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Optimizing Transport Logistics under Uncertainty with Simheuristics: Concepts, Review and Trends

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Abstract: *Background:* Uncertainty conditions have been increasingly considered in optimization problems arising in real-life transportation and logistics activities. Generally, the analysis of complex systems in these non-deterministic environments is approached with simulation techniques. However, simulation is not an optimization tool. Hence, it must be combined with optimization methods when our goal is to: (i) minimize operating costs while guaranteeing a given quality of service; or (ii) maximize system performance using limited resources. When solving NP-hard optimization problems, the use of metaheuristics allows us to deal with large-scale instances in reasonable computation times. By adding a simulation layer to the metaheuristics, the methodology becomes a simheuristic, which allows the optimization element to solve scenarios under uncertainty. *Methods:*This paper reviews the indexed documents in Elsevier Scopus database of both initial as well as recent applications of simheuristics in the logistics and transportation field. The paper also discusses open research lines in this knowledge area. *Results:* The simheuristics approaches to solving NP-hard and large-scale combinatorial optimization problems under uncertainty scenarios are discussed, as they frequently appear in real-life applications in logistics and transportation activities. *Conclusions:* The way in which the different simheuristic components interact puts a special emphasis in the different stages that can contribute to make the approach more efficient from a computational perspective. There are several lines of research that are still open in the field of simheuristics.

Keywords: simheuristics; transportation; logistics; optimization; uncertainty

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1. Introduction

Real-life logistics and transportation (L&T) challenges are usually characterized by different levels of uncertainty. Many of these challenges can be modeled as stochastic optimization problems, and they are often NP-hard and large-scale in nature. Thus, exact optimization methods show limitations when high-quality solutions are required in reasonably short computing times, and approximated optimization methods, such as heuristics and metaheuristics, are usually employed for solving these problems in many practical applications.

When dealing with stochastic uncertainty, many experts employ simulation methods, since they allow for analyzing different scenarios that can be helpful in decision-making processes. Still, simulation is not an optimization tool. Therefore, hybrid simulation-optimization methodologies have been proposed to efficiently cope with large-scale stochastic optimization problems.

Simheuristics, the combination of simulation with metaheuristics, is one of these simulation-optimization methods. Its efficiency as a method for solving different combinatorial optimization problems with stochastic elements has been shown in different studies [1]. According to Juan et al. [2], this is due to its ability to evaluate solutions using simulation and problem-specific analytical expressions. Research related to simheuristics has been growing in recent years as shown in Figure 1, which presents the number of articles indexed per year from the Elsevier Scopus database for the term "simheuristics". These results show an increasing trend in the number of publications involving simheuristics. This trend might be related to the fact that simheuristics is a methodology designed to better cope with the complexity of real problems when searching for the optimal solution in environments under uncertainty, as is the case for many L&T problems [3].

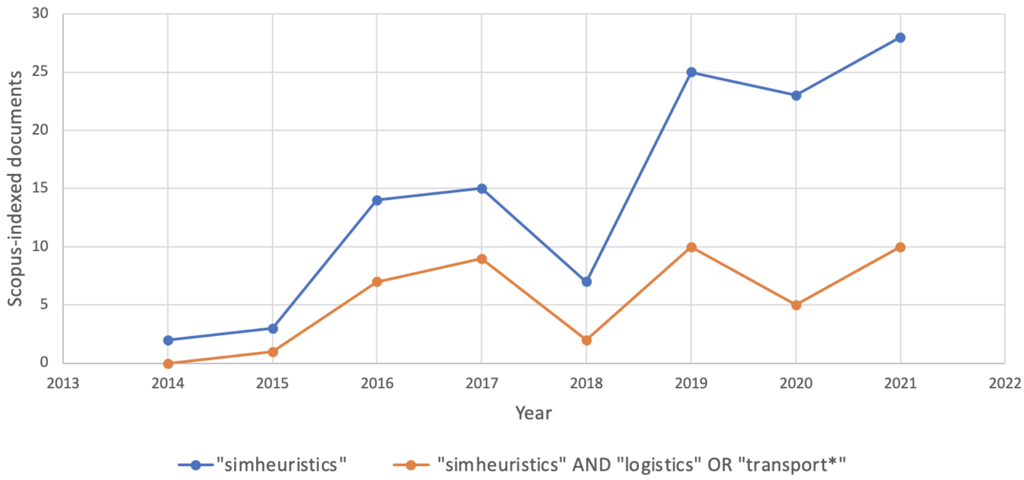

Figure 1. Time evolution of Scopus-indexed documents for 'simheuristics' and 'simheuristics in logistics' or 'simheuristics in transport / transportation' (searched as 'transport*' to include both terms).

The growing interest in the development of these methodologies has motivated the appearance of literature reviews on the use of simheuristics. Hence, Juan et al. [1] compiles all the papers published until 2017. As a complement to this review, our paper presents a literature review on simheuristics applied to optimization problems in L&T, focusing on the analysis of papers published after 2017. Figure 1 also shows an increasing number of articles indexed in the Elsevier Scopus database for the search "simheuristics AND (transport OR logistics)" in the title, abstract, and keywords of publications after 2017. In addition, Figure 2 illustrates the main journals that have published articles indexed in the aforementioned database. One can notice a growing interest in this methodology in journals that belong to areas as diverse as Operations Research, Industrial Engineering, Simulation, and Applied Sciences. All in all, this paper aims at presenting a comparative analysis between the existing simheuritic approaches, highlighting the main problems addressed problems and how different authors have employed simheuristics to tackle uncertainty in L&T optimization problems.

Hence, the main contributions of this work are: (i) an extension of the traditional concept of simheuristics, which also includes a machine learning component to enhance the searching process and reduce computational times; (ii) a review of related works, recently published, in solving different routing problems with stochastic components; and (iii) a cross-problem analysis of the computational results obtained when solving the aforementioned optimization problems, which allows us to extract common patterns on the application of simheuristics in L&T. All these elements make this article a valuable reference for many researchers interested in solving stochastic optimization problems in this field. The rest of the paper is structured as follows: Section 2 contextualizes simheuristics inside the big area of simulation-optimization. Section 3 presents the fundamentals of simheuristics. Section 4 summarizes the applications of simheuristics before 2018 in the L&T field. Section 5 reviews recent applications (on 2018 or after) of simheuristics in L&T. Section 6 illustrates some numerical examples using several simheuristics approaches. Finally, Section 7 summarizes the main conclusions of this work and open research lines.

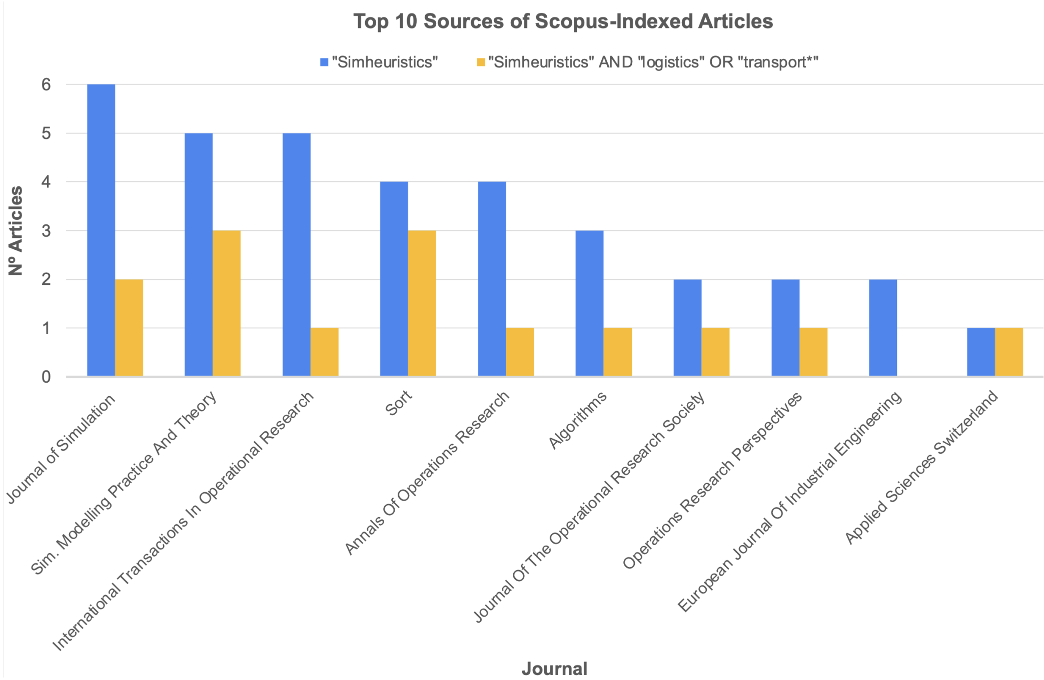

Figure 2. Scopus-indexed articles by Journal for 'simheuristics' and 'simheuristics in logistics' or 'simheuristics in transport / transportation' (searched as 'transport*' to include both terms).

2. Simulation-Optimization and Simheuristics

Since simulation alone cannot be used to solve stochastic optimization problems with large solution spaces, many authors have proposed the combination of simulation and optimization methods to handle such problems [4,5]. Simulation-optimization approaches include different optimization methods, such as mathematical programming, metaheuristics, and machine learning. In addition, statistical and machine learning methods can be used to build surrogate models based on the simulation output [6]. These models represent analytical relations among the system variables, and can be employed to obtain estimates of the simulation output in shorter computing times. Figueira and Almada-Lobo [4] classified simulation-optimization approaches based on the simulation usage. Thus, according to these authors, simulation could be utilized to: (i) evaluate an objective function, or a constraint, in a stochastic optimization problem; (ii) generate solutions for an optimization problem; or (iii) enhance an analytical model. Excellent reviews and tutorials on simulation-optimization approaches can be found in Fu et al. [7], Chau et al. [8], and Jian and Henderson [9].

Hybridizing metaheuristics with simulation is becoming popular as a standard procedure to deal with stochastic optimization problems [10,11]. Glover et al. [12,13], and April et al. [14] are among the first authors discussing the marriage of both methodologies. These authors developed the OptQuest software (www.opttek.com/products/optquest, last accessed on 11 May 2022), a proprietary simulation-optimization engine that is integrated into several commercial simulation packages. Still, being a proprietary software, it performs like a 'black-box' approach, with internal mechanisms that are not fully explained. Following similar principles, simheuristic algorithms also combine metaheuristics with simulation. Hence, they can be classified as a subset of simulation-optimization methods and, in particular, of simulation-based optimization procedures [14]. As it will be discussed later in more detail, simheuristic algorithms are 'white-box' approaches specifically designed to solve large-scale and NP-hard combinatorial optimization problems with stochastic elements, which can be present in the form of stochastic objective functions or probabilistic constraints [15]. Some reviews of simheuristics concepts and applications can be found in Juan et al. [1] and Chica et al. [3].

3. Fundamentals of Simheuristics

The development of simheuristic algorithms was motivated by the need to address real-life optimization problems characterized by high stochasticity. Simheuristics combine metaheuristics with simulations, such as Monte Carlo simulation (MCS), to deal with the stochastic part of the problem. These algorithms belong to the hybrid simulation-optimization methodology used to generate efficient solutions to combinatorial optimization problems with random components. In the L&T field, these stochastic elements can be, for example, random demands or random travel times and might be part of the objective function (e.g., total travel time that depends on random travel times) or the constraints (e.g., probability of delivery times inside given time windows) in the optimization problems.

In real life, we face a huge variety of optimization problems, including vehicle routing problems (VRP), facility location problems (FLP), arc routing problems (ARP), team orienteering problems (TOP), etc. Typically, the goal of each problem is to maximize the total reward or to minimize the total cost associated with the activity. Figure 3 presents an illustrative example of the structure of each of these main optimization problems. For example, the objective function in a VRP is usually to minimize the total cost, which is the sum of fixed plus variable cost. In the TOP, the objective is to maximize the rewards collected by vehicles when visiting customers. Many of the problems that arise in real-life T&L are stochastic in nature. Thus, in a VRP, ARP, or TOP, the time a vehicle needs to travel from one node to another might not be deterministic. On the contrary, it might be influenced by factors like the weather conditions, traffic congestion level, etc. Besides, probabilistic constraints might also be present in real-life problems. These challenges make the problem troublesome. However, simheuristic algorithms allow us to provide high-quality solutions to these problems in short computing times. A traditional mathematical formulation of these stochastic problems is given below:

$$\text{Optimize } f(x) = \mathbb{E}[F(x,T)] \tag{1}$$

$$\text{s.t.:} \quad P(h_i(x,T) \geq l_i) \leq q_i \qquad \forall i \in I \tag{2}$$

$$k_j(x) \leq r_j \qquad \forall j \in J \tag{3}$$

$$x \in X \tag{4}$$

In the previous expression, $F(x,t)$ is the objective function that needs to be optimized, x refers to a possible solution inside the solution space X, and T is a vector of random variables. The term $\mathbb{E}[F(x,t)]$ represents the expected value of the objective function. Equation (1) is the general form of the objective function in a stochastic optimization problem. Constraints (2) represent probabilistic constrains, e.g.: the probability that a customer is visited after a given time $l_i > 0$ is limited by a threshold q_i. Constraints (3) are the traditional deterministic constraints in any optimization problem. Finally, Equation (4) defines the solution space.

In order to solve the aforementioned optimization problem, we can benefit from a simheuristic approach. A schematic presentation of the simheuristic approach is shown in Figure 4. This presentation is an extension of the approach introduced in Juan et al. [2]. The approach starts by defining the deterministic version of the optimization problem. The stochastic problem is simplified in this definition, e.g., the random variables are replaced by their expected values to form an associated mean-value problem [16]. This step is based on the assumption that solutions to the deterministic problem might be promising solutions to the stochastic problem under low and medium uncertainty. Hence, for instance, a solution that minimizes total travel time in the deterministic VRP is likely to be a good-quality solution (in terms of expected travel time) if just a small uncertainty level is introduced into the VRP. Thus, solution x is associated with a deterministic value, $det(x)$, for the deterministic version of the problem, and with a stochastic value, $stoch(x)$, for the stochastic version. The $stoch(x)$ value can be estimated using simulation. Notice, however, that the relationship between $det(x)$ and $stoch(x)$ does not imply the existence of a perfect correlation, especially as the uncertainty level increases. Thus, solution x_1

could be better than solution x_2 in terms of deterministic conditions, but solution x_2 could be better than solution x_1 under stochastic conditions. Accordingly, the relation between their associated values could be presented as $det(x_1) \leq stoch(x_2) \leq stoch(x_1)$ in a minimization problem and $stoch(x_1) \leq stoch(x_2) \leq det(x_1)$ in a maximization problem. The deterministic values present the lower and upper bounds for the stochastic values in the minimization and maximization problems, respectively. Notice also that for large levels of uncertainty, the performance of the solution is too variable to make decisions based on its expected value alone.

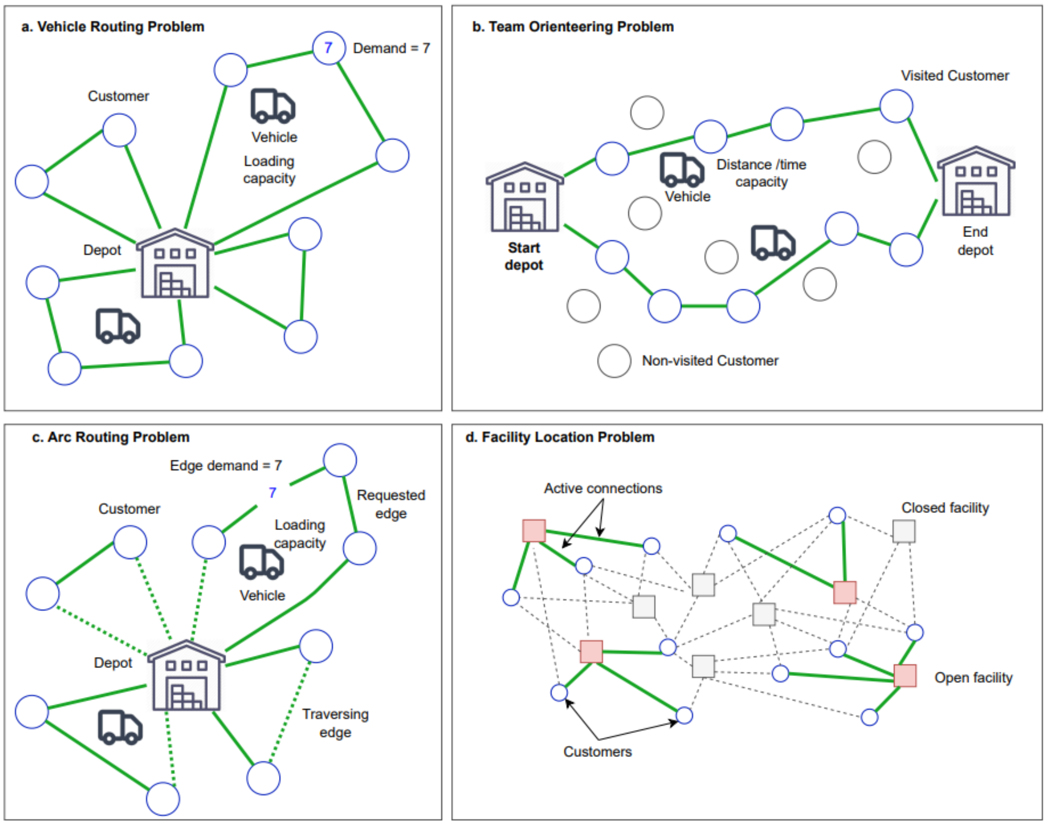

Figure 3. Illustrative examples of the main addressed problems with simheuristics in L&T.

After simplifying the stochastic optimization problem, the first stage of the simheuristic approach starts (Figure 4). A metaheuristic algorithm is responsible for exploring the solution space and generating solutions to the deterministic problem. First, each generated solution x^* is examined to identify whether it is a promising solution or not. In the first case, the solution is assessed using simulation to estimate its stochastic value, $stoch(x^*)$. This value is not limited to the average: it could represent the variance, percentiles, and useful probabilistic information required to compute the reliability of solutions. In this stage, the number of simulation runs is limited, and several techniques could be utilized to speed up the simulation runs, such as techniques presented in Rabe et al. [17] and Fippel and Brainlab [18]. The simulation output is used to: (i) estimate the stochastic performance of solutions; and (ii) update the machine learning component that is added to the approach. Moreover, the machine learning component utilizes the simulation output to: (i) update the parameters of the metaheuristic algorithm to enhance the solution space search for promising solutions under stochastic conditions; (ii) build a prediction model to identify promising solutions and, hence, reduce simulation time; and (iii) develop a surrogate model that can estimate the value of a stochastic objective function or probabilistic constraints for solutions found by the metaheuristic algorithm.

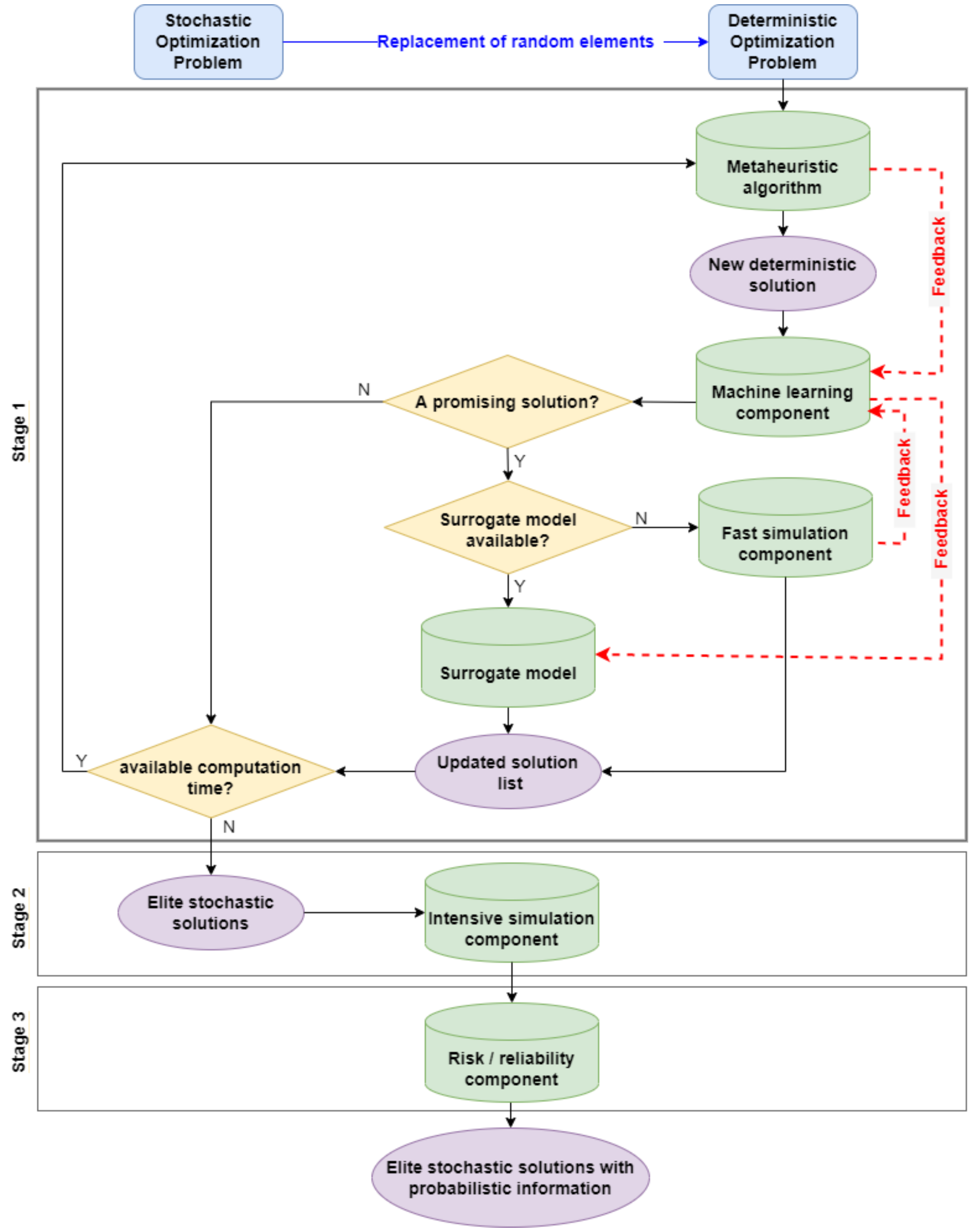

Figure 4. Simulation–optimization approach schema with a machine learning component.

The first stage ends when the maximum allowed time for the stage is reached, and an elite list of solutions is passed to the second stage. This elite list contains solutions with relatively good performance under stochastic conditions. In the second stage, the solutions in the elite list are investigated intensively using a more significant number of simulation runs compared to the investigation in the first stage. The last stage utilizes the simulation output for risk and reliability analysis. The output of this analysis is passed to decision-makers to support them in selecting solutions and, hence, enhance the decision-making process.

4. Initial Works on Simheuristics in L&T

As a solving methodology, simheuristics has succeeded to make pervasive contributions in different fields, such as manufacturing, production, healthcare, transportation, logistics, supply chain management, and so on. In this article, however, we focus in the applications of simheuristics in the L&T field. In particular, this section reviews the simheuristics papers published before 2018. Table 1 summarizes these contributions, mainly the ones indexed in the Elsevier Scopus database.

Table 1. Main simheuristics publications in L&T indexed in Scopus before 2018.

Paper	Considered Problem	Solving Approach	Remarks
Juan et al. [19]	VRP with stochastic demand	Metaheuristics and MCS	considering a safety stock for vehicles capacity, and transform the VRPSD instance to a limited set of CVRP instances
Juan et al. [20]	VRP with stochastic demand	Metaheuristics and MCS	using parallel and distributed computing systems, considering a safety stock for vehicles capacity
Juan et al. [21]	stochastic inventory-routing problems	simheuristics	considering a set of alternative refill policies for each retail center and safety stock
Gruler et al. [22]	VRP	simheuristics	waste collection problem in smart cities
Gruler et al. [23]	multi-depot VRP	simheuristics (biased randomization techniques, metaheuristics, and MCS)	multi-depot stochastic waste collection problem, uncertain demand for waste
Grasas et al. [24]	VRP, ARP, FLP, PFSP	biased randomized procedures (BRPs)	using BRPs based on the use of skewed theoretical probability distributions
Jesica et al. [25]	stochastic uncapacitated FLP	simheuristics	considering the uncertainty on the service costs
Quintero-Araujo et al. [26]	VRP	simheuristics	using horizontal collaboration strategies
Quintero-Araujo et al. [27]	multi-depot VRP	simheuristics	discussing the benefits of horizontal cooperation in transportation activities
Gonzalez-Martin et al. [28]	VRP and ARP	simheuristics	-
Quintero-Araújo et al. [29]	multi-depot VRP	simheuristics	evaluating the impact of horizontal cooperation, using safty stock for demand
Calvet et al. [30]	rich VRP	simheuristics	-

The combination of simulation and optimization has received a lot of attention from researchers. In the beginning, there was not a strong link between these two parts, but over time this connection became stronger when the researchers figured out that the solutions improved significantly when they apply simulation and optimization in an integrated way [2]. One of the initial works, Jung et al. [31] addresses the demand uncertainty by using a simulation-based optimization method. This work proposes a framework to determine the safety stock level in planning and scheduling applications in supply chains. Since the demand is considered an uncertain parameter, MCS is employed in the presence of other uncertain parameters, such as delivery times and production delays. The main limitation of this work is the long time that is required to address problems. Thus, the approach cannot support different tactical analyses with the abundant information provided by simulation. In another work, Wan et al. [32] propose a simulation-based optimization framework for analyzing a supply chain under uncertainty. This framework employs a surrogate model, together with domain reduction and incremental sampling, to capture the relation between decision variables and supply chain performance. They apply the proposed approach to optimize base stocks for a three-stage supply chain.

As one of the first simheuristics, Juan et al. [19] propose a flexible simulation methodology for the VRP with stochastic demands. A simplified VRP model is shown in Figure 3. In this work, the authors consider the VRPSD as a limited set of capacitated VRP (CVRP) by assigning different values to the safety stock level for each problem. Considering a safety stocks helps to reserve a part of the load capacity of the vehicles to deal with unexpected customers with high demands. Hence, the chance of route failure decreases significantly. However, employing safety stock increases the fixed cost in the problem. They applied metaheuristics to solve the CVRP and then a MCS to estimate the expected total costs of different routes obtained. In another research, Juan et al. [20] discuss how parallel and distributed computing systems can be employed to solve the VRPSD efficiently. Using parallel and distributed computing systems decreases the computation time to solve the problem and shows that a near-optimal solution can be obtained in just a few seconds. In this work, safety stock for vehicle capacities is considered to deal with high customer demands and prevent route failure. For each safety stock level, a different scenario is defined for the problem, and they are solved by integrating MCS inside the heuristics process.

Juan et al. [21] propose simheuristics for solving stochastic inventory-routing problems. The goal is to define a routing plan that minimizes the expected total cost of the inventory and routing in a network. This work has two main contributions: first, the methodology can consider personalized refill policies for each retail center, which decreases the total cost significantly compared to other solution approaches; and secondly, the solving approach uses no probability distribution function for the random demand of each retail center. Later, Quintero-Araujo et al. [26] apply horizontal collaboration strategies, which are based on the collaboration of different supply chain sections in urban areas, to analyze the cost reduction in the urban transportation model under uncertainty. They define two scenarios: collaborative and non-collaborative. The first one is considered as one multi-depot VRP, and the other one is modeled as a series of vehicle routing problems. They apply simheuristics based on local search, biased-randomized, and MCS techniques.

Real transportation and logistic problems are characterized by high uncertainty. For example, a smart city problem consists of many random variables. Therefore, applying a deterministic model to solve this problem is unpractical. In this case, Gruler et al. [22] discuss the need for a solution method to consider the waste collection problem in smart cities. They define a deterministic waste collection problem and developed metaheuristics based on a variable neighborhood search framework. Then, they extend the problem to a stochastic version and develop simheuristics for solving it. Their results include a risk analysis considering the variance of the waste level and vehicle safety capacities. In another work, Gruler et al. [23] discuss a multi-depot stochastic waste collection problem with co-operation among vehicles from different depots. In this problem, the demand for collecting waste is considered as a random variable, and a clustered urban area (in the case of a real metropolitan area) is considered. They used a hybrid algorithm combining metaheuristics with simulation. This combination consists of biased-randomization techniques, meta-heuristics, and MCS. Jesica et al. [25] studied the stochastic uncapacitated facility location problem (UFLP), where the service costs are assumed to be random. A simplified facility location problem is illustrated in Figure 3. They apply the simheuristics methodology to solve this problem. First, they use fast saving-based heuristics to obtain the deterministic optimal values and decrease the high computational solving times. Then, they apply simheuristics by combining a metaheuristic with MCS techniques. In the end, the results show that simheuristics can provide optimal solutions in very short computation times.

Working with simheuristics has started in the past decade to find the best solution in problems with uncertainty. It has become a powerful alternative to the use of other stochastic methodologies, such as stochastic programming, fuzzy programming, dynamic programming, etc. [4].

5. Recent Works on Simheuristics in L&T

After defining the simheuristic approach and utilizing it in solving various problems, including combinatorial optimization problems such as the ones in Figure 3, researchers extended their interest in exploring a variety of new problems. Table 2 summarizes some contributions utilizing simheuristics in transportation or logistics; most of these contributions are indexed in the Scopus database after 2018. As explained in Section 4, commonly solved optimization problems are vehicle/arc routing/orienteering problems. Additional constraints were added to these problems to form new variants that present real-world cases that are difficult to solve by employing traditional approaches.

Table 2. Summary of published papers in Elsevier Scupos database since 2018 applying simheuristics in logistics or transportation.

Paper	Considered Problem	Solving Approach	Remarks
Peng et al. [33]	multi-objective route optimization problem	MCS and NSGA-II	introduce data driven strategy to reduce computation time and considered risk assessment
de León et al. [34]	maritime logistics	NSGA-II	combine deterministic and stochastic objectives
Latorre-Biel et al. [35]	vehicle routing problem	machine learning and petri nets	correlated demands were considered
Rabe et al. [36]	team orienteering problem	biased randomized simheuristics	case study associated with the distribution of medical supplied during COVID-19 pandemic
Juan et al. [37]	team orienteering problem	genetic algorithm and MCS	applied to the coordeination of unmanned aerial vehicles
Martínez-Reyes et al. [38]	Location Routing Problem	Iterated Local Search algorithm with MCS	distribution of medical supplies (Personal Protective Equipment)
Ramirez-Villamil et al. [39]	two-echelon vehicle routing problem	simheuristics	case study of a delivery company and consider the CO_2 emission
Ghorpade and Corlu [40]	selective pick-up and delivery problem	GRASP metaheuristic with MCS	variant of traveling salesman problem
Ramírez-Villamil et al. [41]	two-echelon vehicle routing problem	simheuristics	used real data from Bogota, Columbia
Yazdani et al. [42]	evacuation	simheuristics	opposition-based learning concept was developed
Raba et al. [43]	animal feed supply chain	biased-randomization techniques with a simheuristic	propose the combination of internet of things and simheuristics
Onggo et al. [44]	inventory routing problem	MCS within an iterated local search	agri-food supply chain with a single fresh food supplier
Calvet et al. [45]	multidepot vehicle routing problem	MCS with a metaheuristic algorithm	a variant of capacitated vehicle routing problem
Estrada-Moreno et al. [46]	multi-depot vehicle routing problem	simulation within a biased-randomized heuristic	consider weather dependent probability distribution of traveling times
Souravlias et al. [47]	Quay crane scheduling	Iterated Local Search with Monte Carlo Sampling	assumed productivity rates due to the effect of the offshore wind
Reyes-Rubiano et al. [48]	vehicle routing problem	MCS with a multi-start metaheuristic, which also employs biased-randomization techniques	considered limited driving-range capacity of electrical vehicles
Rabe et al. [49]	a multi-period capacitated facility location problem	hybrid modeling approach	in the approach, system dynamics, a heuristic to solve facility location problem, and MCS are combined
Zhou et al. [50]	maritime logistics		a review of simulation and optimization applications in maritime logsitics
Gök et al. [51]	scheduling problem	vehicle routing problem with time window	Scheduling aircraft turnarounds at airports

For example, researchers solved variants of routing problems, such as the multi-depot vehicle routing problem. In this variant, customers are served by limited capacity vehicles departing from different depots. Calvet et al. [45] solved the stochastic demands version of the problem. The two-dimensional vehicle routing problem (2L-VRP) is another variant of the VRP, and the stochastic version was solved by Guimarans et al. [52]. Problems solved using simheuristics are not limited to routing problems. They also include challenges such as the berth allocation problem concerning fining berthing position and time of vessels that arrive at a port [34]. Green logistics and the utilization of autonomous driving vehicles gain importance in the study of smart cities. Thus, researchers have defined problems in the context of smart cities. For example, Reyes-Rubiano et al. [48] solved the vehicle routing problem in which vehicles are electric. Thus, a limited driving range was added as an additional constraint to the traditional VRP, and the driving range of an electric vehicle and the travel time are considered stochastic.

As Table 2 shows, a variety of real-world case studies were solved using a simheuristic approach. For example, Onggo et al. [44] solved the perishable inventory routing problem with stochastic demand. In this problem, fresh food is stored and distributed, while the objective function minimizes costs. They used MCS to handle the stochasticity, and combined MCS with iterated local search. Another example is the case study of distributing medical supplies during COVID-19 pandemic [36]. Simheuristics usage was extended to form a base in decision support systems, such as ones developed by Rabe et al. [53]. These systems are designed to recommend promising solutions for real-world optimization problems. Thus, these systems need to handle complex optimization problems, including uncertainty.

Different types of uncertainty were defined and introduced to optimization problems. Researchers utilized simheuristics to handle stochastic uncertainty in optimization problems. Currently, the simheuristics concept is extended to solve optimization problems considering fuzzy uncertainty. For example, Tordecilla et al. [54] introduced a fuzzy layer to combine simulation, metaheuristics, and fuzzy logic to handle fuzzy uncertainty of travel times and customers' demands. Another type of uncertainty in problem characteristics might be modeled as a correlation between different problem elements. For example, Latorre-Biel et al. [35] considered stochastic and correlated customer demand in the vehicle routing problem, and used simheuristics to solve the VRP.

Simulation is an expensive tool to be used in optimization problems. Thus, approaches are defined to utilize simulation when it is needed to reduce total computation time and still get promising solutions. Rabe et al. [17] discussed several concepts concerning the number of simulation runs and their need. Even though they based their work on a manufacturing system, similar approaches could be considered in transportation and logistics. Speeding up simheuristics is an important issue in real-world cases. Decisions are made in a short time or instantaneously. Therefore, recommended solutions to optimization problems are required within a few seconds. In another work, Muravev et al. [55] use a stochastic two-stage optimization problem to model intermodal terminal main parameters, which is also called dry port. They apply an agent-based system dynamics simulation model and show that the combination of agent-based models with the simulation approaches improves the solutions significantly, and also helps the decision-making process associated with the selection of strategic facility planning in intermodal terminals. In the end, they consider a case study on Yiwu dry port. The results show that the model tries to minimize the costs by reducing the total distance despite increasing traffic flows. Finally, Sibul et al. [56] analyze the navigation along the Northern Sea route considering ice conditions and weather changes. The main objective of this work minimizes the costs despite the decreasing speed of the sailings due to the severe weather conditions. They create a path-finding algorithm to connect the shipping operational parameters with the environmental conditions and used available environment data to test the algorithm.

6. Cross-Problem Analysis of Computational Results

This section presents the results obtained with simheuristics in different works available in the literature, where well-known transport optimization problems under uncertainty conditions are solved. Table 3 lists the seven selected L&T problems and the references used to collect the computational results, while Table 4 presents the solution values reported by the different authors for the listed problems. The first column identifies the reference where the solution values have been gathered, while the second column identifies the problem. Subsequently, the next three columns report their optimal/near-optimal deterministic solution (*OBD*), the solution obtained when their deterministic solution is evaluated in a stochastic scenario (*OBD-S*), and their solution provided by the simheuristic (*OBS*), respectively. Finally, the last two columns show the percentage gaps of the deterministic solution (*OBD*) with respect to the stochastic solutions (*OBD-S* and *OBS*).

Table 3. Selected transportation problems.

Problem	Acronym	Reference
Time Capacitated Arc Routing Problem with Stochastic Demands	TCARPSD	[57]
Arc Routing Problem with Stochastic Demands	ARPSD	[58]
Stochastic Team Orienteering Problem	STOP	[59]
Two-dimensional VRP with Stochastic Travel Times	2L-VRPST	[52]
Electric VRP with Stochastic travel Times	EVRPST	[48]
Capacitated Location Routing Problem with Stochastic Demands	CLRPSD	[60]
VRP with Stochastic Demands	VRPSD	[19]

Table 4. Information on the selected transportation problems.

Reference	Problem	OBD [1]	OBD-S [2]	OBS [3]	GAP [1–2]	GAP [1–3]
Keenan et al. [57]	TCARPSD	3473.0	5014.0	4770.0	44.37%	37.35%
Gonzalez-Martin et al. [58]	ARPSD	5412.7	6223.0	5669.2	14.97%	4.74%
Panadero et al. [59]	STOP	528.2	359.1	468.8	32.02%	11.26%
Guimarans et al. [52]	2L-VRPST	1549.2	1874.6	1825.6	21.00%	17.84%
Reyes-Rubiano et al. [48]	EVRPST	16,490.1	19,995.7	19,339.9	21.26%	17.28%
Quintero-Araujo et al. [60]	CLRPSD	98,587.0	112,464.3	111,545.9	14.08%	13.14%
Juan et al. [19]	VRPSD	816.8	930.3	859.2	13.90%	5.20%

The gaps between the different solutions for the analyzed works are presented in Figure 5, where the y-axis represents the gap between the value of the stochastic solutions with respect to the *OBD*. This value is considered as a lower bound and is used as a reference in a scenario with perfect information of a stochastic optimization problem, while the stochastic value *OBD-S* could be considered as an upper bound to the optimal stochastic solution. Thus, the solution generated by a simheuristic algorithm (*OBS*) lies between these two bounds.

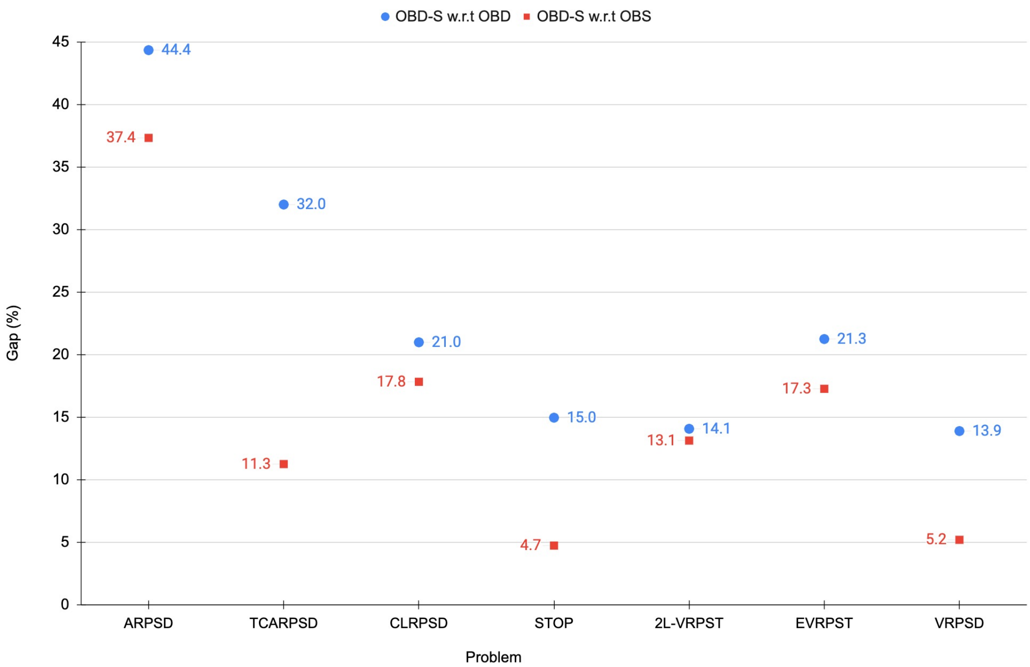

Figure 5. Gaps between *OBS* and *OBD-S* with respect to *OBD* (baseline 0% gap).

According to the results, the solutions provided by the simheuristic (*OBS*) outperform the best deterministic solutions when they are used in a stochastic scenario in the analyzed problems. However, the particular problem under study and its associated uncertainty influence the difference obtained between *OBD* and *OBD-S*. The numerical analyses have shown that the optimal or near-optimal solutions for the deterministic version of the problem are sub-optimal solutions when performed in real scenarios under uncertainty. Thus, in real problems, deterministic solutions (*OBD*) generate inefficient solutions when making decisions, which impacts the costs of the companies. In general, costs increase as the level of uncertainty increases. This requires the implementation of hybrid methodologies, which integrate simulation with metaheuristics when solving stochastic optimization problems.

7. Conclusions and Future Work

This paper has reviewed the concept of simheuristics, which hybridizes simulation with metaheuristic algorithms with the purpose of solving stochastic optimization problems. The manuscript also explains why this optimization approach can be effective when solving NP-hard and large-scale combinatorial optimization problems under uncertainty scenarios, as they frequently appear in real-life applications in L&T activities. The way in which the different simheuristic components interact has been also discussed, putting a special emphasis in the different stages that can contribute to make the approach more efficient from a computational perspective.

Recent applications of simheuristics in L&T have also been commented on, and a numerical summary of previous works illustrating the capabilities of simheuristics to provide high-quality solutions to different stochastic problems in the field is also provided.

There are several lines of research that are still open in the field of simheuristics; among them we can highlight the following ones: (i) the introduction of more advanced machine learning methods–especially those based on supervised learning and reinforcement learning–that enrich the feedback provided by the simulation component to the metaheuristic one, which allow for an accurate classification of promising solutions, and expedite the buildup of surrogate models that can speed up computations even further; (ii) the efficient and easy integration of metaheuristic code developed with modern programming languages with commercial simulators like FlexSim, which currently supports a friendly interaction with Python; and (iii) the extension of simheuristics into fuzzy simheuristics, which allow us to consider non-stochastic as well as stochastic uncertainty, as illustrated in Tordecilla et al. [54].

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