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SIMULATION-BASED MULTI-OBJECTIVE OPTIMIZATION FOR RECONFIGURABLE MANUFACTURING SYSTEM CONFIGURATIONS ANALYSIS

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ABSTRACT

The purpose of this study is to analyze the use of Simulation-Based Multi-Objective Optimization (SMO) for Reconfigurable Manufacturing System Configuration Analysis (RMS-CA). In doing so, this study addresses the need for efficiently performing RMS-CA with respect to the limited time for decision-making in the industry, and investigates one of the salient problems of RMS-CA: determining the minimum number of machines necessary to satisfy the demand. The study adopts an NSGA II optimization algorithm and presents two contributions to existing literature. Firstly, the study proposes a series of steps for the use of SMO for RMS-CA and shows how to simultaneously maximize production throughput, minimize lead time, and buffer size. Secondly, the study presents a qualitative comparison with the prior work in RMS-CA and the proposed use of SMO; it discusses the advantages and challenges of using SMO and provides critical insight for production engineers and managers responsible for production system configuration.

1 INTRODUCTION

Simulation-based optimization allows the decision-maker to systematically search a large decision space for an optimal or near-optimal system design without being restricted to a few pre-specified alternatives (Xu et al. 2016; Niño-Pérez et al. 2018). Simulation-based multi-objective optimization (SMO) can be applied when multiple conflicting objectives exist (Zhang et al. 2017). The benefits of SMO include generating a large set of Pareto-optimal solutions in a single optimization run (Dudas et al. 2014), and developing insights about system performance based on the relationships among the design variables, facilitated by the functional forms of models (Xu et al. 2015). Increasingly, research underscores the importance of utilizing SMO in Reconfigurable Manufacturing Systems Configuration Analysis (RMS-CA) (Manzini et al. 2018).

Reconfigurable Manufacturing Systems (RMS) belong to the type of production systems that enable adding machines to existing operational systems very quickly, in order to respond rapidly, and economically to unexpected surges in market demand (Koren et al. 2018). RMS-CA includes the arrangement of machines, equipment selection, and operation assignments impacting the performance of manufacturing companies (Youssef and ElMaraghy 2007; Youssef and ElMaraghy 2008). RMS-CA is crucial for the manufacturing industry for two reasons. Firstly, RMS-CA is essential for achieving high flexibility, dynamic market demand, increasing customization, high-quality products, flexible batches, and short product life cycles necessary for increased manufacturing competitiveness (Bortolini et al. 2018). Secondly, studies suggest that RMS-CA leads to improved performance when compared to traditional production system configurations, including productivity, responsiveness, and cost (Freiheit et al. 2003; Gu 2017).

Prior efforts focused on multi-objective optimization for RMS-CA are scarce and predominantly adopt Genetic Algorithms (GA)(Renzi et al. 2014). For example, Goyal et al. (2012) applied a GA for obtaining the optimal configuration based on convertibility, utilization of machines, and cost. Similarly, studies applied GAs for rebalancing how tasks are allocated in the machines/stages while either minimizing the number of machines used to reach a certain capacity or maximizing the capacity of the system for a certain number of machines (Wang and Koren 2012; Borisovsky et al. 2013). Likewise, the use of simulation for RMS-CA is sporadic, does not involve multi-objective optimization, and has therefore required considerable calculation efforts to arrive at solutions (Gola and Świć 2016). The above shows that research about SMO for RMS-CA remains limited despite calls for increased understanding and highly relevant for achieving the benefits of RMS (Bensmaine et al. 2011; Ng et al. 2011; Koren et al. 2018).

Against this backdrop, the purpose of this study is to analyze the use of simulation-based multi-objective optimization for RMS-CA problems. Particularly, it investigates one of the salient problems of RMS-CA: determining the minimum number of machines necessary to satisfy demand. This study adopts the non-dominated sorting genetic algorithm NSGA-II (Deb et al. 2002) to achieve SMO for RMS-CA, and presents two contributions.

On the one hand, this study extends prior research done by Koren and Shpitalni (2010), and propose four additional steps for adopting SMO in RMS-CA. A first step involves modeling of RMS configurations in a simulation environment including a routing or a selection interface modeling approach. A second step includes specifying the optimization objectives of interest to a decision-maker, the constraints of the production system, and the simulation parameters. A third step comprehends calculating the outputs of each RMS configuration and determining a best solution. The fourth step consists of understanding the underlying trade-offs of a particular RMS configuration. The results of this study show how these four additional steps including SMO contribute to maximizing production throughput, and minimizing lead time and buffer size.

On the other hand, this study presents a qualitative comparison between the prior work in RMS-CA and the proposed use of SMO by discussing its advantages and challenges. Taken together, the findings of this paper advance understanding of SMO for efficiently performing RMS-CA with respect to the limited time for decision-making in the industry (Ng et al. 2011). The conclusions of this study present important insight for production engineers and managers responsible for production system configuration. The remainder of the paper is structured as follows. Section 2 describes current understanding about SMO and RMS-CA. Section 3 presents the method of this study, and shows its empirical results of SMO for RMS-CA. Section 4 presents the insight facilitated by SMO for RMS-CA and discusses the findings of this study. Section 5 concludes.

2 PROBLEM FORMULATION AND LITERATURE REVIEW

2.1 Simulation-Based Multi-Objective Optimization

Multi-objective optimization is a well known research area that utilizes a variety of methods such as scalarization and posteriori methods. Some of the most used scalarization method are weighted sum method and ε-constraint method among other. Posteriori methods aim to represent the pareto front, which is commonly achieved by using evolutionary algorithms like population-based algorithms, genetic algorithms, or simulating annealing (Touzout and Benyoucef 2019). SMO presents a desirable alternative as the intersection of two powerful decision-making techniques, namely, simulation and optimization (Jian and Henderson 2015). From an optimization perspective, SMO compares the effects of decision variables on the output of a model. From a simulation perspective, SMO takes into account the randomness occurring in a real-life production system. The combined use of simulation and optimization present several benefits when compared to analytical optimization. Analytical optimization assumes that the objective function is a single scalar value, which constitutes a strong simplification for many problems in manufacturing (Freitag and Hildebrandt 2016). For example, manufacturing companies who are evaluating the best RMS configuration may wish to fulfill multiple criteria and be subject to randomness and variability. In such instances, adopting an analytical optimization may not be realistic.

SMO adopts the representation of problems utilized in analytical multi-objective optimization (Yelkenci Kose and Kilincci 2020). The general representation of an SMO problem consisting of a number of objectives and subject to some equality and inequality constraints in the form presented by equation (1).

$$f_i(x) = [f_1(x), f_2(x), \dots, f_n(x),]$$
$$Subjected\ to\ \{g_i(x) \geq 0\ i = 1,2,\dots,m\ h_i(x) = 0\ i = 1,2,\dots,h \tag{1}$$

Where $\boldsymbol{x}$ is the decision variable vector representing a feasible solution, i.e., satisfying the m inequality constraints and h equality constraints; f_i is the objective function to be minimized, and n is the number of objective functions.

Population-based Metaheuristic algorithms, like GAs, are commonly utilized in multi-objective optimization. GAs are a sub-class of evolutionary algorithms based on the theory of natural evolution. The best solutions, or parents, from each generation, are selected and combined, creating offspring solutions with better chances of attaining higher fitness values optimization. NSGA-II is one example of a multi-objective genetic optimization algorithm frequently applied in SMO (Lidberg et al. 2019). When considering the use of multi-objective optimization for RMS challenges, GAs have shown better results in nearing the optimal solutions in a more efficient and timely manner than other optimization algorithms (Renzi et al. 2014). The algorithm uses the fast non-dominated sorting technique and a crowding distance to rank and select the population fronts (Deb et al. 2002). In NSGA-II, multiple objectives are reduced to a single fitness measure by the creation of a number of fronts, sorted according to the non-domination. The result of SMO with NSGA-II leads to a set of solutions in the form of Pareto-optimal solutions where the final desired solution is selected according to some higher-level information of the problem (e.g., throughput, work in progress, or lead time) (Amouzgar et al. 2018). Pareto-optimal solutions include a set of solutions representing efficient, non-dominated solutions, and their possible trade-off. Based on a set of Pareto-optimal solutions, manufacturing managers may analyze the relationship of objectives, and consider individual preferences for arriving at a solution (Muta et al. 2014).

2.2 Reconfigurable Manufacturing Systems Configuration

The selection of the best RMS configuration is among the most important choices in the management of a RMS (Dou et al. 2010). RMS is essential for achieving the overall objectives and characteristics of a production system and its performance (Moghaddam et al. 2018). RMS is a competing alternative to other types of configurations, such as, serial production lines or parallel systems.

Usually a RMS consists of several stages, each stage consists of multiple parallel and identical machines (Koren et al. 2018). RMSs are characterized by cross-over connections after every stage of a production process. Products may be transferred from a machine to any subsequent machine in a cross-over connection. Importantly, in a RMS, each stage of a production process may not necessarily have an identical number of machines (Haddou Benderbal et al. 2017). Therefore, for the same number of machines, there are more RMS configurations than for those of serial production lines. Consequently, RMS-CA covers multiple research issues and structuring levels of the factory (Andersen et al. 2017), and can be partitioned into three sub-problems (Manzini et al. 2018). First, problems determining the minimum number of machines to satisfy demand. This type of problem may include product assignment to machines, production technologies, or product routing. Second, problems defining a specific layout and production process. Third, problems focusing on planning of production and guaranteeing product delivery.

Koren and Shpitalni (2010) propose a method for calculating the number of machines in a system, the first RMS-CA sub problem above. This methos involves (1) determining the minimum number of machines. (2) Calculating the number of possible RMS configurations, including the analysis of a large number of alternative RMS configurations. (3) Reducing the number of RMS configurations by eliminating those

RMS configurations that do not meet demand. (4) Evaluating the performance of the RMS configurations to select a winning one. As will be explained below, SMO can be applied effectively in this method.

2.3 Summary of Literature Review

As introduced in the Sections 1 and 2, the literature on RMS configurations is extensive and frequently resorts to simulation or multi-objective optimization (Wang and Koren 2012). Prior studies on RMS-CA have relied on analytical calculations for determining the minimum number of machines satisfying demand (Koren and Shpitalni 2010). This procedure is essential in manufacturing environments requiring rapid adaptations of capacity and functionality (Renna 2010). However, adopting SMO for RMS-CA constitutes a novel contribution to a classical problem that traditionally requires significant calculation and modeling efforts (Fu et al. 2014; Xu et al. 2016).

RMS-CA is a commonly addressed problem when designing a new RMS (Koren et al. 2018). Prior studies applied analytical optimization or simulation independently to RMS-CA (Talbi et al. 2016). Simulation has also been combined with analytical optimization in the analysis of several RMS configurations (Gola and Świć 2016). However, prior efforts which used simulation and multi-objective optimization require the manual transfer of results from one to the other (Petroodi et al. 2019). To the best of our knowledge, this study is the first proposing SMO for RMS-CA involving several RMS configurations including variable number of stages. An advantage of SMO over previous efforts focusing on multi-objective optimization includes the evaluation of various RMS configurations with a single model. This study proposes two modeling approaches for SMO in RMS-CA including a product routing and selection interface modeling approach. These modeling approaches adopt NSGA-II to evaluate the route of products as a variable in a simulation model containing alternate RMS configurations.

3 METHOD AND RESULTS OF SIMULATION MULTI-OBJECTIVE OPTIMIZATION FOR RECONFIGURABLE MANUFACTURING SYSTEM CONFIGURATION ANALYSIS

This study illustrates the use of SMO in RMS-CA for determining the minimum number of machines necessary to satisfy demand. To do so, this study adopts the above-mentioned method for RMS-CA on an industrial application example. In this example, a manufacturing company designs an RMS that includes a 14.4 minutes machining process. The machining process includes work on three faces of a product, which requires different fixtures, and three different types of machines. The machining process consists of five tasks: four tasks in Face I, one task in Face II, and one task in Face III, as shown in Figure 1. The machining process is subject to disturbances, and machine availability is estimated to be 90% with an average repair time of 5 minutes. The machining process must satisfy a demand of 550 products/day in a 23-hour working day.

According to the method proposed by Koren and Shpitalni (2010), the first step in RMS-CA involves determining the minimum number of machines. Equation (2) is used in order to determine the number machines, M, needed in a balanced system, where D is the daily demand (parts/day), T is the machining time (min./part), A is the machine availability (i.e., 0.9 or 90%), and W is the daily working time (minutes per day). The resulting number of machines, according to the equation (2), is equal to 6.37 which has to be rounded up to M = 7 machines.

$$M = \frac{D * T}{A * W} \tag{2}$$

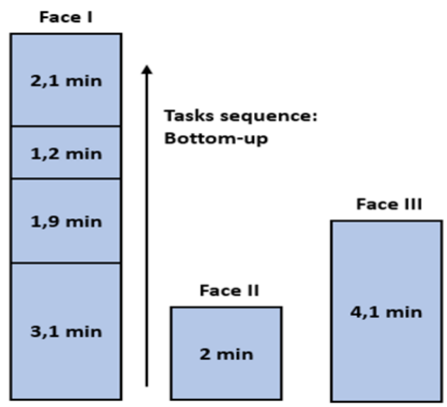

Figure 1: Task sequence for Faces I, II, and III in the machining process.

The second step in RMS-CA involves calculating the number of possible RMS configurations. The total possible number of RMS configurations, *C*, for the *M* machines, arranged in *S* number of stages, is determined by Equation (3), which for this example yields 64 configurations:

$$C = \left(\frac{(M-1)!}{(M-S)!(S-1)!}\right) \tag{3}$$

The third step in RMS-CA comprises the reduction of the number of RMS configurations. Considering that the machining process takes place in three faces of the product and a different fixture is required for every one of these faces, and the systems can be divided into three sub-systems, one for every face. By applying Equation (2) to every sub-system, the equation yields 3.67 for Face I, 0.88 for Face II, and 1.81 for Face III. Consequently sub-systems 1, 2, and 3 require 4, 1, and 2 machines respectively.

Equation (3) determines the number of RMS configurations for every sub-system. For the first sub-system with 4 machines, Equation (3) yields 8 possible RMS configurations arranged in one, two, three, or four stages. The second sub-system comprises only one machine, so it requires only one RMS configuration. The third sub-system involves two machines, and could require two possible RMS configurations (serial or parallel). However, the number of RMS configurations can be reduced to one (parallel) when considering that this sub-system performs only one machining task. Consequently, the machining process involves a total of eight different RMS configurations arranged between three and six stages as shown in Figure 2.

The fourth step of RMS-CA involves evaluating the performance of the RMS configurations. Evaluating the performance of several RMS configurations imposes two challenges. First, assessing performance including simulatenous and multiple objectives. Second, developing multiple stochastic simulation models each representing single RMS configurations, and including the variability in the machining process. In the example above, RMS configurations may include any combinations that consist of three to six stages of machines, together with their inter-stage buffers.

This study argues that SMO together with the optimization algorithm NSGA-II can be effective for addressing these two challenges. In the example above, SMO can assess different combinations of input variables according to the optimization objectives and the system constraints in order to find the best outputs solutions. For example, SMO can determine the most suitable RMS configurations that fulfills demand, minimizes total buffer capacity (TBC) and lead time (LT), and maximizes throughput per hour (TH). Then, NSGA-II can consider multiple factors simultaneously. The optimization engine including NSGA-II evaluates iteratively the feedback from the outputs in order to instruct a new combination of input parameters in the effort to define the Pareto front. Nevertheless, proposing a SMO modeling approach is necessary for evaluating efficiently multiple RMS configurations, including variability of the process, in a single simulation model.

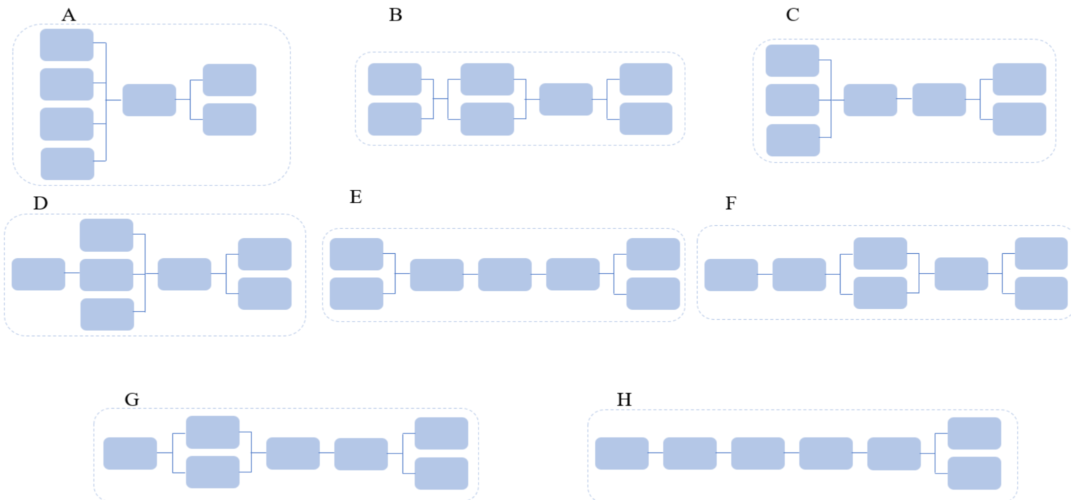

Figure 2: Eight different RMS configurations for the machining process.

Evaluating multiple and alternative RMS configurations with a single simulation model is desirable when compared to multiple simulation models searching independently for the best trade-off solutions. Two modeling approaches are proposed for achieving SMO for RMS-CA with a single model. The proposed modeling approaches are software independent and could be adopted regardless of the software. This study utilizes the software FACTS Analyzer, currently available in our laboratory, for implementing SMO for RMS-CA with a single model that can represent multiple RMS configurations. FACTS Analyzer includes a DES engine wherein almost all the variables declared in the simulation models 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 (Ng et al. 2011).

We refer to the first modeling approach as a routing approach. In the routing approach the optimization algorithm evaluates alternative product routes as input variables and includes a fixed number of machines. In this setup, the routing approach evaluates eight RMS configurations in a single SMO model. Figure 3 presents the routing approach of SMO for RMS-CA. The left-hand side of Figure 3 shows the SMO model including all possible routes for eight RMS configurations. The right-hand side of Figure 3 presents the route for RMS configuration A of Figure 2.

We refer to the second modeling approach for achieving SMO for RMS-CA as a selection interface modeling approach. In this case, the algorithm will generate a different RMS configuration depending on which input variable (interface) is selected in the SMO model. Figures 4 presents the selection interface modeling approach of SMO for RMS-CA. Figure 4 exemplifies the selection interface object and shows that the selection includes eight objects representing the RMS configurations. Figure 4 presents A, C and H RMS configurations contained in the interface object.

The routing and selection interface modeling approach evaluate multiple RMS configurations in a single SMO model. Routing and selection interface modeling differ in the amount of objects used in a model and present unique benefits. The selection interface modeling requires more objects for every SMO model and additional modeling and setup time than the routing one. However, the selection interface modeling approach has a cleaner model representation, which increases understandability for stakeholders and managers unfamiliar with simulation. Oppositely, the routing approach requires less modeling time and is therefore desirable in large scale problems involving multiple machines.

Solving the RMS-CA above, this study applied 30,000 iterations and 30 replications for evaluating the performance of the RMS configurations by SMO. The decision variables for the SMO model include the alternative routes for each RMS configuration and the capacity of buffers in-between machines. The capacity of each buffer is constrained to a range between one and ten products. An additional constraint constitutes the total buffer capacity (e.g., the summation of all inter-stage buffers, from start to finish in the machining process) which may not exceed 20 products. Parameters are evaluated based on unitary buffer increments for each simulation run following the optimization objective functions:

$Maximize\ f1$=TH($\boldsymbol{x}$) : Throughput per hour
$Minimize\ f2$=TBC($\boldsymbol{x}$) : Total Buffer Capacity
$Minimize\ f3$= LT($\boldsymbol{x}$) : Lead Time

Where: TBC <=20

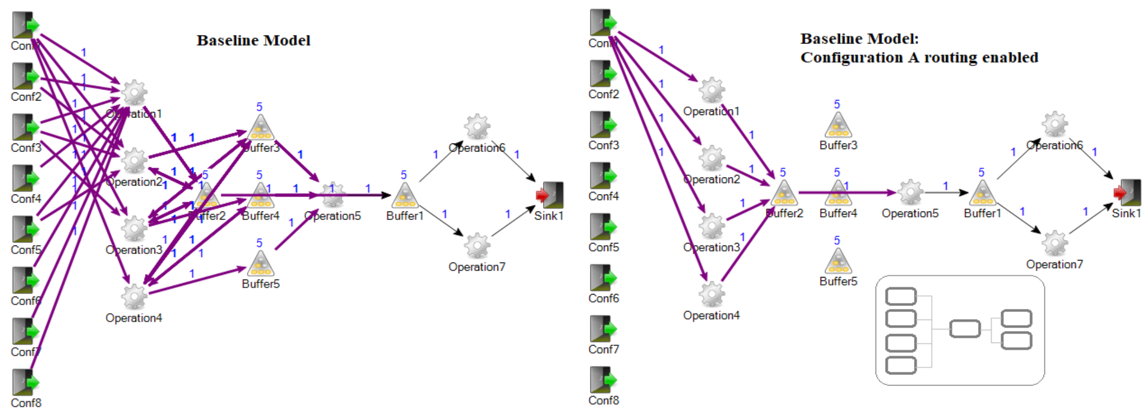

Figure 3: Routing approach of SMO for RMS-CA.

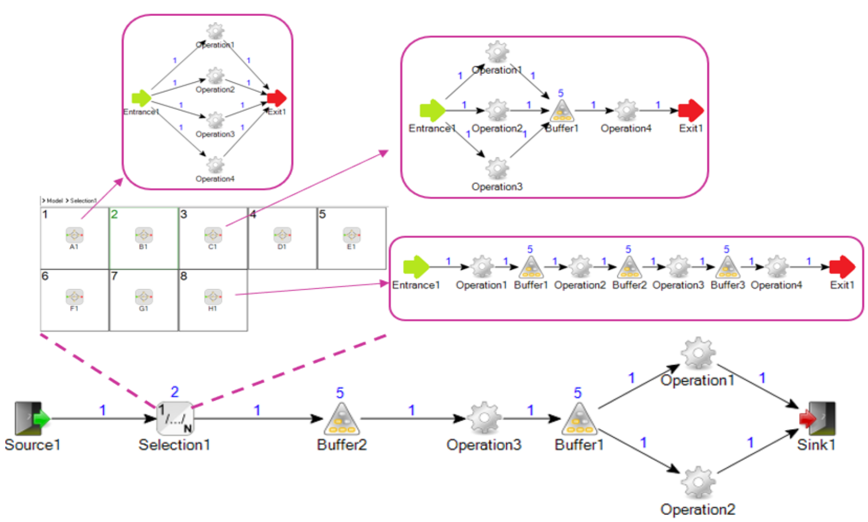

Figure 4: Selection interface modeling approach of SMO for RMS-CA.

3.1 Simulation-Based Multi-Objective Optimization Results

The results from SMO for RMS-CA of the eight RMS configurations is presented in the parallel coordinate plot of Figure 5. Every trace of Figure 5 constitutes the result of a simulation run towards reaching the objective of every RMS configuration. The columns in Figure 5 represent the TH, LT, TBC, and the eight RMS configurations, from A to H. The results from the SMO for the RMS-CA show three clusters of TH. The first cluster includes RMS configurations A and C with a TH range between 21.137 and 25.208. The second cluster involves RMS configurations B and E with a TH range between 20.001 and 21.321. The third cluster contains RMS configurations D, F, G, and H with a TH range between 16.563 and 17.297. Table 1 presents the results of SMO for RMS-CA where each row representsa RMS configuration with its number of stages, and the range of value for TBC, TH, and LT. It is important to note that RMS configurations A and C are the only ones meeting the requirements of 550 parts/day or 23.913 parts/hours for 23 working hours per day.

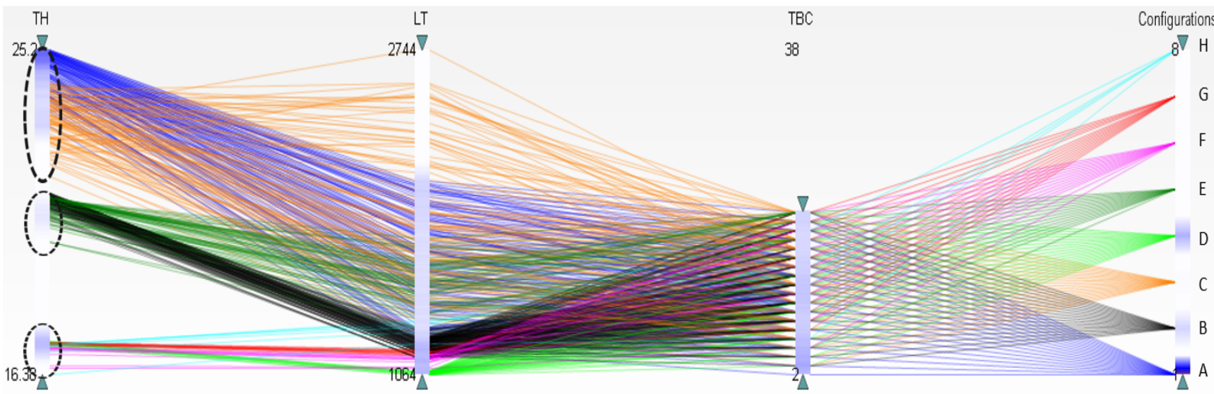

Figure 5: Parallel coordinate plot showing the results from SMO for the RMS-CA of the eight RMS configurations.

Table 1: Results of SMO including stages, total buffer capacity, throughput, and lead time for eight RMS configurations.

RMS configuration	Stages	Total buffer capacity (parts)	Throughput (parts/hour)	Lead time (seconds)
A	**3**	**2-20**	**23.137-25.208**	**1190-2063**
B	4	3-20	20.591-21.321	1158-1256
C	**4**	**9-20**	**21.794-24.301**	**1300-2142**
D	4	3-11	17.165-17.294	1067-1078
E	5	17-20	20.001-21,243	1311-1530
F	5	5-19	16.563-17.242	1100-1162
G	5	6-16	17.046-17.297	1146-1191
H	6	12-19	16.826-17.236	1266-1352

The SMO results for RMS configurations A and C are presented graphically in the parallel coordinate plot of Figure 6 and determine the best trade-off solutions. The green lines in Figure 6 correspond to RMS configurations (both A and C) lying on the Pareto front. RMS configurations A and C are grouped in blue and red circle on the right hand side column. The SMO results reveal that the RMS configuration A satisfies demand with the lowest LT and TBC. The SMO results also exhibit that RMS configuration A, when equipped with a TBC of five in size (2 between first and the second stage, and 3 between the second and the thrid stage) can yield a TH of 24 parts/hr., LT of 1334 seconds and WIP of 9 products.

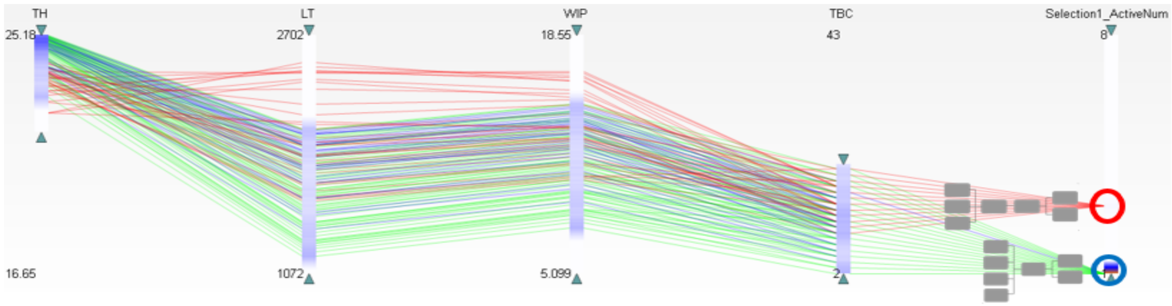

Figure 6: SMO comparison of RMS configuration A and C.

4 INSIGHT FACILITATED BY SIMULATION-BASED MULTI-OBJECTIVE OPTIMIZATION AND DISCUSSION

A core tenant of RMS is designing production systems that enable responding rapidly and economically to unexpected surges in market demand. Adopting SMO in RMS-CA may reveal the underlying trade-offs of selecting an RMS configuration. Consider again the parallel coordinate plot in Figure 5. The SMO results show that RMS configuration A is desirable for meeting a demand of 24 products/hour with the lowest LT and TBC. However, RMS configuration A is disadvantageous for demands ranging between 0 and 17, or 17 and 21 products/hour because other RMS configurations meet the desired throughput at a lower LT and TBC. Such kind of insights provided by SMO is crucial because it tells an equal number of machines with different RMS configurations can yield distinct LT while meeting the required TH. Furthermore, these results highlight the importance of considering alternate RMS configurations.

An additional insight resulting from SMO includes evidencing the efficiency of RMS configurations. We refer again to the results presented in the parallel coordinate plot of Figure 5. The SMO results show that the RMS configurations A to H were subject to equal changes in TBC ranging between two and 20 products, but increases in TBC did not lead to an increase of TH for every RMS configuration. RMS configurations A and C present the highest rise of THP with the increase of TBC. Configurations B and E present a significant increase in the THP dependent on TBC. Oppositely, RMS configurations D, F, G, and H give almost equal THP regardless of changes to TBC. This difference is explained by the presence of bottlenecks and process constraints in the RMS configurations resulting in under-utilized occupation of the buffers. Figure 7 exemplifies the unutilized TBC occupation for configuration D. Figure 7 presents the buffers occupation percentage for configuration D with a TBC = 3 on the left-hand side, and a TBC = 15 on the right-hand side. For the case of TBC = 3, all three buffers have a capacity of one, and for TBC = 15, all three buffers have a capacity of five. This shows a low buffer capacity occupation even when they have a capacity of one which is even lower as the capacity of the buffers increases to five.

RMS-CA focuses on machine arrangement, equipment selection, and operation assignment (Manzini et al. 2018). Prior studies about RMS-CA recognize the importance of understanding trade-off decisions and evaluating multiple objectives leading to superior performance (Bortolini et al. 2018). The results of this study suggest that SMO for RMS-CA leads to a comprehensive understanding of RMS configurations. This study presents two salient findings, including a series of steps for the use of SMO for RMS-CA and a qualitative comparison with the prior work in RMS-CA and SMO.

The findings of this study present novel contributions highlighting the advantages and challenges of SMO for RMS-CA. The study shows that SMO may reduce unnecessary calculations by adopting an optimization algorithm for evaluating multiple RMS configurations in one simulation model. This is important because it shows manufacturing companies may efficiently perform RMS-CA when adopting SMO. This is desirable because of the limited time for decision-making in the industry and the lack of expertise in the design of production systems. The results of this study facilitate adopting SMO for RMS-CA which is essential for uncovering the trade-off between multiple objectives such as TH, LT, and TBC. This finding is critical as it may support the scalability of a production system in response to changing market demands and convertibility of new products, which together constitute two of the underlying reasons for the use of RMS (Andersen et al. 2017).

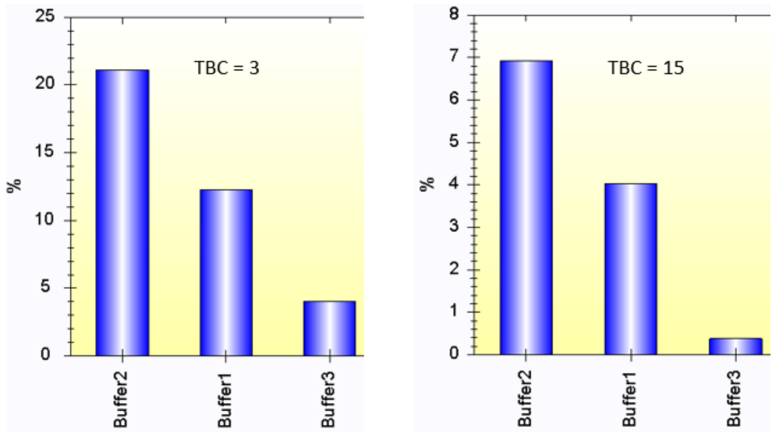

Figure 7: Unutilized TBC occupation for configuration D.

Previous publications identify a number of challenges associated with adopting SMO. For example, the considerable time and effort spent in the development of SMO models and the limited knowledge retrieved by decision-makers from its results (Fu et al. 2014). Similarly, earlier studies point to the adoption of SMO during the design but its sporadic use during the operation of production systems (Xu et al. 2016). Clearly, there exists a need for continued research efforts bridging the gap between SMO and manufacturing practice. Importantly, this study shows that decision-makers may benefit from SMO not only in the selection of the best RMS configurations, but also from the trade-off decisions inherent to a choice involving multiple and conflicting objectives. Thereby, decision-makers may justify the investment of resources by using SMO for RMS-CA. In addition, this study emphasized the importance of SMO for RMS-CA that take into account the changing levels of demand which is crucial as to cope with changes in demand is one of the key underlying reasons for adopting RMS, and therefore must be addressed frequently during the operation of production systems (Koren and Shpitalni 2010). To this extent, this study promotes the use of SMO in RMS beyond the design phase of production systems.

5 CONCLUSIONS

This study analyzed SMO for RMS-CA, and investigated one of its salient problems: determining the minimum number of machines necessary to satisfy the target demand. The study proposed a series of steps for the use of SMO for RMS-CA. Unlike prior research, this study synthesized existing RMS-CA understanding and adopted DES and the well-known multi-objective optimization algorithm, NSGA II, to automatically model, represent and optimize RMS configurations. This study showed that adopting SMO for RMS-CA reveals critical information for selecting an optimal RMS configuration, including the number of stages, machine layout, and trade-offs between multiple objectives such as TH, LT, and TBC. Additionally, this paper suggested a routing and selection interface modeling approach for SMO in RMS-CA. These modeling approaches are critical for analyzing multiple RMS configuration via SMO, and efficiently performing RMS-CA with respect to the limited time for decision-making in industry. In addition, the study qualitatively compared the prior work in RMS-CA and the proposed the use of SMO into an existing four-step procedure. The findings from the results in this paper suggest that SMO can facilitate effective RMS-CA by revealing the trade-offs when the equal number of machines is arranged into different RMS configurations. Generally speaking, the results of this study also suggested that SMO may address RMS-CA problems efficiently by providing graphical, visualization information like parallel coordinate plots. This study is limited by the choice of problem. An immediate step includes verifying the results of this study in industrial cases. Therefore, future work includes applying SMO for RMS-CA to production system design probems found in real-life manufacturing industry. These problems may include additional constraints, such as material handling, investment cost and machine availability.

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