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Research Article

An External Archive-Based Constrained State Transition Algorithm for Optimal Power Dispatch

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This paper proposes an external archive-based constrained state transition algorithm (EA-CSTA) with a preference trade-off strategy for solving the power dispatch optimization problem in the electrochemical process of zinc (EPZ). The optimal power dispatch problem aims to obtain the optimal current density schedule to minimize the cost of power consumption with some rigorous technology and production constraints. The current density of each production equipment in different power stages is restricted by technology and production requirements. In addition, electricity price and current density are considered comprehensively to influence the cost of power consumption. In the process of optimization, technology and production restrictions are difficult to be satisfied, which are modeled as nonconvex equality constraints in the power dispatch optimization problem. Moreover, multiple production equipment and different power supply stages increase the amount of decision variables. In order to solve this problem, an external archive-based constrained state transition algorithm (EA-CSTA) is proposed. The external archive strategy is adopted for maintaining the diversity of solutions to increase the probability of finding the optima of power dispatch optimization problem. Moreover, a preference trade-off strategy is designed to improve the global search performance of EA-CSTA, and the translation transformation in state transition algorithm is modified to improve the local search ability of EA-CSTA. Finally, the experimental results indicate that the proposed method is more efficient compared with other approaches in previous papers for the optimal power dispatch. Furthermore, the proposed method significantly reduces the cost of power consumption, which not only guides the production process of zinc electrolysis but also alleviates the pressure of the power grid load.

1. Introduction

Hydrometallurgical zinc is the main production approach of zinc, accounting for more than 80% of zinc production in the world [1]. The electrochemical process of zinc plays an important role in the hydrometallurgical process of zinc [2]. The power consumption decided by current efficiency and cell voltage is an important economic indicator of electrolytic zinc process. In the process, zinc is deposited in the zinc sulfate solution under the action of direct current. Current efficiency and cell voltage are influenced by current density directly. If the current density is too low, the current efficiency will drop sharply, and zinc deposited on cathodes will be dissolved [3]. If the current density is too high, the temperature of the electrolytic cell will rise and impurities in the solution will increase. At the same time, the increased current density will definitely lead to high cell voltage, which affects the power consumption. The relationship between current density and current efficiency is nonlinear, which may not cause current efficiency to increase as expected. In addition, the current density is also limited by the maximum current strength that the plate can withstand. Due to the complexity of zinc electrolysis process, it is difficult to find a suitable current density for the optimal power dispatch.

Previously, power can be supplied at a constant current density without changing the price of electricity. However, the power sector adopts time-based pricing [4], which means that the price of electricity is high at the peak of electricity consumption, while low at the valley of electricity consumption. If the production process is running at the lowest price period every day, there is no doubt that the daily output of zinc will not be satisfied. It is the same on the basic electricity price period. If the production process is running at the highest price every day, the daily output of zinc will be satisfied. But, this does not achieve the goal of minimizing the cost of power consumption. Our idea is to reasonably allocate the power consumption at different electricity price periods to minimize the cost of power consumption. Therefore, it is necessary to find an optimal power dispatch in different pricing periods [5]. The optimal power dispatch based on time-sharing price counting policy can be formulated as a constrained optimization problem (COP), which is to minimize electricity bills when production and technology constraints are satisfied.

In this paper, the main challenges of optimizing power dispatch are given as follows.

(i) Nonconvex equality constraint function: in the hydrometallurgical process of zinc, the equality constraint function is related to the daily output of zinc, which need to satisfy consumer demand. Due to the small feasible search space, it is difficult to satisfy equality constraint in the search process

(ii) Multiple decision variables: the number of decision variables is decided by the number of production equipment and power supply stages. The value of decision variable depends on not only the electricity price of different periods but also the production and technology requirements

In the literatures, many methods have been designed for solving optimal power dispatch in the zinc electrolysis process. Yang et al. [5, 6] proposed backpropagation and Hopfield neural network for optimal power dispatch. Li and Gui [4] solved power dispatch optimization problem by an improved particle swarm optimization algorithm. Gui et al. [7] designed a hybrid particle swarm algorithm to solve the power dispatch optimization problem. Han et al. [8] tackled this problem by two-stage constrained state transition algorithm. Although these methods can obtain good solutions, the cost of power consumption can be lower by further optimizing the current density. Based on the study of those literatures, the optimal solution can be improved from the daily output of zinc and the current density of each production equipment in different power supply stages.

The optimal power dispatch in EPZ can be formulated as a constrained optimization problem (COP). Some basic techniques have been applied to solve COPs, such as adaptive penalty function technique [9], adaptive trade-off model [10], and Deb's rules [11]. Hybrid techniques in which two or more strategies are integrated to solve COPs have been designed, such as Deb-penalty technique [8]. Improved version techniques have been applied for solving COPs, like improved $(\mu + \lambda)$-constrained differential evolution [12] and improved adaptive trade-off model [13]. However, these techniques rarely consider the diversity of solutions from the perspective of feasible and infeasible solutions. Moreover, it is difficult to find a good solution since the power dispatch model contains the nonconvex equality constraint and multiple decision variables. So maintaining the diversity of feasible solutions and infeasible solutions can be instructive to find a better solution.

In this paper, the constrained state transition algorithm based on external archive with preference trade-off strategy is proposed for the power dispatch problem in electrolytic zinc process. The external archive-based constrained state transition algorithm (EA-CSTA) is different from the constrained state transition algorithm (CSTA) [8] on selecting solutions. The CSTA selects only a current best solution from a set of candidate solutions, while the EA-CSTA adopts an external archive to store multiple potential solutions. In addition, a novel constraint-handling technique, called preference trade-off strategy, is proposed to select solutions from both feasible and infeasible candidates. The novelty and the main contributions of the paper can be summarized as follows.

(1) An external archive strategy is designed to save multiple potential feasible and infeasible solutions. The EA-CSTA achieves the state transition by selecting several potential solutions saved in an external archive, which increases not only the diversity of solutions but also the probability of finding the global solution. In order to expand the search scope of the candidate solutions, translation transformation in STA [14] is modified to share information among potential solutions

(2) The preference trade-off strategy in the proposed method contains both preference and trade-off. Firstly, it is able to adjust the number of feasible and infeasible solutions. Secondly, strategies are different in dealing with feasible and infeasible candidates, which avoid the direct comparison of feasible and infeasible candidates. Also, it increases the diversity of these selected solutions in an auxiliary manner. Some preference strategies are adopted to select solutions, such as adding a penalty factor to normalization. The normalization is capable of dealing with the different scale between cost of power consumption and production constraints

(3) The proposed method is successfully applied to solve the power dispatch optimization problem in EPZ that can bring significant economic profits to the metallurgy industry. In addition, it is conductive to relieve the pressure not only on the power grid but also on the peak power consuming period of power industry

The remainder of the paper is organized as follows. Section 2 introduces the preliminary knowledge of power dispatch model and constraint-handling techniques. In Section 3, the proposed constrained STA with external archive and preference trade-off strategy is elaborated. Results and discussions are presented in Section 4. Finally, Section 5 draws a conclusion of this paper and gives the possible future work.

Table 1: Time-based pricing for the power consumption.

Price	Period	Duration
1.6B	7:00–11:00, 15:00–18:00	7
	18:00–22:00	4
1.0B	11:00–15:00, 22:00–23:00	5
0.7B	23:00–7:00	8

B is the basic price (0.5627RMB/kW · h).

2. Preliminaries

In this section, the power dispatch model is expressed in detail. It contains the objective function which is minimizing the cost of power consumption, technology, and production constraints. Then, some classical and effective constraint-handling techniques are described.

2.1. Problem Formulation. The electrochemical process of zinc is a considerable large amount of power consumption process, which accounts for 80% of the total electrical energy consumption in the hydrometallurgy process of zinc. To encourage customers to consume more power in the valley-load period and less power in the peak-load period, the power sector adopts time-based pricing strategy as shown in Table 1. It means that the price of electricity is high at the peak of electricity consumption, while low at the valley of electricity consumption. The cost of power consumption will be decreased in the case that the electrochemical process of zinc consumes a small amount of electricity in the period of high price and vice versa. However, if the current density is too high or too low, it will not only affect the power consumption but also influence the product quality. To prevent low quality of product and excessive power consumption, it is essentially desired to seek for suitable current density in different pricing periods.

$$\mathrm{Fc} = \sum_{i=1}^{N_t} \mathrm{PW}_i \times T_i \times P_i + \mathrm{Fc0}, \tag{1}$$

where PW_i (kW) decided by voltage and current is the power consumption of ith price period, which can be formulated as (2), T_i (h) is the duration of ith price, P_i is the electricity price (RMB/kW·h) at ith period, and N_t is the number of the price periods; Fc0 is the basic tariff charge of electrochemical process of zinc.

$$\mathrm{PW}_i = \sum_{j=1}^{N_e} V_{ij} \times I_{ij} \times \mathrm{Nc}_j, \tag{2}$$

where V_{ij} (V) and I_{ij} (A) are the voltage and current of ith price period in the jth plant, respectively, Nc_j is the number of cells in the jth plant, and N_e is the number of plants.

$$\begin{cases} V_{ij} = a_0 + a_1 \times \mathrm{Cd}_{ij}, \\ I_{ij} = \mathrm{Np}_j \times S \times \mathrm{Cd}_{ij}, \end{cases} \tag{3}$$

where a_0 and a_1 are obtained by recursive least squares method, Cd_{ij} (A/m^2) is the current density ith price period in the jth plant, Np_j denotes the number of plates in a cell in the jth plant, and S (m^2) is the area of negative plate.

In order to satisfy the techniques and production requirements, the optimal goal should be subject to some constraints, such as the daily yield and the current density. The detailed daily yield constraints can be expressed as follows:

$$h(\mathrm{Cd}) = \sum_{i=1}^{N_t} \sum_{j=1}^{N_e} q \times I_{ij} \times \mathrm{Nc}_j \times E_{ij} \times T_i = G, \tag{4}$$

$$\begin{aligned} E_{ij} = b_0 + b_1 \times \mathrm{Cd}_{ij} + b_2 \times \mathrm{Cd}_{ij}^2 + b_3 \\ \times \mathrm{Cd}_{ij}^3 + b_4 \times \mathrm{Cd}_{ij}^4, \end{aligned} \tag{5}$$

where $h(\mathrm{Cd})$ and G denote the practical daily quantity of zinc (t) and expected goal of daily yield, respectively, q is the electrochemical equivalent of zinc ($q = 1.2202\,\mathrm{g}/A \cdot h$), E_{ij} is the current efficiency of ith price period in the jth plant, and b_0, b_1, b_2, b_3, and b_4 are obtained by recursive least squares method. Technological constraints can be presented as follows:

$$\mathrm{Cd}_{ij_{\min}} \le \mathrm{Cd}_{ij} \le \mathrm{Cd}_{ij_{\max}}. \tag{6}$$

Here, Cd_{ij} denotes the current density of ith price period in the jth plant.

To summarize, the power dispatch optimization model based on the time-sharing policy can be presented as follows.

$$\begin{aligned} \min \quad & \mathrm{Fc}(\mathrm{Cd}) = \sum_{i=1}^{N_t} \mathrm{PW}_i \times T_i \times P_i + \mathrm{Fc0} \\ \text{s.t.} \quad & h(\mathrm{Cd}) = \sum_{i=1}^{N_t} \sum_{j=1}^{N_e} q \times I_{ij} \times \mathrm{Nc}_j \times E_{ij} \times T_i = G, \end{aligned} \tag{7}$$

where

$$\begin{aligned} \mathrm{PW}_i &= \sum_{j=1}^{N_e} V_{ij} \times I_{ij} \times \mathrm{Nc}_j, \\ I_{ij} &= \mathrm{Np}_j \times S \times \mathrm{Cd}_{ij}, \\ V_{ij} &= a_0 + a_1 \times \mathrm{Cd}_{ij}, \\ E_{ij} &= b_0 + b_1 \times \mathrm{Cd}_{ij} + b_2 \times \mathrm{Cd}_{ij}^2 + b_3 \times \mathrm{Cd}_{ij}^3 + b_4 \times \mathrm{Cd}_{ij}^4, \\ \mathrm{Cd}_{ij_{\min}} &\le \mathrm{Cd}_{ij} \le \mathrm{Cd}_{ij_{\max}}. \end{aligned} \tag{8}$$

2.2. Constraint-Handling Techniques. Up to now, there are a large number of techniques for dealing with constraints [15]. In the following part, some common constraint-handling techniques are presented in detail.

2.2.1. Penalty Function Technique. Penalty function technique [16] is one of the most common way to convert constrained optimization problems (COPs) into unconstrained optimization problem. The formula of penalty function can be indicated as follows:

$$\phi(\mathbf{x}) = f(\mathbf{x}) + \sum_{i=1}^{q} \mu_i G_i(\mathbf{x}) + \sum_{j=1}^{m} \mu_j H_j(\mathbf{x}), \tag{9}$$

where $\phi(\mathbf{x})$ is the fitness function which contains the objective function $f(\mathbf{x})$ and constraint violation $(G_i(\mathbf{x}), H_j(\mathbf{x}))$, and μ_i and μ_j are the penalty factors of ith and jth constraint violations. The constraint violation can be described as follows:

$$\begin{cases} G_i(\mathbf{x}) = \max\left(0, g_i(\mathbf{x})\right)^k, & i = 1, \dots, q, \\ H_j(\mathbf{x}) = \max\left(0, \left|h_j(\mathbf{x})\right| - \epsilon\right)^k, & j = 1, \dots, m, \end{cases} \tag{10}$$

where q and m are the number of inequality and equality constraints, $h_j(\mathbf{x})$ is the jth equality constraint, such as the $h(\mathrm{Cd})$ in (4), $g_i(\mathbf{x})$ is the ith inequality constraint, ϵ is the constraint tolerance, and k is normally 1 or 2.

2.2.2. Deb's Rules. Deb's rules originally proposed by Deb [17] is effective for coping with constraints. In this strategy, two solutions can be compared according to the following criteria:

(i) If two solutions are feasible, the one with a better objective function value is chosen

(ii) If two solutions contain a feasible and an infeasible solution, the feasible one is chosen

(iii) If two solutions are infeasible, the one with lower constraint violation is chosen

2.2.3. Adaptive Trade-Off Model. Adaptive trade-off model is a novel constraint-handling technique proposed by Wang et al. [10]. In this strategy, the current generated individuals are divided into three categories according to the feasibility proportion (*fp*) which is the ratio of the number of feasible individuals to the total number of individuals. The potential individuals used for generating offsprings can be selected as follows.

(i) $fp = 0$, nondominated individuals represent the Pareto optimal set [18] of the population, which can be identified in the population as the potential solutions. The top k potential solutions can be selected from the Pareto front

(ii) $fp = 1$, individuals are sorted according to their values of objective function. The top k individuals can be selected as potential solutions to generate offsprings

(iii) $0 < fp < 1$, population is divided into a feasible and an infeasible group. The objective function value of an infeasible individual can be converted as follows:

$$F(\mathbf{x}) = \max\left\{fp * f_{\min} + (1 - fp) * f_{\max}, f(\mathbf{x})\right\}, \mathbf{x} \in Z, \tag{11}$$

where Z is the infeasible group and $f_{\min}$ and $f_{\max}$ are the minimum and maximum objective function value of solutions in the feasible group, respectively. Then, the sum value of normalized objective function value and constraint violation of each solution is compared and sorted to select the top k individuals as the potential solutions to generate offsprings.

3. Constrained State Transition Algorithm Based on External Archive

As previously mentioned, due to the complexity of the power dispatch optimization problem, intelligent or evolutionary algorithms with constraint-handling techniques are introduced to deal with the optimal power dispatch in the literatures. Those solutions of the optimal power dispatch obtained from literatures can be improved from daily output of zinc and current density. In this paper, we propose the constrained state transition algorithm based on external archive and preference trade-off strategy for the optimal power dispatch.

3.1. Modified State Transition Algorithm. In recent years, state transition algorithm (STA) [19] as a novel stochastic intelligent algorithm for global optimization has been broadly applied to different fields, such as image segmentation [20], fractional-order PID controller tuning [21], copper removal and goethite process in the hydrometallurgical process of zinc [22, 23], sensor network localization [24], and other fields [25, 26]. The inspiration of STA is derived from the concepts of state and state transition. A solution is considered as a state and the update of a solution is treated as the process of state transition. The relationship of the current state and the next state can be formulated as follows:

$$\begin{cases} \mathbf{s}_{k+1} = A_k \mathbf{s}_k + B_k \mathbf{u}_k, \\ y_{k+1} = f(\mathbf{s}_{k+1}), \end{cases} \tag{12}$$

where $\mathbf{s}_k \in \mathbb{R}^n$ represents the current state, which is a candidate solution, $\mathbf{s}_{k+1} \in \mathbb{R}^{n\times n}$ is an updated state, and it is a candidate solution set, A_k and B_k stand for state transition matrices, $\mathbf{u}_k$ is a function of $\mathbf{s}_k$ and historical solution, f is the evaluation function in the continuous STA for constraint optimization problems, and y_{k+1} is the function value of $\mathbf{s}_{k+1}$.

In order to solve optimization problems, four state transition operators of continuous STA are designed, which are rotation, translation, expansion, and axesion transformations. The original translation transformation is designed for a line search with current best solution and historical solution. Due to the difficulty of finding feasible space of

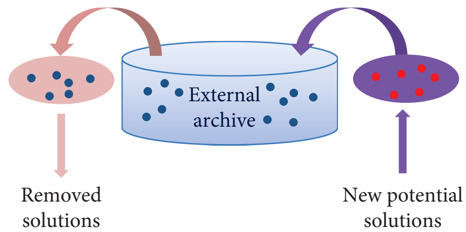

Figure 1: Schematic diagram to illustrate the process of saving potential solutions in the external archive.

optimal power dispatch, we not only need to maintain the diversity of solutions but also need to utilize the information in potential solutions. However, the original translation transformation is invalid if the current best solution and the historical solution are the same. Thus, a modified translation transformation is designed to share information in two potential solutions and keep the validity of this operator. The modified translation transformation can be expressed as follows.

$$\mathbf{s}_{k+1} = \mathbf{s}_k + \beta R_t (\mathbf{s}_k - \mathbf{s}_d), \tag{13}$$

where β is the translation factor, which is a positive constant, $R_t \in \mathbb{R}$is a random variable distributed uniformly in the range of $[0, 1]$, and $\mathbf{s}_d$ is a solution randomly chosen from the external archive.

3.2. Proposed External Archive Scheme. In this part, we adopt an external archive scheme to keep diversity for potential solutions and avoid dropping into local optimum. The differences between EA-CSTA and STA can be summarized as follows: (1) An external archive is designed for saving potential solutions. (2) The STA achieves the state transition by selecting only one best solution, while EA-CSTA designs state transition by selecting multiple potential solutions. EA-CSTA increases the diversity of solutions and the proportion of finding the global optimum.

The illustration of saving potential solutions by external archive is shown in Figure 1. The removed solutions are replaced by the new potential solutions which are selected by preference trade-off strategy from both the current generated candidates and the old potential solutions selected in the last iteration. This operation takes into account both superiority and diversity of solutions, which are two basics for finding global optimum.

3.3. Preference Trade-off Strategy of EA-CSTA. The proposed preference trade-off strategy includes two parts, trade-off and preference scheme, when dealing with rigorous constraints in the power dispatch optimization problem. In the proposed strategy, the trade-off scheme is used to balance the number of potential feasible and infeasible solutions to avoid early-maturing, and the preference scheme is used to select the potential solutions from feasible and infeasible candidates, respectively.

Firstly, a trade-off scheme is designed to calculate the number of potential feasible (*feasi_num*) and infeasible solutions (*infeasi_num*). The *feasi_num* and *infeasi_num* can be calculated as follows.

$$\begin{aligned} feasi\_num &= \begin{cases} SA \times (1 - fp), & 0 < fp < 1, \\ SA, & fp = 1, \end{cases} \\ infeasi\_num &= \begin{cases} SA \times fp, & 0 < fp < 1, \\ SA, & fp = 0, \end{cases} \end{aligned} \tag{14}$$

where SA is a constant, which is the number of potential solutions saved in the external archive and fp is the ratio of feasible candidates in the total candidates. If the number of infeasible candidates is larger than that of feasible candidates, it is difficult to find a good feasible solution. Therefore, more feasible solutions should be selected to guide candidates into feasible region to find a better feasible solution. In contrary, if the number of feasible candidates is larger than that of infeasible candidates, it is easy to mature in the early period and drop into the local optimum. Therefore, more infeasible solutions with lower objective function value should be selected to guide candidates to find better solutions and avoid falling into the local optimum.

Secondly, in the selection of feasible solutions, a preference scheme is adopted to find several feasible potential solutions. Feasible candidates are sorted in ascending order of their objective function values. The top *feasi_num* solutions are saved in the external archive as part of potential solutions.

Thirdly, in the selection of infeasible solutions, another preference scheme, which is called normalized penalty function strategy, is adopted to find several infeasible potential solutions. The normalized penalty function can be described as follows:

$$f_{\text{nor}}(\mathbf{x}) = \frac{f(\mathbf{x}) - \min f(\mathbf{x})}{\max f(\mathbf{x}) - \min f(\mathbf{x})}, \quad \mathbf{x} \in Z, \tag{15}$$

$$G_{\text{nor}}(\mathbf{x}) = \frac{G(\mathbf{x}) - \min G(\mathbf{x})}{\max G(\mathbf{x}) - \min G(\mathbf{x})}, \quad \mathbf{x} \in Z, \tag{16}$$

$$F_{\text{nor}}(\mathbf{x}) = f_{\text{nor}}(\mathbf{x}) + \mu G_{\text{nor}}(\mathbf{x}), \tag{17}$$

where $f_{\text{nor}}(\mathbf{x})$ and $G_{\text{nor}}(\mathbf{x})$ denote the normalized objective function value and the normalized constraint violation, respectively, $F_{\text{nor}}(\mathbf{x})$ is the sum value of normalized objective function value and normalized constraint violation with penalty factor, Z is a set of infeasible candidates, and μ is a constant coefficient, called the penalty factor. There are two types of candidates which contain infeasible solutions: (1) there is no feasible candidate in the current candidates; it is vital to find feasible space. In this case, the top *infeasi_num* candidates with low constraint violation are preferred, and the penalty factor is greater than 1. (2) there exist both feasible and infeasible candidates; it is vital to find a better feasible solution. In this case, the top *infeasi_num* candidates with low objective function values are preferred, and the penalty factor is less than or equal to 1.

The illustration of preference trade-off strategy is shown in Figure 2. Then, in order to illustrate the normalized

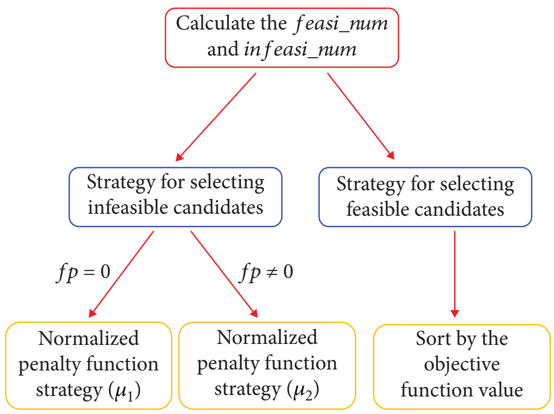

Figure 2: Schematic diagram to illustrate the preference trade-off strategy.

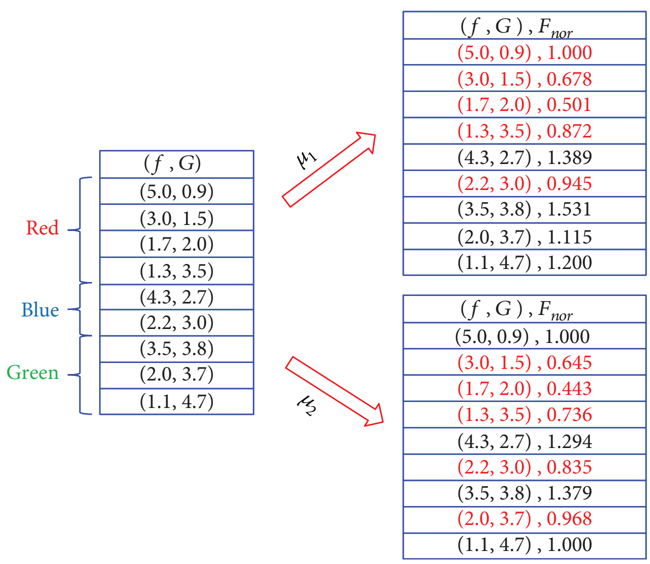

Figure 3: Schematic diagram to illustrate the original data and the normalized data.

penalty strategy with different penalty factors in selecting infeasible solutions, an example is presented in Figure 3.

As shown in Figure 3, the left form is the original data, and the right two forms are the normalized data obtained by normalized penalty strategy with different penalty factors. f and G are the objective function value and constraint violation, respectively. F_{nor} is the sum value of the normalized objective function value and constraint violation with the function of penalty factor. The red, blue, and green represent the red, blue, and green points in Figure 4, respectively. The red marked values in the right two forms are the five selected candidates by sorting F_{nor}. The marked values of the first form on the right give a preference to the candidates with lower constraint violation, while the second form on the right gives a preference to the candidates with lower objective function value.

Figure 4 shows the results obtained by normalized penalty strategy with different penalty factors. The circled points in the left subfigure represent the normalized penalty strategy with higher penalty factor. Apparently, a preference is given to those solutions with less constraint violation which can guide candidates to come into feasible region rapidly. The circled points in the right subfigure show solutions selected by normalized penalty strategy with lower penalty factor. A preference is given to those solutions with lower objective function value which can guide candidates find better feasible solutions.

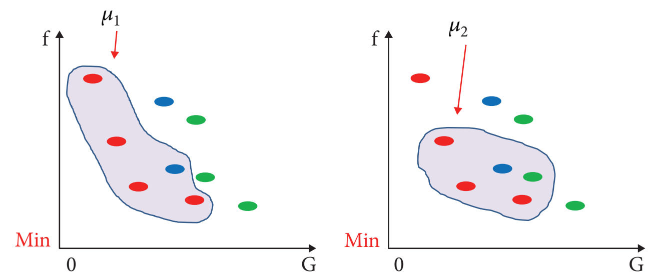

Figure 4: Schematic diagram to illustrate result comparison by normalized penalty strategy with different penalty factors in selecting solutions.

Input:
maxiter: the maximum number of iterations.
SE: the number of samples.
SA: the capacity of the external archive.
archive: the initial solutions.
Output:
Best*: the optimal solution.
for $iter = 1$ **to** *maxiter* **do.**
  if $\alpha < \alpha_{min}$ **then.**
    $\alpha \leftarrow \alpha_{max}$.
  end if.
  if $\delta < \delta_{min}$ **then.**
    $\delta \leftarrow \delta_{max}$.
  end if.
  archive ← expansion (*archive*, γ, *SA*, *SE*, ⋯).
  archive ← rotation (*archive*, α, *SA*, *SE*, ⋯).
  archive ← axesion (*archive*, δ, *SA*, *SE*, ⋯).
  archive ← translation (*archive*, β, *SA*, *SE*, ⋯).
  $\alpha \leftarrow \alpha/fc$.
  $\delta \leftarrow \delta/fc$.
end for.
F_archive ← feval (funfcn, *archive*).
Best* ← sort(*archive*, *F_archive*).

Algorithm 1: Pseudocode of external archive-based STA for constrained optimization problems.

3.4. The Framework of EA-CSTA. The proposed constraint-handling technique, preference trade-off strategy, can be considered as a criterion to choose potential solutions, which is incorporated into EA-CSTA for dealing with COPs. The main procedure of EA-CSTA is given in Algorithm 1.

SA represents the number of selected potential solutions which are stored into external archive. *archive* saves the potential solutions selected by preference trade-off

```
Input:
  State: the candidate solutions.
  SA: the capacity of external archive.
Output:
  archive: the selected potential solutions.
f ← feval (funfcn, State).
[feasi_num, infeasi_num, fp] ← calculate(SA, f).
if 0 < fp< 1 then.
    [feasi_x, infeasi_x, ···] ← divide(f, State, ···).
    S1 ← sort_feasi (feasi_x, feasi_num, ···).
    S2 ← sort_ infeasi_1(infeasi_x, infeasi_num, ···).
    archive ← [S1; S2].
else.
    if fp == 0 then.
        infeasi_num ← SA.
        S2 ← sort_infeasi_2(State, infeasi_num, ···).
        archive ← S2.
    else.
        feasi_num ← SA.
        S1 ← sort_feasi (State, feasi_num, ···).
        archive ← S1.
    end if.
end if.
```

Algorithm 2: Pseudocode of the preference trade-off strategy for dealing with constraint functions.

Table 2: Parameter settings of EA-CSTA.

Parameter	Value
α_{max}	1
α_{min}	1E-4
δ_{max}	3
δ_{min}	1E-4
maxiter	2000
γ	2
β	1
SE	30
μ_1	1.2
μ_2	1
SA	20
fc	2

strategy. γ, β, α, and δ are expansion, translation, rotation, and axesion factors, respectively, and *fc* is decent efficient. *sort* is an ascending order operation for *F_archive* to select the best solution ($Best^*$) from *archive*. Its pseudocode can be described in Algorithm 2.

State are candidates obtained from one of those four transformation operators in EA-CSTA. *feasi_num*, *infeasi_num*, and *fp* can be calculated by the *calculation* function. *feasi_num* and *infeasi_num* are the number of selected feasible and infeasible solutions, and *fp* is the feasibility proportion. *State* can be divided into the *feasi_x* and *infeasi_x* by the *divide* function, and *feasi_x* and *infeasi_x* are the feasible and infeasible candidates. *sort_feasi* is an ascending order operation for selecting the top *feasi_num* candidates as part of solutions (*S*1). *sort_infeasi*_1 and *sort_infeasi*_2 are ascending order operation for F_{nor} to select the top *infeasi_num* candidates as part of solutions (*S*2), and F_{nor} is presented in (17). *archive* is used to save these selected solutions.

Table 3: Summary of 10 benchmark functions.

Fcn	n	Function type	ρ	LI	NI	LE	NE	a
g01	13	Quadratic	0.0111%	9	0	0	0	6
g03	10	Polynomial	0.0000%	0	0	0	1	1
g04	5	Quadratic	52.1230%	0	6	0	0	2
g06	2	Cubic	0.0066%	0	2	0	0	2
g08	2	Nonlinear	0.8560%	0	2	0	0	0
g09	7	Polynomial	0.5121%	0	4	0	0	2
g11	2	Quadratic	0.0000%	0	0	0	1	1
g12	3	Quadratic	4.7713%	0	1	0	0	0
g13	5	Nonlinear	0.0000%	0	0	0	3	3
g23	9	Linear	0.0000%	0	2	3	1	6

4. Experimental Results and Analysis

The proposed EA-CSTA with preference trade-off strategy is employed to solve the power dispatch optimization problem. In this section, standard constrained benchmark problems are used to verify the performance of the proposed EA-CSTA. In addition, several experiments are designed to verify the effectiveness of external archive-based modified STA and the preference trade-off strategy. The optima of power dispatch optimization problem obtained by EA-CSTA are compared with these algorithms, such as two-stage (Deb-penalty technique) constrained state transition algorithm [8], called CSTA, adaptive trade-off model with evolutionary strategy [10], called ATMES, hybrid multiswarm particle swarm optimization [27], called HMPSO, and tree-seed algorithm with Deb's rules [11], called CTSA. Parameter settings of EA-CSTA are given in Table 2.

4.1. Standard Constrained Benchmark Problems. Some standard constrained optimization problems taken from [28] are tested to verify the performance of EA-CSTA. Table 3 shows the details of the standard constrained benchmark problems. The chosen test problems include different types of objective functions (*Fcn*) and various kinds of constraints. Constraints can be classified into four categories: linear inequalities (*LI*), nonlinear inequalities (*NI*), linear equalities (*LE*), and nonlinear equalities (*NE*). a is the number of constraints active at the optimal solution. The ratio of feasible search region in the entire search region is represented as ρ, and the number of decision variables is represented as n. The results of 10 benchmark test functions obtained from EA-CSTA are evaluated from several performance metrics: the best, median, mean, and worst objective function values, and the standard deviation in 30 independent runs. Each independent run has 2000 iterations. The obtained results are presented in Table 4.

Table 4: Statistical results obtained by EA-CSTA for 10 benchmark test functions over 30 independent runs.

Fcn	Optimal	Best	Median	Mean	Worst	St. dev
g01	−15.0000	**−15.0000**	**−15.0000**	**−15.0000**	**−15.0000**	8.9926E-07
g03	−1.0005	**−1.0005**	**−1.0005**	**−1.0005**	**−1.0005**	1.0104E-07
g04	−30665.5538	**−30665.5538**	**−30665.5538**	**−30665.5538**	−30665.5537	2.4317E-04
g06	−6961.8139	**−6961.8139**	**−6961.8139**	−6961.8138	−6961.8135	1.0476E-04
g08	−0.0958	**−0.0958**	**−0.0958**	**−0.0958**	**−0.0958**	1.7681E-14
g09	680.6300	**680.6301**	680.6310	680.6310	680.6322	5.3803E-04
g11	0.7499	**0.7499**	**0.7499**	**0.7499**	**0.7499**	3.3850E-09
g12	−1.0000	**−1.0000**	**−1.0000**	**−1.0000**	**−1.0000**	1.0819E-15
g13	0.0539	**0.0539**	**0.0539**	**0.0539**	**0.0539**	3.0054E-10
g23	−400.0550	−399.9998	−399.9980	−399.9977	−399.9912	1.7320E-03

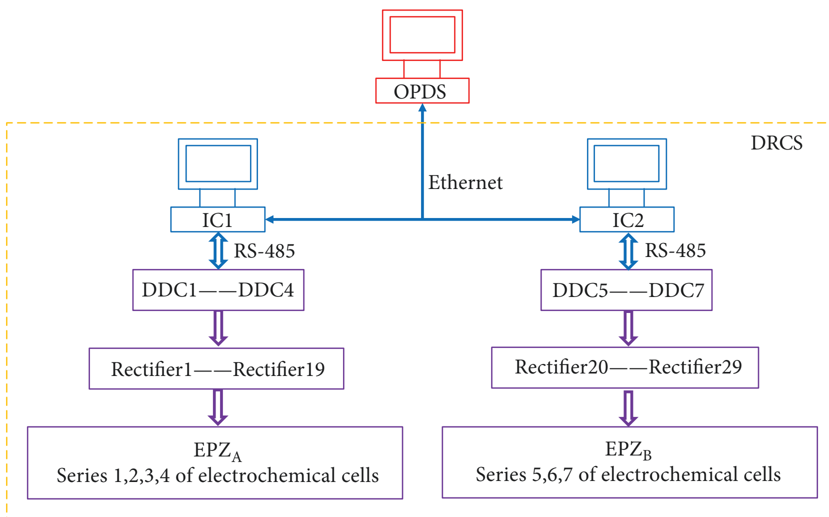

Figure 5: Schematic diagram to illustrate the distributed architecture of OPDCS.

Table 5: Parameter settings of the optimal power dispatch.

Parameter	Value
b_k	[0.785037, 5.855E-4, 2E-6, 3.2094e-9, −1.9052E-12]
Nc_j	[240, 240, 246, 192, 208, 208, 208]
Np_j	[34, 46, 54, 56, 56, 57, 57]
j	[1, 2, 3, 4, 5, 6, 7]
a_k	[2.76284, 0.00093]
i	[1, 2, 3]
Fc0	164,000
$Cd_{ij_{\min}}$	200
$Cd_{ij_{\max}}$	650
G	960
S	1.13

As illustrated in Table 4, according to the success condition ($|f(\mathbf{x}) - f(\mathbf{x}^*)| \leq 0.0001$), the optima of almost all test functions can be found by EA-CSTA, which shows the performance of global search of EA-CSTA. Moreover, the similar "best" and "worst" results in test functions reflect the robustness of EA-CSTA. It is worth noting that some benchmark test functions (g03, g11, g13, and g23) contain equality constraints while the power dispatch optimization problem has equality constraint as well.

4.2. Optimal Power Dispatch under Time-Sharing Price. At present, we take the electrolytic zinc process in the Zhuzhou Smeltery as an example. The purpose of this problem is to minimize the cost of power consumption and satisfy the technology and production constraints [6]. Figure 5 presents the distributed architecture of optimal power dispatch control system (OPDCS) which is consist of an optimal power dispatch system (OPDS) and a distributed rectifier control system (DRCS). There are 2 industrial computers (IC1, IC2) used to transfer signal with 7 direct digit controllers (DDC1 to DDC7) by RS-485 connection. Seven direct digit controllers operate on 29 rectifiers. The DRCS is mainly used for controlling and real-time monitoring of the electrochemical process of zinc (EPZ_A, EPZ_B).

The model of power dispatch optimization problem is given in Section 2. Parameters in the model is presented in Table 5.

Table 6: Statistical results obtained by EA-CSTA with preference trade-off strategy for the optimal power dispatch.

Current density	Value		
Cd_{11}, Cd_{21}, Cd_{31}	**200.0000**	**584.5866**	**650.0000**
Cd_{12}, Cd_{22}, Cd_{32}	**200.0000**	**583.7330**	**649.9999**
Cd_{13}, Cd_{23}, Cd_{33}	**200.0000**	**583.5669**	**650.0000**
Cd_{14}, Cd_{24}, Cd_{34}	**200.0000**	**584.3070**	**650.0000**
Cd_{15}, Cd_{25}, Cd_{35}	**200.0000**	**584.5311**	**650.0000**
Cd_{16}, Cd_{26}, Cd_{36}	**200.0000**	**583.4249**	**650.0000**
Cd_{17}, Cd_{27}, Cd_{37}	**200.0000**	**583.6394**	**650.0000**
$G = 960$	$h(\mathrm{Cd}) =$ **960.0000**		
Fc(Cd)	**1.77765823E06**		

Table 7: Statistical results obtained by EA-CSTA with Deb-penalty technique for the optimal power dispatch.

Current density	Value		
Cd_{11}, Cd_{21}, Cd_{31}	**206.9061**	**566.8309**	**649.9998**
Cd_{12}, Cd_{22}, Cd_{32}	**200.0079**	**643.6587**	**649.9994**
Cd_{13}, Cd_{23}, Cd_{33}	**200.0001**	**611.4888**	**649.9994**
Cd_{14}, Cd_{24}, Cd_{34}	**200.0415**	**555.8642**	**649.9987**
Cd_{15}, Cd_{25}, Cd_{35}	**200.0733**	**506.6455**	**649.9999**
Cd_{16}, Cd_{26}, Cd_{36}	**200.8771**	**545.8322**	**649.9998**
Cd_{17}, Cd_{27}, Cd_{37}	**200.0007**	**638.6569**	**649.9984**
$G = 960$	$h(\mathrm{Cd}) =$ **960.0008**		
Fc(Cd)	**1.77913834E06**		

Table 8: Statistical results obtained by CSTA with Deb-penalty technique for the optimal power dispatch.

Current density	Value		
Cd_{11}, Cd_{21}, Cd_{31}	**200.0000**	**649.6124**	**650.0000**
Cd_{12}, Cd_{22}, Cd_{32}	**200.0000**	**649.9863**	**649.9999**
Cd_{13}, Cd_{23}, Cd_{33}	**200.0000**	**649.9999**	**650.0000**
Cd_{14}, Cd_{24}, Cd_{34}	**200.0000**	**311.9031**	**650.0000**
Cd_{15}, Cd_{25}, Cd_{35}	**200.0000**	**523.2470**	**650.0000**
Cd_{16}, Cd_{26}, Cd_{36}	**200.0000**	**650.0000**	**650.0000**
Cd_{17}, Cd_{27}, Cd_{37}	**200.0000**	**649.7727**	**650.0000**
$G = 960$	$h(\mathrm{Cd}) =$ **960.0039**		
Fc(Cd)	**1.78178080E06**		

To verify the effectiveness of the preference trade-off strategy, the proposed EA-CSTA combining preference trade-off strategy is compared with EA-CSTA combining Deb-penalty technique, and the detailed results are shown in Tables 6 and 7. At the same time, to verify the effectiveness of the modified STA, EA-CSTA combining Deb-penalty technique is compared with CSTA combining Deb-penalty technique, and the detailed results are shown in Tables 7 and 8. As seen in Tables 6 and 7, the practical daily output in Table 6 and the expected daily output are the same, which means that the constraint in power dispatch optimization problem is satisfied, and the practical daily output in Table 7 is not satisfied. Furthermore, the cost of power consumption represented in Table 6 is less than the cost of power consumption represented in Table 7. The effectiveness of preference trade-off strategy can be verified by Tables 6 and 7. As seen in Tables 7 and 8, the cost of power consumption shown in Table 7 is less than the cost of power consumption represented in Table 8. The effectiveness of modified STA can be verified by Tables 7 and 8.

Table 9 shows the cost (RMB/day) of five compared algorithms for optimal power dispatch. The results of cost of power consumption obtained by 5 different algorithms are evaluated from 5 performance metrics: the best, median, mean, and worst values, and the standard deviation in 30 independent runs. The number of iterations is set to 2000 in each independent run. Next, experimental results are discussed from the following aspects.

(1) As presented in Table 9, EA-CSTA significantly provides the best performance in terms of minimum cost of power consumption compared with other algorithms. For the other 4 performance metrics, the values obtained by EA-CSTA are better than that obtained by other algorithms, too. Therefore, it is not easy to fall into local optimum by designing external archive and preference trade-off strategy, which fully maintain the diversity in the iterative process

(2) Compared with CSTA, a diversity mechanism is added in EA-CSTA. In Table 9, the values of 5 performance metrics obtained by EA-CSTA are better than CSTA, which can verify the effectiveness of the proposed external archive. In addition, the results obtained by EA-CSTA are better than ATMES, which can verify the validity of the proposed preference trade-off strategy

Figure 6 shows the convergence curves of minimum cost (RMB/day) over 2000 iterations for optimal power dispatch problem in different algorithms. In Figure 6, a fast convergence can be achieved by EA-CSTA in 300 iterations. A subfigure in Figure 6 illustrates the details among EA-CSTA, HMPSO, and ATMES at the later stage of iteration. As seen in the subfigure, the curve of ATMES vibrates up and down, which means that it is hard to balance the constraints and objective function of the power dispatch optimization problem. Therefore, EA-CSTA always has the extreme performance of convergence and optimality.

5. Conclusions

In this paper, an external archive-based constrained state transition algorithm (EA-CSTA) with preference trade-off strategy was proposed for the power dispatch optimization problem. The external archive was utilized to keep diversity of potential solutions in the process of solving this problem, while the preference trade-off strategy was designed for selecting potential solutions. As the results show, EA-CSTA not only solved almost all benchmark test functions well

Table 9: Cost (RMB/day) of the five compared algorithms for the optimal power dispatch over 30 independent runs.

Method	Min (RMB/day)	Median (RMB/day)	Mean (RMB/day)	Max (RMB/day)	Std. dev
EA-CSTA	**1.77765823E06**	**1.77765976E06**	**1.77766044E06**	**1.77767178E06**	**2.65242092E00**
CSTA [8]	1.78178080E06	1.81128305E06	1.81332091E06	1.85254462E06	1.54851318E04
HMPSO [27]	1.77765969E06	1.77766555E06	1.77766581E06	1.77767522E06	4.26473598E00
ATMES [10]	1.77768962E06	1.77777609E06	1.77813315E06	1.78071949E06	8.57908755E03
CTSA [11]	2.02136700E06	2.07619626E06	2.07809758E06	2.18147177E06	3.95206667E04

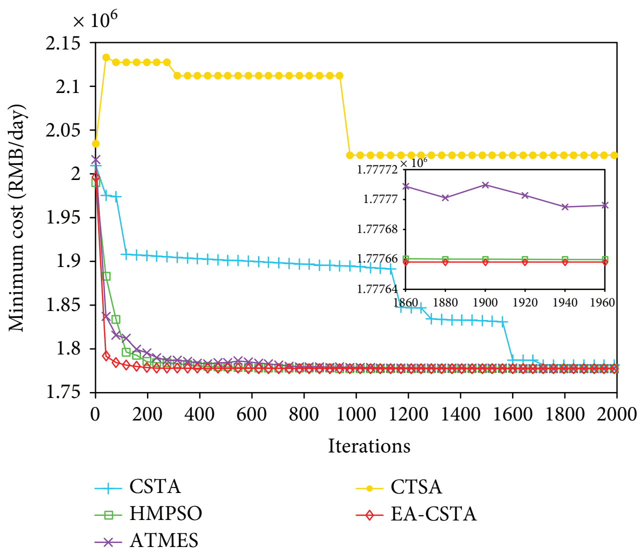

Figure 6: The convergence curves of algorithms on the optimal power dispatch.

but also performed better than other algorithms in the literature in terms of the optimality of solution on the power dispatch optimization problem. The optima of the power dispatch optimization problem can bring significant economic profits to the metallurgy industry. In addition, it is instructive to relieve the pressure not only on the power grid but also on the peak power consuming of power industry.

In the future, the external archive and preference trade-off strategy will be perfected. Moreover, we are considering the possibility of applying the improved EA-CSTA with preference trade-off strategy to some optimization problems in other fields.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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