Simheuristics: a Method of First Resort for Solving Real-life Combinatorial Optimization Problems

Angel A. Juan [a], Manuel Chica [a], Jesica de Armas [a], W. David Kelton [b]

[a] Open University of Catalonia – IN3, Computer Science Dept., Barcelona, Spain
[b] University of Cincinnati, Dept. of Operations, BA, and IS, Cincinnati, USA
{ajuanp, mchicas, jde_armasa}@uoc.edu, david.kelton@uc.edu

Abstract

A large number of decision-making processes in real-life transportation, logistics and production applications can be modelled as NP-hard combinatorial optimization problems (COPs). These real-life COPs are frequently characterized by their large-scale sizes and the need to obtain high-quality solutions in short computing times. This imposes some severe limitations on the use of exact methods, so alternatives such as metaheuristics are required instead. Still, metaheuristics usually assume deterministic inputs and constraints. This is a strong assumption which is not usually in accordance with modern systems, typically characterized by high levels of dynamism and uncertainty. By combining simulation techniques with metaheuristics, simheuristic algorithms are able to cope with real-life uncertainty in a natural way. Simheuristics also facilitate the introduction of variability analysis during the evaluation of alternative solutions to stochastic COPs and, in this sense, they constitute a 'method of first resort'.

Keywords: Simulation-Optimization; Combinatorial Optimization Problems; Simheuristics

1. Introduction

Decision makers in areas such as transportation, logistics, healthcare, production, telecommunication and finance have to face complex challenges that can usually be modelled as combinatorial optimization problems (COPs). Most of these real-life COPs are NP-hard in nature. In practice, this feature limits the use of exact methods to small- and medium-sized instances in which the optimal values can be obtained in reasonable computing times. However, driven by economic and technological factors such as globalization, increasing computer power, information technologies, users' heterogeneity and the existence of large quantities of data, real-life systems are becoming increasingly complex and large-sized. Under this scenario, modern heuristics (metaheuristics) are gaining popularity as the predominant approach for solving real-life COPs, which are large-scale and might contain non-trivial objective functions (e.g., multi-objective, non-smooth) and/or constraints. Metaheuristics allow decision makers to obtain near-optimal solutions to complex and large-sized problems in reasonably low computing times (sometimes even in 'real-time'). Therefore, they have become an extraordinarily useful solving methodology in most application areas where optimization of system resources is needed. Hybrid approaches combining exact with approximate solving methods are also emerging. Thus, matheuristics (Maniezzo et al., 2009) combine metaheuristics with exact methods in order to get the best from both worlds. Typically they employ the metaheuristic component to deal with the global, large-sized problem and the exact component to deal with specific parts of it.

In the Operational Research (OR) literature, both exact optimization methods as well as metaheuristics frequently assume that the problem inputs, the underlying objective functions and the set of optimization constraints are deterministic in nature. This is a strong assumption that usually does not apply when dealing with real-life scenarios, which are characterized by the existence of uncertainty (e.g., random customers' demands, stochastic travelling and processing times, fluctuant prices of raw materials). It is also common to see in the scientific literature exact or metaheuristic approaches that are designed to cope with uncertainty assuming that it can be modelled using Normal or exponential probability distributions, or that the stochastic component can be discretized in a number of reduced scenarios. Unfortunately, these are still strong assumptions and, as a consequence, most deterministic or stochastic optimization models are nothing else but oversimplified versions of real-life systems. It is therefore the case that we end up solving the 'wrong' model, a model which might not be an accurate enough representation of the real system.

Simulation – in its different flavours – is probably the most efficient tool we have to model uncertainty in real-life systems (Lucas et al., 2015). Simulation models allow the analyst to accurately describe stochastic systems in as much detail as necessary in order to reproduce them in a computer environment. This gives the decision makers the opportunity to analyse 'what-if' scenarios; i.e., to explore through the realistic model how different configurations of the system would affect its performance in terms of the key parameters. Simulation itself, however, is not an optimization tool, so when dealing with COPs simulation alone cannot provide more than some insights on which solutions can perform better than others. Still, properly designed simheuristics, hybridization of simulation techniques with metaheuristics, can provide us with the best of both worlds when dealing with stochastic COPs (SCOPs), including random variables and/or probabilistic constraints in their mathematical formulation. Thus, the simulation component deals with the uncertainty in the model and interacts with the metaheuristic component which, in turn, searches the solution space for a near-optimal answer. Even more interesting, when dealing with SCOPs criteria other than just expected cost must be taken into account. In effect, while in deterministic COPs one can focus on finding a solution that minimizes cost or maximizes profits, in a SCOP it is not enough to search for a solution that minimizes expected costs or maximizes expected profits. Due to the stochastic nature of the solutions – they are likely to provide different values each time they are implemented in a scenario under uncertainty – their properties other than its expected value might be also relevant (e.g., the standard deviation or the quartile distribution of the values it generates). All this information about a stochastic solution can be obtained by the simulation component of the simheuristic, allowing for the introduction of risk and/or reliability analysis criteria during the assessment of alternative high-quality solutions to SCOPs. All these characteristics, and the fact that the integration of simulation techniques with metaheuristic algorithms is relatively simple, make simheuristics not only a good alternative for solving SCOPs, but, in fact, a 'method of first resort' when dealing with real-life SCOPs. Notice that this term was initially used by Lucas et al. (2015), who highlighted the benefits of using simulation instead of traditional analytic methods when modelling real-life systems.

2. Related work

As discussed in Soeiro-Ferreira (2013), the combination of metaheuristics with other solving approaches is becoming popular as a good procedure to deal with complex COPs. Some seminal works on the combination of simulation with metaheuristics are reviewed in Bianchi et al. (2009). Still, to the best of our knowledge, it was with the work of Glover et al. (1996, 1999) and April et al. (2003) that popularised the combination of simulation with metaheuristics. These authors were the promoters of OptQuest, a 'black-box' optimization software which is currently integrated into several commercial simulation packages (Eskandari et al., 2011). Typically, in this software a discrete-event or Monte Carlo simulation model is generated for a given system and then the parameters of interest are optimized (Kleijnen and Wan 2007). However, as discussed in Hubscher-Younger et al. (2012), it is not always possible to apply this software out-of-the-box and, instead, it needs to be adapted to the specific characteristics of the problem. Thus, other more flexible and 'white-box' solutions have also been proposed by researchers in the optimization community. In particular, Juan et al. (2015a, 2015b) introduce the term 'simheuristic', describe the fundamental concepts behind this hybrid methodology and review some practical applications in the fields of transportation, logistics, healthcare, production and telecommunication systems. Similarly, Grasas et al. (2016) discuss how the well-known iterated local search (ILS) metaheuristic framework can be extended into a simheuristic framework able to cope with SCOPs in an efficient way. In fact, as it will be shown in some of the examples below, most metaheuristic frameworks can be easily extended to simheuristics. Accordingly, we support the idea that researchers from the optimization community should always integrate simulation in their work when solving large-sized NP-hard COPs in environments where uncertainty is present. This paper builds upon those previous works, analyses some methodological and computational details and provides new examples of applications that illustrate why simheuristics should be considered a first-resort methodology when solving realistic SCOPs.

3. Methodological and computational aspects

In some real-life decision-making processes, time is a critical factor. Thus, for instance, after a period of flight disruption, airlines need to quickly re-assign aircraft, crews and passengers so the latter can reach their destination with the minimum possible delay. Likewise, once the daily orders are known and new data on the city traffic is available, managers of logistics services must quickly re-design their routing plan so that the daily distribution process is as efficient as possible. Similarly, telecommunication networks providing communication and computing services to their mobile users need to quickly re-allocate resources as their users' demand or geographic position vary. Examples could be found in almost any application area of OR. Therefore, as well as having to cope with large-scale, dynamic and stochastic environments, decision-makers might also need to do this under time constraints. This fact has to be taken into account, since simulation methods can be quite demanding in terms of computing times. For this reason, how simulation is effectively integrated into the metaheuristic framework might depend on the specific characteristics of the SCOP being addressed. In general, however, one has to be careful not to let the simulation jeopardize the computing time given to the entire simulation-optimization process, since then the metaheuristic would not perform a good job in searching the solution space. For that reason, we typically use a three-stage approach in our simheuristic algorithms (Figure 1).

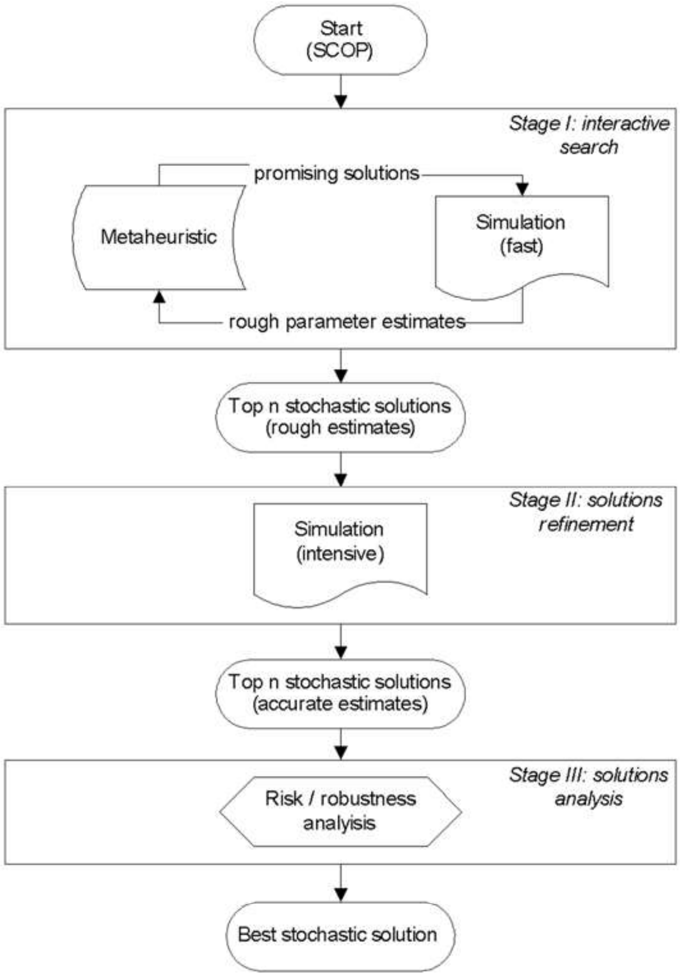

Figure 1 A typical simheuristic framework for solving SCOPs

First, we integrate the simulation into the metaheuristic framework in such a way that only 'fast' simulations are run; i.e., during that stage each simulation is run only a limited number of times in order to obtain rough estimates of the stochastic parameters of interests (e.g., expected cost associated with a given solution). Moreover, simulations are not run over each new solution generated by the metaheuristic component, but only on those solutions that can be considered as 'promising' (e.g., solutions with a good deterministic performance). This way, a reduced set of 'top' stochastic solutions (those performing better according to the selected parameter or parameters) are identified. It is important to notice that, during this stage, simulation – in any of its forms, depending on the problem at hand – is not only used as a natural way to estimate the system parameters, but it also can provide valuable information to the metaheuristic component, so the searching process is simulation-driven (e.g., by updating the current base solution according to the stochastic cost instead of to the deterministic cost). In a second stage, the top stochastic solutions identified in the previous stage are sent throughout a new simulation process, this time using a much larger number of iterations in order to obtain more accurate estimates of the desired parameters. The specific number of iterations might be given by error measures such as the confidence intervals of the chosen parameters and, of course both in the previous stage as in this one some variance-reduction methods – e.g., common random numbers – can be employed in order to reduce the number of runs necessary to reach the desired accuracy level. Finally, a third stage is proposed in order to complete a risk/robustness analysis on the selected solution. As discussed before, other dimensions rather than the expected value of the stochastic solution need to be considered in a stochastic environment. The reason is that a solution with a low expected value could also show more variability than other alternative solutions. Consequently, the decision maker would need more information to decide which solution to choose based on her/his utility function and aversion to risk.

Figure 2 depicts a typical situation in which alternative solutions provided by the simheuristic show different behaviour in terms of each of the dimensions (parameters) considered. In this case, notice that three alternative solutions are plotted; each of these offer the best value in terms of expected or average cost, third quartile or variability (standard deviation). Of course, thanks to the information provided by the simulation, it is also possible to consider more dimensions (e.g., different quartiles) as well as to find intermediate solutions between any pair of the plotted ones (i.e., solutions offering different trade-off values).

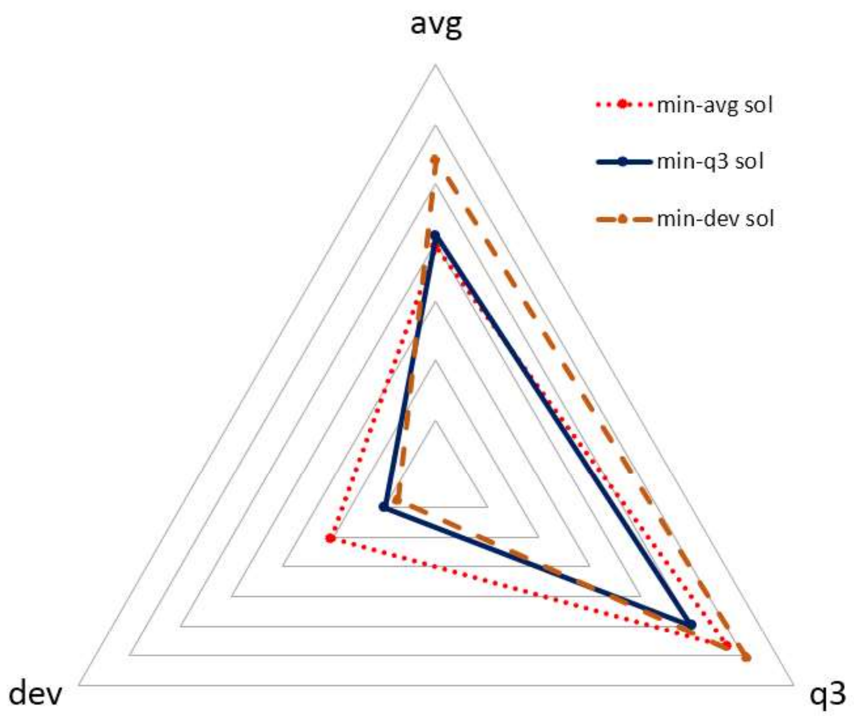

Figure 2 Alternative solutions offering different performance in each parameter

4. Recent examples of applications to transportation and production

This section briefly reviews some recent applications of simheuristic algorithms in the solving of SCOPs in different OR-related areas. The review does not aim to be exhaustive, but only to provide some illustrative examples.

Thus, for instance, in the area of transportation and logistics Gruler et al. (2016) make use of a simheuristic algorithm to support waste collection management in clustered cities, where the levels of waste to be collected are not know in advance but are modelled as random variables. Likewise, Gonzalez et al. (2016) propose a simheuristic algorithm for solving the well-known arc routing problem, but this time considering that customers' demands are random variables instead of deterministic values. These authors show that their approach outperforms other previous works based on analytical methods, which additionally require strong assumptions on the modelling of the customers' demands. Another simheuristic-inspired approach (but not exactly a simheuristic itself) is described in Fikar et al. (2016). Here, the authors integrate a discrete-event procedure with a metaheuristic to synchronize the daily schedule-and-routing plan of several nurses operating in the city of Vienna with the shared vehicles that transport them from one patient to another. Also in this area, Juan et al. (2014b) propose a simheuristic approach for solving the single-period inventory routing problem with stochastic demands, which combines a stochastic inventory management problem allowing stock-outs with a vehicle routing problem. Some preliminary proposals combining simulation with metaheuristics to solve vehicle routing problems with stochastic demands can be found in

Juan et al. (2011, 2013). In the latter work, parallelization issues that allow reducing computing times are also discussed.

Some other examples in the area of scheduling and production include the following ones: Calvet et al. (2016) combine an iterated local search metaheuristic with Monte Carlo simulation to provide solutions to distributed scheduling problems when processing times are modelled as random variables. Likewise, Ferone et al. (2016) combine simulation with a greedy randomized adaptive search procedure to solve the well-known permutation flow-shop problem, this time also considering random processing times, which is much more realistic than assuming deterministic values for them as usually done in the related literature. A similar problem, but using a different metaheuristic framework, is analysed in Juan et al. (2014a). An example of simheuristic application to distributed computer networks can be found in Cabrera et al. (2013). In this work, the authors combine discrete-event simulation with a simple metaheuristic framework to optimize a very-large scale and dynamic network of non-dedicated computers that offer online services over the internet. For additional examples of application in these areas, as well as in different areas, the reader is referred to Juan et al. (2015a, 2015b).

5. Conclusion and future work

In this paper, we have discussed the benefits that the combined use of simulation and metaheuristics can offer to researchers and practitioners in solving real-world combinatorial optimization problems under uncertainty scenarios. Despite the fact that these benefits seem quite evident, and that deterministic optimization models might not faithfully capture the real system behaviour, it is interesting to note that most of the existing literature on applied optimization still does not consider simulation as a necessary component in their solving methods. Likewise, it is surprising that most simulation studies aimed at improving the efficiency of real-life systems do not incorporate metaheuristic optimization methods. As a consequence, the simulation models tend to be quite accurate, but in scenarios with many possible configurations it is likely that significant performance improvements could be attained by using hybrid simulation-optimization methodologies such as the one discussed in this paper.

As a direct consequence, we forecast a significant increase in the use of simheuristics and other hybrid simulation-optimization approaches in the coming years, especially when dynamic real-life systems of large-scale and characterized by random elements need to be analysed and improved. In our view, these systems can be found all around us: in smart cities, in transportation and logistics, in finance, in production and in telecommunication systems. In all these systems, we propose the simulation and optimization communities to embrace hybrid simulation-optimization methodologies – and, in particular, simheuristics – as a method of first resort, since it can provide more insight, additional knowledge and, above all, allow us to optimize (or at least to obtain near-optimal solution to) a much more accurate model of the real system.

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