Cooperative Traffic Control Management for City Logistic Routing

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Abstract

In city logistics, courier express and parcel services (CEP) deal with last mile deliveries in an urban environment. CEP route vehicles to deliver parcels to customers distributed in the cities area. Customers expect fast and reliable services to reasonable prices. As a result, CEP have to plan and execute their routing efficiently. In a city logistic environment, CEP faces several challenges. Especially, travel times between customers are not deterministic but uncertain and differ during the day regarding traffic volumes and stochastic events like congestion. Further, city traffic flows are controlled by traffic control management (TM). TM decisions additionally impact travel times for CEP. This paper shows the impact of TM decisions to travel times and emphasizes the benefit of cooperation planning between CEP and TM.

Keywords: City Logistic, Traffic Management, Vehicle Routing, Dynamic Vehicle Routing, Stochastic Travel Times, Time Dependent Travel Times

1. Introduction

Urbanization leads to an increased individual and freight traffic volume [3, 24]. Globalization results in a worldwide transportation of goods and is another factor for the increasing number of transports in cities [30]. This development is further reinforced by the continuous growth of e-commerce [25]. The online purchase of goods make the delivery process more complex as each customer gets a delivery to his home. As a results of these depicted trends, demand of transports in cities is constantly growing. These transports are generally known as last mile deliveries [13]. To fulfill these transports, courier, express and parcel services schedule vehicles in an urban environment. This is defined as city logistic [34]. CEP distribute products from manufacturers to consumers, who expect fast and reliable service [6]. An efficient transportation planning in cities is challenging. CEP have to plan considering city logistic uncertainties. In particular, travel times are varying regarding traffic volume, following daytime pattern. At the same time travel times are changed by uncertain events like sudden congestion or accidents [7]. CEP must consider varying travel times in tour planning and, if necessary, adjust scheduled tours accordingly [26, 40].

City administrators have a major impact on travel times. Objective of city traffic control managements (TM) is to maintain efficient city traffic by controlling traffic flows in city areas [27, 39]. Therefore, TM uses a number of

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possible actions. This can be changes traffic control light programs, lane control and speed limits. Usually, TM combines sets of actions to so called traffic strategies [27]. Each traffic strategy is suitable for a specific traffic flow pattern. As a result, travel times between city locations situate not only by the occurring traffic volume but also by the traffic strategy applied by TM. Even though the strategy applied by the TM significantly impacts travel times, the strategies are generally not communicated. This research looks into the possibility of improving CEP routing efficiency, if information can be acquired from a cooperative traffic management and included in the tour planning by the CEP. We consider a routing problem, where a vehicle has to serve a set of customers. Travel times are time-dependent, stochastic and depend on the applied traffic strategy. Objective is to minimize the overall travel times. We apply approaches differing in the degree of information provided by TM. Results show, that considering TM-decisions in routing allow an increase in solution quality.

This article is structured as follows: In Section 2, a literature overview about vehicle routing problems in city logistics is given, especially considering uncertain and varying travel times. In Section 3, an overview of traffic management operations is given motivating the introduction of stochastic time-dependent travel times with TM information in Section 4. In Section 5, we define a vehicle routing problem. The results of a computational evaluation are shown in Section 6. This article closes with a conclusion and an outlook of future work in Section 7.

2. Literature Review

The problem can be described as a stochastic dynamic time-dependent vehicle routing problem in a city logistic environment. It is stochastic, because travel times are uncertain and not entirely known at the point of decision [16]. It is dynamic, because rerouting based on new information is allowed. As the research on dynamic vehicle routing problems is vast, the interested reader is referred to the review of Pillac et al. [28]. In sequence, we focus first embedded routing in city logistics environment and then we explicitly consider vehicle routing problem with varying travel times.

2.1. City Logistics

Taniguchi et al. [34] describes city logistics as "the process of totally optimizing the logistics and transport activities by private companies in urban areas while considering the traffic environment, the traffic congestion and energy consumption within the framework of a market economy". City logistics is steadily growing, because of urbanization and e-commerce leads to an increased number of business-to-customers shipments inside cities. The CEP services have to react to a growing parcel market, while competition and therefore price pressure is increasing [25]. According to Dublanc et al. [4], about one fourth of city traffic is related to freight transportation. When compared to rural deliveries, the delivery process of goods in cities is influenced by a significantly higher number of parameters. Challenges arise though traffic regulation and congestion, road condition, road works, limited parking space for stopping for a delivery and varying travel volume. Especially the impact of rush hours on travel times is high [9]. Kim et al. [18] therefore concludes that the research on vehicle routing problems differs for the city areas and classifies them as "City Vehicle Routing Problem". The difference to rural deliveries is the number of involved stakeholder [33]. These stakeholders in city logistics are classified by Taniguchi et al. [34] into residents, shippers, freight carriers and administrators. The stakeholders have different, sometimes opposing, interests and goals. As seen in Figure 1, decisions made by each stakeholder also influences other stakeholders as they share the city environment [18].

Residents interests are not only decreased traffic congestion, air and noise pollution, but also a high level of work and leisure opportunities. Shippers are the manufacturers or retailers of goods and send them to other business or the customers. They are especially interested in a fast delivery, a high service level and high reliability. According to Taniguchi et al., the shippers interest is an undelayed delivery process arriving at the designated arrival time while not damaging the goods [34]. CEP services, representing the freight carriers, handle most of the business to customer deliveries in city logistics. They pick up shipments at a distributing center or directly at the shipper. For delivery, CEP provider use vehicles, which are routed to the customers. In the delivery tour, they are constantly challenged with a high number of customer stops and face many problems of city traffic, e.g. uncertain traffic settings and limited parking spaces. According to Taniguchi et al. city administrators work on the overall development of the city. Their objective is to enhance the city environment for the other stakeholders [33]. Traffic congestion is a major problem for all stakeholders nowadays. According to the European Commission, 9 out of 10 Europeans believe that the traffic
situation of their city could be improved. Consequently, many cities try to optimize their traffic situation with the installation of a traffic control management.

The increase in urban population and therefore freight transports has led to the need for more city logistic research [18, 2]. Figure 2 shows a classification of current city logistic based on the City Logistic review by Kim et al. [18]. The research for each stakeholder with a city logistics research context is symbolized by a circle. If circles overlap, the research considering the overlapping stakeholders is inside the overlapping segment. The color of each circle is an indicator if research has been done. Gray if there is research and white if not. It can be seen that no research so far combines carrier, shipper and administrators. In this paper, we focus on connecting the existing VRP research, which includes mostly carrier and shipper, with the administrators.

2.2. VRP with non deterministic travel times

Because travel times are varying, city traffic is one of the major uncertainties in city logistics. The different travel duration between customers originate from traffic regulation, congestion, varying road condition, road works and also follow a daily pattern with traffic volume [8]. The travel times increase with growing traffic volume. High peaks can be observed around the commuting hours in the morning and evening of workdays. When regarding time-dependent travel times for routing, the travel times are only subject to the daytime. Travel times are also variable as unforeseeable events like accidents or changes from the expected daily patterns in traffic volume occur constantly. The CEP service must regard this in his tour planning and adjust its tours accordingly. For reliable and efficient CEP routing taking the variable travel times into account is important. In this subsection, we look first at VRP literature with stochastic travel times and then at research with time-dependent travel times. Finally, we take a look at stochastic time-dependent VRP literature.

One of the first works considering stochastic travel times was made by Laporte et al. [19]. Here, vehicles have no capacities and each customers must be served while also regarding a service time at each customer. Each vehicle
has a target time for its route with an incurring penalty if the target is not met. It is shown, that instances can be solved with a branch-and-cut approach to optimality. In 2003, Kenyon and Morton consider the routing of a fleet with stochastic travel and service times. First, they reduce the problem with simplifications and then solve the problem with branch-and-cut scheme within a Monte Carlo sampling procedure. The results show that considering stochastic travel times improves routing compared to mean travel times [17]. Taniguchi et al. simulates traffic to reduce travel costs for logistic carriers. Here, two different models were used. First, for a dynamic VRP rerouting was allowed based on variable real time traffic information. The second approach used forecasted traffic information for a preplanned route. The results of the computational testing showed that the dynamic approach reduced costs by 3.7% over the forecasted preplanned trip when conflicted with a congestion event [32]. Taş et al. studied a vehicle routing problem with stochastic travel times, time windows and service costs. The research considers a model for total transportation cost and service costs, which are essential derived from not met time windows. Taş et al. then shows that a Tabu Search algorithm, after an initialization heuristic constructs feasible tours, solves the problem with good results [35].

In 1992, Mlandraki and Daskin introduced a VRP in which the travel times depend on a function of distance and daytime [22]. Ichou et al. prove in 2003, that routing can be improved significantly by using time-dependent travel times over fixed travel times [15]. Van Woensel et al. showed in 2006 that travel times of a service provider could be improved significantly when taking time-depended travel times into account during the optimization. Therefore, the travel times are modeled with a queuing approach to traffic flows [37]. In 2010, Li et. al., studied a VRP variant with time windows and stochastic travel and services times [21]. A framework for processing FCD traffic data into time-dependent travel times has been presented by Ehmke et al. in 2010 [8]. Then, in 2012 Ehmke showed the superiority of a time-dependent vehicle routing over a preplanned static routing of 16% to 20% with a computational study [9].

According to Gao et al. [12], travel times are however both stochastic and time dependent in city logistic. Lecluyse et al. [20] advances Van Woensel et al. [37] work by adding a variability in traffic flows into the queuing approach to add a stochastic effect. A Tabu search is then implemented for the routing. The results of the computational study show that delivery routes can be more reliable and have the potential to reduce operating costs when taking the stochastic and time-dependent effect into account [20].

3. Traffic control management

As mentioned in the Section 2.1, local authorities interest is to enhance the overall prospect of their city [18, 33]. The significant growth of urban traffic has led to traffic congestion, which is one of the main reasons for diminished productivity and standard of living in cities [5]. The traffic infrastructure capacities are nevertheless physically limited. Therefore, a more efficient use of the current infrastructure is needed [27]. One option for the local authorities is the setup of a traffic control management. A TM surveils and controls city traffic infrastructure to ensure safe, efficient and effective traffic flows to minimize congestion.

The traffic infrastructure has a set of operational tools for the TM to influence a given traffic situation. As an example city traffic flows are highly depend on the traffic lights, which are part of the infrastructure [1]. The controllable infrastructure can be roughly classified into the following categories [27]:

- Traffic control lights
- Speed limits
- Lane control
- Information boards

These tools are controlled by actions. An action can be the activation of a different control plan for the intersection traffic signals. The combination of actions is a traffic control strategy. As city traffic situation are reoccurring, the TM has a set of preconfigured traffic control strategies. Each is for a specific traffic situation and is a coordinated plan for all intersection. Strategies can for example change when congestion and emissions are getting critical in certain areas or changes are set up to work with time-depending traffic volume. The TM constantly observes the traffic situation, which is described by current traffic data and forecasts. Traffic data represents traffic volumes, traffic distribution, the active infrastructure settings, weather conditions, road works, congestion, emissions status and can be measured by sensors. The traffic volume roughly follows a day- and week time pattern and can be anticipated from historical data.
Together with the current traffic data the TM can compute a detailed short term traffic and emissions forecast [29, 38]. The traffic situation is altered by events. Events are for example traffic accidents, sudden congestion or a changes in traffic and weather. Events, especially accidents and congestion, can change the traffic situation fast.

A lot of research has been made on the optimization of traffic junctions, which have the highest effect on city traffic [10]. Traffic light phases can be altered in sequence and cycle time. They can have a fixed-time strategy for given time of the day or a traffic responsive strategy, which adopts to current intersection traffic load. The intersection can work isolated or within a coordinated traffic control strategy, thus building a network out intersection for coordinating traffic light phases. This allows for example synchronized green phases, which accelerates traffic flows significantly [1]. Speed limits are used to reduce traffic flows into already congested areas. The traffic management can also close or open street lanes if the road infrastructure allows this.

The decision process by TM can be modeled as control system, as seen in Figure 3 [1]. The TM continuously monitors the traffic situation. Whenever the current traffic situation warrants a change of the traffic control strategy TM takes the associated strategy changes to ensure the best possible mobility. Consequently, the system transition into the next traffic situation. The ability to react quickly to traffic events is critical for an efficient and successful TM. This allows the best chances to keep the traffic in a free flow mode and prohibit a traffic break down. The decisions by the TM can suddenly change traffic flows. Even though, this has direct influence on routing, these TM traffic information are not communicated to companies or private persons. This research looks into if the routing efficiency of a CEP service provider can be improved with an active communication between the CEP service and the traffic control management. Consequently, we have identified the following TM information that could be beneficial when communicated to the CEP:

- Traffic situation
- Traffic control strategy
- Traffic forecast

The information about the current traffic situation, traffic strategies and traffic forecasts could improve the tour planning of a CEP fleet. The TM information would reduce the variability in the planning process compared to using time-dependent travel time data. Furthermore, it enables to react to traffic strategy changes or to include the traffic forecasts into the routing. Additionally the TM could also notify the CEP service in advance of a planned strategy change. Here, one of the major challenges will be to include the traffic control strategy information in the decision support system for the freight carrier.

4. Travel Times induced by Traffic Management

TM decisions, described in Section 3, have a major impact on travel times. Certain strategies may obstruct traffic flows in one area of the city while allowing substantial and fluent traffic in another. This has an impact on both travel
times on single street segments and travel times on links between CEP customers. Here, the links travel time result as the combination of a set of street segment travel times. So, travel times on street segments and links show an overall similar behavior. In the following, we focus on travel times between customers. In this section, we develop the impact of TM-decisions to link travel times. We shortly present the concept of stochastic and time dependent travel-times to depict the influences of TM-decisions.

For street segments, stochastic travel times in city logistic are represented by stochastic distributions like Burr III Type XII or Gamma distribution [31]. For travel time of links, these distributions have to be aggregated. Due to the aggregation, a closed form-distribution can generally not be preserved [14]. Nevertheless, the achieved distributions consist of an expected mean value $\mu$ and an implicit or explicit standard deviation.

Generalized, a travel time realization $\tau_l$ for a link $l$ can be described as the combination of the mean value $\mu_l$ and a noise-distribution $\epsilon_l$ with expected value of zero as depicted in Equation 1.

$$\tau_l = \mu_l \times (1 + \epsilon_l) \quad (1)$$

Traffic volumes and therefore travel times follow a daytime pattern. So, during rush hours, traffic flows increase leading to higher travel times. Time-dependent travel times can be described using time-indices $t \in \{0, ..., t_{max}\}$ as depicted in Equation 2. For every point in time $t$ (e.g. hourly), an individual travel time $\mu_l(t)$ allow considering daytime dependent travel time variation.

$$\tau_l(t) = \mu_l(t) \text{ with } t = \{0, ..., t_{max}\} \quad (2)$$

To achieve a representation for stochastic and time-dependent travel times, Equation 1 and Equation 2 can be combined to Equation 3. Here, for every point in time $t$, an individual travel time $\mu_l(t)$ is combined with a time-dependent noise-distribution $\epsilon_l(t)$. This distribution may vary over the day. So, during night time, stochastic variation might be relatively low.

$$\tau_l(t) = \mu_l(t) \times (1 + \epsilon_l(t)) \text{ with } t = \{0, ..., t_{max}\} \quad (3)$$

Traffic management strategies $S_1, ..., S_n$ can be defined as sets of infrastructure settings. Every strategy specifically influences link travel times by increasing or decreasing the capacity by a certain factor $f_i$. The factor is exemplary depicted in Figure 4. Here, two different strategies are applied over the day. During rush hours, the link capacity is increased to allow a fluent traffic. This behavior suits a main road and might be enabled by phased traffic lights.

![Fig. 4: Exemplary effect of TM on travel times for a link](image)

Let $\delta_l(S_i)$ be the factor for link $l$ regarding strategy $S_i$. Then, the resulting travel times additionally depend on the active strategy $S^*$. Equation 4 displays the influence of TM to the stochastic and time dependent travel time.

$$\tau_l(t) = \delta_l(S^*) \times \mu_l(t) \times (1 + \epsilon_l) \text{ with } t = \{0, ..., t_{max}\}, S^* = \{S_1, ..., S_n\} \quad (4)$$

In essence, the overall travel time depends on the active strategy $S^*$, the daytime $t$ and the realization of the stochastic noise-distribution $\epsilon$. 
5. A dynamic Vehicle Routing Problem with Stochastic Time-dependent Travel Times and TM - Information

To show that the TM provided information is an advantage for the tour planning. We examine the impact for a CEP service, who has to make multiple deliveries within a city network. In the following, we first define the problem, instances and then explain the algorithmic settings.

5.1. Problem description

In this vehicle routing problem, the vehicle has to make deliveries to a set of known customers. The delivery vehicle has to start and end its tour at a depot. The objective is minimize the overall travel time $\tau_{\text{tour}}$ while making a delivery to each customer. The vehicle routing problem is defined as a complete and undirected Graph $G = (V,E,D(t))$ consisting out of vertices $V = \{0,1,...,n\}$. The depot is located at $V_0$. $V_1,...,V_n$ represents the customers. The vehicle can transfer between vertices via the edges $E = \{(i,j)| i,j \in V, i \neq j\}$ with travel time $\tau_{ij}$ between customers $i$ and $j$. Decision points $k$ occur at the beginning of the tour, when the vehicle starts at the depot, and directly after making a delivery when the vehicle is still at the customer location. Here, we make the decision $x$ to travel to a not yet served customer $V_{\text{unserved}}$ to fulfill the delivery. The vehicle can not be rerouted when it is en route to a customer. The travel times $\tau_{ij}$ between customers are vary with different effects as described in section 4. Each customer-customer connection has a time dependent travel time $\tau(t)$. The time dependent travel times are realized over a daytime travel time function. The stochastic effects $(1+\varepsilon)$ varies the travel times of the current time-dependent travel times. For these instances we assume that the simulated TM chooses the traffic control strategies independently from traffic conditions. The TM can use three opposing strategies $S_1,...,S_3$. Each strategy is predefined and differently improves or slows traffic speeds on the edges. This results in a unique effect on the travel time matrices for each strategy. Consequently, if the simulated TM changes its infrastructure settings over the strategy, the travel times between customers changes significantly.

5.2. Instances

We define two different settings for customer location distributions and the number of customer. The two network sizes are either 16 nodes with a depot and 15 customers or in a second setting 64 nodes with a depot and 63 customers. The 64 customer network is denoted as $N_{64}$ and the 16 node network as $N_{16}$. In the first customer location setting, the customers are uniformly distributed in a network $U$. This distribution is derived from a Manhattan grid. The depot is at an outside location. In the second location setting, the customers are clustered $C$. Here, 4 clusters have short inter-cluster customer-customer connections and long travel times between customer locations of different clusters.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Network size</th>
<th>TM effect $\delta$</th>
<th>Stochastic effect $(1+\varepsilon)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>SC_1</td>
<td>16</td>
<td>1.1</td>
<td>1.1</td>
</tr>
<tr>
<td>SC_2</td>
<td>16</td>
<td>1.2</td>
<td>1.1</td>
</tr>
<tr>
<td>SC_3</td>
<td>16</td>
<td>1.1</td>
<td>1.2</td>
</tr>
<tr>
<td>SC_4</td>
<td>16</td>
<td>1.2</td>
<td>1.2</td>
</tr>
<tr>
<td>SC_5</td>
<td>64</td>
<td>1.1</td>
<td>1.1</td>
</tr>
<tr>
<td>SC_6</td>
<td>64</td>
<td>1.2</td>
<td>1.1</td>
</tr>
<tr>
<td>SC_7</td>
<td>64</td>
<td>1.1</td>
<td>1.2</td>
</tr>
<tr>
<td>SC_8</td>
<td>64</td>
<td>1.2</td>
<td>1.2</td>
</tr>
</tbody>
</table>

The stochastic effects on travel times are normal distributed in an interval depending on a percentage of the current time-dependent travel times. Here, we too look at two settings of stochastic effect size $(1+\varepsilon)$. The height of stochastic change of travel times on each edge is randomly calculated in intervals between 0-10% in one setting and between 0% and 20% in the other. The effects change constantly during the simulated delivery tour. The TM effect with the strategy implied travel time matrices either slows or accelerates a travel time on each edge by 10% or 20% and can change uniformly distributed every 15 minutes. Therefore, the travel times between customers results out of equation 4. The combination of these settings results in eight scenarios for each customer distribution as seen in Table 1.
The time-dependent travel times, the stochastic effect and the TM influence are modeled as step function. If a route is longer as a step duration and therefore transition into the next step a linearizing adjustment from Fleischmann et al. is made [11]. This assures that the first in first out properties hold and waiting does not provide benefits.

5.3. Algorithmic settings

Decision points occur at customer locations, where the dispatcher chooses the next customer in the delivery. The decision making process can be visualized with the Markov decision process as seen in Figure 5. A state $S_k$ consists out vehicle location, remaining not served customer deliveries and the currently available traffic situation. Based on this knowledge the dispatcher makes a decision $x$, which could be to travel to the next customer. Then the traffic environment $\omega$ can change and the delivery truck can arrive at a different then expected state $S_{k+1}$.

To show the effectiveness of a cooperation between a freight service provider and a traffic management, we simulate 3 different communication levels. Therefore, the truck dispatcher uses different degrees of information on the traffic situation for the routing.

- No communication $nI$
- Communication about current TM information $tm$
- Communication about current TM information and forecast $tmfc$

In a first scenario, no communication with the TM occurs. However, the dispatcher has access to time-dependent travel times, while in a second scenario, he gets information about the current setting of infrastructure. In the final scenario, he additional gets a traffic forecast from the traffic management. The dispatcher uses a 2-step nearest Neighbor heuristic in all three different settings, which was introduced by Malandraki et al. [23]. First, we use the time-dependent information $nI$. Then, we incorporate the TM information $tm$ into the routing. Here, we have not only know the time-dependent travel times, but also the settings for infrastructure. And finally, we include also include traffic forecasts into the decision making, denoted as $tmfc$. This is the reason for using a 2-step as it possible to use a different matrix for the second step. So, summarized the difference between the 3 settings is, how much information the dispatcher can include in its routing. The stochastic effects on the travel times are of course not known in the planning process. During its delivery tour the vehicle is subject to the stochastic effect, which is used when evaluating the tour travel costs $\tau_{tour}$.

6. Computational Results

For the $N_{16}$ scenarios, we run 100,000 simulations and 1,000 for the $N_{64}$. The number runs is due to the amount of stochastic effects, so that the results are not influenced by a stochastic anomaly. The runs with different settings are programmed in java and run on 2.4 GHz computer with 8 GB ram. Each instance is consequently solved by 2-step nearest neighbor routing with a degree of information: $nI$, $tm$ and $tmfc$.

The results of the computational experiments are shown in Table 2 and are normalized to the $nI$ solution with the time dependent information as this is a known approach routing literature. As expected, solution quality increases significantly regarding the degree of provided information, especially in cases, where TM has a major impact on travel times like in scenarios $SC_2$, $SC_4$, $SC_6$ and $SC_8$. Communicating the current traffic strategy have proven to substantially increase solution quality. The $tm$ solutions allow in all scenarios more efficient routing compared to $nI$ by up to 9% in the uniformed customer setting and up to 5% in the clustered customer setting. Adding information forecasts about future TM decisions further increases solution quality. For all scenarios, $tmfc$ shows the best results outperforming...
Table 2: Computational results each normalized to the \( nI \)

<table>
<thead>
<tr>
<th>Scenario</th>
<th>( U )</th>
<th>( C )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( nl )</td>
<td>( tm )</td>
</tr>
<tr>
<td>SC1</td>
<td>1</td>
<td>0.95</td>
</tr>
<tr>
<td>SC2</td>
<td>1</td>
<td>0.92</td>
</tr>
<tr>
<td>SC3</td>
<td>1</td>
<td>0.96</td>
</tr>
<tr>
<td>SC4</td>
<td>1</td>
<td>0.91</td>
</tr>
<tr>
<td>SC5</td>
<td>1</td>
<td>0.99</td>
</tr>
<tr>
<td>SC6</td>
<td>1</td>
<td>0.94</td>
</tr>
<tr>
<td>SC7</td>
<td>1</td>
<td>0.98</td>
</tr>
<tr>
<td>SC8</td>
<td>1</td>
<td>0.98</td>
</tr>
</tbody>
</table>

\( nI \) by up to 12\% for the uniformed customer distribution and up to 10\% in the clustered customer setting. Especially in the clustered customer distribution, the gap between \( tm \) and \( tmfc \) is large. Here, changes between clusters have a major impact on the overall routing quality. The forecast allow to anticipate future development and efficiently select the point of cluster change. Generally, the gap between the different levels of information decreases with the larger network. However, this most likely is due to the limitation of a nearest neighbor algorithm.

7. Conclusion

In this paper, we investigated the impact of a cooperation between city administrators traffic management and courier, express and parcel services. Regarding daytime, and events like sudden congestion, TM changes the cities infrastructure settings (strategies) to control traffic flows in city areas. These changes have a significant impact of travel times within the city. To include this impact in the planning of a CEP, we extended a vehicle routing problem with stochastic and time dependent travel times. In particular, we added the TM decisions impact to the resulting travel time realizations. For this problem, we compared routing results for different levels of communication levels of information to the CEP. The provided information could contain the currently applied strategy and a forecast for an upcoming strategy change. Routing decisions drawing on this information result in significantly more efficient tours, substantially reducing the overall travel time. In future research, the routing algorithm could be improved, explicitly considering time-dependent travel times and expected future strategy changes. Further, the problem could be extended, e.g., considering time windows or a fleet of vehicles.

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