Reactive and Proactive Routing Strategies with Real-Time Traffic Information

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1. Introduction

The dynamic vehicle routing problem with time windows arises in situations where real-time information is revealed to the fleet manager and he or she have to make decisions in order to modify an initial routing plan according to the new needs. Real-time routing problems are mainly driven by events which are the cause of such modifications. Events take place in time and their nature may differ according to the type of service provided by a motor carrier. The most common type of event is the arrival of a new order.

When a new order is received from a customer, the fleet manager must decide which vehicle to assign to the new customer and the new scheduling that must be followed by that vehicle. In this paper, we investigated several routing policies based, on one hand, in the reaction capacity and the computational power of the fleet management centre and, on the other hand, in the previous existing knowledge about demand that allows the fleet manager to take advantage of existing idle times of vehicles waiting to start a service.

The former type of policies are called *reactive* because, in face of a new customer call, the fleet manager can decide to immediately assign the new order to a vehicle or hold it in a pool of orders until a better knowledge of demand is known. The latter type of policies corresponds to *proactive* strategies where the fleet manager has a certain probabilistic knowledge about demand and he or she uses it to anticipate to a possible call from a new client.

In both type of policies, assignments of new orders are made through a tabu search metaheuristic[1] that takes into account the current state of the vehicles as well as the current traffic conditions of the road network.

2. Decision Support System

The evaluation of the routing policies was made through a decision support system based on decision rules that use real-time information about the state of the vehicles and traffic conditions provided by a Traffic Information System. In our research, such real-time traffic information system is emulated by means of a microscopic traffic simulation software. Such decision support system is framed within an evaluation platform that allows us to simulate with great details the performance of a fleet of vehicles as well as the impact of the decisions taken by the fleet manager in face of unknown events such as new customers requiring service, changes in the current demand or changes in the traffic conditions of the network.

[1] Barceló, J. and Orozco, J.A. (2010). Fleet Rerouting Strategies with Real-Time Traffic Information, Proceedings of the 12th World Conference on Transportation Research.

Given that our research assumes the operation of the vehicles under a strictly urban environment, we use time-dependent travel times as the basis of the computation and assignment of the routing plans.

3. Reactive Strategies

We investigated two types of reactive policies. The first type is to assign a new order as soon as is received by the fleet manager. In the second type of reactive policies, the fleet manager sets acceptance rules for new orders. If those orders fulfil the acceptance conditions, they are then held in a pool of accepted orders until an assignment criterion is met. In this research, we evaluated two pool assignment criteria: i) a periodical assignment (e.g. every hour) and, ii) an assignment based on the imminence of service start time of orders in the pool.

The first criterion can be easily implemented as it only assigns all orders in the pool in a periodical fashion. The second assignment criterion is called Imminence Pool Assignment (IPA) and takes into account the total demand and the earliest service start times of the customers in the pool. Under this criterion, the assignment is triggered when one or both of the following criteria become true:

- The total demand required by the orders is equal or greater than the average vehicle capacity multiplied by a parameter β, $0 \leq \beta \leq 1$.

- The minimum lower bound of the time windows of the customers in the pool is *imminent* or *relatively closed* to be open by the time of evaluation of this criterion. The service at a customer is said to be imminent if the following condition is satisfied:

$$t_c + \frac{\bar{S}}{2} + T^* \geq E^*$$

where t_c is the time of evaluation of the criterion, $\bar{S}$ is the average service time, T^* is the average travel time between the two most distant points in the road network and E^* is the minimum service start time of the customers in the pool.

We have conducted a set of computational tests taking into account various degrees of dynamism (the percentage of new customer calls) as well as different characterizations of demand. Demand was characterized by the width of the time window (narrow and wide time windows) and the geographic location of the customers (randomly located or clustered). Our results show that pooling orders and then assign them lead to similar results than when new orders are assigned as soon as they are received. Nevertheless, the computational effort required by a pooling strategy is much lower than a one-to-one assignment.

4. Proactive Strategies

In the vehicle routing problem with hard time windows, vehicles have to wait if they arrive to a customer location before the time window is open. Moreover, after a vehicle visits the last customer in the assigned sequence, it is generally ordered to travel back to depot. In any case, idle times can be found during the operation of the vehicles.

Under a proactive approach, a fleet manager sets policies to dispatch idle vehicles to zones where there is a high probability that new customer orders will come from that area. In such way, the fleet manager proactively dispatches vehicles in the hope that they will be closer to a new customer when the call is received. A proactive approach assumes that some knowledge about the demand pattern is available and known by the fleet manager. For example, there can be information about the location of frequent and occasional customers as well as the preferred times in which these customers would be serviced. This information can be used to classify customers according to zones or sub-regions and time windows requirements and thereby, a probabilistic distribution can be used to model the new demand pattern.

In our approach, the service area is divided into sub-regions according to available statistical information. Within each sub-region, we defined a parking point where vehicles are allowed to wait. The probabilistic knowledge of demand is modelled by a Poisson process which helps us to compute the probability of receiving at least one new customer order at a given time period. We considered six different proactive policies that can be followed by the fleet manager:

- *Drive-First*. This policy refers to the classical approach of dispatching a vehicle to next customer in the route as soon as a vehicle is ready or has finished a service at a customer.
- *Wait-First*. In this policy, a vehicle is ordered to stay in the current location as long as possible before departing to the next customer location.
- *Delayed-Path*. This policy consists of ordering a vehicle to visit, before arriving to the next scheduled location, zones or sub-regions of the service area where there are is a high probability of new orders.
- *Closed-Parking-Point.* If enough slack time is available, this policy orders vehicle to travel to the closest sub-region and wait at the assigned parking point.
- *Highest-Demand-Parking-Point*. If enough slack time is available, this policy orders vehicle to travel to that sub-region with the highest current probability of receiving at least one new customer call.
- *Lowest-Expected-Cost Policy*. Under this strategy, a vehicle is ordered to follow the policy with the lowest expected cost according to the current traffic conditions and the probabilistic knowledge of demand.

Through a set of computational experiments, that were conducted by appropriately combining the most significant values of the design features on which the fleet management policies depend, we showed that total cost can be minimized when the fleet manager orders vehicles to follow a wait-first policy.