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Using Simheuristics for Supporting Risk-aware Decision Making in Transport and Logistics under Uncertainty Scenarios

Verwendung von Simheuristiken zur Unterstützung risikobewusster Entscheidungen in Transport und Logistik unter Unsicherheitsszenarien

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Abstract: Informed decision making in production and logistics has not only to consider optimisation issues but also uncertainty conditions that are often present in real-life applications. In this context, finding the solution that provides the optimal expected value for a cost or benefit objective function is usually not sufficient, since the variability or risk associated with the proposed solution needs to be measured as well. Accordingly, simulation-optimisation methods are becoming a relevant tool when dealing with complex logistics and production systems. Among these methods, this paper focuses on simheuristics, which have showed their effectiveness in solving large-scale stochastic optimisation problems. We discuss the main principles behind the simheuristics concept, compare this methodology with other similar ones in the simulation-optimisation domain, and provide some insights on their use.

1 Introduction

Optimisation methods are often required whenever a decision maker aims at finding the best-possible configuration for a system (Law and McComas 2002). Often, the associated optimisation 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 characterises these systems. As pointed out by Figueira and Almada-Lobo (2014), simulation-optimisation methods combine simulation and optimisation to use the strengths of both techniques in solving: *(i)* optimisation problems with stochastic components; and *(ii)* simulation models with optimisation requirements.

Metaheuristic algorithms are frequently employed to solve NP-hard and large-scale combinatorial optimisation problems (COPs). Hence, the combination of metaheuristics with simulation techniques (simheuristics) seems a reasonable approach to deal with real-life stochastic COPs, which are often NP-hard and large-scale. Stochastic components can either be integrated in the objective function (e.g., random processing or transport times, random demands, etc.) or in the set of constraints (e.g., deadlines or demands that must be satisfied with a given probability, etc.).

März and Krug (2011) describe four different ways to hybridise simulation with optimisation: *(i)* integration of optimisation into simulation; *(ii)* simulation results are used as initial values of the optimisation component; *(iii)* optimisation results are used for the configuration of the simulation; and *(iv)* simulation is employed to compute the objective function associated with an optimisation problem. In our view, simheuristics do not fall in any of these categories. It could be better described as "integration of simulation into optimization", "simulation results are used for the configuration of the optimization process", and "simulation is not only employed to compute the objective function associated with an optimization problem, but also to better guide the metaheuristic search and to complete a risk or reliability analysis on the generated solutions". Some reviews on simheuristics applications can be found in Juan et al. (2015, 2018).

This paper contributes to the literature on simulation by introducing recent advances in the way the methodology is applied – mainly oriented to make it more efficient and avoid the simulation component being delayed by the optimisation – and presenting new examples of applications in the area of logistics. Based on these examples, the paper also discusses some managerial insights regarding the type of decision-making challenges that are well suited for simheuristics, and provides some lines for future research.

2 The Simheuristic Approach

Simheuristic approaches assume a positive and significant correlation between the value (e.g., cost) of a solution (e.g., a vehicle routing plan) when it is applied in a deterministic environment and its expected value when it is applied in a stochastic environment. In most practical applications, this assumption seems to be reasonable, especially when the uncertainty level is low or moderate. Nevertheless, this 'relationship assumption' can be empirically verified in each case by comparing the 'deterministic' and 'stochastic' values associated with a series of solutions. In scenarios with a high uncertainty level, the expected value of a solution might not be a good key performance indicator due to the high variability (risk) associated with individual realisations of the stochastic solution. The existence of correlation among deterministic and stochastic values implies that it is possible to generate a set of 'promising' solutions for the stochastic COP through the generation of a number of high-quality solutions for the deterministic COP. As depicted in Figure 1, given a stochastic problem, its deterministic counterpart is considered. This can be done, for instance, by replacing all random variables by their expected values. Then, a metaheuristic algorithm is run in order to perform an efficient search within the solution space associated with the deterministic COP. This iterative search process aims at finding a set of high-quality feasible solutions for the deterministic COP.

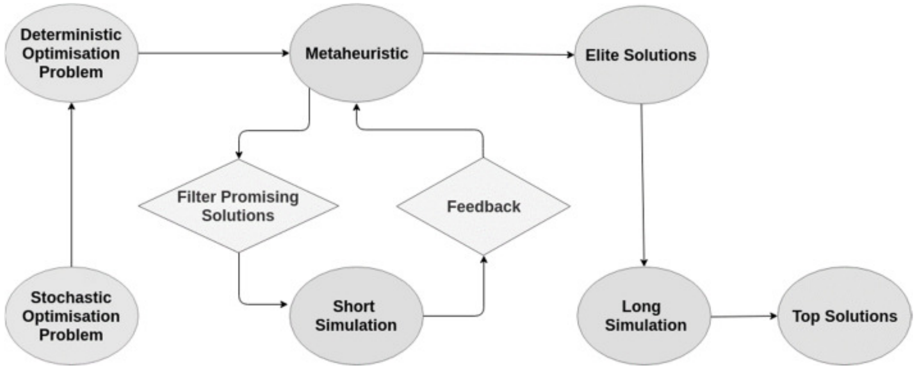

Figure 1: *A schematic description of the simheuristics concept*

During the iterative search process, the algorithm has to assess (estimate) the quality (or feasibility) of each of these promising solutions when they are considered as solutions of the stochastic COP. One natural way to do this is by taking advantage of the capabilities that simulation methods offer to manage randomness. Thus, uncertainty can be modelled throughout a best-fit probability distribution without having to assume a normal or exponential behaviour, as other methods do. During the interactive search process, only promising solutions (i.e., those that perform well in the deterministic environment) are sent to the simulation component. Moreover, for each promising solution, 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 to 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 superior solutions for the stochastic COP. They can also provide feedback to the metaheuristic so that it intensifies exploration of promising searching areas (e.g., by defining the base solution in a trajectory-based metaheuristic or the parents' population in a population-based metaheuristic). Once the computational time assigned to the iterative search process has expired, a set of superior are provided. More accurate estimates can be then obtained for each of these superior by employing simulations with a larger number of runs. These new estimates can then be used to re-rank the solutions as well as to obtain additional information on the probability distribution of the stochastic solution itself. 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 not only be interested in obtaining the solution that optimises its expected value, but he or she might be also interested in analysing 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.

A final aspect to consider is the potential use, as a limiting value, of the best solution found by the metaheuristic for the deterministic COP. In real-life systems, it is usually the case that the higher the uncertainty level the higher the system's expected cost is. In those cases, it is possible to use the value of the near-optimal solution for the deterministic COP as a lower bound for the value of the optimal solution for the stochastic COP. Also, whenever the best-found solution for the deterministic COP is employed in a stochastic environment, its value becomes an upper bound of the optimal solution for the stochastic COP.

3 Related Work

This section reviews some recent work related to the simheuristics concept or similar concepts such as the more generic one of simulation-based optimisation. In particular, we focus on research articles in the areas of logistics, transport, and production.

In the area of logistics and transport, Guimarans et al. (2017) present a simheuristic approach for solving the aircraft recovery problem with stochastic delays. The authors combine a large neighbourhood search algorithm with a constraint programming model. This approach includes Monte Carlo simulation (MCS) at different stages of the search process. MCS is used to control the search, consider the variability of the system, and evaluate the behaviour of the solutions. A dynamic programming approach in combination with a simulation model is used by Bayliss et al. (2016). The authors describe their research as a simheuristic approach to solve the problem of vehicle ferry revenue management, which involves maximising revenue by varying prices for different types of vehicles.

Layeb et al. (2018) propose a new simulation-based optimisation model for a scheduling problem in stochastic multimodal freight transport systems. These authors consider stochasticity of demand and travel times. The simulation model is coupled with an optimisation technique. The optimiser sends a path to the simulator. Then, the simulator tests this path and gives the corresponding costs to the optimiser. Finally, the optimiser applies the search algorithm to find a better path which is tested by the simulator, and so on. The algorithm combines tabu search, neural networks, and scatter search.

Another approach by Jackson et al. (2018) combines discrete-event simulation and a genetic algorithm to find nearly-optimal inventory policies in stochastic multi-product inventory systems. These authors state that the key advantage of such a simulation-driven approach is the possibility to trace inventory dynamics in details and utilise risk and reliability analysis in decision-making process.

To support housekeeping decisions in a complex, dynamic and stochastic environment, a discrete-event simulation model embedded in a local search heuristic is introduced by Cordeau et al. (2015). This approach was developed for the housekeeping problem in a transshipment container terminal with the overall objective of finding the vehicle schedule that minimises both vehicle travel times and waiting times.

Schumacher et al. (2017) present an approach for the improvement of cross docking operations in a parcel transhipment terminal using an extended local search algorithm with discrete-event simulation. After solving the optimisation model, the results are transmitted to a discrete-event simulator to consider stochastic factors. The findings are used in a simulation model for evaluation of the optimisation model with the purpose to improve both models. For instance, the constraints of the optimisation model are adapted using simulation results.

In the area of production, González-Neira and Montoya-Torres (2019) present a simheuristic for a bi-objective stochastic permutation flow-shop scheduling problem (FSP). In order to gain a greater influence of research in real industrial practice, scheduling problems should take uncertainties and more than one objective into account. However, most publications on this topic still consider a deterministic problem. The authors state that there are more than five literature reviews for deterministic FSP from the last five years, while for the stochastic and uncertain variants there are only two literature reviews in the last eighteen years. To overcome this gap, they propose a metaheuristic procedure coupled with MCS to obtain a complete set of Pareto-optimal solutions.

4 An Example of Application to UAV Surveillance

In the unmanned aerial vehicle (UAV) surveillance routing problem, a limited fleet of drones with driving-range limitations have to visit a series of target zones in order to complete a monitoring operation. This operation typically involves taking images or registering key performance indicators. Whenever this surveillance action is repeated periodically, one logical goal to achieve is to complete each cycle of visits as fast as possible, so that the number of times each target zone is visited during a time interval is maximised. Since bad weather conditions and other factors might influence travel times, they are modelled as random variables. Reliability issues are also considered, since random travel times might cause that a route cannot be successfully completed before the UAV runs out of battery. This problem can be modelled as a multi-trip vehicle routing problem with stochastic travel times and maximum route length (see Figure 2).

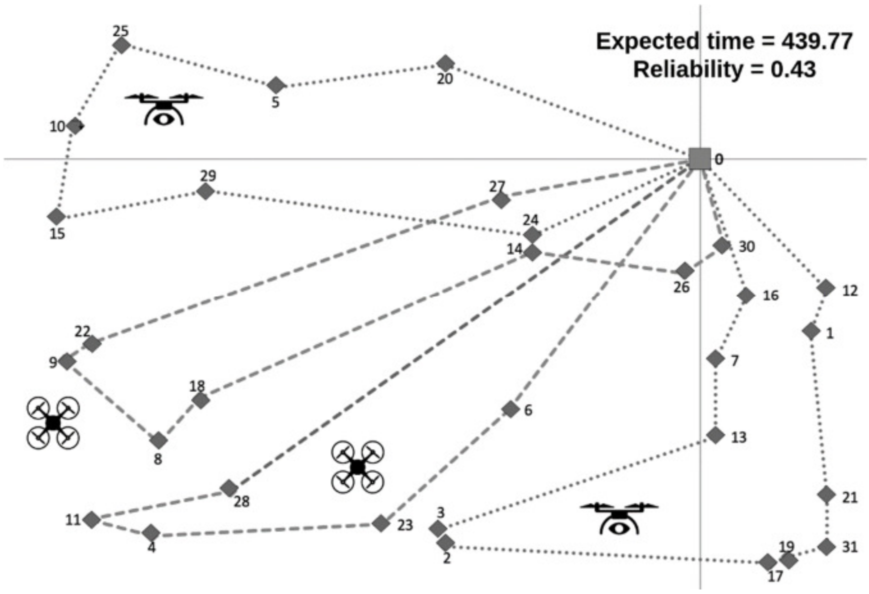

Figure 2: *A simheuristic application concerning UAV surveillance*

In order to solve this stochastic optimisation problem, a simheuristic algorithm can be used to generate a series of superior solutions (surveillance-routing plans) that offer near-optimal expected times (for the cycle completion) as well as high reliability levels. In our case, the simheuristic consisted of the following stages: *(i)* a biased-randomised version of a routing heuristic was employed to generate a new routing plan for the underlying vehicle routing problem; *(ii)* each route in the previously generated plan was assigned to a UAV following a first-arrived-first-served rule (i.e., as a UAV finishes its currently assigned route and it returns to the depot, it selects the longest route among the ones yet available); *(iii)* the monitoring plan is then simulated -taking into account the probability distributions modelling travel times-, thus generating estimates for the expected time necessary to complete the cycle and for the reliability of the plan; and *(iv)* while there is still computing time available, the process is repeated from the first step onwards and a short list of best solutions found – both in terms of total expected time as well as in terms of variability and reliability – is provided at the end.

5 An Example of Application to Facility Location

In the facility location problem, some degree of uncertainty (e.g., customers' demands, service costs, etc.) should be expected in real-life applications. In these cases, optimisation goals other than the minimum expected cost can be considered. In this regard, a simheuristic approach can generate several alternative solutions, each of them offering different values for each of the goals or dimensions considered, e.g.: the solution with minimum expected cost, the one which minimises the third quartile of the cost values obtained when it is run multiple times, or the solutions offering a good trade-off between expected cost and standard deviation of the cost values obtained when they are run multiple times, i.e.: among those solutions with low expected costs, we might be interested in identifying the ones showing a relatively low variability or risk.

Figure 3 shows a series of box plots associated with different alternative solutions for a stochastic facility location instance. The first solution ('det') represents the best-found solution for the deterministic version of the problem (this solution is then applied in a stochastic environment, providing different outcomes represented in the box plot); the second solution ('min avg') is the one that minimises the expected value; the third solution ('q3') is the one minimising the third quartile; finally, the fourth solution ('min dev') is the solution with the minimum standard deviation. In all the cases, the term 'OF' refers to the number of facilities that are activated in the corresponding solution. As expected, solutions with a higher number of open facilities show less variability in scenarios with random demands, since changes in the demands can be better 'absorbed' by a larger network of facilities.

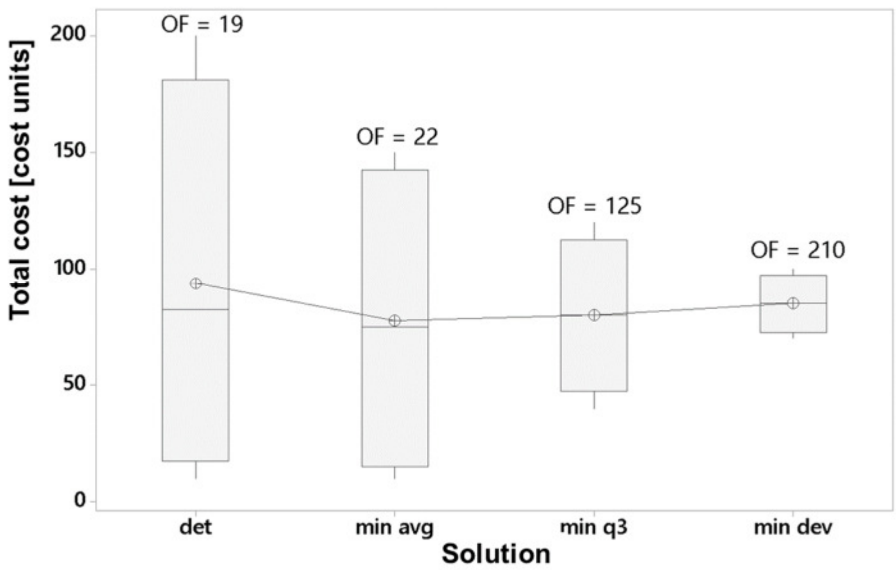

Figure 3: *A simheuristic application concerning facility location*

6 Managerial Insights

From the previous examples and our experience in solving similar stochastic optimisation problems, it is possible to identify a series of characteristics where simheuristic algorithms are especially well-fitted as solving approaches. Thus, managers should consider simheuristics as a serious solving methodology whenever the following characteristics are encountered:

- The combinatorial optimisation problem being considered presents stochastic components such as random input variables or probabilistic constraints.
- The random behaviour in these input variables can be accurately modelled by means of probability distributions (e.g., by employing historical data). These distributions do not necessarily have to be the normal or the exponential ones, and each variable might follow a different distribution.
- Given a solution for the deterministic version of the problem, it is possible to estimate some of its associated parameters (e.g., expected value, variance, quartiles, etc.) by running a discrete event or MCS experiment.
- A correlation exists between the value of a given solution when applied in a deterministic scenario and its value when applied in a stochastic scenario.
- The optimisation problem is NP-hard and large-scale, meaning that it will not be easily solved using traditional stochastic programming methods, especially if these involve the use of exact optimisation approaches.
- Computing time is a relevant issue, and high-quality solutions are needed to be obtained in just a few minutes.
- The goal of the manager is not limited to minimising or maximising the expected value of the objective function; instead, other characteristics of the

probabilistic solutions need to be considered as well, e.g.: their variability, risk, and reliability levels, their quartiles, etc.

7 Open Challenges

Simheuristic algorithms have been successfully applied to a wide range of fields. From a methodological point of view, there are many open research lines which may boost the efficiency and use of these algorithms. For instance, there is no scientific and generally accepted approach or guidelines to set the number of runs in each simulation. This decision is related to a trade-off between computing time and accuracy of the estimates. However, there are ways to decrease the number of runs without decreasing the accuracy, e.g., by integrating variance-reduction techniques into the algorithm (Deininger 2019).

Another key element in these algorithms that has not been intensively studied is the rules to decide when a solution is labelled as ‘promising’ and thus is assessed by the simulation component. Obviously, the proportion of those solutions depends on the computing time available and the computing time needed to assess a single solution. A fast exploratory study may help to estimate the correlation between the measures of interest in the deterministic and the stochastic environments, which can then be used to set a value for the proportion.

In the big data era, it is highly interesting to explore the potential of data analysis in optimisation applications. There are many potential uses such as parameter fine-tuning, speeding-up algorithms, and predicting promising search spaces. Moreover, integrating machine learning techniques in metaheuristics (learnheuristics) constitute a natural approach for solving problems with dynamic inputs. Thus, the hybridisation of simheuristics and machine learning is a suitable approach to deal with the increasing stochasticity and dynamism of real-world problems (Calvet et al. 2017). Finally, the use of machine learning techniques may enhance the efficiency of simheuristic algorithms if used, for example, to set the number of scenarios or to choose the rules to send a solution to the simulation component in a reactive way learning from the previous solutions visited.

8 Conclusions

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

Integrating simulation into a metaheuristic framework can be done in multiple ways. This paper has highlighted some best practices that have shown to be useful in order to avoid common pitfalls. Thus, some recommendations are provided to assign a balanced amount of computing time to the simulation component, to take full benefit from the simulation results to better guide the metaheuristic search, and to make more informed decisions on candidate solutions by completing a risk analysis based on the use of graphical statistical tools and multiple statistics. Current challenges and open research lines have been also pointed out. In particular, the combination of simheuristics with learnheuristics to deal with stochastic and dynamic optimisation problems seems to have a huge potential.

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