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Procedia CIRP 104 (2021) 1837–1842

www.elsevier.com/locate/procedia

54th CIRP Conference on Manufacturing Systems

Optimizing reconfigurable manufacturing systems: A Simulation-based Multi-objective Optimization approach

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Abstract

Application of reconfigurable manufacturing systems (RMS) plays a significant role in manufacturing companies' success in the current fiercely competitive market. Despite the RMS's advantages, designing these systems to achieve a high-efficiency level is a complex and challenging task that requires the use of optimization techniques. This study proposes a simulation-based optimization approach for optimal allocation of work tasks and resources (i.e., machines) to workstations. Three conflictive objectives, namely maximizing the throughput, minimizing the buffers' capacity, and minimizing the number of machines, are optimized simultaneously while considering the system's stochastic behavior to achieve the desired system's configuration.

Keywords: Simulation-based Optimization, Manufacturing Systems, Reconfigurability, Multi-Objective;

1. Introduction

Reconfigurability of manufacturing systems is an important consideration for the manufacturing industry, especially when designing a new system. In the current fiercely competitive market, manufacturing companies face numerous challenges due to aggressive global competition, increasing market segments, emerging regional/local requirements, new material, and technologies, changing regulations, fluctuating customer demands, and ever-increasing demands for new product features, etc. [1]. These challenges create uncertainties and unforeseen market variations [2,3]. How fast and cost-effective a system can adjust its capacity and functionalities according to the demand and product changes is one of the major systems design characteristics to consider [4,5]. These challenges encourage the manufacturing system designers to pay careful attention to the reconfigurability of the system.

The concept of Reconfigurable Manufacturing Systems (RMS) can be defined as an attempt to accomplish demand fluctuations and scalable capacities in a more efficient manner [6,7]. Despite RMS's advantages in handling the challenges mentioned earlier, designing these systems is a complex task that requires the use of optimization and simulation techniques. For decades, several optimization techniques are used to model and design the RMS. Considering that most of the complex combinatorial problems found in RMS have been classified as NP-hard problems, metaheuristic methods gained more attention from the researchers in the field [7]. Simulation techniques have also been successfully used and established as a powerful tool for designing and analyzing manufacturing systems [8–11]. Simulation techniques are usually used to understand the system's behavior for a set of input variables, among other advantages that they provide for testing different scenarios. Among the simulation techniques, Discrete Event Simulation (DES) is one of the most used in the literature due to the RMS characteristics.

Simulation-based methods are acknowledged to be a effective solution technology in the digitalization of

10.1016/j.procir.2021.11.310

manufacturing systems, especially when different system configurations or processes need to be validated [12]. Despite both simulation and optimization techniques' attractiveness and power, research studies showed their shortcomings when applied separately. Most of the optimization studies simplified the problem by ignoring the system's uncertainty and variability that resulted in inaccurate solutions. On the other hand, simulation techniques become computationally impractical or unattainable when the complexity of the model and the number of input variables increases [13]. To overcome these drawbacks, Simulation-Based Optimization (SBO) emerged as a powerful method enabling the use of advantages of both simulation and optimization. The SBO has successfully proven to be a decisive supporting approach for achieving improvements in manufacturing systems. In studies like [14–16], SBO methods have been applied to RMS challenges such as configuration and process planning problems. When considering multi-objective optimization perspective and the RMS challenges, genetic algorithms (GA) have shown a better performance in efficiency when finding optimal or near optimal solutions [7]. In addition, NSGA-II [17] is one of the most employed optimization GAs due to its outstanding performance in facing multi-objectives problems [18,19].

Although SBO has already been employed to optimize RMS, there are less than a handful of attempts to cope with multiple objectives and simultaneously deal with several design challenges such as task assignment and resource assignment to workstations, and system configuration.

This study contributes to the RMS research domain by proposing a simulation-based multi-objective optimization (SMO) approach for optimal systems configuration while considering the dynamic behaviour of RMS, addressing the task assignment and resource assignment, and optimizing three objectives simultaneously, namely throughput, buffers' capacity, and the number of machines.

The remaining of the paper is structured as follows. Section 2 provides a brief overview of the RMSs design challenges and some of the previous related works. The proposed SMO approach is described in Section 3. Section 4 presents the test case used to validate the approach. Finally, results are presented in Section 5.

2. Literature Review

According to [20], the design of an RMS has to address three main areas, namely, the system configuration, the system's components, and the process planning.

The system configuration refers to how machines and components are arranged in the system [20]. The way the machines of the system are arranged, impacts the functionality, productivity, and scalability of the system [21]. Research usually focuses on optimizing the assignment of machines to the workstations.

The system's components refer to the type and number of machines and components of the system. This considers the total number of machines needed to achieve the desired production capacity [20]. This is a crucial consideration for capacity planning and, therefore, for the scalability of the system. Research usually focuses on optimizing the total number of machines in the system.

Process planning refers to how work tasks are allocated to the machines and balanced throughout the manufacturing system. This activity will directly impact the reconfiguration effort and the system's efficiency to change its capacity [22,23]. Research usually focuses on finding the optimal allocation of work tasks to workstations.

The three mentioned areas have been tackled by researchers using different approaches and methods. A review of the most relevant studies is provided below.

Youssef and ElMaraghy [24] addressed the system configuration area. The authors used a GA and tabu search (TB) for the optimization of a multi-part RMS, finding out the optimal RMS configuration and the effect of the availability of the machines in this process. Goyal et al. [25] also tackled the system configuration and presented a GA-based approach for obtaining the optimal configuration based on convertibility, utilization of machines, and cost. Dou et al. [26] tackled both the system configuration and the process planning areas by developing a GA-based optimization algorithm to identify the optimal configuration, in terms of the tasks assigned to the workstations and the type of machines for a multi-part system. Koren's et al. [4] study dealt with the system's components and process planning areas by proposing a method for designing scalable manufacturing systems. This was achieved by rebalancing how tasks are allocated in the workstations while trying to either minimize the number of machines used to reach a certain capacity or maximize the system's capacity for a certain number of machines. Some other studies, such as [27–30] have focused on the process planning area. They have used a GA to find the best load balancing by optimizing a single objective, e.g., maximize system productivity, minimize setup times, minimize reconfiguration cost, etc.

In summary, the prior efforts predominantly adopted optimization methods, but the use of multi-objective optimization is scarce. When considering the use of optimization for solving RMS challenges, most of the studies adopted the GA. Additionally, the three RMS introduced areas are widely studied but rarely addressed simultaneously. Furthermore, the use of simulation for addressing RMS challenges is sporadic and does not involve multi-objective optimization.

To cope with the dynamic and stochastic behavior of RMS (e.g., machines failure) and considering multiple objectives simultaneously, this study proposes an SMO approach. To the best of the authors' knowledge, this is the first attempt to apply the SMO approach for dealing with all three main design areas, i.e., finding the optimal system configuration, the optimal number of machines, and the optimal work task allocation. The optimization objectives considered are to maximize the throughput, to minimize the buffers capacity and number of machines.

3. The Proposed SMO Approach

In this study, an SMO is proposed to simultaneously maximize throughput per hour (THP), minimize the buffer, and the total number of machines, while providing the optimal work tasks allocation for every configuration for the minimum and maximum allowed number of machines in an RMS. In other words, the SMO approach provides a way to obtain the highest possible THP with the minimal number of resources in terms of the number of machines and buffers' capacity, including the optimal task allocation. This could support the system scalability aspect because it can provide the optimal way to add resources (machines in this case) to an existing RMS.

The proposed approach needs to consider multiple factors simultaneously, which increase the complexity of the problem exponentially. The main elements of the SMO are the simulation model and the optimization engine. The process begins by generating a simulation model of a feasible (existing) solution. The simulation enables testing different combinations of input parameters according to the optimization objectives and the system constraints to find the best output solutions. The optimization engine iteratively evaluates the feedback from the outputs of the simulation to instruct a new combination of input parameters to define the Pareto front. Fig. 1 shows a graphical representation of the proposed SMO, including the optimization parameters and how the optimization engine uses them. This study benefits NSG-II for the optimization part due to its outstanding performance in dealing with multi-objective optimization problems.

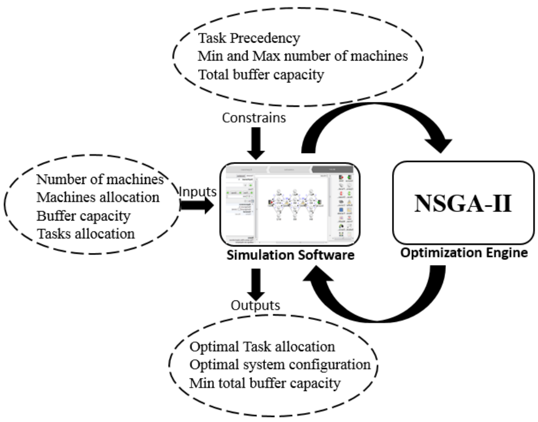

Fig. 1. Graphical representation of the proposed SMO

The optimization objectives and constraints of the RMS considered in this study are presented in equation 1 to 3 and 4 to 11 respectively.

List of notations

j workstation index
i, r task index
k machine index
S number of workstations
N number of tasks
M number of machines
M_{max} maximum number of machines in each workstation
M_{min} minimum number of machines that must be assigned for production
B_j buffer capacity for workstation j
B_{min} minimum safety buffer
B_{max} maximum buffer capacity
P Set of precedence relationships ($r, i \in P$ if and only if task r is an immediate predecessor of task i)
x_{ij} 1 if task i is assigned to workstation j; 0 otherwise
y_{kj} 1 if machine k is assigned to workstation j; 0 otherwise

Three conflicting optimization objectives are defined as follows.

$Maximaze\ f1 = THP^{*}$:Throughput per hour (1)
$Minimize\ f2 = \sum_{j=2}^{S} B_{j-1}$:Total Buffer Capacity (2)
$Minimize\ f3 = \sum_{k=1}^{K_{max}} \sum_{j=1}^{J} y_{kj}$:Total number of Machines(3)

The following constraints should be satisfied when optimizing the RMS.
Task assignment: each task must only be assigned to one workstation.

$$\sum_{j=1}^{S} x_{ij} = 1,\ \forall i = 1,2,\dots,N \tag{4}$$

Precedence relationships: a task can only be assigned to a station only if all its predecessors are assigned to the same workstation or earlier workstations.

$$\sum_{j=1}^{S} j\left(x_{rj} - x_{ij}\right) \leq 0,\ \forall (r, i) \in P \tag{5}$$

Machine assignment: each machine must only be assigned to one workstation

$$\sum_{j=1}^{S} y_{kj} = 1,\ \forall k = 1,2,\dots,M \tag{6}$$

Technological requirement: a task can only be assigned to a workstation if it has the required machinery to perform the task.

$$C_{ik} \times x_{ij} \leq y_{kj}$$
$$\forall k = 1,2,\dots,M; i = 1,2,\dots,N; j = 1,2,\dots,S \tag{7}$$

Workstation usage: at least one machine should be assigned to each workstation

$$\sum_{k=1}^{M} y_{kj} \geq 1,\ \forall j = 1,2,\dots,S \tag{8}$$

Space limitation: Workstations cannot have more than a certain number of machines

$$\sum_{k=1}^{M} y_{kj} \leq M_{max},\ \forall j = 1,2,\dots,S \tag{9}$$

Machine usage: The assigned machines to workstations cannot exceed the total number of available machines. Moreover, to ensure the production, at least a certain number of machines should be assigned to workstations.

$$M_{min} \leq \sum_{k=1}^{K_{max}} \sum_{j=1}^{J} y_{kj} \leq M \tag{10}$$

Buffer capacity: The in-between workstations buffer should not become less than a certain safety buffer and should not exceed the maximum buffer capacity.

$$B_{min} \leq B_{j-1} \leq B_{max} \quad j = 2,\dots,S \tag{11}$$

The applicability of the proposed SMO approach is shown using a test case. A description of the test case used is provided in the next section.

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* $THP = \frac{\#\text{products}}{\text{simulation horizon} - \text{warmup}}$

4. Test Case Description

This case consists of a machining process that takes 960 seconds divided into 36 tasks. Furthermore, due to space limitations and the machining processes' technological constraints, some tasks (i.e., 3, 17, and 33) need to be performed in three different types of machines. The process is subject to disturbances, and machine availability is considered 90% with a 5 minute mean time to repair. The RMS consists of three workstations with two buffers in between. Machines in the same workstation perform the same tasks sequence. There is space for up to 6 machines in each workstation, and it is assumed that the material handling system can deliver parts to them. A minimum of 12 machines can be used in the system. It is also assumed that installed machines cannot be removed and need to be used in future configurations when scaling up the system. Fig. 2, shows a system with four machines in each workstation and extra space for up to two extra machines in each workstation. Therefore, the RMS taken into account can vary from 12 to 18 machines distributed in three workstations.

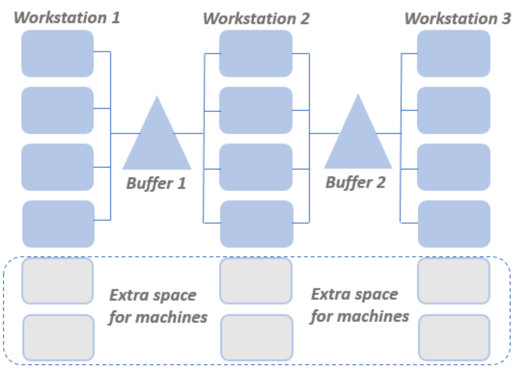

Fig. 2. RMS layout example

The well-known multi-objective optimization algorithm, NSGA-II, has been used to solve this problem with 100000 iterations.

A baseline simulation model has been developed using a DES software called FACTS Analyzer [31]. In this research, FACTS Analyzer acts as a DES engine used for the animation and the optimization. The FACTS model serves as the basis for the iterative execution of the combinations of input parameters according to the optimization objectives and constraints.

5. Results and Discussion

This section presents the results of the optimization. The results presented in Table 1 refer to the non-dominated solutions. Table 1 shows the solution ranges for the THP with the different numbers of machines in the system and for the buffer capacities needed for achieving that THP. "B1" and "B2" refer to the capacity range of buffer 1 and 2, respectively, and TBC refers to the total buffer capacity range (TBC = B1 + B2). In addition, another interesting result that can be extracted from Table 1 is the average THP that can be gained from every machine added to the system. If we consider the highest THP reached for every number of machines, the average gained throughput is approximately 2.97.

Table 1. Throughput and buffers capacity

	THP	B1	B2	TBC
12 M	40.226-41.261	5-30	5-30	10-60
13 M	43.423-44.045	5-20	5-25	10-45
14 M	46.781-47.708	5-25	5-25	10-45
15 M	50.17-50.56	5-10	5-25	10-30
16 M	52.77-53.916	5-35	5-45	10-80
17 M	56.136-56.996	5-50	5-50	10-85
18 M	58.288-59.135	5-30	5-25	10-55

Table 2 presents how the results for system configuration and task allocation presented in Table 1 can be achieved. WS 1, WS 2, and WS 3 represent the number of parallel machines in workstations 1, 2, and 3, respectively. The fifth column shows the number of tasks performed in each workstation (no. of tasks workstation 1/no. of tasks workstation 2/no. of tasks workstation 3).

Table 2: Configuration and work tasks allocation.

	WS 1	WS 2	WS 3	Tasks per WS
12 Machines	2	4	6	5/14/17
13 Machines	2	6	5	4/19/13
14 Machines	2	6	6	4/17/15
15 Machines	3	6	6	6/16/14
16 Machines	6	5	5	16/10/10
17 Machines	6	5	6	15/9/12
18 Machines	6	6	6	13/12/11

Notice that the number and location of the machines presented in Table 2 have not considered the reconfiguration steps when scaling up the system. Considering a rigid system where installed machines are not movable, the reconfiguration steps need to consider the existing system architecture. Therefore, every new configuration needs to reuse the previous layout to achieve the next configuration. Considering this constraint, Fig. 3 presents the reconfiguration steps if the system would be scaled up from 12 to 18 machines. The THP and TBC ranges presented only consider the non-dominated solutions. In addition, this figure also shows the number of tasks performed in each workstations and the total task time in seconds per workstation for the different configurations obtained from the optimization in order to obtain the THP range presented.

Another observed result from Fig. 3 is how the scalability consideration changed the configuration presented in Table 2 for the system with 12, 13, 14, and 15 machines. The results presented in Table 2 were isolated, so no future reconfigurations were considered. Therefore, instead of 2-4-6 for 12 machines, 2-6-5 for 13 machines, 2-6-6 for 14 machines, and 3-6-6 for 15 machines, they have been changed to 4-4-4, 5-4-4, 5-4-5, 6-4-5, respectively. Consequently, this consideration has a small compromise in the THP for those configurations, as seen when comparing Fig. 3 with Table 1.

Essentially, Fig. 3, provides a helpful understanding and view of the system, including the optimal location of futures machines in case of future capacity increases are needed. Knowing where to add future machines in advance can be convenient and cost-effective when designing the system, especially when investing in the material handling system.

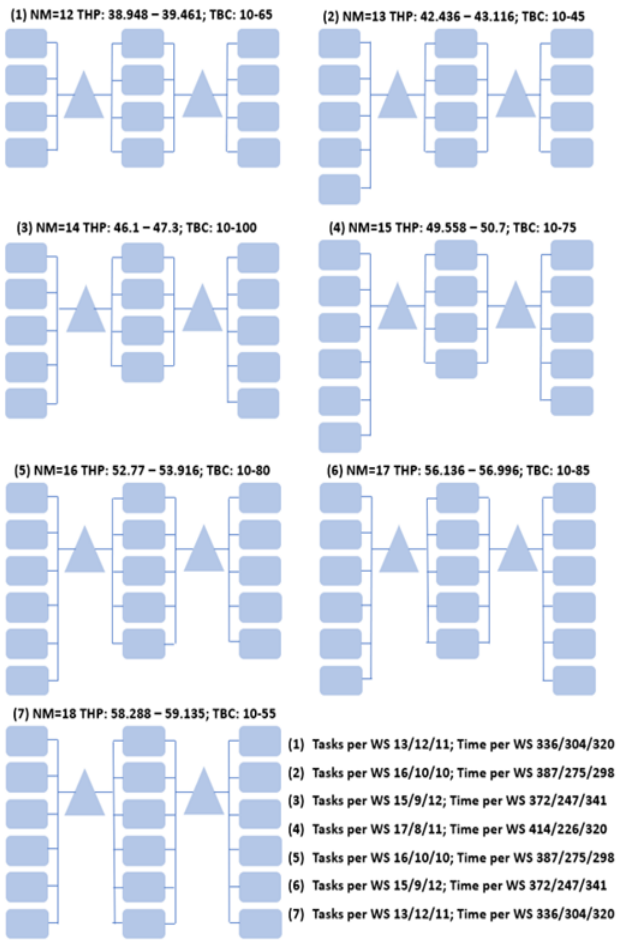

Fig. 3. Reconfiguration steps, Throughput, total buffer capacity, and task allocation

Another important aspect of the design of manufacturing systems is the buffer capacity consideration. Fig. 3 also shows the optimized allocation of the buffer capacities for the given configurations.

Moreover, Fig. 4 shows a comparison of the THP progression as the TBC increases between 0 and 35 for the systems presented in Fig. 3. Fig. 4 also shows that the curve between THP and TBC starts to saturate early. On the other hand, different machine availability and MTTR values could impact significantly in this relationship. Nonetheless, the red parallel dashed lines revealed that M number of machines, for some TBC values, can provide the same THP than M+1 machines. Hence, the parallel coordinate plot (PCP) can support decision-makers with the visualization and understanding of this trade-off situation in which the capacity of the system can be increased either by adding machines or

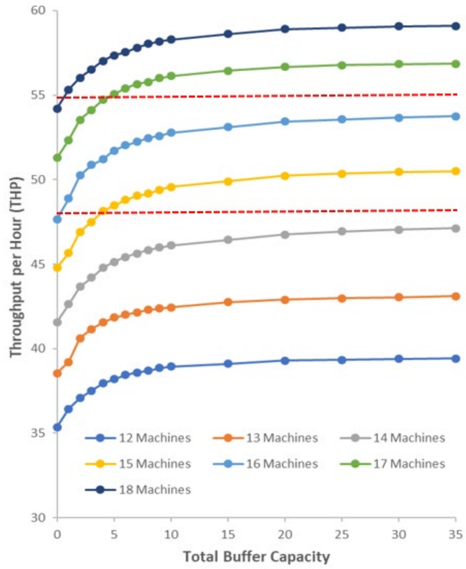

Fig. 4. Throughput over total buffer capacity

more buffers capacity. However, there are many more factors that can affect decision-making tasks in manufacturing companies. The use of tools like the PCP (see Fig. 5) can support the knowledge extraction and display which choices are available according to different constraints. Fig. 5 shows the PCP over the objectives of the optimization. The columns from left to right represent THP, the total number of machines, the number of machines in every workstation, and the buffers' capacity. Nonetheless, more variables could be included. In the plot, solutions including 15, 16, and 17 machines have been coloured in blue, red, and green, respectively, to show the considerable overlapping production rate and buffer capacity among the different numbers of machines. Accordingly, the PCP can help decision-makers visualize the trade-off situation between THP, the number of machines, and buffer capacity.

6. Conclusions

This paper introduces a SMO approach that can be used for the design of RMS. The SMO approach used has proven to be successful when designing new manufacturing systems. The presented approach provides the optimal way to fulfill determined productivity. This approach demonstrates the importance of considering reconfigurability during the design

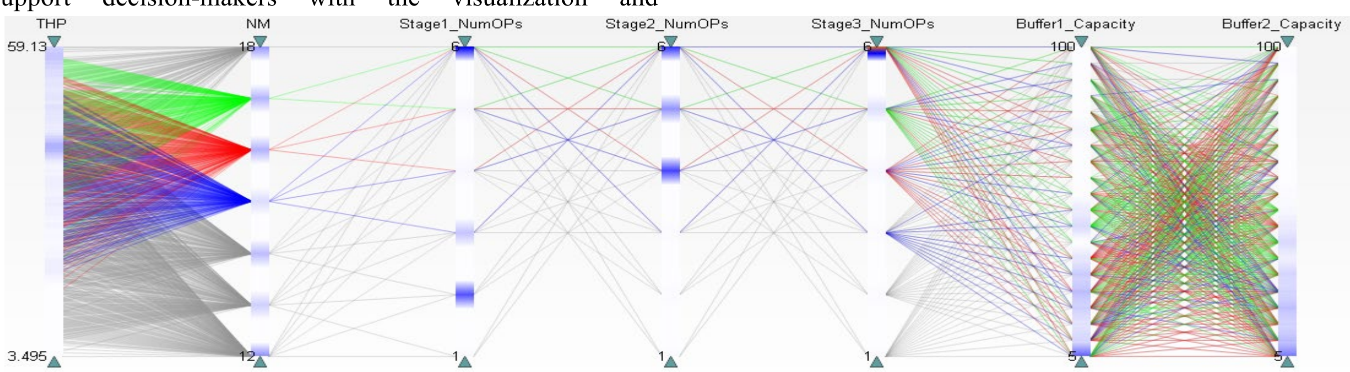

Fig. 5. Parallel coordinates

phase. Future needed information can be supported in the form of graphs/plots and tables covering most of the design aspects needed for decision makers to reconfigure the system rapidly.

Despite the slight reduction in productivity for 12, 13, and 14 machines, it is important to remark that the overall THP over the manufacturing system's lifetime when going from 12 to 18 machines is practically insignificant. Nonetheless, it is an essential aspect to be aware of when designing new scalable manufacturing systems.

Lastly the TBC as the summation of the individual buffers has significantly impacted the total THP. However, when considering the non-dominated solutions, in some configurations, one of the buffers can have a larger capacity range that the other. Therefore, their individual impact on the THP also depends on the selected configuration.

The RMS design factors treated in this paper are essential. However, many other factors, like system lifecycle, reconfiguration frequency, product family and generation, and investment cost, etc., need to be considered in future studies. The use of the proposed SMO approach is not limited to just RMSs and could be applied to other types of manufacturing systems. This would requires adjusting the approach to the new design requirements and constraints. This will be investigated in future publications.

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