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On Profitableness of Considering Dynamics in Forwarding Agencies

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Abstract—**Pickup and Delivery Problems, where customers may both receive and send goods, are an extension to classical Vehicle Routing Problems. We do not make the assumption common in literature that goods may only be picked up after all deliveries have been completed. Thereby we model industry problems encountered by freight forwarding agencies, which have to deal with dynamic pickups and deliveries in an integrated manner. The approach we take evaluates the benefits of dynamic optimization anticipating varying travel times as well as unknown customer orders in the specific environment of freight forwarding agencies. On test instances with customer distributions common in forwarding industries single depot problems are analyzed with very encouraging results.**

Keywords: vehicle routing, pickup and delivery, dynamic, varying travel times, discrete optimization

1 Introduction

Distribution costs have an immense impact on the total costs of products. This is mainly induced by the necessary transportation between members of the supply chain and end customers. Therefore, the optimization of distribution processes offers potential cost savings. The main focus of this work will be on forwarding agencies handling less-than-truckload (LTL) freight. LTL freight is a type of cargo which is on the one hand too large or heavy to be transported by means of standard courier services and on the other hand the amount is by far too low for full truckloads. Consequently, direct transportation from origin to destination would be too expensive. Hence, the main idea is to consolidate enough small shipments to efficiently conduct transportation for the majority of the distance. In preparation of this transport it is necessary to pick up commodities from different customer locations in the origin region (preliminary leg). At the transshipment point consignments with the same destination region are grouped on trucks heading for this region and are transported to a consolidation center in the destination region. Upon arrival they are transshipped again on smaller trucks and distributed to the customers in the destination region (subsequent leg), as illustrated in Figure 1.

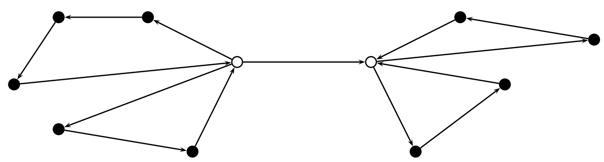

Figure 1: Less-than-truckload freight network

Nearly every transshipment point collects as well as rolls out goods. Thus, typical forwarding agencies perform the pickups and the deliveries conjoined on the same vehicle. 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 local region. Within the operations of forwarding industries vehicle capacity is crucial, because sometimes single loads require large amounts of the total vehicle capacity. Furthermore, inquiries of business customers cannot be neglected as sometimes suggested in approaches dealing with dynamic customer orders. The performance is mainly influenced by two dynamic aspects: First, due to developments in information and communication technology, the agencies receive inquiries shortly before the actual pickup. That is, up to 50 percent of all orders are unknown at the beginning of the day. Second, unexpected traffic situations are endangering the scheduled pickups, though traffic information is increasingly available. Especially in urban areas for many roads rush hour traffic jams are known. Surprisingly, this information is hardly used within forwarding agencies, even though vehicle location is available in realtime. Consequently, forwarding agencies are experiencing lateness of shipments and poor utilization of vehicles.

Recapitulatory, forwarding agencies are still facing the problem that they have to manage lots of shipments, vehicles, restrictions, and especially dynamics in customer orders and unexpected traffic situations disrupting the planned schedule. Thus, the goal is to evaluate the benefits of an intelligent planning system, assisting forwarding agencies in routing vehicles efficiently.

The paper is organized as follows. At the beginning, Section 2 gives a brief literature review. Thereafter, Sec-

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tion 3 depicts the optimization approach to analyze the impact of considering changing travel times and the possible impact of anticipating customer orders arriving over the planning horizon. Finally, Section 4 gives computational results.

2 Literature Review

Static routing problems have been studied extensively in the past and the interest is now increasingly on dynamic routing problems. Most static or dynamic real world routing problems from combinatorial optimization, including the Pickup and Delivery Problem (PDP) we modeled, are $\mathcal{NP}$-hard and cannot be solved to optimality within reasonable time. In fact, the most effective exact algorithms proposed so far consistently solve problems containing about 50 customers [1]. Hence, usually heuristics are applied. Nagy and Salhi compare different heuristic algorithms to solve large Pickup and Delivery Problems [2].

Before discussing some approaches covering dynamic problems, it is necessary to define the term *dynamic*. Larsen introduced a good definition to differentiate static from dynamic problems, based on two aspects: "First, not all information relevant to the planning of the routes is known by the planner, when the routing process begins. Second, information can change after the initial routes have been constructed" [3]. Psaraftis as well tried to differentiate between static and dynamic problems and listed detailed attributes to differentiate between them [4]. Examples relevant for dynamics in forwarding agencies are: new or dropped out customers, new or altered time windows, vehicle break downs requiring rescheduling, altering quantities to pick up, varying travel times (e.g., traffic jams), vehicle breakdowns, and varying service times.

There are primarily two ways to solve dynamic problems. First, a priori models which account in their optimization strategy for changes which might occur. Second, dynamic models which restart computing new solutions, every time new information is available. General solution concepts for PDP, though for single vehicles, are given by Gribkovskaia et al. [5].

Kenyon and Morton built a priori models considering stochastic travel times as well as stochastic service times [6]. One model tries to minimize the time likely required to finish all tours, while another model maximizes the probability to finish all routes within a given time. Both models utilize a branch-and-cut approach to solve the problem.

Dynamic models can be differentiated in models which anticipate and consider possible incoming orders and models which simply start recomputing, if new information is available. One method for the last mentioned approach of iterative planning might be to find tours of a pure static problem and with each new information available the generated routes are updated. Savelsberg and Sol applied a branch-and-price approach on such a problem, there each new information triggers recalculation of previous results [7]. The general advantage of this approach is, that it is possible to modify existing methods to adapt to dynamic problems. These methods might be simulated and deterministic annealing, genetic algorithms, tabu search, ant colony systems, adaptive memory, or variable neighborhood search. To be able to apply various methods in a short period of time, it is often necessary to execute them parallel [8]. Nonetheless the results of such approaches are limited, because possible benefits of anticipating results are not used.

Jaillet and Wagner consider online routing problems and analyze the value of advanced information using competitive ratios [9]. The work is dedicated to online traveling salesman and traveling repairman problems. The performance of online algorithms is measured using competitive ratios (i.e., worst case ratio of the online algorithm's cost in comparison to the costs of an optimal offline algorithm). The authors analyzed objectives optimizing the server's interest and the customers' interest. As well as they introduced a disclosure date, the point of time at which requests become known, ahead of the dates at which requests can first be served. This is similar to the degree of dynamism Larsen introduced earlier [10].

Hiller et al. present a column generation algorithm, to route a fleet of service vehicles to unknown service locations [11]. They analyze, if the reoptimization gap or the reoptimizaton model error is more significant. The authors give the original strategy (named ZIBDIP), based on a set partitioning formulation and some simplified strategies for high load situations. For three test days computational experiments were conducted. The original strategy was used for low loads and the simplified models were used in high loads. Experiments show that all simplified models reduced the optimality gap. With respect to costs only two simplified models were competitive against ZIBDIP. Still the model error of most high load models leads to worse long-term behavior than the original strategy. The results suggest to keep the original model, but use simplified reoptimization models. The tested algorithms increased the long term cost more than the model errors before. Further, the authors claim that, if reoptimization is not working properly, this is not cured by using suboptimal solutions to the reoptimization problem [11]. These results confirm the results of Bertsimas and Simchi-Levi, who state that - depending on specific cases - results of exact reoptimization are satisfying [12].

Schönberger et al. accept or reject customer orders based on the expected profit (i.e., a vehicle routing problem with profits). Therefore, the expected profit is compared to the additional costs of a request. In the beginning various orders have to be combined, as a single order is not sufficient to profitable conduct a tour [13]. However, order rejection within forwarding agencies is generally not applicable. Another approach from Aksen and Aras connects the customer selection with a profit maximization (i.e., the objective is not to minimize the distance, but to maximize the profit). Accordingly, the travel costs as well as the profit for each customer have to be known. Similar to the standard problem time windows can be considered [14]. Again, this is not applicable in forwarding agencies, which are committed to service all customers.

Promising results motivate to extend the multiple scenario approach suggested by Bent and van Hentenryck [15], 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. Alternatively, and for forwarding agencies even more promising, seems the approach from Kunze [16]. The author built aggregates, representing geographical regions and the time to service and to travel these regions are estimated. Dynamically incoming orders are considered, though no capacities are included.

Fleischmann et al. consider a dynamic routing system where customer orders arrive at random during the planning period. Every customer request requires a transport from a pickup location to a delivery location with given time windows, though no capacity is considered. Additionally, the authors consider forecasted and dynamically changing travel times obtained from a traffic management center. The forecasted travel times account to regular rush hour congestion in certain streets. Two events trigger recalculation: new orders or vehicles done with one order. The authors use an assignment and an insertion heuristic algorithm. The assignment algorithm considers all vehicles and all open orders simultaneously. The insertion algorithm integrates new orders into the current schedule at the point of the arrival of this order. The resulting schedule is improved by resequencing and reassigning the orders. Results indicate that the flexible assignment algorithm outperforms the simple assignment and insertion algorithm. This advantage is increasing with higher levels of dynamism [17].

Branke et al. derive theoretical results about the best waiting strategies for one and two vehicle cases [18]. 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 the additional customer. They state that, if only few customer orders are unknown, it is better to use preplanned route and insert new customers. On the other hand, if requests are expected customer orders should be anticipated. Further, known or unknown arrival times are considered and time lacks of vehicles are used to insert new customers or to wait. Branke et al. prove that for a single vehicle it is not beneficial to wait and that benefits will prevail even for more customers. This is solely valid for a small number of new customers. Generally, with a large number of customers waiting is unlikely to be of any benefit.

Powell 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 [19]. Instead of creating routes beforehand and different to Powell's approach focusing on forecasting and the assignment problem. Van Hemert and La Poutré try a new approach [20]. 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. Still, customer requests are handled dynamically and a solution is provided in real-time. Three criteria differentiate their dynamic routing approach from static ones. First, vehicles are allowed to pass through nodes without servicing customers. Second, loads become available while vehicles are already on route. Third, loads do not necessarily have to be assigned to vehicles. Consequently, their objective is to carry as many loads as possible to the central depot. The performance is measured by the total number of loads generated in a given time period. In practice, various customers requests are often emanating in the same geographical region. Van Hemert and La Poutré try use the fact that the number of service requests from different regions might vary (e.g., production capacities in specific customer regions). Therefore, it might be beneficial to service regions with high probability of customer requests (i.e., service fruitful regions). The authors use an evolutionary algorithm that offers to maintain various candidate solutions and therefore reacts on changes. 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. Vehicles might take a long time to pick up any load and return to the depot. This assumption might hold for other pickup and delivery tasks, but does not fit with forwarding agencies. The distances are usually higher than in other delivery areas and in far off regions combined pickup and deliveries allow tremendous savings. The criteria differ from the ones assumed in our approach. The expected service and travel times within the region are already assumed. Similar to van Hemert and La Poutré loads become available during route execution, but within forwarding agencies it is absolutely necessary to pickup all available nodes and evenly important, the time windows of customers have to be considered.

Most approaches are dealing either with varying travel times or dynamic customers, some also consider both but rarely Pickup and Delivery Problems including both are analyzed. In particular, the special requirements of forwarding agencies are not considered. Additionally, various papers show performance improvements with a pri-

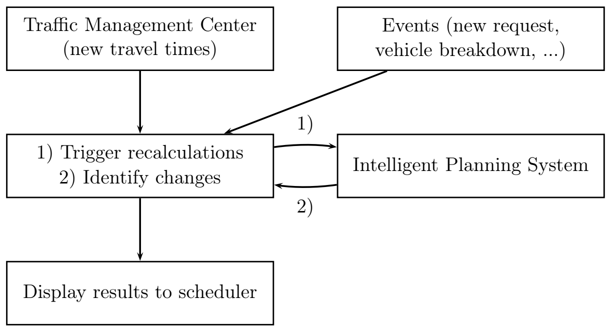

Figure 2: Structure of a dynamic routing system

ori or dynamic problems over static ones, but rarely it is evaluated, if it is economically beneficial to invest in dynamic routing. Thus, we focus on evaluating, if forwarding agencies might benefit from approaches anticipating events and routing in real-time. For this reason we analyze the potential improvements of dynamic routing in forwarding agencies and determine, if it is economically advantageous.

3 Optimization Approach

Pickup and Delivery Problems are appropriate to model decision problems of forwarding agencies, where customers may both receive and send goods. These companies exhibit high operational costs, among other things due to high gasoline prices and toll payments in Germany, additionally the competition is tough. Consequently, the objective is to find a set of minimum cost routes, starting and ending at a single depot and serving demands of numerous customers. Furthermore, vehicle capacity, driving time restrictions and especially tight time windows hinder the operations in forwarding agencies. An optimization approach considering dynamics occurring in forwarding agencies will help to pick up and deliver goods on time and avoid sudden rescheduling.

Figure 2 illustrates the functionality of a dynamic routing system. Every time new information is available, either travel times or customer requests, the intelligent planning system is started. The idea of such a planning system is that anticipating future changes will produce considerably less route changes than systems purely recalculating.

Problems dealing with dynamic data are difficult to compare, because the degree of dynamism and the number of known and unknown customers (n_v, n_z) is likely to vary. Therefore the effective degree of dynamism is crucial for evaluating the results of different scenarios. We measured the degree of dynamism essentially in the way Larsen, Madsen and Solomon suggested [10]. The extended degree of dynamism, which incorporates individual customer time windows and thereby accounts for widely varying time windows, is used. The value of equation (1) is always between zero and one, because $l_i - t_i$ (latest arrival time at customer, order arrival time respectively) is always less than or equal to T (time horizon). Usually, greater response time offers more flexibility, because the number of potential options is higher. That is, the more time is available to react (the response time), the more likely it is to find satisfying solutions for this event.

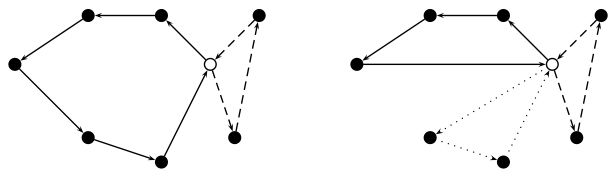

Figure 3: Example of dynamic routing

$$edod_{tw} = \frac{1}{n_v + n_z} \sum_{i=1}^{n_v+n_z} \frac{T - (l_i - t_i)}{T} \tag{1}$$

On the one hand we consider varying travel times, caused by traffic jams, stoppages, breakdowns, etc. and the possible impacts. An example with two vehicles is given in Figure 3. Assuming the originally planned route (left side) would be for vehicle one (solid line) to service five customers and for vehicle two (dashed line) to service two. In the process time windows have to be respected, because otherwise high penalties or long periods with idle waiting are induced. In the example vehicle number one is stuck in a traffic jam after visiting three customers and will not be able to service the remaining customers on time. Within the forwarding industry not servicing customers is not an option. Either an additional vehicle has to be hired to service these customers and maybe high penalties have to be paid for lateness or - and much better - one of the other vehicles, in this example vehicle two (dotted line), might be able to take care of these customers on time (right side). This decision process could be supported by an online planning algorithm. We considered how often planned routes are endangered, to evaluate the benefits of such an approach. The robustness of the solution is analyzed to be able to estimate the benefits from routing algorithms anticipating traffic jams.

On the other hand we considered dynamically arriving orders. In reality customer orders are canceled, but this is generally not a problem. All other customers can still be serviced on time, in the worst case the vehicle might be idle for some time and utilization decreases. Far more difficult to handle are orders arriving throughout the day. Our industry partners did not have the data available to provide the exact times of order arrivals. On that account we decided to assume the best time for order arrivals, namely directly after the tour start. In this case the companies do have the most time to react to each incoming order. Of course, in reality orders arrive during the day and therefore our results indicate less impact caused by dynamics as the company might actually ex-

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perience. In addition, this assumption is a lower bound on the daily performance and the company will definitely experience at least the impact computed. At the beginning, routes for all known orders are planned, then we added stepwise incoming, therefore unknown, customer orders and analyzed the results.

To analyze potential savings a PDP is formulated as a mixed integer linear programming model. Here, the common assumption in the PDP literature that goods may only be picked up after all deliveries have been completed is not necessary. The PDP can be defined as follows. Let $G = (V_0, E)$ be a graph where $V_0 = \{v_0, v_1, ..., v_n\}$ and $V = V_0 \backslash \{v_0\}$ are vertex sets and $E = \{(v_i, v_j) : v_i, v_j \in V_0; i \neq j\}$ is the arc set. Every vertex of V corresponds to a customer, and vertex v_0 represents the depot at which at most m vehicles are based. The decision variable m limits the number of vehicles, which can be used in the optimal solution and with E is associated a distance matrix $C = (c_{ij})$. The model, objective function and constraints are given below in equations (2) to (15).

$$\text{Min} \quad \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{m} c_{ij}x_{ijk} + Z * \sum_{j=2}^{n}\sum_{k=1}^{m} x_{1jk} \qquad (2)$$

In the above formulation the *objective function* minimizes the total distance traveled or travel time respectively. In addition, the number of vehicles used is minimized (2). Without minimizing the number of vehicles, the model would probably use more vehicles to minimize the total distance or travel time. However, in forwarding agencies every additional vehicle costs a lot more than a few additional kilometers or minutes traveled.

$$\text{s.t.} \quad \sum_{i=1}^{n}\sum_{k=1}^{m} x_{ijk} = 1 \quad \forall \quad j = 2, ..., n \qquad (3)$$

$$\sum_{i=1}^{n} x_{ijk} - \sum_{i=1}^{n} x_{jik} = 0 \quad \forall \quad j \in N; \quad k \in K \qquad (4)$$

$$\sum_{j=1}^{n} x_{1jk} \leq 1 \quad \forall \quad k \in K \qquad (5)$$

The *customer and vehicle related constraints* ensure that every customer is visited (3). Theoretically, it is possible that a vehicle visits a customer and leaves another one. Of course that is not possible in reality and has to be precluded (4) and (5).

$$f_{ijk} \leq C \quad \forall \quad i, j \in N; \quad k \in K \qquad (6)$$

$$f_{ijk} \leq x_{ijk} \sum_{h=2}^{n} (q_h + p_h) \quad \forall \quad i, j \in N; \quad k \in K \qquad (7)$$

$$\sum_{i=1}^{n}\sum_{k=1}^{m} f_{ijk} - q_j = \sum_{i=1}^{n}\sum_{k=1}^{m} f_{jik} - p_j \quad \forall \quad j = 2, ..., n \qquad (8)$$

The *flow related constraints* limit the capacity for all vehicles k on all edges (6). A flow of goods is only possible, if a vehicle is actually traveling from node i to node j (7). Of course the load is reduced or increased only by the amount of customer orders (8). These constraints implicitly avoid subtours, therefore also produce lots of constraints and provoke a $\mathcal{NP}$-hard problem [2].

$$e_i \leq a_{ik} \quad \forall \quad i \in N; \quad k \in K \qquad (9)$$

$$a_{ik} \leq l_i \quad \forall \quad i \in N; \quad k \in K \qquad (10)$$

$$a_{ik} + s_i + c_{ij} - R * (1 - x_{ijk}) \leq a_{jk} \quad \forall \quad i, j = 2, ..., n; \quad k \in K \qquad (11)$$

$$e_1 + c_{1j} - R * (1 - x_{1jk}) \leq a_{jk} \quad \forall \quad j = 2, ..., n; \quad k \in K \qquad (12)$$

$$a_{ik} + s_i + d_{i1} - R * (1 - x_{i1k}) \leq a_{1k} \quad \forall \quad i = 2, ..., n; \quad k \in K \qquad (13)$$

$$x_{ijk} = \{0, 1\} \quad \forall \quad i, j \in N; \quad k \in K \qquad (14)$$

$$f_{ijk} \geq 0 \quad \forall \quad i, j \in N; \quad k \in K \qquad (15)$$

The *time windows and travel time constraints* are equations (9) to (13). Constraints (9) and (10) let the vehicles arrive at the earliest at the beginning of a time window and require the service to take place at the latest at the end of the time window. Equations (11) ensure the time consistency. Based on the arrival time of vehicle k at customer i the necessary service time s_i is added and the departure time is calculated. The departure time plus the travel time and the arrival at the next customer location j has to be at least this high. These constraints are not valid for the depot node, otherwise no valid routes would be found. One possibility to solve this problem is to create for each vehicle one virtual depot node, that is, every vehicle has a virtual depot node for the start of each tour and one for the end of the tour. Here, the problem is solved in a different way. The equations (12) and (13) ensure the time consistency from the depot node to the first customers and for the return to the depot. Finally, the last equations are formal definitions.

Based on this model the impacts of varying travel times and dynamic order arrival are analyzed. It is important to keep in mind that the graphical customer distribution might affect the results drastically. Of course in such a setting the deliveries are known at the beginning of the planning horizon and the number of unknown pickups determine the degree of dynamism.

4 Computational Analysis

First the problem was solved under the idealistic assumption that all data are known in advance. This provides a base to benchmark the impact of varying travel times and dynamic order arrival. For solving GAMS and the CPlex 10.0 branch-and-cut framework was used. Exemplarily, we illustrate this with modified datasets based on the Solomon Instances of type R and C. The number of vehicles used, distances between customer, and order arrival times vary for different datasets. For all instances analyzed we limited the available solver time to gain results in reasonable time.

We generated optimal routes assuming all orders known and analyzed the impact of real life traffic by means of performing robustness analysis on the instances. This helped us to see how long a traffic jam or extension of travel time might be, before the solution was influenced significantly. Individual values of each customer indicated critical tours. Overall, we were able to predict to what extend the prior computed solutions would be applicable and to what point in time lateness occurs or new vehicles might be needed. We performed several experiments for different customer distributions, vehicle capacities, and time windows. All were impacted by changes in travel time, though cases with high concentration of customers in local regions were influenced less than cases with dispersed customers or mixed distributions.

Similar to the real-life routes the generated routes are not very robust. This is due to the fact that they are based on standard travel times, but especially in urban areas traffic jams occur often. Anticipating these in routing may help forwarding agencies, which have problems fulfilling customer demands on-time. The anticipation should not be globally (i.e., adding 10 percent to the travel time), because this would induce more idle time and waiting at customer locations. Instead more sophisticated approaches, for example, time dependent and dynamically reacting models, promise success.

In addition to varying travel times we analyzed the impact of unknown customer orders. The number of unknown customer orders is ranging from 0 to 52 percent. Still, the service times and the time windows of different customers were supposed to be constant. The delivery orders were known, while the unknown requests were pickup orders. Instead of generating the order arrival times via a Poisson process, we assumed the additional orders are known after the tour start. Considering the definition of the degree of dynamism, this is a lower bound for the actual dynamic. This assumption is likely to improve the results under dynamism, but never delivers worse results than forwarding agencies might experience actually.

We analyzed to what extend the variable order income has an impact on the already planned routes for different customer distributions. Therefore, we fixed the solution of all known customers before the planning starts, because already loaded and traveling vehicles cannot be reloaded. Now the problem was solved with each newly arriving customer order. Results show that if the extended degree of dynamism is above 0.5 and customer distribution of type R, generally two more vehicles (K) are needed. Table 1 illustrates this for four instances. Instances with dispersed customers and a high number of unknown customers (U) experience a strong impact. With only few unknown customers, the traveled distances (D) increase only slightly. Datasets with clustered customers are impacted similarly, but due to the proximity of the customer location the solution is more flexible to integrate dynamic events.

Table 1: Static vs. Dynamic Optimization

	Static		Dynamic			
Instance	K	D	K	D	U	$edod_{tw}$
R25-1	8	618.3	10	742.2	0.52 %	0.53
R25-2	8	618.3	8	686.0	0.24 %	0.53
C25-1	3	191.8	4	259.0	0.52 %	0.62
C25-2	3	191.8	3	191.8	0.28 %	0.62

The instances of type R are those most similar to customer distributions of common forwarding agencies. In cases of type R with dispersed customers fluctuations in travel speed show great impact on the results. Of course the distance traveled and time spent servicing customers induces costs, but the major cost drivers in forwarding agencies are the number of vehicles used. Overall, for instances of type R and a $edod_{tw}$ above 0.5 two more vehicles are needed.

The results we found indicate that considering dynamic data might be useful in forwarding agencies, but it is still unclear, if an invest is economically reasonable. Generally, companies have to pay penalties for lateness as high as the operating costs for one vehicle for one day. Additionally, all results consistently show that in dynamic situations additional vehicles are required.

To compute the benefits of considering varying travel times, for all datasets the probability of late deliveries are computed and weighted with individual penalty costs for each late delivery. Of course nonmonetary consequences like image, lost customers or even additional efforts to service the customer on time are not considered. Dynamic order income likely requires a higher number of vehicles and therefore is the main cost driver; additionally extra kilometer costs are added. In cases with few unknown customers (less than 25 percent) the risk to not finish routes and the risk of lateness increase only moderately. It is likely that no new vehicles are needed, because the increase of route execution time is below 10.95 percent (i.e., few extra costs). Cases with high degrees of dynamism (above 0.5) and lots of unknown customers (above 50 percent) are endangered by lateness. The increase of route execution time is above 20.04 percent and likely more than two additional vehicles are needed (i.e., high extra costs). Even though pure static planning induces additional costs, in cases of low dynamics an invest might be noneconomical and critical consideration is needed. In cases of high dynamics, especially with varying travel times, optimization with anticipation is favorable.

5 Conclusions and Future Work

Overall the results show that the anticipation of changing travel times and dynamic customer orders within forwarding agencies is very promising and, if fluctuations of both are high enough, even economically advantageous. The further examination of the degree dynamism regarding travel times and customer distribution might be interesting. Especially, the development and evaluation of fast dynamic algorithms with strategies to anticipate customer orders and travel times considering the specific requirements mentioned above is an important field of research.

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