The Structure Optimization of Main Beam for Bridge Crane Based on An Improved PSO

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***Abstract*—The structure optimization of main beam is a nonlinear constrained optimization problem, which is important for bridge crane to save manufacturing cost on quality assurance. The modified particle swarm optimization (MPSO) with feasibility-based rules [1], which was advanced to solve mixed-variable optimization problems, is proposed to optimize the structure of main beam in order to find the optimal parameters so as to make minimize the deadweight of main beam. The comparison results with the enumeration algorithm illustrated that MPSO can get best optimal solutions in much less calculation numbers.**

***Index Terms*—Structure optimization, particle swarm optimization, enumeration algorithm**

I. INTRODUCTION

The bridge crane is an important equipment of lifting and transporting for lightening the intensity of labor and improving the operating efficiency. It can raise an object vertically and move it horizontally, which is mainly applied to materials assembly and unassembly and transportation between fixed span in workshop of factories, storehouse, and in the freight yard of railway and port. The deadweight of a crane metal construction is an important economic indicator for measuring the performance of the crane. Therefore, on the premise of the reliability service of the crane, its deadweight should be lightened as far as possible. As is known to all, the main metal construction composing the bridge crane is the bridge, which is put on the orbital supported by the upright post on either side, and can be driven back-and-forth. Therefore, the structural design for a bridge is important in the engineering design of the crane. In the design of the bridge, the quality of the main beam can directly influence the performance of the bridge which will obviously influence the performance of the bridge crane.

Enumeration algorithm, also called lattice algorithm, is commonly used to find optimum parameters for the main beam structure optimization problem. The optimum results may precise, however, it needs much time and large numbers of calculations especially for problems which have many variables with large range for value. So enumeration algorithm is unfit for those engineering problems which request high efficiency to obtain the optimal results. Evolutionary algorithms, such as Genetic Algorithm, Evolutionary Strategies, Evolutionary Programming and Ant Colony Algorithm, etc. have been proposed to solve unconstrained and constrained optimization problems during the past few years[2-6]. Particle swarm optimization (PSO) was a global stochastic algorithm proposed by Dr. Kennedy and Dr. Eberhart in 1995 [7,8]. Its idea was based on the simulation of simplified social models such as bird flocking and fish schooling. PSO is independent of the mathematic characteristics of the objective problem, and has gained much attention and been successfully applied in a variety of fields mainly for unconstrained continuous optimization problems [9-10] due to its simple concept, easy implementation and quick convergence [11]. However, like other evolutionary algorithms, PSO also lacks an explicit constraint-handling mechanism. In addition, all design variables should be continuous for PSO to solve optimization problems. However, most real-world engineering problems are constrained ones, and the variables are usually of the different kinds of types. So how to handle constraints and how to value the different kinds of variables are important for PSO in solving mixed-variable constrained nonlinear optimization problems. In this paper, a modified particle swarm optimization (MPSO) proposed by Sun et al. [1] is used to find optimal parameters for the structure optimization of main beam in which all design variables are integer, so as to minimize the deadweight of the main beam.

II. PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimization (PSO) was proposed as a global evolutionary algorithm by Dr. Kennedy and Dr.

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doi:10.4304/jcp.6.8.1585-1590

Eberhart in 1995 [7,8], its idea was based on the simulation of simplified social models such as bird flocking and fish schooling. In PSO, it assumes that in a D-dimensional search space $S \subseteq R^D$, swarm consists of N particles, each particle having no volume and no weight, holding its own velocity and denoting a potential solution. The trajectory of particle in the search space is dynamically adjusted by updating the velocity of each one, according to its own flying experience as well as the experience of neighbor particles (built through tracking and memorizing the best position encountered). Particle i is in effect an D-dimensional vector $\vec{x}_i = (x_{i1}, x_{i2}, \ldots, x_{iD}) \in S$. Its velocity is also a D-dimensional vector $\vec{v}_i = (v_{i1}, v_{i2}, \ldots, v_{iD}) \in S$. The best historical position visited by the particle i, called p_{best}, is a point in S and is denoted as $\vec{p}_i = (p_{i1}, p_{i2}, \ldots, p_{iD})$, and the best historical position that the entire swarm has passed, called g_{best}, is denoted as $\vec{p}_g = (p_{g1}, p_{g2}, \ldots, p_{gD})$. To particle i, the next flying velocity and position are updated as follows [12]:

$$\begin{aligned}\vec{v}_i(t+1) =& \omega \vec{v}_i(t) + c_1 \mathbf{r}_1 (\vec{p}_i(t) - \vec{x}_i(t)) + \\ & c_2 \mathbf{r}_2 (\vec{p}_g(t) - \vec{x}_i(t))\end{aligned} \tag{1}$$

$$\vec{x}_i(t+1) = \vec{x}_i(t) + \vec{v}_i(t+1) \tag{2}$$

where ω is a parameter called the inertia weight, c_1 and c_2 are positive constants respectively referred as cognitive and social parameters, $\mathbf{r}_i (i = 1, 2)$ is such a $D \times D$ diagonal matrix that each diagonal element is a random number uniformly distributed in the range [0,1].

The best historical position of particle i and the swarm are given respectively by the following equations:

$$\vec{p}_i(t) = \begin{cases} \vec{p}_i(t-1) & \text{if } f(\vec{x}_i(t)) > f(\vec{p}_i(t-1)) \\ \vec{x}_i(t) & \text{otherwise} \end{cases} \tag{3}$$

$$\begin{aligned}\vec{p}_g(t) \in & \{\vec{p}_0(t), \vec{p}_1(t), \ldots, \vec{p}_N(t)\} | f(\vec{p}_g(t)) = \\ & \min\{f(\vec{p}_1(t)), f(\vec{p}_2(t)), \ldots, f(\vec{p}_N(t))\}\end{aligned} \tag{4}$$

where f is the objective function, N is the swarm size.

III. THE MATHEMATICAL MODAL OF THE MAIN BEAM STRUCTURE

A. The design variables

For the bridge crane, the object of the main beam structure design is to minimize the dead-weight of the main beam, which is depended on the structural size of the section. Fig. 1 shows the parameters of the sectional size for the main beam.

As is known to all, the deadweight of a main beam has a crucial importance on the structural size of the section of the main beam. The parameters are listed as follows:

$$\begin{aligned}\vec{x} &= (x_1, x_2, x_3, x_4, x_5, x_6)^T \\ &= (h_1, B_2, d_1, d_2, d_3, d_4)^T\end{aligned}$$

where h_1 is the web height of the main beam, B_2 is the width of the lower cover plate, d_1 and d_2 are respectively the thickness of the upper and lower cover plates, d_3 and d_4 are the thickness of the main and auxiliary cover plates.

B. The objective function

The main object of the structural optimization of the bridge crane is to achieve the minimum deadweight of the main beam, so the objective function $f(\vec{x})$ is the deadweight of the main beam. The weight of the main beam includes the weight of the track, the weight of the main and auxiliary plates, and the upper and lower flange plates composing the box girder, and the weight of the transverse division plate for guaranteeing the local stability.

$$\begin{aligned}\min f(\vec{x}) =& (s^2 + (B_1 + x_2)x_3) + \\ & (x_5 + x_6)x_1)/L\gamma + W_1 + W_2\end{aligned} \tag{5}$$

where s, W_1 and W_2 are the weights of the orbit, the transverse diaphragm and the longitudinal rib, respectively. L is the span of the main beam and γ is the density of the material.

C. The objective function

In order to guarantee the crane run well, the main beam of the bridge should be satisfy some constrained conditions such as intensity, stiffness, stability and some requirements on the manufacture. Therefore, the constraints include:

(1) Constraint on the positive stress

In consideration of the influence of the external applied load on the bridge, the main beam will be suffered with the plumb and horizontal moment, which will cause the positive stress on any section. In order to satisfy the requirement on the intensity, the maximum positive stress should satisfy:

$$\sigma = \frac{M_V}{W_x} + \frac{M_H}{W_y} \le [\sigma] \tag{6}$$

where M_H is the maximum moment brought by the horizontal inertial force on the main beam when the cart starts or stops. M_V is the maximum vertical moment brought by the regular loads and travelling loads on the main beam. $[\sigma]$ is the stress needed by the steels.

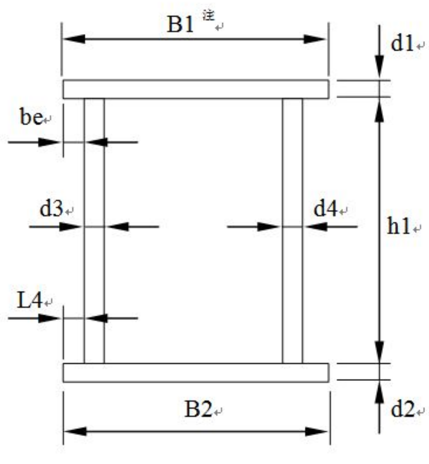

Figure 1 The parameters of the sectional size for the main beam

(2) Constraint on the shear stress

When the heavy dolly moves to the both ends supporting of the main beam, and the cart is just on the starting or stopping, the supporting section will has the maximum shear stress. In order to satisfy the requirement on the intensity, the shear stress should satisfy:

$$\tau = \tau_1 + \tau_2 + \tau_3 \leq [\tau] \tag{7}$$

where τ_1 is the shear stress caused by the shear force on the supporting of the main beam, τ_2 is the shear stress caused by the eccentric torsion which is put on the main beam by the walking board, wire and the weight of the operating organization, τ_3 is the shear stress caused by the eccentric torsion on the main beam produced by the horizontal inertial force of the heavy dolly movement. $[\tau]$ is the shear stress needed by the steel.

(3) Constraint on the still stiffness of the plumb

When the heavy cart locates on the midspan of the bridge, the maximum still deflection should satisfy

$$f_v \leq [f]_v \tag{8}$$

where $[f]_v$ is the allowable still deflection of the plumb.

(4) Constraint on the still stiffness of the horizon

When the cart starts or stops, the inertia force of the dolly will make the bridge produce deflection on the horizon. When the dolly is heavy and just on the midspan, the deflection on the horizon will be the maximum. In order to guarantee the stability of the bridge, the maximum deflection on the horizon should satisfy

$$f_H \leq [f]_H \tag{9}$$

where $[f]_H$ is the horizontal allowable still deflection.

(5) Constraint on the dynamic stiffness

In order to guarantee the stability of the bridge, the weaken vibration cycle of main beam without load should satisfy

$$T = 2\pi\sqrt{\frac{M}{K}} \leq [T] \tag{10}$$

where M is the conversion quality of the dolly, K is the stiffness of the bridge on the vertical, $[T]$ is the allowable ringing period.

(6)Constraint on the ratio between height and thickness of the web plate

With both the transverse and vertical stiffening plates exist, the ratio of height and thickness of web plate should satisfy

$$\frac{h_1}{d_3} \leq m_1 \tag{11}$$

where m_1 is the allowable ratio of height and thickness of web plate.

(7) Constraint on the ratio between width and thickness of the cover plate

In order to guarantee the local stability of the compression cover plate, the ratio of width and thickness of cover plate should satisfy

$$\frac{B_2}{d_2} \leq m_2 \tag{12}$$

where m_2 is the allowable ratio of width and thickness of cover plate.

(8) Constraints on the ratio between span and height, and the ratio between span and width of the main beam

With the intensity and stiffness satisfied, the following constraints also should satisfy

$$\frac{L}{h_1} \leq m_3 \qquad \frac{L}{B_2} \leq m_4 \tag{13}$$

where L is the span of the crane, m_3 and m_4 respectively represents the ratio of span and height, and the ratio of span and width.

(9) Constraint on the thickness of the broadwise stiffened plate

The thickness of stiffening plate is determined by the local bearing stress caused by wheel-pressure, so the bearing stress should satisfy

$$\sigma_c \leq [\delta]_c \tag{14}$$

where $[\sigma]_c$ is the allowable bearing stress.

(10) Constraints on the variables

Besides the constraints mentioned above, all design variables should satisfy

$$\begin{aligned}
&h_{1\min} \leq h_1 \leq h_{1\max}\\
&B_{2\min} \leq B_2 \leq B_{2\max}\\
&d_{1\min} \leq d_1 \leq d_{1\max}\\
&d_{2\min} \leq d_2 \leq d_{2\max}\\
&d_{3\min} \leq d_3 \leq d_{3\max}\\
&d_{4\min} \leq d_4 \leq d_{4\max}
\end{aligned} \tag{15}$$

IV. THE CONSTRUCTION OPTIMIZATION OF MAIN BEAM FOR BRIDGE CRANE BASED ON MPSO

The MPSO algorithm with feasibility-based rules as constraint-handling mechanism was proposed by Sun et al. [1] for solving mixed-variable optimization problems. Different kinds of variables are valued in different ways, and a turbulence operator was proposed in the updating of velocity to expand the search range of each particle and consequently avoid premature convergence. The experimental results showed that the MPSO algorithm can solve the pure discrete, the pure integer or hybrid discrete-integer problems well. In order to simplify the problem, all variables are dealt integer in the structure optimization of main beam for the bridge crane. Therefore, in this paper, MPSO is proposed to optimize the construction of main beam for bridge crane.

A. Feasibility-based rules

Referring to [13], feasibility-based rules employed in this paper are described as follows:

(1) Any feasible solution is preferred to any infeasible solution.

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(2) Between two feasible solutions, the one having better objective function value is preferred.
(3) Between two infeasible solutions, the one having smaller constraint violation is preferred.

Based on the above criteria, in the first and the third cases the search tends to the feasible region rather than infeasible one, and in the second case the search tends to the feasible region with good solutions. In brief, such a simple rule aims at obtaining good feasible solutions.

B. Constraint-handling mechanism

In the MPSO algorithm, the feasibility-based rules method was proposed to handling the constraints. According to feasibility-based rules proposed in Ref. [13], the constraint violation of each particle should be calculated to judge whether the particle is in feasible region. In MPSO, the violation to constrained functions was calculated by the following equation:

$$viol(\vec{x}) = \sum_{j=0}^{m} \max(0, g_j(\vec{x})) + \sum_{k=0}^{l} \max(0, abs(h_k(\vec{x}))) \tag{16}$$

where $g_j(\vec{x})$ is the inequality function and $h_k(\vec{x})$ is the equality function, m and l are the number of inequality and equality functions respectively.

According to the feasibility-based rules, the best historical position of each particle will be replaced by $\vec{x}_i(t+1)$ at any of the following situations:

(1) $\vec{p}_i(t)$ is infeasible, but $\vec{x}_i(t+1)$ is feasible;

(2) Both $\vec{p}_i(t)$ and $\vec{x}_i(t+1)$ are feasible, but $f(\vec{x}_i(t+1)) < f(\vec{p}_i(t))$;

(3) Both $\vec{p}_i(t)$ and $\vec{x}_i(t+1)$ are infeasible, but $viol(\vec{x}_i(t+1)) < viol(\vec{p}_i(t))$.

C. Treatment of mixed-variables in MPSO

In the MPSO algorithm, the values of non-continuous variables were proposed to get according to the velocity. All variables are random generated in their upper and lower bounds when they are initialized. For integer variables, simply truncating the real values to integers $int(x_{ij}(t)), j = 1, 2, \ldots, n_i$; the closest discrete value to the generated value will be set as the value of the discrete variable. In iterations, non-continuous variables update their values in smallest step, that is, the new value will be chosen from the neighborhood of the former value according to the velocity. The handling mechanism for the different kinds of variables is shown as follows:

```
Begin
  If x_id is a discrete variable
    Suppose x_id(t) = dv_d[j];
    If v_id(t+1) > 0
      If dv[j] is the first or last value in the set of discrete values
        x_id(t+1) = dv_d[j];
        random generate a new value for v_id(t+1);
      Else
        If x_id(t) + v_id(t+1) >= dv_d[j+1]
          x_id(t+1) = dv_d[j+1];
          v_id(t+1) = dv_d[j+1] - dv_d[j];
        Else
          If x_id(t) + v_id(t+1) <= dv_d[j-1]
            x_id(t+1) = dv_d[j-1];
            v_id(t+1) = dv_d[j] - dv_d[j-1];
          Else
            x_id(t+1) = dv_d[j];
            random generate a new value for v_id(t+1);
          End If
        End If
      End If
    Else
      If dv[j] is the first of last value in the set of discrete values
        x_id(t+1) = dv_d[j];
        random generate a new value for v_id(t+1);
      Else
        If x_id(t) + v_id(t+1) >= dv_d[j+1]
          x_id(t+1) = dv_d[j+1];
          v_id(t+1) = -(dv_d[j+1] - dv_d[j]);
        Else
          If x_id(t) + v_id(t+1) <= dv_d[j-1]
            x_id(t+1) = dv_d[j-1];
            v_id(t+1) = -(dv_d[j] - dv_d[j-1]);
          Else
            x_id(t+1) = dv_d[j];
            random generate a new value for v_id(t+1);
          End If
        End If
      End If
    End If
  End If
  If x_id is an integer variable
    If v_id(t+1) > 0
      If x_id(t) + v_id(t+1) > x_id(t)
        x_id(t+1) = int(x_id(t+1)) + 1;
      Else
        x_id(t+1) = int(x_id(t+1)) - 1;
      End If
    Else
      x_id(t+1) = int(x_id(t+1));
  End If
  If x_id is a continuous variable
    x_id(t+1) = x_id(t) + v_id(t+1);
  End If
End If
```

In the processing procedure of different kinds of variables, dv_d is an array which is used to keep all known values for d-th discrete variable.

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D. MPSO

In order not to converge to the local optima prematurely which is caused by the utilization of the feasibility-based rules, in the MPSO algorithm, the average velocity of the swarm was considered as a turbulence factor to change the flying direction of particles which was expected to expand the search range so as to improve the diversity of the swarm and avoid premature convergence. The new updating equations for velocity and position are defined as follows:

$$\begin{aligned} v_{id}(t+1) =& \omega(v_{id}(t) - \omega' \bar{v}_d(t)) \\ &+ c_1 r_1 (p_{id}(t) - x_{id}(t)) \\ &+ c_2 r_2 (p_{gd}(t) - x_{id}(t)) \end{aligned} \quad (17)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (18)$$

where ω is a parameter called the inertial weight, c_1 and c_2 are positive constants respectively referred as cognitive and social parameters, r_1 and r_2 are random numbers uniformly distributed in the range of [0,1], ω' is a turbulence parameter, $\bar{v}_d(t)$ represents the average velocity of the swarm on dimension d which is calculated as follows:

$$\bar{v}_d(t) = \frac{1}{N} \sum_{i=0}^{N} v_{id}(t) \quad (19)$$

where N is the swarm size.

E. Description of the algorithm for structure optimization of main beam

The pseudocode of MPSO for the structure optimization of main beam is given as follows:

Begin
  Parameter setting, including the swarm size N, inertia weight ω, cognitive parameter c_1, social parameter c_2 and turbulence parameter ω', $t = 0$;
  Initialize positions: For each dimension of particle i, random generate a value in the upper and lower bounds. Set $int(x_{id}(t))$ as the value of integer variable and the closest discrete value as the value of discrete one;
  Initialize velocity for each particle;
  Calculate the violation and fitness of each particle;
  Generate the best history position of each particle: $\vec{p}_i(t) = \vec{x}_i(t), i = 1, 2, \ldots, n$;
  Generate the best history position of the swarm: find $\min f(\vec{p}_i(t))$ where $viol(\vec{p}_i(t)) = 0$, set $\vec{p}_g(t) = \vec{p}_i(t)$ if $f(\vec{p}_i(t))$ is minimal;
  While the stopping criterion is not met
    For each particle i in the swarm
      Updating the velocity and position using (17) and (18);
      Call the handling procedure for different kinds of variables;
      Calculate the violation value using (16);
      Calculate the fitness value;
      Update the best history position of particle i according to feasibility-based rules;
    End for
    Update the best history position of the swarm: find $\min f(\vec{p}_i(t))$ where $viol(\vec{p}_i(t)) = 0$, set $\vec{p}_g(t) = \vec{p}_i(t)$ if $f(\vec{p}_i(t))$ is minimal;
  End While
End

IV. EXPERIMENTAL RESULTS AND SOME DISCUSSIONS

In order to evaluate the performance of MPSO with feasibility-based rules to optimize the structure of main beam for bridge crane, the enumeration algorithm is also run. Given the fixed lifted load $Q = 5 - 200(t)$, span $L = 10 - 70(m)$, the safety factor of intensity $n_1 = 1.48$. The density and the yield limit of the steel respectively are set $\gamma = 7.85(t/m^3)$ and $\sigma_s = 235$ MPa, modulo of elasticity $E = 206000$ MPa, the additional dead weight factor of main beam $kzh = 1.3$, the dead weight factor $kq = 0.31$, the impulse coefficient $\phi_4 = 1.19$, the factor of constrained bending stress $kys = 1.15$. In addition, $L_4 = 30(mm)$ and $be = 30(mm)$.

The parameters in MPSO are set as follows: the inertia weight ω, the turbulence parameter ω' and the cognitive parameter c_1 are decreased linearly from 0.9 down to 0.4, 0.5 down to 0 and 3.6 down to 2 respectively. The social parameter c_2 are increased from 0.2 up to 2. Total individuals are 40. The largest evolutionary generation is 10000. In order to evaluate the performance of MPSO in optimizing the structure of main beam, the enumeration algorithm, which is famous for accuracy on the results, is employed to obtain the best optimal solution at first.

Table 1 shows the results obtained by the enumeration algorithm, and Table 2 gives the results obtained by MPSO on 10 respectively runs.

Compared Table 2 to Table 1, it can be easily seen that MPSO obtained better results than the enumeration algorithm, this is because in order to save the calculation time, the step size of h_1 and B_2 are set to 100, while in MPSO, this is not constrained. Seen from Table 2, the maximum calculation number to find the best optimal solution needs 400040, the minimum number only needs 83440, the average number is 290148, all of which are much less than 48234496 needed by the enumeration

Table 1 the results obtained by enumeration algorithm

h_1	2400
B_2	1100
d_1	8
d_2	8
d_3	8
d_4	8
$f(\vec{x})$	17.91
calculation number	48234496

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Table 2 The results obtained by MPSO algorithm.

	h_1	B_2	d_1	d_2	d_3	d_4	$f(\vec{x})$	calculation number
1	2778	1054	6	6	6	6	17.60	83440
2	2763	1070	6	6	6	6	17.60	400040
3	2784	1048	6	6	6	6	17.60	88200
4	2763	1070	6	6	6	6	17.60	400040
5	2775	1057	6	6	6	6	17.60	140200
6	2765	1068	6	6	6	6	17.60	400040
7	1775	1057	6	6	6	6	17.60	189400
8	2763	1070	6	6	6	6	17.60	400040
9	2763	1070	6	6	6	6	17.60	400040
10	2765	1068	6	6	6	6	17.60	400040

VI. CONCLUSIONS

It is the first time to use particle swarm optimization to optimize the structure of main beam for bridge crane. The experimental results showed that the improved particle swarm optimization can find the best result as the enumeration algorithm which is always reliable for structure optimization of main beam. In addition, it can reduce much more calculation numbers than the enumeration algorithm, which provide a good reference for solving other mechanical optimization problems, especially for problems which have high requirement on the time efficiency.

ACKNOWLEDGMENT

This work was supported in part by Natural Science of Shanxi under Grant 2008011027-2 and Youth Foundation of Taiyuan University of Science and Technology under Grant No. 20103012.

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