Frontiers of Information Technology & Electronic Engineering
www.jzus.zju.edu.cn; engineering.cae.cn; www.springerlink.com
ISSN 2095-9184 (print); ISSN 2095-9230 (online)
E-mail: jzus@zju.edu.cn

A combination weighting model based on iMOEA/D-DE*

Mingtao DONG†, Jianhua CHENG†‡, Lin ZHAO

College of Intelligent Systems Science and Engineering, Harbin Engineering University, Harbin 150001, China

†E-mail: hbdmt@hrbeu.edu.cn; chengjianhua@hrbeu.edu.cn

Received Oct. 13, 2020; Revision accepted Feb. 19, 2021; Crosschecked Dec. 9, 2021; Published online Apr. 1, 2022

Abstract: This paper proposes a combination weighting (CW) model based on iMOEA/D-DE (i.e., improved multiobjective evolutionary algorithm based on decomposition with differential evolution) with the aim to accurately compute the weight of evaluation methods. Multi-expert weight considers only subjective weights, leading to poor objectivity. To overcome this shortcoming, a multiobjective optimization model of CW based on improved game theory is proposed while considering the uncertainty of combination coefficients. An improved mutation operator is introduced to improve the convergence speed, and thus better optimization results are obtained. Meanwhile, an adaptive mutation constant and crossover probability constant with self-learning ability are proposed to improve the robustness of MOEA/D-DE. Since the existing weight evaluation approaches cannot evaluate weights separately, a new weight evaluation approach based on relative entropy is presented. Taking the evaluation method of integrated navigation systems as an example, certain experiments are carried out. It is proved that the proposed algorithm is effective and has excellent performance.

Key words: Combination weighting; MOEA/D-DE; Game theory; Self-learning ability; Relative entropy
https://doi.org/10.1631/FITEE.2000545 **CLC number:** TP18; TN967.2

1 Introduction

The shortcomings of traditional testing methods, i.e., sometimes testing is impossible to carry out and the subjective indices cannot be evaluated, can be overcome by the evaluation method applied to integrated navigation systems. Therefore, this field has attracted increasing attention from scholars (Wang XL et al., 2017). The evaluation results can discern the differences between various systems, thereby providing technical support for decision makers and offering guidance for system optimization. The integrated navigation system contains a lot of indices with different attributes and multi-level characteristics. Indices with complex features put forward higher requirements for evaluation methods. The means to widen the application of the evaluation method to an integrated navigation system requires further studies.

Combination weighting (CW) is one of the key tools of evaluation methods, and the accuracy of CW directly affects the evaluation result. Scholars have carried out a lot of research on CW, and the solutions include mainly the direct approach (Jiao et al., 2016; Cheng et al., 2019a; Zhu et al., 2019; Lv et al., 2020; Pan et al., 2020), single objective model approach (Xu and Cai, 2012; Liu and Hu, 2015; Dai and Niu, 2017; Zhou RX et al., 2017; Zhang ZC and Chen, 2018), multiobjective model approach (Shi et al., 2012; Yin et al., 2016; Cheng et al., 2019b), and CW approach based on game theory (GT) (Lai et al., 2015; Sun LJ et al., 2016; Li AH, 2017; Yang et al., 2018; Dong et al., 2020).

‡ Corresponding author

* Project supported by the National Natural Science Foundation of China (Nos. 61633008, 61773132, and 61803115), the 7th Generation Ultra Deep Water Drilling Unit Innovation Project Sponsored by Chinese Ministry of Industry and Information Technology, the Heilongjiang Provincial Science Fund for Distinguished Young Scholars, China (No. JC2018019), and the Fundamental Research Funds for the Central Universities, China (No. HEUCFP201768)

ORCID: Mingtao DONG, https://orcid.org/0000-0002-9929-5210

In previous studies, the improved analytic hierarchy process (AHP) was employed to compute the subjective weight (SW), the enhanced entropy method (EM) was used to compute the objective weight (OW), and the weighted sum approach (WSA) was applied to establish the CW model. The combination coefficients (CCs) were set according to the preference of decision makers (Pan et al., 2020). SW was computed by AHP, the correlation method was used to compute the OW, and two different weights were combined by the WSA. CCs were determined by the variation coefficient of each weight based on AHP (Lv et al., 2020). Generally, SW and OW were computed by AHP and EM, respectively. WSA was used to combine different weights, and the difference between various methods is in the solutions of CC (Jiao et al., 2016; Cheng et al., 2019a; Zhu et al., 2019). The influence of CC on evaluation results was analyzed, and CCs were selected by subsequent results (Jiao et al., 2016). CCs were directly set in some studies (Cheng et al., 2019a; Zhu et al., 2019). In the above literature, WSA was employed to establish the CW model based on SW and OW. The solutions of CCs are simple and have low precision.

The direct approach has poor accuracy, and therefore the single objective model approach was proposed to solve the problem. To reflect the consistency of subjective and objective information, where SW was obtained by matter-element analysis and OW was acquired by EM, a single objective model was presented by combining index values with weights, and CCs were obtained by solving the model (Dai and Niu, 2017). In a different approach, SW was computed by AHP, and OW was computed by the rough EM. A single objective model was established based on the minimum deviation, and CCs were computed by the cooperative game method (Zhang ZC and Chen, 2018). Alternatively, OW was obtained by the rough set method, and SW was derived by AHP. Combined with the scheme value, a linear objective model was proposed based on the principle of maximizing variance. Therein, CCs were computed by the Lagrange multiplier method (LMM) (Liu and Hu, 2015). For the multi-expert weight, the weighted arithmetic average operator was used to transform weights into CW. From the perspective of minimizing group disharmony, a nonlinear optimization model based on deviation function was established, and the model was computed by the genetic algorithm (Xu and Cai, 2012). In a further study, SW and OW were obtained by fuzzy AHP and the projection pursuit method, respectively. The single objective model was established based on the principle of the minimum relative entropy, and the model was computed by LMM (Zhou RX et al., 2017). The above literature shows that the single objective model approach must use the index values, and that the model is most commonly computed by LMM. The accuracy of the index depends on the dimensionless method. So, the accuracy of the single objective model approach is low, and it is not suitable for the complex optimization model.

A double-objective model of CW was subsequently proposed, which was transformed into a single-objective optimization model by WSA. LMM was employed to compute CCs (Yin et al., 2016). Considering the randomness of the weight itself and the consistency between weight vectors, a nonlinear multiobjective model of CW was also established. The model was transformed into a single objective model by WSA. An improved particle swarm optimization (PSO) algorithm was proposed to compute CCs (Shi et al., 2012). A different multiobjective model was established by expert weights, and the model was based on the uncertainty of CCs and the consistency of weights. WSA was used to transform the model into a single objective model, and the modified differential evolution (DE) algorithm was applied to compute CCs (Cheng et al., 2019b). When the multiobjective model is transformed into a single-objective model, it is difficult to obtain model coefficients accurately. This is a shortcoming of the multiobjective model approach. In comparison with the single-objective model, the multiobjective model of CW can express the relationship between different weights in a comprehensive way.

The CW model based on GT was further established, and the condition of the optimal first order was used to compute CCs based on the differential property of matrix (Lai et al., 2015). Furthermore, fuzzy AHP and EM were used to compute SW and OW respectively, and the CW model was established based on GT. Therein, CCs were computed by the differential property of matrix (Sun LJ et al., 2016). In another model, SW and OW were computed by AHP and EM, respectively. Two weights were combined into CW based on GT, and CCs were computed based on the differential property of matrix (Yang et al., 2018). Aiming at the problem that traditional CW based on GT may obtain negative weights, an improved combination weighting method based on GT (ICWGT) was proposed, where CCs were computed by LMM (Li AH, 2017). Dong et al. (2020) obtained CW by the idea of GT, which was combined with SW and OW. SW was obtained by interval AHP, and OW was acquired by information entropy. The condition of the optimal first order was used to compute CCs. The above studies demonstrated that the GT-based CW approach is a new idea in CW, which is essentially a single-objective model approach. Based on the above literature, it is clear that the uncertainty of CCs in a CW model should be considered.

In the past decades, many intelligent algorithms have been applied to multiobjective optimization problems. Many scholars have focused on intelligent algorithms for a multiobjective optimization model of CW (Shi et al., 2012; Cheng et al., 2019b). The multiobjective optimization problem was transformed into several scalar optimization subproblems. The subproblems were optimized at the same time, which could generate a highly uniform distribution of solutions. This method was named multiobjective evolutionary algorithm based on decomposition (MOEA/D) (Zhang QF and Li, 2007). Li H and Zhang (2009) proposed the further developed MOEA/D-DE, a combination of MOEA/D and DE algorithm, which has the ability to deal with the complex Pareto front (PF). Simulation results showed that this new algorithm is better than MOEA/D. The MOEA/D and DE algorithm subsequently became the most popular of these new intelligent algorithms.

When a multiobjective optimization model is nonlinear and contains an equality constraint, the convergence of the DE algorithm is insufficient. Das and Suganthan (2011) reviewed the basic concepts of discrete evolutionary algorithm and presented its applications for multiobjective, constrained, large-scale, and uncertain optimization problems. Ye et al. (2013) summarized existing problems of the DE algorithm, and reported the main issue that it is necessary to choose suitable parameters to ensure the success of the algorithm. Al-Dabbagh et al. (2018) pointed out that the performance of the DE algorithm dependeds on the control parameters which determine the solution quality and search efficiency. Current studies have focused on how to optimize the control parameters. Zhang CM et al. (2014), for example, proposed an adaptive adjustment strategy of F and CR, where F represents the mutation control parameter and CR represents the crossover control parameter, and the parameters were obtained adaptively by the fitness value. Moreover, Fan and Yan (2016) presented an adaptive DE algorithm, which was used to control the partition evolution of parameters and the adaptive mutation strategy. The mutation strategy was automatically adjusted with the population evolution, and parameters were evolved in their own partition to find the near-optimal value adaptively. Li YZ et al. (2020) presented an improved DE algorithm based on a dual mutation strategy to reduce the influence of the mutation strategy and parameter selection on the DE algorithm. Wu et al. (2013) introduced both an improved mutation operator and a parameter adaptive strategy in the DE algorithm. Ding et al. (2020) described an adaptive strategy that can adaptively select the differential mutation operator with the population evolution. In the above literature, the latest achievements in MOEA/D and DE algorithm were summarized. The CW model with nonlinear characteristics contains an equality constraint, which puts forward higher requirements for the robustness of intelligent algorithms.

The solutions of CW were systematically described in the literature, and their advantages and disadvantages were subsequently analyzed. Each of them may provide a new idea for solving the multiobjective optimization problem of CW. The purpose of this paper is to propose a multiobjective optimization model of CW based on improved MOEA/D with differential evolution (iMOEA/D-DE). First, a multiobjective optimization model of CW based on improved GT is developed to overcome the poor objectivity of the multi-expert weight. Second, due to the CW model being nonlinear and containing an equality constraint, MOEA/D-DE has the disadvantage of poor convergence. Therefore, inspired by Wu et al. (2013), an improved mutation operator is introduced, and a new adaptive mutation constant and crossover probability constant are proposed. Finally, a new weight evaluation approach is presented to evaluate CW.

2 Multiobjective optimization model of CW

Cheng et al. (2019b) proposed a multiobjective optimization model of the multi-expert weight, which is based on the uncertainty of CCs and the weight consistency. The multi-expert weight was composed of expert weights, and had poor objectivity. A double-objective constrained optimization model was developed to overcome these drawbacks, and an improved adaptive penalty function was described to handle the constrained problem, but the penalty coefficient was difficult to obtain accurately (Cheng et al., 2021). In this paper, an improved GT is introduced and a new multiobjective model of CW is proposed to address this limitation. The equality constraint included in the CW model makes the solution more complex, and thus the multiobjective optimization method is introduced to deal with this constraint.

2.1 Multiobjective optimization model

2.1.1 CW model based on improved GT

The CW model based on GT aims to seek a balance between the weights of different weight methods, so as to minimize the deviation between CW and each weight. Suppose that n weighting methods are used to compute the weight value. A weighting method contains the SW method (Cheng et al., 2019a) and the OW method (Dai and Niu, 2017). Each weight is $\boldsymbol{w}_i=(w_{i1}, w_{i2}, \cdots, w_{im})$, i=1, 2, ⋯, n, and m is the number of indices. Let CCs of CW be $k_1, k_2, \cdots, k_n$. Then CW can be obtained by WSA:

$$\boldsymbol{W} = \boldsymbol{w}_1 k_1 + \boldsymbol{w}_2 k_2 + \cdots + \boldsymbol{w}_n k_n = \sum_{i=1}^{n} \boldsymbol{w}_i k_i, \quad (1)$$

where $k_i \geqslant 0$ and $\sum_{i=1}^{n} k_i = 1$.

To minimize the deviation between CW and each weight, the CW model based on GT is established:

$$\min \left\| \sum_{i=1}^{n} \boldsymbol{w}_i k_i - \boldsymbol{w}_j \right\|_2, \ j = 1, 2, \cdots, n, \quad (2)$$

where $\|\cdot\|_2$ is the 2-norm of a matrix.

According to the differential property of the matrix (Lai et al., 2015), the optimal condition of Eq. (2) is

$$\begin{bmatrix} \boldsymbol{w}_1\boldsymbol{w}_1^{\mathrm{T}} & \boldsymbol{w}_1\boldsymbol{w}_2^{\mathrm{T}} & \cdots & \boldsymbol{w}_1\boldsymbol{w}_n^{\mathrm{T}} \\ \boldsymbol{w}_2\boldsymbol{w}_1^{\mathrm{T}} & \boldsymbol{w}_2\boldsymbol{w}_2^{\mathrm{T}} & \cdots & \boldsymbol{w}_2\boldsymbol{w}_n^{\mathrm{T}} \\ \vdots & \vdots & & \vdots \\ \boldsymbol{w}_n\boldsymbol{w}_1^{\mathrm{T}} & \boldsymbol{w}_n\boldsymbol{w}_2^{\mathrm{T}} & \cdots & \boldsymbol{w}_n\boldsymbol{w}_n^{\mathrm{T}} \end{bmatrix} \begin{bmatrix} k_1 \\ k_2 \\ \vdots \\ k_n \end{bmatrix} = \begin{bmatrix} \boldsymbol{w}_1\boldsymbol{w}_1^{\mathrm{T}} \\ \boldsymbol{w}_2\boldsymbol{w}_2^{\mathrm{T}} \\ \vdots \\ \boldsymbol{w}_n\boldsymbol{w}_n^{\mathrm{T}} \end{bmatrix}. \quad (3)$$

A set of solutions $\{k_1, k_2, \cdots, k_n\}$ can be obtained by solving Eq. (3). After normalization, $k_i^* = k_i \big/ \sum_{i=1}^{n} k_i$ can be obtained. Subsequently, CW is

$$\boldsymbol{W}^* = \sum_{i=1}^{n} \boldsymbol{w}_i k_i^*. \quad (4)$$

CW depends on Eq. (4), while the result of this formula depends on Eq. (3). Therein, negative results may be obtained, resulting in a negative weight. Therefore, a CW model based on improved GT is introduced (Li AH, 2017). The new CW model is

$$f_1(\boldsymbol{k}) = \min_{k_1, k_2, \cdots, k_n} \sum_{i=1}^{n} \left| \sum_{j=1}^{n} k_j \boldsymbol{w}_i \boldsymbol{w}_j^{\mathrm{T}} - \boldsymbol{w}_i \boldsymbol{w}_i^{\mathrm{T}} \right|, \quad (5)$$

where $|\cdot|$ is the absolute value and $\boldsymbol{k}=(k_1, k_2, \cdots, k_n)$.

The constraint of Eq. (5) is

$$\sum_{i=1}^{n} k_i = 1, \quad (6)$$

where n indicates the number of weights.

2.1.2 Uncertainty of CW

Based on mathematical statistics, the real weight value of each index is a random value. The weight values of different weighting methods are sample values of the true weight. Different weighting methods bring uncertainty to CW. The Shannon information entropy is usually used to describe this uncertainty (Shi et al., 2012). The uncertainty of CW is (Cheng et al., 2019b)

$$\max f_2(\boldsymbol{k}) = -\sum_{i=1}^{n} k_i \ln k_i. \quad (7)$$

Since $0 \leqslant k_i \leqslant 1$ and the objective function f_2 contains "ln" function, the minimum value of CC cannot be taken as 0, but is assumed to be 0.01. The constraint of the uncertain model is the same as in Eq. (6), but the value range of k_i becomes $0.01 \leqslant k_i \leqslant 1$.

2.1.3 A new multiobjective optimization model of CW

Considering that CW is based on improved GT and the uncertainty of CW, the multiobjective optimization model of CW is proposed as

$$\min F(\boldsymbol{k}) = \left(f_1(\boldsymbol{k}), f_2(\boldsymbol{k})\right), \tag{8}$$

$$\sum_{i=1}^{n} k_i = 1, \tag{9}$$

where $F(\boldsymbol{k})$ is the objective function.

Eq. (7) is a maximum optimization model, while model (5) is a minimum optimization model. Two models with different characteristics cannot be linked together to form a multiobjective optimization model. Hence, model (7) is converted into a minimum model. Next, it is combined with Eq. (5) to obtain Eq. (8). Eq. (9) is the common constraint of f_1 and f_2, and the value range of k_i is $0.01 \leqslant k_i \leqslant 1$.

2.2 CW based on the multiobjective optimization method

The constraints in the multiobjective optimization model make the solving process rather difficult. Wang Y et al. (2009) summarized the progress of constraint processing technology in the optimization model. Among the solutions, the multiobjective optimization method transforms the constraint into objective functions, and these functions are treated as different objective functions, which can overcome the drawback of difficulty to accurately obtain the penalty coefficient. In this study, the multiobjective optimization method is used to deal with the constraint.

The CW model contains an equality constraint, which is usually transformed into an inequality constraint (Wang Y et al., 2009):

$$\left|\sum_{i=1}^{n} k_i - 1\right| - \delta \leqslant 0, \tag{10}$$

where δ is a tolerance value of equality constraint, and is generally a small positive number of 0.001 or 0.0001. In general, the degree to which the CC violates the equality constraint can be expressed as

$$f_3(\boldsymbol{k}) = \max\left\{\left|\sum_{i=1}^{n} k_i - 1\right| - \delta, 0\right\}, \tag{11}$$

where $f_3(\boldsymbol{k})$ is the infeasibility degree of $\boldsymbol{k}$. Through combining Eq. (11) with Eq. (8), the multiobjective optimization method is used to transform them into a multiobjective optimization model with three objective functions. Therefore, the three-objective optimization model of CW is formulated as

$$\begin{cases} \min F(\boldsymbol{k}) = \left(f_1(\boldsymbol{k}), f_2(\boldsymbol{k})\right), \\ \max f_3(\boldsymbol{k}), \end{cases} \tag{12}$$

where $\boldsymbol{k} = (k_1, k_2, \cdots, k_n)$, and f_3 is called the feasible solution.

3 CW model based on iMOEA/D-DE

In Section 2, the multiobjective optimization model of CW is presented. The CW model is nonlinear and contains an equality constraint, which makes it difficult to be solved. The MOEA/D-DE (Li H and Zhang, 2009), an improved algorithm of MOEA/D, is capable of dealing with the problem with complex PF. The CW model puts forward a higher requirement for the distribution and convergence of the MOEA/D-DE algorithm, and thus an iMOEA/D-DE algorithm is proposed.

3.1 iMOEA/D-DE

3.1.1 Classical MOEA/D-DE

The main idea of MOEA/D is to break down the multiobjective optimization model into several scalar subproblems, and use their neighborhood information problems to optimize all subproblems simultaneously. The DE operator and polynomial mutation operator are used to generate new solutions. The important formulas of MOEA/D-DE are as follows:

1. Use the Tchebycheff approach to aggregate function values, which are obtained by decomposition operation:

$$\min g^{\mathrm{te}}(\boldsymbol{k} \mid \boldsymbol{\lambda}, \boldsymbol{z}^*) = \max_{1 \leqslant i \leqslant m} \left\{\left| f_i(\boldsymbol{k}) - z_i^* \right| \lambda_i\right\}, \tag{13}$$

where $\boldsymbol{z}^*$ is the reference point, $z_i^* = \min\left\{f_i(\boldsymbol{k})\right\}$, the weight vector satisfies $\boldsymbol{\lambda} = (\lambda_1, \lambda_2, \cdots, \lambda_m)$, $\lambda_i \geqslant 0$, and $m=3$ represents the number of objective functions.

2. Determine the renewal range and produce new individuals:

$$P=\begin{cases}B(i), & \text{rand} < \delta_1,\\ \{1,2,\cdots,N\}, & \text{otherwise},\end{cases} \tag{14}$$

where δ_1 denotes the probability that parent solutions are selected from the neighborhood, rand is a random mumber within [0, 1], N is the population size, and $B(i)=\{i_1, i_2, \cdots, i_T\}$, and, $\boldsymbol{\lambda}^{i_1}, \boldsymbol{\lambda}^{i_2}, \cdots, \boldsymbol{\lambda}^{i_T}$ are the nearest T vectors of $\boldsymbol{\lambda}^i$.

The DE operator and polynomial mutation operator are used to generate new individuals:

$$\bar{y}_k=\begin{cases}x_k^{r_1}+F\times\left(x_k^{r_2}-x_k^{r_3}\right), & \text{for probability CR},\\ x_k^{r_1}, & \text{for probability } 1-\text{CR},\end{cases} \tag{15}$$

$$y_k=\begin{cases}\bar{y}_k+\sigma_k\times\left(b_k-a_k\right), & \text{for probability } p_{\mathrm{m}},\\ \bar{y}_k, & \text{for probability } 1-p_{\mathrm{m}},\end{cases} \tag{16}$$

$$\sigma_k=\begin{cases}(2\times\text{rand})^{\frac{1}{\eta+1}}-1, & \text{rand} < 0.5,\\ 1-(2-2\times\text{rand})^{\frac{1}{\eta+1}}, & \text{otherwise}.\end{cases} \tag{17}$$

In Eq. (15), CR denotes the crossover probability with a value range of 0–1, and F is a scalar number with a value range of 0–1. Let $r_1=i$, randomly select r_2 and r_3 from P, and use the DE operator to generate $\bar{\boldsymbol{y}}$; $\bar{y}_k$ is the k^{th} element in $\bar{\boldsymbol{y}}$. Three individuals $\boldsymbol{x}^{r_1}, \boldsymbol{x}^{r_2}$, and $\boldsymbol{x}^{r_3}$ are selected from their parents; x_k^i is the k^{th} element of $\boldsymbol{x}^i$. In Eqs. (16) and (17), p_{m} is the mutation rate, η stands for the distribution index, and a_k and b_k are the lower and upper bounds of the k^{th} decision variable, respectively.

3.1.2 Improved mutation operation

The DE/rand/1 operator is used in the differential mutation stage of MOEA/D-DE (Li YZ et al., 2020), in which the operator is beneficial to global search, but not conducive to improving the convergence rate of the algorithm. Various operators have different characteristics and are suitable for different problems. In the CW model, the existence of equality constraint leads to a very small proportion of the feasible region in the search space and a large degree of dispersion, and the constraint requires the operator to have a better global and convergence rate. Therefore, the improved mutation operation is introduced in the differential mutation stage (Wu et al., 2013).

Based on the DE/rand/1 operator, the idea of improved mutation operation is to sort three individuals by their fitness values, which are randomly selected from their parents. Assume that the order is $\boldsymbol{x}_{a,G}$, $\boldsymbol{x}_{b,G}$, and $\boldsymbol{x}_{c,G}$. Taking the optimal $\boldsymbol{x}_{a,G}$ as the mutation reference vector and the difference between the suboptimal and the worst individual ($\boldsymbol{x}_{b,G}-\boldsymbol{x}_{c,G}$) as the difference vector, the improved mutation operation is obtained as follows:

$$\boldsymbol{V}_{i,G+1}=\boldsymbol{x}_{a,G}+F\left(\boldsymbol{x}_{b,G}-\boldsymbol{x}_{c,G}\right). \tag{18}$$

It is known that the improved mutation operation takes $\boldsymbol{x}_{b,G}-\boldsymbol{x}_{c,G}$ as the difference vector, which is beneficial to improve the convergence rate. Hence, Eq. (15) can be updated to

$$\bar{y}_k=\begin{cases}x_k^a+F\times\left(x_k^b-x_k^c\right), & \text{for probability CR},\\ x_k^{r_1}, & \text{for probability } 1-\text{CR}.\end{cases} \tag{19}$$

3.1.3 Adaptive strategy with self-learning ability

In MOEA/D-DE, F and CR are both constant values in the DE operator, and remain the same during the evolution process. They have an important impact on the performance of the algorithm, and parameter selection is usually associated with the problem. The CW model with the equality constraint is nonlinear, which makes the model more difficult to be solved, and the constant values of F and CR are hard to adapt. Taking the adaptive idea from the literature (Wu et al., 2013), a new adaptive strategy is proposed. According to the state of population evolution, an adaptive strategy with self-learning ability is formulated, which is independent of the optimization problem. As shown in Fig. 1, F and CR are coded simultaneously with the individuals. In each generation, $\boldsymbol{x}_{i,G}$ has a corresponding $F_{i,G}$ and $\text{CR}_{i,G}$ value. The initial values of F and CR are randomly selected within the scope of their respective values. In the process of evolution, if a better individual cannot be produced in five generations, it indicates that the relevant parameters are not suitable and need to be reset. If one or more better individuals are produced within five generations, the relevant parameters should be retained. The parameter with the most reserved times is the most appropriate parameter. Obviously, inappropriate parameters are constantly reset, and the ultimate goal is the most appropriate parameter that is consistent with the basic idea of the evolutionary algorithm.

$\boldsymbol{x}_{1,G}$	$F_{1,G}$	$\mathrm{CR}_{1,G}$
$\boldsymbol{x}_{2,G}$	$F_{2,G}$	$\mathrm{CR}_{2,G}$
⋮	⋮	⋮
$\boldsymbol{x}_{N,G}$	$F_{N,G}$	$\mathrm{CR}_{N,G}$

Fig. 1 Adaptive coding format

Based on the above idea, a parameter adaptive strategy with self-learning ability is proposed:

$$F_{i,G+1}=\begin{cases}F_{\max}-\mathrm{rand}\times(F_{\max}-F_{\min}), & c=0,\\ F_{i,G}, & \text{otherwise},\end{cases} \tag{20}$$

$$\mathrm{CR}_{i,G+1}=\begin{cases}\mathrm{CR}_{\min}+\mathrm{rand}\times(\mathrm{CR}_{\max}-\mathrm{CR}_{\min}), & c=0,\\ \mathrm{CR}_{i,G}, \ \text{otherwise},\end{cases} \tag{21}$$

where c represents the number of optimal individuals generated in the five generations, $F_{\max}$ and $F_{\min}$ are the maximum and minimum values of F respectively, and $\mathrm{CR}_{\max}$ and $\mathrm{CR}_{\min}$ are the maximum and minimum values of CR respectively.

In the CW model, the existence of equality constraint makes the feasible region more discrete, which requires better diversity in the initial stage of evolution. With regards to F, to maintain the diversity of individuals, F is required to decrease from $F_{\max}$. As the algorithm iterates, F is required to decrease to avoid damage to the optimal solution to retain valuable information. The decrease amplitude is the value of $F_{\max}-F_{\min}$.

The value of CR determines whether the mutation vector or the target vector is used in the crossover operation (Zhang CM et al., 2014). When a better individual is produced, the test vector should take the variation vector with a greater probability; thus CR should be taken at a larger value. On the contrary, if the test vector takes the target vector with higher probability, CR should take a smaller value. In the early evolution, the feasible solutions are widely distributed and there are bad individuals, and hence CR should be taken at a smaller value. Therefore, CR increases gradually from $\mathrm{CR}_{\min}$, and the decrease amplitude is the value of $\mathrm{CR}_{\max}-\mathrm{CR}_{\min}$.

In the process of evolution, if a better individual cannot be produced within five generations, then c is equal to 0 and a new F is produced using rand until a better individual is produced. As the algorithm iterates, F and CR are gradually changed towards the best solution. The complexity of the CW model makes F and CR change dynamically. Thus, F and CR have self-learning ability.

3.1.4 Flow of iMOEA/D-DE

The MOEA/D-DE is combined with improved mutation operation and the adaptive strategy with self-learning ability to obtain the iMOEA/D-DE algorithm.

Step 1: The population size is N, the number of neighborhood weight vectors of each weight vector is T, the probability of selecting parent individuals from neighborhood is δ_1, the child solution number replaced is n_r, and the maximum number of iterations is $G_{\max}$.

Step 1.1: For i=1, 2, ⋯, N, set $B(i)=\{i_1, i_2, \cdots, i_T\}$, where $\boldsymbol{\lambda}^{i_1}, \boldsymbol{\lambda}^{i_2}, \cdots, \boldsymbol{\lambda}^{i_T}$ are the nearest T weight vectors of $\boldsymbol{\lambda}^i$.

Step 1.2: Generate the initial population P with scale N randomly, assuming that $\mathrm{FV}^i=F(\boldsymbol{x}^i)$. The initialization reference point is $\boldsymbol{z}=(z_1, z_2, \cdots, z_m)$, where m is the number of objective functions.

Step 2: According to Eq. (14), select the update matching/updating range.

Step 2.1: Suppose that $r_1=i$ and that two indices r_2 and r_3 are randomly selected from P. Three individuals are then sorted by g^{te} to obtain the variation reference and difference vectors.

Step 2.2: Judge whether the new optimal individuals are generated within the five generations, that is, whether the parameter c is greater than zero. F and CR are adaptively adjusted by Eqs. (20) and (21), respectively. If c is greater than zero, it is assigned zero value. According to DE and the polynomial mutation operator, a new solution $\boldsymbol{y}$ is generated by parameter p_{m}.

Step 2.3: Judge $\boldsymbol{y}$, and if it exceeds the feasible region, it will be randomly selected in the feasible region. If $z_j > f_i(\boldsymbol{y})$, set $z_j = f_i(\boldsymbol{y})$, $j=1, 2, \cdots, m$.

Step 2.4: Suppose that $c_a=0$.

(1) If $c_a=n_r$ or P is an empty set, then turn to step 3; otherwise, randomly select index j from P;

(2) If $g^{te}\left(\boldsymbol{y}|\lambda^j, z\right) \leqslant g^{te}\left(\boldsymbol{x}^j|\lambda^j, z\right)$ is satisfied, then $\mathrm{FV}^j = F\left(\boldsymbol{x}^j\right)$, $c_a=c_a+1$, and $c=c+1$;

(3) Remove j from P and proceed to step 1.

Step 3: Judge whether the program termination condition is met; if it is not, go to step 2.

Step 4: Output the objective function value and the optimal solution set.

3.2 A new weight evaluation approach

To evaluate the rationality of the CW model, the weight evaluation approach must be used. Existing weight evaluation approaches, however, have some drawbacks: (1) Using the weight value and the index value to compute the deviation function, the result is affected by the accuracy of the index conversion method (Shi et al., 2012); (2) The weight evaluation approach and scheme ranking are linked together (Song and Yang, 2004), which is not applicable to the problem with the weight only. Hence, it is necessary to propose a new weight evaluation approach for CW.

CW combines SW and OW. When CW is obtained, CW and each weight are independent, and can be regarded as independent discrete distributions. From the perspective of CW and each weight, the deviation between two distributions should not be too large and should tend to be consistent; the relative entropy can represent the deviation between two distributions.

Definition 1 (Zhou YF and Wei, 2006) Assuming that $x_i \geqslant 0$, $y_i \geqslant 0$ ($i=1, 2, \cdots, n$), $\sum_{i=1}^{n} x_i = 1$, and $\sum_{i=1}^{n} y_i = 1$, then $h(\boldsymbol{x}, \boldsymbol{y}) = \sum_{i=1}^{n} x_i \log_a(x_i/y_i)$ is called the relative entropy of $\boldsymbol{x}$ relative to $\boldsymbol{y}$, where $\boldsymbol{x}=(x_1, x_2, \cdots, x_n)$ and $\boldsymbol{y}=(y_1, y_2, \cdots, y_n)$. Its main properties are as follows:

(1) $\sum_{i=1}^{n} x_i \log_a(x_i/y_i) \geqslant 0$;

(2) The necessary and sufficient condition of $\sum_{i=1}^{n} x_i \log_a(x_i/y_i) = 0$ is that $x_i=y_i$ for all i.

Based on the above properties, when x and y are two discrete distributions, the relative entropy can be used as a measure of their coincidence. The weight evaluation measure of CW can then be obtained as follows:

$$D(\boldsymbol{w}) = \sum_{i=1}^{m}\left(\sum_{j=1}^{n} \boldsymbol{W}_j \ln\left(\frac{\boldsymbol{W}_j}{\boldsymbol{w}_j^i}\right)\right), \tag{22}$$

where $\boldsymbol{W}=(\boldsymbol{W}_1, \boldsymbol{W}_2, \cdots, \boldsymbol{W}_n)$ is the CW vector and $\boldsymbol{w}=(w_1, w_2, \cdots, w_m)$ is the weight vector, and the relationship between $\boldsymbol{W}$ and $\boldsymbol{w}$ is discussed in Eq. (1). The smaller the relative entropy, the smaller the difference between CW and each weight.

4 Results and discussion

Experiments are carried out to verify the effectiveness of the proposed approach. First, to verify the performance of iMOEA/D-DE, two kinds of test instances are used for comparison with MOEA/D-DE (Li H and Zhang, 2009). Second, to verify the performance of the proposed algorithm in the CW model, the iMOEA/D-DE is compared with MOEA/D (Zhang QF and Li, 2007), MOEA/D-DE, and NSGA-II (Deb et al., 2002). Finally, the weight evaluation approach is verified in the CW model.

4.1 Test instance experiments

In this study, two kinds of test instances with different properties are selected by the characteristics of CW, where the number of the objective functions is 2 and 3, separately. The first is a two-objective test instance ZDT (Zhang QF and Li, 2007) and the second group is a three-objective test instance DTLZ (Zhang QF and Li, 2007), which are used to test the PF.

The MOEA/D-DE is compared with the iMOEA/D-DE. To ensure the comparability of test results, the same parameters are set in both algorithms, and readers can refer to Li H and Zhang (2009) for parameter selection. The parameters are set as follows: the value range of F is [0, 1], and its initial value is set to 0.5; the value range of CR is [0, 1], and its initial value is set to 0.5; the distribution index of η is 20; the polynomial variation rate p_m is $1/n$ (n is the number of decision variables); the number of neighborhoods T is $0.1N$; the probability of selecting parents from neighborhood δ is 0.9; the child solution number replaced n_r is 2; the population size of ZDT is 100; the population size of DTLZ is 300.

To evaluate the distribution and convergence of the algorithm, the inverted generational distance

(IGD) (Ishibuchi et al., 2018; Sun YN et al., 2019) is introduced. The smaller the IGD, the better the distribution and convergence of the PF. IGD requires the target object to obtain real PF. Two kinds of test instances meet the requirements, and IGD is as follows:

$$\mathrm{IGD}=\frac{\sum_{p\in p^*}\mathrm{dist}(p,\mathrm{PF})}{|p^*|}, \tag{23}$$

where p^* is a set of reference points for IGD, PF indicates the nondominated solutions generated by the algorithm, and dist(p, PF) is the nearest distance from p to PF.

Table 1 lists the results of the two algorithms in ZDT and DTLZ. MOP is the multiobjective optimization problem. Each test instance runs 20 times to compute the mean value, standard deviation (STD), and the minimum value (min) of IGD. The bold font indicates that the values represent excellent performances. The iMOEA/D-DE is better than the MOEA/D-DE with respect to the standard deviation of IGD, and the performances of these two algorithms are equivalent to the minimum value of IGD. However, iMOEA/D-DE is worse than MOEA/D-DE in the mean value of IGD, because the middle point of iMOEA/D-DE for the mean value of IGD is smaller than that of MOEA/D-DE. Hence, the performances of these two algorithms are similar, indicating that the iMOEA/D-DE algorithm is effective.

Table 1 IGD of ZDT and DTLZ

MOP	MOEA/D-DE			iMOEA/D-DE		
	Mean	STD	Min	Mean	STD	Min
ZDT1	**0.0090**	0.0224	**0.0039**	0.0097	**0.0117**	**0.0039**
ZDT2	0.7132	**0.0732**	0.6093	**0.6344**	0.1197	**0.0094**
ZDT3	**0.1769**	0.0499	**0.0101**	0.2143	**0.0457**	0.0127
ZDT4	**5.3854**	2.8069	0.8114	6.3351	**2.7644**	**0.6679**
ZDT6	**0.3378**	0.2289	**0.0018**	0.7504	**0.1831**	0.0019
DTLZ1	**6.1287**	4.2944	0.2926	7.1037	**3.9490**	**0.2906**
DTLZ2	**0.2360**	**0.0090**	**0.2047**	0.2419	0.0207	0.2105

4.2 CW model experiments

For the integrated navigation system, OW depends on the simulation data. Taking the accuracy index in the index layer in the literature (Cheng et al., 2019b) as an example, the weights of the first three experts are (0.3, 0.2, 0.5), (0.2, 0.3, 0.5), and (0.2, 0.4, 0.4). According to the simulation results of the integrated navigation system in Table 2, the objective weights are (0.3148, 0.3431, 0.3421) by EM (Jiao et al., 2016). OW and SW are substituted into Eq. (12) to obtain the three-objective optimization model of the CW. To verify the effectiveness of iMOEA/D-DE in the CW model, it is compared with MOEA/D, MOEA/D-DE, and NSGA-II. The parameters of the four algorithms refer to the parameters in Section 4.1 and the parameters in each reference.

Since the multiobjective model of CW is unable to obtain real PF, IGD cannot be used to measure the performance of the algorithm. The hyper-volume (HV) (Tian et al., 2016; Cai et al., 2021) is used to measure the distribution and convergence of the algorithm, and is described as

$$\begin{aligned}&\mathrm{HV}(P,\boldsymbol{r})\\&=\mathrm{Volume}\Big(\bigcup_{F\in P}[f_1,r_1]\times[f_2,r_2]\times\cdots\times[f_m,r_m]\Big),\end{aligned} \tag{24}$$

where P is the optimal solution set, and the reference point is $\boldsymbol{r}=(r_1, r_2,\cdots, r_m)$. HV is designed to find an area sum or volume sum of optimal solution relative to the reference point. MOEA/D is used to plot the figure of the CW. According to the CW distribution in Fig. 2, the reference point is set as $\boldsymbol{r}=(0, 1.3, 0.5)$. The larger the HV, the better the distribution and convergence of the algorithm.

Table 2 Results of the integrated navigation system

System	Pitch angle (′)	Roll angle (′)	Azimuth angle (′)	Speed accuracy (m/s)		Position accuracy (m)		Fault tolerance coefficient	Robust coefficient
				Eastward	Northward	Eastward	Northward		
System 1	0.3479	0.3441	7.5550	0.0097	0.0149	1.0018	0.7977	0.0240	25.2336
System 2	1.6524	1.6995	21.4081	0.0259	0.0421	2.4346	1.8481	0.0097	2.8988
System 3	1.0547	1.0349	34.5051	0.0414	0.0681	3.8297	2.8655	0.0075	2.0173
System 4	0.3479	0.3441	7.5539	0.0097	0.0149	1.0018	0.7976	0.0369	50.5542
System 5	1.6732	1.7034	34.5672	0.0415	0.0681	3.8297	2.8664	0.0048	0.3101

In Table 3, HVs of four algorithms are given. The order of HVs from large to small is: iMOEA/D-DE, NSGA-II, MOEA/D-DE, and MOEA/D. The HV of iMOEA/D-DE is the largest, which indicates that the proposed algorithm has the best distribution and convergence performance.

4.3 Multi-expert weight and CW experiments

Based on the literature (Cheng et al., 2019b), the multi-expert weight of the integrated navigation system is shown in Table 4, and the test data calculated by CW is shown in Table 2. The CW combines three SWs with one OW. The three weights are expert 1, expert 2, and expert 3. D and C in Table 4 indicate two index layers. D indicates the device layer. C includes the accuracy, stability, and usability in the index layer. OW is computed by EM from the data in Table 2. The results are shown in Table 5. Since there are no test data for indices in the function layer, there is only the multi-expert weight. Four weights are substituted into Eq. (12), and CWs are subsequently computed by iMOEA/D-DE. The results are shown in Table 6.

To compare the multi-expert weight with CW, the comparison curves of two weights are plotted, as shown in Fig. 3. The difference between the multi-expert weight and CW is whether the fourth weight is SW or OW. It can be seen from Fig. 3 that the existence of OW changes the size of each CW component. Each weight of the multi-expert weight is SW without OW, while the CW includes both SW and OW. The objectivity of weight is reflected in the source of data. The data of OW comes from the index attribute value, while the data of SW comes from experts, which has the advantage of strong explanation. CW is objective

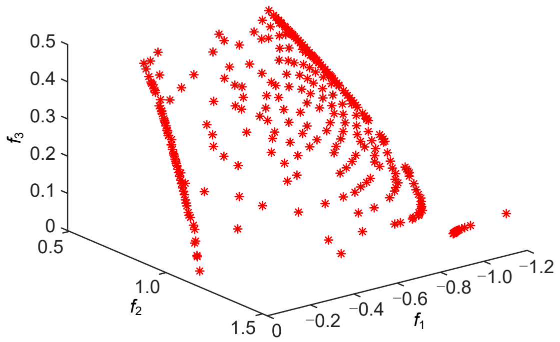

Fig. 2 Figure of the CW model based on MOEA/D

Table 3 HV values of the four algorithms

Algorithm	HV	Algorithm	HV
iMOEA/D-DE	13.245	MOEA/D-DE	9.841
MOEA/D	9.346	NSGA-II	12.348

Table 4 Weights of the three experts

Expert	Weight			
	Index layer=D		C	
Expert 1	(0.3, 0.3, 0.1, 0.1, 0.1, 0.1)	(0.3, 0.2, 0.5)	(0.5, 0.5)	(0.1, 0.4, 0.5)
Expert 2	(0.3, 0.1, 0.15, 0.15, 0.15, 0.15)	(0.2, 0.3, 0.5)	(0.6, 0.4)	(0.2, 0.3, 0.5)
Expert 3	(0.4, 0.2, 0.2, 0.1, 0.05, 0.05)	(0.2, 0.4, 0.4)	(0.4, 0.6)	(0.4, 0.1, 0.5)

Table 5 Objective weight (OW) of the integrated navigation system

Index	OW
Device layer indices	(0.1717, 0.1717, 0.1717, 0.1416, 0.1717, 0.1717)
Accuracy indices in the index layer	(0.3148, 0.3431, 0.3421)
Stability indices in the index layer	(0.1124, 0.8876)
Usability indices in the index layer	(0.2431, 0.2458, 0.5112)

Table 6 Combination coefficient (CC) and combination weighting (CW)

Index	CC	CW
Device layer indices	(0.2466, 0.2655, 0.2089, 0.2795)	(0.2852, 0.1903, 0.1543, 0.1250, 0.1229, 0.122)
Accuracy indices in the index layer	(0.0013, 0.0420, 0.0141, 0.9427)	(0.3084, 0.3419, 0.3498)
Stability indices in the index layer	(0.0010, 0.8492, 0.1476, 0.0021)	(0.5693, 0.4306)
Usability indices in the index layer	(0.0379, 0.0032, 0.8405, 0.1183)	(0.3694, 0.1292, 0.5013)

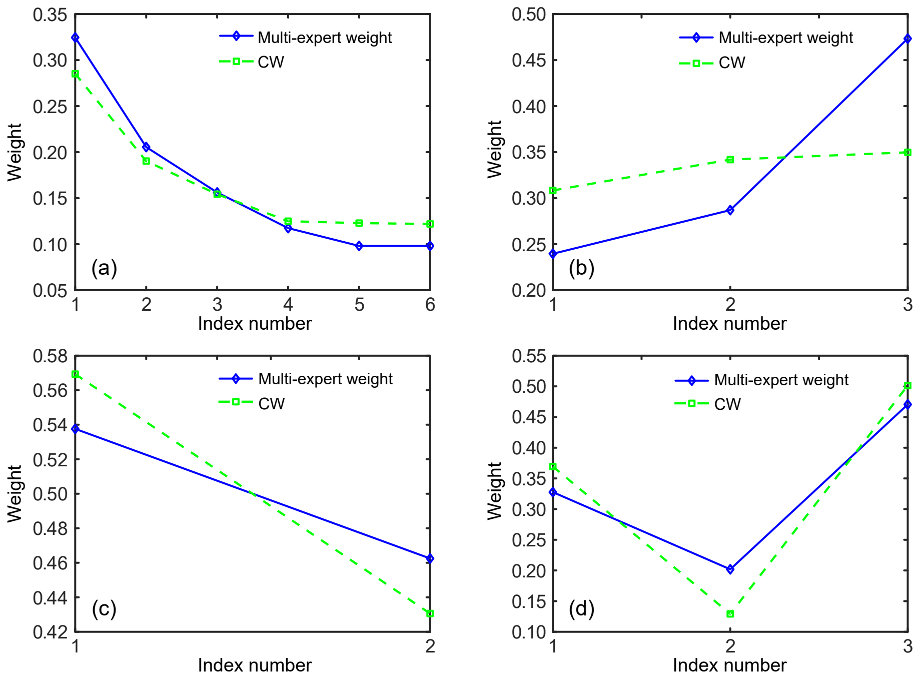

Fig. 3 Comparison of the multi-expert weight and CW: (a) weights of the device layer; (b) weights of precision index in the index layer; (c) weights of stability index in the index layer; (d) weights of usability index in the index layer

and interpretable at the same time, thus overcoming the drawback of multi-expert weight. Therefore, CW is more reasonable and objective than the multi-expert weight.

4.4 Experiments with the new weight evaluation approach of the multi-expert weight and CW

To verify the new weight evaluation approach, experiments are carried out with examples in the literature (Shi et al., 2012). Compared with the results of the two different methods in the reference, the weights of these methods are compared. Using the CW value and each weight value in this study, the relative entropy values of weights are computed by the new weight evaluation approach. The results are 0.134, 0.270, 0.0694, and the results are consistent with the size relationship in the literature. The results are more prominent different, which proves that the proposed approach is feasible. Since the multi-expert weight is composed of three subjective weights and CW is composed of four weights, two cases can be considered: three-weight and four-weight. The results are shown in Table 7.

When CW has only three weights, it is in the multi-expert weight mode, and the relative entropy values obtained by two weights show little difference (except the accuracy index). As the model coefficients of the multi-expert weight are artificially set, the accuracy of the multi-expert weight is not high enough; thus, it is not convincing. When CW contains four weights, it is objective and more scientific. Compared with the mode of three weights, adding the fourth weight makes the relative entropy values of the accuracy index and stability index increase rapidly. The increase of device index and usability index is common. It shows that the introduction of OW has an impact on CW, which makes the distribution between CW and each weight worse. However, the objectivity of CW increases.

Table 7 Relative entropy values of weights of two groups

Group	Device index	Accuracy index	Stability index	Usability index
Three-weight	0.185	0.153	0.069	0.462
	0.151	0.056	0.050	0.323
Four-weight	0.234	0.153	0.682	0.524
	0.151	0.056	0.050	0.323

5 Summary

In this paper, a multiobjective optimization model of CW based on improved GT and an iMOEA/D-DE algorithm are proposed. The main contributions of this paper are as follows:

1. The multiobjective optimization model of CW based on improved GT is presented to overcome the drawback of poor objectivity of the multi-expert weight. The uncertainty of CW is also considered.

2. The iMOEA/D-DE algorithm is presented. First, the improved mutation operation is introduced to improve the convergence rate of the algorithm. Second, an adaptive strategy with self-learning ability is described to overcome the shortcomings that F and CR in classical DE algorithms are constant values and that they cannot adapt to the multiobjective optimization model with nonlinearity and equality constraint. The adaptive strategy with self-learning ability depends on the changes of the fitness value within five generations.

3. A new weight evaluation approach based on relative entropy is presented to evaluate the rationality of the CW.

4. Experiments are carried out on test instances, on the CW model in the evaluation approach of the integrated navigation system and on the new weight evaluation approach. Results show that the proposed algorithm has excellent performance in certain aspects, as well as good distribution and convergence performance.

In the future, the solution of multiobjective optimization model of CW can be further improved. The main directions are proposed as follows: (1) The in-depth study on MOEA/D should be carried out to make the algorithm more suitable for the CW model, so as to be extended to multiobjective optimization problems with nonlinearity and equality constraint. (2) The new intelligent algorithms with better performance should be used to solve the CW model.

Contributors

Mingtao DONG and Jianhua CHENG raised the research questions and the ideas to solve them. Mingtao DONG designed the research. Jianhua CHENG processed the data. Mingtao DONG drafted the paper. Lin ZHAO helped organize the paper. Mingtao DONG and Jianhua CHENG revised and finalized the paper.

Compliance with ethics guidelines

Mingtao DONG, Jianhua CHENG, and Lin ZHAO declare that they have no conflict of interest.

References

Al-Dabbagh RD, Neri F, Idris N, et al., 2018. Algorithmic design issues in adaptive differential evolution schemes: review and taxonomy. *Swarm Evol Comput*, 43:284-311. https://doi.org/10.1016/j.swevo.2018.03.008

Cai XY, Xiao YS, Li MQ, et al., 2021. A grid-based inverted generational distance for multi/many-objective optimization. *IEEE Trans Evol Comput*, 25(1):21-34. https://doi.org/10.1109/TEVC.2020.2991040.

Cheng JH, Dong MT, Liu JX, 2019a. Accuracy performance evaluation method of integrated navigation system based on two-level FCE. Chinese Control Conf, p.3869-3874. https://doi.org/10.23919/ChiCC.2019.8866447

Cheng JH, Dong MT, Qi B, 2019b. An OW-FCE model based on MDE algorithm for evaluating integrated navigation system. *IEEE Access*, 7:178918-178929. https://doi.org/10.1109/ACCESS.2019.2957522

Cheng JH, Dong MT, Zhao L, 2021. A combination weight method based on MOEA/D. *Contr Decis*, 36(12):3056-3062 (in Chinese). https://doi.org/10.13195/j.kzyjc.2020.0592

Dai SY, Niu DX, 2017. Comprehensive evaluation of the sustainable development of power grid enterprises based on the model of fuzzy group ideal point method and combination weighting method with improved group order relation method and entropy weight method. *Sustainability*, 9(10):1900. https://doi.org/10.3390/su9101900

Das S, Suganthan PN, 2011. Differential evolution: a survey of the state-of-the-art. *IEEE Trans Evol Comput*, 15(1): 4-31. https://doi.org/10.1109/TEVC.2010.2059031

Deb K, Pratap A, Agarwal S, et al., 2002. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Trans Evol Comput*, 6(2):182-197. https://doi.org/10.1109/4235.996017

Ding JL, Chen JX, Ma XR, 2020. Multi-objective optimization of light oil production in atmospheric distillation column based on self-adaptive differential evolution. *Contr Decis*, 35(3):604-612 (in Chinese). https://doi.org/10.13195/j.kzyjc.2018.0794

Dong PY, Wang HW, Chen Y, 2020. GRA-TOPSIS emitter threat assessment method based on game theory. *J Beijing Univ Aeronaut Astronaut*, 46(10):1973-1981 (in Chinese). https://doi.org/10.13700/j.bh.1001-5965.2019.0543

Fan QQ, Yan XF, 2016. Self-adaptive differential evolution algorithm with zoning evolution of control parameters and adaptive mutation strategies. *IEEE Trans Cybern*, 46(1):219-232. https://doi.org/10.1109/TCYB.2015.2399478

Ishibuchi H, Imada R, Setoguchi Y, et al., 2018. Reference point specification in inverted generational distance for triangular linear Pareto front. *IEEE Trans Evol Comput*, 22(6):961-975. https://doi.org/10.1109/TEVC.2017.2776226

Jiao JL, Ren HL, Sun SZ, 2016. Assessment of surface ship environment adaptability in seaways: a fuzzy comprehensive evaluation method. *Int J Nav Arch Ocean Eng*, 8(4): 344-359. https://doi.org/10.1016/j.ijnaoe.2016.05.002

Lai CG, Chen XH, Chen XY, et al., 2015. A fuzzy comprehensive evaluation model for flood risk based on the combination weight of game theory. *Nat Hazards*, 77(2):1243-1259. https://doi.org/10.1007/s11069-015-1645-6

Li AH, 2017. Research on Safety Assessment Methods of Quayside Container Crane. PhD Thesis, Wuhan University of Technology, Wuhan, China (in Chinese).

Li H, Zhang QF, 2009. Multiobjective optimization problems with complicated Pareto sets, MOEA/D and NSGA-II. *IEEE Trans Evol Comput*, 13(2):284-302. https://doi.org/10.1109/TEVC.2008.925798

Li YZ, Wang SH, Yang B, 2020. An improved differential evolution algorithm with dual mutation strategies collaboration. *Expert Syst Appl*, 153:113451. https://doi.org/10.1016/j.eswa.2020.113451

Liu HJ, Hu YR, 2015. An evaluating method with combined assigning-weight based on maximizing variance. *Sci Program*, 2015:290379. https://doi.org/10.1155/2015/290379

Lv LS, Deng ZH, Meng HJ, et al., 2020. A multi-objective decision-making method for machining process plan and an application. *J Clean Prod*, 260:121072. https://doi.org/10.1016/j.jclepro.2020.121072

Pan XX, Liu H, Huan JJ, et al., 2020. Allocation model of carbon emission permits for the electric power industry with a combination subjective and objective weighting approach. *Energies*, 13:706. https://doi.org/10.3390/en13030706

Shi L, Yang SL, Ma Y, et al., 2012. A novel method of combination weighting for multiple attribute decision making. *J Syst Eng*, 27(4):481-491 (in Chinese). https://doi.org/10.3969/j.issn.1000-5781.2012.04.008

Song GX, Yang DL, 2004. Combination weighting approach based on the decision-maker's preference and consistency of weighting methods. *Syst Eng Electron*, 26(9):1226-1230, 1290 (in Chinese). https://doi.org/10.3321/j.issn:1001-506X.2004.09.020

Sun LJ, Liu YY, Zhang BY, et al., 2016. An integrated decision-making model for transformer condition assessment using game theory and modified evidence combination extended by D numbers. *Energies*, 9(9):697. https://doi.org/10.3390/en9090697

Sun YN, Yen GG, Yi Z, et al., 2019. IGD indicator-based evolutionary algorithm for many-objective optimization problems. *IEEE Trans Evol Comput*, 23(2):173-187. https://doi.org/10.1109/TEVC.2018.2791283

Tian Y, Zhang XY, Cheng R, et al., 2016. A multi-objective evolutionary algorithm based on an enhanced inverted generational distance metric. IEEE Congress on Evolutionary Computation, p.5222-5229. https://doi.org/10.1109/CEC.2016.7748352

Wang XL, Wang X, Zhu JF, et al., 2017. A hybrid fuzzy method for performance evaluation of fusion algorithms for integrated navigation system. *Aerosp Sci Technol*, 69:226-235. https://doi.org/10.1016/j.ast.2017.06.027

Wang Y, Cai ZX, Zhou YR, et al., 2009. Constrained optimization evolutionary algorithms. *J Softw*, 20(1):11-29 (in Chinese). https://doi.org/10.3724/SP.J.1001.2009.03363

Wu LH, Wang YN, Yuan XF, et al., 2013. Fast self-adaptive differential evolution algorithm for power economic load dispatch. *Contr Decis*, 28(4):557-562 (in Chinese). https://doi.org/10.13195/j.cd.2013.04.80.wulh.013

Xu ZS, Cai XQ, 2012. Minimizing group discordance optimization model for deriving expert weights. *Group Decis Negot*, 21(6):863-875. https://doi.org/10.1007/s10726-011-9253-7

Yang B, Lai CG, Chen XH, et al., 2018. Surface water quality evaluation based on a game theory-based cloud model. *Water*, 10(4):510. https://doi.org/10.3390/w10040510

Ye HT, Luo F, Xu YG, 2013. Differential evolution for solving multi-objective optimization problems: a survey of the state-of-the-art. *Contr Theory Appl*, 30(7):922-928 (in Chinese). https://doi.org/10.7641/CTA.2013.12016

Yin FL, Lu L, Chai JP, et al., 2016. Combination weighting method based on maximizing deviations and normalized constraint condition. *Int J Secur Its Appl*, 10(2):39-50. https://doi.org/10.14257/ijsia.2016.10.2.04

Zhang CM, Chen J, Xin B, 2014. Distributed differential evolution algorithm with adaptive parameters. *Contr Decis*, 29(4):701-706 (in Chinese). https://doi.org/10.13195/j.kzyjc.2013.0080

Zhang QF, Li H, 2007. MOEA/D: a multiobjective evolutionary algorithm based on decomposition. *IEEE Trans Evol Comput*, 11(6):712-731. https://doi.org/10.1109/TEVC.2007.892759

Zhang ZC, Chen L, 2018. Analysis on decision-making model of plan evaluation based on grey relation projection and combination weight algorithm. *J Syst Eng Electron*, 29(4): 789-796. https://doi.org/10.21629/JSEE.2018.04.13

Zhou RX, Pan ZW, Jin JL, et al., 2017. Forewarning model of regional water resources carrying capacity based on combination weights and entropy principles. *Entropy*, 19(11): 574. https://doi.org/10.3390/e19110574

Zhou YF, Wei FJ, 2006. Combination weighting approach in multiple attribute decision making based on relative entropy. *Oper Res Manag Sci*, 15(5):48-53 (in Chinese). https://doi.org/10.3969/j.issn.1007-3221.2006.05.010

Zhu XC, Niu DP, Wang X, et al., 2019. Comprehensive energy saving evaluation of circulating cooling water system based on combination weighting method. *Appl Therm Eng*, 157:113735. https://doi.org/10.1016/j.applthermaleng.2019.113735