forward algorithm could effectively solve DEED problem, showing that the resulting approach of peak shaving and valley filling could significantly save economic costs and reduce emissions under the same load.

Keywords: dynamic economic/emission dispatch (DEED); multi-objective optimization; differential evolution; crisscross optimization; plug-in electric vehicles (PEVs)

1. Introduction

Economic dispatch (ED) is a kind of the key problems for power systems, whose purpose is to look for the optimal scheduling of generators to make the economic cost minimum. As more and more attention has been paid to the environment, emission is to be taken into account as part of ED. This leads to the research on economic emission dispatch (EED). EED is only focused on the optimal scheduling for a certain period of time (usually 1 h) actually, whereas the DEED focus on the whole dispatching periods of time to make the total economic cost and pollution emissions minimum with consideration of certain constraints [1–4].

The DEED problem considering the valve point effect is a complex optimization problem characterized by nonlinearities, severe constraints, and multi-peaks. In the literatures, various traditional mathematical methods [5–9] such as non-linear programming (NLP), Lagrange Relaxation

(LR) for solving the DEED problem have been proposed. Many traditional methods have several limitations it requires that the objective functions should be differentiable and the problem domain should be convex. Thus, these traditional mathematical methods are not appropriate to deal with non-convex, non-smooth, and multi-objective problems such as DEED problem. To overcome the limitation of the traditional methods, modern heuristic algorithm such as DE algorithm [10], bat algorithm [11], and harmony search (HS) [12] are employed to deal with the complex DEED problem. One advantage of heuristic methods for solving DEED problem is that the models of the operation constraints becomes more practical. Different from traditional methods mentioned above, heuristic methods do not require the objectives and constraints to be continuous and differentiable. Therefore, high quality solutions could be obtained. However, the solutions generated by heuristics optimization methods may be trapped into premature on account of the shortcomings in balancing the local exploitation and global exploration. Therefore, to overcome the dilemma, combinatorial optimization algorithms which integrate two or more optimization strategies have been put forward to make the global searching ability improved and convergence rate accelerated. For example, in recent years, different hybridization algorithm such as hybrid bat algorithm [11], multi-objective stochastic search technique (MOSST) [13], hybrid DE-PSO [14], hybrid bare-bones PSO (BBPSO) [15], hybrid bee colony optimization algorithm [16], hybrid DE (HDE) [17] have been introduced to obtain better quality solutions. At present, many intelligent optimization algorithms and hybrid optimization algorithms could be applied to handle complex problems. Choose the appropriate algorithm based on the actual problem and they may have achieved good results. For example, an improved estimation of distribution algorithms (EDAs) proposed in [18] has good performance in dealing with complex problems; reference [19] put forward a novel intelligent optimization namely Ideal gas optimization algorithm and its superiority has been proved; reference [20] put forward an improved island-based Cuckoo search that enhances the diversity of population and global search ability, and has good convergence ability; reference [21] proposed several improved algorithms and applied them to the optimization of fuzzy controllers in servo systems. Compared with the single algorithm, a combinatorial optimization method may require more time to calculate and involves more parameters, but it could take advantage of each single algorithm to lead to a good optimal solution. Thus, it is significant and essential to evolve new hybrid algorithms for better solving the DEED problem.

As global energy issues become more serious, primary energy sources dominated by petroleum resources are increasingly depleted, greenhouse effect and air pollution are getting worse, governments have realized the importance of energy conservation and emission reduction for the sustainable development of human society. Due to the high energy efficiency, low carbon and noise pollution and low operating costs [22,23], plug-in electric vehicles (PEVs) have gained extensive attention and becomes an indispensable part to solve energy and environmental problems. However, the growing number of PEVs would further increase the difference of peak-to-valley, the stochastic charging behavior of PEVs will result in additional load requirements [24,25]. Therefore, it is urgent to solve the dispatch issue of PEVs and to formulate an optimal dispatch scheme for the power system. In [26,27], PEVs act as a reserve to help to reduce and regulate the load. In [28], the influence of PEVs on the load curve and economic cost was discussed. In [29,30], it showed that fossil fuel vehicles would be replaced by PEVs of potentially flexible load demand by reducing exhaust emissions. In [31], the framework, advantages and challenges of V2G technology, as well as the main methods to implement V2G technology under satisfying various constraints were summarized. In [32], a DEED model considering the large penetration of PEVs was put forward, and the adaptive multi-objective DE algorithm had been put forward to deal with the model. However, environmental factors were only considered as constraints, and only the scenario of PEVs charging was considered in the model. In [33], a self-learning teaching-learning based optimization (SL-TLBO) strategy had been introduced to deal with DEED problem with the consideration of PEVs loads. However, only four charging scenarios were considered in the SL-TLBO method, and it neglects the fact that PEVs have the ability of peak shaved and valley filled. In [34], the DEED problem considering PEVs was investigated, and an optimal scheduling result was produced, however, the difficulty of controlling the random charging/discharging behaviors of PEVs does not need to be considered. In [35], a new type of valley filling strategy was proposed, which used PEVs to centrally coordinate charging. Moreover, a decentralized PWM-based algorithm was introduced in [36] to coordinate PEV charging to make the total load curve smooth. However, the proposed strategies in [35,36] only consider the V2G technology and ignore the G2V technology. In [37], in order to alleviate concerns about battery lifetime, the PEVs were presented to act as distributed storage devices. In [38], the purchasing of load transfer service was discussed by optimizing dispatch of the charging and discharging of PEVs using the decentralized way.

This paper aims to establish a dynamic economic/emission scheduling model with the consideration of PEVs for the purpose to shave peak and fill valley, these influences of PEVs on economic cost and emissions are analyzed. More specifically, a new multi-objective algorithm framework, developed according to a hybrid method, combining a DE algorithm and a recent CSO algorithm is put forward to solve DEED problem with the consideration of penetration of PEVs; a repair technique is put forward to deal with various constraints efficiently. For simplicity of presentation, the proposed approach is referred to as multi-objective differential evolution and crisscross optimization (MODECSO). Experiments on a 5-unit system are carried out to prove the feasibility and effectiveness of the put forward strategy. The results illustrate that the put forward MODECSO algorithm can generate well distributed Pareto optimal solution of DEED, verifying that the peak shaving and valley filling methods of PEVs can effectively reduce operating costs and emissions of polluting gases under the same load conditions.

The key contributions are summarized as follows:

- In optimization model of the dynamic economic/emission multi-objective dispatching problem, the PEVs are considered for the purpose to achieve peak shaving and valley filling. According to the put forward model, DEED problem with consideration of PEVs is surveyed. Currently, there is very limited work being done for solving the DEED problem considering PEVs to shave peak and fill valley, particularly on the research of influence on DEED problem brought from different G2V and V2G demands. This is a multi-peak and nonlinear multi-objective optimization problem. In existing work, DEED considered with PEVs only studies the scheduling of PEVs, the effect of G2V and V2G technologies do not need to be considered. The load shaved during peak period is distributed to each PEV, and in order to implement valley filling, a water-filling algorithm [36] has been employed. As a result, a new 24-h load curve would be produced for the DEED problem.
- A new application of the hybrid heuristic algorithm integrating CSO and DE is presented for robust, efficient, and accurate optimization of the DEED involving PEVs. A new multi-objective differential evolution and crisscross optimization (MODECSO) is put forward. MODECSO has the following properties. (1) The elitist reservation strategy and crowding entropy and fuzzy-based mechanism are employed to generate the Pareto optimal front (POF) that overcomes the shortcomings of the weighted sum strategy. (2) For the purpose to make convergence rate accelerated, the global optimal quantity is introduced to improve the horizontal crossover operator. (3) A new adaptive parameter method with self-learning ability is put forward. By using this strategy, there is no need to try out appropriate mutation and crossover constant for each optimization problem, and the algorithm can evolve to suitable control parameter values automatically according to the evolution process.
- Some infeasible solutions may carry important information that is useful for finding the optimal solutions. To ensure the diversity of the offspring, a repair technique is proposed to deal with the constraints to avoid discarding useful infeasible solutions. During the optimizing process, instead of penalty function, the heuristic constraint handling method is used in solving various constrains effectively. Moreover, it does not need to select penalty factors as well as any other parameters, besides it also could direct these infeasible solutions into the feasible domain.

2. The Dynamic Economic/Emission Dispatch Model with Consideration of Plug-In Electric Vehicles

2.1. Objective Functions

Two types of objective functions, called, fuel cost and pollution emission, are considered, which are described in detail as follows.

(1) Fuel cost: The objective function of fuel cost of generators is decided according to their active output. However, the opening of intake valve of steam turbine suddenly would result in valve point effect [22], the accuracy of solution would be affected if it is ignored. When such a nonlinear factor is considered, the objective function of fuel cost F_f [39] is shown as follows:

$$F_f = \sum_{i=1}^{N}\sum_{t=1}^{T}\left\{a_i P_{i,t}^2 + b_i P_{i,t} + c_i + \left|e_i \sin\left[f_i\left(P_i^{\min} - P_{i,t}\right)\right]\right|\right\} \tag{1}$$

where N is the number of units, T is an entire scheduling period, a_i, b_i, c_i, e_i and f_i are the cost coefficients of the ith unit, $P_{i,t}$ is the active output of the ith unit at the tth period, and $P_i^{\min}$ is the minimum active output of the ith unit.

(2) Emission amount function: The emission function of various pollution gases is shown as follows [40–42]:

$$F_e = \sum_{i=1}^{N}\sum_{t=1}^{T}\left[\alpha_i + \beta_i P_{i,t} + \gamma_i (P_{i,t})^2 + \xi_i \exp(\lambda_i P_{i,t})\right] \tag{2}$$

where α_i, β_i, γ_i, ξ_i, λ_i are the emission coefficients of the ith unit.

2.2. Constraints

This study considers the following six constraints.

(1) Active power limits:

$$P_i^{\min} < P_i < P_i^{\max} \tag{3}$$

(2) Power balance constraints:

Power balance equation for each scheduling period with consideration of both the discharging and charging behavior of PEVs can be shown as:

$$\sum_{i=1}^{N} P_{i,t} + P_{\mathrm{disch},t} - PD_t = P_{\mathrm{loss},t} + P_{ch,t} \tag{4}$$

where $P_{ch,t}$ is the charging load and $P_{\mathrm{disch},t}$ is the discharging power during the tth period, respectively. PD_t is the power load demand and $P_{\mathrm{loss},t}$ is the system losses during the tth period, shown as follows [43]:

$$P_{loss,t} = \sum_{i=1}^{N}\sum_{j=1}^{N} P_{i,t} \times B_{i,j} \times P_{j,i} \tag{5}$$

where the B_{ij} is the transmission network loss coefficients.

(3) Ramp rate limits:

$$P_{i,t} - P_{i,t-1} < UR_i \tag{6}$$

$$P_{i,t-1} - P_{i,t} < DR_i \tag{7}$$

where UR_i and DR_i are the ramp rate of the ith generator.

(4) Battery storage capacity limit:

For the purpose to guarantee the battery life and operational safety, the remaining capacity $SOC(t)$ must meet the following requirement.

$$SOC_{\min} < SOC(t) < SOC_{\max} \tag{8}$$

where $SOC_{\min}$ is the lower limitation of battery power, $SOC_{\max}$ is the upper limitation of battery power.

(5) Charging and discharging power constraints of PEVs:

$$P_{disch,j,t} \leq P_{disch,j}^{\max} \tag{9}$$

$$P_{ch,j,t} \leq P_{ch,j}^{\max} \tag{10}$$

where $P_{disch,i}^{\max}$ and $P_{ch,i}^{\max}$ represent the maximum discharging power and charging load of the jth PEV.

(6) Power balance constraints of PEVs:

$$SOC_t = SOC_{t-1} + \xi_c \times P_{ch,t} \times \Delta t - \frac{P_{disch,t}}{\xi_D} \times \Delta t - D \times \Delta S \tag{11}$$

where ξ_c represents the charging efficiency and ξ_D represents the discharging efficiency, Δt is the scheduling period, D is the driven distance, and ΔS is the average power consumption per unit distance.

2.3. Problem Formulation

The DEED problem is a dynamic multi-objective non-convex complicated problem characterized by nonlinearities, severe constraints, and multi-peaks. Making the economic cost minimum and making the total emission of pollution gases minimum, as the two purposes of the DEED problem, are mutually competing. Integrating the objective functions and constraints, the mathematical model of DEED is expressed as follows:

$$\begin{array}{l} \min\ [F_f(x), F_e(x)] \\ st\ :\ \begin{cases} g(x) = 0 \\ h(x) \leq 0 \end{cases} \end{array} \tag{12}$$

where $g(x)$ and $h(x)$ represent equality constraints and inequality constraints, respectively.

2.4. Constraints Handling

The DEED characterized by multi-peak, non-linearity and severe constraint, is a dynamic non-convex complicated optimization problem [44]. Some updated solutions are difficult to satisfy all the constraints, they may be usually not feasible in the early period, which is not conducive to the exploration and exploitation for the feasible domains. Even if some solutions are feasible in this generation, they turn into unfeasible after crossover operator and mutation operator in the next generation. When considering various constraints, especially equality constraints, this situation would be much worse. To solve this difficulty, a repaired technique is put forward for the infeasible solutions to promote them to move into the feasible domains. The implementation procedure the repair technique put forward has been presented as follows:

Step 1: The decision variables are arranged into matrix form:

$$P = \begin{bmatrix} P_1^1 & P_2^1 & \cdots & P_N^1 \\ P_1^2 & P_2^2 & \cdots & P_N^2 \\ \cdots & \cdots & \cdots & \cdots \\ P_1^T & P_2^T & \cdots & P_N^T \end{bmatrix}$$

where P_n^t represents the active output of the nth unit at the tth time interval.

Step 2: Suppose that the dispatching process begins with the first time period, thus set t = 1.

Considering the both constraints of the ramp rate limits and generator capacity, two boundary values are used for each generator during the tth time period, which are given by:

$$P_{i,t}^{\max} = \begin{cases} P_i^{\max} & \text{if } t == 1 \\ \min\left[P_i^{\max}, (P_{i,t-1} + UR_i)\right] & \text{otherwise} \end{cases} \tag{13}$$

$$P_{i,t}^{\min} = \begin{cases} P_i^{\min} & \text{if } t == 1 \\ \max\left[P_i^{\min}, (P_{i,t-1} - DR_i)\right] & \text{otherwise} \end{cases} \tag{14}$$

Step 3: Check feasibility of the updated candidate solution at the tth time as follows:

$$\left| \delta = \sum_{i=1}^{N} P_{i,t} - P_{loss,t} - PD_t \right| \leq \varepsilon \tag{15}$$

Here, ε is a tolerance limit. If the solution satisfies the constraint, end Step 3; otherwise, carry out Step 3.1.

Step 3.1: Set the cycle number $k_{\max}$ and start the loop.
Step 3.2: Randomize all generator numbers, and make a small contribution to all generators.

$$P(t,\ Rg(q)) = P(t,\ Rg(q)) + \delta \tag{16}$$

where Rg is a random sort of all generators (q = 1, 2, ... , N). Check that the updated candidate solution exceeds the upper and lower limits. If the updated solution exceeds the lower limit:

$$\begin{aligned} \delta &= P(t,\ Rg(q)) - P_t^{\min}(Rg(q)) \\ P(t,\ Rg(q)) &= P_t^{\min}(Rg(q)) \end{aligned} \tag{17}$$

If the updated solution exceeds the upper limit:

$$\begin{aligned} \delta &= P(t,\ Rg(q)) - P_t^{\max}(Rg(q)) \\ P(t,\ Rg(q)) &= P_t^{\max}(Rg(q)) \end{aligned} \tag{18}$$

Step 3.3: Carry out the next generator until all generators have completed the process.
Step 3.4: Recheck the feasibility of the repaired solution. If the solution satisfies the constraint, stop at Step 3, otherwise check if the number of loops reaches the maximum threshold $k_{\max}$. Terminate the equation repair process if iteration reaches the preset maximum number, otherwise return to Step 3.2.
Step 3.5: If the iteration reaches the pre-scheduled number, and the solution is still infeasible, then the solution is initialized and proceeds directly to the next step.

3. The Proposed Approach

The proposed optimization algorithm MODECSO and the strategy of PEV of the purpose to shave the peak and fill the valley are described. As mentioned above, the dispatch results of the power system largely depend on the load demand. The large-scale PEVs are permeated to the grid, if they are not under control, the peak-to-valley difference will be directly intensified, and thus would impose a negative effect on power system scheduling. However, it can be improved if the appropriate PEV dispatch method is implemented. V2G and G2V technologies are employed to shave the peak and fill the valley in this paper. During the peak period, the remaining power reserved in PEV battery is transmitted to the grid by V2G technology. During the valley period, the valley filling is achieved by charging the PEVs.

3.1. The Proposed Algorithm

3.1.1. Crisscross Optimization Algorithm

The CSO algorithm is a novel swarm optimization algorithm put forward by Meng et al. [45]. Different from other artificial intelligence algorithms, CSO consists of two search mechanisms, called horizontal crossover operator and vertical crossover operator. The two operators complete search task in coordination with the competition operator.

(1) Horizontal crossover:

Horizontal crossover is a crossover of the same dimension of the paired individuals. The parent individual X_i is executed the horizontal crossover with parent individual X_j at the dth dimension, the offspring MS_{hc} can be expressed as:

$$\begin{cases} MS_{hc}(i,d) = r_1 \times X_{i,d} + (1-r_1) \times X_{j,d} + c_1 \times \left(X_{i,d} - X_{j,d}\right) \\ MS_{hc}(j,d) = r_2 \times X_{j,d} + (1-r_2) \times X_{i,d} + c_2 \times \left(X_{j,d} - X_{i,d}\right) \end{cases} \tag{19}$$

where r_i $(i = 1,2)$ is random values within [0, 1]. c_1, c_2 are expansion coefficients within [−1, 1].

(2) Vertical crossover:

Different from the horizontal crossover operator, the vertical crossover is a crossover between two different dimensions in one individual. $MS_{vc}(i, d_1)$ can be expressed as:

$$MS_{vc}(i,d_1) = r \times X_{i,d_1} + (1-r) \times X_{i,d_2} \tag{20}$$

where $d_i(i = 1,2)$ is dimension of the ith individual, r is random values within [0, 1].

(3) Improved horizontal crossover

In our work, an improvement is done on the horizontal crossover operator in order to make the convergence rate accelerated. All the individuals are pairwise coupling randomly. According to the fitness value, each pair is divided into two categories, namely winners and inferiors. The inferior individual carries out the horizontal crossover with the winner individual, and by introducing the global optimal solution, the winner individual carries out horizontal crossover with the global optimal solution instead of inferior individual, showing in the equation below:

$$\begin{array}{l} \text{if } fit(X_j) < fit(X_i) \\ \begin{cases} MS_{hc}(i,d) = r_1 \times X_{i,d} + (1-r_1) \times X_{j,d} + c_1 \times \left(X_{i,d} - X_{j,d}\right) \\ MS_{hc}(j,d) = r_2 \times X_{j,d} + (1-r_2) \times X_{gbest,d} + c_2 \times \left(X_{j,d} - X_{gbese,d}\right) \end{cases} \end{array} \tag{21}$$

where $X_{gbest,d}$ is the global optimal solution.

3.1.2. Differential Evolution Algorithm

DE algorithm is a random optimization algorithm put forward by Rainer and Price [46]. Three important operators are consisted in DE, namely mutation, crossover, and selection operator.

(1) Mutation operator:

For each target individual $X_i^g = (x_{i,1}^g, x_{i,2}^g, \cdots, x_{i,n}^g)$, the corresponding mutation vector $V_i^g = (v_{i,1}^g, v_{i,2}^g, \cdots, v_{i,n}^g)$ is decided by:

$$V_i^g = X_{r1}^g + F(X_{r2}^g - X_{r3}^g) \tag{22}$$

where g is the evolutionary generation, F is the mutation constant within [0, 1], r_1, r_2 and r_3 are the individual indexes which is different from each other, and selected from the population randomly.

(2) Crossover operator:

For each mutation vector V_i^g, a candidate individual $U_i^g = (u_{i,1}^g, u_{i,2}^g, \cdots, u_{i,n}^g)$ is generated according to the following rule.

$$u_{i,j}^g = \left\{ \begin{array}{ll} v_{i,j}^g, & rand_j \leq CR \text{ or } j = randn_i \\ x_{i,j}^g, & rand_j > CR \text{ or } j \neq randn_i \end{array} \right\} \tag{23}$$

where CR is a cross probability constant within (0, 1), $randn_i \in (1, 2, \ldots, n)$ is a randomly selected index of variables.

(3) Selection operator:

In the selection process, the DE algorithm adopts the greedy mechanism, and only the individual with good fitness enters the next generation.

The DE's performance is often decided by the choice of control parameters. Thus, an adaptive parameter method with self-learning ability [47] has been applied. Initially, the control parameters of F and CR for each solution are randomly generated in [0, 1] expressed as Figure 1, respectively. To generate new solutions, $\dot{F}_i$ and $\dot{CR}_i$ are calculated as Equations (24) and (25). If the fitness of parents is less than the offspring, the parents and the parent's control parameters F and CR will be replaced by the offspring and the offspring's control parameters $\dot{F}$ and $\dot{CR}$. In the end, only individuals with a favorable fitness value and the corresponding control parameters can be retained to the next-generation as follows:

$$F_i = F_{r1} + rand \times (F_{r2} - F_{r3}) \tag{24}$$

$$CR_i = CR_{r1} + rand \times (CR_{r2} - CR_{r3}) \tag{25}$$

X_1^t	F_1^t	CR_1^t
X_2^t	F_2^t	CR_2^t
X_3^t	F_3^t	CR_3^t
$\cdots$	$\cdots$	$\cdots$
X_{NP}^t	F_{NP}^t	CR_{NP}^t

$\Rightarrow$

$\dot{F}_1^t$	$\dot{CR}_1^t$	TX_1^t
$\dot{F}_2^t$	$\dot{CR}_2^t$	TX_2^t
$\dot{F}_3^t$	$\dot{CR}_3^t$	TX_3^t
$\cdots$	$\cdots$	$\cdots$
$\dot{F}_{NP}^t$	$\dot{CR}_{NP}^t$	TX_{NP}^t

Figure 1. The individual code map.

3.2. Optimization Strategy

In the proposed model, due to the two objective functions restricted and contradicting with each other, it is not possible to exist a set of solutions that make them obtain the optimal solution simultaneously. Therefore, the Pareto optimal solution would be preferred to solve the multi-objective optimization problem. What's more, the elitist reservation strategy, crowding entropy and fuzzy-based mechanism are applied to generate the POF and extract the best compromise solution.

3.2.1. The Elitist Reservation Strategy

Initially, the empty external archive with a certain size is created. The individuals with better performance are kept in the external archive created. As evolution progresses, the offspring generated by evolution are compared with all individuals in the current archive, and only the solutions with better performance can survive to the archive. Only three cases would be produced when the newly generated solution compares with the current archive: (1) if a member or members of the archive dominate the newly generated solution, the newly generated solution is rejected; (2) if a member or members of the archive is dominated by the newly generated solution, the dominated solutions in the archive are deleted and the newly generated solution joins in the archive; and (3) newly generated solutions and all the archive members are not dominated by each other, the newly generated solution joins in the archive. Whether the newly generated solution enters the archive or not is decided according to the three rules.

3.2.2. Crowding Entropy-Based Diversity Measure

In order to determine the density of a solution, the crowding distance [48] and distribution entropy have been taken into adequate account at the meantime. Based on the above discussion, combined with distribution entropy and the crowding distance, the crowding entropy [47] is employed to calculate the crowding degree accurately. The distribution of a solution on each objective can be well described by the entropy concept.

The distribution entropy of the ith solution associated with the jth objective is shown as follows:

$$E_{i,j} = -\left[pl_{ij}\log_2\left(pl_{i,j}\right) + pu_{ij}\log_2\left(pu_{i,j}\right)\right] \tag{26}$$

$$pl_{ij} = \frac{dl_{ij}}{c_{ij}} \tag{27}$$

$$pu_{ij} = \frac{du_{ij}}{c_{ij}} \tag{28}$$

$$c_{ij} = dl_{ij} + du_{ij} \tag{29}$$

where dl_{ij} is the distances of the ith solution to its lower neighbor solution on the jth objective, and du_{ij} is the distances to its upper neighbor solution. Note that although the distribution of the solution can be correctly described by the distribution entropy, the crowding degree of the solution cannot be reflected exactly. The crowding entropy can be expressed as follows:

$$CE_i = \sum_{j=1}^{k} \frac{c_{i,j}E_{ij}}{f_j^{\max} - f_j^{\min}} = -\sum_{j=1}^{k} \frac{dl_{ij}\log_2\left(pl_{i,j}\right) + du_{ij}\log_2\left(pu_{i,j}\right)}{f_j^{\max} - f_j^{\min}} \tag{30}$$

The crowding degree of solutions on each objective space can be accurately reflected by the crowding entropy.

If the number of solutions in the external archive has been bigger than the set value Nc, the redundant solution would be removed by calculating the crowded entropy. For the purpose to maintain the diversity of solutions, a "del" phase-out strategy is adopted, whose details are presented in [49,50]. When the solution with the smallest crowded entropy is eliminated every time, the congestion entropy of the solution of the external archive is recalculated. A Pareto solution could be obtained with the characteristics of uniform distribution and good diversity by "eliminating" gradually.

3.2.3. Fuzzy Theory

Based on the Pareto optimal set that we get, a Pareto optimal solution is extracted as the best compromise solution according to the employ fuzzy-based mechanism. In this work, the membership function is shown as [51]:

$$u_m^i = \begin{cases} 1, & f_i^m \le f^{m,\min} \\ \frac{f^{m,\max} - f_i^m}{f^{m,\max} - f^{m,\min}}, & f^{m,\min} < f_i^m < f^{m,\max} \\ 0, & f_i^m \ge f^{m,\max} \end{cases} \tag{31}$$

$$u_i = \frac{\sum_{m=1}^{N_{obj}} u_i^m}{\sum_{i=1}^{N_c} \sum_{m=1}^{N_{obj}} u_i^m} \tag{32}$$

where $f^{m,\min}$ is the minimum value and $f^{m,\max}$ are the maximum value of the mth objective function. N_{obj} is the number of objectives and u_i is the satisfaction of the ith Pareto optimal solution.

3.3. Multi-Objective Differential Evolution and Crisscross Optimization Algorithm

Owning of the distinctive crossover operator and greedy selection operator, CSO algorithm displays better global search performance when employed to deal with optimization problems. However, it has fewer control parameters and the adjustment strategy is simple. For some objective functions, satisfactory results cannot be obtained. The DE algorithm has fast convergence rate, but it tends to fall into premature convergence. For the purpose to enhance the performance of algorithm, an improved CSO is combined with a modified DE algorithm to create a hybrid algorithm called MODECSO. At the same time, the elitist reservation strategy and crowding entropy are introduced to form the MODECSO algorithm.

The implementation procedure of MODECSO is detailed as follows:

Step 1: Initialize the population and set the parameters of the algorithm.
Step 2: Compute the fitness function.
Step 3: Create an empty external archive.
Step 4: While *iter* < *Maxiter* do.
Step 5: Select a solution in the external archive as global optimal solution randomly.
Step 6: Perform improved horizontal crossover operation.
Step 7: Carry out three operations in the ADE algorithm.
Step 8: Compute the fitness function.
Step 9: Update the whole population and control parameters.
Step 10: Update the external archive according to Sections 3.2.1–3.2.3.
Step 11: Carry out vertical crossover operation.
Step 12: Compute the fitness function.
Step 13: Update the population.
Step 14: Update the external archive according to Sections 3.2.1–3.2.3.
Step 15: End while.

4. Simulation and Analysis

For the purpose to verify feasibility and advantages of the put forward MODECSO algorithm, three different case studies have been employed to simulate. They are: (a) a 10-unit DEED; (b) a 5-unit DEED considering PEVs for valley filling; and (c) a 5-unit DEED considering PEVs to the shave peak and fill valley, respectively. Figure 2 displays the proposed MODECSO algorithm flow chart for solving DEED.

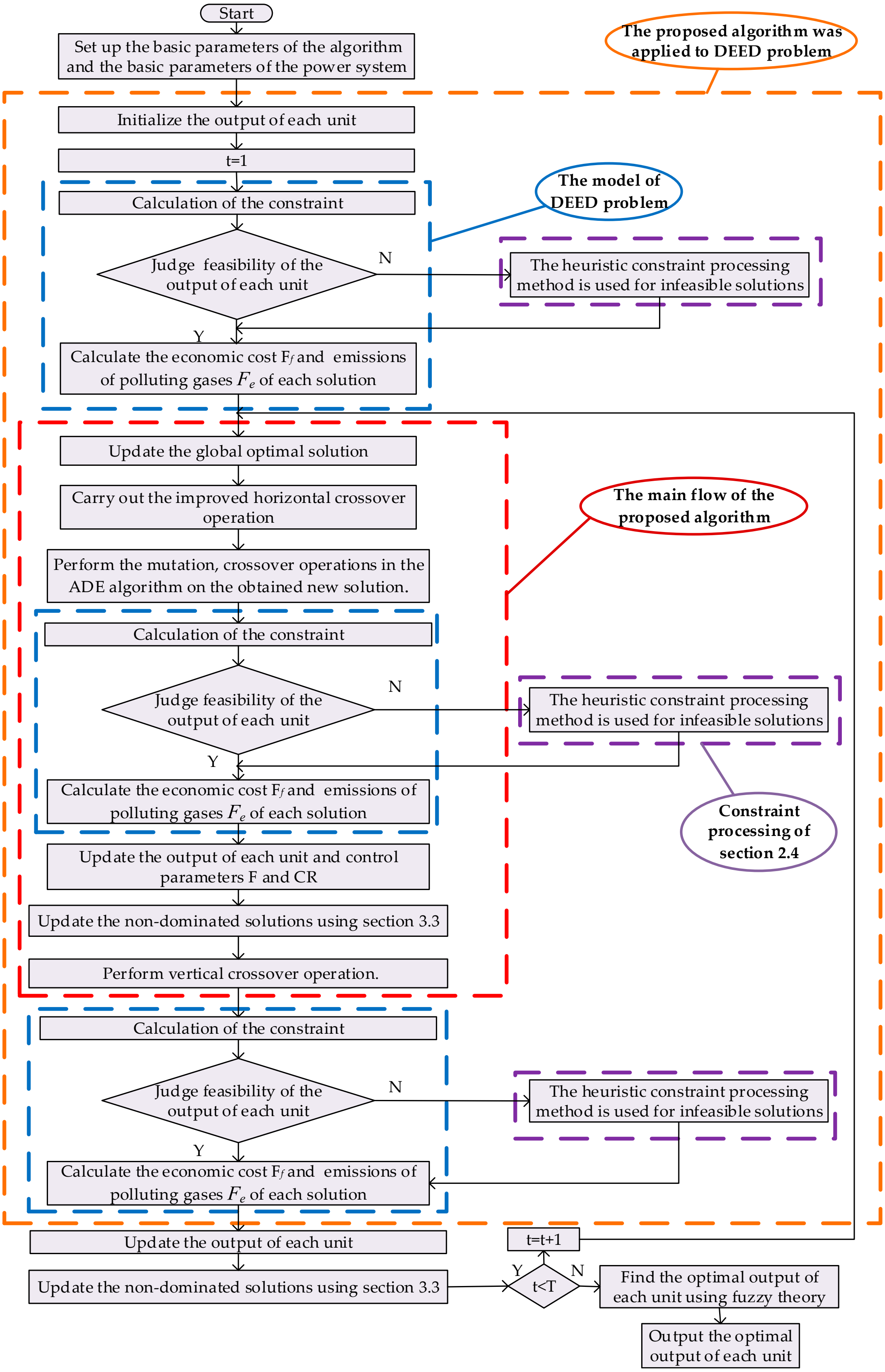

Figure 2. The flow chart of multi-objective differential evolution and crisscross optimization (MODECSO) algorithm for solving dynamic economic/emission dispatch (DEED) problem.

The system load adopts a 24-h dispatch period. The parameters involved in the multi-objective MODECSO algorithm have been shown as follows: the maximum number of iterations $G_{\max}$ sets as 4000, the size of population sets as 100. Initially, the normal distributions which the mean value is 0.5 and standard deviation value is 0.1, is employed to generate F and CR, respectively; the size of external archive Nc is 50; the value of vertical crossover operator P_v is set as 0.8 [46]. The number of PEVs sets as 40,000 [52]. All the PEVs are needed to fully charge before 7:00 am and the control center [31,37,52] would control charging/discharging behaviors of PEVs. The charging efficiency ξ_c is 0.8 and the discharging ξ_D efficiency also is 0.8; $S_{\min}$ is 20% and $S_{\max}$ is 90%. The number of PEVs required is calculated as follows: At periods 11th and 12th, the load data in Table 1 appears the peaks. If the load during the 10th period is selected as the basis for the peak shift, then the total load that peak shaved is 52 MW. It is assumed that travel distance of each PEV is 40 km/day, in other words, the consumption SOC of each PEV is 0.25. Then, for each PEV, it may be that the SOC is V2G scheduled equal to 0.45 ($SOC_{\max} - SOC_{\min} - 0.25$). According to the simulation results, the battery capacity was determined to be 36 kWh. A fixed charging/discharging power (P_{ch}/P_{disch}) of 6.6 kW is selected [52]. If the V2G lasts for 1 h, the vehicle's consumption SOC is about 0.3, less than 0.45. This means that when V2G is needed, the power stored in the battery is sufficient for 1 h. Assuming that each PEV participating in the V2G takes only 1 h, the needed number is approximately 7879 ($52 \times 1000/6.6$). As a result, the number of PEVs is enough for V2G.

In all experiments, each optimization algorithm runs 30 times independently to avoid randomness. For the sake of fairness, the maximum number of the function evaluations for each algorithm is the same.

Table 1. Load data without plug-in electric vehicles (PEVs).

Hour/h	Load/Mw	Hour/h	Load/Mw	Hour/h	Load/Mw	Hour/h	Load/Mw
1	410	7	626	13	704	19	654
2	435	8	654	14	690	20	704
3	475	9	690	15	654	21	680
4	530	10	704	16	580	22	605
5	558	11	720	17	558	23	527
6	608	12	740	18	608	24	463

(1) **Case 1**: *DEED problems without PEVs.*

For the purpose to demonstrate the performance of the put forward multi-objective MODECSO algorithm for the DEED problem, the classic ten-machine system is introduced to simulate in this paper. Physical characteristics of each generator, 24-h load demand, and operating cost coefficients could be gotten in [53], the PEVs are not considered in the simulation. Figure 3 displays the results of several algorithms for solving DEED problems. The specific results of several algorithms proposed in [53–56] for solving the DEED problem are expressed as Table 2.

Showing as Table 2 and Figure 3, the economic cost obtained by the MODECSO algorithm is the lowest. Although the pollution emission is slightly higher than [55], the satisfaction of the compromise solution gotten by MODECSO algorithm is the best one by using the fuzzy theory. Although the proposed algorithm does not show an advantage in terms of time cost, this is within an acceptable range. Due to the retain of the diversity of the offspring and exploiting the important information of infeasible solutions, the repair process of the infeasible solution is carried out. The analysis indicates the advantage and effectiveness of the proposed MODECSO algorithm in solving DEED problem.

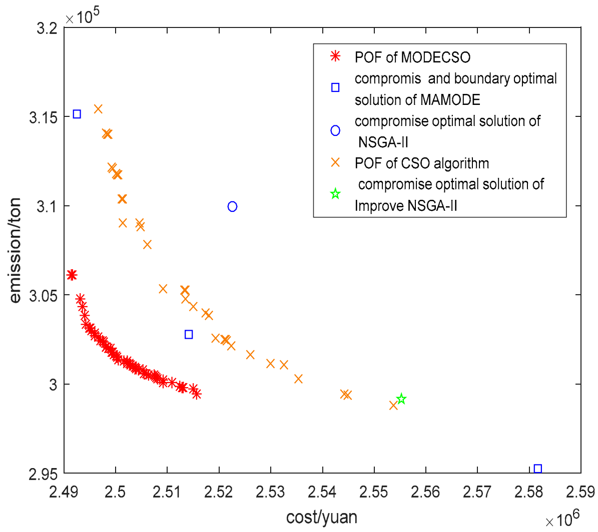

Figure 3. Comparison of results of different algorithms.

Table 2. Specific results of several algorithms for solving DEED problem.

Algorithm	Selected Target	Cost/Yuan (10^6)	Emission/Ton (10^5)	The Satisfaction of the Compromise Solution	CPU Time (min)
NSGA-II [53]	Best cost Best emission Compromise	— — 2.5226	— — 3.0994	— — 0.18137	-
CSO [54]	Best cost Best emission Compromise	— — 2.5013	— — 3.0905	— — 0.19086	**3.89**
Improved NSGA-II [55]	Best cost Best emission Compromise	— — 2.5552	— — 2.9924	— — 0.20476	**3.47**
MAMODE [56]	Best cost Best emission Compromise	2.4925 2.5817 2.5141	3.1512 2.9524 3.0274	— — 0.20667	**3.15**
MODECSO	Best cost Best emission Compromise	2.4712 — **2.4882**	— 2.9214 **3.0226**	— — **0.21633**	**3.42**

To further verify effectiveness of the parameter self-learning method and improved horizontal crossover in the MODECSO algorithm, four scenarios are compared in the classic ten-machine test system.

a. F and CR are constants and remain the same throughout the iteration.
b. F and CR adopt linear adaptive strategy. During the whole iteration process, the control parameter F decreases with the iterations, and CR increases with the iterations.
c. F and CR adopt the self-learning strategy of parameters proposed in this paper.
d. F and CR adopt the self-learning strategy of parameters, but the improved horizontal crossover operations do not be performed.

The comparison of the result of different control parameters is shown in Figure 4, and the result of the improved horizontal crossover operation is expressed as Figure 5.

As shown in Figures 4 and 5, the adaptive parameter method with self-learning and improved horizontal crossover operator is effective in solving the DEED problems.

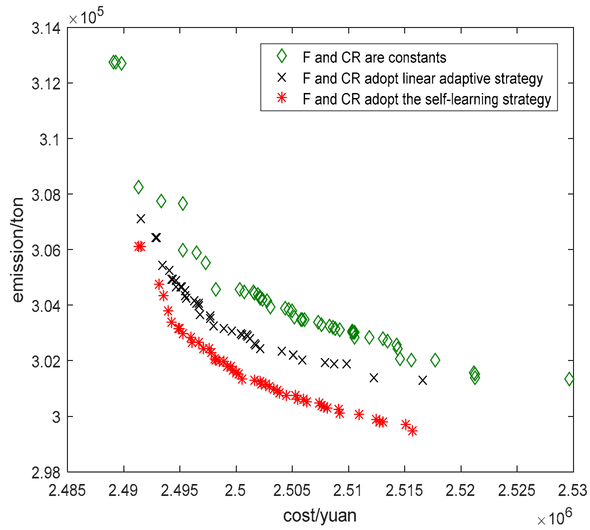

Figure 4. Comparison of results of different parameters.

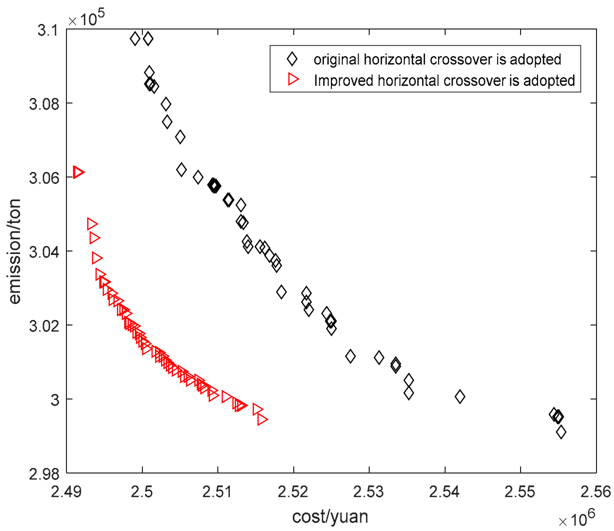

Figure 5. Comparison of results of improved horizontal crossover.

(2) **Case 2**: *The DEED problem with the consideration of G2V technology for valley filling.*

In Case 2, a five-machine test system is introduced. The load requirements are shown in Table 1, and operating cost parameters, the physical characteristics of each generator are obtained from [35], the valley filling is achieved by using the G2V technology. The purpose is to analyze benefits of load distribution by the water-filling algorithm [36], with consideration of two different charging strategies which are described as follows:

(i) **Case 2.1**: *The charging load of PEVs conforms to the four charging scenarios.*

In Case 2.1, four different charging scenarios are modeled to make the comparison and evaluation about the influences on DEED problem for the power system, there are: (1) Electric Power Research Institute (EPRI); (2) off-peak charging profile; (3) peak charging profile; and (4) stochastic charging profile. The probability distribution of the four charging scenarios in each hour is listed in Table 3. Figure 6 shows the new load demands after considering PEVs of four scenarios. The dispatch results of the four cases are expressed in Figure 7 and Table 4.

Table 3. Four charging scenarios.

Scenario 1: EPRI charging scenario							**Scenario 2**: Off-peak charging scenario						
Time	Charging probability (%)						Time	Charging probability (%)					
1:00–6:00	10	10	9.5	7	5	3	1:00–6:00	18.5	18.5	9	9	4	4
7:00–12:00	1	0.3	0.3	1.3	2.1	2.1	7:00–12:00	0	0	0	0	0	0
13:00–18:00	2.1	2.1	2.1	1	0.5	0.5	13:00–18:00	0	0	0	0	0	0
19:00–24:00	1.6	3.6	5.4	9.5	10	10	19:00–24:00	0	0	0	0	18.5	18.5
Scenario 3: Peak charging scenario							**Scenario 4**: Random charging scenario						
Time	Charging probability (%)						Time	Charging probability (%)					
1:00–6:00	0	0	0	0	0	0	1:00–6:00	5.7	4.9	4.8	2.4	2.6	9.7
7:00–12:00	0	0	0	0	0	0	7:00–12:00	8.7	4.8	1.1	3.2	2.1	5.7
13:00–18:00	18.5	18.5	18.5	18.5	9	9	13:00–18:00	3.8	2.2	2.1	6.1	3.2	2.2
19:00–24:00	4	4	0	0	0	0	19:00–24:00	2.8	2.2	5.5	2.5	3.5	8.2

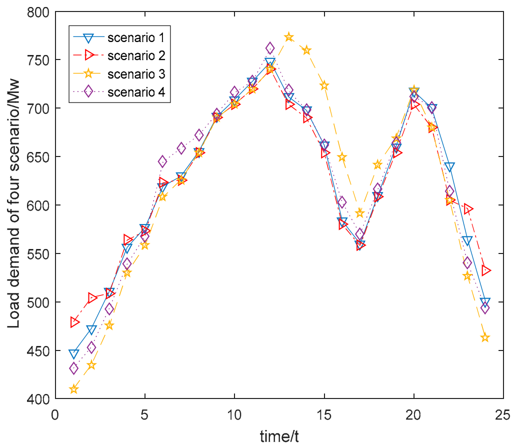

Figure 6. Load demand of four scenarios.

Table 4. Optimal compromise solutions of four charging scenarios.

Scenarios	Cost/Yuan/10^4	Emission/Ton/10^4	Peak Load/Valley Load
Scenario 1	4.8392	1.9107	1.6712
Scenario 2	**4.8017**	**1.8955**	**1.5437**
Scenario 3	4.8616	1.9398	1.8863
Scenario 4	4.8393	1.9108	1.7650

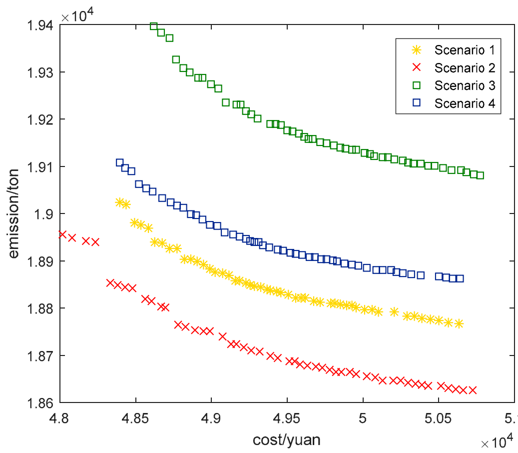

Figure 7. Pareto optimal front (POF) of four charging scenarios.

As shown in Figure 6, when PEVs is charged in off-peak periods, the newly generated load curve is relatively smooth and the peak-to-valley difference is the smallest. Moreover, as shown in Figure 7 and Table 4, comparing among the four charging methods, the cost of off-peak charging is 48,017 yuan/day and the emission of air pollutants is 18,955 ton/day, ranking the first lowest among four charging scenarios. Conversely, the cost of peak charging is 48,616 yuan/day, and the emission of air pollutants is 19,398 ton/day, which are the highest among four charging scenarios. Ranking the second lowest is the EPRI charging profile scenario in the cost and emission, and ranking the third place is stochastic charging behavior. Therefore, under the same load demand condition, prioritizing to charge during the off-peak period could save 1.24% in cost and could reduce 2.34% in the air emission.

(ii) Case 2.2: *Charging requirements are assigned by the water-filling algorithm.*

In Case 2.2, the load data and load demand of PEVs are exactly the same as those in Case 2.1, but the load demands of PEVs were distributed by the water-filling algorithm. It pours power (PEVs load demand) into the valley with the main purpose of minimizing load changes. The new load demand of 24-h after filling the valley is expressed as Figure 8, and the results obtained by MODECSO are expressed as the Figure 9 and Table 5.

The valley filling strategy can better decrease the difference of peak-to-valley and is able to smooth the load curve. According to Figure 9, as can be seen that the scheduling result using the valley filling strategy is better than the scheduling of the four charging scenarios under the same load conditions.

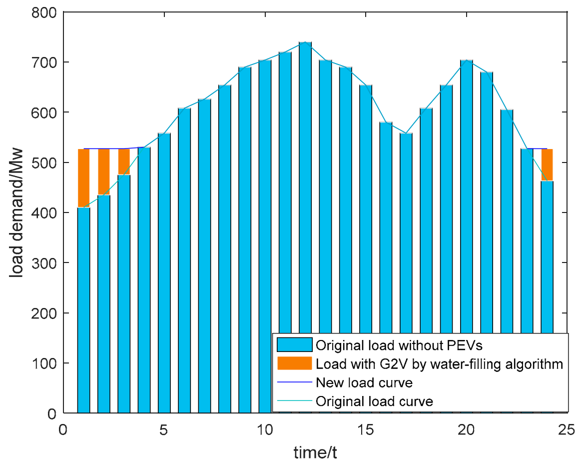

Figure 8. New 24-h load curve after valley filling.

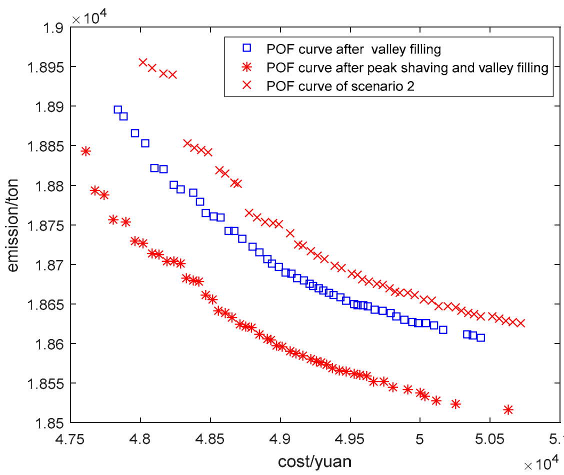

Figure 9. Scheduling results of three strategies.

Table 5. 24-h output of per unit under optimal scheduling in Case 2.2.

Hour/h	P1/Mw	P2/Mw	P3/Mw	P4/Mw	P5/Mw	PEV/Mw
1	72.41	94.12	112.26	125.60	137.57	−126
2	72.38	97.01	122.68	124.46	125.42	−101
3	70.15	101.26	112.12	129.41	128.97	−61
4	70.22	93.87	115.04	127.79	134.93	−6
5	72.19	89.73	126.56	147.17	128.78	0
6	75.00	91.88	135.25	178.07	135.41	0
7	73.89	98.08	135.57	192.34	134.31	0
8	75.00	96.25	152.41	199.49	139.70	0
9	74.25	102.99	172.26	209.36	141.05	0
10	74.38	110.00	175.00	213.79	141.13	0
11	74.36	120.04	173.89	214.11	148.39	0
12	75.00	122.00	175.00	216.21	163.24	0
13	74.47	115.12	172.90	210.28	141.59	0
14	74.06	103.00	173.60	209.16	140.11	0
15	72.62	98.33	161.14	196.33	134.54	0
16	74.04	95.15	127.15	154.71	135.89	0
17	70.89	97.87	132.19	129.66	133.79	0
18	71.03	96.16	154.13	163.11	131.22	0
19	73.58	96.13	156.40	197.40	139.34	0
20	72.69	114.86	174.16	211.48	141.13	0
21	73.45	96.43	175.00	206.68	138.05	0
22	71.14	97.08	138.53	170.86	134.98	0
23	67.24	94.32	113.76	127.78	138.78	-9
24	70.95	92.14	117.49	131.12	130.24	-73
Cost: 4.7837 × 10^4; emissions: 1.8896 × 10^4						

(3) **Case 3:** *DEED problem using G2V and V2G for valley filling and peak shaving.*

In Case 3, the optimal scheduling result of solving DEED problem using G2V and V2G technologies is given. The loads of the 11th and 12th periods are both set as the value of the 10th periods which is 704 MW, so the load that peak shaved at the two periods are 16 MW and 36 MW. The number of PEV and the discharge power of each PEV have been given. The power that each PEV can provide is 23.4 KW. As described before, 80% of PEVs is considered to participate in V2G technology, the total applicable power is 748.8 MW, more than the total load that peak shaved, that is, 52 MW. Hence, it is available for PEVs to realize the purpose of peak shaving.

The new 24-h load curve after valley filling and peak shaving are shown in Figures 9 and 10, which show the POF under three different strategies. Showing as Figure 9 and Table 6, the scheduling result after using the G2V and V2G technologies is better than the scheduling result of only G2V technology used.

According to Tables 5 and 6, after adopting V2G and G2V technologies, the economic cost of the power system dispatch is 47,676 yuan/day, and the pollutant gas emission is 18,797 tons/day. However, the economic cost generated by using only the G2V technology used is 47,837 yuan/day, and the pollutant gas emission is 18,896 tons/day. Therefore, in the same situation, using both G2V and V2G technology could save 167 yuan/day in terms of the economic cost and could reduce 99 ton/day in the air emission than only using G2V technology. In order to further illustrate the advantages of peaking shaving and valley filling, the result of Case 2.1 is included in Figure 10 for the purpose to compare. Scenario 2 fills the valley to some extent, however, it is not comprehensive and systematic as the G2V technology. Obviously, the economic cost and air emission after using G2V and V2G technology (or only using G2V technology) are better than the four scenarios of Case 2.1 (the off-peak charging costs 48,017 yuan/day and emits air pollutants with the amount of 18,955 ton/day). This implies that great significance should be attached to control the behaviors of charging and discharging for PEVs.

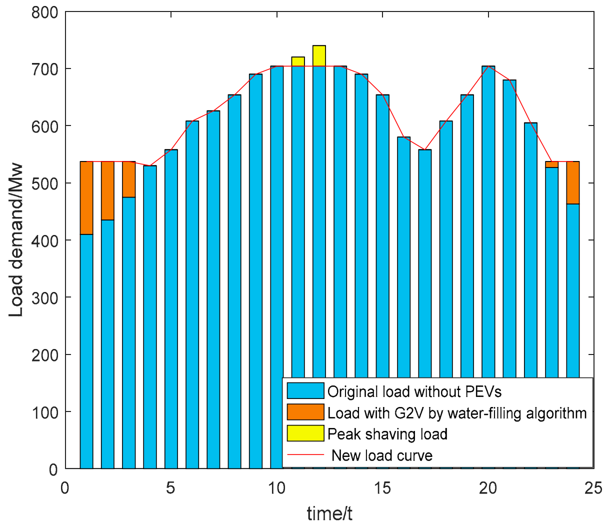

Figure 10. New 24-h load curve after valley filling and peak shaving.

Table 6. 24-h output of per unit under optimal scheduling in Case 3.

Hour/h	P1/Mw	P2/Mw	P3/Mw	P4/Mw	P5/Mw	PEV/Mw
1	69.84	96.85	117.84	125.69	140.50	−134.5
2	71.06	98.15	122.53	129.03	129.86	−109.5
3	69.59	94.27	122.17	129.33	135.30	−69.5
4	70.64	95.45	120.04	127.41	137.11	−14.5
5	74.10	95.87	121.61	132.77	140.16	0
6	74.06	98.51	137.85	167.54	137.71	0
7	75.00	97.25	124.91	197.37	139.70	0
8	72.89	96.61	149.27	206.38	137.68	0
9	75.00	103.37	174.42	205.95	141.15	0
10	74.37	109.35	175.00	211.89	143.79	0
11	74.47	111.98	173.51	210.15	144.27	16
12	73.37	111.77	172.91	211.62	144.71	36
13	74.89	110.74	174.80	210.31	143.56	0
14	74.41	103.08	171.09	207.15	144.18	0
15	74.15	99.24	160.17	194.40	134.88	0
16	71.27	98.06	120.17	160.14	137.45	0
17	71.92	95.46	124.33	133.52	139.22	0
18	74.16	97.01	131.93	175.88	136.69	0
19	73.75	97.75	153.38	200.72	137.29	0
20	74.18	109.13	173.76	215.98	141.30	0
21	74.34	99.59	174.24	209.97	131.44	0
22	71.21	96.46	140.77	172.02	132.07	0
23	70.28	91.49	123.54	131.98	133.34	−17.5
24	72.17	95.44	129.06	127.08	126.81	−81.5
Cost: 4.7676×10^4; emissions: 1.8797×10^4						

Finally, the three cases are briefly summarized here. Case 1 shows the effectiveness and advantage of MODECSO algorithm in dealing with the DEED problems according to compare with several other algorithms. Cases 2 and 3 prove that under the same load, the introduction of PEVs for valley filling and peak shaving decrease the difference of peak-to-valley and smooth the load curve relatively, and could reduce the cost and pollution gas emissions.

5. Conclusions

This work established a DEED model with consideration of PEVs, using G2V and V2G technology to realize the purpose of peak shaving and valley filling; the associated influences on economic cost and pollution emission have been discussed. The optimal scheduling results are generated based on different V2G and G2V loads. A new multi-objective hybrid optimization algorithm (called MODECSO) based on adaptive differential evolution and crisscross algorithm is used to deal with the model under three conditions. Case 1 shows the advantage and effectiveness of the put forward MODECSO algorithm in dealing with DEED problem, whereas Case 2 and 3 demonstrate that it is effective of the method of using PEVs for the purpose to shave peak and fill valley. Experimental results show that under the same load conditions, it can save costs and reduce emissions of pollution gas by load transfer, this provides a new way for solving the DEED problem. The finding suggests that receiving revenue in the V2G process is of significance for PEV owners, which will affect the willingness to attend V2G in a large extent. Some policies should also be developed to encourage PEV owners to join in such an activity. In addition, some renewable energy sources such as solar could also be taken into account which is beneficial to energy conservation and emission reduction for the sustainable development of human society.

Author Contributions: P.M. put forward the analysis method, made the simulation and wrote the paper; L.W. provided ideas and analyzed the simulation results, and H.Z. and Z.L. were responsible for the chart part.

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