Multi-Objective Design Optimization of Flexible Manufacturing Systems

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One of the basic components of Industry 4.0 is the design of a flexible manufacturing system (FMS), which involves the choice of parameters to optimize its performance. Discrete event simulation (DES) models allow the user to understand the operation of dynamic and stochastic system performance and to support FMS diagnostics and design. In combination with DES models, optimization methods are often used to search for the optimal designs, which, above all, involve more than one objective function to be optimized simultaneously. These methods are called the multi-objective simulation–optimization (MOSO) method. Numerous MOSO methods have been developed in the literature, which spawned many proposed MOSO methods classifications. After that, four MOSO methods are selected, according to this classification, and compared through a detailed case study related to the FMS design problem. All of these methods studied are based on Design of Experiments (DoE). Two of them are metamodel-based approaches which integrate Goal Programming (GP) and Desirability Function (DF), respectively.

Keywords: flexible manufacturing system ; multi-objective simulation-optimization method ; discrete event simulation ; design of experiments ; simulation metamodel ; goal programming ; desirability function ; grey relations analysis ; VIKOR method

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1. Introduction

The fourth industrial revolution, known as industry 4.0, is considered the upcoming significant technology development as it allows customers to receive their products based on their expectations in terms of product varieties and quantiles [1]. Industry 4.0 can be attributed to its broadening focus on automation, decentralization, system integration, cyber-physical systems, etc. [2]. One of the basic components of Industry 4.0 is the Flexible Manufacturing System (FMS), which is an advanced production system that interconnects machines, workstations, and logistics equipment, the entire manufacturing process being coordinated with the computer. FMS is intended for manufacturing tasks of large typological diversity, for high complexity, for ensuring timely delivery, and for minimal manufacturing costs, while production is unpredictable, organized in small batches, and has frequent changes [3].

Discrete Event Simulation (DES) is a powerful tool for analyzing and optimizing FMS for the purpose of design, modeling, and ongoing performance [4]. A simulation of an entire manufacturing system involves the identification of organization machines, robots, and the layout of the system, also involving multiple processes in the system. In particular, the design of FMS involves the choice of parameters and their value to optimize its performance. DES models allow the user to understand system performance and assist in behavior prediction and to support FMS diagnostics and design. However, DES responds to what-if questions as a tool for system evaluation; by itself, it cannot provide answers to how-if questions [5]. Moreover, DES is essentially a trial-and-error approach and is, therefore, time consuming and does not provide a method for optimization. In fact, many researchers have attempted to combine simulation and optimization procedures to provide a complete design solution with desired properties [6]. The problem of locating the most preferred alternative system design by using experimental evaluations performed using a computer DES is known as the Simulation Optimization (SO) problem.

The main classification criterion for SO approaches is the number of output performance measures. There are two groups of SO methods [7]. The first group is named Single-Objective Simulation Optimization (SOSO) approaches, which are focused on optimizing a single performance measure. The second group, which is studied in this research, covers Multi-Objective Simulation Optimization (MOSO) approaches. MOSO is an area of decision making of multiple criteria that is concerned with mathematical optimization problems that involve more than one objective function to be optimized simultaneously.

2. General Literature Review of MOSO Methods

MOSO methods are an area of multiple-criterion decision making that optimize multiple performance measures via simulation. In MOSO literature, there are three main classification criteria for organizing these methods.

- According to the articulation of the preferences of the Decision Maker (DM). This first classification criterion is proposed by Rosen et al. [8]. Four groups of methods are possible and include the following: (1) a priori MOSO methods when the DM expresses their preferences before optimization is conducted; (2) a posteriori MOSO methods (in these methods, the DM selects a solution at the end of the search. Although this approach avoids the disadvantage of the a priori approach by taking into account preference information only at the end of the optimization process, it can lead to extremely high computational costs); (3) a progressive articulation of DM preferences (also named Interactive MOSO Methods) (the progressive approaches repeatedly solicit preference information from the DM to guide the optimization process). These methods enable DM to change his preferences during the optimization process by incorporating knowledge that only becomes available during the search. Interactive methods may be useful when simulation runs are expensive and the DM is readily available to provide input. Finally, the fourth group involves (4) non preference MOSO methods that operate without regard to the preference of DM.

- According to the research set and variables nature. This second classification criterion is proposed by Hunter et al. [7]. Three groups of methods are possible, including the following: (1) MOSO on finite sets, called Multi-Objective Ranking and Selection (MORS); (2) MOSO with integer-ordered decision variables; and (3) MOSO with continuous decision variables. In the context of integer-ordered and continuous decision variables, researchers focus on methods that provably converge to a local efficient set under natural ordering. Furthermore, these methods of the three groups can also be viewed two groups according to the type of the final solution: global solution versus local solution [7]. The MORS methods provide a global solution, in which simulation replications are usually obtained from every point in the finite feasible set, and the estimated solution is the global estimated best. In addition, metaheuristics methods (named also random search) such as simulated annealing, Genetic Algorithms (GA), Tabu Search (TS), etc., also provide global solutions. Metaheuristics methods are efficient because they appropriately control stochastic error. However, the task is more challenging as it results in a number of solutions with different trade-offs among criteria, also known as Pareto optimal or efficient solutions.

- According to the use or non-use of metamodels. This third classification is proposed implicitly in many research studies such as in Barton and Meckesheimer [9], do Amaral et al. [10], etc. A metamodel or model of the simulation model simplifies the SO in two ways: The metamodel response is deterministic rather than stochastic, and the run times are generally much shorter than the original simulation. The metamodel is used to identify and estimate the relationship between the inputs and outputs of the simulation model, forming a mathematical function that is used to evaluate possible solutions in the optimization process. For example, Hassannayebi et al. [11] highlight that the adoption of metamodel-based SO in industry and service problems has grown due to its potential to reduce the number of simulation rounds necessary in the optimization process. Note that the MOSO methods, which are based on the metamodel, also provide a global solution such as that discussed in the second classification criterion.

3. FMS Design Literature Review

The study of Diaz et al. [12] presents a MOSO approach for a reconfigurable production lines subject to scalable capacities. The production line produces two product families and is composed of 18 workstations. The authors utilized a Non-Dominated Sorting Genetic Algorithm II (NSGA-II), a variant of GA to address the assignment of the tasks to workstations and buffer allocation for simultaneously maximizing the Throughput Rate (TR) and minimizing total buffer capacity. Červeňanská et al. [13] explored an MOSO of an FMS via a scalar simulation-based optimization method. The authors integrated a simulation with Design of Experiment (DoE) and Weighted Sum and Product multi-objective methods to optimize the total number of products, the Mean Flow Time (MFT), the Machine UTILization (MUTIL), and the average costs per unit of part. The modeled FMS produces two different products with eight workstations using parallel automated work machines.

The paper of Hussain and Ali [14] studied the impact of four design and control factors, control architectures, sequencing flexibility, buffer capacity, and scheduling rule on the performance of an FMS. The studied FMS is composed of six Computer Numerical Control (CNC) machines producing six different types of parts. The system is evaluated on the basis of make-span, average MUTIL, and the average Waiting Time (WT) of parts at the queue using the Taguchi–Grey multi-objective method. Apornak et al. [15] considered a multi-objective optimization of five performance measures in FMS. The authors addressed the optimal set of queues capacity, queues discipline, conveyor and transporter's speed, and operational setup times in an FMS with objectives of minimization of the average WT of raw materials, two average Process Times (PT), as well as the transporter and assembler product outputs. The studied FMS is composed of three work stations producing various kinds of seats for the freight cars. Using DoE, the authors simulated and collected the performance measure of 36 random scenarios. Regression analysis was then used to describe the metamodel of each performance measure. Consequently, the Response Surface Methodology (RSM) was applied to optimize the five objective functions.

Ahmadi et al. [16] proposed two Evolutionary Algorithms (EA): NSGA-II and NRGA are applied and compared to simultaneously combine the improvement of the make-span and stability of the schedule. This stability is evaluated by measuring the deviation of start and completion times of each job between prescheduled and realized schedule. The simulation is used to evaluate the state and condition of the machine breakdowns on a variety of manufacturing systems. Freitag and Hildebrandt [17] used a multi-objective simulation-based optimization to create a control strategy for an FMS by considering earliness and tardiness performance measures. This paper investigates the effect of 10 different attributes, which are the PT, the average PT of all waiting jobs, the Setup Time (ST), the average ST of all waiting jobs, the number of remaining operations, the time in system, the time in queue, the batch family size, the time until operational due date, and the average time until operational due date. The authors used the GA coupled with the simulation to solve the scheduling rule choice problem for a complex FMS.

Ammar et al. [18] investigated the size of the number of workers to be assigned to an FMS as well as the skills that each worker must have in a multi-objective optimization problem. The two objectives considered are minimizing the expected labor cost associated with the manufacturing team and minimizing the expected average task TR. The proposed multi-objective simulation optimization approach is applied to the design of teams of a manufacturing system; using the EA NSGA-II connected to a simulation model developed using Arena. Dengiz et al. [19] implemented a multi-objective optimization method of an FMS based on simulation through DoE, a regression meta-model, and the Goal Programming (GP) method. The authors have modeled and simulated by the ARENA simulation software an FMS with four workstations. Then, they applied the multi-objective optimization method to optimize the TR and MFT in the system by taking into consideration the number of operator, the velocity of material handling, the number of tool, scheduling rules, and the number of pallets as design and control parameters.

Using simulation results, Bouslah et al. [20] developed and solved a mathematical model based on RSM. The main objectives of the authors were to determine the optimal batch size, the optimal hedging level, and the economic sampling plan design, which minimized the average total holding cost, which includes the storage of the Work In Process (WIP) and final inventory stock, the average backlog cost, the average cost of sampling, the average costs of 100% inspection and rectification of the rejected batches, the average cost of transportation, and the average cost of replacement of non-conforming items sold to the consumer. However, the authors did not mention any details on the structure of the simulated manufacturing system. Iç et al. [21] considered a case study of simulation-based multi-objective optimization using the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method hybridized with the Taguchi design technique. The studied production system is an FMS department composed of four CNC machining centers and producing three part types. The authors based their optimization case on the cycle time, TR, and work in queue as performance measures. In addition, they used five factors as decision variables. These factors are the number of cutting tools, the number of operators, the number of pallets, the velocity of transporter robots, and the pallet selection strategy.

The paper of Wang et al. [22] applies an MOSO method to a flexible shop scheduling problem. The two investigated objective functions are the minimum of the maximum PT and the minimum of the maximum machine load. The main considered constraints are the production resources and the technological process. The scheduling model of an FMS is established using simulation software and integrated to NSGA-II EA. In Zhang et al. [23], a hybrid method based on hybrid GA and TS is used to address a multi-objective FMS scheduling problem. Two objectives, which are the make-span and the starting time deviations, are considered to improve schedule efficiency and stability. A case of study of six machines FMS was studied with four different job arrivals rate and six different number of job arrivals.

Azadeh et al. [24] integrated simulations with the GP method and DoE technique to address a multi-objective scheduling problem of an FMS. The proposed method was applied on a real textile shop floor to minimize make-span and tardiness. The authors determined the decision parameters by using the DoE technique by estimating the effects the dyeing machine type, the temperature of the printing, the temperature and the number of center machines, and the scheduling rules through meta-modeling. Then, they used GP to find the optimal values of these decision variables, which are subject to a set of technical and managerial constraints. Um et al. [25] presented the simulation based multi-objective optimization of the design of an FMS with Automated Guided Vehicles (AGVs). Their principal objectives were to minimize congestion and utilization and to maximize TR based on many parameters including the number, velocity, and dispatch rule of AGV, part types, scheduling, and buffer sizes. In this paper, the authors considered a nonlinear programming method combined to evolution strategy. Nonlinear programming was used to determine the design parameters of the system through multi-factorial and regression analyses, and an evolution strategy was used to verify each parameter for simulation-based optimization.

Syberfeldt et al. [26] describe the use of Artificial Neural Networks (ANN) and EA as MOSO methods to the manufacturing cell at Volvo Aero. The two investigated objectives were the maximization of cell utilization and the minimization of overdue components considering the component inter-arrival times and due date as decision criteria. Kuo et al. [27] proposed a practical case of the Grey-based Taguchi method as a MOSO method for a company that provides integrated circuit packaging services. The authors aimed to optimize TR and cycle time performance for ink marking machines to avoid backlog of orders or lost customers, and the TR of the system must be increased. They based their methodology on five three-level control factors, which are the PT, the machine buffer size, the time between adjustment, the ratio of the adjusted PT to original PT, and the mean time between failures.

Oyarbide-Zubillaga et al. [28] focused on the determination of the optimal preventive maintenance frequencies for multi-equipment systems. The authors apply simulation and NSGA-II to the multi-objective optimization problem of preventive maintenance activities to minimize the system’s cost and to maximize profit by considering the production speed, the percentage of unavailability of a machine due to corrective maintenance, and the fraction of time before and after the last maintenance as control factors. The system cost was defined as the sum of the preventive and corrective maintenance, the production speed lost, and the quality costs for each of the machines. Profit is the result of selling non-defective products. Park et al. [29] presented a method for determining the design and control parameters of an FMS with multi-objective performance via a fully factorial DoE, regression analysis and trade-off programming. A hypothetical FMS with six workstations was modeled and simulated. The number, speed, and dispatching rules of AGVs, in addition to the number of pallets, the buffer sizes, and the loading, routing scheduling rules, were considered as control parameters. These eight parameters were simultaneously determined by compromising performance measures of TR, delay, MUTIL, and WIP that are formulated using regression analysis.

4. The Proposed Conceptual Classification of MOSO for FMS Design

There are many MOSO methods applied for FMS design. According to the previous literature review, it is better to classify them in three main groups: Group A, Group B, and Group C, as detailed in **Table 1**. This classification is applicable regardless of the articulation of DM's preferences. It should be noted that all of the previous MOSO methods that are applied in the design of FMS are global solutions.

Table 1. The proposed MOSO classification for FMS design.

	The Use of DoE	The Use of Metamodel	Description
Group A	Yes	Yes	First, using designing simulation experiments. Second, applying optimization method on metamodel. A priori DM preferences are generally applied.
Group B	Yes	No	First, using designing simulation experiments. Second, applying multi criteria optimization method on experiments. A priori DM preferences are generally applied.
Group C	No	No	Iterative simulation and optimization using principally metaheuristics for random design research such as simulated annealing, genetic algorithms, etc. Only in this group, the articulation of the preferences of the DM is important.

Table 2 summarizes the methods and techniques used in the MOSO methods used for FMS design. The presence of a cross "X" in a row and column intersection means that the research study stated in row use the method mentioned in column. It shows that all of the previous studies have applied a global solution method. These methods can be classified easily according the proposed classification in three groups (A, B, and C). Group C contains complex optimization techniques using metaheuristics, such as (GA, TS, EA, etc.). The performance of MOSO methods is not guaranteed because there is an absence of comparative studies. None of the previous studies has compared different MOSO methods.

Table 2. MOSO classification for FMS design (since year 2000).

Study	Method	Number of Objectives	Number of Factors	The Decision Maker's Preferences				The Research Set and Variables Nature			The Use of or Not
				A Priori	A Posteriori	Progressive	No-Preference	Ranking and Selection	Integer DV	Continuous DV	No Metamode
[12]	NSGA II	2	2				X				X
[13]	DoE, Weighted Sum, Weighted Product	3	2	X				X	X		
[14]	Taguchi design, GRA	2	4		X			X			
[15]	DoE, Regression metamodel, RSM	5	8				X		X		
[16]	NSGA-II, NRGA	2	2		X						X
[17]	Genetic Programming	2	10		X						X
[18]	NSGA-II	2	2		X						X
[19]	DoE, Regression meta-model, GP	2	5	X					X		
[20]	RSM	8	3				X		X		

Study	Method	Number of Objectives	Number of Factors	The Decision Maker's Preferences				The Research Set and Variables Nature			The Use of or Not
				A Priori	A Posteriori	Progressive	No-Preference	Ranking and Selection	Integer DV	Continuous DV	No Metamode
[21]	Taguchi (DoE), TOPSIS	3	5				X	X			X
[22]	NSGA-II	2	2		X						X
[23]	GA, TS	2	2				X				X
[24]	DoE, Regression meta-model, GP	2	5	X					X	X	
[25]	Non-Linear Programming, Evolution Strategy	3	6				X				
[26]	EA, ANN	2	2		X						X
[27]	Taguchi, GRA	2	5		X			X			
[28]	NSGA-II	2	3		X				X		X
[29]	DoE, regression metamodel	4	8	X							

5. Case Study

Researchers' main contribution is to fill these gaps in the literature and to conduct a study of several relatively straightforward simulation-based FMS optimization methodologies that cover almost all categories of optimization methods classification. Researchers' study investigates and compares the applicability and performances of the Goal Programming (GP), the Desirability Function (DF) method, the Grey Relational Analysis (GRA), and the VlseKriterijuska Optimizacija I Komoromisno Resenje (VIKOR) method.

The FMS investigated is inspired by Pitchuka et al. [30]. An FMS is a manufacturing system characterized by a certain flexibility that allows the system to react in the case of changes. This flexibility is considered to fall into two categories. The first one, called routing flexibility, generally covers the system's ability to be changed to produce new product types. The second category is called machine flexibility, which consists of the ability to use various machines to perform the same manufacturing operation on a part.

- To capture the FMS flexibility effect on its performance, this research adopts different machine LAYOUT (LAYOUT) for the studied FMS. Indeed, Functional Layout (FL) and Cellular Layout (CL) are the two most used machine layouts in FMSs. In FL, functionally similar machines are grouped into departments, and all machines of every department can perform production operations for any incoming part [31]. However, CL is made up of independent manufacturing cells. Each of these cells is made up of different machine types dedicated to the treatment of similar parts grouped into families. In addition, this work aimed also to measure the effect of part Batch Size (BS), part Inter-Arrival Time (IAT), and scheduling RULEs (RULE) on FMS performances (**Table 3**). The IAT, defined as the difference between the arrival times to the FMS of two consecutive parts, is generally generated by common probabilistic laws. In addition, parts are grouped into batches to reduce the machine's setup repetitions and transport times between work stations [31]. Furthermore, parts arriving at any work station are made to wait in a queue until the required machine becomes available. Once this required machine is idle, parts must be selected from the waiting queue based on scheduling rules [32][33][34]. As shown in **Table 3**, each of the considered FMS factors considered is studied with 2 levels.

All these methods are based on the DoE technique. They must be preceded by a design of experiments to program and sometimes analyze the simulation results. Moreover, these four multi-objective optimization methods have in common the type of preferences of the DM; indeed, they are all based on an a priori decision of the DM for the choice of the objectives. On the other hand, the two methods GP and DF use the simulation-based metamodel technique and combine continuous and integer decision variables to solve the multi-objective optimization problem, while the two other methods, GRA and VIKOR, are based on the RS technique and use exclusively integer decision variables. The solutions reached by the GP and DF methods are then global and those reached by the GRA and VIKOR methods are local. Researchers are interested in four multi-objective optimization methods in the context of the FMS. An application on an FMS system will be used as a basis to compare the performances of these methods. It is mainly a matter of comparing the deviations between their results and the expected target values.

The proposed methodology is essentially made up of three stages. Each of these stages consists of various steps. In the first stage, the primary step starts with the FMS factors levels and performance measures selection and definition. Consequently, DoE is constructs and corresponding simulation models are developed using ARENA 14 discrete event simulation software. In the final step of this first stage, simulations are run to collect data for every studied performance measure. These simulation results are then analyzed in the second phase by one of the four adopted multi-objective optimization methods. The steps of this phase are discussed in detail in the following paragraphs. Finally, the optimum factors levels are adopted in the last stage of the multi-objectives optimization meth.

Table 3 summarizes the performance of the four MSOSO methods being compared. Signs '+' and '-' are assigned to the optimization methods based on their achieved optimization results and their applicability. A '+' is assigned to each method resulting in a good optimization result which is expressed by a reasonable or small deviations. On the other hand, a '-' is assigned to each method that leads to an optimization result characterized by high deviations. For the applicability, a '-' is assigned to each method that requires a high level of analysis and expertise. In the opposite case, a '+' is assigned to this optimization method. These methods are then classified according to assigned signs. Any method obtaining two '+' signs will be considered the most efficient. On the other hand, if it obtains two '-' signs, it will be considered the most mediocre one. In the case where the optimization method obtains both signs '+' and '-' the classification gives priority to the obtained optimization result. The best method is VIKOR, which belongs to the group B in the proposed classification. It is followed by the GP method, from group A, since it reaches good optimization results, although it requires a considerable analysis effort. The GRA method, from group B, comes in third rank and the DF method, from the group A, closes the classification at the last rank. This classification shows that the use of optimization methods based on metamodel does not always give the best results.

Table 3. MOSO performances

MOSO	Group	Optimization result	Applicability	Rank
GP	A	+	-	2
DF	A	-	-	4
GRA	B	-	+	3
VIKOR	B	+	+	1

Various MOSO methods have been presented, developed, and used in the literature. These methods have been the subject of numerous classifications. However, the performance of these methods is not guaranteed due to the lack of comparative studies. Moreover, these classifications have been very diverse and rarely related to the specific domain of manufacturing systems.

The objective of this research is two-fold. First, researchers proposed a new conceptual classification of the MOSO methods applied to the context of MFS design. Second, four MOSO methods are selected according to this classification, and compared through a case study related to the FMS design problem inspired by the literature. This comparison is based on the quality of the optimal solutions obtained by these methods as well as the degree of difficulty of their applicability through the necessary analysis effort and the degree of expertise of the user of these methods. All these studied methods are based on the DoE. Two of them are metamodel-based approaches that incorporate the GP and the DF, respectively. The other two methods are not metamodel-based approach and incorporate GRA and VIKOR respectively. The comparative results show that the VIKOR method can lead to better optimization than the GP, GRA and DF methods in order. It is clear thus that the use of MOSOs based on meta-models does not give the best solution in all situations.

This entry compares four MOSO methods applied in the context of FMS design. Some future research perspectives should be addressed:

- In this entry, four MOSO methods are compared. Two methods belong to group A of the proposed new classification while the other two belong to group B. The extension of the current comparison to other MOSO methods belonging to group C is the first of researchers' interesting perspectives;
- The studied MOSO methods have been applied on a model of an FMS inspired from the literature. This model has six machines grouped in two cells in the CL and three departments in the FL. In addition, this FMS processes only four products grouped into two families. Extending the comparison performed in this entry to real and more complex FMSs to evaluate the reliability of MOSO methods is the second of researchers' interesting perspectives.
- The experimental design developed in this comparison study and which is the basis for the simulation results used in the analysis and generation of optimization solutions is based on the four factors IAT, BS, RULE, and LAYOUT. These four factors are explored on the basis of two levels each. This number of factors and levels remains relatively limited

and generates a limited number of experiments. The comparison of MOSO Methods in Manufacturing Systems characterized by a large number of factors and levels is the third of researchers' interesting perspectives.

- The application of the compared MOSO methods goes through different steps to generate optimization solutions. These steps usually require the intervention of a user to transfer the results from one step to another. The integration of these analysis and optimization steps into the simulation software, as in the case of the OptQuest tool in several simulation tools, would be a very interesting perspective

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