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Availability Analysis of Reconfigurable Manufacturing System Using Simulation-Based Multi-Objective Optimization

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Abstract. Nowadays, manufacturing companies face an increasing number of challenges that can cause unpredictable market changes. These challenges are derived from a fiercely competitive market. These challenges create unforeseen variations and uncertainties, including new regional requirements or regulations, new technologies and materials, new market segments, increasing demand for new product features, etc. To cope with the challenges above, companies must reinvent themselves and design manufacturing systems that seek to produce quality products while responding to the changes faced. These capabilities are encompassed in Reconfigurable Manufacturing Systems (RMS), capable of dealing with uncertainties quickly and economically. The availability of RMS is a crucial factor in establishing the production capacity of a system that considers all events that could interrupt the planned production. The impact of the availability in RMS is influenced by the configuration of the systems, including the number of resources used. This paper presents a case study in which a simulation-based multi-objective optimization (SMO) method is used to find machines' optimal task allocation and assignment to workstations under different scenarios of availability. It has been shown that considering the availability of the machines affects the optimal configuration, including the number of resources needed, such as machines and buffers. This study demonstrates the importance of the availability consideration during the design of RMS.

Keywords. Reconfigurable Manufacturing System, Simulation, Multi-Objective Optimization, Availability.

1. Introduction

Due to the current dynamic and competitive manufacturing industry, reconfigurability of manufacturing systems (RMS) is considered by many companies that require a design of a new system. Nowadays, the manufacturing industry often faces unpredictable market changes, causing many challenges for manufacturing companies [1]. These challenges are derived from a fiercely competitive market which creates unforeseen variations and uncertainties such as new regional requirements or regulations, new technologies, and materials, new market segments, the ever-increasing demand for new product features, etc. To cope with the aforementioned challenges, the RMS concept emerged seeking to

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produce quality products while efficiently responding to the changes that must be faced [2,3].

The capability of RMS to cope with the uncertainties and unforeseen changes in the market depends upon several aspects, including its ability to change its configuration and production planning but also depends on the availability of the components of the system. The availability of RMS is a crucial factor in establishing the production capacity of a system that considers all events that could interrupt the planned production. The impact of the availability in RMS will be different depending on factors such as the configuration of the system and the number of resources used [4]. This paper shows the importance of resource availability in RMS and how unreliable resources impact different RMS depending on the system's configuration.

The design of RMS is considered an NP-hard complex combinatorial problem that can be supported by the use of simulation and optimization methods. Metaheuristics approaches, especially genetic algorithms such as NSGA II, have proven to be efficient in dealing with RMS design challenges [5,6]. Despite the fact that simulation-based optimization (SBO) approaches have been previously used to optimize RMS, the consideration of multiple objectives to simultaneously deal with several design challenges is scarce. Therefore, a case study is presented in which a SMO method is used to find the optimal task allocation and assignment of machines to workstations. The assessment of an optimal scenario will consider different availabilities in the system under two conflicting optimization objectives: maximizing throughput (THP) and minimizing the total buffer's capacity (TBC).

2. Literature review

2.1. Reconfigurable manufacturing systems

RMS is a system designed to change the system's structure, software, and hardware to adjust the production and its functionality. RMS is designed based on market demand [7]. Moreover, it must be designed for reconfiguration when necessary. This reconfiguration requires installation cost and cost in the start-up phase, characterized by malfunctions and breakdowns of these machines [8].

The design and management of RMS have to address three areas, system configuration, system components, and process planning [3].

- System configuration refers to the layout of machines and components of the system. The performance and characteristics of manufacturing systems are highly dependent on the system configuration [9].
- System components refer to the number of resources, whether they are machines, operators, or both. It is one of the essential aspects when considering capacity planning and scalability of the system. In other words, it considers the number of resources that are necessary to achieve the target production capacity.
- Process planning refers to the work task allocation in the system. A process plan defines the production process's sequence [10]. This area seeks to comply with production requirements by representing the information necessary to plan the production process and identify the components that make up the production process. In addition, the ability of machines and the manufacturing system to change when

necessary makes the use of classical approaches to planning very difficult in RMSs [3].

2.1.1. Workstation disturbances

In the manufacturing industry, machine availability is one of three significant factors in calculating overall equipment effectiveness. It considers all events that could have interrupted the planned production time, provided that it has been stopped for a significant period. In addition, the availability of RMS is a determining factor in establishing the production capacity of a system [11].

The notion of "availability" expresses the probability that the machine is available in a given condition at a given time. To calculate its value, both MTTF (mean time to failure) and MTTR (mean time to repair) must be taken into account [12].

$$Availability = \frac{MTTF}{(MTTF+MTTR)} \tag{1}$$

MTTF indicator measures the elapsed time between failures. This value is a crucial indicator when pursuing an increase in the reliability and availability of machines. It is the mean time between consecutive failures, i.e., the average time a machine is repaired until its subsequent failure.

MTTR is a measure of the maintainability of repairable equipment and parts. It represents the average time required to repair a breakdown until equipment activity is restored.

2.2. Simulation-based multi-objective optimization

Optimization can be defined as the maximization or minimization concerning one or several objective functions that determine the best results. The results are considered feasible if they satisfy all the problem's constraints or infeasible if at least one of them is not satisfied. The solution obtained after solving the model that yields the best value in the objective function is considered optimal. Consequently, optimization is considered an excellent tool in decision support [13].

SMO can be described as the intersection of two powerful decision-making techniques, simulation and optimization [14]. From an optimization perspective, SMO compares the impact of decision variables on model outcomes. From a simulation perspective, SMO considers the randomness that occurs in the real production system. This is an advantage when compared to other optimization methods that assume that the objective function is a single scalar value, resulting in a powerful simplification for many manufacturing problems [15].

One of the main advantages of using SMO for RMS over other optimization methods is the inclusions of more details such as the uncertainty and variability of manufacturing systems. Similarly, constraints can be applied at a greater detail than other optimization methods. Through simulation, users can analyze how a system responds to different inputs and subsequently determine its performance. In contrast, the optimization algorithm uses the simulation results to provide feedback and find the optimal solution through an iterative method. [16]

The majority of the studies that have used optimization for RMS have generally focused on the configuration or the process planning areas, either separately or combined, regardless of whether it is a single or multi-objective optimization[5,6]. However, the use of SBO and more specifically SMO towards RMS is scarce when compared to optimization techniques [1]. Furthermore, some researchers identify SBO as a promising tool that needs to be further researched to target the RMS challenges [5]. In addition, the unavailability of the resources in RMS is usually neglected. Some of the prior publications that have considered the availability of the resources of the system and employed SMO towards RMS such as, [17,18], have studied the systems for specific availability. Against this backdrop, this paper proposes using SMO to study how different availability considerations impact RMS. Consequently, this paper presents a case in which SMO is used to address different availability considerations of RMS while targeting the process planning, components of the systems and optimal configuration for maximum THP and minimum TBC. TBC is understood as the summation of the in-between buffers of the RMS.

3. Problem formulation and results of the SMO

The problem analyzed consists of a single product production line process that takes 335.38 seconds. It is assumed that the number of workstations is fixed at three units. Each workstation has at least one machine, and machines within the same workstation perform the same task sequence. The process must consider the precedence constraints. These constraints are shown in Figure 1. The arrows indicate the order of preference among the tasks, while the colors indicate that the tasks under the same color and are next to each other's must be performed together in the same workstation. These constraints can be used to group the tasks and reduce the number of total tasks from 87 to the number of zoning constraints which is 28. It should be noted that each task can only be performed once in the whole process, so it can only be assigned to a single workstation. Furthermore, there are buffers in-between workstations.

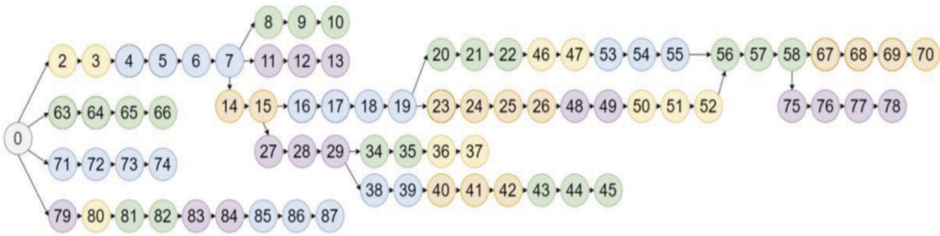

Figure 1. Precedence graph.

The approach used in this study is software-independent and could be implemented regardless of the software. This study used the software FACTS Analyzer to construct the simulation model and implement SMO. Figure 2 present the simulation model. FACTS Analyzer includes a Discrete-Event Simulation (DES) engine where the variables declared in the simulation model can be used as the input variables for the optimization algorithm, and multiple output variables and their functions can be set as the multiple objectives for a SMO problem using NSGA-II [19]. This approach consists of two parts that interact between each other's, the simulation model and the optimization engine. Feasible solutions in the simulation model enabled by the combination of the input parameters are iteratively assessed by the optimization engine following the optimization constraints and objectives while pursuing the optimal output solutions. In this process, the optimization engine feedback to the simulation model a new combination of input parameters in order to converge to the optimal or near-optimal set values that form the desired system.

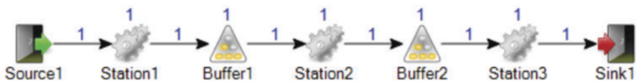

Figure 2. General simulation model Facts.

The optimization objectives used seek to maximize the THP and minimize the TBC, as seen in equations 1 and 2:

$Maximize\ f1 = THP$: Throughput Per Hour (2)

$Minimize\ f2 = \sum_{j=2}^{S} B_{j-1}$: Total Buffer Capacity (3)

Subject to precedence constraints (87). The constraints are used for setting the precedence of the tasks. The TBC is limited between 2 when each of the buffers in the systems has a capacity of 1 and 24 products.

Where: $B_j \in \{1,2,3,4,\ldots 23\}$ j=1,2
j workstation index
B_{min} = 1 minimum safety buffer
B_{max}= 24 maximum buffer capacity
S number of workstations

3.1. First scenario

For the first scenario, only one machine per workstation was considered. The SMO performed several experiments using different disturbances in the machines. In these experiments, the availability of the workstations has been modified from 70% to 100%, in steps by 5%. It is important to note that machines in the systems must have the same availability. The MTTR has been set for one minute. In this scenario, the optimization used the conflicting objectives defined by equations 2 and 3 for maximum THP and minimum TBC.

The results of the first scenario are shown in Figure 3. These results refer to the non-dominated solutions. Each optimal point solution in Figure 3 represents the maximum THP reached for a specific TBC and is constructed by the optimal allocation capacity of each buffer and the optimal tasks allocation to workstations of the specific system considered. This figure shows the increase of THP as more buffers are added to the system for different availability scenarios. As seen in the figure the less availably of the machines, the more impact will have the TBC on the system. It is essential to note the trade-off decisions that this figure presents since sometimes a specific THP can be achieved either with a lower TBC and higher availability or the opposite. This is an important decision that managers need to consider when designing a new RMS.

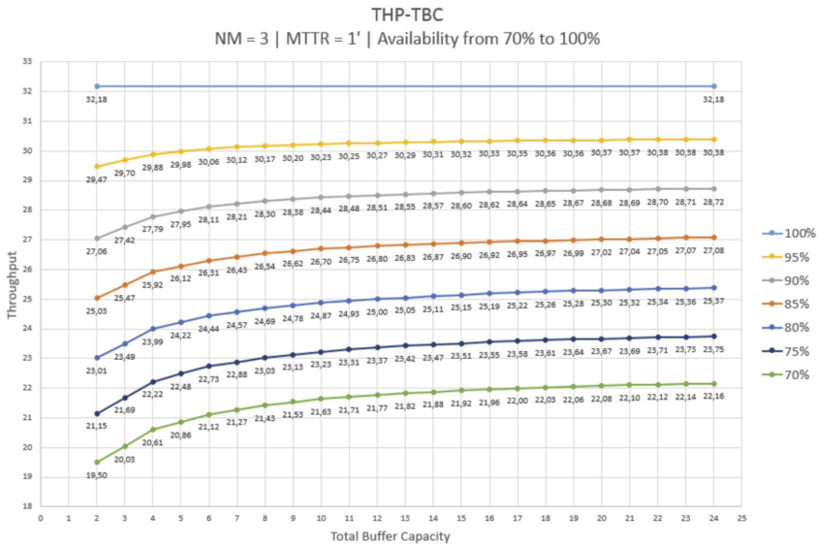

Figure 3. Impact of availability over the objectives for 3 machines system.

Another core tenant of RMS is process planning. Another aspect of this approach is the work task allocation for maximum THP and minimum TBC. Table 2 presents the results of the optimization for the cases in which the TBC is 10. From left to right, the table presents the availability considered in the experiment, the cycle time of workstations 1, 2, 3, the THP obtained for the different availabilities in the systems, and the optimal work tasks allocation obtained from the optimization. After considering the zoning constraints, the total number of tasks could be grouped into 28. Therefore, the right part of the table shows all 28 tasks (from T1 until T28), and below each task is a number from 1 to 3, representing in which workstation that task is performed. In addition, the color background in the cell that represents tasks also indicates in which workstation the tasks are performed (white for workstation 1, light grey for workstation 2, and dark grey for workstations 3). It can be seen that the work task allocation is independent of the availability. In this specific case, the configuration of the machine did not change since there are only 3 machines, 1 per workstation.

Table 1. Work task allocation for 3 machines system and TBC = 10.

Availability	CT WS1	CT WS2	CT WS3	THP	T1	T2	T3	T4	T5	T6	T7
70%	111.88	111.80	111.70	21.63	1	1	1	1	1	1	2
75%	111.88	111.80	111.70	23.23	T8	T9	T10	T11	T12	T13	T14
80%	111.88	111.80	111.70	24.87	1	2	3	3	2	2	3
85%	111.88	111.80	111.70	26.70	T15	T16	T17	T18	T19	T20	T21
90%	111.88	111.80	111.70	28.44	2	1	1	2	2	3	2
95%	111.88	111.80	111.70	30.23	T22	T23	T24	T25	T26	T27	T28
100%	111.88	111.80	111.70	32.18	2	3	2	3	3	3	3

In the second scenario, the scalability of RMS was studied by analyzing how much THP can be gained per added machine to the RMS and how the system must be reconfigured in terms of system configuration and work task allocation for maximum THP and minimum TBC. This experiment also examines how the system availability affects the RMS as new machines are added to the system. In this scenario, the starting model is the same as in the first scenario: a system with three workstations separated by buffers. In this case, the availability of the machines in the system is set to 90%, and the MTTR remains equal to one minute. In this second scenario, the optimization also used the conflicting objectives defined by equations 2 and 3 for maximum THP and minimum TBC.

Figure 4 presents the optimization results for the second scenario. The trend lines show that the system's availability has a more significant impact on the RMS as the system uses more machines. In other words, the fewer resources the RMS has, the fewer disturbances the system will face for the same availability in the machines. This figure also shows the maximum production capacity that can be obtained depending on the number of machines and the TBC used in the RMS. Consequently, this figure can be used to determine how to scale up or down the systems.

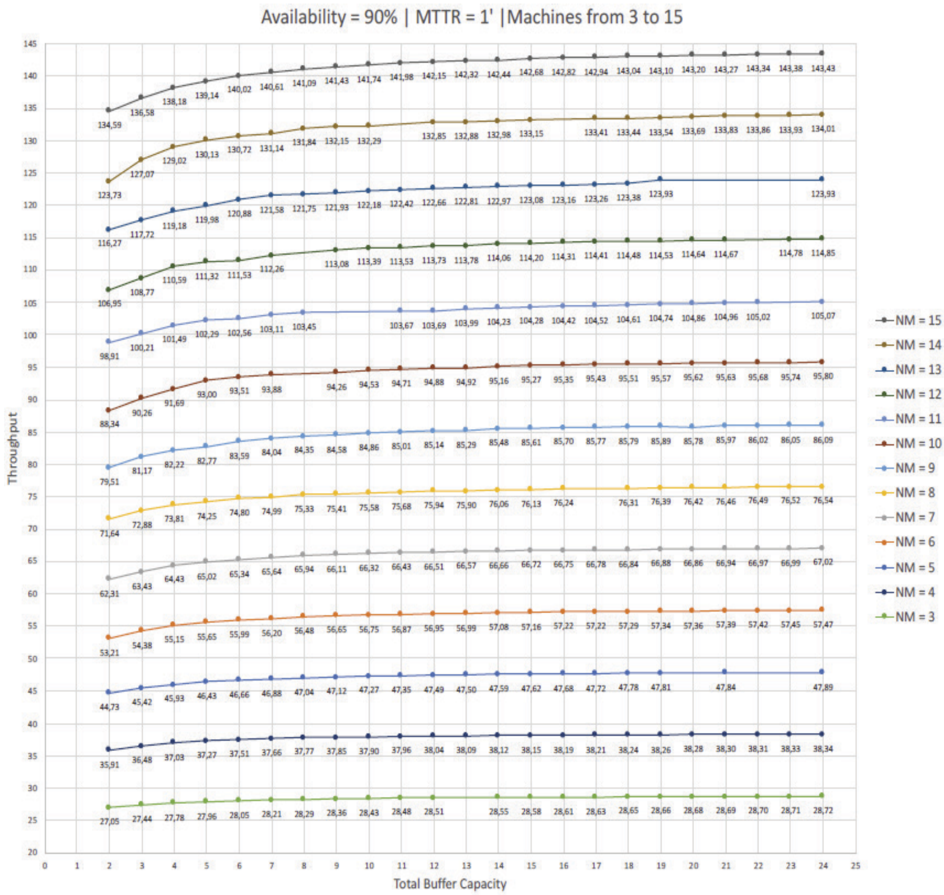

Figure 4. Throughput over total buffer capacity.

Another view of the results from the optimization is presented in Table 2. In this case, the table can be used to obtain a greater understanding and view of the system, including the optimal location for future machines in case of future capacity increases, which are needed for the system with a TBC equal to 12. The table also shows the optimized allocation of the buffers' capacities for the selected TBC. The first row of the table indicates the number of machines used in the RMS. In the next three rows the number of machines in workstations 1, 2, and 3 consecutively. These three rows provide the optimal way to configure the RMS from 3 to 15 machines. The next three rows provide the optimal way to allocate the capacity of each buffer, keeping the TBC set to 12. The following 28 rows show how to optimally allocate each task depending on the number of machines used in the RMS. Finally, the last three rows present the cycle time of each workstation for the defined experiments. As an example of how the results from the optimization can be extracted, compared and presented to the decision-makers, Table 2 presents the case for a TBC equal to 12. However, the used SMO approach can support the knowledge extraction and display which choices are available according to different constraints, including the whole range of buffers capacities studied. Essentially, knowing in advance where to add future machines for capacity increments, how to allocate the tasks into the workstations, and how to distribute the capacity of the buffers can be convenient and cost-effective when designing the system, primarily when investing in the material handling system.

Table 2. System configuration and work task allocation for TBC = 12 in the second scenario.

NM	3	4	5	6	7	8	9	10	11	12	13	14	15
NM WS1	1	2	3	2	2	2	4	1	1	7	8	4	8
NM WS2	1	1	1	1	3	2	4	4	1	2	4	6	3
NM WS3	1	1	1	3	2	4	1	5	9	3	1	4	4
TBC	12	12	12	12	12	12	12	12	12	12	12	12	12
BC1	5	6	6	6	5	6	5	6	5	7	6	6	6
BC2	7	6	6	6	7	6	7	6	7	5	6	6	6
T1	1	1	1	1	1	1	1	2	1	1	1	1	1
T2	1	1	1	1	1	1	1	2	2	1	1	1	1
T3	2	3	3	1	2	1	1	3	3	3	2	2	3
T4	3	2	1	2	3	2	3	3	3	3	1	3	1
T5	1	1	1	1	1	1	1	2	3	1	1	1	1
T6	2	1	1	1	1	1	1	2	3	1	1	1	1
T7	3	1	1	1	1	2	1	3	3	1	2	1	1
T8	2	1	1	1	1	1	1	2	3	1	1	2	1
T9	1	1	1	3	1	2	1	2	3	1	1	2	1
T10	2	1	2	3	2	3	1	3	3	2	1	2	2
T11	2	3	2	3	3	3	2	3	3	2	1	2	2
T12	1	1	1	3	2	2	2	2	3	1	1	3	1
T13	1	2	1	3	2	3	2	2	3	3	1	3	1
T14	1	3	2	3	2	3	2	3	3	3	3	3	2
T15	3	1	1	3	2	3	1	3	3	1	2	1	1
T16	2	1	1	1	2	2	1	2	3	1	1	2	1
T17	2	2	1	1	2	3	2	3	3	1	2	2	2
T18	3	1	1	3	2	3	1	3	3	1	2	2	3
T19	3	2	1	3	2	3	2	3	3	1	2	2	3
T20	3	2	3	2	2	3	2	1	1	3	2	2	3
T21	3	2	3	3	2	3	2	3	3	1	2	2	3
T22	1	3	1	2	3	2	3	1	1	1	1	3	1
T23	3	2	3	3	3	3	3	3	3	1	3	2	3
T24	1	1	2	1	2	1	1	1	2	2	1	1	1
T25	2	1	2	2	2	3	1	1	2	2	1	1	1
T26	2	1	2	2	3	3	1	2	2	2	1	1	2
T27	3	3	3	2	3	3	2	3	3	3	2	1	3
T28	3	3	3	3	3	3	2	3	3	3	2	3	3
CT WS1	111,88	84,44	67,66	55,99	47,54	41,74	37,47	32,20	29,98	28,13	26,24	23,75	22,60
CT WS2	111,60	82,50	66,10	54,50	48,03	41,70	37,10	33,40	27,60	27,60	25,78	24,12	21,57
CT WS3	111,90	84,00	66,30	56,30	48,10	42,13	37,10	33,92	30,87	27,77	22,40	23,93	22,48

A third scenario was designed in order to consider machines' investment costs in terms of their availability. This scenario investigates the trade-off between investing in more availability of the machines or more machines to reach the desired production capacity. This optimization investigates how to obtain the maximum production capacity for a system, from 3 to 16 machines and for each number of machines considered, the availability is studied from 70% to 95%. In this scenario, the optimization used only one objective to maximize the THP as defined by equation 2. The buffers are set with a capacity of 20 each, and the MTTR remains 1 minute as in previous experiments. Therefore, the optimization used the tasks allocation to workstations and the distribution of the TBC (set to 20) among the buffers as input variables to maximize the THP.

Figure 5 shows the results from the optimization in terms of THP over availability for the different number of machines where the red dashed lines represent the cheapest way to reach a specific THP (see below). The figure shows the maximum production capacity that can be produced depending on the number of machines used in the RMS and their availability. Since specific THP values can be reached with a different number of machines depending on their availability, the figure shows the importance of considering the availability when designing a new RMS.

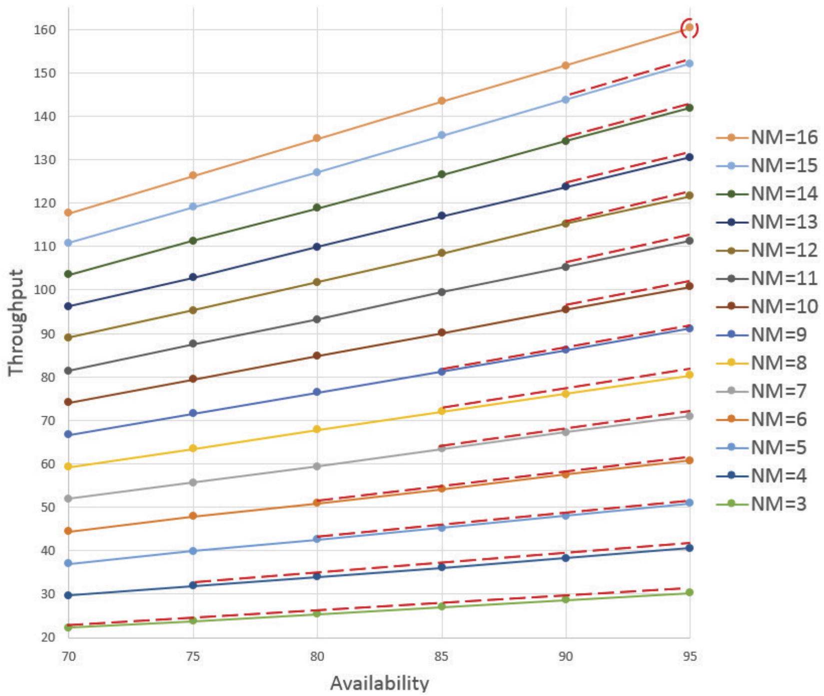

Figure 5. Throughput over availability for the different number of machines.

To cost-wise put the trade-off between availability and number of machines in perspective, a coefficient cost per machine depending on its availability has been estimated, see Table 3. Note that the values shown in the table are estimated for this experiment.

Table 3. Estimated cost.

Availability	70%	75%	80%	85%	90%	95%
Coefficient Cost	1	1.05	1.1	1.15	1.20	1.25

Considering the estimated cost presented in Table 3, the red dashed lines of Figure 5 represent the cheapest way to reach a specific THP when considering the estimated cost in Table 3. The observed trend indicates that as the number of machines increases, fewer availability points are cost-wise optimal for each RMS. This trend suggests two consequences: firstly, that above a certain number of machines, the most cost-efficient RMS is always the one with the highest availability; and secondly, it is more optimal cost-wise to have fewer machines with a high availability than having more machines with less availability. However, it is important to know that the results obtained depend on the estimated cost coefficient. Consequently, the considered factors combined with many others can be different and affect the decision-making task.

4. Conclusions

The availability of RMS impacts its ability to meet the desired demand. The use of SMO for analyzing the availability of RMS has been proposed. The considered case showed that SMO is a powerful approach when comparing different RMS based on their availability. In addition, this approach can be supportive for managers and stakeholders with the trade-off decisions that arise when designing a new RMS. The information obtained from the SBO approach includes the RMS number of machines, configuration, buffers capacity allocation, work task allocation, and the production rate for different availabilities.

The results from the paper showed that the availability analysis of the RMS affects the configuration selection and the decision of the needed number of machines together with buffers capacity allocation. The proposed SMO approach is not limited to only RMS but other types of manufacturing systems with a large number of workstations and resources could also be studied.

As future work, this study will focus on analyzing the availability for aspects such as the material handling of RMS. In addition, different availabilities for different workstations in the RMS is another interesting aspect that may be considered within the proposed SMO approach.

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