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DISTRIBUTION PLANNING IN A WEATHER-DEPENDENT SCENARIO WITH STOCHASTIC TRAVEL TIMES: A SIMHEURISTIC APPROACH

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ABSTRACT

In real-life logistics, distribution plans might be affected by weather conditions (rain, snow, and fog), since they might have a significant effect on traveling times and, therefore, on total distribution costs. In this paper, the distribution problem is modeled as a multi-depot vehicle routing problem with stochastic traveling times. These traveling times are not only stochastic in nature but the specific probability distribution used to model them depends on the particular weather conditions on the delivery day. In order to solve the aforementioned problem, a simheuristic approach combining simulation within a biased-randomized heuristic framework is proposed. As the computational experiments will show, our simulation-optimization algorithm is able to provide high-quality solutions to this NP-hard problem in short computing times even for large-scale instances. From a managerial perspective, such a tool can be very useful in practical applications since it helps to increase the efficiency of the logistics and transportation operations.

1 INTRODUCTION

The design of effective distribution routes can usually be modeled as a combinatorial optimization problem (COP). In the scientific literature, it has been frequently assumed that these problems were deterministic in nature. However, this assumption is often an unrealistic one that may lead to suboptimal solutions when uncertainty is present. Among other sources of uncertainty, weather conditions might have a significant impact on travel times which, in turn, might affect the total distribution cost. In stochastic COPs, uncertainty is identified with random variables following a probability distribution (Juan et al. 2011a). Stochastic COPs may be solved by designing a solution usable for any specific scenario (aprioristic or robust optimization) or by taking decisions each time uncertain information is revealed (on-line or reactive optimization). When there is complete uncertainty, the last strategy is mostly preferred (Jaillet and Wagner 2008).

In this paper, the distribution problem is modeled as a multi-depot vehicle routing problem (VRP) with stochastic travel times. These travel times are not only stochastic in nature, but the specific probability distribution used to model them depends on the particular weather conditions on the delivery day. Some

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of the earliest works in the field of stochastic vehicle routing problems were based on exact methods (Gendreau et al. 1995), which guarantee the optimality of the solution. However, due to the complexity of these problems, those approaches are only feasible for small-scale instances. In contrast, approaches including heuristics (Dror and Trudeau 1986) and metaheuristics (Bianchi et al. 2006) usually provide near-optimal solutions in reasonable computing times, even for realistic size instances. Accordingly, the stochastic version of the multi-depot VRP considered in this paper is addressed with the use of a simheuristic algorithm. As described in Juan et al. (2015a), a simheuristic is an optimization-simulation framework that combines metaheuristics and simulation (Monte Carlo, discrete-event, agent-based, etc.) to solve a stochastic COP. This hybrid approach has been successfully implemented in several fields, including: Internet computing (Cabrera et al. 2014), transportation (Gonzalez-Martin et al. 2016; de Armas et al. 2017), or production scheduling (Gonzalez-Neira et al. 2017). The main advantages of simheuristics are their flexibility, accuracy, and relatively easy implementation.

Since assignation and routing issues are often interrelated, this problem is a two-stage decision process, where the assignment map will affect the quality of the posterior routing. In the multi-depot VRP with stochastic travel times, a set of customers with known demands must be served by a fleet of homogeneous capacitated vehicles departing from one among several capacitated depots. Moreover, the travel times between each pair of customers, or between each customer and each depot, are random variables following a given probability distribution. These probability distributions might also vary according to the specific weather conditions on the delivery day. In this paper, we will assume that transportation costs will depend upon these travel times. Thus, the main goal of this problem is to determine the customer-to-depot assignment plan and the subsequent routing plan that minimizes the total expected cost of the distribution activity. This optimization process has to take into account the aforementioned constraints on the capacity of each vehicle as well as on the capacity of each depot.

The remainder of this paper is structured as follows: Section 2 motivates the problem considered in this work by providing a real-life case study; in Section 3 some existing work on stochastic versions of the multi-depot VRP is reviewed; Section 4 describes the problem in more detail; our simulation-optimization approach to solve the problem is introduced in Section 5; Section 6 provides a series of computational experiments that contribute to illustrate the efficiency of our approach; and, finally, Section 7 highlights the main conclusions of this work as well as some open research lines.

2 MOTIVATING THE PROBLEM: THE IRISH CASE

The reliability of the travel times associated with road transportation depends on a number of factors such as demand fluctuations, traffic incidents, and climate events. Some authors (Lamm et al. 1990; Ibrahim and Hall 1994; Agarwal et al. 2005; Maze et al. 2006; Rakha et al. 2008) have studied on the extent to which the clima impacts the road traffic conditions, reporting that rain, snow, and fog reduce the free-flow speed (up to 43% in the case of heavy snow), the speed-at-capacity (up to 14% in the case of heavy rain), and the road capacity (between 10% and 17% in the case on rain, and up to 27% due to snow), resulting in an increment of travel time.

Travel times are usually evaluated by means of congestion functions, i.e., the travel time is considered as a function of the traffic volume in a given road segment. The most common congestion functions (United States 1964; Spiess 1990) also include traffic characteristics, such as road capacity and free-flow speed. Thus, the observed influence of climate upon these traffic characteristics will result in a modification of the travel times obtained by the congestion functions. Additionally, as a consequence of the variation of the travel times in the different roads of the traffic networks, drivers will change their route choices, providing a different map of congestion and, in turn, different travel times. Traffic assignment models derive the congestion maps and the corresponding travel times for different traffic and weather conditions. Thus, the probabilistic distribution of travel times can be obtained by means of traffic assignment models and link congestion functions considering the impact of weather upon the traffic characteristics, which is the most practical way. Nevertheless, the probabilistic distributions can also be based on recorded data.

The economic and social consequences of this increment are already a source of concern for stakeholders and policymakers, and might become even more important when considering the effect of climate change. We can talk about direct and indirect costs caused by larger travel times. The direct ones refer to the loss of productivity, and within the indirect ones, larger fuel consumption with the corresponding health and environmental impact can be highlighted (Tagliapietra and Zachmann 2018).

According to IPCC (2014), climate change is forecasted to bring more intense weather events more frequently. For instance, events of high-intensity precipitation are expected to increase across Europe while the number of events of heavy snowfall will increase in northern Europe (Nogal et al. 2018).

In the case of Ireland, climate change is expected to notably increase the frequency of heavy precipitation events during winter, up to a significant 20% during this century (Gleeson et al. 2013). This might worsen the existing costs and delays due to climate-related events (e.g., Brazil et al. 2017). For instance, in February 2018, 5 days of snow-related traffic disruptions all over the country caused losses for the transport companies estimated at more than 160m Euro. As a consequence, most of the stores and retailers had to close because of the problems with the goods supply.

The adaptation to weather-related impacts the land-based transport networks is identified as a key strategy to minimize the consequences of climate change (Nogal et al. 2016). This paper introduces the consideration of the weather events when planning the transportation logistics, given that the optimal planning associated with good climate conditions might be far from the actual optimal choice under disruptive climate events. Thus, modifying the logistics according to the weather warnings provided by the meteorological agencies seems a realistic and practical way of adaptation to climate change.

For instance, the Irish Meteorological service Met Eireann classifies the weather warnings into Green, Yellow, Orange, and Red in alignment with the common European framework. Each warning level has associated specific weather characteristics; e.g., the orange warning status due to rain is related to rainfalls of 50mm to 70mm in 24 hrs, or 40mm to 50mm in 12 hrs, or 30mm to 40mm in 6 hrs. Therefore, it is possible to infer the traffic conditions in stochastic terms of speed and capacity associated with each weather warning status, allowing the estimation of the corresponding travel times and costs.

3 RELATED WORK

This section reviews related work on two of the main topics discussed in this paper: *(i)* stochastic multi-depot VRPs; and *(ii)* simheuristic approaches in logistics and transportation.

3.1 The Stochastic Multi-Depot VRP

To the best of our knowledge, only a limited number of works have addressed stochastic versions of the multi-depot VRP. Thus, for instance, Tillman (1969) expands a well-known heuristic to address it. The procedure proposed may be applied to demands with Poisson, exponential, normal, binomial or chi-squared distributions. In Chan et al. (2001), a location routing problem with stochastic demands is analyzed. The random demands are estimated in advance, before the vehicle location-routing decisions are made. Tatarakis and Minis (2009) study the stochastic multi-depot VRP considering both the case in which products are stored dedicatedly or together in a compartment. Dynamic programming algorithms are proposed to determine the minimal routing cost, and an optimal routing policy is derived to decide whether a vehicle has to return to the depot for a reload after serving the current customer or should continue to the next customer. In Zuhori et al. (2012), the authors solve the stochastic multi-depot VRP in three phases: first a nearest neighbor classification method is used for grouping the customers; then, the sum-of-subsets method is applied for routing; and finally, the routes are optimized via a greedy heuristic. They aim at minimizing the number of routes and, accordingly, the number of vehicles needed. None of the aforementioned works deals with the multi-depot VRP with stochastic times and considering capacitated depots, which is the realistic scenario considered in our work.

3.2 Simheuristic Approaches to Solve Stochastic COPs

Simheuristics have been used to solve stochastic COPs that arise in different fields. The first application of simheuristics was in the area of VRPs. Thus, Juan et al. (2011a) consider a vehicle-routing problem with stochastic demands and design a basic simheuristic approach to solve this problem. The authors continue the study of the stochastic VRP in Juan et al. (2013) with the analysis of the parallel and distributed computing techniques. Juan et al. (2014b) consider the stochastic version of an inventory routing problem with stock-outs and design a simheuristic to cope with this hybrid inventory and vehicle routing problem. Juan et al. (2014a), on the other hand, propose a simheuristic algorithm for solving the permutation flow-shop problem with stochastic processing times. An example of a simheuristic application for solving the arc-routing problem with stochastic demands is discussed in Gonzalez-Martin et al. (2016). Another interesting application of the simheuristic approach is in the area of waste collection management. Gruler et al. (2017) consider the stochastic waste-collection problem with a single-depot. de Armas et al. (2017) analyze the stochastic uncapacitated facility location problem with a simheuristic approach. Pagès-Bernaus et al. (2017) consider the problem of designing e-commerce supply chains and propose a simheuristic approach for the stochastic capaciated facility location problem that arises in this context. Very recently, Gruler et al. (2018) tackle a stochastic multi-period inventory routing problem with a variable neighborhood search simheuristic and Panadero et al. (2018) use the same approach in the context of selecting a portfolio of projects under uncertainty.

4 THE MULTI-DEPOT VRP WITH STOCHASTIC TRAVEL TIMES

In the multi-depot VRP under a weather-dependent scenario, travel times are assumed to be random variables following specific probability distributions. Thus, let $G = \{V, E\}$ be a undirected graph, where $V = V_f \cup V_c$ is the vertex set including the depots or facilities (V_f) and the customers (V_c), and $E = \{\{u, v\} : u, v \in V_c, u \neq v\} \cup \{\{u, v\} : u \in V_c, v \in V_f\}$ is the edge set connecting vertices in V. Each customer $i \in V_c$ has a positive demand $d_i > 0$ that has to be serviced. Each depot $f \in V_f$ has assigned a maximum number of vehicles, m_f, and has no demand. All vehicles are supposed to have the same capacity Q, with $Q >> max\{d_i\}$. Thus, the service capacity of a depot is limited by $m_f \cdot Q$. Traveling each edge in E has associated a travel time based cost $T_{ij} = T_{ji} > 0$, which is a random variable. The probability distribution (or its specific parametrization) that each time-based cost follows depends upon the weather conditions. A solution to this problem is a set of customer-to-facilities maps and the related plans of round-trip routes departing from each depot that covers all customer demands while satisfying all the capacity constraints (both the ones related to the depots as well as the ones related to the vehicles). As in most VRPs, it is assumed that each customer can only be visited once by a single vehicle.

Concerning the travel time random variable modeling, log-normal distributions have been used by a number of authors to model stochastic travel times (Kaparias et al. 2008, Rakha et al. 2010). The main reason is, as Castillo et al. (2014) note, that this distribution family allows for modeling of positively skewed data, which is an important characteristic to take into account. Moreover, Castillo et al. (2014) study conditions for stability with respect to minimum and maximum operators and they recommend that, despite log-normal family models are not stable with respect to location changes, they refer to scale changes, and are, therefore, appropriate for travel times.

The main goal in this case is to find a feasible solution that minimizes the total expected travel time costs, while satisfying the customer demands and the capacity constraints. Even in its deterministic version, this problem represents a challenge since it integrates a combinatorial assignment problem – in which each customer is assigned to one facility – with several VRPs, one per facility. By also including the stochastic component, the problem becomes even more difficult to solve, which justifies the use of a simulation-optimization approach as the one introduced in this paper. Figure 1 shows a possible solution for a particular instance.

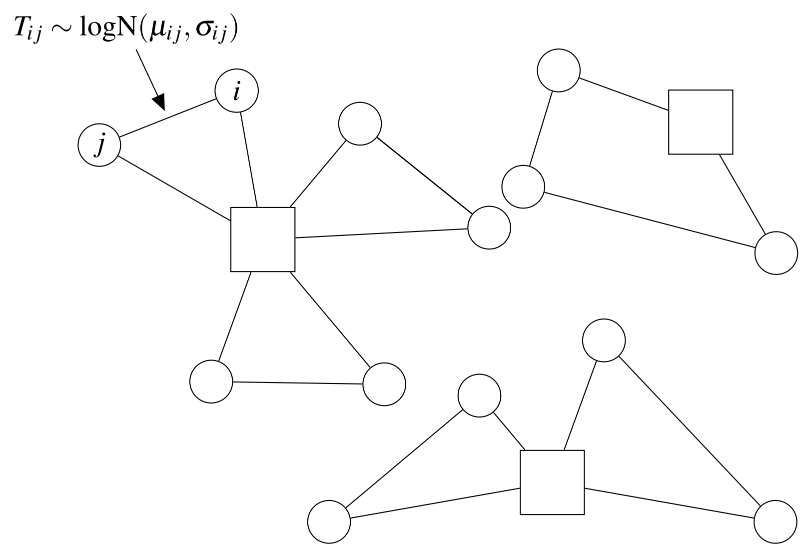

Figure 1: Possible solution for multi-depot VRP with three depots depicted by squares and several customers represented by circles. Travel times are modeled with log-normal distributions.

5 OUR SIMHEURISTIC APPROACH

Our approach relies on two facts: *(i)* the multi-depot VRP with stochastic travel times can be considered a generalization of the multi-depot VRP, i.e., the latter can be seen as a particular case of the former whenever the random demands have zero variance; and *(ii)* despite the fact that the stochastic version has never been studied before, there exist efficient algorithms for solving the deterministic one. The general ideas behind our approach, which relies on a metaheuristic framework, are described next. Initially, given an instance of the multi-depot VRP with stochastic travel times, it is transformed into a deterministic instance by replacing each random travel time by its expected value. A set of high-quality solutions for the deterministic version is then obtained by using an efficient metaheuristic algorithm that combines biased randomization with iterated local search (Juan et al. 2015b). While the search takes place, Monte Carlo simulation is employed to assess the performance of these promising solutions for the stochastic version. We define the best solution as the one with the lowest total expected travel-time based cost. This assessment is carried out according to the following steps: *(i)* run hundreds of executions (until the stopping criteria are reached), where each execution implies the generation of random values for each stochastic travel time according to the associated probability distribution, which in turn will depend upon the specific weather conditions; *(ii)* assess the performance of each solution by estimating the total expected time-based cost as the average of the total time-based costs obtained at the end of each execution; and *(iii)* use the simulation feedback to better guide the searching process inside the metaheuristic. Figure 2 shows the flow chart of the complete algorithm. In the first stage of the algorithm, an iterated local search (ILS) (Lourenço et al. 2010) is proposed for the generation of new maps. Given that it is critical to evaluate as many assignment maps as possible in the available computing time, every time a map is generated, its deterministic routing cost is estimated by using the well-known savings heuristic (Clarke and Wright 1964). Each solution considered promising from the deterministic point of view passes to a fast simulation process (i.e., low number of replications) to estimate its stochastic cost. Later it is considered whether this solution is ranked as elite solution considering its stochastic cost. This process is repeated until the stopping criterion is reached. Once the "Interaction between metaheuristic driven search and simulation" phase is done, an intensive refinement step is performed. For each of the elite maps obtained in the first stage, a more intensive routing algorithm is applied. Of course, the number of elite maps to consider will depend on the available time and computing resources. The vehicle routing algorithm employed in our tests is the SR-GCWS-CS proposed by Juan et al. (2011b). It encapsulates a biased-randomized version of the popular savings heuristic into a multi-start process, which is noticeably enhanced by the use of a cache memory and a 'splitting' technique. A more intensive simulation process is applied for each solution obtained for the deterministic version. A local search is applied, in which from the current assignment customers-depot, it is tried to reassign to a depot those customers who are closest to the customers already assigned. If the stochastic cost of this new customers-depot assignment improves after the simulation and routing process, the local search process is performed. This process is repeated as long as there is improvement in the stochastic cost. Finally, an analysis of risk and reliability is conducted over the elite solutions obtained in this second stage.

6 COMPUTATIONAL EXPERIMENTS AND DISCUSSION

The methodology described in this paper has been implemented as a Java application. All the experiments have been run in an Intel Xeon E5-2630 v4 CPU at 2.20 GHz and 32 GB RAM. For our problem, no benchmark instances exist. Therefore, we adapted first five instances of well-known sets of benchmark instances from the MDVRP described in Cordeau et al. (1997) (instances p01 to p05). In these instances, we have assumed that each distance unit is equivalent to each time unit and, as a consequence, the total distance cost is the total time cost.

In our experiments, in order to model the stochasticity, values for the distances (i.e., times) between customers and customer-depots in each deterministic benchmark have been assumed as the expectation for the travel time density distribution under a log-normality assumption. The scale parameter, in this illustrative approach and without loss of generality, has been assumed as constant (equivalent to assume a constant coefficient of variance) and equal to 0.05. That is, the travel time distribution between customers i and j is setup as $T_{ij} \sim \text{logN}(\mu_{ij}, \sigma_{ij})$ with $E[T_{ij}] = \exp\left(\mu_{ij} + \sigma_{ij}^2/2\right) = d_{ij}$ and $Var[T_{ij}] = \left(\exp(\sigma_{ij}^2) - 1\right) d_{ij}^2$, where d_{ij} is the deterministic travel time between both nodes. In practice, the scale parameter σ_{ij} was setup in 0.05.

Stochastic distributional departures due to weather-related conditions have been considered by extending the previous model for the good weather conditions to the one for condition $k, (k \in \mathbb{R})$, $T_{ij}^{k)}$, as a log-normal density distribution with expectation equal to $d_{ij}(1+k)$ and variance $\left(\exp(0.05^2) - 1\right)\left(d_{ij}(1+k)\right)^2$. It is straightforward to see that case $k = 0$ corresponds to the good weather condition. Notice that, on one hand, when the value of k increases, the weather conditions become worse in mean and in variance and, on the other hand, $E[T_{ij}^{k)}] \to E[T_{ij}^{0)}] = d_{ij}$ and $Var[T_{ij}^{k)}] \to Var[T_{ij}^{0)}]$ when $k \to 0$.

With this configuration, we performed 100 simulations of the minimal expected cost, per each one of the instances and for five weather conditions which are represented by different values of $k, (k = 0, 0.25, 0.5, 0.75, 1)$.

Under the good-weather scenario (i.e., $k = 0$), Figure 3 shows the estimation of the kernel density for the distribution of the simulated minimum expected cost for the instance p01, for 100, 1,000, and 10,000 simulations. On one hand, it is noticeable that minimum reported values are really close to the best known solution for the deterministic case. From the practical point of view, it is important to note that around one forth of the total simulated minimum expected costs are located close to the baseline minimal cost (BLC). This proportion is a guide for choosing the appropriate number of simulations to be performed. This is a potential consequence of the proposed algorithm, which shows a relation between the solutions for the stochastic version and for the deterministic version. In other words, the best solutions for the deterministic version are likely to be also high-quality solutions for the stochastic version. Even more, the relation is expected to be stronger as the travel time variances tend to zero. On the other hand, it is also interesting to observe the dependency on the seed values and the multimodal distribution of the results, which might imply that a high number of simulations are needed in order to properly estimate the minimum expected cost in the left tail of the distribution.

Regarding the assessment of the cost increments due to worse weather conditions, Table 1 displays the relative increments (in percentage) with respect to the baseline minimal cost derived from the best known

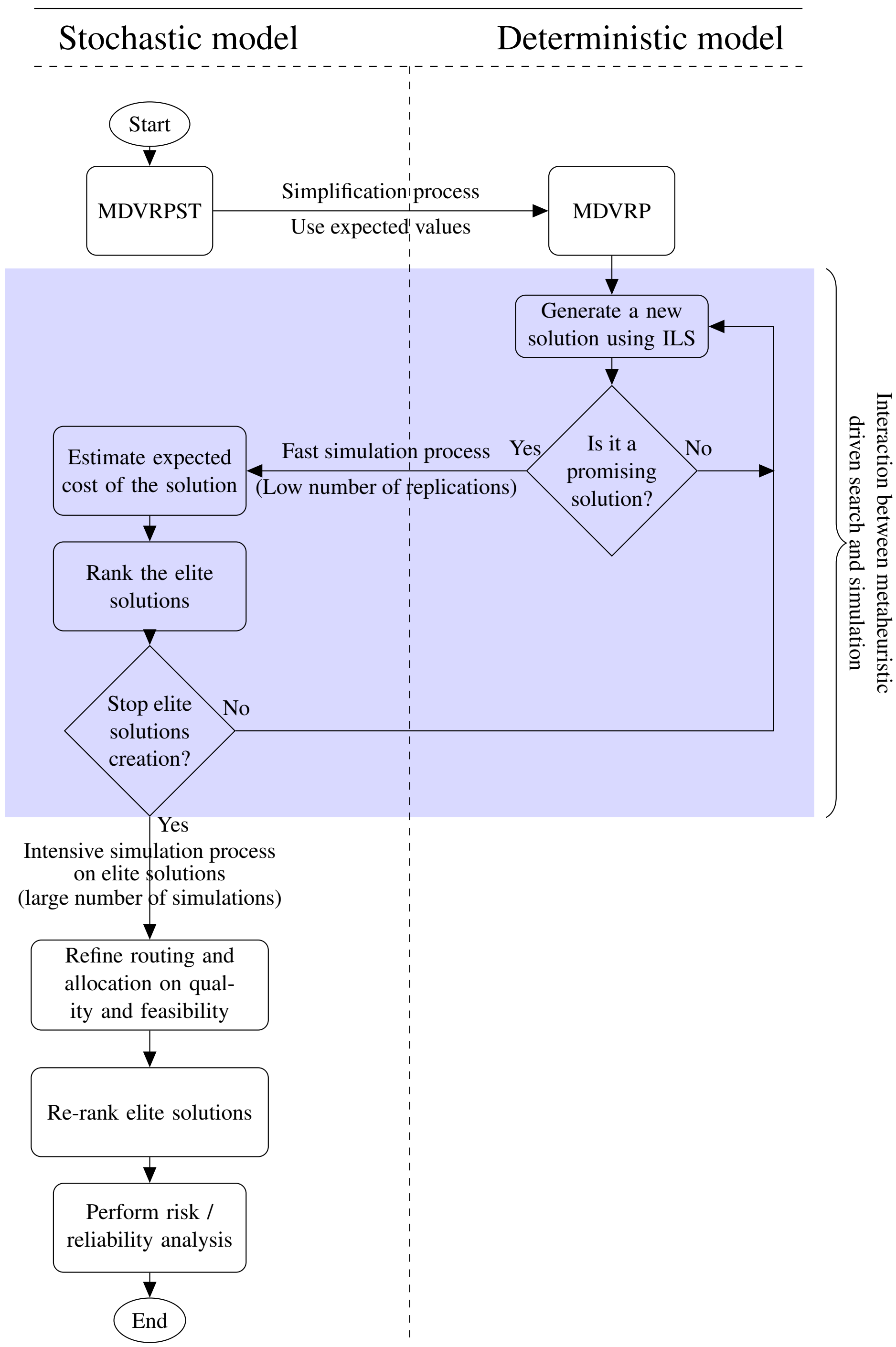

Figure 2: Flow chart of the simheuristics proposal.

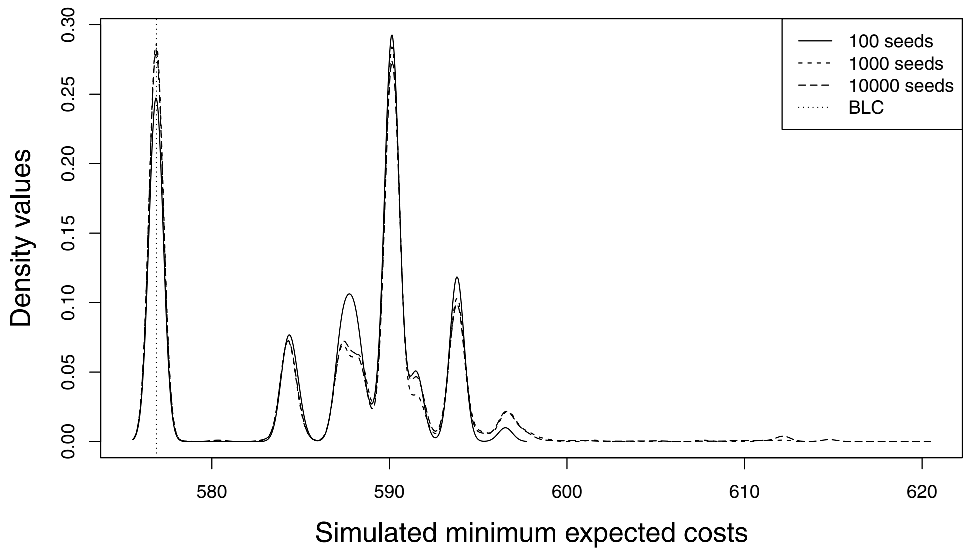

Figure 3: Estimated kernel density for the distribution of the simulated minimum expected costs for the instance p01 with 100, 1,000, and 10,000 seeds and $k = 0$. The dotted vertical line corresponds to the best known solution under the deterministic scenario (BLC).

solution for the deterministic case. It is interesting to note that no matter the complexity of the instance, the dilatation coefficient induced by k values is translated in terms of minimum expected cost increments. This a natural consequence of the homothetic global k-effect transformation of the stochastic distribution of travel times. In a managerial approach, in a more realistic scenario, a weighted result is expectable, under a different weather condition in each one of the edges of the network.

Table 1: Results for different weather conditions described by k values and applied to 5 instances (p01 to p05). For each instance, characteristics of the instance, BLC and relative increments (in percentage) with respect to BLC are given.

PInstance	p01	p02	p03	p04	p05
# customers	50	50	75	100	100
# vehicles	4	2	3	8	5
vehicle capacity	80	160	140	100	200
# depots	4	4	5	2	2
BLC	576.87	473.53	641.19	1,001.04	750.03
$k = 0$	-0.01	-0.04	-0.01	0.26	0.23
$k = 0.25$	24.98	24.90	24.98	25.33	25.29
$k = 0.5$	49.98	49.94	49.98	50.40	50.35
$k = 0.75$	74.97	75.05	74.98	75.46	75.41
$k = 1$	99.97	99.92	99.97	100.53	100.47

7 CONCLUSIONS AND FUTURE WORK

In this paper, we have addressed the basic strategy for solving an Irish-based realistic scenario, in which the distribution plans need to take into account weather conditions. The scenario has been modeled as a capacitated multi-depot vehicle routing problem with stochastic travel times. As the distribution costs are based on these travel times, our goal is to minimize the total expected time-based cost while satisfying all customer demands and capacity constraints. In order to address this complex problem, a simheuristic algorithm has been proposed. Our approach relies on the combination of a well-tested metaheuristic for solving the deterministic version of the multi-depot vehicle routing problem with Monte Carlo simulation. Simulation is employed not only to assess the quality of the solutions provided by the metaheuristic in a stochastic environment, but also to provide feedback to the metaheuristic in order to make the searching process more efficient. In addition, simulation can also provide valuable data to complete a risk analysis for each of the 'elite' solutions found by the simheuristic algorithm.

Some of the most promising research lines that this work opens include the heterogeneity of the weather effect of the network, as well as the possibility of extending the problem to a multi-period one, where weather forecasts and alerts are used to decide about the actual demands to be served to each customer at any given day of the period as well as to decide about the specific depot that has to cover each customer on that day.

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