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# Anticipating Emission-Sensitive Traffic Management Strategies for Dynamic Delivery Routing - Revision-

Felix Köster, Marlin W. Ulmer, Dirk C. Mattfeld, Geir Hasle  
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Dear Editors:

we thank you for the opportunity to revise our paper. In the new version, we have addressed the concerns of Reviewer 1 with respect to practical problem and benchmark policies. Please find the review and our detailed responses in the following.

## **Reviewer 1**

### **Review**

#### **Synopsis**

This paper has formulated a dynamic vehicle routing problem with stochastic changes of travel time matrices (DVRPMC). The authors have treated the problem as a Markov decision process model and applied a heuristic based policy selection (both fleet dispatching and path selection) with the objective of minimizing overall travel time.

This paper is a resubmission of a previous version of the same paper after addressing some of the corrections from the reviewers of the first round. I can see that most of the stated modifications has been performed.

#### **General Technical Comments**

My primary concern with this paper lies in the applicability of the solution at hand. Although the authors have acknowledged in Page 9 Line 480-482 that the Traffic Management Strategies (TMS) may have unintended consequence on the output capacities, they have failed to express a major limitation of such TMSs in reducing the emissions hotspots. Thus, the basis for the problem at hand is questionable. I would like to see a concrete example in the paper which describes a practical way of implementing a TMS

where the travel time is increased without increasing the externalities e.g. higher emissions at the bottlenecks created at the periphery of the metered cordon. If diversion of vehicles from central business districts (CBD) happens globally using variable message signs (VMS) or telematics, then the routing problem is similar to what is stated in Huang et al. (2017). I see that the authors have compared a static policy with their optimized policy. However, I would like to see a comparison provided by Huang et al. (2017) and the proposed algorithm. Also, the way authors have argued that sequencing of customers is separate from path selection is not clear to me. I would like to see a better explanation on this issue.

## Response

We thank the reviewer for the generally positive assessment of our work. The reviewer has two major concerns:

1. The assumptions made in the paper about TMS's decisions and the impact on emissions need to be justified more clearly.
2. Even though the problem addressed is stochastic and dynamic, the determination of initial routes is one part of the problem. This sub-problem is related to the work by Huang et al. (2017). A comparison with the approach in Huang et al. (2017) would further strengthen the contribution of the work.

In the new version, we address both remarks. We give a clearer justification for our assumption made. We further highlight that our static policies are in fact similar to the methods proposed in Huang et al. (2017). Please find our detailed response to the two remarks in the following.

1. The assumptions we make about the TMS base on well-known measures such as traffic light coordination. These measures have been established in the traffic research community as well as in practice for a long time. As we describe in the paper, the particular measures for our case study of Braunschweig are directly taken from Braunschweig's TMS project. We give one example in Figure 8(b) of our paper. For all details of the project, we refer to UVM (2015a,b) and to <http://www.uvm-bs.de/>.

Another interesting question, the reviewer raises, is whether the TMS's decisions do not lead to increased overall emissions because vehicles are redirected. Our response is twofold:

- First, the TMS focuses mainly on nitrogen oxides (NO<sub>x</sub>). Different than for example CO<sub>2</sub>, NO<sub>x</sub> is not easily distributed by wind but accumulates in local hot spots. Furthermore, NO<sub>x</sub> in high

concentration is a major health risk. Thus, the TMS' objective is to avoid high local NO<sub>x</sub> concentrations. We compare in Figure 9 and in Figure 11 the traffic in hot spots during times of critical concentration. We show that vehicles avoid these areas leading to a more leveled emission.

- Second, we agree that the reviewer's concern could be valid, that reducing emissions in a small area of the city may it may significantly increase overall emissions. To show that this is not the case, we analyze the impact on CO<sub>2</sub> in Section A3 in the Appendix. We calculate the CO<sub>2</sub> emissions based on assumption of Ehmke et al. (2016), Huang et al. (2017) and show that we are able to reduce emissions even though the objective of the logistic service provider is not the reduction in emissions.
2. We thank the author for this helpful remark. Even though the focus of our work is on dynamic real-time control of vehicles during the day, determining initial tentative routes is one part of the algorithm. A suitable determination is also important because we use a static policy as a benchmark to evaluate the impact of dynamic control. As indicated in the previous version of the paper, we follow Huang et al. (2017) in the determination of the static routes. We have now clarified this in the new version of the paper. Huang et al. (2017) address a static and deterministic problem with time dependent travel times as well as a static and stochastic extension. The sequence of customers is static (A-B-C-D), but the paths can differ. More specific, they allow different paths between the customers A and B, B and C, C and D based on the time-dependent or stochastic travel times. To this end, they used a modified Dijkstra-algorithm to determine the shortest paths. They do not allow the change of the customer sequence, for example A-C-B-D. In our work, we allow both: In every decision point, we allow reordering the sequence of remaining customers *and* we consider path flexibility between customers. In our case, the shortest path between two customers can change due to a change of the travel time matrix. As Huang et al. (2017), we incorporate this path flexibility by using the modified Dijkstra-algorithm.

Huang et al. (2017) extend their work by incorporating stochastic travel times. Again, their solution is a static route but with flexible paths between the customers. They solve small instances with a two-stage stochastic program and develop a "Route-First, Path Second"-heuristic. In this heuristic, they determine the best route based on expected travel time values. In their evaluation, the path is then selected based on the travel time realization. This heuristic achieves optimal solutions in 9 of 10 cases. In our paper, we use the same idea

for our static policies. We fix the sequence of customers but allow path flexibility. However, calculating the expected travel time values is challenging because of the connection between travel times and the stochastic emissions. Thus, we sample travel time realizations and determine our paths on the sampled values. As Huang et al. (2017), we allow path flexibility in our evaluation.

In the new version of the paper, we updated the literature review and now discuss this relationship in more detail. We also refer to it in the motivation and definition of our benchmark policies. We thank the reviewer for this remark. It helps to further embed our work in the literature and to strengthen the contribution.

### Specific Comments

1. Abstract: The abstract contains more information than necessary especially on how TMS works. The authors need to clearly state what is done in the paper, how it was done, some numeric results, and some clear implications.
2. Page 2 Line 97: Strange use of the phrase “coordinated traffic light interval”. Suggested phrase “improved coordination of traffic signals”
3. Page 7 Line 366: “. . . trajectory of has a peak above action level . . . .” missing word/s between ‘of’ and ‘has’
4. Figure 3 and 4: Needs more description in the figure caption rather than the main text.
5. Page 22 lines 1190-1196: Consider revising. Speed does not decrease monotonically with capacity, neither does emissions. Please be cognizant of these basic non-linear relationships throughout the paper.
6. Figure 9: Add descriptions of C and F in the caption. Need more discussion on why the travel time did not reduce in “Polluted” areas under static policies. It may not be this intuitive for the readers.
7. Figure 10: consider revising caption- “Reduction of (?) with respect to . . . .”

### Responses:

1. We updated the abstract with respect to your recommendations.
2. Thank you. We changed it to “coordinately changing the traffic light intervals in the affected area.”
3. Thank you. We removed the “of”.

4. Thank you. We followed your suggestion and extended the description of the figures.
5. We are unsure about the remark. We do not assume linearity in our speeds and/or emissions. As we state throughout the paper, we analyze a variety of different speed patterns based on the TM-decision. Our emissions follow a stochastic Gaussian process based on historical observations.
6. Thank you. We followed your suggestion and extended the description of the figure.
7. Thank you. We followed your suggestion and extended the description of the figure.

## References

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- Huang Y, Zhao L, Van Woensel T, Gross JP (2017) Time-dependent vehicle routing problem with path flexibility. *Transportation Research Part B: Methodological* 95:169–195.
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Highlights for *Anticipating Emission-Sensitive Traffic Management Strategies for Dynamic Delivery Routing*

- First paper considering traffic management decisions in dynamic vehicle routing
- Comprehensive Markov decision process model allowing the consideration of stochastic and correlated travel times
- Dynamic routing policies anticipating potential future traffic management decisions
- Comprehensive case study for the city of Braunschweig based on a real-world street network, realistic traffic management, and historic emission developments
- High quality solution with benefits for logistic service providers and traffic management

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# Anticipating Emission-Sensitive Traffic Management Strategies for Dynamic Delivery Routing

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## Abstract

Traffic pollution is an increasing challenge for cities. Emissions such as nitrogen dioxides pose a major health threat to the city's inhabitants. These emissions often accumulate to critical levels in local areas of the city. To react to these critical emission levels, cities start implementing dynamic traffic management systems (TMS). These systems dynamically redirect traffic flows away from critical areas. These measures impact the travel speeds within the city. This is of particular importance for parcel delivery companies. These companies deliver goods to customers in the city. To avoid long delivery times and higher costs, companies already adapt their routing with respect to changing traffic conditions. Still, a communication with the TMS may allow anticipatory planning to avoid potentially critical areas in the city. In this paper, we show how communication between TMS and delivery companies results in benefits for both parties. To exploit the provided information, we develop a dynamic routing policy anticipating potential future measures of the TMS. We analyze our algorithm in a comprehensive case study for the TMS of the city of Braunschweig, Germany, a city often used as reference for a typical European city layout. We show that for the delivery company, integrating the TMS' information in their routing algorithms reduces the driving times significantly. For the TMS, providing the information results in less traffic in the polluted areas.

*Keywords:* Dynamic Vehicle Routing, Emissions, Traffic Management, Stochastic and Correlated Travel Times

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## 1. Introduction

The demand for city transportation, individual and freight, is increasing through continuous growing e-commerce and urbanization. This general increase in transportation has led to substantial challenges for both urban municipalities and logistic service providers. Both parties operate within the urban traffic environment and an information exchange suggests itself. However, a communication has not been established yet. In this research, we analyze how the exchange of information, more specific, the provision of traffic control information from the urban municipalities to the service providers leads to benefits for both parties' objectives.

Urban municipalities need to enable effective and efficient transportation. Still, they also need to provide a livable environment for the citizens without pollutions (Zhou et al. 2015). As an example, an EU regulation limits the yearly average air pollution in cities to  $40 \mu\text{g}/\text{m}^3$  of  $\text{NO}_2$  (EU 2015). To enforce these regulations, many German cities like Braunschweig or Potsdam install *emission-sensitive online traffic management systems* (TMS) to dynamically control traffic flows based on current and expected emission levels (Diegmann et al. 2010). The city's TMS constantly monitors the pollution levels in hot-spot areas, where the emissions tend to be critical (Boltze and Kohoutek 2010, Celikkaya et al. 2016). If the emission levels exceed a threshold, the TMS changes the *traffic strategy* (Han et al. 2015). These changes reduce and/or increase traffic capacity in certain areas of the city by adapting traffic light programs and speed controls. In essence, access to polluted areas is limited while traffic around and out of the hot-spots areas is accelerated by coordinately changing the traffic light intervals in the affected area. These traffic strategies are dynamically changed during the day with respect to emission levels. Furthermore, the emissions are subject to stochastic elements like weather conditions and congestion. In many cases, reliable predictions of future emission levels are possible only for a limited time horizon.

Major producer of urban emissions is the freight transport sector, especially

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Courier, Express and Parcel companies (CEPs). According to the US Environmental Protection Agency, CEPs account for about 20% of the CO<sub>2</sub> emissions of all mobile sources, and for about 50% of the NO<sub>x</sub> and nearly 40% of the PM<sub>x</sub> emissions (Inventory 2005). Recently, CEPs initiate eco-friendly programs (DHL 2016, UPS 2016). Nevertheless, in practice, CEPs often ignore emissions in their transport activities due to the high cost-pressure keeping in mind that last-mile delivery is responsible for more than 50% of the overall delivery costs (Bernau et al. 2016). Hence, CEPs optimize and update their delivery routes with respect to delivery costs (Ehmke et al. 2016a). One of the main costs factors are the drivers' working times. Because TMS decisions impact the travel times within the city, these costs indirectly depend also on emissions. More specific, a traffic strategy may change an individual shortest path and/or the travel time between two customers. Each traffic strategy induces an individual travel time matrix and a change in the traffic strategy may render a current routing plan inefficient. Furthermore, a mere reaction to new information may be insufficient. Anticipation of potential future changes is necessary. There are two measures to avoid inefficient planning by anticipation. The TMS can communicate the next planned decisions to the service provider and the provider can estimate potential future decisions based on current information by means of predictive analytics. The derived information needs then to be integrated in the planning algorithm.

In this research, we present dynamic routing policies for CEPs anticipating potential traffic strategy changes. We focus on a CEP-routing problem where the TMS provides information about the current and the near-future traffic strategy. The problem under consideration can be defined as *dynamic vehicle routing problem with stochastic changes of travel time matrices* (DVRPMC). A fleet of vehicles delivers goods to a set of customers. A set of travel time matrices is given, each representing a traffic strategy. Initially, the goods are assigned to the vehicles. While the vehicles are on the road, the traffic strategy and, therefore, the travel time matrix changes based on stochastic emission developments. At any point of time, the dispatcher has access to the current

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175 and near-future traffic strategy as well as the current emission levels. Based on  
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177 90 this information, the dispatcher can dynamically adapt the planned routes for  
178 each vehicle of the fleet. The objective is to minimize the expected travel times  
179 for delivery.  
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181 In the according Markov decision process model of the DVRPMC, we experi-  
182 ence curses of dimensionality in all capacities. The number of states is vast  
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184 95 because of the exponential increase with respect to the number of customers.  
185 The information space models the potential emission changes and is therefore  
186 continuous. Finally, the action space is large since it incorporates routing deci-  
187 sions. To account for the large state and information space, in every decision  
188 point, we apply a heuristic policy sampling emissions and evaluating current  
189 decisions with potential future developments. To account for the large action  
190 100 space, our policy identifies *critical* areas in the matrix with potentially long  
191 travel times. We incorporate these areas in the travel time matrix in such as  
192 way that we can solve the resulting model with state of the art routing software  
193 for delivery planning. The solution determines the current routing plan and the  
194 next customer to visit.  
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199 We evaluate our method for a case study for the City of Braunschweig,  
200 Germany. Braunschweig represents the layout of a “standard” medium-sized  
201 city and is therefore often used as reference city in mobility research (DLR 2017).  
202 We draw on historical emission observations and test the policy for instance  
203 settings varying in the number of vehicles and the TMS’s impact. We compare  
204 110 our policy with static routing and dynamic routing on current information. Our  
205 analysis provides two main managerial implications:  
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- 209 1. Our anticipatory dynamic routing method reduces travel times for the  
210 CEP on average by 6.8% and up to 16.0%. The reduction is particularly  
211 115 high if the number of deliveries per vehicle is large and the impact of the  
212 TMS’s decisions is high.  
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- 214 2. A cooperation between city’s TMS and CEP leads to an average reduction  
215 of CEP-traffic in polluted areas by 54.6%. The cooperation is therefore  
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231 highly beneficial for both parties.  
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234 120 Our contributions are as follows. This paper is the first quantifying and  
235 analyzing how a cooperation of traffic management and CEP lead to benefits  
236 for both. With the DVRPMC, we provide a new and relevant dynamic routing  
237 problem reflecting emissions and TMS in the decision making. We further pro-  
238 vide a comprehensive Markov decision process model enabling the depiction of  
239 stochastic *correlated* travel times, a feature generally neglected in the literature.  
240 125 Our work is similar to the recent suggestion by Gendreau et al. (2016) to draw  
241 on a “set of suitable designed scenarios” for different travel time patterns.<sup>1</sup> Our  
242 presented solution method is able to incorporate correlation and significantly  
243 improves solutions with respect to the objectives of CEP and TMS.  
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247 130 This paper is outlined as follows. We present TMS in §2. In §3, we model  
248 the DVRPMC as a Markov decision process. We present our policy and the  
249 benchmark heuristics in §4. In §5, we compare the policies for a case study of  
250 the City of Braunschweig. The paper concludes with a summary and an outlook  
251 in §6.  
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## 256 135 **2. Traffic Management**

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258 In this section, we describe how the TMS changes their strategies and how a  
259 strategy changes the travel times within the city. The TMS controls the urban  
260 traffic flows with respect to many different influencing factors such as commuter  
261 travel, accidents, and congestion. Recently, TMS additionally considers the  
262 emission levels within the city which are often highly volatile and require short-  
263 140 term reactions. In this paper, we focus on the TMS’ decision making with  
264 respect to these emissions. We first depict how the TMS monitors the emissions  
265 at hot-spots within the city. We then show how these emissions impact the  
266 traffic strategy.  
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271 <sup>1</sup>For a comprehensive literature review, we refer to §A.1 in the Appendix.  
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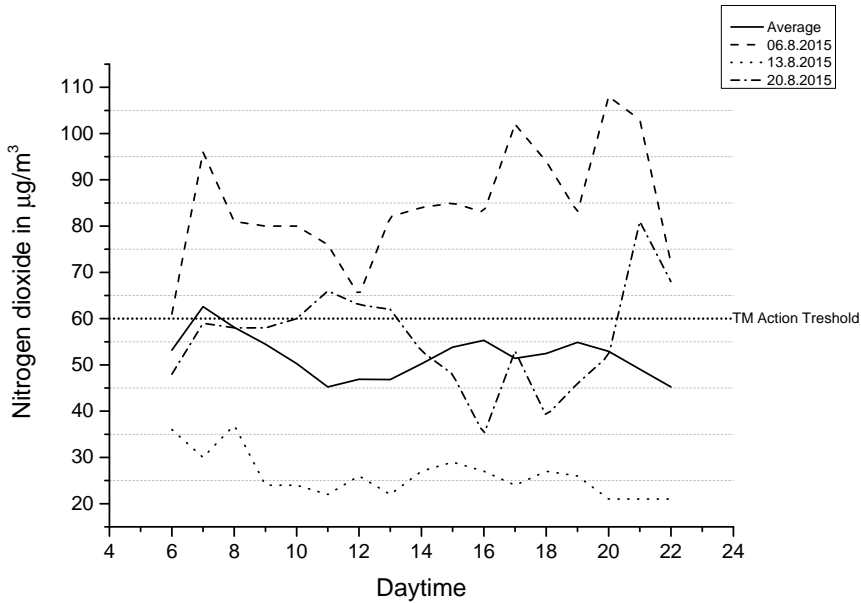


Figure 1: Three different  $\text{NO}_2$  trajectories

145 *2.1. Emission Monitoring*

In the city area, a set of hot-spot stations is given:  $\mathfrak{S} = \{\sigma_1, \dots, \sigma_m\}$ , each monitoring an individual local emissions behavior  $N(\sigma) \in \mathbb{R}_+$ . The emissions are monitored at certain measurement times  $\mathcal{I} = \{I_1, \dots, I_{\max}\}$ . In Braunschweig, the emissions are measured every hour.

150 The values of  $\text{NO}_2$  over the day show a stochastic behavior. To display the volatility and stochasticity, we analyze three consecutive Wednesdays for Braunschweig along with the average of the data set in Figure 1. The graph shows the  $\text{NO}_2$  pollution in  $\mu\text{g}/\text{m}^3$  on the y-axis and the time of the day on the x-axis. The threshold forcing a reaction of the TMS is  $\tau = 60$ , indicated  
 155 by the dotted horizontal line. In two out of three trajectories, we observe a morning peak at 8 a.m., followed by a drop around noon and a rise in the later afternoon to evening. This roughly corresponds to commuting traffic. However, we observe major differences for all three trajectories. The trajectories of the 6<sup>th</sup> of August shows high emission levels the entire day. One week later, the

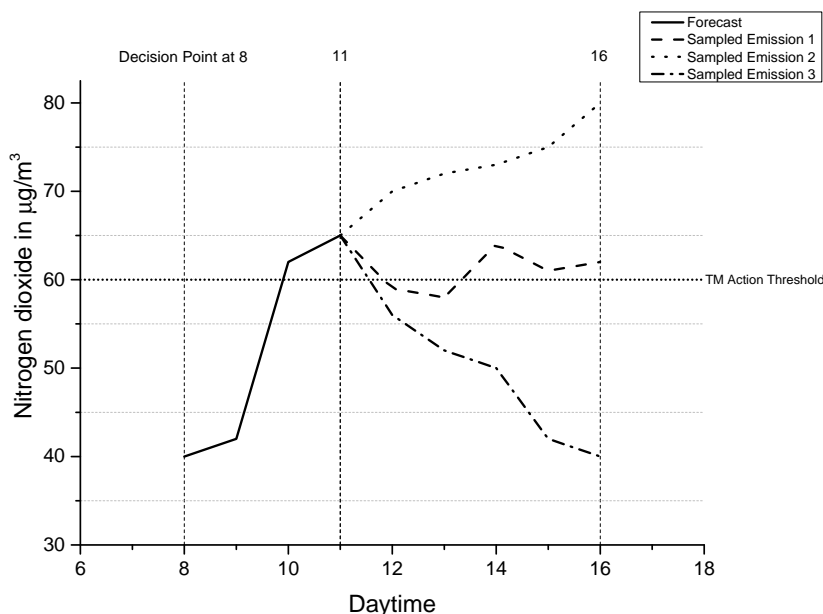


Figure 2: Emission Forecast and Three Potential Emission Developments

160 pollution is low with about  $25 \mu\text{g}/\text{m}^3$ . On the 20<sup>th</sup> of August, the trajectory  
 166 has a peak above action level from 10 a.m. to 2 p.m. Thus, each individual  
 167 trajectory may lead to a significantly different reactions of the TMS.

169 Usually, the TMS is able to forecast the emission developments  $\mathcal{N}_F$  for a  
 170 certain horizon  $F$ . That means that within this horizon, the emission devel-  
 172 opment can be estimated with high accuracy. After this horizon, the emission  
 173 development is uncertain.

175 Figure 2 shows an example of this forecast and three potential later emission  
 176 developments at one station. The current point of time is 8 in the morning. The  
 177 current emission level is 40. In this example, a forecast horizon of 3 hours is  
 178 assumed. That means that until 11 a.m., the development of the emissions is  
 179 known. This is indicated by the solid line. In the example, the emission level  
 180 rises above the threshold at 10 a.m. At this point of time, the TMS needs  
 181 to react. After 11 a.m., the development is uncertain. Figure 2 shows three  
 182 potential realizations, each leading to different reactions by the TMS. The first

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175 development indicated by the dashed line leads to two additional reactions. The  
second development indicated by the dotted line leads to no further reactions  
(at least no changes induced by this station). The third development leads to a  
change from active to inactive again.

If the emission level  $N(\sigma)$  at station  $\sigma$  exceeds the threshold level  $\tau$ , the  
180 status of this area is set to “active”. This status change forces a reaction to avoid  
further pollution in this area. If the emission level drops under the threshold  
value, the status is set to “inactive” again. Consequently, each hot-spot has two  
statuses.

2.2. *Traffic Strategy*

185 In case the threshold for one or several hot-spots is exceeded, the traffic  
management reacts. Each reaction activates a specific *traffic strategy*. A traffic  
strategy is an orchestrated set of traffic actions such as traffic light or speed  
control. The aim of a traffic strategy is to allow a steady flow out of a critical  
area and to avoid further flows into this area.

190 The statuses of all hotspots can be modeled as an  $m$ -dimensional binary  
vector. Each vector results in an individual traffic strategy. Thus, the overall  
set of strategies is at most  $2^m$ . In the following, we describe in a small example  
how a status-change of a hot-spot changes the traffic strategy. Figure 3 shows  
a network with only one hot-spot station and therefore two potential strategies.  
428 The network in this example is a Manhattan-style-grid of overall 40 segments.  
195 The hot-spot station is located in the center of the grid and is indicated by  
the triangle. This one hot-spot station leads to two potential strategies. These  
strategies vary in the travel time on each segment. The travel time is either 5  
433 , 10, or 20 minutes per segment, indicated by the solid black, solid grey, and  
434 dashed black line. The “inactive” Strategy 1 allows the same travel time of 10  
200 minutes on all segments of the network indicated by the grey lines. The sec-  
436 ond, “active” strategy leads to heterogeneous travel times within the city. This  
437 strategy aims on avoiding downtown traffic around the hot-spot. Thus, around  
438 the hot-spot, the travel times per segment is increased to 20 minutes while at

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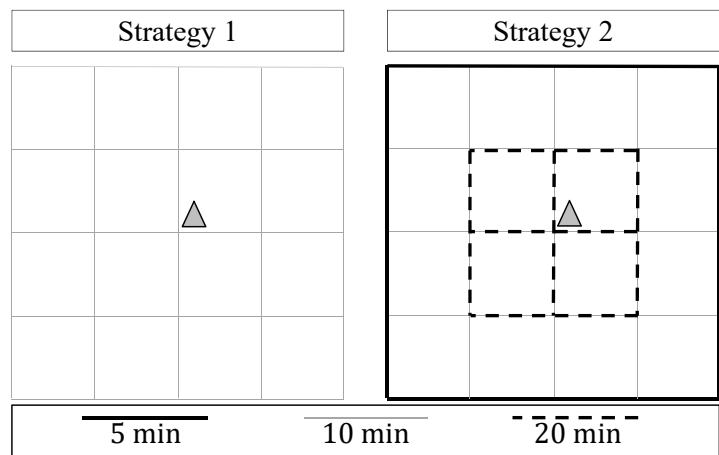


Figure 3: Example of a Hot-Spot Station and two Strategies: The example depicts a Manhattan-grid network. The hot-spot is indicated by the triangle in the center. The line types indicate different travel times for different segments of the network.

205 the outskirts of the network, the travel times are reduced. A communication of this information by the TMS incentivizes drivers to avoid downtown and use the fast alternative segments.

For the purpose of presentation, Figure 3 is a simplified depiction. The traffic strategies are more complex than depicted in the example. First of all, the example ignores that the flow capacity out of the critical central area is usually increased while the capacity into the area is decreased. Second, there are usually several hot-spot stations distributed in the city.

### 3. The DVRPMC

In this section, we define the dynamic vehicle routing problem with stochastic changes of travel time matrices (DVRPMC). We first give a problem statement. We then define the problem as a route-based Markov decision process (MDP, Ulmer et al. 2016). We end this section with an example of the MDP.



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### 3.1. Dynamic Vehicle Routing Problem

The problem under consideration is a parcel delivery problem where a fleet of vehicles delivers parcels to a set of customers. Initially, the parcels are distributed to the vehicles. Over the day, the parcels are delivered. For each vehicle, the route may be dynamically adapted due to newly revealed travel time information.

Mathematically, a fleet of  $o$  vehicles  $\mathcal{V} = \{v_1, \dots, v_o\}$  delivers goods to a set of known customers  $\mathcal{C} = \{C_1, \dots, C_n\}$ . (In the case study in §5, a customer represents a *district* within the city.) The network is defined as a complete Graph  $G = (\nu, \epsilon)$  consisting out of nodes  $\nu$  and edges  $\epsilon$ . The customers  $\mathcal{C}$  are located on a subset of the nodes. Node  $D$  represents the depot. Each customer has the same service time  $t^s$ . The travel time matrix  $M$  between the customers is stochastic and depends on the traffic strategies introduced in §2. Each strategy induces a travel time matrix. In the event that a vehicle is on the road during a strategy change, the remaining travel time is determined by the function  $\Delta$ . Function  $\Delta(M_{\text{old}}, M_{\text{new}}, C_{\text{origin}}, C_{\text{destination}}, \delta)$  bases on the old and new matrices  $M_{\text{old}}, M_{\text{new}}$ , the corresponding customers the vehicle traverses between  $C_{\text{origin}}, C_{\text{destination}}$ , and the time already spent on the connection  $\delta$ . This function  $\Delta$  may be chosen freely. In our computational experiments, we model this function by considering the current position of the vehicle in the city's street segments. We then draw on the Dijkstra-procedure for time-varying travel times from Fleischmann et al. (2004).

There are two types of decision making. First, the dispatcher decides about the initial assignment of goods to vehicles. This assignment is permanent because the goods are loaded to the vehicles. Second, for each vehicle, the dispatcher dynamically routes the vehicles. To this end, the dispatcher initially determines a route  $\theta = (D, C_1^\theta, \dots, D)$  serving all assigned customers and returning to the depot. Over the day, the matrix  $M$  may change several times. This instantly changes the travel times for all vehicles. This change also impacts a vehicle currently traversing between two customers. The sequence of customers of a vehicle can only be changed when arriving at a customer. Be-

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cause dispatcher and drivers usually communicate via mobile phones, we do not allow diversions. When the vehicle arrives at a customer, this customer is serviced and, therefore, neglected in future considerations. At this point, the dispatcher can update the route of this vehicle. The objective is to minimize the expected sum of travel times for all vehicles.

### 3.2. Markov Decision Process

255 The DVRPMC is a stochastic and dynamic vehicle routing problem and can be modeled as a route-based Markov decision process. In a Markov decision process, decision states are connected by decisions and stochastic transitions. In each decision state, a decision is determined and the revelation of stochastic information leads to the next decision state.

260 For the DVRPMC, the initial state  $S_0$  consists of the set of customers  $\mathcal{C}$  and the current travel time matrix  $M_0 \in \mathcal{M}$  of the overall set of travel time matrices  $\mathcal{M}$ . In the initial decision, the goods of the customers are distributed to the vehicles. After that, the assignment of customers is permanent. Thus, the MDPs for the vehicles are independent and we can consider each vehicle individually.

A vehicle starts and ends its tours at the depot  $D$ . A decision point  $k$  occurs if the vehicle is located at a customer. A state  $S_k = (t_k, l_k, \mathcal{C}_k, \theta_k, M_k, N_k)$  consists of the point of time  $t_k$ , the vehicle's current location  $l_k$ , the customers still to visit  $\mathcal{C}_k \subseteq \mathcal{C}$ , the current planned tour  $\theta_k$ , the active travel time matrix  $M_k \in \mathcal{M}$ , and the vector  $N_k$  representing the current emission levels for every station  $\sigma \in \mathfrak{S}$ . Decisions  $x_k \in \mathcal{X}(S_k)$  are made on the routing update  $\theta_k^x$  and therefore the next customer to visit  $C_{next}$ . The costs of the decision is the travel time  $R(S_k, x)$  to the next customer  $C_{next}$ . Notably,  $R(S_k, x)$  is a random variable due to possible matrix changes. The stochastic transition  $\omega_k$  consists of the vehicle traveling to the next customer, serving the customer, and a potential change of the active travel time matrix. Thus,  $\omega_k$  changes the time  $t_{k+1}$  to the point of time the vehicle is located at location  $l_{k+1}$  of the now served customer  $C_{next}$ . The new planned route  $\theta_{k+1}$  is set as  $\theta_k^x$  without  $C_{next}$ . The point of

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623 time  $t_{k+1}$  is uncertain due to potential stochastic matrix changes. It further  
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280 changes the emission levels of vector  $N_k$  and the according matrix  $M_k$  to  $M_{k+1}$   
625 and  $N_{k+1}$ . The new state is then  $S_{k+1} = (t_{k+1}, l_{k+1}, C_{k+1}, \theta_{k+1}, M_{k+1}, N_{k+1})$ .  
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627 A termination state  $S_K = (t_K, D, \emptyset, \theta_K, M_K)$  is given in case  $C_K = \theta_K = \emptyset$  and  
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629  $l_K = D$ .

630 A solution for the DVRPMC is a decision policy  $\pi \in \Pi$ . A policy  $\pi =$   
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632  $(X_0^\pi, \dots, X_{K-1}^\pi)$  is a sequence of decision rules  $X_k^\pi$ . For a state  $S_k$ , a decision  
633 rule determines the according decision  $x = X_k^\pi(S_k)$  to take. The objective of the  
634 DVRPMC is to find an optimal policy  $\pi^*$  that minimizes the expected overall  
635 travel time as depicted in Equation 1.  
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$$638 \quad \pi^* = \arg \min_{\pi \in \Pi} \mathbb{E} \left[ \sum_{k=0}^K R(S_k, X_k^\pi(S_k)) | S_0 \right] \quad (1)$$

### 641 3.3. Example

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290 In the following, we give an example for the MDP. We draw on the same  
643 network introduced in §2. In the example, we consider one vehicle and two  
644 customers still to serve. The locations of the vehicle, customers, the depot, and  
645 the current planned tour are depicted in Figure 4. The vehicle is indicated by  
646 the grey circle, the customers by the black circles, and the depot by the square.  
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648 The state is depicted on the left. For the purpose of presentation, we omit  
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650 further state information such as point of time or emissions. As we can see,  
651 the current traffic strategy is Strategy 1 from the example in Figure 3. This  
652 strategy results in homogeneous travel times for each segment. In the center  
653 and on the right side of Figure 4, two potential decisions are shown. Decision  
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655  $x_1$  determines the visit of Customer 2 followed by the visit of Customer 1. The  
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300 planned tour leads through the city center. Decision  $x_2$  reverses the sequence  
657 of visits. The planned tour avoids the city center. Once a decision is made,  
658 the vehicle starts traveling to the first customer of the tour. During travel, the  
659 traffic strategy and thus the arrival time and travel time matrix may change.  
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661 The next decision point occurs when the vehicle has served the next customer.  
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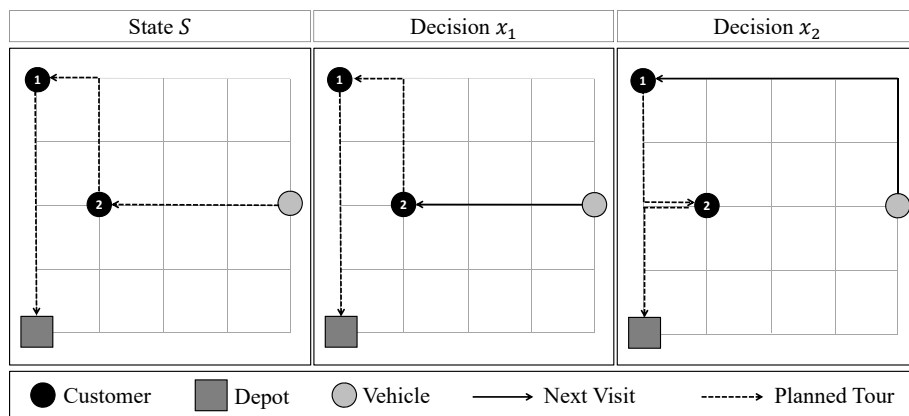


Figure 4: Example of the Markov Decision Process: The figure depicts a decision state and two potential routing decisions.

#### 4. Method

In this section, we describe our method. We first give a brief motivation why anticipation is beneficial. We then present the steps of the method process in one decision point as well as the algorithmic procedure. Finally, we describe the tuning of the algorithm and the benchmark policies.

##### 4.1. Motivation

Solving the MDP by recursion is hardly possible due to the curses of dimensionality. The state space is vast because a state contains the set of customers to visit as well as the (continuous) emission levels at all stations. The number of decisions is large because decisions are made about the update of route  $\theta_k$ . Finally, the transitions reveal new emission levels. Thus, the number of potential transitions is nearly infinite and the expected travel times are difficult to calculate. Instead of solving the MDP, we present a heuristic method. This method aims on minimizing the expected travel time while avoiding “critical” areas likely to be impacted by changes in the emission level and the travel time matrices, respectively. Revisiting the examples in Figure 3 and Figure 4, we see that, based on the current travel time matrix, decision  $x_1$  leads to a planned tour duration of 100 minutes. Decision  $x_2$  leads to a duration of 120 minutes.

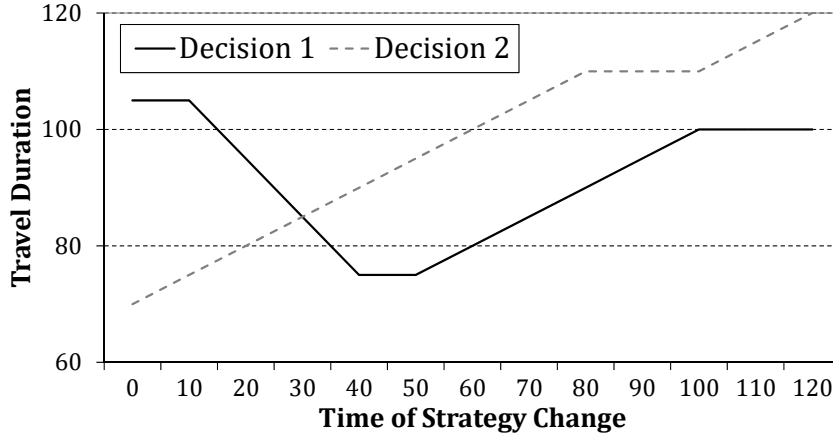


Figure 5: Impact of Strategy Change on Routing Decisions

Still, in case the emission level downtown is exceeded and the TMS changes to Strategy 2, these durations may change.

Figure 5 shows the realized travel duration for each decision assuming a strategy change and ignoring any service times. For the sake of simplicity, we ignore potential future routing updates and only look at one potential change. The x-axis depicts the (future) time when the change to Strategy 2 occurs. The y-axis shows the according travel duration for decisions  $x_1$  and  $x_2$ . Comparing the two decisions, we observe that an early change may lead to a longer duration for Decision 1 and a shorter duration for Decision 2. Decision 2 avoids the critical downtown area only operating on the outskirts. If the time until the strategy change increases, this behavior changes. Furthermore, we observe that Decision 1 highly profits from a strategy change in about 50 minutes. At that point of time, the vehicle has left the downtown area. Now, it can exploit the faster travel in the outskirts resulting from Strategy 2. In essence, we see that the quality of a decision significantly depends on the changes in the traffic strategies. Anticipation of future changes is necessary.

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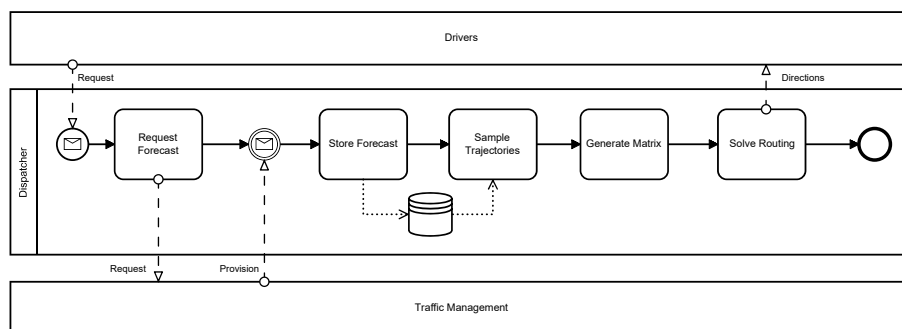


Figure 6: BPMN-Model of the Decision Process

#### 340 4.2. Procedure

In this section, we give a general overview over the procedure applied in the decision process. We provide algorithmic details in the next section. To anticipate future changes, we can draw on two different sources of information: the forecast provided by the TMS as well as information derived from the stochastic emission process. In this section, we describe how our methods uses both sources of information to derive a routing decision. To this end, our method draws on the given information by the TMS and samples potential emission developments over the day. These sources of information are used to derive an anticipatory travel time matrix. Based on this matrix, our policy applies an industrial standard solver to minimize the duration of the updated routing (Hasle and Kloster 2007).

The process is described in Figure 6 using the business process model and notation-language (BPMN). Figure 6 shows the three participants, the drivers, the dispatcher, and the traffic management. The process starts when a driver requests new directions from the dispatcher. At that point of time, the dispatcher requests a forecast from the traffic management. Once the forecast is provided, it is stored and used to generate samples of potential future emissions. Each of these samples provides a development of travel time matrices for the remaining customers, the driver still needs to serve. Based on these matrices, a “target” matrix is determined to allow the application of the standard

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847 solver. The routing update resulting from the solver is then communicated to  
848 the driver.  
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#### 851 4.3. Algorithm

852 Pseudocode of our method is presented in Algorithm 1. Inputs of the algo-  
853 rithm are the point of time  $t_k$ , the end of the sampling horizon  $t_{\max}$ , a current  
365 854 location  $l_k$ , the set of customers to visit  $\mathcal{C}_k$ , the current emission level  $N_k$ , and  
855 the set of  $\iota$  measurement times  $I_1, \dots, I_\iota$  with  $t_k \leq I_1 < I_2 < \dots < I_\iota \leq t_{\max}$ .  
856 Notably, we do not assume a time limit for the vehicles but our method requires  
857 an estimate  $t_{\max}$  when the vehicles returned to the depot. This estimate is  
858 necessary to determine how far the emissions need to be sampled. Because the  
859 exact time depends on future realizations and decisions, it cannot be determined  
370 860 with certainty but is approximated by a heuristic.  
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862 The algorithm generates  $H$  potential trajectories of emissions  $\tilde{N}^i, i = 1, \dots, H$ .  
863 A trajectory is generated by function *GenerateTrajectory()* with input param-  
864 eters  $N_k$ , the forecasted emission levels  $\mathcal{N}_F$  and  $\mathcal{I}$ . Notably, each trajectory is a  
375 865  $m \times \iota$ -dimensional matrix of emission values. Each entry represents the emission  
866 in one of the  $\iota$  measurement times at one of the  $m$  stations. The generation  
867 of the trajectories relies on the information given by the traffic management  
868  $\mathcal{N}_F$  until the forecasting horizon  $F$ . After the horizon, the algorithm samples  
869 emissions.  
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871 In each measurement point, each trajectory  $\tilde{N}$  induces a traffic strategy and  
872 therefore a travel time matrix  $M(I, \tilde{N})$  for the set of customers  $\mathcal{C}_k$  and the cur-  
873 rent location  $l_k$ . These matrices are generated with function *GenerateMatrix()*  
874 with input the current emission levels  $\tilde{N}$ , the set of customers  $\mathcal{C}_k$ , and the lo-  
875 cation of the vehicle  $l_k$ . Overall, the algorithm obtains  $\iota \cdot H$  matrices. These  
385 876 matrices are summarized to a single target matrix  $M^*$  by taking the average of  
877 the individual matrices' values.  
878

879 Based on this matrix  $M^*$ , we determine the routing with minimal travel du-  
880 ration by function *Solve()*. The obtained route  $\theta_k^x$  is the update of our routing.  
881 This routing is implemented until the next decision point occurs.  
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**Algorithm 1: Anticipatory Routing Algorithm**

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**Input :** Point of Time  $t_k$ , End of Time Horizon  $t_{\max}$ , Current Location  $l_k$ , Customers  $\mathcal{C}_k$ , Current Emission Level  $N_k$ , Forecasted Emission Levels  $\mathcal{N}_F$ , Measurement Times  $\mathcal{I}$

**Output :** Routing Update  $\theta_k^x$

- 1  $h \leftarrow 1$
- 2 // Initialization
- 3  $M^* \leftarrow 0_{|\mathcal{C}_k|+1, |\mathcal{C}_k|+1}$
- 4 **while**  $h \leq H$  // For the Number of Samples
- 5 **do**
- 6      $\tilde{N} \leftarrow 0_{m, \iota}$
- 7      $\tilde{N} \leftarrow \text{GenerateTrajectory}(N_k, \mathcal{N}_F, \mathcal{I})$  // Generate Trajectory
- 8      $i \leftarrow 1$
- 9     **while**  $i \leq \iota$  // Generate Matrices
- 10     **do**
- 11          $M \leftarrow 0_{|\mathcal{C}_k|+1, |\mathcal{C}_k|+1}$
- 12          $M \leftarrow \text{GenerateMatrix}(\tilde{N}_i, \mathcal{C}_k, l_k)$
- 13          $M^* + = \frac{1}{H \cdot \iota} M$  // Update Target Matrix
- 14          $i \leftarrow i + 1$
- 15     **end**
- 16      $h \leftarrow h + 1$
- 17 **end**
- 18  $\theta_k^x \leftarrow \text{Solve}(l_k, \mathcal{C}_k, M^*)$  // Solve Routing Problem
- 19 **return**  $\theta_k^x$

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Notably, for the first decision point of the DVRPMC, the customers need to be distributed to the vehicles before the vehicles leave the depot. To determine the initial distribution, we apply the same procedure. We estimate the future development and determine the routing that minimizes the according travel times.

#### 4.4. Tuning

In the following, we describe the functions of Algorithm 1 in detail.

**Determination of the Horizon** The value  $t_{\max}$  should reflect the point of time the vehicle is assumed to have returned to the depot. To determine  $t_{\max}$ , we solve the routing problem based on the current matrix  $M_k$  by means of a nearest-neighbor heuristic.



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**GenerateTrajectory** We set the number of samples to  $H = 50$ . The trajectories are a combination of the forecast until horizon  $F$ . Then, the emissions are sampled. We generate the sampled realizations by a Gaussian process. The properties of the process are derived from the historical observations. For detail of the process, we refer to §A.2 of the Appendix.

**GenerateMatrix** The matrix for each strategy is determined by a shortest-path, time-dependent Dijkstra-procedure.

**Solve** For every vehicle and every state, we need to solve an open TSP starting from the current location, serving the remaining customer, and ending at the depot. To this end, we draw on the commercial solver SPIDER (Hasle and Kloster 2007). For each open TSP, we run the solver for 20 seconds. The initial VRP is solved via SPIDER as well. The runtime for the VRP is set to 500 seconds. Random checks show the solver is generally able to find the optimal solution within this amounts of time.

#### 4.5. Benchmark Policies

In this section, we define the benchmark policies differing in the initial assignment and in the dynamic adaptations of routing. First, to analyze the impact of the initial distribution of parcels, we analyze three static routing heuristics each with a different initial distribution. Static policies determine the routing once and then follow the determined sequence of customers regardless of future changes. These policies are denoted with  $\pi^S$ . We test three static policies each utilizing different degrees of information (none, current, and forecasted information). The first static policy  $\pi_N^S$  does not draw on any information and determines the routing based on the travel times when no hotspot is active. The second policy  $\pi_C^S$  determines the routing based on the current travel time Matrix  $M_0$ . The third static policy  $\pi_F^S$  integrates the forecasted travel times. Notably, policy  $\pi_F^S$  is similar to the heuristic policy introduced in Huang et al. (2017) for a static and stochastic, time-dependent vehicle routing problem.

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430 To analyze the impact of dynamic updates of routing and forecasts, we  
present a dynamic benchmark policy  $\pi_C^D$  only drawing on the current infor-  
mation. The initial distribution is similar to  $\pi_C^S$ . Following the notation, our  
presented method can be denoted as a dynamic policy with forecasts,  $\pi_F^D$ . Over-  
all, we analyze five different policies, the static policies  $\pi_N^S$ ,  $\pi_C^S$ ,  $\pi_F^S$  and the two  
435 dynamic policies  $\pi_C^D$  and  $\pi_F^D$ .

## 5. Case Study

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In this section, we present the case study for the city of Braunschweig. We first define the instance settings in §5.1. We then compare the results of the five policies and show the benefits of dynamic routing and anticipation in §5.2. 440 Finally, we analyze the results in detail in §5.3. We show in particular, how our policy leads to less traffic in polluted areas.

### 5.1. Instances

The instance design comprises the city layout of Braunschweig as well as the hotspots and the emission development. In the following, we present the layout and road network of Braunschweig as well as the locations of the hot-spots. We 445 then describe the data we derive the emission developments from. Finally, we define how the TMS decision’s impact the travel times within the city.

#### *Layout: City of Braunschweig*

The city of Braunschweig is a medium sized city of about 240,000 residents. 450 The road network consists of three rings around the city center and resembles a very typical European city layout. Braunschweig has one small inner-city street ring around the city center and one larger city ring. An outer-city highway ring encircles the city by about 75 % except on the east side. The street network for the simulation is created with data from OpenStreetMap. The road data 455 was selected and then filtered and processed to its state as seen in Figure 7. It contains 880 arcs and 567 nodes. The road network is represented in black. The

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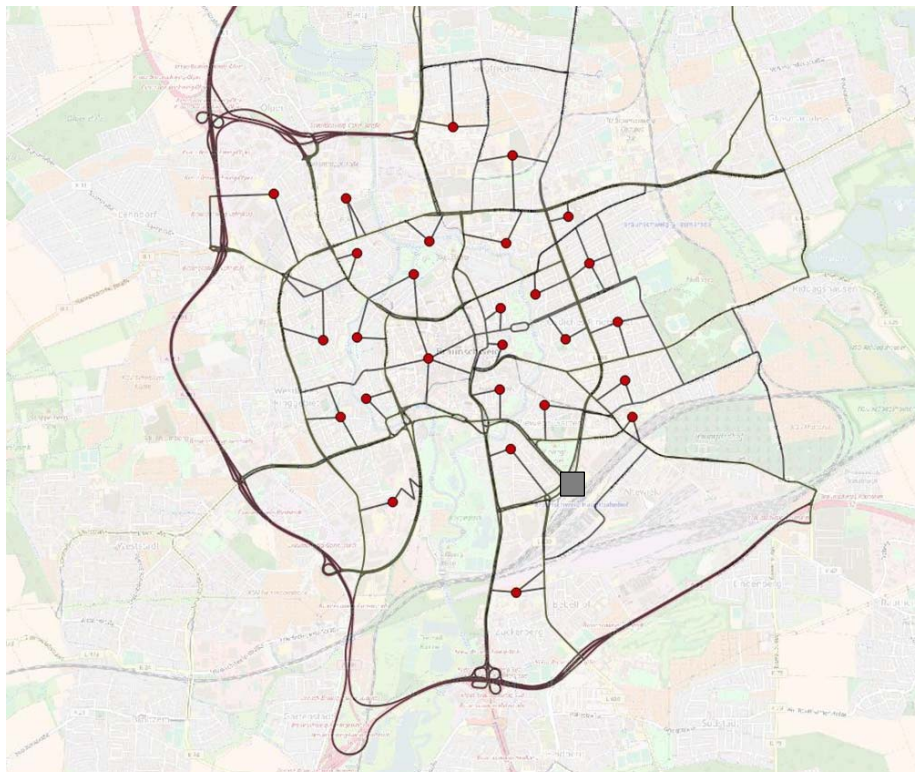


Figure 7: City Layout of Braunschweig (©OpenStreetMap)

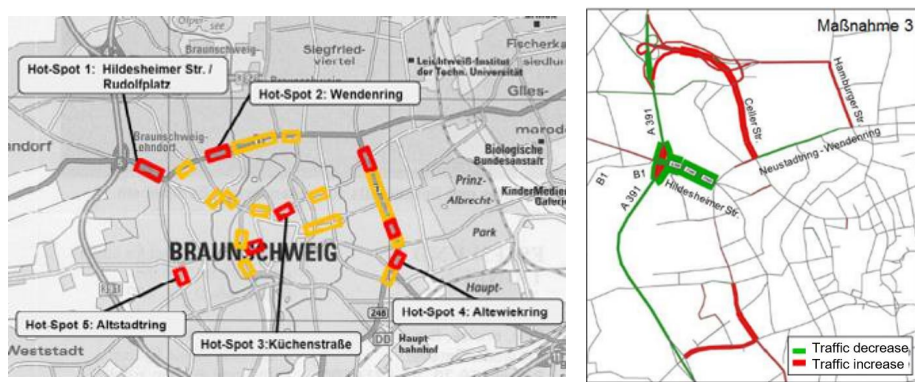
depot is represented by the grey square. It is located at the DHL distribution center of Braunschweig in the south-east.

Instead of single customers, the city is divided into a set of 27 districts. The districts  $C_1, \dots, C_{27}$  are represented by the dots in the map. Each district represents an actual residential cluster in Braunschweig.

### *Hot-Spot Layout*

In the following, we describe the hot-spot layout. The layout is proposed by the city's working group on traffic management UVM (2015a,b). These hot-spots are already installed. The left side of Figure 8a shows the five hot-spot locations in Braunschweig where emissions are measured on a hourly basis. The according red boxes indicate areas where the yearly  $\text{NO}_2$  average exceeds 40

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(a) Hot-Spots and critical pollution areas in the City of Braunschweig (b) Effect of Traffic Management Actions on Hot-Spot 1

Figure 8: Hot-Spots in City of Braunschweig UVM (2015a,b)

$\mu\text{g}/\text{m}^3$  and the yellow boxes indicate areas, where  $\text{NO}_2$  pollution is critical and lies between  $36$  to  $40 \mu\text{g}/\text{m}^3$  on average.

It has been shown that the emissions at Hot-Spots 2 and 5 are strongly correlated to the emissions of other hot-spots. Thus, they are excluded and only the other three Hot-Spots 1, 3, and 4 are considered in the study. If the threshold at a hot-spot is exceeded, according measures are taken. The impact of the measures for Hot-Spot 1 is depicted in Figure 8b. Green road segments represent a decrease in traffic and red segments reflect an increase in traffic. We see that traffic in the affected area (Hildesheimer Str.) is redirected to adjacent areas (Celler Str., Hamburger Str.). Similar measures are taken if the threshold at the other two hot-spots is exceeded. Overall, this leads to  $2^3 = 8$  potential strategies.

*Emissions*

The emission trajectories are derived from an air pollution data set provided by Environmental Department of Lower Saxony, Germany. The original data is summarized on city level. Even though there is a correlation between the emission levels within a city, the levels can vary significantly within different parts of the city. Thus, for each of the hot-spots, we draw on the emission

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development of a different city but on the same day. We select the data of Braunschweig, Osnabrück and Hannover. The latter two cities are in vicinity to Braunschweig and their data shows a strong Pearson coefficient correlation of 0.75 and 0.65 compared to the data set of Braunschweig. Each of the three hot-spots corresponds its trajectory data to an individual monitoring point from a three month period in the beginning of 2016. The data set comprises 90 days.

#### *Impact of Traffic Strategies*

We differentiate between two types of road segments. The first segment represents main roads connecting the districts. These roads are mainly affected  
495 by the TMS decisions and the speed on these roads depends on the applied traffic strategy. The second type of segments represents smaller side-roads. The speed on these segments is set to 25 km/h lying between the averages of major EU cities (Statista 2008).

For the roads affected by TMS decisions, we vary the impact of the traffic  
500 strategies on the travel speeds. We generate four different speed patterns. These patterns differ in the assumed speed in areas with increased and decreased traffic capacities. In areas with decreased capacity, we generate instances with medium and high impact. A medium impact sets the average travel speed to 10 km per hour. A high impact decreases the speed to 5 km per hour. In areas with  
505 increased capacity, the medium impact increases speed to 30 km per hour while high impact increases the speed to 40 km per hour. The combination results in 4 different impact settings: medium decrease-medium increase, medium decrease-high increase, high decrease-medium increase, and high increase-high increase.

#### *Fleet Size and Service Time*

510 We vary the number of vehicles between 2 and 5. To reflect realistic working hours, we vary the service time per district with respect to the number of vehicles. If the number of vehicles is small, a vehicle serves more districts. Thus, the service time per district is short. The service times are 15 minutes for 2 vehicles, 30 minutes for 3 vehicles, and 60 minutes for 4 and 5 vehicles.

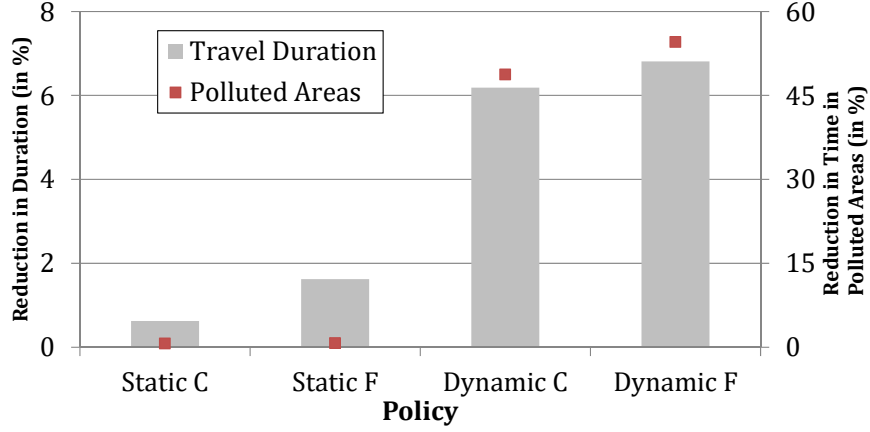


Figure 9: Comparison of the Policies: Reduction in Travel Time and Time Spent in Polluted Areas. Letter “C” indicates the policies relying on current information. Letter “F” represents policies forecasting future developments.

## 5.2. Reduction in Travel Duration

In this section, we depict the improvement of the policies compared to the static policy without any information  $\pi_N^S$ . We define the improvement of a policy as the travel duration reduction of a policy  $\pi$  compared to  $\pi_N^S$ . Let  $\Delta(\pi)$  denote the average travel duration for policy  $\pi$ . Then, the improvement is defined as

$$\frac{\Delta(\pi_N^S) - \Delta(\pi)}{\Delta(\pi_N^S)}.$$

That means, that the improvement reflects the percentual decrease in travel duration compared to  $\pi_N^S$ . In the same way, we calculate the improvement with respect to the amount of time vehicles spend in a polluted area. The average results are summarized in Figure 9. On the x-axis, the four policies are depicted. The left y-axis and the bars show the improvement in travel duration. The right y-axis and the squares show the improvement with respect to travel in polluted areas. We see a strong correlation between improvement in travel time and time spent in polluted areas. The proposed policy  $\pi_F^D$  outperforms all other policies with respect to reduction in travel time and time spent in polluted areas. The

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530 average improvements compared to the static benchmark policy are 6.8% in  
travel time and even 54.6% with respect to travel through polluted areas. That  
means that the time spent in polluted areas is less than half compared to the  
static benchmark policy. Comparing the static and the dynamic routing poli-  
cies, we observe a significant gap in improvement. The static policies drawing  
535 on current and even forecasted information lead to reductions of less than 2% in  
both travel time and time spent in polluted areas. Thus, dynamic reactions to  
the TMS decisions are highly beneficial. The dynamic policy  $\pi_C^D$  only drawing  
on current information already provides improvements of about 6%. Integrat-  
ing forecasts about future developments further increases the improvement. The  
540 same tendency can be observed by analyzing the fuel consumption for the differ-  
ent policies as shown in §A.3 in the Appendix. Dynamic reaction and forecasts  
reduce the required fuel and, therefore, the emissions significantly.

The individual results can be found in Table A3 in the Appendix. Generally,  
we observe a slight increase in improvement with an increasing number of vehi-  
545 cles. This can be explained that, with an increase in the number of vehicles, each  
vehicle serves less districts. That means that the routing flexibility of a vehi-  
cle decreases. While the differences for varying number of vehicles is relatively  
small, we observe a significant variance with respect to the traffic strategy's  
impact on the travel times. In the following, we analyze this phenomenon in  
550 detail.

### 5.3. *The Impact of TMS*

In this section, we analyze the impact of the TMS on the travel duration and  
the routing decisions. First, we show that the improvement of dynamic routing  
and anticipation increases when the impact of the TMS-decisions on the travel  
555 times is high. Then, we analyze how the dynamic routing changes the time  
vehicles spend in polluted areas in detail.

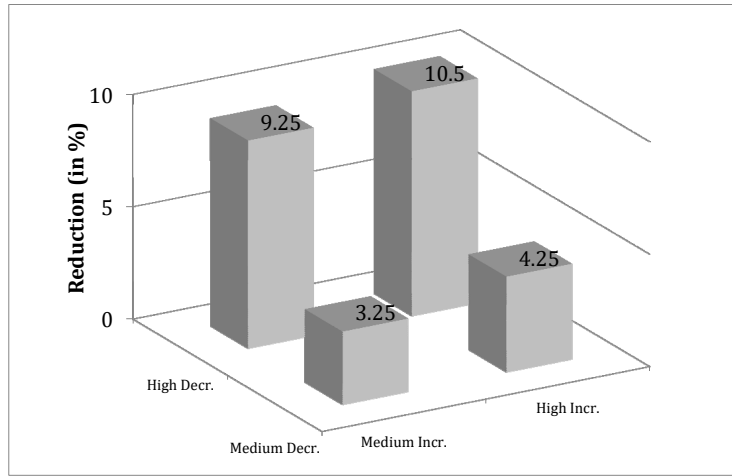


Figure 10: Reduction in Travel Times for Varying TM-Impact on Travel Times

#### *Varying the Impact on Travel Times*

In the following, we analyze how the improvement changes with respect to the TMS's impact on the travel time. To this end, we differentiate the results by the speed pattern. We recall the four speed patterns as medium decrease-  
 560 medium increase, medium decrease-high increase, high decrease-medium increase, and high increase-high increase. For each of these patterns, the average improvement is shown in Figure 10. We observe that the differences between medium and high increase is relatively small. That indicates that spending  
 565 significant resources to increase the speed in non-polluted areas may not be beneficial for CEPs. Comparing the differences between medium and high decrease, we observe a different behavior. While the improvement for a medium decrease is relatively low, the improvement reaches nearly 10% for a high decrease of travel times in polluted areas. That means in cases where the TMS  
 570 significantly reduces capacity in polluted areas (or even bans traffic in these areas), anticipation and dynamic rerouting becomes of particular importance.



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1408 *Travel Through Polluted Areas*

1409 In the previous section, we have shown how dynamic and anticipatory rout-  
1410 ing results in a reduction of travel time for the CEP. We now show how the  
1411 cooperation between CEP and TMS results in significant reduction of traffic  
575 1412 through the polluted areas. To this end, we compare the routing behavior  $\pi_F^D$   
1413 to  $\pi_N^S$  for the instance settings with 2 vehicles and high impact of the TMS.  
1414 Figure 11 visualizes how often a vehicle traverses a polluted area. Green seg-  
1415 ments indicate that a vehicle travels this segment at times the segment was not  
1416 affected by pollution. That means that the vehicle travels these segments in  
1417 580 times when there is no decrease in capacity in and into these segments.  
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1420 This also applies for segments such as the outer-city highway ring in the  
1421 west of Braunschweig which is never affected by TMS decisions. Red segments  
1422 indicate segments where a vehicle travels while this segment is polluted. The  
1423 widths of the red segments indicate the frequency with which a polluted segment  
585 1424 is used. The more often a segment is used, the wider is the red line. On the left  
1425 side the results for the static routing by policy  $\pi_N^S$  is shown. On the right side  
1426 the results for the dynamic and anticipatory policy  $\pi_F^D$  are depicted.  
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1431 First, we recall that the locations of the three hot-spots are in the west of  
1432 590 Braunschweig, in the city center, and in the east of Braunschweig. Comparing  
1433 static and dynamic routing, we observe a significant reduction of travel time  
1434 in the western hot-spot area. In the dynamic routing policy, the vehicles often  
1435 use the outer-city highway ring and avoid the hot-spot area in case of pollution.  
1436 Similar behavior can be observed for the downtown hot-spot. Notable is the  
1437 development around the eastern hot-spot. Generally, no improvement by the  
1438 595 dynamic routing can be observed. In some segments, there is even a more  
1439 intense use of the roads despite pollution and reduced speed. This behavior  
1440 indicates that in the east of Braunschweig, there is a bottleneck. In this part  
1441 of town, there is no alternative for the vehicles to avoid this critical area. In  
1442 contrast to the western part of Braunschweig, there is no outer-city highway  
1443 600 ring. This is an interesting observation and may assist city planners in their  
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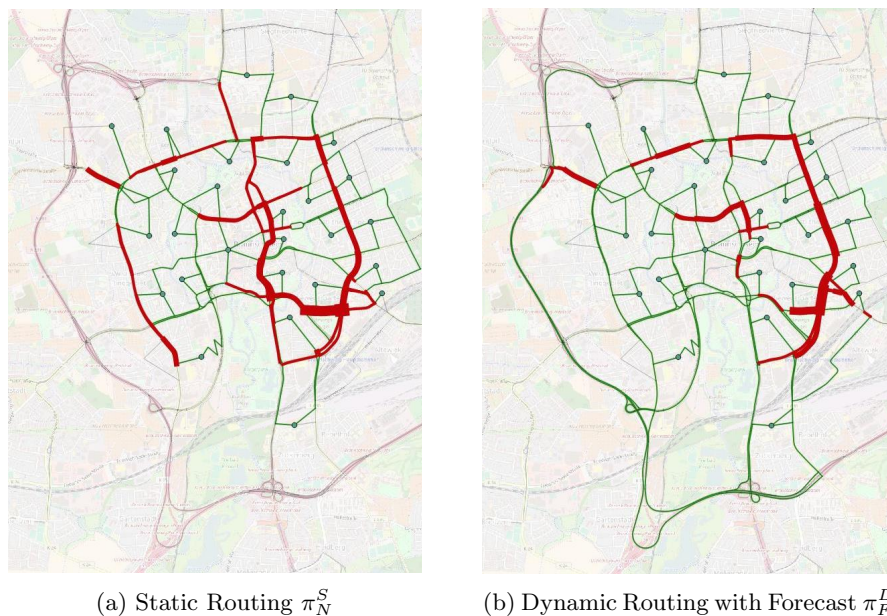


Figure 11: Travel through Polluted Areas (©OpenStreetMap)

decisions on improvements of the road network. A bypass in the east may be highly beneficial.

## 6. Conclusion

605 Many cities worldwide face significant challenges with air pollution. To avoid high emission levels in local areas of the city, city municipalities implement traffic management systems (TMSs). The TMS dynamically controls traffic flows. In several hot-spots, the TMS monitors emission levels and reacts in cases the levels exceed a threshold. A reaction is an orchestrated set of actions leading  
610 to a traffic strategy. Each strategy changes the capacities in the road network and thus the travel times in the affected areas. Courier and parcel services (CEPs) route a fleet of vehicles to serve customers within the city. Thus, the CEPs are particularly impacted by the TMS' decision. In this paper, we have shown how a CEP's reaction to and anticipation of potential strategy changes  
615 reduces travel time significantly. To this end, we have presented an anticipatory

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dynamic routing policy. Our policy samples future emission levels and strategy changes to avoid critical areas in the city. We apply our policy for the city of Braunschweig, often used as a reference for a typical European city layout. Our method provides benefits for the the service provider and the city. First, it reduces the CEP's average travel times by up to 16%. Second, it reduces the time vehicles spent in polluted areas by more than 50%. Thus, a close cooperation between TMS and CEP leads to a win-win-situation.

There are several avenues for future research. Even though Braunschweig reflect a typical city layout with a ring structure, it may be worthwhile to analyze our policies for other city networks. As we have seen, even anticipatory routing may not prevent all travel through polluted areas. Our policy is therefore an indicator for potential bottlenecks in a city network. Future research may use the presented problem and method to evaluate the impact of road network decisions such as the addition of a new bypass or the increase in road capacity. It may also be promising to further increase the cooperation between TMS and CEPs by defining strategies enabling efficient and fast delivery.

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## 1821 APPENDIX

1822  
1823 In the Appendix, we present an overview on related literature in §A.1. We  
1824 further present the individual results in §A.4.

### 1827 785 A.1. Literature

1828  
1829 In this section, we give a brief overview of the related literature. We focus on  
1830 vehicle routing for emission reduction, on routing with stochastic travel times  
1831 and on anticipation in dynamic vehicle routing problems.

#### 1833 Emissions

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790 The work on *Green* vehicle routing for emission reduction has seen a signifi-  
1835 cant increase in the last years. The objective is either to minimize the delivery  
1836 fleet’s emissions by optimizing driving speed (Bektaş and Laporte 2011, Demir  
1837 et al. 2014, Franceschetti et al. 2013) or by considering different emissions for  
1838 different travel arcs in their routing (Figliozzi 2010, Eglese and Bektas 2014,



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1856 795 Ehmke et al. 2016b, Turkensteen and Hasle 2017). Generally, CEPs work in a  
1857 highly competitive environment. In our research, we therefore assume that a  
1858 CEP aims on minimizing routing costs and not emissions. However, as we show  
1859 in §5, the reduction of routing costs in cooperation with TMS simultaneously  
1860 reduces emissions in critical areas substantially.  
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1862  
1863 800 *Stochastic Travel Times*  
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1865 The DVRPMC can be classified as a dynamic vehicle routing problem with  
1866 stochastic travel times. This class of problems is scarcely considered in the liter-  
1867 ature. Dynamic problems usually consider uncertainty in demands or requests  
1868 while VRPs with stochastic travel times are generally considered in a static  
1869 setting (Ulmer 2017). In Table A1, we present an overview on stochastic travel  
1870 805 times. We classify work with respect to the problem model and the compu-  
1871 tational study. We differentiate models by the *Type* of the problem, VRP or  
1872 dial-a-ride (DARP). We analyze whether a model is dynamic and whether it  
1873 considers emissions or the correlation of travel times. We analyze the computa-  
1874 tional studies with respect to the applied method and the instances. We depict  
1875 810 anticipatory methods integrating stochastic information in decision making. We  
1876 further differentiate whether the instances base on real data for emissions and  
1877 road network.  
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1880 First work on stochastic travel times is presented Laporte et al. (1992). The  
1881 815 paper evaluates a priori tours with respect to stochastic travel times. Kenyon  
1882 and Morton (2003) compare routing with stochastic travel times to routing  
1883 with mean travel times. Their research shows that solving the stochastic VRP  
1884 is superior to the routing with mean travel times. Taniguchi and Shimamoto  
1885 (2004) compare an a priori route calculated with a traffic forecast to a dynamic  
1886 VRP, where the latest traffic information becomes available. Here, the traffic is  
1887 820 inflicted with a congestion. The dynamic rerouting approach reduced costs by  
1888 3.7% compared to the a priori tours. For our problem, the origin and the impact  
1889 of the traffic influence is different compared to Taniguchi and Shimamoto (2004).  
1890 Further, the approach by Taniguchi and Shimamoto (2004) is not anticipatory  
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1912 825 but only reactive. Ando and Taniguchi (2006) determine a priori routes given  
1913 stochastic travel times and time windows. They show that their anticipatory  
1914 method reduces both costs and emissions.

1915 Huang et al. (2017) address a static and deterministic routing problem with  
1916 time-dependent travel times as well as a static and stochastic extension. The  
1917 sequence of customers is static, but the paths can differ. More specific, they  
1918 830 allow different paths between the customers based on the time-dependent and/or  
1919 stochastic travel times. To this end, they used a modified Dijkstra-algorithm  
1920 to determine the shortest paths. They do not allow the change of the customer  
1921 sequence. In our work, we consider both: In every decision point, we allow  
1922 reordering the sequence of remaining customers *and* we consider path flexibility  
1923 835 between customers. In our case, the shortest path between two customers can  
1924 change due to a change of the travel time matrix. As Huang et al. (2017), we  
1925 incorporate this path flexibility by using the modified Dijkstra-algorithm.  
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1931 Huang et al. (2017) extend their work by incorporating stochastic travel  
1932 840 times based on congestion. Again, their solution is a static route but with flex-  
1933 ible paths between the customers. They solve small instances with a two-stage  
1934 stochastic program and develop a “Route-First, Path Second”-heuristic. In this  
1935 heuristic, they determine the best route based on expected travel time values. In  
1936 their evaluation, the path is then selected based on the travel time realization.  
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1939 845 This heuristic achieves optimal solutions in 9 of 10 test cases. In our paper,  
1940 we use the same idea for our static policies  $\pi_C^S$  and  $\pi_F^S$ . We fix the sequence of  
1941 customers but allow path flexibility. However, calculating the expected travel  
1942 time values is challenging because of the connection between travel times and  
1943 the stochastic emissions. Thus, we sample travel time realizations and deter-  
1944 mine our paths on the sampled values. As Huang et al. (2017), we allow path  
1945 850 flexibility in our evaluation. In our computational evaluation, we show that the  
1946 dynamic adaption of customer sequences provides significant benefit compared  
1947 to static sequences.  
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1951 The only works in dynamic routing explicitly considering stochastic travel  
1952 times in model and solution method are provided by Schilde et al. (2014) and  
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Table A1: Classification of Stochastic VRP literature

Paper	Model				Computation		
	Type	Dynamism	Emission	Correlation	Anticipation	Emissions	Network
Laporte et al. (1992)	VRP	-	-	-	-	-	-
Miller-Hooks and Mahmassani (2000)	VRP	✓	-	-	-	-	-
Fu (2002)	DARP	-	-	-	-	-	-
Kenyon and Morton (2003)	VRP	-	-	-	✓	-	-
Taniguchi and Shimamoto (2004)	VRP	✓	-	✓	-	-	-
Ando and Taniguchi (2006)	VRP	-	✓	✓	-	✓	✓
Xiang et al. (2008)	DARP	✓	-	-	-	-	-
Lecluyse et al. (2009)	VRP	-	-	✓	-	-	-
Yan et al. (2013)	VRP	✓	-	-	-	-	-
Schilde et al. (2014)	DARP	✓	-	✓	✓	✓	✓
Cimen and Soysal (2017)	VRP	✓	✓	-	✓	-	✓
Huang et al. (2017)	VRP	-	-	-	✓	-	✓
This work	VRP	✓	✓	✓	✓	✓	✓

Cimen and Soysal (2017). Schilde et al. (2014) present a dynamic dial-a-ride problem with stochastic requests and travel times. The authors consider congestion and therefore correlation in travel times. They sample both requests and travel times to generate and evaluate routing plans. Cimen and Soysal (2017) present work on minimizing fuel consumption. This fuel consumption is directly related to the vehicle’s emissions. They solve the problem by means of approximate dynamic programming.

Our problem is further related to work on time-dependent travel times. For these problems, travel matrices change over the course of the day (Van Woensel et al. 2008, Li et al. 2010, Ehmke and Mattfeld 2010, Ehmke et al. 2012). But unlike our problem, the transition between the matrices are deterministic.

#### *Anticipation in Dynamic Vehicle Routing*

In dynamic vehicle routing, routes are adaptively changed with respect changing environment and newly available information (Ulmer et al. 2016). The work on dynamic vehicle routing gains increasing interest in the research community. For a general overview on dynamic vehicle routing, we refer to Ritzinger et al. (2015). In most of the works on dynamic vehicle routing, the dynamic and stochastic environment represents new customers requesting service. The dynamic environment in our research is the impact of the TMS’s decision on the CEP’s travel times.

Anticipatory methods in dynamic vehicle routing integrate stochastic infor-

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mation in their decision making. Due to the generally large information space, the applied methods draw on samples of the stochastic distribution. A prominent method is the multiple-scenario approach (MSA) where plans are generated and evaluated based on sampled information (Bent and Van Hentenryck 2004, Hvattum et al. 2006, Ghiani et al. 2012, Voccia et al. to appear). The sampling-method from Ghiani et al. (2009) uses sampling to evaluate how new information changes the current plan. Our method is therefore related to the work by Ghiani et al. (2009). Further, sampling methods simulate trajectories of the Markov decision process to evaluate a decision’s outcome. These methods are known as rollout or lookahead algorithms (Goodson et al. 2017, Ulmer et al. to appear). Finally, there is an increasing amount of work applying approximate dynamic programming to dynamic vehicle routing (Meisel 2011, Schmid 2012, Ulmer et al. 2017).

### 890 A.2. Emission Sampling

In this section, we give details on how we sample the emissions. We draw on a Gaussian process with varying mean value and standard deviation per hour. The mean values and standard deviations are derived from the training data set and are shown in Table A2. Given a current hour, the process samples the change in emission level for the next hour by means of a normal distribution based on the mean values and the standard deviation. For example, given an emission level of 55.000 in hour 17, the expected emission level for hour 18 is  $55.000 + 3.500 = 58.500$ . The sampled emission level is  $55 + \mathcal{N}(3.500, 4.621)$  with  $\mathcal{N}$  the normal distribution.

### 900 A.3. Fuel Consumption

In this section, we analyze how the policies impact the fuel consumption of the fleet. Notably, the fuel consumption is impacted by a variety of factors such as speed, varying weights, road gradients, acceleration, etc. To realistically capture all these factors, a fine-grained traffic simulation is required. We do not have access to this kind of simulation. We solely focus on the speed of the

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Table A2: Values for the Emission Process

Hour	Mean Value	Standard Deviation
9	9.938	7.262
10	-3.125	5.397
11	-9.375	6.459
12	-3.563	3.790
13	1.313	3.19
14	-2.625	6.098
15	1.688	5.834
16	4.313	2.941
17	-1.063	3.572
18	3.500	4.621
19	1.563	7.322
20	3.625	6.317
21	-5.188	5.109
22	2.625	11.323
23	-1.875	7.635
24	-2.188	6.229

vehicles. Thus, the purpose of the following study is merely to give a tendency how fuel consumption changes for different policies.

To calculate the fuel consumption, we draw on the equation presented in Franceschetti et al. (2013). As suggested in Ehmke et al. (2016a), we ignore load and assume an empty vehicle. For arc  $a$ , we calculate the fuel consumption  $\psi_a(v)$  given a speed  $v$ . The equation can then be written as follows:

$$\psi_a(v) = \lambda \left( kN_e V \frac{d_a}{v} + \gamma\beta d_a v^2 + \gamma\alpha\mu d_a \right). \quad (\text{A1})$$

Parameter  $d_a$  describes the distance associated with arc  $a$ . The other parameters  $N_e, V, \lambda, k, \gamma, \beta, \alpha$  describe engine details. For these parameters, we directly follow the parametrization given in Ehmke et al. (2016a). Parameter  $\mu$  indicates the weight of the vehicles. We assume the weight of a standard vehicle with  $\mu = 6350$  kg.

Based on Equation (A1), we calculate the average fuel consumption for the static policy  $\pi_N^S$ , the dynamic policy based on current information  $\pi_C^D$ , and the dynamic policy integrating forecasts  $\pi_F^D$ . Notably, we only calculate the fuel

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920 consumption for the travel between the districts and ignore the fuel consumption  
within the districts. We select the instance settings with high TMS-impacts and  
vary the number of vehicles between 2 and 5. We calculate the average reduction  
of policies  $\pi_C^D$  and  $\pi_F^D$  compared to  $\pi_N^S$  similar to the reduction in travel time.  
The average reduction of policy  $\pi_C^D$  in fuel consumption is 8.7% (10.0% in travel  
925 time). The average reduction of policy  $\pi_F^D$  is 9.2% (10.5% in travel time). The  
reductions are therefore slightly lower compared to the reductions in travel time.  
Still, dynamic updates of the route plans and anticipation of future development  
not only reduce travel time but also fuel consumption significantly compared to  
static planning.

#### 930 *A.4. Results*

Table A3 depicts the results for the individual instance settings. For different  
fleets sizes and each speed pattern (increase/decrease), the average travel  
duration and the time in polluted areas is shown for each policy.

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Table A3: Individual Results

Speed	Travel Duration				Time in Polluted Areas			
	high-high	high-low	low-low	low-high	high-high	high-low	low-low	low-high
<b>2 Vehicles</b>								
$\pi_N^S$	180.1	157.4	181.1	157.5	25.4	25.5	33.7	26.0
$\pi_C^S$	177.4	155.2	178.7	156.2	24.3	24.8	33.9	25.6
$\pi_F^S$	174.8	155.7	176.2	156.0	24.1	25.1	33.0	25.9
$\pi_C^D$	153.9	148.2	158.0	148.2	13.0	14.3	17.7	14.2
$\pi_F^D$	151.7	147.0	154.5	148.1	10.9	13.1	17.4	13.6
<b>3 Vehicles</b>								
$\pi_N^S$	251.2	228.6	250.9	228.8	37.0	36.5	36.2	35.1
$\pi_C^S$	244.2	226.3	249.8	229.7	37.8	35.6	37.0	32.3
$\pi_F^S$	243.9	224.7	243.0	226.6	37.0	35.9	35.6	35.3
$\pi_C^D$	224.6	220.3	231.6	224.3	16.6	17.2	21.8	17.9
$\pi_F^D$	223.8	218.5	226.3	222.1	14.5	14.8	17.1	18.0
<b>4 Vehicles</b>								
$\pi_N^S$	414.6	388.1	412.8	389.6	38.4	38.5	36.2	32.0
$\pi_C^S$	411.7	387.1	413.0	387.7	39.2	39.1	37.0	30.6
$\pi_F^S$	411.2	386.4	406.4	386.7	40.4	38.8	35.6	30.4
$\pi_C^D$	387.7	381.2	391.7	382.2	18.9	18.8	21.8	16.6
$\pi_F^D$	384.4	379.7	386.0	381.5	15.5	16.8	17.1	15.5
<b>5 Vehicles</b>								
$\pi_N^S$	501.1	461.9	487.8	467.6	51.5	37.8	39.7	47.3
$\pi_C^S$	497.6	459.7	492.4	466.8	52.1	38.0	41.4	46.2
$\pi_F^S$	495.1	459.8	483.0	464.7	51.0	39.0	40.0	46.5
$\pi_C^D$	463.9	452.7	464.1	457.7	22.1	18.8	20.3	23.3
$\pi_F^D$	459.2	452.0	458.7	456.3	18.3	17.4	17.5	21.8