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Study on Methods of Synthetically Optimizing Mechanics Properties for Principal-Dimension-Limited Ships

Yang Song-lin[1], Chen Shu-ling[1], Li Mi[1] and Sun Xiao-bo[1]

Summary

In this paper, a mathematical model of synthetically optimizing navigation performances and structural properties for principal-dimensions-limited ships is constructed. Basing on parallel algorithm, genetic algorithm (GA) and chaos algorithm, then a parallel genetic chaos algorithm basing on delicate variables' segments is advanced. This composite algorithm is programmed by VC++ into software which has a user-friendly graphical interface of good interactivity and applied to solving that mathematical model of synthetically optimizing navigation performances and structural properties for principal-dimensions-limited ships.

Quantities of computation results of different solving methods show that compared with other methods such as GA, chaos algorithm and their parallel algorithms, this composite algorithm can overcome GA's premature convergence and is reliable and efficient so that it lays a solid foundation for form optimization and design evaluation of principal-dimensions-limited ships.

keywords: navigation performance, structural property, synthetical optimization, parallel genetic chaos algorithm, delicate variable's segment

Introduction

Optimization theory is now widely applied to science research, business management, military affairs and many other fields.

Optimization methods can be divided into conventional and modern. The former usually can't avoid falling into local optimization so that it's not suitable for complicated optimization of multi-variable, multi-constraint and multi-objective function. Genetic algorithm, one of modern optimization methods, has strong global optimization ability so that it has been applied to complicated optimization of ship engineering. But to those optimizations which have many design variables, it'll take a long time for GA to compute and if cutting down the GA generation, it's very likely to develop premature convergence. Therefore, the authors bring forward a parallel genetic chaos algorithm based on delicate variables' segments and succeed in applying this composite method to the synthetical optimization of navigation performances and structural properties for principal-dimensions-limited ships.

Parallel genetic chaos algorithm for optimization solution

GA is a new kind of optimization method developed on the basis of Darwin's Evolutionism and Mendel's genetics theory of random exchange. Compared with

[1]Jiangsu University of Science & Technology, Zhenjiang, Jiangsu Province, 212003, China

traditional optimization methods, GA has many advantages such as fast computation speed, strong ability of global search and good robustness. Great deal of research and application indicate that GA has outstanding capability of solving complicated synthetical optimization.

GA, however, is serial in substance so that it costs much time to compute and has relatively lower efficiency when solving optimizations that involve many design variables. Parallel algorithm gives us the idea of combining them to quicken the computation.

On the other hand, GA tends to converge prematurely when dealing with optimizations that have multiple objective functions and multiple constraint conditions which result in extraordinarily big population size and very complex fitness function. Thereby chaos algorithm again gives the authors an idea of adding it to the combined parallel genetic algorithm to overcome the shortcoming.

The parallel genetic chaos algorithm based on delicate variables' segments solves the optimization in such a way:

(1) Divide each delicate variable's value range into several segments and cross these segments completely (Delicate variable is variable whose little change of value will arouse great change of objective function's value). Then combine each segments group with remaining variables' value ranges as the GA's operation scope. Finally, assign a value to GA's population size and run GA for adequate generations. For example, an optimization has 6 design variables, 2 of which are delicate variables. The value range of one is divided into 3 equal segments and the value range of the other is divided into 4 equal segments. We can get 12 segments groups after crossing these 7 segments completely by 3×4. Combine each segments group with the other 4 variables' value ranges and 12 operation scopes for GA are obtained in the end.

(2) On the base of 1), pick out several best results of GA and compute again by chaos algorithm over a certain interval around each best result in order to find the final best result.

GA's essential procedure

(1) Coding: Each design variable is regarded as a gene and coded for computer to compute. There're many coding methods such as binary coding, denary coding. In this paper, we apply floating-point number method for the sake of coding and decoding many variables quickly.

(2) Determining the fitness function: the string composed of all the genes is called chromosome. To an optimization without constraint conditions, chromosome's

objective function is its fitness function. To an optimization with constraint conditions, its fitness function value should include information from two aspects: chromosome's objective function value and degree of satisfying the constraint conditions.

(3) Initializing the population: In this paper, we chose 6 items as the information of each generation. They're chromosome, its fitness value, its relative fitness value, its cumulative fitness values, lower limit of every gene and upper limit of every gene. According to the population size, same amount of values are randomly chosen within each design variable's limit to compose the chromosomes as the first generation population.

(4) Genetic operations:

Selection operator: It's very important for evolution. It selects the best chromosomes of current generation and reserves them as samples to compare with the next generation. Many methods have been put forth. The authors use the roulette method.

Crossover operators: p_c is one important parameter in GA system. In this paper, p_c is 0.85.

Mutation operator: p_m is another parameter, in this paper $p_m$is 0.1.

(5) Stopping the computation: We set a maximal generation number. When the program execute to that generation, it will stop automatically. In the course of computation, we can also trace its convergence; when the difference between current and last generation fitness values is less than a certain value (for example, 1.0e-5), we will stop it in advance.

Chaos algorithm

Chaos optimization is implemented by chaos variable. The authors choose a widely-used Logistic mapping to produce the chaos variable:

$$z_{k+1} = \mu z_k(1 - z_k)$$

where the time of iterative mapping k=0, 1, 2, ...

It's easy to prove that when μ=4, above equation is fully in chaos state, which means by iterative mapping, the equation can randomly produce all values within (0, 1) except 0.25, 0.5 and 0.75. Because chaos algorithm is sensitive to initial value, n different chaos variables can be obtained by assigning n different initial values within (0, 1) to the equation except 0.25, 0.5 and 0.75.

In this paper, the authors adopt twice-mapping chaos algorithm. Its steps are as follows:

(1) Initialization: Assign n different initial values $z_{i,0}$ to the equation and get n different chaos variables $z_{i,k+1}$ (i =1, 2, ... , n).

(2) First mapping as the following formula shows:

$$x_{i,k} = c_i + d_i z_{i,k}$$

where c_i and d_i are constants that convert chaos variable $z_{i,k}$ into optimization design variable $x_{i,k}$. If the range of design variable's value is [a_i, b_i], then $c_i = a_i$, $d_i = b_i - a_i$.

(3) Computation of the objective function value: Set $\mathbf{X}_k$ as the vector of $x_{i,k}$ and its corresponding objective function value as f_k. At the beginning, suppose the optimal value $f^* = f_0$ and its corresponding $\mathbf{X}_0$ as the optimal solution $\mathbf{X}^*$. During the process of computation, once any f_k is larger than f^*, set $f^* = f_k$ and continue the computation, comparison and replacement.

(4) Second mapping: If f^* remains the same value after several times of step 3), map secondly as the following formula shows:

$$x_{i,k\prime} = x_i^* + \alpha_i z_{i,k\prime}$$

where $k\prime$ is iterative time of second mapping ($k\prime$=0, 1, 2, ...), α_i is a small adjustive constant.

(5) Computation of the objective function value: Similar to step 3), compute $f_{k\prime}$ of $X_{k\prime}$.

(6) If termination condition is satisfied, stop the algorithm; if not, repeat step 5).

Mathematical model of synthetical optimization

There're 3 parts of synthetical optimization of navigation performances and structural properties for principal-dimensions-limited ships: navigation performances, structural mechanics properties and limited principal dimensions.

The authors use the weighted sum of rapidity, sea-keeping ability and maneuverability as the sub-objective function of navigation performances; use the weighted sum of static and dynamic properties as the sub-objective function of structural mechanics properties; and use function whose value changes in a linear way according to the ship principal dimensions as the sub-objective function of limited principal dimensions. The weighted sum of these 3 sub-objective functions is just the general objective function. Stability, buoyancy and some other characteristics as well as limits of design variables form the constraint conditions. The mathematic model is described in detail as follows:

Design variables

The synthetical optimization of navigation performances and structural properties for principal-dimensions-limited ships involves many factors. After analyzing and comparing their importance, 12 parameters are selected as the main design variables: ship length L, ship breadth B, draft T, block coefficient C_B, mid-ship section coefficient C_M, water plane coefficient C_{WP}, longitudinal position of buoyancy center x_{CB}, diameter of screw propeller D_P, disk area ratio A_E/A_O, pitch ratio P/D_P, rotation speed of propeller N and target velocity V_t. Their vector is as follow:

$$\mathbf{X} = \{L, B, T, C_B, C_M, C_{WP}, x_{CB}, D_P, A_E/A_O, P/D_P, N, V_t\}^T$$

Objective function

Suppose $P(\mathbf{X})$ is the general objective function, $P_N(\mathbf{X})$ is the sub-objective function of navigation performances, $P_S(\mathbf{X})$ is the sub-objective function of structural mechanics properties and $P_C\ (Y)$ is the sub-objective function of limited principal dimensions. Then,

$$P(\mathbf{X}) = A_P P_N(\mathbf{X}) + B_P P_S(\mathbf{X}) + C_P P_C(Y)$$

$$P_N(\mathbf{X}) = A_{P1} C_{sp} + A_{P2} M_v + A_{P3} S_v; \quad P_S(\mathbf{X}) = B_{P1} J(\mathbf{X}) + B_{P2} D(\mathbf{X})$$

and,

$$\begin{array}{llll} 0 < Y \le Y_1, & P_C(Y) = 0; & Y_1 < Y \le Y_2, & P_C(Y) = C_1(Y - Y_1); \\ Y_2 < Y \le Y_3, & P_C(Y) = C_2(Y_3 - Y); & Y_3 < Y, & P_C(Y) = 0. \end{array}$$

Where $A_P \ge 0$, $B_P \ge 0$, $C_P \ge 0$, $A_P + B_P + C_P = 1$; $A_{P1} \ge 0$, $A_{P2} \ge 0$, $A_{P3} \ge 0$, $A_{P1} + A_{P2} + A_{P3} = 1$; $B_{P1} \ge 0$, $B_{P2} \ge 0$, $B_{P1} + B_{P2} = 1$. Y is one of ship's limited principal dimensions; Y_1, Y_2 and Y_3 are custom values of this principal dimension according to different limiting requirements.C_{sp}, M_v and S_v are respectively normalized forms within [0,1] of rapidity criterion C ($C_{sp} = P_E/\Delta^{2/3} V_s^3 \eta_o \eta_R \eta_H$, Δ—displacement, P_E—effective power, η_o—screw efficiency in the open, η_H—hull efficiency, η_R—relative rotation efficiency), maneuverability criterion M ($M = p_L V_{arL} + p_T V_{arT} + p_C V_{arC}$, V_{arL}—straight line stability coefficient, V_{arT}—turning quality coefficient, V_{arC}—course change coefficient, p_L,p_T and p_C —- weight numbers) and sea-keeping ability criterion S(S is the weighted sum of normalized forms of pitching angle and heaving amplitude within [0,1]). $J(\mathbf{X})$ and $D(\mathbf{X})$ are normalized forms within [0,1] of static and dynamic criteria of ship structure.

Constraint conditions

Equation constraints

1) Balance between buoyancy and displaced weight: $\rho LBTC_B = \Delta$; 2) Balance between effective thrust T_E and resistance R; 3) Balance between torque received by screw from main engine M_d and torque from hydrodynamic resistance M_p.

Inequality constraints

1) Ranges of 12 design variables' values; 2) Cavitation requirement for screw propeller according to Kelly formula; 3) Initial stability height $G_M > h$; 4) Maximal rolling angle $\Phi_a \leq b^{\circ}$; 5) Relative turning diameter $D_{s'} < c$.

Example

Optimization computation

The mathematic model shows that the synthetical optimization of navigation performances and structural properties for principal-dimensions-limited ships involves at least 12 design variables, 3 equation constraints and 5 inequality constrains (If including the upper and lower limit of each design variable, there'll be 28 inequality constrains). Evidently, it's a very complicated engineering optimization. Applying the parallel genetic chaos algorithm based on delicate variables' segments, the authors programme the solving software.

Here take a large-sized medium-speed inland transport ship for example. Its displacement is 43000t, breadth is limited no more than 29.5m and it has double propellers. The ranges of its design variables' values are listed in Tab. 1:

Table 1: Range of Design Variables

	L (m)	B (m)	T (m)	C_B	C_M	C_{WP} (m)	x_{CB} (m)	D_P	A_E/A_O (r/m)	P/D_P (kn)	N	V_t
Upper limit	219	28	8.8	0.59	0.94	0.74	-2.0	5.7	0.5	0.5	129	23.5
Lower limit	240	31	9.7	0.696	0.99	0.78	0	6.5	0.9	1.1	160	26

The authors assign values as: A_P=0.63, B_P=0.25, C_P=0.12; A_{P1}=16/21, A_{P2}=5/21, A_{P3}=0; B_{P1}=1, B_{P2}=0; $Y = B$, Y_1=28.5, Y_2=29.5, Y_3=29.7; C_1=0.8, C_2=4; $J(\mathbf{X}) = (10000 - 0.28L^{0.9624}B^{0.9014}T^{0.883}C_B^{0.037})/3000$.

On a Pentium 4 computer (1.5GHz/CPU clock speed, 512MB/memory and 40GB/hard disk storage capacity), the authors run GA of 6000 generations, parallel GA of 600 generations, chaos algorithm, parallel chaos algorithm and parallel genetic chaos algorithm. The results are as Tab. 2 shows:

The results also include other 20 parameters which are omitted here such as wake fraction, thrust deduction fraction, initial stability height, rolling period, rudder area and wetted area, etc.

From the results, we can see that 3 equation constraints are satisfied to a degree of more than 99.8% and the inequality constraints are all satisfied to a degree of 100%. These indicate that this solving method is reliable.

Then, three kinds of objective function are calculated with parallel genetic chaos algorithm of 300 generations. The results are as Tab. 3 shows:

Table 2: Calculation Results of Different Methods

Items	GA (6000 generations)	Chaos algorithm	Parallel GA (600 generations)	Parallel chaos algorithm	Parallel genetic chaos algorithm (300 generations)
General objective function value	0.77904	0.76478	0.79500	0.78934	0.80721
L(m)	227.28	227.1	225.5	220.6	220.4
B(m)	29.44	29.47	29.50	29.50	29.49
T(m)	9.124	9.160	9.081	9.430	9.235
C_B	0.6837	0.6812	0.6910	0.6802	0.6955
C_M	0.9746	0.9796	0.9900	0.9763	0.9870
C_{WP}	0.7439	0.7545	0.7400	0.7446	0.7432
x_{CB} (m)	-1.1423	-1.6776	-1.297	-1.882	-1.651
D_P (m)	6.391	6.169	6.300	6.345	6.386
A_E/A_O	0.5033	0.5888	0.5277	0.5292	0.5096
P/D_P	0.8046	0.8895	0.8919	0.8630	0.8681
N (r/m)	140.2	137.6	131.1	133.0	130.0
V_t (kn)	23.84	23.66	23.58	23.50	23.51
$1/C_{sp}$	69.30	67.42	70.25	69.71	70.85
Quantity of screw	2	2	2	2	2
Screw type	AU	AU	AU	AU	AU
Quantity of blade	4	4	4	4	4
Displacement (t)	43081.27	43057.08	42999.07	43002.96	43012.00
T_E (kN)	1892.91	1866.33	1835.10	1822.67	1824.38
Resistance (kN)	1893.04	1867.18	1835.07	1822.80	1824.91
M_p (kN·m)	2241.14	2274.91	2268.47	2236.18	2252.04
M_d (kN·m)	2241.29	2275.95	2268.44	2236.34	2252.70
η_o	0.6862	0.6718	0.6886	0.6884	0.6910
P_E (kW)	23210.01	22722.55	22262.63	22035.48	22066.83
Main engine power (kW)	33459.24	33504.06	31833.39	31743.65	31264.52
Froude number (F_r)	0.2598	0.2580	0.2581	0.2600	0.2602

Analysis

5 points of conclusions are drawn after comparing and analyzing those different solving methods from Tab. 2

a. The values of 6000-generationed GA's and 600-generationed parallel GA's general objective functions are respectively 0.77904 and 0.79500. The former is lower than the latter by 2.05%, which means obvious premature convergence of GA.

b. The values of chaos algorithm's and parallel chaos algorithm's general objective functions are respectively 0.76478 and 0.78934. The former is lower than the latter by 3.21%, which means parallel algorithm is more efficient.

c. The parallel chaos algorithm is based on segments of delicate variables (That is to say, divide delicate variables' value ranges into segments and cross these segments completely. Subsequently, combine each segments group with remaining variables' value ranges to form the operation scopes. At last, compute by chaos algorithm within each scope in a parallel way). So besides **b**, we can also reach another conclusion from the comparison between the values of chaos algorithm's and parallel chaos algorithm's general objective functions that algorithm based on delicate variables' segments is better.

d. The values of parallel genetic chaos algorithm's general objective function is 0.80721. It's higher than those of parallel chaos algorithm and parallel GA by 2.26% and 1.54%. These 2 data tell us that parallel genetic chaos algorithm based on delicate variables' segments is the best among these methods in solving complicated engineering optimizations of multi-objectives, multi-constraints and multi-variables.

Conclusion

In this paper, a parallel genetic chaos algorithm based on delicate variables' segments is put forward and applied to synthetical optimization of navigation performances and structural properties for principal-dimensions-limited ships. Computation results show that this solving method not only can overcome GA's premature convergence, but also is of high efficiency. It provides an effective way for engineering optimization design of multi-objectives, multi-constraints and multi-variables. Plentiful optimization examples indicate that this software runs steadily and reliably. It lays a solid foundation for overall evaluation of ship design and integrated decision of ship parameter. In the meanwhile, we feel that it's a worthy and meaningful research on how to form the mathematical model of more comprehensive ship optimization (for instance, adding ship general layout to optimization or adding navigation environment as constraint) and how to find more suitable and better solving methods.

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