A Framework to Incorporate Decision-Maker Preferences Into Simulation Optimization to Support Collaborative Design

Selçuk Gören, Ahlem Baccouche, and Henri Pierreval

Abstract—**In this paper, we are concerned with the use of simulation optimization to handle collaborative design problems where more than one decision-maker is involved. We assume that the designers cannot enumerate all their considerations in closed-form, precise mathematical expressions but they can examine the merits of solutions with respect to their preferences and can compare candidate solutions with one another. We propose a three-stage framework to take the decision-makers' such considerations into account. The first step is to obtain a diverse set of designs that can all be considered efficient in terms of a performance metric (i.e., the objective function values of the simulation optimization model). These solutions are then passed on to the decision-makers to be analyzed in terms of their preferences that could not have been previously considered. Finally, the most appropriate solution is chosen. We address the problem encountered in the first step as a multimodal optimization problem. We address the second and the third subproblems as a preference aggregation problem in the social choice theory. We also illustrate the effectiveness of the proposed approach through a supply chain design problem inspired from the literature. We use the crowding clustering genetic algorithm as an example to demonstrate the first step. We use a multiplicative variant of the popular analytic hierarchy process to illustrate how the second and the third steps can be handled.**

Index Terms—**Analytic hierarchy process, collaborative design, decision-maker preferences, multimodal optimization, preference aggregation, simulation optimization, supply chain.**

I. Introduction

When designing systems, it is often necessary to determine the optimal values of some system parameters (e.g., the number of cranes in an harbor, the number of servers in a communication network, the buffer sizes, and the transportation lot-sizes in a manufacturing system) to obtain the best system performance. Simulation is one of the most widely used operations research methods for such problems [1], [2]. Simulation is preferred because of the complexity of the studied systems and of the presence of stochastic features. Moreover, one can easily change the parameters of the simulation model and re-evaluate the new system performance. If numerous parameters, however, are to be determined, the number of feasible solutions usually becomes too excessive to employ a trial-and-error search procedure. In such a case, it is necessary to use a simulation optimization method, which incorporates a search strategy [3].

Most simulation optimization approaches suggested in [3]–[5] provide a single solution to the design problem. This solution is deemed to be efficient due to its good performance in terms of the objective function that is employed in the simulation model. In some design problems, however, the judgment of how efficient a solution is can depend on other considerations than typical objective functions such as the cost, the average waiting time, or the average level of work-in-progress (WIP) inventory. In other words, the final solution to the design problem can be based on additional factors (e.g., the ease of implementation of a solution, the required time for implementation, the reliability of the design, and the availability of required resources), which can be judged to be of different importance by different decision-makers [6], depending on their responsibilities, expertise, and roles in the design team [7].

In such cases, one may think of employing multiobjective simulation optimization. Each relevant criterion can be formulated as a separate objective function and they can either be combined into a single composite objective function or can be optimized simultaneously to obtain a set of nondominated (i.e., Pareto-optimal) solutions. However, this type of approach may not be suitable for supporting group decisions. Another important difficulty is that in many cases the considerations of each decision-maker cannot be known in their entirety in advance, can be implicit or qualitative, or simply cannot be expressible in terms of objective functions or constraints. Moreover, some considerations are very difficult to quantify. As a consequence, they may not be formally included in the initial definition of the design problem. Furthermore, every simulation model, being a simplified representation of reality, cannot incorporate every single detail about the system, and generally involves simplifying assumptions, which again implies that some considerations may be overlooked or omitted.

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To cope with such issues, this paper addresses the problem of determining a design that can be found acceptable by several decision-makers (typically a design team), who may have different types of implicit considerations to be taken into account. We suggest an approach that aims at obtaining a solution that is the result of the cooperation between different decision-makers, rather than at imposing an "optimal" solution to everyone. In this respect, we suggest first to find a limited set of different designs that can be considered efficient by the decision-making team. The solutions are afterward passed on to each decision-maker to be examined in accordance with his/her own preferences. Finally, a collective solution that reflects the group choice is agreed upon. The rest of this paper is organized as follows. In Section II, we briefly review the use of simulation optimization for design problems. In Section III, we present the proposed three-staged methodological framework. In Section IV, the proposed approach is illustrated on a supply chain problem taken from the literature. In this section, we show how a multimodal simulation optimization algorithm can be used to search for a diverse set of efficient alternatives. We also illustrate how to aggregate individual preferences into a collective solution using a few analytic hierarchy process (AHP) variants with several levels of importance given to the decision makers of the group. Finally, our concluding remarks and future research directions are presented in Section V.

II. Simulation Optimization to Assist Designers

Simulation optimization is a frequently used operations research tool for the solution of various engineering problems and in the design of complex systems. Simulation optimization methods search for the best possible values of a vector of input variables (e.g., the number of machines and the number of operators), so as to optimize an objective function (e.g., expected total cost). There are several ways of formulating a simulation optimization problem. Tekin and Sabuncuoglu [3] express it as follows:

$$z^* = \min_{\boldsymbol{x}\in D} f(\boldsymbol{x}) \tag{1}$$

where $\boldsymbol{x} = [x_1, \ldots, x_n]^T$ is a vector of input variables in the domain $D = D_1 \times \ldots \times D_n$, D_i being the respective domain of x_i, $f(\boldsymbol{x})$ is the performance of $\boldsymbol{x}$ (evaluated using simulation), and z^* denotes the optimal objective value. The objective function is generally in the form of $f(\boldsymbol{x}) = \mathbb{E}[G(\boldsymbol{x}, \omega)]$, where $\mathbb{E}$ is the expectation operator. The quantity $G(\boldsymbol{x}, \omega)$ is called the sample performance, where ω represents the stochastic effects in the system.

We refer the reader to [3]–[5] and [8]–[10] for a review of theoretical developments and applications of simulation optimization. The techniques used for simulation optimization can roughly be divided into four categories: statistical methods (e.g., response surface methodology, ranking and selection, and multiple comparison procedures), metaheuristics [e.g., simulated annealing, tabu search, and evolutionary algorithms (EAs)], stochastic optimization (random search and stochastic approximation), and other methods that include ordinal optimization and sample path optimization. Li *et al.* [11] compare the most popular metamodeling techniques (e.g., regression and kriging). Regarding design problems, Pierreval and Paris [12] suggest more complex representations of design solutions to be able to address the so-called simulation configuration problems.

As noted in [13], most studies in the literature consider a single objective to be optimized. This can turn out to be insufficient to appropriately characterize a design solution. Recently, an increasing number of scholarly studies have addressed multiobjective problems so that (1) in the above formulation becomes simultaneous (vector) minimization of m separate objective functions

$$z^* = \min_{x\in D} f_1(\boldsymbol{x}), \ldots, f_m(\boldsymbol{x}). \tag{2}$$

Multiobjective algorithms usually search for a Pareto set [14]. As highlighted in [13], classical simulation optimization approaches implicitly assume that the solution found is the most preferable solution for the end user, which may not be the case in practice, in particular when we deal with a collective decision-making problem. In addition, these approaches assume that the design problem is totally determined by its constraints and objective function(s).

In this respect interactive optimization methods have emerged to better incorporate decision-maker preferences into the optimization process. Unfortunately, interactive optimization has not attracted a significant research attention from the simulation optimization community, even though there are a few studies (see [15]). The reason is especially when the simulation model is stochastic, long runs or high number of replications may require too many decision-maker interventions for the approach to be practical. Rosen *et al.* [13] suggest an alternative approach. The authors first obtain a functional relation between the inputs and outputs of the simulation model using response surface methodology. This function is then optimized taking the preferences of the decision-maker into account (see also [16]). Unfortunately, this approach has two shortcomings with respect to the problem addressed in this paper. The first is that it is not suitable for cases where a group of decision-makers instead of just a single decision-maker exist, and second, it relies on the assumption that the decision-makers have enough quantitative knowledge about what they have in mind in advance, so that the required metamodel can be built and parameterized. In practice, however, it is difficult to formulate mathematical models that capture the preferences of the decision-makers accurately. Although incorporating cooperation has attracted some attention in the simulation literature (see [17]), to the best of our knowledge, it has never dealt within the simulation optimization context. In the next section, we suggest an approach to cope with such issues.

III. Three-Stage Framework: Multimodal Optimization and Preference Aggregation

A. General Principles

As noted in [18], decision-makers might prefer a solution with slightly lower performance to the one with the best

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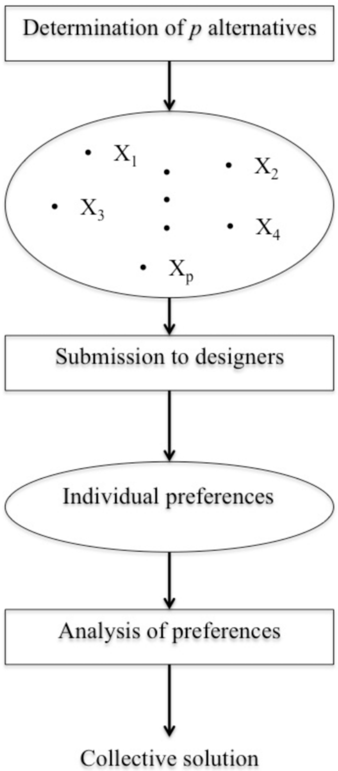

Fig. 1. Proposed three-stage approach.

performance as long as the former is considered efficient enough and provides other advantages. The additional advantages might not be quantitative and measurable so that they can be incorporated into a simulation model easily. For example, the decision-maker may want to avoid solutions that are difficult to implement, which is a subjective criterion that requires expert opinion of the decision-maker. In this respect, providing several efficient solutions to choose from instead of only the "best" obtained using a classical simulation optimization technique, can offer more flexibility to the decision-makers. Our aim is to create and exploit this flexibility through a three-stage approach, which is summarized in Fig. 1.

The first step consists of providing the design team with a set S of p efficient solutions (i.e., $|S| = p$). Efficiency here is characterized with respect to some performance measure(s) (e.g., the level of WIP inventory, the average waiting time of customers in the system, and the total transportation cost), which can be estimated using simulation.

We assume that no team member would accept a solution that is not efficient enough. Therefore, formally, we are interested in obtaining a set $S \subset D$ with the property

$$f(\boldsymbol{x}) \leq (1+\theta)z^*, \forall \boldsymbol{x} \in S \tag{3}$$

where $\theta > 0$ is a small real number. Here, θ can be interpreted as the maximum percentage of degradation in performance that the decision-makers are willing to accept (e.g., 5%). To achieve the aimed flexibility, it is important that the solutions obtained in this stage are different enough from one another. A true flexibility can only be obtained with diverse alternatives, for similar designs are expected to have similar characteristics.

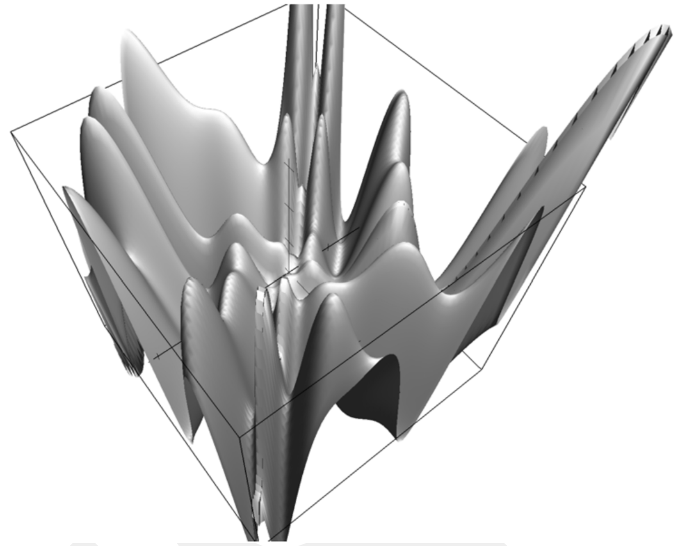

Fig. 2. Multimodal function.

Once a diverse set of designs is available, the decision-makers can analyze the solutions and determine how well each solution meets their considerations. Note that the considerations used in this step are different from those incorporated in the objective function(s) at the beginning. Finally, in the third step, the preferences identified using the insights gained in the previous step are aggregated to determine a solution that is likely to be collectively acceptable. In the following, we present how to address the first stage. Next, we will deal with how preferences are collected and processed to suggest a collectively acceptable solution.

B. Finding Diverse Set of Efficient Solutions: Multimodal Simulation Optimization Approach

We suggest addressing the first subproblem using multimodal optimization to find a set S of p diverse alternatives that are efficient and different enough. Multimodal optimization deals with finding the local optima of a multimodal function (see Fig. 2).

Classical optimization techniques would need multiple restart points and multiple runs with the hope that a different solution will be discovered every run. As an alternative, several metaheuristics have been used for multimodal optimization in [19]–[22]. Among different metaheuristics, EAs have been found to have an advantage in multimodal optimization [23] due to their population-based approach. Most of the existing studies in the literature are concerned with the optimization of a continuous function $f : \mathbb{R}^n \to \mathbb{R}$. As far as simulation optimization is concerned, multimodal optimization seems to have been little addressed in the literature.

Classical evolutionary simulation optimization has been discussed in [24]. In this paper, we employ a multimodal algorithm to lead the search for local optima of (1) in the feasible region. Afterward, among these local optima, those that are

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considered efficient enough are selected in accordance with (3) to obtain the set S of p efficient and diverse solutions. One benefit of EAs lies in the fact that the use of a population allows niches [25] to be defined and managed throughout the optimization process.

Niches divide the population into different subpopulations and drive them toward different local optima. Identifying and maintaining niches is a key mechanism in multimodal optimization since we aim at finding different-enough efficient solutions. Niching is known to reduce the effect of genetic drift (i.e., convergence to a single optimum) that is observed in standard EAs. Various niching approaches (e.g., crowding, clearing, clustering, and sharing) have been studied in [26]–[29].

Among various multimodal optimization methods in the literature, several can be used to handle the first subproblem. For the sake of illustration, in Section IV, we will use a recently published crossover based EA, namely the crowding clustering genetic algorithm (CCGA) that has been reported to have superior efficiency in comparison to other methods on standard multimodal tests functions [30]. However, other types of algorithms can be used for the same purpose in our methodology.

C. Incorporating the Preferences of the Decision-Makers

Once p different enough alternatives with acceptable performances are identified, we incorporate the preferences of the decision-makers. Incorporating the decision-maker's preferences into the optimization process has been well studied, especially in the interactive optimization literature. The preferences of the decision-maker can be articulated in three possible ways: *a priori*, progressively, and *a posteriori*. In *a priori* formalization, the preferences are gathered before the optimization process. As explained earlier, this paper handles the case where the decision-makers cannot precisely quantify their preferences in terms of objective functions or value/utility functions. Hence, *a priori* articulation is not suitable for the problem that we consider. In progressive formalization, the decision-maker intervenes in optimization process intermittently to guide the search procedure to interesting parts of the feasible region. As mentioned earlier, this option is also not practical when using simulation optimization. Hence, we opt for employing an *a posteriori* articulation of the preferences, In this stage, we assume that even if a decision-maker may find it difficult to express all his/her considerations quantitatively, he/she can still accurately determine how well a solution satisfies his/her needs and which solution appears to be the most preferable one, once several candidates are presented for his/her evaluation. All the members of the decision-making team must examine the candidates and express their own judgments. Besides the performance of the alternatives, as they all have acceptable performance levels, other considerations such as the execution costs, the easiness of implementation, the technical difficulties that can be encountered, and the end-user acceptance can play an important role in this step. Such considerations can be quite difficult to include in a simulation model beforehand.

Several methods exist in the literature to express group preferences (see [7]), and therefore, could be used in the methodology suggested in this paper. In accordance with the method selected in the next stage, for example, the candidate solutions can be compared pair by pair by each decision-maker, and can be collected in a pair wise comparison matrix, as it will be explained later.

IV. Application to Supply Chain Problem

A. Problem Addressed

Optimization is often required when addressing supply chain problems [31]. The use of simulation in this context is common (see [32], [33]). Our purpose in this section is to illustrate the proposed framework on an application problem that is inspired from the industry and is described in [34]. The considered supply chain is composed of two sites: a supplier and a distribution center. The supplier manufactures the products, which are then transported to the distribution center in a truck. The customer demand is withdrawn from the distribution center when there are available products. If it is found out that no product is available upon arrival of a customer demand, a production order is sent to the supplier to replenish the stock in the distribution center. Three types of parts $P_m, m = 1, 2, 3$ are produced. The demand for the products is based on the following mix: $65\%P_1, 25\%P_2$, and $10\%P_3$.

The supplier's manufacturing system consists of a production line of three consecutive workstations. The inventory of raw material is assumed to be infinite. The production is controlled in accordance with the just-in-time philosophy. Specifically, different Kanban loops are used to control the production of each type of product. The parts spend deterministic amounts of processing times in each workstation. The production is performed in batches with constant lot-sizes that are to be determined. A truck delivers batches of products to the distribution center. The transportation lot-size for each product type is also constant once determined. A truck visits the supplier at every 4 h.

The design problem consists in determining the values of the following parameters for each part type.

1) $KB_m \in [10, 30]$: Number of Kanban cards for part type m.
2) $TLS_m \in [1, 20]$: Transportation lot-size for part type m.
3) $PLS_m \in [1, 10]$: Production lot-size for part type m.

In other words, the vector $\boldsymbol{x} = [\text{KB}_1, \text{KB}_2, \text{KB}_3, \text{TLS}_1, \text{TLS}_2, \text{TLS}_3, \text{PLS}_1, \text{PLS}_2, \text{PLS}_3]^T$ encodes a configuration of the considered system. The objective is to minimize the average manufacturing cost and the average inventory holding cost associated with the WIP buffers. Formally, we consider the following problem:

$$\min_{\boldsymbol{x}} f(\boldsymbol{x}) = hI(\boldsymbol{x}) + \sum_{m=1}^{3} c_m N_m(\boldsymbol{x}) \quad (4)$$

where h is the inventory cost incurred by holding one unit WIP (of any part type) for one unit time, $I(\boldsymbol{x})$ is the average WIP inventory level, c_m is the manufacturing cost incurred by processing one part of type m per unit time, and N_m is the average number of parts of type m actively processed in

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workstations. We estimate $f(\boldsymbol{x})$ using a long nonterminating simulation run for any given configuration $\boldsymbol{x}$. The run length is decided to be 80 000 h in our experimentation, with a warm-up period of 4000 h (to allow the system to reach the steady-state) after some preliminary runs.

Recall that the first stage of the proposed methodology consists of providing the design team with a limited set S of p efficient solutions. Efficiency in this example is characterized by the average manufacturing and inventory holding cost, which is estimated using simulation as explained before.

B. Stage 1: Finding Diverse Set of Efficient Solutions

Among the various multimodal optimization methods available in the literature, several can be used to handle this stage. For the sake of illustration, we use a recently published crossover-based EA, called the CCGA, which has been reported superior in identifying and maintaining different niches on standard multimodal tests functions in comparison with alternative methods [30]. CCGA provides a mechanism for generating multiple optima by combining a clustering strategy to form niches and a crowding method to eliminate genetic drift by introducing competitions between clusters of the same niche.

In CCGA, an initial population of size PopNum is randomly generated. The population is afterward randomly arranged in PopNum/2 couples of parents. Each couple is subject to a crossover operation to generate two children (offspring). Next, the iterative part of the algorithm begins. At each iteration, the children $C_i, i = 1, \ldots, \text{PopNum}$, are paired with their nearest parent under a distance metric $D(.,.)$ to form clusters, which corresponds to a standard crowding method with a crowding factor of PopNum. The individuals within each cluster are then sorted according to their fitness values and the individual with the highest fitness value is called the center of that cluster, denoted by CC_j for cluster j. Next, the clusters are sorted in ascending order of fitness values of their centers and nearby clusters are merged to avoid identifying too close clusters as different niches, if necessary (see step 5 in Algorithm 1). The concept of peak detection, however, is utilized to prevent truly different niches from being destroyed, just because their centers happen to be too close to each other under the metric $D(.,.)$. Finally, the centers of the surviving clusters and a set of uniformly distributed individuals that are generated anew to keep the population size constant at PopNum, constitute the parents of the next generation, and the next iteration begins. The algorithm terminates when a given number of generations is reached. Qing *et al.* [30] do not use mutation and rely merely on crossover and on the introduction of new individuals in step 5 to maintain diversity while solving their example problem. Note that in orthodox genetic algorithms, a fine-tuned mutation operator is usually necessary to avoid genetic drift and premature convergence of the algorithm. In the case of the CCGA, since the algorithm is intrinsically designed to avoid genetic drift via clustering and crowding mechanisms, omitting mutation is considered justifiable.

We coded the CCGA algorithm in the C++ language, where the fitness evaluations are carried out with the help

Algorithm 1 Crowding Clustering Genetic Algorithm

Step 1. Initialize a uniformly distributed population with the size *PopNum*.

Step 2. Recombine parents to generate *PopNum* children.

Step 3. For each parent $P_j, j = 1, \ldots, PopNum$, construct a cluster. Put each child $C_i, i = 1, \ldots, PopNum$, into the cluster of its nearest parent P_j under the distance metric $D(.,.)$.

Step 4. For each cluster $j, j = 1, \ldots, PopNum$, select the fittest individual CC_j as the center of cluster. For the other individuals in the cluster, calculate their distances to the center; select the maximum distance as the radius of cluster j, denoted by CR_j.

Step 5. Sort the clusters in ascending order of their fitness. Define a set of *reserved clusters* $RC = \emptyset$. Each cluster i in RC has a center RCC_i, and a radius RCR_i, which has been calculated in the previous step. Compare cluster $j, j = 1, \ldots, PopNum$ with the current clusters in RC, and if for all i, $D\big(CC_j, RCC_i\big) > RCR_i$, or $Peak\big(CC_j, RCC_i\big) = 1$, place CC_j into RC, and update the radius of the cluster as $\min\big(CR_j, D\big(CC_j, RCC_i\big)\big)$. Here, the *peak detection condition* is

$$Peak\big(CC_j, RCC_i\big) = \begin{cases} 1, & \text{if } f\Big(\frac{CC_j + RCC_i}{2}\Big) > \frac{f(CC_j) + f(RCC_i)}{2}, \\ 0, & \text{otherwise.} \end{cases} \quad (5)$$

Step 6. Let NRC be the number of elements in the set of reserved clusters RC. Generate $(PopNum - NRC)$ additional uniformly distributed individuals. These individuals and the centers of clusters in RC form the next generation.

Repeat Step 2–Step 6 until the maximum generation number *MaxGen* is reached.

TABLE I
SELECTED SOLUTIONS

No	Average Cost	KB_1	KB_2	KB_3	TLS_1	TLS_2	TLS_3	PLS_1	PLS_2	PLS_3
1	8314.11	20	13	13	18	12	6	1	2	7
2	8537.20	20	13	13	20	6	7	10	6	4
3	8752.36	22	19	19	18	18	3	5	6	5
4	8880.00	20	16	16	19	9	9	1	8	10
5	8932.74	18	18	18	18	14	14	6	5	7

of a simulation model. In our CCGA implementation, we use a vector of nine integers (i.e., $\boldsymbol{x} = [\text{KB}_1, \text{KB}_2, \text{KB}_3, \text{TLS}_1, \text{TLS}_2, \text{TLS}_3, \text{PLS}_1, \text{PLS}_2, \text{PLS}_3]^T$) as our chromosomes, a single-point crossover operation during the recombination, and the Euclidian distance as the distance metric to form niches and to select reserved clusters (steps 2 and 5 in Algorithm 1, respectively). After several empirical test runs, the population size is taken to be 50 and the stopping criterion is to reach 500 generations.

We obtain 39 solutions, which are the centers of the reserved clusters. The best solution has an objective function value of 8314.11.

C. Stage 2: Selecting Promising Solutions

We now assume that the decision-making team consists of three decision-makers, who find losing a maximum of, say, 7.5% degradation in the performance to be acceptable, as long as there are significant benefits in terms other considerations, such as the easiness of implementation or the sustainability of the design. We are left with five alternative designs, which are given in Table I.

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Algorithm 2 AHP Algorithm

Step 1. Construct the comparison matrices $A^a = \{r^a_{ij}\}$, where r^a_{ij} is the judgment of the decision-maker $a = 1, \ldots, d$ as how design i compares to design j for all $i, j \in \{1, \ldots, k\}$. We use the linear scale from 1 to 9 suggested in [36] (see Table II) for the intensity values of the comparisons. If i is preferred to j, r^a_{ij} is the actual intensity value, else if j is preferred to i, r^a_{ij} is the reciprocal of the intensity value.

Step 2. For each decision-maker, obtain the priority vector $F^a = \gamma \prod_{j=1}^{k} \left(r^a_{ij}\right)^{\frac{1}{k}}, a = 1, \ldots, d$, where γ is a normalizing constant whose value is determined such that $\sum_{i=1}^{k} F^a_i = 1$.

Step 3. Rank alternative design i according to its preference score R_i, which is obtained by GMM. That is, $R_i = \prod_{a=1}^{d} \left(F^a_i\right)^{\frac{1}{d}}$. Note that R is not normalized, for it would not change the ranking.

D. Stage 3: Selecting the Collectively Acceptable Solution

The objective of this stage is to determine which of the p solutions could be found acceptable by the entire design team. We address this problem as a preference aggregation problem in social choice theory. Among a plethora of possible techniques, we have selected the AHP to handle this stage, as it is well-known, can handle qualitative or subjective judgments, is used by many researchers and is flexible enough to accommodate different perspectives such as unequal weights of decision-makers, and various scales to be used during pairwise comparisons (e.g., to handle different attitudes of different decision-makers toward risk). Indeed, Vaidya and Kumar [35] review 150 articles investigating the use of AHP in a wide range of applications. AHP, developed by Saaty [36], has often been used in the last two decades to model subjective decision-making processes based on multiple attributes. In a recent review [37], the author observes that many tools can be used in connection with AHP, such as mathematical programming, metaheuristics, quality function deployment, and Strengths, Weaknesses, Opportunities, and Threats (SWOT) analysis.

It is known that a shortcoming of the original AHP is its inability to guarantee a consistent rank ordering of alternatives when identical copies of alternatives are added to the set [38]. That is, independence of irrelevant alternatives is not guaranteed. Fortunately, a multiplicative variant of the original AHP, which does not suffer from such possible rank reversals, is already available in [38]. We use this multiplicative AHP variant in this paper.

AHP requires determining pairwise comparison matrices of solutions either by a consensus voting or by aggregating individual judgments. In the case of consensus voting, decision-makers agree upon a single value for each pairwise comparison. Since this process is tedious and time consuming, often the method of combining individual judgments is preferred [39]. The geometric mean method (GMM) and the weighted arithmetic mean method (WAMM) are two widely used methods to combine individual pairwise comparisons into a collective judgment. When equal importance is given to all the members in a decision-making team, GMM seems to be considered as the appropriate method for combining judgments [40]–[42]. In this paper, we use GMM to aggregate individual preferences.

The algorithm is summarized in Algorithm 2, given that we have k alternative solutions in the second stage and we have d decision-makers in the design team.

To illustrate the procedure of deciding on a collective design, consider the first decision-maker. Suppose that he/she prefers design 2 to design 1 because the production batch sizes are larger in design 2 and in his/her judgment, it is desirable to have longer production runs with minimal setup and changeover times.

Consider now the second decision-maker. Suppose that he/she prefers design 3 to design 2 because production batch sizes are smaller in design 3 and in his/her judgment, this provides the production process with flexibility, which is useful for example in case of rush orders or unexpected breakdowns.

To keep the example short, we assume that the rankings of alternatives for decision-makers 1, 2, and 3 are $(2 \succ 5 \succ 1 \succ 3 \succ 4)$, $(5 \succ 3 \succ 4 \succ 2 \succ 1)$, and $(3 \succ 5 \succ 2 \succ 4 \succ 1)$, respectively, where $A \succ B$ denotes that A is preferable to B. It is important to recall that these rank orderings are not due to the resulting average costs of the designs as all the alternatives have very good cost values, but due to personal judgments and preferences of the decision-makers. We now aggregate these preferences to obtain a single collective design.

Step 1: Assume that the comparison matrices are as follows:

$$A^1 = \begin{bmatrix} 1 & \frac{1}{4} & 2 & 4 & \frac{1}{2} \\ 4 & 1 & 6 & 8 & 2 \\ \frac{1}{2} & \frac{1}{6} & 1 & 2 & \frac{1}{4} \\ \frac{1}{4} & \frac{1}{8} & \frac{1}{2} & 1 & \frac{1}{6} \\ 2 & \frac{1}{2} & 4 & 6 & 1 \end{bmatrix}$$

$$A^2 = \begin{bmatrix} 1 & \frac{1}{2} & \frac{1}{6} & \frac{1}{4} & \frac{1}{8} \\ 2 & 1 & \frac{1}{4} & \frac{1}{2} & \frac{1}{6} \\ 6 & 4 & 1 & 2 & \frac{1}{2} \\ 4 & 2 & \frac{1}{2} & 1 & \frac{1}{4} \\ 8 & 6 & 2 & 4 & 1 \end{bmatrix}$$

$$A^3 = \begin{bmatrix} 1 & \frac{1}{4} & \frac{1}{8} & \frac{1}{2} & \frac{1}{6} \\ 4 & 1 & \frac{1}{4} & 2 & \frac{1}{2} \\ 8 & 4 & 1 & 6 & 2 \\ 2 & \frac{1}{2} & \frac{1}{6} & 1 & \frac{1}{4} \\ 6 & 2 & \frac{1}{2} & 4 & 1 \end{bmatrix}.$$

Step 2: We obtain the following priority vectors:

$$F^1 = \begin{bmatrix} 0.1427 & 0.4690 & 0.0756 & 0.0434 & 0.2694 \end{bmatrix}^T$$
$$F^2 = \begin{bmatrix} 0.0434 & 0.0756 & 0.2694 & 0.1427 & 0.4690 \end{bmatrix}^T$$
$$F^3 = \begin{bmatrix} 0.0434 & 0.1427 & 0.4690 & 0.0756 & 0.2694 \end{bmatrix}^T.$$

Step 3: We obtain the scores vector

$$R = \begin{bmatrix} 0.0645 & 0.1716 & 0.2121 & 0.0776 & 0.3241 \end{bmatrix}^T.$$

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TABLE II
LINEAR SCALE SUGGESTED BY SAATY [36]

Intensity of Preference	Definition
1	Equal preference
3	Weak preference of one over another
5	Essential or strong preference
7	Demonstrated preference
9	Absolute preference
2, 4, 6, 8	Intermediate values between two adjacent judgments
Reciprocals of above	

TABLE III
EXPONENTIAL SCALE SUGGESTED BY TRIANTAPHYLLOU *et al.* [43]

Intensity of Preference	Definition
e_0	Equal preference
e_1	Indifference threshold
e_2	Weak preference
e_3	Commitment threshold
e_4	Strong preference
e_5	Dominance threshold
e_6	Very strong preference
Reciprocals of above	

Therefore, from this scores vector R, we deduce the ranking: $(5 \succ 3 \succ 2 \succ 4 \succ 1)$. We can see that solution 5 receives the highest score and therefore it is the one that will be suggested.

1) Some Variations: In the above example, we assumed that all decision-makers are equally important. If this assumption is not true in an application, Algorithm 2 can be modified to cover cases where different decision-makers with varying importance. For that case, the most frequently used approach is to aggregate the preferences of the decision-makers according to the WAMM. Specifically, we modify step 3 in Algorithm 2 as follows.

"Rank alternative design i according to its preference score R_i, which is obtained by WAMM. That is, $R_i = \sum_{a=1}^{d} w^a F_i^a$, where w^a is the weight assigned to decision-maker a, $a = 1, \ldots, d$, and we should have $\sum_{a=1}^{d} w^a = 1$."

To illustrate, assume that in the above example, $\boldsymbol{w} = \begin{bmatrix} 0.8 & 0.1 & 0.1 \end{bmatrix}^T$ represents the weights of the decision-makers. Then, $F^a, a = 1, 2, 3$ are unchanged but the new aggregate preference score is

$$R' = \begin{bmatrix} 0.1228 & 0.3970 & 0.1343 & 0.0566 & 0.2894 \end{bmatrix}^T.$$

Therefore, from the new scores vector R', we deduce the ranking $(2 \succ 5 \succ 3 \succ 1 \succ 4)$ instead of $(5 \succ 3 \succ 2 \succ 4 \succ 1)$. We can see that solution 2 (instead of 5) receives the highest score, and therefore, it is the one that will be suggested. Note that the new ranking is very much like the ranking of decision-maker 1 $(2 \succ 5 \succ 1 \succ 3 \succ 4)$ due to his/her overwhelming weight of 0.8.

Second, we previously used the original linear ranking due to Saaty [36] in step 1. The scale issue is a complex problem. No single scale can always be classified as the best. We refer the reader to [43] for comparisons of various scales and a discussion on what factors have to be analyzed to determine the appropriate scale. In some applications, for example, an exponential scale is more relevant. Step 1 of Algorithm 2 can easily be modified to accommodate the new scale. Suppose that we were to use the following exponential scale given in Table III, with $e_n = e^{0.5n}, n = 0, \ldots, 6$.

Using Tables II and III, we can reasonably assume the following transformations from the linear scale to the exponential scale: $1 \to e_0$, $2 \to e_1$, $4 \to e_3$, $6 \to e_4$, and $8 \to e_5$. Consequently, the new analysis is as follows.

1) The comparison matrices are as follows:

$$A^1 = \begin{bmatrix} 1 & 0.0498 & 2.7183 & 20.0855 & 0.3679 \\ 20.0855 & 1 & 54.5982 & 148.4132 & 2.7183 \\ 0.3679 & 0.0183 & 1 & 2.7183 & 0.0498 \\ 0.0498 & 0.0067 & 0.3679 & 1 & 0.0183 \\ 2.7183 & 0.3679 & 20.0855 & 54.5982 & 1 \end{bmatrix}$$

$$A^2 = \begin{bmatrix} 1 & 0.3679 & 0.0183 & 0.0498 & 0.0067 \\ 2.7183 & 1 & 0.0498 & 0.3679 & 0.0183 \\ 54.5982 & 20.0855 & 1 & 2.7183 & 0.3679 \\ 20.0855 & 2.7183 & 0.3679 & 1 & 0.0498 \\ 148.4132 & 54.5982 & 2.7183 & 20.0855 & 1 \end{bmatrix}$$

$$A^3 = \begin{bmatrix} 1 & 0.0498 & 0.0067 & 0.3679 & 0.0183 \\ 20.0855 & 1 & 0.0498 & 2.7183 & 0.3679 \\ 148.4132 & 20.0855 & 1 & 54.5982 & 2.7183 \\ 2.7183 & 0.3679 & 0.0183 & 1 & 0.0498 \\ 54.5982 & 2.7183 & 0.3679 & 20.0855 & 1 \end{bmatrix}.$$

2) We obtain the following priority vectors:

$$F^1 = \begin{bmatrix} 0.0531 & 0.7146 & 0.0131 & 0.0039 & 0.2152 \end{bmatrix}^T$$
$$F^2 = \begin{bmatrix} 0.0039 & 0.0131 & 0.2152 & 0.0531 & 0.7146 \end{bmatrix}^T$$
$$F^3 = \begin{bmatrix} 0.0039 & 0.0531 & 0.7146 & 0.0131 & 0.2152 \end{bmatrix}^T.$$

3) We obtain the scores vector

$$R'' = \begin{bmatrix} 0.0094 & 0.0792 & 0.1263 & 0.0140 & 0.3211 \end{bmatrix}^T$$

by aggregating the F^a using GMM. We deduce the ranking: $(5 \succ 3 \succ 2 \succ 4 \succ 1)$. We can see that solution 5 receives the highest score, and therefore, it is the one that will be suggested.

Incidentally, this ranking agrees with the ranking we have obtained previously using the linear scale of Saaty [36].

Even though we have shown that the AHP algorithm can neatly handle stage 3 of the proposed methodological framework, let us once more remind the reader that relevant methods in the multicriteria decision making literature can be used to obtain rankings for each decision-maker. Likewise, individual rankings can be combined using any appropriate method in social choice theory.

V. CONCLUSION

In several design problems, a solution can have collective consequences that are experienced by different people with different responsibilities (typically, a team of designers). In such cases, the problem should be addressed in a collective manner so that everyone's considerations are taken into account. It is not uncommon that the considerations of the decision-makers are not known entirely in advance, are implicit or qualitative. As a consequence, they may not be included in the initial definition of the optimization problem, and can only be taken into account once a candidate solution is proposed. To cope with such difficulties, we suggest a possible methodological approach, which aims at introducing flexibility by providing

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several efficient candidate solutions and then aggregates the preferences of the decision-makers.

We show how a multimodal simulation optimization can be used to provide several distinct good solutions. As most approaches based on metaheuristics, we are not certain that the local optima will be found and we have to rely on the efficiency of the niching strategy and the implemented genetic algorithm. We, however, provide p solutions rather than a single one; this decreases the risk of missing a good efficient solution. The CCGA is used in our illustration because of its reported encouraging performance in the literature. Meanwhile, other algorithms can also be used with minor modifications on the methodology that we propose (e.g., multipopulation methods, such as [44]). Similarly, AHP is selected to analyze preferences of the decision-makers due to its wide use in the literature. Again, other methods in multicriteria decision making literature could be used to rank alternatives designs and consequently the preferences of the decision-makers could be aggregated using other methods in social choice theory.

Several further research directions can be highlighted. First, the proposed framework can be improved. Probably the most important improvement is taking stochastic issues in the selection of solutions and in the aggregation procedure (e.g., incorporating statistical comparisons) into account in a better way. Second, the proposed framework is only a first-attempt to handle the problem of group decision-making where some concerns cannot be incorporated into the model beforehand due to certain reasons. Alternative approaches may be developed to address the problem. Comparison of these alternatives and identifying the circumstances under which each alternative performs the best could be a worthwhile study. Another fruitful research direction could be investigating other techniques of preference aggregation, especially those that can deal with fuzzy or uncertain preference relations, and those that can allows an interaction with the decision-makers (see [13], [14], [45], [46]). Along with the same lines, the sensitivity or robustness of the framework to the choice of individual algorithms in steps 2 and 3 could be investigated. In other words, further analysis is needed analyze how final solution changes if we change the algorithms used in step 2 or step 3. Let us finally note that computational time could be reduced through parallelization of the proposed approach.

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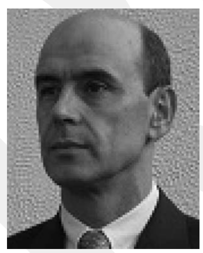

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