A Three-Level Decision Support Approach Based on Multi-objective Simulation-Optimization and DEA: A Supply Chain Application

Luís Pedro Gomes, António Vieira, Rui Fragoso, Dora Almeida, Luís Coelho, and José Maia Neves

Abstract Decision-making in multi-objective problems is a complex problem with several approaches existing in the literature. Many such approaches typically combine simulation and optimization methods to achieve a robust tool capable of providing useful information to decision-makers. While simulation helps decision-makers to test alternative scenarios and allows uncertainty to be considered, optimization enables them to find the best alternatives for specific conditions. This paper proposes an alternative approach consisting of three levels, wherein we use simulation to model complex scenarios, simulation-optimization to identify the scenarios of the Pareto-front, and Data Envelopment Analysis to identify the most efficient solutions, including those not belonging to the Pareto-front, thereby exploiting the benefits of efficiency analysis and simulation-optimization. This can be useful when decision-makers decide to consider scenarios that, while not optimum, are efficient for their decision-making profile. To test our approach, we applied it to a supply chain design problem. Our results show how our approach can be used to analyze a given system from three different perspectives and that some of the solutions, while not optimum, are efficient. In traditional approaches, such scenarios could be overlooked, despite their efficiency for specific decision-making profiles.

Keywords Simulation · Multi-objective simulation-optimization · Data envelopment analysis · Supply chain design · Decision-making · Efficiency

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1 Introduction

Decision-making is an essential process in every business. The decision-makers may require proper methods to help them, especially when dealing with complex systems where the objectives under analysis conflict with themselves, such as in multi-objective complex problems [1]. Some of these methods include the use of optimization and simulation to find solutions that are suitable for decision-makers [2–4].

Simulation is extremely useful and insightful when dealing with the dynamics of systems with considerable variability. It can easily incorporate randomness in any process, enabling the analysis of what-if scenarios. This can lead to valuable insights being obtained, including those triggered by events that were previously not considered or those triggered by propagations throughout the time of certain events, potentially leading to overlooked events considerably affecting the system's overall performance. Even so, simulation is not traditionally used to find optimum solutions. Conversely, optimization can be used to find the best or the best set of solutions, including the set of non-dominated solutions in multi-objective problems [5]. As these methods have pros and cons, many authors combine both in different frameworks. For instance, Wang et al. [3] combined the simulation of the behavior of subway passengers to refine a multi-objective optimization to minimize train operation costs and passenger waiting times. Ramirez et al. [4] used simulation and optimization to minimize oil and gas industry costs and time. Nnene et al. [2] used simulation and optimization to solve a transit network design problem, in which simulation evaluates alternative network solutions by simulating travel demand on them while a multi-objective optimization algorithm searches for efficient network solutions. Simulation-optimization is thus a powerful decision-making tool that has the ability to capture intricate relationships and interactions among several entities in a real-world complex system and identify the best design point [6]. This approach searches design points within the design space to optimize performance measures [7].

The first and most important principle of efficiency is to obtain the best result through the minimum use of resources [8]. Therefore, the success of an organization depends on its efficiency, so the measurement of efficiency helps not only to identify inefficiencies but also helps in the development of the organization through the elimination or minimization of these inefficiencies [8]. Taleb [9], for instance, integrated discrete event simulation and data envelopment analysis (DEA) to measure performance and evaluate the efficiency of potential resource allocation configurations for future performance improvement in emergency departments.

Despite the importance of previous approaches, specific decision-makers may be willing to explore certain dominated or non-optimum scenarios due to individual preferences or because, in their view, there can be other scenarios that, while dominated, are more efficient [10].

Our motivation was to develop a decision-making approach that allows decision-makers to choose the most efficient solution for their specific preferences, in a set of high uncertainty, even though it is a dominated one.

To test our approach, we selected a hypothetical case study consisting of a supply chain design problem, in which simulation is a well-known effective tool to aid decision-makers [6, 7].

This paper is structured as follows. The next section covers the methodology adopted for this research. Namely, the section briefly covers the proposed approach and describes the problem that was considered to apply the proposed approach. In its turn, the third section presents and discusses the obtained results. Finally, the last section discusses the main conclusions of this research.

2 Data and Methodology

This section describes the hypothetical case adopted to apply our approach (the first subsection) and the methodology followed in this research (the second subsection), particularly the three levels of decision-support that were incorporated. This description also details how each of the decision-making levels was modeled.

2.1 A Supply Chain Design Problem

This subsection describes the case that was considered for our research. In this sense, we decided to consider the problem of supply chain design, in which several suppliers can be selected to provide materials to a manufacturing company. Supplier selection is of extreme importance, therefore a comprehensive approach to decision-making is highly desirable [11].

The company receives orders modeled with a negative exponential distribution with an average of 15 min, where each order can consume up to nine stock units of a particular material. The company can partner with five suppliers in the market for necessary supplies. The suppliers have proposed to the company the delivery times and fixed costs with orders that are shown in Table 1.

Table 1 Suppliers data

Supplier	Average lead time (days) used in the poisson distribution	Fixed cost per order (€)
Supplier1	21	500
Supplier2	24	500
Supplier3	41	100
Supplier4	13	2000
Supplier5	6	5000

Regarding the company costs, it was decided to use a variable rupture cost modeled by the Poisson distribution with an average value of 1500€. We opted for this approach to add increased variability to the model. The company faces the problem of considering several objectives and defining the best supply chain configuration for different decision profiles, namely by considering the following parameters:

- The number of suppliers (there is one parameter for the definition of the existence of each supplier in each simulation scenario);
- Quantity to order;
- Reorder point for the material.

2.2 Proposed Approach: A Three-Level Decision Support Approach

In a general way, the proposed approach consists, in the first phase, of the modeling and simulation of the case. In the second phase, multi-objective simulation optimization (MOSO) is used to obtain a set of non-dominated solutions based on a decision profile that seeks to maximize some objectives and minimize others. Finally, in the third phase, using Data Envelopment Analysis (DEA), we respond to the decision-maker preferences not incorporated in the second phase. Figure 1 represents a general scheme of the proposed approach.

First Level—Modeling and Simulation

As can be seen, the first level comprises the traditional steps in a simulation approach. Usually, these studies start by defining the problem and the parts that will be modeled and analyzed. In a simulation, when modeling the problem, different approaches can be used, e.g., process modeling or agent modeling. In our case, we used SIMIO (Version 15), which allows the user to use concepts of both approaches in an integrated way [12]. Once the model is developed, it must be validated so the user has confidence in the feedback obtained by the model. In this sense, since we adopted a hypothetical case study, our validation process mainly consisted in varying specific parameters of the model until the desired outcome was reached when analyzing processes, such as variation of stock throughout simulation time, variation of stockouts, and duration of orders to suppliers, among others. If this was an actual case study, this process should be adapted so that the results obtained by the simulation model could match previous observations from the field or data.

As an established method for manufacturing and logistics purposes [13], simulation is particularly well suited to studying complex transportation and logistics systems, with many elements that must be coordinated for the system to function smoothly [14]. Therefore, simulation can significantly promote a multi-decision con-

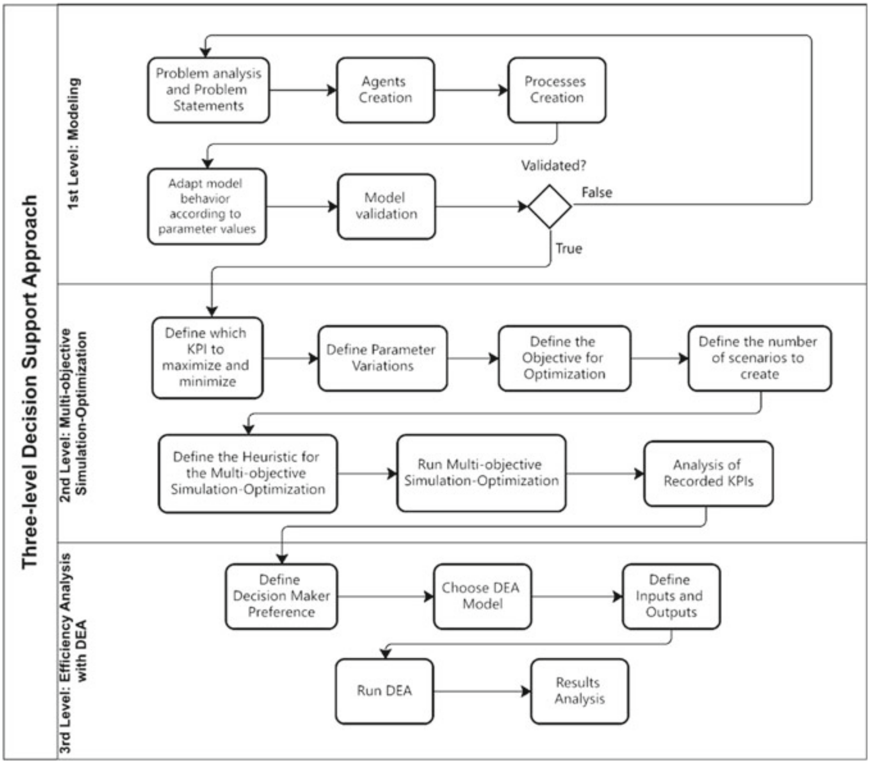

Fig. 1 General scheme of the proposed approach

text that deals with supply chain issues by enabling quantitative assessment of problems originated upstream and downstream of supply chains [15]. The main characteristic of modeling and simulation is its ability to represent business processes of production systems, including, among others, demand forecasts and inventory purchase orders [16, 17]. By simulating a system, managers can test different configurations and identify the most efficient way to operate it [18]. While several processes were defined for the many actions performed in the model by the entities, two main processes can be highlighted. The first considers the internal orders, represented in Fig. 2, and the second consists of the external orders, depicted in Fig. 3.

The internal orders arrive at random intervals and with random material quantities (defined according to the parameters in Table 1. If the material stock is enough, the order is filled, and the quantity supplied is deducted from the existing stock. A material stockout is generated if the amount of stock is insufficient. When the material stock is below the reorder point, an order is generated for the material suppliers.

In the supplier ordering process, a supplier is randomly chosen, and if the selected supplier has an order in transit, another supplier may be chosen, and the order is placed. After this, a random time delay occurs according to the supplier's specifi-

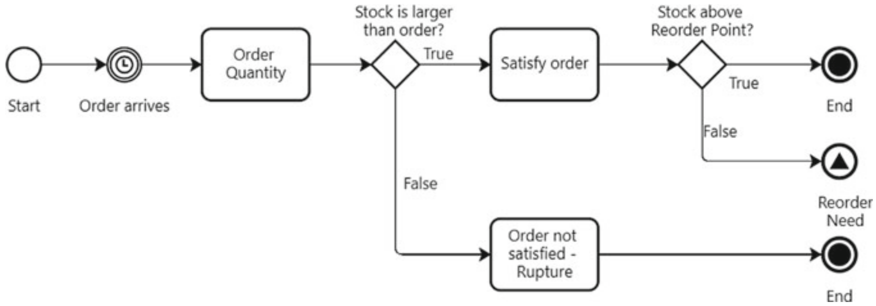

Fig. 2 Process for internal client orders

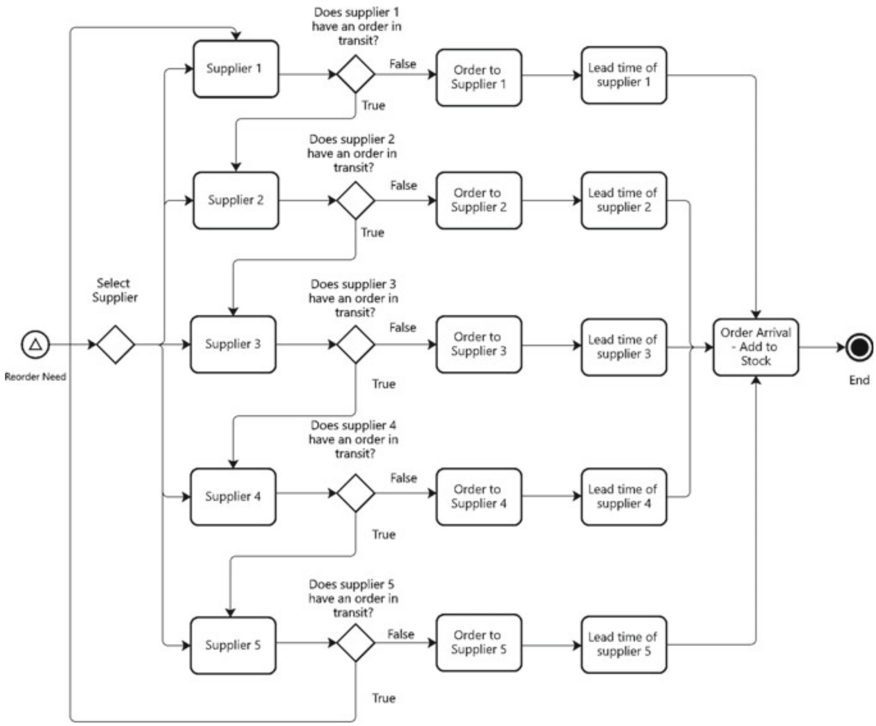

Fig. 3 Process used for orders for suppliers

cations (see Table 1). When the order arrives, the order's quantity is added to the material stock, and the process ends.

Second Level: Multi-objective Simulation-Optimization

Notwithstanding the traditional benefits of the former level—i.e., using modeling simulation, this is, indeed, an approach with its limitations. This allows users to observe the effects of randomness in selected objectives. However, this does not allow users to determine the best or the best set of scenarios to use under specific established criteria.

Several approaches have been proposed for this purpose, e.g., from the classical stochastic approximation algorithms, response surface methodology, and sample path optimization, to the meta-heuristic approaches including genetic algorithm, simulated annealing, and tabu search (see, for example [19–21] for a survey in this regard). For instance, such approaches may start by limiting the set of possibilities with a method and, after that, applying another method to establish additional performance indicators (when first using optimization and then simulation) or obtain the optimum scenarios after an initial reduction of possibilities (when first using simulation and then optimization). While this is a useful and interesting approach, ours works differently. Instead, the second level does not limit the set of scenarios at the beginning nor the end, i.e., it does not exclude any scenario before simulating a specific number of replications. It evaluates the performance of each scenario and changes the parameters to create scenarios with better performance until the maximum number of scenarios has been created.

In a more detailed way, to use the simulation-optimization approach proposed for the second level, the user has to define the objectives that should be maximized or minimized, as well as the range of values that can be used for the parameters. Thus, each decision-maker profile can establish its preferences. Lastly, the maximum number of scenarios to be created is also defined. Once this setup is done, the simulation optimization engine establishes a set of initial scenarios and runs them for the defined simulation length. Afterward, the obtained objectives are recorded, and a heuristic is used to determine, based on the recorded objectives, the next parameter values to use in the new scenarios that will be created automatically. This process is repeated until the previously defined maximum number of scenarios finishes running. At that point, the scenarios with the best set of parameters and objectives for the considered decision-maker should be obtained, and a Pareto front analysis can be performed with these scenarios, getting a set of non-dominated scenarios.

At this level, the MOSO is used. Real-world optimization problems, such as attaining the lean logistics goal of minimizing inventory while maximizing service level, usually lead to multiple contradictory objectives [5].

The difficulty arises since these give rise to a set of optimal compromise solutions rather than a single optimal solution [5]. As such, it is important to find not just one optimal solution but as many as possible. This way, the decision maker will be better positioned to choose when more compromise solutions are uncovered [5].

The first step consists of defining the objectives that should be maximized and minimized. Supply chain management aims to provide a high service level and simultaneously minimize operating costs [22]. Thus, the main objective considered for our case was the service level, which in this case, is the proportion of orders fulfilled. Regarding the objectives to minimize, the following were considered: total costs and average stock level. Total costs include stock-out costs, holding costs, and ordering costs. The service level is calculated as the percentage of filled orders. Finally, the range of values that can be used for the parameters must also be established. In this case, the parameters included the number of suppliers (from 1 to 5), the rule for their selection (represented in Fig. 3), the quantity to be ordered, and the order point. The maximum number of scenarios to be created was defined as 400. After these steps, the OptQuest ®for SIMIO®is used, in which the simulation-optimization engine establishes a set of initial scenarios and runs them for the defined simulation length. Afterward, the obtained objectives are recorded, and a heuristic is used to determine, based on the recorded objectives, the following parameter values to be used in the new scenarios to be created. This process is repeated until the previously defined maximum number of scenarios has run out. At that point, the obtained scenarios can be submitted to a Pareto front analysis. The service level was defined as the primary response, a minimum of three and a maximum of 50 replications (due to computation availability), a confidence level of 95%, and a relative error of 0.1.

Third Level: Efficiency of Dominated and Non-dominated Scenarios with Data Envelopment Analysis

Obtaining the set of non-dominated scenarios for a given system is an interesting and insightful milestone for decision-makers by itself. However, specific decision-makers may be willing to explore other dominated scenarios since, in their view, there can be different scenarios that, while dominated, are more efficient. Because of this, we decided to complement our approach with the third level, which allows users to evaluate every generated scenario by quantifying their efficiency using DEA. Likewise, in the second level, different decision-maker profiles can be defined using different DEA parameters in the third level.

DEA is aimed at measuring the Decision-Making Units (DMUs) performance according to a predefined decision-maker preference [23]. One of the primary goals of DEA is to measure the efficiency of a DMU through a scalar measure that ranges between zero (the worst performance) and one (the best performance) [24]. One of the pitfalls of DEA is that it does not have a good indicator of model fit [25]. However, this obstacle has been replaced by the satisfaction of a set of theoretical properties: (i) the measure takes values between zero and one; (ii) be monotone; (iii) invariance of the units; (iv) invariance of the translation; and (v) the DMU evaluated is Pareto Koopmans efficient if and only if the measure has a value of one [25].

A DEA analysis should clearly identify what is to be achieved from that analysis [26]. According to Chopra [27], the goal in the design of a supply chain is to structure it in a way that meets customer needs (in this specific case, represented by Service

Table 2 Inputs and outputs are defined according to the decision maker's different preferences

Decision maker preference	Inputs	Outputs
Aversion to high stock levels	Lead time; Total costs; Average stock level	Service level
Aversion to low service level	Total costs; Average stock level	Service level
Aversion to risk exposure	Total costs; Lead time	Service level; Average stock level

Level, therefore, to be maximized) in a cost-effective manner (being Total Costs, Lead Time, and Average Stock Level representatives of costs, therefore, to be minimized). With that in mind, in this paper, we identify the following three hypothetical possible preferences of a decision-maker:

1. Aversion to high stock levels.
2. Aversion to low service level.
3. Aversion to risk exposure.

The first is related to the efficiency with the minimum stock level. The second concerns the highest level of stock, and finally, the third is associated with a possible aversion to risk (minimizing the possible occurrence of disruptions). Table 2 shows the inputs and outputs defined according to the different profiles of preference of the decision maker.

If both input reduction and output enhancement are desirable goals in a particular application (as in this case, to maximize consumer needs and minimize costs), then a slacks-based measure (SBM) may provide the appropriate model structure to capture a DMU's performance measure [28]. The SBM is an addition to additive models by introducing a measure that makes their efficiency assessment invariant to the units of measure used for the different inputs and outputs [23]. The measure selected was the measure proposed by Tone [29]. This measure satisfies the ensuing properties: (i) it is always between zero and one; (ii) the measure is equal to one if and only if the rated DMU is Pareto-Koopmans efficient; (iii) it is units invariant, and (iv) it is strongly monotonic in inputs and outputs [30]. In the SBM proposed by Tone [29], the K DMU is described by vectors of inputs and outputs, such that:

$$X_{\kappa} = X\lambda + S^{-}; Y_{\kappa} = Y\lambda - S^{+} \tag{1}$$

Where X and Y indicate respectively the matrix of inputs of dimension (m x n) and the matrix of outputs of dimension q1 (h x n), associated with the frontier where the terms S are slacks [31]. Slacks allow non-equality constraints, which indicates that the DMU operates within the frontier, to be expressed by equalities. Efficiency optimization can thus be considered as an exercise in choosing the slacks and the weights of the components of the vector $\boldsymbol{\lambda}$, such that:

$$\min \rho = \frac{1 - \left(\frac{1}{m}\sum_{i=1}^{m}\frac{S_i^-}{x_{ik}}\right)}{1 - \left(\frac{1}{h}\sum_{r=1}^{h}\frac{S_r^+}{x_{rk}}\right)} \tag{2}$$

st:
$x_{ik} = \sum_{j=1}^{n} x_{ij}\lambda_j + S_i^- \quad i = 1, \ldots, m$
$y_{rk} = \sum_{j=1}^{n} y_{rj}\lambda_j + S_r^- \quad r = 1, \ldots, m$
$\lambda \geq 0;\ \ S^- \geq 0;\ \ S^+ \geq 0$

In this model, the DMU is said to be efficient with a value of unity if, and only if, the DMU is on the frontier of the production possibility set with no input and output slack [32].

3 Results

This section presents and discusses the results of applying the proposed approach to the selected problem. In this sense, we show the results that can be obtained at each decision level with our approach in separate subsections.

3.1 Results from the First Level

In terms of decision support, this level allows users to analyze the evolution throughout the simulation time of particular objectives and specific selected performance indicators. This can be helpful for users that already know the parameters they want to experiment with or if they want to understand in more detail what happens in a given scenario. This, indeed, is similar to what most traditional simulation studies can use. Figure 4 shows the run of a simulation experiment.

The first thing that should be highlighted is the simulation optimization's capacity to generate solutions near the Pareto frontier, despite the randomness that occurs throughout each scenario and the wide range of parameters that can be used.

3.2 Results from the Second Level

From the results of the second level, we obtained 360 scenarios with a service level higher than 0,5, of which 21 were non-dominated. Figure 5 shows the results that were obtained.

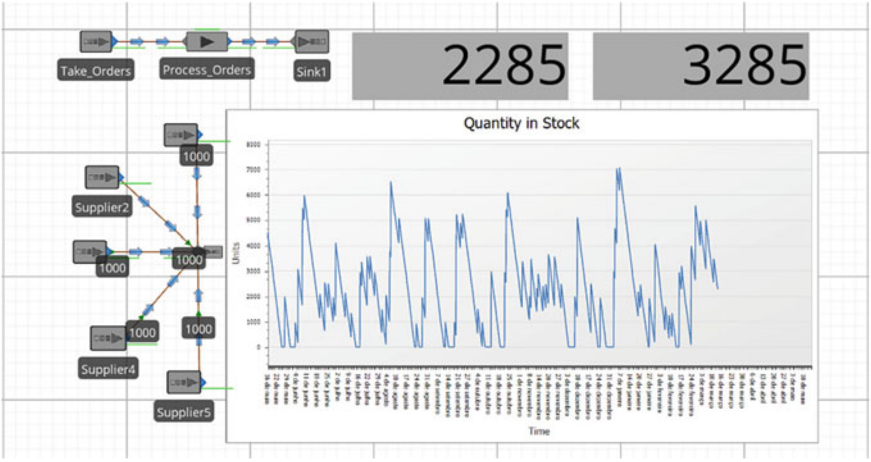

Fig. 4 Run of a simulation experiment

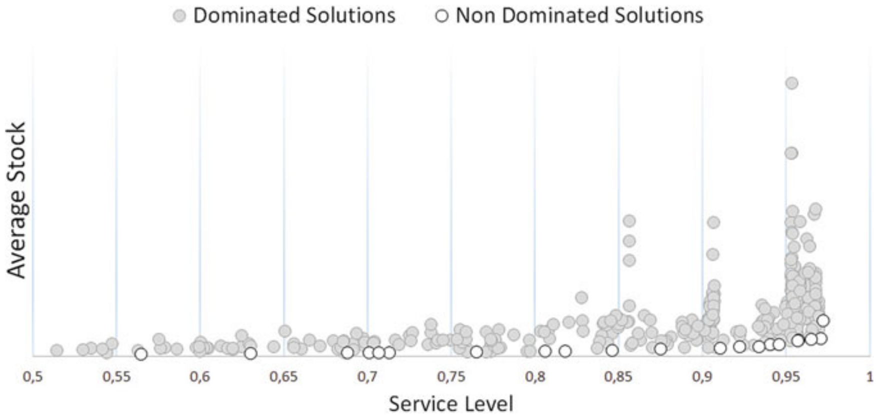

Fig. 5 Sim-Optimization results

3.3 Results from the Third Level

For the decision-maker who has an aversion to stock stocks, the results obtained from the application of DEA allowed to extract of 22 efficient DMUs. Figure 6 graphically represents the comparison between non-dominated scenarios and efficient DMUs, from a decision-maker's perspective that values stock minimization. From its analysis, it is possible to see that 14 scenarios are simultaneously non-dominated and efficient, and eight dominated scenarios are efficient. These scenarios all exhibit a service level greater than 0.75. Finally, thirteen of the non-dominated scenarios are not efficient from the perspective of a decision-maker that values low stocks. Figure 7 shows the results obtained for the decision-maker with the profile for the aversion

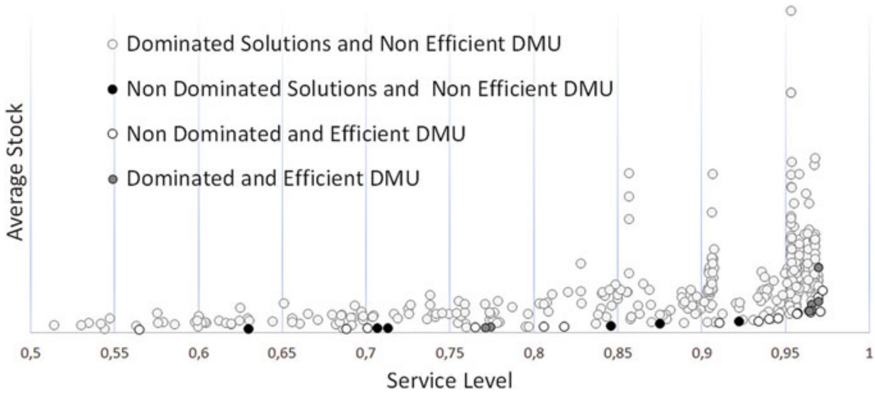

Fig. 6 Non-dominated, dominated scenarios, and efficient DMUs for stock minimization

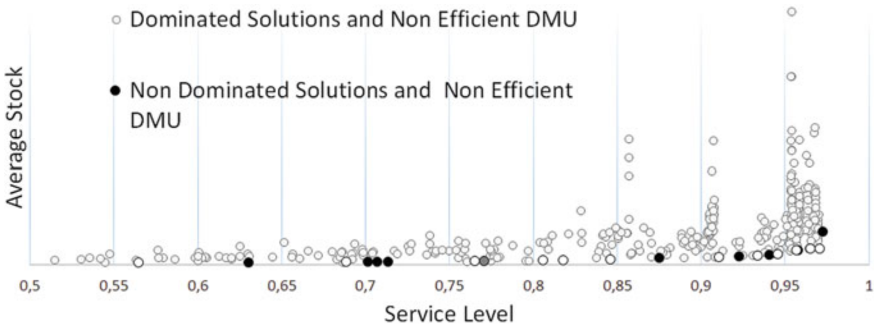

Fig. 7 Non-dominated, dominated scenarios, and efficient DMUs for service level maximization

to low service levels. For the decision-maker profile that values the service level, 12 efficient DMUs were obtained. It is observed from the analysis of Fig. 6 that the vast majority of the efficient DMUs are non-dominated scenarios, with 9 having a service level higher than 0.8. Only one dominated scenario is an efficient DMU. Moreover, a total of eight non-dominated scenarios are not efficient DMUs from the perspective of a decision-maker who values high levels of service. Four have a level of service lower than 0.8. We also highlight that 12 efficient DMUs are also efficient DMUs in the previous decision-making profile that was analyzed, i.e., the aversion to high stock levels. Regarding the third decision-maker profile that was defined, consisting of the aversion to risk exposure, Fig. 8 illustrates the obtained results.

As can be seen, 23 efficient DMUs were obtained. All the efficient DMUs have a service level higher than 0.95. These results can be justified because the average stock level was used as an output for this decision profile. We also highlight the slight overlap between the efficient DMUs in this profile and the efficient solutions, consisting of merely two, as visible in Fig. 7. We also observe little overlap between the efficient DMUs in this profile and the efficient DMUs in the other decision profiles,

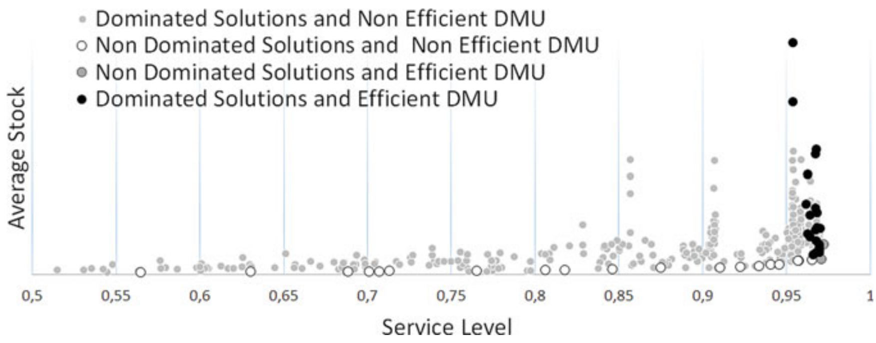

Fig. 8 Non-dominated, dominated scenarios and efficient DMUs for risk minimization

namely six DMUs between the aversion to risk and stock profiles and one between aversion to low service level and risk exposure. In fact, the DMU in question is the only one efficient in the three decision profiles and is simultaneously not dominated.

4 Conclusions

This paper proposed an alternative approach for analyzing multi-objective problems, considering uncertainty and efficiency. The approach consists of modeling and simulating a system's dynamics and generating a set of scenarios in pursuit of the Pareto-front. The result is a set of dominated and non-dominated scenarios, which are then analyzed with DEA, considering different decision profiles and both dominated and non-dominated scenarios.

Accordingly, although dominated, we obtained efficient solutions for a given decision-maker profile. Likewise, we also obtained non-dominated solutions that are not efficient for specific decision profiles. We did not discuss the values of the parameters under analysis that originated such scenarios, as that would focus the analysis on the considered problem and not on the approach, which is the scope of this research. Thus, this approach allows the efficiency of solutions to be considered, as well as the non-dominance of others, including the dynamics and uncertainty of complex systems and different decision profiles.

Regardless, our research has some limitations, which should steer our future research endeavors. As a main limitation, we highlight the use of a hypothetical. Real problems may reveal additional interesting challenges and insights into our approach. The selection of suppliers is random, which limits our approach. Different rules could be implemented, including alternative optimization methods or even artificial intelligence, e.g., reinforcement learning. To improve the robustness of the proposed approach, sensitivity analysis should be run in future research.

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