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Blending Glowworm Swarm Optimization Algorithm with Thermal-Mechanical Coupling Finite Element Model for Optimization Method of Box Structure Welding Technology

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Abstract

Welding sequence is the important influence factor of the temperature field and residual stress and deformation in welding structure, At present, determining the welding sequence is usually based on experience and test method. For complex structure it is very difficult to get the optimum welding sequence. This study is aiming to settle the problem of solving the optimum welding sequence of complex box welding structure. In our study, we take the welding deformation as objective function, and then, associate glowworm swarm optimization algorithm with thermal-mechanical coupling and nonlinear thermal elastoplastic finite element model to optimize numerical simulation, eventually the optimum welding sequence is determined. Optimization results demonstrate that the optimum welding sequence obtained by our method has small welding deformation and little change rate. At the same time, our method is faster, more accurate, more effective than the traditional experience or test method.

Keywords: *box welding; welding sequence; glowworm swarm optimization algorithm (GSOA); finite element model*

1. Introduction

Welding sequence is the important influence factor of the temperature field and residual stress and deformation in welding structure, so high quality welded structure requires carefully arrange the welding sequence in the welding technology process[1-3]. At present, the scholars determine the welding sequence based on experience and test method. The choice of welding sequence is $2^{(m-1)\,!}\times(m\text{-}1)!$ for a welding structure with m weld joints(consider the welding direction, if not welding sequence is $(m\text{-}1)!$). The more complex the structure becomes, the larger the optional welding sequence is. It is not obviously feasible to get the optimum welding sequence only by experience or test. Intelligent optimization algorithm does not depend on gradient information, has the merits of global, parallel efficient optimal performance, good versatility and strong robustness. It provides a new idea and means for solving the large-scale nonlinear problem, and has been widely used in welding optimization design.

Glowworm swarm optimization algorithm (GSOA) is that a new type of swarm intelligence optimization algorithm which mimics natural glowworm mating and foraging behavior was proposed by Krishnanand K N and Ghose D in 2005[4]. GSOA is simple, has strong global search ability, and has certain adaptability to the search space. Further more, the algorithm is not sensitive to parameter selection, and has strong robustness and good convergence performance [5]. So far, the GSOA has been applied in multimodal function optimization [6], knapsack problem [7], multi-robot system simulation [8], cluster analysis [9] and picture processing [10], in these areas the GSOA has achieved good results. In order to get the optimum welding sequence in huge optional welding

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sequence, we come up with glowworm swarm optimization algorithm combined with thermal-mechanical coupling and nonlinear thermal elastoplastic finite element model to optimize the welding sequence, and then get the optimum welding sequence.

This paper is organized as follows. Section 2 introduces the model of the problem and comes up with the glowworm swarm optimization algorithm optimization model used in welding sequence. Section 3 presents the results of the experiments. The paper is concluded by Section 4.

2. Welding Sequence Optimization

2.1. The Model of the Problem

The constraint conditions are: don't consider the influence of the direction of welding, input of welding heat is constant, clamping positioning method is constant, welding procedure parameters are constant. Using the box structure of virtual studio as an example, we take the problem as the following welding structure: size of the box is 420 mm×190 mm×280 mm, thickness is 6 mm, plate is 16MnR. Structure has four two pieces of welds, that is to say, there are 8 welds in the structure. The number of optional welding sequence is 7!, optional welding sequence is optimization variable.

2.2. The Establishment of the Glowworm Swarm Optimization Algorithm Optimization Model

2.2.1. Optimization Variable Settings: Each glowworm is defined as an optional welding sequence, so in the initial population there are (m-1)! glowworms. At q moment, the ith glowworm's position is $x_i(q)=\left[x_i^{(1)}(q),x_i^{(2)}(q),x_i^{(3)}(q),...,x_i^{(n)}(q)\right]$, the pth component is $x_i^{(p)}(q)$. Moment q is defined as the number of iterations($q\in[1,N]$, N is the maximum number of iteration). $x_i^{(p)}(q)$ is defined as welding sequence number($x_i^{(p)}(q)\in[1,(m-1)!]$).

2.2.2. Optimization Model: The minimum welding sequence of welding distortion is the optimum welding sequence in the optimization model. The smaller the value of the welding deformation function is, the smaller welding deformation is. Welding deformation function is defined as formula (1).

$$O(L,U,I,\eta,v,A,q_v,a,c,\phi,\delta,e,\omega)=0.86\times10^{-6}q_vL+Aq_v\times\frac{a}{c\phi\delta}+0.86\times10^{-6}\times\frac{eq_vL^2}{8\omega} \quad (1)$$

In formula(1), q_v is the welding energy input, L is the total length of weld(unit: cm), U is the arc voltage, I is the welding current(unit: A), η is the arc thermal efficiency, v is welding speed(unit: cm/s), A is empirical coefficient, a is material linear expansion coefficient, c is heat capacity of materials, ϕ is material density, δ is thickness of sheet metal, e is distance between weld center and neutral axle, ω is second moment of area.

In glowworm swarm optimization algorithm, objective function is defined as the reciprocal of welding deformation function, so the optimization problem is transformed into solving maximum problem. The greater the objective function value is, the smaller the welding deformation function value is. At q moment the ith glowworm's fluorescein concentration $l_i(t)$ is defined as the current objective function value.

2.2.3. Optimization Rules:

(1) Fluorescein updates rule: update rule can be seen in formula (2).

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$$l_i(t) = l_i(t-1) + \gamma f(x_i(t)) - \rho l_i(t-1) \tag{2}$$

In formula (2), ρ is fluorescein volatile coefficient, γ is the extraction proportion of fitness, $l_i(t\text{-}1)$ is previous moment fluorescein value, $\gamma f(x_i(t))$ is a percentage of current objective function value, $\rho l_i(t\text{-}1)$ is volatile fluorescein values.

(2**)** Movable probability updates rule: the movement direction is determined by the glowworm neighbors' fluorescein concentration. Movable probability updates rule can be seen in formula (3).

$$p_{ij}(t) = \frac{l_j(t) - l_i(t)}{\sum_{k \in N_i(t)} l_k(t) - l_j(t)} \tag{3}$$

In formula (3), $P_{ij}(t)$ indicates movable probability of the i th glowworm moving to its neighbors' j th glowworm, $j \in N_i(t)$, $N_i(t) = \left\{ j : \left\| x_j(t) - x_i(t) \right\| < r_d^i(t); l_i(t) < l_j(t) \right\}$ indicates the neighbor collection of ith glowworm at time t, $\|x\|$ is the norm of x.

(3) Location updates rule: location updates rule is shown in formula (4).

$$x_i(t+1) = x_i(t) + s\left(\frac{x_j(t) - x_i(t)}{\left\| x_j(t) - x_i(t) \right\|} \right) \tag{4}$$

In formula (4), $x_i(t+1)$ is the glowworm's new location of next time, s is mobile step. $P_{ij}(t)$ chooses movement direction according to roulette method. The better the glowworm's location, the higher the value of fluorescein, this also states that the objective function is optimal.

(4) Neighborhood range updates rule, see formula (5).

$$r_d^i(t+1) = \min\left\{ r_s, \max\left\{ 0, r_d^i(t) + \beta(n_t - |N_i(t)|) \right\} \right\} \tag{5}$$

In formula (5), r_s is the sensing range of glowworm, $r_d^i(t)$ is the dynamic decision-range of ith glowworm at t moment, β is the rate of neighborhood change, n_t is neighbor threshold.

Algorithm performs above four optimization rules in the process of iterative calculation, more glowworms finally gather around the glowworms which have higher fluorescein values through (m-1)！glowworms continuous movement.

(5) Disturbance updates rule: in order to guarantee the diversity of the glowworm population and solve the global optimal solution quickly, the definitions and related formulas are as below.

Definition 1(Round-robin factor ζ) ζ performs perturbation operation for glowworm individual according to the three time slices. The definition of three time slices of ζ is shown in formula (6).

$$\xi = \left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \right\} \tag{6}$$

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In formula (6), the first time slice is the matrix $\begin{bmatrix}1\\0\\0\end{bmatrix}$, the second time slice is the matrix $\begin{bmatrix}0\\1\\0\end{bmatrix}$, the third time slice is the matrix $\begin{bmatrix}0\\0\\1\end{bmatrix}$.

Definition 2 (Rotary disturbance) The state of glowworm individual x_i performs rotary disturbance according to formula (7).

$$x_i^M = x_i + \begin{cases} x_i \times \tau_1, if\,(q\%3) == 1 \\ x_i \times \tau_2, if\,(q\%3) == 2, (1 \le i \le (m-1)!) \\ x_i \times \tau_3, if\,(q\%3) == 0 \end{cases} \tag{7}$$

In formula (7), x_i indicates the ith glowworm individual, x_i^M indicates the new individual which has performed rotary disturbance, q indicates the current number of iteration and $q \le \frac{3D}{4}$, D is the maximum number of iteration. τ_1 、 τ_2 and τ_3 are the products of matrix $\begin{bmatrix} N(0,1) \\ Cauchy(0,1) \\ T(q) \end{bmatrix}$ and the three time slices of ζ, $\tau_1 = \begin{bmatrix} N(0,1) \\ Cauchy(0,1) \\ T(q) \end{bmatrix}\begin{bmatrix}1\\0\\0\end{bmatrix}$, $\tau_2 = \begin{bmatrix} N(0,1) \\ Cauchy(0,1) \\ T(q) \end{bmatrix}\begin{bmatrix}0\\1\\0\end{bmatrix}$, $\tau_3 = \begin{bmatrix} N(0,1) \\ Cauchy(0,1) \\ T(q) \end{bmatrix}\begin{bmatrix}0\\0\\1\end{bmatrix}$. N(0,1) is Gaussian distribution. $Cauchy(0,1)$ is standard cauchy distribution. $T(q)$ is t distribution which takes the number of iterations q as the degree of freedom of parameter.

From formula(7) we can see, on the basis of x_i we increase the random disturbance of different distribution, which makes the glowworm quickly jump out of local extreme value point and converge to the global extreme value point. Rotary disturbance doesn't need human intervention and has good adaptability.

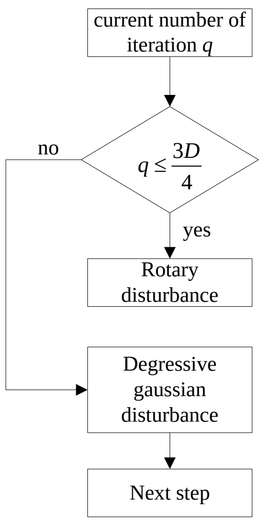

Figure 1. The Flow Chart of Disturbance Updating Rule

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Definition 3 (Degressive gaussian disturbance) The state of glowworm individual x_i performs degressive gaussian disturbance according to formula (8).

$$x_i^N = x_i + x_i \times \frac{N(0,1)}{q} \tag{8}$$

In formula (8), x_i indicates the ith glowworm individual, x_i^N indicates the new individual which has performed degressive gaussian disturbance, q indicates the current number of iteration and $\frac{3D}{4} < q \le D$, D is the maximum number of iteration. $\frac{N(0,1)}{q}$ indicates that along with the increase of the number of iterations, gaussian disturbance ability decreases.

The flow chart of disturbance updating rule is shown in Figure 1.

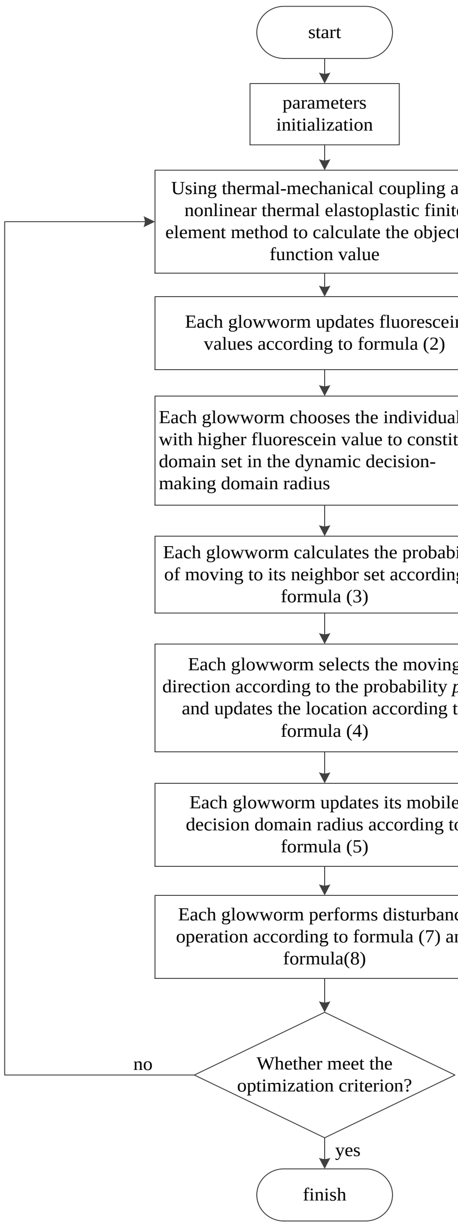

Figure 2. The Process of Optimization Algorithm

2.2.4. Optimization Algorithm: Optimization algorithm process is shown in Figure 2. In optimization algorithm, firstly, we perform numerical simulations according to thermal-mechanical coupling and nonlinear thermal elastoplastic finite element model, secondly, we calculate the welding deformation function value according to formula(1), and then we can get the objective function value. Optimization criteria is defined as whether the iteration has achieved the maximum number of iteration.

3. Experiment Results and Analyses

3.1 Physical Property Parameters of Welding Material

Thermal physics and mechanical parameters of materials change with temperature, which plays an important role for welding simulation accuracy. In this paper, welding material is steel Q345, whose physical performance and mechanical performance parameters change with temperature as shown in Table 1. The internal and external difference method is adopted to obtain the high temperature performance parameters(more than 800 ℃), and according to the yield strength under different temperature of steel Q345, material parameter settings in the finite element model we adopt bilinear follow-up reinforcement parameters.

Table 1. The Physical and Mechanical Properties of steel Q345 at High Temperature

temperature T/℃	thermal conductivity λ/(W.m^{-1}. ℃$^{-1}$)	specific heat Cp/(J.kg^{-1}. ℃$^{-1}$)	linear expansion coefficient α/(10^{-6}℃$^{-1}$)	yield strength $\sigma_{0.2}$/MPa	elastic modulus E/GPa	density ρ/(kg.m^{-3})	poisson's ratio μ
20	53.17	461	7.31	345	210	7 850	0.3
200	47.73	523	10.99	317	201	7 840	0.3
400	39.57	607	13.2	267	185	7 830	0.3
600	36.01	678	13.9	160	160	7 820	0.3
800	33	700	14	120	120	7 810	0.3

3.2. Test Parameter Settings of the Glowworm Swarm Optimization Algorithm

Test parameter settings of the glowworm swarm optimization algorithm are shown in Table 2. We use optimization algorithm to select the optimum welding sequence from 7! welding sequences, the optimum welding sequence is 37285461.

Table 2. Test Parameter Settings

glowworms scale n	maximum number of iteration D	control the fluorescein value ρ	evaluate the function value γ	control the neighbor range β	neighborhood threshold n_t	initial value of fluorescein l_0	moving step length s
7!	200	0.4	0.6	0.08	5	5	0.3

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3.3. Performance Analysis

When welding sequence is “12345678”, the welding deformation is 1.329. We compare the welding deformation of eight sets of data (7 randomly selected groups of welding sequence and the obtained optimum welding sequence) and welding sequence(12345678), calculate the deformation and the change rate. Comparison results are shown in Table 3.

Table 3. Welding Deformation Value and Change Rate

welding sequence	3728 5461	4268 1537	6847 1253	8236 4517	7546 2381	3876 1542	2531 7684	5836 4217
deformation /mm	1.329	1.864	1.921	1.792	1.956	1.981	1.829	1.902
change rate (%)	8.09	24.36	22.81	19.09	23.95	10.36	23.53	18.52

From Table 3 we can see, welding sequence has a big influence on welding deformation. In addition, the optimum welding sequence (37285461) has the minimum deformation and the smallest change rate. Obviously, the optimal welding sequence has the best efficiency.

In order to further illustrate the accuracy and rationality of optimization results, we make actual measurement of above 8 sets welding deformation, and compare the calculated value and measured value, see Table 4.

Table 4. The Contrast between Measured value and Calculated Value

welding sequence	3728 5461	4268 1537	6847 1253	8236 4517	7546 2381	3876 1542	2531 7684	5836 4217
calculated value /mm	1.329	1.864	1.921	1.792	1.956	1.981	1.829	1.902
measured value /mm	1.292	1.810	1.863	1.739	1.895	1.921	1.772	1.846
calculation error (%)	2.9	3.0	3.1	3.0	3.2	3.1	3.2	3.0

From Table 4 we can see, the deformation law of calculated value is basically in line with measured value for the eight sets of data. The average calculation error is 3.06%, the error of the optimum welding sequence is 2.9%, so our method is reasonable and accurate.

4. Conclusions

In this paper, we adopt glowworm swarm optimization algorithm combined with thermal-mechanical coupling and nonlinear thermal elastoplastic finite element model to optimize the welding sequence. Through analysis of the measured results and calculated results, we can see our method is faster, more accurate, more effective than the traditional experience or test method. Optimization results show that welding sequence has significant impact on welding deformation, and the optimized welding sequence can effectively reduce the welding deformation. For a specific geometry the optimum welding sequence is not unique, it depends on the type of constraint, there will be the optimum welding sequence in given constraint conditions. At the same time, our method is not only be used for the complex box beam welding structure of virtual studio, but also for other complex welding structure, it is a universal calculation method. But welding residual deformation control that relies solely on changing the welding sequence is failing to meet production requirements, the direction of future work is to make the welding residual deformation meet the technical requirements by combining other production technology and crooked control technology.

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