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Research on genetic algorithm-based rapid design optimization

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1. Introduction

Modern product design is market and customer oriented design. The response speed to markets by enterprises is one of the important factors of enterprise competition. To obtain the responding advantages, the methodology of rapid design (RD) is applied widely in enterprises. Variant design often used by the enterprises is to change local dimensions and configurations of design instances so as to achieve the purpose of RD. On the other hand, the product designed should be verified and optimized to assure of the reliability of new product and the optimization of designed structure [1, 2]. Common optimization process is to model the designed product in finite element software and then optimize its structure based on finite element analysis. Thus every time modifying the design, repeated modelling, analysis and optimization are needed, which will result in low efficiency and cannot satisfy the demand of RD.

The application of product knowledge existing already into product optimization based on genetic algorithm (GA) can avoid the repeated modeling and analyzing and result in improved design efficiency. This paper reports our research on GA-based rapid optimization method. In the next section, the RD method is overviewed and discussed as well as its key issues. In Section 3, general mathematical model of mechanical product rapid optimization is introduced. The GA-based rapid optimization process and its fitness determination are discussed in detail in Section 4. Then, an example of H-beam is illustrated to apply GA and BP neural network into design optimization in detail. Finally, the opportunities for future research will be pointed out.

RD is developed from concurrent engineering technology proposed at International conference CIRPF in 1992 [3]. The aim of RD is to shorten product design cycle. Many researchers studied on RD and gave definition to it [4-6]. Anyway, RD is a design method integrated with customer requirement, technology, product structure, product information, product development trend and so on. It is an active rapid response design from enterprises. Summarily the key issues of RD include the followings [7-9]:

1. Product modularization. It is to partition a series of product modules according to product function, structure and performance so as to satisfy customers' diverse requirements by selecting and combining different modules.

2. Product configuration. It is to select, combine, vary and optimize the instance modules and design products customers require based on design rules, constraints, resources, structures, ontology and so on.

3. Variant analysis. It is to analyze product sensitivity of shape, structure and topology, and optimize design parameters.

2. Genetic algorithm-based RD optimization

2.1. General model of product rapid optimization

General mathematical model of constrained optimization can be denoted by

$$\left.\begin{aligned} &min\, f(X), \quad X\in R^n \\ &s.t. \quad g_u(X)\ge 0, \quad u=1,2,\dots,m \\ &h_v(X)=0, \quad v=1,2,\dots,p<n \end{aligned}\right\} \tag{1}$$

where X denotes the design variable and R^n denotes a nonempty set; $g_u(X)$ denote inequality constrains and $h_v(X)$ denote equality constrain.

The RD of mechanical product is mainly to modify the local dimensions and configurations of design instances existing already, during the process of which the factors such as strength, weight, cost and so on are focused on by designers. In general cases, the constraints include that stress should be less that the allowable stress of materials and that displacement should be less that allowable displacement of design and the objectives of optimization include weight/cost and so on. Thus, the mathematical model of problems as in (1) can be denoted by

$$\left.\begin{aligned} &min\, f(X) \\ &d_{max}\le[d] \\ &X_{min}\le X\le X_{max} \end{aligned}\right\} \tag{2}$$

where d_{max} and $[d]$ denote the maximum displacement and allowable displacement of designed structure respectively; X_{min} and X_{max} denote the upper limit and lower limit of design variable respectively and $f(X)$ denotes the optimization objectives.

2.2. Genetic algorithm-based rapid optimization

Genetic algorithm can only solve unconstrained problem directly, while commonly problems except high constraint problem cannot be converted into unconstrained problems directly[10]. Equality constraint can be incorporated into fitness function, while inequality constraint needs penalty function to be incorporated into fitness function for optimization solution. The common form is presented as [11]

$$\left.\begin{array}{l} f(x)+rp(x) \\ p(x)\begin{cases} =0 & x\in X \\ >0 & x\notin X \end{cases} \end{array}\right\} \tag{3}$$

where $f(x)$ denotes the original fitness function, $p(x)$ denotes penalty function, r denotes positive coefficient and X denotes feasible solution domain. According to different design requirements and problems, penalty function varies. Penalty function is one of the key factors of genetic algorithm to solve constraint problems, which can be denoted by [12]

$$\left.\begin{array}{l} P(X)=f(X)+rg(x) \\ g(x)=\dfrac{d_{\max}}{[d]}-1 \end{array}\right\} \tag{4}$$

Then, new fitness function can be denoted by

$$F(X)=C_0-P(X) \tag{5}$$

where C_0 is a constant to assure that $F(X)$ is positive.

It can be seen easily that $F(X)$ is a function for $f(X)$ and d_{max}. That is

$$F(X)=F\left(f(X),d_{max}\right) \tag{6}$$

Obviously, fitness of the structure designed can be calculated after getting the $f(X)$ and d_{max} based on the design instances and furthermore the rapid optimization of the structure can be carried out.

According to the requirements of RD, the better way is to compute the fitness without the help of finite element software. The steps of genetic algorithm-based rapid optimization can be described briefly as follows: Firstly generate initial population and compute the fitness, then judge whether the individual satisfies the optimization conditions. If not, execute the genetic operation and recomputed fitness until the optimization conditions are satisfied; else if, output the optimum individual. Finally, decode to obtain the approximately optimum solution. Detailed process is illustrated in Fig. 1. Obviously, fitness determination is the key problem of GA-based rapid optimization. In our research, the fitness is determined by back propagation (BP) neural network [13]. Here, unnecessary conceptual details about BP neural network won’t be given and the factual application will be represented in the next section.

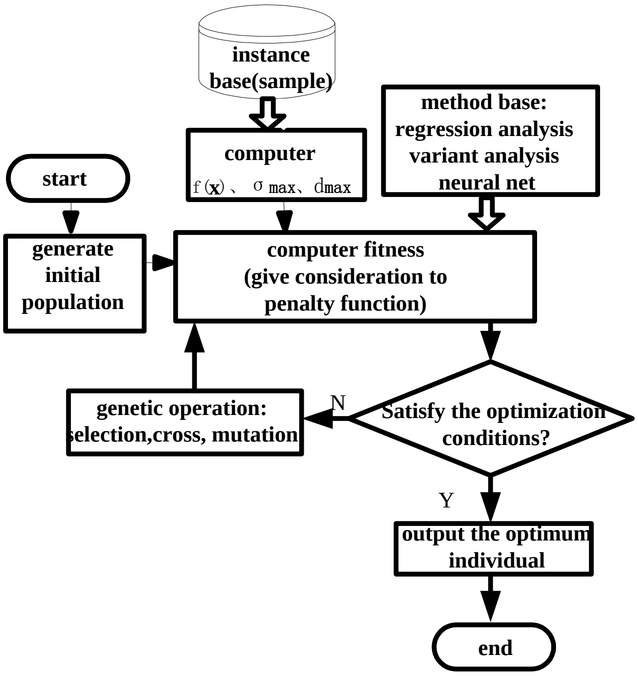

Fig. 1 Process of genetic algorithm -based rapid optimization

3. Case study

3.1. Application sample selection

H-beam is a common structure in engineering and thus selected as shown in Fig. 2 for our research whose parameter and usage are as follows:

- length: 1 m;
- freedom constraint: fixed at both ends;
- $E=6.69\text{e}10\,\text{Pa}$;
- $\mu=0.26$;
- density: 2700 kg/m^3;
- force: 1000 N on the middle.

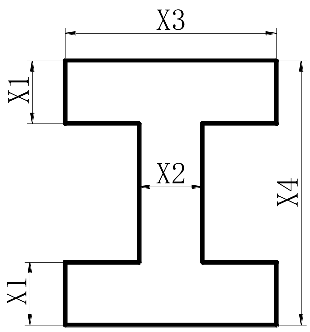

Fig. 2 Model of selected H-beam

Finite element analyse on 25 samples is carried out by uniform design methodology of $U_{25}\left(5^4\right)$ to obtain the displacement after the force [14]. The analysis results are shown in Table 1 as well as displacement and weigh tested, where D denotes the maximum deformation, W denotes the weight of the sample and $X1$, $X2$, $X3$ and $X4$ denote the structure parameters. The analysis result of sample 1is given in Fig. 3.

Table 1

Analysis results by $U_{25}\left(5^4\right)$

No	*X1*	*X2*	*X3*	*X4*	D(mm)	W(kg)
1	2	2	80	100	0.0432	3.994
2	2	3	100	40	0.187	3.962
3	2	4	20	60	0.211	2.371
4	2	5	60	20	1.21	2.496
5	2	6	40	80	0.0604	4.805
6	3	2	40	40	0.325	2.402
7	3	3	60	60	0.0938	4.072
8	3	4	80	80	0.0397	6.053
9	3	5	20	100	0.0461	4.602
10	3	6	100	20	0.586	5.335
11	4	2	20	20	2.44	1.435
12	4	3	40	100	0.0378	4.649
13	4	4	60	40	0.173	4.742
14	4	5	100	80	0.0275	9.048
15	4	6	80	60	0.0532	7.426
16	5	2	60	80	0.0496	5.772
17	5	3	80	20	0.632	6.474
18	5	4	100	100	0.0185	10.61
19	5	5	40	60	0.0822	5.07
20	5	6	20	40	0.347	2.964
21	6	2	100	60	0.0599	10.11
22	6	3	20	80	0.076	3.463
23	6	4	40	20	1.08	3.994
24	6	5	80	40	0.108	8.58
25	6	6	60	100	0.0187	9.734

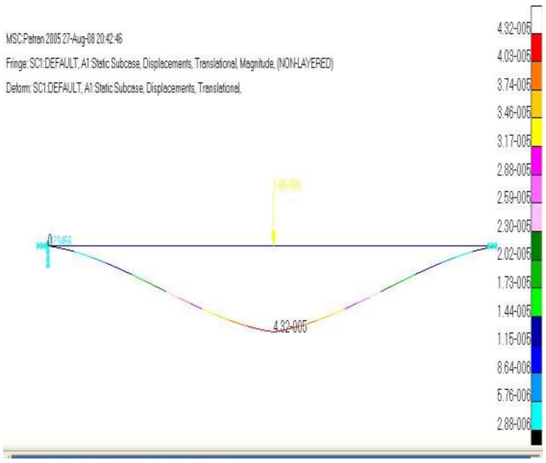

Fig. 3 Displacement cloud of sample 1

3.2. BP neural network training

Let $X1$, $X2$, $X3$ and $X4$ be the design variable be the optimization object and d be the constraint. Two sub-BP neural networks shown in Fig. 4 are constructed with inputs of $X1$, $X2$, $X3$ and $X4$ and corresponding outputs of d and w. The number of hidden layers can be deducted by Kolmogorov principle: $2 \times 4 + 1 = 9$. The corresponding outputs can be determined by the two sub-BP neural networks [15].Using samples to train the both networks, the weight and threshold of each layer can be obtained with the deviation of 10e-5.

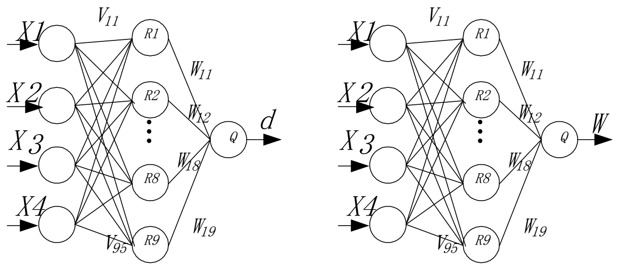

Fig. 4 sub-BP neural networks constructed

3.3. GA-based optimization

3.3.1. Optimization modelling

Let the equation (2) be optimization model, penalty function be equation (3) and fitness function be equation (4) with $r = 2$ mm, $C_0 = 45$ and $[d] = 0.2$ mm. Thus, the optimization model can be denoted by

$$\begin{cases} \min W\left(X1, X2, X3, X4\right) \\ d_{max} \le 0.2 \\ 2\text{mm} \le X1 \le 6\text{mm} \\ 2\text{mm} \le X2 \le 6\text{mm} \\ 20\text{mm} \le X3 \le 100\text{mm} \\ 20\text{mm} \le X4 \le 100\text{mm} \end{cases} \tag{6}$$

The fitness function can be denoted by

$$F\left(X\right) = 45 - 3W\left(X\right) - 2\left(\frac{d\left(X\right)}{0.2} - 1\right),$$

$$X = \left[X1, X2, X3, X4\right]$$

where $d(x)$ and $w(x)$ are obtained by BP neural network.

3.3.2. Genetic coding

Take $X1$, $X2$, $X3$ and $X4$ as chromosomes for genetic coding by binary code. The chromosome length are 32 bits, of which 1 ~ 8 bits represent $X1$, 9 ~ 16 bits represent $X2$, 17 ~ 24 bits represent $X3$ and 25 ~ 32 bits represent $X4$.

3.3.3. Genetic operation

(1) Selection. The roulette algorithm is adopted to select individuals.

(2) Crossover. A two points of partly cross-recombination method is adopted to crossover with probability of Pc. Pc denotes crossover probability, which is usually an experience value. In this research, according to the reference provided by Whitley D. [16], let Pc=0.9. The crossover is illustrated by the following simple example.

Let two individuals form the initial population

$A = A1\ A2\ A3\ A4\ A5\ A6\ A7\ A8\ \ldots\ A32;$

$B = B1\ B2\ B3\ B4\ B5\ B6\ B7\ B8\ \ldots\ B32.$

For instance, a crossover zero is selected from population chromosome at random. Then the following results of crossover will be obtained as shown in Table 2.

Table 2

Operation of crossover

Selected individuals	Position of crossover
*A*1*A*2*A*3*A*4*A*5*A*6*A*7*A*8…*A*32	4.6…(at random)
*B*1*B*2*B*3*B*4*B*5*B*6*B*7*B*8…*B*32	4.6…(at random)
crossover	Resulting individuals
*A*1*A*2*A*3*A*4|*A*5*A*6|*A*7*A*8…*A*32	*A*1*A*2*A*3*A*4|*B*5*B*6|*A*7*A*8…*A*32
*B*1*B*2*B*3*B*4|*B*5*B*6|*B*7*B*8…*B*32	*B*1*B*2*B*3*B*4|*A*5*A*6|*B*7*B*8...*B*32

3.3.4. Mutation

Mutation refers to change the genes of chromosome with probability of Pm. Pm denotes mutation probability, which is also usually an experience value. In this research, according to the reference provided by Whitley D. [16], let Pm =0.02. Randomly select tow bits from the population chromosome for mutation and let the bit of 1 change into 0 and the bit of 0 into 1. For example

$$A = A1\ A2\ A3\ A4|10|A7\ A8\ \ldots A32;$$

$$A' = A1\ A2\ A3\ A4|01|A7\ A8\ \ldots A32.$$

3.3.5. Optimization results

After 605 generations' iteration, the optimization result tends to converge. Hereat, the fitness value is 37.5110735949702 and the chromosome denotes as 00101011001110010010001101100111, which can be decoded for the following representations:

"00101011" denotes $X1$ = 2.6745 mm;

"00111001" denotes $X2$ = 2.8941 mm;

"00100011" denotes $X3$ = 30.9803 mm;

"01100111" denotes $X4$ = 52.313 mm.

Let $X1$ be 3 mm, $X2$ 3 mm, $X3$ 31 mm and $X4$ 52 mm.

Also, the displacement predicted by BP neural network is 0.195421 mm. Compared with the result of 0.205 mm from the finite element analysis shown in Fig. 5, it can be concluded that the deviation is about 5%.

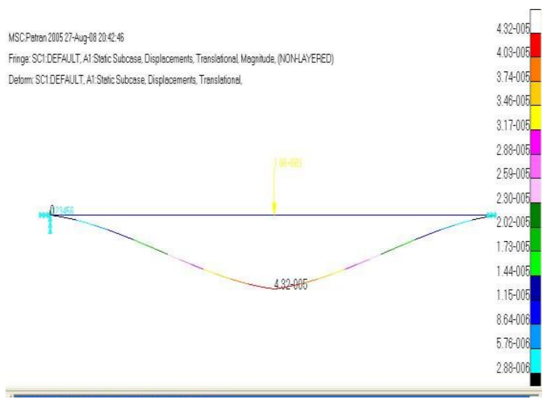

Fig. 5 Displacement cloud after optimization

4. Conclusions

The work reported here on GA-based rapid optimization is a beginning of mechanical product RD and optimization. This research seeks to realize RD and optimization by reusing design instances, design knowledge and design documents without the help of finite element software. The above research shows that design optimization based on GA combines with BP neural network is feasible and it can avoid repeated finite element modelling and analysis which results in improved efficiency. The future work is to consider how to improve the prediction accuracy of BP neural network and accuracy of fitness calculation for complex model.

The main tasks of this research are as follows:

1. The conception of GA-based rapid optimization to avoid repeated finite element modeling and analyzing is proposed.

2. Based on the analysis on general mathematical model of mechanical product rapid optimization, the mathematical model of GA-based rapid optimization is presented.

3. The process of GA-based rapid optimization combined with BP neural network is derived and the fitness determination of GA Optimization is discussed in detail.

4. An example of H-beam is illustrated to apply GA and BP neural network into design optimization in detail.

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GENETINIU ALGORITMU PAGRĮSTOS GREITOJO PROJEKTAVIMO OPTIMIZACIJOS TYRIMAS

R e z i u m ė

Siekiant konkurencinio pranašumo, įmonėse plačiai taikoma greitojo projektavimo metodologija. Į gaminį orientuotos žinios, taikomos jam optimizuoti ir pagrįstos projekto reikalavimais, padeda išvengti pakartotinio modeliavimo bei analizės, pagerina projektavimo efektyvumą. Pirmiausia išnagrinėjama greitojo projektavimo technologija. Antra, naudojamas bendras mechaninio gaminio greitojo optimizavimo matematinis modelis. Trečia, genetiniu algoritmu pagrįstas greitojo optimizavimo procesas sujungtas su BP neuroniniu tinklu, detaliai aptartas genetinio algoritmo tinkamumas. Ketvirta, remiantis aptartais kriterijais buvo apskaičiuoti H tipo sijos poslinkiai. Rezultatai parodė, kad genetinio algoritmo metodas užtikrina skaičiavimo tikslumą. H tipo sijos pavyzdys detaliai iliustruoja genetinio algoritmo ir BP neuroninių tinklų pritaikymą projektavimui optimizuoti. Straipsnyje pateikto tyrimo rezultatai yra tinkami naudoti greitajam projektavimui ir optimizavimui.

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RESEARCH ON GENETIC ALGORITHM-BASED RAPID DESIGN OPTIMIZATION

S u m m a r y

To obtain the competition advantages, the methodology of rapid design (RD) is applied widely in enterprises. Product oriented knowledge applied into product optimization based on design instances can avoid the repeated modeling and analyzing and result in improved design efficiency. Firstly, RD technology is overviewed. Secondly, general mathematical model of mechanical product rapid optimization is introduced. Thirdly, the process of GA-based rapid optimization combined with BP neural network is derived and the fitness determination of GA Optimization is discussed in detail. Fourthly, on the basis of the uniform trial, the displacement of the H-beam has been calculated. The result shows that the methods are feasible to calculate the fitness of GA with good precise. Finally, an example of H-beam is illustrated to apply GA and BP neural network into design optimization in detail. The research in this paper, however, is beneficial to the application of RD and optimization.

Keywords: genetic algorithm, rapid design, optimization.

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