Research on Scheduling Problem of Manufacturing/remanufacturing Hybrid Systems

Si Huang*, Lin Liu, Yuting Yang, Yuli Duan and Linying Huang
School of Management, Hefei University of Technology, Hefei, Anhui, China

*2018214021@mail.hfut.edu.cn

Abstract. Remanufacturing plays a significant effect on saving social resources, developing green economy and reducing enterprise cost. Aiming at a production scheduling problem in manufacturing/remanufacturing hybrid systems we investigated, a multi-objective optimal scheduling model is built. The goals of optimization are to minimize total equipment idle time, total delivery delay and total setup time which are consistent with actual needs of the enterprise. An improved NSGA-II is adopted to increase the population diversity and improve the search performance. The similarity degree S is employed to evaluate the diversity of population in this paper. Crossover and mutation operations are adjusted adaptively based on S. This algorithm is applied to an engine manufacturing enterprise compared with the original genetic algorithm. The analysis of experimental results shows that the way in this paper has certain superiority.

1. Introduction
The activities of remanufacturing can economize the costs of production and efficiently lower the pollution to the environment, which is a significant way to sustainable development and realize cyclic economy. The process of remanufacturing has production links, some uncertain factors and complicated cooperation relationships compared with the traditional manufacturing process, making it tough for the traditional production scheduling optimization method to satisfy the demands of the remanufacturing production process.

Many scholars and experts come up with different solutions to the remanufacturing scheduling problem and made contributions to this theme. Polotskia et al.[1] thought over the switch of equipment production mode. In order to satisfy the various needs of customers for products, they optimized the switching process of equipment production mode to minimize the total cost. Giglio et al.[2] comprehensively optimized batch size and workshop efficiency in a hybrid manufacturing/remanufacturing system that produces multiple products. Lou et al.[3] researched the production capacity constraints in manufacturing/remanufacturing system, and established three batch decision models under different conditions. Liu et al.[4] had a research on the remanufacturing process scheduling problem in an inconclusive environment, and put forward the corresponding compounded intelligent algorithm to solve it.

In the manufacturing/remanufacturing hybrid production system, the multi-objective optimization is more in line with the practical needs. On the grounds of the features of the problem, this paper optimizes based on NSGA-II, and uses similarity to improve the genetic operator.
2. Hybrid scheduling problem of manufacturing and remanufacturing

2.1. Problem description
A company’s engine component production line is a hybrid manufacturing/remanufacturing system that can produce both new products and re-products. One equipment corresponds to a process of product processing, and the processing of all products needs to flow in a single direction in which the equipment is arranged. According to process requirements, new products are processed in accordance with the conventional process route (process1→process2→process 3→…→process m), while the processing of remanufactured products needs to skip some procedures in the conventional process route and directly enter the later process for processing. However, the flow direction of components during processing remains consistent with the conventional process route. The main features of the manufacturing/remanufacturing line are:

(1) Each equipment needs a preparation time when it is converted from a new product manufacturing method to a remanufacturing method and vice versa;

(2) Each process has an enough buffer zone, and only after one part is completed can another part be processed;

(3) The equipment used in each process is fixed, and each process has only one equipment.

The scheduling needs to decide the processing sequence of the parts to be processed on each equipment (the start and end time of each component on each piece of equipment). The optimization goal is to put off the delivery of the total parts and minimize the total equipment vacant time, on the grounds of the requirements of the company. Minimum period and minimum total equipment setup time.

2.2. Mathematical model
The parameters used in this article is shown as follows.

(1) \( N \): total number of products;

(2) \( M \): total number of equipment;

(3) \( t_{ij} \): processing time of the \( i \)th products on the \( j \)th equipment;

(4) \( b_j \): number of parts processed on the \( j \)th equipment;

(5) \( ts \): equipment preparation time when the method is changed;

(6) \( r_{kj} \): the mode of production of the \( k \)th part on the \( j \)th equipment, \( k= 1,2..., b_j \). when produced as a new product, \( r_{kj} = 0 \); otherwise, \( r_{kj} = 1 \);

(7) \( d_i \): delivery date of part \( i \);

(8) \( t_{sij} \): the start time of the \( k \)th machined part on the \( j \)th equipment, \( k= 1,2..., b_j \);

(9) \( t_{fij} \): the completion time of the \( k \)th machined part on the \( j \)th equipment;

(10) \( O_j \): the \( j \)th equipment’s occupancy time;

(11) \( P_j \): the total time of the actual machining parts of the \( j \)th equipment.

**Definition 1** Equipment occupancy time \( O_j \) refers to the total time span occupied by the equipment from the processing of the first part of the equipment to the last part (i.e. \( b_j \)) assigned by the equipment.

\[
O_j = \max_{k=1,2,...,b_j} t_{f_{kj}} - \min_{k=1,2,...,b_j} t_{s_{kj}}.
\]

**Definition 2** The idle time of equipment refers to the time during which no parts are being processed during the occupied time of the equipment. It (the \( j \)th equipment) should be \((O_j-P_j)\).

The optimization model can be described as follows:

\[
\min z_1 = \sum_{j=1}^{m} \left( \max_{k=1,2,...,b_j} t_{f_{kj}} - \min_{k=1,2,...,b_j} t_{s_{kj}} - \sum_{i=1}^{b_j} t_i \right) \tag{2.1}
\]

\[
\min z_2 = \sum_{i=1}^{n} \max(0, t_{f_{im}} - d_i) \tag{2.2}
\]

\[
\min z_3 = \sum_{j=1}^{m} \sum_{k=2}^{b_j} \left| r_{kj} - r_{k(k-1)} \right| \tag{2.3}
\]

2
Versity of the population. When S is small, the population is relatively dispersed, 
and reproduction of similar individuals makes the algorithm easy to fall into local optimal. In this paper, similarity degree S is defined to inherit to offspring 1. Look for genes that are not in the crossover points of the parent 1 but in parent 2, and insert the position of the missing gene in the offspring 1 in sequence. The crossover mode is shown in Figure 1.

Equations (2.1) to (2.3) are optimization goals, which respectively represent the minimization of the total equipment idle time, the total component delivery delay and the total equipment setup time; Equation (2.4) is the component start processing time constraint, divided into four Discussion of this situation; Equation (2.5) is the constraint on the relationship between the completion time and the start time of each component on each equipment, that is, on each equipment, the completion time of the component equals to the start processing time plus the processing time; Equation (2.6) is non-negative constraints on decision variables.

3. Improved multi-objective adaptive genetic algorithm

3.1. Coding
Individual coding adopts the serial number full arrangement and combination of the processing sequence of parts on the first equipment. For example, individual (1,4,3,2) means that parts are processed in the sequence of 1-4-3-2.

3.2. Crossover and mutation operations
This paper adopts the sequential crossover (OX) method[5]to generate offspring. Two crossover points are randomly generated from parent generation 1 and the genes between them maintain the same position to inherit to offspring 1. Look for genes that are not in the crossover points of the parent 1 but in parent 2, and insert the position of the missing gene in the offspring 1 in sequence. The crossover mode is shown in Figure 1. Mutation operation is of great significance for jumping out of local optimum. In this paper, two mutation points were randomly generated and two genes were exchanged for mutation. The mutation mode is shown in Figure 2.

3.3. Adaptive crossover and mutation probabilities based on similarity degree
With the continuous evolution of the population, the similarity of scheduling schemes increases, which makes the algorithm easy to fall into local optimal. In this paper, similarity degree S is defined to measure the diversity of the population. When S is small, the population is relatively dispersed, decreasing P_c and P_m; When S is large, the population tends to be uniform, increasing P_c and P_m. P_c and P_m can be adjusted adaptively to avoid the rapid convergence caused by the continuous crossover and reproduction of similar individuals[6].

\[
\begin{align*}
\text{s.t.} & \quad ts_{kj} = \begin{cases} 
0, & k = 1; j = 1 \\
{t_f}_{k(j-1)}, & k = 1; j = 2,3,\cdots,m \\
\max \{ {t_f}_{k(j-1)},( {t_f}_{k(j-1)} + r_j - r_{(k-1)}) x_k \}, & k = 2,3,\cdots,b; j = 1 \\
\max \{ {t_f}_{k(j-1)},( {t_f}_{k(j-1)} + r_j - r_{(k-1)}) x_k \}, & k = 2,3,\cdots,b; j = 2,3,\cdots,m \\
t_f_{kj} = ts_k + t_y_j, & k = 1,2,...,b; j = 1,2,3,...,m \\
ts_{kj}, t_f_{kj}\geq 0, & k = 1,2,...,b; j = 1,2,3,...,m
\end{cases}
\end{align*}
\]

Equations (2.1) to (2.3) are optimization goals, which respectively represent the minimization of the total equipment idle time, the total component delivery delay and the total equipment setup time; Equation (2.4) is the component start processing time constraint, divided into four Discussion of this situation; Equation (2.5) is the constraint on the relationship between the completion time and the start time of each component on each equipment, that is, on each equipment, the completion time of the component equals to the start processing time plus the processing time; Equation (2.6) is non-negative constraints on decision variables.

\[
\begin{align*}
\text{Definition 3} & \quad \text{Suppose the population has N individuals and each individual contains n genes, then the value of the } j^{th} \text{ gene of the N individuals forms the set } X_j. \text{ The times that the } j^{th} \text{ gene value of the } i^{th}
\end{align*}
\]
individual in the population repeats in $X_i$ is recorded as $c_{ij}$. The similarity of the $j^{th}$ gene in the $N$ individuals is:

$$S_j = \frac{1}{N} \sum_{i=1}^{N} c_{ij} = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} c_{ij}$$

(3.1)

The similarity of individuals in the population is:

$$S = \frac{1}{nN^2} \sum_{j=1}^{N} \sum_{i=1}^{N} c_{ij}$$

(3.2)

**Property 1** The maximum value of $S$ is 1 for $n \leq N$.

**Demonstration** When all the individuals of the population are exactly the same, the maximum degree of similarity is achieved. At this point, $c_{ij} = N, \forall i, j$

$$S = \frac{1}{nN^3} \sum_{j=1}^{N} \sum_{i=1}^{N} c_{ij} = \frac{1}{nN^3} \sum_{j=1}^{N} \sum_{i=1}^{N} N = \frac{1}{nN^3} \times nN^3 = 1$$

(3.3)

End.

**Property 2** When $n \leq N$, if $\frac{N}{n}$ is an integer, the minimum value of $S$ is $\frac{n}{n}$; otherwise, it is slightly greater than $\frac{n}{N}$.

**Demonstration** The occurrence frequency of gene "1", gene "2" …… gene "n" is set respectively $c_j(1), c_j(2)…… c_j(n)$ in $X_j$, $(0 \leq c_j(1), c_j(2)…… c_j(n) \leq N$, and they are integers), then

$$\sum_{i=1}^{n} c_j(x) = N$$

(3.4)

$$S_j = \frac{1}{N^2} \sum_{i=1}^{N} c_j(x)^2$$

(3.5)

The formula tells us that, $\frac{x_1 + x_2 + \ldots + x_n}{n} \leq \frac{\sqrt{x_1^2 + x_2^2 + \ldots + x_n^2}}{n}$. Thus,

$$S_j \geq \frac{1}{N^2} \times \left( \frac{\sum_{i=1}^{n} c_j(x)}{n} \right)^2 = \frac{1}{N^2} \times \frac{N^2}{n} = \frac{1}{n}$$

(3.6)

$$S \geq \frac{1}{n} \sum_{j=1}^{n} \frac{1}{n} = \frac{1}{n}$$

(3.7)

(only if $c_j(1) = c_j(2) = \ldots = c_j(n) = \frac{N}{n}$ take equal sign, that is, if $\frac{N}{n}$ is an integer, the minimum value is $\frac{1}{n}$)

End.

Therefore, the calculation formula of crossover probability and mutation probability based on similarity degree is as follows:

$$P_{c_\epsilon} = P_{c_{min}} + (P_{c_{max}} - P_{c_{min}}) \times \frac{n \times S - 1}{n - 1}$$

(3.8)

$$P_{m_\epsilon} = P_{m_{min}} + (P_{m_{max}} - P_{m_{min}}) \times \frac{n \times S - 1}{n - 1}$$

(3.9)

**3.4. Algorithm steps**

The algorithm flow of adaptive NSGA-II is shown in Figure 3.
4. Example analysis

The improved NSGA-II and traditional NSGA-II are respectively used in the production scheduling of an engine manufacturing enterprise’s manufacturing/remanufacturing hybrid system to generate scheduling sequences for problems with n=20, 25, and 30. Table 1 shows the processing time, delivery time and type (manufacturing 0/ remanufacturing 1) of each workpiece on each equipment.

Table 1. Processing time, delivery time and type of workpiece.

| Number | Delivery time | 0/1 | The processing time of the component on each equipment is $t_{ij}$ |
|--------|---------------|-----|-------------------------------------------------|
|        |               |     | E1 | E2 | E3 | E4 | E5 | E6 |
| 1      | 274           | 1   | 11 | 22 | 7  | -  | 10 | 21 |
| 2      | 162           | 1   | 8  | -  | 26 | 19 | -  | 27 |
| 3      | 244           | 0   | 18 | 29 | 13 | 19 | 17 | 9  |
| 4      | 182           | 0   | 8  | 15 | 9  | 6  | 5  | 11 |
| 5      | 267           | 0   | 13 | 9  | 16 | 30 | 12 | 30 |
| 6      | 164           | 1   | 17 | 21 | 27 | -  | -  | 24 |
| 7      | 331           | 1   | 26 | 19 | -  | 17 | 6  | 30 |
| 8      | 253           | 1   | 25 | -  | -  | -  | 9  | 16 |
| 9      | 279           | 0   | 15 | 28 | 28 | 26 | 16 | 29 |
| 10     | 304           | 0   | 25 | 18 | 19 | 17 | 19 | 12 |
| 11     | 211           | 1   | 29 | 16 | -  | -  | 6  | 13 |
| 12     | 259           | 0   | 18 | 26 | 5  | 11 | 12 | 15 |
| 13     | 188           | 1   | 29 | -  | 28 | -  | 18 | 16 |
| 14     | 278           | 1   | 21 | 19 | -  | 23 | 15 | 11 |
| 15     | 254           | 0   | 6  | 10 | 7  | 9  | 15 | 30 |
| 16     | 221           | 0   | 8  | 16 | 29 | 12 | 6  | 17 |
| 17     | 152           | 0   | 23 | 30 | 23 | 17 | 23 | 30 |
| 18     | 271           | 0   | 21 | 24 | 20 | 11 | 28 | 29 |
| 19     | 254           | 1   | 25 | -  | 9  | 22 | 10 | 27 |
| 20     | 306           | 1   | 8  | 23 | -  | 13 | 22 | 19 |
4.1. Evaluation index of algorithm performance

(1) Inverted Generational Distance \([7]\). If the IGD value is smaller, the algorithm will perform more convergent and diverse.

\[
IGD(S, P^*) = \frac{\sum_{x \in P^*} \text{dist}(x, S)}{|P^*|}
\]  

(4.1)

\(S\) is the Pareto-optimal solutions obtained by the algorithm, and \(P^*\) is the Pareto-optimal front. We mix the non-dominated solutions obtained after running all two kinds of algorithms for 20 times, and selected the non-dominated solution as \(P^*\). \(\text{dist}(x, S)\) represents the minimum Euclidean distance of an individual \(x \in P^*\) to \(S\).

(2) Uniform Index \(SP\). Smaller \(SP\) means the distribution of solutions is more uniform.

\[
SP = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (\overline{d} - d_i)^2}
\]

(4.2)

\(\overline{d}\) denotes the mean of \(d_i\).

\[
d_i = \min_{j \neq i, a \in A} \{\sum_{a \in A} f_a(A_i) - f_a(A_j)\}, i, j = 1, 2, ..., N; i \neq j
\]

(4.3)

(3) Algorithm Stability Index \(\Delta_{SP}\). Smaller \(\Delta_{SP}\) means the algorithm is more stable.

\[
\Delta_{SP} = \frac{1}{N_{\text{RUN}}} \sum_{i=1}^{N_{\text{RUN}}} |SP_i - \overline{SP}|
\]

(4.4)

4.2. Experimental results

The parameters of the algorithm are as follows: the population size is 60. For improved NSGA-II, 0.9 is value of the maximum cross probability, 0.1 is value of the minimum cross probability, 0.1 is value of the maximum mutation probability, 0.01 is value of the minimum mutation probability. For NSGA-II, the crossover probability is 0.9 and the mutation probability is 0.1. The algorithm iterates 300 times, and each group of experiments is run for 20 times. Each index is taken the average value. The algorithm program was programmed in Python. The simulator runs on a Windows 10 operating system computer with a 1.80GHz Intel (R) Core (TM) CPU. Table 2 presents the algorithm results.

| Quantity of work | \(IGD\) | \(SP\) | \(\Delta_{SP}\) |
|------------------|--------|-------|---------------|
|                  | NSGA-II | Improved NSGA-II | NSGA-II | Improved NSGA-II | NSGA-II | Improved NSGA-II |
| 20               | 49.838  | 50.957 | 13.379       | 12.664 | 3.133 | 2.743 |
| 25               | 120.776 | 115.043 | 20.417 | 18.214 | 6.261 | 5.404 |
| 30               | 201.989 | 195.216 | 21.413 | 15.765 | 9.026 | 8.770 |
4.3. Algorithm simulation analysis
From the data analysis in the table, it can be seen that the improved NSGA-II has the same effect as the original algorithm when the workpiece size is small. With increase of the size of workpiece, the diversity and distribution uniformity of the Pareto front obtained by the improved algorithm are better. Moreover, the algorithm has good stability and higher quality of solution set. The main reason for this result is that the improved algorithm uses the population similarity to measure the similarity of individuals and adaptively adjusts the crossover probability and mutation probability to avoid too fast convergence.

5. Conclusion
In this paper, manufacturing/remanufacturing production scheduling problems are studied and modeled. Aiming at this kind of problems of poor quality and diversity of Pareto solution set obtained by NSGA-II algorithm, an improved NSGA-II algorithm is proposed, which adaptively adjusts genetic operators by using population proximity degree. Experimental analysis shows that the improved algorithm has certain advantages in solving this kind of problems.

Acknowledgments
This research was supported by the College Students' Innovative Entrepreneurial Training Plan Program under the Grant Nos.: S202010359157. This research was supported in part by the National Natural Science Foundation under the Grant Nos.: 71521001 and Anhui Province Natural Science Foundation under the Grant No.: 1908085MG223.

References
[1] Polotski V, Kenne J P and Gharbi A. Optimal production scheduling for hybrid manufacturing-remanufacturing systems with setups. 2015 J. Journal of Manufacturing Systems. 37 703-14
[2] Giglio D, Paolucci M and Roshani A. Integrated lot sizing and energy-efficient job shop scheduling problem in manufacturing/remanufacturing systems.2017 J. Journal of Cleaner Production. 148 624-41
[3] Gaoxiang Lou. Manufacturing/Remanufacturing hybrid batch decision-making considering outsourcing and capacity constraints 2011 J. Journal of System Management. 20 549-55
[4] Mingzhou Liu, Xi Zhang, Conghu Liu, Mingxin Zhang and Maogen Ge. Optimization method for remanufacturing workshop scheduling under uncertain environment 2014 J. Journal of Mechanical Engineering. 50(10) 206-12
[5] Haolin Li and Shangjie Ding. Research on machine tool machining task scheduling based on genetic algorithm. 2011 J. Science and Technology Review. 20 27-30
[6] Haitao Cao. Research on multi-objective flexible job-shop scheduling problem based on improved NSGA-II 2019 D. Hangzhou: Zhejiang University of Technology
[7] Han Hu and Zhenyu LI. Overview of performance evaluation index of multi-objective evolutionary algorithm. 2019 J. Software Guide 18(9) 1-4