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A SIMHEURISTIC APPROACH FOR THE STOCHASTIC TEAM ORIENTEERING PROBLEM

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ABSTRACT

The team orienteering problem is a variant of the well-known vehicle routing problem in which a set of vehicle tours are constructed in such in a way that: *(i)* the total collected reward received from visiting a subset of customers is maximized; and *(ii)* the length of each vehicle tour is restricted by a pre-specified limit. While most existing works refer to the deterministic version of the problem and focus on maximizing total reward, some degree of uncertainty (e.g., in customers' service times or in travel times) should be expected in real-life applications. Accordingly, this paper proposes a simheuristic algorithm for solving the stochastic team orienteering problem, where goals other than maximizing the expected reward need to be considered. A series of numerical experiments contribute to illustrate the potential of our approach, which integrates Monte Carlo simulation inside a metaheuristic framework.

1 INTRODUCTION

This paper tackles a variant of the team orienteering problem (TOP) where travel times are stochastic. We consider the problem of a company that carries out repairs. The company employs m repair people who are each paid to work for T hours per day. The repairs are spread out over a geographical area and the repair people must travel to each site to work on a job. At the start of each day, the company receives a list of repair jobs that it has been asked to carry out, and it needs to make decisions over which of these jobs are accepted and how to assign them to its staff.

Each job has an associated reward value, which is known in advance. We assume that the travel time between each pair of jobs is a random variable following a known distribution. This means that standard methods for deterministic problems are not suitable, and a simulation-optimization approach might be necessary to account for the system randomness. Simulation-based approaches for vehicle routing problems have become popular in recent years, as can be seen for instance in the works of Faulin et al. (2008) and Juan et al. (2014). In this case, we use a simheuristic algorithm (Juan et al. 2015). In addition to the use of simheuristics, biased randomization techniques are also employed in our approach. Biased-randomized techniques consist in the use of skewed probability distributions (such as the Geometric one) to introduce non-uniform randomness into a constructive heuristic (Juan et al. 2013). Hereby, higher probabilities are assigned to the most promising movements during the constructive process. This allows to run the heuristic multiple times (each time following a slightly different constructive pattern), without losing the logic behind the heuristic, i.e., without altering too much the selection criterion in which the heuristic is based on. As empirically analyzed in Grasas et al. (2017), biased randomization is a fast way to enhance the performance of most constructive heuristics. Notice that the use of a Uniform probability distribution will not be efficient at all, since it would completely destroy the logic behind the heuristic by assigning the same probabilities to all movements regardless how promising they are. Some successful applications of biased randomization strategies can be found in Dominguez et al. (2014) and Dominguez et al. (2016), among others. Accordingly, the main methodological contribution of this paper is the hybridization of a biased-randomized constructive heuristic (which allows to quickly generate a large number of promising solutions in a short computing time) with a simheuristic framework (which is designed to deal with the stochastic component of the problem).

In the stochastic team orienteering problem (STOP), several statistical properties of the generated solution should be considered apart from its associated expected reward. In effect, in a stochastic environment one could be interested in solutions that offer high reliability or robustness in terms of the number of times that the threshold is violated or the number of jobs served out of time, i.e.: we will consider one solution (distribution plan) A to be more robust than other B if, and only if, A shows a better behavior than B when both are considered under a stochastic scenario. In other words, we are not only interested in measuring the cost of each solution, but also on how well can each solution support uncertainty conditions without degenerating in other properties such as the aforementioned ones. In this regard, our simheuristic approach is able to generate several alternative solutions, each of them offering different values for each of the terms considered. The remaining sections of this paper are structured as follows: Section 2 reviews related work on the TOP. Details of the particular problem dealt with in this paper are provided in Section 3. Section 4 gives an overview of the proposed simheuristic approach. A series of computational experiments are described and analyzed in Section 5. Finally, Section 6 summarizes the highlights of this paper and proposes some future research lines.

2 LITERATURE REVIEW

The original *orienteering problem* was introduced in 1987 (Golden et al. 1987). Here, the authors considered the deterministic version of the problem, in which one vehicle chooses the set of nodes to visit as well as the visiting order during a specified time interval. Many variations have been considered since then, and the recent review by Gunawan et al. (2016) provides an excellent overview.

We focus here on the team orienteering problem first introduced in Chao et al. (1996). Recent methods used to solve the deterministic version of the problem have included particle swarm optimization (Dang et al. 2013), simulated annealing (Lin 2013), genetic algorithms (Ferreira et al. 2014), a Pareto mimic algorithm (Ke et al. 2015), and branch-and-cut (Dang et al. 2013) or branch-and-cut-and-price algorithms (Keshtkaran et al. 2015).

The stochastic version of the orienteering problem has only received attention in recent years, with benchmark instances being published only after 2010. To the best of our knowledge, previous work has only considered the single-tour problem rather than the team orienteering problem that we describe here. There is also some variation in which aspects of the problem are stochastic. For example, the original stochastic orienteering problem assumes that only the scores associated with each node are stochastic (Ilhan, Iravani, and Daskin 2008), whereas Campbell et al. (2011), Papapanagiotou et al. (2014), Verbeeck et al. (2016), Evers et al. (2014) study the case we describe here in which travel times are stochastic.

In developing solutions to the STOP, one critical question is how to deal with tours which exceed the designated time limit. In Teng et al. (2004), exceeding the time limit incurs in a penalty that is proportional to the amount exceeding the time limit. A similar approach is used in Lau et al. (2012). An alternative concept is presented in Tang and Miller-Hooks (2005), where the probability of exceeding the time limit must be lower than a threshold value. The problem presented by Campbell et al. (2011) is partially different since they do not force the vehicle to return to a set of depots but, instead, it can stop at any location once the time limit is reached. Also, penalties are incurred if a vehicle does not manage to visit a scheduled node within the time limit. In contrast, Evers et al. (2014) keep the hard constraint on the tour length that is used in the deterministic version of the problem and abort the route if the expected return time to the depot is equal to the remaining time. In the previous works, solving methodologies such as variable neighborhood search metaheuristics and two-stage stochastic optimization were employed.

3 PROBLEM DESCRIPTION

As stated previously, this paper focuses on the stochastic team orienteering problem. The team is composed of m vehicles, and there is a soft time constraint, T, for completing each route. In the deterministic case, this time constraint is a strong one. Here, we instead use the percentage of iterations in which the time constraint is exceeded as an indication of the robustness of the solution. The set of possible points to visit can be described by an undirected graph $G = (N, E)$, where $N = 1, 2, \dots, |N|$ is the set of nodes or points, and E is the set of edges. Each node $i \in N$ has a constant score $u_i > 0$. Scores can only be collected on the first visit to a node. Edges have a random travel time associated with them, T_{ij}. We do not assume symmetric travel times (i.e., it can happen that $T_{ij} \neq T_{ji}$), since the symmetric assumption might be unrealistic in many situations due to variable traffic conditions.

The final solution to the problem is a set M of m paths, where each path is defined by an array of nodes starting from node 1 (starting depot) and ending at node $f_m = |N|$ (ending depot). The objective function is the sum of scores.

Writing this out more formally, the objective function can be written as:

$$\max \sum_{m \in M} \sum_{(i,j) \in A} u_i \cdot x_{ijm} \tag{1}$$

where: $A = \{(i, j), (j, i)/i, j \in N, i \neq j\}$ is the set of directed arcs, and x_{ijm} is a binary decision variable which equals 1 if the arc $(i, j) \in A$ is in the path m and 0 otherwise. Thus, the objective function sums the scores collected at all of the visited nodes.

The constraints are given below with some explanations provided. We first present the constraint on the expected time taken to complete a tour:

$$\sum_{(i,j) \in A} x_{ijm} \cdot E[T_{ij}] \leq T \qquad \forall m \in M \tag{2}$$

Each point is visited at most once during the tour:

$$\sum_{m \in M} \sum_{(i,j) \in A} x_{ijm} \leq 1 \tag{3}$$

We always start at the start node (node 1) and always finish at the end node:

$$\sum_{j \in N} x_{1jm} = 1 \qquad \forall m \in M \tag{4}$$

$$\sum_{i \in N} x_{if_m m} = 1 \qquad \forall m \in M \tag{5}$$

Finally, the vehicle leaves each node it visits, except the finish node:

$$\sum_{i \in N} x_{ihm} - \sum_{j \in N} x_{hjm} = 0 \qquad \forall h \in N \sim \{1, f_m\}, \forall m \in M \tag{6}$$

In our computational experiments, we have used the Log-Normal probability distribution to model the random travel times. In a real-world application, historical data could be used to model each time by a different probability distribution. As discussed in Juan et al. (2011), the Log-Normal distribution is a more natural choice than the Normal distribution when modeling non-negative random variables. The Log-Normal has two parameters, namely: the location parameter, μ, and the scale parameter, σ. According to the properties of the Log-Normal distribution, these parameters will be given by the following expressions considering stochastic travel times between nodes i and j:

$$\mu_{ij} = \ln(E[T_{ij}]) - \frac{1}{2}\ln\left(1 + \frac{Var[T_{ij}]}{E[T_{ij}]^2}\right) \quad (7)$$

$$\sigma_{ij} = \left|\sqrt{\ln\left(1 + \frac{Var[T_{ij}]}{E[T_{ij}]^2}\right)}\right| \quad (8)$$

where, for our numerical experiments, we have assumed $E[T_{ij}] = t_{ij}$ (i.e., the travel costs of the deterministic instances) $\forall i, j \in \{1, 2, \ldots, |N|\}$, and $Var[T_{ij}] = 0.05 \cdot t_{ij}$ (i.e., a relatively low variability level).

4 OUR SIMHEURISTIC APPROACH

Our approach is based on the biased randomization of a constructive heuristic, which is similar to those proposed by Tang and Miller-Hooks (2005) and Dang et al. (2013). The process of generating a set of M vehicle tours is described in detail in Figure 1. This is a modified insertion procedure, where the first customer in each tour is randomly selected among the list of non-served customers. Then, the next nodes are inserted, taking into account the ratio of added duration to additional reward, as given in Equation 9 (in this equation, it is assumed that a node i is being inserted between nodes j and k in a route):

$$(t_{ji} + t_{ik} - t_{jk} + s_i)/u_i \quad (9)$$

In our case, however, instead of selecting the node which minimizes this evaluation function at each step, a biased-randomized selection process is used: the list of candidate nodes is sorted according to the previously defined ratio, and then a skewed probability distribution is used to select the next node, i.e.: the better a node matches the ratio criterion, the higher probability it receives for being selected in the next step of the constructive process. In this work we use the Geometric probability distribution since it has been well-tested in other biased-randomization processes (Juan et al. 2009, Juan et al. 2010). The heuristic finishes when no more nodes can be added to the routes without violating the threshold T.

This heuristic is used inside a multi-start algorithm, which will keep the solution with the lowest cost obtained so far. However, this solution could involve high risk if we consider stochastic travel times, as it happens in the real-world. Therefore, we have included a simulation phase in the algorithm, so that each time a new best solution is obtained it is tested through Monte Carlo simulation in order to estimate the following values: *(i)* its reliability, measured in terms of the percentage of nodes served later than the threshold T; and *(ii)* the number of time units by which it exceeds that threshold. Thus, a pool of the best r solutions is kept (e.g., $r = 5$). This simulation phase should not consume too much time, and for this reason only a few executions of the simulation are performed on each new 'promising' solution. Once the algorithm finishes, longer simulations are performed with the pool of best-found solutions in order to increase the accuracy of their reliability level and also to provide additional data for completing a risk analysis. Figure 2 shows a flowchart of this simheuristic approach.

5 COMPUTATIONAL RESULTS

Our algorithm was coded in Java and tested on a Core i5 CPU @ 2.4GHz and 4GB RAM. For our computational experiments, the set of benchmark instances proposed in Chao et al. (1996) were employed. These instances are deterministic, so we extended them considering Log-Normal distributions as described before. Observe that the original TOP instances are a particular case of these extended instances when $Var[T_{ij}] = 0, \forall i, j \in \{1, 2, \ldots, |N|\}$.

First, the results produced by our algorithm for the deterministic case have been compared with the best-known solutions (BKS) in the literature. Thus, Table 1 shows the rewards of the BKS in the second

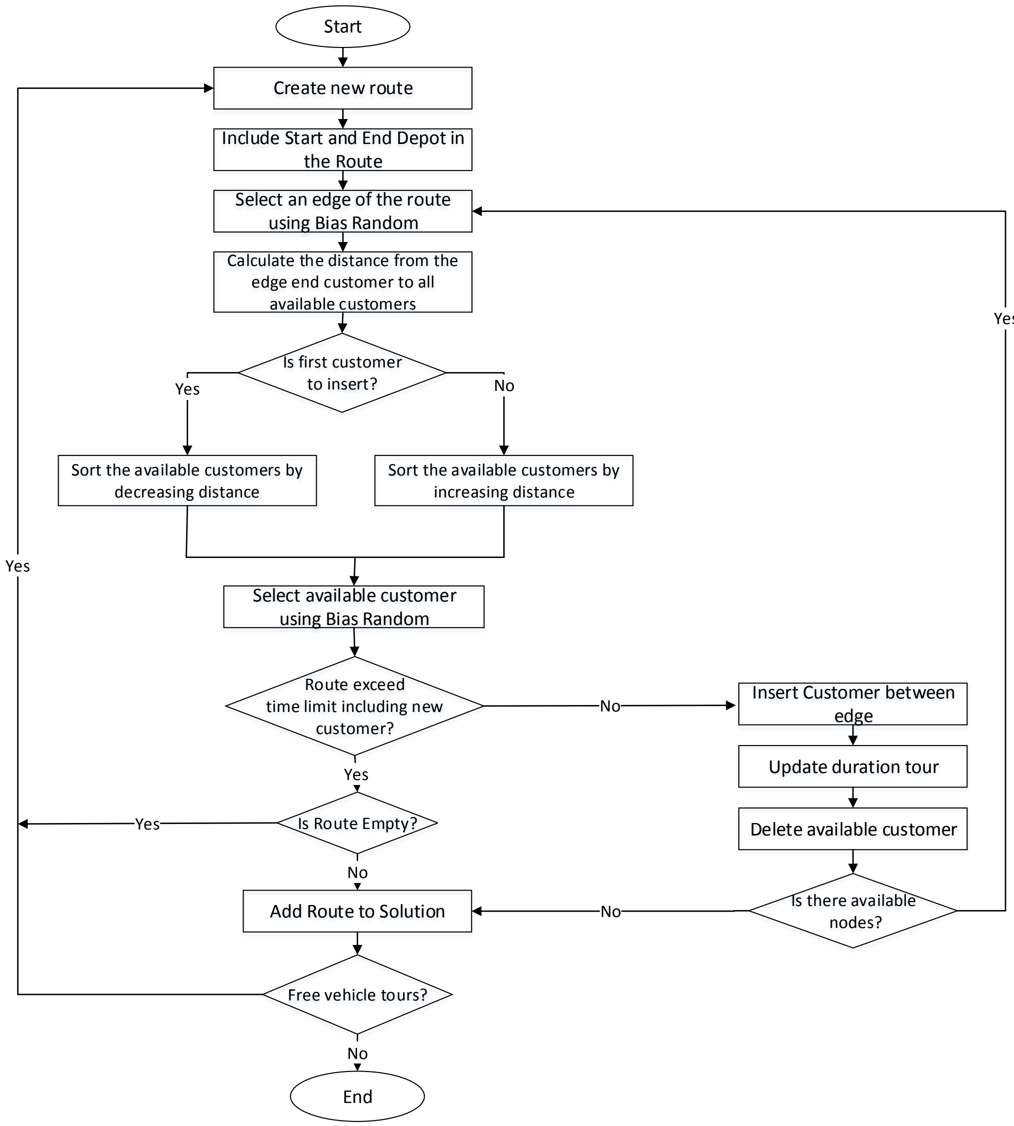


Figure 1: Biased-Randomized Heuristic

columns, and the rewards obtained by our algorithm in the third column for a set of randomly-selected instances. Notice that our algorithm is able to reach the BKS in all instances. We next wish to check how robust (i.e., reliable) the solutions to the deterministic problem are if we use stochastic travel times instead of deterministic ones. MCS is used to generate random realizations of the tours with Log-Normal travel times. The next two columns in Table 1 show the percentage of nodes served outside of the corresponding threshold and the total time exceeded. The last column corresponds to the execution times in seconds.

In a similar way, our simheuristic approach is used in the stochastic scenario with the goal of obtaining more robust solutions (in terms of both number of nodes served out of the threshold and time exceeded). The last four columns in the table show the associated results. Notice that, most of the time, robust solutions in terms of number of nodes served out of the threshold are the same as robust solutions in terms of time exceeding the threshold. Figure 3 depicts three graphics (each of them for a different problem instance) with a comparison of three different solutions considering four different dimensions: total reward, number of served nodes, number of nodes served out of the threshold, and total time exceeded. The three solutions compared are: *(i)* the best solution found for the deterministic scenario; *(ii)* the most robust solution obtained

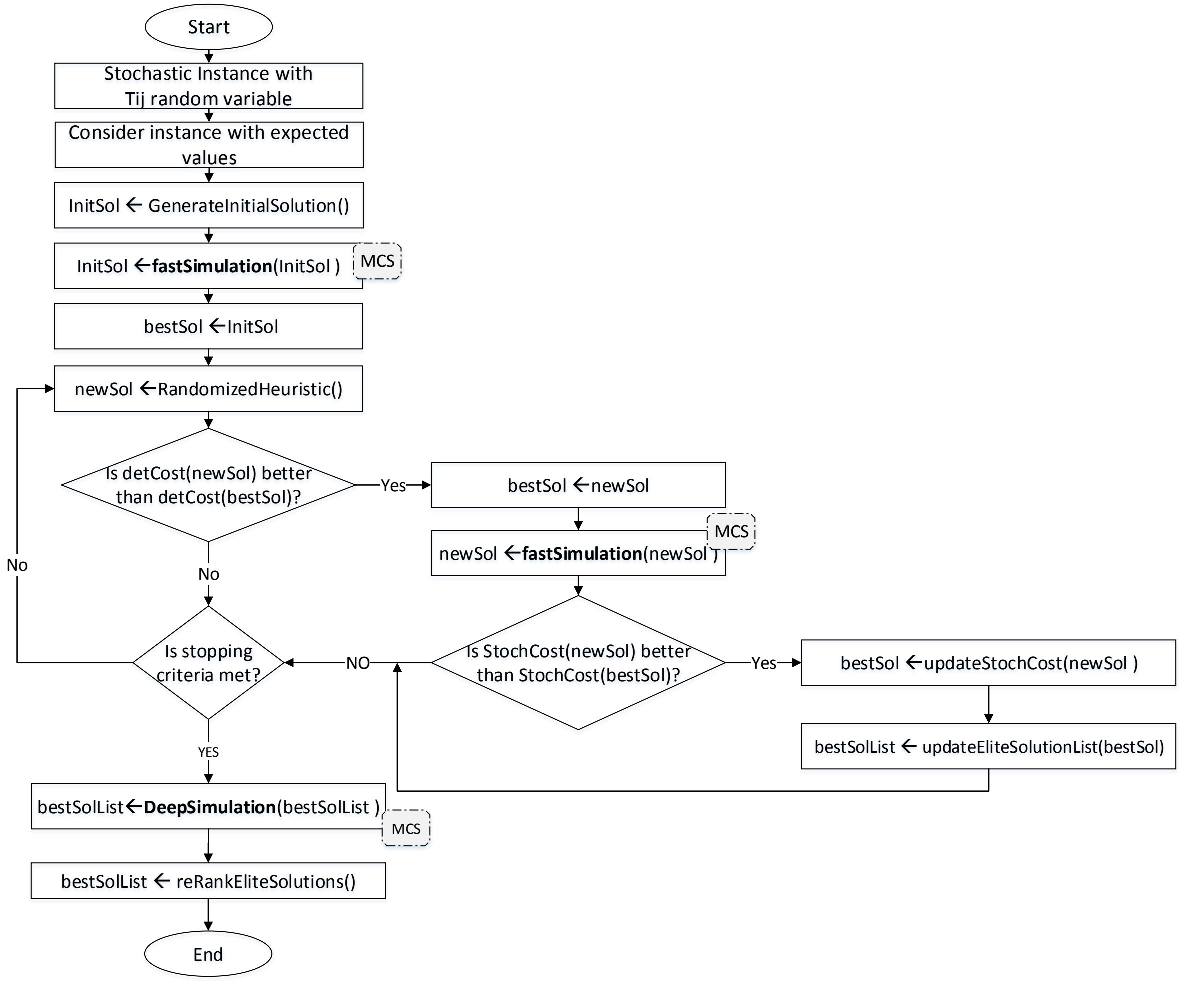


Figure 2: Simheuristic approach

for the stochastic scenario; and *(iii)* a solution that, being more robust than the deterministic one, involves too little reward to be considered as an alternative.

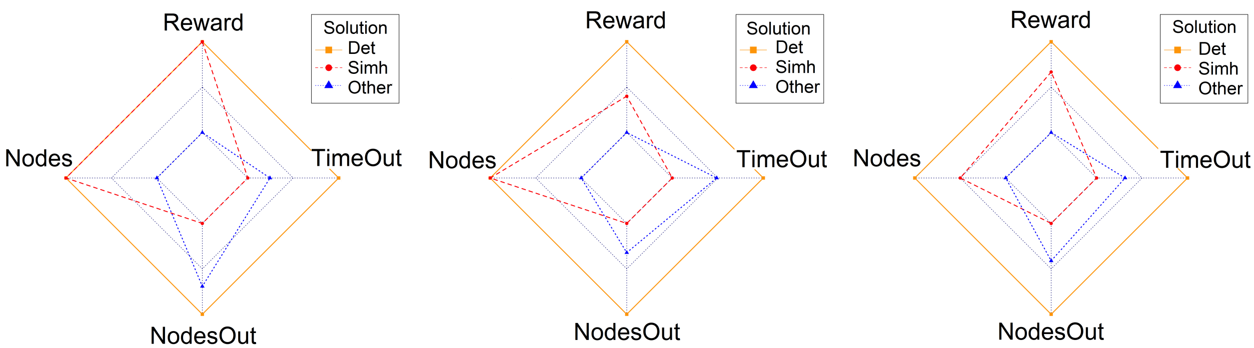
In some occasions, our approach reaches a solution with the same reward as the deterministic one, but with some additional features that make it more reliable when times are stochastic. In other cases, it is necessary to accept a reduction in total reward to obtain a more robust solution. Nevertheless, the decision maker might prefer a more robust solution since the customers served out of time may involve an additional cost due to customers' dissatisfaction for being served after the due time. In addition, servicing a customer out of the threshold involves working overtime, which usually leads to higher costs for the company.

Figure 4 and Figure 5 show the boxplots for the solutions (distribution plans) of two problem instances when a large number of simulation runs are executed. The best-found solution for the deterministic scenario (*Det*) and our best solution for the stochastic one (*Simh*) are compared in terms of time exceeding the threshold and percentages of nodes served out of the threshold –notice that we are considering the performance of both distribution plans, *Det* and *Simh*, under a stochastic scenario.

As stated before, the averages are better for the stochastic solutions even when the reward is kept (instance $p2.2.i$). Notice also the high risk associated with deterministic solutions, which is generated by the presence of a large number of outliers. In the case of the instance $p1.4.j$, where the simheuristic algorithm obtains a solution with less reward than the deterministic one, this is compensated by a much higher reliability.

Instance	BKS	Deterministic Scenario				Stochastic Scenario			
	Reward	Reward	Nodes Out (%)	Time Out	Run Time (s.)	Reward	Nodes Out (%)	Time Out	Run Time (s.)
p1.4.j	75	75	10	15.76	2.88	60	3	3.92	3.14
p2.2.c	140	140	6	8.09	1.37	100	0	0.09	1.24
p2.2.g	200	200	4	9.56	1.83	165	1	2.15	1.04
p2.2.i	230	230	4	12.22	2.16	230	3	9.68	2.93
p2.3.e	120	120	4	4.02	0.08	90	3	2.19	1.24
p3.4.h	240	240	5	11.79	9.23	230	4	7.60	5.20
p3.4.e	140	140	6	8.04	5.73	130	7	6.38	4.42
p3.4.f	190	190	5	7.52	0.11	130	2	2.02	0.89

Table 1: Deterministic solutions



(a) p2.2.i (b) p1.4.j (c) p3.4.h

Figure 3: Comparing solutions in different dimensions

6 CONCLUSIONS

This paper has discussed a stochastic version of the team orienteering problem, and how simulation can be combined with heuristic algorithms to obtain solutions that do not only provide high quality results in terms of expected cost but also satisfy other desirable characteristics such as robustness. The computational experiments show that the best solutions under a deterministic environment might suffer from a high degree of variance when used in a realistic scenario under uncertainty –e.g., random travel times. Thus, these solutions are not reliable or robust since, in practice, they might generate additional costs due to unsatisfied customers or overtime working hours. In contrast, a simheuristic approach such as the one considered here, is able to find a reasonable balance between different quality dimensions of a solution, including expected cost but also variability of this cost under a stochastic environment.

In future work, we plan to: *(i)* enrich the heuristic component of our approach by trying different prioritizing criteria; *(ii)* make use of the information provided by the simulation to better guide the search process of the metaheuristic component –e.g., making the selection of the reference solution a simulation-driven process; and *(iii)* extend the computational experiments to analyze how results vary as different probability distributions are used to model stochastic times and dependencies among these times are also considered.

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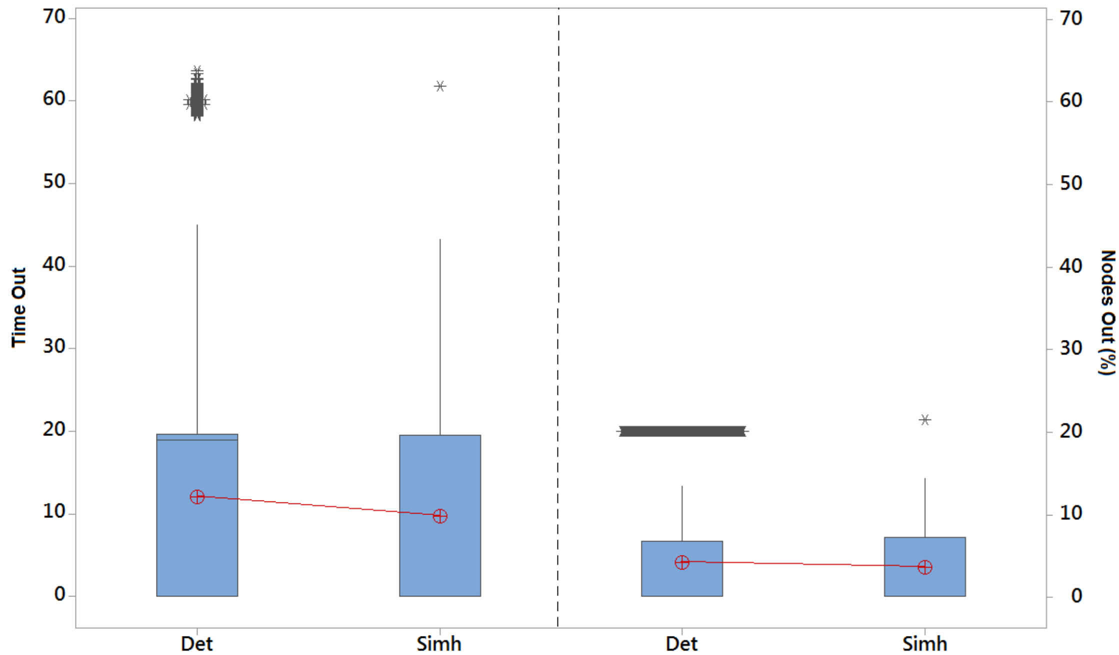

Figure 4: Boxplots of the deterministic and the stochastic solution (instance p2.2.i)

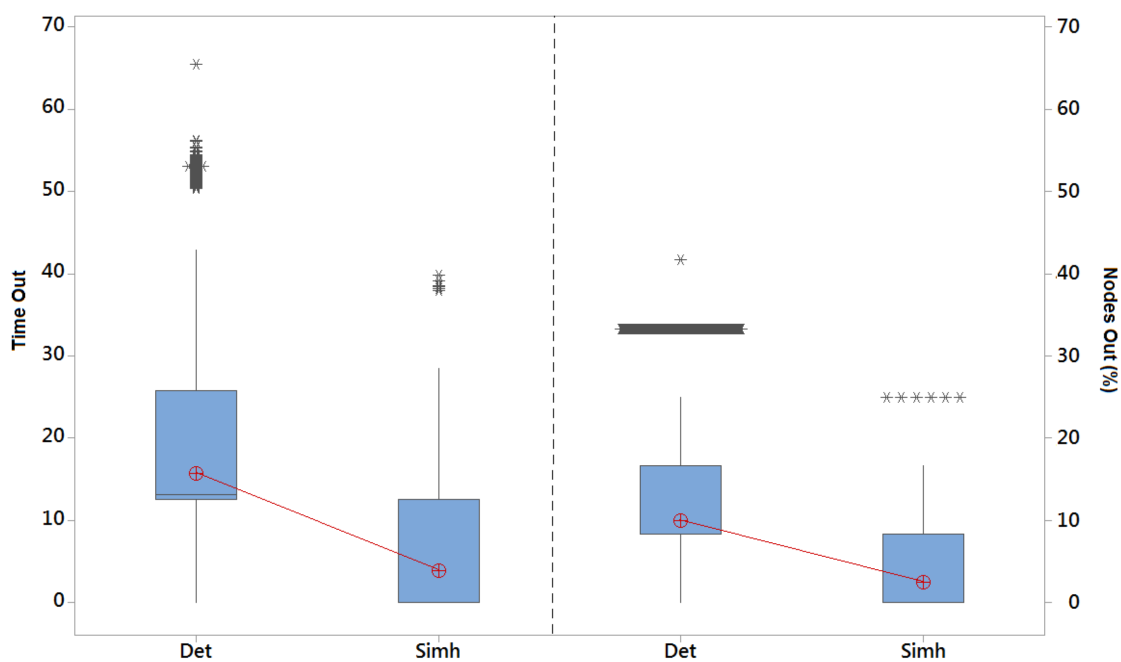

Figure 5: Boxplots of the deterministic and the stochastic solution (instance p1.4.j)

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