Multidisciplinary design optimization of complex products based on data fusion and agent model

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Abstract

Multidisciplinary design optimization (MDO) of complex products is discussed in this article. For the characteristics of higher order, high-dimensional, multi-input and multi-output in design of complex products, application of MDO in design and optimization of complex products is difficult. An effective MDO framework combined with the method of data fusion and agent model is proposed. Firstly, date fusion is applied to deal with the process with a large number of incomplete, vague and uncertain in complex product's evaluation and optimization; secondly, agent model is used to reduce the complexity of the MDO model; and finally, MDO is applied to complex products design and optimization according to the collaborative design and optimization method. In order to identify the feasibility of this method, the design of diesel engine motion mechanism is discussed and shown a good result. The current study provides a powerful tool for complex products designing and optimization and owns great theory and practical values.

Keywords: Complex Products, MDO, Date Fusion, Agent model

1 Introduction

Complex products are composed by a number of associated or interacted components (factors). Design of complex products involves different coupled disciplines and large numbers of design variables, which lead to multi-inputs and multi-outputs in the design process. The design freedom of complex products is greatly reduced while the field of knowledge involved in the design process increase [1]. As shown in Figure 1, the stage of conceptual design owns the highest degree of freedom for there is less knowledge involved; along with the design stage increased, the design freedom will rapid decreased for there are more and more design knowledge and involved knowledge.

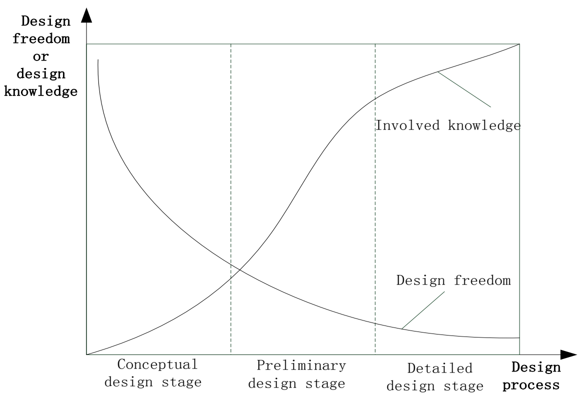

FIGURE 1 Design process of complex products

In order to reduce the difficulty of product development and obtain the best performance of complex products, it is important to consider the coupled performance in various disciplines and discover the potential information in the design process. Traditional design optimization method neglects the coupling of different disciplines and cannot deal with large number of design variables and often leads to the failure of design process, and then multidisciplinary design optimization (MDO) method is developed [2].

MDO takes advantage of the interactions between disciplines as well as to improve the product development time and has emerged as a new technology dealing with the design of complex systems. MDO were applied primarily to design of aeronautics, astronautics and automobile, and the techniques have been in development over the last decade [3, 4], including: (1) MDO theory and algorithms research [5, 6], including system modelling and decomposition, optimization algorithms and the methods of space design searching; (2) Methods of multidisciplinary analysing [7, 8], including mathematic model, sensitivity analysis, design of experiment, agent model and so on; (3) Research of software integration framework for MDO based on the in-depth study of MDO theory and methods.

However, for the characteristics of higher order, high dimensional, multi-input and multi-output in complex systems, application of MDO in design and optimization of complex products is difficult. The purpose of this article is presenting an effective framework for the design of complex products combined with the method of data

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fusion, agent model and MDO. Firstly, date fusion is applied to deal with the process with a large number of incomplete, vague and uncertain in complex product's evaluation and optimization; secondly, agent model is used to reduce the complexity of the MDO model; and finally, MDO is applied to complex product design and optimization according to the collaborative design and optimization method. In order to identify the feasibility of this method, the design of diesel engine motion mechanism is discussed and shown a good result.

2 Principles of data fusion for complex systems

Data fusion was firstly applied in the field of military. According to the statistics, 54 data fusion systems in the military electronic systems have been applied in the United States up to 1991, and 87% have been used for experimental prototype, which proved to be usefulness. Oregon State Science and Technology Research Institute have carried out for research and discussion of the theory and application of a wide range of data fusion; New York State University has set up a multi-source information fusion centre for the research of fusion framework; and British BAE System company has developed a new technology which is called distributed data fusion and integration (Decentralized Data Fusion, DDF). In recent years, the technology of data fusion is greatly developed, and the research has been applied in automatic control, target identification, traffic control, process monitoring, navigation, repair of complex machine and robot, and so on.

2.1 DEFINITION AND THEORY OF DATA FUSION

Data fusion is an information process used for decision-making and estimation according to certain criterion and the information obtained by several sensors. The objective of data fusion is to derive more information by data combination and synergism and improve the effectiveness of the sensor system. Currently, data fusion has been a combination of many traditional disciplines and emerging multi-disciplinary engineering. Because of the highly development and mutual penetration of these disciplines and fields, data fusion methods exhibit the characteristics of diversity and pluralism. The general data fusion technologies include association analysis, judgment or detection theory and estimation theory. Association analysis is a method can be used for mining hidden implicit relationship between the data appear to be unrelated. Data fusion is a great technology dealing with the MDO problem of complex products, which involves the characteristics of higher order, high dimensional, multi-input and multi-output.

2.2 DATA FUSION METHOD BASED ON ASSOCIATION ANALYSIS

The process is described as follow:

(1) Questionnaire module: gathering the feedbacks of design parameters from the expert and providing data for optimal design. The experts evaluate the design parameters with scores ranging from 1 to 10 which represent the importance of the parameters;

(2) Database or data warehouse: saving feedback information collected from the questionnaires;

(3) Normalize of the design parameters: The normalized of the design parameters can be expressed as follows:

$$y=(x\text{-Min Value})/\ (\text{Max Value-Min Value}), \qquad (1)$$

where: x, y are the values before and after conversion respectively; Max Value, Min Value are the maximum and minimum of the samples respectively.

(4) Evaluation of the weight of the parameters: determine the weight of every design parameters.

(5) Information fusion: checking and correcting the reduction's parameters according to the expert's evaluation. In order to verify the validity of the model, the correlation coefficient and the target residuals need to be obtained. Correlation coefficient, also known as linear correlation coefficient, is an indicator measuring the linear correlation between the variables. The target residual is the difference between the observed and predicted values, that is, the difference between the actual observations and regression estimates.

(6) User Interface: show the optimized results to the designer.

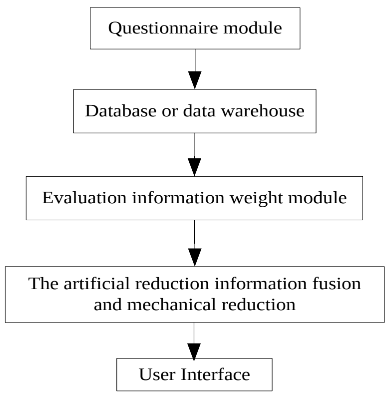

FIGURE 2 Data fusion-based evaluation and optimization architecture

3 Agent Model for complex products

The efficiency of MDO for complex products is seriously affected by large number of optimization variables and large scale of analysis model. Agent model is useful in reducing the analysis time. As shown in Figure 3, the agent model constructs math function in design space to express the relationship between the design variables and the system response. In the other word, agent model uses math function taking the place of simulation analysis. Because the math function is much simpler than simulation model, it can sharply cut down the design and analysis time.

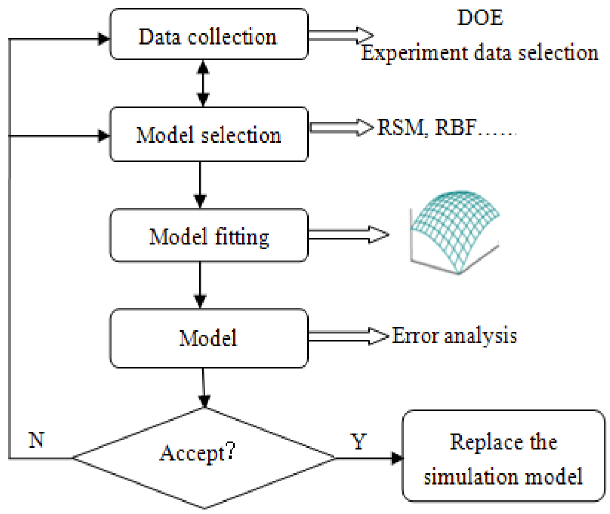

FIGURE 3 Design flow of MDO based agent model [10]

The common agent models are response surface model (RSM), Radial basis function neural network model (RBS) and so on. RSM is based on the knowledge of statistics and mathematic and using simple mathematical expressions (commonly the lower level polynomial) take the place of actual analysis model. Two-level polynomial model is the most commonly used agent model and can be expressed as follow [11]:

$$\tilde{F}(X) = a_0 + \sum_{i=1}^{N} b_i x_i + \sum_{i=1}^{N} c_{ii} x_i^2 + \sum_{ij(i<j)} c_{ij} x_i x_j \,. \tag{2}$$

Here N is the number of input various, x_i is the ith input various, a, b and c are the polynomial coefficients.

As an example, agent model for the function of $Y = X_1^3 + 4X_2$ is shown in Figure 4. Firstly, get samples by orthogonal experiment; secondly, establish the function of second-order response surface model.

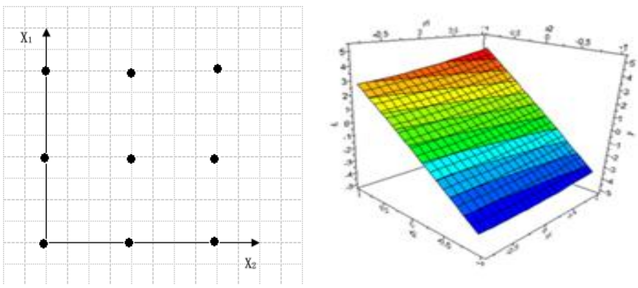

FIGURE 4 Construction Process of agent model formulation

And then, accuracy of agent model can be evaluated by the residual sum of squares:

$$R = \sum_{i=1}^{n} (F(X_i) \text{-} \tilde{F}(X_i))^2 \,. \tag{3}$$

4 MDO of complex products based on data fusion and agent model

In response to the large number of incomplete and uncertain reasoning process presented in the design and optimization process of the complex products, a theoretical framework for the multi-disciplinary design optimization of complex products is proposed this paper. Detail of the MDO framework combined with the method of data fusion and agent model is shown in Figure 5.

Basing the analysis of the MDO problem of complex products, the optimization objectives, constrains and variables can be extracted and large number of samples would be obtained based on the design of experiment (DOE). Then, data fusion algorithm is used to analyse the relationship between the objectives, constraints and design variables, and then the weight of each parameter can be obtained. In order to reduce the difficult of the MDO problem, the smaller weight parameters would be ignored. At the same time, data mining algorithm is often used for finding the potential information between the design parameters and objectives. At last, the agent model can be obtained using the method of response surface or neural networks to improve the MDO efficiency.

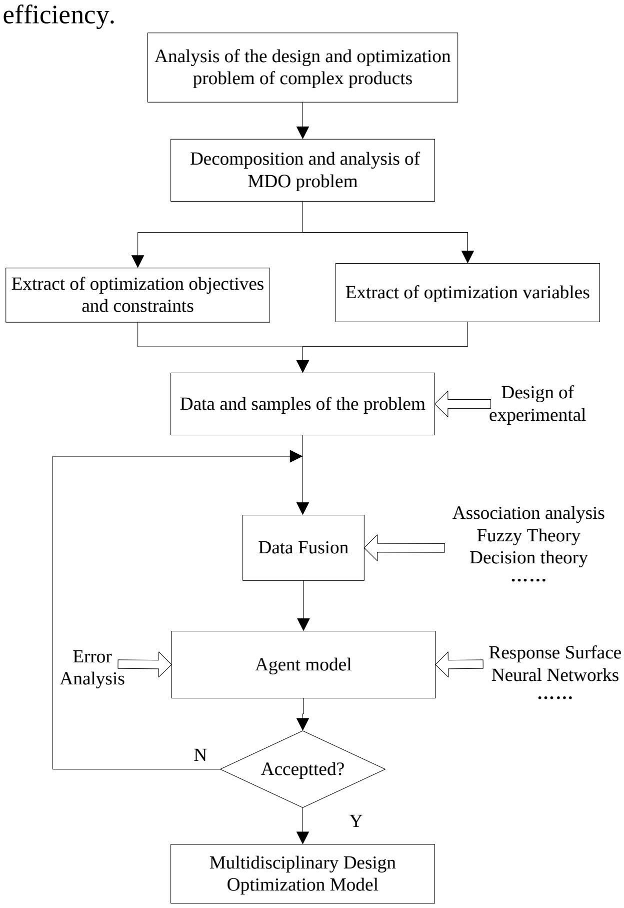

FIGURE 5 Framework of Multidisciplinary design optimization for complex products

5 Case studies

The diesel engine is a typical complex product. Designing of various parts of the diesel engine affects its overall performance. However, because of the large number of design parameters and their potential relationship, the best performance of the diesel engine is hard to obtain. The diesel engine motion mechanism of the diesel engine is selected as the complex product to identify the feasibility of MDO framework proposed above.

5.1 DESCRIPTION OF THE PROBLEM [12]

It is a typical multidisciplinary design optimization problem, which comes to different disciplines such as lightweight, thermal, vibration, kinematic and et.al. In this paper, three-dimensional parametric model of crankshaft-connecting rod-piston is founded. The dynamic characteristics of crankshaft-connecting rod-piston system is simulated in the software of ADAMS(Figure 6), getting the largest load of the small head of the connecting rod, which will be set as the boundary conditions for further analysis. The performance of modal and thermal of the piston is analysed by software of ANSYS. At the same time, the structural strength of the connecting rod can be got. In the end, the MDO platform is founded in the soft of ISIGHT for getting the best comprehensive performance of the diesel engine system.

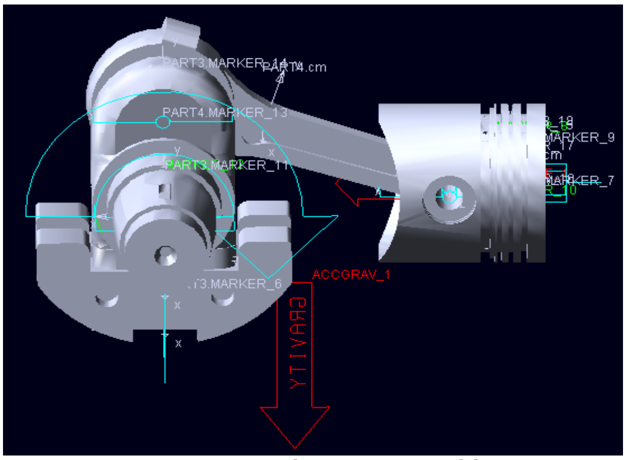

FIGURE 6 Diesel sports agency model

Table 1 lists the design parameters in the optimization of the diesel motion mechanism. D1, TK1…TK9, Hs_h and Hs_cs are design parameter. FEEQ1, FREQ1, FREQ3, STMAX and UMAX are design constraints and V is the objective function.

TABLE 1 the meaning of the link parameters (Unit: mm)

Variables	Initial value	Constraint	Remarks
TK1	27	25<TK1<29	Width of big ending of connecting rod
TK2	21.6	18<TK2<22	Width of small ending of connecting rod
TK3	15	13<TK3<17	Height of connecting rod side
TK4	8	6<TK4<10	Height of connecting rod notch
TK5	10	8<TK5<12	Transition radius of small ending of connecting rod
TK6	60	55<TK6<65	Transition radius of big ending of connecting rod
TK7	5	3<TK7<7	Transition radius of small end of connecting rod notch
TK8	7	5<TK8<9	Arc centre distance of big end of connecting rod notch
TK9	26	24<TK9<28	Centre distance of small end connecting rod notch to the centre of small end
Hs_h	8	6<Hs_h<10	Height of piston top shore
Hs_cs	5	3<Hs_cs<7	Depth of piston ring groove
D1	23	20<D1<26	Aperture of small ending of connecting rod
FREQ1			The first frequency of link
FREQ2			The second frequency of link
FREQ3			The third frequency of link
STMAX			Maximum stress of link in the compressed condition
UMAX			Maximum displacement of the lower link maximum load
V			Connecting rod volume

5.2 ANALYSIS OF MDO PROBLEM BASED ON DATA FUSION

Here, connecting rod, which involves many variables is selected to do data fusion analyses. The number of design parameters which affects the designing of connecting rod is fifteen. Based the design of experiment (DOE), it forms 400 effective historical data. Because of great difference between the design parameters, these parameters are normalized by the normalized linear conversion function. At the same time, the weight values of the design parameters are obtained by the method of least squares. It can be seen in Table 2 that the weights of nine parameters are below 0.05. These parameters can be removed from the design parameters because they own less impact on the optimization results. In the last, six parameters (D1, TK1, TK2, TK4, FREQ1, FREQ2) are selected as the design parameters. And then the complexity of the MDO process greatly reduced.

TABLE 2 Weight of the design parameters

Parameter	D1	TK1	TK2	TK3	TK4	TK5	TK6	TK7
Weight	0.1053	0.0613	0.1186	0.0127	0.0721	0.0094	0.0108	0.0062
Parameter	TK8	TK9	FREQ1	FREQ2	FREQ3	STMAX	UMAX	Co-coefficient
Weight	0.0007	0.0118	0.3407	0.1984	0.0383	0.0051	0.0086	0.9878

Furthermore, the correlation coefficient is calculated at 0.9878, which means the high degree of correlation between the optimization parameters, constraints and optimization goals. Compared to the mathematical models established by fifteen parameters (see Table 1) whose correlation coefficient is calculated at 0.9823, the mathematical models established by six parameters shown a great predictive ability. This fully illustrated that data fusion algorithm can reduce the dimension of MDO problem and greatly improve the efficiency.

5.3 MULTIDISCIPLINARY DESIGN OPTIMIZATION OF THE PROBLEM [12]

Collaborative optimization (CO) [13-15] is a two-level MDO algorithm proposed by Kroo basing the consistency constraints algorithm. The top level is called system optimizer, which optimizing the system variables in order to satisfy the compatibility and minimize the system objective. Every subsystem level optimizes the design variables in the subspace for minimizing the minimum mean square. The collaborative optimization solves the system design variables under the condition of meeting the subsystem constrains. At the same time, the system variables keep unchanged when optimizing the subsystem optimization. This algorithm avoids complex system analysis and makes every subsystem do the analysis and optimize simultaneously, which owns great convergence and reliability.

According to CO, the crankshaft-connecting rod-piston system can be divided into system level and subsystem level. The objective of the system level is to minimal the system mass, and the subsystem level includes four sub-disciplines which completes the analysis respectively under different constraints shown in Figure 7. For instance, connecting rod does the vibration and structural strength analysis, the piston does the vibration and thermal analysis and the whole system do the dynamics analysis.

Considering the objectives and constraints, the system optimization model can be founded:

$$\begin{cases} find\ \ x = \left(TK1...TK7, Hs_h, Hs_{cs}, D1\right) \\ \min\ \mathrm{W} = \mathrm{W1} + \mathrm{W2} \\ s.t.\ \sigma \le \sigma_{\max} \\ \quad T \le T_{\max} \\ \quad f \ge f_{\min} \\ \quad x^l \le x \le x^u \end{cases} \tag{4}$$

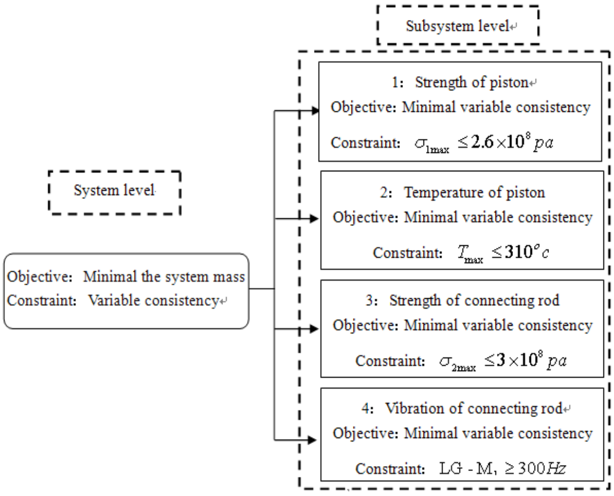

FIGURE 7 Collaborative multidisciplinary design optimization model of the diesel engine

Here x is the design variables, W is system mass, σ is the constraint of strength analysis, T is the constraint of thermal analysis, f is the constraint of vibration analysis, x^l and x^u are the lower and up limit of the design variables listed in Table 1.

According to the collaborative optimization algorithm and the MDO framework proposed above, the MDO collaborative model of crankshaft-connecting rod-piston is established in the soft of ISIGHT (see Figure 8):

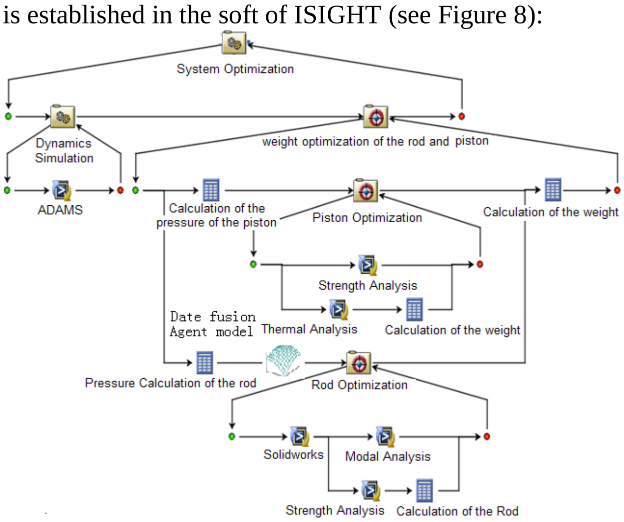

FIGURE 8 MDO collaborative model of crankshaft-connecting rod-piston

5.4 ANALYSIS RESULT

Selecting the nonlinear quadratic programming algorithm as the optimization algorithm, we obtain good results after the crankshaft-connecting rod-piston did 25 iterations, the piston subsystems did 699 iterations and connecting rod did 1961 iterations. Because agent model technology is used, the optimization time is reducing from more than 20 hours to less than 6 hours.

The results show that: mass of the system reduced from 1.02kg to 0.94kg, reduced about 7.51%, which is acceptable. The results of the design variables are listed in Table 3.

TABLE 3 Result of the design variables (Unit: mm)

Variables	TK1	TK2	TK4	Hs_h	Hs_cs	D1
Before optimization	27	21.6	8	8	5	23
After optimization	25.9	18	6	6	6.9	25.5

As shown in Table 4, the objective (system mass) gets the best result after several iterations and satisfies the constraint conditions. It also can be seen that the objective of diesel engine motion mechanism will affect the other disciplines (just like the subject of stress and natural frequent of the connection rod) because of the conflict and coupling of different disciplines. However, MDO along with agent model the second-order response surface model (RSM) and orthogonal array experimental method solved the problem and shown a good result.

TABLE 4 Comparison results of constraint and objective functions

Variables	Max stress of the piston (Pa)	Max temperature of the piston (ºC)	Max stress of the connection rod (Pa)	1st frequent of the connection rod (Hz)	System mass (Kg)
Before optimization	1.55e8	295	1.51e8	393	1.02
After optimization	1.31e8	300	2.1e8	300	0.94

6 Conclusions

In order to deal with the difficulty of the higher order, high-dimensional, multi-input and multi-output in MDO of complex products, an effective MDO framework combined with the method of data fusion and agent model is proposed in this paper. According to the MDO framework, date fusion is applied to deal with the process with a large number of incomplete, vague and uncertain in complex product's evaluation and optimization; agent model is used to reduce the complexity of the MDO model and improve the optimize efficiency. In order to identify the feasibility of the MDO framework, collaborative optimization algorithm and the MDO framework is applied to design of diesel engine motion mechanism and shown a good result. The current study provides a powerful tool for complex products designing and optimization and owns great theory and practical values.

Acknowledgments

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