Chapter 4

Discrete Event Simulation Combined with Multiple Criteria Decision Analysis as a Decision Support Methodology in Complex Logistics Systems

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Additional information is available at the end of the chapter

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1. Introduction

Discrete Event Simulation (DES) is a decision support tool that is extensively used to solve logistics and industrial problems. Indeed, the scope of DES is now extremely broad in that it includes manufacturing environments, supply chains, transportations systems and computer information systems [1]. However, although its usage spreads dramatically, few authors, practitioners or users are able to fully understand and apply the methodology in order to derive its full potential.

While alone, the DES methodology is a tool that improves user comprehension of a system, it has sometimes been incorrectly stigmatized as a method, a “crystal ball.” Indeed, a DES model should not be built to accurately predict the behavior of a system, but rather used to allow decision makers to fully understand and respond to the behavior of the variables (elements, resources, queues, etc.) of the system and the relations between those variables. However, depending on the complexity of the system, a deeper analysis and evaluation of the system behavior and variable tradeoff analyses may be a complicated task, since logistics problems, by nature, are composed of several elements interacting among themselves simultaneously, influencing each other in a complex relationship network, often under conditions that involve randomness. Further, the observation and evaluation of numerous decision criteria is required, led by multiple goals (often intangible and even antagonistic) and commonly running across long time horizons where the risks and uncertainties are salient elements.

In order to expand the capacity of DES to support decision making, other decision support methodologies may be incorporated, thereby adding greater value to the model and strengthening the overall capacity of the decision-making process. Consequently, the proposal of this chapter is to incorporate Multiple Criteria Decision Analysis (MCDA) into a DES model.

In this context, the DES model is built to analyze the operational performance of the system's variables, based on several alternative system configurations. From this point on, a multi-criteria decision model should be applied to the DES results, bringing to light and taking into account an evaluation of the decision-making priorities and judgments of decision makers over the decision criteria and thus formally studying the tradeoff between the performances of the decision criteria in the DES model. Therefore, the main objectives of this chapter are to:

- Understand the capabilities of DES as a decision support methodology in complex logistics systems;
- Show the most important aspects of a decision-making process;
- Build and implement a Decision Support System (DSS) that merges the DES and MCDA methodologies to serve as a catalyst to improve the decision-making process;
- Present a real case study to analyze the establishment and operational configuration of a new steel production plant, an example of a complex and multifaceted logistics system; and
- Draw conclusions on the application of this hybrid DSS methodology.

2. The application of DES in complex logistics systems as a DSS

A DES model is a mathematical/logical structure that represents the relationships among the components of a system. It has long been one of the mainstream computer-aided decision-making tools because of the availability of powerful computers. Traditionally, DES has been efficiently employed to simulate complex logistics systems owing to its capacity to replicate the behavior of the system, to represent all its relevant physical aspects and to provide decision-making insights into how to respond.

The DES methodology presented in this paper is based on the steps proposed by [2]. Those steps are summarized and graphically represented by [3], which divide the development of the model into three main stages (Figure 1):

a. Conception: definition of the system and its objectives, as well as data collection and conceptual modeling;
b. Implementation: preparation of the computer model itself, verification and validation; and
c. Analysis: simulation runs and sensitivity and results analysis.

In fact, a DES methodology represents a wider concept, with possible applications in numerous industries and expertise areas, from ordinary daily activities (e.g., the service process in a bank) to situations of elevated complexity (e.g., understanding the evolution of a country's economic indicators or its weather forecasting system).

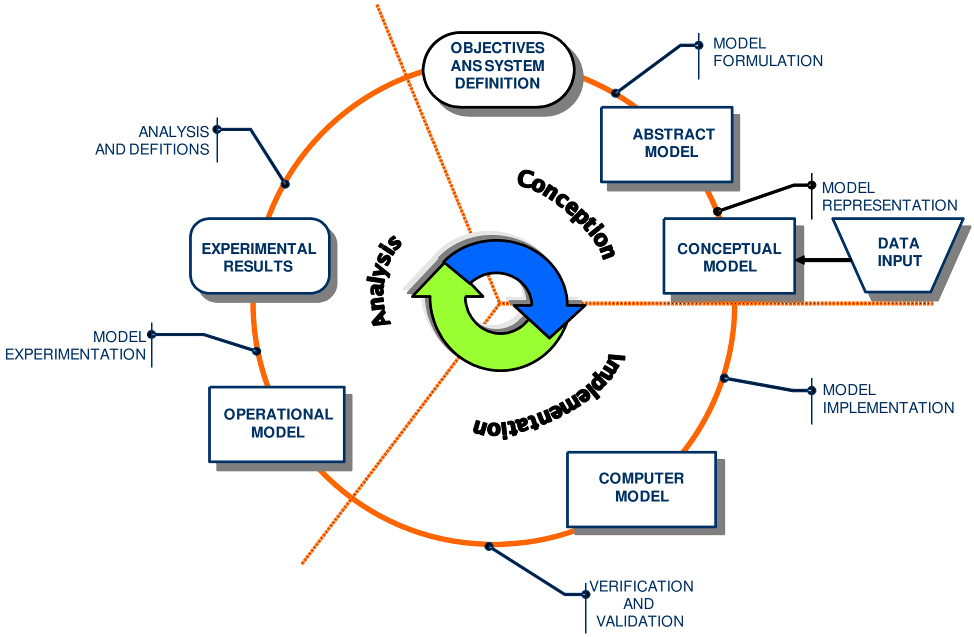

Figure 1. Development of a simulation model [3]

However, the work of [3] defines the DES methodology in the reverse way, namely by clarifying what a DES model is not:

- A crystal ball: the simulation is not able to predict the future, but it can predict, within a selected confidence interval, the behavior of the system;
- A mathematical model: the simulation does not correspond to a mathematical/analytical set of expressions, whose outputs represent the behavior of the system;
- An optimization tool: the simulation is a tool of analysis of scenarios that can be combined with other tools of optimization;
- A substitute for logical/intelligent thought: the simulation is not able to replace human reasoning in the decision-making process;
- A last resource tool: currently, the simulation is one of the most popular techniques applied in operational research (OR); or
- A panacea to resolve all considered problems: the simulation technique works efficiently in a specific class of problems.

However, the complete definition of the DES methodology must be based on the advantages of its use. The characterization of the simulation tool as the concatenation of the procedures of building of a model that represents a system and its subsequent experimentation that aims at observing and understanding the behavior of the system already suggests its main purpose, namely to allow the observer/modeler to carry out "what if" analysis using the system. Indeed, "what if" is the best statement to illustrate the purpose of the simulation methodology. [4] emphasizes the potential of "what if" analysis when affirming that the decision maker, in possession of a DES model, is capable of assuming any appropriate situation or scenario and analyzing the response of the system under such circumstances. Asking "what if" means nothing more than exploring the model, challenging its parameters and examining the impact of the proposed changes on the system.

Then, one can define the main functions of the DES simulation technique as:

- To analyze a new system before its implementation;
- To improve the operation of an already existent system;
- To better understand the functioning of an already existent system; and
- To compare the results from hypothetical situations (“what if” analysis).

Further, the main reasons for its usage include the following [4]:

- The real system still does not exist; the simulation is used as a tool to project the future;
- Experimenting with the real system is expensive; a simulation methodology is used in order to avoid unnecessary expenses with regard to system stoppages and/or modifications to the *modus operandi* of the system; and
- Experimenting with the real system is not appropriate; simulation should be used in order to avoid replicating extreme situations with the real system (e.g., a fire in a building).

A disadvantage of simulation is that even though one can explore wide-ranging problems, they cannot usually be “solved.” The simulation methodology does not provide the user with information about the "correct" solution of the problem explored. Instead, it provides subvention for the pursuit of alternatives that best fit the needs of the user's understanding of the problem. Thus, each user, through his or her own vision of the problem, can find particular (and often different) answers for the same model. This characteristic is emphasized by [5] in the work presented in a compilation organized by [6], in which the ultimate goal of modeling and the simulation methodology is discussed.

This discussion begins with the seemingly endless appeal of computational models and the promise that one day, supported by the growing power of computational processing, users will be able to completely and accurately represent a given system using the “perfect" model. However, it is unlikely that a model representing 100% of a given system will ever be built. Even the simplest of models carries a huge list of internal and external relationships between its components in a process under constant renewal and adaptation.

This conclusion reflects the inevitable necessity of working with models that are "incomplete." This is equivalent to carrying out simulation studies within the boundaries that govern the interpretation and representation of real systems. Decision makers are rarely conceptually capable of recognizing the validity of an "incomplete" model, resulting in their inability to work under such boundary conditions. This means that, under the watchful eyes of an "unprepared” decision maker, working with an "incomplete" model may not seem to be an alternative that provides valid results or allows useful analysis.

However, this assumption is not true. Working with "incomplete" models that represent and link those elements relevant for understanding and fulfilling the aspiration of the modeler is a requirement. The importance of this topic is such that [7] proposes techniques to reduce the complexity of simulation models in the conception and design stage and proves the feasibility of this procedure without utility loss entailment to the model. Thus, for a significant number of decision makers, applying this modeling and simulation methodology as a reliable tool for systems analysis is complicated. However, what should be the ultimate goal of such a modeling and simulation technique?

[8] states that a modeling and simulation methodology, considering both its potential and weaknesses, might play an important role in the process of "changing the mentality" of decision makers. As such, the developed model must fundamentally represent the apperception of the decision maker of the modeled system, no matter how incomplete or inaccurate it is. Built from the perspective of the decision maker, a model can become a "toy," allowing him or her to play fearlessly and avoid arousing any distrust and thus providing valid results and allowing useful analysis.

The technique of modeling and simulation fits well with the final goal of becoming an element of learning and its prediction function. In fact, both these goals represent nothing more than achieving a good understanding of the real system so that one can act efficiently on it. Furthermore, this technique should be part of a broader effort to solve the problem, which may range from the application of complementary system-solving methodologies (optimization models, mathematical/statistical analysis, financial and economic analysis, etc.) to its application to the psychological/rational aspects of the decision makers and/or senior executives of the company.

3. Decision-making processes, DSSs and tradeoff studies

Whenever there exists a single variable objective/utility function or when a decision is based on a single attribute, no decision making is involved: the decision is implicit in a single measurement unit. However, it is recognized that logistics systems are most commonly related to multiple attributes, objectives, criteria and value functions. As the alternatives become more complex, immersed in multiple relationships and interactions between variables and functions, and as it becomes necessary to combine those numerous aspects into a single measure of utility, some methodological help in the decision-making process becomes essential.

As stated by [9], decision making is a dynamic process; it is a complex search for information, full of detours, enriched by feedback from all directions, characterized by gathering and discarding information, and fueled by fluctuating uncertainty as well as indistinct and conflicting concepts. Moreover, the human being is a reluctant decision maker rather than a swiftly calculating machine.

For these reasons, successful decision making is one of the least understood or reputable capabilities in most organizations. Even though, as previously presented in this chapter, DES helps frame the problem and establish a defensible course of action, making good decisions and setting priorities is a further and much harder task. A DES model uses analysis to break things down in order to provide information only, not necessarily the right answers or directions for the decision maker. Thus, DES modeling could offer great potential for modeling and analyzing logistics processes. For example, DES models can dynamically model different samples of parameter values such as arrival rates or service intervals, which can help discern process bottlenecks and investigate suitable alternatives. However, while the DES output is tangible, decision making must often rely on intangible information, which raises the question of how to help organizational decision makers harness the incredible complexity of the interaction between logistics problem's variables and the wealth of data available from the analysis of DES models.

3.1. DSSs

DSSs, a type of information system designed to support semi-structured or unstructured managerial activity [10], are ideally suited to bridge the gap between information (tangible and intangible) and decision makers. A properly designed DSS (such as that shown in Figure 2) is an interactive software-based system intended to help decision makers compile useful information from a combination of raw data, documents, personal knowledge and business models in order to identify problems and help make decisions.

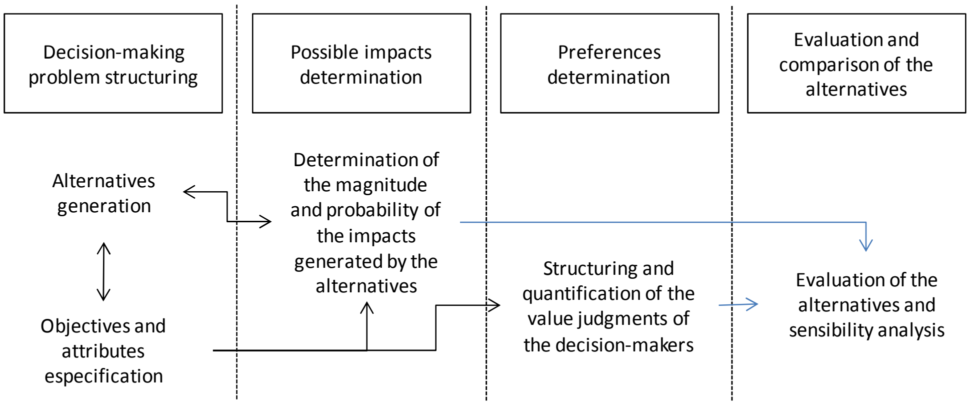

Figure 2. Structuring a DSS application [11].

DSSs, especially in the form of spreadsheets, have become mainstream tools that organizations routinely use to improve managerial decision making [12] often by importing data from enterprise-wide information systems into spreadsheets to address specific business problems. Moreover, DSSs also have the potential to serve as a catalyst to improve the decision-making process, as they provide the capability to organize and share as well as to create knowledge, providing structure and new insights to managers [13].

The most important capability of a DSS might be the possibility of carrying out tradeoff studies. A tradeoff study is the choice of one alternative solution when you have limited decision-making resources that may result in long- or short-term outcomes [14,15]. The main objective of a tradeoff study is thus to arrive at a single final score for each of a number of competing alternative scenarios, using normalizing criteria scoring functions and combining these scores through weighted combining functions.

However, the biggest contribution of a DSS application to evaluating a logistics problem is in pointing out solutions based on decision-making judgments, thus capturing companies' aspirations and worries. For this reason, when conducting anything other than a rough or obvious tradeoff study, careful and honed expert attention must be given to properly choose the criteria scoring functions, weights and inputs – especially if they are in any way subjective. This approach requires, during the process of capturing decision-making judgments, the adoption of an OR intervention tool that should pursue the so-called *facilitated modeling process*. This process requires the operational researcher to carry out the whole intervention jointly with the client, from helping structure and define the nature of the problem of interest to supporting the evaluation of priorities and development of plans for subsequent implementation [16].

3.2. Facilitated modeling process

The traditional way of conducting OR intervention in logistics problems is so-called *expert modeling*, namely when the decision maker hires OR consultants to objectively analyze a problem situation. The result of this kind of intervention is often the recommendation of an optimal (or semi-optimal) solution. Nevertheless, when dealing with problems at a strategic level, complexity rises and the expert mode of intervention may not be appropriate. [16] present two of the main reasons for its inadequacy:

- The lack of agreement on the scope and depth of the problem situation to be addressed; and
- The existence of several stakeholders and decision makers with distinct and often conflicting perspectives, objectives, values and interests.

Facilitated modeling intervention aims to overcome these issues by structuring decisions in complex and strategic logistics problems. It mainly helps in the negotiation of conflicts of interest during all phases of a decision-making process, taking into consideration different opinions and ideas related to the scope and definition of the problem as well as divergences in the output analysis, values and interest in the results.

In a facilitated modeling approach, the OR consultant must work not only as an analyst, but also as a facilitator and negotiator of conflicts in order to reach a common, satisfactory and useful decision about the problem definition, investigation and resolution. Almost every step taken in the intervention – from defining the problem to creating and analyzing models and providing recommendations – is conducted interactively with the team, in a so-called "helping relationship" [17] between OR consultants and their clients. In Figure 3, [16] define the activities of an OR consultant working as a facilitator in all steps of a facilitated modeling process.

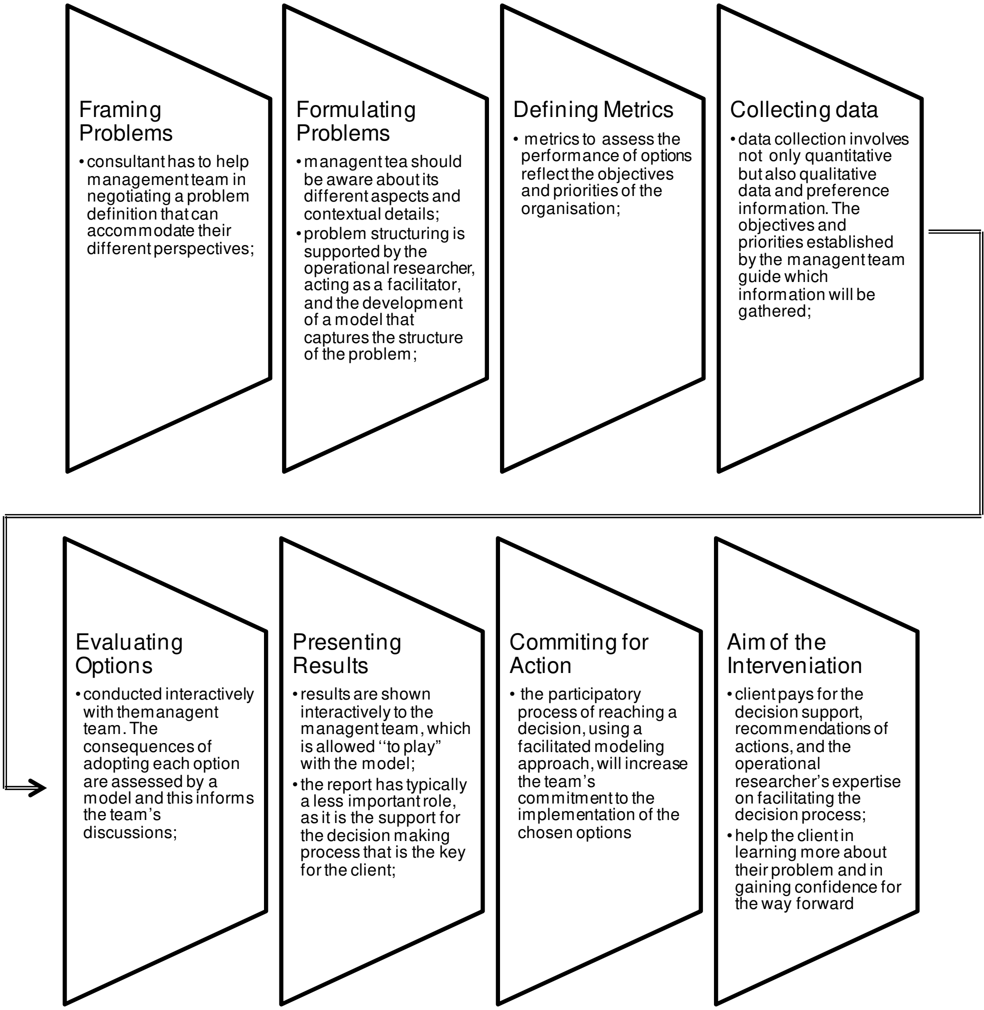

Figure 3. Activities of an OR consultant in a facilitated modeling process [16]

Further literature review based on [16] describes the four main assumptions taken under the facilitated intervention modes:

- Even the tangible aspects of problem framing and formulating, defining metrics and evaluating results have their salience and importance depending on how decision makers subjectively interpret them [18,19]. Different decision makers will perceive a given tangible variable in diverse ways because of their distinct interests and goals. This complicates problem modeling for decision makers [16];
- Following from the above consideration, subjectivity is unavoidable and thus it should be considered when solving a problem. The different perceptions of a problem as well

as distinct points of view and backgrounds may lead to a much better interpretation of a given problem and bring new ideas and concepts, leading to a better result [20,21];
- Despite the fact that experts recommend optimal (or semi-optimal) solutions, decision makers are rarely interested in the best alternative, but rather in a satisfactory one. Satisfactory alternatives also represent a feasible solution in the political, financial and environmental fields. Further, all logistics systems are inevitably too complex to be integrally modeled and they are thus subject to necessary simplifications and assumptions. Any model should thus be seen as a guide, a general indicator of the system behavior, rather than a precise indicator of the performances of the system's variables [22,23]; and
- The decision maker's involvement in the whole process increases the commitment to implement the proposed solution. This involvement increases confidence in the decision-making process. It is a physiological factor of having our voice heard and ideas, preferences and beliefs taken into consideration during all steps of the process [24–26].

It is important to note that neither of the two modes of intervention (i.e., expert or facilitated) is necessarily the best. [22] and [26] argue that for operational and well-defined problems, when there is a clear objective to be optimized or an unquestionable structure of the problem, the expert mode is usually appropriate. However, complex problems may require a facilitated intervention. In this case, the facilitator encourages divergent thinking while helping participants explicitly explore their particular perspectives of the problem. The next step is to stimulate and drive convergent thinking, consolidating a single and fully representative interpretation and perspective of the problem.

Consequently, facilitated modeling is the doorway to building an efficient DSS application. In this paper, we propose the employment of facilitated modeling via the implementation of an MCDA model. Section 4 describes the development and employment of a DSS tool to support strategic decisions about the planning and sizing of a complex logistics system – in this case, a steel production plant and its logistical elements (stockyards, transportation fleet, etc.). Such a tool is able to analyze and evaluate its performance and execute a tradeoff study of possible configurations and operational results.

4. Hybrid DSS: A combination of DES and MCDA

The developed DSS tool represents a hybrid software application combining the techniques of DES modeling with MCDA. The DES methodology will be supported by the Scenario Planning (SP) methodology, which uses hypothetical future scenarios to help decision makers think about the main uncertainties they face and devise strategies to cope with these uncertainties [27]. The SP methodology can be described as the following set of steps:

- Define a set of n strategic options (ai).
- Define a set of m future scenarios (sj).
- Each decision alternative is a combination of a strategic option in a given scenario (ai–sj).
- Define a value tree, which represents the fundamental objectives of the organization.

- Measure the achievement of each decision alternative (ai–sj) on each objective of the value tree using a 100–0 value scoring system.
- Elicit the weights of each objective in the value tree using swing weighting (anchoring on the worst and best decision alternatives in each criterion).
- Aggregate the performances of each decision alternative (ai–sj) using the weights attached to the objectives in the value tree, finding an overall score for the decision alternative.

The SP approach is an extension of MCDA. The SP/MCDA methodology was thus applied in this work using the propositions of [27], which confirm the use of the MCDA methodology as a supporting tool to decision makers in situations of high complexity with potentially significant and long-term impacts. MCDA is a structured DSS technique for dealing with problems in which multiple and complex criteria influence decision making [28], as it allows for the visualization of the rational/logical structure of the problem by representing and quantifying the importance of its elements, relating them to the overall goal and allowing the execution of further tradeoff studies as well as benchmark and sensitivity analyses. The methodology organizes and synthesizes information, includes measures objectively and considers the value judgments of decision makers [29] in an interactive and iterative process. The value judgments of decision makers are captured as preference compensation, thus creating a robust tradeoff instrument.

Several authors have reviewed the utilization of the MCDA methodology as a decision support tool. The 10 major advantages of MCDA, summarized by [28], are the maintenance of the unity of the problem, complexity understanding, criteria interdependence relationship representation, capability of measuring criteria preference, maintenance of consistency, synthesis, tradeoff evaluation, consideration of decision makers' value judgments and consensus reaching. Thus, the goal sought by the MCDA methodology is to identify good and robust alternatives, granting coherence and offering a good tradeoff between different objectives that guide problem resolution. In that way, the multi-criteria analysis in this work will be performed after the results of the DES model have been obtained.

5. Case study

5.1. Problem and objectives

A Brazilian steel company is establishing a new plant in the country's northeast region. The inputs to the plant production as well as the finished goods will all be handled through a private port located very close to the plant. Iron ore and coal are among the main steelmaking process inputs. Coal is imported from various locations around the world and is delivered to the terminal by a chartered vessel fleet, according to a procurement schedule. Iron ore is owned by the company and thus it comes from two distinct Brazilian regions, northeast (NE) and southeast (SE), with remarkable differences in physical properties. The transportation of iron ore from its original locations to the company's private port will be performed by the company's private dedicated fleet, which will operate in a closed-loop circuit. The company's private port operates two berths for unloading, which are able to accommodate small capesize vessels (DWT 120,000 tons). One berth is dedicated exclusively to iron ore unloading and the other to coal unloading.

Thus, the main objectives of this study are (i) to size the company's own vessel fleet (dedicated to supplying iron ore to the plant) and (ii) to determine the storage area assigned to the two types of iron ore (SE and NE). This is because they must be stored separately owing to their physical characteristics and properties in order to avoid any restriction or interruption in the plant steelmaking process based on the poor supply of inputs. This work does not cover the transportation, storage or processing of coal.

5.2. Problem definition

The first step of the problem is the intervention of the OR consultant as a facilitator that focuses on identifying the decision-making group and assessing how it comprehends and evaluates the problem, scopes the decision situation and structures the problem efficiently. These steps correspond to Steps 1 to 4 in Figure 4. The aim here is to put together the full problem representation by considering all the aspects of the facilitated modeling process presented in Section 3.2.

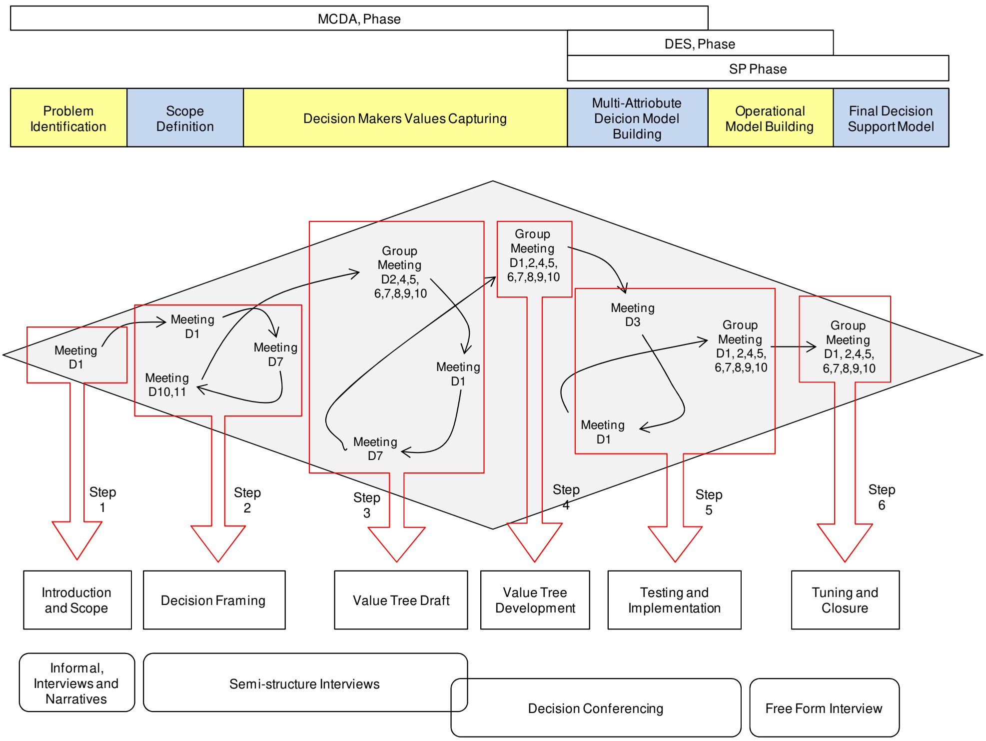

Figure 4. Complete modeling process of a hybrid DSS application (based on [30]).

The next step corresponds to the DES+SP phase of the problem resolution. Based on all the information derived from Steps 1 to 4 in Figure 4 by the OR consultant, the DES model representing the real system should be able to evaluate all the results and variables necessary to help measure system performance, according to the decision maker's criteria. Further, the DES model is built to analyze the proposed logistics system based on several possible system configurations. From this point on, a DSS application, based on a multi-criteria analysis of the results obtained from the DES model of each proposed alternative, was carried out. Through this analysis, it was possible to:

- Determine the "best" size of the iron ore supply vessel fleet required to meet demand for the planned cargo; and
- Assess the capacity of the stockyards for the two types of iron ore (SE and NE).

5.3. Input parameters

All input parameters were provided by the company or derived from the in-depth statistic analysis of the available data. In all considered scenarios, an annual iron ore demand of 5 MTPY (million tons per year) was considered. As mentioned before, iron ore is supposed to be supplied by a dedicated vessel fleet operating in closed-loop system. Moreover, the project fleet is composed of small capesize vessels, while the largest ship able to dock at the port has a 120,000-ton capacity. Table 1 lists the input data for all scenarios.

Parameter	Value	Unit
Planned Demand	5	mtpy
Vessels Capacity	120.000	tonnes
Travel Time (Plant-NE)	2.7	days
Berthing Time (NE Port)	1.5	days
Travel Time (Plant-NE)	7.9	days
Berthing Time (SE Port)	1.4	days
Berthing Time (Private Port)	3.25	days

Table 1. Input data for all scenarios.

However, a number of variables were considered in the simulation run process:

- Company fleet: number of vessels in the company's private fleet;
- SE/NE iron ore percentage: the iron ore employed in the steelmaking process is originally from either the SE or the NE regions of Brazil (see Figure 5). Owing to the specific physical and technical characteristics of each iron ore type, the percentage of SE iron ore may vary from 30% to 40% of the final composition of the steel process output. Although the production department prefers working with the maximum percentage of SE iron ore because of its enhanced physical properties, the procurement and transportation departments prefer working with the minimum percentage of SE iron

ore given the larger distance from the company's private port to the SE port compared with to the NE port;

- Stocks capacities: storage capacities (in tons) for each type of iron ore (SE and NE); and
- Chartering: this variable determines whether vessels are chartered during the periods when the vessels of the company fleet are docked for maintenance. Dockage is carried out every 2 and ½ years, and ships may be unavailable from 7 to 40 days. Chartering vessels with the same operational characteristics is particularly difficult, especially for short time periods.

Thus, with the variation of the proposed variables, it was possible to create a hall of simulation scenarios, which will be evaluated later.

Figure 5. Representation of the iron ore transportation process from the SE and NE ports to the company's private port.

5.4. Scenario creation

Ten viable scenarios were created for further evaluation using MCDA. These scenarios cover a range of input parameters and variables of the DES model, as listed in Table 2.

In Table 2, the first seven scenarios simulate a two-vessel operation, while the last three scenarios encompass a three-vessel fleet. Next, the first alternated variable is the necessity of vessels chartering during the fleet docking period. Thereafter, until scenario 6, the proportion of iron ore from each source (NE and SE) changes. Scenario 7 is a sensitivity analysis of Scenario 4, with a reduced storage capacity. From Scenarios 8–10, the proportion of iron ore from SE and NE is altered, but under the assumption of a three-vessel operation.

Scenarios	Vessels Fleet	% Min. SE Iron Ore	Stock Capacity (tonnes)		Rely on chartering ?
			NE	SE	
Scenario 1	2	30	550,000	225,000	No
Scenario 2	2	30	550,000	225,000	Yes
Scenario 3	2	35	500,000	275,000	No
Scenario 4	2	35	500,000	275,000	Yes
Scenario 5	2	40	475,000	300,000	No
Scenario 6	2	40	475,000	300,000	Yes
Scenario 7	2	35	375,000	275,000	Yes
Scenario 8	3	30	185,000	235,000	No
Scenario 9	3	35	170,000	275,000	No
Scenario 10	3	40	155,000	315,000	No

Table 2. Description of the analyzed scenarios.

This table identifies a clear tradeoff between the number of vessels in the company fleet and the storage capacity required for each iron ore type, for example, by comparing Scenario 1 with Scenario 8. The simulation results are presented in Section 5.7.

5.5. Decision criteria: Value functions and multi-criteria analysis

The decision-making process implies capturing the value judgments of decision makers through the assignment of value functions to the relevant criteria and sub-criteria and the further positioning of the results of the scenarios on a value function scale. All evaluations and considerations were performed with the participation of representatives of the following areas of the company: Operations, Procurement, Transportation (Railroad and Navigation), Inventory Management and Finance.

The relevant criteria and sub-criteria considered in the system characterization, their descriptions and value functions are described below. The assignment of the scores associated with all decision criteria to each of the 10 previously considered scenarios is presented, as derived from the DES results.

- Power plant stoppages: Number of days per year that the plant stops production because of the lack of iron ore supply. The value function of this criterion is given as follows: when no interruption occurs in the operation of the steel production plant (0 days of interruption), the scenario gets a maximum score (1). If there is only 1 day of interruption, the scenario gets a score of 0.5. Two days of interruption corresponds to a score of 0.25 and 3 days to a score of 0.125. Thereafter, the score varies linearly until the scenario with 18 days of interruption, which scores 0. Between intervals, the value function varies linearly and thus aims at representing the extremely high costs of production resuming after any stoppage (Figure 6).

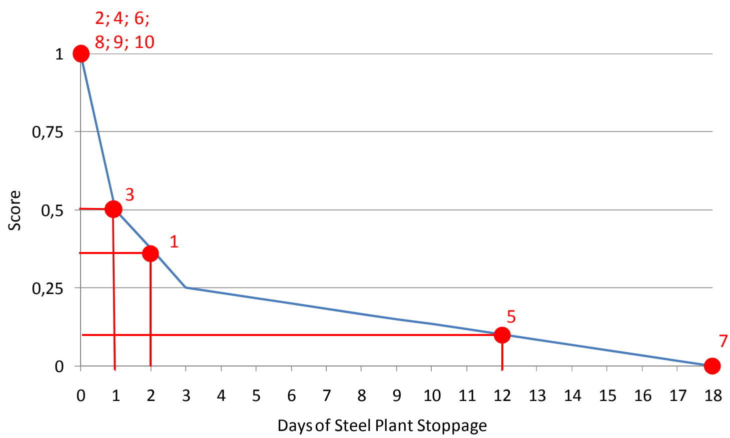

Figure 6. Determination of value function – days of production plant stoppage.

- Investment net present value (NPV): As the system modeled represents the internal logistics operation of the company, there is no revenue generation. Investment NPV is therefore directly related to the need for financial investment into the project (size of the company's fleet, need for vessel chartering, etc.). The results for Investment NPV are obtained based on the parameters provided by the company (Table 3).

Parameter	Unit
Vessel Acquisition Value	Mi US$
Financed Percentage	%
Interests	%
Amortization Period	years
Grace Period	years
Vessel's Service Life	years
Return Rate	%/year
NPV Financed (per vessel)	Mi US$
NPV Own Capital (per vessel)	Mi US$
Chartering Costs (per vessel)	US$/day

Table 3. Economic parameters of the investment.

The Investment NPV value function displays linear behavior, with a maximum score (1) assigned to the lowest total Investment NPV scenario and a minimum score (0) to the highest Investment NPV scenario (Figure 7).

- Annual fleet operational costs: This takes into account all the operational costs of the company fleet, such as fuel, port costs and running costs (crew, insurance, administrative costs, taxes, etc.). The components of the fleet operational costs are presented in Table 4.

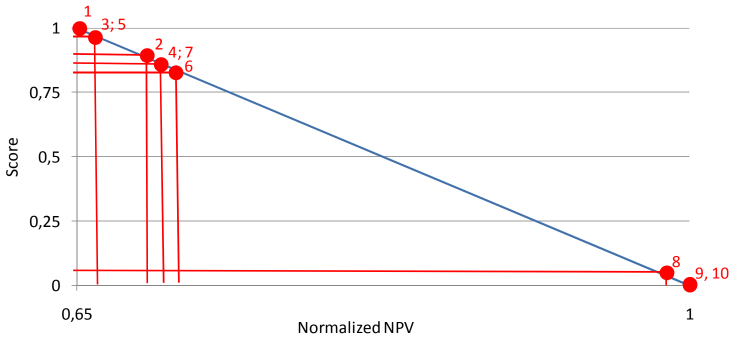

Figure 7. Determination of value function – NPV.

Parameter	Unit
Fuel Cost (at route)	(US$/day)/vessel
Fuel Cost (at port)	(US$/day)/vessel
Running Costs	(US$/day)/vessel
Mooring Cost at Plant Port	(US$/mooring)/vessel
Mooring Cost at NE Port	(US$/mooring)/vessel
Mooring Cost at SE Port	(US$/mooring)/vessel

Table 4. Components of the fleet operational costs.

Similar to NPV, the value function of this criterion is linear, with a maximum score (1) assigned to the scenario with the lowest total operational costs and a minimum score (0) assigned to the highest operational costs (Figure 8).

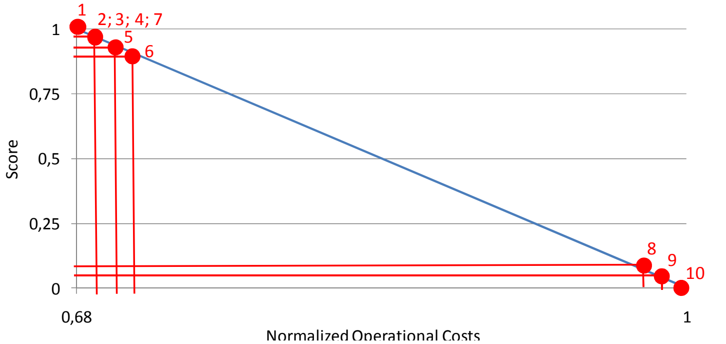

Figure 8. Determination of value function – operational costs.

- Stock below the safety level: This represents the time percentage that the plant's stock remains below the minimum inventory safety level, but it results in no interruption to the steelmaking process. The safety stock level is defined as 15 days of the plant's input consumption. This parameter aims at representing the risk of interruption to plant production. A value function of this criterion assigns a maximum score (1) to a zero percentage (0%) of observation days of stock below the safety level and a minimum score (0) to the highest percentage. The variation between these extremes is linear (Figure 9).

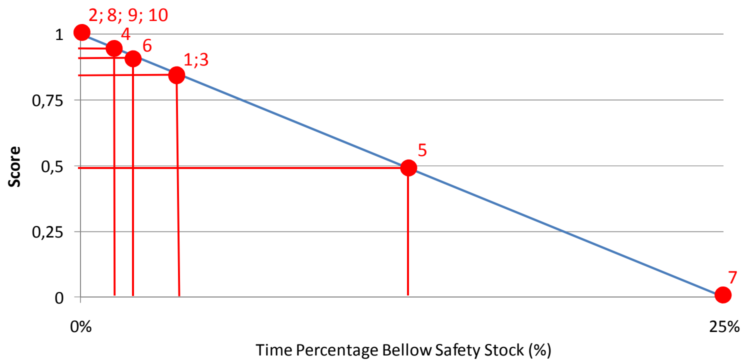

Figure 9. Determination of value function – time below the safety stock level.

- SE/NE iron ore percentages: Operationally, the plant, owing to its physical characteristics, would rather work with SE than it would with NE iron ore. The scenarios are simulated within a discrete distribution of the percentage of SE iron ore (40%, 35% and 30%) and the value function is given as follows: 40% - valued as maximum (1), 35% - assigned with an intermediate score (0.5) and 30% - valued as minimum (0) (Figure 10).

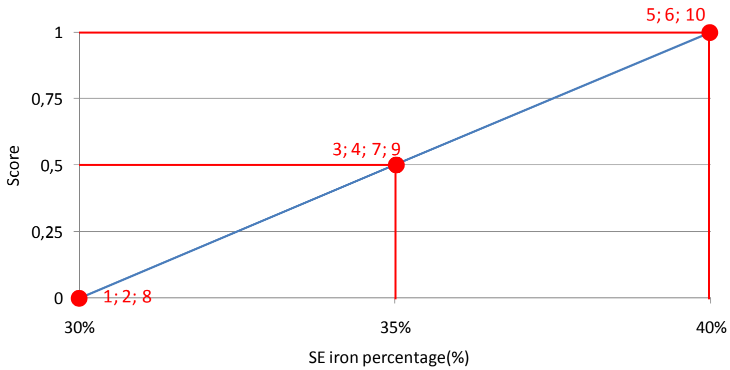

Figure 10. Determination of value function – SE/NE iron ore origin percentage.

- Stock capacity: The company project includes a stockyard that is able to store 775,000 tons of iron ore. For obvious reasons, configurations with lower storage areas are preferred, representing less area commitment. Thus, in accordance with the established value function, the scenario with lower storage capacity gets a maximum score (1) and that with a higher capacity gets a minimum score (0), with linear variation between these extremes (Figure 11).

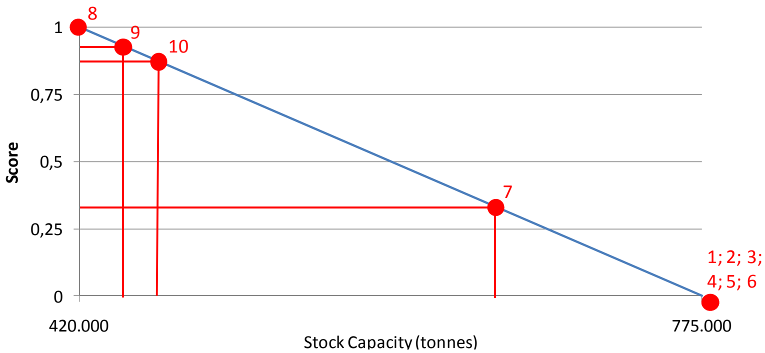

Figure 11. Determination of value function – stock capacity.

- Average supported queuing time: This refers to the average time that vessels can queue at the iron ore terminals without affecting the delivery of inputs. Vessels have to obey the queuing disciplines in both iron ore terminals. This is an uncertain parameter, since a scenario that supports lower queues is riskier than one that supports high levels of the queuing in terms of the fulfillment of planned demand. Moreover, the behavior of queue patterns at Brazilian iron ore terminals is regulated by fluctuations in global demand. The scenario with the largest average supported queuing time scores 1 (maximum), while the shortest time scores 0 (minimum) (Figure 12).

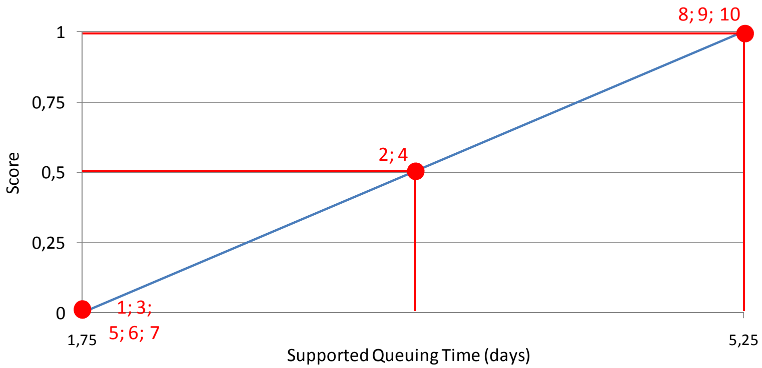

Figure 12. Determination of value function – supported queuing time.

- Chartering: This criterion assumes only binary values, namely relying or not on chartering spare vessels. Thus, scenarios with no chartering reliance receive a maximum score (1) and scenarios where chartering spare vessels is considered to be an option receive a minimum score (0). As previously mentioned, such behavior occurs because of the difficulty in chartering vessels that meet the specific operational characteristics demanded, especially for short time periods (Figure 13).

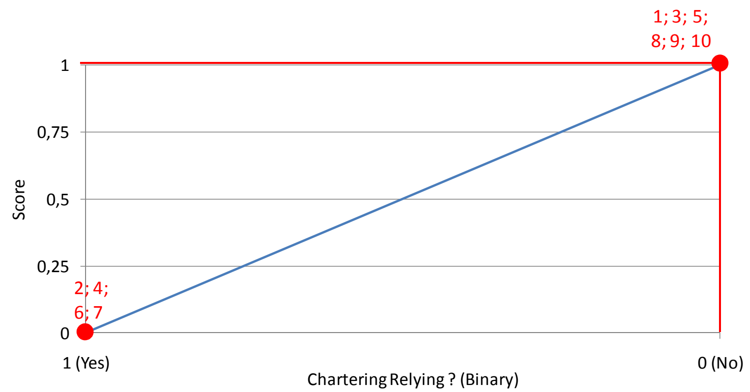

Figure 13. Determination of value function – chartering.

- New mission allocation waiting time: This represents the average number of hours that each vessel of the company fleet waits to be allocated to a new mission (new route to any of the iron ore suppliers). Thus, a higher new mission waiting time, on one hand means fleet idleness, whereas, on the other hand, represents less risk to input supply to the plant. The value function assigns, for the lowest waiting time value observed, the maximum score (1) and to waiting times greater than 24 hours, the minimum score (0). Between 0 and 24 hours, the variation of the value function is linear (Figure 14).

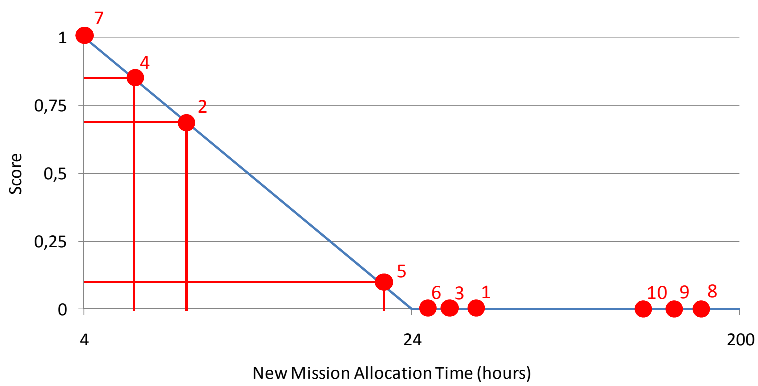

Figure 14. Determination of value function – new mission allocation time.

5.6. Model validation

Because the real system is still a future project, there is no historic operation database for validating the model's results. Thus, in order to validate the model, the analytical calculations of the fleet's operational parameters were compared.

Suppose the following initial scenario (fully deterministic):

- 30% of the cargo comes from SE;
- Vessel fleet composed of three Panamax class ships (70,000 tons);
- No restriction on storage;
- Queues at loading terminals of 5 days in the NE terminal and 7 days in the SE terminal;
- Travel times of 1.5 days (one way) from the plant port to the NE terminal and 4 days (one way) from the plant port to the SE terminal;
- 1 day mooring time at the loading terminals and 2.5 days at the unloading terminals;
- One unloading berth at the plant terminal;
- No downtime (offhire) nor docking; and
- No unloading queues at either terminal;

Vessels cycle times can be calculated as shown in Table 5.

	Empty Trip	Loading Queue	Loading	Loaded Return Travel	Unloading Queue	Unloadin	Total
NE	1,50	5,00	1,00	1,50	0,00	2,50	**11,50**
SE	4,00	7,00	1,00	4,00	0,00	2,50	**18,50**

Table 5. Cycle time composition (in days).

As the availability of vessels in these analytical calculations is 100%, in 25 years we have 9,125 days of operation. Using the cycle times data shown in Table 5, and keeping the proportions of SE iron ore at 30%, we make the following calculations:

- 11.5 days / cycle × 70% × # of cycles + 18.5 days / cycle × 30% × # of cycles = 9,125 days.

Thus, the amount of full cycles (round trips) per vessel is 670, i.e., 469 cycles between the plant and the NE terminal and 201 cycles between the plant and the SE terminal. Through these calculations, under these conditions (with no queuing when unloading) and with a three-vessel fleet, it would be possible to operationalize 2,010 cycles in 25 years, adding up 140.7 million tons, or 5,628 MTPY. Further, considering 2.5 days of berth occupancy for each unloading process, we reach a berth occupation rate of 55% (5,025 days in 9,125 available days).

A DES model run was then carried out under the same criteria. The results obtained from the DES simulation model are shown in Table 6, compared with the analytical results.

The 98% average adherence of the DES simulation model was considered to be satisfactory and thus the model was validated.

5.7. DES simulation result

Twenty replications (of 25 years each) of the DES model were run for each scenario described in Section 5.4. The results are shown in Table 7.

Description	# cycles in 25 years	Demanda (million tonnes)	Berth Occupancy Rate
Analytic Calculation	2.010	140,70	55%
DES Simulation Model	1.961	137,25	54%
Accurancy	98%	98%	98%

Table 6. Cycle time composition (in days).

Scenarios	% Demand Met	Lack of Inputs (days/year)	NPV Total (norm.)	Total Annual Operational Costs (norm.)	% Time Below Safety Stock	Average Suppported Queuing Time (days/cycle)		New Mission Allocation Time (h/cycle)
						NE	SE	
Scenario 1	99	2	0.65	0.68	5	1.75	1.25	44
Scenario 2	100	0	0.70	0.69	0	3.50	2.50	11
Scenario 3	99	1	0.66	0.69	5	1.75	1.25	35
Scenario 4	99	0	0.71	0.69	2	3.50	2.50	7
Scenario 5	99	12	0.66	0.70	13	1.75	1.25	22
Scenario 6	100	0	0.72	0.71	3	1.75	1.25	29
Scenario 7	99	18	0.71	0.69	25	1.75	1.25	4
Scenario 8	100	0	0.99	0.95	0	5.25	3.75	161
Scenario 9	100	0	1.00	0.97	0	5.25	3.75	146
Scenario 10	100	0	1.00	1.00	0	5.25	3.75	118

Table 7. Results obtained by the DES model.

The analysis in Table 5 demonstrates that those scenarios operating with fleets of three vessels (Scenarios 8–10) reached a higher performance level regarding the operational criteria and service levels (average supported queuing time, time below safety stock level, days of input lacking). Furthermore, these scenarios are less risky to the system, less susceptible to uncertainties, less demanding on storage areas and more tolerant of queues at the iron ore supplier's terminals. However, the costs of these configurations are higher compared with the other scenarios in terms of the initial investment needed or the operational costs.

Among the first seven scenarios, which assume a two-vessel fleet, the comparison of similar scenarios in which variations only concern the reliability or not of chartering spare vessels (e.g., Scenarios 1 and 2, 3 and 4, 5 and 6) allows us to conclude that the chartering process is responsible for improving the operational results despite leading to increased costs. Moreover, it is noticeable that a higher percentage of SE iron ore incurs higher costs because of the greater distance between the input supplier and the steel production plant. Section 5.7 contemplates the MCDA.

5.8. MCDA

The decision-making process was based on the assignment of weights to the decision criteria listed in Section 5.5. The process is now presented. The following methodological step is the assignment of scores associated with all the decision criteria in each of the 10 previously considered scenarios. Table 8 shows the importance of classifying the decision criteria and calculating the normalized weights associated with each of them. The criteria order of importance was defined unanimously by the group of decision makers.

Criterion #	Criterion	Priority	Weight (100/Priority)	Normalized Weight
1	Power Plant Stoppages	1	100.0	30
2	Net Investment Present Value (NPV)	2	50.0	15
3	Total Annual Operational Costs	2	50.0	15
4	% Time Below Safety Stock	3	33.3	10
5	Average Queuing Supported Time	4	25.0	8
6	Stocks Capacities	5	20.0	6
7	NE/SE Iron Ore Input Proportion	5	20.0	6
8	Vessels Chartering	6	16.7	5
9	New Mission Allocation Time	6	16.7	5
	Sum		**332**	**100**

Table 8. Importance of the decision criteria and normalized weights.

The criterion considered to be most important for the company was the number of days per year when the plant stops production owing to poor supply. This is an extremely critical criterion. Subsequently, the criteria related to costs are the most important (i.e., NPV and operational costs), followed by those related to operational risks (i.e., the safety stock level and uncertainty related to the average supported queuing time at iron ore terminals). After those criteria, the subsequent priorities are storage capacity, proportion of NE/SE iron ore input, stipulation of chartering vessels and new mission waiting time. From the simulation results shown in Table 7, the scores associated with all considered scenarios are presented in Table 9.

Scenario	Criterion 1	Criterion 2	Criterion 3	Criterion 4	Criterion 5	Criterion 6	Criterion 7	Criterion 8	Criterion 9
Scenario 1	0.38	1.00	1.00	0.80	0.00	0.00	0.00	1.00	0.00
Scenario 2	1.00	0.86	0.97	1.00	0.00	0.00	0.50	0.00	0.65
Scenario 3	0.50	0.97	0.97	0.80	0.50	0.00	0.00	1.00	0.00
Scenario 4	1.00	0.83	0.97	0.92	0.50	0.00	0.50	0.00	0.85
Scenario 5	0.10	0.97	0.94	0.48	1.00	0.00	0.00	1.00	0.10
Scenario 6	1.00	0.80	0.91	0.88	1.00	0.00	0.00	0.00	0.00
Scenario 7	0.00	0.83	0.97	0.00	0.50	0.35	0.00	0.00	1.00
Scenario 8	1.00	0.03	0.16	1.00	0.00	1.00	1.00	1.00	0.00
Scenario 9	1.00	0.00	0.09	1.00	0.50	0.93	1.00	1.00	0.00
Scenario 10	1.00	0.00	0.00	1.00	1.00	0.86	1.00	1.00	0.00

Table 9. Score by scenario and by criterion.

Thus, the application of the normalized weights considered for each criterion (Table 8) results in a final score for each scenario. The scenarios are ranked in Table 10.

Rank #	Scenario	Final Score
1	Scenario 4	0.78
2	Scenario 2	0.74
3	Scenario 6	0.72
4	Scenario 10	0.64
5	Scenario 9	0.62
6	Scenario 3	0.61
7	Scenario 8	0.60
8	Scenario 1	0.55
9	Scenario 5	0.50
10	Scenario 7	0.38

Table 10. Ranking of final scores for the 10 scenarios.

Table 10 shows that the scenario that has the highest final score is Scenario 4. The final scores of Scenarios 2 and 6 are, however, close to that of Scenario 4. Scenario 2 differs from Scenario 4 only by showing a smaller proportion of SE iron ore, while Scenario 6 employs a higher proportion of SE iron ore than does Scenario 4. However, Scenario 6 supports less queuing time compared with Scenarios 4 and 2.

Scenario 10 is ranked fourth, virtually tied with Scenarios 9, 8 and 3. Scenario 3 is similar to Scenario 4, but with no vessels chartering and a lower average supported queuing time. The difference between Scenarios 10, 9 and 8, which are those with a dedicated three-vessel fleet operation, is in the proportion of SE iron ore employed in the steelmaking process: 40%, 35% and 30%, respectively.

Given the proximity of the final scores of the three best-ranked scenarios (Scenarios 4, 2 and 6), a reasonable configuration is thus chosen between them. These three scenarios are composed by fleets of two vessels, which leads to close NPV values and total operational costs, similar total storage capacities (775,000 tons), a reliance on chartering vessels during fleet docking periods and no interruptions in the steelmaking process. Therefore, the final selection between these three scenarios is based on the average supported queuing time in the supplier’s terminal and the SE iron ore percentage.

Scenario 2, second in the overall ranking, has the lowest SE iron ore percentage (30%), while Scenario 6, third in the overall ranking, has the highest SE proportion (40%). However, Scenario 6 supports only 50% of the average queuing time of Scenarios 2 and 4 (1.75 days versus 3.5 days). The final recommendation is thus Scenario 4 because its high average queuing time compared with Scenarios 2 and 6 and its intermediate percentage of SE iron ore.

5.9. Sensitivity analysis

After obtaining the first recommended alternatives, further analyses may be performed through a sensitivity analysis by changing the weights of the criteria and priorities as well as through the generation of new alternative solutions. Another alternative is the reapplication of the MCDA model, after the elimination of the less promising alternatives (in this case, Scenarios 1, 5 and 7, which obtained final scores lower than 0.60). Following the removal of these scenarios, there will be a redistribution of the normalized scores and thus the evaluation of the remaining alternatives will become a more robust process. Although the range of evaluation scenarios and possible solutions may be lost, the decision-making process certainly becomes more meticulous and accurate.

In addition, sensitivity analysis regarding other aspects such as value functions may be performed in order to observe the behavior and responses of the system as a whole to variations in data inputs. Another point to consider is the participation of several specialists to establish the criteria and their importance weights, as this commitment increases credibility to the study.

6. Conclusion

Firstly, it is important to keep in mind that the DSS methodology proposed in this chapter is not a solution optimizer methodology that necessarily indicates the best decisions to make. This chapter contributes to the decision-making literature by showing how DSSs can bridge the gap between enterprise systems and decision makers. Implementing the proposed DSS would provide companies with a distinct competitive advantage: when following the hybrid methodology steps exemplified, the proposed DSS tool could certainly guide and orientate decision making based on technical and practical fundamentals. Moreover, such a methodology may involve a team of several experts in the definition of criteria and weights, corroborating decision-making credibility. In that way, human evaluation capability and judgments should never to be left alone in any decision-making process.

However, the main conclusion of this study confirms the efficacy of using DES in a broader and more complex environment compared with the development and application of a simplistic model. The proposed DSS tool works as a catalyst to improve the decision-making process, deriving the capabilities of a DES model and surpassing its shortcomings through the employment of MCDA to allow for further tradeoff studies. The DES and MCDA combined methodology has been shown to be effective as a complex logistics problem decision-making support tool. Further, the developed DSS tool, with some minor modifications, would be applicable for the evaluation of similar logistics systems.

Merging MCDA and DES can enhance the interaction between model development and users/customers, thereby improving model development and the analysis of the results. This interaction is an important quality issue in DES models, especially those that promote social change, namely those that help users make better decisions [31]. Therefore, quality improvement for DES can be investigated when using MCDA in combination.

Another important contribution of this chapter is the possibility of choosing alternatives based on various relevant and often antagonistic criteria, usually ignored by skewed decision-making processes, which are primarily guided by the financial aspects (costs/income) of each proposed solution. Moreover, in a conventional simulation study, scenario evaluations are usually based on a single criterion (related mostly to operational aspects) and the classification of two scenarios: viable or not viable. By observing, developing and working from a more extensive and complete evaluation perspective, including the participation of several experts in setting criteria and priorities, decision making becomes a more inclusive and trustful process.

6.1. Future research and recommendations

We believe that there is a great field to be explored in science management and DSSs by applying the presented hybrid methodology, especially in strategic environments such as Supply Chain Management and Supply Chain Strategy. For example, a manufacturing plant could be redesigned based on the company's objectives and marketing department's intentions using a specific set of products (for further discussion, see [32,33]).

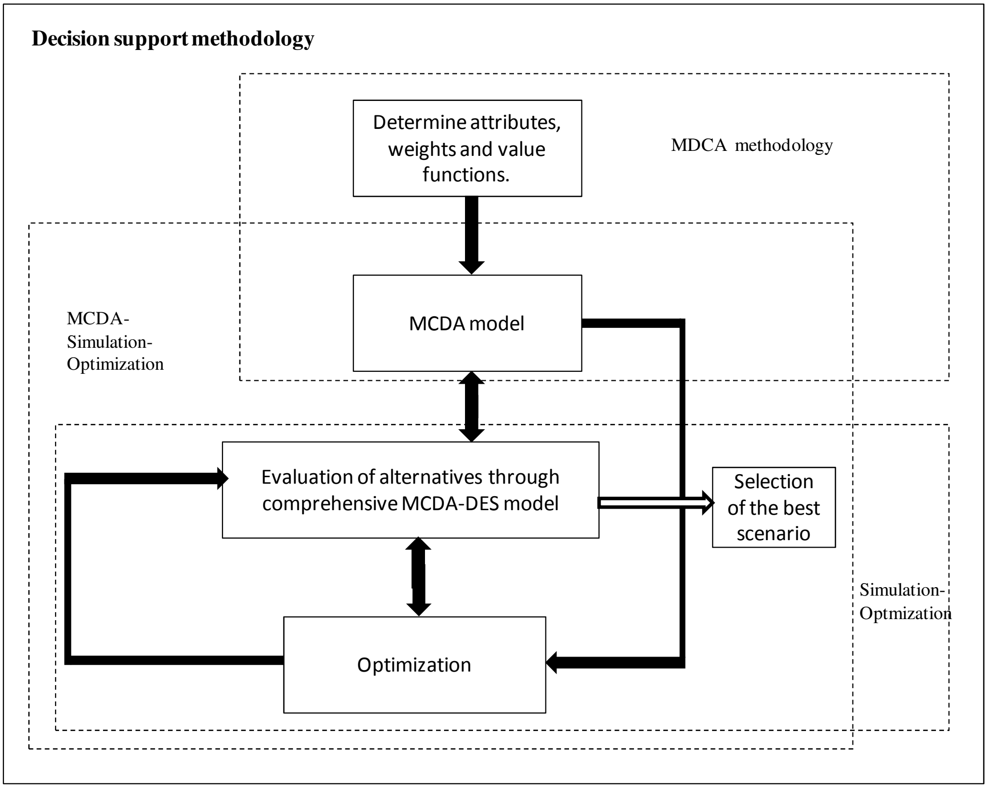

Figure 15. Framework of the simulation/optimization/MCDA methodology.

In addition, MCDA has a potential interface in simulation/optimization problems during the definition of the objective function. Converting objectives and values into an input/output assessment framework improves the scope of the study. In logistics systems, for example, DES has a greater capability to deal with randomness, increase the comprehension of the system and thus generate new ideas and solutions. Further, MCDA increases the visualization, measurement and weight of values and objectives through a set of attributes, while the methodologies of optimization for simulation (see [34]) enhance the elaboration, comparison and determination of the optimal or most efficient scenario. A framework for a more complex methodology for a DSS is presented in Figure 15, illustrating how these three methodologies may be implemented.

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