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Power scheduling optimization under single-valued neutrosophic uncertainty

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ABSTRACT

Optimization problems with improper expression of constraints exist widely in practical engineering. In order to achieve a reasonable degree of constraints satisfaction, this paper investigates a single-valued neutrosophic optimization method to deal with system uncertainty. Firstly, an equivalent model based on single-valued neutrosophic entropy is proposed to transform the original problem into a crisp multi-objective optimization problem. The Pareto-front of the optimization problem is then obtained by a multi-objective state transition algorithm. Finally, the best solution is determined by a multi-criteria decision making method. A practical example of a zinc electrowinning process is used to illustrate the effectiveness and advantage of the developed new optimization approach, which provides a more cost-effective solution to decrease the electricity utility charge and satisfy the daily output production requirements.

1. Introduction

Uncertainties in real-world optimization problems are inevitable due to factors such as the fluctuation of external loads, the variation of material properties, and the lack of complete knowledge of models [1]. Based on the characteristic of uncertainties, there are three description methods to represent the uncertain information: probability model, bounded model, and fuzzy model [2]. To deal with uncertainties in human behavior and expert judgment, optimization under fuzzy environment has received considerable interest over the last decade [3,4].

A practical example of the optimization problem with fuzzy uncertainties is the power scheduling problem. As one of the most important operations in zinc electrowinning process, power scheduling optimization aims to minimize the electricity charge under the power time-of-use pricing and satisfy the requirement of daily output [5]. However, with the development of intelligent manufacturing, it is necessary for the target of zinc daily output to be adjusted within a certain range according to the market demand and environmental conditions [6]. Thus, in power scheduling optimization process, the constraint of zinc daily output is rendered uncertain.

The nature of the output target fluctuations is fuzziness rather than randomness when deciding the best output target. To handle ambiguity and imprecise information, the fuzzy set (FS) was introduced by Zadeh [7] in 1965. When considering both the truth and falsity attributes, the intuitionistic fuzzy set (IFS) presented by Atanassov [8] uses membership degree and non-membership degree to describe the vague information. In order to mimic human decision-making process, Smarandache [9] proposed the neutrosophic set to deal with indeterminate and inconsistent information. Additionally, Wang et al. [10] introduced the concept of single-valued neutrosophic (SVN) set which is more suitable for real-world uncertain situations [11].

Deterministic power scheduling optimization problem has been studied by many researchers. For instance, Yang [5] proposed an optimization method based on Hopfield neural network which decreases the power consumption significantly. Some intelligent optimization algorithms such as two-stage state transition algorithm [12], single loop simulated annealing algorithm [13], and particle swarm optimization algorithm [14] have been applied to the optimal power scheduling design. These methods are effective to find the optimal solution under a given constraint of daily output, but they cannot handle the optimization problem with imprecise information.

Current research on neutrosophic optimization is mainly based on Werners's approach [15] and the findings have been applied to several real-life problems, such as the welded beam structure design [16], truss design [17], and electronic products assignment

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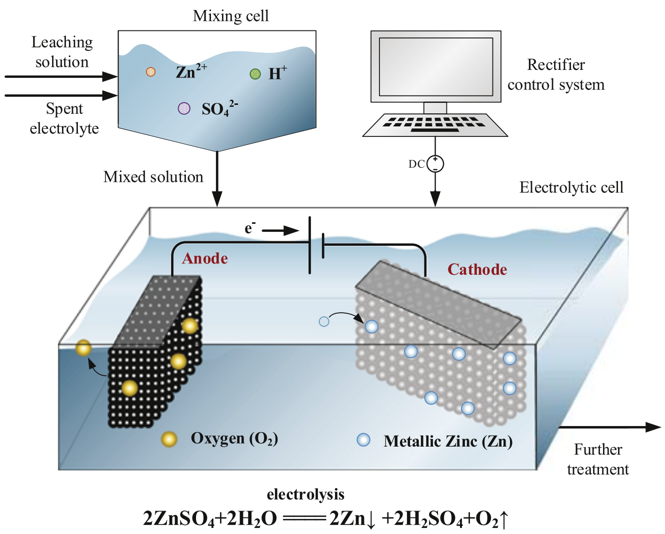

Fig. 1. Electrolytic cell of zinc electrowinning process.

problem [18]. However, the methods based on Werners's approach is complex when calculating the membership of objectives and constraints. The aims of this study is to address the power scheduling optimization problem with uncertainties and derive an optimization technique for problem with SVN constraints.

The objectives of this paper are in four areas. (1) the optimization model with SVN constraint is established to more accurately capture the actual production condition, and this model has stronger ability to represent human preference; (2) an efficient way to deal with the SVN uncertainties is proposed based on the symmetric cross entropy, and the original problem is transformed to a multi-objective optimization problem; (3) the use of the multi-objective state transition algorithm to find the Pareto-optimal solutions can obtain more effective results compared with other classical multi-objective evolutionary algorithms; and (4) the multi-criteria decision making strategy is developed to select the final best solution, which achieves the highest evaluation of the technical and economic indicators.

This paper is organized as follows. In Section 2, the power scheduling optimization problem with neutrosophic uncertainty is formulated. The neutrosophic optimization method and decision-making strategy is introduced in Section 3. Section 4 analyzes the experimental results and Section 5 presents a conclusion of this paper.

2. Modeling and analysis for power scheduling

In this section, the optimization model of power scheduling with fuzzy uncertainties is established. To better reflect the requirement of intelligent manufacturing, the uncertainty of zinc daily output is described as a single-valued neutrosophic set.

2.1. Process analysis

The zinc electrowinning process contains several series potroom and each potroom has several parallel electrolytic cells. The zinc electrowinning process (shown in Fig. 1) includes the reactions taking place between substances in different physical states (solids, liquids, and gases), and these reactions are influenced by many factors. In general, the throughput of zinc electrowinning process is highly depended on the current flow and zinc to acid ratio (the ratio of zinc sulphate and sulphuric acid). The current density determines whether there are enough electrons for zinc ions to deposit on the cathode surface. The zinc to acid ratio will influence the extent of zinc dissolution.

In order to analyze the power scheduling characteristics, the modeling of the zinc electrowinning process is built based on the following reasonable assumptions [19]:

Assumption 1. The electrolyte temperature dose not fluctuate significantly (approximately $40 \pm 2°C$), and it is assumed to be a constant.

Assumption 2. The concentration of impurity ions (Co^{2+}, Ni^{2+}) contained in the solution is less than 1mg/L, and the influences of the impurity ions are ignored.

Assumption 3. Under the similar manufacturing condition and the electricity supply systems, the current density and the zinc to acid ratio in each potroom are considered to be the same.

Then, the cost of electricity in the zinc electrowinning process with power scheduling can be computed by

$$J = J_0 + \sum_{i=1}^{n} p_i W_i \tag{1}$$

where J means the total electricity utility charge per day, including capacity electricity charges (J_0) and watt-hour electricity charges ($\sum_{i=1}^{n} p_i W_i$); n is the number of electricity price periods in one day; p_i and W_i are the price and the consumption of the electricity in the ith period, respectively. Since the number of plant series is m, the electricity consumption of the jth plant in the ith period is related to voltage V_{ij}, current L_{ij}, and duration of the ith period t_i, then

$$W_i = \sum_{j=1}^{m} V_{ij} L_{ij} t_i. \tag{2}$$

Based on the theory of electrochemical reaction mechanism [19], V_{ij} and L_{ij} can be modeled as follows

$$\begin{aligned} V_{ij} &= V(d_i, C_{Zn,i}, C_{H,i}) \\ &= N_j(\alpha_1 - \alpha_2 \ln(\alpha_3 C_{H,i}^{-1}) - \alpha_4 \ln(\alpha_5 C_{Zn,i}) + \alpha_6 \lg d_i \\ &\quad + \alpha_7 d_i (\alpha_8 + \alpha_9 C_{H,i} - \alpha_{10} C_{Zn,i})^{-1} + \alpha_{11} d_i) \end{aligned} \tag{3}$$

$$L_{ij} = L(d_i) = d_i O_j a \tag{4}$$

where d_i is the current density in the ith period; $C_{Zn,i}$ and $C_{H,i}$ represent the concentration of Zn^{2+} and H^+ in the ith period, respectively; $\alpha_1, \alpha_2, \ldots, \alpha_{11}$ are the parameters; N_j, O_j and a are the number of cells in the jth plant, the plates number of a cell in the jth plant, and the area of the cathode plate, respectively.

In the zinc electrowinning process, the daily output of zinc g is also an important target which revels the manufacturing capacity and product reliability [20]. It can be expressed as

$$g(d_i, C_{Zn,i}, C_{H,i}) = \sum_{i=1}^{n} \sum_{j=1}^{7} q L_{ij} \eta_i t_i \tag{5}$$

where q means the electrochemical equivalent of zinc; and η_i is the current efficiency modeled by

$$\begin{aligned} \eta_i &= \eta(d_i, C_{Zn,i}, C_{H,i}) \\ &= \beta_1 + \beta_2 \exp(\beta_3 + \beta_4 \lg d_i) C_{Zn,i}^{1.6} C_{H,i}^{-0.2} (\beta_5 \exp(\beta_6 \\ &\quad + \beta_7 \lg d_i) C_{Zn,i} C_{H,i}^{-0.2} + \beta_8 C_{Zn,i}^{0.6})^{-1} d_i^{-1} \end{aligned} \tag{6}$$

where $\beta_1, \beta_2, \ldots, \beta_8$ are the parameters.

The optimization problem of the power scheduling is formulated based on (1)–(6) in the following subsections.

2.2. Modeling of the objective function

The purpose of the power scheduling in the zinc electrowinning process is to minimize the total electricity charge by adjusting the current density and the concentration of Zn^{2+} and H^{+}. The objective function can be formulated as

$$\begin{aligned} \min \quad & J(d_i, C_{Zn,i}, C_{H,i}) \\ & = J_0 + \sum_{i=1}^{n} \sum_{j=1}^{m} V_{ij} L_{ij} t_i p_i \\ \text{where } & V_{ij} = V(d_i, C_{Zn,i}, C_{H,i}) \quad \text{and} \\ & L_{ij} = L(d_i). \end{aligned} \tag{7}$$

In (7), objective function J includes the transcendental functions and it is a non-convex optimization problem with multiple local optima. Thus, the optimization method should have good property for global search.

2.3. Modeling of the constraint function

In order to meet the industrial requirements of the zinc electrowinning process, the optimal solution is subject to the following two certain constraints.

(1) Daily output of zinc (g): Taking into account the intelligent manufacturing strategy in manufacturing focused countries such as China, the daily output target needs to be adjusted based on the market demand and production capacity. It is more appropriate to use a fuzzy set to describe the daily output target instead of a set of fixed constants. Single-valued neutrosophic set can provide a more convenient tool to handle practical imprecision and ambiguity. The definition of single-valued neutrosophic set is given as follows:

Definition 1. Let X be a universe. A single-valued neutrosophic set $\widetilde{Z}$ over X is characterized by a truth-membership function $T_{\widetilde{Z}}$, an indeterminacy-membership function $I_{\widetilde{Z}}$, and a falsity-membership function $F_{\widetilde{Z}}$, which can be defined as

$$\widetilde{Z} = \{\langle x, T_{\widetilde{Z}}(x), I_{\widetilde{Z}}(x), F_{\widetilde{Z}}(x)\rangle | x \in X\}$$

where $T_{\widetilde{Z}} : X \to [0,1]$, $I_{\widetilde{Z}} : X \to [0,1]$, and $F_{\widetilde{Z}} : X \to [0,1]$ with $0 \le T_{\widetilde{Z}}(x) + I_{\widetilde{Z}}(x) + F_{\widetilde{Z}}(x) \le 3$ for all $x \in X$.

Using single-valued neutrosophic set to describe the uncertainty in power scheduling optimization, the truth-membership can reflect the acceptance degree of the zinc daily output, and the falsity-membership can indicate the rejection degree of the zinc daily output. The indeterminacy-membership function can describe the uncertainty degree of accepting or rejecting the zinc daily output. In practical manufacture process, the decision markers have an optimal daily output target within a specific range. It is thus natural to use single-valued triangular neutrosophic number (SVTrN-number) in some pessimistic way [21] to describe the fuzzy information.

Based on the concept proposed in [22,23], the SVTrN-number $\widetilde{g}$, truth-membership $T_{\widetilde{g}}$, indeterminacy-membership $I_{\widetilde{g}}$, and falsity-membership $F_{\widetilde{g}}$ functions of the daily output target can be respectively defined as

$$\widetilde{g} = \langle (g_{\min}, g_{opt}, g_{\max}); \varpi, \nu, \mu \rangle$$

$$\text{with } T_{\widetilde{g}}(g) = \begin{cases} \varpi\left(\frac{g-g_{\min}}{g_{opt}-g_{\min}}\right), & g_{\min} \le g \le g_{opt} \\ \varpi\left(\frac{g_{\max}-g}{g_{\max}-g_{opt}}\right), & g_{opt} \le g \le g_{\max} \\ 0, & \text{otherwise} \end{cases}$$

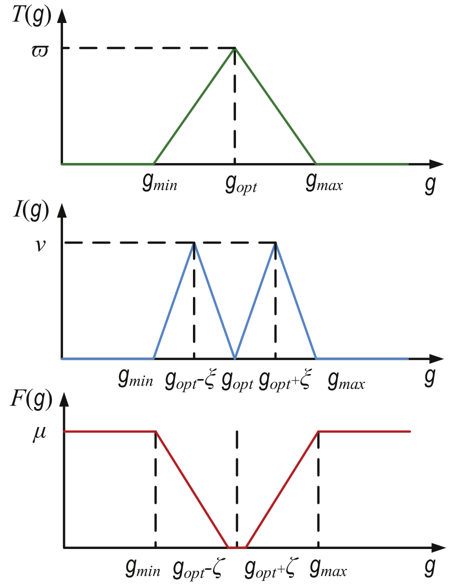

Fig. 2. Truth-membership, indeterminacy-membership, and falsity-membership functions of single-valued triangular neutrosophic number.

$$I_{\widetilde{g}}(g) = \begin{cases} \nu\left(\frac{g-g_{\min}}{g_{opt}-\xi-g_{\min}}\right), & g_{\min} \le g \le g_{opt}-\xi \\ \nu\left(\frac{g_{opt}-g}{\xi}\right), & g_{opt}-\xi \le g \le g_{opt} \\ \nu\left(\frac{g-g_{opt}}{\xi}\right), & g_{opt} \le g \le g_{opt}+\xi \\ \nu\left(\frac{g_{\max}-g}{g_{\max}-g_{opt}-\xi}\right), & g_{opt}+\xi \le g \le g_{\max} \\ 0, & \text{otherwise} \end{cases}$$

$$F_{\widetilde{g}}(g) = \begin{cases} \mu\left(\frac{g_{opt}-\zeta-g}{g_{opt}-\zeta-g_{\min}}\right), & g_{\min} \le g \le g_{opt}-\zeta \\ 0, & g_{opt}-\zeta \le g \le g_{opt}+\zeta \\ \mu\left(\frac{g-g_{opt}-\zeta}{g_{\max}-g_{opt}-\zeta}\right), & g_{opt}+\zeta \le g \le g_{\max} \\ \mu, & \text{otherwise} \end{cases}$$

where g_{opt} is the optimal daily output; $g_{\min}$ and $g_{\max}$ represent the lower and upper tolerance. The SVTrN-number of the daily output is depicted in Fig. 2. In a typical decision making process for the power scheduling, the preference is to accept the daily output attained the optimal value g_{opt} and reject it beyond the range of $[g_{\min}, g_{\max}]$. Moreover, in the interval $[g_{opt}-\zeta, g_{opt}+\zeta]$, the falsity-membership value is the lowest while the truth-membership value is not always the highest. It indicates that the decision makers are reluctant to reject the values between $g_{opt}-\zeta$ and $g_{opt}+\zeta$, but at the same time, they do not fully accept these values. Thus, based on this pessimistic modeling approach, the assessment of zinc daily output can be regarded as more reasonable.

Thus the constraint function of daily output can be modeled as

$$g(d_i, C_{Zn,i}, C_{H,i}) \cong \langle (g_{\min}, g_{opt}, g_{\max}) \rangle$$

where $\cong$ represents equality in neutrosophic sense.

(2) Decision variables ($\boldsymbol{x}_i = [d_i, C_{Zn,i}, C_{H,i}]$): According to the manufacturing requirements and equipment capacity, the threshold limits of the decision variables in real applications are as follows: $d_{i,\min} \le d_i \le d_{i,\max}$, $C_{Zn,i,\min} \le C_{Zn,i} \le C_{Zn,i,\max}$, $C_{H,i,\min} \le C_{H,i} \le C_{H,i,\max}$.

3. Single-valued neutrosophic optimization approach

In this section, the SVN optimization problem for power scheduling is transformed to a bi-objective optimization problem with crisp model. Then, the multi-objective state transition algorithm is used to solve this problem. The best solution is selected from the Pareto-front by the multi-criteria decision making method.

3.1. Equivalent crisp model

In general, the decision makers' main target is to find the value from the selected set with the highest degree of acceptance, least degree of rejection and indeterminacy. To deal with the fuzziness in the power scheduling optimization problem, the constraint with single-valued neutrosophic number is transformed to three objectives as follows:

$$\begin{aligned} &\max\ T_{\tilde{g}}(g)\\ &\min\ I_{\tilde{g}}(g)\\ &\min\ F_{\tilde{g}}(g)\\ &\text{s.t.}\ \ 0 \le T_{\tilde{g}}(g)+I_{\tilde{g}}(g)+F_{\tilde{g}}(g) \le 3\\ &\qquad T_{\tilde{g}}(g) \ge F_{\tilde{g}}(g)\\ &\qquad T_{\tilde{g}}(g) \ge I_{\tilde{g}}(g)\\ &\qquad T_{\tilde{g}}(g), I_{\tilde{g}}(g), F_{\tilde{g}}(g) \in [0,1], g \ge 0. \end{aligned} \tag{8}$$

Thus, the SVN optimization problem can be modeled as a crisp problem with four objectives. To decrease the computational complexity of the four-objective optimization problem, the single-valued neutrosophic symmetric cross-entropy [24] is adopted to combine the three objectives about daily output into one objective.

First, we give the concept of single-valued neutrosophic cross-entropy.

Definition 2. Assume that $P = \langle T_P, I_P, F_P\rangle$, and $Q = \langle T_Q, I_Q, F_Q\rangle$ are two neutrosophic numbers, where $T_P, I_P, F_P, T_Q, I_Q, F_Q \in [0, 1]$. The cross-entropy $E(P, Q)$ between P and Q includes three elements, which is defined as follows:

$$E(P,Q) = E^T(P,Q) + E^I(P,Q) + E^F(P,Q)$$

where $E^T(P, Q)$, $E^I(P, Q)$, and $E^F(P, Q)$ are the cross-entropy of the truth-membership, the indeterminacy-membership, and the falsity-membership between P and Q, respectively. They are explained as follows:

$$\begin{aligned} E^T(P,Q) &= T_P \log_2 \frac{T_P}{T_Q} + (1-T_P)\cdot \log_2 \frac{1-T_P}{1-0.5(T_P+T_Q)}\\ E^I(P,Q) &= I_P \log_2 \frac{I_P}{I_Q} + (1-I_P)\cdot \log_2 \frac{1-I_P}{1-0.5(I_P+I_Q)}\\ E^F(P,Q) &= F_P \log_2 \frac{F_P}{F_Q} + (1-F_P)\cdot \log_2 \frac{1-F_P}{1-0.5(F_P+F_Q)}. \end{aligned}$$

Based on Shannon's inequality [24], $E(P, Q) \ge 0$, and $E(P,Q) = 0$ if and only if $T_P = T_Q$, $I_P = I_Q$, and $F_P = F_Q$. Thus, the value of $E(P, Q)$ can indicate the discrimination degree of P from Q. Moreover, to avoid the priority given to the different order in the cross-entropy, a symmetric discrimination information measure $H(P, Q)$ is used

$$H(P,Q) = E(P,Q) + E(Q,P).$$

Obviously, the smaller the difference between P and Q, the smaller $H(P, Q)$ is. Hence, we define the ideal daily output g^* as $g^* = \langle \varpi, 0, 0\rangle$, and the three objectives in (8) can be modified as

$$\min\ H(g, g^*).$$

Therefore, let $\boldsymbol{x}$ represent the decision variables, the SVN optimization problem can be transformed to an equivalent crisp model as

$$\begin{aligned} &\min\ J(\boldsymbol{x})\\ &\min\ H(g(\boldsymbol{x}), g^*)\\ &\text{s.t.}\ \ 0 \le T_{\tilde{g}}(g)+I_{\tilde{g}}(g)+F_{\tilde{g}}(g) \le 3\\ &\qquad T_{\tilde{g}}(g) \ge F_{\tilde{g}}(g)\\ &\qquad T_{\tilde{g}}(g) \ge I_{\tilde{g}}(g)\\ &\qquad T_{\tilde{g}}(g), I_{\tilde{g}}(g), F_{\tilde{g}}(g) \in [0,1], g \ge 0\\ &\qquad \boldsymbol{x} = [\boldsymbol{d}, \boldsymbol{C}_{Zn}, \boldsymbol{C}_H]\\ &\qquad \boldsymbol{d}_{\min} \le \boldsymbol{d} \le \boldsymbol{d}_{\max}, \boldsymbol{C}_{Zn,\min} \le \boldsymbol{C}_{Zn} \le \boldsymbol{C}_{Zn,\max}\\ &\qquad \boldsymbol{C}_{H,\min} \le \boldsymbol{C}_H \le \boldsymbol{C}_{H,\max}. \end{aligned} \tag{9}$$

The problem shown in (9) is a bi-objective nonlinear optimization problem. There are many exist techniques to deal with such multi-objective problem [25–27]. In this paper, we use the multi-objective state transition algorithm to find all promising solutions.

3.2. Multi-objective state transition algorithm

State transition algorithm (STA) [28–30] is a global optimization method which is inspired by the control theory of state transition and state space. To guarantee the search ability of state transition algorithm, there are three state transition operators to generate candidate solutions, via:

$$\boldsymbol{x}_{k+1} = \boldsymbol{x}_k + \kappa_1 \frac{1}{n\|\boldsymbol{x}_k\|_2} R_1 \boldsymbol{x}_k \tag{10}$$

$$\boldsymbol{x}_{k+1} = \boldsymbol{x}_k + \kappa_2 R_2 \boldsymbol{x}_k \tag{11}$$

$$\boldsymbol{x}_{k+1} = \boldsymbol{x}_k + \kappa_3 R_3 \boldsymbol{x}_k \tag{12}$$

representing the rotation transformation, expansion transformation, and axesion transformation, respectively; $\boldsymbol{x}_k$ is the candidate solution in the kth generation; κ_1, κ_2, and κ_3 are transformation factors; R_1, R_2, and R_3 mean the matrix with specific elements. The rotation transformation is used to search local area and the expansion transformation has strong global search ability. The axesion transformation has a function of single dimensional search. STA has been applied successfully in image segmentation, optimal control, industrial optimization, and production scheduling problems [31–33]. For multi-objective optimization problems, there exists a multi-objective state transition algorithm (MO-STA) [34,35] which can efficiently obtain Pareto-front with well-distributed candidates. Therefore, in this paper, MO-STA method is applied to deal with the problem in (9). After using three transition operators, given in (10)–(12), to generate candidate solutions, the selection strategies are introduced as follows:

(1) Constrained nondominated sorting

When choosing between two candidate solutions, a feasible solution takes precedence over an infeasible solution. If both solutions are feasible, we adopt a solution which can Pareto dominate another one. If both solutions are infeasible, we adopt a solution with smaller constraint violation. Thus, the candidates can be sorted to different fronts.

(2) Crowding distance sorting

In order to maintain the diversity of solutions, the crowding distance of the candidates x_ι can be computed by

$$D = \sum_{i_m=1}^{M} \frac{f_{i_m}(x_{\iota+1}) - f_{i_m}(x_{\iota-1})}{f_{i_m}^{\max} - f_{i_m}^{\min}}$$

where ι is the solution number in a front; M means the number of objective functions; $f_{i_m}^{\max}$ and $f_{i_m}^{\min}$ represent the maximum and minimum value of f_{i_m}. In the same front, a more effective strategy is to adopt a solution with a larger crowding distance.

Algorithm 1 Pseudo-code for the MO-STA method

Input:
$iter_{\max}$: the maximum number of iterations
SE: search enforcement
$Best$: the initial solution
Output:
$Optimum$: a set of optimal solutions
for $k = 1$ **to** $iter_{\max}$ **do**
  if $\kappa_1 < \kappa_{1,\min}$ **then**
    $\kappa_1 \leftarrow \kappa_{1,\max}$
  end if
  $State \leftarrow$ state transition operators $(Best, SE, \cdots)$
  $archive \leftarrow$ constrained nondominated sorting $(State)$
  $archive \leftarrow$ crowding distance sorting $(archive)$
  $Best \leftarrow$ sample from $archive$
  $\kappa_1 \leftarrow \frac{\kappa_1}{fc}$
end for
$Optimum \leftarrow archive$

The structure of the MO-STA method is shown in Algorithm 1. Firstly, we define the parameters and randomly generate the initial solution. The parameter *SE* represents the search enforcement, which means *SE* candidates are generated by every transformation operator. To enforce the local search ability, the rotation factor κ_1 is decreased from $\kappa_{1,\max}$ to $\kappa_{1,\min}$ with the base *fc*. Then, during the optimization process, the candidates are selected by using constrained nondominated sorting strategy and the promising candidates are saved in the variable called *archive*. The crowding distance sorting strategy is used to filter the candidates such that the similar solution can be removed. Finally, when the terminal condition is satisfied, the solutions stored in variable *archive* will be considered as the optimal solution set.

3.3. Multi-criteria decision making based on TOPSIS

Multi-objective state transition algorithm can provide a set of optimal solutions for the decision makers to choose a final best solution. To evaluate the power scheduling solutions in the Pareto-front ($X = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_h\}$), three technical and economic indicators are considered, which are current efficiency, cell voltage, and specific electric energy consumption. These three indicators can give a more reliable measure to analyze the electricity cost (J) and zinc daily output (g). TOPSIS (the technique for order preference by similarity to an ideal solution) [36,37] is a classical multi-criteria decision making method that aims to select the best alternative solution not only close to the ideal solution but also far away from the negative ideal solution. TOPSIS has been a technique of choice for solving multi criteria optimization industry related process problem, such as electrical discharge machining process [38], economical control chart design [39], and modern manufacturing processes [40]. Thus, the decision making strategy based on TOPSIS technique for power scheduling optimization is developed in this paper.

The criteria of the decision making process are as follows:

(1) Average current efficiency (η): As shown in (6), the current efficiency can reflect the ratio of the actual mass of zinc liberated from an electrolyte by the passage of current to the theoretical mass liberated according to Faraday's law. The higher the current efficiency, the more economical the electrowinning process. Thus, the current efficiency is a benefit attribute.

(2) Average cell voltage (V): As shown in (3), the cell voltage is strongly related to the electric energy consumption. The lower the cell voltage, the lower the cost. Therefore, the cell voltage is a cost attribute.

(3) Average specific energy consumption (SEC): The specific energy consumption is applied to describe the energy consumption which is used to produce 1 ton of zinc, and it can be defined as

$$SEC = \frac{W}{g}$$

where W is the total electric energy consumption and g is the zinc output. The specific energy consumption also is a cost attribute.

Based on these three criteria, the steps of TOPSIS technique are introduced as follows:

Firstly, we establish the decision matrix (DM) with respect to the criteria and the alternatives ($X = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_h\}$):

$$DM = \begin{bmatrix} e_{11} & e_{12} & \cdots & e_{1h} \\ e_{21} & e_{22} & \cdots & e_{2h} \\ e_{31} & e_{32} & \cdots & e_{3h} \end{bmatrix} = \begin{bmatrix} \eta(\boldsymbol{x}_1) & \eta(\boldsymbol{x}_2) & \cdots & \eta(\boldsymbol{x}_h) \\ V(\boldsymbol{x}_1) & V(\boldsymbol{x}_2) & \cdots & V(\boldsymbol{x}_h) \\ SEC(\boldsymbol{x}_1) & SEC(\boldsymbol{x}_2) & \cdots & SEC(\boldsymbol{x}_h) \end{bmatrix}.$$

Then, the decision matrix is normalized by the following equation:

$$r_{uv} = \frac{e_{uv}}{\sqrt{\sum_{v=1}^{h} e_{uv}^2}} \qquad v = 1, 2, \ldots, h$$

where u is the criterion's number and v is the alternative's number.

Thirdly, the weighted normalized decision matrix is calculated by

$$z_{uv} = \omega_u r_{uv} \qquad v = 1, 2, \ldots, h$$

where ω_u is the weight of the uth criteria.

Since the current efficiency is a benefit attribute and the cell voltage and the specific energy consumption are cost attributes, the ideal positive solution and the ideal negative solution of these three attributes are determined as follows:

$$z_1^+ = \max z_{1v} \quad \text{and} \quad z_1^- = \min z_{1v}$$
$$z_2^+ = \min z_{2v} \quad \text{and} \quad z_2^- = \max z_{2v}$$
$$z_3^+ = \min z_{3v} \quad \text{and} \quad z_3^- = \max z_{3v}.$$

According to the weighted normalized decision matrix, the distances from each alternative to the ideal positive solution and ideal negative solution are as follows:

$$q_v^+ = \sqrt{\sum_{u=1}^{3}(z_{uv} - z_u^+)^2} \text{ and } q_v^- = \sqrt{\sum_{u=1}^{3}(z_{uv} - z_u^-)^2}$$
$$v = 1, 2, \ldots, h.$$

Finally, the preference value of each alternative is calculated by

$$s_v = \frac{q_v^-}{q_v^- + q_v^+} \qquad v = 1, 2, \ldots, h.$$

At the end of the calculation, the larger the value of s_v, the better the decision of alternative $\boldsymbol{x}_v$.

3.4. Optimization framework

A comprehensive study of neutrosophic theory and optimization techniques has resulted in the framework of the proposed SVN optimization method, which is shown in Fig. 3. Considering the fuzziness information in the power scheduling optimization, the single-valued neutrosophic number is used to describe the daily output. In order to minimize the falsity-membership and indeterminacy-membership and maximize the truth-membership of the daily output, the symmetric cross-entropy is adopted and then the original neutrosophic optimization problem is transformed to a bi-objective optimization problem. After using the

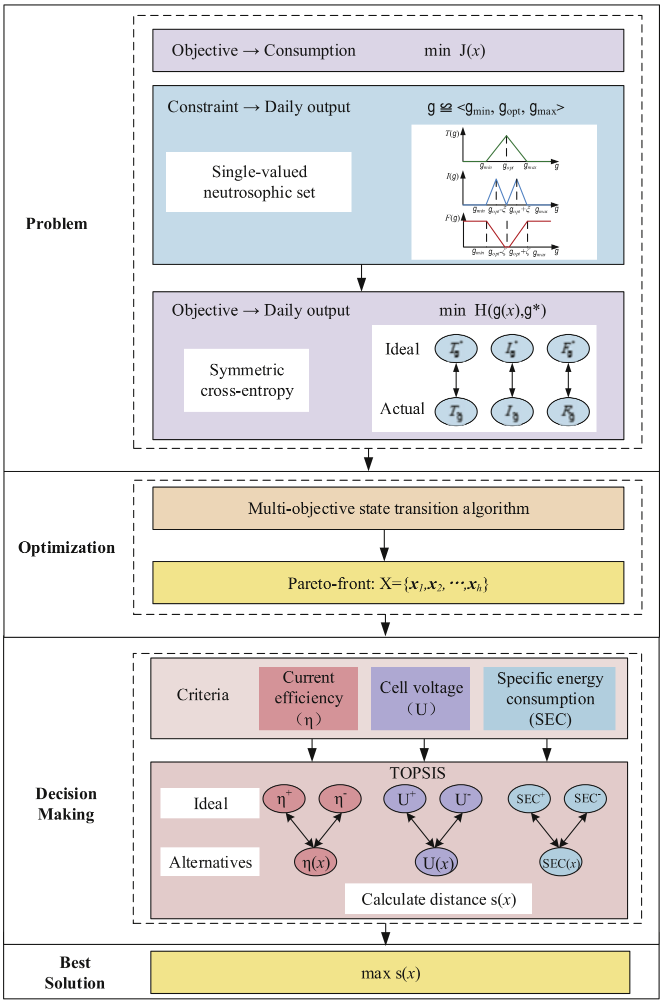

Fig. 3. Framework of the power scheduling optimization method.

Fig. 4. Electrowinning process in a smeltery of the case study.

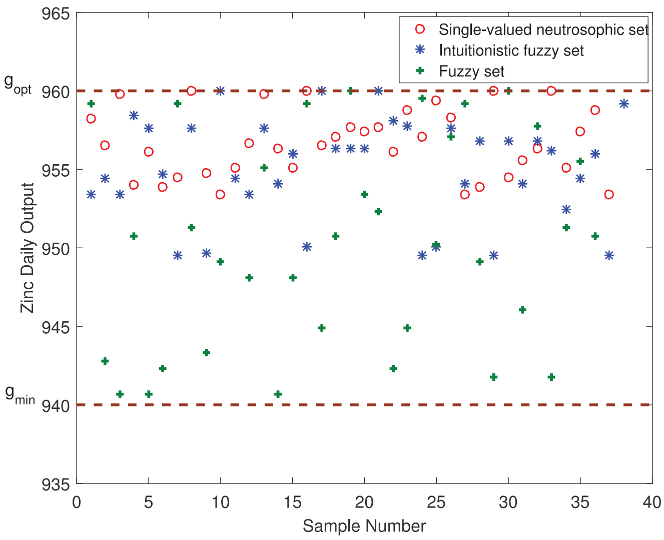

Fig. 5. Comparison of the results under fuzzy set, intuitionistic fuzzy set, and SVN set.

multi-objective state transition algorithm, a set of Pareto-optimal solutions are obtained. The TOPSIS technique is then applied to select the best final solution based on the three evaluation criteria in the zinc electrowinning process.

4. Experiments and discussion

To verify the applicability of the proposed single-valued neutrosophic model and optimization approach for the power scheduling in the zinc electrowinning process, simulation studies are conducted and described in this section. All the results are obtained using MATLAB R2017b on a desktop computer (3.60 GHz Interl Core i7, 8 GB of RAM).

In this paper, the electrowinning process in Zhuzhou Smeltery, which is a major zinc production company in China (see Fig. 4 [19]), is investigated as a case study. The parameters of the optimal power scheduling model in Zhuzhou Smeltery are as follows [19]: the number of potroom series $m = 7$, the cells number in each plant $N = [240, 240, 246, 192, 208, 208, 208]$, the plate number of a cell in each plant $O = [34, 46, 54, 56, 56, 57, 57]$, the area of the plate $a = 1.13$, and the limitations of decision variables $[\boldsymbol{d}_{\min}, \boldsymbol{d}_{\max}, \boldsymbol{C}_{Zn,\min}, \boldsymbol{C}_{Zn,\max}, \boldsymbol{C}_{H,\min}, \boldsymbol{C}_{H,\max}] = [100, 650, 45, 60, 160, 200]$.

According to the time-of-use pricing policy in Hunan Province in 2018, time is divided to on-peak, mid-peak, and off-peak periods which reflect the level of demand on the electricity network. During off-peak periods electricity prices will be cheaper than at other times. Shown in Table 1 is a typical pricing arrangement, in which ϕ means the basic electricity price.

Table 1
Time-of-use pricing in the case study.

Period	Time of day		Price	Duration (hour)
On-peak	07:00-11:00	15:00-22:00	1.6ϕ	11
Mid-peak	11:00-15:00	22:00-23:00	1.0ϕ	5
Off-peak	23:00-07:00		0.7ϕ	8

4.1. Feasibility verification of the SVN set

In the case study of electrowinning process, the optimal daily output is set to $g_{opt} = 960$ tons with allowable tolerance of 20 tons. To verify the feasibility of SVN set, we compare the performance of zinc daily output under different uncertain environments. Under intuitionistic fuzzy environment, we consider the truth-membership degree and falsity-membership degree. Under fuzzy environment, we only use the truth-membership degree to describe the uncertainty. Fig. 5 shows that the zinc daily output using SVN set is closer to the optimal target value. To be more specific, Table 2 shows the upper and lower bounds of zinc daily

Table 2
Zinc daily output under different uncertain environments.

Target value	Fuzzy set	Intuitionistic fuzzy set	SVN set
960 with allowable tolerance of 20	[940.69,960.03]	[949.49,960.01]	[953.38,960.00]

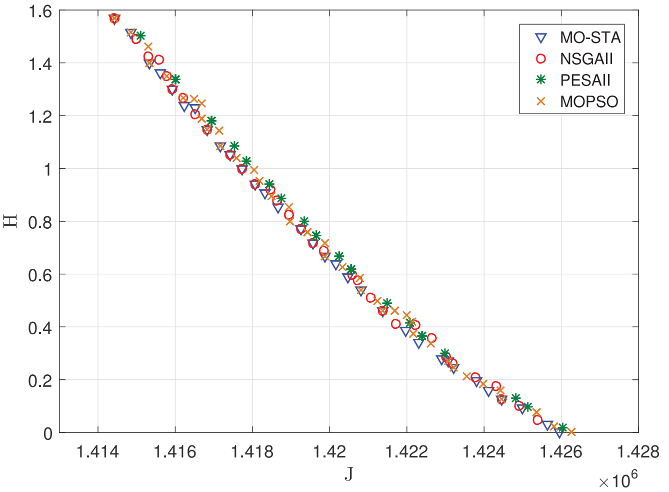

Fig. 6. Pareto-fronts obtained by MO-STA, NSGAII, PESAII, and MOPSO.

Table 3
Comparison results of the spacing metric (S) and hypervolume metric (HV).

Methods	S		HV	
	Mean	Std.Dev	Mean	Std.Dev
PESAII	247.7053	40.7827	9.7819e+03	102.3456
MOPSO	246.7150	163.7829	1.0012e+04	2.9304e+03
NSGAII	201.5489	38.3193	1.0960e+04	**55.1543**
MO-STA	**80.8478**	**37.3417**	**1.1098e+04**	76.7677

output under different environments. It can be observed that distribution range under SVN description is smaller than that under fuzzy and intuitionistic fuzzy description. Thus, SVN set has stronger ability to describe the uncertainty and represent the human preference.

4.2. Performance analysis of the MO-STA method

The parameters in MO-STA method are: $\kappa_{1,\max} = 1, \kappa_{1,\min} = 1e-4, \kappa_2 = 1, \kappa_3 = 1, SE = 40, iter_{\max} = 1000$. In order to analyze the performance of the MO-STA method, the nondominated sorting genetic algorithm II (NSGAII) [41], the Pareto envelope-based selection algorithm II (PESAII) [42], and the multiple objective particle swarm optimization (MOPSO) [43] are applied to optimize the same problem for comparison. According to previous studies, all of these three methods (NSGAII, PESAII, and MOPSO) are classical multi-objective optimization methods and they have been used successfully in many numerical and engineering problems. We adopt the parameter settings of NSGAII, PESAII, and MOPSO used in [41–43] in this performance evaluation study.

The Pareto-fronts obtained by MO-STA, NSGAII, PESAII, and MOPSO are shown in Fig. 6. It shows that the optimal solutions obtained by MO-STA is similar to that of NSGAII and MOPSO, and the solutions of PESAII are mostly dominated by that of MO-STA. It indicated that the MO-STA has competitive ability to deal with multi-objective optimization problems. Table 3 shows the quantitative analysis of these Pareto-fronts based on two performance metrics: spacing (S) [35] and hypervolume (HV) [44]. For Pareto-front $X = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_h\}$, the diversity and convergence performance can be analyzed as follows:

- Spacing metric (S): The spacing metric is used to evaluate the diversity among solutions, which can be calculated by

$$S(X) = \sqrt{\frac{1}{h-1}\sum_{v=1}^{h}(S_{average} - S_v)^2},$$

$$\text{where } S_v = \min_{v \neq v'}\left\{\sum_{i_m=1}^{M} |f_{i_m}(x_v) - f_{i_m}(x_{v'})|\right\}$$

$$S_{average} = \frac{1}{h-1}\sum_{v=1}^{h} S_v.$$

  The smaller the values of S, the better the distribution of solutions.
- Hypervolume metric (HV): The hypervolume metric can reflect the accuracy, diversity, and cardinality of solutions. Given a reference point $f^* = (f_1^*, f_2^*, \ldots, f_M^*)$ whose value is worse than every objective function values of X, the hypervolume metric can be calculated by

$$HV(X, f^*) = VOL\left(\bigcup_{x \in X}[f_1(x), f_1^*] \times \cdots \times [f_M(x), f_M^*]\right),$$

  where $VOL(\cdot)$ means Lebesgue measure. The larger the value of HV, the better the convergence and diversity performance of the methods.

In Table 3, each algorithm is executed independently for 20 trails. For the diversity metric (S), the performance of MO-STA is more stable and better than that of NSGAII, PESAII, and MOPSO. As for convergence metric (HV), the mean value of MO-STA is larger than that of NSGAII, PESAII, and MOPSO. The quantitative analysis shows that the MO-STA method can provide a more accurate and more diverse Pareto-front for a multi-objective optimization problem.

In terms of the computational complexity of the optimization algorithm, we base on the computational complexity analysis in [45]. Let the number of objectives be M, the size of the population be SE, and the size of the archive be S_A. Then the computational complexity of MO-STA, NSGAII, SPEAII, and MOPSO within one generation is $O(M \cdot SE^2)$, $O(M \cdot SE^2)$, $O(M \cdot (SE + S_A)^2)$, and $O(M \cdot SE^2)$, respectively. Thus, the MO-STA method is more efficient to optimize the power scheduling problem, and it is also a competitive method to solve multi-objective optimization problems.

4.3. Analysis of the decision making results

Based on the Pareto-optimal solutions obtained by the MO-STA method, Fig. 7 shows the electricity cost (J) and zinc daily output (g) of these solutions, and the evaluation results based on TOPSIS technique are represented by the color of each point. The solution with the largest evaluation value is selected as the final best solution. To give more explicit analysis of evaluation strategy, we take 10 samples (including the final best solution) from the Pareto-optimal solutions, and their normalized decision value of three criteria are shown in Fig. 8.

In Fig. 8, Sample 1 is the final best solution. We observe that the current efficiency of Sample 1 is much higher than that of others and its specific energy consumption is small. Considering the practical manufacture experience, the weights of the criteria in TOPSIS technique are set as $\omega = [0.5, 0.2, 0.3]$. Thus, Sample 1 offers better performance than others.

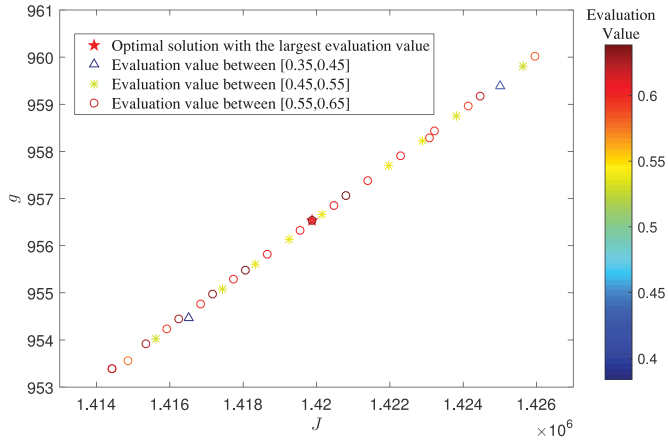

Fig. 7. Evaluation results using TOPSIS technique.

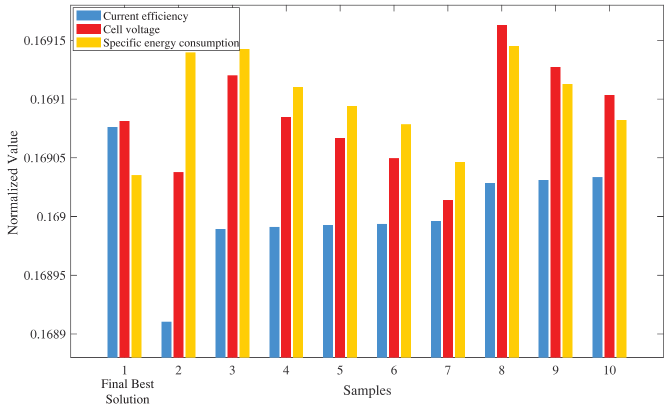

Fig. 8. Normalized decision value of three criteria.

Table 4
Comparison between deterministic optimization and SVN optimization.

Method		Deterministic Optimization	SVN Optimization
Decision variable	$\boldsymbol{d}$(A/m^2)	[261,317,650]	[100,573,650]
	$\boldsymbol{C}_{Zn}$(g/L)	[60,45,60]	[60,61,60]
	$\boldsymbol{C}_H$(g/L)	[200,200,200]	[160,161,162]
J(Chinese Yuan)		1.5922e+6	1.4199e+6
g(ton)		960.0017	956.5412
Time(second)		1.98	3.50

4.4. Comparison of the results using the proposed SVN optimization and deterministic optimization

To demonstrate the practical significance of the proposed SVN optimization for zinc electrowinning process, the deterministic optimization result based on two-stage state transition algorithm [12] is used for comparison. Since the deterministic problem pays more attention to finding the solution satisfied the equality constraint of daily output, the objective function value about electricity cost needs to be traded off. In this paper, the constraint of daily output is considered as a single-valued neutrosophic number, and it gives more opportunity to search for the solution with lower electricity cost. From Table 4, it shows that using SVN optimization method, the zinc daily output is 956.5412 tons which is less than that of deterministic method by 0.36%. However, compared with deterministic optimization, the electricity cost under the proposed method in this paper decreases by 10.8%. The execution time to solve SVN optimization problem (3.50s) is longer than that of deterministic problem (1.98s), but it is still well within the range acceptable by most in industrial processes.

5. Conclusion

In this paper, the SVN uncertainty of zinc daily output has been considered during the optimization of the power scheduling in the zinc electrowinning process. We have proposed a transformation method based on SVN symmetric cross entropy to handle the fuzzy constraint of the zinc daily output. Then the equivalent crisp multi-objective optimization model was established. The Pareto-front of this problem was searched by MO-STA. To select the final best solution, the multi-criteria decision making strategy based on TOPSIS technique was adopted. The experimental simulation results firstly verified that the SVN description method has better ability to capture the characteristic of fuzzy uncertainty. Then the optimization performance of MO-STA was compared with other three multi-objective optimization algorithms. The feasibility of the multi-criteria decision-making strategy was confirmed by solving the power scheduling problem. Furthermore, the results of SVN optimization was compared with that of the deterministic optimization. The power scheduling optimization case study has shown that the proposed method can decrease the electricity consumption by over 10% and the zinc daily output can still satisfy the fuzzy requirement. Our future work will further study the SVN optimization methods to solve problems with uncertain parameters existed in both objectives and constraints.

Declaration of Competing Interest

None declared.

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