Int j simul model 17 (2018) 4, 702-711
ISSN 1726-4529 Original scientific paper

GENETIC ALGORITHM-BASED DESIGN AND SIMULATION OF MANUFACTURING FLOW SHOP SCHEDULING

Chen, W.[*,**] & Hao, Y. F.[***,#]

[*] Research Center for Enterprise Management, Chongqing Technology and Business University, Chongqing 400067, China

[**] School of Management, Chongqing Technology and Business University, Chongqing 400067, China

[***] College of Mathematics and Statistics, Chongqing Technology and Business University, Chongqing 400067, China

E-Mail: haoyf@ctbu.edu.cn ([#] Corresponding author)

Abstract

This paper applies the non-dominated sorting genetic algorithm (NSGA) to the design of non-compact flow shop scheduling plan, and successfully solves the multi-objective optimization problem considering process connection. Specifically, an NSGA-based scheduling strategy was developed after analysing the features of the non-compact flow shop in manufacturing enterprises, and an improved algorithm was created for the multi-objective optimization of non-compact flow shop scheduling considering process connection. The research results show that: the improved NSGA is a desirable way to solve the multi-objective optimization of non-compact flow shop scheduling, as it ensures the population diversity and guarantees the evolution effect; this algorithm is more realistic than traditional algorithms, which overlooks the process connection; the case simulation and analysis reveal that the established multi-objective scheduling model for non-compact flow shop enjoys good adaptability. The research finding carries profound theoretical and practical significance for enterprises, e.g. improving the scheduling of non-compact flow shop, production efficiency and response to market situations.

(Received, processed and accepted by the Chinese Representative Office.)

Key Words: Non-Dominated Sorting Genetic Algorithm (NSGA), Manufacturing Enterprises, Non-Compact Flow Shop, Multi-Objective Job Shop Scheduling

1. INTRODUCTION

The market today is a wide-open arena of challenges and opportunities. To survive the fierce competition, traditional manufacturing must satisfy the increasingly personalized demand with diversified products. However, the traditional production plans and management methods cannot meet the needs of modern production, leading to low efficiency, poor yield and long delivery time [1]. To solve the problem, many enterprises have started to manufacture various types of products in small batches [2].

As it takes more processes to manufacture the complex products, the significance of scheduling is on the rise in the manufacturing process [3]. Nevertheless, new manufacturing systems often face scheduling optimization problems, owing to the limitations of different production systems and control systems [4]. This gives birth to non-compact flow shop scheduling (FSS) and the optimization algorithms for various scheduling theories. Thanks to the advanced computer technology, the applicability and feasibility of these algorithms have been greatly improved [5]. The existing studies on scheduling mainly focus on the following four aspects.

(1) The application of genetic algorithm (GA) and backpropagation neural network (BPNN) algorithm in multi-objective scheduling problems: Shen and Yao combined the GA and BPNN into GA-BP algorithm, creating an excellent solution to job shop scheduling problems with various products and small batch orders [6]; Jia et al. proved that double-population diploid adaptive immune algorithm and ant colony optimization (ACO) algorithm

show good applicability in solving hybrid job shop scheduling and flexible job shop scheduling [7]; Mohapatra et al. integrated collaborative algorithm with the GA, optimized the integrated algorithm through genetic programming (GP), and thus developed a multi-population GA for vertical and horizontal collaborative scheduling [8].

(2) The application of multi-objective intelligent genetic algorithms (e.g. non-dominated sorting genetic algorithm-the second version (NSGA-II)): Alghazi et al. adopted multi-objective intelligent genetic algorithms to find the Pareto solution set of scheduling problems and identified the optimal solution using the analytic hierarchy process (AHP) [9]. Kaushik and Vidyarthi improved multi-objective intelligent genetic algorithms with object-oriented, segmented coding and refinement techniques, and successfully applied the improved algorithms and simulation technology to solve parallel job shop scheduling problems [10].

(3) The application of intelligent search algorithms in multi-objective optimization problem: Maghsoudlou et al. discovered that the intelligent search algorithms with preference information enhance the local search ability when solving scheduling problems [11]. However, Frutos et al. argued that intelligent search algorithms are less flexible and expandable than the GA, which impedes the development of the search algorithm [12].

(4) Multi-objective flexible scheduling problems and related algorithms: Han et al. suggested that the classical algorithm of Pareto optimization, if modified based on discretization and simulated annealing, can break the balance within the population and achieve a higher level of balance [13]; Liu and Huang found that the combination between Pareto algorithm and adaptive immune genetic algorithm can improve the search ability of the optimal solution and maintain the population diversity [14]; in addition, we can prevent the stagnation of the ACO algorithm and enhance the global search ability, using the iteratively generated neighbourhood solution as the Pareto solution for non-compact flow shop sorting.

To sum up, the optimization targets are often idealized in existing studies. For instance, the processes in the job shop are generally assumed to be closely connected, failing to consider the time gap between the processes in real-world non-compact flow shop. Thus, the optimization results of the previous research may deviate from the actual scheduling situation. To solve the problem, this paper designs a dynamic scheduling algorithm for non-compact flow shop [15], puts forward the concept of process tree, and develops an algorithm of single objective scheduling optimization.

This research has profound theoretical and practical meanings. For one thing, this paper makes up for the lack of research into the multi-objective scheduling of non-compact flow shop through the simulation of non-compact flow shop scheduling and implementation of the NSGA; for another, the simulation and optimization of the scheduling process help enterprises improve their production efficiency and response to market situations.

2. TARGET OPTIMIZATION THEORY ON DYNAMIC SCHEDULING AND NSGA PROCESS

2.1 NSGA process

Inspired by Darwin's theory of evolution, the GA was proposed by J. H. Holland in 1975. This classic algorithm simulates the process of natural selection. Starting with the initial population, the individuals with relatively high adaptability to the environment are selected through crossover and mutation. On this basis, the most adaptable individual, i.e. the optimal solution, can be obtained through iterative reproduction (see Fig. 1). Despite its good performance in single objective optimization, the GA is not a desirable solution to multi-objective optimization problems.

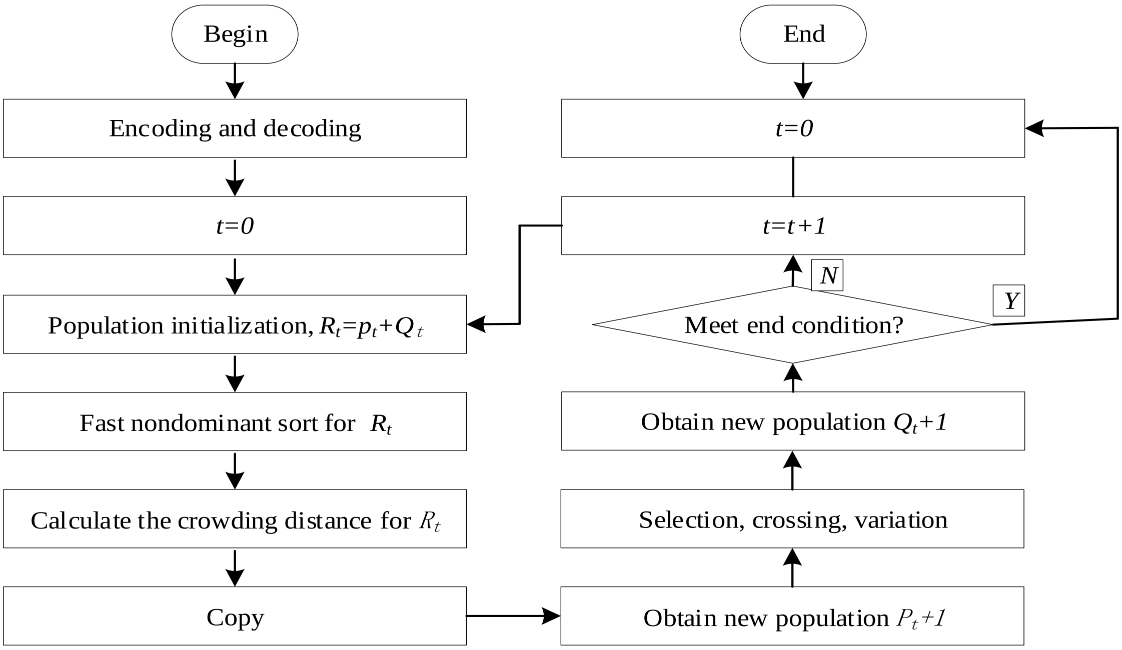

Figure 1: The operation flow chart of the traditional NSGA-II.

For multi-objective optimization, it is only possible to derive a set of optimal solutions rather than the global optimal solution. This set is also known as the set of Pareto optimal solutions. In light of this, scholars have developed the NSGA, a solution to multi-objective optimization. This algorithm still faces many problems, such as the complex solution process, the lack of elite preservation mechanism, and the low solving efficiency. To overcome these problems, the NSGA-II has been designed with the addition of fast dominated sorting, elite preservation judgement strategy and crowding distance measurement. The new algorithm manages to simplify multi-objective optimization and improve the computing efficiency.

2.2 NSGA fast non-dominated sorting

The comparison sorting for traditional single-objective optimization does not apply to multi-objective optimization. When dealing with non-compact flow shop scheduling, the NSGA has no fundamental difference from traditional algorithms in the replication, crossover and mutation of genes. The main difference lies in the face that the NSGA adopts the classification based on dominance relations. The non-dominated individuals of the population are classified with the earliest classified ones being allocated to the optimal layer. This process is repeated until all individuals are classified (see Fig. 2).

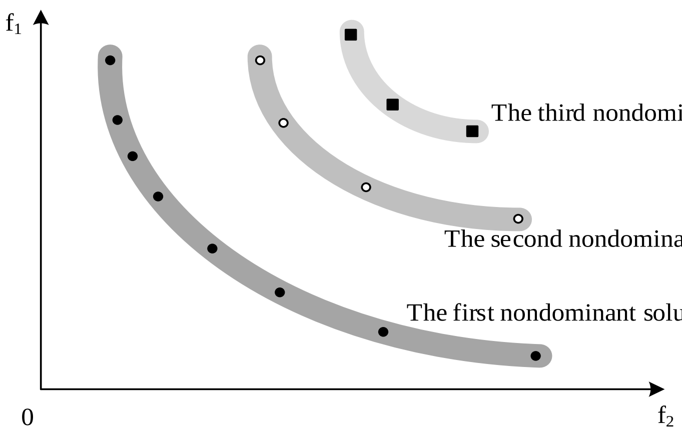

Figure 2: Fast non-dominated sorting.

2.3 NSGA crowding distance computation

The computation of crowding distance aims to use the aggregation of other solutions around a solution as the sorting criterion for individuals in the same layer. For non-compact flow shop scheduling, the crowding distance of individuals in each layer is calculated after sorting the set of non-dominated solutions according to the objective function. The non-dominated sorting and crowding distance computation are illustrated in Fig. 3 below.

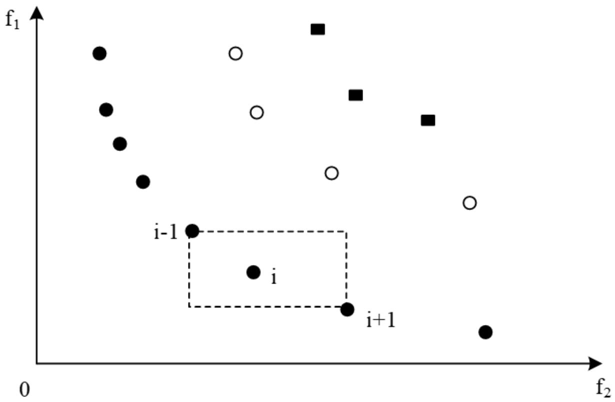

Figure 3: Non-dominated sorting and crowding distance computation.

2.4 NSGA elite preservation strategy

The implicit elite preservation strategy was adopted as follows. Let N be the number of individuals in the parent population P_t and that in the child population Q_t. The individuals of the two populations are combined into a new population R_t, which contains 2N individuals. Then, the top-ranking N individuals are obtained by non-dominated sorting and crowding distance computation, forming a new parent population P_{t+1}. By this process, the parent population is subjected to replication, crossover and mutation, producing the child population Q_{t+1}. These steps are repeated until the completion of the evolutionary solution (see Fig. 4).

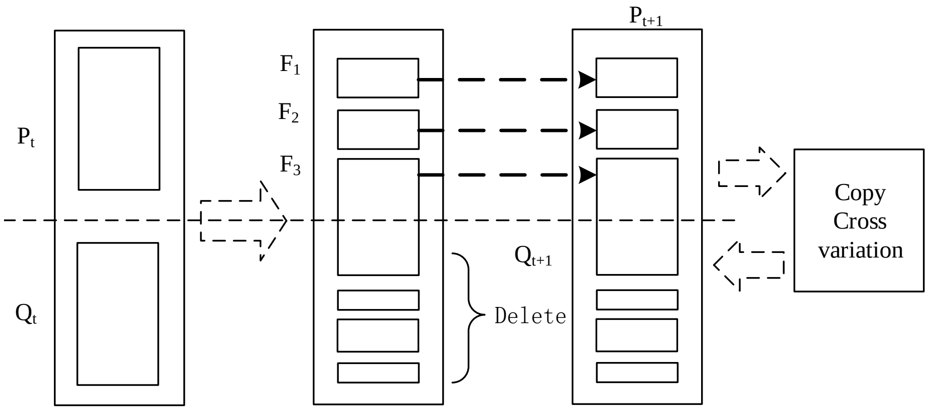

Figure 4: Elite preservation strategy.

3. PROCESSING STRATEGY AND SCHEDULING ALGORITHM FOR NON-COMPACT FLOW SHOP PROBLEMS

3.1 Processing strategy for process connection of non-compact flow shop

To quantify the connection between processes, this paper innovatively proposes the concept of process connection coefficient ρ, and explains its meaning and computing principle. This coefficient can eliminate the invalid solution in the crowding distance computation for the parent and child populations before the non-dominated sorting, thereby reduces the computing complexity. The specific calculation method can be illustrated as follows:

$$\rho = \alpha \sum \rho_1 + \beta \sum \rho_2 + \gamma \left(1 - \prod \rho_3\right) \tag{1}$$

where ρ is the overall process connection coefficient of the non-compact flow shop scheduling plan, consisting of a time connection coefficient, a cost connection coefficient, and a quality connection coefficient; ρ_1 is the time connection coefficient of each process in the non-compact flow shop; ρ_2 is the cost connection coefficient of each process in the non-compact flow shop; ρ_3 is the quality connection coefficient of each process in the non-compact flow shop, which is measured by the yield. The ρ_1, ρ_2 and ρ_3 can be calculated as follows:

$$\rho_1 = \frac{s_{ij}^{\mathrm{k1k2}}}{T}, \rho_2 = \frac{\mu_{ij}^{\mathrm{k1k2}}}{U}, \rho_1 = \frac{\omega_{ij}^{\mathrm{k1k2}}}{\omega} \tag{2}$$

where s_{ij}^{k1k2}, μ_{ij}^{k1k2} and $\omega_{ij}^{\mathrm{k1k2}}$ are the time, cost and yield of the connection between machine k2 and the previous machine k1 of process *j* for job *i*, respectively; the denominators are standard workspan, direct cost and process yield, respectively.

3.2 Modelling of non-compact flow shop scheduling

(1) Defining variables

The modelling of non-compact flow shop scheduling involves the following main variables: *m* – the total number of machines; *n* – the total number of jobs; *k* – the serial number of machines; *i* – the serial number of jobs; *j* – the serial number of processes; g_i – the total number of processes for job *i*; T_i – the makespan for job *i*; m_i – the number of machines available for process *j* of job *i*; O_{ij}^k – the process *j* of job *i* on machine *k*; t_{ij}^k – the time for process *j* of job *i* on machine *k*; F_{ij}^k – the makespan for process *j* of job *i* on machine *k*.

$$F_{ij} = F_{i(\mathrm{j}-1)} + t_{ij}^k;\ Q_{ij}^k = \begin{cases} 1, \text{Process } j \text{ of job } i \text{ on machine } k \\ 0, \text{Otherwise} \end{cases} \tag{3}$$

(2) Mathematical expression of model optimization

Based on the above scheduling model, the optimization was carried out against the sets of the three objectives: time, cost and yield (*T*, *C*, *Q*). The optimization target can be expressed as: min (*T*, *C*, *Q*), where *T*, *C* and *Q* are the total makespan, processing cost and failure rate of the non-compact flow shop scheduling plan.

a. Makespan: the optimization aims to achieve the minimal makespan.

$$T = \max_{1 \le i \le n} \{F_{ij}^k\} \tag{4}$$

b. Processing cost: the optimization aims to minimize the processing cost, which is obtained by accumulating the costs of all jobs.

$$C = \sum_{i=1}^{n} \sum_{j=1}^{g_i} Q_{ij}^k t_{ij}^k c_k \tag{5}$$

c. Failure rate of processed jobs: The processing quality is measured by the pass rate, i.e. the product of the pass rates of all processes. The pass rate is positively correlated with the optimization level of the scheduling and the quality of the processing. The failure rate is denoted as *Q*. The optimization aims to minimize the value of *Q*.

$$Q = 1 - \prod_{i=1}^{n} \prod_{j=1}^{g_i} Q_{ij}^k q_{ij}^k \tag{6}$$

4. PROCESS EXPANSION AND SIMULATION OF NON-COMPACT FLOW SHOP

4.1 Process expansion

It is assumed that two jobs need processing, two machines are available and five processes are required for the processing. According to the traditional process theory, the standard process disjunction diagram is shown in Fig. 5. For non-compact flow shop, the original process path needs to be expanded (Fig. 6), because the process connections are added between the traditional processes. Comparing Figs. 5 and 6, it can be seen that the number of machines was increased to five, including two physical ones and three virtual ones, and that the number of processes grew to eight.

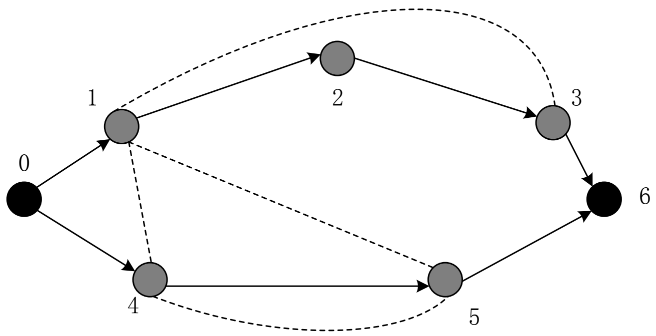

Figure 5: Sample standard process disjunction diagram.

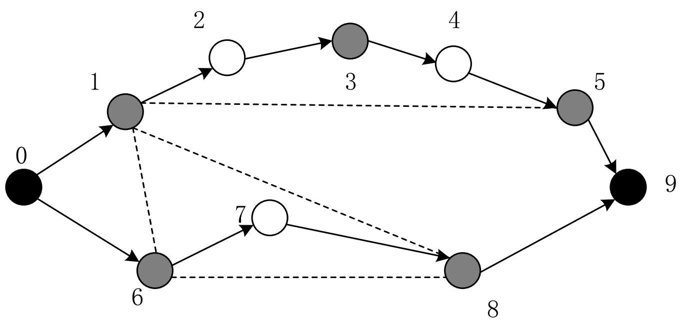

Figure 6: Sample disjunction diagram after process expansion.

4.2 Improvement of NSGA

(1) Encoding and decoding

Coding, the key to the optimization of GA, refers to converting the feasible solutions of the flow shop to symbols understandable to GA. The reverse conversion is considered as decoding. Here, real number coding is introduced to separate the chromosome into two parts: the machine chromosome and the process chromosome. The former determines the machine for job processing while the latter determines the process sequence (Fig. 7).

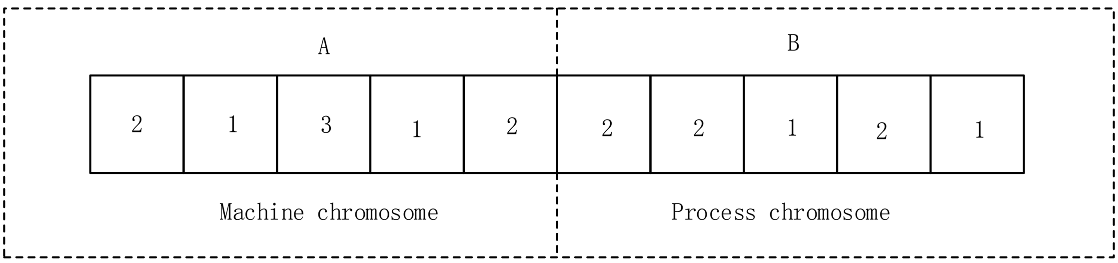

Figure 7: Real number coding.

(2) Crossover and mutation

Crossover stands for the creation of a new chromosome through replacing or recombination of certain genes in the parent chromosome. This is an effective way to obtain new individuals, as it satisfies the demand for search in the solution space and reduces the child's damage to the parent model. Here, the multi-point crossover is adopted for the machine chromosome, while the POX crossover method is adopted for the process chromosome (Fig. 9).

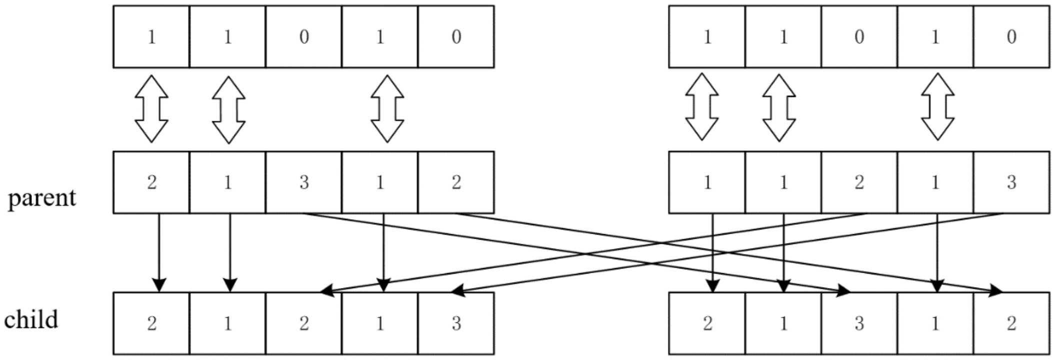

Figure 8: The crossover of machine chromosome.

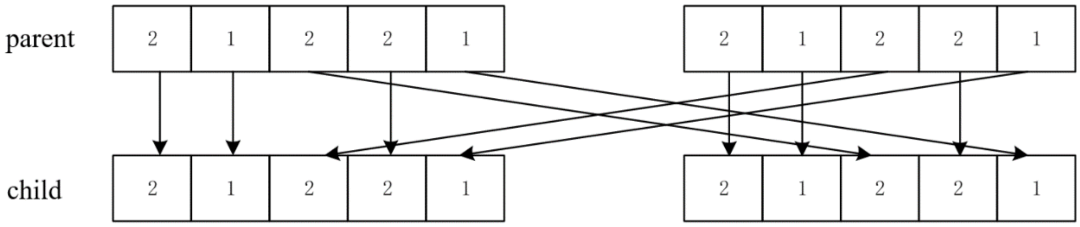

Figure 9: The crossover of process chromosome.

Mutation refers to the repair and supplementation of the missing genes in chromosome crossover. This operation improves the search accuracy of the optimal solution for GA. Here, the mutation of the machine chromosome is realized by the machines' random selection of gene segments (Fig. 10); the mutation of the process chromosome is achieved through swap, i.e. the genes of two randomly selected positions are exchanged (Fig. 11).

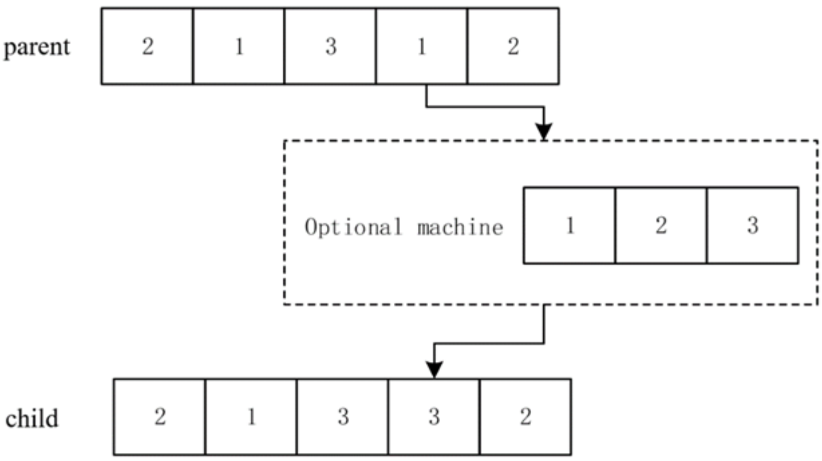

Figure 10: The mutation of machine chromosome.

Finally, the author carried out the simulation analysis of non-compact flow shop scheduling. The modified NSGA was adopted to find the optimal makespan (T), processing cost (C) and yield (Q).

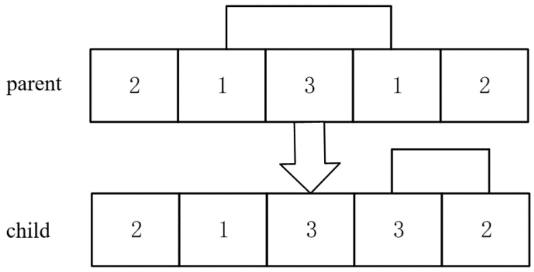

Figure 11: The mutation of process chromosome.

The variations of the optimal solutions are recorded as Fig. 12. Next, the results of the modified NSGA were compared with those of other scheduling algorithms. The objective was assumed as $0.7(T) + 0.3(C) = 1$, and each algorithm was run 10 times. Fig. 13 compares the scheduling results of the original NSGA and those of the modified NSGA. It can be seen that the improved NSGA achieved better adaptability, more desirable results, less fluctuation and faster convergence.

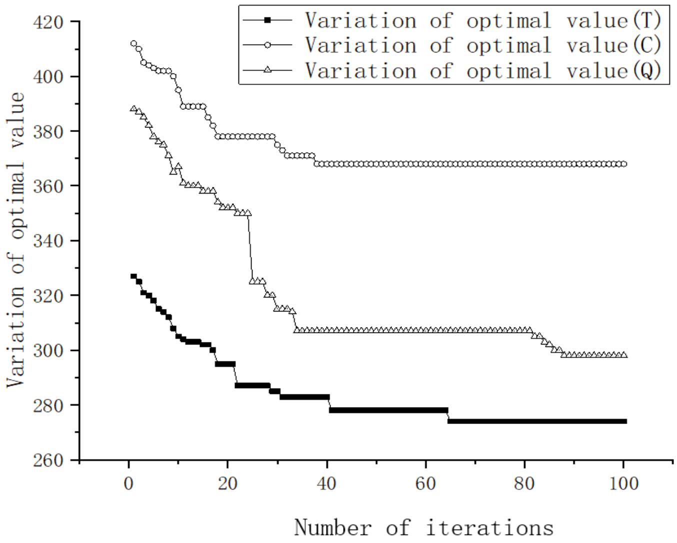

Figure 12: Variations of the optimal solutions.

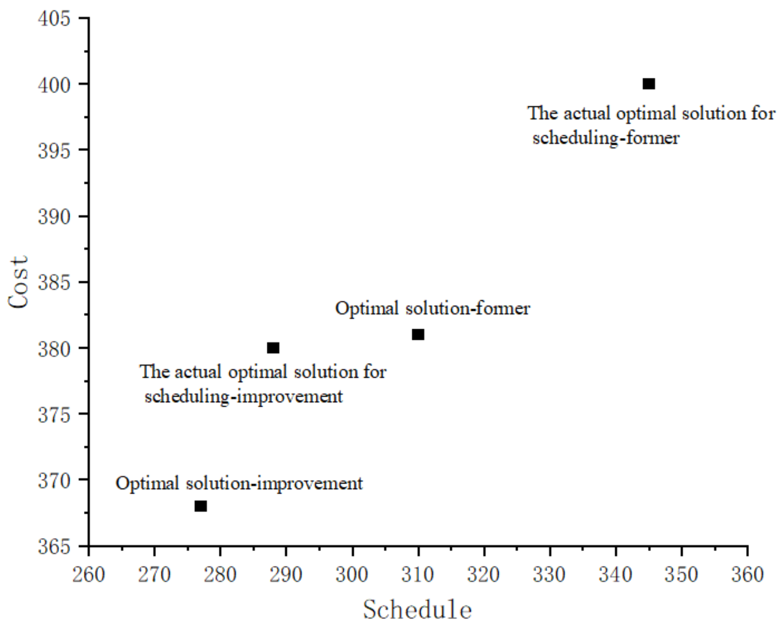

Figure 13: Comparison of scheduling results.

5. CONCLUSIONS

In this paper, the NSGA is modified to solve the non-compact flow shop scheduling. The following conclusions were drawn through multi-objective scheduling theory, process expansion of non-compact flow shop and the example analysis:

(1) The manufacturing industry needs to fulfil the new demands arising from the new economic environment. The traditional scheduling theories can no longer satisfy the current demand, due to the overlook of the process connection in non-compact flow shop.

(2) The traditional GA was improved innovatively through crossover and mutation, such that it could fit in with the scheduling of non-compact flow shop. This move ensures population diversity and preserves elite individuals in the evolution process.

(3) Through theoretical analysis and case simulation, it is proved the NSGA adapts well to non-compact flow shop scheduling. The research finding carries profound theoretical and practical significance, e.g. improving manufacturing efficiency, saving enterprise operating cost and improving enterprise benefits.

ACKNOWLEDGEMENTS

The authors acknowledge funding from the National Social Science Foundation of China (Project No. 18CGL003), as well as the contributions from all partners of the mentioned projects. Besides, Hao Yifei is the corresponding author and can be contacted at: haoyf@ctbu.edu.cn.

REFERENCES

[1] Xu, Z.; Ming, X. G.; Zheng, M.; Li, M.; He, L.; Song, W. (2015). Cross-trained workers scheduling for field service using improved NSGA-II, *International Journal of Production Research*, Vol. 53, No. 4, 1255-1272, doi:10.1080/00207543.2014.955923

[2] Rabiee, M.; Zandieh, M.; Ramezani, P. (2012). Bi-objective partial flexible job shop scheduling problem: NSGA-II, NRGA, MOGA and PAES approaches, *International Journal of Production Research*, Vol. 50, No. 24, 7327-7342, doi:10.1080/00207543.2011.648280

[3] Ji, B.; Yuan, X.; Yuan, Y. (2017). Orthogonal design-based NSGA-III for the optimal lockage co-scheduling problem, *IEEE Transactions on Intelligent Transportation Systems*, Vol. 18, No. 8, 2085-2095, doi:10.1109/tits.2016.2630718

[4] Cruz, A.; Vélez, W.; Thomson, P. (2010). Optimal sensor placement for modal identification of structures using genetic algorithms – a case study: the olympic stadium in Cali, Colombia, *Annals of Operations Research*, Vol. 181, No. 1, 769-781, doi:10.1007/s10479-009-0576-6

[5] Mohapatra, P.; Nayak, A.; Kumar, S. K.; Tiwari, M. K. (2015). Multi-objective process planning and scheduling using controlled elitist non-dominated sorting genetic algorithm, *International Journal of Production Research*, Vol. 53, No. 6, 1712-1735, doi:10.1080/00207543.2014.957872

[6] Shen, X.-N.; Yao, X. (2015). Mathematical modeling and multi-objective evolutionary algorithms applied to dynamic flexible job shop scheduling problems, *Information Sciences*, Vol. 298, 198-224, doi:10.1016/j.ins.2014.11.036

[7] Jia, J.; Chen, J.; Chang, G.; Wen, Y.; Song, J. (2009). Multi-objective optimization for coverage control in wireless sensor network with adjustable sensing radius, *Computers & Mathematics with Applications*, Vol. 57, No. 11-12, 1767-1775, doi:10.1016/j.camwa.2008.10.037

[8] Mohapatra, P.; Benyoucef, L.; Tiwari, M. K. (2013). Integration of process planning and scheduling through adaptive setup planning: a multi-objective approach, *International Journal of Production Research*, Vol. 51, No. 23-24, 7190-7208, doi:10.1080/00207543.2013.853890

[9] Alghazi, A.; Elazouni, A.; Selim, S. (2013). Improved genetic algorithm for finance-based scheduling, *Journal of Computing in Civil Engineering*, Vol. 27, No. 4, 379-394, doi:10.1061/(asce)cp.1943-5487.0000227

[10] Kaushik, A.; Vidyarthi, D. P. (2016). An energy-efficient reliable grid scheduling model using NSGA-II, *Engineering with Computers*, Vol. 32, No. 3, 355-376, doi:10.1007/s00366-015-0419-9

[11] Maghsoudlou, H.; Afshar-Nadjafi, B.; Niaki, S. T. A. (2016). A multi-objective invasive weeds optimization algorithm for solving multi-skill multi-mode resource constrained project scheduling problem, *Computers & Chemical Engineering*, Vol. 88, 157-169, doi:10.1016/j.compchemeng.2016.02.018

[12] Frutos, M.; Olivera, A. C.; Tohmé, F. (2010). A memetic algorithm based on a NSGAII scheme for the flexible job-shop scheduling problem, *Annals of Operations Research*, Vol. 181, No. 1, 745-765, doi:10.1007/s10479-010-0751-9

[13] Han, Y.-Y.; Gong, D.-W.; Sun, X.-Y.; Pan, Q.-K. (2014). An improved NSGA-II algorithm for multi-objective lot-streaming flow shop scheduling problem, *International Journal of Production Research*, Vol. 52, No. 8, 2211-2231, doi:10.1080/00207543.2013.848492

[14] Liu, C.-H.; Huang, D.-H. (2014). Reduction of power consumption and carbon footprints by applying multi-objective optimisation via genetic algorithms, *International Journal of Production Research*, Vol. 52, No. 2, 337-352, doi:10.1080/00207543.2013.825740

[15] Shang, C.; Srinivasan, D.; Reindl, T. (2016). Generation-scheduling-coupled battery sizing of stand-alone hybrid power systems, *Energy*, Vol. 114, 671-682, doi:10.1016/j.energy.2016.07.123