On demand waste collection for smart cities: a case study*

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Abstract. The neat and clean surrounding is the main driving force for any city to be called a smart city. In order to address current societal and business challenges, the objective is to provide a solution to enable collection-on-demand of wastes by connecting waste data and users/customers with the waste management system. In that context, the focus is to improve the waste collection process in terms of collection cost, collection time, and CO2. Within the overall objective, an important goal that needs to be solved is waste collection on demand and the present paper addresses this by tackling the optimization problem related to the routing. Application of the presented solution to a case study with real data collected in the municipality of Ålesund, Norway, is presented. This study also shows a comparison of three popular optimization algorithms for solving vehicle routing problems (VRP) and multiple vehicle routing problems (MVRP), to identify a suitable algorithm for the case study, introducing a data-driven model. Five constraints with alternative objectives of distance and cost minimization are considered.

Keywords: Smart City · Sustainability · Waste Management · Optimization · MVRP

1 Introduction

For a sustainable future, addressing the development goals (SDGs) is crucial [1]. In order to transform society into smart circular communities and cities, SDG 11 - Sustainable Cities and Communities, and SDG 12 - Responsible Consumption and Production, are important. Smart cities need smart waste management and an essential step to achieve it is scheduling and planning the collection route. Additionally, enabling optimized management for the collection of the waste gives a

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significant contribution to the municipalities' budgets and linked environmental hazards. Different constraints (e.g., noise pollution, safety, privacy, etc.) should be considered in planning the collection route(s) since it leads to a sufficient and sustainable system which reflects the inhabitants' needs.

The traditional urban waste collection is mainly done by collecting the waste from all the bins regardless of the status of bins (full or not) considering fixed predetermined routes and schedules and transporting it to the disposal station. This is a vehicle routing problem (VRP). According to the current practices, it is up to the user to move his/her waste bin to a nearby collection point for the next pick up adding more uncertainties.

The waste collection cost is very high and involves many types of costs such as labor costs, maintenance costs, fuel costs, etc. Therefore, the collection process problem has been addressed enormously recently. The proposed solutions range between optimizing the collection routes and collection of selected bins by considering the filling levels. Different researchers solved this problem as a multi-objective optimization problem by considering priorities other than the shortest distance. Mohsenizadeh et al. [2] added the impact of CO2 emissions from the transportation activities, while Nemachnow et al. [3] added the best service to the shortest distance. Abdallah et al. [4] developed waste collection routes by selecting the waste bins with predicted high filling levels based on historical data. While Mamun et al. [5] used sensor technology to monitor the waste bins and send the filling level in real-time. In [6] the importance of awareness in sustainability in waste collection process is tackled via Cyber-Physical Systems, a mathematical model is described, which incorporates routing, assignment, and scheduling problems. In [7] multi-objective optimization approach to generate a route by minimizing the route distance and maximizing the amount of waste is presented. In [8] the optimization problem of wet waste collection and transportation in Chinese cities is solved in terms of a chance-constrained low-carbon vehicle routing problem, while in [9] a priority considered green vehicle routing problem model in a waste management system is constructed paying particular concern to the possibility of immediate waste collection services for high-priority waste bins, e.g., those containing hospital or medical waste.

The main objective of this study is two-fold:

- To compare various optimization algorithms for standard Multiple Vehicle Routing problems (MVRP) and identify suitable approaches to get optimal collection routes.
- To develop a data-driven optimized routing and scheduling for waste collection and transportation

We consider several objectives linked to Key Performance Indicators (KPIs) such as time consuming, CO2 producing and financial costs for sustainable smart cities, thereby addressing SDGs 11 and 12. To this purpose, we define single and multi-objective optimization problems to address routing and scheduling under a variety of constraints, identify suitable algorithms to address the optimization problems, and discuss possible gains from using collection-on-demand. The addressed case study is the one of Ålesund municipality, where real data have been collected. The cooperation between NTNU (Norwegian University of Science and Technology) and local municipalities (i.e., Ålesund Kommune) ensures that the definition of the optimization problem is realistic and adapted to local regulations. The proposed solution is dynamic and interactive.

This paper is organized as follows: Section 2 presents the problem and a comparison between different approaches. Section 3 describes a case study of on demand waste collection in Ålesund municipality. Finally, section 4 provides the conclusion of this study.

2 Problem Formulation

A trade-off between conflicting objectives, e.g., environmental and economic goals, motivates multi-objective optimization problems. Additionally, it is required to incorporate constraints, such as number of available trucks, capacities, cost per working hour, time, and distance. Several scenarios can be taken under consideration for optimal routing and trip scheduling as described later.

2.1 Problem description

The optimization problem is a VRP or MVRP with the goal of allocating a number of filled bins for each truck (i.e., task allocation problem) and finding optimal routes based on the real-time data (e.g., traffic data). The problem can be solved considering several scenarios, such as:

– One vehicle, one disposal center: this is a simple scenario where we have only one vehicle and one disposal station. The vehicle has to start from a starting point and collect the trash from all the filled bins and end up in the disposal station. This is a simple traveling salesman problem (TSP) which can be solved by heuristic algorithms.
– Many vehicles, one disposal center: this is a traditional MVRP, where the bins must be divided between a number of vehicles in order to optimize the objective function (e.g., minimize the cost, minimize the collection time, minimize the travelling distance, . . .).
– Many vehicles, many disposal centers: this is a similar problem to the previous one where we add more disposal stations.
– Static problem vs. dynamic problem: static problem is fixed, and the optimal routes are calculated at the beginning of the time window (e.g., in the beginning of the day, midnight). While in the dynamic problem, the routes are subject to re-calculation during the collection process if there is new data such as traffic data, filling level, priority level, inputs from vehicles (drivers).

The data-driven model depends on available GIS data and real-time data:

- Maps: roads, bins' locations, starting points, disposal stations' locations.
- Bin attributes (location, capacity, priority).
- Road attributes (directions, speed limit, noise, safety, real speed).
- Disposal centers (location, capacity, type).
- Vehicles (location (GPS), capacity, cost of use, emission rate).

The waste collection problem and the data flow are depicted in Figure 1.

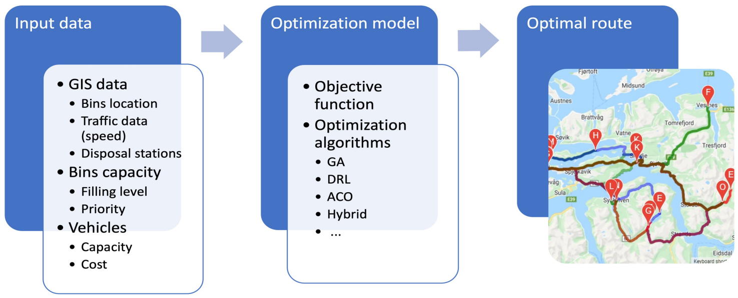

Fig. 1. The optimization problem and the data flow for the waste collection problem

2.2 Problem representation

The problem can be represented by a graph $G = (V, E)$ with a set of N nodes V and a set of edges E (such that E_{ij} connects node i with node j). Nodes are bins locations, starting points, and disposal stations. Let c the number of vehicles. Hereafter we consider several alternatives for objective functions.

Optimization problem with single objective function: Following [10], we formulate the optimization problem with a single objective function (e.g., minimizing the total driving distance or cost) and for one depot.

Let d_{ij} the distance or cost for using the path from node i to node j, with depot node $\{0\}$. The binary variable x_{ij} is equal to 1, if the path from node i to node j is part of the solution, and 0 otherwise. $r(S)$ denotes the minimum number of vehicles needed to serve set S of nodes.

$$\min(f) = \sum_{i\in V}\sum_{j\in V} d_{ij}x_{ij}$$

subject to

$$(1) \quad \sum_{i=1}^{N} x_{ij} = 1 \qquad \text{for } j = 1, 2, \ldots, N$$

$$(2) \quad \sum_{j=1}^{N} x_{ij} = 1 \qquad \text{for } i = 1, 2, \ldots, N$$

$$(3) \quad \sum_{i\in V} x_{i0} = c$$

$$(4) \quad \sum_{j\in V} x_{0j} = c$$

$$(5) \quad \sum_{i\notin S}\sum_{j\notin S} x_{ij} \geq r(S), \ \forall S \subseteq V$$

$$(6) \quad x_{ij} \in \{0, 1\} \quad \forall i, j \in V\,.$$

Constraints (1) and (2) state that each node is visited by exactly one vehicle. Constraints (3) and (4) state that the number of vehicles leaving the depot $\{0\}$

is the number of vehicles entering the depot and equal to c. Constraints (5) are the capacity constraints, which ensure that the routes must be connected and not exceed the vehicle capacity.

A weighted sum as objective function: One objective function incorporates several objectives, such as minimizing the driving distance, minimizing the collection time, or minimizing the collection cost. In this case, the objective function can written as,

$$\min(f) = \sum_{i=1}^{n} w_i f_i \,,$$

where w_i are weights and n is the number of objectives.

Multi-objective function: In this case, several objective functions are considered simultaneously with the goal of finding Pareto optimal solutions. A Pareto optimal solution cannot be improved in any of the objectives without degrading at least one of the other objectives. The multi-objective optimization problem can be formulated as, $\min(f_1, f_1, ..., f_n)$, where n is the number of objectives.

In the following, we also consider cases of the MVRP with multiple depots as formulated by Kulkarni and Bhave [11, Sec. 4].

2.3 Comparisons of OR-tools, GA, and DRL for four standard MVRP problems

As depicted in Figure 1 and discussed in the introduction, a variety of optimization algorithms exist that can be used to address MVRPs such as our waste collection problem. In order to choose an algorithm to be used in the case study, three optimization algorithms are compared in terms of performance when addressing a set of four standard MVRP. We choose three popular algorithms that are relevant to this kind of problems. The first algorithm that is used is based on the OR-tools [12]. This is an open-source library recently developed by Google that can solve combinatorial optimization problems using a Constraint Programming solver with a Local Search implementation on top. It includes a toolbox for solving MVRP, [13]. The CP-SAT solver [14] uses a lazy clause generation solver on top of an SAT solver. OR-Tools is an open source software that suites well for optimization problems in vehicle routing [12]. The second approach is based on Genetic Algorithms (GA) and it is used for solving both constrained and unconstrained optimization problems [15]. GA is a well known meta-heuristic algorithm which can generate high-quality solutions to optimization and search problems.The third approach is based on Deep Reinforcement Learning (DRL) and combines reinforcement learning and deep learning [16]. The DRL concept deals with the problem of learning by trial and error to make decisions on a computational agent. This approach is the most popular among the machine learning techniques for solving VRP [17].

Our experimental setting was conducted on four standard VRP problems that are defined by the number of depots, vehicles, customers and maximum load for each vehicle, see Figure 2. We consider low numbers of customers, but also more complex problems with a higher number of customers (20,50,100,120). The problems can be found in the project repository [18]. We address problems with different conditions over three rounds. The minimum cost and minimum calculation time for each solver are given in Figure 2.

MVRP Comparing different algorithms		Problem							
		n20d3c5D1		n50d3c3D2s6		n100d3c2D3s1		n120d3c3D3s10	
Testing Round	Algorithm	Calc. Time (Second)	Min Cost (Distance)	Calc. Time (Second)	Min Cost (Distance)	Calc. Time (Second)	Min Cost (Distance)	Calc. Time (Second)	Min Cost (Distance)
1st Round	Ortools	0.084	4.869	0.134	7.114	0.464	9.642	0.579	9.512
	Genetic Algorithm	0.408	5.56	1.701	6.689	9.779	10.731	15.445	11.337
	Reinforcement Leanring	1.13	5.385	2.18	6.887	5.395	10.588	12.041	10.546
2nd Round	Ortools	0.039	4.869	0.132	7.114	0.335	9.642	0.614	9.512
	Genetic Algorithm	0.382	5.56	1.69	6.487	9.415	11.031	15.216	11.223
	Reinforcement Leanring	0.843	5.37	2.19	6.896	7.197	9.585	11.639	10.19
3rd Round	Ortools	0.041	4.869	0.14	7.114	0.354	9.642	0.569	9.512
	Genetic Algorithm	0.403	5.67	1.687	6.494	9.044	10.301	14.541	11.291
	Reinforcement Leanring	0.94	4.955	2.14	6.881	5.79	10.424	12.107	10.846

Problem instances							
n20d3c5D1s1		n50d3c3D2s6		n100d3c2D3s1		n120d3c3D3s10	
n	20	n	50	n	100	n	120
d	3	d	3	d	3	d	3
c	5	c	3	c	2	c	3
D	100	D	200	D	300	D	300
s	1	s	6	s	1	s	10

Description	
	n = total number of customers
	d = number of depots
	c = number of vehicles available in each depot
	D = maximum load for each vehicle
	s = sample number

Result table	
Index	Stronger → Weaker
(Min Cost) Simple problems	ORtools > DRL > GA
(Min Cost) Complex problems	ORtools > DRL > GA
(Min Calc. Time) Simple problems	ORtools > GA > DRL
(Min Calc. Time)Complex problems	ORtools > DRL > GA

Fig. 2. Comparisons of results with OR tools, GA, DRL algorithms for four standard MVRPs.

In each of the three rounds of the four problem instances considered, OR-tools has the shortest calculation time. In eight cases, OR-tools find the best solution, while it finds the second-best solution in one case and the third-best solution in three case. Overall, OR-tools was able to achieve a good decrease of the objective function value with small calculation times, both for problems with 20, 50, 100 or 120 customers in our particular case. Hence, OR-Tools has been chosen as solver for the case study.

3 Case study: On demand waste collection in Ålesund municipality

Ålesund in Norway is a small but smart city joined United Nations Cities program, which focuses on the applications of smart innovation and digital technology. We initially consider three trucks (vehicles) and 27 bin stations (locations). The truck drivers utilize Google map and traffic data to choose their routes during the work. The administrative officers plan to find the optimal schedules for the on demand waste collection, i.e., the set of driving paths with the lowest cost. The cost could be distance, time or the combination with several indicators. The objective function reflects KPI concept by considering minimal distance, time and financial cost. The administrative planners will guide the drivers to collect bins in the bin stations until arriving at the assigned destination (some of 27 bin stations) as planned in the scheduled routes.

The description of the case study is organized as following. We introduce the data and a set of optimization problems in Sec.3.1. The experimental result for five constraints can be found in Sec.3.2. In Sec.3.3, two use cases with multiple constraints are described and addressed. The datasets, source codes, results could be downloaded from here [18].

3.1 A set of waste collection problems

The dataset provided by Ålesund municipality includes 27 disposal center locations. For the case studies, we assume there is only one kind of trash bin. We track and manually set other problem parameters such as the number of trucks c and numbers of bins at a position (S_d). The parameters are listed in Table 1. The depot positions compose of disposal centers and bin locations. The distance matrix M_d and the time matrix M_t have been obtained using Google map APIs at 2022/03/19 22:52:41.

For the case study, we consider a set of MVRP constraints which we assume to be relevant for the waste collection problem in Ålesund municipality. ①**Multiple starts & ends** means each vehicle might be assigned an individual start depot and stop depot. The start and stop depot lists are saved in S_s and S_e. ② **Capacity Constraints** means each vehicle has limited capacity for the quantity, for example the weight or the volume. In our research this quantity is the maximum bin number for each vehicle by S_c. In this case, we also assign a demand (quantity to be picked up) to each depot position (using S_d). ③**Pickups and Deliveries** has pairs of pickup and delivery locations in the list S_{pd}. This requires for each pair that the bins in the pickup location should be picked up first and delivered to the delivery location by the same vehicle. It means each item must be picked up before it is delivered. ④**Penalties and Dropping Visits** introduces a penalty list S_p, it records the extra cost if the depot position is dropped by the vehicle. In this case, the objective function is the total distance together with the sum of all dropped locations' penalties. ⑤**Time Window Constraints** requires vehicles to arrive at depots within the time period in the list S_{tw}. In this case, vehicles may wait at a location for a waiting time T_w and are assigned a maximum running time T_{max}.

Parameter values for the constraints are presented in Table 2. For all experiments, we let $d = 3$ and $c = 3$. Table 2 also presents our set of optimization problems, which is defined by the set of constraints, combinations of multiple constraints and two baseline experiments. The baseline examples with a single end depot are MVRPs with $S_s = S_e = [3, 3, 3]$ and $S_s = [3, 5, 6]$, $S_e = [3, 3, 3]$, respectively. They are used for comparison. With exception of constraint ⑤ (Time Window Constraints), which requires the time matrix M_t, the constraints only use the distance matrix M_d.

Table 1. List of parameters

	Parameters	**Value**
M_d	distance matrix	each directed edge has a distance.
M_t	time matrix	each directed edge has a time.
d	number of depots	each bin position can be a depot.
c	number of vehicles in total	
S_s	start depots list	each depot has an index.
S_e	end depots list	each depot has an index.
S_d	demand list	each location has a demand.
S_c	capacity list	each vehicle has the maximum quantity that it can hold.
S_{pd}	pairs of pickup and delivery locations	the indexes for the locations
S_p	penalty list	each location has a penalty, which is the extra cost if drop this position.
S_{tw}	time window list	each location has one travel time window with the start and stop time. the unit is minute.
T_w	the allow waiting time	(default) 30 mins
T_{max}	the maximum time per vehicle	(default) 30 mins
w_1	weighted rate for manhour cost, M_t	(default) 10 NOK / min
w_2	weighted rate for vehicle cost, M_d	(default) 1 NOK / m

Table 2. List of constraints

Constraints No	**Parameters with assumed value**
Common constraints	$d = 3 \quad c = 3$
One start & end	S_s=S_e=[3, 3, 3]
Multiple starts & one end	S_s = [3, 5, 6] S_e = [3, 3, 3]
① Multiple starts & ends	S_s = [3, 5, 6] S_e = [5, 6, 3]
② Capacity Constraints	S_d = [1, 3, 2, 0, 4,.., 4] S_c = [25, 25, 30]
③ Pickups & Deliveries	S_{pd} = [[19, 2], [10, 11]]
④ Penalties & Dropping Visits	S_p = [20, 20, 20, 19,..., 10, 1, 1, 2, 4, 2, 4]
⑤ Time Window Constraints	S_{tw} = [[0, 15], [7, 12], [10, 15], ..., [0, 5]]
⑥ Multiple constraints	① & ②
⑦ Multiple constraints	① & ② & ③
⑧ Multiple constraints	① & ② & ③ & ④
⑨ Multiple constraints	$w1 \times M_t + w2 \times M_d$
⑩ Multiple constraints	⑨ & ⑤
⑪ Multiple constraints	⑨ & ⑤ & ②
⑫ Multiple constraints	⑨ & ⑤ & ② & ③ & ④

3.2 Results for problems with simple constraints

Figure 3 (a) presents the results. The total distance in ① **Multiple starts & ends** decreases compared to the baseline experiments because the vehicles could stop more freely. The ② **Capacity Constraints** has higher distance in total, since the vehicles may be full during the work. When requiring ③**Pickups and Deliveries**, we see an increase of distance due to the given pickup and deliveries sequence. ④**Penalties and Dropping Visits** allows for dropping some depots and a smaller total distance than in the baseline experiments.

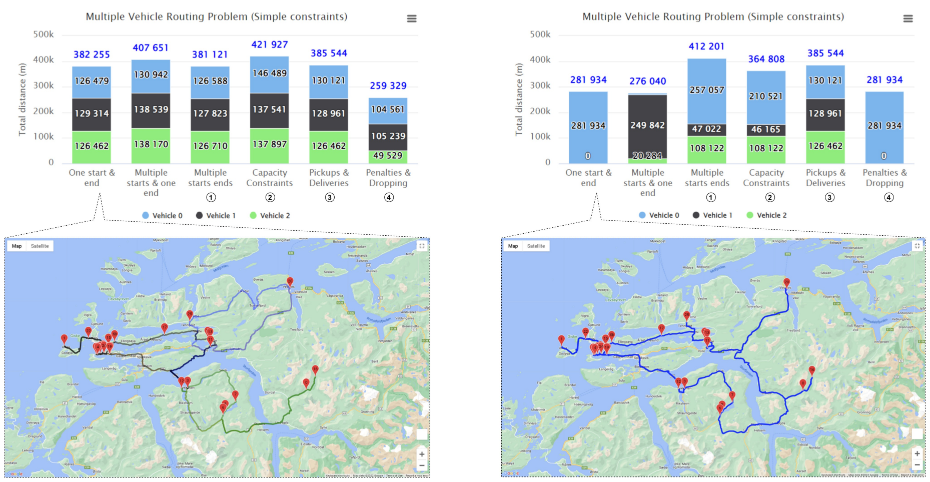

Fig. 3. The experiments result for simple constraints. (a) is with the distance limitation and (b) is without distance limitation

For Figure 3 (a), we set distance limitations for each vehicle to be $(2 \times \max(m_d \in M_d))$, while the vehicles' driving distances are not limited in the experiments whose results are shown in Figure 3 (b). The difference is mostly work load distributed on just one vehicle in the calculation result except the ③**Pickups and Deliveries**. Therefore, it is critical to set the reasonable distance limitation first to keep the work load balance for each vehicle no matter what's the other constraints.

When our objective is to minimize the time cost instead of the distance cost, time matrix M_t is used to replace the distance matrix M_d as the input of the calculation. In this condition, we marked one start & end (time) in Figure 4 (a) to distinguish the target is to minimize the total time cost, not total distance. This is the baseline compared with ⑤**Time Window Constraints** result. The total distance is also marked with the total time in different Y axes. The increase of time is much more compared with the increase of distance. Because of the exist of time window, most of the time cost is the waiting time, but not the vehicle running time.

3.3 Results for problems with multiple constraints

In this section, there are two use cases described with the results. The first case is to minimize the distance with a priority list of four constraints, and the second one focuses to find the optimal financial cost with multiple constraints by a weighted sum of distance and time cost.

Case 1. Find an optimal schedule to minimize the distance cost under the multiple constraints with priority
In this case, we assume the officer wish to find the multiple constraints affection on the distance cost for the vehicle schedule. It only relates to the distance matrix M_d and is composed of ⑥ ⑦ ⑧. They are the multiple constraints adding simple constraints ① ② ③ ④ one by one as Table 2.

Figure 4 (b) shows sometimes the constraints for the capacity may help to find better solution by chance. Meanwhile, the pickup and deliveries constraints cause much more distance cost compared to the same single constraint ③. And the result of the penalties and dropping in this case is similar with ④ in total value. The multiple constraints for the distribution of vehicles could have more balanced load like compare ④ and ⑧. Sometimes it fails to find the solution if the constraints are more than three kinds and not including penalty constraints.

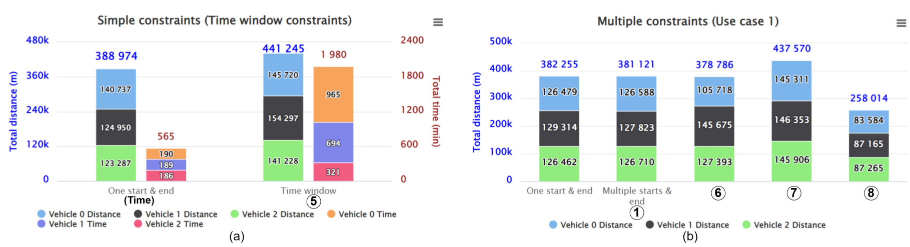

Fig. 4. The experiments result (a) Time window constraint , (b) Multiple constraints use case 1.

Case 2. Explore the lowest financial cost with multiple constraints
In case 2, the officer plans to explore the optimal schedule with lowest financial cost, which happens more often in the real world. The weighted sum (Section 2.3) is utilized to compute the financial cost based on the fixed weighted parameters w_1 and w_2 (Table 1). The financial cost is computed by $f = w_1 f_1 + w_2 f_2$, where f_1 is the time objective and f_2 is the distance objective. Therefore, we uses three aspects to reflect the results in Figure 5 (c). They are total financial cost (black), time (orange), distance (blue). The experiment with the constraint ⑨ uses the financial cost as the objective with distance limitation only, and works as a baseline with the rest three multiple constrains configuration. The constraints ⑩ ⑪ ⑫ are the multiple ones adding simple constraints ⑤ ② ③ ④ as Table 2. When ③ is added to ⑪, there is no solution. Therefore, we add ④ together with ③ to to ⑪ as ⑫.

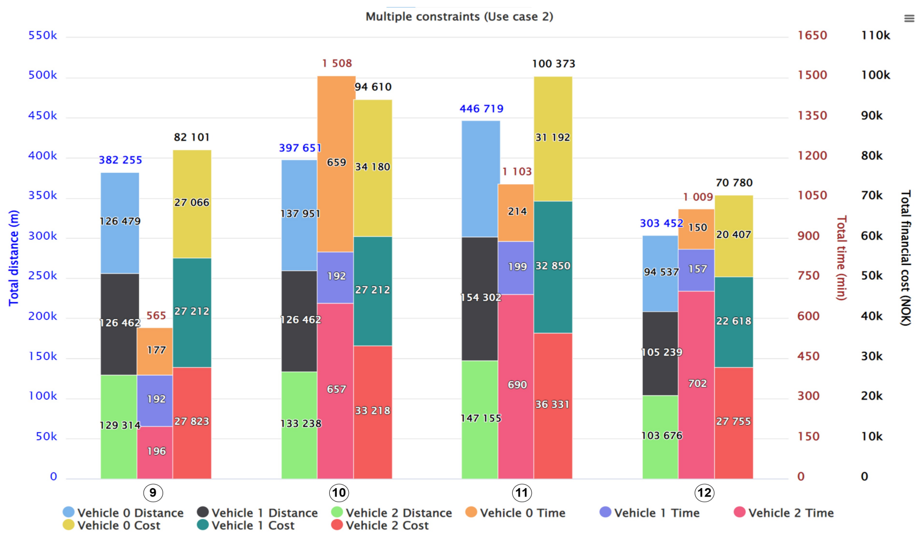

Fig. 5. The experiments result of multiple constraints use case 2.

Compared with (9) and (10), much more waste of time happens compared with the increase of distance. This is because the financial cost is mainly affected by the distance factor with higher w_1. The (2) capacity constraint directly causes the decrease of the time and inevitable rising of the distance, which finally causes more financial cost. The (4) is the main factor to solve (12) because there is no solution only adding (3) on (11). The results reflect the larger decrease of distance in distance and financial cost.

4 Conclusion, limitations and future work

This study presents a comparison of three optimization algorithms (OR tools, GA algorithm, DRL) for four standard MVR problems and found that OR-tools outperforms others for these specific problems. Further, a data-driven model has been introduced which gives a dynamic interactive solution to the waste collection problem. We propose to use hybrid approaches to improve the performance of the optimization algorithms. The proposed multi-objective cost clarifies how the use of multiple constraints can be addressed and solved in real time. This optimization takes into account KPIs as consumed time, CO2 producing, financial cost in the decision making process. It has been shown how on demand routing is useful for the minimization of fuel consumption and the effectiveness of the data-based management.

We present results for a set of waste collection problems with real data, five constraints, along with the two alternative objectives of distance and cost minimization. Here, we prioritized constraints and included them successively into the problem formulation. We considered single objective functions and a weighted sum as objective function, representing the financial cost and considering both distance and time. The results also cover all the simple constraints except the multiple starts & ends.

There are several directions for future work building on the presented study. Firstly, parameter values for the constraints have been based on our assumptions (about e.g., capacities or time windows). The optimization algorithm employed for the case study fails to find a solution when constraints are too strict and of many types. The constraints ④ ② ③ ① are negative with higher cost from the strongest to the weakest and ⑤ is strongly positive. ① could be positive sometimes. These classification is made on our experiments by quality and it could be more convincing if we use real world constraints values in the future. It might also be worthy to analyze the result in the quantitative view. A further direction for future work would be to compare results form experiments conducted at several times of the day / week. Ålesund is a small city with minor changes in traffic patterns. Actually, there are more than 30 groups of distance and time matrices collected for the targeted depots list by Google Map API. The comparison of the result shows it brings tiny changes to the result when the temporal changes of raw data are small. In the future, we plan to focus more on the analysis on the traffic data in the large cities. The present solution can be improved by the use of customer satisfaction and real time measurements, such as waste fill-level to dynamically set an adaptive optimal routing. To this purpose data on waste fill-level in a waste bin in real-time, temperature and bin location need to be obtained, i.e. collecting them through IoT devices. Ongoing and future research is addressing these questions.

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