Dynamic Multi-Period Vehicle Routing with Touting

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Abstract

This paper introduces a dynamic vehicle routing problem with touting as demand management technique, where customers that have not yet placed an order can be actively encouraged to order a service sooner. Touting the right customers, such as those located nearby customers who already placed orders, allows for more efficient routes over time. However, it also increases the frequency of visits at such touted customers which leads to smaller collection volumes.

To tackle this trade-off, we propose several strategies to decide which customers to tout and when, and combine these touting strategies with two rolling-time horizon dynamic vehicle routing algorithms. The different strategies are empirically compared in a simulation based on a real-world waste collection problem. We demonstrate that touting indeed allows to significantly reduce the travel distance in a dynamic vehicle routing problem.

Keywords: Routing, multi-period, demand management, touting, metaheuristics

1 Introduction

In this paper, we consider a vehicle routing problem (VRP) with due dates and customer orders (e.g., for collections of goods) arriving dynamically over time. We specifically investigate the option to actively approach customers and encourage them to order sooner, a demand management technique known as touting. We assume that all customers are loyal and regular customers, so touting will
not increase overall demand, just shift the timing of the demand. Because of this, touting may seem
counter-productive, because it is likely to increase the number of required visits to a customer as
customers are encouraged to order earlier, and thus smaller amounts. However, as we show in this
paper, by specifically touting customers that fit well with the already acquired customer orders,
touting can significantly reduce the distances travelled to service all customers. To the best of our
knowledge, this is the first paper considering touting strategies in vehicle routing.

We propose several heuristics to decide which customers should be touted, and when, in order to
minimize overall distances travelled. The touting strategies are then combined with a vehicle routing
algorithm operating on a rolling time horizon. We test the resulting algorithms in a simulation
based on a real-world waste-collection problem of an industry partner that motivated our work.
Note that the focus of this study is not on proposing a novel algorithm to solve dynamic VRPs,
but on linking dynamic VRP solvers to the demand management technique of touting.

We would like to stress that the idea of touting is not limited to waste collection; it can
be beneficial in a wide variety of similar dynamic vehicle routing problems, involving collection,
delivery, or service. For example, companies that offer preventive maintenance services may need to
repeatedly serve customers by known deadlines and could contact certain customers to service their
requests early. In delivery problems with deadlines, we likewise may want to pro-actively contact
certain customers whom we believe likely to be interested in a delivery (of food, for instance) and
whose locations fit well with the current planned routes. In the following, we stick to the waste
collection application to explain our approach.

The paper is organized as follows. We start with a review of related literature in Section 2,
followed by a description of the considered problem in Section 3. Section 4 explains the proposed
touting strategies as well as the methodology to solve the routing problem. The simulation model
with empirical results of the different strategies are presented in Section 5. Finally, Section 6
summarizes the paper and suggests some avenues for future research.

2 Literature review

Vehicle routing is a very large and diverse research area (Braekers et al., 2016), and even the class
of dynamic vehicle routing problems would be too large to be covered here. The reader may refer
to Pillac et al. (2013), Ritzinger et al. (2016), Ulmer et al. (2020), or Soeffker et al. (2021) for
detailed reviews on dynamic VRP literature.

In this section, we will focus on the papers most relevant to our work, primarily on the class
of multi-period vehicle routing problems (MPVRPs). These problems can be further classified into
static or dynamic. In static problems, all data is available upfront. Although in our problem the
customers arrive dynamically over time, we plan on a rolling horizon, and each sub-problem could
be regarded as a static problem. In this sense, our problem is related to those static problems
involving due dates. Athanasopoulos and Minis (2013) presented a general model for the MPVRP, where the tasks have time windows and allowed visit days. Each period has a time constraint and the objective was to minimize transportation cost of the entire horizon. Archetti et al. (2015) and Larrain et al. (2019) considered customer release and due dates, and their objective is to minimize the distance travelled as well as the inventory holding cost at the depot until the goods are shipped to the customers.

In the dynamic MPVRP, new orders arrive dynamically over time and the initial plan may need to be revised to include the new information. In this case, an optimal solution found at the beginning of a period may not be necessarily optimal in the next period since the set of customers has changed (Ozbaygin and Savelsbergh, 2019). Angelelli et al. (2007) studied a variant in which a set of orders are revealed at the beginning of each time period and they have to be served either in that period or in the next one by a single uncapacitated vehicle. The plans are modified at the beginning of each period depending on the new orders. Bostel et al. (2008) studied this problem in a technician routing context. Wen et al. (2010) optimized the routes such that the total customer waiting time and travel time are minimized, and daily workload of the vehicles is balanced over the planning horizon. Cordeau et al. (2015) addressed an auto-carrier transportation problem with heterogeneous fleet and introduced penalties for late deliveries. To address dynamic nature of the problem, a rolling-horizon approach is used.

While the above papers assume that the plan can only be changed once at the beginning of every period (as we do in our paper), some authors have considered the case where the plan may be changed as soon as a new order arrives, re-directing the vehicle to follow the updated plan. Ninikas et al. (2014) allowed diversion from the current plan for new orders requesting urgent service, while due dates of regular orders still need to be obeyed. Their objective is minimizing overall transportation cost and maximizing the number of urgent customers covered over the horizon. Dayarian et al. (2015) and Dayarian et al. (2016) analyzed the case where the customers have stochastic demands. The initial plan is constructed using the probabilistic information and during the day, if the realized demand is higher than expected, vehicles are diverted to the depot to unload. Angelelli et al. (2009) studied different strategies to solve a 2-period routing problem. At the beginning of each period, they route a fleet of uncapacitated vehicles using the known customers. Then, while the vehicles are travelling, new orders arrive and the routes are replanned. The new plan may postpone some customers originally scheduled today to the next day. The objective is to service all requests with minimum average cost. Ulmer et al. (2018) studied the same problem by increasing the number of periods in the planning horizon. However, their objective is to maximize the number of same-day services.

In some studies, knowledge on future demands is used in route planning. Subramanyam et al. (2017) modeled the problem as a robust multi-stage optimization problem that hedges against customer order uncertainty, whose support functions are known from historical orders. The objective of the problem is minimizing the transportation cost over the planning horizon. Billing et al. (2018)
also used historical data to obtain probabilities that customers place an order at a period and used these to make decisions about whether existing orders should be served today or be postponed to a later period. Finally, Albareda-Sambola et al. (2014) modelled the dynamic VRP as a prize-collecting VRP by assigning prize measures to known customers using the information on future orders. They aim at routing the known customers such that the plan is also convenient for likely future requests. Ferrer and Alba (2019) considered a waste collection problem with prediction of the fill levels of the containers. The route planning is done based on these predictions.

Few papers consider demand management to decrease transportation costs. Estrada-Moreno et al. (2019) analyzed effects of price discounts offered to customers to relax their preferred delivery day by one day, either to the day before or after the preferred day. The aim is to minimize total distribution cost and discounts paid over the planning horizon. Yildiz and Savelsbergh (2020) solved a simplified setting, where all the nodes are located on a line with the depot on one end. They considered discounts in exchange for delivery day flexibility, however assumed that they are accepted by the customers with a certain probability only. The customer set is static in both studies. Recently, food delivery problems have become important, especially if many people are in quarantine. Certain customers may be offered price discounts for some delivery slots in order to have more efficient plans (Yang and Strauss, 2017; Yang et al., 2016).

Our problem is conceptually also similar to the Stochastic Inventory Routing or Vendor Managed Inventory Routing Problems, where the decisions are centralized at the supplier and the customer demand is stochastic. Some papers in this area (Coelho et al., 2014, Markov et al., 2018, Markov et al., 2020) assume that the supplier can precisely monitor the inventory level at customer sites, and needs to ensure that customers do not have stock-outs. The aim is to minimize both the transportation and inventory holding costs. Other papers assume that the supplier has no knowledge of the inventory levels and will only observe the inventory level when arriving at the customer (Jaillet et al., 2002, Huang and Lin, 2010, and Ketzenberg and Metters, 2020). Hence, the plans are based on expected values and recourse actions are defined if the plans do not meet the actual requirements of the customers. Our problem sits between the above two cases: the supplier cannot monitor their customer’s inventory levels, but it is possible to call (tout) a customer, offer them a service, and if the customer places an order, also learn about the amount to be collected.

Therefore, our study extends the current literature of multi-period vehicle routing problem by introducing the concept of touting, i.e., actively approaching a customer with the purpose to elicit orders earlier, and combining this demand management technique with routing decisions.

3 Problem Definition

Our work is motivated by the real-world application of a UK waste collection company. It is essentially a dynamic vehicle routing problem with capacity constraints, time constraints (daily and weekly working time limits for the drivers) and due dates. We assume that all customers are
regular customers known to the company, as the number of new customers is negligible. Customers accumulate waste over time according to a random process, and when the amount of accumulated waste reaches a certain percentage of their storage capacity, they request a collection, specifying the amount of waste to be collected. Any collection request is expected to be serviced within a certain number of days, the order’s due date. Routes are planned on a daily basis, i.e., every evening the routes are decided for the following day. The overall objective is to minimize the total distance driven per amount of waste collected.

While smart sensors installed at the client’s premises could allow an accurate monitoring of a customer’s inventory level, in practice this is too expensive and therefore is not preferred. Instead, historical data may be used to forecast a customer’s inventory level. Customers do not have to pay for the collection service, since the company earns money from selling the recycled waste. Nevertheless, customers perceive collection as somewhat disruptive to their business and therefore prefer less frequent collections. If the driver knows the client’s premises, this reduces the time needed to collect the waste. For this reason, the company has decided to assign to each driver a designated service area. Thus, service areas for each driver can be considered independently, and in this paper we only address the problem for a single vehicle starting from and ending at a single depot.

3.1 Touting for the vehicle routing problem

Our paper focuses primarily on the touting aspect. Before finalising the next day’s tour, the company can attempt to elicit additional orders via touting, i.e., actively approaching a customer and suggesting collection. The customer will accept this offer with a probability depending on the current fill level of the storage tank. If the touted customer accepts the offer, it will be serviced on the next day’s tour.

Let us emphasize again that touting does not generate additional demand, it just nudges a customer to order earlier, and as a consequence, the amount to be collected is less than if the company had just waited for the customer to place the order. While this implies more frequent visits to a customer picking up smaller amounts, and thus higher cost, it also allows to influence the timing of the order, thus opening the opportunity to save travel distance by visiting neighboring customers on the same day, or moving demand from high-demand periods to low-demand periods.

Figure 1 illustrates the sequence of decisions and the random events in a planning day. The chart on the right shows the flow of events between 5pm and 6pm.
Let us illustrate the basic idea behind touting with a simple example: Assume the demand of each order is one, the capacity of the vehicle is four, and each customer must be served within
two days. Figure 2 shows the locations of 8 customers, four of which (unfilled circle) are known customers on day 1 and the others will place their order on day 2. If touting is not used, the planner would route the corresponding known customers on each day, and obtain a result as depicted in Figure 2a. With touting, the planner may predict some customers who are likely to order soon, and tout for example customer 7, as its location is close to customers that would be visited tomorrow. If the customer accepts, it can then be serviced on the next day, and the resulting tours would look like in Figure 2b, with a significantly shorter overall distance.

3.2 Markov Decision Process Representation

We provide a dynamic programming formulation of the problem in order to help clarify the structure of the decision problem (even though one cannot directly solve it in this way). To that end, let us define the state, decisions, rewards, exogeneous information and the state transitions of the Markov decision process that underpins our problem. With this terminology, we then can formally state its dynamic programming formulation.

3.2.1 Stages, States and Decisions

We consider a finite planning horizon with a discrete time grid of decision epochs \( k \in \{1, \ldots, K\} \) (stages) which are chosen sufficiently small such that the probability of observing more than one arrival within any given epoch is negligible. This time grid spans multiple days and we distinguish the set \( E \) of epochs at the end of each day in the planning horizon from those epochs \( k \notin E \) during the day.

This distinction is important because we make a different type of decisions during the day than at the end of the day: at \( k \notin E \), we observe whether or not a collection request comes in, and subsequently decide whether to tout a customer (and if so, whom – expressed by a decision variable \( x^t \)), and then observe whether the touted customer responds positively to the offer. At \( k \in E \), we observe no further new information but schedule customers to be served on the next day based on all requests (including touted ones) received to date, expressed by a decision vector \( x^r \).

At stage \( k \), the system is in a state \( S_k \), which has the information of all customers in the population, \( C \), with a triplet \( S_k = (q, d, a) : c \in C \). The value \( q \) denotes the requested quantity to be collected from a customer, with \( q > 0 \) if there is an outstanding order, and 0 otherwise. Next, \( d \) corresponds to the deadline of the collection request if the order is outstanding, or has no meaning if \( q = 0 \). Note that this notation allows us to also handle the case that orders remain unfulfilled beyond their deadline. Finally, \( a \) represents the customer’s collection history, an array of collection dates and collection amounts, which we use to predict the fill level at each customer and subsequently decide whether a customer would be touted or not. Recall that we assume a finite and known customer population \( C \); covering them all in the state means that we do not need to explicitly carry the locations of the customers.
3.2.2 Rewards, Exogenous Information and State Transitions

Our overall objective is to minimize the expected routing cost across all days in the planning horizon. Routing costs are incurred only at the end-of-day stages $k \in E$ where we need to plan the final schedules for the next day; we denote the routing cost of serving (some of the) requests of state $S_k$ as expressed through decision $x^r$ by $f(S_k, x^r)$. Infeasible routing decisions $x^r$ result in $f(S_k, x^r) = \infty$. During the day we only collect orders and make touting decisions, but incur no immediate costs.

Exogenous information arrives at the beginning of each decision epoch in the form of a stochastic arrival process that indicates whether a new customer request $S_{c_{new}} = (q, d)$ has arrived from customer $c$ with a requested specific quantity $q$ and delivery deadline $d$. Subsequently, we decide at stage $k \notin E$ on the touting and will then observe further exogenous information in the form of whether the touted customer will accept the offer, as well as what quantity would be available. We assume that a touted request must always be scheduled for the next day. Therefore, for the touted customers who accepted collection, $d$ is set to the next day.

The state transition during the day ($k \notin E$) is written as $S_{k+1} = S_k \cup S_{c_{new}} \cup S^{t}$: this shall mean that we overwrite the state information on customer $c$ with $S_{c_{new}}$ for any newly arrived request, and likewise any touted customers. At the end of the day ($k \in E$), we schedule to serve certain customer requests $S(x^r)$ for the next day, which then are removed from the pool of orders to be served by setting the corresponding indicator $q = 0$ and adding the collection information to the corresponding collection history $a$. We use the shorthand notation $S_{k+1} = S_k \setminus S(x^r)$ to represent this transition.

3.2.3 Dynamic Programming Formulation

With this notation, we now can express the problem as a dynamic program. Let $V_k(S_k)$ be the value function at stage $k$ and state $S_k$; more specifically, it is the minimal expected cost from stage $k$ until the end of the time horizon $K$ and is given by:

$$V_k(S_k) = \begin{cases} 
\mathbb{E}_{S_{c_{new}}} \left[ \min_{x^t} \mathbb{E}_{S^{t}} V_{k+1}(S_k \cup S_{c_{new}} \cup S^{t}) \right] & \forall k \notin E, k < K + 1, \\
\min_{x^r} f(S_k, x^r) + V_{k+1}(S_k \setminus S(x^r)) & \forall k \in E. 
\end{cases}$$

The boundary condition is given by $V_{K+1}(S_k) = 0$ for all states $S_k$ (since we simply assume that there are no further orders coming in on the final day in the planning horizon).

Clearly, this dynamic program is intractable due to its large state space and the fact that it involves vehicle routing problems in each stage $k \in E$. Therefore, we present in the following sections a heuristic approach of tackling this problem.
4 A rolling horizon route planning heuristic

Our paper focuses on integration of demand management with route planning via touting. The actual route planning algorithm used is secondary, but necessary to evaluate our strategies empirically. In this section we will therefore briefly describe our routing algorithm.

Given the dynamic nature of the problem, planning is done on a rolling horizon. That is, at the end of each day, we solve a multi-period VRP with all the order data available. On the next day, we execute the plan for this day, remove all serviced customers from the set of orders, and add any new orders that arrived during this day. Then we solve the next multi-period VRP with this new order data and the cycle repeats.

To solve the VRP of each day, we chose to use large neighborhood search (LNS). This was motivated by the fact that VRP is NP-hard and thus an exact method is computationally expensive, but also because for a dynamic problem, solving each sub-problem of the rolling horizon procedure exactly doesn’t guarantee overall optimality anyway, as we will later demonstrate in Section 6.2.

LNS starts by constructing an initial solution via cheapest insertion. The orders are sorted according to their due dates and the ones having the earliest due dates are considered first. Out of those, the customer that can be inserted with the least additional driving distance is inserted, and the procedure is repeated until all orders have been scheduled. This procedure ensures all capacity and time constraints are obeyed and creates new routes as needed. An overview of the algorithm is given in Algorithm 1, where $d_{ij}$ stands for the driving distance between nodes $i$ and $j$.

**Algorithm 1 Initial Solution Construction**

Input: List of Unscheduled Customers

1: while Unscheduled Customers List not empty do
2: Put the customers having the earliest due dates into the Priority List
3: while Priority List not empty do
4: for all customers in Priority List do
5: for all possible insertion positions in the fleet do
6: if insertion of customer $i$ between nodes $j$ and $k$ is feasible then
7: Calculate the insertion cost as:
8: $(-d_{jk} + d_{ji} + d_{ik})$
9: end if
10: end for
11: end for
12: Determine the customer with the least insertion cost, i.e., customer $i$
13: Perform the cheapest insertion for customer $i$
14: Delete customer $i$ from Priority List and Unscheduled Customers List
15: end while
16: end while

The improvement step follows the removal and repair heuristics introduced in Ropke and Pisinger (2006). In each improvement step, some customers are removed from the current solu-
tion either randomly, or based on worst marginal distance, proximity to depot, time, or demand. They are then re-inserted into the partial solution using greedy and regret insertion heuristics, see Algorithm 2 for an outline, where \( x \) and \( f(x) \) stand for a solution and its total traveled distance, respectively.

**Algorithm 2 An LNS Framework to Solve Multi Period VRP**

1: Construct an initial solution, \( x_{\text{init}} \)
2: \( x_{\text{best}}, x_{\text{previous}} \leftarrow x_{\text{init}} \)
3: \textbf{while} \( \text{iter} \leq \text{maximum number of iterations} \) \textbf{do}
4: \hspace{1em} Select a removal rule randomly
5: \hspace{1em} Determine \( q\% \) of the scheduled customers according to the removal rule
6: \hspace{1em} Remove the determined customers from the current solution
7: \hspace{1em} Select an insertion rule randomly
8: \hspace{1em} Insert the removed customers into the solution according to the insertion rule, obtain a new solution, \( x_{\text{current}} \)
9: \hspace{1em} \textbf{if} \( f(x_{\text{current}}) < f(x_{\text{previous}}) \) \textbf{then}
10: \hspace{2em} \( x_{\text{previous}} \leftarrow x_{\text{current}} \)
11: \hspace{1em} \textbf{end if}
12: \hspace{1em} \textbf{if} \( f(x_{\text{current}}) < f(x_{\text{best}}) \) \textbf{then}
13: \hspace{2em} \( x_{\text{best}} \leftarrow x_{\text{current}} \)
14: \hspace{1em} \textbf{end if}
15: \textbf{end while}

5 Integrating demand management and route planning

Let us assume that an initial plan based on the orders received so far is given, and that we have a given route to execute for the next day. We then attempt to make it more efficient by exploiting information (from a forecasting model) about a set of potential customers whom we could contact to elicit their business.

More specifically, our aim is to identify customers who are likely to request service in the near future and to tout the ones that would make the overall plan better. To determine a customer to tout, we may consider different criteria, such as required detour from the next day’s route, distance from the depot, or whether it is possible to cover that potential customer in the near future. Figure 3 illustrates these criteria using a solution with four scheduled customers (circles) and a depot (rectangle) as well as several potential customers. In Figure 3a, touting customer 5 seems more advantageous than touting customer 6 in terms of the required detour to insert the customer. Figure 3b shows an example where it may be more beneficial to tout a customer far from the depot if the vehicle is travelling in its neighborhood, than a customer close to the depot, as the latter may be easily included in another tour. Finally, other potential customers in the neighborhood of a potential customer may also be taken into account to decide which customer to tout. If there are many potential customers in the neighboring area, then another vehicle may be
sent to cover that area on another day. In Figure 3c, Customer 5 has many neighbors, whereas Customer 6 has only one, which makes Customer 6 more relevant to tout.

![Diagram of customer routes and neighborhoods](image)

- a. Effect of detour amount
- b. Effect of distance from the depot
- c. Effect of demand in neighborhood

Figure 3: Factors in selecting the most relevant customer to tout

5.1 Relevance measure

We define a relevance measure for each potential customer that takes into account all three criteria mentioned above. Let $N$ be the set of potential customers that may be added to the route, and $V_t$ be the set of customers already planned for the next day. We index the depot as 0. For a potential customer $i \in N$, the detour amount is calculated by determining the cheapest insertion cost $c_i$, i.e., for each pair of consecutive nodes $(j, k)$ in the next day’s route with distance $d_{jk}$, the insertion cost is calculated as $c_i = \arg\min_{j, k \in V_t \cup \{0\}} (d_{ji} + d_{ik} - d_{jk})$. Let $I_i$ be the cost of exclusively covering customer $i$ by a single vehicle, i.e., $I_i = d_{0i} + d_{i0}$. Finally, we define a demand
measure $p_i$ for customer $i$ based on its neighbors at a distance of less than $\rho$, formally defined as $N_\rho(i) = \{j \in N | d_{ij} \leq \rho\}$. Let $Q_i = \sum_{j \in N_\rho(i) \cup \{i\}} q_j$ be the total demand of $i$ and its neighbors, where $q_i$ stands for the demand of customer $i$.

We define $p_i = Q_i/C$, $i \in N$, with $C$ the capacity of the vehicle, as a measure to assess whether it is worthwhile to drive to an area where customer $i$ is located. If $p_i$ is high, it means that there is high demand in the area and the vehicle would go there anyway to service these customers. Then customer $i$ can be covered along with other customers nearby by another vehicle in the near future, hence it does not necessarily need to be touted right away. However, if $p_i$ is low, meaning that customer $i$ is alone or has few demand around, then it is beneficial to include it in the next day’s route.

The relevance measure of a potential customer $i$ is then calculated as $r_i = \alpha c_i - \beta I_i + \gamma p_i$ where $\alpha$, $\beta$ and $\gamma$ are the weights assigned to each criterion. The lower the relevance value is, the more beneficial to tout that customer since we want to include those customers with a) small detour amount from the next day’s tour, b) long distance from the depot, and c) little demand nearby.

### 5.2 Waiting vs. touting

Obviously touting only makes sense if the route planned for the next day still has sufficient capacity to incorporate additional customers. On the other hand, if there is little demand and there are no customers who have to be serviced on the next day because of their due date, then it may be more beneficial to simply wait for new orders to arrive and not send the vehicle out at all. Consequently, we only consider touting when the utilization of next day’s vehicle is under a threshold, $\Delta\%$ of vehicle capacity, the vehicle must be dispatched because at least one customer must be served the next day, and serving all these urgent customers still allows for some slack in time to potentially serve others.

While we apply this waiting rule in combination with all touting heuristics, waiting is of course also possible if touting is not used. This strategy is then called *wait-if-possible*, where if the vehicle utilization of the next day’s route is under $\Delta\%$ of its capacity and there are no customers due next day, then we check whether it is possible to shift the customers in the initial plan to the following day without deteriorating the objective function. If this is possible, the vehicle is not dispatched, hoping that next day we receive orders from conveniently located customers such that we can come up with a more efficient plan. The scheduled jobs remain in the set of open orders. De Bruecker et al. (2018) also stated that instead of having multiple half days work, it may be more advantageous to have a complete day off. For example, the drivers might use these off days for training purposes.
5.3 Customers considered for touting

Touting customers when they have only accumulated a very small amount of waste will not only annoy the customer, but also lead to very frequent collections of tiny amounts. On the other hand, only touting customers which are predicted to order soon anyway may severely restrict the choice of customers to tout. In the following, we restrict touting to customers whose predicted fill level is at least 50% of their tank capacity. Section 6.4.2 will examine the algorithm’s sensitivity to this choice.

5.4 Touting heuristics

We propose the following heuristics to tout customers:

- *tout using distance per litre*: This heuristic touts customers in order of the benefit its inclusion would have on the total distance per litre of waste collected, given that the customer is inserted at the position requiring the smallest additional detour.

- *tout using relevance measures*: This approach first touts the customer which has the highest relevance measure.

It is possible to insert more than one additional customer via touting. We thus also test whether it is beneficial to re-optimize the VRP after the inclusion of every customer, and before the next touting is attempted. More specifically, we distinguish between

- *tout without re-optimization*: Here, we only add customers to the next day’s route without re-optimizing all tours.

- *tout & re-optimize*: This strategy allows re-optimizing the routing decisions after the addition of the touted customer in the next day’s route.

In all cases, touting continues until either there are no further potential customers or it is not feasible to add another customer to the next day’s route. Furthermore, a customer is only touted as long as its insertion does not violate time and capacity feasibility of the solution and if and only if the forecasted solution, obtained after the touting strategy is applied, is better than the current solution, i.e., it has smaller total distance per litre of collected waste value.

6 Experimental study

In this section, we first introduce the instances we use in the experiments. Then, we show that for a dynamic multi-period VRP, solving each period’s subproblem with an exact method is no
better than the LNS heuristic we employ in this paper. Finally, we perform simulation studies to investigate the proposed touting strategies. The heuristics as well as the simulations were implemented in Java and all computations were performed on a PC equipped with an Intel Core i7 2.60 GHz processor and 32 GB of RAM.

6.1 Problem Instances

In the experiments, we use real world data from a waste collection company operating in the UK. The company has several depot locations across the country and each depot has dedicated drivers who cover different geographical areas. Customers’ waste is accumulated in tanks at a random rate which depends on the size of their business. When the accumulated waste is close to the maximal tank capacity, the customer requests a collection. They also state the lead time they require, typically seven working days beginning from the day of request.

In the experiments, we use one of the depots of the company and the historical data for two drivers who operate for that depot. The dataset covers three months of waste collections of these two drivers. Each collection order includes the customer’s name, postcode, date when the waste collection order has been placed, and the amount of waste requested to be collected. Customer locations are shown in Figure 4 where the depot is represented by a red house. Total numbers of collections in the instances are 273 and 260, whereas the numbers of unique customers in the network are 142 and 125 for drivers 1 and 2, respectively. The dataset, which includes these historical orders as well as the problem parameters, such as vehicle capacity and time limits is available at Mendeley data ([dataset] Keskin et al., 2020).

![Figure 4: Locations of the customers and the depot for two drivers](image)

The service time at a customer location is substantial and cannot be ignored. It consists of a
constant setup time and a variable collection time. Setup time includes preparing and dismantling the collection tools before and after the collection, respectively, whereas the collection time is the time spent on actually removing the waste from the tank and is proportional to the amount of waste collected. Since the company does not have records of the times the drivers spend on customer sites, we estimate these service times using linear regression based on data from different drivers’ operations. We collected 430 data points and using these values, we found the service time can be approximated by $t_S = 12.06 + 0.01565x$, where $x$ is the amount of waste collected in litres and $t_S$ is the service time in minutes.

We use this historical data of the company directly in the experiments presented in Section 6.2, whereas in Section 6.3, we use a simulated data, which is generated using the properties of this data.

### 6.2 Comparing exact and heuristic VRP solvers

Since the requests arrive continuously over time and the problem is solved with a rolling time horizon, an optimal plan for a particular planning horizon may become sub-optimal after arrival of new orders, i.e., solving each period’s VRP to optimality does not guarantee that the overall solution is optimal. For this reason, and because of the computational time required by exact solvers, we use the LNS described in Section 4 in our experiments. However, in order to judge the quality of this heuristic, we compare it with an exact solver. Note that each method is applied to solve the problem for a given single stage on a rolling horizon, rather than solving the whole dynamic problem for the entire planning horizon. The mathematical model can be found in the Appendix, and has been solved using CPLEX. In LNS, maximum number of iterations is set to 4,000, and the removal rules select half of the customers to be removed from the current solution. Note that while the heuristic method is initialized in each period with the remaining routes from the previous solution, CPLEX solves the new problem from scratch.

Table 1 presents the results of both approaches tested on two real-world order datasets. As the heuristic has a randomized component, results are averaged over 30 runs, while the mathematical model is deterministic and solved only once. Capacity utilization is calculated by dividing the amount of waste collected by the vehicle capacity. Lead time shows the average number of days between the day a customer requests a collection and the day it is served. The computational time is the total time to solve the problems over 3-month horizon. Interestingly for these problem instances, the approach using the LNS heuristic to solve the every-day routing problem is able to find solutions with even smaller total distance than if the exact method is used to solve each day’s VRP. While this may seem surprising, this is due to the loss of overall optimality of the exact method when applied on a rolling horizon. In fact, optimal solutions are often more brittle to changes than heuristically generated ones. These findings have been previously pointed out also in other studies (Brinkmann et al., 2020, Powell et al., 2000). We take these results as confirmation that the chosen LNS heuristic is fit for purpose.
Table 1: Comparison of results of solution approaches using exact and heuristic algorithms

<table>
<thead>
<tr>
<th>Subproblems are solved</th>
<th>Driver 1</th>
<th>Driver 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>exactly</td>
<td>heuristically</td>
</tr>
<tr>
<td>Total distance (km)</td>
<td>13,327</td>
<td>12,943</td>
</tr>
<tr>
<td>Average lead time (days)</td>
<td>2.52</td>
<td>2.52</td>
</tr>
<tr>
<td>Average capacity utilization</td>
<td>62.24%</td>
<td>62.78%</td>
</tr>
<tr>
<td>Number of routes</td>
<td>55.0</td>
<td>54.5</td>
</tr>
<tr>
<td>Average number of customers served per route</td>
<td>4.96</td>
<td>5.01</td>
</tr>
<tr>
<td>Computational time (sec)</td>
<td>13,205</td>
<td>28.92</td>
</tr>
</tbody>
</table>

6.3 A simulator for demand management

In the previous subsection we used the real-world order data. However, touting changes the time of ordering due to some touted customers ordering sooner than expected, and thus, in order to test and compare different touting strategies, we needed to create a simulator based on the real-world data that would allow the touting algorithm to interact with customers.

Therefore, we first create simulated data based on the real instances introduced in Section 6.1. To achieve this, we keep the customer locations the same, as visualized in Figure 4, however, rather than using a historical set of orders as in the previous subsection, we assume that customers accumulate waste over time, with the amount accumulated each day following a normal distribution with mean $\mu$ and variance $\sigma^2$. The parameters of the waste accumulation distributions are derived from real data on the order amounts and the times between consecutive orders using maximum likelihood estimation, and are assumed fixed throughout the simulation. These distributions are The storage capacity of each customer is set to the maximum amount collected from the corresponding customer. For each customer, the initial amount of waste at the start of the simulation is chosen uniformly at random between 0% and 95% of its capacity. Then, on each planning day, a random value, which represents the waste generated by that customer on that day, is generated according to the customer’s demand distribution and its accumulated waste is increased accordingly.

The customers request service when their accumulated waste reaches 90% of their storage capacity. When touted before they would usually order, they will agree to a collection with probability $P_{accept} = \frac{f}{0.9G}$, where $f$ is the amount of waste accumulated and $G$ is the customer’s storage capacity. In other words, their probability of accepting a collection increases linearly with the amount of waste accumulated. The neighborhood threshold used in relevance measure calculation, $\rho$, is set to 25 kilometres.

In this section, we have set a simulation environment in order to analyse both the vehicle dispatching rules, and the benefits of touting. We used instances which are created using demand distributions of the customers based on three months of collections by two drivers as presented above. The dataset including the distribution parameters of each customer’s waste accumulation, tank storage capacities as well as the distance and travel time matrices is available at Mendeley.
data ([dataset] Keskin et al., 2020). The simulation horizon has been set to 240 days, corresponding to one business year.

6.4 Analysis of demand management strategies

Here, we present the results for the touting strategies presented in Section 5.4. We will start with an analysis of the weights in the calculation of our relevance measure. We usually assume that only customers with a predicted amount of accumulated waste that is greater than half of their storage capacity are considered for touting, although we will vary this threshold in Section 6.4.2. Finally, we demonstrate the advantage of touting by comparing it with approaches that don’t use touting. The key objective to minimize is the distance per litre collected, as the total volume collected depends on the touting strategy and thus distance alone is not a suitable objective.

6.4.1 Relevance measure parameters

The relevance measure proposed in Section 5.1 is a linear combination of three criteria. To better understand the importance of the different criteria, we run an experiment using the tout using relevance measures & re-optimize approach where the relevance is calculated using only one of the criteria, or equal weighting of the different criteria. The results presented in Tables 2 and 3 show that using an equal weighting in the calculation gives better results for both drivers.

<p>| Table 2: Results of different relevance measure parameter values for Driver 1 |</p>
<table>
<thead>
<tr>
<th>Parameter Values</th>
<th>$\alpha, \beta, \gamma = 1/3$</th>
<th>$\alpha = 1$</th>
<th>$\beta = 1$</th>
<th>$\gamma = 1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance travelled</td>
<td>34,081</td>
<td>34,222</td>
<td>34,561</td>
<td>34,626</td>
</tr>
<tr>
<td>Capacity utilization</td>
<td>92.7%</td>
<td>92.3%</td>
<td>92.5%</td>
<td>91.5%</td>
</tr>
<tr>
<td>Number of routes</td>
<td>149</td>
<td>149</td>
<td>149</td>
<td>150</td>
</tr>
<tr>
<td>Volume collected</td>
<td>1,654,133</td>
<td>1,652,366</td>
<td>1,655,031</td>
<td>1,651,385</td>
</tr>
<tr>
<td>Number of customers served</td>
<td>845</td>
<td>849</td>
<td>842</td>
<td>859</td>
</tr>
<tr>
<td>Average lead time (days)</td>
<td>3.81</td>
<td>3.80</td>
<td>3.84</td>
<td>3.76</td>
</tr>
<tr>
<td>Distance per litre collected</td>
<td>0.02060</td>
<td>0.02071</td>
<td>0.02088</td>
<td>0.02097</td>
</tr>
</tbody>
</table>

<p>| Table 3: Results of different relevance measure parameter values for Driver 2 |</p>
<table>
<thead>
<tr>
<th>Parameter Values</th>
<th>$\alpha, \beta, \gamma = 1/3$</th>
<th>$\alpha = 1$</th>
<th>$\beta = 1$</th>
<th>$\gamma = 1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance travelled</td>
<td>31,842</td>
<td>31,990</td>
<td>31,975</td>
<td>32,331</td>
</tr>
<tr>
<td>Capacity utilization</td>
<td>93.6%</td>
<td>93.3%</td>
<td>93.6%</td>
<td>92.9%</td>
</tr>
<tr>
<td>Number of routes</td>
<td>207</td>
<td>207</td>
<td>207</td>
<td>208</td>
</tr>
<tr>
<td>Volume collected</td>
<td>2,323,357</td>
<td>2,322,271</td>
<td>2,323,227</td>
<td>2,318,948</td>
</tr>
<tr>
<td>Number of customers served</td>
<td>924</td>
<td>926</td>
<td>923</td>
<td>935</td>
</tr>
<tr>
<td>Average lead time (days)</td>
<td>4.21</td>
<td>4.24</td>
<td>4.22</td>
<td>4.19</td>
</tr>
<tr>
<td>Distance per litre collected</td>
<td>0.01371</td>
<td>0.01378</td>
<td>0.01376</td>
<td>0.01394</td>
</tr>
</tbody>
</table>
A one-sided paired t-test shows that the equal weighting of the three criteria is significantly better at 0.05 level than any of the individual criteria, for both drivers (Table 4).

Table 4: Paired one-sided t-test results that compare the performances of different parameter values and different threshold values

<table>
<thead>
<tr>
<th>Setting</th>
<th>Driver 1</th>
<th>Driver 2</th>
<th>Accumulation thresholds</th>
<th>Driver 1</th>
<th>Driver 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha = 1$</td>
<td>0.001</td>
<td>0.0020</td>
<td>25% - 50%</td>
<td>0.35</td>
<td>2.71e-05</td>
</tr>
<tr>
<td>$\beta = 1$</td>
<td>2.93e-14</td>
<td>0.0070</td>
<td>75% - 50%</td>
<td>1.54e-07</td>
<td>3.83e-15</td>
</tr>
<tr>
<td>$\gamma = 1$</td>
<td>5.33e-18</td>
<td>5.15e-17</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 5: Results of different accumulation threshold values

<table>
<thead>
<tr>
<th>Accumulation Threshold</th>
<th>Driver 1</th>
<th>Driver 2</th>
<th>Driver 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>25%</td>
<td>50%</td>
<td>75%</td>
</tr>
<tr>
<td>Distance travelled (km)</td>
<td>34,104</td>
<td>34,081</td>
<td>34,346</td>
</tr>
<tr>
<td>Capacity utilization</td>
<td>92.5%</td>
<td>92.7%</td>
<td>92.0%</td>
</tr>
<tr>
<td>Number of routes</td>
<td>149</td>
<td>149</td>
<td>150</td>
</tr>
<tr>
<td>Volume collected</td>
<td>1,656,267</td>
<td>1,654,133</td>
<td>1,650,268</td>
</tr>
<tr>
<td># Possible Toutings</td>
<td>74</td>
<td>75</td>
<td>76</td>
</tr>
<tr>
<td># Successful Toutings</td>
<td>56</td>
<td>53</td>
<td>46</td>
</tr>
<tr>
<td># Touted Customers</td>
<td>126</td>
<td>107</td>
<td>83</td>
</tr>
<tr>
<td>Number of customers served</td>
<td>868</td>
<td>845</td>
<td>825</td>
</tr>
<tr>
<td>Average lead time (days)</td>
<td>3.77</td>
<td>3.81</td>
<td>3.88</td>
</tr>
<tr>
<td>Distance per litre collected</td>
<td>0.02059</td>
<td>0.02060</td>
<td>0.02081</td>
</tr>
<tr>
<td>Computational time (sec)</td>
<td>274.7</td>
<td>227.6</td>
<td>195.6</td>
</tr>
</tbody>
</table>

6.4.2 Accumulation threshold

We use a minimum accumulation threshold to determine which customers may be considered for touting. The default setting in this paper is 50%. We increase it to 75% and decrease it to 25%, then we compare the performances of all values for tout using relevance measures & re-optimize strategy. In Table 5, the number of possible and successful toutings shows the number of days when touting potential customers has been possible, i.e., there is spare capacity of the vehicle to be dispatched, and out of those days, when at least one customer could be added, respectively. Addition of potential customers is not always possible either due to a lack of customers that can feasibly be added or customers having rejected the offers. The number of touted customers shows the total number of potential customers added to the plan in the days when the touting is successful. We also report the average lead time, i.e., the number of days between the day a customer requests a collection and the day it has been serviced. According to the results presented in Table 5, touting customers earlier, i.e., when their accumulated level is 25% of their capacities, results in more
efficient plans over the planning horizon in terms of both total distance travelled per litre of waste collected and the number of routes used for both drivers. If the vehicles are hired from a third-party logistics company and their cost is based on the number of days they go out, then having fewer routes means a lower cost. While the accumulation threshold decreases, we observe that both the number of successful toutings and the number of touted customers increase because the set of potential customers that are considered in touting also gets larger. Therefore, there are more customers to tout and it is easier to find more appropriate customers from a larger set. One could argue that visiting customers more frequently could decrease the efficiency, but only customers who do not deteriorate the distance per litre criterion are touted. On the other hand, in the 75% setting, since the set of potential customers is smaller, fewer customers can be approached. This decreases the advantage of touting by not being able to reach the appropriate customers, which results in higher distance traveled per collected amount. We again perform one-sided paired $t$-tests in order to validate the results. The test statistics for the comparisons between 25% and 50% as well as between 50% and 75% are summarized in Table 4. As can be seen, the difference between 50% and 75% is significant for both drivers, while the difference between 25% and 50% is significant only for one of the drivers. Because customers generally prefer to have fewer collections, we conclude that 50% is a suitable threshold.

### 6.4.3 Benefit of touting strategies

Based on the above analysis, we now test different touting strategies for both drivers using the accumulation threshold of 50% and equal weighting for the relevance parameters ($\alpha = \beta = \gamma = 1/3$).

Tables 6 and 7 summarize the average results of 100 simulations. The results in the no-touting column are obtained without applying any strategies, i.e., they belong to the solutions of the rolling horizon route planning heuristic only. Column 3 summarizes the results obtained by the wait-if-possible strategy without touting. The results of tout using distance per litre, abbreviated by dist./lt., and tout using relevance measures, abbreviated by relevance, are grouped according to whether they are applied along with re-optimization or not. tout without re-optimization strategies are given in the fourth and fifth columns, whereas the last two columns summarize the results of tout & re-optimize strategies.

The results reveal that the default rolling horizon planning that solves a VRP each day and sends out a vehicle if there is an open customer order is a rather inefficient strategy. The simple wait-if-possible strategy that delays sending out the truck until there is either sufficient demand or it has to be sent out because of an imminent due date is dramatically more efficient (29.3% for Driver 1, 11.8% for Driver 2). This makes sense because occasional waiting means the pool of waiting orders is larger, allowing to construct more efficient tours. On top of this, touting is able to further improve efficiency by roughly 4%. The differences between the touting strategies are relatively small, except a generally poor performance of the distance per litre priority rule together with re-optimization. As re-optimization is computationally rather expensive, it seems
not worthwhile. Without re-optimization, the distance per litre and relevance heuristics perform comparable for Driver 1, while the relevance heuristic is substantially better for Driver 2. We thus conclude that overall, the relevance measures without re-optimization is the most sensible choice. The results of the statistical tests are reported in Table 8.

### Table 6: Results of different strategies for Driver 1

<table>
<thead>
<tr>
<th>Strategies</th>
<th>wait-if-possible</th>
<th>No Re-optimization</th>
<th>Re-optimization</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Dist./Lt.</td>
<td>Relevance</td>
<td>Dist./Lt.</td>
</tr>
<tr>
<td>Distance travelled</td>
<td>50,214</td>
<td>34,061</td>
<td>34,082</td>
</tr>
<tr>
<td>Capacity utilization</td>
<td>58.9%</td>
<td>92.4%</td>
<td>92.5%</td>
</tr>
<tr>
<td>Number of routes</td>
<td>233</td>
<td>149</td>
<td>149</td>
</tr>
<tr>
<td>Volume collected</td>
<td>1,647,289</td>
<td>1,653,471</td>
<td>1,651,478</td>
</tr>
<tr>
<td>Number of possible toutings</td>
<td>-</td>
<td>76</td>
<td>76</td>
</tr>
<tr>
<td>Number of successful toutings</td>
<td>-</td>
<td>55</td>
<td>53</td>
</tr>
<tr>
<td>Number of touted customers</td>
<td>-</td>
<td>122</td>
<td>113</td>
</tr>
<tr>
<td>Number of customers served</td>
<td>814</td>
<td>850</td>
<td>847</td>
</tr>
<tr>
<td>Average lead time (days)</td>
<td>2.40</td>
<td>3.81</td>
<td>3.82</td>
</tr>
<tr>
<td>Imp. wrt to wait-if-possible</td>
<td>-41.5%</td>
<td>-4.4%</td>
<td>4.3%</td>
</tr>
<tr>
<td>Computational time (sec)</td>
<td>105.9</td>
<td>119.5</td>
<td>130.0</td>
</tr>
</tbody>
</table>

### Table 7: Results of different strategies for Driver 2

<table>
<thead>
<tr>
<th>Strategies</th>
<th>wait-if-possible</th>
<th>No Re-optimization</th>
<th>Re-optimization</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Dist./Lt.</td>
<td>Relevance</td>
<td>Dist./Lt.</td>
</tr>
<tr>
<td>Distance travelled</td>
<td>37,762</td>
<td>32,173</td>
<td>31,840</td>
</tr>
<tr>
<td>Capacity utilization</td>
<td>80.8%</td>
<td>93.8%</td>
<td>93.9%</td>
</tr>
<tr>
<td>Number of routes</td>
<td>240</td>
<td>207</td>
<td>207</td>
</tr>
<tr>
<td>Volume collected</td>
<td>2,326,717</td>
<td>2,333,967</td>
<td>2,321,127</td>
</tr>
<tr>
<td>Number of possible toutings</td>
<td>-</td>
<td>124</td>
<td>124</td>
</tr>
<tr>
<td>Number of successful toutings</td>
<td>-</td>
<td>88</td>
<td>89</td>
</tr>
<tr>
<td>Number of touted customers</td>
<td>-</td>
<td>162</td>
<td>165</td>
</tr>
<tr>
<td>Number of customers served</td>
<td>879</td>
<td>931</td>
<td>925</td>
</tr>
<tr>
<td>Average lead time (days)</td>
<td>3.58</td>
<td>4.22</td>
<td>4.23</td>
</tr>
<tr>
<td>Imp. wrt to wait-if-possible</td>
<td>-13.4%</td>
<td>3.7%</td>
<td>4.7%</td>
</tr>
<tr>
<td>Computational time (sec)</td>
<td>106.3</td>
<td>133.4</td>
<td>153.3</td>
</tr>
</tbody>
</table>

Further observations complement the analysis. The number of tours is the greatest for no-touting, since the truck is always sent out if there is an open customer order. wait-if-possible follows no-touting and the touting strategies have very close numbers for both drivers. Average lead time is the shortest in no-touting since all customers are serviced as soon as possible, while the touting strategies provide solutions with longer average lead times, due to the increased number of customers served per day. On the other hand, wait-if-possible has longer average lead time compared
to the touting strategies. This is the effect of touted customers, which are served one day after they are approached. When the routes are re-optimized after the addition of the touted customers, the existing customers may be redistributed to other routes such that total distance is lower compared to the initial solution. Hence, a better solution is obtained for this set of customers. However, as new customers arrive on subsequent days, the previously shifted customers may prevent obtaining a good solution. It may be even harder to tout more customers. This is evident from the total number of touted customers, being higher in without re-optimization strategies.

In addition, we again validate by performing one-sided paired $t$-tests that the differences are statistically significant. Here, the alternative hypothesis assumes that one strategy is better than another. We make a cross comparison for each pair of strategies within the same group, i.e., when touting is not performed, no-touting and wait-if-possible are compared; when touting is performed, using distance per litre or relevance measure is compared; and finally, touting with and without re-optimization results are also compared. The test statistics for both drivers’ results are summarized in Table 8. In order to simplify the presentation, we assign numbers 1, 2, 3, 4, 5 and 6 for strategies no-touting, wait-if-possible, tout without re-optimization using distance/litre, tout without re-optimization using relevance measures, tout & re-optimize using distance/litre and tout & re-optimize using relevance measures, respectively. Strategy pair column shows the strategies compared each other, i.e., (1,2) stands for the comparison between no-touting and wait-if-possible strategies.

Table 8: Paired one-sided t-test results that compare different touting strategies (1-no-touting, 2-wait-if-possible, 3-tout using distance/litre without re-optimization, 4-tout using relevance measures without re-optimization, 5-tout using distance/litre & re-optimize and 6-tout using relevance measures & re-optimize).

<table>
<thead>
<tr>
<th>Strategy pairs</th>
<th>Driver 1 p values</th>
<th>Driver 2 p values</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1,2)</td>
<td>8.60e-120</td>
<td>4.15e-67</td>
</tr>
<tr>
<td>(3,5)</td>
<td>6.90e-44</td>
<td>1.49e-32</td>
</tr>
<tr>
<td>(4,6)</td>
<td>0.414</td>
<td>0.007</td>
</tr>
<tr>
<td>(3,4)</td>
<td>0.399</td>
<td>2.46e-08</td>
</tr>
<tr>
<td>(5,6)</td>
<td>1.44e-45</td>
<td>9.56e-37</td>
</tr>
</tbody>
</table>

As an example, Figure 5 depicts a simulation day in which the tout using relevance measures & re-optimize strategy has been performed. The depot is represented by an orange house and the customer set in the current plan involves customers 1-5. The planned route for the next day is depicted on the left with a total distance of 94 miles and 9,000 litres of waste collected. Customers 6 and 7, which are shown in the right figure, with demands of 1,200 and 1,000 litres of waste are found as potential customers. Because their addition is feasible in terms of capacity and time, they are touted and included in the current plan. As a result, the vehicle could collect 2,200 litres of additional waste with only 4 miles of detour. Distance travelled per litre collected has decreased from 0.0104 to 0.00875.
Finally, in order to demonstrate that the benefits of touting are independent of the algorithm used to solve the routing problem, we conducted another set of simulation experiments. Here, we only use the construction heuristic to obtain a solution, we do not improve it by means of LNS. The details of this heuristic are outlined in Algorithm 1. Similarly, in touting with re-optimization strategies, while re-optimizing the solution after considering a touted customer, only the initial solution is constructed, it is not further improved. Tables 9 and 10 present the results for Drivers 1 and 2, respectively. The findings are analogous to those obtained with the more sophisticated heuristic.

![Figure 5: Route plans before and after touting potential customers](image)

### Table 9: Constructive heuristic results of different strategies for Driver 1

<table>
<thead>
<tr>
<th>Strategies</th>
<th>no-touting</th>
<th>wait-if-possible</th>
<th>No Re-optimization</th>
<th>Re-optimization</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance travelled</td>
<td>53,305</td>
<td>40,186</td>
<td>39,844</td>
<td>39,733</td>
</tr>
<tr>
<td>Capacity utilization</td>
<td>58.7%</td>
<td>93.1%</td>
<td>93.9%</td>
<td>94.0%</td>
</tr>
<tr>
<td>Number of routes</td>
<td>233.7</td>
<td>147.5</td>
<td>146.3</td>
<td>146.1</td>
</tr>
<tr>
<td>Volume collected</td>
<td>1,647,289</td>
<td>1,647,289</td>
<td>1,648,149</td>
<td>1,648,236</td>
</tr>
<tr>
<td>Number of possible toutings</td>
<td>-</td>
<td>-</td>
<td>41</td>
<td>51</td>
</tr>
<tr>
<td>Number of successful toutings</td>
<td>-</td>
<td>-</td>
<td>19</td>
<td>23</td>
</tr>
<tr>
<td>Number of touted customers</td>
<td>-</td>
<td>-</td>
<td>25</td>
<td>38</td>
</tr>
<tr>
<td>Number of customers served</td>
<td>814</td>
<td>814</td>
<td>822</td>
<td>821</td>
</tr>
<tr>
<td>Average lead time (days)</td>
<td>2.15</td>
<td>4.44</td>
<td>4.36</td>
<td>4.34</td>
</tr>
<tr>
<td>Distance per litre collected</td>
<td>0.03236</td>
<td>0.02440</td>
<td>0.02418</td>
<td>0.02411</td>
</tr>
<tr>
<td>Imp. wrt to wait-if-possible</td>
<td>-32.7%</td>
<td>-</td>
<td>0.9%</td>
<td>1.2%</td>
</tr>
<tr>
<td>Imp. wrt to no-touting</td>
<td>-24.6%</td>
<td>25.3%</td>
<td>25.5%</td>
<td>26.3%</td>
</tr>
<tr>
<td>Computational time (sec)</td>
<td>0.02</td>
<td>0.45</td>
<td>0.47</td>
<td>0.52</td>
</tr>
</tbody>
</table>
Table 10: Constructive heuristic results of different strategies for Driver 2

<table>
<thead>
<tr>
<th>Strategies</th>
<th>wait-if-possible</th>
<th>No Re-optimization</th>
<th>Re-optimization</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Dist./Lt.</td>
<td>Relevance</td>
<td>Dist./Lt.</td>
</tr>
<tr>
<td>Distance travelled</td>
<td>46,427</td>
<td>41,436</td>
<td>40,662</td>
</tr>
<tr>
<td>Capacity utilization</td>
<td>81.0%</td>
<td>93.7%</td>
<td>94.9%</td>
</tr>
<tr>
<td>Number of routes</td>
<td>239.3</td>
<td>207.0</td>
<td>204.6</td>
</tr>
<tr>
<td>Volume collected</td>
<td>2,326,717</td>
<td>2,326,717</td>
<td>2,329,985</td>
</tr>
<tr>
<td>Number of possible toutings</td>
<td>-</td>
<td>79</td>
<td>81</td>
</tr>
<tr>
<td>Number of successful toutings</td>
<td>-</td>
<td>45</td>
<td>47</td>
</tr>
<tr>
<td>Number of touted customers</td>
<td>-</td>
<td>66</td>
<td>67</td>
</tr>
<tr>
<td>Number of customers served</td>
<td>879</td>
<td>879</td>
<td>901</td>
</tr>
<tr>
<td>Average lead time (days)</td>
<td>2.82</td>
<td>5.00</td>
<td>4.77</td>
</tr>
<tr>
<td>Distance per litre collected</td>
<td>0.01996</td>
<td>0.01781</td>
<td>0.01746</td>
</tr>
<tr>
<td>Imp. wrt to</td>
<td>wait-if-possible</td>
<td>2.0%</td>
<td>2.4%</td>
</tr>
<tr>
<td></td>
<td>no-touting</td>
<td>10.8%</td>
<td>12.5%</td>
</tr>
<tr>
<td>Computational time (sec)</td>
<td>0.0240</td>
<td>0.8855</td>
<td>1.0689</td>
</tr>
</tbody>
</table>

Since these results are obtained by using only the initial solution construction heuristic, it is expected that re-optimization results in better solutions. Compared to using the LNS heuristic, of course, the solution quality is on average 14.9% and 22.3% poorer in terms of total distance per litre collected. In addition, average lead times are longer in this approach, except for the \textit{no-touting} strategy. This is due to the nature of the construction heuristic, which tries to fill the next day’s vehicle. Since more jobs are scheduled in the first vehicle, the average lead time decreases. Overall, these results demonstrate that touting relevant customers improves the efficiency in the long-run, independent of the method to solve the VRP.

7 Conclusion

We have presented a dynamic multi-period vehicle routing problem as faced by a UK waste collection company. It is solved on a rolling-horizon with a Large Neighborhood Search to solve each individual VRP. The paper introduces an idea to integrate demand management into the tour planning via a method called \textit{touting}. Touting consists of contacting a customer expected to order a collection soon, and nudge them to place their order now. While this means smaller amounts are collected and the customers need to be visited more frequently, it opens up the opportunity for the company to visit a customer when they are nearby anyway, potentially reducing the overall distance travelled.

We have proposed different strategies for touting potential future customers. Using real world data from waste collection industry, we have shown that touting appropriate future customers on relevant days may save a considerable amount of fuel due to decreased total distance travelled per litre of waste collected. Furthermore, the number of tours required is shown to be smaller if the touting strategies are followed, which may provide additional monetary benefits from the vehicle
acquisition costs. Although these advantages are shown using a real-world waste collection problem, the idea of exploiting knowledge of demand and active management of that demand in the form of touting can be applied to many routing problems in which customers arrive dynamically.

This research opens up several directions for future research. First, in this study, the decisions are made at each time period. Future work may attempt to make decisions more dynamically after each new order is obtained. Second, we have considered a single-vehicle routing problem as our industry partner uses fixed service regions per driver for operational reasons. While we anticipate that results carry over to VRPs with multiple vehicles, this should be demonstrated. Third, the most successful strategy for touting was the proposed relevance measure that is a linear combination of three criteria with equal weighting. Additional criteria such as the customer’s own anticipated demand could be integrated, and the weighting of the criteria could be more sophisticated. Finally, another future work may include incentivising customers by offering discounts at the time of touting to increase the probability that they accept the offer.

Acknowledgements

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References


8 APPENDIX - Mathematical model for the static VRP at each time period

Here, we present the mathematical formulation for the routing subproblem on a day within the planning horizon. \( T = \{1, 2, \ldots, h\} \) stands for the planning horizon for the day the problem is solved and is a subset of the whole horizon. Let \( C = \{1, \ldots, n\} \) be the set of known customers, which have not yet been serviced at the beginning of the planning day. A depot is located at vertex 0. \( c_{ij} \) and \( t_{ij} \) stand for the distance and travel time between vertices \( i \) and \( j \). The vehicle has a tank capacity \( Q \). Let the amount of goods to be collected from customer \( i \) and the due date of the order be \( q_i \) and \( d_i \), respectively. Hence, the last period in the planning horizon, \( h \), is determined by the latest due date of the customers. Each day \( t \in T \) has a time limit, i.e., the vehicle should be back at the depot before \( T_{\text{max}}^t \). Furthermore, there is a limit \( T_{\text{max}} \) on the total time spent over the planning horizon, e.g., weekly working time limit according to the hours of service regulations. The decision variable \( x_{ijt} \) is 1 if and only if arc \((i, j)\) is traversed on day \( t \). \( u_{ijt} \) and \( \tau_t \) track the tank load of the vehicle upon traversing arc \((i, j)\), and total time spent on day \( t \), respectively. The mathematical model is formulated as follows:

\[
\text{minimize} \quad \sum_{t \in T} \sum_{i,j \in C} c_{ij} x_{ijt}
\]

subject to

\[
\sum_{j \in C} x_{ijt} = 1 \quad \text{for } i \in C \quad (2)
\]

\[
\sum_{j \in C} x_{ijt} = \sum_{j \in V} x_{jit} \quad \text{for } i \in C, t \in \{1 \ldots d_i\} \quad (3)
\]

\[
\sum_{j \in C} u_{ijt} - \sum_{j \in C} u_{j0t} = q_i \sum_{j \in C} x_{ijt} \quad \text{for } i \in C, t \in \{1 \ldots d_i\} \quad (4)
\]

\[
u_{ijt} \leq Q x_{ijt} \quad \text{for } i, j \in C, t \in T \quad (5)\]

\[
\sum_{j \in C} u_{j0t} - \sum_{j \in C} u_{0jt} = \sum_{i, j \in C} q_i x_{ijt} \quad t \in T \quad (6)
\]

\[
\sum_{i, j \in C} (t_{ij} + s_i) x_{ijt} \leq \tau_t \quad t \in T \quad (7)
\]

\[
\tau_t \leq T_{\text{max}}^t \quad t \in T \quad (8)
\]

\[
\sum_{t \in T} \tau_t \leq T_{\text{max}} \quad (9)
\]

\[
x_{ijt} \in \{0, 1\} \quad \text{for } i, j \in C, t \in T \quad (10)
\]

\[
u_{ijt}, \tau_t \geq 0 \quad \text{for } i, j \in C, t \in T \quad (11)
\]

The objective function minimizes the total distance travelled over the remaining planning
periods. Constraints (2) ensure that each customer is serviced in one of the periods until their due date, whereas Constraints (3) establish the flow conservation. Constraints (4)–(6) track the load of the vehicle and ensure that the tank capacity is not exceeded. Constraints (7) calculate arrival time at the depot after completion of the route and Constraints (8) make sure that it does not exceed the time limit in each period. Total time limit over all periods is satisfied by Constraint (9). Finally, (10)–(11) define domains of the decision variables.