CHEMICAL ENGINEERING TRANSACTIONS

VOL. 71, 2018

A publication of AIDIC

The Italian Association of Chemical Engineering
Online at www.aidic.it/cet

Guest Editors: Xiantang Zhang, Songrong Qian, Jianmin Xu

ISBN 978-88-95608-68-6; **ISSN** 2283-9216

DOI: 10.3303/CET1871071

Multi-step Optimization of Chemical Production Workshop Based on Improved Particle Swarm Optimization

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The scheduling problem of chemical production workshop is a weak link of computer integrated manufacturing system, and efficient production scheduling is the key to shorten the production cycle, and to improve production efficiency and economic benefits. This paper analyzes and studies the basic characteristics of the chemical production scheduling problem, and establishes a scheduling model for it. Based on the swarm intelligence algorithms, an improved particle swarm optimization (IPSO) and a genetic algorithm-based improved particle swarm optimization (GAIPSO) are proposed to solve the scheduling problem of chemical workshops and are verified. The results show that the IPSO is superior to the basic PSO in the convergence speed and the reliability of the solution to avoid falling into a local optimal solution and the "premature" problem, which improves the global search capabilities.

1. Introduction

With the development of society and the advancement of science and technology, the scale of production of companies has grown and the complexity of products has also increased. The chemical industry (Todd, 2009) is an important component of China's national economy. Chemical products (Tepper, 2010) are complex in processing and various in types, which involve all aspects of our lives. In the context of global market competition (John, 2001), traditional management experience and technology have been unable to meet the requirements of modern enterprise production (Silver, 1998), in order to enable production to be carried out efficiently and steadily, how companies increase production efficiency and reduce costs are effective means for companies to increase their competitiveness (Haldun Aytug, 2005; Krajewski, 2010). Therefore, the scheduling optimization of workshop production process is the focus of attention in the development of manufacturing, management, and operational technologies. The efficient and optimized production scheduling (Johnson, 2010) is the basis and guarantee for companies to shorten production cycles, improve production efficiency, and increase resource utilization rate. The swarm intelligence algorithms (Zheng, 2013) mainly include the ant colony optimization (ACO) (Yan, 2003) and the particle swarm optimization (PSO), which are algorithms based on the principle of ant foraging and bird predation. Because of the concise concept, they are relatively easy to implement, so they have been widely used in solving optimization problems and in the computer fields. The basic problem of chemical production workshops (Coello, 2007; Vallada, 2011) is the optimization problem of production and processing of M parts on N machines under certain constraints. Although there are current studies on the multi-step optimization problem for chemical production (Panwalkar, 1982; Kuo, 2006), how to effectively use swarm intelligence algorithms to improve production efficiency still needs further exploration. Based on the swarm intelligence algorithms, this paper establishes a scheduling model for the scheduling of chemical workshops, and uses IPSO to solve the generation of the "premature" phenomenon on the shop scheduling problem and validates them.

2. Chemical production workshop scheduling model

2.1 Chemical production workshop scheduling problem

The scheduling problem of a chemical workshops (Man, 2000) generally refers to the reasonable arrangement of the operations of the production process, including the processing sequence of the workpiece and the

Please cite this article as: Wu D., Wang L., Ying Y., 2018, Multi-step optimization of chemical production workshop based on improved particle swarm optimization, Chemical Engineering Transactions, 71, 421-426 DOI:10.3303/CET1871071

control of the production volume, on the premise of satisfying the constraint conditions. According to the production method, they can be divided into closed-loop workshops and open-loop workshops. The three most important elements of the scheduling problem and their inclusion are shown in figure (1) below.

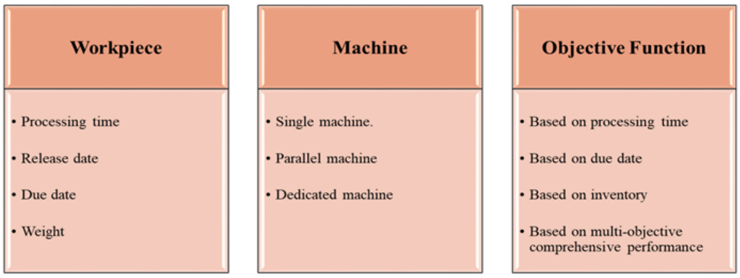

Figure 1: Elements of the scheduling problem

2.2 Characteristics of chemical production workshop scheduling problem

The scheduling problem of chemical workshops can be divided into various types according to different standards, including single machine scheduling, parallel scheduling and flow-shop scheduling according to the complexity; according to the processing characteristics of the operations, it can be divided into dynamic scheduling and static scheduling. Usually scheduling problems have following characteristics:

(1) Complexity: As the size of the company increases, the complexity of the specifications, processes, and time of the processing parts also increases exponentially, so it is necessary to find a suitable algorithm to solve the optimal solution under various constraints.

(2) Ambiguity: In actual chemical production workshops, there are many uncertain factors that will lead to uncertainty and ambiguity in the processing time. For example, raw materials cannot be supplied on time, machine emergencies and workers' different training levels would increase the ambiguity of the workshop scheduling problem.

(3) Many constraints: In the chemical workshops, the production process is subject to many constraints, including the limited manpower and resources, chemical process constraints, cost constraints and changes and uncertainties of the workshop environment and so on.

(4) Multi-objective: There are many goals in the chemical production workshop scheduling problem, such as minimum cost, shortest processing time, least inventory, minimum flow time, etc. These goals may conflict with each other but there are opportunities for them to promote each other as well. Therefore, when constructing the model, we must first make clear of the goal, or assign the weight of each goal to achieve the multi-objective optimization results.

2.3 Algorithm of chemical production workshop scheduling problem

The scheduling problem of chemical workshops is a typical NP problem, and it is one of the difficulties in the combination optimization. The multi-step optimization of chemical production workshops is an important branch of production scheduling, and the scheduling models established due to different constraints and objectives are not the same. At present, the solution methods for the scheduling problem of chemical workshops mainly include two types: the exact algorithm and the approximate algorithm (Bierwirth, 2014), as shown in the following figure (2). The intelligent optimization algorithms involve multiple fields and provide new ideas and methods for the scheduling problems with complexity.

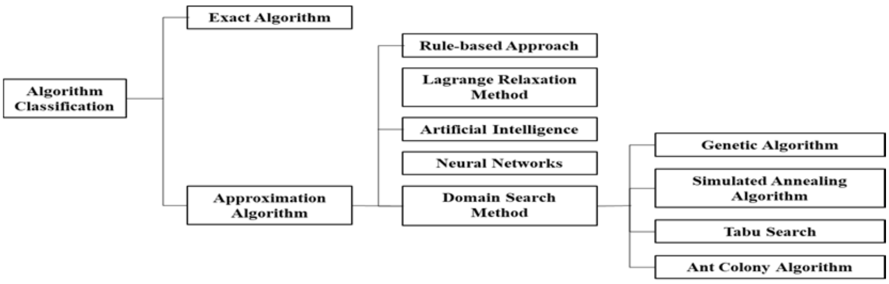

Figure 2: Algorithm of workshop scheduling problem

2.4 Chemical production workshop scheduling system model

The chemical production workshop scheduling system model is described as follows: in the chemical workshop there are M machines $\{M\_1, M\_(2), \ldots, M\_m\}$ to process N chemical parts $\{S\_1, S\_(2), \ldots, S\_n\}$, the satisfied constraints are shown in Figure (3) below:
Under constraint conditions, the production scheduling model of the chemical workshop is:

$$\text{F\_}min = \sum\_(j=1)\text{^}n ⟦(t\_ij⟧ \; B\_ij) + \sum\_(j=1)\text{^}(M\_(i-1)) C\_(iD\_ij \; D\_(i(j+1))) \quad (1)$$

Where, C represents the time it takes for the same machine to change the molds due to different product specifications.

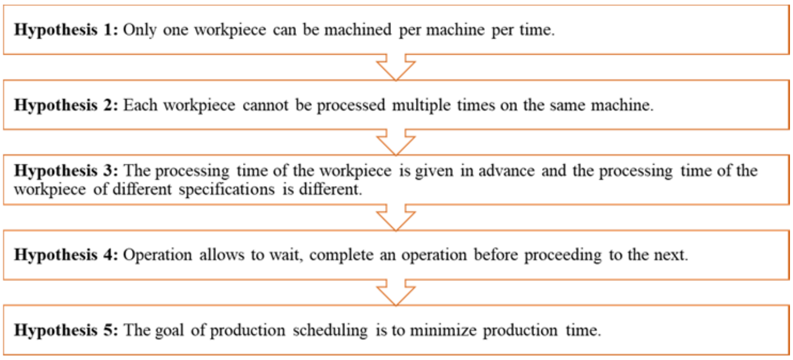

Figure 3: Hypothesis for production scheduling model

3. IPSO

3.1 Basic PSO

Particle Swarm Optimization (PSO) is a computer technology that simulates the prey behavior of birds. The algorithm is an optimization algorithm based on the iteration, it can perform the collaborative search among populations by updating the position and velocity of particles with no volume or mass within certain behavior rules, so as to achieve optimal solutions for the complex problems. Early PSO was successfully applied to the discrete optimized single machine scheduling, which effectively shortens the production cycle. However, with the complication of production process and steps, in the actual production and application, the algorithm easily falls into a local optimum, and problem such as decrease of convergence speed has occurred. The standard PSO is shown as follows:

$$\text{v(k+1)} = \text{wv (k)} + c\_1 \, r\_1 \, (p\_ib \, (k) - x(k)) + c\_2 \, r\_2 \, (p\_gb \, (k) - x(k)) \quad (2)$$

$$\text{x(k+1)} = x(k) + x(k+1) \quad (3)$$

$$C\_1 \text{ (k)} = C\_1\text{^}\infty + (C\_1\text{^}0 - C_1^{\infty}) \left[1 - \frac{k}{K}\right] \quad (4)$$

$$C_2\text{(k)} = C_2^{\infty} + (C_2^{0} - C_2^{\infty}) \left[1 - \frac{k}{K}\right] \quad (5)$$

Where v and x denote the update speed and position of the particle, k denotes the number of iterations. W denotes the inertia weight, which is used for balancing and adjusting the global and local search capability of the algorithm. p_{ib} and p_{gb} represent the optimal solution of the particle itself and the optimal solution of the population, respectively. c_1, c_2 denotes the learning factors.

3.2 Improvement strategy for basic PSO

The basic PSO has a fast convergence speed, but it easily falls into a local optimum. In order to enable basic PSO to combine with local and global advantages, we update and improve the PSO, the formula is as follows:

$$\text{v(k+1)} = \text{wv (k)} + c_1 r_1 \alpha\big(p_{ib}(k) - x(k)\big) + c_1 r_1 (1-\alpha)\big(p_{ib}(k) - x(k)\big) + c_2 r_2 (p_{gb}(k) - x(k)) \quad (6)$$

$$\text{W=} \left\{ \begin{array}{cc} w_{min} + \frac{(w_{max} - w_{min})(f - f_{min})}{f_{avg} - f_{min}} & f \le f_{avg} \\ w_{max} & f > f_{avg} \end{array} \right\} \quad (7)$$

Where, f represents the fitness value of the current particle; α is the variable weight; w_{min} and w_{max} represent the minimum and maximum inertia weights.The algorithm calculation flow chart is shown in figure (4) below.

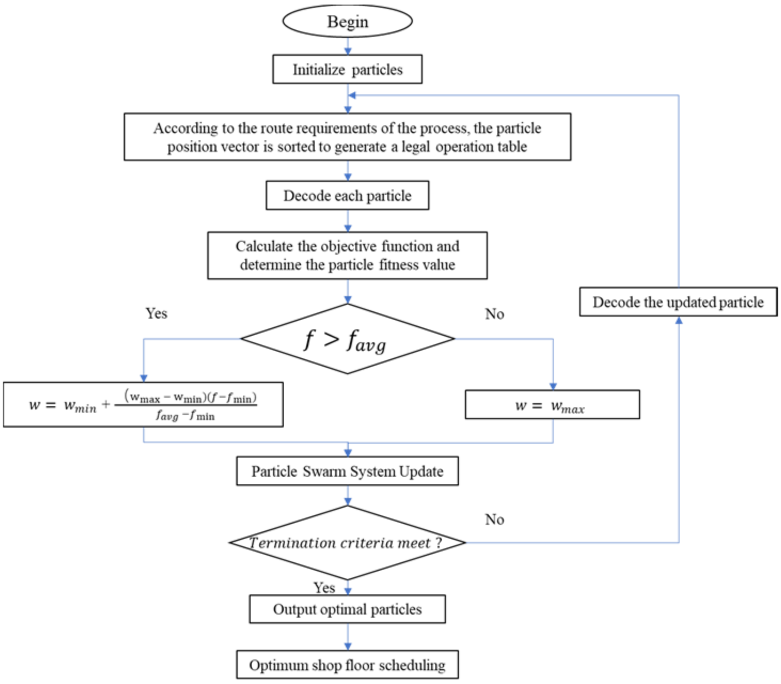

Figure 4: Improved PSO for workshop scheduling optimization

3.3 Improvement strategy for GAIPSO

Genetic algorithm is an adaptive algorithm that is highly random, parallel, and suitable for solving complex optimization problems. It uses the process of evolution, replication, crossover, and mutation of "chromosomes" to ultimately achieve the survival of the fittest and converges on the best chromosomes, so that the optimal solution is obtained. The biggest feature of this algorithm is the global solution space search and implicit parallelism. It is combined with PSO and applied to the multi-step optimization problem of chemical workshops.

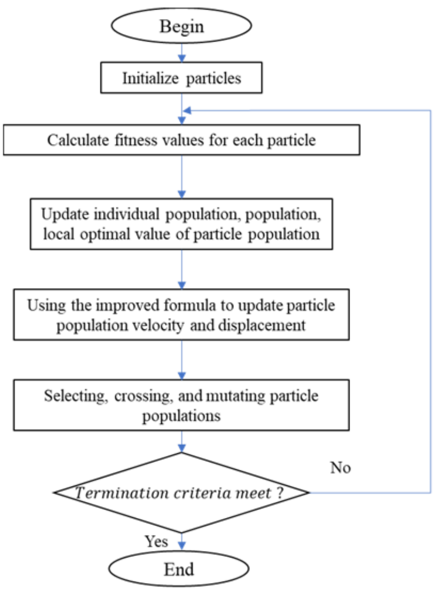

Figure 5: Flow chart of GAIPSO

4. Case analysis of chemical production workshop

4.1 Experiment introduction

In order to verify the effectiveness of the improved algorithm, this paper conducts a simulation test on the MatLab platform to verify it. This experiment takes a group of a certain chemical workshop as the object, assumes that there are 6 workpieces of different specifications which can be produced on 6 machines, the time for mold changing and the required processing time are shown in Table (1) and Table (2).

Table 1: Mold changing time/h

Workpiece	a	b	c	d	e	f
a	0	0.5	0.45	0.5	0.5	0.6
b	0.5	0	0.45	0.7	0.45	0.45
c	0.45	0.55	0	0.6	0.6	0.5
d	0.6	0.5	0.5	0	0.5	0.5
e	0.55	0.6	0.5	0.5	0	0.7
f	0.5	0.5	0.55	0.55	0.45	0

Table 2: Processing time/h

Workpiece	a	b	c	d	e	f
Processing Time	1	3	2	5	8	6

4.2 Experimental results and analysis

Based on the above data, the standard PSO and the IPSO are respectively tested. The experimental parameters are set to: the maximum number of iterations is 100, the learning factor is 0.7, the crossover rate is 0.8, the mutation rate is 0.08, and the variable weight α is 0.5. The comparison of the minimum completion time, machine utilization rate, and convergence speed of the three algorithms is shown in Tables (3), (6) and (7). From the minimization of the maximum completion time in Table (3), it can be seen that the total processing time used by the improved algorithm is reduced and the quality of the solution is improved.

Table 3: Result of maximum completion time of different algorithm

Workpiece	Maximum	Minimal	Average	Standard Deviation
PSO	66	52	58.50	2.0155
IPSO	61	52	55.80	1.0600
GAIPSO	59	52	54.50	1.00200

From the point of view of the machine utilization rate of the three algorithms in Table (6), the utilization rate of each machine of the IPSO has been improved, and the effect of the GAIPSO is better than that of the IPSO.

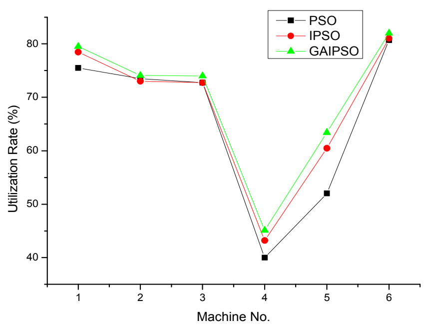

Figure 6: Machine utilization of different algorithm

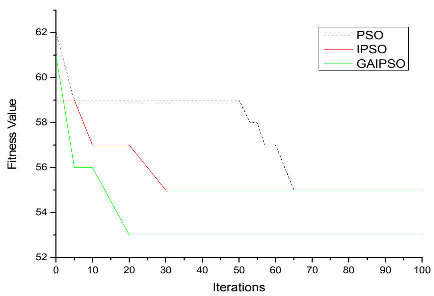

Figure 7: Machine utilization of different algorithm

From the convergence speeds of the three algorithms shown in Figure 7, the convergence speed of the IPSO is significantly higher than that of the basic IPSO, while maintaining a certain convergence speed, it also ensures the accuracy of the solution, and the GAIPSO algorithm finds the optimal solution faster than the

IPSO, which improves the computational efficiency and avoids waste of manpower and resources. Through the comparison of the three algorithms, the feasibility and superiority of the IPSO in multi-step optimization of chemical production workshops are verified, which has important practical significance and value.

5. Conclusion

This paper studies the scheduling problem of chemical production workshop based on the IPSO. The specific research results are as follows:
(1) This paper analyzed the basic characteristics and research status of the chemical workshop scheduling problem, and established a scheduling model for it.
(2) Based on swarm intelligence algorithms, this paper proposed the IPSO and GAIPSO to solve the scheduling problem in chemical workshops, and designed the calculation flowchart for the corresponding algorithms.
(3) This paper verified the problem of applying IPSO and GAIPSO in the scheduling problem of chemical production workshops, the results showed that the IPSO is superior to the basic PSO in convergence speed and the reliability of the solution, which avoids problems of falling into a local optimal solution and the "premature" problem, and it also improves global search capabilities.

Acknowledgement

Fund Project: Natural Science Research Projects in Jiangsu Higher Education Institutions (17KJB520033).

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