TRAFFIC INFORMATION AND DYNAMIC VEHICLE ROUTING IN FORWARDING AGENCIES

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ABSTRACT

This paper considers a routing and scheduling problem of forwarding agencies handling less-than-truckload (LTL) freight. On the one hand, the performance of these companies is influenced by unknown customer orders, increasingly received shortly before the actual pickup. On the other hand, the transport times between two consecutive points in a route sometimes vary significantly. The objective is to avoid lateness of orders and increase equipment utilization. In the following we present an approach using a look ahead capability for travel times and anticipation of customer orders.

Keywords: dynamic vehicle routing, anticipation, pickup and delivery, forwarding agency, less-than-truckload freight, varying travel times, unknown customers, clustering, tabu search

INTRODUCTION

The worldwide transportation of cargo is steadily growing as well as the transport volume of forwarding agencies handling less-than-truckload freight. The performance of these companies is strongly influenced by varying transport times between two consecutive points due to traffic jams. Surprisingly, traffic information is hardly used within the forwarding industry, even though vehicle location is available in real-time. Numerous unknown customer orders, increasingly received shortly before the actual pickup, are impacting the performance, too.

Typical forwarding agencies perform the pickups and the deliveries conjoined. They have to cope with hundreds of pickups and deliveries each day and a few tens of vehicles are necessary to service the customers in the short-distance traffic region. Furthermore, inquiries of business customers cannot be neglected. In the following we focus on the integration of unknown customers, whose unexpected order arrival is often responsible for late deliveries and increase of costs. So far real-time approaches solving pickup and delivery problems (PDP) with inhomogeneous goods, capacities of general cargo, time windows, varying travel times, and unknown customer orders are missing. Thus, the objective is to develop a customized dynamic routing model capable of handling all requirements and assisting forwarding agencies in routing vehicles efficiently in real-time.

LITERATURE REVIEW

In dynamic routing there are approaches solely based on a priori information whereas others are purely dynamic or combinations of both. Pure recalculation or iterative planning might be used to find routes of a pure static problem and with new information available the generated routes are updated. Savelsbergh and Sol (1998) applied a branch-and-price approach on such a problem, where new information triggers recalculation of previous results. Nonetheless, the results of such approaches are limited, because possible benefits of anticipating events are not used. In the following concepts anticipating customer orders are introduced.

Powell (1988) was one of the first to review the idea of forecasting uncertainties within dynamic routing, though the focus is on job assignment to maintain a steady flow of work. Van Hemert and La Poutré (2004) try a new approach. The authors do not consider the distances traveled or the number of vehicles; instead they solely try to cover the expected workload of the area. They try to use the fact that the number of service requests from different regions might vary. Therefore, it might be beneficial to service regions with high probability of customer requests. The authors conclude that, if the time restriction to deliver loads is beyond a certain point, it is best to perform routing for pickup and delivery only. In contrast to the approach of van Hemert and La Poutré it is absolutely necessary for forwarding agencies to pickup all available orders.

Haghani and Jung (2004) consider a dynamic problem similar to the one described, where requests can be pickup or delivery requests. The approach uses a genetic algorithm with continuous travel times. The routes are adjusted at several points of a time interval. Already loaded delivery orders are fixed, but pickup orders can be reassigned, if required. The results show that the dynamic approach outperforms the static one, especially when the uncertainty in travel time information increases. The travel time model is similar to that of Ichoua et al. (2003). The links are classified in categories, each with a certain speed and a time dependent ratio of this speed. The product gives the updated speed, which is input for a time dependent shortest path algorithm.

Promising results motivate to extend the multiple scenario approach suggested by Bent and van Hentenryck (2004), which permanently generates routing plans considering known and future requests. According to a consensus function the plan which offers the best flexibility at the actual point in time is chosen. Branke et al. (2005) instead derive theoretical results about the best waiting strategies for the one and the two vehicle case. Some deterministic waiting strategies and an evolutionary algorithm for waiting strategies are presented. The results show that a proper waiting strategy reduces detours and allows to service additional customers. They state that, if only few customer orders are unknown, it is better to use preplanned routes and insert new customers. On the other hand, if requests are expected customer orders should be anticipated. Jaillet and Wagner (2006) consider online routing problems and analyze the value of advanced information using competitive ratios. The work is dedicated to online traveling salesman and traveling repairman problems and show improved competitiveness results for both.

Hiller et al. (2006) present a column generation algorithm. They analyze if the reoptimization gap or the reoptimizaton model error are more significant. The authors give an original strategy, based on a set partitioning formulation and some simplified strategies for high load situations. One of these simplified models is using a fixed arrival time for a virtual contractor. In reality these are unassigned orders. The simplification is motivated by the fact that real contractors accept or decline requests. Additionally, a simple algorithm, which inserts new requests with minimal costs with respect to the original model and “2-exchange” are used for comparison. The results confirm the results of Bertsimas and Simchi-Levi (1996), who state that depending on specific cases, results of exact reoptimization are satisfying. Ichoua et al. (2006) exploit in a similar motivated approach the knowledge about future demands for real-time vehicle dispatching. The strategy is based on probabilistic knowledge about future demands. Therefore, dummy customers are integrated into the routes for a better coverage of the territory and computational experiments are performed.

The list of related approaches could easily be further extended, but most approaches are dealing either with varying travel times or dynamic customers, some also consider both (Fleischmann et al. 2004, Potvin et al. 2006) but rarely PDPs including both are analyzed. In particular, the special requirements of forwarding agencies are not considered.

OPTIMIZATION APPROACH

The objective within a first step was to determine how far and under what premises freight forwarding agencies might benefit from a real-time intelligent planning system. In a second step anticipation of both travel times and unknown customer orders built an essential part of the intelligent planning system to assist forwarding agencies. Therefore, we model a multi-stage mixed integer problem representing the pickup and delivery problem of forwarding agencies, which is able to operate under variable (A) transport time and (B) demand conditions. The following focuses on part B (integration of unknown customers), details to part A are given in Wohlgemuth and Clausen (2009). The anticipation of unknown customer orders is achieved by customer clustering and using an implicit tour structure. Newly arriving orders are immediately integrated and the implicit tour structure is updated as well as, upon arrival of new information, the reoptimization is triggered. In practice, the problem has to be solved within a certain time; therefore a tabu search for this intelligent planning system is developed.

In this context an implicit tour structure enables the assignment of later pickup orders in the most efficient way. Figure 1 illustrates the idea of an implicit tour structure. Three tours are planned including the known customer orders (black nodes). Based on experience, historical data, or demand density and customer dispersion for different regions possible or expected orders can be computed. These are compared with actual orders of the region before the tour start. In a static planning one vehicle would service the two customers in the lower left corner only and would return to the depot from the customer nearest to the depot. Opposed to that an anticipatory strategy includes the possible orders into the planning. For example, the region in the bottom right corner is likely to experience two orders (colored nodes), but right now no vehicle is traveling there. An anticipating algorithm reserves the necessary travel time and capacity (e.g., via a cluster (rectangle)), to service the customers in the lower right corner, if that seems favorable. These orders are then assigned to the vehicle servicing the customers in the lower left corner. In that way the original static tour is traveled in the reversed way, if possible. After the service of the known customer orders, the service of additional orders emanating in the neighborhood is feasible. In this manner all expected, but unknown, orders will be considered.

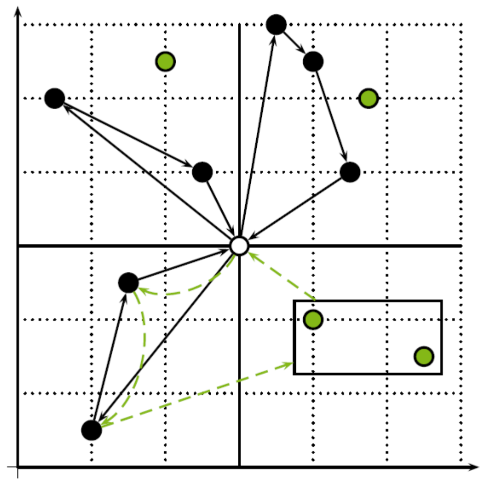

Figure 1 – Customer clustering and implicit tour structure

Considering objective function, degree of dynamism, and demand rate, we developed a modified tabu search to solve the planning task at hand. The tabu search explores only parts of the solution space by moving at each iteration to the most promising neighbor of the current solution, even if this requires a decrease of the objective function. Cycling is avoided by using a tabu list, where recently considered solutions are blocked out for a number of iterations. The neighborhood of a solution contains only solutions, where a removed customer can be inserted approximately to a customer complying all restrictions under time dependent travel times.

The tabu search has a look ahead capability allowing to service all customers during the planned routes without or nearly without extra tours. Prerequisite of such smooth tour changes is that, among other things, the customer alterations are known in time, the orders are pickup orders and the remaining capacity is sufficient. The approach is able to plan routes in real-time during the tour execution, but also use anticipation to avoid or minimize sudden rescheduling. Therefore, the routes include customer clusters with potential orders, which are constructed from historical data and serve as placeholder for possible service requests.

Before clustering it is necessary to define the traits, which determine cluster characteristics, size and structure. A trait or attribute is a particular feature, distinguishing quality, or characteristic, describing an object or cluster. In clustering a trait is often the proximity according to some defined distance measure. Most promising traits for the clustering of pickup orders of forwarding agencies are the *customer locations* and the *resulting travel times between indi-*

vidual customers (similarity measure) as well as *time windows*, *order frequencies* and *order sizes*. In this scenario with time windows and time dependent travel times agglomerative hierarchical clustering is most appropriate. The chosen clustering method has the ability to relative fast cluster huge amounts of data and does not require weighted traits. Moreover, many real-data sets may have different point densities in different regions of the data space; therefore, the consideration of different point densities is possible. Additionally, the algorithm can handle asymmetric travel time matrices. After all clusters and their members are determined, using this information allows the integration of unknown customers into the implicit tour structure.

The performance of the tabu search with dynamic customers with clusters and without clusters is analyzed in Table 1 with dynamic Solomon instances, where using clusters on average does not lead to longer overall travel times (*t*). Overall 63 customers cannot be served on time (*k*) using pure dynamic optimization, which can slightly be improved with customer clustering so that the service level increases to 94.92 percent. The main advantage and cost saving potential of clustering is that the number of vehicles (*m*) can be reduced in three cases.

Table 1 Dynamic customers (mR1XXc) and dynamic customers with clusters (mR1XXd)

No.	*t*	*m*	*k*	No.	*t*	*m*	*k*	Δt	Δm	Δk
mR101c	2044.20	20	3	mR101d	2020.37	20	3	-23.83	0	0
mR102c	1984.12	19	10	mR102d	2025.91	19	9	41.79	0	-1
mR103c	1720.77	17	6	mR103d	1797.50	16	6	76.73	-1	0
mR104c	1586.31	14	3	mR104d	1450.46	13	6	-135.85	-1	3
mR105c	1935.86	16	7	mR105d	1899.28	16	2	-36.57	0	-5
mR106c	1801.79	16	6	mR106d	1857.64	15	2	55.85	-1	-4
mR107c	1630.73	14	7	mR107d	1636.75	14	6	6.02	0	-1
mR108c	1386.78	12	3	mR108d	1416.04	12	6	29.26	0	3
mR109c	1490.93	13	2	mR109d	1469.57	13	3	-21.36	0	1
mR110c	1520.18	13	8	mR110d	1520.18	13	8	0.00	0	0
mR111c	1581.66	14	3	mR111d	1573.40	14	5	-8.27	0	2
mR112c	1383.33	12	5	mR112d	1383.33	12	5	0.00	0	0

CONCLUSION AND OUTLOOK

This paper describes the successfully tested strategy for clustering customers for a PDP incorporating practical complexities, which received only little attention in literature. The presented tabu search is capable of industrial size problems and performs also well with time dependent travel times, which is very helpful in decreasing the probability of lateness due to rush hours slow-downs within PDPs customized for forwarding agencies. Experiments with the integration of customer clusters for instances with dispersed customers prove in test data sets that quite often no additional or less vehicles are needed and the overall travel times could be reduced slightly. In regions with clustered customers and regions with a mix of clustered and dispersed customers however the number of vehicles remains mainly unchanged and for the already low level of lateness no general impact could be found, what is also true for the total travel time. The ongoing research will focus on the refinement of the described cluster strategy for data sets with various customer distributions and the improved integration of both travel time anticipation and customer clusters.

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