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Research on Multi-object Job-shop Scheduling Strategy under Uncertain Environment

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***Abstract*—In this paper, we propose an improved PSO algorithm to optimize the RBF neural network（IPSO-RBF）for function approximation on the basis of the multi-objective stochastic scheduling model established by predecessors using stochastic programming knowledge. The experimental results show that the improved algorithm can solve the job-shop scheduling problem. The accuracy and speed of the solution have been improved.**

Keywords —multi-object; job-shop scheduling; IPSO-RBP uncertain environment

I. INTRODUCTION

In recent years, with the concept of “Made in China 2025”, the intelligentization of manufacturing has become an important trend for the survival and development of enterprises. The scientific and effective scheduling scheme can produce high-quality products that can best meet customer needs with shorter production cycle and lower cost, thereby improving the economic and social benefits of the enterprise. Among them, the realization of intelligent job-shop scheduling is a key issue that needs to be solved urgently. Previous studies on scheduling problems have focused on ideal deterministic scheduling. However, the production operation of an enterprise is actually a complex dynamic uncertainty system. There are a large number of uncertain factors, such as processing time fluctuations of products in the production process, sudden failure of processing equipment, raw material prices and delivery time. Waiting for changes in market demand, etc. These uncertain factors often lead to poor or even infeasible performance of the established production scheduling scheme, which restricts the practical application of scheduling research. Therefore, it is more and more urgent and necessary to introduce dynamic uncertainty constraints and fully consider the influence of uncertain factors to develop an optimal scheduling scheme with strong robustness and adaptability to uncertain environments.

II. DESCRIPTION OF UNCERTAINTY JOB-SHOP SCHEDULING PROBLEM

The Uncertainty Job-Shop Scheduling Problem (UJSSP) can be described as: n workpieces N_i (i = 1, 2, ..., n) are in a certain order on m machine tools M_j (j = 1, 2, ..., m) processing,Each workpiece is divided into K processes, recorded as WP_{ik} .the order of each workpiece, the fuzzy processing time of each process, and the fuzzy delivery time of the workpiece are pre-specified, and the processing order and processing on all machine tools that satisfy the given process of the workpiece are required. Under the condition of time, the processing order of each workpiece on each machine tool is determined, so that the average satisfaction time of all workpiece completion time with respect to the delay or delay of delivery is maximized. And the following assumptions are made to the scheduling model above:

1) Any machine M_j can only process at most one workpiece at a time;

2) After the start of any process, it cannot be interrupted;

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3) Workpiece N_i The kth process of N_i can only start processing after the completion of the k-1th process of the workpiece;

4) The same processing priority is available between different workpieces;

5) Any workpiece N_i can be processed on at most one machine at a time.

III. MODELING OF MULTI OBJECTIVE JOB-SHOP SCHEDULING UNDER UNCERTAINTY

Uncertain job shop scheduling will be affected by random factors, so this paper first introduces the relevant mathematical description of stochastic programming, followed by the determination of multi-objective function, and finally modeling.

A. Stochastic programming concept and relative schduling strategy description

[1]Suppose D is a decision vector, R is a random vector with known probability distribution, and x objective functions determined by D and R are marked as $f_i(D,R), 1 \le i \le \mathrm{x}$, which is subject to y constraint functions $h_j(D,R), 1 \le j \le y$.

Because both objective function and constraint function are random, the objective and constraint can only be described in the form of confidence probability. In this way, the corresponding chance constraint is expressed as $\mathrm{P}\left(h_j(D,R) \le 0\right) \ge \gamma_j, 1 \le j \le y$,where P denotes the probability that random event $h_j(D,R) \le 0$ occurs, and γ_j is a confidence probability; if the goal of the planning problem is to make. $f_i(D,R), 1 \le i \le \mathrm{x}$ is as small as possible, and the confidence probability is δ_i: then any objective function is expressed as:

$$\min \ \bar{f}_i$$

$$\text{s.}t.\ P\{f_i(D,R) \le \bar{f}_i\} \ge \delta_i, 1 \le i \le \mathrm{x}$$

In summary, a multi objective stochastic programming model based on multiple chance constraints is expressed as:

$$\min \ \left[\bar{f}_1, \bar{f}_2, \bar{f}_3, \ldots, \bar{f}_x\right]$$

$$\text{s.}t.P\{f_i(D,R) \le \bar{f}_i\} \ge \delta_i, 1 \le i \le \mathrm{x}$$

$$P\{h_j(D,R) \le 0\} \ge \gamma_j, 1 \le j \le \mathrm{y}$$

The relational formula $\left(\bar{f}_1, \bar{f}_2, \bar{f}_3, \ldots, \bar{f}_x\right)$ represents the weighted sum between X variables.

In a real shop environment, the machining time of the workpiece on the equipment is a random quantity obeying a certain probability distribution (often an exponential distribution), so the completion period of the workpiece is also random, and the delivery period constraint can be described as an opportunity constraint.Therefore, the definition of the delivery period constraint described in the form of the opportunity constraint is as follows：

$$\forall T_i \in U_n, P\{(ct_i - ot_i) \le 0\} \ge \gamma_j \\ 1 \le i \le m, 1 \le j \le n \tag{1}$$

Among them, T_i represent m production tasks of the workpiece, U is the n subsets generated by classifying the production tasks, ot_i is the delivery time required for all tasks (pre-set), ct_i is the completion period for each task, and γ_i is the confidence probability that each subset specifies a guaranteed delivery time without delay.

B. Determination of multi-objective function

Shorter completion times and lower cost are the two basic goals of scheduling.[2] For an order that requires production scheduling, due to the difference in the degree of process complexity of the included components, you can take the "shortest completion time of the slowest workpiece task" as the time target, completion time is denoted as ct ,set the probability of the letter α , and use the opportunity constraint to describe for:

$$min\ \ \bar{c}t$$

$$s.t.\ P\left\{\sum_{i=1}^{m} ct_i \le \bar{c}t_i\right\} \ge \alpha \tag{2}$$

Similarly, take "the sum of the processing costs of all workpieces is the smallest" as the cost target, set the probability of the letter as β , use the opportunity constraint to describe as：

$$min\ \ s\bar{p}$$

$$s.t.\ \ p\left\{\sum_{i=1}^{m}\sum_{k=1}^{K_i} sp\left(WP_{ik}, M_j\right) \le s\bar{p}\right\} \ge \beta \tag{3}$$

Where sp is the cost， $sp\left(WP_{ik}, M_j\right)$ is the cost function.

So, the stochastic programming model for shop scheduling is:

$$min\ [\bar{c}t,\ s\bar{p}]$$

$$s.t.\ P\left\{\sum_{i=1}^{m} ct_i \le \bar{c}t_i\right\} \ge \alpha\ ;$$

$$p\left\{\sum_{i=1}^{m}\sum_{k=1}^{K_i} sp\left(WP_{ik}, M_j\right) \le s\bar{p}\right\} \ge \beta\ ;$$

$$\begin{gathered}\forall T_i \in U_n, P\{(ct_i - ot_i) \le 0\} \ge \gamma_j, \\ 1 \le i \le m, 1 \le j \le n\end{gathered} \tag{4}$$

IV. ALGORITHM DESIGN AND IMPLEMENTATION

In the choice of algorithm, this paper selects IPSO-RBF neural network to approximate the random function because of RBF's ability of remarkable function approximation [3], and finally uses genetic algorithm to solve the scheduling problem.The following describes the design and implementation of specific algorithms.

A. RBF neural network

The RBF neural network is a three-layer feedforward network with a single hidden layer.[4]It simulates the neural network structure of local adjustment and mutual coverage of the receiving domain in the human brain, and is composed of an input layer, a radial base layer and an output layer. [5]The action function of the radial base unit often takes the Gaussian function, and the output of the layer of neurons is：

$$D_i = \exp\left(\frac{\|I - C_i\|^2}{2\theta_i}\right); i = 1,2,\ldots,m \tag{5}$$

Where: D is an n-dimensional network input vector; Ci is the central vector of the Gaussian function in the same dimension as D, i is the base width parameter, and m is the radial base (hidden layer) number of neurons.

The output of the output layer is:

$$Y = \sum_{i=1}^{m} w_i D_i \tag{6}$$

Where: w_i is the weight coefficient of the i-th hidden node to the output layer.

B. IPSO–Improved particle swarm optomization

In the mid-1990s, Dr. Eberhart and Dr. Kennedy jointly invented a new swarm intelligence computing technology [6], the particle swarm optimization algorithm（PSO）, The central principle is to search the best solution by means of mutual cooperation and information sharing mechanism among individuals in a population. PSO's speed and position update formula is:

$$V_{id}^{t+1} = W \times V_{id}^{t} + C1 \times Rand \times (P^{best}_{id} - P_{id}^{t}) + C2 \times Rand \times (p^{best}_{gd} - P_{id}^{t}) \tag{7}$$

$$P_{id}^{t+1} = P_{id}^{t} + V_{id}^{t+1} \tag{8}$$

where Vidt+1 represent idth particle speed of current iteration; W is the initial weight; Vidt represent idth particle speed of previous iteration; Rand represent random function in [0, 1]; C1, C2 are learning factors, and the general value is 2; Pbestid represent the idth particle's best local position and Pbestgd is the best global position among all particles;

and Pidt is the position of idth particle in the previous iteration.

The PSO algorithm has no crossover and mutation operations. The algorithm structure is relatively simple and fast, but there are still some shortcomings, sometimes the phenomenon of "oscillation" of particles near the global optimal solution occurs. To avoid this problem, This paper proposes to improve the PSO algorithm, called IPSO,improved parcicle swarm optimization algorithm in which the weight w is improved by reference [7]. , so that inertia weight w is reduced from the maximum weight to the minimum weight when the algorithm is iterated, as follow :

$$w = w_{\max} - iter_{cu} \times \frac{w_{\max} - w_{\min}}{iter_{sum}} \tag{9}$$

Where w_{max} is the maximum inertia weight; w_{min} is the minimum inertia weight; $iter_{cu}$ is the current iteration number; $iter_{sum}$ is the total number of iterations of the algorithm.

The second improvement is the introduction of a shrink factor [8] in the speed update. The shrinkage factor method guarantees the convergence of the search process in mathematical theory and produces a higher quality solution than the standard PSO algorithm.The improved formula is:

$$V_{id}^{t+1} = S[W \times V_{id}^{t} + C1 \times Rand \times (P^{best}_{id} - P_{id}^{t}) + C2 \times Rand \times (p^{best}_{gd} - P_{id}^{t})] \quad (9)$$

$$S = \frac{2}{\left|2 - \theta - \sqrt{\theta^2 - 4\theta}\right|}; \theta = C1 + C2 > 4 \tag{10}$$

C. Hybrid Optimization Method of RBF Network Based on IPSO

When the RBF network is applied, parameters of the center vector of the Gaussian function, the base width vector and network weights should be fully sure, if these parameters are set incorrectly, it will cause the approximation accuracy to drop or even the RBF network to diverge.This requires the use of the IPSO algorithm to optimize the RBP. The specific optimization process is explained below.

The first is to determine the RBF network structure, and then integrate the base width vector to be optimized, the center vector of the Gaussian function and the initial value of the network weight into a vector, as the location vector to be optimized by the IPSO algorithm.

The particle coding format searched in the N-dimensionalspace is:particle position || particle velocity || objective function. For example, if the network structure of the RBF is 2-3-1, then there are 12 parameters that need to be optimized, and the encoding format is{x1,x2,...,x12,v1,v2,...,v12,f(x1,x2,...,x12)},Where x1-x4 corresponds to the base width vector, x5-x8 corresponds to the Gaussian function center vector, and x9-x12 corresponds to the weight.

D. GA solves multi-objective scheduling problem

After training the RBF with the IPSO algorithm, the relevant network structure and optimal parameters are obtained. Embed the trained network into the GA, check the rationality of the chromosome, and calculate the target output of the chromosome[9].

Coding design: The key step in designing an intelligent optimization algorithm based on genetic algorithm to solve the shop scheduling problem is how to encode the chromosome of the genetic algorithm to ensure that all generated chromosomes can be decoded into one available scheduling plan in the evolution process of the genetic algorithm . For the shop scheduling problem, due to the complexity of its structure, the resources of the scheduling system, the multi-constraints of the product process and the diversity of the scheduling objectives, the calculation of the algorithm is large, and the coding design is for the time and space resources in the operation of the genetic algorithm. The consumption has a significant impact. In practical applications, most of the decimal coding is used, and the coding method needs special design. In the coding design, the storage characteristics of the coding in space and the effectiveness and complexity of decoding must be considered.

The algorithm-based representations proposed by Gen, Tsujimura, and Kubota are chosen in the algorithm of this paper [10]. The scheduling scheme is coded as a sequence of operations, each gene representing a process, all steps of the same workpiece are assigned the same decimal symbol, and then interpreted according to the order in which they appear in a particular chromosome. For the n×m job shop scheduling problem of M machine tools with n workpieces, one chromosome contains n×m genes, and the symbol of each workpiece will appear m times in the chromosome. Each gene represents a specific process of a workpiece. To ensure the technical constraints of the workpiece, it can be seen that any arrangement of genes in the chromosome can always produce a feasible schedule.

Fitness calculation: Embed the trained RBFNN into the GA to calculate the actual output of the chromosome[11], According to formula (1), it is first determined whether the order delivery period requirement is met. If it is not satisfied, the chromosome is eliminated, and then the completion time and cost are given different weights according to the degree of tendency. After the calculation is completed, the chromosomes are sorted from good to bad, and selection is made.

Cross: Use the job-based machine crossover (JMX), optionally two workpiece, and swap the machine numbers of the parent individual corresponding to the workpiece. like, having processs op1(113 |232 |312) and op2（212| 123| 112）,This means that the three workpieces separated by "|" and the process of intersecting the workpiece2 areX1（113| 123 |312）and X2（212 |123 |112).

Variation: randomly select a location, select a machine different from the current machine number in the optional machine set corresponding to this process, and replace the current machine.

V. Experiment Simulation

The data source of this experiment is to simulate a factory instance through MATLAB simulation software using Monte Carlo generate 300 sets of data samples, 200 sets of training samples, and 100 sets of test samples.

The factory received an order.The three workpieces of the lead time completion requirements are 80%,85%,70%, so the value of gamma in formula (1) is 0.8, 0.85, 0.7, respectively.and the weight of completion time and cost was set to 0.5 for the company.

In the IPSO algorithm parameter selection, the particle population is 30, the learning factor is 2, and the weight is 0.85.The experimental simulation runs 300 times.The optimal scheduling sequence The experimental results of the optimal scheduling sequence and completion time are shown in the following table 1.

TABLE I. Table 1 Results of simulation

work piece	Scheduling sequence	Mean completion time	Mean cost	Completion rate
A	1 4 2 3	125	168	85%
B	2 1 2 1	150	172	88%
C	3 2 4 2	108	112	75%

In terms of error and convergence speed, as shown in Figure 1, a significant improvement is achieved.

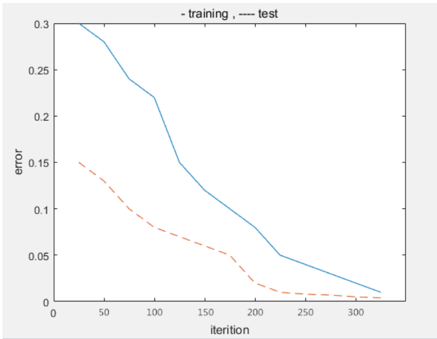

Fig.1. Error convergence curve

VI. Conclusion

In this paper, the multi-objective function approximation of RBF neural network is proposed by using IPSO algorithm. The simulation results show that the method is applied to the problem of shop scheduling in uncertain environment, under the condition of ensuring the minimum completion time and the lowest cost of the workpiece. It improves the convergence speed and is superior to the general RBF neural network, which is feasible.

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