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Study on Method of Robust Multidisciplinary Collaborative Decision for Product Design

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Abstract: A robust method for decentralized multidisciplinary collaborative decision was presented which adopts interval to describe the uncertainty of decision variables and non-cooperative game theory to model the relationship between design teams under decentralized decision environment. Considering the Rational Reaction Sets (RRS) from non-cooperation game theory as design constraint in the decision space, multidisciplinary collaborative decision is described as interval based constraint solving problem and then a two-step solving approach was proposed to obtain final robust decision scheme of product design. The first step is to eliminate initial range of decision variables using consistency algorithm and the second step is to search the robust decision point in consistent interval with design capability indices as judgment rule of robustness. A new kind of feasibility censor based immune chaotic algorithm for model solving was designed. Design of bear and rotor system involves complex coupled relationship of dynamic and tribology and is a typical multidisciplinary conflict and decouple problem. A robust and powerful decision method between different disciplines can not only quicken design process of bear and rotor, but also improve the design quality. To show the problem, a typical elastic bear and rotor system with single disk is used as example to validate the effectiveness and reliability of proposed decision approach.

Key words: Decentralized collaborative decision, game theory, immune chaotic algorithm, design capability indices, bear and rotor design

INTRODUCTION

Traditional design methods often consider problems from the point of single domain or single discipline and do not take into account knowledge fuse and collaborative decision between multiple disciplines. Recently, multidisciplinary collaborative decision has become the focus of study in design domain and some new decision ideas and decision methods have been developed. Among them the most natural and widely practiced one is to integrate all decision-making responsibilities into a single system-level team who mainly handles communication and interdisciplinary interaction and finally makes the global feasible decisions. The other teams are only responsible for providing disciplinary analysis when requested. This is in nature a centralized decision-making approach and it can not deal with complex multidisciplinary decision problems involving thousands of variables (Berkes, 1990). Two in-depth surveys of this single-level approach and their variants are presented by Balling and Sobieski (1996) and Sobieski and Haftka (1997). In practice, there is not any one design team can master all design knowledge and design tools from different disciplines involved in product realization, greater autonomy should be assigned to the disciplinary teams to make local decision and perform disciplinary analysis (Xiao *et al*., 2007). In real decentralized decision process of complex product realization collection of decision information is generally difficult because different design teams may lie in different sections within a same enterprise or related sections of different enterprise. So, such centralized decision approaches are not competent any more for practical product realization any more and the effective decentralized decision approaches are imperative. For this, bi-level decision-making approaches have been developed which decomposed the multidisciplinary problem into a set of discipline level subprolems and one system level problem. Disciplinary teams are assigned the authority to make local decision as well as perform analysis. Braun *et al*. (1997) and Kroo *et al*. (1996) proposed Collaborative Optimization (CO) in which auxiliary variables are introduced to replace the couple

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variables in each sub-problem so that they can be solved concurrently. Sobieski and Kroo (2000) improved CO using response surface methodology. Another approach widely practiced for collaborative decision is Concurrent Sub-Space Optimization (CSSO) in which disciplinary team solves sub-problems concurrently while the system level team coordinates, removes conflict and achieves multidisciplinary feasibility (Sobieski, 1988). Although, two level decision approaches achieve decentralized collaborative decision by assigning design authority to disciplinary teams and overcome the limitations of centralized approach, frequent iterations between system level team and disciplinary teams make its convergence not be guaranteed in theory.

Application of game theory in design is spurred by its success in economics. Vincent firstly applied game theory in product design successfully (Vincent, 1983). Badhrinath and Rao (1996) presented multi players game and using the leader/follower game protocol to model the relations between product designs and manufacturing. Lewis and Mistree (1997) systematically studied all three protocols and illustrated the use of principles of game theory to model the iteration among engineering teams in decision making. These game protocols have been shown to be effective in representing interactions between engineering teams and facilitate each design team making its decision from overall perspective.

In this study non-cooperative game theory is used to model the relationships between design teams under decentralized decision environment and try to achieve decoupling of variables subject to different disciplines through Rational Reaction Sets (RRS) which here implies a set of solutions that an isolated decision maker constructs as a function of unknown information from other decision makers. A RRS is viewed as a constraint in the decision space of variables and all RRSs from various disciplines constitute a constraint net for multidisciplinary decision of product realization. With intervals to describe uncertainty of variables, multidisciplinary collaborative decision is turned to interval based constraint solving problem. For this a two-step solving approach is developed in which consistency algorithm is adopted firstly to eliminate the initial range of decision variables and then search robust design scheme in consistent interval with design capability indices as the judgment rule of robustness.

Bear and rotor is a kind of important assembly in high-velocity rotating machinery such as turbine, aero-engine and rocket-engine. Its design often involves multi disciplines, such as dynamic and tribology and needs collaborative decision of designers from different disciplines or sections to achieve conflict decouple. Considering its importance and typical characteristics, this study selected an elastic rotor system with single disk as design object to show the proposed decision method.

COLLABORATIVE DECISION APPROACH BASED ON NON-COOPERATION GAME

Multidisciplinary collaborative decisions: A typical feature of multidisciplinary collaborative decision problems is that design constraints from multi disciplines are coupled with each other through decision variables, which means that some decision variables generally exist in constraints from not just single discipline but multi different disciplines. So, determination of these variables needs global analysis from overall perspective. This requires bidirectional information flow between designers and none should only pursue optimum of individual objective. This indicates the necessity of collaboration in product realization process and here collaboration is the result of gaming between designers whose aim is to find a system level Nash-equilibrium scheme meeting all designer's requirements. Figure 1 shows such a coupled decision Eq. 1 involving two disciplines.

In Fig. 1, two variable sets X_1 and X_2 are controlled, respectively by two designers D_1 and D_2 and the intersection of two sets is vacant, that is $X_1 \cap X_2 = \phi$. Y_1 and Y_2 are respectively the objectives of two disciplines and G_1, G_2, respectively the constraints set. X_{12} denotes the variables which are controlled by discipline 1 but have effect on decision of discipline 2. And X_{21} is just on the contrary. So, objective of discipline 1 is determined by X_1 and X_{21} together and objective of discipline 2 is determined by X_2 and X_{12} together.

Another feature of multidisciplinary collaborative decision is geographical distribution of design teams who work under decentralized environment in practice. Subject to different disciplines, they are often distributed in geography and master different design knowledge and tools of respective discipline. One can't replace another

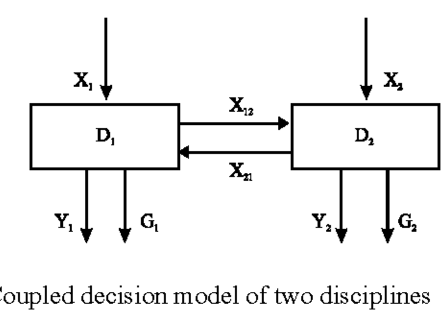

Fig. 1: Coupled decision model of two disciplines

because no single one designer or design team can master all design knowledge and tools from various disciplines to finish the whole design and analysis of product realization. This once again indicates that study of effective decentralized decision approach is imperative.

$$\begin{cases} \min: Y_1 = f_1(X_1, X_{21}) \\ \text{s.t}: G_1(X_1, X_{21}) > 0 \\ \quad X_{21} \in X_2 \\ \min: Y_2 = f_2(X_2, X_{12}) \\ \text{s.t}: G_2(X_2, X_{12}) > 0 \\ \quad X_{12} \in X_1 \end{cases} \tag{1}$$

Non-cooperation game theory: Design teams may not have the necessary information they need to make a decision. Each design team will have to make assumption, many times worst case, about the information needed from other teams because of interpersonal computational or organizational isolation. This scenario is known as Nash non-cooperative formulation (Nash, 1951).

Non-cooperation which here does not means that designers voluntarily turning their back on each other. Rather, it should imply involuntarily non-cooperation through organizational or information barriers among decision makers. So non-cooperation refers to decentralized decision process where designers have to make decisions in isolation due to organization barriers and geographical constraints. Its mathematical models are suitable for formulating decisions in collaborative design and its central idea is construction of RRS which denote the rational reaction of coupled disciplines to decision made by each other. For example, in Fig. 1 assume two designers respectively control a single design variable x_1 and x_2 with y_1 and y_2 as respective objective, where:

$$y_1 = 2x_1^2 + 5x_2^2 - \frac{1}{3}x_1 x_2 \text{ and } y_2 = 6\, x_1^2 + x_2^2 - 8x_1 x_2$$

For simplicity, constraints are not considered here and RRSs of two disciplines can be obtained using mathematics analysis method as follows:

$$\frac{\partial y_1}{\partial x_1} = 0 \Rightarrow 4x_1 - \tfrac{1}{3}x_2 = 0 \Rightarrow x_1 = \tfrac{1}{12}x_2$$
$$\frac{\partial y_2}{\partial x_2} = 0 \Rightarrow 2x_2 - 8x_1 = 0 \Rightarrow x_2 = 4x_1$$

A RRS is a mapping that relates the values of design variables controlled by one designer's to values of designer variables controlled by other designers. Replacing coupled variables with RRSs can achieve full decoupling and conflict resolution among multi coupled disciplines. This makes coupled collaborative decision completely become the decision on local variables controlled by individual discipline, but they are indeed globally feasible decisions considering all related factors.

Under decentralized decision environment decision maker cannot determine their local variables unless coupled variables have been known. For example, designer 1 cannot fix X_1 with Y_1 as objective until X_{21} are determined. In the same way, designer 2 need know information of X_{12} to determine X_2 with Y_2 as objective. Therefore, the relationship between $X_{12}(X_{21})$ and X_2 (X_1) is necessary to achieve collaborative decision among coupled disciplines. This is achieved in game theory by constructing RRS between different disciplines. They are such as $X_{12} = RRS_1(X_1)$, $X_{21} = RRS_2(X_2)$ which satisfy: $\forall X_{21}, \in X_2$, f_1 (X_1, $RRS_1(X_1)$) = min, f_1 (X_1, (X_{21}), $\forall X_{12}, \in X_1$, f_2 (X_2, RRS_2 (X_2)) = min, $f_2(X_2$, (X_{12}). Therefore, coupled decision Eq. 1 will become decoupled decision model Eq. 2 using RRS.

$$\begin{cases} \min: Y_1 = f_1(X_1, RRS_1(X_1)) \\ \text{s.t}: G_1(X_1, RRS(X_1)) > 0 \\ \min: Y_2 = f_2(X_2, RRS(X_2)) \\ \text{s.t}: G_2(X_2, RRS_2(X_2)) > 0 \end{cases} \tag{2}$$

In Lewis's study the RRS is constructed based on experimental approach using sampling in a nonlocal design space. Design of Experiments (DOE) technique is used to sample different design points from solution space of one designer. These points are then fed to another designer's model and the model solved using optimization method. This process is repeated a number of times and then a response is created linking the solution of one designer as a function of the solution of anther (Lewis and Mistree, 1997).

RRS constraint net based robust collaborative decision approach: A RRS is essentially an equation in term of decision variables. Hence, all RRSs from various disciplines compose a function group in decision space. The commonly adopted approach for solving Nash non-cooperation decision-making problems is explicitly calculating the various RRSs and then finding their intersection by solving the function group. But a point worthy of noting is that sometimes not all decision variables are coupled ones and only a coupled variable corresponds to one and only one RRS. So, in Nash non-cooperation decision-making problem the count of RRSs is sometimes less than the count of decision variables, which will result in more than one decision scheme met for the RRS function group according to the solving principle of function group.

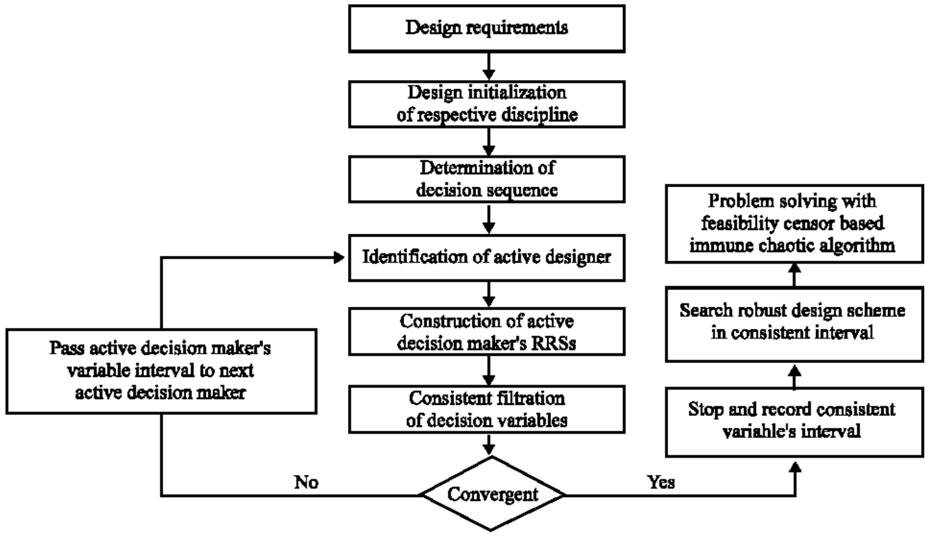

Fig. 2: RRS constraint net based robust collaborative decision model

In fact, a RRS can be viewed as a design constraint on decision variables and all RRSs constitute a constraint net in decision space. Interval is a type of natural and predominant manner to describe uncertainty of variables which can effectively reduce iterations of design process and is very convenient for designers to determine the initial rough range of decision variables. Based on above ideas, decentralized multidisciplinary collaborative decision problems will be modeled as RRS constraint net based interval constraint solving problems in this study.

Figure 2 shows the proposed robust collaborative decision flow, which begins with design requirement and ends with obtaining the Nash equilibrium scheme:

(1) Proposition of design requirement
(2) Design initialization of respective discipline, including determination of decision, variables, constraint, objective and the rough initial range of decision variables based on designer's experience
(3) Determination of the sequence for decision-making. Alternative decision making is adopted here which means at any time point only one decision-maker is active and others are all in inactive state
(4) Identification of active decision maker
(5) Evaluation of active decision-maker's RRSs using mathematical analysis or RSM and all those RRSs of active decision-maker form a constraint net in decision space of itself
(6) Consistency checking of variable's intervals of active decision-maker by consistency algorithm and eliminate the region in variable's interval which are sure not including Nash equilibrium
(7) If variable's interval converges, then stop and turn to step 8. Otherwise, turn to step 4 and pass the variable's interval of active decision-maker down to next active one
(8) Algorithm stops and records the consistent intervals of decision variables
(9) Construct robust decision model based on consistent interval of variables and design capability indices
(10) Solve model using feasibility censor based immune chaotic algorithm

CONSISTENCY ALGORITHM FOR INTERVAL FILTRATION OF DECISION VARIABLES

Propagation of constraint is widely practiced approach for consistency checking of constraint (Li and Xiong, 2002). In this study, product realization is viewed as a process during which intervals of decision variables become small gradually and shrink into a point finally. Every time when a decision is made, constraint will propagate to deduce new interval of decision variables and if there is any one interval to be found empty, then conflict happens.

Generally in the initial stage of decision process, decision-makers determine the rough range of decision variables based on experience knowledge firstly and then adopt consistency algorithm to remove the redundant sub-intervals to reduce the searching space of design variables, which will quicken the efficiency of searching for robust scheme in the consistent interval in next step. Here, a consistency filtration algorithm based on interval arithmetic and arc consistency is designed which adopts interval constraints to estimate the consistent interval of decision variables. Before explaining details of the algorithm, some related definitions should be given out at first.

Definition 1: Interval vector: With R denotes the set of entire real numbers and RI denotes set of all closed intervals, $[a, b] \in RI$ means $\{x|a \le x \le b, x \in R\}$ and RI^n denotes n-dimension space on RI. If there are $X_1, X_2, \ldots, X_n \in RI$, then $X = [X_1, X_2, \ldots, X_n]^T \in RI^n$ is called the n-dimension interval vector on RI.

Definition 2: Extension of interval: Assumed that function mapping $f: R^n \rightarrow R$. If there is a interval mapping $F: RI^n \rightarrow RI$. Which makes $f(x_1, x_2, \ldots, x_n) \in F(X_1, X_2, \ldots, X_n)$ stands for $X_1, X_2, \ldots, X_n \in RI$, giving that $\forall x_1 \in X_1, x_2 \in X_2, \ldots, x_n \in X_n$ then F is called the interval extension of f.

Definition 3: Correlative matrix of constraint: After analyzing the relationship between constraints and variables, a matrix describing inclusion relationship between them is constructed which is called correlative matrix of constraint in which row and column denote constraint and variable, respectively.

$$M(ij) = \begin{cases} 1, \text{ constraint i include variable j} \\ 0, \text{ constraint i not include variable j} \end{cases}$$

The pseudo code of proposed consistency algorithm for interval filtration is showed as follows:

```
Do
{For j=1 to l
    For i=1 to k
        If (M(ij)=1) then
            ∩X_j = F_i^j(X_q), X_q ∈ X and q ≠ j
        End If
        If (∩X_j = φ) then
            Conflict happens and designer must give out new initial
            range of variables again.
        End If
    End For
End For} While (not convergent of variable range)
```

The operation rules of interval arithmetic are as follows:

$[a, b]+[c, d] = [(a+c), (b+d)]$
$[a, b]-[c, d] = [(a-d), (b-c)]$
$[a, b]\times[c, d] = [\min(ac, ad, bc, bd), \max(ac, ad, bc, bd)]$
$[a, b]/[c, d] = [\min(a/c, a/d, b/c, b/d), \max(a/c, a/d, b/c, b/d)]$

ROBUST DECISION MODEL BASED ON CONSISTENCY INTERVAL

The objective of robust decision is to reduce quality loss of product which often results from two type of

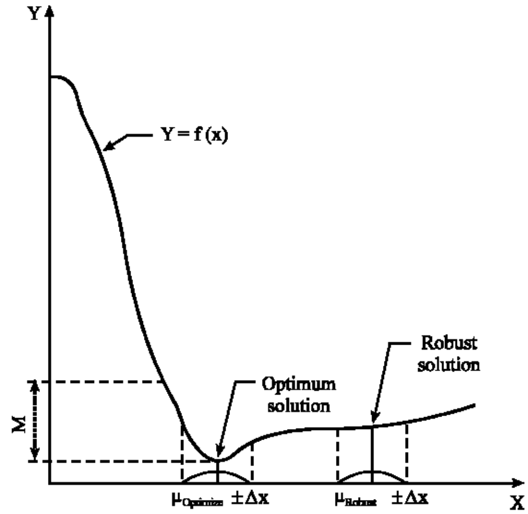

Fig. 3: Robust design considering the variation of variables (Chen and Lewis, 1999)

disturbed source classified as noise and uncertain parameters. Noise includes the environmental factors such as operational temperature and voltage. They are often uncontrollable and can be described as stochastic variables subject to some type of probability distribution. To gain some degree of flexibility for decision scheme, decision variables should be allowed to vary within a range without greatly affecting the product performance negatively. In this type of robust decision relating with uncertain variables, performance deviation are contributed by the variations of controllable decision variables rather than the noise factors. This means performance deviation can be controlled within an acceptable range by selecting robust value for decision variables. What is relevant to this study is the later, that is, robust decision considering uncertain designs variables which are often due to manufacturing and technical factors in practice.

The philosophy behind this type of robust decision is shown in Fig. 3.

For purpose of illustration, assume that the performance is a function of only one variable x. Generally, in this type of robust decision, to reduce the deviation of response caused by variations of decision variables. Instead of seeking the optimum value, decision-makers are more inclined to select the flat part of performance curve near the performance target. If the objective is to move the performance function toward target M, robust decision of this study is to study how to determine decision variables to make the resulting variation of performance response is always in the acceptable range when decision variables vary within the region $\pm\Delta x$ of their means.

The difference between robust decision and optimum decision lies in that the later only pursue optimization of decision objective and ignore the influence of variation of decision variables on performance of product. But robust decision stress on making decision based on balance between decision objective and objective fluctuation. For a minimum problem, the general formulation of robust decision can be described as:

Given:
$x \in [x^L, x^U],\ \Delta x$
$x^L = (x_1^L, x_2^L, ..., x_n^L)$
$x^U = (x_1^U, x_2^U, ..., x_n^U)$
Find: x
Minimize: $[u_f, \sigma_f]$

$$\text{Subject to:}\quad g_j + k_i \sum_{i=1}^{n} \left|\frac{\partial g_j}{\partial x_i}\right| \Delta x_i \tag{3}$$

where, x denotes decision variable and Δx denotes variation of x. u_f is the means of objective. σ_f is the deviation of objective and g_i is the design constraint. Equation 3 is a general model of robust decision for minimum problem which can also be applied to other type of problems once some modifications are made to it. Equation 3 can be converted into maximum formulation based on prior analysis where UR is the upper bound of decision objective.

$$\text{Maximize:}\quad [UR - u_f, \frac{1}{\sigma_f}] \tag{4}$$

In the same way, for maximum problem and the matched problem, their objective function can be expressed respectively as follows where, LR is the low bound of decision objective:

$$\text{Maximize:}\quad [u_f - LR, \frac{1}{\sigma_f}] \tag{5}$$

and

$$\text{Maximize:}\quad [\min[UR - u_f, u_f - LR], \frac{1}{\sigma_f}] \tag{6}$$

In view of the statistics probability distribution of stochastic variables, the new objectives can be normalized as follows:

$$\text{Maximize}: C_{dk} = C_{du} = \frac{UR - u_f}{3\sigma_f} \tag{7}$$

$$\text{Maximize}: C_{dk} = C_{dl} = \frac{u_f - LR}{3\sigma_f} \tag{8}$$

$$\text{Maximize}: C_{dk} = \min\left[\frac{UR - u_f}{3\sigma_f}, \frac{u_f - LR}{3\sigma_f}\right] = \min\,[C_{du}, C_{dl}] \tag{9}$$

where, C_{dk} is called design capability indices which means the satisfaction degree of product performance to design requirements (Chen *et al*., 1999). In a case in which larger is preferred, all possible design solutions meet design requirements when u_f-LR>3σ. In a case in which the design performance is required to be as small as possible, all possible design results fall into the target range of design requirement when UR-u_f>3σ. And in the case in which nominal is preferred, all possible design results fall into the range between UR and LR and the target value is the midpoint between these two limits in which all possible results meet the requirement when min [UR−u_f, u_f−LR]>3σ. So, C_{dk}>1 in fact means that fluctuated product performance caused by variation of decision variables are always within the permissive range of design requirement. This shows that decision scheme is robust and the robustness increases with the increase of value of C_{dk}. The philosophy of above ideas is showed in Fig. 4.

In all above formulas, UR and LR are appointed by designer and u_f and σ_f are calculated as follows:

$$u_f = f(x) \tag{10}$$

$$\sigma_f = \Delta y = \sqrt{\sum_{i=1}^{n} (\tfrac{\partial y}{\partial x_i})^2 \Delta x_i^2} \tag{11}$$

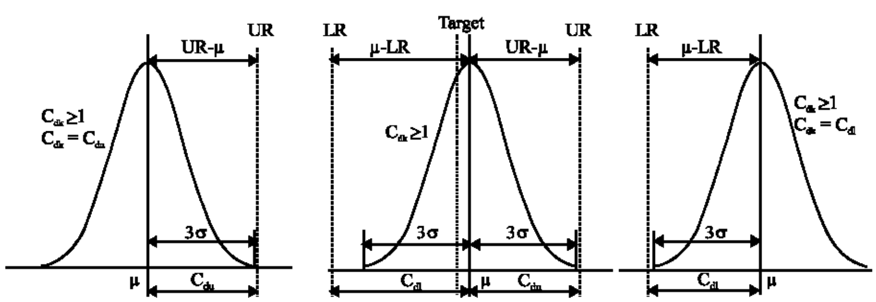

Fig. 4: Design capability indices (Chen *et al*., 1999)

According to arc consistency of constraints we can know that all constraints are sure to be satisfied by any value within the consistent interval of decision variables. So, the robust decision based on consistent interval will not consider detailed disciplinary constraints any more and the robust decision model with design capability indices is described as:

$$\text{Given}: x \in [x^{\bar{L}}, x^{\bar{U}}], \Delta x$$
$$x^{\bar{L}} = (x_1^{\bar{L}}, x_2^{\bar{L}}, \ldots, x_n^{\bar{L}})$$
$$x^{\bar{U}} = (x_1^{\bar{U}}, x_2^{\bar{U}}, \ldots, x_n^{\bar{U}})$$

Find: x
Maximize: $C_{dk} = (C_{dk1}, C_{dk2} \ldots C_{dkk})$
s.t: $C_{dki} > 1, i = 1,2,\ldots,k$ (12)

This is a multi objectives constraint optimization model. It can be easily noted that a typical feature of this model is that its objective and constraint is same, that is to say every objective function is also a constraint function. With this feature we propose a new feasibility censor based immune chaotic algorithm.

FEASIBILITY CENSOR BASED IMMUNE CHAOTIC ALGORITHM

Aiming at the founded robust decision model, a feasibility censor based immune chaotic algorithm is developed for model solving. New algorithm adopts clone extension and clone mutation of immune algorithm to guarantee global optimization and chaotic algorithm to perform more meticulous local searching. Sensitivity to the initial value, traverse and dynamization of chaotic variables make chaotic algorithm be easier to skip out local optimum and find the global optimized solution (Li and Jiang, 1998). And also the super mutation is applied to those inferior antibodies within antibody troop to improve the variability of troop which can prevent algorithm from stagnating into the local optimum. In view of the feature of proposed robust decision model, the feasibility censors based approach is adopted to deal with constraint which means that for any antibody, its feasibility will be judged at first. If it is feasible for all constraints, then add it into the antibody troop. Otherwise, if any one of constraints cannot be satisfied, this antibody will be abandoned.

The details about the new algorithm are shown as follows:

(1) **Parameters setting:** Determine the size of antibody troop N_0, amount of antibodies for clone selection N_s, multiple of clone extension q, mutation probability P_m and amount of antibodies for super mutation N_m
(2) Production of initial population X_0
 (2a) Let j = 0. If a antibody includes l genes, then select randomly l initial value $z_i^0[0,1]$ (i = 1, 2,..., l)
 (2b) Adopt Logistic model of Eq. 13 to produce l chaotic variables:

$$z_i^{j+1} = \mu z_i^j (1 - z_i^j) \tag{13}$$

where, z is chaotic variables, i is the sequence number of chaotic variables, j is amount of iteration, μ is chaotic factor which generally equal to 4. Antibody is encoded by real number. So, l chaotic variables will be mapped to solution space of real number with Eq. 14:

$$x_i = \underline{x}_i + z_i^{j+1}(\overline{x}_i - \underline{x}_i) \tag{14}$$

 (2c) Judge whether or not the antibody satisfies all constraints, that is, to judge whether

$$C = \sum_{i=1}^{k} \{\min(0, (I_i - 1))\}^2 = 0$$

 stands. If yes, then add the antibody into antibody troop and let j = j+1. Otherwise, abandon it
 (2d) if j = N_0-1, then turn to step 3. Otherwise, turn to step 2b
(3) Calculate fitness of antibody to antigen and order antibodies according to descending fitness which here is view as the linear weighted addition and calculated as Eq. 15:

$$\psi(X) = \sum_{i=1}^{k} (\omega_i I_i) \tag{15}$$

where, ψ(X) is fitness of antibody and ω_i is weight of objective i
(4) **Clone selection:** To select the first N_s antibodies to form the antibody troop X_s for clone extension
(5) **Clone extension:** Each antibody in X_s is replicated q times to form antibody troop X_c. That is:

$$x_1 + x_2 + \ldots + x_N \xrightarrow{\text{clone extension}} \{x_1^1 + x_1^2 + \ldots + x_1^q\} + \ldots + \{x_N^1 + x_N^2 + \ldots + x_N^q\}$$

(6) **Clone mutation:** Every antibody in X_c is performed little-step gauss mutation to produce a new troop of antibody X_m. Specifically, an antibody include two piece of information (x,σ) in which x show a point in solution space and x' denote deviation of x. In the

same way, the antibody in son generation also includes two piece of information x' and σ' which are calculated respectively as:

$$\sigma' = \sigma e^{N(0,\,\Delta\sigma)} \tag{16}$$

$$x' = x+N(0,\Delta\sigma') \tag{17}$$

where, N(0, Δσ) is independent gauss stochastic number vector with means as 0 and deviation as σ

(7) Combine the father generation X_0 and son generation X_m. That is $X_0 \cup X_m$. After checking the feasibility of all antibodies in $X_0 \cup X_m$, the antibodies not satisfying constraints are abandoned and the rest is ordered according to descending fitness. In the ordered antibody troop, the first N_0 antibodies are selected to form new antibody population X_U from which N_s antibodies are then selected for meticulous local search.

Firstly, the neighborhood of each antibody for local search is constructed. The neighborhood of some point is an l-dimension sphere with r as radius and centered at this point. For convenience, the super cube is adopted to approximate the sphere to construct neighborhood. A super cube neighborhood of some point is a cube with 2r as radius and centered at this point. That is:

$$\prod_{i=1}^{l}[x_i - r_i, x_i + r_i]$$

Assume $x = (x_1, x_2,\ldots, x_l)$ is the antibody for local search. The new antibody produced by local search can be calculated with following formula:

$$x' = x + r(2z^{j+1} - 1) \tag{18}$$

where, $z^{j+1} = (z_1^{j+1}, z_2^{j+1},\ldots,z_l^{j+1}) \in (0,1)^l$ is the vector of chaotic variables.

$$x_i' \in [x_i - r_i, x_i + r_i],\ x' \in \prod_{i=1}^{l}[x_i - r_i, x_i + r_i],\ r = (r_1, r_2,\ldots,r_l)$$

is the neighborhood's radius vector of antibody. Adaptable search strategy is adopted for local search, which means the antibody with greater fitness is searched more meticulous with smaller search radius. So, the neighborhood radius of search is defined as:

$$r_i = \exp\left(-\frac{\delta(N_s - i)}{N_s}\right) \tag{19}$$

where, δ is the controlling parameter of neighborhood radius.

(8) In order to prevent algorithm from stagnating into local optimum, the worst N_m antibodies within X_U are selected to perform super mutation to increase variability of antibody troop. Here, super mutation operator adopt uniform mutation rather than gauss mutation because the later can produce antibodies only nearby the original ones, but the uniform mutation can produce antibodies far away from the original ones, which makes larger solution space can be explored.

Uniform mutation produces new antibodies generally through adding random number from some range onto the genes of original antibodies. It basic method is showed as:

$$x_i' = x_i + \Delta_i\ \alpha_i r \text{ and } (0, 1)\ (i = 1, 2\ldots l) \tag{20}$$

where, α_i is the contracting factor of range and rand (0, 1) is the random number within the range [0, 1]. Δ_i is defined as:

$$\Delta_i = \begin{cases} \underline{x}_i - x_i, & r \text{ and } (0,1) < 0.5 \\ \overline{x}_i - x_i, & r \text{ and } (0,1) \geq 0.5 \end{cases} \tag{21}$$

(9) Judge whether or not the stopping criterion is met. If yes, then stop and output the antibody with largest fitness as the optimum solution and the decision scheme of product realization. Otherwise, let $X_0 = X_U$ and turn to step 3.

DESIGN OF A BEAR AND ROTOR SYSTEM

Bear and rotor system is a pivotal assembly in large-scale rotating machinery. In its design, tribology and dynamics affect each other and constraint each other, which result in complex couple relation between them. So, this assembly's design is a multidisciplinary collaborative decision problem considering synthetically both tribology and dynamics performance requirement.

Only guaranteeing machinery working well in steady area is not enough to design rotating machinery with good stability. Stability margin is also an important factor needed to be considered in design of such machinery, that is designed machinery should possess some degree of stability margin to resist all kinds of outside interference. So, robust design approach should be adopted to the design of this type of machinery in order to obtain robust product scheme.

A single disk and elastic rotor with symmetrical mass is taken as example to validate the effectiveness and reliability of proposed robust decision approach. This shafting is representative and typical for it is the

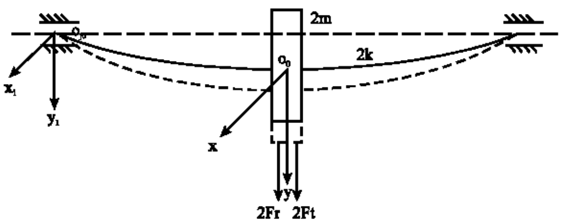

Fig. 5: Elastic rotor with singular disk and symmetrical mass

simplified model of bear and rotor system in real large-scale rotating machine. It is the basis for design of complex large-scale shafting. Reliability guaranteed by tribology and stability guaranteed by dynamics are of equal importance in design of this shafting and they are two areas of mutual coupling, which makes design of this shafting complex and need collaborative decision considering synthetically tribology and dynamics (Xie, 1999). Figure 5 is the sketch map of this shafting in which a disk with mass 2 m = 520 kg is fixed on the midpoint of a piece of elastic shaft with no mass and the rigidness on midpoint of the shaft is $2k = 2.104\times10^{8}$ N m^{-1}. The working rotation velocity is N = 3000 rpm and the diameter of shaft is d = 114 mm. Shaft is mounted on a pair of ellipse bears. The points o_{j0}, o_0 in Fig. 5 denote respectively the center of shaft neck and center of disk in the state of static balance. The real lines show positions of shaft and disk in the state of static balance and the broken lines show positions of shaft and disk in the state of eddy. The deviations of disk' center and of shaft neck's center from their respective static positions are different due to the elasticity of shaft. Two coordinate systems xo_0y and $x_1o_{j0}y_1$ are established in which the origins are respectively the central position of disk o_0 and central position of shaft neck o_{j0} in state of static balance. (x, y) and (x_1, y_1) represent deviation from static balance position of disk's center and shaft neck's center, respectively. Design objective of this shafting is to select appropriate structural and operational parameters for the bears in order to make all requirements of tribology and dynamics be satisfied and also designed shafting possess some degree of stability margin.

For shaft is mounted on two symmetrical ellipse bears, only one of them is designed here. The main design variables of ellipse bear include length to diameter ratio denoted as l/d, clearance ratio denoted as ψ and ellipticity represented as γ. Design variable and objective of tribology are respectively selected as ψ and increase of temperature ΔT. Design variables of dynamics are selected as l/d and γ and objective as minimum logarithmic decay ratio δ_{min}.

(1) Decision model of tribology and dynamics

The decision model of tribology is described as:

$$\text{Given}:\begin{cases}(l/d)\in[(l/d)^L,(l/d)^U]\\ \gamma\in[\gamma^L,\gamma^U]\end{cases}$$
$$\text{Find}: \psi^{rbt}\in[\psi^L,\ \psi^U]$$
$$\text{s.t: } C_f=(C_{f1}, C_{f2},..., C_{fn})$$
$$\text{Minimize: } \Delta T$$

where, $C_i(i = f\,1,\dots,fn)$ is design constraints of tribology which mainly include minimum thickness of oil film, press of bear and consumption of power.

The decision model of dynamics is described as:

$$\text{Given}: \psi\in[\psi^L,\psi^U]$$
$$\text{Find}:\begin{cases}(l/d)^{rbt}\in[(l/d)^L,(l/d)^U]\\ \gamma^{rbt}\in[\gamma^L,\gamma^U]\end{cases}$$
$$\text{s.t: } C_d=(C_{d1}, C_{d2},..., C_{dm})$$
$$\text{Minimize: } \delta\text{min}$$

$C_j(j = d1,\dots,dm)$ are the design constraints of dynamics which mainly include critical rotation velocity, unbalance response and instability rotation velocity.

(2) Determination of initial feasible range of design variables

Length to diameter ratio has notable influence on the performance of bear. For dynamic pressure bear, increase of l/d will result in reduction of quantity of oil leakiness, decrease of pressure loss of oil film and weakening of the carrying capacity. Generally l/d ratio is selected from the range [0.1, 3.0].

Clearance ratio has also great influence on minimum thickness of oil film and carrying capacity of bear. Too large clearance ratio will lead to decrease of carrying capacity but too little one may lead to damage of bear due to fast rising temperature. So, ψ generally lies in the range [0.0001, 0.006].

Based on experience, ellipticity generally is limited in the range [0,0.9].

(3) Because constraints and objectives of both tribology and dynamics can be evaluated only through simulation rather than analysis method, so the RRSs of two disciplines can be obtained by RSM. Finally, the RRSs of tribology and dynamics are, respectively as follow:

$$l/d = -0.218840+1383.333762\psi-446826.244264\psi^2$$
$$\gamma = 0.754360-132.786656\psi+17226.595085\psi^2$$
$$\psi = -0.005678-0.016118(l/d) + 0.040872\gamma+\dots0.064420\gamma(l/d)-0.014230(l/d)^2-0.074273\gamma^2$$

(4) Consistency filtration for range of decision variables

Various RRSs from tribology and dynamics constitute constraint net of collaborative decision of bear design. The general consistency filtration algorithm which combines arc consistency algorithm with interval arithmetic is adopted to filtrate the initial range of decision variables and final consistent intervals of variables are showed in Table 1.

(5) Search for robust value of design variables in the consistent intervals

To find the robust design solution in the consistency intervals, parameters of feasibility censor based immune chaotic algorithm are set as follows. Size of initial troop of antibody N_0 is 50. Amount of antibodies for clone selection N_s is 20. Multiple of clone extension q is 5. Mutation probability (P_m) is 1. Amount of antibodies for super mutation is 20 and algorithm will stop after 20 generations. Variation of each variable is set as 10% of the size of respective consistency interval. The upper limit of design objective ΔT of tribology is set as 40 and lower bound of design objective δ_{min} of dynamics is set as 0.1. The robust design results are shown in the Table 2.

After obtaining the consistency variables interval, if not the robust decision approach but the optimum approach is applied to find product realization scheme, then the resultant scheme is shown in Table 3. The objective of optimum decision is same as the one of robust decision.

From the results shown in Table 1-3 we can see that two schemes from both robust decision and optimum decision all satisfy design requirements. But the minimum logarithmic decay ratio of robust decision scheme is less than the one of optimum decision scheme and increase of temperature of robust scheme is larger than that of optimum scheme. This is because the optimum approach pursues only the optimum of objective without considering the robustness of scheme which means sensitivity of design scheme to variable's variation and probable resultant violation of constraint or degrades of product's performance. However, in another hand, robust decision approach tries to find a design scheme which can resist some degree of variation in small range of variable based on considering synthetically optimization of objective and variation of objective. It makes the response of objective function always lie within the permissible range limited by prescribed upper and lower bound when decision variables vary stochastically in some range. This can be validated by the fact that the design capability indices of robust decision approach is 2.376, but design capability indices of optimum approach is 0.884. So, the decision scheme obtained by robust approach is more reliable than the scheme obtained by optimum approach.

The diagrams below just show the concept of robustness in this study, that is, instead of seeking the optimum value, decision-makers are more inclined to select the flat part of performance curve near the performance target. Figure 6, although the minimum logarithmic decay ratio corresponding to 0.6975, the

Table 1: Initial range and consistency interval of decision variables

Variables	Low bound of initial range of variables	Upper bound of initial range of variables	Low bound of consistency interval of variables	Upper bound of consistency interval of variables
l/d	0.1000	3.000	0.3000	1.000
ψ	0.0001	0.006	0.0015	0.003
γ	0.0000	0.900	0.5000	0.800

Table 2: Robust design result of single disk and elastic rotor with symmetrical mass

l/d	ψ	γ	Unbalance response α (μm)	Minimum logarithmic decay rate δ_{min}	Instability rotation velocity n_{st} (r min^{-1})	Critical rotation velocity n_c (r min^{-1})
0.5898	0.0025	0.5431	23.7590	0.1598	12424.0400	38165.6309
Load of bear W (N)	**Eccentricity (ε)**	**Eccentric angle (θ)**	**Minimum thichness of oil film h_{min}(μm)**	**Consumption of power N_t(kw)**	**Leaked quantity of oil Q (mL sec^{-1})**	**Increase of temperature (Δt)**
2548	0.3730	76.4494	0.0387	1.0722	119.7355	5.2346

Table 3: Optimum design result of single disk and elastic rotor with symmetrical mass

l/d	ψ	γ	Unbalance response α (μm)	Minimum logarithmic decay rate δ_{min}	Instability rotation velocity n_{st} (r min^{-1})	Critical rotation velocity n_c(r min^{-1})
0.6975	0.0029	0.5000	26.4390	0.2914	10633.6975	38165.6309
Load of bear W (N)	**Eccentricity (ε)**	**Eccentric angle (θ)**	**Minimum thichness of oil film h_{min}(μm)**	**Consumption of power N_t (kw)**	**Leaked quantity of oil Q (mL sec^{-1})**	**Increase of temperature (Δt)**
2548	0.4003	75.9420	47.5100	1.1194	145.2153	4.5059

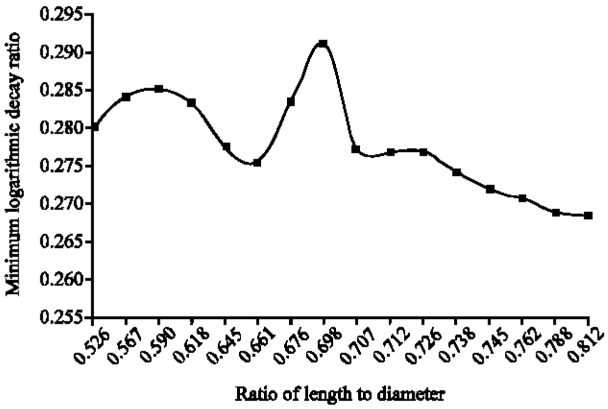

Fig. 6: Variation of minimum logarithmic decay ratio to ratio of length to diameter

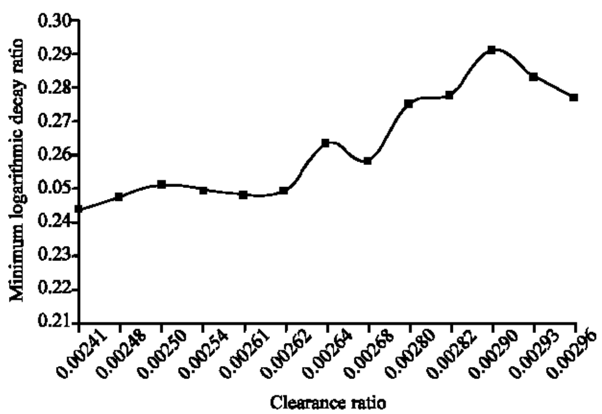

Fig. 7: Variation of minimum logarithmic decay ratio to clearance ratio

optimum value of ratio of length to diameter, is larger than that corresponding to 0.5898, the robust value of ratio of length to diameter, the curve near the robust value is more flat than curve near optimum value. This means that the dynamic performance of designed bear and rotor system adopting the robust value is more capable of resisting the variation of ratio of length to diameter than that adopting optimum value. Figure 7, we can see same scenario that the curve near robust value of clearance ratio 0.0025 is more flat than that near the optimum value 0.0029. In the same way, from the curve in Fig. 8, we also can see that the robust value and optimum value of ellipticity are, respectively 0.500 and 0.543.

Using traditional design method to deal with decentralized multidisciplinary decision problems often incurred many times of iterations between different disciplines. Taking bear and rotor design as example, in traditional design process it is firstly designed by one designer (dynamics or tribology) and then all design

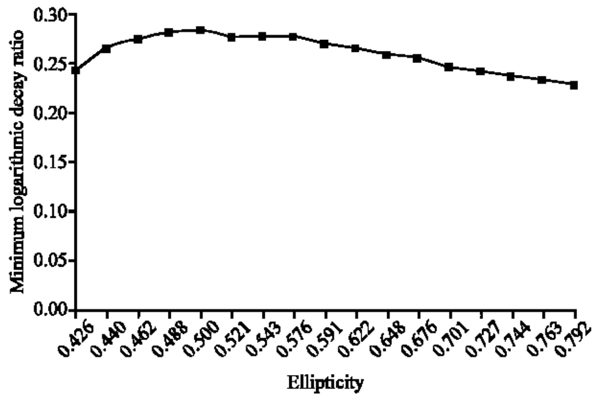

Fig. 8: Variation of minimum logarithmic decay ratio to ellipticity

information is sent to second designer (tribology or dynamics). The second designer makes decisions based on the first designer's decisions and if he can make his own decision to finish the design, then the whole design process is finished. Otherwise, if second designer can not make rational decisions based on the first designer decisions, then second designer will feedback some conflict information to first designer to modify his decision. This process is called iteration. Often the design can not be finished within just one iteration. This process may be complex and long which leads to the decline of design efficiency and quality. Unlike traditional method, the proposed multidisciplinary collaborative decision method in this study just need to transmit the RRS of one discipline to another, then each discipline can make his proper decision based on the RRS just in once. From this view, we can see that proposed collaborative decision method is more robust and efficient than traditional method. And also the information amount transmitted between different disciplines is reduced greatly compared to traditional method. It is exciting that this advantage will be doubled when a design process involves more disciplines.

CONCLUSIONS

The complex modern product realization processes requires collaborative study from different disciplines. In collaborative design environment, designers subject to different disciplines are distributed geographically. So, a powerful distributed multidisciplinary collaborative decision method is a guarantee to design a qualified product. We use principles from non-cooperation game theory to model the relationship between engineering teams and facilitate collaborative decision making under decentralized decision environment. The proposed decision approach in this study can be divided into two steps. Firstly, non-cooperation game theory is adopted to model the relationships between distributed design teams in geography and decentralized multidisciplinary collaborative decision problem are described as RRS constraint net based interval constraint solving problem. A kind of general consistency algorithm for range filtration is designed to eliminate the redundant region in initial intervals of decision variables to obtain consistent interval vector of variables. This can reduce the space of decision variables effectively and enhance the efficiency of searching for robust scheme. Because any value of decision variables in consistent interval satisfies all design constraints, detailed disciplinary constraints are not considered any more for the systemic search within consistent interval, which make problem solving be easier and efficiency improve greatly. Secondly, a roust decision model is constructed based on consistent intervals and design capability indices with which the robust design decision scheme is obtained by systemic search using feasibility censor based immune chaotic algorithm. Proposed approach in this study reveals the connotation and nature of multidisciplinary collaboration decision problem and can achieve genuine decentralized collaborative decision. Decision process is consistent with general real process of engineering design and so has strong practicability and generalization. Bear and rotor is a kind of important assembly in turbine, aero-engine and rocket-engine whose design involves conflict decouple of dynamic and tribology. The complex coupled relationship between the two disciplines often lead to decline of efficiency and quality of rotor design. Present proposed collaborative decision method is mainly designed for network based collaborative design environment where traditional design method can not achieve decentralized collaborative decision. Proposed decision method is applied to the design of an elastic rotor with single disk in network based collaborative environment. The design process shows that proposed method is easy to implement and the design results validates the effectness and efficiency.

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