An Improved Intelligent Ant Colony Algorithm for the Reliability Optimization Problem in Cyber-Physical Systems

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Abstract—**In this paper the torsion bar optimization problem of reliability is considered. Since this problem is a difficult optimization problem, an improved intelligent ant colony algorithm is proposed to solve the problem. This algorithm comprises five stages. First stage is the initialization of pheromone and the sensor node configuration. The second stage is to select the next sensor node. The third stage is to update the pheromone of the sensor node path. The fourth stage is to acquire the best path by computing the shortest distance. The last stage is to output the global optimal solution. To evaluate performance of the proposed algorithm, it is compared with the ant colony optimization algorithm and the genetic algorithm. The experimental results show that the proposed algorithm performs better than them.**

Index Terms—**Intelligence algorithm, CPS, Optimization, Reliability, Manufacturing**

I. INTRODUCTION

Global competition and rapidly changing customer requirements are demanding increasing changes in manufacturing environments.

Enterprises are required to constantly redesign their products and continuously reconfigure their manufacturing systems [1-3]. Traditional approaches to manufacturing systems do not fully satisfy this new situation. Many authors have proposed that artificial intelligence will bring the flexibility and efficiency needed by manufacturing systems.

The growing complexity of industrial manufacturing and the need for higher efficiency, greater flexibility, better product quality and lower cost have changed the face of manufacturing practice [4-7]. In addition to the technical issues, modern manufacturing technology is interdisciplinary in nature and allows the application of different knowledge from other scientific fields such as manufacturing, computer science, management, marketing and control systems [8]. Manufacturing has also shifted from mass production, to a more controlled one. We have to make sure that we can do it effectively if we want to make any profit [9].

Genetic algorithms [10, 11] use ideas from population genetics for solving complex global optimization problems. Bos applies a procedure based on the combination of a genetic and a gradient guided optimization algorithm for the design of a second generation supersonic transport aircraft [12, 13]. Karafyllidis has developed a method for designing a dedicated processor, which executes a cellular automaton algorithm that simulates the photolithography process [14]. The genetic algorithm is used to find a cellular automaton with discrete state space[15], having the smallest possible lattice size and the smallest possible number of discrete states [16], the results of which are as close as possible to the results of the cellular automaton with continuous state space. However a pool of potential candidate solutions evolve through reproduction [17] and mutation of the fittest and elimination of the least promising solutions of each generation are made extinct.

Since the last decade, attempts are being made to solve combinatorial optimization problems using an intelligent ant colony algorithm [18]. Hu and al. proposed an intelligent ant colony algorithm to solve flow shop rescheduling problem. However the intelligent ant colony algorithm is easy to fall into convergence of local optimum [19].

Purpose of this work is to present a new improved intelligent ant colony algorithm to solve the torsion bar optimization problem of reliability in intelligent manufacturing. The aim is to optimize a common objective function which takes into account both reliability and production criteria. The reminder of this

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paper is structured as follows. Section II illustrates the model and steps of the proposed improved intelligent ant colony algorithm. Section III describes the mechanics model of the torsion bar. Section IV analyzes and compares the results obtained by the proposed algorithm. Finally some conclusions are made in section V.

II. The Improved Intelligent Ant Colony Algorithm

A. Algorithm Model

The system model is expressed as follows.

$$\tau_{ij}^{new} = \rho \cdot \tau_{ij}^{old} + \alpha \cdot \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \tag{1}$$

Where m is the number of ants, ρ is durability, α is the volatile coefficient, τ_{ij} is the residue information between the sensor node i and j.

B. Algorithm Steps

Step 1: The sensor node configuration and the initialization of pheromone.

Step 2: To select the next sensor node according to the expression (2) and (3).

$$p_{ij}^{k}(t+1) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha}(\eta_{ij})^{\beta}}{\sum_{r \in s}[\tau_{ir}(t)]^{\alpha}(\eta_{ir})^{\beta}}, & j \in \{0,1,\cdots,n-1\} \\ 0, & j \notin \{0,1,\cdots,n-1\} \end{cases} \tag{2}$$

$$j = \begin{cases} \arg\max_{i \in j(k)} \{[\tau_{ij}(t)]^{\alpha}(\eta_{ij})^{\beta}\}, & q \le q_0 \\ S, & q > q_0 \end{cases} \tag{3}$$

Where q_0 is the initial parameters, q is a random number, η_{ij} is the heuristic information transform from the sensor node i to the sensor node j. β is the relative importance of expectation information. S is a random number determined by the expression (2).

Step 3: To update the pheromone of the sensor node path according to the expression (4) and (5).

$$\tau_{ij}(t+1) = \rho\tau_{ij}(t) + (1-\rho)\Delta\tau_{ij}^{k} \tag{4}$$

$$\Delta\tau_{ij}^{k} = \begin{cases} Q, & (i,j) \in T^{k} \\ 0, & (i,j) \notin T^{k} \end{cases} \tag{5}$$

Where Q is an constant, T^k is the past path of the ant k.

Step 4: To acquire the best path by computing the shortest distance when all ants go through all the sensor nodes. To update the pheromone of the best path according the following expression (6) and (7).

$$\tau_{ij}^{new} = \rho \cdot \tau_{ij}^{old} + \alpha \cdot \Delta\tau_{ij}^{k} \tag{6}$$

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{1}{d^{*}}, & (i,j) \in T^{k} \\ 0, & (i,j) \notin T^{k} \end{cases} \tag{7}$$

Where d^* is the distance of the best path.

Step 5: To output the optimal solution.

C. Algorithm Flow Chart

The algorithm flow chart is shown in Fig. 1.

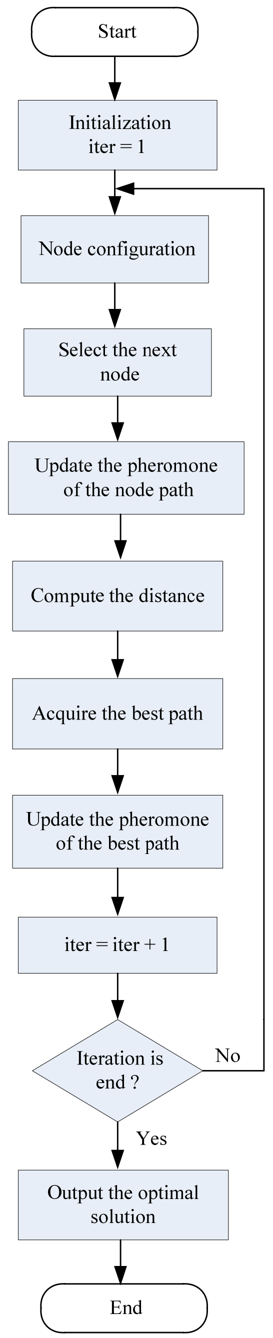

Figure 1. Algorithm flow chart

D. Algorithm Application Case

Coal transportation profit optimization:

We take a coal transportation enterprise as an example, there are three producing areas and five demanding areas. The shipment of the three producing areas is 18, 8, 16 respectively. The demand of five demanding areas is 6, 10, 8, 12, 6 respectively. The transport price of producing area 1# is 9, 19, 4, 8, 9, their upper limit of transportation is 1, 1, 4, 3, 2, and the cost of their transportation losses is 1, 4, 3, 4, 2. The transport price of producing area 2# is 1, 9, 7, 29, 5, their upper limit of transportation is 3, 3, 1, 2, 2, and the cost of their transportation losses is 1, 9, 2, 7, 9. The transport price of producing area 3# is 1, 19, 6, 9, 3, their upper limit of transportation is 1, 3, 0, 2, 4, and the cost of their transportation losses is 6, 9, 11, 1, 9.

According to the conditions given above, the results were got when the algorithm was applied. The results were shown in Table 1. The coal transportation profit is 285 unit according to the simulation results.

TABLE 1

THE OPTIMIZATION RESULTS

Sending area / Transportation area	1	2	3	4	5
1	0	6	8	2	2
2	0	0	0	4	4
3	6	4	0	6	0

E. Algorithm Application Prospect

The application field of the algorithm is wide.

a) Routing problem. Such as the vehicle routing, TSP, etc.
b) Allocation problem. Such as secondary allocation, graph coloring, frequency allocation, etc.
c) Scheduling problem. Such as workflow workshop, project scheduling, group workshop, etc.
d) Subset problem. Such as multiple backpack, maximum independent set, the biggest picture, etc.
e) Machine learning problem. Such as the bayesian network, the fuzzy system, allocation rules, etc.

III. MECHANICS MODEL OF THE TORSION BAR

The Mechanics model of the torsion bar is shown as the following expression (8).

$$F = \frac{16DT}{\pi(D^4 - d^4)} \tag{8}$$

Where T is the torsion bar and d is the inner diameter. D is the outer diameter.

The torsion bar is shown in Fig. 2.

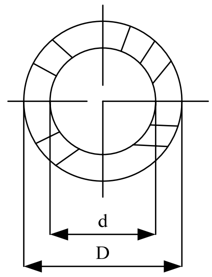

Figure 2. Torsion bar

According to the stress strength interference theory, the state equation is shown as the following expression (9).

$$g(X) = r - F \tag{9}$$

Where r is the material strength. Random variable is shown as the following expression (10).

$$X = [r \;\; d \;\; D \;\; T] \tag{10}$$

For partial derivation, we get the following expression (11).

$$\frac{\partial g(X)}{\partial X^T} = [\frac{\partial g}{\partial r} \;\; \frac{\partial g}{\partial d} \;\; \frac{\partial g}{\partial D} \;\; \frac{\partial g}{\partial T}] \tag{11}$$

IV. TESTING RESULTS AND DISCUSSIONS

A. Normal Distribution

The designing parameters of a clothing manufacturing was shown as follows.

$$\begin{cases} (\mu_T, \sigma_T) = (788532,\ 9973.35)\ N \cdot mm \\ (\mu_r, \sigma_r) = (775.8,\ 47.7)\ MPa \\ N \geq 6500 \\ \beta > 3 \end{cases} \tag{12}$$

Where β was the reliability index. N was the working cycle.

We defined the objective function as the following expression (13).

$$\begin{cases} f_1(x) = \dfrac{\pi}{4}(x_2^2 - x_1^2) \\ f_2(x) = \dfrac{\partial R}{\partial x_1} \\ f_3(x) = \dfrac{\partial R}{\partial x_2} \end{cases} \tag{13}$$

The geometry size constraint was shown as the following expression (14).

$$\begin{cases} 0 \leq d \leq 50mm \\ 0 \leq D \leq 50mm \end{cases} \tag{14}$$

Position and speed of 150 sensor nodes were randomly generated. We assumed the learning factor was 1.6 and the inertia factor decreased from 1 to 0.2.

After 55 times iteration, we got the optimal solution. The results of the three algorithms were shown in Table 2.

TABLE 2

RESULTS OF THE THREE ALGORITHMS IN NORMAL DISTRIBUTION

GA		ACO		IIACA	
Objective function values	Variable value	Objective function values	Variable value	Objective function values	Variable value
f1=188.57	d=20.8764	f1=175.85	d=20.9985	f1=174.26	d=20.3214
f2=0.5763	D=22.9978	f2=0.5998	D=22.8753	f2=0.5285	D=22.5021
f3=0.7548		f3=0.7989		f3=0.7462	
β=3.1947		β=3.2861		β=3.3975	

It was indicated that the improved intelligent ant colony algorithm could reduce the area of section so as to save materials. It also improved the reliability index. The reason was that the improved intelligent ant colony algorithm could select sensor nodes to grasp the whole face of the solution space. So the improved intelligent ant colony algorithm avoided the possibility of getting into the local optimal solution. It found the global optimal solution. Its searching speed was faster than others.

B. Arbitrary Distribution

The designing parameters of a clothing manufacturing was shown as the expression (15).

We defined the objective function as the expression (13) and the geometry size constraint as the expression (14).

Position and speed of 150 sensor nodes were randomly generated. We assumed the learning factor was 2.5 and the inertia factor decreased from 1 to 0.2.

After 65 times iteration, we got the optimal solution. The results of the three algorithms were shown in Table 3.

TABLE 3

RESULTS OF THE THREE ALGORITHMS IN ARBITRARY DISTRIBUTION

GA		ACO		IIACA	
Objective function values	Variable value	Objective function values	Variable value	Objective function values	Variable value
f1=188.57	d=27.8653	f1=175.85	d=27.5673	f1=289.35	d=27.3857
f2=0.5763	D=34.0991	f2=0.5998	D=33.9842	f2=0.5273	D=32.4165
f3=0.7548		f3=0.7989		f3=0.7659	
β=3.1893		β=3.1952		β=3.2869	

It was indicated that the improved intelligent ant colony algorithm could save materials because it could reduce the area of section. It also improved the reliability. The reason was that the improved intelligent ant colony algorithm could select sensor nodes to grasp the whole face of the solution space. So the improved intelligent ant colony algorithm avoided the possibility of getting into the local optimal solution.

$$\begin{cases} (T) = [7.5169\times10^5 N\cdot mm, 9.738\times10^3 N\cdot mm, 8.5637\times10^{10}(N\cdot mm)^3, 4.3825\times10^{15}(N\cdot mm)^4] \\ (r) = (795.6873MPa, 51.1037MPa, -8.1342\times105MPa^3, 1.5634\times108MPa^4) \\ N \geq 6500 \\ \beta > 3 \end{cases} \tag{15}$$

C. Lost Package Changes

Experiments were finished in the NS-2 simulation environment. The number of sensor nodes was 150 and initial energy of the node was 150 units. Sensor nodes were random distribution. The results of simulations were presented in Fig. 3.

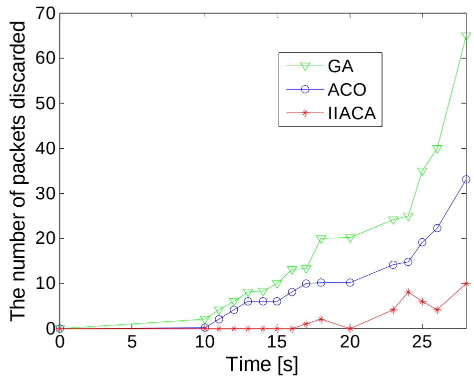

Figure 3. Lost package changes

Abscissa denoted time and y coordinate denoted the number of packets discarded. We assumed sensor nodes would begin to lose package when there were 35 packets in the wait queue. The results showed that the improved intelligent ant colony algorithm was better than others. It was not easy to cause the network congestion because the package was relatively balanced.

D. Surplus Energy Situation of Sensor Nodes

The results of simulations were presented in Fig. 4. Abscissa denoted time and y coordinate denoted the surplus energy. It was indicated that the improved intelligent ant colony algorithm was better than others. Because the energy consumed in each path was balanced in the improved intelligent ant colony algorithm. It would not make the network early lose balance because of too much consume of energy. So the whole network of life was prolonged.

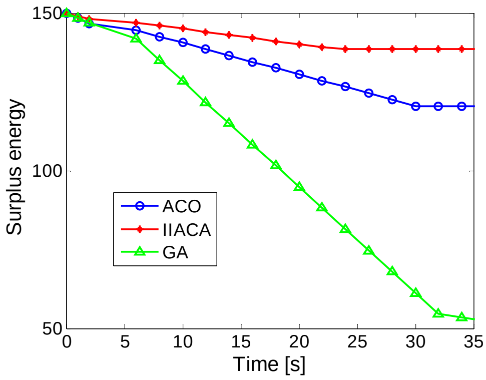

Figure 4. Surplus energy situation

V. Conclusions

In this paper we developed an improved intelligent ant colony algorithm for solving the optimization problem of reliability which related to material costs and benefits in the intelligent manufacturing industry.

An improved intelligent ant colony algorithm was designed to optimize the reliability of torsion bar in intelligent manufacturing. Then we tested and compared the three existing algorithms. Our analyses showed that the improved intelligent ant colony algorithm performed better than the genetic algorithm and the ant colony optimization algorithm in term of reliability, costs and energy saving. It could improve the performance of the whole network effectively. And it prolonged the lifecycle of the torsion bar in the manufacturing system.

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