NSGA-II with Q-learning for the integrated process planning and scheduling problem with reconfigurable machines

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Abstract: In this paper, we address the integrated process planning and scheduling problem (IPPS) with reconfigurable machine tools (RMTs). For solving the problem, we adopt an online approach where both decisions are integrated, thus simultaneously taken. We propose a novel metaheuristic, Q-NSGA-II, which combines the Non-Dominated Sorting Genetic Algorithm (NSGA-II) with Q-learning. This approach dynamically adjusts the crossover probability after each iteration using Q-learning, aiming to improve the search process. The proposed metaheuristic was compared to three standard NSGA-II variants with fixed crossover probabilities (0.1, 0.5, and 0.9). The four metaheuristics were tested for solving an instance from the literature, and the results demonstrated that Q-NSGA-II provides better results than its static counterparts in terms of quality and stability. This suggests that Q-NSGA-II has the potential to be a strong competitor in the IPPS domain, warranting further investigation and comparison with other existing solution approaches.

Keywords: Q-Learning, Reconfigurable Manufacturing Systems, Reconfigurable machine tools, Integrated Process planning and Scheduling, NSGA-II, Adaptive operator selection.

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1. INTRODUCTION

The integration of various production planning activities has demonstrated substantial economic benefits (Fleischmann et al., 2000). However, the increased computational complexity associated with these integrated approaches, particularly for practical size instances and those involving complex setups such as reconfigurable manufacturing systems (RMS), poses considerable challenges.

RMS represents a complex family of manufacturing systems designed for rapid adjustment of its components for quick and efficient change in the production capacity, conversion from one product type to another, or introduction of new products. RMS is designed around six core characteristics that permit the system's flexibility and adaptability. The primary three characteristics according to Koren (2010) are:

- Scalability: Which represents the capacity to adjust the production quantity.
- Convertibility: Which represents the capacity to change the product being manufactured.
- Customization: Which indicates the range of products that the system can be converted to (also named product family).

The core element of RMS is the reconfigurable machine, which can operate in various configurations, each offering specific production capacities and task ranges.

In our study, we focus on the reconfigurable machine tool (RMT). More specifically we study the integration between process planning and scheduling (IPPS), in a shop floor composed of RMTs.

Process planning and scheduling are distinct planning activities involving different decisions and constraints. In process planning, the primary considerations are how to manufacture a product (execution of operations) and the amount of time required for manufacturing one unit. Scheduling, on the other hand, is concerned with determining when to execute various operations and the amount of product (number of units) to manufacture (Scallan, 2003).

Usually, the two activities are performed separately and sequentially. First, a process plan is determined for each product, it involves sequencing the operations and assigning them to machines, with consideration of technical constraints about tool requirements and Tool Approach directions (TADs) limitations. These technical considerations significantly increase the computational burden of process planning and make integration of other decisions more challenging. The primary objectives in process planning are typically minimizing total production time and cost.

Once process plans are finalized, scheduling determines the order in which operations are executed on each machine, it is concerned with the start and completion dates of operations on machines. The goal is often to minimize makespan (the date of completion of all products). However, scheduling decisions need to consider machine configurations and the time required for configuration changes in the case of RMS (Bensmaine et al., 2014).

While both scheduling and process planning deal with time, they approach it from different angles. Process planning focuses on the amount of time required for executing an operation or manufacturing a part, while scheduling dives deeper into the specific moments in which production takes place.

This separated hierarchical planning process is known as the offline approach, even though this approach is relatively simple to apply, it gives sub-optimal solutions since fixed process plans limits scheduling, thus we integrate both activities in what's known as an Online approach.

1.1 Literature Review

A literature review on the potential of IPPS problems with RMS in enhancing sustainability in manufacturing was presented in Zhang et al. (2022), the authors emphasized the significance of IPPS-RMS integration as a facilitator for achieving sustainability goals, while also acknowledging the inherent complexities associated with such problems.

In a process planning related work, Kazemisaboor et al. (2021) investigated a process planning problem where product sequencing decisions were made after the individual process plans were determined and adopted an offline approach for solving it.

In a more scheduling related work, Mahmoodjanloo et al. (2022) studied the distributed job shop rescheduling problem with RMS, whereas Fan et al. (2022) studied the Flexible Job shop scheduling with machine reconfigurations (FJSP-MR) and proposed a genetic algorithm to solve it, however in both works, the sequence of operations of each job was predetermined and for the first work the operations assignment to machines was also fixed. These decisions are typically made in the process planning phase.

The IPPS with RMS problem was first discussed in Bensmaine et al. (2014) where the authors proposed an online heuristic approach to minimize the makespan, the authors compared it to an offline approach and found that the heuristic performed better. In a similar work Morganti et al. (2020) solved the RMS with IPPS problem using a heuristic while considering process quality.

Despite promising results from previous studies, the IPPS problem with reconfigurable machines remains under-explored. Notably, existing research in this area lacks metaheuristic approaches for solving this complex problem.

In this paper, we solve the IPPS problem with RMTs where tools and TADs requirements are considered. To solve this problem, we explore the potential of a Reinforcement Learning technique, specifically Q-learning, to enhance the performance of a NSGA-II (Non-dominated Sorting Genetic Algorithm II) metaheuristic.

2. METHODS

2.1 Problem formulation

We consider a shop floor composed of a set of reconfigurable machines where each machine can operate in different configurations. These configurations may involve altering processing speed for the same operation or changing functionality (TADs) to accommodate different operations. The objective is to determine an optimal sequence (process plan) and schedule for executing the operations of different products to minimize both the makespan and the total production cost, including processing and changeover costs.

The problem is multi-objective in nature with two optimization objectives: minimizing the makespan and minimizing the total cost composed of processing cost of operations as well as, machine, configuration, and tool changeover costs. Indeed, cost consideration is critical in traditional process planning problems. The machines have a set of TADs and available tools. The assignment of operations to these machines depends on the specific requirements of each operation.

Table 1 illustrates a solution representation with two parts P1 and P2. P1 consists of three operations, while P2 has four. There are also two RMTs, each with two possible configurations.

Table 1 can be read from left to right, column by column. Each column represents a processing step. For example, the first column indicates that operation OP1 of P2 is processed first on Machine M2 set in configuration C2 using tool T1. In the following column, a different operation OP3 from a different part P1 is processed simultaneously on Machine M1. This highlights the need to track:

- **Configuration and tool changeovers:** These are tracked for each machine to account for the time and cost required to switch from one configuration/tool to another for processing the sequence of operations.
- **Machine changeovers:** These are tracked for each part to determine when a part is moved from one machine to another, and the time and cost incurred.

Table 1: An example of a solution representation with two products.

Product	P2	P1	P1	P2	P2	P1	P2
Operation	OP1	OP3	OP1	OP4	OP3	OP2	OP2
Machine	M2	M1	M2	M1	M2	M2	M1
Configur-ation	C2	C2	C2	C1	C2	C1	C1
Tool	T1	T1	T5	T3	T1	T1	T1

Figure 1 presents the Gantt chart corresponding to the solution depicted in Table 1 with a makespan of 29. It visually highlights the processing of operations and machine, configuration, and tool changeovers.

Initially, Machine 1 (M1) is set to configuration 2 (C2) with tool T1, while M2 is also in C2 with T1. M1 starts processing operation OP3 of product P1, and simultaneously, M2 processes OP1 of product P2. M1 finishes processing OP3 first (at time t=4) and needs to prepare for the next operation. This involves a changeover to C1 and a tool changeover to T3. While M1 undergoes these changes, P1 is transported to M2.

P1 arrives at M2 after P2 is released (t=7). However, P1 cannot be processed immediately due to the ongoing tool changeover on M2. Also, no configuration change is necessary for P1's operation (OP1) since it requires the same configuration (C1) used for P2's operation (OP1).

The complexity of the IPPS problem with RMTs is evident in this Gantt chart, particularly the challenge of tracking these various changeover events effectively.

Despite its strengths, parameter control remains a persistent challenge in NSGA-II and in evolutionary algorithm research in general (Tao et al., 2023). This is particularly true for the crossover probability, a key factor influencing the balance between exploration and exploitation of the search. This parameter may require dynamic adjustments between different problem sizes and between iterations.

Adaptive operator selection is a low-level integration of Machine learning in metaheuristics, aiming to enhance overall performance. The rationale behind adjusting operators' values adaptively lies in the fact that operators in specific values may excel at specific stages of the search process but perform sub-optimally at others (Karimi-Mamaghan et al., 2022).

We use the Q-learning algorithm to dynamically adjust the crossover probability of NSGA-II based on previous iteration results, updating the values in the Q-table. The states in this context represent crossover values, covering 11 states from 0 to 1 in increments of 0.1 $\{0, 0.1, \ldots, 1\}$, and the corresponding actions are $+0.1$, 0, or -0.1.

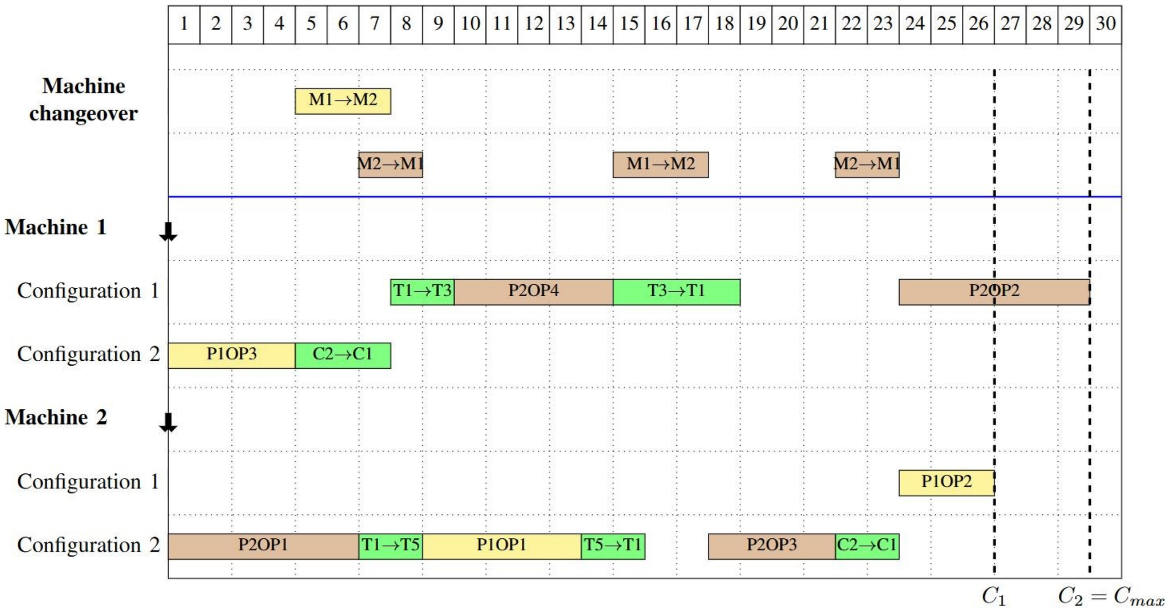

Figure 1: The Gantt chart corresponding to the example solution

2.3 Solution approach

To solve this problem, we use the NSGA-II metaheuristic which is an evolutionary algorithm and one of the most widely employed multi-objective algorithms in solving process planning related problems (Khan et al., 2022). It has three key features: i) utilization of a non-dominated sorting approach, arranging population solutions into fronts of non-dominated solutions; ii) incorporation of a crowded comparison operator in solution selection to preserve diversity; and iii) implementation of an elitism selection procedure that combines parent and offspring solutions, prioritizing best solutions according to the non-dominated sorting and crowded distance comparison approaches (Deb et al., 2002).

3. RESULTS AND DISCUSSION

Preliminary tests were conducted on the data proposed in Youssef and ElMaraghy (2006), with 2 parts of 20 and 12 operations processed on 3 reconfigurable machines.

We set the parameters of the reward function based on the parameters in Tao et al. (2023), the initial crossover probability at 0.5. The number of iterations was fixed at 100.

To assess the performance of the solution methods, each method was executed for 10 runs, and we used the Hypervolume (HV)—a multi-objective indicator to evaluate their performance.

HV is a valuable metric that assesses the quality of a set of non-dominated solutions. It simultaneously considers two important aspects: how close the solutions are to the true

Pareto front (convergence) and how well-distributed they are across the objective space (diversity).

It is calculated as the volume of the objective space that is dominated by the solution set. To compute this, a reference point is defined. This reference point represents the worst possible outcome on each objective. In this case, the reference point is set to the vector of maximum objective values seen in all the evaluated sets (Talbi, 2009). Figure 2 illustrates the space considered as the Hypervolume indicator between a given front and reference point Z_{ref}.

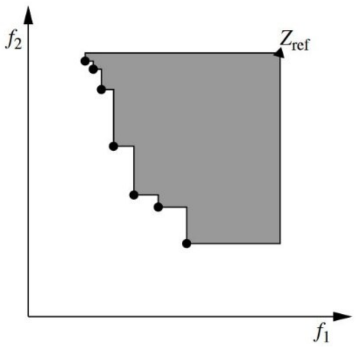

Figure 2: The space that represents the Hypervolume value.

Table 2 presents the average values (AVG) of HV of the ten runs for each method, alongside the standard deviation (STD) and the coefficient of variation (CV), calculated as $\frac{STD}{AVG}$.

From the results we observe that the best CV is achieved by setting NSGA-II with a 0.1 crossover probability with a value of 0.21. Close to it in terms of CV is QNSGA, but a closer look at the average Hypervolume AVG reveals that QNSGA outperforms NSGA-II 0.1 with a value of 2083. While NSGA-II 0.5 demonstrates a good average, it exhibits higher variability. Lastly, NSGA-II 0.9 displays the worst performance in both quality (AVG) and stability (CV).

Table 2: Results obtained for the tests on Youssef and ElMaraghy (2006) instance

Hypervolume	NSGA0.1	NSGA0.5	NSGA0.9	QNSGA
AVG	1830.43	2507.19	1787.61	2083.85
STD	394.44	871.54	942.28	472.80
CV	0.215	0.347	0.527	0.226

Figure 3 illustrates the learning curves of the three best runs (that have the largest HV values).

As evident from the figure, the three best runs don't exhibit the same learning behavior. This suggests that the most adequate crossover probabilities might not be fixed for all runs of the same data instance. Additionally, more parameter tuning for the Q-learning variables and further tests with larger number of iterations are still required to draw solid conclusions.

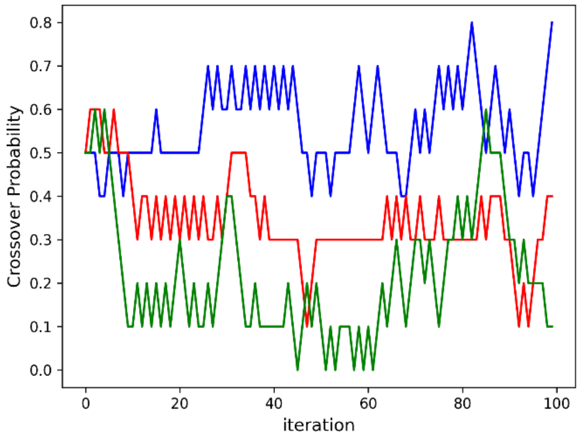

Figure 3: The learning curves of the three best runs.

4. CONCLUSION

This work investigated the Integrated Process Planning and Scheduling (IPPS) problem with Reconfigurable Machine Tools (RMTs). We proposed a metaheuristic, Q-NSGA-II, which uses Q-learning to dynamically adjust the crossover probability within the NSGA-II algorithm. Q-NSGA-II was compared to three standard NSGA-II variants with fixed crossover probabilities. Our findings demonstrate that Q-learning has the potential to improve the solution quality obtained by NSGA-II. However, further refinement of the Q-learning parameters and additional test instances are necessary to generalize these observations.

The current research lays the groundwork for future exploration. The development of an exact solution approach would be valuable for benchmarking and validating the efficiency of both Q-NSGA-II and other proposed approaches. Additionally, future work can incorporate more complex scenarios by considering constraints such as due dates and exploring modular RMTs, where auxiliary modules are required to obtain specific machine configurations.

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