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# Dynamic reconfiguration optimization of intelligent manufacturing system with human-robot collaboration based on digital twin

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ABSTRACT

In Industry 4.0, the emergence of new information technology and advanced manufacturing technology (e.g., digital twin, and robot) promotes the flexibility and smartness of manufacturing systems to deal with production task fluctuation. Digital twin-driven manufacturing system with human-robot collaboration is a typical paradigm of intelligent manufacturing. When production task changes, manufacturing system reconfiguration with dynamic opeartion task allocation between operator (human) and robot is a key manner to maintain the production efficiency of intelligent manufacturing system with human-robot collaboration. However, the differences between operator and robot are neglected during reconfiguration of manufacturing system with human-robot collaboration. To promote the reconfiguration accuracy and production efficiency, a dynamic reconfiguration optimization method of intelligent manufacturing system with human-robot collaboration based on digital twin is proposed in this paper, which the different characteristics between operator and robot are considered during reconfiguration optimiztion. Firstly, a multi-objectives optimization model is constructed involving minimum production cost, minimum production time, and minimum idle time to assign operation tasks between operator and robot, where human factor is considered to ensure the production efficiency of operator. Second, non-dominated sorting genetic algorithm-II (NSGA-II) is adopted to solve the proposed dynamic reconfiguration optimization model. Finally, a case study is provided to demonstrate the effectiveness of the proposed reconfiguration optimization method for intelligent manufacturing system with human-robot collaboration.

## 1. Introduction

In Industry 4.0 era [1,2], the production model gradually transforms from mass customization to mass personalization [3], which requires more flexible and intelligent manufacturing system. Human-robot collaboration [4–6] integrated with flexibility and smartness is suitable for coping with production task fluctuation, where the configuration of manufacturing system with human-robot collaboration could be adapted dynamically, that is, reconfiguration of manufacturing system [7,8]. Besides, digital twin [9–11] is the key enabler to enhancing the reconfiguration efficiency and accuracy of manufacturing systems with human-robot collaboration.

Reconfigurable manufacturing system (RMS) [12] was proposed two decades ago to cater to mass customization with the flexibility of part family [13]. The flexibility of manufacturing system can be divided into two aspects – scalability and convertibility. The scalability [14,15] of manufacturing system refers to improving the production throughout, which the convertibility within a specific part family is considered [16]. With the transformation of production mode, it is more important to improve the convertibility of manufacturing system. Reconfigurable machine tools (RMT) [17,18] as the key facility of RMS is a good attempt to increase RMS convertibility. Moreover, a concept of delayed reconfiguration named as D-RMS [19,20] was proposed to handle the RMS convertibility. It can maintain partial production activities during reconfiguration to reduce the negative influence of reconfiguration. Recently, with the development of robot technology, the flexibility of manufacturing derived from human-robot collaboration becomes increasingly important [21], which can integrate new information and communications technology (e.g. IoT [22], AI [23], Big data [24], Digital twin [9], etc.) more effectively and increase the accuracy of

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reconfiguration resulting in higher productivity. However, the existing researches on human-robot collaboration prefer to address the issues about interaction between operator and robot (e.g., Gesture recognition [25], Measurement of trust [26], fluency evaluation [27], etc.). There is limited study focusing on the configuration changes due to production task fluctuation with the consideration of the different characteristics between operator and robot. Thus, a dynamic reconfiguration optimization method of intelligent manufacturing system with human-robot collaboration based on digital twin is proposed in this paper. We consider the different characteristics between operator and robot are considered as well to optimize the operation task assignment process and increase productivity through high collaboration efficiency between operator and robot.

The remainder of this paper is organized as follows: Section 2 reviews the related works. Section 3 analyzes the specific problem to be solved in this paper in detail. Section 4 elaborates on the proposed dynamic reconfiguration optimization model that is solved by NSGA-II. Section 5 validates the proposed method through a case study. Section 6 concludes this paper.

## 2. Related works

This section reviews the related works involving reconfigurable manufacturing systems, human-robot collaboration in manufacturing system, and digital twin of manufacturing system.

### 2.1. Reconfigurable manufacturing systems

In the scope of the traditional RMS, the most common reconfiguration manner is to adapt configuration function through modularity and integrability [28], that is, removing, replacing and adding modules with standard physical and soft interfaces. Bortolini et al. [7] proposed an optimization model for the dynamic management of RMS considering the dynamic changes of auxiliary module. It is a typical study that applies the philosophy of the traditional RMS. Wang and Koren [14] studied the scalability planning method for RMS through the adaption of machine tools. Deif and ElMaraghy [15] explored a similar scalability issue. The concept of delayed reconfigurable manufacturing system (D-RMS) proposed by Huang et al. [19,20] also focused on the module changes to realize rapid convertibility. Besides, the module adaption can be used at machine level to complete reconfiguration of RMS as well. Wang et al. [17] proposed a decision tree-based configuration design method for RMT with dynamically changing the modules of RMT. Huang et al. [18] studied digital twin-RMT design based on modular structure. Morgan et al. [29] proposed smart RMT for catering to the requirement of industry 4.0. However, modular reconfiguration is not efficient and cost-effective for high diversity demand during the mass personalisation era. The reconfiguration philosophy should be expanded to explore a more intelligent and flexible way. Collaborative robots have the potential ability to make simple, quick, and cheap reconfiguration [21]. It is meaningful and necessary to investigate the reconfiguration method based on manufacturing system with human-robot collaboration for future industry.

### 2.2. Human-robot collaboration in manufacturing system

Recently, human-centric manufacturing gradually come into view when discussing futuristic industry [6], where human-robot collaboration in manufacturing system is the core topic. Lu et al. [30] proposed human-centric manufacturing system framework and human-centric human-robot collaboration framework for Industry 5.0. The core idea of Lu's study is to focus on the operator's comfort level with additional optimization objectives, which will be specified in the optimization model of this paper. Liu et al. [4] explored the application of remote human-robot collaboration based on cyber-physical system for a hazardous manufacturing environment. Li et al. [5] proposed proactive human-robot collaboration as a foreseeable informatics-based cognitive manufacturing to predict patio-temporal cooperation and Self-organize teamwork. Matheson et al. [21] reviewed the applications of human-robot collaboration in manufacturing and analyzed the future trends in human-robot collaboration. Also, as the enabler technology of manufacturing system with human-robot collaboration, the concept of human-cyber-physical systems (HCPS) [31] is discussed towards human-centric smart manufacturing. Hietanen et al. [32] proposed a depth-sensor and interactive Augmented Reality (AR) based model for monitoring manufacturing process to ensure safety during human-robot collaboration. Hashemi-Petroodi [33] focused on the design and control of hybrid human-robot collaborative manufacturing systems, where human and robot perform a variety of tasks (manual, automated, and hybrid tasks) in a shared workspace. Ansari et al. [34] addressed the collaboration issues between human and cyber physical production system(CPPS) from the angle of complementarity whereby human competences and CPPS autonomy together derive supplementary capability and reciprocal learning, which focused on the dominant or eligible conditions to solve a problem between human and CPPS.

### 2.3. Digital twin-driven manufacturing system and human-robot collaboration

The development of digital twin is symbolic progress of industry 4.0, which was proposed by Grieves in his production management lecture at the University of Michigan [35]. In the manufacturing domain, Tao et al. [36] proposed digital twin workshop with five dimension model as a new paradigm for industry 4.0. Liu et al. [37] addressed the scheduling problem of digital twin workshop, considering feature, process, and machine tools simultaneously. Tao et al. [38] summarized the state-of-the-art involving digital twin in industry. In addition, digital twin is suitable for enhancing the reconfigurability of manufacturing system. Huang et al. [18] build a digital twin of RMT for the rapidly changing configuration of RMT. Leng et al. [39] studied the digital twin-driven rapid reconfiguration method of manufacturing system through open architecture model. Cai et al. [40] integrated digital twin with AR to rapidly retrieve physical configuration into the virtual space for optimizing the configuration of manufacturing through simulation. As for digital twin-driven human-robot collaboration, Bilberg et al. [41] discusses an object-oriented event-driven digital twin of a flexible assembly cell coordinated with human-robot collaboration to operate dynamic skill-based tasks allocation between human and robot considering traditional workload balance. Similarly, Lv et al. [42] proposed digital twin-based human-robot collaboration assembly framework improves the overall assembly efficiency and reduces the workload of human, which attempts to optimize the trajectory of robots and ensure the safety of human-robot collaboration assembly. Kousi [43] investigated the design and reconfiguration of human-robot collaborative assembly lines based on digital twin without consideration of the different characteristics between operator and robot. Liu et al. [44] investigated the cognitive digital twin-driven human-robot collaborative assembly to promote cognition of human-centric assembly based on augmented reality. Shi et al. [45] proposed a cognitive digital twin framework for manufacturing system with human-robot collaboration based on the 5 G communication network.

Above all, RMS is a typical paradigm for intelligent manufacturing in the industry 4.0 era, in which the digital twin is a key enabler technology to enhance the effectiveness of intelligent manufacturing. The introduction of robot and the emergence of human-robot collaboration bring new issues when reconfiguration of manufacturing system. However, on the one hand, the existing studies associated with RMS generally neglects the active functions of the robot during reconfiguration, on the other hand, the investigations of human-robot collaboration focus more on intuition recognition and cooperative action between operator and robot. So far, the reconfiguration issue between operator and robot considering the different characteristics is rarely mentioned in the

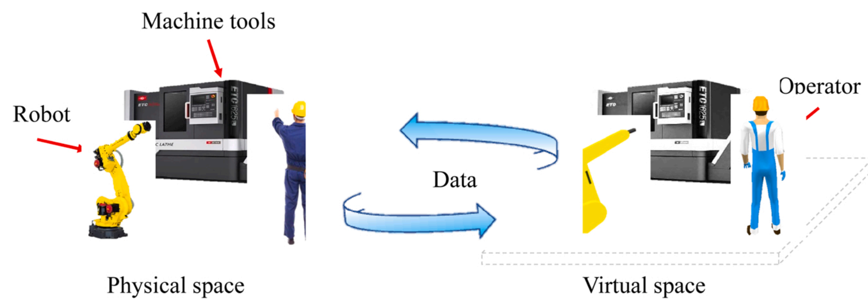


**Fig. 1.** Digital twin of manufacturing system with human-robot collaboration.

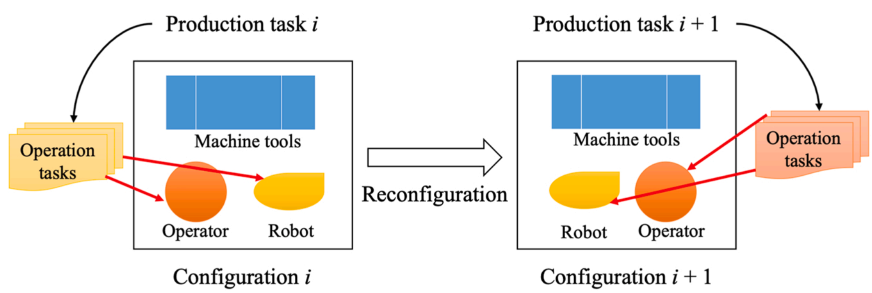


**Fig. 2.** Reconfiguration of manufacturing system with human-robot collaboration.

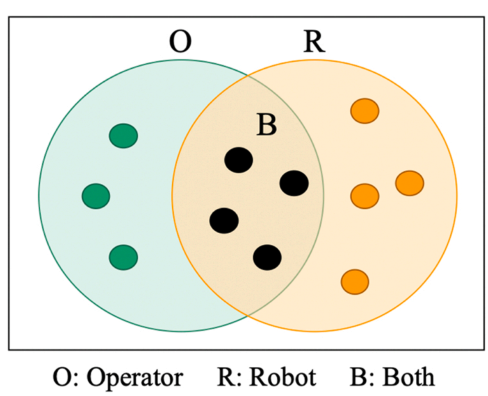


**Fig. 3.** Operation task classification.

existing literature, which is the gap to be filled in this paper.

## 3. Problem analysis

A typical manufacturing system with human-robot collaboration consists of one machine tool, one robot, one operator and other necessary components to complete a specific production task. The corresponding digital twin of manufacturing system with human-robot collaboration is shown in Fig. 1. Due to the seamless data transmission between physical space and virtual space, digital twin of manufacturing system with human-robot collaboration can track its operation states in a high-fidelity way and optimize the production process efficiently.

The mission of manufacturing system is to complete production task that can be divided into several operation tasks according to some specific rules (e.g., Machining features, fixtures, etc.). A manufacturing system with human-robot collaboration will complete production tasks around the machine tools, which operator and robot will assist to complete these processes. Different operation tasks can be assigned to operator or robot resulting in different configurations of manufacturing system, that is, reconfiguration of manufacturing system, as shown in Fig. 2.

Due to human factors and technology-driven robot, operator and robot show different efficiency and effectiveness when completing a specific work. In other words, operator and robot are not good at the same work. Generally, operator is good at creative works, however, robot is good at simple, repetitive work. The cooperation efficiency between operator and robot depends on the operation task assignment results, which determines the production efficiency of the corresponding manufacturing system. When production task changes, manufacturing system with human-robot collaboration should be reconfigured to meet the new requirements. How to determine the operation tasks assignment between operator and robot is the key problem to ensure the reconfiguration effectiveness, which will be solved in this paper by optimizing operation tasks assignment considering the different characteristics of operator and robot.

## 4. Dynamic reconfiguration optimization method

The dynamic reconfiguration of manufacturing system with human-robot collaboration will be elaborated around operation tasks assignment optimization in this section. Firstly, the necessary assumption and nomenclature will be given. And then, the optimization model with multiple objectives will be presented. Finally, the adopted computation algorithm will be described in detail.

### *4.1. Assumption and nomenclature*

To derive a simple yet insightful optimization model, the following assumptions are made for dynamic reconfiguration of manufacturing system with human-robot collaboration.

(1) Only the main components in manufacturing system with human-robot collaboration are considered during optimization modelling, including operator, robot, and machine tools.
(2) The digital twin of manufacturing system with human-robot collaboration is already existing. Namely, the construction of digital twin is out of the scope of this paper and the optimization process is performed based on the existing digital twin framework.

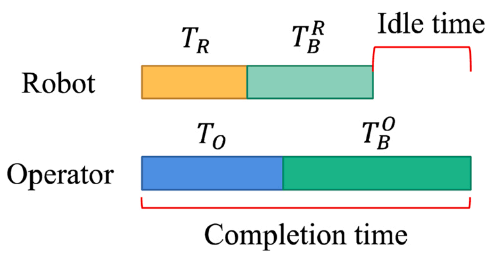


**Fig. 4.** Idle time calculation.

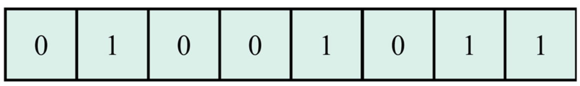


**Fig. 5.** Chromosome example.

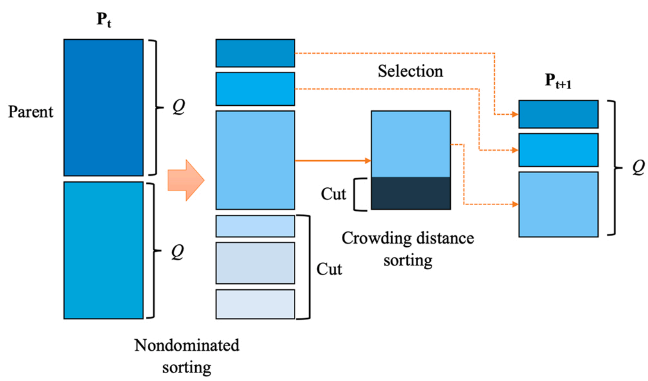


**Fig. 6.** Nondominated sorting and crowding distance sorting processes.

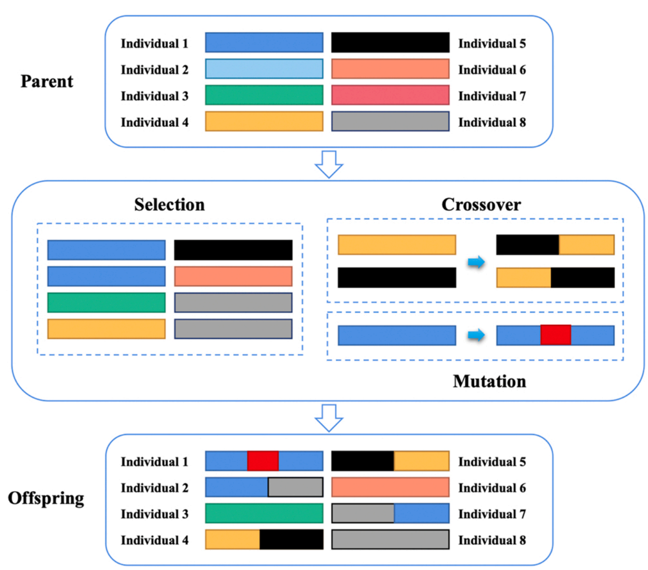


**Fig. 7.** Offspring generation based on selection, crossover and mutation.

(3) Production task changes have been already known in this paper. One production task can be divided to several operation tasks. The classification of operation tasks is around the human-robot collaboration. In other words, operation task can be divided into three types, including operation task only for operator, operation task only for robot, and operation task for both operator and robot, as shown in Fig. 3. Operator is good at handling complex and creative operation tasks that could be done by operator only due to the work is out of the ability of robot, however, robot can execute simple and repetitive operation tasks better. Besides, some operation tasks should be completed by robot only (e.g. dangerous scenario, pollution, etc.).

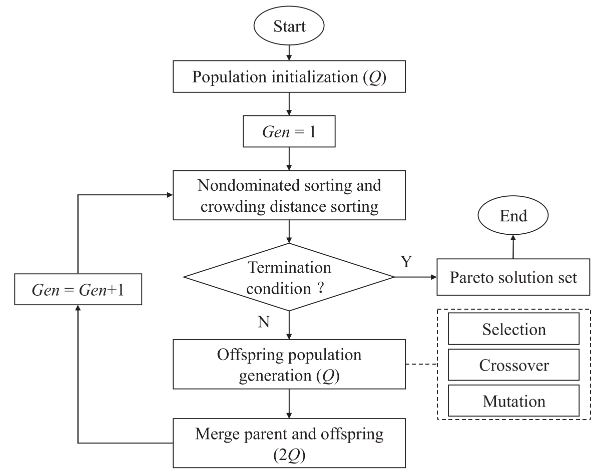


**Fig. 8.** NSGA-II execution flowchart.

(4) Reconfiguration optimization is executed around the operation task assignment among the three types. The production task and operation tasks information are already given for optimization.
(5) Production task dynamics is an iterative process. The dynamic reconfiguration optimization model is constructed based on one production task with several operation tasks.
(6) One production task and the corresponding operation tasks should be entirely completed in the assigned manufacturing system.
(7) There is an upper limit on the types of operation task assigned to operator. Namely, operator cannot handle infinite operation tasks due to the limitation of human factor.

In addition, the nomenclature for the optimization model is given in below.

| | |
|---|---|
| $O$ | The operation tasks set for operator only |
| $R$ | The operation tasks set for robot only |
| $B$ | The operation tasks set for both of operator and robot, that is, human-robot collaboration operation tasks |
| $N$ | The total types set of operation task |
| $C_i^O$ | The cost of operator when completing *i*th type of operation task |
| $C_i^R$ | The cost of robot when completing *i*th type of operation task |
| $\lambda_i$ | Collaboration factor. Labelling the operation task assigned to operator or robot |
| $\mu$ | Operator factor. Counting the number of operation tasks assigned to operator. |
| *Taskmax* | The maximum types of operation task for operator |
| *Mass* | An extra-large number |
| *makespan* | Maximum completion time |
| $V$ | Idle time between operator and robot |
| $T_R$ | Operation time of operation tasks for robot only |
| $T_B^R$ | Operation time of robot when handling operation tasks for both operator and robot |
| $T_O$ | Operation time of operation tasks for operator only |
| $T_B^O$ | Operation time of operators when handling operation task for both operator and robot |
| $T_i^R$ | The per operation time of robot when handling *i*th type of operation tasks |
| $T_i^O$ | The per operation time of operator when handling *i*th type of operation tasks |
| $D_i$ | The number of *i*th type of operation task |
| $\lambda_i$ | Collaboration factor and Decision variable. Labelling the operation task assigned to operator or robot. $\lambda_i = \left\{ \begin{array}{ll} 1, & \textit{Collaboration subtask assigned to robot} \\ 0, & \textit{Collaboration subtask assigned to operator} \end{array} \right\}$ |

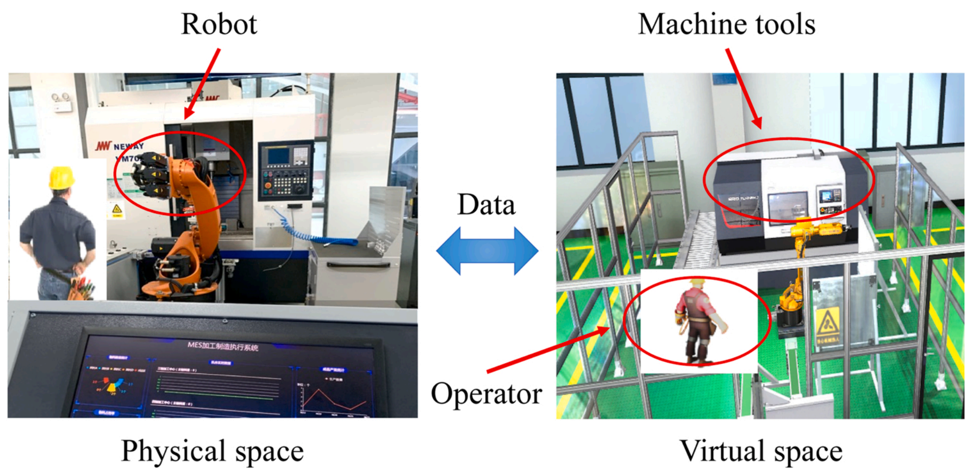


**Fig. 9.** Digital twin of machining station.

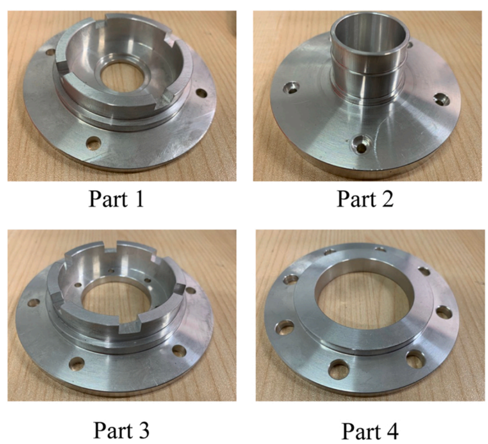


**Fig. 10.** Part family.

### *4.2. Mathematical model*

The mathematical model of dynamic reconfiguration for manufacturing system with human-robot collaboration contains three optimization objectives, including minimum operation cost, minimum operation time, and minimum idle time between operator and robot, as shown in Eqs. (1)–(3). In addition, the corresponding constraints can be referred to as Eq. (4) to (11).

#### *4.2.1. Minimize*

$$C = \sum\nolimits_{i\in O} D_i C_i^O + \sum\nolimits_{i\in R} D_i C_i^R + \sum\nolimits_{i\in B} D_i\left[C_i^R\lambda_i + C_i^O(1-\lambda_i)\mu\right] \tag{1}$$

$$makespan = \max\left(T_R + T_B^R, T_O + T_B^O\right) \tag{2}$$

$$V = \left|\left(T_R + T_B^R\right) - \left(T_O + T_B^O\right)\right| \tag{3}$$

s.t.

$$O + R + B = N \tag{4}$$

$$O\cap R = \varnothing \& O\cap B = \varnothing \& B\cap R = \varnothing \tag{5}$$

$$T_R = \sum\nolimits_{i\in B} D_i T_i^R \tag{6}$$

$$T_O = \sum\nolimits_{i\in O} D_i T_i^O \tag{7}$$

$$T_B^R = \sum\nolimits_{i\in B} D_i T_i^R \lambda_i \tag{8}$$

$$T_B^O = \sum\nolimits_{i\in B} D_i T_i^O (1-\lambda_i)\mu \tag{9}$$

$$\mu = \left\{\begin{array}{ll} 1, & \left(\sum\nolimits_{i\in O} 1 + \sum\nolimits_{i\in B}(1-\lambda_i)\right) \le Taskmax \\ Mass, & Otherwise \end{array}\right\} \tag{10}$$

The first objective aims at minimizing the total operation cost of operation tasks executed by human-robot collaboration referring to Eq. (1). The first item of Eq. (1) denotes the total operation cost of operation tasks that should be completed by operator only. The second item of Eq. (1) denotes the total operation cost of operation tasks that should be completed by robot only. The third item of Eq. (1) calculates the total operation cost of operation tasks that can be completed by both operator and robot. Besides, the operator factor $\mu$ in the third item is used to recognize how many types of operation tasks are assigned to operator, including the exclusive operation tasks for operator and collaborative operation tasks assigned to operator, which a penalty mechanism is adopted if the task types assigned to operator exceed the upper limit *Taskmax* referring to Eq. (10).

The second objective denotes the minimum of maximum completion time of the assigned production task with specific operation tasks referring to Eq. (2), that is, minimum of *makespan*. The first item of Eq. (2) means the total operation time of robot to complete the exclusive operation tasks for robot and the collaborative operation tasks assigned to robot. The second item of Eq. (2) means the total operation time of operator to complete the exclusive operation tasks for operator and the collaborative operation tasks assigned to operator. Due to operator and robot will be activated at the same time when a new production task arrives, the maximum operation time of operator or robot is adopted as *makespan* in this paper.

The third objective is constructed to address the idle issue between operator and robot according to Eq. (3). The completion time of operator and robot could be different resulting in idle time that do harm to production efficiency promotion. Namely, the less idle time, the better production efficiency. Here, the absolute value of the completion time differences between operator and robot is used to calculate the idle time as shown in Fig. 4.

There are necessary constraints for the dynamic reconfiguration optimization model referring to Eqs. (4)–(10). Eq. (4) means the summation of the exclusive operation tasks of operator and robot and the collaborative operation tasks, which ensure complete assignment of all operation tasks. Eq. (5) denotes the intersection among exclusive operation task set for operator, exclusive operation task set for robot and

**Table 1**
Production task information.

| Part no. | Quantity | Operation task |
|---|---|---|
| Part 1 | 15 | Unload from AGV (1); Workblank check (2); Upload to machine (3); Clamp part (4); |
| Part 2 | 25 | Change tool (5); NC programming (6); Unload from machine (7); Burring (8); Clean (9); |
| Part 3 | 20 | Inspection (10); Upload to AGV (11) |
| Part 4 | 40 | |

collaborative operation task set is an empty set, that is, every operation task will be assigned only once. Eqs. (6) and (7) present calculation details of the total operation time relevant to exclusive operation tasks for robot and operator respectively. Eqs. (8) and (9) calculate the operation time of collaborative operation tasks assigned to robot and operator respectively.

### 4.3. Solution algorithm of optimization model

The proposed dynamic reconfiguration optimization model is typical multiple objective optimization (MOO) problem. There are many successful algorithms for MOO problems, including evolutionary algorithms (e.g. NSGA, NSGA-II, etc.), tabu search, particle swarm optimization, etc. NSGA-II is the most popular solution algorithm for MOO problems in recent years [46]. NSGA-II can reduce the complexity of non-inferior sorting genetic algorithms with high computation efficiency and good convergence results. Therefore, NSGA-II is adopted in this paper to solve the proposed dynamic reconfiguration optimization model.

The typical procedure of NSGA-II includes seven main steps, as shown in the following.

**Step 1**. Coding. A chromosome of NSGA-II means a solution of operation task assignment, which is the combination operation task types tagged by operator or robot referring to collaboration factor $\lambda_i$. An example is given in Fig. 5. This coding example means that the 1st, 3rd, 4th and 6th operation task (different types) are assigned to operator and the reminder types of operation task are assigned to robot. Although the types of operation task are denoted using a mathematical set, operation task sort will be executed firstly for computation convenience.

**Step 2**. Population initialization. The initial population is generated randomly involving $Q$ individuals.

**Step 3**. Nondominated sorting and crowding distance sorting. The initial population is divided into several fronts according to the non-inferior solution level of each individual. When merging parent and offspring resulting in $2Q$ size, the population size should be modified to $Q$. The crowding distance sorting when including a specific front led to the new population size exceeding $Q$. Fig. 6 shows the sorting details.

**Step 4**. Termination condition. If the maximum generation is reached, the optimization process is complete, and the Pareto optimal solution will be obtained; otherwise, switch to the next step.

**Step 5**. Offspring population generation. Generating offspring population through selection, crossover, and mutation, as shown in Fig. 7. Firstly, tournament selection is adopted to randomly select two individuals from the parent population based on nondominated sorting and crowding distance sorting. Secondly, binary crossover algorithm is adopted to determine the crossover position randomly. Thirdly, polynomial mutation algorithm is used to randomly change specific genes of the parent chromosome.

**Step 6**. Merge parent population and offspring population. Merge the parent population and the offspring population to obtain a new population with the size of $2Q$. Again, go back to step 3 for fast nondominated sorting.

The flowchart of the adopted NSGA-II for dynamic reconfiguration optimization of manufacturing system with human-robot collaboration is shown in Fig. 8.

**Table 2**
Classification of given operation tasks.

| Operation task no. | Operator only | Robot only | Both |
|---|---|---|---|
| 1 | | | √ |
| 2 | √ | | |
| 3 | | | √ |
| 4 | | | √ |
| 5 | | | √ |
| 6 | √ | | |
| 7 | | | √ |
| 8 | | | √ |
| 9 | | √ | |
| 10 | | | √ |
| 11 | | | √ |

**Table 3**
Operation cost and time of operation tasks.

| Operation task type | Operation task no. | Operation cost per unit | | Operation time per unit | |
|---|---|---|---|---|---|
| | | Operator | Robot | Operator | Robot |
| Operator only | 2 | 12 | | 1 | |
| | 6 | 40 | | 4 | |
| Robot only | 9 | | 10 | | 1.5 |
| Both | 1 | 24 | 10 | 2.5 | 2 |
| | 3 | 36 | 25 | 3 | 2 |
| | 4 | 24 | 15 | 2 | 1 |
| | 5 | 60 | 45 | 5 | 3.5 |
| | 7 | 36 | 25 | 3 | 2 |
| | 8 | 24 | 15 | 2 | 1 |
| | 10 | 12 | 10 | 1 | 0.5 |
| | 11 | 24 | 10 | 2.5 | 2 |

## 5. Case study

The implementation of the proposed dynamic reconfiguration method of manufacturing system with human-robot collaboration will be provided in this section to validate its effectiveness, which is based on a typical machining station consisting of one machining center, one industrial robot and one operator. The digital twin of the machining station is also constructed for monitoring its production activities and optimizing its configuration dynamically, as shown in Fig. 9.

A specific part family is assigned to the machining station, as shown in Fig. 10. The corresponding production task is shown in Table 1, where the operation task details are given as well. The number behind the operation task name is the label of operation tasks respectively for computation convenience.

Considering the different characteristics of human and robot, the operation tasks are classified into three types, including operation task for operator only, operation task for robot only, and operation task for both operator and robot, as shown in Table 2. In addition, the total quantity of each operation task is 100 according to Table 1.

The operation cost per unit and operation time per unit based on the classification of operation tasks are given in Table 3. Moreover, the necessary information for optimization should be preset, including $Taskmax = 5$, $Mass = 100$.

The optimization solution will be executed using NSGA-II. Preset necessary parameter of NSGA-II, that is initial population size = 50, Maximum iteration = 20. The computation is executed by Python on a laptop with 2.3 GHz CPU, 16 GB RAM. The convergence process is shown in Fig. 11, where the mean and variance of crowding distance are

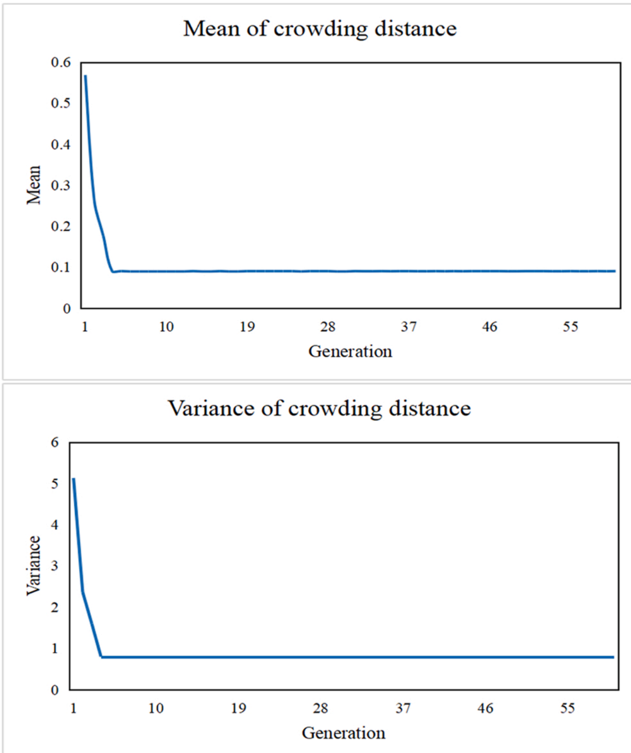


**Fig. 11.** Convergence process.

adopted to track the convergence process.

Pareto optimal solution can be obtained when convergence, as shown in Fig. 12. The three objectives are adopted as the axis of Pareto front graph, where rank 1, rank 2 and rank 3 are labeled with different colors.

Randomly selecting two solutions from rank 1 in Fig. 12. And the corresponding objective values and operation task assignment results are given in Table 4.

According to the selected solution 1, operation task 1, operation task 2, operation task 6, operation task 10, and operation task 11 are assigned to operator, and operation task 3, operation task 4, operation task 5, operation task 7, operation task 8, and operation task 9 are assigned to robot. Due to operation task 2 and operation task 6 should be done by operator only, three more operation tasks are assigned to operator without exceeding the total operation task upper limits of operator

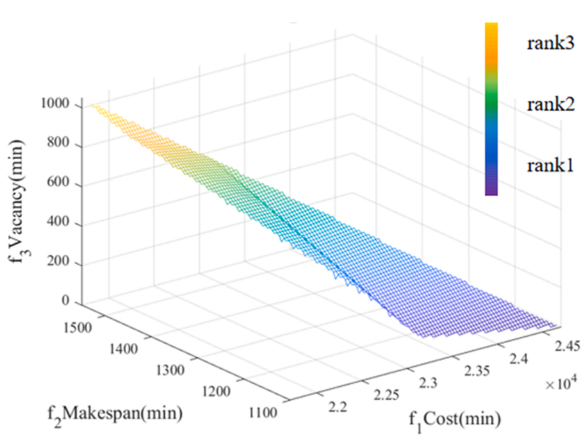


**Fig. 12.** Pareto optimal solution.

**Table 4**
Selected solutions.

| Solution | Cost | Makespan | Vacancy | Operation task assignment | |
|---|---|---|---|---|---|
| | | | | Operator | Robot |
| 1 | 24700 | 1100 | 0 | 1, 2, 6, 10, 11 | 3, 4, 5, 7, 8, 9 |
| 2 | 23400 | 1150 | 50 | 2, 5, 6, 10 | 1, 3, 4, 7, 8, 9, 11 |

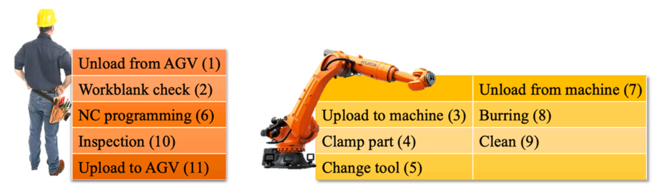


**Fig. 13.** Manufacturing system configuration of selected solution 1.


**Fig. 14.** Manufacturing system configuration of selected solution 2.

($Taskmax = 5$). Also, the vacancy between operator and robot is zero, which shows good collaboration efficiency between operator and robot. The corresponding configuration of manufacturing system with human-robot collaboration is shown in Fig. 13.

Similarly, according to the selected solution 2, operation task 2, operation task 5, operation task 6, and operation task 10 are assigned to operator, and operation task 1, operation task 3, operation task 4, operation task 7, operation task 8, operation task 9, operation task 11 are assigned to robot. Due to the operation cost and time of operation task 5 for operator being higher than robot, it is reasonable to use operation task 5 to replace operation task 1 and operation task 11 to obtain relatively balanced workload between operator and robot compared with the selected solution 1. Moreover, the skill switches of operator are less with four operation tasks in this solution, which will promote operator efficiency as well. The corresponding configuration of manufacturing system with human-robot collaboration is shown in Fig. 14.

In addition, the adopted digital twin of manufacturing system with human-robot collaboration can be used to simulate the effectiveness of the different solutions in the virtual space. And then, the dynamic reconfiguration decision of the manufacturing system with human-robot collaboration can be made based on the simulation results. Finally, the corresponding manufacturing system with human-robot collaboration in the physical space will receive the reconfiguration solution from the virtual space via data transmission and assign the operation tasks of new production task between operator and robot correctly, as shown in Fig. 15.

## 6. Conclusion

Digital twin-driven manufacturing system with human-robot collaboration is the typical paradigm of intelligent manufacturing to deal with production task fluctuation rapidly and efficiently, which reconfiguration of manufacturing system with human-robot collaboration based on dynamic task assignment between operator and robot could be executed to promote production efficiency. Also, the digital twin can be used to monitor production processes and improve


**Fig. 15.** Reconfiguration verification process based on digital twin.

reconfiguration accuracy due to seamless data transmission between physical space and virtual space and high-fidelity virtual model.

How to optimize the reconfiguration process of manufacturing system with human-robot collaboration is the key problem, which the different characteristics between operator and robot should be concerned to promote production efficiency after reconfiguration. Therefore, a dynamic reconfiguration optimization method of intelligent manufacturing system with human-robot collaboration based on digital twin is proposed in this paper. Firstly, a multiple objectives optimization model is constructed to explore the best operation task assignment solution between operator and robot, including minimum production cost, minimum production time, and minimum idle time. The different characteristics between operator and robot are considered during optimization modeling, which human factor is adopted to reduce physiological fatigue of operator during reconfiguration. Secondly, the typical solution to the MOO problem is adopted in this paper to calculate the proposed optimization model. Finally, a case study is provided to implement the proposed dynamic reconfiguration optimization method of intelligent manufacturing system based on digital twin. The results show that the proposed method can assign the operation tasks to operator and robot reasonably resulting in reasonable configuration of intelligent manufacturing system. However, the adopted manufacturing system in this paper involves one machine tool, one operator, and one robot only, more complex manufacturing scenarios should be studied in future work. Besides, other operation factors of operator and robot could affect the optimization effectiveness, which is a significant investigation direction in future work as well.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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