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A Simheuristic for the Waste Collection Problem with Stochastic Demands in Smart Cities

Simheuristischer Ansatz zur Optimierung der Müllentsorgung mit stochastischer Nachfrage in Smart Cities

Aljoscha Gruler, Angel A. Juan, Universitat Oberta de Catalunya, Barcelona (Spain), aljoscha.gruler@gmail.com, ajuan@uoc.edu

Christian Fikar, Patrick Hirsch, University of Natural Resources and Life Sciences, Vienna (Austria), christian.fikar@boku.ac.at, patrick.hirsch@boku.ac.at

Carlos Contreras Bolton, Universidad Andrés Bello, Santiago de Chile (Chile), ccontreras@gmail.com

Abstract: This paper describes a simheuristic to improve urban waste collection processes. Growing city-populations around the world lead to an increased importance of an effective organisation in basic municipal activities such as waste management. The Waste Collection Problem (WCP) can be formulated as a special instance of the well-known Vehicle Routing Problem (VRP), which has been subject to extensive research over the last decades. While traditional VRP and WCP solution approaches consider deterministic problem input variables, the complexity and uncertainty of real-life problem settings such as the collection of urban waste calls for new approaches. As such, the contribution of this paper is the development and description of a simheuristic methodology for the WCP through the combination of an efficient heuristic with Monte Carlo simulation, leading to realistic and reliable routing solutions.

1 Introduction

Cities are becoming ever-more complex systems. About half the world's population is currently living in urban areas, and it is projected that this percentage will increase to 70% in 2050 (United Nations, 2008). Many municipalities struggle to cope with newly arising challenges, as the existing urban infrastructure and organization does not meet the necessary standards concerning economic, social and environmental changes in urban areas (European Comission, 2011).

Nowadays, many cities across the world develop so called Smart City initiatives, which include a wide range of aspects to help municipalities make better use of their resources. A typical application field for such initiatives is waste management, as inefficient garbage collection can lead to several negative impacts such as traffic

congestions, unnecessary pollution and high noise levels, combining to a decreased urban standard of living (Mattoni et al. 2015; Tranos and Gertner 2012; Neirotti et al. 2014). Furthermore, waste management is a major cost factor with annual per capita costs of up to 200€ only for the collection of urban waste in European cities (The World Bank 2012).

Increasingly, the research society has turned its attention to the Waste Collection Problem (WCP), which is usually formulated as a special instance of the well-known Vehicle Routing Problem (VRP) (Beliën et al. 2011). The aim of the 'classical' VRP consists of optimising the costs of serving a range of customers with a capacitated vehicle fleet stationed at a central depot, whereby (i) every node is served by only one vehicle, (ii) all routes start and end at central depot, (iii) no customer is served twice, and (iv) the vehicle capacity cannot be exceeded (Daneshzand 2011). In this context, the WCP can be seen as reversed VRP, whereby a certain demand (i. e. waste) is collected from a range of customers (i.e. waste containers). A more detailed description of the WCP formulated as VRP is given in Sector 2.

The VRP has been subject to extensive research, especially in the development of different optimisation methods (e.g. metaheuristics). While the VRP was usually formulated as deterministic problem in the past, new powerful solution methods for stochastic VRP problem settings have been presented in the past years, which can be applied to a range of real-life instances. Caceres-Cruz et al. (2015) define such real-life VRP applications as rich VRP's, characterized by additional problem constraints (e.g. time windows) and a high level of uncertainty, i.e. stochastic inputs. A typical example of a rich VRP is the WCP, as urban waste collection is characterized by different uncertain input variables such as travel times within cities and garbage levels in waste containers. Furthermore, constraints such as opening hours of waste disposal sites and driver lunch breaks need to be considered for a realistic representation of the problem.

This paper presents a simheuristic approach as proposed by Juan et al. (2015) to solve the WCP. In line with the current trend in research to develop powerful hybrid approaches to solve optimisation problems, simheuristics combine simulation methods with (meta-) heuristics to consider the stochastic nature in real-life optimisation problems. After outlining the WCP as VRP and current research on the WCP in Sector 2, the fundamentals of our simheuristic methodology are presented in Sector 3. In the following, a simheuristic for the WCP is outlined in Sector 4, before the last sector gives a short conclusion and outlook on possible further work on the problem.

2 The WCP in the Context of VRP Research

The VRP is one of the most famous combinatorial problem settings and has been subject to intensive research over the last decades. As a special VRP instance, the WCP can be outlined on a graph $G = (N, E)$. Thereby, N defines a set of vertices $N = \{n_0, n_1, \dots, n_i, n_{i+1}, n_{i+m}\}$. A number of (homogeneous) collection vehicles with vehicle maximum capacity VMC are located at the central depot n_0. Furthermore, i waste containers with waste levels w_i are presented through the node sub-set $\{n_1, \dots, n_i\}$. An additional constraint of the WCP in comparison to the traditional VRP is that waste collection vehicles have to empty themselves at a landfill (waste disposal site), once they have reached their vehicle capacity or before

returning to the depot. The landfills are presented by the nodes $\{n_{i+1}, n_{i+m}\}$. The travel costs (which might be actual costs, distances or environmental impact) $c_{i,j}$ of moving between two nodes are represented by a set E of edges.

In Figure 1 below, a WCP with two routes can be seen. Note that in route 1, the collection vehicle serves a range of waste containers, empties itself at a landfill and then returns to the central depot. In route 2 however, the collection vehicle collects waste until its vehicle capacity is reached, empties itself and then continues its route. Thus, a vehicle might empty itself and then continue its route (which is usually the case). A time window constraint at the central depot, defining the daily operating hours, prevent one vehicle from collecting the waste of all containers on a single route.

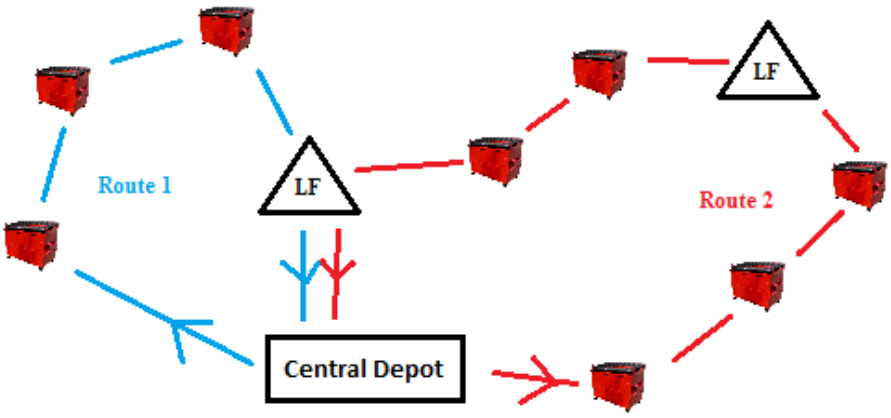

Figure 1: *Example of a WCP with two Routes*

The WCP as described above has been subject to a wide range of research. Most publications are based on different metaheuristic approaches such as Tabu Search, GRASP or Simulated Annealing. For example, Kim et al. (2006) present a meta-heuristic approach based on Simulated Annealing which they implement in a commercial route planning software. In corporation with a North American waste collection service provider, they report route savings of up to 10% using their metaheuristic approach. To our best knowledge, their publication also provides the only publicly available benchmark for the WCP, which is based on real-life problem settings taken from their case studies and includes 10 different instances ranging from 102-2100 nodes per instance (these benchmarks are used to implement and test the proposed simheuristic as presented in the following sectors).

Using the same benchmarks to validate their findings, Benjamin & Beasley (2010) propose a hybrid approach combining variable neighbourhood- with tabu search approach, whereas Buhrkal et al. (2012) apply an adaptive large neighbourhood search. While these papers present competitive WCP solution methods, a major drawback is that they assume the WCP to be a deterministic problem setting. Considering the high level of uncertainty in urban waste collection, this is an unrealistic assumption.

In a case study presented by Johansson (2006), analytical modelling is connected with discrete-event simulation to evaluate different scheduling and routing policies considering real-time input data. The paper suggests savings of up to 26% in waste collection mileage through more informed routing decisions, leading to an operational waste management cost decrease of 10% in the Swedish city of Malmö. Similar to the approach presented in this paper, Johansson thereby considers stochastic waste levels to improve routing decisions.

3 Fundamentals of our Simheuristic Methodology

The simheuristic to solve the WCP is based on the metaheuristic framework combined with simulation as proposed by Juan et al. (2015) and outlined in Fig. 2 below. This framework can be applied to a wide range of stochastic combinatorial optimisation problems (COP's). Their approach makes use of the fact that there are many powerful solution methods (e.g. metaheuristics) to deterministic COP instances, and that the solution of a deterministic COP leads to acceptable and promising solutions to their stochastic counterparts.

Consider a stochastic COP in which certain input variables experience some level of uncertainty. In a simplification process, the deterministic counterpart to this problem is considered by replacing random/stochastic input variables with deterministic values. This might be done for example by estimating a stochastic value based on past experience. Note that these deterministic estimates have to be more or less reliable. In realistic problem settings like the WCP, we believe that reliable experience values exist to obtain good estimates.

In the following, the interaction between metaheuristic optimisation and simulation starts (highlighted by the light-blue background). Using any efficient (meta-) heuristic optimisation algorithm, new solutions to the deterministic COP are created. Each newly created solution is tested on its solution quality. If it is considered a promising solution, a fast simulation process is run with the problem setting, meaning that the input variable which was 'simplified' to create a deterministic COP instance is simulated a defined number of times. Using the results of the first simulation run, the quality and feasibility of promising deterministic COP solutions in a stochastic environment can be estimated. Note that it might happen that a very promising deterministic COP solution is discarded at this point due to the low quality or infeasibility of its stochastic counterpart.

Depending on the results, the most promising stochastic COP results (the 'elite solutions') are chosen to be run in a larger, more extensive simulation process. After the second simulation process, another quality and feasibility evaluation is made. In the following, the most promising elite solutions are subject to a reliability analysis, which is another advantage of the suggested simheuristic. A reliability analysis extends the information that can be retrieved through the optimisation process, as the simulation runs are used to evaluate the number of times that a suggested solution can be completed without any failures when considering simulated stochastic inputs. Using this additional information, decision makers can base their final decision not only on solution-costs, but also on the solution-reliability.

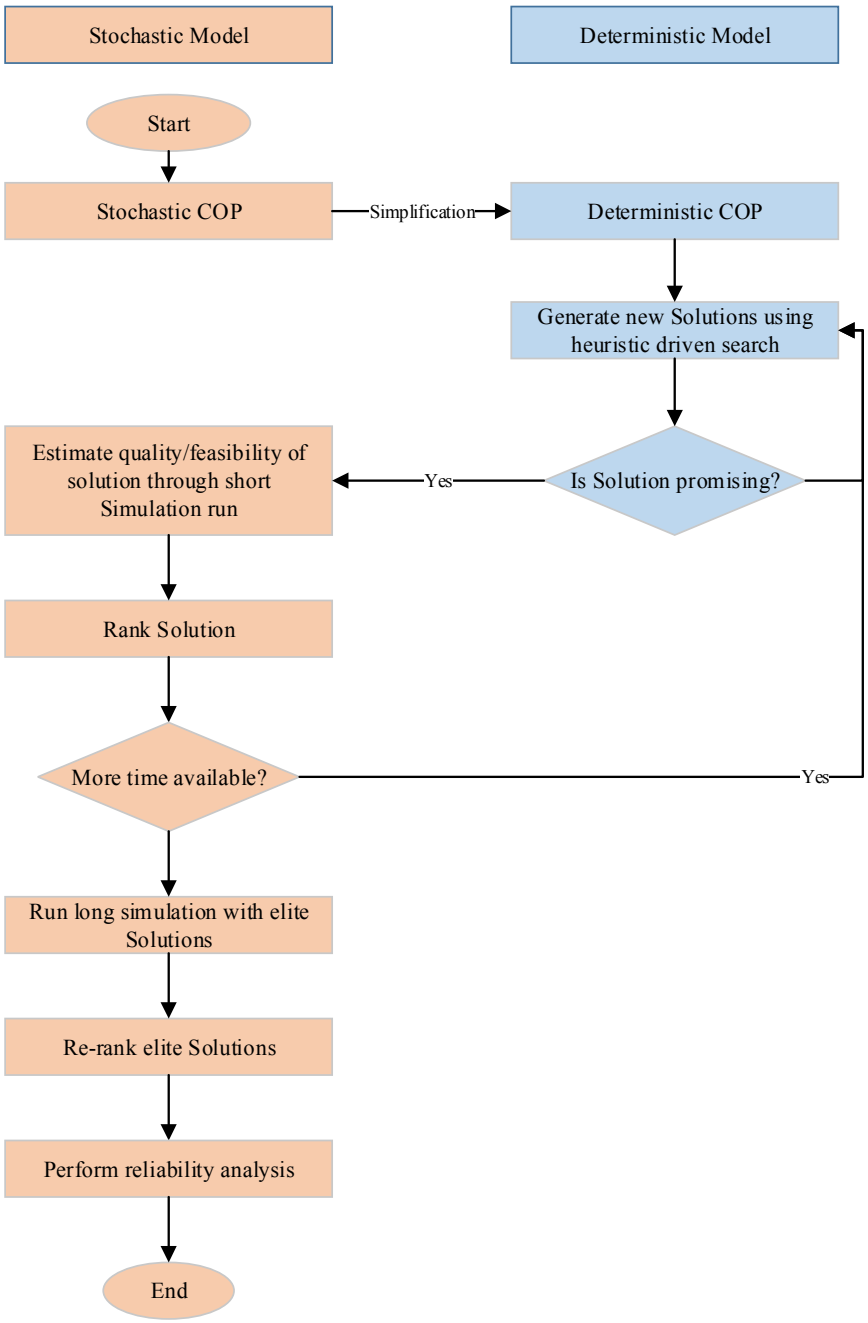

Figure 2: *Simheuristic Methodology as suggested by Juan et al. (2015)*

4 A Simheuristic for the WCP

In urban waste collection, route planners can never be sure about the actual travel times or waste levels at the containers. This paper will present a simheuristic methodology to cope with the stochastic nature of waste levels in the collection of garbage in the following.

The amount of waste in urban garbage containers are constantly frequented by a high number of people disposing very different amounts of waste. Furthermore, there are no fixed time schedules for waste disposal, leading to a high uncertainty concerning actual waste amounts to be collected by a waste collection vehicle when it arrives at a collection site. In the following, a heuristic to solve the deterministic WCP is presented in Sector 4.1. A simheuristic approach combining this heuristic with simulation is then proposed in Sector 4.2.

4.1 A Heuristic Approach to Solve the Deterministic WCP

The first step in our simheuristic approach is the simplification of the stochastic WCP into a deterministic problem instance. Instead of considering stochastic waste levels w_i^{st} at each waste container *i,* the expected waste levels based on past experience is used. To solve the deterministic WCP with waste levels w_i^{det}, we propose the use of an extended version of the well-known Clarke-and-Wright Savings heuristic (CWS). This algorithm starts of by building an initial solution by supplying each customer on a single route with a single vehicle, as seen in (a) in Fig. 3 below. Note that this is the worst possible feasible solution to a VRP, as it will include the highest possible costs. Based on this initial solution, the CWS iteratively merges some of the routes in order to serve more than one customer on a single route, as seen below above (b) (Laporte 2007).

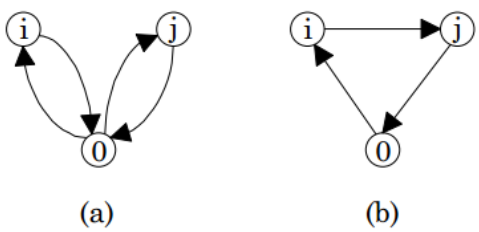

Figure 3: *Merging of Routes through the CWS*

The merging process is based on savings associated to a pair of customers. These savings define the reduction in the overall cost function of serving each customer with a single vehicle, as proposed in the initial solution, compared to combining these customers on an edge and serving them with the same vehicle. For example, savings s_{ij} of connecting customers i and j are computed through $s_{ij} = c_{0i} + c_{0j} - c_{ij}$. All the computed possible savings are listed on a savings list. During the following merging process of a feasible VRP solution, the algorithm iteratively selects the edge with the highest possible savings potential from the savings list as long as (i) no capacity constraints are violated, and (ii) the nodes defining the edges are next

to the depot. As always the edge with the highest possible savings is chosen to construct VRP solutions, the CWS is a so called greedy algorithm.

The original CWS is improved through a randomization technique obtained by combining the CWS with Monte Carlo simulation (MCS), which can be seen as a set of techniques that use statistical distributions and random numbers to solve stochastic and deterministic problem settings (Law 2007). While the original CWS always chooses the edge with the highest potential savings, we use a biased randomization approach at each iteration during the solution construction. While the edge with the highest savings is chosen with the highest probability, all feasible edges are potentially available in the route construction. Using this approach, the algorithm calculates a number of different problem solutions while avoiding getting stuck in a local minima through the edge selection process improved by MCS.

Furthermore, the original CWS algorithm is improved by clustering nodes that are close to each other, making sure they are served by the same customer and a cache memory technique as proposed by Juan et al. (2011a). Finally, all routes of the obtained WCP solution are further optimised by applying the Lin-Kernighan heuristic (LKH), which is a famous adoption of the λ-opt algorithm (Helsgaun 2009).

The suggested heuristic is tested and verified using the benchmarks provided by Kim et al. (2006) and the results of Benjamin & Beasley (2010) and Buhrkal et al. (2012). Their results over all 10 problem instances in comparison to our competitive heuristic approach can be seen in Table 1. With an average percentage gap of 0.8%, our heuristic leads to the current best-known solution in 4 of the 10 benchmark instances.

Table 1: *Results of the proposed Heuristic*

Instance	Kim et al.	Benjamin & Beasley	Buhrkal et al.	Our Heuristic	%-Diff. to Best Benchmark
102	205.1	183.5	**174.5**	157.7	-9.6
277	527.3	464.5	**447.6**	463.3	3.5
335	205.0	204.5	**182.1**	193	6.0
444	87.0	89.1	**78.3**	85.3	8.9
804	769.5	725.6	**604.1**	616.4	2.0
1051	2370.4	**2250.2**	2325.7	2244.7	-0.2
1351	1039.7	915.1	**871.9**	968.9	11.1
1599	1459.2	1364.7	**1337.5**	1219.9	-8.8
1932	1395.3	1262.8	**1162.5**	1170.3	0.7
2100	1833.8	**1749.0**	1818.9	1652.4	-5.5
Average					***-0.8***

4.2 Using Simulation to Consider Stochastic Waste Levels

For the simulation part of the simheuristic, not the complete vehicle capacity VMC is considered for the solution calculation of WCP. It is assumed that a certain safety capacity (1-k) is considered by route planners in the construction of the route, as it is possible that the actual stochastic demands exceed the deterministic demand levels considered earlier. For this reason, the homogenous VMC for all vehicles is multiplied by a load factor k, leading to a new vehicle maximum capacity $VMC^* = VMC \times k$ with which the deterministic solutions are calculated. Note that a high value of k will lead to a low safety stock and a lower total number of routes and vice versa.

Using vehicle maximum capacities VMC^* for the calculation, the heuristic proposed in Sector 4.1 is applied to get a high-quality deterministic WCP solution. For each solution that is considered as promising, waste levels for each customer are simulated using MCS various times. Thereby, different customer demands w_i^{st} are modelled with a log-normal distribution based on a mean equal to each customer's deterministic waste level w_i^{det} and a certain variance (e.g. 10%).

Based on the load factor k, each stochastic solution consist of the base costs provided by the heuristic for the deterministic WCP and the estimated corrective actions necessary for route failures. These expected route failures are calculated based on the number of simulation runs in which the stochastic waste levels exceed the original vehicle capacity VMC, which is penalized with the costs for an additional trip to a landfill. Note that higher values for k will lead to low base costs (through the use of a higher load factor/lower safety capacity) but higher additional costs through more route failures and vice versa. Furthermore, this approach leads to an estimate of each solution reliability by dividing the amount of route failures with the number of simulation runs.

Based on the results after the first simulation run, the most promising stochastic elite solutions are defined. Waste levels for these solutions are simulated in an extensive second simulation run, leading to a list of solution proposals ranked according to their overall expected costs and reliabilities. As the whole process can be run with low computational effort, different values for k and the influence on the solutions can be tested, as outlined in the detail by (Juan et al. 2011b).

5 Conclusion and Future Outlook

This paper proposes a simheuristic approach to solve the WCP through the combination of an efficient heuristic with Monte Carlo simulation. The methodology allows the consideration of stochastic waste levels in garbage containers, leading to more realistic and reliable routing solutions in waste management. Using the results of the competitive heuristic based on the famous CWS for the VRP to solve the simplified deterministic WCP as outlined in this paper, Monte Carlo simulation is used to simulate different waste levels and obtain results for the more realistic stochastic WCP. On the one hand, the simulation procedure leads to results based on the expected additional penalty costs for route failures (i. e. additional trips to waste disposal sites) and the basic route costs. On the other hand, a further result dimension is added by estimating the reliability of each route depending on a

collection vehicle load factor, giving waste management decision takers additional information in their routing choices.

In the development of Smart Cities, municipalities can make use of cheap and efficient tracking and tracing technologies such as volumetric sensors implemented into waste containers to obtain reliable initial values for the suggested simheuristic. Instead of basing the mean value for the simulation on experience values, such volumetric sensors (which are already being applied in various European cities) could be used to obtain more reliable initial waste levels, allowing decision takers to calculate their routes with lower variance and a higher load factor for the collection vehicles. For an extensive overview over tracking and tracing technologies used to improve waste management see Faccio et al. (2011). In the future, a case study in which volumetric sensors are implemented in waste containers in the Catalonian city Sabadell to improve their municipal waste management using the presented simheuristic is planned.

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