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A multi-principle module identification method for product platform design*

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Abstract: In today's competitive global business environment, platform strategy presents an opportunity for manufacturing companies to juggle increased customer demand for customized products and the inherited complexity and increased development cost that comes with it. The goal of this paper is to support module identification as an essential part of a module-based platform strategy approach. Based on various existing methods, this paper abstracted three principles, which include an internal clustering principle, an external independence principle, and an overall stability principle. The three principles should be holistically considered, and be simultaneously satisfied during the module identification. Both conceptual and mathematical modeling of the proposed multi-principle module identification method are elaborated. Then an improved strength Pareto evolutionary algorithm (ISPEA2) is used to address the multi-principle module identification problem and find the Pareto-optimal set. A fuzzy compromise selection method base on fuzzy set theory is also used to select the best compromise Pareto solution. An industrial case study in a turbo expander manufacturing company is provided to illustrate practical applications of the research. Finally, the result obtained by the proposed approach is compared with other established optimization approaches.

Key words: Module identification, Modularization principles, Multi-objective optimization, Improved strength Pareto evolutionary algorithm (ISPEA2), Turbo expander

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1 Introduction

In today's highly competitive global business environment, platform-based strategy has been proven to be beneficial for enterprises to reduce cost, increase product variety, decrease product lead time, cope with the emerging customized requirements, and improve manufacturing flexibility (Simpson, 2004). There are two basic types of platforms, namely, the module-based platform and the scale-based platform. The former depends on different configurations of modules to generate a variety of products, whereas the latter scales one or multiple variables of the platform to create products of varying performances (Li *et al.*, 2008).

One of the key challenges of module-based platform design is to identify and determine which components may be grouped together to form a module (Jiao *et al.*, 2007). Much research has been carried out, from different viewpoints, in the module identification field, as follows.

1. Internal interactions clustering viewpoint

The internal clustering viewpoint requires that components with a high degree of interactions should be clustered to form an individual module (Yu *et al.*,

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2011). In other words, the interactions between components within a module must be maximized. Therefore, this principle is also known as the 'internal clustering principle', which represents a well-known principle in module design. In the past, a number of other clustering algorithms have been developed to cluster components based on their interactions (Tseng *et al.*, 2008). Sanchez (1993) suggested that the aim of module design is to identify components with a high degree of interactions. Sosa *et al.* (2004) analyzed the internal interactions from the energy, material, spatial, and informational aspects. Ulrich (1995) suggested that modules are identified in a way that interactions within a module might be high.

2. External interactions independence viewpoint

The external independence viewpoint suggests that the coupling degree between different modules must be minimized (Ulrich, 1994). The primary purpose is to keep different modules independent of each other as much as possible. Therefore, this viewpoint is also called the 'external independence principle', which is a well-known modularization principle. Part of the modularity definition states that "the unintended interactions between modules are minimized". Huang *et al.* (2006) adopted a fuzzy clustering matrix to evaluate the external interaction value in the matrix by five basic recycling attributes. Kimura *et al.* (2001) took multi-characteristics into consideration, such as technological stability, functional upgrade ability, long life, and so on. Umeda *et al.* (2008) proposed a modular identification method that derives modular structure based on both life cycle properties and geometric information.

3. Overall system reliability viewpoint

The objective of modular identification is to separate the system into independent modules (Newcomb *et al.*, 1996). It is important to evaluate modularity within a holistic view of the total system. The overall system reliability viewpoint requires that the components that may affect the same set of functional requirements should be grouped together to form a module. Hence, components within a module should address the same set of functional requirements. Therefore, certain functional requirements will ideally only be affected by one particular module. This viewpoint is called the 'overall reliability principle'. Ji *et al.* (2013) proposed an effectiveness-driven modular design method which takes all effectiveness scenarios into consideration and balances the granularity and composition of modules among all possible forms during the clustering process. The modularity is evaluated in a holistic view of the total system. Li *et al.* (2013) proposed a holistic integrated product modularisation method based on flow analysis, a design structure matrix and fuzzy clustering to compose a flexible platform. Holtta-Otto and de Weck (2007) used a singular value modularity index and a non-zero fraction to analyze the degree of modularity in view of the total system.

Based on a thorough investigation of different existing methods, there has been little attempt to integrate the three principles and regard them together as a to-be-solved multi-objective optimization problem (MOOP). This paper proposes the three modularization principles that should be holistically considered and simultaneously satisfied during the module identification.

It is important to point out that each of these three principles is deliberately chosen to address a particular aspect. For instance, the external independence principle aims to minimize the complexity, whereas the overall reliability principle's goal is to improve the quality. Additionally, these principles are not entirely isolated, but rather mutually related. Hence, the three principles should be simultaneously satisfied in order to achieve the design goal.

Recently, evolution multiobjective optimization, which applies evolution computation to multiobjective optimization has attracted a great deal of attention (Feng *et al.*, 2010; Cheng *et al.*, 2013; Martínez-Morales *et al.*, 2013; Gao *et al.*, 2014). Many multi-objective genetic algorithms have been proposed. The recent research includes strength Pareto evolutionary algorithm (SPEA) (Zitzler and Thiele, 1998), non-dominated sorting genetic algorithm (NSGA) (Srivans and Deb, 1995), niched Pareto genetic algorithm (NPGA) (Horn and Nafpliotis, 1994) and some improved versions, strength Pareto evolutionary algorithm 2 (SPEA2) (Zitzler *et al.*, 2001), and non-dominated sorting genetic algorithm-II (NSGA-II) (Deb, 2002). This paper focuses on a multi-principle module identification method and used an improved strength Pareto evolutionary algorithm (ISPEA2) to address the previously introduced multi-principle modularization problem. A fuzzy-based mechanism is also used to extract a Pareto-optimal solution as the best compromise in trying to eliminate the imprecise nature of a human decision.

2 Conceptual modeling of multi-principle modularization

From the above discussions, it is evident that the three modularization principles are not unfamiliar to the design community. Furthermore, each principle has been individually adopted by different methods. However, there has been little attempt to integrate the three principles and regard them together as a to-be-solved MOOP. This section presents the conceptual modeling of the proposed multi-principle module identification method. The identified principles are treated as a 'three objectives' optimization problem, and the ISPEA2 is used to find the Pareto-optimal set. The fuzzy-based selection mechanism is also used to extract the best Pareto-optimal solution (Abido, 2006).

Fig. 1 illustrates the conceptual modeling of the proposed multi-principle module identification method. The left half of the model indicates that the modularization must simultaneously follow three principles which serve to address different aspects (i.e., cost, complexity, and quality) of the product platform. This represents the main research problem of this study. The right half of the model indicates the improved multi-objective optimization method (i.e., by treating the three principles as three optimization objectives) that is utilized to solve the research problem. The following section elaborates how the conceptual model can be formulated as a rigorous mathematical optimization model, which can be used to solve real world module identification issues.

3 Mathematical modeling of multi-principle modularization optimization problem

3.1 Internal clustering principle

The internal clustering principle requires that components that have high interaction must be clustered in the same module (Wang and Wei, 2005). Calculation of the internal clustering is based on the functional and physical synthetic interactions between components. Suppose the system consists of a total of N components; M is the number of identified modules; and N_i is the number of components in the ith module M_i, i=1, 2, …, M.

1. Construct the interaction matrix between components

$$\boldsymbol{R}=\begin{bmatrix} r_{1_1,1_1} & r_{1_1,1_2} & \cdots & r_{1_1,j_q} & \cdots & r_{1_1,M_{N_M}} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ r_{1_{N_1},1_1} & r_{1_{N_1},1_2} & \cdots & r_{1_{N_1},j_q} & \cdots & r_{1_{N_1},M_{N_M}} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ r_{i_p,1_1} & r_{i_p,1_2} & \cdots & r_{i_p,j_q} & \cdots & r_{i_{N_1},M_{N_M}} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ r_{M_{N_M},1_1} & r_{M_{N_M},1_2} & \cdots & r_{M_{N_M},j_q} & \cdots & r_{M_{N_M},M_{N_M}} \end{bmatrix}, \quad (1)$$

where r_{i_p,j_q} is the interactions between the pth and qth components within the module M_i.

2. Calculate the internal clustering degree within the modules

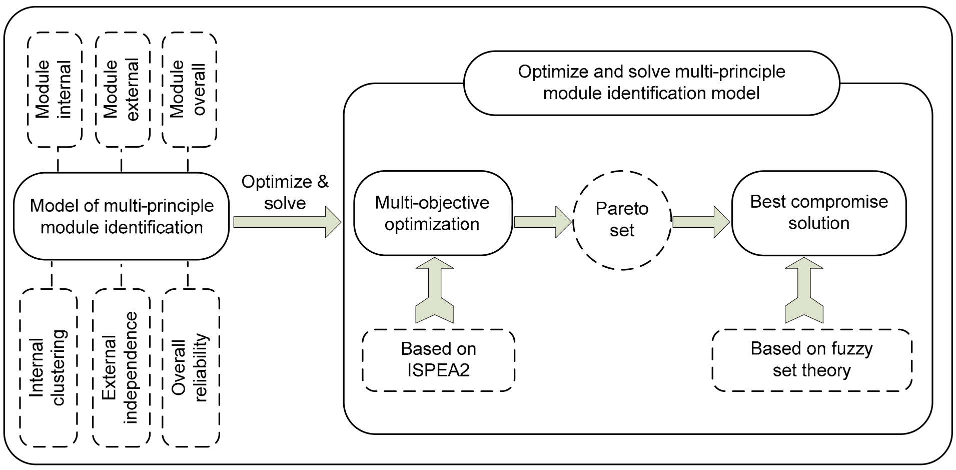

Fig. 1 Conceptual modeling of the multi-principle module identification method

The ith module's clustering degree O_i can be calculated using Eq. (2), whereas all the modules' combined clustering degree O can be computed via Eq. (3).

$$O_i=\sum_{p=1}^{N_i-1}\sum_{q=p+1}^{N_i} r_{i_p,j_q} \Big/ \sum_{p=1}^{N_i-1}\sum_{q=p+1}^{N_i} 1, \tag{2}$$

$$O=\sum_{i=1}^{M}\left[\sum_{p=1}^{N_i-1}\sum_{q=p+1}^{N_i} r_{i_p,j_q} \Big/ \sum_{p=1}^{N_i-1}\sum_{q=p+1}^{N_i} 1\right]. \tag{3}$$

3.2 External independence principle

Calculation of the external independence is based on the interactions between components (Meng and Jiang, 2006). The external independence can be measured by the interactions between components according to the results of the matrix derived from Eq. (1). Eq. (4) is used to compute the coupling degree R_j^i between module M_i and module M_j, whereas Eq. (5) is used to calculate the combined coupling degree R among all modules of the engineered system.

$$R_j^i=\sum_{p=1}^{N_i}\sum_{q=1}^{N_j} r_{i_p,j_q} \Big/ \sum_{p=1}^{N_i}\sum_{q=1}^{N_j} 1, \tag{4}$$

$$R=\sum_{i=1}^{M-1}\sum_{j=i+1}^{M}\left[\sum_{p=1}^{N_i}\sum_{q=1}^{N_j} r_{i_p,j_q} \Big/ \sum_{p=1}^{N_i}\sum_{q=1}^{N_j} 1\right]. \tag{5}$$

3.3 Overall reliability principle

The overall reliability principle evaluates modularity in a holistic view of the total system. It is required that components affecting the same set of functional requirements should be grouped together to form a module (Kreng and Lee, 2003). Within this research, the method proposed by Kreng and Lee (2003) is employed to measure how well this principle has been followed. The fundamental assumption is that, when the consistency between components within a module toward certain functional requirements becomes higher, the information content of the module becomes lower. Therefore, the fuzzy entropy of the module can be regarded as a measure of the consistency between the module's components towards certain functional requirements, as well as an indicator of how well the overall reliability principle has been satisfied.

1. Build the probability matrix of every physical component

For the probability matrix $\boldsymbol{F}$ of every physical component in meeting every functional requirement (Kreng and Lee, 2003),

$$\boldsymbol{F}=\begin{bmatrix} f_{11}^1 & f_{11}^2 & \cdots & f_{11}^v & \cdots & f_{11}^\eta \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ f_{1N_1}^1 & f_{1N_1}^2 & \cdots & f_{1N_1}^v & \cdots & f_{1N_1}^\eta \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ f_{ib}^1 & f_{ib}^2 & \cdots & f_{ib}^v & \cdots & f_{ib}^\eta \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ f_{MN_M}^1 & f_{MN_M}^2 & \cdots & f_{MN_M}^v & \cdots & f_{MN_M}^\eta \end{bmatrix}, \tag{6}$$

where f_{ib}^v means the probability that the bth component contained within the ith module, and M_i will meet the vth functional requirement. According to the evaluation theory of fuzzy mathematics, the values of f_{ib}^v are subjectively assigned by the designer according to the scales of 9, 7, 4, 1, 0, with the scores of 9 to 0, each representing highest, higher, middle, lower, lowest probability, respectively. This specific scale was chosen as it has proven effective in various previous studies for similar settings (Wang *et al.*, 2006).

2. Develop a mathematical optimization model of the overall reliability

Considering the fuzzy entropy of product design requirements and the distribution of product differentiation (Kreng and Lee, 2003), the reliability I of the product is

$$I=\sum_{i=1}^{M}\sum_{v=1}^{\eta} w_v E(\mathrm{DR}_v^i)\left[1-\frac{\mathrm{SSD}_v^i}{(\mathrm{SSD}_v^i)_{\max}}\right]\Big/ M, \tag{7}$$

$$E(\mathrm{DR}_v^i)=\frac{-1}{\ln(N_i)}\sum_{b=1}^{N_i}\left\{\frac{f_{ib}^v}{\sum_{b=1}^{N_i} f_{ib}^v}\ln\left[\frac{f_{ib}^v}{\sum_{b=1}^{N_i} f_{ib}^v}\right]\right\}, \tag{8}$$

$$\mathrm{SSD}_v^i=\sum_{b=1}^{N_i}\left(f_{ib}^v-\overline{f_i^v}\right)^2,\ \overline{f_i^v}=\sum_{b=1}^{N_i} f_{ib}^v \Big/ N_i, \tag{9}$$

where w_v stands for the weight of the vth functional requirement; $E(\mathrm{DR}_v^i)$ reflects the fuzzy entropy between the ith module with the vth functional requirement; SSD_v^i means the sum of different mean square values of the vth functional requirement of the ith module; and $\overline{f_i^v}$ describes the average probability of different components within the ith module to meet the vth functional requirement (Kreng and Lee, 2003).

3.4 Constraint conditions

The following constraint conditions are defined to achieve the lowest couplings between modules, the highest coupling degree with the module, and the overall reliability of the platform. The mathematical representations of these constraint conditions are illustrated by

$$\sum_{v=1}^{\eta} w_v = 1, \quad 0 \le w_v \le 1, \tag{10}$$

$$N = \sum_{i=1}^{M} N_i, \; M_{\min} \le M \le M_{\max}, \tag{11}$$

$$\mathrm{SSD}_v^k < (\mathrm{SSD}_v^k)_{\max}, \; 0 \le N_i \le N, 0 \le r_{r_p, j_q} \le 1. \tag{12}$$

4 Multi-principle modularization optimization based on ISPEA2

4.1 Constraint conditions

The multi-principle modularization problem is transformed to a multi-objective optimization problem by treating the mathematical representations of the three modularization principles as three objective functions. From a mathematical point of view, a MOOP with n objective functions can be loosely posed as the following (Rao, 1991):

$$\begin{gathered}\text{minimize/maxmize } F(x) = \left(f_1(x), f_2(x), \cdots, f_n(x)\right), \\ \text{subject to} \\ g_j(x) \le 0, h_k(x) = 0, \; j = 1,2,\cdots,J; \; k = 1,2,\cdots,K, \end{gathered} \tag{13}$$

where x is the decision vector, $f_i(x)$ is the corresponding objective function, and J and K are the number of inequality and equality constraints, respectively.

4.2 Improved strength Pareto evolutionary algorithm

ISPEA2 is a new model of multi-objective genetic algorithm (MOGA) that features more effective crossover, and it will result in diverse solutions in both objective and variable spaces (Kim *et al*., 2004). ISPEA2 can be regarded as a particular type of SPEA2 with three additional mechanisms (Kim *et al*., 2004): (i) neighborhood crossover that allows crossing over individuals located near each other in the objective space; (ii) mating selection that reflects all good solutions within the archive; (iii) application of two archives to maintain diverse solutions in both objective and variable spaces.

The algorithm flow of ISPEA2 is as follows:

Procedure: ISPEA2
Parameters: N-population size
$\underline{N}$-archive size
T-maximum number of generations
Begin
Initialization:
Generate an initial population P_0 and N random individuals
Create two empty archives: A_0^O and A_0^V
Repeat
Fitness assignment:
For each individual in P_t, A_0^O and A_0^V
Environmental selection:
From P_t, A_0^O and A_0^V creating new archives A_{t+1}^O, A_{t+1}^V
If
the number of individuals in A_{t+1}^O and $A_{t+1}^V > \underline{N}$
Then
Archive truncation in the objective space A_{t+1}^O, and archive truncation in the variable space A_{t+1}^V
End if
Neighborhood crossover and mutation operation:
Generate P_{t+1} by copying A_{t+1}^O
$t=t+1$
Until $t \ge T$
Print all non-dominated solutions in the final population and archive
End

4.3 Best compromise solution based on fuzzy set theory

After a Pareto-optimal set is obtained by carrying out the ISPEA2, the best compromise solution must be selected. Due to the imprecise nature of human decision-making, a fuzzy mechanism is used to extract the best compromise solution (Abido, 2006). The ith objective function of a solution in the

Pareto-optimal set F_i is represented by a membership function μ_i, as illustrated by

$$\mu_i = \begin{cases} 1, & F_i \le F_i^{\min}, \\ \dfrac{F_i^{\max} - F_i}{F_i^{\max} - F_i^{\min}}, & F_i^{\min} \le F_i \le F_i^{\max}, \\ 0, & F_i \ge F_i^{\max}, \end{cases} \tag{14}$$

where $F_i^{\max}$ and $F_i^{\min}$ are the maximum and minimum values of the ith objective function, respectively. For each non-dominated solution k, the normalized membership function u^k is calculated by

$$\mu^k = \frac{\sum_{i=1}^{N_{\mathrm{obj}}} \mu_i^k}{\sum_{j=1}^{L} \sum_{i=1}^{N_{\mathrm{obj}}} \mu_j^k}, \tag{15}$$

where L represents the number of non-dominated solutions, whereas N_{obj} describes the number of optimization objectives. The best compromise solution is the one that achieves the maximum μ^k. In addition, the ranking of non-dominated solutions can be obtained by arranging all solutions within the Pareto-optimal set in the descending order according to their membership functions.

5 Case study

5.1 Turbo expander and multi-principle module identification base date calculation

In this section, a case study will be provided to demonstrate that the proposed multi-principle module identification method can be applied to real-world modular design problems. The focal product to be modularized is a turbo expander. A turbo expander is a centrifugal or axial flow turbine through which a high pressure gas is expanded to produce power. The application area for such a turbo expander may be, for example, to drive a compressor. Fig. 2 illustrates a structure of a typical turbo expander, and Table 1 summarizes a list of its key components. All data used in this case study was collected from a manufacturing enterprise located in China that is specialized in developing heavy machinery.

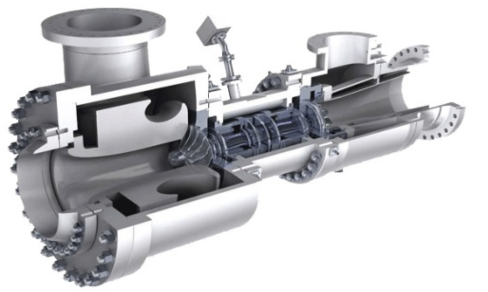

Fig. 2 Structure of the turbo expander

Table 1 List of key components of the turbo expander

No.	Name	No.	Name
1	Fuselage	22	Oil filter
2	Base	23	Aftercooler
3	Fan volute	24	Closures
4	Nozzle	25	Bladeless diffuser
5	Expander impeller	26	Inlet chamber
6	Rotor	27	Return pipe
7	Fan cove	28	Pneumatic membrane
8	Expander impeller	29	Sheet heat exchanger
9	Sensor holder	30	Tank
10	Operation panel	31	Three screw pump
11	Axis sensor	32	Thermostatic valve
12	Machine switches	33	Bladder accumulators
13	Turbocharger impeller	34	Electric control box
14	Joint bearings	35	Anti-spill plug
15	Inlet pipe	36	Oil window parts
16	Gland	37	Cooling water valve
17	Cold box	38	Magnet sensor
18	Reducing valve	39	Spindle
19	Exhaust pipe	40	Intermediates
20	Support bracket	41	Bearing pedestal
21	Oil cooler	42	Nameplate

Following the steps of the previously developed approach, at first the interaction matrices between all individual components of the turbo expander are developed. The results are summarized in Table 2. Next, the key functional requirements of the turbo expander are collected by means of customer satisfaction analysis (Szymanski and Henard, 2001). The specific requirements include: (1) motion reliability, (2) expansion ratio, (3) security, (4) thermal deformation, (5) noise, (6) product dimensions, (7) quality,

(8) durability, (9) modeling, and (10) wear rate. The probability matrix is developed to quantify the probability of every component in satisfying different functional requirements. The relative probabilities are assigned according to the scales of 9, 7, 4, 1, 0. We choose this scale referring to the previous study (Wang *et al.*, 2006). The results are summarized in Table 3. Here the specific data within the synthetic interaction matrix and the probability matrix were all provided by the manufacturing enterprise based on its existing database.

The analytic hierarchy process (AHP) is an established decision-making approach that allows the determination of the priority of multiple optimization criteria which are difficult to quantify otherwise (Saaty, 1988). The relative weight of importance for each functional requirement is calculated using AHP, with the results illustrated in Table 4. It has to be noted that, although the AHP method was used, these numerical weights were essentially assigned based on subjectivity. Therefore, the reliability of the final result under varying weights needs to be tested further. This was accomplished utilizing a sensitivity analysis. The results of the sensitivity analysis indicate that the final module identification scheme was insensitive to the weight change (i.e., 5% change).

Table 3 Probability matrix of each component in satisfying the customer requirement

	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9	P_{10}
K_1	9	1	4	7	4	9	0	1	9	4
K_2	7	9	4	0	4	7	9	4	7	1
K_3	7	7	4	9	4	9	4	7	9	4
K_4	9	7	7	4	0	1	7	7	4	7
K_5	1	9	7	4	7	1	7	9	4	9
K_6	7	1	4	7	7	4	9	7	4	7
K_7	7	4	4	9	4	9	1	7	1	9
K_8	4	4	7	1	7	9	7	4	7	4
K_9	7	9	9	7	4	7	9	7	9	7
K_{10}	7	4	1	7	7	4	4	4	0	1
K_{11}	9	7	1	0	4	4	0	1	4	4
K_{12}	7	7	4	1	1	7	9	9	7	4
K_{13}	4	7	7	9	4	9	4	4	7	7
K_{14}	7	4	1	9	4	4	1	4	0	1
K_{15}	9	4	4	7	4	1	4	0	4	7
K_{16}	7	7	4	7	1	7	7	7	9	0
K_{17}	4	1	4	9	7	9	4	1	4	7
K_{18}	7	7	0	1	7	4	4	9	7	4
K_{19}	4	4	7	4	4	9	9	7	4	7
K_{20}	9	1	4	0	7	4	7	9	1	9
…	…	…	…	…	…	…	…	…	…	…
K_{40}	0	7	9	4	7	7	9	0	7	1
K_{41}	4	1	4	0	1	1	0	4	1	7
K_{42}	1	0	1	7	1	0	1	1	7	0

Table 2 Coupling matrices between interacting components of the turbo expander

	K_1	K_2	K_3	K_4	…	K_{39}	K_{40}	K_{41}	K_{42}
K_1	1	0.246	0.463	0.445	…	0.433	0.365	0.634	0.459
K_2	0.246	1	0.267	0.734	…	0.172	0.262	0.641	0.125
K_3	0.463	0.267	1	0.243	…	0.249	0.328	0.238	0.021
K_4	0.445	0.734	0.243	1	…	0.416	0.179	0.315	0.196
K_5	0.257	0.561	0.147	0.256	…	0.261	0.563	0.173	0.257
K_6	0.563	0.435	0.318	0.349	…	0.483	0.319	0.276	0.191
K_7	0.247	0.364	0.342	0.369	…	0.376	0.183	0.524	0.361
K_8	0.339	0.098	0.517	0.716	…	0.423	0.542	0.621	0.116
…	…	…	…	…	…	…	…	…	…
K_{37}	0.361	0.473	0.432	0.846	…	0.161	0.347	0.362	0.475
K_{38}	0.637	0.452	0.367	0.662	…	0.627	0.433	0.516	0.269
K_{39}	0.433	0.172	0.249	0.416	…	1	0.467	0.316	0.244
K_{40}	0.365	0.262	0.328	0.179	…	0.467	1	0.246	0.319
K_{41}	0.634	0.641	0.238	0.315	…	0.316	0.246	1	0.317
K_{42}	0.459	0.125	0.021	0.196	…	0.244	0.319	0.317	1

Table 4 Relative weight for every customer requirement

Customer requirement	Relative weight
Motion reliability	W_1=0.108
Expansion ratio	W_2=0.219
Security	W_3=0.126
Thermal deformation	W_4=0.063
Noise	W_5=0.061
Product dimensions	W_6=0.105
Quality	W_7=0.059
Durability	W_8=0.148
Modeling	W_9=0.067
Wear rate	W_{10}=0.044

5.2 Multi-objective optimization by ISPEA2 and best compromise solution

Based on the three modularization principles, the design variable is set as δnd_i, and the objective functions include: (1) the clustering degree within modules must be maximized; (2) the coupling degree between modules must be minimized; and (3) the overall reliability of modules must be maximized.

The multi-principle modularization was carried out under the constraint conditions explained in Section 3.4. The component combination is treated as the gene fragment in a genetic algorithm and the initial population is generated according to the mode of random combination. As the searching performance of ISPEA2 will slow down after accession, the value of generation times K is to be set at a moderate level. The chosen parameters are set as follows: generation times K=400, initial population size N=150, crossover rate P_c=0.8, and mutation rate P_m=0.02. In terms of the chromosome minimum length which represents the quantity of modules, the minimum length M_{min} is set to be 2, and the maximum length M_{max} to be 12.

Based on the research methodology explained in Section 4.3, the best, most suitable compromise solution is selected based on fuzzy set theory. According to the result of chromosome constitutions and design variable values, six modules are identified: the final modularity scheme of the turbo expander is: (1) frame module {1, 2, 3, 7, 10, 20, 40, 42}; (2) expander module {4, 6, 8, 18, 19, 28, 39, 41}; (3) turbo module {13, 14, 25, 26}; (4) lubrication module {15, 16, 22, 24, 27, 30, 31, 35, 36}; (5) cooler module {17, 21, 23, 29, 32, 37}; and (6) control module {9, 11, 12, 33, 34, 38}.

5.3 ISPEA2 vs. other approaches

To test the efficiency and the solutions' distribution of ISPEA2, we compare ISPEA2 with SPEA2 and NSGA-II. SPEA2 and NSGA-II are two established multi-objective optimization algorithms, which can provide competitive results in solving MOOPs (Mitra and Gopinath, 2004; Su *et al.*, 2014). All three simulations were conducted under the same hardware conditions (i.e., Intel Core i5 processor, 4 GB memory). Table 5 summarizes the comparison between the three algorithms in terms of computing time, quantity of non-dominated solutions, and crossover probability. To ensure reliability of the computed results, each algorithm is repeated 10 times and the average is reported. The ISPEA2 demonstrated an evidently better performance than the NSGA-II and SPEA2 in terms of both computing efficiency and accuracy.

Table 5 Comparison of different algorithms

Algorithm	Computing time (s)	Quantity of non-dominated solution (%)	Crossover probability (%)
ISPEA2	54.37	37.60	86
NSGA-II	86.42	28.30	81
SPEA2	72.68	34.10	74

6 Conclusions

This paper attempts to support the module identification by integrating fundamental principles. Based on a thorough study of numerous existing methods, this paper abstracted three principles that should be holistically considered and simultaneously satisfied in the module identification: (1) internal clustering principle, (2) external independence principle, and (3) overall reliability principle. The resulting multi-principle modularization problem is solved as a MOOP. Both conceptual and mathematical modeling of the proposed multi-principle modularization method is presented. The ISPEA2 is used to find an optimal solution that satisfies all three principles. The fuzzy-based selection mechanism is used to extract a Pareto-optimal solution as the best compromise to eliminate the imprecise nature of human decision-making.

The ISPEA is compared with two other established multi-objective optimization methods in terms of computing time, quantity of non-dominated solutions, and crossover probability. The result reveals that the ISPEA2 demonstrated a better performance than the NSGA-II and SPEA2 in terms of both computing efficiency and accuracy to solve the multi-principle module identification problem.

It is also expected that the proposed new method will help deepen the understanding of modularization, and to enhance modularization effectiveness in practice. Future research will include recent hybrid heuristics for optimization and the application of the proposed method in a more complex product, for instance from the automotive or aerospace domain.

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中文概要

题　目：一种支持产品平台设计的多准则模块划分方法

目　的：研究多准则约束下的产品模块划分方法，为企业建立稳健的模块化产品平台奠定基础。

方　法：采用改进的多目标进化算法对建立的多准则模块划分数学模型求解，并采用模糊集合评价机制进行最优解的寻取，得到基于多准则模块划分方法的产品模块划分结果。

结　论：通过改进的多目标进化算法求解多准则模块划分模型，能够得到有效支持产品平台设计的产品模块划分方案。通过与已有优化方法的比较验证了本文提出的多准则模块划分方法的优越性。

关键词：模块划分；模块化准则；多目标优化；改进的强度帕累托进化算法；透平膨胀机