Concept Optimization for Mechanical Product Using Genetic Algorithm

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Conceptual design is the first step in the overall process of product design. Its intrinsic uncertainty, imprecision, and lack of information lead to the fact that current conceptual design activities in engineering have not been computerized and very few CAD systems are available to support conceptual design. In most of the current intelligent design systems, approach of principle synthesis, such as morphology matrix, bond graphic, or design catalogues, is usually adopted to deal with the concept generation, in which optional concepts are generally combined and enumerated through function analysis. However, as a large number of concepts are generated, it is difficult to evaluate and optimize these design candidates using regular algorithm. It is necessary to develop a new approach or a tool to solve the concept generation. Generally speaking, concept generation is a problem of concept synthesis. In substance, this process of developing design candidate is a combinatorial optimization process, viz., the process of concept generation can be regarded as a solution for a state-place composed of multi-concepts. In this paper, genetic algorithm is utilized as a feasible tool to solve the problem of combinatorial optimization in concept generation, in which the encoding method of morphology matrix based on function analysis is applied, and a sequence of optimal concepts are generated through the search and iterative process which is controlled by genetic operators, including selection, crossover, mutation, and reproduction in GA. Several crucial problems on GA are discussed in this paper, such as the calculation of fitness value and the criteria for heredity termination, which have a heavy effect on selection of better concepts. The feasibility and intellectualization of the proposed approach are demonstrated with an engineering case. In this work concept generation is implemented using GA, which can facilitate not only generating several better concepts, but also selecting the best concept. Thus optimal concepts can be conveniently developed and design efficiency can be greatly improved.

Key Words : Conceptual Design, Genetic Algorithm, Optimization, Concept Generation, Intelligence

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1. Introduction

Conceptual design is the first step in the overall process of product design. However, it is a crucial and creative process, in which an optimal concept satisfying design requirements is required to be developed as a design result using a certain method or tool in order to implement the next detailed design. This above process is called concept generation. For a mechanical product its performance, quality, cost, and market to time are mainly embodied through the design concept. Compared with the detailed design stage, more emphases are laid on innovation of a concept which concerns the high level activities of brain in the conceptual design stage. So a large quantity of expert knowledge and brain intelligence are necessary in this process. Since it is a preliminary stage of product design, imprecision, uncertainty and lack of design information emerge. Thus the process of conceptual design can be regarded as a highly intellectualized, non-linear, and isomerous process (Park et al., 2003). As a result, the current conceptual design activities in engineering field have not been computerized to assist designer and it is still in a manual design stage which undoubtedly has an ill effect on the design efficiency, period, and quality to a large extent. The intellectualization and automatization of conceptual design has been a critical problem in the field of intelligent design.

Now in most of intelligent design systems, approaches of principle synthesis are widely used. Ermer et al.(1993) utilized bond-graphs and function-based models to develop a CAD system for conceptual design in engineering. Redfield (1992) employed bond-graphs as a tool to implement approach of system synthesis in mechanical system conceptual design. Zou (2003) introduced morphology matrix incorporating function carrier database to generate a number of mechanism systems on the basis of function analyse. Hoeltzel et al.(1990) suggested knowledge-based approaches for the creative design of mechanism, in which morphology matrix was used to implement the creative synthesis of mechanism. Yao and Huang (1998) proposed a "three steps" structure model of design catalogues for conceptual design of mechanical transmission and applied it in the intelligent design system.

Most of the above approaches have used a kind of tool such as morphology matrix, bond graph, or design catalogues incorporating expert system to deal with the concept generation, in which concepts are usually combined and enumerated through function analysis. However, as a large number of combined concepts are generated with these tools, it is difficult to evaluate them one by one to obtain the best concept using regular algorithm. It is necessary to develop a new approach or a tool to solve the concept generation.

2. Combination of Genetic Algorithm and Conceptual Design

In nature, concept generation for mechanical product is a problem of combinatorial optimization and at the same time it is a problem of concept synthesis. The process of concept design can be viewed as a global optimization of a population consisting of different concepts, viz. a process of decomposing the general function into many function units which are the simplest sub-functions after function decomposition, then searching the corresponding function carriers in knowledge base for each function unit, generating numerous design candidates through different combinations, and finally selecting the best design concept by evaluation and decision-making. It is obvious that the optimization is a process of searching the best concept solution in a large state-place, which is usually conducted at random because of the complexity of the state-place. If this search is implemented blindly, it will inevitably result in combination explosion. For example, if n is the number of function units and m is the number of function carriers for each function unit, the number of combined concept solutions will be m^n. The key of conceptual design is how to find the optimal solution by minimizing the searching space and controlling the searching process adaptively according to certain rules (Shu et al., 2002). Genetic algorithm based on the evolution theory and genetics principles provides us with such a rule of survival of the fittest, which is in accordance with the concept generation rule that a concept matching design requirements to the greatest extent is the best concept. Thus genetic algorithm is adopted in this work to solve the problem of combinatorial optimization in concept generation.

Genetic algorithm is essentially a probability search-based optimization approach by simulating the mechanisms of selection, crossover, and mutation in the evolution process of nature. In the searching process, the knowledge for searching place can be acquired and accumulated automatically, and this searching process can be adaptively controlled using fitness function. Finally the optimal solution can be received accompanying this step-by-step evolution process. Compared with popular optimization algorithms, genetic algorithm has many novel characteristics. At first, a certain coding technology is used to encode the design variables, thus genetic algorithm takes variable coding as operation object and not the variables themselves. Secondly, the search process of GA is implemented according to fitness information and does not depend on derivative information of design problem. Finally, genetic algorithm is a global optimization approach based on population, in which a method of parallel search is used to improve the search efficiency (Lim, 2004), viz. the search process starts with a population made up of many individuals and does not start with a single individual. When the number of individuals consisting in a population is comparatively large, genetic algorithm is more effective than other traditional algorithms. The objective of this research is to propose an approach for generating design concept of mechanical product automatically using genetic algorithm.

3. Mathematical Description of Genetic Algorithm

Concept design can be viewed as an optimization process, in which the best concept satisfying certain function requirements such as motion type and motion trajectory, is required to be searched in a large concept solution set under certain design constraints, including structure constraint, intensity constraint, reliability constraint, cost constraint, life constraint, and application condition, et al. The optimization of concept generation can be described in mathematical equations as follows:

$$\left.\begin{aligned} &\max_{1\le i\le n} V[P_i(x_1, x_2, \cdots, x_m)] \\ &=[V(P_1), V(P_2), \cdots, V(P_n)] \\ &\qquad s.t.\ P_i \in (P_1, P_2, \cdots, P_n); \\ &\qquad\quad g(x_1, x_2, \cdots, x_m) \le 0; \\ &\qquad\quad h(x_1, x_2, \cdots, x_m) = 0; \\ &\qquad\quad (x_1, x_2, \cdots, x_m) \in R^m \end{aligned}\right\} \quad (1)$$

where P_i is the i-th design concept belonging to $(P_1, P_2, \cdots, P_n)$, $(P_1, P_2, \cdots, P_n)$ is a concept set determined by a certain method such as morphology matrix, V is a mapping from a solution space to a real number field and can be viewed as a measurable expression of a solution's performance, $V(P_i)$ is the objective evaluation value of P_i which indicates the extent of P_i matching the total design objective, (x_1, x_2, x_m) is a group of design variables corresponding to a product concept, which describes the structure, constitution, dimension and performance of a product concept and can be regarded as a substitute for a concept, R^m is the definition field corresponding to $(x_1, x_2, \cdots, x_m)$, and $g(x_1, x_2, \cdots, x_m) \le 0$ and $h(x_1, x_2, \cdots, x_m) = 0$ are the required constraint conditions for $(x_1, x_2, \cdots x_m)$.

It is obvious that genetic algorithm is used to optimize concepts according to the above mathematical model, viz. to find a concept P_i belonging to $(P_1, P_2, \cdots, P_n)$ and ensure that $V(P_i)$ arrives at a maximum. A series of solutions should be acquired at first, then to find the best candidate and better candidate in the process of concept generation.

4. Key Technologies of Genetic Algorithm-based Concept Generation

The following gives an example of 4-position special purpose machine tool to investigate some key technologies on genetic algorithm.

4-position machine tool can accomplish four working positions, viz., drilling, broaching, reaming, assembling and unassembling workpiece. Before using genetic algorithm, function decomposition is conducted at first according to design task and function structure tree is acquired in Fig. 1. Then we can draw the motion-converting function figure by analyzing the motion's difference of transmission chain from motor to working mechanisms, as shown in Fig. 2, where the meanings of motion-converting function symbols are detailedly illuminated in Table 1. There are three cutting tools to implement drilling, broaching, and reaming, respectively, which are assembled in headstock and driven by a special motor as shown in Fig. 2(a). Fig. 2(b) shows the transmission chain from motor to worktable and headstock, which implement the indexing motion and the feed motion respectively and constitute the major motion of 4-position machine tool.

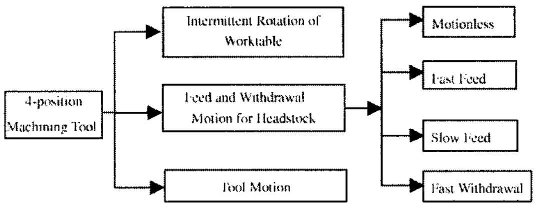
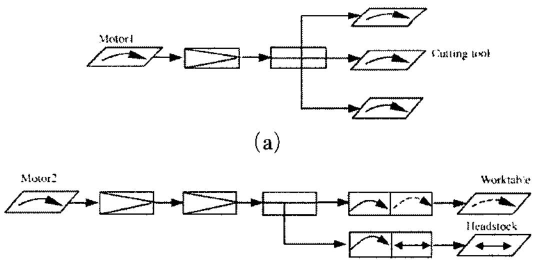


Fig. 1 Function structure of 4-position machine tool



(a)

(b)

Fig. 2 Motion-converting function figure

Through selecting the proper function carriers for main function units, representing every function unit with y-coordinate and representing the corresponding solution with x-coordinate, the morphology matrix is constructed in Table 2.

4.1 Individual coding

The initial population's generation starts with individual coding. In the conceptual design, several coding approaches are usually adopted,

Table 1 Meaning of motion-converting fnction symbol

Symbol	Meaning
	Continuous Rotation
	Reciprocating Translation
	Intermittent Rotation
	Deceleration
	Continuous Rotation → Intermittent Rotation
	Continuous Rotation → Reciprocating move
	Motion embranchment

Table 2 Morphology matrix of 4-position machine tool

Function unit	symbol	Solutions for function unit			
		1	2	3	4
1 Motor		Asynchronous motor S_{11}	D.C. motor S_{12}	Actuating motor S_{13}	Step-by motor S_{14}
2 Deceleration		Belt transmission S_{21}	Chain drive S_{22}	Gear drive S_{23}	Worm drive S_{24}
3 Deceleration		Belt transmission S_{31}	Worm drive S_{32}	Chain drive S_{33}	Planetary drive S_{34}
4 Intermittent rotation of worktable		Geneva mechanism S_{41}	Inperfect gear device S_{42}	Worm-cam intermittent mechanism S_{43}	Cylindrical-cam intermittent mechanism S_{44}
5 Headstock move		Slider-crank mechanism S_{51}	Cylindrical cam mechanism with a translating follower S_{52}	Disk cam mechanism with an oscillating follower and rocker-Slider mechanism S_{53}	Disk cam mechanism with a translating follower S_{54}

including the commonly used one-dimensional string structure coding, multi-dimensional structure coding, and tree-structure coding based on genetic programming presented by Koza (1992). The method of one-dimensional binary coding based on morphology matrix is introduced in this paper (Huang et al., 2002). In the morphology matrix shown in Table 1, there are five major function units and each possesses four optional function solutions. A large number of concept individuals can be generated by selecting one function carrier for each function unit at random and combining them using different combinatorial ways. It is apparent that the number of combined concepts is $4\times4\times4\times4\times4=1024$. For example, $S_{11}+S_{21}+S_{32}+S_{42}+S_{53}$ and $S_{11}+S_{23}+S_{33}+S_{41}+S_{54}$ denote two combined concepts among them. It is noticeable to remain the physical or geometrical consistency among function carriers when combining them, that is to say, combined solution must satisfy certain constraint conditions, otherwise the combined concept is a non-feasible solution. When calculating its fitness value, a penalty factor should be exerted on it to reduce its fitness value as explained in section 4.3. In the process of individual (chromosome) coding, every solution (gene) is coded firstly. Gene coding is expressed with two digits binary string which can represent four optional solutions to every function unit, viz., 00, 01, 10, and 11. In Table 2, combination 1 ($S_{11}+S_{21}+S_{32}+S_{42}+S_{53}$) and combination 2 ($S_{11}+S_{23}+S_{33}+S_{41}+S_{54}$) are represented with binary strings as 0000010110 and 0010100011, respectively. After generating the best concept, its coding can be decomposed into corresponding solutions to function units using the opposite decoding approach.

4.2 Population initialization

Genetic algorithm is an optimization approach based on population, which is composed of an amount of individuals. Accordingly, a certain number of concept individuals are required to constitute an initial population. In this paper, a certain number of individuals are randomly generated first according to constraint conditions. Then the individuals with better fitness are selected from them and fed into the initial population. This process is continuously performed until the number of individuals in initial population arrives at a scheduled number. As a result, initial population of a certain scale is constructed through generating a number of binary coding strings.

4.3 Calculation of fitness

In genetic algorithm, fitness is used to evaluate the performance of individual. It is correspondent to objective function of optimization model and the calculated fitness has an effect on heredity and variation of population. In this paper, fitness value is calculated using a method of quantitative evaluation to the concept individual. For the reason that the concept to realize the general function is constructed with consistent function units, the fitness of individual equals weighted sum of the fitness of each gene, as calculated in Eq. (2)

$$F_i=\sum_{j=1}^{m}G_{ij}\cdot W_j/\eta \tag{2}$$

In Eq. (2), F_i is the fitness value of the i-th individual (concept) where $1\leq i\leq l$ and l is the number of concepts, G_{ij} is the fitness value of the j-th gene (function unit) of the i-th individual where $1\leq j\leq m$ and m is the number of genes. W_j is the weight of the j-th gene which represents the importance of different function unit where the weight of 5 function units is orderly 0.2, 0.15, 0.15, 0.25, and 0.25. η is a penalty factor defined as

$$\eta=\begin{cases}K & \text{if not consistent}\\ 1 & \text{otherwise}\end{cases} \tag{3}$$

where K is a large number defined as 100 when function carriers combining to a concept are not consistent.

It can be seen that the calculation of concept individual's fitness is based on the calculation of function units' fitness, which can reflect satisfaction of the function carrier to function unit. The fitness value of function unit is calculated by

$$G_j=\sum_{k=1}^{n}f_j(V_{jk})\cdot W_{jk} \tag{4}$$

Table 3 The function carrier knowledge base for "intermittent rotation of worktable"

Mechanism type	Function	Performance indexes					
		Kinematic performance	Dynamical performance	Reliability	Structural compactness	Economy	Environmental impact
Ratchet mechanism	Intermittent rotation	0.858	0.429	0.715	0.715	0.858	0.715
Imperfect gear device	Intermittent rotation	0.715	0.286	0.715	0.572	0.286	0.572
Cam intermittent mechanism	Intermittent rotation	0.858	0.858	0.858	0.715	0.286	0.429
Internal epicycle intermittent mechanism	Intermittent rotation	1	0.715	0.572	0.858	0.143	0.429

where G_j is the fitness value of the j-th function unit, V_{jk} is the k-th evaluating index of the j-th function unit where $1 \leq k \leq n$ and n represents the number of evaluating indexes, W_{jk} is the weight value of correspondent index where

$$\sum_{k=1}^{n} W_{jk} = 1 \tag{5}$$

and $f_j(V_{jk})$ is the evaluating value giving by function carrier knowledge base.

The corresponding knowledge base of function carrier is required to be built first by means of object-oriented method, which includes the titles of function carrier and the related knowledge for each function carrier, such as function, evaluation indexes, and consistency conditions, etc. The related knowledge for function carrier comes from the design code, design handbook, technology materials, and experts' experience for machine tool. Taking the function carriers of "intermittent rotation of worktable" as an example, the associated knowledge in knowledge base is described as Table 3.

The above numerical values for mechanisms are acquired by means of a method of fuzzy quantization. Usually the performance for mechanisms are expressed with semantic mode, including 7 types, viz. very good, good, somewhat good, fair, somewhat poor, poor, and very poor, which can be converted into the numerical values between 0 and 1, viz. 1, 0.858, 0.715, 0.572, 0.429, 0.286, 0.143, and 0. Thus semantic evaluation for the performance of different mechanisms can be quantitated as different numerical values shown in Table 3.

4.4 Genetic operators

In the concept generation, there are three major operators, including reproduction, crossover, and mutation (Zhou et al., 1999), each of which is discussed as follows.

4.4.1 Reproduction

The aim of reproduction is to improve the average fitness of population and embody the evolution principle of the survival of the fittest in nature. The mode of selection adopted in this paper combines proportional fitness assignment and roulette wheel selection. After ranking of individual's fitness, coding strings with better fitness are reproduced to the next generation by being selected from population of father generation which can ensure the accomplishment of global search with a high searching efficiency.

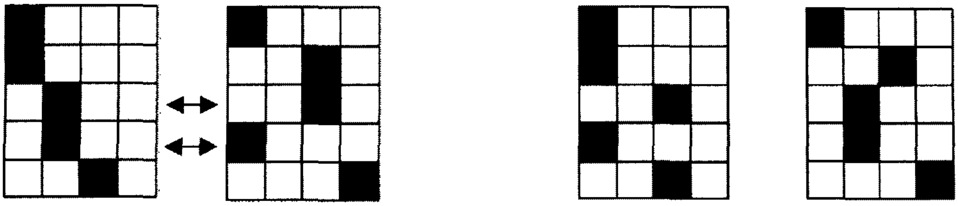
4.4.2 Crossover

The aim of crossover is to generate new individuals to embody the superiority of recombination in biology. Double-point crossover is used here, and depicted as follows.

$$\begin{array}{l|l|l} \text{A: }000 & 00101 & 10 \\ \text{B: }001 & 01000 & 11 \end{array} \xrightarrow{\text{Crossover}} \begin{array}{l} \text{A': }000\ 01000\ 10 \\ \text{B': }001\ 00101\ 11 \end{array}$$

Double-point

Where two concept individuals are selected at random, then two exchanging position are generated at random, and next the correspondent



A B A' B'

Before crossover After crossover

Fig. 3 Crossover operator

binary digits belonging to two strings between these two positions are exchanged. As a result of it, two new individuals are generated. In the example of 4-position machine tool, crossover process is based on the foundation of morphology matrix and it belongs to a plane-crossover mode. Suppose there are two concept individuals in which individual A is 0000010110 and individual B is 0010100011, the crossover process is expressed as above and can be shown by morphology matrix, as illustrated in Fig. 3.

4.4.3 Mutation

The aim of mutation is to enhance the diversity of new individuals in population by simulating the gene variation in biology, viz., the variation of population is accomplished by selecting other solution for function unit in solution set to replace the current solution. In the process of mutation, an integer is generated randomly at first to determine the position of mutation, and then according to a provided mutation rate, the value of this position is changed ($1 \rightarrow 0$, $0 \rightarrow 1$) to generate a new individual.

4.5 Criterion for heredity termination

In the process of concept generation based on GA, there are two criteria for heredity termination, viz. satisfaction degree criterion and the maximum generation criterion. Satisfaction degree criterion is that the changing value of average fitness for continuous some generations doesn't exceed a certain threshold value k and maximum generation criterion is only when the number of heredity generations arrives at the maximum generation, the process of genetic operation terminates. Satisfaction degree criterion is utilized in this paper. After a new population is generated by reproduction, crossover, and mutation, the individuals of the population are evaluated to decide whether the evaluating result satisfies this condition. Otherwise, the process of genetic operator is repeated until the best solution is acquired.

4.6 Optimization result

Generally speaking, when the process of genetic operator is convergent, the best concept for each of continuous four generations can be selected to construct a group of satisfactory solutions. Thus more than one optional concept is generated including the best concept and other better concepts by ranking them in terms of the fitness value of each. In the case of 4-position special machine tool, the number of total concepts is 20 ($l=20$), the number of function units is 5 ($m=5$), and each function unit possesses 4 solutions. The crossover rate is 0.65, the mutation rate is 0.05, and terminating threshold $k=10^{-2}$. By programming with Matlab 6.5 to compute it, the best solution and three better solutions are acquired as a result. Combination mode for each solution can be acquired by decoding as shown in Table 4. The sketch of the best concept for 4-position machine tool is shown in Fig. 4.

Table 4 Concept solutions for 4-position machine tool

Concept solutions	Combination mode	Fitness value
Optimal concept	$S_{11}+S_{21}+S_{32}+S_{41}+S_{52}$	0.839
Better concept 1	$S_{11}+S_{21}+S_{34}+S_{42}+S_{53}$	0.810
Better concept 2	$S_{11}+S_{21}+S_{32}+S_{41}+S_{54}$	0.782
Better concept 3	$S_{11}+S_{21}+S_{32}+S_{43}+S_{51}$	0.723

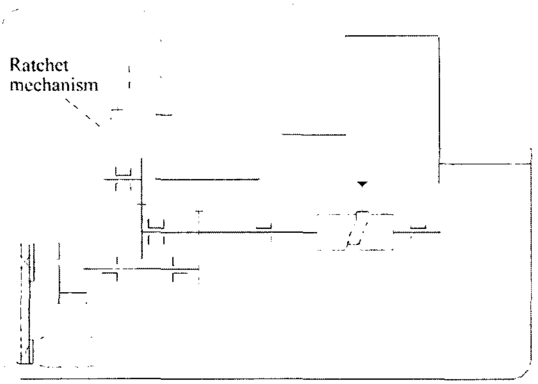


Fig. 4 The sketch of the best concept

5. Conclusions

Concept optimization of mechanical product is a dominant part for mechanical design. In this paper concept generation is implemented using GA, which can facilitate not only generating several better concepts, but also selecting the best concept. Thus concept can be generated automatically and design efficiency can be improved. However, the proposed approach only solves some simple design problem. For those complicated design problems, the approach isn't perfect enough to deal with them and requires an integrated intellectualized design platform to support it. Therefore, expert system and other intellectualized system should be combined with it.

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References

Ermer, G., Rosenberg, R. et al., 1993, "Steps toward Integrating Function-based Models and Bond-graphs for Conceptual Design in Engineering," *Automated Modeling for Design, ASME*, Vol. 47, No. 11, pp. 47~62.

Hoeltzel, D. A. and Chieng, W. H., 1990, "Knowledge-based Approaches for the Creative Synthesis of Mechanisms," *Computer Aided Design*, Vol. 22, No. 1, pp. 57~67.

Huang, H., Zhao, Z. and Guan, L., 2002, "Intelligent Conceptual Design Based on Genetic Algorithm," *Journal of Computer-aided Design & Computer Graphics*, Vol. 14, No. 5, pp. 437~441.

Koza, J. R., 1992, Genetic Programming: on the Programming of Computers by means of Natural Selection, The MIT Press, Cambridge, pp. 94~99.

Lim, O. K., Hong, K. S., Lee, H. S. et al., 2004, "Initial Design Domain Reset Method for Genetic Algorithm with Parallel Processing," *KSME International Journal*, Vol. 18, No. 7, pp. 1121~1130.

Park, J. H. and Seo, K. K., 2003, "Approximate Life Cycle Assessment of Product Concepts Using Multiple Regression Analysis and Artificial Neural Networks," *KSME International Journal*, Vol. 17, No. 12, pp. 1969~1976.

Redfield, R. C. and Krishnan, S., 1992, "Towards Automated Conceptual Design of Physical Dynamic Systems," *J of Engineering Design*, Vol. 3, No. 3, pp. 187~204.

Shu, Q. and Hao, B., 2002, "An Automatic Conceptual Design System for Mechanical Products," *China Mechanical Engineering*, Vol. 13, No. 19, pp. 1676~1678.

Yao, Z., Huang, Z. and Shen, G., 1998, "Study on the Structure Catalogues for Conceptual Design of Mechanical Transmission," *China Mechanical Engineering*, Vol. 9, No. 6, pp. 53~55.

Zhou, M. and Sun, S., 1999, Genetic Algorithm: Principle and Application, National Defence Industry Press, Beijing, pp. 45~59.

Zou, H., Tian, Y., Guo, W. et al., 2003, "Methodology for Conceptual Design of Mechanism System," *J of Shanghai Jiaotong University*, Vol. 37, No. 5, pp. 668~673.