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PRODUCTION PLANNING FOR MASS CUSTOMIZATION AND RECONFIGURABLE MANUFACTURING SYSTEMS

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Abstract: *Mass customization requires flexible manufacturing systems like Reconfigurable Manufacturing Systems (RMS) to offer low-cost and high-volume production. An operational challenge is to manage the reconfiguration for the trade-off between the benefits of diversity in manufacturing and the difficulty of complexity in planning. This paper formulates a bi-objective mixed-integer non-linear programming mathematical model to integrate optimization of process planning and flexible job-shop scheduling for producing multi-unit mass-customized products in an RMS. The objectives are to minimize the total penalty for tardiness and the total cost, including reconfiguration, setup, processing, work-in-process transportation, and holding costs. The Archived Multiobjective Simulated Annealing (AMOSA) and Non-Dominated Sorting Genetic Algorithm II (NSGA-II), combined with some constraint handling techniques, are applied to solve the formulated problem. A small instance is solved with an exhaustive search to validate the mathematical model and the programming of these two approximate solution approaches. Both approximate solution approaches could obtain some exact Pareto-optimal solutions in a shorter computation time. Three larger instances are solved. Results show that the proposed constraint handling technique to repair the start time of operation helps yield better approximate Pareto-optimal solutions that have smaller objective values. Additionally, NSGA-II is advantageous over AMOSA in dealing with this problem.*

Key Words: ***reconfigurable manufacturing system; mass-customized products; process planning; flexible job-shop scheduling***

1. INTRODUCTION

Several companies are considering Mass Customization (MC) as a new production strategy to improve overhead, price, profit, and company success (Shao, 2020). Even though it is a common understanding that we need MC, there is still a long way ahead to define how to implement it successfully. Many companies, like miaddidas, could not achieve the expected success. This is due to the challenges facing the operational implementation of MC. Eventhough the enablers are well identified, how to implement them is yet not quite clear. One main enabler of MC is flexible and agile manufacturing systems (Jain et al, 2021) such as Reconfigurable Manufacturing Systems (RMS). RMS is designed at the outset for a rapid shift in structure and hardware and software components to quickly adjust production capacity and functionality within a part family in response to sudden changes in the market or regulatory requirements (Koren et al., 2019). RMSs can potentially advance MC significantly (Andersen et al., 2018). However, managing high demand uncertainty while maintaining low costs and fast delivery poses a challenge. In response, production planning, including scheduling and process planning, must evolve to handle increased product variety and competition (Phanden et al., 2013). To successfully implement MC, the overall manufacturing costs need to be reduced while satisfying customer requirements. This can be achieved by integrating process planning and scheduling in RMS. This paper contributes to the MC implementation research by proposing an integration of process planning and scheduling to produce mass-customized products most efficiently in an RMS.

This study built a bi-objective mixed-integer mathematical model to solve the integrated optimization of process planning and scheduling within a short planning horizon to minimize the total tardiness penalty and the total manufacturing cost, including machine reconfiguration, setup, processing, and Work-In-Process (WIP) handling costs. The Archived Multiobjective Simulated Annealing (AMOSA) algorithm and the Non-dominated Sorting Genetic Algorithm II (NSGA-II) algorithm are adopted and combined with the problem-specific constraint-handling techniques to solve the mathematical model. Numerical experiments analyze the performance of these two solution approaches.

The rest of this paper is structured as follows. The first section discusses a literature review. The second section introduces the mathematical model, two approximate solution approaches NSGA-II and AMOSA, and constraint handling techniques. The third section, discusses the performance of adapted NSGA-II and AMOSA. Finally, the last section summarizes the contribution of this work and gives some perspectives for future studies.

2. LITERATURE REVIEW

This paper focuses on mathematical programming for RMS process planning and scheduling to produce multiple multi-unit mass-customized products. Table 1 summarizes the reviewed literature's problems, objectives, models, and solution approaches addressing process planning and scheduling optimization in RMS. These are 48 articles searched by the keywords “Reconfigurable manufacturing system” AND “Process planning” and “Reconfigurable manufacturing system” AND “Scheduling” in four scientific academic literature databases (ScienceDirect, SpringerLink, Taylor and Francis Online, IEEE Xplore).

As shown in Table 1, only two studies integrated process planning and scheduling. Chaube et al. (2012) (Paper 47) did not consider the transportation cost, yet it highly impacts scheduling and process planning decisions. Also, it only considers a single product. Bensmaine et al. (2014) (paper 48) proved the higher performance of an integrated approach over a sequential one. However, they did not consider costs; they only optimized time-related performance. Whereas cost is an important criterion in decision-making. This paper overcomes these gaps by focusing on multi-products, including all costs, and also considering time as the objective function.

As shown in Table 1, some studies built Mixed-Integer Linear/Non-Linear programming (MILP/MINLP) mathematical models to determine the start time of each operation. The start time is a continuous decision variable. Integer decision variables seem inevitable when formulating the mathematical model for process planning and scheduling optimization in RMS owing to the countability of machines and configurations to be selected. Based on the above, this study built a mixed-integer programming mathematical model to integrate process planning and scheduling optimization in RMS for multi-unit mass-customized products.

Genetic algorithm (GA) based algorithms are the most popular approximate solution approaches, followed by simulated annealing (SA) to the process planning and scheduling problems in RMS. These two algorithms are often adapted to be problem-specific or combined with the Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) to improve their performance in solving the formulated mathematical models. They are employed alongside other algorithms, such as the Strength Pareto Evolutionary Algorithm (SPEA-II) and Multiobjective Particle Swarm Optimization (MOPSO) to compare their performance.

A few studies used commercial optimizers or exhaustive search to obtain exact optimal solutions to small-scale problems. This is a good way to validate mathematical models and check whether constraints are complete or conflicting. Despite that, it is necessary to develop approximate solution approaches because the computation of exact solution approaches would be time-consuming to obtain exact optimal solutions in real production scenarios, especially for large-scale problems with many parts and operations to be processed. Given the above, this study decided to use the exhaustive search to solve small instances. It also adapted NSGA-II and AMOSA as practical solution approaches for large instances. The exhaustive search is also used to validate the NSGAII and AMOSA approaches.

The Legend for table 1 is as follows: O.P.: Optimization Problem; P. Or PP.: Process Planning; SC.: Scheduling; Ob.: Objectives; C.: Cost; T.: Time; Sol.: Solution; Ex.: Exact; G.: GAMS ; CX:CPLEX; ES.: Exhaustive Search; L.: LINGO; GU: Gurobi; App.: Approximative; Alg.: Algorithm; Ad.: Adapted.

Table 1. *Summary of articles addressing process planning and scheduling optimization in RMS*

	O.P.		Ob.			Sol. approaches	
	P	S	C	T		Ex.	App.
1	√		√		NLP		GA & tabu search
2	√		√		ILP		GA
3	√		√		0-1 NLP		GA
4	√		√		NLP		SA-based approach
5	√		√		NLP		SA-based approach
6	√		Others		0-1 LP		NSGA-II
7	√		√		0-1 NLP		NSGA-II & TOPSIS
8	√		√		0-1 NLP		NSGA-II & TOPSIS
9	√		√		ILP	G	
10	√		√		ILP	G	
11	√		Others		ILP		NSGA-II
12	√		√	√	NLP		NSGA-II
13	√			√	0-1 NLP		NSGA-II & TOPSIS
14	√		√	√	ILP		NSGA-II & AMOSA
15	√		√	√	ILP		Three hybrid heuristics
16	√		√	√	0-1 NLP		NSGA-II & TOPSIS
17	√		√	√	0-1 NLP		NSGA-II & NSGA-III
18	√		√	√	NLP		NSGA-II & AMOSA
19	√		√	√	0-1 LP		NSGA-II & SPEA-II
20	√		√	√	0-1 NLP		AMOSA & TOPSIS
21	√		Others		0-1 NLP	ES	
22	√		√		MINLP		NSGA-II & MOPSO
23	√		√	√	MILP		NSGA-II & AMOSA
24	√		√		0-1 NLP		GA
25	√		√		0-1 NLP	CX	GA
26	√		√		ILP	G	Lagrangian relaxation
27	√		Others		ILP	CX	
28		√	√	√	NLP		NSGA-II &MOPSO
29		√	√	√	NLP		Shannon Entropy
30		√	√	√	NLP		NSGA-II & MOPSO
31		√		√	MILP		Immune alg.
32		√	√	√	MINLP		original heuristic
33		√	√	√	0-1 NLP	L	NSGA-II
34		√	√	√	MILP		NSGA-II &MOPSO
35		√		√	0-1 NLP		Advantage actor-critic
36		√	√		MINLP		GA-based alg.
37		√	Others		ILP		original alg.
38		√	√		MILP	CX	
39		√		√	NLP		priority rule method
40		√		√	LP		Social network
41		√		√	MILP	CX	
42		√		√	MILP		Equilibrium optimizer
43		√		√	MILP		original alg.
44		√		√	MILP		GA & a local search
45		√		√	0-1 LP	GU	
46		√	√		MILP	L	improved GA
47	√	√	√	√	NLP		Ad. NSGA-II
48	√	√		√	NLP		original heuristic

3. PROBLEM FORMULATION AND SOLUTION APPROACHES

This paper presents a deterministic model for mass-customized production, considering the components and parts required for each product. Each product consists of multiple part variants, with each part variant following an operation precedence graph. Jobs involve producing part variants, including machine setup, reconfiguration, and WIP handling. Jobs are identified by a triplet Identifier (ID), distinguishing between products, part variants, and their order within the part family. These jobs are executed in a Reconfigurable Manufacturing System (RMS) with multiple machines and configurations. The study focuses on flexible job-shop scheduling, where operations can be performed by feasible machine and configuration pairs. WIPs are generated after the first operation and transported between machines, with occasional holding until the machine is available. The study formulates an operations research problem for mass customization in RMS, providing input parameters like due dates and part information for production planning. The output includes optimal operation sequences, machine configurations, and start times for each job, integrating process planning and flexible job-shop scheduling.

3.1. Mathematical model

The following assumptions help simplify the mathematical model:

1. All parts and products are qualified.
2. Raw materials and material handling equipment are always available.
3. Preemptions and breakdowns aren't considered.
4. Layout reconfiguration is not considered in this study. Which is true for most RMSs today.
5. In the beginning, all machines are idle.

Indices:

i, i'	Indices of mass-customized products
v, v'	Indices of part variants
j, j'	Indices of the third number of jobs' IDs
q, q'	The ordinal position indices of operations in jobs' operation sequences
l, l'	The ordinal position indices of operations in sequences of operations performed on machines
e, e'	Indices of operations
m, m'	Indices of machines
g, g'	Indices of configurations

Parameters:

I	Set of products
D_i	Due date of product i
W_i	A scalar for measuring the penalty of product i's tardiness per time unit
OP	Set of operations
$MG_{e,m,g}$	=1 if operation e is feasible on machine m with configuration g. = 0 if not
V	Set of part variants
FT_v	Time of transporting a WIP corresponding to part variant v per distance unit
FC_v	Cost of transporting a WIP corresponding to part variant v per distance unit
HC_v	Cost of holding a WIP corresponding to part variant v per time unit
$VP_v = \{e, \ldots, e'\}$	Set of operations to process a part variant v
$K_{v,e} = \{\ldots, e', \ldots\}$	Set of operations precedent to operation e in a job of part variant v
$PT_{e,v,m,g}$	Time of performing operation e for part variant v on machine m with configuration g
$PC_{e,v,m,g}$	Cost of performing operation e for part variant v on machine m with configuration g
$ST_{e,v,m,g}$	Setup time to perform operation e for part variant v on machine m with configuration g
$SC_{e,v,m,g}$	Setup cost to perform operation e for part variant v on machine m with configuration g
$J_{i,v}$	Number of parts belonging to part variant v in product i
M	Set of machines
$Z_{m,m'}$	Distance between machine m and machine m'
G_m	Set of configurations on machine m
A_m	Initial configuration on machine m
$RT_{m,g,g'}$	Machine reconfiguration time from configuration g to configuration g' on machine m
$RC_{m,g,g'}$	Machine reconfiguration cost from configuration g to configuration g' on machine m

Decision variables:

Independent decision variables	
$\rho_{i,v,j,q}$	Operation at the q^{th} position in the operation sequence of $Job_{i,v,j}$
$\alpha_{i,v,j,q}$	Machine to perform operation $\rho_{i,v,j,q}$
$\varphi_{i,v,j,q}$	Configuration on machine $\alpha_{i,v,j,q}$, and to perform operation $\rho_{i,v,j,q}$
$\beta_{i,v,j,q}$	Start time to perform operation $\rho_{i,v,j,q}$

Auxiliary decision variables:

$c_{i,v,j,q}$	Completion time of operation $\rho_{i,v,j,q}$
T_i	Tardiness of product i
$B_{m,l}$	Start time set for operations from the l^{th} ordinal position on machine m
$i_{m,l}$	Product index of the l^{th} operation performed on machine m
$v_{m,l}$	Part variant index of the l^{th} operation performed on machine m
$j_{m,l}$	Job index of the l^{th} operation performed on machine m
$q_{m,l}$	Ordinal position index of the l^{th} operation performed on machine m in the operation sequence of $Job_{i_{m,l},v_{m,l},j_{m,l}}$
$\rho_{m,l}$	Operation of the l^{th} performed on machine m
$\beta_{m,l}$	Start time to perform operation $\rho_{m,l}$

$\varphi_{m,l}$	Configuration to perform operation $\rho_{m,l}$

The first objective of this mathematical model is to minimize the total penalty cost for mass-customized products that are not completed on time. The corresponding penalty cost coefficient weights the tardiness time of each delayed product. Compared with minimizing the total tardiness time of all the delayed mass-customized products, this objective function considers customers' distinct tolerance for tardiness.

$$\text{Min} \sum_{i=1}^{|I|} T_i \times W_i \quad (1)$$

The tardiness of each mass-customized product is given in equation (2).

$$T_i = \max\left(c_{i,v,j,|VP_v|} - D_i, 0\right) \ \forall i \in I, \forall v \in V, \forall j \in \{1, \dots, J_{i,v}\} \quad (2)$$

The completion time of each operation in the above equation is defined by equation (3).

$$c_{i,v,j,q} = \beta_{i,v,j,q} + PT_{\rho_{i,v,j,q}, v, \alpha_{i,v,j,q}, \varphi_{i,v,j,q}}$$
$$\forall i \in I, \forall v \in V, \forall j \in \{1, \dots, J_{i,v}\}, \forall q \in \{1, \dots, |VP_v|\} \quad (3)$$

The second objective is to minimize the sum of the total machine reconfiguration cost (MRC), the total setup cost in preparation for performing all operations (PSC), the total cost of performing all operations (PPC), the total WIP transportation cost (WFC), and the total WIP holding cost (WHC) for a given MC task.

$$\text{Min MRC} + \text{PSC} + \text{PPC} + \text{WFC} + \text{WHC} \quad (4)$$

The machine reconfiguration occurs when two consecutive operations are performed on one machine with different configurations. If two consecutive operations are performed on one machine with the same configuration, the values of the reconfiguration time and reconfiguration cost are equal to 0.

$$\text{MRC} = RC_{m, A_m, \varphi_{m,1}} + \sum_{m=1}^{|M|} \sum_{l=1} RC_{m, \varphi_{m,l}, \varphi_{m,l+1}} \quad (5)$$

The setup occurs when two consecutive operations performed on one machine are different or they are performed for two different part variants. Even if these two consecutive operations and the corresponding two part variants are identical, there is a setup when different configurations perform them. In this situation, machine reconfiguration and setup still co-exist. The parameters of their time and cost are not to be confused because the time and cost of machine reconfiguration incurred by changes in the hardware structure are determined by the configurations before and after the change. Meanwhile, the time and cost of setup incurred by adjusting machine processing functionality through the software are determined by the operation to be performed and its corresponding part type. There is always a setup for the first operation on each machine.

$$\text{PSC} = \sum_{m=1}^{|M|} \left(SC_{\rho_{m,1}, v_{m,1}, m, \varphi_{m,1}} + \sum_{l=2} SC_{\rho_{m,l}, v_{m,l}, m, \varphi_{m,l}} \right)$$
$$\forall \rho_{m,l} \neq \rho_{m,l-1} \vee \forall v_{m,l} \neq v_{m,l-1} \vee \forall \varphi_{m,l} \neq \varphi_{m,l-1} \quad (6)$$

The total machine reconfiguration cost (MRC) and the total setup cost (PSC) depend on the sequences of operations being performed on machines, the configurations selected to perform those operations, and the part variants. Auxiliary decision variables $\rho_{m,l}$, $v_{m,l}$ and $\varphi_{m,l}$ in equations (5) and (6) above, along with the other auxiliary decision variables $i_{m,l}$, $j_{m,l}$, $q_{m,l}$ and $\beta_{m,l}$, are defined by the following formulas:

$$B_{m,1} = \{\beta_{i,v,j,q}\} \forall m \in M, \forall \beta_{i,v,j,q} | \alpha_{i,v,j,q} = m,$$
$$\forall i \in I, \forall v \in V, \forall j \in \{1, \dots, J_{i,v}\}, \forall q \in \{1, \dots, |VP_v|\} \quad (7)$$

$$i_{m,1}, v_{m,1}, j_{m,1}, q_{m,1} = \underset{i,v,j,q}{argmin}\, B_{m,1},$$
$$\rho_{m,1} = \rho_{i_{m,1}, v_{m,1}, j_{m,1}, q_{m,1}}, \varphi_{m,1} = \varphi_{i_{m,1}, v_{m,1}, j_{m,1}, q_{m,1}},$$
$$\beta_{m,1} = \beta_{i_{m,1}, v_{m,1}, j_{m,1}, q_{m,1}} \ \forall m \in M \quad (8)$$

$$B_{m,l+1} = \{\beta_{i,v,j,q}\}$$
$$\forall m \in M, \forall l \in N+, \forall \beta_{i,v,j,q} | \alpha_{i,v,j,q} = m \wedge \beta_{i,v,j,q} > \beta_{m,l},$$
$$\forall i \in I, \forall v \in V, \forall j \in \{1, \dots, J_{i,v}\}, \forall q \in \{1, \dots, |VP_v|\} \quad (9)$$
$$i_{m,l}, v_{m,l}, j_{m,l}, q_{m,l} = \underset{i,v,j,q}{argmin}\, B_{m,l}$$
$$\rho_{m,l} = \rho_{i_{m,l}, v_{m,l}, j_{m,l}, q_{m,l}}, \varphi_{m,l} = \varphi_{i_{m,l}, v_{m,l}, j_{m,l}, q_{m,l}},$$
$$\beta_{m,l} = \beta_{i_{m,l}, v_{m,l}, j_{m,l}, q_{m,l}} \ \forall m \in M \quad (10)$$

Formula (7) gives the set of all operations performed on each machine. Equations in (8) find indices of the first operation performed on each machine and identify the selected configuration and the start time to perform this operation. Formula (9) and equations in (10) repeat the same idea as formula (7) and equations in (8) to identify every operation in the order in which they are performed on machines.

According to equation (11), the total cost of performing all operations is determined by the selected machine and configuration pairs to perform operations, which, intuitively, are merely relevant to the decision-making in process planning. The selection of machine and configuration pair to perform each operation will be affected by the decision-making in flexible job-shop scheduling because of the availability of machines in RMS. It will also be affected by distances between machines in RMS as there are tradeoffs between machine reconfiguration and WIP transportation for performing some operations. Hence, the total cost of performing all operations is relevant to decision-making in both process planning and flexible job-shop scheduling.

$$\text{PPC} = \sum_{i=1}^{|I|} \sum_{v=1}^{|V|} \sum_{j=1}^{J_{i,v}} \sum_{q=1}^{|VP_v|} PC_{\rho_{i,v,j,q}, v, \alpha_{i,v,j,q}, \varphi_{i,v,j,q}} \quad (11)$$

In this study, both cost and time spent on transporting a WIP are directly proportional to the distance of that transportation, which is equal to the distance between two machines performing two consecutive operations before and after that WIP transportation. Besides, the cost and time for transporting WIPs corresponding to different part variants over per distance unit are presumably not the same.

$$\mathrm{WFC} = \sum_{i=1}^{|I|}\sum_{v=1}^{|V|}\sum_{j=1}^{J_{i,v}}\sum_{q=1}^{|VP_v|-1} FC_v \times Z_{\alpha_{i,v,j,q},\alpha_{i,v,j,q+1}} \quad (12)$$

Except for WIP transportation, the time remaining between two consecutive operations in a job is considered a WIP holding time. The values of the cost parameter for holding WIPs corresponding to different part variants also vary.

$$\mathrm{WHC} = \sum_{i=1}^{|I|}\sum_{v=1}^{|V|}\sum_{j=1}^{J_{i,v}}\sum_{q=1}^{|VP_v|-1} HC_v \times \left(\beta_{i,v,j,q+1} - c_{i,v,j,q} - FT_v \times Z_{\alpha_{i,v,j,q},\alpha_{i,v,j,q+1}}\right) \quad (13)$$

The decision variables are subject to the following constraints:

$$MG_{\rho_{i,v,j,q},\alpha_{i,v,j,q},\varphi_{i,v,j,q}} = 1$$
$$\forall i \in I, \forall v \in V, \forall j \in \{1, \dots, J_{i,v}\}, \forall q \in \{1, \dots, |VP_v|\} \quad (14)$$

$$\beta_{i,v,j,q+1} \geq c_{i,v,j,q} + FT_v \times Z_{\alpha_{i,v,j,q},\alpha_{i,v,j,q+1}}$$
$$\forall i \in I, \forall v \in V, \forall j \in \{1, \dots J_{i,v}\}, \forall q \in \{1, \dots, |VP_v| - 1\} \quad (15)$$

$$\beta_{i,v,j,q'} \geq c_{i,v,j,q} \; \forall i \in I, \forall v \in V, \forall j \in \{1, \dots J_{i,v}\},$$
$$\forall q \in \{1, \dots, |VP_v| - 1\}, \forall \rho_{i,v,j,q} \in K_{v,\rho_{i,v,j,q'}}, \quad (16)$$

$$\beta_{m,1} \geq RT_{m,A_m,\varphi_{m,1}} + ST_{\rho_{m,1},v_{m,1},m,\varphi_{m,1}} \quad \forall m \in M \quad (17)$$

$$\beta_{m,l+1} \geq \beta_{m,l} + PT_{\rho_{m,l},v_{m,l},m,\varphi_{m,l}}$$
$$\forall m \in M, \forall l \in N+, v_{m,l} = v_{m,l+1} \wedge \rho_{m,l} = \rho_{m,l+1} \wedge \varphi_{m,l} = \varphi_{m,l+1} \quad (18)$$

$$\beta_{m,l+1} \geq \beta_{m,l} + PT_{\rho_{m,l},v_{m,l},m,\varphi_{m,l}} + RT_{m,\varphi_{m,l},\varphi_{m,l+1}} + ST_{\rho_{m,l},v_{m,l},m,\varphi_{m,l}}$$
$$\forall m \in M, \forall l \in N+, v_{m,l} \neq v_{m,l+1} \vee \rho_{m,l} \neq \rho_{m,l+1} \vee \varphi_{m,l} \neq \varphi_{m,l+1} \quad (19)$$

$$\rho_{i,v,j,q} \in VP_v \quad \forall i \in I, \forall v \in V, \forall j \in \{1, \dots, J_{i,v}\}, \forall q \in \{1, \dots, |VP_v|\} \quad (20)$$

$$\beta_{i,v,j,q} \in R+ \; \forall m \in M, \forall i \in I, \forall v \in V, \forall j \in \{1, \dots, J_{i,v}\}, \forall q \in \{1, \dots, |VP_v|\} \quad (21)$$

$$\alpha_{i,v,j,q} \in M \forall i \in I, \forall v \in V, \forall j \in \{1, \dots, J_{i,v}\}, \forall q \in \{1, \dots, |VP_v|\} \quad (22)$$

$$\varphi_{i,v,j,q} \in G_{\alpha_{i,v,j,q}} \forall i \in I, \forall v \in V, \forall j \in \{1, \dots, J_{i,v}\}, \forall q \in \{1, \dots, |VP_v|\} \quad (23)$$

Constraint (14) indicates that the selected machine and configuration pairs can perform the corresponding operations. Constraint (15) ensures that the start time to perform an operation cannot be earlier than the sum of the previous operation's completion time and the WIP transportation time between these two consecutive operations in the corresponding job's operation sequence. Constraint (16) guarantees that an operation cannot be earlier than the completion of those operations that are precedent to this operation in the corresponding operation precedence graph. Constraint (17) states that the first operation on each machine cannot start until the machine reconfiguration and the setup in preparation for performing this operation have been finished. According to constraint (18), if two consecutive operations are the same and are performed on the same machine with the same configuration for the same part variant, the start time of the latter operation cannot be earlier than the completion time of the previous operation. If not, constraint (19) restricts the subsequent operation from starting until the previous operation has been completed and the machine reconfiguration and setup in preparation for performing the subsequent operation have been finished. Constraints (20-23) point out that the values of the independent decision variables are within the feasible domain of definition.

3.2. Solution approaches

The mathematical model above is multiobjective, and there is no single best solution for all objectives. For this, the non-dominated concept is employed to find Pareto-optimal solutions. NSGA-II is an evolutionary algorithm widely used in the literature to tackle many optimization problems. This study adopted NSGA-II with AMOSA to solve the formulated NP-hard problem since local search methods like SA would need large computation time to find optimum solutions for large instances (Zhang et al., 2019). The formulated problem is NP-hard because it engages flexible job-shop scheduling, which has been proved NP-hard.

In the program of NSGA-II and AMOSA algorithm, four multi-dimensional lists are created to place the values of independent decision variables $\rho_{i,v,j,q}$, $\alpha_{i,v,j,q}$, $\varphi_{i,v,j,q}$ and $\beta_{i,v,j,q}$ in elements. The numeric data types of elements in three multi-dimensional lists encoding $\rho_{i,v,j,q}$, $\alpha_{i,v,j,q}$, and $\varphi_{i,v,j,q}$ are integers. The numeric type of elements in the multi-dimensional list encoding $\beta_{i,v,j,q}$ is floating point.

A solution to the formulated process planning and flexible job-shop scheduling integrated optimization problem is represented as an object with the above four multi-dimensional lists as its properties.

In the NSGA-II program, a class is defined to create objects representing a population of solutions, called individuals. The initial population evolves by repeatedly applying the selection, crossover, and mutation operators in generations. As shown in Fig. 1, this study applied the uniform crossover on the selected "parent" individuals to generate new "offspring" individuals. For the integer independent decision variables $\rho_{i,v,j,q}$, $\alpha_{i,v,j,q}$, and $\varphi_{i,v,j,q}$, the integer division (denoted by the symbol '//' in Fig. 1) is adopted to obtain integer values. The mutation operator is shown in Fig. 2.

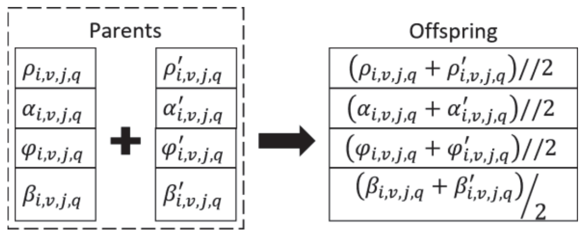

Fig. 1. *The uniform crossover operator of NSGA-II*

In the AMOSA program, the initial solution is improved by stochastic perturbations in iterations to generate new candidate solutions. The perturbation of the AMOSA algorithm in this study is the same as the mutation operator of NSGA-II shown in Fig. 2.

Some independent decision variables are not subject to the constraints in the mathematical model by the crossover and mutation operators in NSGA-II and the perturbation in AMOSA. Such infeasible solutions existing in generations/iterations adversely affect the performance of the adopted NSGA-II and AMOSA algorithms for obtaining approximate Pareto-optimal solutions. This work checked the feasibility of all solutions generated after the crossover and mutation operations in NSGA-II and the perturbation operations in AMOSA and repaired infeasible ones. As shown in Fig. 3, four sets of independent decision variables $\rho_{i,v,j,q}$, $\alpha_{i,v,j,q}$, $\varphi_{i,v,j,q}$ and $\beta_{i,v,j,q}$ in each solution are modified sequentially. This modifying order is logical and should not be disturbed; otherwise, remodifying the values that have been checked and repaired will be unavoidable.

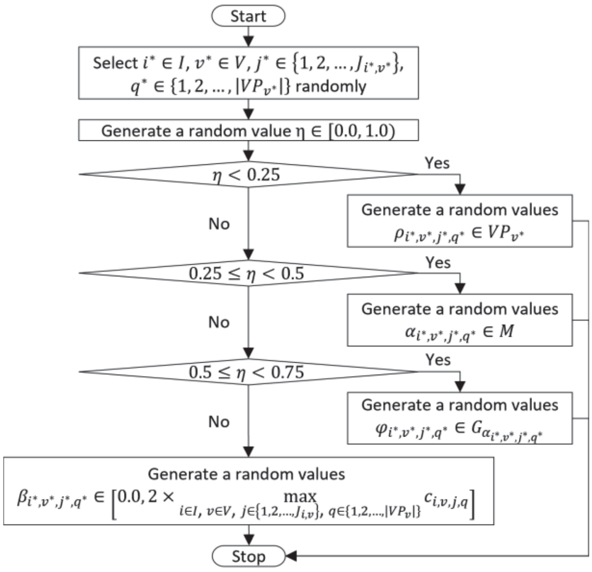

Fig. 2. *The mutation operator of NSGA-II in this study*

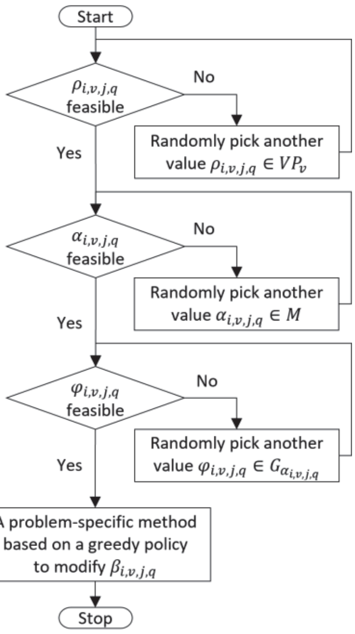

Fig.3. *The flowchart of repairing infeasible solution*

Infeasible independent decision variables $\rho_{i,v,j,q}$, $\alpha_{i,v,j,q}$, and $\varphi_{i,v,j,q}$ are repaired by randomly picking another value from their domains of definition. The repairing assignment is repeated until the repaired independent decision variable becomes feasible. This repairing method is simple and effective for these three set of independent decision variables, thanks to the limited number of values in their domains of definition.

This study proposed a problem-specific method based on a greedy policy to modify all the values of the independent decision variables $\beta_{i,v,j,q}$ in each solution. All the modified values are feasible and are expected to drive the values of two objective functions to be as small as possible. A problem is that values of the independent decision variables $\beta_{i,v,j,q}$ are mutually influential. Any modification of the start time of an operation may lead to the start time of its subsequent operations not only in the same job but also performed on the same machine becoming infeasible, which creates a chain reaction. The difficulty in modifying this set of independent decision variables is finding a modifying order in which all the values that have been modified will always be feasible when the start time of any other operation is modified.

The procedure in the following pseudocode overcomes this difficulty and applies a greedy policy to modify the start time of each operation:

For $\forall i \in I, \forall v \in V, \forall j \in \{1,2,\dots,|J_{i,v}|\}$, $\forall q \in \{1,2,\dots,|VP_v|\}$:

  If $\beta_{i,v,j,q+1} < c_{i,v,j,q} + FT_v \times Z_{\alpha_{i,v,j,q},\alpha_{i,v,j,q+1}}$:

    Set $\beta_{i,v,j,q+1} = c_{i,v,j,q} + FT_v \times Z_{\alpha_{i,v,j,q},\alpha_{i,v,j,q+1}}$

Sort all $\beta_{i,v,j,q}$ in ascending order on machines to form the auxiliary decision variables $\beta_{m,l}$, save all auxiliary decision variables $\beta_{m,l}$ in set P

While $P \neq \emptyset$:

  Find the minimum value in P and save the corresponding operation index (e^*), the corresponding machine index (m^*) performing operation e^*, the corresponding configuration (g^*) performing operation e^*, the corresponding ordinal position index (l^*) of the sequence of operations performed on machine m^*, the corresponding product index (i^*), the corresponding part variant index (v^*), index (j^*) to identify the corresponding job, and the corresponding ordinal position index (q^*) in the operation sequence of Job_{i^*,v^*,j^*}

  If $l^* = 1$ & $q^* = 1$:

    Set $\beta_{m^*,1} = RT_{m^*,A_{m^*},\varphi_{m^*,1}} + ST_{e^*,v^*,m^*,g^*}$

  If $l^* = 1$ & $q^* > 1$:

    Set $\beta_{m^*,1} = max\left(c_{i^*,v^*,j^*,q^*-1} + FT_{v^*} \times Z_{\alpha_{i^*,v^*,j^*,q^*-1},m^*},\ RT_{m^*,A_{m^*},\varphi_{m^*,1}} + ST_{e^*,v^*,m^*,g^*}\right)$

  If $l^* > 1$ & $q^* = 1$:

    If $v^* = v_{m^*,l^*-1}$, $e^* = \rho_{m^*,l^*-1}$, $g^* = \varphi_{m^*,l^*-1}$:

      Set $\beta_{m^*,l^*} = \beta_{m^*,l^*-1} + PT_{\rho_{m^*,l^*-1},v_{m^*,l^*-1},m^*,\varphi_{m^*,l^*-1}}$

    Else:

      Set

$\beta_{m^*,l^*} = \beta_{m^*,l^*-1} + PT_{\rho_{m^*,l^*-1},v_{m^*,l^*-1},m^*,\varphi_{m^*,l^*-1}} + RT_{m^*,\varphi_{m^*,l^*-1},g^*} + ST_{e^*,v^*,m^*,g^*}$
If $l^* > 1$ & $q^* > 1$:
If $v^* = v_{m^*,l^*-1}$, $e^* = \rho_{m^*,l^*-1}$, $g^* = \varphi_{m^*,l^*-1}$:
Set $\beta_{m^*,l^*} = max\left(c_{i^*,v^*,j^*,q^*-1} + FT_{v^*} \times Z_{\alpha_{i^*,v^*,j^*,q^*-1},m^*},\ \beta_{m^*,l^*-1} + PT_{\rho_{m^*,l^*-1},v_{m^*,l^*-1},m^*,\varphi_{m^*,l^*-1}}\right)$
Else:
Set $\beta_{m^*,l^*} = max\left(c_{i^*,v^*,j^*,q^*-1} + FT_{v^*} \times Z_{\alpha_{i^*,v^*,j^*,q^*-1},m^*},\ \beta_{m^*,l^*-1} + PT_{\rho_{m^*,l^*-1},v_{m^*,l^*-1},m^*,\varphi_{m^*,l^*-1}} + RT_{m^*,\varphi_{m^*,l^*-1},g^*} + ST_{e^*,v^*,m^*,g^*}\right)$
Delete this minimum value from P

4. EXPERIMENTAL RESULTS AND ANALYSES

Due to the lack of benchmark instances and the opportunity for practical application, the validation of the proposed model and the evaluation of the adapted NSGA-II and AMOSA with constraint handling techniques were done through numerical experiments. All data in numerical examples are randomly generated. The experiments are conducted on a laptop computer powered by an Intel Core i7-12700H CPU (2.30 GHz) and 16 GB of RAM. Algorithms are programmed in PyCharm. The version used is 2021.1.1. Python 3.8 has been configured as a project interpreter.

4.2 Numerical experiments to solve small examples

The mathematical model is validated through tests on a small numerical example, ensuring feasibility and constraint adherence. Exhaustive search is then employed to obtain exact Pareto-optimal solutions for this example. To confirm their accuracy, these exact solutions are compared with approximate solutions generated by adapted NSGA-II and AMOSA algorithms with constraint handling techniques. Proper parameter settings using Design of Experiments (DOE) are employed for both algorithms. With these settings, both adapted NSGA-II and AMOSA algorithms successfully obtain exact Pareto-optimal solutions in 6 out of 10 runs, as detailed in the provided data repository.

4.2 Numerical experiments to solve large examples

Three larger numerical examples are solved to compare the performance of two approximate solution approaches and test them without the proposed constraint handling technique to repair the start time of operations. In programs of the adapted NSGA-II and AMOSA without the proposed constraint handling technique to repair the start time of operations, all the other constraint handling techniques to repair infeasible independent decision variables $\rho_{i,v,j,q}$, $\alpha\_{i,v,j,q}$ and $\varphi_{i,v,j,q}$ are retained, but not the proposed constraint handling technique to repair infeasible start time of operations $\beta_{i,v,j,q}$. The infeasible solutions are checked, and their objective values are multiplied with a large penalty coefficient so that infeasible solutions are probably dominated by other solutions in generations/iterations and cannot be retained in the final archives in NSGA-II or AMOSA. However, individuals in the first generation in NSGA-II and the initial two solutions in AMOSA are generated by using the proposed constraint handling technique to make sure they are feasible.

Four metrics, Quality Metric (QM) to maximize, Mean Ideal Distance (MID) to minimize, Diversification Metric (DM) to maximize, and Number of Pareto-optimal Solutions (NPS) to maximize, defined by Nemati-Lafmejani et al. (2019) are adopted in the numerical experiments. QM is determined by dividing the cardinal of the set of overall non-dominated solutions by the cardinal of the original set of Pareto-optimal solutions. This study uses all the approximate Pareto-optimal solutions obtained for the same numerical example to calculate this metric. MID measures the relative distance of approximate Pareto-optimal solutions. DM shows the diversity of approximate Pareto-optimal solutions. NPS is the number of the approximate Pareto-optimal solutions obtained in each run.

There are four programs for NSGA-II with the proposed constraint handling technique to repair the start time of operations, AMOSA with the proposed constraint handling technique to repair the start time of operations, NSGA-II without the proposed constraint handling technique to repair the start time of operations, AMOSA without the proposed constraint handling technique to repair the start time of operations. Each program is run three times to solve each numerical example. For each numerical example, the parameters in NSGA-II and AMOSA with and without the proposed constraint handling technique to repair the start time of operations are adjusted to keep the average computation time of these four programs acceptable. Table 2 summarizes the performances of the different approaches. It shows that for each numerical example, the approximate Pareto-optimal solutions obtained by NSGA-II in shorter computation time are better than those obtained by AMOSA, as the mean objective values of approximate Pareto-optimal solutions obtained by NSGA-II are smaller than those obtained by AMOSA, no matter with or without the proposed constraint handling techniques to repair the start time of operations. Therefore, NSGA-II outperforms AMOSA in solving the formulated problem, although the approximate Pareto-optimal solutions obtained by AMOSA are more diverse than those obtained by NSGA-II.

The approximate Pareto-optimal solutions obtained by both NSGA-II and AMOSA with the proposed constraint handling technique to repair the start time of operations are better than those obtained without the proposed constraint handling technique. Thus, the superiority of the proposed constraint handling technique to repair the start time to operations is validated.

5. CONCLUSION AND FUTURE WORKS

This study contributes to the MC implementation research by proposing how production can be planned for multiple MC products in an RMS. It proposes an integrated optimization of process planning and flexible job-shop scheduling within an RMS for producing multiple multi-unit mass-customized products. It overcomes gaps identified in the literature by considering all related costs, time factors, and multi-products. It allows determining the optimal operation sequence for each part in each product, identifying the best machine configuration for each operation, and scheduling the operations on machines in the most efficient order and time. The research adopts NSGA-II and AMOSA algorithms, supplemented with constraint-handling techniques, to solve the formulated problem. A notable contribution to the literature is the development of an effective constraint-handling technique for repairing the start time of operations, applicable to various solution approaches for scheduling problems. However, a significant limitation is the lack of real instances for validation, suggesting that future research should focus on validating the sustainability of RMS. RMSs not only offer customized flexibility but also contribute to developing sustainable production systems. Moreover, the integration of quality-related performances into reconfigurable process plans is highlighted. With the rise of Industry 4.0, machine learning approaches are identified as promising solutions for various manufacturing challenges within RMSs, including process planning and scheduling.

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Table 2. *Metrics values in the numerical experiment to solve larger examples*

Examples	Solution approaches	Average computation time (seconds)	$\sum_{run=1}^{run=3}\sum_{k=1}^{NPS} f_{1_k} / NPS / 3$	$\sum_{run=1}^{run=3}\sum_{k=1}^{NPS} f_{2_k} / NPS / 3$	$\sum_{run=1}^{3} QM / 3$	$\sum_{run=1}^{3} MID / 3$	$\sum_{run=1}^{3} DM / 3$	$\sum_{run=1}^{3} NPS / 3$
1	NSGA-II with PCHT	41.58	6842.44	5735.73	0.33	0.90	613.94	5.00
	AMOSA with PCHT	44.71	17898.33	8383.62	0.00	0.56	2654.83	3.67
	NSGA-II without PCHT	43.54	15336.78	7989.15	0.00	0.97	485.16	2.33
	AMOSA without PCHT	46.82	22519.33	9352.75	0.00	1.00	719.22	2.00
2	NSGA-II with PCHT	432.02	823948.83	338178.34	0.33	0.51	10302.65	2.67
	AMOSA with PCHT	464.31	1161484.22	391305.78	0.00	0.32	48834.92	1.67
	NSGA-II without PCHT	481.88	1223527.33	400309.52	0.00	0.67	68540.05	1.67
	AMOSA without PCHT	495.67	1263060.50	418108.93	0.00	1.00	18913.26	2.00
3	NSGA-II with PCHT	1439.41	16927137.00	5269137.67	0.67	0.00	0.00	1.00
	AMOSA with PCHT	3796.62	22398484.67	6108165.967	0.00	0.00	0.00	1.00
	NSGA-II without PCHT	1626.51	25479690.33	6693666.53	0.00	0.00	0.00	1.00
	AMOSA without PCHT	3891.48	25392941.00	6571883.30	0.00	0.00	0.00	1.00

Legend: PCHT = the proposed constraint handling technique is used to repair the start time of operations