PRODUCTION SCHEDULING PROBLEM BASED ON MULTI-FACTOR DYNAMIC ANALYSIS ALGORITHM

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***ABSTRACT**: The production scheduling problem has a negligible influence on the production efficiency of manufacturing industry and the development of manufacturing companies. In order to find suitable algorithm and improve the scheduling efficiency of the production workshop, this paper proposes an improved multi-factor dynamic analysis algorithm based on the knapsack problem and several mathematical algorithms, analyzes the complexity and the correlation of the production scheduling problem in the workshop, and constructs a model for the workshop production scheduling problem. The research shows that the fitness landscape analysis helps to predict and understand the algorithm's spatial search behavior; For the three solution methods of the knapsack problem, the longer the distance from the optimal solution, the lower the average value, and the distance between the solution and the optimal solution is positively correlated with the average value of the item; when the multi-factor dynamic analysis algorithm is used to solve the scheduling problem of the workshop, relative ideal results could be obtained within a limited time period; if the test parameters are adjusted accordingly, better results could be obtained. This study provides a theoretical basis for improving the production scheduling efficiency of the manufacturing workshop, and has certain theoretical and social value for promoting the development of manufacturing industry.*

***KEYWORDS**: production scheduling, multi-factor analysis, dynamic analysis algorithm, combinatorial optimization problem*

1 INTRODUCTION

The production plan of the manufacturing enterprise is implemented according to the scheduling of the supply chain system. Under the existing production processes and equipment conditions, the production activity should be reasonably planned according to the market conditions or customer requirements so as to comprehensively improve the optimal performance of the supply chain system scheduling (Hu et al., 2012; Huang et al., 2018; Vand et al., 2018; Setiawan et al., 2016; Bierwirth and Mattfeld, 1999). From the development situation of the manufacturing industry and related researches we can know that, for manufacturing enterprises, the production scheduling is the key technology and core content in the manufacturing management process (Chryssolouris and Subramaniam, 2000; Chen et al., 2012; Masin et al., 2007). Solving the minimum processing time of products is one of the most valuable optimization methods for the production scheduling problem of the workshop. Optimizing the production scheduling scheme of the supply chain system in the workshop can effectively improve customers' satisfaction of the product delivery time, shorten the delivery cycle and increase product productivity of the manufacturing companies (Vinod and Sridharan, 2009; Papadopoulou and Mousavi, 2007).

The solution and the optimization algorithm of the production scheduling problem in the workshop lack of standards and theoretical basis, and the solutions of the algorithm have a great correlation with the characteristics of the scheduling problem itself (Käschel et al., 2002; Tang et al., 2014). As the most difficult combinatorial optimization problem, the workshop scheduling problem is also one of the key issues to be solved in the manufacturing field (Schruben, 2008; Liu et al., 2008; Jiang et al., 2017; Ren et al., 2018; Mehrjoo and Bashiri, 2013). Single optimization algorithm may have defects or inadaptability problems, and using combinatorial optimization algorithm to solve this kind of production scheduling problems can integrate the effectiveness and accuracy of multiple algorithms, and it can effectively search for the optimal solutions in the solving process (Vinod and Sridharan, 2011; Castillo and Gazmuri, 2015).

Based on the above problems, it is currently a top priority to find an efficient algorithm that can solve the optimal solution for complex production scheduling problems in the workshops (Markowitz and Wein, 2000; Yang and Shen, 2012; Li et al., 2008). Therefore, based on the existing optimization algorithms and the knapsack problem, this paper first analyzes the characteristics of the production scheduling problem in the workshop, explores the factors affecting the structure of the workshop scheduling problem, and proposes a combinatorial multi-factor dynamic analysis algorithm, thereby searching and solving the optimal solutions for the scheduling problem and its combination problem. This paper provides a theoretical support for the study of workshop scheduling problems, and lays a theoretical foundation for the algorithm setting of such problems and the combinatorial optimization problems.

2 BASIC THEORY OF MULTI-FACTOR DYNAMIC ANALYSIS ALGORITHM

2.1 Combinatorial optimization problem

The multi-factor dynamic analysis algorithm includes the combinatorial optimization algorithm, which can search for the optimal solutions continuously in the search process. Generally, combining the local search method with the intelligent algorithm can improve the effectiveness and efficiency of the algorithm. The FDC method was first applied to the genetic algorithm, it analyzes the combinatorial optimization problem by studying the correlation of the distance between the function value and the solution. In the coding algorithm, the correlation can be obtained by the fitness of the function values and the correlation coefficient of the distance. The correlation coefficient is a pure number without units, and its absolute value determines the degree of correlation.

For a specific problem, if the value of the correlation coefficient is very small, it indicates that there is a long distance between the obtained solution and the optimal solution, and the quality of the solution is very poor; if the value of the correlation coefficient is very large, it indicates that there is a short distance between the obtained solution and the optimal solution, and the quality of the solution is very good. The optimal solution may be in the vicinity of the local optimal solution, and this can provide an analysis basis for the fitness landscape. The correlation coefficient of the solution can guide the range and region of the search. When the correlation coefficient is larger, it continues to search for the local optimal solution in this range; when the correlation coefficient is smaller, the search range is expanded to search for the global optimal solution.

The earliest application of the correlation is in the genetic algorithm, foreign scientist Gold Berg discussed the similarity theory and the genetic algorithm mode, and applied the concepts to the specific problems and algorithms to calculate the correlation between the two; in addition, the correlation of the solution also represents the correlation of the local optimal solution and the global optimal solution, as well as the coincident region of the search space. Therefore, the FDC algorithm analysis and the spatial search method can effectively improve the efficiency of problem solving and the accuracy of the solution.

2.2 Fitness theory

The fitness problem is composed of neighborhood structures. Its feasible fitness solutions are a curve or a 2D curved surface in the search space. It can also be said that the landscape of the fitness is a vector graph with marks. In the field of optimization, fitness is defined as a triad (Ω, N, f). Where Ω is the feasible solution set of the search space, f is the specific solution in the feasible solution set, N is the neighborhood structure of the solution, and for each feasible solution, a solution set has been specified. The neighborhood structure links the solutions in different search spaces together. In local search, the problem is generally solved based on one solution according to the neighborhood structure. In the fitness landscape, the types of the points are shown in Figure 1, and the evaluation indicators of the fitness is shown in Figure 2. The fitness landscape analysis helps to predict and understand the behavior of algorithm in spatial search.

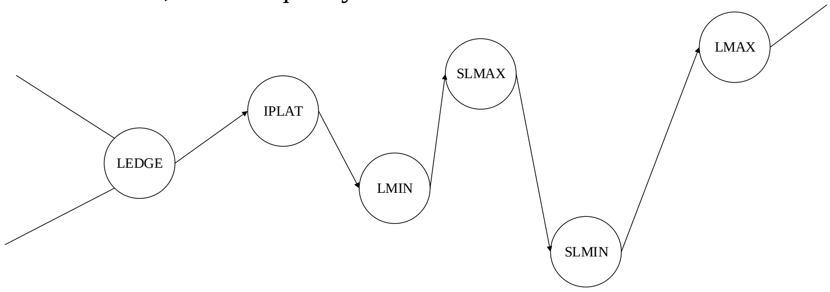

Fig. 1 Types of points in fitness landscape

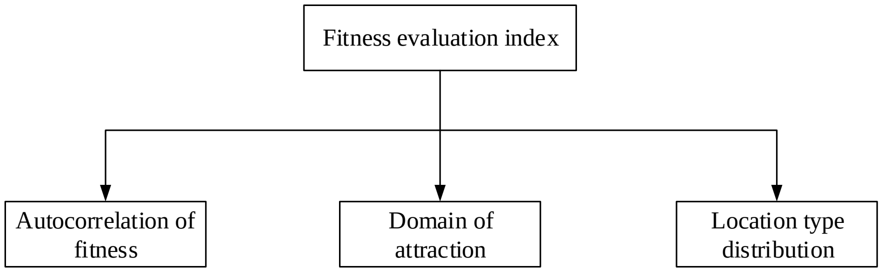

Fig. 2 Evaluation indicators of fitness

Taking the knapsack problem as an example to obtain useful information in the search space, for each problem, calculate the distance between the optimal solution and the known solution so as to obtain its degree of correlation, then find the optimized information through the calculation results. The content of the backpack problem is: a mountaineer can carry outdoor supplies with a maximum weight of 30kg, assume that the mountaineer can carry 10 kinds of items, and the weight and price of each item are known, how to choose the items to be carried so that the things could function the best for mountaineer.

According to the description of the problem, from the perspective of the maximum allowable weight, there are three handling methods, first, if the solution exceeds the maximum weight, the value of the excess item becomes zero; second, if the solution exceeds the maximum weight, then it is removed from the spatial search; third, if the solution exceeds the maximum weight, then 2 times the value of overweight item is deducted from the total price. The correlation coefficients calculated by the three methods is shown in Table 1.

Table 1. Correlation coefficient results of the three methods

Method	Relevant coefficient
First	-0.31
Second	-0.63
Third	-0.45

It can be seen from Table 1 that the correlation coefficients are all not higher than -0.31. Around the optimal solution, the landscape of the neighbor solutions is gradually reduced, this is because for solutions that satisfy the conditions, the total weights are close to the maximum allowable weight, one more item will cause overweight, which is why the correlation coefficient is relatively low. The correlation coefficient obtained by the second method is -0.63, which is the highest value among the three methods. There is no information that can indicate that the decline in the value of the backpack is not conducive to the increase of the item. When all the results are completed, and found that there's unfavorable situation in which the weight has exceeded the limit, after the problem is tried many times, the unfavorable situation is weakened. The average correlation coefficient obtained by the third method is -0.45. The third method is different from the first two methods, it uses the penalty factor, and the correlation coefficient can indicate that the knapsack problem has higher fitness. The influence of the change of strategy and the penalty factor makes the weight and the value have an approximate range, so the correlation of the model is higher.

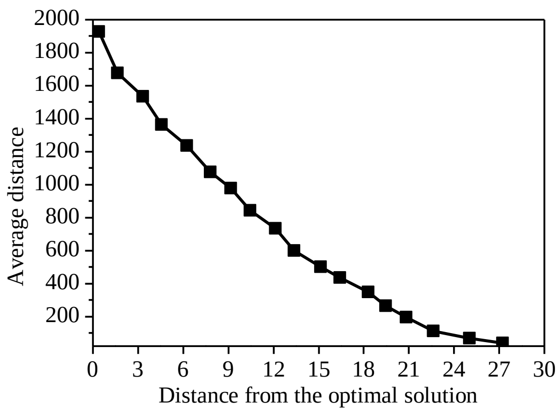

Fig. 3 The result of the first method

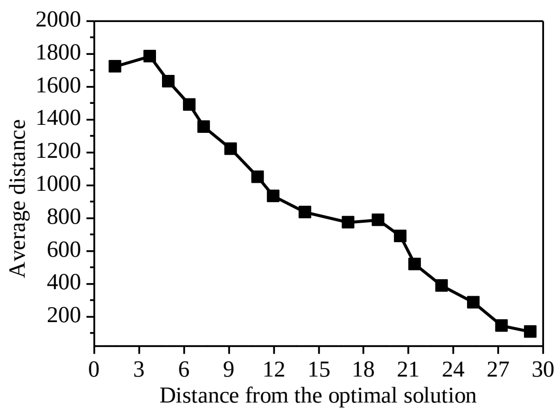

Fig. 4 The result of the second method

The average values of the solutions of the distance between the solution and the optimal solution of the three methods are shown in Figures 3, 4 and 5, from which we can see that, the longer the distance from the optimal solution, the lower the average value, and the distance between the solution and the optimal solution is positively correlated with the average value of the item, and the solutions have similar structures in the search space.

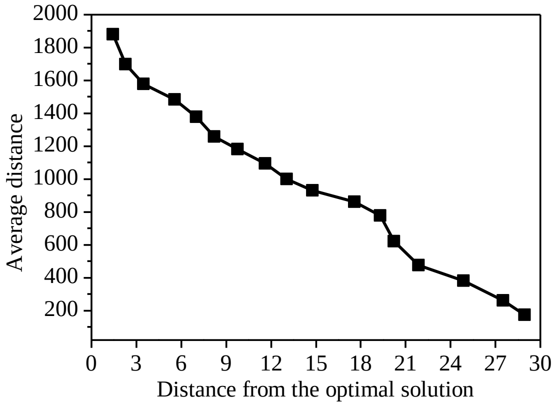

Fig. 5 The result of the third method

3 PRODUCTION SCHEDULING BASED ON DYNAMIC ANALYSIS ALGORITHM

3.1 Algorithm selection

The model of the production scheduling problem is: for the process in which machines of a certain number process workpieces of a certain number within a certain period of time, the goal is the completion time of all workpieces is the shortest, or the target cost is the minimum, or the manufacturing cost is the lowest, etc. The constraints are: each workpiece must complete all processing procedures, each machine can only process one workpiece at a time, the machine cannot be interrupted until the processing is completed. The 3×3 production scheduling extraction diagram is shown in Figure 6, and the 3×2 production scheduling extraction diagram is shown in Figure 7.

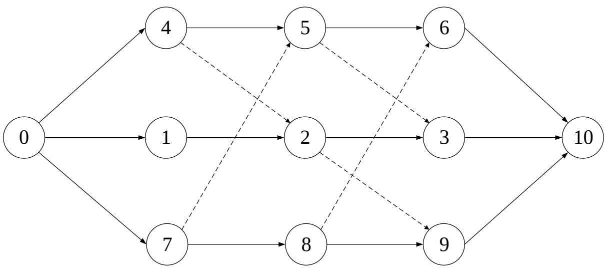

Fig. 6 3×3 disjunctive graph model for scheduling problem

In the production scheduling problem, a part of the problem has a large correlation with the feasible solution, the other part of the problem has no correlation with the feasible solution, and the same situation also exists in the structure. When we analyze the production scheduling problem, the workshop scheduling also have these problems in itself, and we need to analyze the globality of the problem.

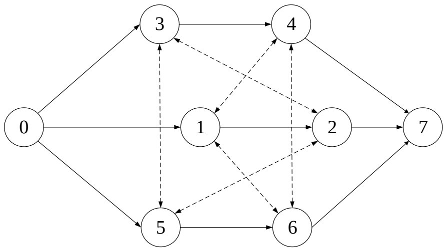

Fig. 7 3×2 disjunctive graph model for scheduling problem

When selecting the algorithm, since the production scheduling is a large-scale production activity, the multi-factor dynamic analysis algorithm is usually adopted; in this algorithm, crossover and mutation are the key operations that can change the structure. In the multi-factor dynamic analysis algorithm, the choice between crossover and mutation is especially important. When the solution of the problem has more correlation, after finding the local optimal solution, the crossover method can be used to search for the optimal solution. If the crossover method does not work, we can reduce the crossover in the neighborhood and increase mutation appropriately, so as to achieve the purpose of quickly finding the optimal solution.

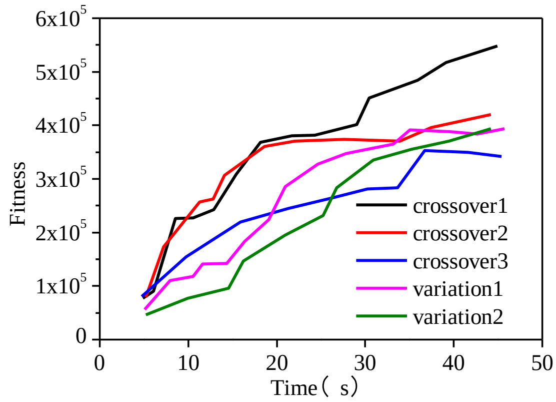

Fig. 8 Dynamic test results of production scheduling

As shown in Figure 8, for typical problems that need to be solved by mutation operation and cannot be solved by crossover operation, the obtained optimal solutions are different. For large-scale production scheduling problems, using only the mutation operation and not the crossover operation can yield better solutions, which proves that the feasible solutions have less similar structures.

For the design of multi-factor dynamic algorithm, the following conclusions are obtained.

When analyzing the local optimal solutions of the problem, the near-optimal solutions have more identical or similar structures, which increase the crossover probability of the algorithm. Conversely, when only the mutation operation is applied to calculation, the local optimal solutions can be quickly found, and then turns to the crossover operation to further optimize the local optimal solutions, thereby finding the global optimal solution. The crossover and mutation algorithms should be rationally selected to dynamically adjust the production scheduling algorithm.

3.2 Dynamic analysis algorithm for production workshop scheduling

Based on the dynamic analysis algorithm, the solving ability of the multi-factor dynamic algorithm is adopted to dynamically adjust the algorithm, so as to quickly obtain the optimal solution of the production workshop scheduling. When estimating the search space structure, there are two situations, the first is that the specific problem randomly generates a group solution and optimizes it, if the structures of the solutions are generally the same, then it is speculated that there is only one global optimal solution, or the global optimal solutions are clustered in a small region, then fix the segment and recode, use the local search algorithm, increase crossover and reduce mutation to get the optimal solution; second, the feasible solutions are in multiple subsets, there're more identical solutions in a same subset, and there're fewer identical solutions in different subsets, indicating that the optimal solutions in the space are distributed all over the space. At this time, we need to find the optimal solutions in each subset and search for the rest part of the optimization algorithm in the sub-space, and finally obtain multiple global optimal solutions.

According to the fitness landscape, the dynamic analysis algorithm is reasonably designed to solve the production scheduling problem. The design rules are as follows: first, generate M random solutions in the search space, and set the threshold and size of the Backbone as the basis for judging the type of the problem; second, use the optimization algorithm to iterate and get different feasible solutions; third, compare the feasible solutions, if its size is larger, go to step 4, otherwise go to step 5; fourth, select solutions with the same part from the feasible solutions and carries out local optimization calculation on them, meanwhile, increase crossover and reduce mutation probability; fifth, divide the feasible solutions into multiple subsets, reduce crossover probability and increase mutation, and continue the local optimization, then go back to step 4, the calculation steps are shown in Figure 9.

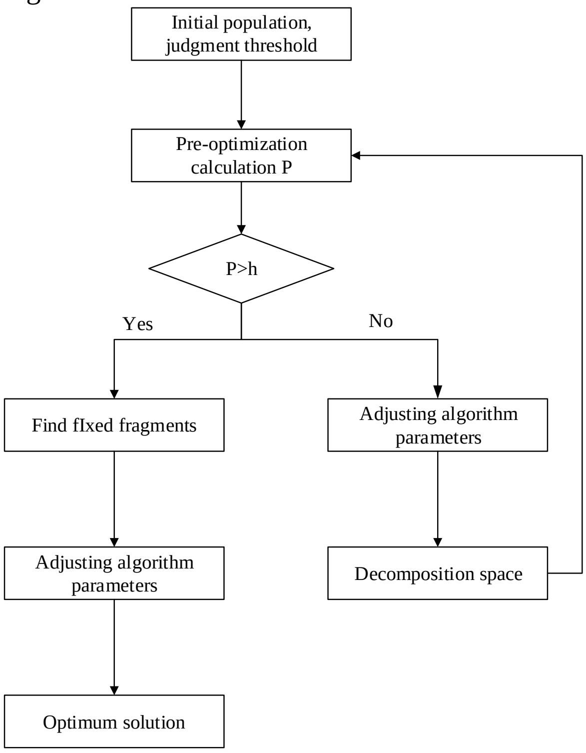

Fig. 9 Flow of the algorithm

This paper takes a specific case as an example to analyze the problem of workshop scheduling in multi-factor dynamic analysis algorithm. The population size takes N=100, the threshold is 0.6, the best number is 12, the maximum number of iterations is 250, and the maximum number of allowed steps is 40. The C language programming was adopted to implement the operation, 20 DS-class and DP-class standard test questions were adopted for the test, and the obtained calculation results are shown in Table 2.

As can be seen from the table, for the results of the 20 standard test questions, DS01, DS07, DP10, and DP14 can quickly find the optimal solutions in a short time, the times are all within 10 seconds, and the solution speed is very fast. For the DS2 question which is more difficult, it obtained better results within an average time of 14.6 seconds, in the case of 30 runs, the optimal value was obtained 9 times. For the questions DP16-DP20 which are more difficult, no optimal solution has been found, indicating that the multi-factor dynamic analysis algorithm cannot truly reflect the fitness landscape of the problem, complex problems generally have very complicated fitness landscape, and it's very difficult to get the optimal solutions. From the calculation results, the ideal results have been obtained in a limited time, and if the test parameters are properly adjusted, better results can be obtained.

Table 2. Calculation results of the multi-factor dynamic algorithm

Problem	Scale	Historically Optimal	Mean value	Current optimum	Margin ratio	Time
DS01	5×5	65	65	65	0	1.2
DS02	10×5	939	939	940	0.0032	14.6
DS03	10×10	977	977	978	0.0213	17.2
DS04	10×15	1218	1218	1217	0.0341	22.9
DS05	15×15	1260	1260	1259	0.0127	23.2
DS06	15×20	1241	1241	1243	0.0087	25.2
DP07	20×10	1241	1241	1241	0	6.7
DP08	15×10	1190	1190	1193	0.0131	29.5
DP09	15×10	1356	1356	1359	0.0024	13.4
DP10	15×10	1784	1784	1786	0	17.9
DP11	15×10	1850	1850	1853	0.0053	17.5
DP12	15×10	1719	1719	1721	0.0051	9.6
DP13	20×10	1721	1721	1722	0.0012	13
DP14	20×10	1542	1542	1542	0	9.8
DP15	20×10	1888	1888	1890	0.002	15.3
DP16	20×10	1272	1305	1324	0.0212	33.4
DP17	15×15	1419	1441	1451	0.0157	34.6
DP18	15×15	1205	1248	1252	0.0244	37.8
DP19	15×15	1236	1264	1274	0.0251	32.5
DP20	15×15	1231	1252	1262	0.0113	32.9

4 CONCLUSIONS

Aiming at the problem that the production scheduling in the manufacturing industry is complicated and difficult to solve, this paper proposed an improved multi-factor dynamic analysis algorithm, analyzed the complexity and correlation of the production scheduling problem in the workshop, and constructed a model for the workshop scheduling problem. The main conclusions are as follows:

(1) For the production scheduling problem of the workshop, the fitness landscape analysis method can help predict and understand the behavior of the algorithm in spatial search. The analysis of the knapsack problem shows that the longer the distance from the optimal solution, the lower the average value of the solutions of the problem, and the distance between the solution and the optimal solution is proportional to the average value of the item.

(2) When analyzing the workshop production scheduling problem, the crossover and mutation algorithms should be selected reasonably and the production scheduling algorithm should be adjusted dynamically, so as to quickly find the local optimal solutions, and then further optimize to find the global optimal solution.

(3) Using the multi-factor dynamic analysis algorithm designed according to the fitness landscape to solve the workshop scheduling problem helps to obtain ideal results for the scheduling problems, namely the feasible solutions of the problem; if the test parameters are properly adjusted, better results can be obtained.

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