DESIGN OF MULTI-OBJECTIVE FLOW SHOP SCHEDULING METHOD BASED ON HYBRID GENETIC ALGORITHM

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ABSTRACT: Optimization of the flow shop scheduling (FSS) is to integrate various favourable resources, improve the production efficiency of the workshop, and bring more economic benefits to the enterprise when meeting the conditions of production equipment and workpiece processing flow. In view of the shortcomings of the existing hybrid differential evolution algorithm and hybrid genetic algorithm (HGA), for the multi-objective FSS problem, this paper applies the improved HGA to solve a set of effective FSS solution under the multi-objective system. The study found that the multi-objective genetic algorithm has greater differences and the solution is more difficult; the multi-objective optimization problem can be solved by the objective function and the constraint function; the optimal scheduling value obtained by the HGA is better than the existing hybrid differential evolution algorithm; the production decision support system provides an optimized decision-making plan for the flow shop so as to improve production efficiency.

KEYWORDS: flow shop scheduling (FSS), hybrid genetic algorithm (HGA), hybrid differential evolution algorithm, production decision support system.

1 INTRODUCTION

With the development of manufacturing technology, the production scale of enterprises has been getting larger, the complexity requirements has been getting higher, the market competition has been becoming much fiercer, and the requirements for enterprise production management and production process monitoring have been also getting higher (Li et al., 2015). The scheduling problem of the production process in the manufacturing workshop is the core of the development in the manufacturing system operation technology, management technology and optimization technology. A compact scheduling solution can greatly reduce the production and processing costs, shorten the processing completion cycle, and improve the production utilization rate of manufacturing resources, thus greatly improving the economic efficiency of manufacturing industry (Chamnanlor et al., 2014; Ziaeifar et al., 2012). Multi-objectiveness is the root of the FSS complexity. Different objectiveness gives different expectations to decision makers. Lowering costs, improving work efficiency, and improving resource utilization all affect different production scheduling decisions, so, multi-objective optimization of FSS is important for the overall development of the enterprise (Desprez et al., 2009). The FSS problem is a simplified model of various actual production scheduling. It’s generally divided into traditional flow scheduling problem, mixed flow scheduling problem, and other scheduling problem related to time sequence (Rashidi et al., 2010).

In many FSS processes, various factors and indicators are mutual related to each other. For the multi-objective scheduling problems, the multi-objective production scheduling model with energy saving as an indicator should be taken into consideration (Bozorgirad and Logendran, 2016; Zhang et al., 2013). The current research has achieved certain results by applying the integrated flow genetic algorithm, BP neural network algorithm, dual-population amphiploid adaptive immune algorithm, and ant colony optimization algorithm in the FSS process (Pargar and Zandieh, 2012). However, the model proposed by the relevant algorithm will often ignore the rescheduling, the random processing time of the workpiece and the weight ratio of the workpiece, and cannot consider the actual situation of all scheduling problems (Lin and Chen, 2015). In this paper, based on the multi-objective FSS problem, an improved HGA is applied to solve a set of effective FSS solution under the multi-objective system.
2 RESEARCH STATUS OF PRODUCTION DECISION AND WORKSHOP SCHEDULING

2.1 Method for solving FSS problem

As the innovation economy continues to expand, manufacturing is developing toward the direction of innovation, multi-type and small-quantity (Danping et al., 2012). The FSS problem is, in the final analysis, the problem of resource allocation. The material usage of the unit workpiece is certain, and the resource allocation mainly refers to the equipment allocation (Nejati et al., 2014). The same type of workpiece has the same machining process, and it is difficult for one single workpiece to realize the distribution of equipment for flow scheduling. However, different types of workpieces generally have different processing operations. Therefore, it is relatively easier to implement flow scheduling for mixed workpieces (Tayeb et al., 2017; Mirsanei et al., 2011). FSS has the characteristics of complexity, multi-objectiveness and dynamic randomness etc., which also determines that the study of scheduling problems should reflect the actual production process (Joule et al., 2009). Many scholars divide FSS into single resource flow shop scheduling, dual resource flow shop scheduling and multi-resource flow shop scheduling according to the type and quantity of resource constraints; or divide it into static scheduling and dynamic scheduling according to the processing characteristics of the operation (Liou et al., 2013).

Petri net can be used to describe the evolutionary relationship between events and analyse the dynamic nature of the system. Petri nets have the advantages of reachability, boundedness and security etc. (Rahimi-Vahed et al., 2009). At present, the scheduling methods commonly used in flow shops include the operations research method, heuristic scheduling method, simulation-based method, and artificial intelligence-based method etc. The commonality of these scheduling algorithms is to seek optimal algorithms (Zhang et al., 2010).

2.2 Multi-objective optimization scheduling of flow shop

In the production scheduling of the flow shop, different departments show different expectations on the shop scheduling. However, in the actual production process, the scheduling problem is only completed by experienced managers, and the exact solution cannot be obtained. Commonly used multi-objective optimization scheduling methods for flow shop include vector evaluation method, Pareto-based method, weight and method, target planning method and compromise-based adaptive value allocation method. Despite of these optimized scheduling methods, the research on multi-objective FSS problem has not formed a set of systematic method and theory. The complexity of actual FSS far exceeds that of simple scheduling system, and its scheduling algorithm has poor universality. Fig.1 shows the energy consumption statistics scheme of the flow shop. The total energy consumption of the flow shop includes processing energy consumption, preparation energy consumption, transportation energy consumption, waiting energy consumption and other energy consumption. The shop scheduling model is determined by production environment, processing technology and processing information.

![Figure 1. Pipeline workshop energy consumption statistics program](image-url)

3 MULTI-OBJECTIVE HYBRID GENETIC ALGORITHM DESIGN

3.1 Petri net model of FSS

Different from the spatial position coordinates, the Petri net system also includes the quantitative relationship between the capacity and the change of the position and its extension resources. Therefore, the six-tuple PN=(P, T, F, K, W, M0) constitutes the Petri net, where N=(P, T, F) constitutes the base network of Petri, and K, W and M0 are capacity function, weight function and initial identification, respectively. It has been quite complicated to model a simple system by using the Petri net model, and it will cause disorders with system analysis and control. Thus, with the development of software engineering science, a cognitive methodology has been formed, and a new object-oriented Petri nets is proposed. An object subnet of the object-oriented Petri net represents a type of entity, which only represents the state and behaviour of this type of entity. The entities are independent of each other, and communication between the two subnets is
achieved through the change of the message position. Based on production processes, production methods, production equipment and workshop information etc., we built Petri net models and filtered out a lot of useless information, which plays a key role in the design and analysis of hybrid genetic algorithms, but it is difficult to restore all the information of the entire production system.

3.2 Hybrid genetic algorithm design

Compared with the single-objective genetic algorithm, the multi-objective genetic algorithm has greater difference and the solution is more difficult. The multi-objective optimization problem can be solved by the objective function and the constraint function. The main essential features of genetic algorithm are group search strategy and simple genetic operator, which have global search ability. The genetic operation is random in the whole process, and the current value can be used to derive the subsequent search set. Fig.2 shows the basic flow of the genetic algorithm, where the initial population is randomly generated and the individual adaptation value is calculated; if the algorithm satisfies the convergence condition, the search result is output; otherwise, the copy operation, the cross operation and the mutation operation are sequentially performed until satisfying the convergence conditions. Fig.3 depicts the flow chart of the hybrid genetic algorithm. First, parameter initialization is used to randomly generate the initial population, calculate the individual’s dominance and value level. Then, the individual with zero level input is saved and updated in the non-inferior solution set; if satisfying the genetic algorithm condition, all solutions shall be output; otherwise, two individuals are randomly selected and the individuals with smaller levels are copied, and the mutation operation is then implemented by the adaptive cross operation of the simulated annealing algorithm.

It’s assumed that the flow shop has six workpieces and six processing equipment, and each workpiece has multiple processing steps. In order to find the optimal FSS method,

The processing time Tij in the jth process of the workpiece i is given as:

$$T_{ij} = N_{ij} \times t_{ij} + P_{ij}$$  \hspace{1cm} (1)

where: Nij represents the number of parts required in the jth process of the workpiece i; tij is the unit processing time in the jth process of the workpiece i; Pij is the preparation time required for the jth process part of the workpiece i.

The processing time and processing equipment matrix can be established with the known number of parts, unit processing time, preparation time, workpiece processing time and equipment allocation. Table 1 lists the FSS genetic solution parameters. According to these parameters, the optimal production cycle can be obtained through the simulation experiment.

![Figure 2. Basic flow of genetic algorithm](image)

**Figure 3. Hybrid genetic algorithm flow chart**

<table>
<thead>
<tr>
<th>Sample population number</th>
<th>Cross probability</th>
<th>Mutation probability</th>
<th>Iteration</th>
<th>Cross length</th>
</tr>
</thead>
<tbody>
<tr>
<td>200</td>
<td>0.9</td>
<td>0.01</td>
<td>100</td>
<td>1</td>
</tr>
</tbody>
</table>
4 MULTI-OBJECTIVE SCHEDULING OPTIMIZATION AND SYSTEM DEVELOPMENT IN FLOW SHOP

4.1 Multi-objective scheduling optimization in flow shop

In fact, the FSS problem stems from its multi-objectiveness. It’s optimized from the aspects of production cycle, cost, and waiting time for meeting the interests of multiple parties; by continuously understanding the decision-making environment, the scheduling optimization plan is continuously revised until finding the most satisfactory optimized scheduling solution. Due to environmental and human factors, the workpiece production might be lagged behind in the actual flow shop. If the idle time of one workpiece before production is less than the preparation time, the lag will occur, and also be transmitted downward; but if making up for the lag time, the workpiece preparation time may be insufficient, further resulting in reworks. Fig. 4 shows the functional relationship between the lag time and the rework rate. With the extension of the lag time, the rework rate first increases and then tends to be unchanged. The hybrid differential evolution algorithm is a widely used optimization method now: the global search operation is performed in the entire flow shop, and 20% of the optimal individuals are selected for local search operations to improve the algorithm performance. Furthermore, the analytic hierarchy process is also used in the multi-objective evaluation decision-making scheme. The basic steps are: first establish a hierarchical structure model and construct all the judgment matrices in each level, then calculate the weight vector and perform consistency check, and finally calculate the combined weight vectors, make the combined consistency check and perform the hierarchical total sorting. Assuming that the machining sequence and machine constraints of each workpiece are determined in advance, a total of M workpieces in the flow shop need to process N operations, and each workpiece contains multiple routes or multiple processing operations, then:

Maximum production cycle: \( T1=\max t_{ini} \) \hspace{1cm} (2)

Maximum lag time: \( T2=\max(t_{ini}-d_i) \) \hspace{1cm} (3)

Total lag time of the workpiece:
\[
T3=\sum_{i=1}^{n} \max (t_{ini}-d_i)
\]

Total rework rate:
\[
F=\frac{\sum_{i=1}^{n} m_i (S_{ini}(\tau_{ini}) + \sum_{i=1}^{n} (c_k^i) \sum_{j=1}^{n} (\alpha_{k}^i d_i + \beta_{k}^i d_i))}{1}
\]

In this paper, hybrid genetic algorithm and hybrid differential evolution algorithm were used respectively. Fig. 5 shows the optimal value convergence graph of hybrid genetic algorithm. The two graphs are the results of multi-objective scheduling schemes for two different complexity workpieces, which clearly indicates that the optimal scheduling value can be obtained, but the value obtained by the hybrid genetic algorithm is better than the existing hybrid differential evolution algorithm.

4.2 Development of production decision support system

The production decision support system is an important part of the manufacturing FSS decision.
The development of the production decision support system can be used in the production management process of the enterprise, providing an optimized decision-making plan for the flow shop and improving its production efficiency. The overall framework of the production decision support system includes demand forecast support system, marketing decision support system, production decision support system, procurement decision support system and comprehensive budget support system. Fig.6 shows the overall architecture of the production decision support system, where the five support systems control the overall production plan, production plan, scheduling plan and production cost budget of the entire flow shop. Fig.7 shows the overall process of the system. The material demand plan is determined by predicting the main production plan to make purchasing decisions, while the product cost is determined by the production operation plan. In the production management information system, it is necessary to determine the product process route, equipment capability information, production personnel capability and basic information of the pipeline; the working time of the workpiece should be set to predict the support system. Fig.8 shows the functional modules of the production decision support system. The whole module includes equipment management, process management, production personnel management, integrated production planning, main production planning, production operation planning, production control and production cost accounting etc.

Figure 6. Overall architecture of production decision support system

Figure 7. Overall system flow

Figure 8. Functional module of production decision support system

5 REQUIREMENTS FOR THE PAPER

In this paper, for the multi-objective flow shop scheduling problem, an improved hybrid genetic algorithm was used to solve a set of effective FSS scheduling scheme under multi-objective system. The specific conclusions are as follows:

(1) The research on multi-objective FSS problem has not yet formed a systematic method and theory. The complexity of actual flow shop scheduling far
exceeds the simple scheduling system, and the scheduling algorithm is less versatile.

(2) Both the hybrid genetic algorithm and the hybrid differential evolution algorithm can obtain the optimal scheduling value, but the hybrid genetic algorithm obtains better values than the existing hybrid evolutionary difference algorithm.

(3) The overall framework of the production decision support system includes the demand forecast support system, the marketing decision support system, the production decision support system, the procurement decision support system and the comprehensive budget support system. The development of the production decision support system provides an optimized decision-making plan for the flow shop and also increase its productivity.

6 REFERENCES


