Mingtao DONG, Jianhua CHENG, Lin ZHAO, 2022. A combination weighting model based on iMOEA/D-DE. *Frontiers of Information Technology & Electronic Engineering*, 23(4):604-616. https://doi.org/10.1631/FITEE.2000545

A combination weighting model based on iMOEA/D-DE

Key words: Combination weighting; MOEA/D-DE; Game theory; Self-learning ability; Relative entropy

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Motivation

1. Multi-expert weight considers only subjective weights, leading to poor objectivity. The traditional combination weighting (CW) does not consider the uncertainty of combination coefficients.

2. The CW model is nonlinear and contains an equality constraint, which makes it difficult to solve.

3. Existing weight evaluation approaches are not applicable to the problem with the weight only.

Main idea

1. We propose a CW model based on iMOEA/D-DE.

2. We propose a multiobjective optimization model of CW based on improved game theory while considering the uncertainty of combination coefficients.

3. An adaptive mutation constant and crossover probability constant with self-learning ability are proposed to improve the robustness of MOEA/D-DE.

4. A new weight evaluation approach based on relative entropy is presented.

Method

A CW model based on improved game theory (GT) is

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

The uncertainty of CW is

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

The equality constraint can be expressed as

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

The three-objective optimization model of CW is formulated as

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

Method

$\boldsymbol{x}_{1,G}$	$F_{1,G}$	$CR_{1,G}$
$\boldsymbol{x}_{2,G}$	$F_{2,G}$	$CR_{2,G}$
$\vdots$	$\vdots$	$\vdots$
$\boldsymbol{x}_{N,G}$	$F_{N,G}$	$CR_{N,G}$

Fig. 1 Adaptive coding format

A parameter adaptive strategy with self-learning ability is proposed:

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

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

The new weight evaluation approach can be obtained as follows:

$$D(w) = \sum_{i=1}^{m} \left(\sum_{j=1}^{n} W_j \ln \left(\frac{W_j}{w_j^i} \right) \right) .$$

Major results

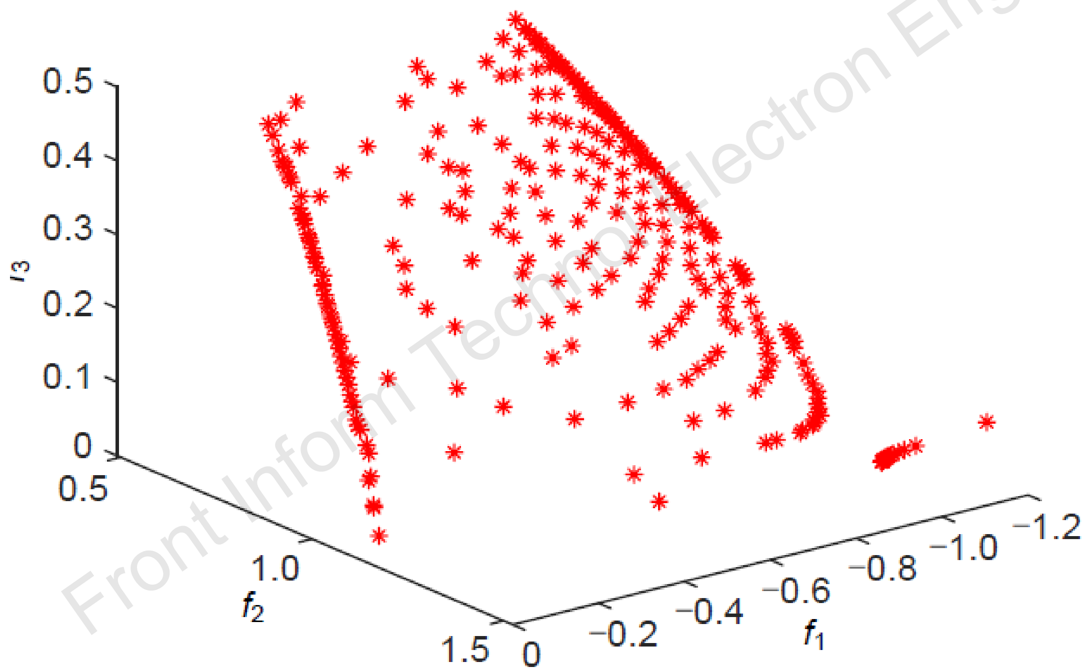

Fig. 2 Figure of the CW model based on MOEA/D

Major results (Cont'd)

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

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

Major results (Cont'd)

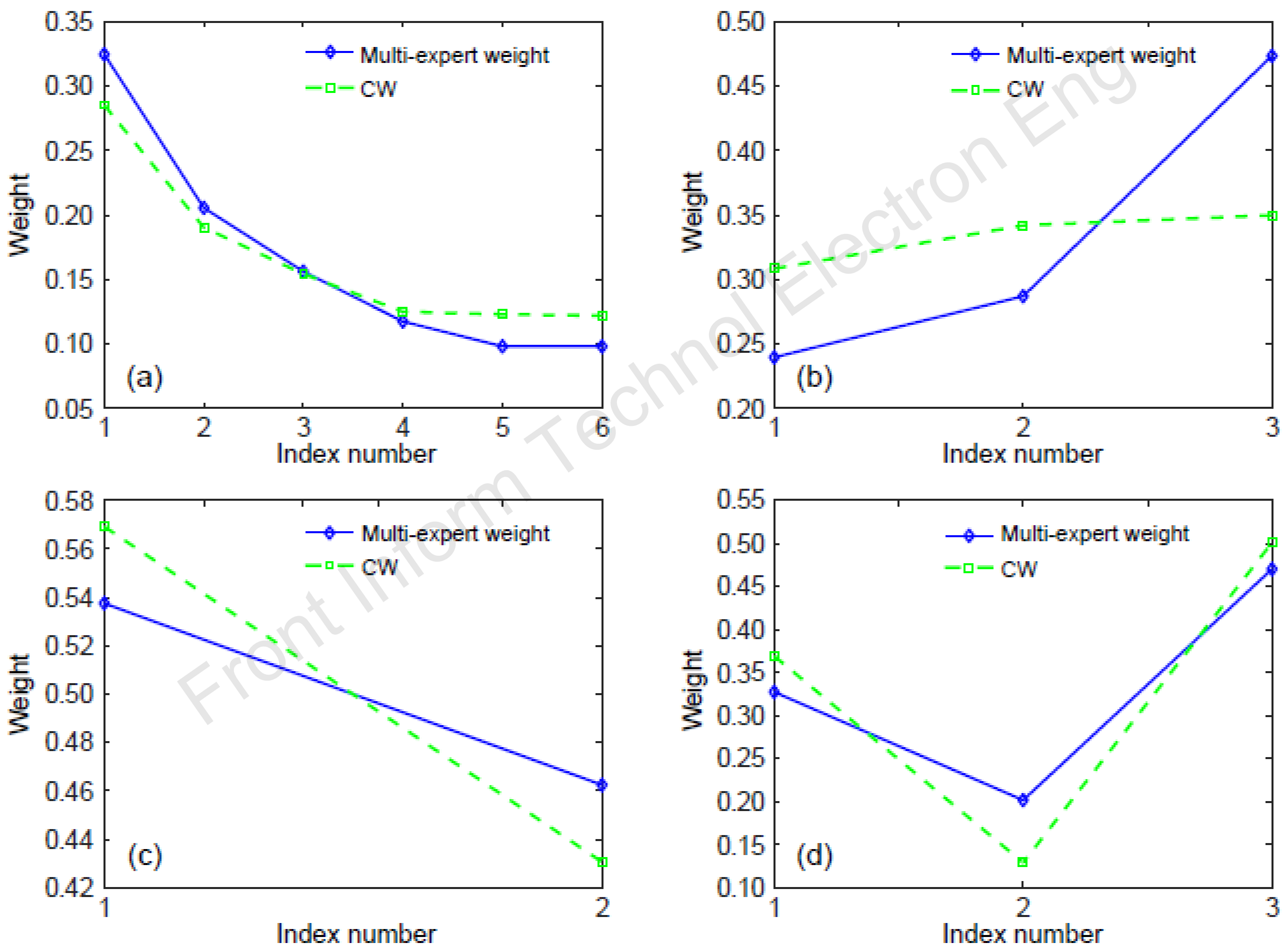

Fig. 3 Comparison of the multi-expert weight and CW: (a) weights of the device layer; (b) weights of precision index in the index layer; (c) weights of stability index in the index layer; (d) weights of usability index in the index layer

Conclusions

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.

Conclusions (Cont’d)

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