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Research Article

Bi-Objective Optimization Method and Application of Mechanism Design Based on Pigs' Payoff Game Behavior

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It takes two design goals as different game players and design variables are divided into strategy spaces owned by corresponding game player by calculating the impact factor and fuzzy clustering. By the analysis of behavior characteristics of two kinds of intelligent pigs, the big pig's behavior is cooperative and collective, but the small pig's behavior is noncooperative, which are endowed with corresponding game player. Two game players establish the mapping relationship between game players payoff functions and objective functions. In their own strategy space, each game player takes their payoff function as monoobjective for optimization. It gives the best strategy upon other players. All the best strategies are combined to be a game strategy set. With convergence and multiround game, the final game solution is obtained. Taking bi-objective optimization of luffing mechanism of compensative shave block, for example, the results show that the method can effectively solve bi-objective optimization problems with preferred target and the efficiency and accuracy are also well.

1. Introduction

Multiobjective optimization problem in actual engineering design is very common. The essential characteristics of multiobjective optimization are as follows: (1) there exist several objective interests; (2) the status of the various objectives are different and have conflicts. The solution methods are diverse; the latest research is as follows: Akbari and Ziarati [1] applied a novel bee swarm optimization method to obtain a uniformly distributed Pareto front. Ismail et al. [2] proposed a new self-organizing genetic algorithm for multiobjective optimization problems to obtain a better value as compared to the existing weighted-sum methods. Lee et al. [3] used the multiobjective fuzzy optimization method to obtain the optimal parameters of rotor experimental apparatus. Ding et al. [4] proposed a new multiobjective optimization algorithm named KSVC-SPEA to effectively achieve the overall performance of injection molding machine.

In recent years, considering the similarity between multiobjective design and the game, game theory has been used to solve multiobjective design problems, especially for practical problems in engineering fields. According to the different behaviors of each game player seeking for benefit, the game can be divided into noncooperative game and cooperative game. In a noncooperative game, each player benefits from competitive behavior patterns and the typical models are Nash equilibrium game model and the Stackelberg oligopoly game model. A cooperative game is defined as game players abiding by a binding agreement, benefiting from cooperative behavior patterns. The typical binding agreements contain three types, which are known as the "self-interest do not harm the others" (competitive and cooperative game model), "You have me, I have you" (coalition cooperative game model), and "all for one and one for all" (unselfish cooperative game model). About noncooperative game to solve multiobjective design, Spallino and Rizzo [5] proposed a noncooperative game optimization method based on evolutionary strategy in the multiobjective design of the composite laminate, which treated each game player as an equal body and eventually found a Nash equilibrium point through negotiation functions. Neng-gang et al. [6] established a multiobjective game design technology roadmap and key indicators based on the Nash equilibrium model and the Stackelberg oligopoly game model and successfully applied to multiobjective optimization design such as gravity dam, structure of arch-arch ring, and luff mechanism of compensative sheave block. In the use of cooperative games to solve multiobjective design, Chen and Li [7] proposed three-tier two-objective optimization method and applied this method to the manufacture of concurrent product and process optimization; Neng-gang et al. [8] adopted a competitive-cooperative game model to conduct a multi-objective optimization design and obtained a good design. However, whether the non-cooperative game methods or the cooperative game methods are used to solve multi-objective design problems, if the game method is selected, behavior modes of all players remain unchanged during the whole process. But this is an ideal situation. Each player's behavior is diverse in many survival games in nature. Neng-gang et al. [9] proposed a mixed game model according to the diversity of behavior patterns caused by differences in resources and endowment of each player. Through the bionics of the survival mechanisms of reproduction of lizard species, a typical mixed game model is presented, which consists of both competitive behavior patterns and cooperative behavior patterns of "all for one and one for all" and "benefits oneself but do not harm other people". This method is very good to solve the oneness problem of constructing payoff functions, but there exist two shortcomings as follows. (1) It can only be applied to three objectives or more than three objectives and cannot solve two-objective optimization problems. (2) It cannot solve "principal and subordinate" optimization problems. That is, it cannot solve the optimization problem with target preference. To compensate this deficiency and improve the game method for solving optimization problems, bi-objective optimization method is proposed based on pigs' payoff behavior, which can be applied in two-objective optimization problem with target preference.

2. The Basic Idea

2.1. Pigs' Payoff Game Model

American economist named Nash (the Nobel economic prize winner) has proposed "Pigs' Payoff". It is shown in Figure 1 and is as follows: there are a big pig and a small pig in

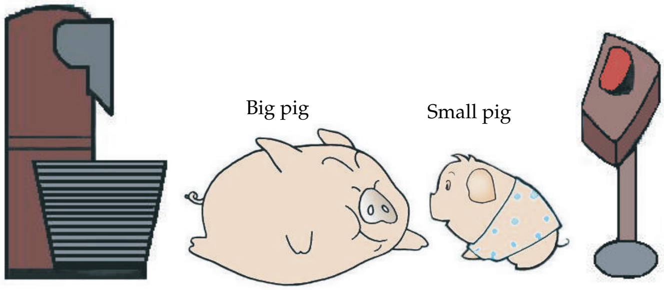

Figure 1: The picture of pigs' payoff.

Table 1: The payoff matrix.

Pigs' payoff	Small pig	
	Pressing the button	Waiting
Big pig		
Pressing the button	(5, 1)	(4, 4)
Waiting	(9, −1)	(0, 0)

the pigsty. One side of the pigsty has food slot and the other side has food control button. Whether the big pig or the small pig will pay 2-unit energy cost if it presses the food control button and 10-unit food will fall into food slot in return. If the big pig first arrives in the food slot, the benefit ratio of the big pig to the small pig is 9 : 1. If the big pig and the small pig arrive in the food slot at the same time, the benefit ratio of the big pig to the small pig is 7 : 3. If the small pig first arrives in the food slot, the benefit ratio of the big pig to the small pig is 6 : 4. The payoff matrix is shown in Table 1. In premise of both the big pig and small pig having intelligence, the final game result is that the big pig presses the button and the small pig dose not press the button but chooses to wait [10].

From the result of the behavior, the strategy of waiting is a selfish behavior of non-cooperation and the strategy of pressing the button is a collective behavior of cooperation. Hence, two game players (the big pig and the small pig) adopt two different behavior modes and constitute a hybrid game mode. The equilibrium solution (4, 4) is Pareto solution.

2.2. The Technology Principle

$$\begin{aligned}
&\text{The design variables: } \mathbf{X} = (x_1, x_2, \ldots, x_n) \in \Omega^n, \\
&\text{let the objective functions be minimized: } F(\mathbf{X}) = (F_1(\mathbf{X}), F_2(\mathbf{X})) \longrightarrow \min, \\
&\text{subject to constraint conditions: } g_k(\mathbf{X}) \le 0 \quad (k = 1, 2, \ldots, q),
\end{aligned} \tag{2.1}$$

where n is the number of design variables. q is the number of constraint conditions. Ω^n is the feasible space of design variables.

Meanwhile, the definition of game is as follows: G_m represents one game. If G_m has 2 players (Illustration: the implication of number of players is equal to the number of objective functions), the sets of available strategies are denoted by $\mathbf{S}_1$, $\mathbf{S}_2$. The payoff functions are u_1, u_2. Hence, the game with 2 players can be written as $G_m = (\mathbf{S}_1, \mathbf{S}_2; u_1, u_2)$.

The basic idea for bi-objective optimization method based on game is as follows: (1) there are 2 design objectives, which are seen as 2 players and the design variables $\mathbf{X}$ are divided into strategy subsets $\mathbf{S}_1$, $\mathbf{S}_2$ of the corresponding players by certain technical methods. (2) According to the specific game model, mapping relationships are established between the payoff functions u and objective functions F. (3) Each player takes its own payoff function as its objective and gets a single-objective optimal solution in its own strategy subset. So this player obtains the best strategy versus other players. The best strategies of all players form the group strategy in this round. The final equilibrium solutions can be obtained through multiround game according to the convergence criterion.

The payoff function u is closely related to the game model. The different behavior characteristics of the big pig and small pig, respectively, are assigned to the corresponding game players based on pigs' payoff game behavior model; then, the payoff functions u is constructed according to the corresponding behavior characteristics.

3. The Key Technology and Structure of the Algorithm

3.1. Game Player's Strategy Subset Computation

Fuzzy mathematics has been successfully used in the related design fields with the multidisciplinary cross research. Fuzzy mathematics has been successfully applied in filter design [11], T-S fuzzy systems [12, 13], and T-S fuzzy stochastic systems [14] and abundant research results are obtained. In this paper, the design variables are divided into each game players strategy subsets ($\mathbf{S}_1$, $\mathbf{S}_2$) by calculating the impact factor and fuzzy clustering based on fuzzy mathematics.

Computation steps are as follows.

(1) Optimize 2 mono-objectives; then obtain optimal solution $F_1(\mathbf{X}_1^*)$, $F_2(\mathbf{X}_2^*)$, where

$$\mathbf{X}_i^* = \left\{x_{1i}^*, x_{2i}^*, \ldots, x_{ni}^*\right\} \quad (i = 1, 2). \tag{3.1}$$

(2) Every x_j is divided into T fragments with step length Δx_j in its feasible space; Δ_{ji} is an impact factor (x_j affecting the objective f_i) and is shown as

$$\Delta_{ji} = \frac{\sum_{t=1}^{T}\left|F_i\left(x_{1i}^*, \ldots, x_{(j-1)i}^*, x_j(t), x_{(j+1)i}^*, \ldots, x_{ni}^*\right) - F_i\left(x_{1i}^*, \ldots, x_{(j-1)i}^*, x_j(t-1), x_{(j+1)i}^*, \ldots, x_{ni}^*\right)\right|}{T \cdot \Delta x_j}. \tag{3.2}$$

To avoid the different functions' self-affecting, make impact factors dimensionless:

$$\Delta_{ji} = \frac{\Delta_{ji}}{\left|F_i(\mathbf{X}_i^*)\right|}. \tag{3.3}$$

(3) All samples classification $\Delta = \{\Delta_1, \Delta_2, \ldots, \Delta_n\}$, the classification of j is $\Delta_j = \{\Delta_{j1}, \ldots, \Delta_{j2}\}$ $(j = 1, \ldots, n)$, and Δ_j means the impact factor set of j on all the players. The purpose is classifying highly similar samples as one classification; this paper uses a similar degree approach to reflect the samples' similarity relation. Select any two samples Δ_k and Δ_l and analyze their similarity relation; define a fuzzy relation function by normal distribution:

$$\mu_i(\Delta_k, \Delta_l) = \exp\left(-\frac{|\Delta_{ki} - \Delta_{li}|}{(1/m)\sum_{i=1}^{m}|\Delta_{ki} - \Delta_{li}|}\right) \quad (k, l = 1, 2, \ldots, n;\ k \neq l;\ i = 1, 2), \tag{3.4}$$

where $\mu_i(\Delta_k, \Delta_l)$ is the fuzzy relation between Δ_k and Δ_l in the ith objective function.

The correlation degree of Δ_k and Δ_l is

$$r_{kl} = \frac{1}{2}\sum_{i=1}^{2}\frac{\min_{i\in\{1,2\}}|\Delta_{ki} - \Delta_{li}| + 0.5\max_{i\in\{1,2\}}|\Delta_{ki} - \Delta_{li}|}{|\Delta_{ki} - \Delta_{li}| + 0.5\max_{i\in\{1,2\}}|\Delta_{ki} - \Delta_{li}|}. \tag{3.5}$$

(4) Establish the matrix $\mathbf{R}$ based on r_{kl} and do fuzzy clustering to matrix $\mathbf{R}$:

$$\mathbf{R} = \begin{vmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nn} \end{vmatrix}. \tag{3.6}$$

Classification results of Δ represent the classification results of $\mathbf{X}$ because of a one-to-one relationship between $\Delta = \{\Delta_1, \Delta_2, \ldots, \Delta_n\}$ and $\mathbf{X} = \{x_1, x_2, \ldots, x_n\}$.

(5) According to fuzzy clustering, divide the design variables $\mathbf{X}$ into strategy subsets $\mathbf{S}_1, \ldots, \mathbf{S}_m$ and assign the strategy subset to the corresponding player by the average value of impact factors. According to a statistical viewpoint [15], when the number of design variables and objective functions is small, we can directly divide variable sets $\mathbf{X}$ into strategy space $\mathbf{S}_1$, $\mathbf{S}_2$ according to the value of impact factor. When the number design variables and objective functions are large, fuzzy clusterings are needed. Meanwhile, according to experience, we can first classify variables with strong correlation as a sample to reduce the complexity of clustering analysis.

Input system's classification control value is M and maximal sample number is P; each with sample as one classification, the system is $\Delta_1, \Delta_2, \ldots, \Delta_n$.

The steps of clustering are as follows.

(1) Calculate the correlation degree r_{kl} and build matrix $\mathbf{R}^{(0)}$; attention: $r_{kl} = r_{lk}$, $r_{kl} > 0$.

(2) Set maximum value of matrix $\mathbf{R}^{(0)}$ to be r_{ab}, $r_{ab} = \max_{k,l\in\{1,2,\ldots,n\}} r_{kl}$ and classify Δ_a and Δ_b into a new classification Δ_s; if the sample number is larger than P, then combine the second maximal value of $\mathbf{R}^{(0)}$.

(3) Combine $\Delta_c(c = 1,2,\ldots,n; c \neq a, c \neq b)$ and Δ_s into a new classification system, calculate its correlation degree, and build a new matrix $\mathbf{R}^{(1)}$; the correlation degree of any classification Δ_c and Δ_s is $r_{cs} = \min\{r_{ca}, r_{cb}\}$.

(4) Repeat procedures (1), (2), and (3) until the system classification number equals control value M.

3.2. Behavior Modes and Construction of Game Payoff Functions

The characteristic of the small pig is competitive behavior mode and its corresponding game payoff function is as follows:

$$u_i = \frac{F_i}{\overline{F}_i} \quad (i = 1,2), \tag{3.7}$$

where $\overline{F}$ is a reference value, which can eliminate the differences in the magnitude for each objective function. In this paper, the initial objective function value is chosen to be $\overline{F}$.

The characteristic of the big pig is cooperative behavior mode and its corresponding game payoff function is as follows:

$$u_i = w_{ii}\frac{F_i}{\overline{F}_i} + \sum_{j=1(j\neq i)}^{m} w_{ij}\frac{F_j}{\overline{F}_j} \quad (i = 1,2), \tag{3.8}$$

where $\sum_{j=1}^{m} w_{ij} = 1$ value of w_{ii} reflects the degree of considering its own interest. The greater the value is, the lower the cooperative degree is.

3.3. Algorithm Procedures and Flow Chart

(1) Obtain strategy subset $\mathbf{S}_1$, $\mathbf{S}_2$ attached to each player through calculating the impact factor and fuzzy clustering.

(2) Payoff functions u_i to any ith player ($i = 1, 2$) is constructed according to the characteristic of the small pig and big pig proposed by Section 3.2 above.

(3) Generate the initial feasible strategies in the strategy set of each player randomly and then form a strategy permutation $s^{(0)} = \{s_1^{(0)}, s_2^{(0)}\}$.

(4) Let $\overline{s}_1^{(0)}$, $\overline{s}_2^{(0)}$ be the corresponding complementary set of $s_1^{(0)}$, $s_2^{(0)}$ in $s^{(0)}$. For any player i ($i = 1,2$), solve the optimal strategy $s_i^* \in \mathbf{S}_i$, and make payoff minimum $u_i(s_i^*, \overline{s}_i^{(0)}) \rightarrow \min(i = 1,2)$;

(5) Define optimal strategy permutation $s^{(1)} = s_1^* \cup s_2^*$. Then judge the feasibility of $s^{(1)}$. If $g_k(s^{(1)}) \leq 0$ ($k = 1,2,\ldots,q$) does not satisfy, turn to step (3). Otherwise, compute the distance between $s^{(1)}$ and $s^{(0)}$ which is called the Euclidean norm. Then examine whether the distance satisfies the convergence criterion $\|s^{(1)} - s^{(0)}\| \leq \varepsilon$ or not (ε is a decimal parameter given in advance). If it satisfies, the game is over; if not, let $s^{(1)}$ displace $s^{(0)}$ and turn to step (4) to repeat.

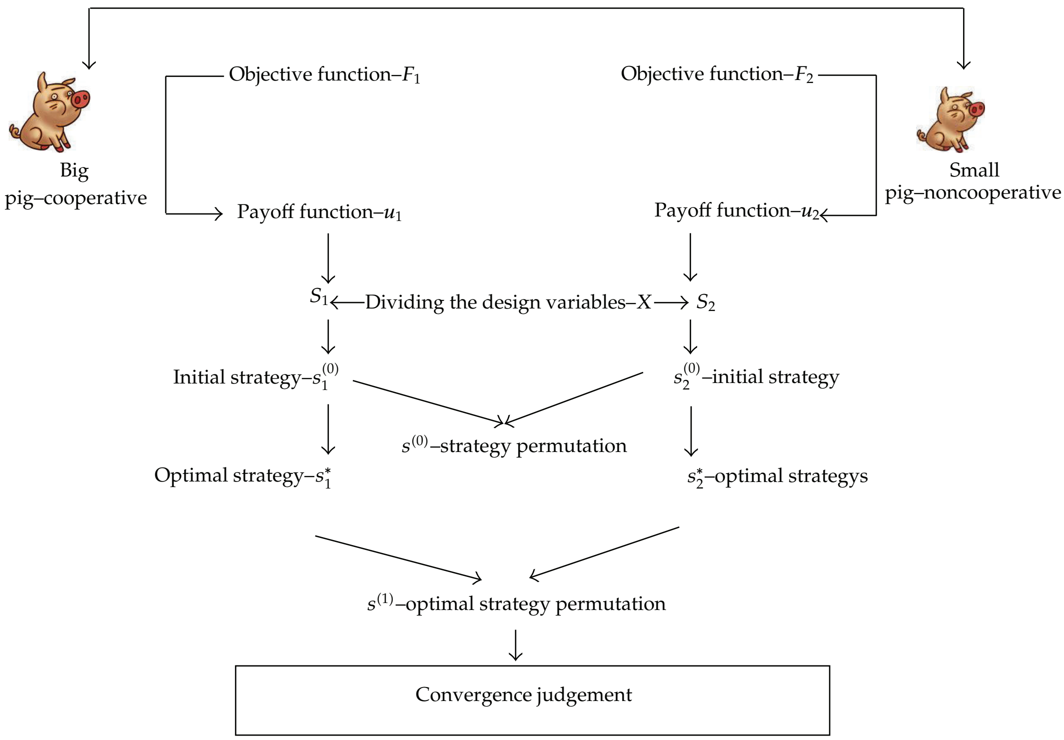

Figure 2: The algorithm chart.

The algorithm chart is shown in Figure 2 (illustration: if the big pig stands for F_1, then the small pig stands for F_2 and if the big pig stands for F_2, then the small pig stands for F_1).

4. Bi-Objective Optimization Model of Luff Mechanism of Compensative Sheave Block

4.1. The Design Model

The luff mechanism of compensative sheave block is a working device, which can realize mechanical loading range and is widely used in hoisting machinery. In its working process, there exists the stability goal; namely, the goods need to move along the horizontal path. On the other hand, there also exists the economic goal; namely, it needs less energy consumption. So, design problems have multiobjective optimization issues.

The luff mechanism of compensative sheave block is shown in Figure 3. The design variables are $\mathbf{X} = (x_1, x_2, x_3, x_4, x_5)$. Constraints need to meet upper and lower limits of design variables and amplitude range cannot exceed the prescribed range. The objective functions are F_1 (stability index) and F_2 (economic index).

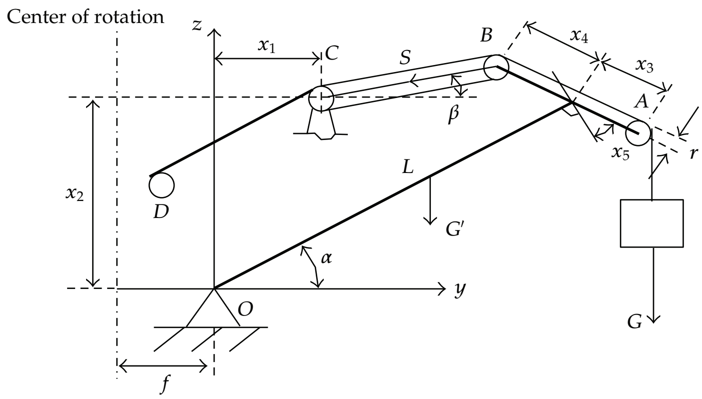

Figure 3: The luff mechanism of compensative sheave block.

4.2. The Objective Function of the Stability Index

Consider

$$R = L\cos\alpha + x_3\sin(\alpha + x_5) + f + r, \tag{4.1}$$

where R is the amplitude of fluctuation and α is the elevation.

The mechanism in the biggest amplitude is the starting point and the rise quantity relative to the starting point is $\Delta z(t)$ in any time t,

$$\Delta z(t) = L(\sin\omega t - \sin\alpha_1) + x_3[\cos(\alpha_1 + x_5) - \cos(\omega t + x_5)], \tag{4.2}$$

where $\omega = (\alpha_2 - \alpha_1)/T$ is angular velocity, T is the total time of the fluctuation, α_1 is the elevation in $R_{\max}$ (the maximum luffing), and α_2 is the elevation in $R_{\min}$ (the minimum luffing).

The fall quantity relative to the starting point is $\Delta l(t)$ in any time t due to the rope releasing:

$$\Delta l(t) = \frac{m_b}{m_q}(l_1 - l(t)), \tag{4.3}$$

where m_q is the number of wire rope of lifting pulley and m_b is the number of wire rope of compensation pulley, where

$$\begin{aligned} l_1 &= \sqrt{[L\cos\alpha_1 - x_4\sin(\alpha_1 + x_5) - x_1]^2 + [L\sin\alpha_1 + x_4\cos(\alpha_1 + x_5) - x_2]^2}, \\ l(t) &= \sqrt{[L\cos\omega t - x_4\sin(\omega t + x_5) - x_1]^2 + [L\sin\omega t + x_4\cos(\omega t + x_5) - x_2]^2}, \\ \Delta h(t) &= \Delta z(t) - \Delta l(t), \end{aligned} \tag{4.4}$$

where $\Delta h(t)$ is the deviation relative to the starting point in any time t.

So, the objective function of the stability index is as follows:

$$F_1 = \sup_{t\in[0,T]} \Delta h(t) - \inf_{t\in[0,T]} \Delta h(t). \tag{4.5}$$

4.3. The Objective Function of the Economic Index

The energy consumption is $P(t)$ in any time t.

$$P(t) = M_q(t)\omega, \tag{4.6}$$

where $M_q(t)$ is the torque. For no frame balance system, it is as follows:

$$M_q(t) = \frac{G}{9.8}[L\cos\omega t + x_3\sin(\omega t + x_5) + r] - \frac{m_b}{m_q}\frac{G}{9.8}(z_B\cos\beta - y_B\sin\beta) + \frac{G'}{9.8}L\xi\cos\omega t, \tag{4.7}$$

where $y_B = L\cos\omega t - x_4\sin(\omega t + x_5)$, $z_B = L\sin\omega t + x_4\cos(\omega t + x_5)$, G is the gravity of the goods, $\beta = \mathrm{arctg}((z_B - x_2)/(y_B - x_1))$, G' is the gravity of the arm frame, and ξ is the ratio of the distance (center of gravity of the arm frame from O point in Figure 3) to arm length-L.

So, the objective function of the economic index is as follows:

$$F_2 = \int_0^T P(t)dt = \omega\int_0^T M_q(t)dt. \tag{4.8}$$

5. The Application in Mechanism Design

5.1. Calculation Statement

The paper takes the luff mechanism of compensative sheave block (shown in Figure 3) as application object. $G = 31360\,\mathrm{N}$, $G' = 13720\,\mathrm{N}$, $L = 14\,\mathrm{m}$, $f = 0.7\,\mathrm{m}$, $\xi = 0.5$, $r = 0.2\,\mathrm{m}$, $m_b = 6$, $m_q = 2$. $R_{\max} = 12\,\mathrm{m}$, $R_{\min} = 5.8\,\mathrm{m}$, $-0.4 \le x_1 \le 0.5$, $3 \le x_2 \le 8$, $0.4 \le x_3 \le 0.8$, $0.3 \le x_4 \le 0.7$, $0 \le x_5 \le 0.43633$. The total fluctuation time is 40 seconds ($T = 40$ seconds). The smallest unit time is 1 second. The more-detailed mechanism instructions can refer to [16]. Meanwhile, a group of realistic optimization design parameters ($x_1 = -0.030$, $x_2 = 4.040$, $x_3 = 0.550$, $x_4 = 0.370$, $x_5 = 0.160$) is listed [16].

5.2. Single-Objective Optimization Results

Consider

$$\begin{aligned} \mathbf{X}_1^* &= (0.01897, 4.08848, 0.51854, 0.53969, 0.33220), \qquad F_1(\mathbf{X}_1^*) = 0.01558\,\mathrm{m}, \\ \mathbf{X}_2^* &= (0.00954, 4.83460, 0.77453, 0.57673, 0.31204), \qquad F_2(\mathbf{X}_2^*) = 2.946\,\mathrm{kJ}. \end{aligned} \tag{5.1}$$

The impact factors are shown in Table 2.

Table 2: The impact factors.

Impact factors Δ_{ji}	Design variables				
	x_1	x_2	x_3	x_4	x_5
Objective functions					
F_1	95.53	85.86	29.75	21.57	1.78
F_2	17.12	13.99	5.34	5.27	0.36

Table 3: The impact factors of strategy subsets to objection functions.

Impact factors	Strategy subsets	
	$\mathbf{S}_a$	$\mathbf{S}_b$
Objection functions		
F_1	90.695	17.700
F_2	15.555	3.657

5.3. Fuzzy Clustering

Consider $\Delta_1 = (95.53, 17.12)$, $\Delta_2 = (85.86, 13.99)$, $\Delta_3 = (29.75, 5.34)$, $\Delta_4 = (21.57, 5.27)$, $\Delta_5 = (1.78, 0.36)$,

$$\mathbf{R} = \begin{pmatrix} * & 1.66393 & 1.54728 & 1.52919 & 1.54697 \\ & * & 1.52336 & 1.50450 & 1.53111 \\ & & * & 1.34602 & 1.54624 \\ & & \text{Symmetry} & * & 1.60735 \\ & & & & * \end{pmatrix}, \tag{5.2}$$

$M = 2$, and $P = 3$. Because $r_{12} = 1.66393$ is the maximum value of matrix $\mathbf{R}$, x_1 and x_2 belong to one class. Namely, $\mathbf{S}_a = \{x_1, x_2\}$ and $\mathbf{S}_b = \{x_3, x_4, x_5\}$. The impact factors bof strategy subsets to objection functions are shown in Table 3.

According to Table 3, because the maximum value is 90.695, $\mathbf{S}_a = \mathbf{S}_1 = \{x_1, x_2\}$ is the strategy subset of F_1. $\mathbf{S}_b = \mathbf{S}_2 = \{x_3, x_4, x_5\}$ is the strategy subset of F_2.

5.4. Calculation Results

There exist two kinds of cases. Case 1 is that the big pig stands for F_2 and the small pig stands for F_1. Case 2 is that the big pig stands for F_1 and the small pig stands for F_2.

We take case 1; for example, the detailed calculation steps are as follows.

(1) Take the corresponding values of the initial design in strategy subsets $\mathbf{S}_1$, $\mathbf{S}_2$ as the initial feasible strategies $s_1^{(0)}$, $s_2^{(0)}$. Then, form a strategy permutation $s^{(0)} = \{s_1^{(0)}, s_2^{(0)}\}$.

(2) Perform the following two single-objective optimization.

Table 4: The iterative process of Case 1.

Game round	Design variables					Objective functions	
	x_1/m	x_2/m	x_3/m	x_4/m	x_5/rad	F_1/m	F_2/KJ
Initial strategy	0.02968	4.09656	0.59710	0.56809	0.04602	0.06290	34.819
Bout 1	−0.02685	4.06819	0.68734	0.30528	0.35235	0.04682	30.382
Bout 2	0.06769	4.15154	0.63034	0.46589	0.30726	0.03309	32.764
Bout 3	−0.01810	4.07167	0.69530	0.32966	0.41033	0.03157	30.829
Bout 4	0.00422	4.09241	0.72985	0.30224	0.40272	0.02267	31.060
Bout 5	−0.00605	4.06225	0.58250	0.49698	0.02102	0.01581	33.438
Bout 6	−0.00605	4.06225	0.58250	0.49698	0.02102	0.01581	33.438

(a) Seek the optimal strategy $s_1^* \in \mathbf{S}_1$ and minimize the payoff function,

$$u_1\left(s_1^*, s_2^{(0)}\right) = \frac{F_1\left(s_1^*, s_2^{(0)}\right)}{F_1\left(s_1^{(0)}, s_2^{(0)}\right)} \longrightarrow \min. \tag{5.3}$$

(b) Seek the optimal strategy $s_2^* \in \mathbf{S}_2$ and minimize the payoff function,

$$u_2\left(s_1^{(0)}, s_2^*\right) = w_{22} \times \frac{F_2\left(s_1^{(0)}, s_2^*\right)}{F_2\left(s_1^{(0)}, s_2^{(0)}\right)} + w_{21} \times \frac{F_1\left(s_1^{(0)}, s_2^*\right)}{F_1\left(s_1^{(0)}, s_2^{(0)}\right)} \longrightarrow \min. \tag{5.4}$$

(3) Define strategy permutation $s^{(1)} = s_1^* \cup s_2^*$. Then, justify the feasibility of $s^{(1)}$. If $s^{(1)}$ does not satisfy constraint conditions, turn to step (1). Otherwise, compute $\sqrt{\sum_{j=1}^{5}(((x_j^{(1)} - x_j^{(0)})/x_j^{(0)})^2/5)}$ and examine whether it satisfies the convergence precision ε (ε is 0.0001 in this paper). If it satisfies, the game is over; if not, let $s^{(0)} = s^{(1)}$ and turn to step (2) to iteration loop.

Illustration: for case 2, u_1 is constructed according to cooperative behavior mode and u_2 is constructed according to noncooperative behavior mode.

(1) For case 1, $w_{22} = 0.5$, $w_{21} = 0.5$, calculation starts from the initial strategy $\mathbf{X}^0 = (0.02968, 4.09656, 0.59710, 0.56809, 0.04602)$ and obtains convergence value $\mathbf{X}^* = (-0.00605, 4.06225, 0.58250, 0.49698, 0.02102)$ after six rounds game and $F_1 = 0.01581$ m, $F_2 = 33.438$ KJ. Iterative process is shown in Table 4.

(2) For case 2, $w_{11} = 0.5$, $w_{12} = 0.5$, calculation starts from the initial strategy $\mathbf{X}^0 = (0.19247, 4.17230, 0.42101, 0.31284, 0.31592)$ and obtains convergence value $\mathbf{X}^* = (0.01724, 4.08923, 0.40303, 0.30493, 0.43130)$ after four rounds game and $F_1 = 0.14471$ m, $F_2 = 28.255$ KJ. Iterative process is shown in Table 5.

The compared results are shown in Table 6. (Illustration: multiobjective fuzzy optimization method is adopted in [17] and multiobjective Nash equilibrium game method is adopted in [6]).

Table 5: The iterative process of Case 2.

Game round	Design variables					Objective functions	
	x_1/m	x_2/m	x_3/m	x_4/m	x_5/rad	F_1/m	F_2/KJ
Initial strategy	0.19247	4.17230	0.42101	0.31284	0.31592	0.03357	33.212
Bout 1	0.05860	4.02781	0.40414	0.30544	0.40052	0.02428	32.968
Bout 2	0.18459	4.17053	0.41018	0.30223	0.39318	0.03514	32.457
Bout 3	0.01724	4.08923	0.40303	0.30493	0.43130	0.14471	28.225
Bout 4	0.01724	4.08923	0.40303	0.30493	0.43130	0.14471	28.225

Table 6: The compared results.

Reference	Design variables					Objective functions	
	x_1/m	x_2/m	x_3/m	x_4/m	x_5/rad	F_1/m	F_2/KJ
[16]	−0.030	4.040	0.550	0.370	0.160	0.05935	31.166
[17]	−0.02199	4.14131	0.76369	0.44838	0.32446	0.04325	30.174
[6]	0.11480	4.08089	0.40800	0.30067	0.41340	0.01604	33.140
Method in this paper							
Case 1	−0.00605	4.06225	0.58250	0.49698	0.02102	0.01581	33.438
Case 2	0.01724	4.08923	0.40303	0.30493	0.43130	0.14471	28.225

The comparison of deviation trajectory (cases 1 and 2, [6, 16, 17]) is shown in Figure 4.

According to Table 6, we can know that F_1 in case 1 is better than [6, 16, 17] and case 2, and that F_1 in case 2 is the worst. According to Figure 4, the deviation trajectory in case 1 is better than [6, 16, 17] and case 2. F_2 in case 2 is better than [6, 16, 17] and case 1. F_2 in case 1 is the worst. The results show that the method can effectively solve bi-objective optimization problems with preferred target and that multiobjective fuzzy optimization method [17] is an effective method without preferred target (both F_1 and F_2 are better than realistic optimization results [16]).

By analyzing the results, we can know three conclusions as follows. (1) The game player with noncooperative characteristic of the small pig has greater advantage in the pursuit of its own interests than the game player with cooperative characteristic of the big pig. (2) If the designers have target preference, they need to take the preferred target as the small pig side and take another target as the big pig side. (3) The satisfactory equilibrium solution can be obtained through less iteration rounds because the design variables are decomposed into the strategy subset owned by 2 game players.

To reveal the influence of w_{ii} on the final solutions, w_{ii} = 0.1, 0.3, 0.5, 0.7, respectively. The results are shown in Tables 7 and 8. In case 1, the big pig stands for F_2 and the greater the value of w_{22} is (the cooperative degree is lower), the better the final value of F_2 is. In case 2, the big pig stands for F_1 and the greater the value of w_{11} is (the cooperative degree is lower), the better the final value of F_1 is.

6. Conclusions

(1) One new bi-objective optimization game method is proposed. Two design goals can be regarded as two game players, the design variables set can be regarded as

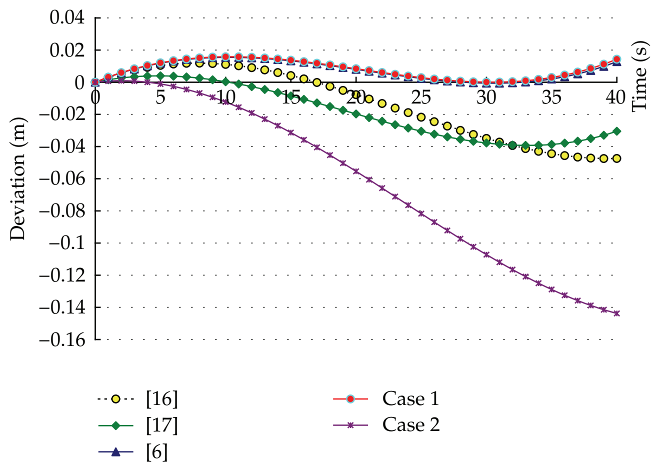

Figure 4: The comparison of deviation trajectory.

Table 7: The influence of w_{22} on the final solutions in Case 1.

w_{22}	Design variables					Objective functions	
	x_1/m	x_2/m	x_3/m	x_4/m	x_5/rad	F_1/m	F_2/KJ
0.1	0.00034	4.06904	0.49224	0.57956	0.07845	0.01569	33.585
0.3	−0.00605	4.06225	0.59757	0.48890	0.00316	0.01574	33.481
0.5	−0.00605	4.06225	0.58250	0.49698	0.02102	0.01581	33.438
0.7	0.01812	4.09616	0.58756	0.48979	0.37132	0.01588	32.383

Table 8: The influence of w_{11} on the final solutions in Case 2.

w_{11}	Design variables					Objective functions	
	x_1/m	x_2/m	x_3/m	x_4/m	x_5/rad	F_1/m	F_2/KJ
0.1	0.03455	4.11824	0.40770	0.30283	0.39273	0.15709	27.850
0.3	0.00833	4.08878	0.40770	0.30283	0.39273	0.15380	27.973
0.5	0.01724	4.08923	0.40303	0.30493	0.43130	0.14471	28.225
0.7	0.02928	4.10112	0.40770	0.30283	0.39273	0.14075	28.377

strategy subsets named $\mathbf{S}_1$, $\mathbf{S}_2$, and the constraints in multiobjective problems can be regarded as constraints in the game method. Through the specific technological means, the design variables can be divided into each game players strategy subsets ($\mathbf{S}_1$, $\mathbf{S}_2$) and two payoff functions u are constructed based on pigs' payoff game behavior.

(2) The solution step of game player's strategy subset is presented. The design variables are divided into strategy spaces owned by the corresponding game player by calculating the impact factor and fuzzy clustering.

(3) The big pig's behavior is cooperative but the small pig's behavior is noncooperative. The different behavior characteristics of the big pig and small pig, respectively, are assigned to the corresponding game players based on pigs' payoff game behavior.

The paper constitutes a hybrid game mode and proposes the detailed solution steps.

(4) For optimization problems with preferred target, the designers need to emphasize one design goal. For this problem, there exist traditional methods such as weighting method (by adjusting the weight of each goal), hierarchical sequence method (by adjusting the objective optimization order), and goal programming method. In this paper, one new bi-objective optimization game method is proposed based on pigs' payoff game behavior for solving optimization problems with preferred target. It takes bi-objective optimization of luffing mechanism of compensative shave block; for example, the results show that the method can effectively solve the bi-objective optimization problems with preferred target (designers need to take the preferred target as the small pig side and take another target as the big pig side), the efficiency and accuracy are well, and the solution is obtained only through fewer game rounds.

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