Proceedings of the 2018 Winter Simulation Conference
M. Rabe, A. A. Juan, N. Mustafee, A. Skoogh, S. Jain, and B. Johansson, eds.

SIMHEURISTICS APPLICATIONS: DEALING WITH UNCERTAINTY IN LOGISTICS, TRANSPORTATION, AND OTHER SUPPLY CHAIN AREAS

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ABSTRACT

Optimization problems arising in real-life transportation and logistics need to consider uncertainty conditions (e.g., stochastic travel times, etc.). Simulation is employed in the analysis of complex systems under such non-deterministic environments. However, simulation is not an optimization tool, so it needs to be combined with optimization methods whenever the goal is to: (i) maximize the system performance using limited resources; or (ii) minimize its operations cost while guaranteeing a given quality of service. When the underlying optimization problem is NP-hard, metaheuristics are required to solve large-scale instances in reasonable computing times. Simheuristics extend metaheuristics by adding a simulation layer that allows the optimization component to deal with scenarios under uncertainty. This paper reviews both initial as well as recent applications of simheuristics, mainly in the area of logistics and transportation. The paper also discusses current trends and open research lines in this field.

1 INTRODUCTION

Real-life optimization problems are often *NP-hard* and large-scale in nature, which makes traditional exact methods inefficient to solve them – at least in reasonable computing times. Thus, the use of heuristic and metaheuristic algorithms to obtain high-quality solutions in low computing times is required. With the increasing advances in computing hardware and software, simulation has become a 'first-resource' method for analyzing complex systems under uncertainty (Lucas et al. 2015). Thus, simulation is frequently employed in areas such as logistics and transportation, manufacturing, supply chain management, or smart cities. These systems are modeled and then simulated to get insights on their performance under different base scenarios. Simulation, however, is not an optimization tool. Thus, whenever a decision maker aims to find an optimal configuration for a system, she requires the use of optimization methods (Law and McComas 2002). Often, the associated optimization problems are addressed by assuming deterministic inputs and constraints, which allows us to simplify them but at the cost of not considering the real-life uncertainty that characterizes these systems.

As pointed out by Figueira and Almada-Lobo (2014), simulation-optimization methods are designed to combine the best of both worlds in order to face: *(i)* optimization problems with stochastic components; and *(ii)* simulation models with optimization requirements. Among these simulation-optimization methods, the

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combination of simulation with metaheuristics is a promising approach for solving stochastic optimization problems that are frequently encountered by decision makers in the aforementioned industrial sectors (Glover et al. 1996; Glover et al. 1999). A discussion on how random search can be incorporated in simulation-optimization approaches is provided by Andradóttir (2006), while reviews and tutorials on simulation-optimization can be found in Fu et al. (2005), Chau et al. (2014), and Jian and Henderson (2015). Among the different simulation-optimization approaches, this paper will focus on simheuristics, which can be seen as a specialized case of simulation-based optimization (April et al. 2003). Simheuristic algorithms integrate simulation methods inside a metaheuristic optimization framework to deal with large-scale and *NP-hard* stochastic optimization problems. Hybridization of simulation techniques with metaheuristics allows us to consider stochastic variables in the objective function of the optimization problem, as well as probabilistic constraints in its mathematical formulation (Fu 2002). As discussed in Juan et al. (2015), the simulation component deals with the uncertainty in the model and provides feedback to the metaheuristic component in order to guide the search in a more efficient way. Notice also that, when dealing with stochastic optimization problems, performance statistics other than expected values must be taken into account: while in deterministic optimization one can focus on finding a solution that minimizes cost or maximizes profits, a stochastic version of the problem might require that we analyze other statistics such as its variance, different percentile values, or its reliability level – i.e., the probability that the solution is still feasible once executed, which is not guaranteed if the random components can affect some optimization constraint. The simulation component can provide all these statistics, thus allowing for the introduction of risk-analysis criteria during the assessment of 'elite' solutions.

The main contributions of this paper are: *(i)* to provide a commented review of both initial and recent applications of simheuristics, mainly in the area of logistics and transportation; and *(ii)* to analyze trends as well as open research lines, e.g., statistical strategies that improve computing performance, the inclusion of more advanced simulation models, and the extension to 'agent-based' simheuristics that benefit from parallel and distributed computing strategies. Section 2 presents an overview of the fundamental ideas related to the concept of simheuristics. Section 3 reviews some of the initial applications of simheuristics to the field of logistics and transportation, while Section 4 performs a similar task with more advanced and recent applications. Section 5 analyzes applications of simheuristics to other areas, such as manufacturing, Internet computing, or finance. Section 6 discusses the main trends and open research lines in this emerging area. Finally, Section 7 summarizes the main ideas of this article.

2 SIMHEURISTICS FUNDAMENTALS

Since real-life optimization problems are frequently addressed with the use of metaheuristics, it seems logical to consider a combination of metaheuristics and simulation techniques to deal with stochastic variants of these problems. A simheuristic algorithm is a simulation-optimization approach oriented to cope with an optimization problem efficiently, typically a combinatorial optimization problem, containing stochastic components. These can either be located in the objective function (e.g., random demands, random travel times) or in the set of constraints (e.g., customers' demands that must be satisfied with a given probability, deadlines that have to be met with a given probability). Being heuristic methods, they do not guarantee finding the optimal solution but will find high quality, robust solutions.

Simheuristic approaches assume that, in scenarios with moderate uncertainty (variance), high-quality solutions for the deterministic version of an optimization problem are also likely to be high-quality solutions for its corresponding stochastic version – notice that this does not imply that the best solution for the deterministic optimization problem has to be the best solution for the stochastic version. In most practical applications, this 'correlation' assumption seems to be reasonable. Also, in scenarios with extreme uncertainty levels, individual outcomes can be extremely diverse and, therefore, in those cases it might make no sense to optimize traditional measures such as the expected cost; focusing on finding robust solutions may be a better option in these cases. Thus, it is possible to generate several 'promising' solutions for the stochastic optimization problem through the generation of a number of high-quality solutions for the

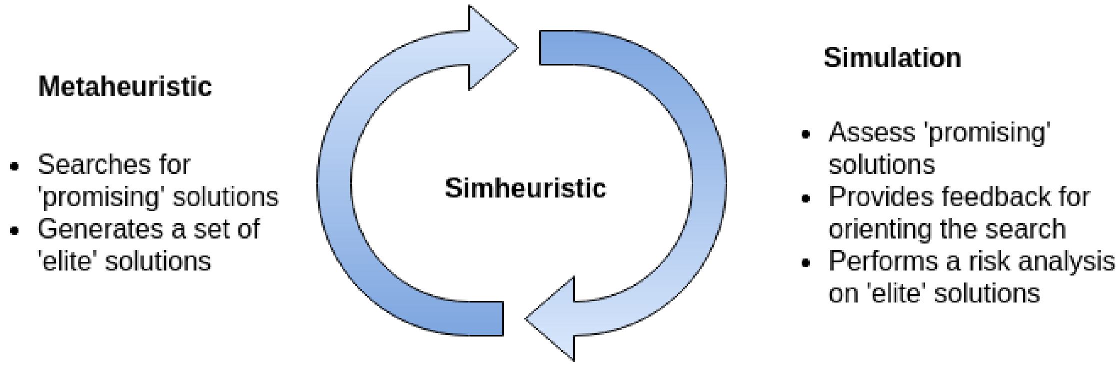

Figure 1: Role of each component in a simheuristic approach.

deterministic version. The deterministic counterpart of a stochastic optimization problem can be found, for instance, by replacing all random variables by their expected values. Then, a metaheuristic algorithm is run in order to perform an efficient search inside the solution space associated with the deterministic version of the problem. This iterative search process aims at finding a set of high-quality feasible solutions for the deterministic version. During the iterative search process, the algorithm has to estimate the quality (or feasibility) of each of these promising solutions when they are considered as solutions of the stochastic problem. One natural way to do this is by taking advantage of the capabilities that simulation methods offer to manage uncertainty. Each random event can be modeled throughout using a best-fit probability distribution – either theoretical or empirical – without having to assume normal or exponential behavior as other methods do. During the interactive search process, only solutions that perform well in the deterministic environment are sent to the simulation component. Moreover, for each of these solutions, just a reduced number of replications are run, since only rough estimates are necessary at this stage. This strategy allows for controlling the computational effort employed by simulation during the interactive search process, thus leaving enough time for the metaheuristic to perform an intensive search of the solution space. The estimated values provided by the simulation can then be used to keep a ranked list of 'elite' solutions for the stochastic problem. They can also provide feedback to the metaheuristic in order to intensify the exploration of promising search areas. Once the computational time assigned to the iterative search process has expired, the elite solutions are examined via more intensive simulation runs, thus obtaining estimates of higher accuracy and precision. The role of each simheuristic component is summarized in Figure 1.

Simulation runs can also be used to obtain additional information on the probability distribution of the quality of each solution. This complementary information can then be used to introduce risk analysis criteria in the decision-making process. In effect, since the objective function is stochastic, a decision maker might be interested in not only obtaining the solution that optimizes its expected value (or another specific measure of interest), but she might be also interested in analyzing the probability distribution of the values generated by several alternative solutions with similar expected values. This risk-analysis capability is one of the major advantages that simheuristics (and other simulation-based approaches) can offer in a natural way due to the ability of metaheuristics to generate a plethora of high-quality alternative solutions and also due to the ability of simulation to provide a random sampling of observations for each proposed solution. Another aspect to consider is the potential use of the best solution found by the metaheuristic for the deterministic version of the optimization problem. In many real-life systems, increasing the uncertainty level might generate additional costs that will eventually increase the overall system expected cost. Thus, for instance, increasing the variance in random variables such as customer demands or traveling and servicing times might lead to random observations exceeding the available load capacity or the available time to complete the service, thus causing penalty costs. In those cases, it is possible to use the value $det(s^*)$ of the near-optimal solution s^* for the deterministic version of the problem as a lower bound for the value $stoch(s^{**})$ of the optimal solution s^{**} for the stochastic version. Whenever s^* is applied in a stochastic

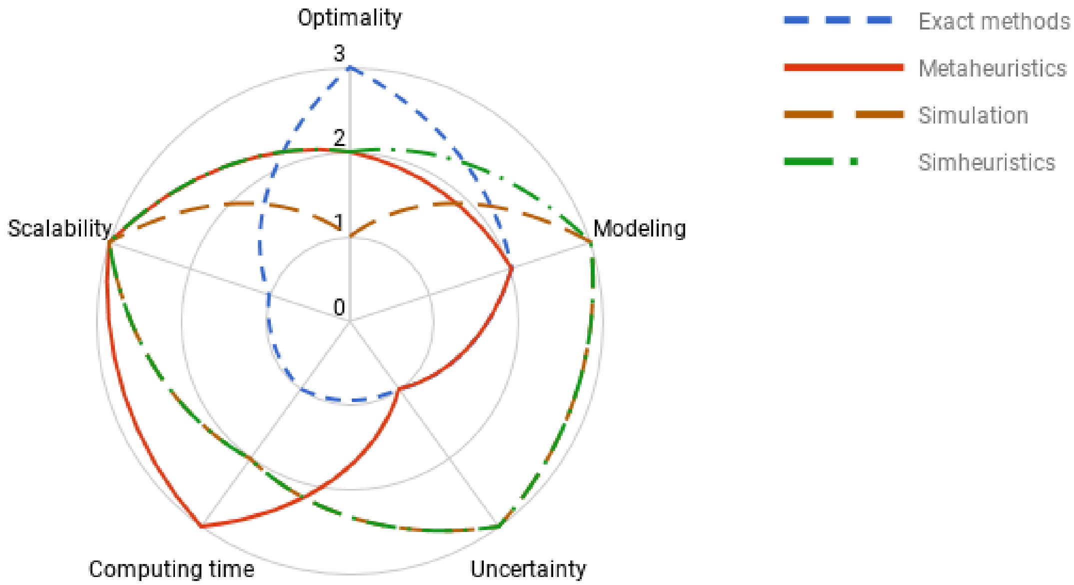

Figure 2: Comparison of different methodologies.

environment with the goal of minimizing costs, its value $stoch(s^*)$ is an upper bound of the optimal solution for the stochastic version, i.e.: $det(s^*) \leq stoch(s^{**}) \leq stoch(s^*)$.

Figure 2 compares different simulation and optimization methods, and how they perform in each of the five considered dimensions: *(i)* capacity to generate optimal solutions (optimality); *(ii)* flexibility in modeling complex systems (modeling); *(iii)* capacity for modeling uncertainty (uncertainty); *(iv)* computing time required to provide the requested output (computing time); and *(v)* capacity for dealing with large-size instances (scalability). Exact methods are the only ones able to guarantee optimality of solutions, but they might require unreasonable computing times when solving *NP-hard* problems of large scale, and they have difficulties to model non-smooth objective functions, too (Ferrer et al. 2016). On the contrary, metaheuristics are usually able to generate near-optimal solutions for large-scale *NP-hard* problems in relatively short computing times, but they are not well suited to model complex system interactions, especially when they include uncertainty. Finally, simulation methods can be used to account for uncertainty in a natural way, although they lack the optimization capabilities of exact and metaheuristic methods. By employing simulation methods, simheuristic algorithms aim at extending the capabilities of classical metaheuristics in the modeling and uncertainty dimensions. In both dimensions as well as in computing times and scalability, they can also outperform exact methods for large-scale instances of *NP-hard* optimization problems.

3 INITIAL APPLICATIONS IN LOGISTICS AND TRANSPORTATION

This section reviews some initial applications of simheuristics to the field of logistics and transportation. In these works, one can observe that the integration between the simulation and metaheuristic components had not yet been fully achieved, that computational issues were only starting to be understood, and that the feedback provided by the simulation component to the metaheuristic was rather limited. Still, some interesting ideas were emerging, e.g., use of concepts from reliability theory, use of safety stocks to increase the 'robustness' of the solutions, or use of log-normal distributions to model positive random variables in optimization problems – which had been traditionally modeled by means of less-realistic normal or exponential distributions that could easily harm the validity of the model and, thus, endanger the value of the entire study. For instance, Juan et al. (2011) consider a stochastic vehicle-routing problem in which a set of customers with random demands must be serviced by a fleet of vehicles departing from a depot. While there are some fixed costs associated with the planned distribution routes, the existence of uncertainty might also give rise to additional variable costs. In effect, in those cases in which the service demand of a route exceeds the actual vehicle capacity, a 'route failure' will occur, thus making the proposed solution infeasible. To 'repair' this failure, some corrective action must be needed – e.g., a non-planned round-trip to the depot to reload the vehicle. Typically, corrective actions will increase the variable cost of the distribution process. To reduce the probabilities of suffering route failures, the authors propose the use of safety stocks in the vehicles, i.e., reserving a part of the load capacity to deal with unexpectedly high demands during the actual distribution. Notice, however, that employing safety stocks also increases the fixed costs, since more routes will be needed. Simulation allows for estimating the variable costs associated with each candidate solution and also provides an estimate of its reliability. Here, the decision maker might be interested in a solution with a low total expected cost that, at the same time, provides high reliability. While this seminal work introduces a two-stage algorithm in which the metaheuristic component acts independently of the simulation, an integrated version of the algorithm is proposed in Juan et al. (2013), where the use of parallel and distributed computing: *(i)* speeds up the execution times; and *(ii)* shows that, at least for all tested instances, near-optimal solutions can be obtained in 'real time' (a few seconds) by employing concurrent executions of the algorithm. In the inventory routing problem, a set of retail centers have to be serviced from a central warehouse facility. Each retail center owns an inventory, which is managed by the central facility. For each retail center, the inventory level at the end of a period depends on the initial stock level and also on its customers' demands during that period. These customers' demands are modeled as random variables. Therefore, at the end of each period there might be some costs associated with inventory holding and inventory stock-outs. These costs might be incorporated into the decision-making process and added to the routing costs. In order to solve this problem, Juan et al. (2014b) propose a hybrid approach combining simulation with an efficient vehicle-routing metaheuristic. Thus, simulation is employed to estimate the expected inventory costs associated with each combination of retail center and refill policy. Next, for each refill policy, a routing metaheuristic is used to estimate the total costs, including inventory plus routing costs. In a series of numerical experiments, the authors show how this simheuristic approach can consider personalized refill policies for each customer, which allows it to outperform other standard refill approaches.

4 RECENT APPLICATIONS IN LOGISTICS AND TRANSPORTATION

This section reviews some recent applications of simheuristics, both in logistics and transportation (L&T). As depicted in Figure 3, in these applications, one can notice an increasing level of integration of the simulation and the metaheuristic components. Initially (low level), the simulation was employed after the optimization component with the goal of evaluating the quality of the solution provided by the latter component in a stochastic environment. Later (medium level), there is a higher integration between both components, and simulation is also employed to provide feedback that is used by the optimization to improve the search process (typically by using a stochastically-driven base solution from which new solutions are generated). Also, both methodologies are combined to provide a risk or reliability analysis on a set of 'elite' solutions. Finally (high level), computational issues are considered in order to reduce computing times, and goals other than optimizing expected values are taken into account.

Gruler et al. (2017a) discuss the need for optimizing urban waste collection in modern smart cities and formulate the problem as an extension of the vehicle-routing problem. The authors first develop a competitive metaheuristic, based on a variable neighborhood-search framework, to solve the deterministic variant. Then, they extend their approach into a simheuristic to cope with unexpected waste levels inside the containers. Their algorithm is tested using a large-scaled benchmark set for the waste-collection problem with several realistic constraints. Their results include a risk analysis considering the variance of the waste level and vehicle safety capacities. An extension of the previous waste-collection problem to a multi-depot

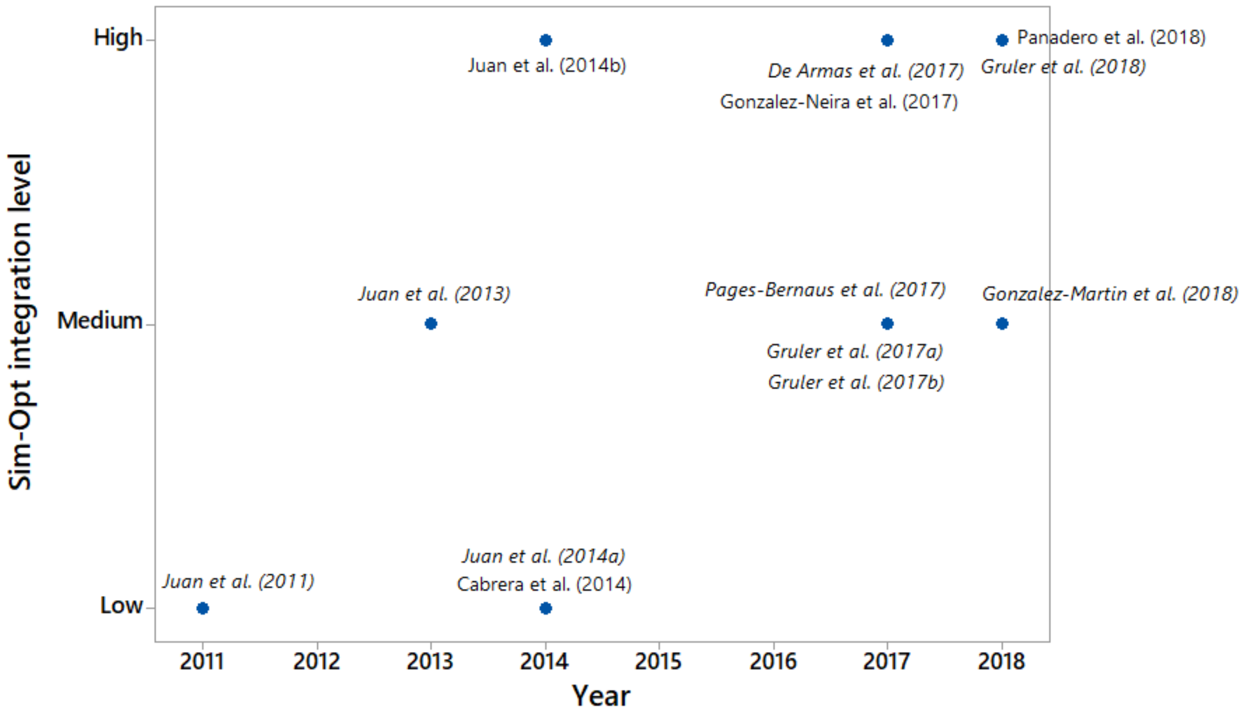

Figure 3: Evolution of Sim-Opt integration level (papers in italics correspond to the L&T area).

version is discussed in Gruler et al. (2017b), where horizontal cooperation strategies are employed to enhance the quality of the solution in clustered urban areas and large cities. The authors employ an iterated local-search metaheuristic to deal with the underlying multi-depot vehicle-routing problem. According to their computational experiments, the use of horizontal cooperation among vehicles belonging to different city districts (or even to different metropolitan areas) shows to be an effective strategy when dealing with uncertainty in waste levels.

The uncapacitated facility-location problem with stochastic service costs is analyzed in De Armas et al. (2017). First, the authors propose an extremely fast savings-based heuristic, which generates real-time solutions for the deterministic version of the problem. This can be extremely useful in telecommunication applications, where ‘good’ solutions are needed in just a few milliseconds for large-scale networks. The heuristic is then integrated into an iterated local-search framework, which allows us to compare it against state-of-the-art algorithms for the deterministic version. Finally, the metaheuristic is extended into a simheuristic and employed to solve the stochastic variant. As pointed out by the authors, the simulation layer is not only used to assess the stochastic value of the solutions generated by the iterated local search component, but the feedback from the simulation is also used to better guide the search process. In particular, the base solution inside the iterated local search is chosen according to the stochastic value provided by the simulation. These authors also introduce a procedure that ‘filters out’ non-promising deterministic solutions, so they are never sent to the simulation component to avoid an inefficient use of computing time. The paper also discusses the convenience of considering complementary goals to the minimization of expected costs, e.g., solutions that minimize a given percentile, and solutions with different trade-off levels of expected cost and variability.

Gonzalez-Martin et al. (2018) propose a simheuristic algorithm for solving the arc-routing problem with stochastic demands. Here, the authors use Monte Carlo simulation to extend the RandSHARP heuristic (Gonzalez-Martin et al. 2012), which was originally designed to solve the deterministic version of the problem. During the design of the routing plan, they make use of safety stocks, which allow vehicles to deal with unexpectedly high demands during the actual distribution process. These authors also introduce a reliability index to measure the ‘robustness’ of each solution with respect to possible route failures caused by random demands. By ensuring solutions with high reliability levels, they reduce the the overall cost of corrective actions associated with route failures.

Pages-Bernaus et al. (2017) consider a stochastic version of the capacitated facility-location problem, proposing two facility-location models representing alternative distribution policies in e-commerce (outsourcing vs. in-house distribution). The models consider stochastic demands as well as more than one regular supplier per customer. Then, two different methodologies are proposed to solve these models. While the first one is a classical two-stage stochastic-programming approach (which employs an exact solver), the second one is a simheuristic algorithm based on an iterated local-search framework. Computational experiments show that the former can be used to tackle only small-sized instances, while the latter allows for dealing with large-scale instances in reasonably short computing times. The multi-period inventory-routing problem with stochastic customer demands is analyzed by Gruler et al. (2018). A variable neighborhood search is extended into a simheuristic algorithm to consider variations in the forecasted demands. With the aim of finding optimal refill policies for each customer and period combination, the authors take into account that the quantity serviced at the beginning of one period will affect the inventory levels at the end of that period. These inventory levels will also be affected by the random demand associated with each customer in that period. The total cost to be minimized will be the aggregation of both inventory and routing costs. Notice that the interdependences between consecutive periods, due to the existence of random demands, introduce additional complexities in the underlying optimization problem that can be conveniently addressed by simulation.

5 OTHER APPLICATIONS OF SIMHEURISTICS

In this section, several applications of simheuristics to fields other than logistics and transportation are reviewed. These applications range from manufacturing (scheduling problems) to Internet computing or computational finance. Thus, Juan et al. (2014a) analyze the permutation flow-shop problem with stochastic processing times. This is a generalization of the well-known permutation flow-shop problem, in which the processing time of each job in each machine is a random variable following a positive probability distribution. A simheuristic algorithm is proposed to deal with this *NP-hard* and stochastic combinatorial optimization problem. Simulation is used here to determine which solution, among the set of elite deterministic solutions, shows a lower expected makespan when considering stochastic times. This strategy assumes that there is a strong correlation between high-quality solutions for the deterministic version of the problem and high-quality solutions for the stochastic version. The best-found solution for the deterministic problem will not necessarily be the best-found solution for the stochastic version since the resulting makespan of the former might be quite sensitive to variations in the processing times. The information provided by the simulation is also employed to perform a survival analysis of alternative solutions with similar expected makespan. Thus, the probabilities of completing the jobs before a given deadline can be compared among different solutions.

A completely different application is in Internet computing, where systems can benefit from the use of personal and non-dedicated computers. Being non-dedicated, these resources show random behavior regarding the times they are on-line (available) and off-line. Accordingly, their availability levels are lower than those of traditionally employed dedicated resources. Thus, in order to use non-dedicated resources in cloud-computing environments, it becomes necessary to solve the problem of how to attain high availability levels for the Internet services deployed over them. Most approaches on how to guarantee high service availability levels with non-dedicated resources are based on the introduction of high degrees of redundancy into the system. However, this practice leads to inefficient use of computational resources and, therefore, to higher operational costs. Accordingly, Cabrera et al. (2014) propose a simheuristic to generate cost-efficient configurations of non-dedicated resources able of supporting Internet services with a high availability level. In particular, they deal with the stochastic combinatorial optimization problem of determining a minimum-cost configuration of non-dedicated resources able to support a service while maintaining the service-availability level over a user-defined threshold. The main idea behind their solution approach is to design a metaheuristic algorithm that, starting from a feasible but costly solution, performs an oriented local search trying to replace expensive resources with cheaper ones, usually offering somewhat lower availability levels. For each new configuration generated in this iterative process, a discrete-event simulation is employed to estimate the new global availability of the service. This estimation is then used to check if the new and less-expensive configuration offers an availability level higher than the one specified by the user. Previously published proposals for availability-aware service deployment required use of restrictive assumptions – e.g., identical replicas of a service, series or parallel topologies, small-scale scenarios, or specific probability distributions. All these unrealistic assumptions are unnecessary in the simheuristic approach. According to the numerical experiments run by the authors, their algorithm is able to provide optimal solutions quickly in small-sized scenarios, while it can also be used in more realistic scenarios to generate good solutions in real time.

The distributed assembly permutation flowshop problem, in which different parts of a product are completed in a first stage – by a set of distributed flowshop lines – and then assembled in a second stage, is analyzed in Gonzalez-Neira et al. (2017). This work considers a stochastic version of the problem, where both processing and assembly times are modeled as random variables. Being that the main goal is minimization of the expected makespan, the authors also discuss the need for considering other measures of statistical dispersion in order to account for risk. This is done by means of a simheuristic algorithm, which also analyzes the performance of the algorithm under different uncertainty levels. As already observed in other previous work, the results show that, as the variance level increases, the less appropriate is making use of the best deterministic solution as a potential solution of the stochastic version of the problem.

Finally, an application to computational finance is introduced in Panadero et al. (2018). This paper discusses the problem of selecting the best portfolio of projects in which to invest. As the pool of project proposals increases and more realistic constraints are considered, the problem becomes *NP*-hard, which requires the use of metaheuristics. The goal is to maximize the expected net present value of the inversion, while considering random cash flows and discount rates in future periods, as well as a rich set of constraints including the maximum risk allowed. A variable neighborhood-search metaheuristics is constructed and extended to a simheuristics. After a series of computational experiments, several conclusions are reached, among them: *(i)* a relation between the expected net present value and risk is not necessarily linear; *(ii)* project interdependencies – as measured by the correlation between cash-flows from two projects – can be regarded as a limit to the volume of projects that can be included in a portfolio; *(iii)* a near-optimal solution to the deterministic version of the problem is generally sub-optimal in a stochastic environment; and *(iv)* as anticipated, a near-optimal solution to the stochastic version gives rise to a higher (expected) net present value than a near-optimal solution to the deterministic version evaluated in a stochastic environment.

6 TRENDS AND OPEN RESEARCH LINES

From the previous reviews, some of the following trends in the use of simheuristics can be identified and are expected to play a relevant role in future publications on this topic, therefore constituting open research lines to be yet fully explored:

- *A higher level of simulation-optimization integration*: a deeper integration between the metaheuristic component and the simulation component, including increasing use of the feedback provided by the simulation to better guide the search for better solutions.
- *Additional objectives*: a rising interest in considering optimization goals different from the expected value of a solution for the stochastic optimization problem; this includes measuring other statistics (e.g., variances, percentiles, and tail probabilities), reliability or robustness levels, and even considering multi-objective optimization problems.

- *Systems of increasing complexity*: moving from isolated logistics or transportation problems to integrated problems that reflect the complexity of supply networks, where interactions between different echelon stages also need to be considered in order to increase global efficiency.
- *Use of more sophisticated simulation approaches*: as the complexity of the systems increases, more advanced simulation approaches (e.g., discrete-event simulation or agent-based simulation) are required to take into account the dynamic and possibly nonstationary time-evolution of the system and the interactions among its many components.
- *Enhanced identification of promising solutions*: to speed up the computations, during a typical simheuristic process only a reduced set of solutions are classified as 'promising' and sent to the simulation component; enhanced strategies to classify a new solution as a promising one can be employed – e.g., analytical methods that quickly estimate the statistics that the simulation will provide, or probabilistic classification methods such as simulated annealing.
- *Statistically significant number of runs*: in some of the examples reviewed in this paper, a 2-stage approach is used; in the first stage, the promising solutions are simulated using a reduced number of runs, while in the second stage longer simulations are executed on the 'elite' solutions provided in the first stage to increase the statistics' accuracy and precision. However, statistical concepts (e.g., confidence intervals) could be employed to set the precise number of runs required in each stage in order to obtain estimates with a given level of precision.
- *Extending the application fields*: so far, most simheuristics have been applied in the area of transportation (vehicle- and arc-routing problems), logistics (facility-location problems), and production (scheduling problems). However, similar stochastic optimization problems can be found in other application fields such as telecommunications, finance, health-care systems, and smart cities.
- *Heuristic-supported simulation*: while the examples reviewed here refer to optimization problems in which simulation is used to support the search carried out by the metaheuristic (simulation-supported metaheuristic optimization), it is also possible to use heuristics or metaheuristics to optimize certain system parameters during a large simulation experiment.
- *Integration with machine learning*: being a flexible and relatively simple approach, simheuristics can be integrated with machine-learning approaches and, in particular, with learnheuristics in order to consider optimization problems with dynamic inputs (Calvet et al. 2017).
- *Multi-population simheuristics*: all the examples reviewed here are based on single-population metaheuristics; however, integration of simulation within multi-population metaheuristics (e.g., genetic algorithms, etc.) might be worth exploring, too, since different individuals in a population might be based on different statistics obtained from the simulation component.
- *Agent-based simheuristics*: similar to the way agent-based modeling and simulation extends the more traditional concept of discrete-event simulation and benefits from distributed and parallel computing systems, one could consider agent-based simheuristics as a multi-agent extension of the simheuristic concept, where each agent is an autonomous and differentiated simheuristic algorithm that interacts with the rest of the agents while searching for a near-optimal solution to a complex and stochastic combinatorial optimization problem (Figure 4).

7 CONCLUSIONS

This paper has discussed the convenience of combining simulation with metaheuristics for dealing with real-life optimization problems under uncertainty conditions. Pure simulation models are not enough to optimize a complex system. Similarly, pure deterministic optimization methods do not allow for the incorporation of random inputs and probabilistic constraints that frequently appear in most real-life decision-making processes. As systems in sectors such as transportation and logistics, supply-chain management, telecommunication networks, or finance become more complex and large-scale, the use of simheuristics and other similar simulation-optimization approaches becomes necessary if uncertainty has to be taken

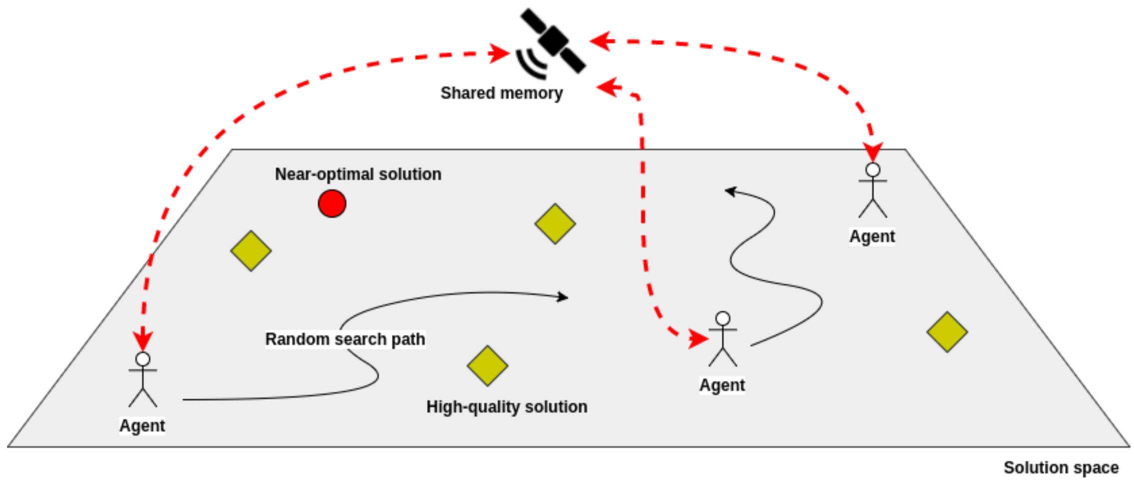

Figure 4: Scheme of an agent-based simheuristic approach.

into account to ensure model validity. Integrating simulation into a metaheuristic framework can be done in multiple ways. This paper has reviewed some initial and some recent applications of simheuristics to different areas, which cover fields from logistics and transportation to finance. The possibility of completing a risk analysis on the stochastic solution has also been outlined. A number of current trends and open research lines have been identified and commented on. In particular, the combination of simheuristics with learnheuristics to deal with stochastic and dynamic optimization problems seems to have a huge potential, as well as the extension to the concept of agent-based simheuristics that can benefit from parallel and distributed computing paradigms.

ACKNOWLEDGEMENTS

This work has been partially supported by the Erasmus+ programme (2017-1-ES01-KA103-036672).

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