RESEARCH ON MANUFACTURING FLOW SHOP SCHEDULING METHOD BASED ON MULTI-OBJECTIVE EVOLUTIONARY ALGORITHM

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ABSTRACT*: Nowadays, the manufacturing of electronic product is developing vigorously. It is of great significance to study how to improve the utilization rate of core manufacturing equipment through production management and achieve the goal of energy saving, environmental protection and efficiency enhancement. For this, this paper firstly takes the manufacturing pipeline of DTSD178 smart meter as the research object based on the multi-objective evolutionary algorithm, and studies the process time and energy consumption of three kinds of boards (the same total process time): main board (MB), communication board (CB) and video board (VB) on different machines, to determine the characterization parameters of the multi-objective scheduling model, that is, the process time PT and the energy consumption E*. Then, selecting the above two parameters as the optimization objectives, the multi-objective permutation flow shop scheduling (FSS) model in manufacturing was established. The research results show that the multi-objective scheduling model can be conductive to obtain the optimal scheduling solution, to solve the multi-objective permutation FSS problem, and achieves the purpose of improving equipment utilization and reducing energy consumption. This shall provide reference for policy makers to guide actual production.*

KEYWORDS*: manufacturing, multi-objective evolutionary algorithm, flow shop scheduling (FSS), optimization.*

1 INTRODUCTION

The Flow Shop Scheduling (FSS) is one of the important parts in production management since the Industrial Revolution (Tasgetiren et al., 2010). In the manufacturing enterprises of high-tech electronic products, core manufacturing equipment is often very expensive and high energy-consuming. Thus, it’s very worth studying on how to reasonably deploy production resources and determine the process flow, in order to achieve the minimum total production time, the lowest equipment idling rate and the least energy consumption (Gao et al., 2011).

At present, many scholars at home and abroad have studied the FSS problem. Guan Long et al. used energy distribution method to make an energy-saving design of production workshops with temperature as a parameter, and controlled the energy consumption of the workshop to some extent (Deng et al., 2012); Pan et al. think that the shutdown method controls the energy consumption between the steps to a certain extent (Pan et al., 2008); Li et al. proposed an energy calculation model for the single machine scheduling problem (Li & Ma, 2017); Sang et al. used the completion time and average power cost as parameters to analyse the scheduling problems (Sang et al., 2012). Based on the existing research, it can be found that most scholars regard the no-load energy consumption of individual machine as the energy-saving design point, but ignoring the uncertainty of the actual production processing system and the energy consumption in the flow production process. Therefore, there is still much room for promoting the energy conservation and emission reduction.

In view of this, the paper takes the total process time and the total idle energy consumption as the optimization objectives, and builds a multi-objective scheduling model based on the multi-objective evolutionary algorithm. Then, the optimal scheduling solution was simulated and calculated. The research results have the positive significance for guiding the production scheduling decision-making.

2 OVERVIEW OF MULTI-OBJECTIVE EVOLUTIONARY ALGORITHM

The common algorithms for the multi-objective scheduling problems in manufacturing include simulated annealing algorithm, ant colony algorithm, immune algorithm, differential evolution algorithm and multi-objective evolutionary algorithm. Among them, multi-objective evolutionary algorithm is widely used to solve multi-objective scheduling problems. It has the characteristics of simple mechanism, strong retrieval ability and excellent robustness, especially for the large-scale scheduling problems with multi-sequence elements, multi-constraints, and large retrieval amount (Marichelvam et al., 2014). The basic idea of the evolutionary algorithm is to first randomly generate an initial population of size N; after fast non-dominated sorting, to set reasonable congestion degree, elite retention strategy, SBX, polynomial variation, competition selection; to produce new generations through the basic operation of genetic algorithm, and so on, until trigger the end condition. The most commonly used multi-objective evolutionary algorithm flow is shown in Figure 1.

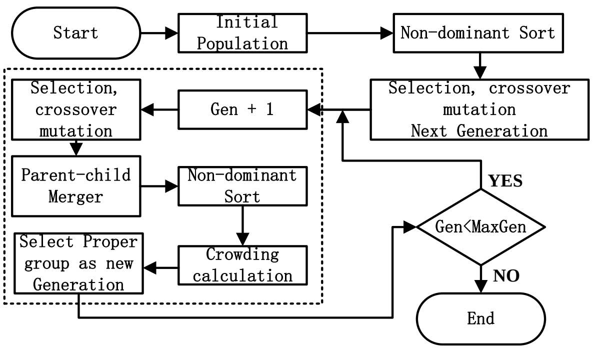

Fig. 1 Flow Block Diagram of Multi-objective Evolutionary Algorithms

To solve the multi-objective optimization, it's often difficult to achieve the optimal solution on all indicators. For this. Italian economist Pareto proposed a multi-objective optimization algorithm (Pan et al., 2011), which is described as follows:

Let the n-dimensional decision factor of the multi-objective problem be X, then the feasible domain of the decision factor is:

$$S = (x_1, x_2, x_3, \ldots, x_n) \ (1)$$

The evaluation objective is expressed as:

$$F(X) = Min\ (f_1(X), f_2(X), f_3(X), \ldots, f_m(X)) \ (2)$$

Among them, the P inequality constraints are:

$$\text{Limit A} = g_i(X) \text{ and Limit A} \geq 0,\ i \in P \ (3)$$

The Q equality constraints are:

$$\text{Limit B} = h_j(X), \text{ and limit B} = 0, j \in Q \ (4)$$

The optimal solution of the Pareto multi-objective optimization algorithm is that under the premise of satisfying the formulas (3) and (4), if no X∈ S, for any X∈S, there is $f_i(X) \leq f_i(X^*)$, and then the X* is called the Pareto optimal solution of the multi-objective problem. From the perspective of production management, the Pareto optimal solution is an ideal state of resource allocation. With the fixed resources and no worsening situation, the Pareto optimal solution cannot be further optimized any more. In actual production, the Pareto optimal solution is often a set.

In the multi-objective evolutionary algorithm, non-dominated sorting, congestion degree calculation, and genetic iterative algorithms are the main operations. The non-dominated sorting divides the different scheduling schemes into different levels of Pareto frontiers; the congestion degree calculation disperses the obtained Pareto frontiers and preserves the diversity; then, the elitism selection and evolution are carried out through genetic algorithm. Individuals in the population are calculated separately for the objective function and the Pareto front is obtained; finally, the next generation of the population is further iterated according to the front and the congestion degree until the set maximum genetic algebra is reached.

3 MANUFACTURING FLOW SHOP SCHEDULING METHOD

3.1 Mathematical expression of multi-objective scheduling problem

Flow shop scheduling can be generally divided into open FSS and permutation FSS. For open FSS, different products need to take the same or similar processes, but there is no sequence between the processes, e.g., there is no absolute sequential order for the installation of the meter board and the back cover (Luo et al., 2011; He & Hui, 2007). Permutation flow shop scheduling means that different products need to take the similar process, and the same sequence of processing, e.g., the main board, communication board and the video board of electric meter all need to go through three steps of PCB fabrication, chip-mounting and paint spraying.

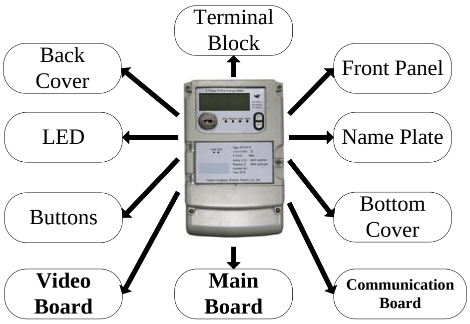

Fig. 2 Key components of smart meter DTSD178

As shown in Figure 2, there are three key boards in the smart meter DTSD178: the meter main board (MB), the communication board (CB) and the video board (VB), which need to be PCB-fabricated, chipmounted, and sprayed sequentially (as shown in Figure 3)

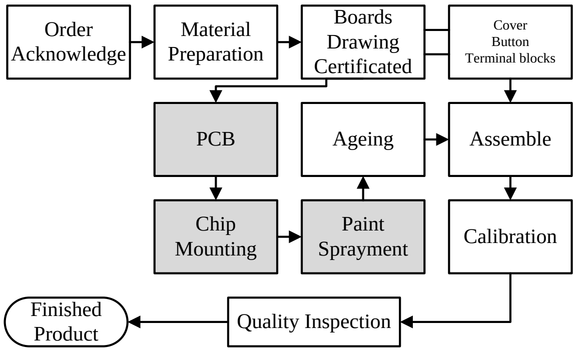

Fig. 3 Common processes for main board, communication board and video board

For the above workflow, three core machines are mainly used, namely PCB machine, chip mounter and paint sprayer. Each machine has four basic states: start, work, standby, and stop, where work and standby states are energy-consuming. The main parameters of the three machines are shown in Table 1.

The same batch of MB, CB and VB on different machines has different processing time, as shown in Table 2. Supposing that there are two FSS solutions of A and B, when one board is produced on any machine, other boards cannot be processed on this machine simultaneously. This paper designs two kinds of FSSs to study the energy and time consumption under different pipelines. The two FSS solutions are as follows:

Solution A: Follow the order of MB, CB, and VB, which are represented by red, yellow, and blue respectively, and expressed as SA={MB, CB, VB}.

Solution B: Follow the order of VB, CB, and MB, and the colour under each parameter is the same as that of Solution A. It is expressed as SB={VB, CB, MB}.

Table 1. Main machines of PCB, chip mounter and paint sprayer

	Processes	Manufacture	Type	Voltage	Operating Power	Idle Power
1	PCB	PANDA	STENCIL LASER G 6080	380V	2800VA	1500VA
2	Chip Mounter	SIMENS	High Speed SIPLACE D4i	380V	4500VA	3500VA
3	Paint Sprayer	SXR	SXR551L-CM	220V	1000VA	400VA

Table 2. Time cost in processes of different boards

Board Type	PCB	Chip Mounter	Paint Sprayer
Main Board	60 Min	40Min	20Min
Communication Board	40Min	20Min	60Min
Video Board	60Min	20Min	40Min

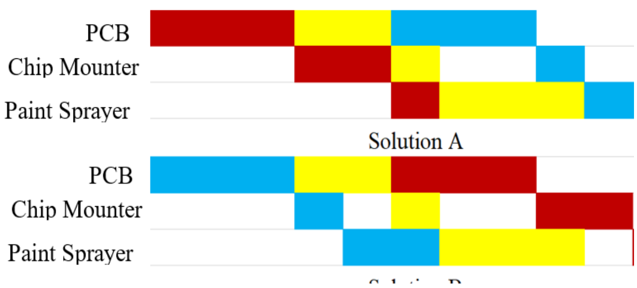

Fig. 4 Processing Time Cost of Different Solutions

The graphical representation of the two solutions is shown in Figure 4. The time-consumption and power-consumption results obtained from the two solutions are shown in Tables 3 and 4.

From Table 3 and 4, it can be seen that when taking the boards as the research objects in the two solutions, the total time is 520 minutes, and there is no case that the board is waiting for machining, so the process based on the board can no longer be optimized; however, based on the power consumption analysis, the idle time of the solution A is 20 minutes less than in the chip mounting process, and then it can save 1.2 kWh for the same board per batch, therefore, SA>SB. There are six possible process sequences in this scenario. As the board types and processes increase, it will be more complicated to manually calculate the Pareto optimal solution.

Table 3. Time cost for each kind of board

	Solution A		**Solution B**	
Object Board	Total Time (Min)	Idle Time (Min)	Total Time（Min)	Idle Time (Min)
Main Board	120	0	220	0
Communication Board	180	0	180	0
Video Board	220	0	120	0
Total	520	0	520	0

Table 4. Power consumption for each kind of machine

	Solution A		**Solution B**	
Item	Total Time (Min)	Idle Time (Min)	Total Time（Min)	Idle Time (Min)
PCB	160	0	160	0
Chip Mounter	80	100	80	120
Paint Sprayer	120	100	120	100
Power Total	15.47	6.5	15.47	7.7

3.2 Multi-objective energy-saving permutation scheduling model

Under the conditions of reasonable processing technology, the energy consumption of the machine is related to the idle time. The permutation flow shop scheduling method can balance the idle time of the machine, thereby reducing the machine's no-load energy consumption and the total energy consumption of all machines (Castro, 2010; Lei, 2012). In view of the multi-objective permutation flow shop scheduling problem in manufacturing, this paper establishes an energy-saving scheduling model, in order to minimize the total time and total energy consumption of the same batch. It's expressed as:

$$\mathrm{PT} = \sum_{i=1}^{B} t(i,M) \quad (5)$$

$$\mathrm{t(i,j)} = \max\{\mathrm{t(i-1,j)}, \mathrm{t(i,j-1)}\} + \mathrm{T(i,j)}$$

where

$$\mathrm{t(1,1)=T(1,1), i=2,3,\ldots,B;\ j=2,3,\ldots M} \quad (6)$$

$$E^* = \sum_{j=1}^{M} \sum_{i=1}^{B} P_j^* * t^*(i,j) \quad (7)$$

$$t^*(i,j) = \max\{[\mathrm{t(i,j-1)} - \mathrm{t(i-1,j)}], 0\}$$

where $t^*(1,1) = 0$, i=2,3,…B,j=2,3,…M (8)

$$S_{\mathrm{Pareto}} = \begin{cases} minE^* \\ min\mathrm{PT} \end{cases} \quad (9)$$

where,

B-type of board; B_i represents the i-th board;

M-type of machine; M_i is the i-th machine;

P-load power; P_i is the operating power of the i-th machine;

P*-no-load power; P*i is the no-load power of the i-th machine;

S-scheduling solution; S_i is the i-th solution, and S_i = {Bi, Bj, ..., Bn} represents an arrangement of n kinds of boards;

T(i,j)-the process time of the i-th board on machine j, and i=1, 2,...n j=1, 2,...m;

t(i,j) - the actual consumption time of the i-th board on machine j, and i = 1, 2, ... n j = 1, 2, ... m;

t*(i,j) - the idle time of the i-th board before starting processing on machine j, and i=1, 2,...n j=1, 2,...m;

PT—The total time consuming of the process; PT_i is the total time consuming of the scheduling solution S_i;

E*—total idle energy consumption; E*i is the total idle energy consumption of the scheduling solution S_i.

3.3 Simulated research on multi-objective energy-saving permutation scheduling model

According to the above analysis, firstly, the random population should be established and initialized, and the population size should be determined. Secondly, the population is subjected to rapid non-dominated sorting, and then the genetic evolution is implemented to obtain the next generation population. Finally, the obtained sub-populations are subject to elite retention and competition by merging the father-son population and excluding the duplicate individuals under the premises of retaining the original dispersity, to form the new population, which is taken as a new parent population (Azadeh et al., 2015).

Based on the above-mentioned scheduling model and multi-objective algorithm, the three boards of DTSD178 smart meter were simulated and analysed. The software MATLAB2010A was used, and the algorithm parameters were set, as shown in Table 5.

The simulation was performed using a single variable method, to determine the optimal parameter combination as {100, 50, 0.8, 0.05}. After running the multi-objective evolutionary algorithm for 20 times, the total process time PT and total idle energy consumption E* of the multi-objective scheduling problem were obtained. In the Table 5 below, "1" stands for Main Board, "2" for Communication Board, and "3" for Video Board.

The simulation results of the smart meter FSS problem are shown in Table 6. It can be seen from Table 6 that due to less variables, the total process time PT of the scheduling solution {2, 3, 1} is 500 minutes, and the total idle energy consumption E* is 6.5 kWh, without considering the problem of temporary planning changes. This solution can be used as the optimal solution for this.

Table 5. Parameters in MATLAB of multi-objective evolutionary algorithms

	P1	**P2**	**P3**
MaxGen	50	100	200
Population	20	50	100
Crossover Probability	0.7	0.8	0.9
Mutation Probability	0.01	0.05	0.1

Table 6. Solutions of total process time cost and idle energy cost

SL	**PT**	**E^***	**Solution**
1	520	6.5	1,2,3
2	540	6.6	1,3,2
3	500	7.7	2,3,1
4	500	6.5	2,1,3
5	540	6.6	3,1,2
6	520	7.7	3,2,1

Therefore, when multiple processes are carried out simultaneously, the energy-saving scheduling solution may have a trade-off relationship between total process time and total idle energy consumption, and Pareto's solution will appear in the form of a solution set. At this point, decision makers can choose a solution with low energy consumption or short time as a FSS solution according to production needs.

4 CONCLUSIONS

Taking the manufacturing FSS of DTSD178 smart meter as research objects, this paper analyses the multi-objective evolutionary algorithm, and studies the three machines of PCB, chip-mounter and paint sprayer, as well as their no-load power. Then, it establishes a multi-objective scheduling optimization model. The main conclusions are as follows:

(1) The characterization parameters of the multi-objective scheduling model (energy-saving sequence scheduling model) were selected. By studying the process time and energy consumption of MB, CB and VB (the same total process time) on different machines, it proves the correctness for selecting the process time and energy consumption as the characterization parameters of the scheduling model;

(2) A multi-objective energy-saving permutation scheduling model was established, in order to minimize the total idle process and total idle energy consumption of the same batch and solve the multi-objective permutation flow shop scheduling problem in manufacturing;

(3) The practicability of the above scheduling model was verified by simulation analysis. The paper conducts simulated analysis for the three kinds of boards of DTSD178 smart meter, and obtains the total process time PT and the total idle energy consumption E*; when these two parameters are the minimum, the optimal solution can be obtained.

5 ACKNOWLEDGEMENTS

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