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ASSESSMENT OF THE INTERACTION BETWEEN CONGESTION AND CARRIERS' ROUTE DECISION: A CASE STUDY

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ABSTRACT

To quantify the economic impact of congestion on freight transportation, the traditional approach focuses on the congestion-related delays and value-of-time of freight. This approach, however, ignored the fact that the transportation service providers had modified their operations in response to congestion, especially the expected recurrent-congestion. These adaptive responses may include the employment of additional vehicles on roads, the application of technical innovations facilitating route optimization, and the iterative improvements of tours through self-learning. The context of our case study is a transportation service provider, which distributes freight from a provincial depot of a mail order company to its affiliated local retail stores. The aim of the case study is to quantify the impact of congestion from the viewpoint of an individual carrier considering that the carrier had adapted its behaviors in response to congestion. The impacts of congestion on vehicle routes are quantified with key performance indicators, such as number of tours (fleet size), average number of customers per route, VHT (vehicle hours traveled), VKT (vehicle kilometer traveled). Moreover, these three strategies are compared to make a reasonable route decision under congested conditions for the transportation service provider.

KEYWORDS: Recurrent congestion, non-recurrent congestion, impact of congestion, traffic model, vehicle routing, distribution network

1. INTRODUCTION

Congestion is a common phenomenon in urban and suburban areas. From a supply chain's point of view congestion negatively affects the reliability of logistics processes. From a carrier's perspective, congestion has an adverse influence on its operation costs and productivity.

Congestion can be generally divided into two kinds, recurrent congestion and non-recurrent congestion. The reasons for the recurrent congestion are morning and evening peak hours, long-term road works, and insufficiency of road capacity on several links (bottleneck). The non-recurrent congestion is caused by short-term road works, accidents, weather conditions and further non-predictable stochastic events resulting in temporal restrictions of link capacity. Recurrent congestion is the repeated phenomenon every day and is expected for the road users. However, non-recurrent congestion is stochastic and results in an additional unexpected delay of travel time. The recurrent congestion and non-recurrent congestion both increases the average travel time as well as the variance of travel time.

To quantify the economic impact of congestion on freight transportation, the traditional approach focuses on the congestion-related delays and value-of-time of freight. The congestion-related delay of a truck is the observed truck travel time in congested roads minus free-flow travel time. This approach assumes that the vehicles have the same routes in congested and free-flow situation. However, the transportation service providers, as intelligent agents in the transportation market, had modified their vehicle routes in response of congestion, especially the expected recurrent-congestion. As vehicles travel more slowly on congested roads, the reduced transport efficiency induces the carrier to adopt more trucks to carry out the same amount of pickup and delivery tasks to maintain high level of customer service. This phenomenon may lead to an increase in the number of tours, travelled vehicle-kilometers, fuel consumption, number of drivers and drivers' working hours. In contrast, the capacity utilization of vehicles is reduced.

The context of our case study is a transportation service provider, which distributes freight from a regional depot of a mail order company to its affiliated local retail stores. The aim of the case study is to quantify the impact of congestion from an individual carrier's perspective considering that the carrier had adapted its vehicle routes in response to recurrent congestion. The objective of the vehicle route adaption is to find a new optimum of vehicle routes in the congested situation instead of the old optimum in a congestion-free situation. Besides modification of vehicle routes in response to recurrent congestion, the transportation service operators have also other measures to mitigate the negative effects of congestions. Examples are the redesign of logistic networks, application of flexible time window, off-peak delivery, better communication with the receivers about the delivery status and dynamic routing in case of non-recurrent congestion. However, these measures are not in the scope of this paper.

Considering this background, this paper presents first a traffic model based on the network of trunk roads in Germany (all the freeways and federal roads). This model represents the average traffic load on each trunk road in the course of a day through our calibration. The travel time between any two facilities of the mail order company's distribution network (depot or local retail stores) is then obtained in three forms: free-speed travel time, average travel time and time-dependent travel time (for every time slot of 15 minutes in our study). The last reflects the time-dependent characteristics of the congestion, as the severity of traffic congestion varied temporally in a day. Then, a case study in the context of the carrier mentioned above is carried out, who distributes the commodities from the regional depot to local retail stores. The carrier is supposed to construct vehicle tours with three different strategies separately: using free-speed travel time, average travel time and time-dependent travel time. A vehicle routing algorithms is applied here to optimize the tour. The tour built with free-speed travel time is the ideal tour under a completely congestion-free condition. The tour with time-dependent travel time is the tour carried out in the reality, which is resulted from the iterative learning ability of the carrier. The impacts of congestion on vehicle routes, interpreted as the difference between the tours constructed with free-speed travel time and time-dependent travel time, are quantified with key performance indicators (KPIs), such as number of tours (fleet size), average number of customers per route, VHT (vehicle hours traveled), VKT (vehicle kilometer traveled). Moreover, these three strategies are compared to make a reasonable route decision under congested conditions for the transportation service provider.

The paper is organized as follows. We first review the relevant literature on the interplay between congestion and logistic operations, especially from a carrier's perspective. We then describe our calibrated traffic model of Germany. Subsequently, we describe the case study. In the concluding section, we state our principal findings and directions for further research.

2. LITERATURE REVIEW

The first strand of research into the impact of road traffic congestion on logistical operators uses analytical or conceptual models. Rau et al. (1991) presents an analytical model to examine the interrelationship between highway traffic congestion and just-in-time (JIT) manufacturing/inventory management. The traffic congestion has the major impact on inventory holding costs, in-transit inventory costs and stockout costs for the perspective of a shipper. Figliozzi (2010) suggests an analytical model to study the impact of congestion on commercial vehicle tours in terms of tour characteristics and cost. Eisele et al. (2010) presents a conceptual model, named as freight box, to visualize and calculate the effects of geographic area, commodity type and time period on freight mobility and reliability.

Other studies have adopted expert interviews to study the impact of congestion on logistical operations. McKinnon (1999) investigated the effects of traffic congestion on the internal workings of seven distribution centers through in-depth interview. He finds out that firms with "leaner" logistical operations are more vulnerable to traffic congestion than firms with relaxed schedules. Congestion is one of many factors influencing the investment decision on advanced handling equipments and IT systems. Regan and Golob (2001) surveyed trucking companies in the area of California. The trucking operators' perceptions of congestion and the severity of congestion-induced problems (missed schedule, driver frustration, accidents etc.) were reported. Sankaran et al. (2005) have examined the impact of congestion in the Auckland Region of New Zealand on supply chains through in-depth interview into a total of eight enterprises, including manufacturers, distributors and logistics/transport service providers. Since these surveys are practically about perceptions of congestion and people are more sensitive to non-recurrent congestion than to recurrent-congestion, these studies concentrated more on the consequence of non-recurrent congestion, which cause unexpected delays in transportation and probably disruptions in subsequent phases of supply chain.

A further study of Conrad and Figliozzi (2010) has introduced an algorithm and parameters to incorporate the effects of congestion on time-dependent travel time matrices. Google Maps calculates the free-flow travel and distance between each pair of customers. Bottlenecks are modeled as point locations surrounded by areas of reduced travel speed, which induce the variation in travel times.

3. MODEL

3.1. Overview

To quantify the direct impact of traffic congestion we have combined traffic model and optimization algorithm. The macro-level traffic model provides the travel time variance during the time of a day. The optimization algorithm, namely the vehicle routing algorithm, presents the optimization practice of individual trucking operators at a micro-level. Another advantage of using traffic model is its dynamic. We can build any network capacity reduction in the traffic model (reflecting the consequence of events such as road works, accidents), and then obtain the new changed time-dependent travel time matrix.

Our model is based on MATSim (www.matsim.org), an activity-based multi-agent traffic model. We have chosen MATSim for two reasons. First, vehicles may only enter a subsequent link with a given rate corresponding the link's capacity and must stay on the link for a given time duration with respect to the link's free speed. A waiting queue is built for a link when the vehicles' arrival rate exceeds the link's capacity. The queue model by Charypar et al. (2007) allows us to obtain the time-dependent travel time considering the relationship between the actual travel demand on a link and the link's capacity; and the FIFO property (overtaking is not possible), is also guaranteed. Second, MATSim uses an evolutionary algorithm to find an optimal traffic assignment in the way that each vehicle can moderate its departure time and change its route iteration by iteration, until the user equilibrium is achieved. The evolutionary algorithm reflects the learning ability and the adaptive actions of real road users, who can select uncongested routes and times to combat the impact of congestion.

The network of our model is a Europe-wide road network with focus on Germany. It includes trunk roads (all the freeways and federal roads) in Germany, important freeways in foreign countries and most of the border crossing-links in order to distribute the transit traffic evenly on the roads in German border regions. Every road is described by attributes such as free speed, capacity and number of lanes. Our study is to quantify the impact of recurrent congestion on the trunks roads on the vehicle routes of a transportation service provider.

3.2. Agent Plans

We have used publically available data (BVU et al., 2007) to construct the agents' mobility plans (including passenger agents and commercial vehicle agents). The data from BVU includes all trips undertaken on the total road network of Germany (including all road types), which have different travel distance. As the short-distance trips are only performed on our truck network with a much lower probability in comparison with long-distance trips, we have reduced the number of short-distance trips in the data from BVU to a certain extent. In other words, the congestion on the trunk roads is caused by the long-distance trips primarily. The short-distance trips can only impact the congestion on the long-distance network with a reduced probability.

The data from BVU gives us the traffic volume between NUTS3 zones (NUTS is the abbreviation for Nomenclature of Units for Territorial Statistics[1], which is a European standard for the administrative division of a EU country). We transformed the trips between NUTS3 zones to trips between nodes in our network by using a multinomial logit model (see figure 1). We assumed that the nodes in our network are the places of residence.

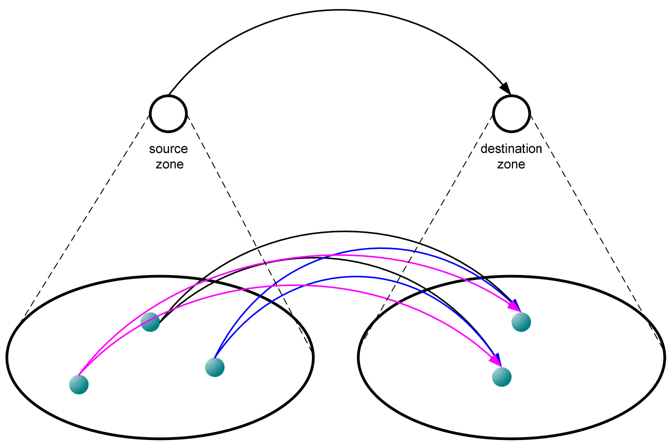

Figure 1. Distribution of the traffic volume data between NUTS3 zones to nodes in the NUTS3 zones

The number of trips between a node i in the source zone O and a node j in the destination zone D, denoted as N_{ij}^{OD}, is

$$N_{ij}^{OD} = N^{OD} \cdot w_i^o \cdot \frac{e^{-d_{ij}/\bar{d}}}{\sum_{j \in D} e^{-d_{ij}/\bar{d}}}$$

where:
- N^{OD}: the number of trips from source zone O and destination zone D
- w_i^o: the weight of node i in the source zone O
- d_{ij}: distance between node i und node j
- $\bar{d}$: average distance between node i and all possible destination nodes in the destination zone D

The parameter w_i^o presents the probability that trips start from the node i among all possible nodes in the source zone O. We gave more weight to nodes that are not incident to freeways. Therefore, most of the agents start their trips on federal roads or county roads in the source zone. In this way we could increase the traffic on non-freeway links in our long-distance network, leading to a more realistic traffic count in our model.

[1] http://en.wikipedia.org/wiki/Nomenclature_of_Territorial_Units_for_Statistics

The parameter $\bar{d}$ implicates the sensitivity to the travel distance difference. For short interzonal trips or trips between adjacent zones ($\bar{d}$ is small), the travel distance play an important role for a traveler (who is for example at the origin node i) in the destination decision (decision for a destination node in the Zone D). So the traveler tends to choose destination nodes with shorter travel distance. However, for long-distance trips between non-adjacent zones, the travel distance plays a less important role for the traveler's destination node decision.

Each agent's plan includes all of its activities on a normal working day. The activities are attributed with type, location, starting time and duration. All the agents execute their daily plans concurrently on the network and require transportation capacity of the network when travelling from the current location to the location of the next activity. Moreover, the agent is able to choose an alternative route instead of a congested route, which makes the links on the alternative route more overcrowded. The travel time increase on congested links is thus correlated with the increase on its possible alternative links.

3.3. Calibration

The traffic model is calibrated at the link level with respect to the link's daily traffic volume and daily traffic distribution curve (Fitschen et al., 2009). We modeled the diurnal variation of passenger agents by using data from Infas/DLR 2010 that gives us a distribution of the starting time of trips dependent on the purpose of the trip and the length of the trip. Here too, we only considered long-distance trips over 25km. We modeled the diurnal variation of commercial freight agents by using an artificial distribution of their starting times. The distribution of the starting times of passenger agents and commercial freight agents is shown in figure 2. To account for the trips less than 25km, we have defined the agent type "commuter", which has a trip from home to work starting at 8 am with standard deviation of 2 hours and also a back trip starting at 17 am with the same standard deviation.

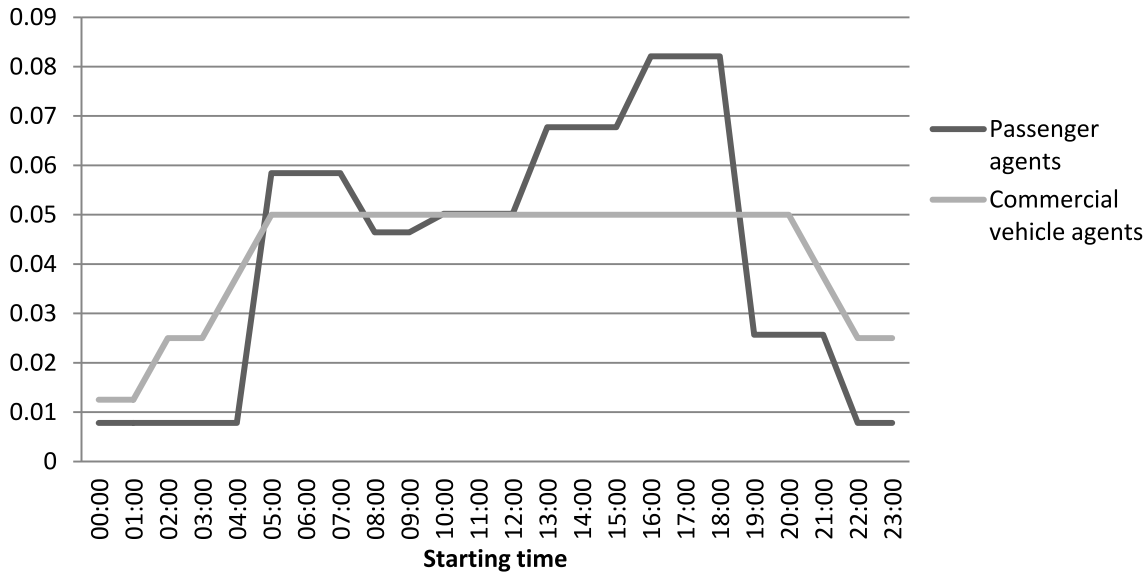

Figure 2. Distribution of the starting times of passenger cars and commercial freight agents

The results of the calibration process are shown in figure 3, where we compare the simulated daily traffic volume with the traffic census from Fitschen et al. 2009 on randomly selected links in Germany. As demonstrated in Figure 3, we have achieved a relative good match between the simulated data and the traffic census data (Fitschen et al., 2009). Figure 4 show the simulated daily traffic distribution on several links. We have also compared this simulated distribution curve with the types of daily traffic load distribution curve provided in (Fitschen et al., 2009). Through justification of starting travel time of agents we have also achieved a certain similarity.

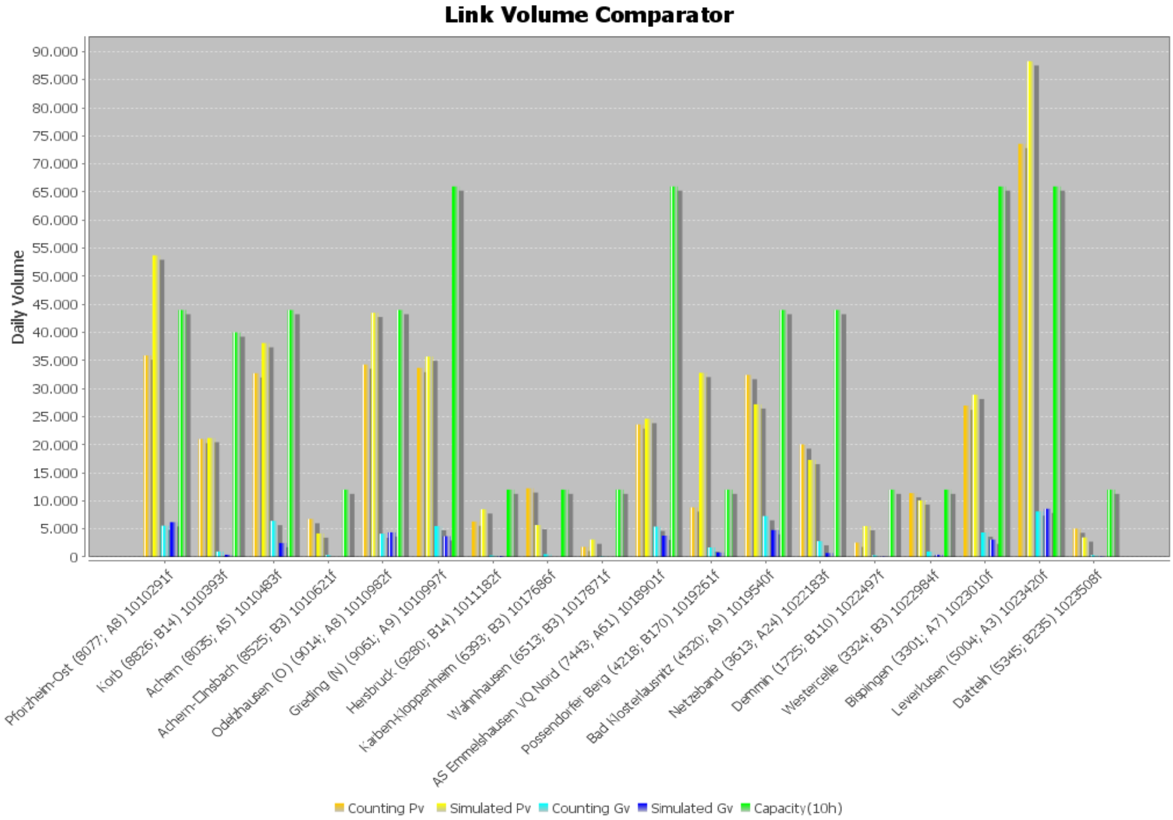

Figure 3. Counting passenger vehicles (Couting Pv), simulated passenger vehicles (Simulated Pv), counting commercial vehicles (Counting Gv), simulated commercial vehicles (Simulated Gv) and road capacity per day of several roads in Germany

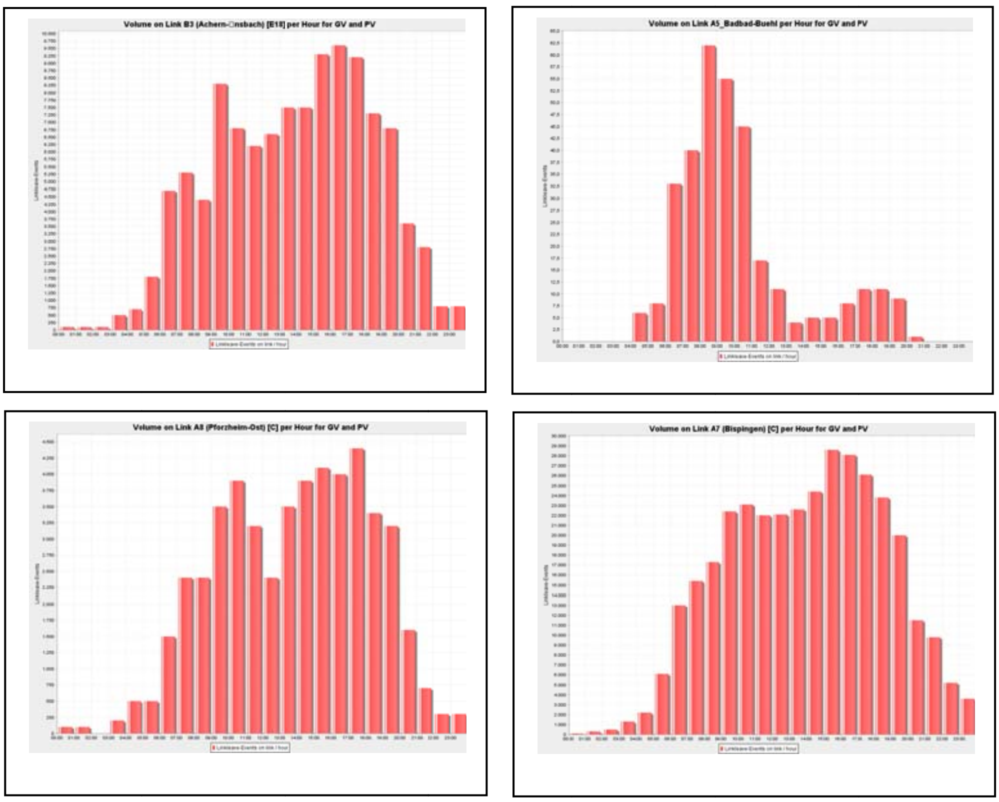

Figure 4. Simulated diurnal variation of traffic volumes on several links

Due to computation performance the agents in our model represent only1% typical trunk road users and in the simulation the capacity of the roads is also reduced correspondingly. The scaling factor 1% is probably not reasonable for the urban network, in which each road has a relatively small throughput. However, for the trunk roads in Germany, in which each road has the minimum capacity of 1100 vehilces/hour, this scaling factored is considered practical. Through the travel behaviors of the agents, we could get an insight into the traffic load on each road during the day and thus the recurrent congestions both spatially and temporally (see Figure 3 and Figure 4).

3.4. Vehicle Routing

For solving the VRP problems, the vehicle routing algorithms based on ruin-and-recreate principle (Schrimpf et al. 2009) is applied. It was implemented in Java and can be downloaded from MATSim freight package. In every iteration, it partly destroys an existing solution for the VRP and recreates a full solution. If the quality of the new solution is better than a certain threshold, it is accepted. Two strategies for the ruin step are applied and in each iteration one of the two strategies is randomly selected. The first strategy is a random-ruin strategy, which select a job (delivery for a retail store) randomly and remove it from the vehicle route. The second strategy is a radial-ruin strategy that clears all jobs in a randomly selected area. The recreation strategy inserts the unassigned jobs where insertion costs are minimal. Unassigned jobs are inserted into the existing routes with a best-insertion-algorithm.

For solving the time-dependent vehicle routing in scenario 3, the time-dependent travel cost between any two logistic locations, which is an input for the ruin-and-recreate, is calculated by the time-dependent shortest path search algorithm in MATSim (Lefebvre et al. 2007). The time-dependent shortest path search algorithm reads the simulation results of our traffic model, which records when a vehicle enters and leaves a link. We have set travel time (40 euro/hour), travel distance (1.2 euro/km) as two cost drivers of the vehicle routing problem.

4. A CASE STUDY OF A MAIL ORDER COMPANY

4.1. Distribution Network of the Mail Order Company and the VRP Problems

The mail order company in our study owns a nationwide hub-and-spoke distribution network in Germany. The distribution process is divided into two sub-procedures. In the first sub-procedure, the freight is distributed from the central warehouse to the 10 regional warehouses, which are denoted as red squares in Figure 5. And then, in the second sub-procedure, the freight is transported from a regional warehouse to its affiliated local retail shops. The total amount of local retail stores is 702, which are dispersed 16 federal states in Germany and whose locations are marked as green cycles in Figure 5.

The geographical area of our study is the German federal state Baden-Württemberg (in southwest of Germany, Figure 5 on the right). A depot and 100 local stores are dispersed in an area of 35,000 km^2. Due to the reason of data privacy, we have repositioned the locations of the 100 retail stores to 44 communities in the area (see green cycles in Figure 5) using a monte-carlo-simulation. We assumed that the number of retail stores in a community is dependent on the population of that community. As the amount of communities is less than the amount of retail stores, several retail stores might be located in the same community.

Each local retail store makes an order per week, containing the amount of commodities in different assortments. The carrier collects the orders made by the local stores during the week and delivers the commodities from the depot to the local stores in the course of the next week. The time window of the depot is between 6:00 and 23:00, while the time window of local stores is between 6:00 and 18:00. The truck is loaded up overnight so that it could deliver freight the following day. Therefore, the loading time at depot does not need to be considered in the tour planning. The service time at each shop location (for unloading) is 20 minutes. The capacity of a truck is 42 cubic meter. The order amount of a local store is simulated according to observed values, which have an average value of 7 cubic meters. All these restrictions (time windows, service times, truck capacity and lot sizes) are based on realistic values in practice.

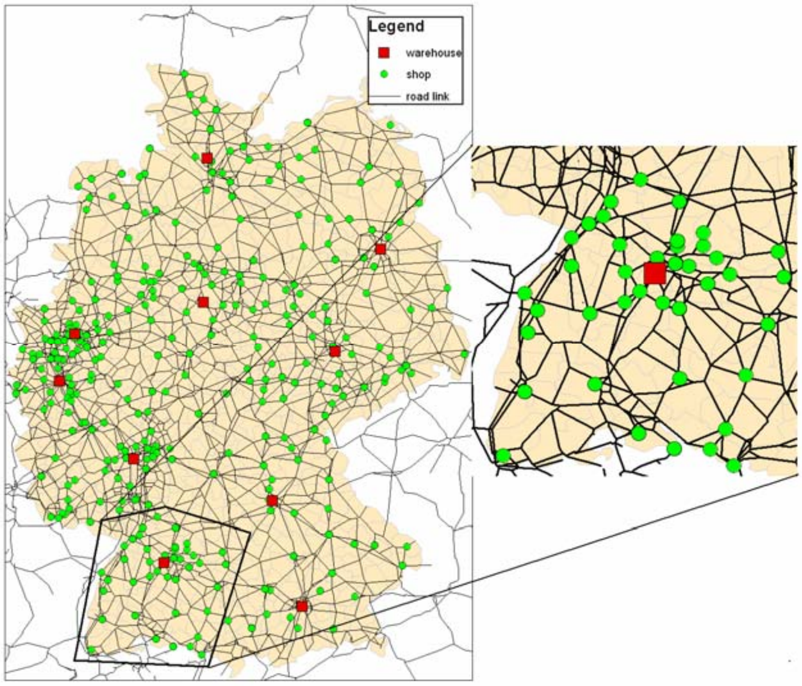

Figure 5. Distribution network of a mail order company in Germany and in the federal state Baden-Württemberg

4.2. Travel Costs

After the definition of the VRP problem of the investigated carrier, the travel costs for solving the VRP problem can then be obtained from our traffic model. Our multi-agent traffic model was calibrated for building the recurrent congestion on German trunk roads as described in the previous section.

For the free-flow scenario, the travel time on each link is a constant, which is the length of the link divided by the allowed maximal speed on that link. A shortest path search algorithm (provided by MATSim) is used to calculate the route of the minimal travel time between any two nodes in the logistics network. The results build the impedance matrix for the vehicle routing algorithm. To get the time-dependent travel time, we have first constructed a time-dependent network with the events occurring during the simulation, which is one of the MATSim simulation output files. This time-dependent network contains the time-dependent travel times on each link of our road network, whose time slot is 15 minutes. Then the time-dependent shortest path algorithm (Lefebvre et al. 2007) is used to calculate the time-dependent shortest path between any two logistics locations. The table below is a part of our free-flow and time-dependent travel times, which demonstrates the variation of travel times in dependence on the departure time of agents. Using the time-dependent travel times we can then get the average travel time between two locations in the logistical network.

Table 1. Time-dependent travel times (in minutes) between two logistic locations

from	to	Freespeed Travel Time	06:00	06:15	06:30	06:45	07:00	07:15	07:30	07:45	08:00
depot_Sinde	DE11_1	46.0	48	48	53	53	49	49	48	48	52
depot_Sinde	DE11_2	17.0	17	19	20	22	20	19	19	18	22
depot_Sinde	DE11_3	28.0	28	29	27	29	28	28	28	28	30
depot_Sinde	DE11_4	20.0	21	21	23	25	23	23	22	22	25
depot_Sinde	DE11_5	10.0	11	11	13	15	12	12	12	11	15
depot_Sinde	DE11_7	62.0	65	66	67	68	65	68	67	64	67
depot_Sinde	DE11_8	18.0	19	20	18	20	21	24	22	18	36
depot_Sinde	DE11_10	20.0	21	21	23	25	23	23	22	22	25
depot_Sinde	DE11_11	10.0	10	10	10	10	11	10	10	10	11
depot_Sinde	DE11_12	39.0	39	40	38	40	39	38	39	40	41
depot_Sinde	DE11_17	35.0	47	42	47	51	51	48	45	49	51
depot_Sinde	DE11_18	28.0	39	33	38	38	44	45	36	54	55
depot_Sinde	DE11_19	67.0	77	75	75	81	81	80	80	78	80
depot_Sinde	DE11_33	21.0	22	21	21	23	22	21	21	21	23
depot_Sinde	DE12_1	61.0	66	65	70	72	69	69	70	69	73
depot_Sinde	DE12_2	44.0	46	47	53	51	49	48	57	56	58
depot_Sinde	DE12_3	38.0	41	42	43	46	44	44	53	52	52
depot_Sinde	DE12_6	21.0	28	26	26	21	22	23	21	24	22
depot_Sinde	DE12_8	51.0	53	53	56	58	57	55	65	63	65
depot_Sinde	DE12_10	41.0	47	47	49	54	55	53	58	53	61
depot_Sinde	DE12_13	34.0	40	39	42	48	46	41	46	45	53
depot_Sinde	DE12_14	68.0	70	72	73	76	75	73	78	77	81
depot_Sinde	DE12_16	18.0	18	18	18	20	19	18	18	18	19

4.3. Results of Case Study

Without congestion and any uncertainties, the carrier plans tours with free speed travel time, which builds the scenario 1. However, for the practical operations under congested condition we can assume that the carrier has considered the deterministic recurrent congestion beforehand in its tour decision. It is a plausible assumption since the carrier has to improve its tours continuously to get a better position in the competitive freight transportation market. Therefore, the carrier plans tours with average travel time in scenario 2 and with time-dependent travel time in scenario 3. Table 2 shows the tour patterns in the defined 3 scenarios beforehand and Table 3 shows several key performance indicators of the solutions. As the planning period of the carrier is a week, the time dimension of the values in the two tables is a week.

Table 2. Vehicle tours in 3 scenarios

Scenario 1 (free speed travel time)	Scenario 2 (average travel time)	Scenario 3 (time-dependent travel time)
1. depot_Sindelfingen - DE11_1 - DE11_31 - DE11_29 - DE11_16 - DE11_15 - depot_Sindelfingen 2. depot_Sindelfingen - DE11_14 - DE11_21 - DE13_9 - DE13_16 - DE13_3 - depot_Sindelfingen …… 18. depot_Sindelfingen - DE12_17 - DE12_24 - DE11_22 - DE11_25 - DE11_4 - DE11_26 - depot_Sindelfingen	1. depot_Sindelfingen - DE11_11 - DE13_9 - DE13_8 - DE13_14 - DE13_15 - DE12_25 - depot_Sindelfingen 2. depot_Sindelfingen - DE14_17 - DE14_16 - DE11_13 - DE11_7 - DE11_34 - DE11_17 - depot_Sindelfingen …… 18. depot_Sindelfingen - DE13_5 - DE13_13 - DE13_11 - DE13_17 - DE12_20 - DE12_16 - depot_Sindelfingen	1. depot_Sindelfingen - DE14_5 - DE14_16 - DE14_7 - DE14_4 - DE14_10 - DE14_11 - depot_Sindelfingen 2. depot_Sindelfingen - DE14_17 - DE13_1 - DE13_8 - DE13_18 - DE13_2 - DE13_13 - depot_Sindelfingen …… 18. depot_Sindelfingen - DE12_16 - DE12_25 - DE12_8 - DE12_24 - DE12_9 - DE12_19 - depot_Sindelfingen

Table 3. Key performance indicators of 3 scenarios

Value/per week	Scenario 1 (free speed travel time)	Scenario 2 (average travel time)	Scenario 3 (time-dependent travel time)
Number of tours	18	18	18
VHT (vehicle hours traveled)	59.6	62.3	66.1
VKT (vehicle kilometer traveled)	4578	4672	4881
Number of served customers per tour	5.6	5.6	5.6
Total Duty time (hours)	92.9	95.6	99.4
Average duty Time per vehicle (hours)	5.2	5.3	5.5

As shown in the table 3, the number of vehicle tours remains the same in the three scenarios. The reason is that the capacity of a vehicle (42 cubic meters) and the total demand of all customers (approximately 700 cubic meters) have decided the number of tours. As our time windows are consistent at all shops (6:00-18:00) and have a relatively large slot (12 hours), they have almost no impact on the number of tours. But in certain VRP problems with tight and even conflicting time windows (for example for the distribution problem of courier service operator or manufacturer operating JIT logistics), the time window restriction does have a certain impact on the number of tours. As the average duty time per vehicle is between 5.2 and 5.5 in three scenarios, the even more aggravated congestion can only make the VHT or duty time per vehicle longer, but cannot increase the number of tours. So the number of tours stays resistant to the congestion to a great extent in the case of our case study.

Die difference of the KPIs in scenario 1 and 2 are not so considerable. As our average travel time obtained in section 4.2 is the average value in the course of the day, it is very similar to the free speed travel time. The reason is that the German long-distance network is constructed with sufficient reserve capacity and the travel speed of vehicles is only limited at a few road sections or in peak hours. But in scenario 3, the tour solver calculates with the time-dependent travel times and the peak hour effect is noticeable, as our vehicles must deliver goods between 6 and 18 o’clock and this time slot is just the peak hour times. Besides the extended VHT in scenario 3 in comparison with scenario 1, the VKT is also increased to some extent. The monetary value of the increase of VKT (1.2 euro/km) is even greater than the increase of VHT (40 euro/h) in case of our problem configuration. There are two reasons for it. On one side, the tour patterns have changed (see table 2) due to a changed impedance matrix in the case of congestion. On the other side, in the phase of the execution of the planned tour, the driver could change the route and take probably a detour to avoid the congestion. The relatively considerable increase of VKT indicates the potential to find an alternative route in case of congestion in the German long-distance network.

Obviously the TDVRP in scenario 3 is a strategy to copy with recurrent congestion, since it considers the temporal dynamic of traffic congestion. The strategy in scenario 2 should be used carefully in the tour planning. First, the time dimension of the average value should be determined. And the time dimension is dependent on the concrete VRP problem. In our case it may be more reasonable to calculate the average travel time between 6:00 and 18:00, instead of the average travel time of a day (between 0:00 and 23:59).

5. CONCLUSIONS AND FUTURE WORK

As conclusion, the paper combines traffic model and vehicle routing algorithm to study the interrelationship between congestion and carriers' tour decision. The study is carried out under the assumption, that the carrier considers the expected recurrent congestion in its tour decision. The recurrent congestion on the German trunk roads are quantified for a carrier. As results, our study reveals that the impact of congestion depends on the nature of a concrete VRP problem. Due to the relatively large time window and thus slack in the logistical schedule, the distribution network of the mail order company is not vulnerable to the recurrent-congestion. The monetary increase of extended VKT is even greater than the of extended VHT due to congestion. This also indicates the good potential to find an alternative route in the long-distance network of Germany in case of congestion. The next step of our study will concentrates on the stochastic non-recurrent congestion, which is more interesting in the era of just-in-time logistics for a reliable logistical service.

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