Modeling interactions of cars and freight vehicles in urban areas for speed and travel time prediction

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Modeling interactions of cars and freight vehicles in urban areas for speed and travel time prediction

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ABSTRACT

The prediction of journey speeds is important for decision making - not only for travelers, but also for businesses such as urban freight companies. Journey speed is total travel distance divided by total travel time, including all delays and additional stopping times. So far, methodologies to model these interactions between cars and urban freight vehicles at an aggregated level have not yet received much attention, although the demand for urban freight is growing. However, these methodologies are required to identify solutions for optimal management and regulation of urban freight.

This paper proposes a novel approach to model the interactions between cars and urban freight vehicles for journey speed prediction in urban areas based on the multi-modal macroscopic fundamental diagram (MFD). To ensure transferability to many applications, we formulate the model in a generic way. We apply the proposed model to a synthetic network with parameters oriented towards European cities to illustrate the model’s applicability and discuss trade-offs in regulation of urban freight. As data related to (urban) freight movements (e.g., route planning and load factors) are currently often treated as private resources by involved freight companies, our generic model also provides a foundation to integrate actual freight data as soon as they are available for cities as a consequence from the ongoing, continuous digital transformation. Thus, the new approach not only helps cities on deriving urban freight strategies to optimize the overall traffic in the network, but also helps businesses to make better decisions.

Keywords: urban freight transport; MFD; traffic flow; municipal decision-making; logistics; goods movement
**INTRODUCTION**

In urban areas, many vehicles of different modes and services compete for scarce road space, e.g., cars, public transport buses, pedestrians, cyclists, utility vehicles and urban freight vehicles. The between-vehicle interactions among all of these vehicles create negative externalities – among them additional congestion. So far, the plethora of multi-modal interactions and their congestion effects in urban transportation networks have only received little attention. However, the gap is beginning to close, especially the case of interactions between buses and cars (1, 2) and the case of ride sharing vehicles and cars (3). Contrary, among the less considered interaction cases is the case between cars and urban freight vehicles (UFV) in urban areas, although the latter have a substantial contribution to the urban traffic that is even expected to increase further in the following years (4).

In recent years, the externalities of urban freight transport (UFT) on urban areas (e.g., congestion, emission of noise and pollutants) have been analyzed by, e.g., (5, 6, 7). In addition to the mentioned works, (8) and (9) take a closer look at potential approaches to minimize the negative effects of UFT and the related UFV movement inside urban areas (e.g., by shifting deliveries to off-hours).

In urban transportation networks with UFVs operating alongside cars, the vehicles’ journey speed is an important input for business and policy decisions to optimize profits or social costs. The journey speed is the total traveled distance over the total travel time and includes all delays from stopping and moving. The more accurate and reliable this input becomes, the better decisions can be made. In urban traffic, cars and UFVs interact physically due to their different behavior and vehicle dimensions. For example, UFVs stop more frequently and for other purposes (e.g., for delivering shipments) than cars and their acceleration is slower. These interactions make a reliable speed prediction more complex and difficult. As physical vehicle interaction always leads to a decrease in all vehicles’ journey speeds, too optimistic journey speed predictions could be costly for businesses and could lead to inefficient control and regulation measures as well as long-term infrastructure investment decisions for the urban transportation network. So far, however, methods to capture these interaction delays in the journey speed prediction for car and UFV traffic in urban areas at the network level are not existing.

In this paper, we use recent advances in macroscopic modeling of vehicles’ journey speed in urban transportation networks with the macroscopic fundamental diagram (MFD) (10, 11, 12, 13) to address this gap. Based on the MFD, we propose a model that makes interaction speeds of cars and UFVs better predictable, likely to improve business and policy decisions. The underlying modeling idea is that bi-modal urban network traffic consisting of cars and UFVs is similar to bi-modal urban traffic consisting of buses and cars, for which a variety of flexible and promising approaches already exist (1, 2, 14, 15), but with the difference that many UFV network design parameters are random variables rather than fixed parameters, e.g., stop distance, stop duration, vehicle headway.

The transferability of bus network modeling approaches to urban freight follows from three main reasons: first, the obstruction on the road is happening mostly on the curb-side lane, e.g., buses and UFVs double park when no separate infrastructure is available. Second, UFV operations share various similarities with buses such as driving from stop to stop to perform their service at each stop, while UFVs are expected to stop longer than buses. Third, the involved operators are faced with similar design questions (e.g., route planning, headway). Thus, using existing methods for bi-modal traffic with buses for UFV operations could achieve more reliable and accurate speed predictions.

To predict journey speeds accurately from an aggregated network perspective, one key
aspect is to understand when a bottleneck is activated and congestion starts to emerge in the urban transportation network. For buses operating on a regular schedule, the bottleneck activation is quite deterministic, whereas UFVs do not operate on a regular schedule, but have their routes, delivery stop locations and their headway (the number of required vehicles) planned based on shipment demand (origin, destination, time). With bottleneck activation by UFVs being a random process, its microscopic prediction is difficult, while its macroscopic prediction relies on the expected values of these random variables describing UFV operations. Another aspect that supports the macroscopic approach is the limited availability of microscopic freight transport data (e.g., actual temporal and spatial movement of UFVs) as addressed by, for example, (6, 16). For example, (16) address the potential benefits of an increased and centralized (i.e., consolidated at a central point that is administered by municipal decision-makers) data availability for the quality of municipal decision-making processes as well as their positive effect on the urban transportation network. Various research efforts exist to enhance data availability and accessibility (cf. reviews (6, 17, 18)), where especially for filling the gap of microscopic data availability respectively central data accessibility between different actors, various methods can be applied reaching from simulation (cf. (19) to empirical data collection (cf. (20).

To illustrate the model’s applicability and discuss trade-offs in regulation of urban freight, we apply the proposed journey speed prediction model to an synthetic network with parameters oriented towards European cities. The parameters’ values are taken from freight activities in Hamburg, Cologne and Nuremberg, where BIEK (i.e. German Parcel and Express Logistics Association, a domain-related association) publishes aggregated freight data on a regular basis. In the following, we summarize first the fundamental concepts of each associated domain, namely urban freight transport and macroscopic traffic modeling to make all readers familiar with these concepts. Then we show how the interaction delays between cars and UFVs can be captured at an aggregated network perspective for journey speed prediction. Thereafter, we show for applicability of the speed prediction model for policy scenario analyses. We end this paper with a discussion and outlook for future research.

LITERATURE REVIEW
Predicting journey speeds in urban areas of mixed traffic with UFVs and cars requires knowledge from at least three domains. First, how urban freight transport is organized and how it interacts with other urban transportation systems. Second, how UFVs routes are obtained from supply of vehicles and demand of shipments. Third, how speed can be predicted given the presence and flow of vehicles. In the following, we present the fundamental concepts for each of the three domains.

Urban Freight Transport
The domain of urban freight transport (UFT) has been on the agenda of researchers for more than two decades until now. In recent years, various overarching works have been presented by, for example, (7), (6) and (21) with regard to UFT as well as directly related terms like for instance: city logistics, urban logistics, urban goods movement and urban freight distribution.

One sub-topic inside the UFT domain is freight demand management (FDM). (5) define FDM as ‘the area of transportation policy that seeks to influence the demand generator - to achieve urban freight systems that increase economic productivity and efficiency; and enhance sustainability, quality of life, and environmental justice’ and understand it as the freight-related equivalent to passenger demand management. Exemplary measures in FDM are initiatives for temporal delivery
shifts (e.g., to off-hour or to off-peak) or for receiver-led consolidation (e.g., by coordinating with similar demands in the proximity). Aiming at sustainable urban freight systems, (5) showed that FDM can have significant contribution to reducing both the freight traffic as well as the overall traffic and thus the congestion inside the urban transportation network.

In their recent work, (22) suggested further approaches for the sustainable and efficient integration of UFT into the urban transport network. Among others, they assign a central role to the coordination of deliveries and suggest further investigations with this focus. The suggestion has been picked up by (16) and (23) as a starting point to identify additional approaches to increasing coordination in urban delivery processes. To contribute to the further development of cities in the direction of smart cities, they study the potential benefits of an increased and centralized (i.e., collected from various data sources and consolidated in a central data infrastructure) availability of both macroscopic and microscopic freight data for municipal decision-making processes. From their perspective, the data availability is expected to increase in the course of the following years as a consequence of the continuous digital transformation of existing business processes. Based on that, enabling cities to access and process available freight data would be crucial in order for cities to meet their responsibility to, on the one hand, maximize the productivity and efficiency of the urban transportation network, while, on the other hand, minimizing the negative side effects of the associated traffic volume - in particular: congestion and emissions.

Vehicle Routing Problems
The operations of UFVs are faced with a variety of mathematical optimization tasks, e.g., routing, capacity planning, scheduling. Typically, these tasks represent combinatorial optimization problems that aim at finding an optimal solution inside a pre-defined search space.

One prominent problem is the Vehicle Routing Problem (VRP) that is used to plan optimal routes for delivering shipments using an existing vehicle fleet. The objective is to assign a set of vehicles to a set of customers to satisfy their demands while minimizing the total traveled distance. The vehicles start their tour at a central depot and return to the same depot after finalizing the planned tour.

Originating from that basic VRP principle, different types of VRP exist and can be classified, for example, based on involved constraints, e.g., access time windows, environmental cost. An overview on VRP in the UFT domain can be found, for example, in (24). VRPs also occur beyond the UFT domain - structured overviews on existing VRPs have been presented by, for example, (25) and (26).

Macroscopic Fundamental Diagram
Predicting journey speeds in urban road networks on an aggregate level has been of interest since more than fifty years (27, 28) with its most recent development being the macroscopic fundamental diagram (MFD) (11). The general idea is to predict not only the average journey speed, but also its distribution in the network as a function of variables that cover the demand and physical properties of the network. Predicting speeds on an aggregate level with the MFD is much faster than using a traffic simulator, but slightly less accurate (29).

The MFD, originally for car transportation only, describes the relationship between the number of vehicles circulating in the network \( N \) and their collective production of vehicle kilometers \( \Pi \) and journey speed \( v \) of vehicles that includes all driving and standing time throughout the journey. Figure 1 shows the typical MFD shape: while production of vehicle kilometers first
FIGURE 1: Typical MFD shape: a travel production-accumulation relationship; b speed-accumulation relationship.

increases with the number of vehicles until congestion starts and production decreases with the number of vehicles as Figure 1a, the average journey speed declines with the number of vehicles in the network due to congestion as seen in Figure 1b.

The shape of the MFD is a characteristic fingerprint of each network and can either be obtained analytically or from measurements (simulation, stationary detectors or floating car data) (30). Multi-modal interactions between different transport modes are captured in multi-modal MFDs that quantify the joint travel production and network average journey speed of all modes as a function of each modes’ vehicle accumulation. Multi-modal MFDs can also be estimated analytically (15, 31, 32) or from measurements (1, 2), where the analytical methods reportedly face difficulties in capturing the complexity of multi-modal traffic in multi-modal MFDs, leaving the measurement method as the robust alternative.

MODELING CAR AND UFV INTERACTIONS

The proposed speed model links the number of cars $N_C$ and number of UFVs $N_{UFV}$ in an urban road network to their respective average journey speed $v_C$ and $v_{UFV}$. These journey speeds include the interaction effects of the two vehicle types as well as any stopping and moving time inside the urban transportation network. Thus, we have to focus on stopping and moving time to fully understand journey speeds (33). In the following paragraph, we present the assumptions for the speed prediction model to model car-UFV interactions.

First, in Figure 2a we illustrate an abstract sequence of events involved in a typical shipment delivery process, an UFV stopping process that creates a temporal bottleneck for other vehicles in the network that are consequently experiencing longer stopping times. It can be derived from Figure 2a that many factors influence the stopping time of UFVs, e.g., distance between parking position and target destination in step 1 or visibility and accessibility of building entrance in step 4. Second, the dimensions (e.g., weight) of UFVs are larger compared to cars, impacting their acceleration. This leads to the behavior shown in Figure 2b where the two vehicle types’ moving speeds (not journey speeds) converge in congestion, while in free flow UFV speeds are slightly lower than car speeds due to reduced acceleration. Third, the urban freight network design
variables and many delivery process variables from Figure 2a are stochastic processes where the bottleneck is not activated on a regular basis. Fourth, the UFV operator determines the routes, the sequence of delivery stops and the amount of shipments for each UFV before all vehicles leave the depot as seen in the vehicle routing graph in Figure 2c. In other words, the number of stops, the stop locations and the (planned) routes are, determined either manually or automated using, e.g., VRP solvers (commercially available software), known for all UFVs in the network once they are circulating. They are not changed during a tour, e.g., due to congestion. Once a UFV delivered all shipments, it returns to the depot.

The input of the model, i.e., $N_C$ and $N_{UFV}$, are linked to the output of the model, i.e., $v_C$ and $v_{UFV}$, using the multi-modal MFD as shown in Eqn. 1. The interactions are captured in the multi-modal MFD using the two-fluid theory of town traffic (33) for car traffic, extended to the
multi-modal MFD (35).

\[
\begin{pmatrix}
  v_C, \\
  v_{UFV}
\end{pmatrix} = MFD \begin{pmatrix}
  N_C, \\
  N_{UFV}
\end{pmatrix}
\] (1)

The average journey speed expressed in the MFD includes the moving and stopping times of all vehicles inside the network. Therefore, multi-modal interaction delays can be separated into the average additional time for moving \( p_m \) and stopping \( p_s \) per unit distance that is nothing else than the impact on pace, the inverse of speed (35). Then, the total pace of vehicles \( p \) corresponds to the pace without interactions \( p_0 \) and the two delays \( p_m \) and \( p_s \) as shown in Eqn. 2.

\[ p = p_0 + p_m + p_s \] (2)

In this particular interaction case of cars and UFVs, we consider that the differences in vehicle dimensions create additional moving delays for cars \( p_m \) and that the delivery stopping process creates additional stopping delays \( p_s \) for cars. In the following two subsections, we explain each of the mentioned, additional delays in detail.

### Moving delays

For the moving delays, let us first define that \( \vartheta \) indicates the moving speed of vehicles that does not include any stopping times. Thus, this speed differs from the average network speed \( v \) from the MFD. The moving delays \( p_m \) result from the different vehicle dimensions, leading to the behavior observed in Figure 2b. Recall that the moving speeds of both vehicle types differ in the free flow, but converge in congestion. The additional moving delays for each vehicle can then be obtained using Eqn. 3 as the difference in moving speeds that include vehicle interactions with other vehicle types \( \vartheta_{\text{interaction}} \) and are without vehicle interactions with other vehicle types \( \vartheta_{\text{no interaction}} \).

\[ p_m = \frac{1}{\vartheta_{\text{interaction}}} - \frac{1}{\vartheta_{\text{no interaction}}} \] (3)

### Stopping delays

We derive from Figure 2a that the total delivery time per stop \( \tau \) results from two main factors, namely urban topography \( T \) (e.g., building accessibility, number of floors) and the delivery process \( D \) (e.g., total amount of shipments per stop, amount of shipments per delivery, average dimension of a single shipment, distribution of shipments at a stop location, availability of parking areas). We consider that the average delivery stopping time in a network is \( \bar{\tau} \) in units seconds per stop is network-specific and captures, e.g., parking behavior and policy, and must be calibrated from data. We propose to model the delay per stop \( \tau \) inspired by a Cobb-Douglas production function with inputs \( T \) and \( D \) as introduced in Eqn. 4. The inputs \( T \) and \( D \) are, like in economics, aggregated variables that can be, but are not limited to, the examples from the previous paragraph. We adopt such a macroscopic and aggregated perspective to ensure that this framework applies to as many different delivery processes as possible. Consequently, for each specific application, the inputs \( T \) and \( D \) have to be customized.

\[ \tau = \bar{\tau} \cdot T^{\theta_T} \cdot D^{\theta_D} \] (4)

This Cobb-Douglas formulation not only naturally ensures that \( \tau > 0 \), but also uses parameters \( \theta_T \) and \( \theta_D \) as output elasticities. They allow to adjust or determine whether delays are...
produced with increasing, decreasing or constant returns to scale. The inputs can also be understood as intermediate goods and are thus themselves outputs of another production function. We define the specific inputs for $T$ and $D$ in the next section, where we show policy analyses with this model. With inputs specified for an UFV application, all the parameters must be calibrated from data.

Importantly, $\tau$ is for a single stop, but Eqn. 2 requires the additional stopping delay per unit distance. Therefore, we scale each stop’s delay $\tau$ by the average distance between UFV stops $d$ as given in Eqn. 5 that results from the vehicle routing graph.

\[ p_s = \frac{\tau}{d} \]  

(5)

\textbf{Inhomogeneity of delays}

The delays expressed in Eqns. 3 and 5 assume a homogeneous presence of delays along an urban corridor. In their current formulation, they are formulated such that every car would experience $p_m$ and $p_s$. In real urban road networks, not every car is experiencing these delays all the time, however, every car is experiencing the average delays from interacting and not interacting with UFVs along its journey. Thus, let us define that $P$ is a random variable for moving and stopping separately. Each variable has outcomes $P = p$ in case of interactions and $P = 0$ in case of no interactions. Then, the expectation of additional delays can be obtained as formulated in Eqn. 6.

\[ E[P] = 0 \cdot \Pr(P = 0) + p \cdot \Pr(P = p) = p \cdot \Pr(P = p) \]  

(6)

There are two ways to obtain information about the probabilities $\Pr$. First, learn them from data which is possible for UFV operators because they have access to their vehicles’ trip recorders and to commercially available car speed recordings. Second, if no such access to data exists, they can be approximated using (analytical) formulae. As this data is currently not available, we can only introduce the idea to learn the probabilities from data. Until the data becomes available, we approximate, and thus simplify, the probabilities for the moving process with a uniform distribution (encountering a UFV while driving corresponds to the fraction of UFVs from all vehicles) and for the stopping process with a binomial distribution (encountering one, two, N-times an UFV stopping per unit distance) following the ideas discussed by (35).

\textbf{POLICY SCENARIOS: MANAGING URBAN FREIGHT}

In this policy analyses we study four different scenarios of parcel delivery in dense urban areas with the previously introduced speed model for an abstract synthetic network. The delivery process is assumed to follow the sequence in Figure 2a. We focus on scenarios that emphasize different features of UFV operations and that are discussed for UFV regulation (e.g., (9)): (1) all-day normal UFV operations, (2) restricting UFV operations during peak times, (3) more recipients at delivery stops for the same amount of shipments, (4) cooperation of UFV operators that increases routing and vehicle loading efficiency. All scenarios are compared for the same exogenous, dynamic loading profile of cars in the network.

For this parcel delivery service, we define that $T$ (urban topology) and $D$ (delivery process) follow production functions like Eqn. 4. All inputs into $T$ and $D$ are normalized by their calibration value. This ensures that $\tau = \overline{\tau}$ (the average delivery duration) holds at the calibration point. Furthermore, each input has an output elasticity of $\theta$ that can capture whether delays are produced with decreasing, constant or increasing returns to scale.
First, urban topography $T$ is expressed by the number of floors of buildings $H$ as defined in Eqn. 7. Intuitively, for parcel delivery services, the average delivery time increases with the average number of building floors in the city.

$$T = \left( \frac{H}{\bar{H}} \right)^{\theta_H}$$

Second, we consider that $D$ results from the average amount of shipments per delivery stop $S$, the average shipment dimensions (e.g., weight and volume) $W$, and the distribution of shipments to recipients at a delivery stop, expressed in the Gini index $G$. For $G = 1$, one recipient receives all the shipments, while for $G = 0$, each shipment has another recipient. When $S$, $W$ or $G$ increase, the average delivery stopping time increases. Eqn. 8 shows the resulting production function for $D$.

$$D = \left( \frac{S}{\bar{S}} \right)^{\theta_S} \cdot \left( \frac{W}{\bar{W}} \right)^{\theta_W} \cdot \left( \frac{S + G(1-S)}{\bar{S} + \bar{G}(1-\bar{S})} \right)^{\theta_G}$$

For this policy analyses, we parameterize the functions with data from a survey on UFV parcel delivery operations from German cities (34, 36). We summarize the resulting parameters of UFV operations and of the defining features of the abstract synthetic network in Table 1. The urban transportation network has a symmetrical grid layout with 15 blocks of 100 m length on each side. Thus, the network covers an area of 2.25 km$^2$. Dense German cities reportedly have a demand of at least 1000 parcels per km$^2$ and day (34, 36) that we scale to a total demand of 10000 shipments in the network for the policy analyses to describe high demand seasons, e.g. Christmas. We define that the resulting parameters of the vehicle routing algorithm for UFVs are those given in Table 2. Last, we set the output elasticities as follows $\theta_T = 0.3$, $\theta_D = 0.7$ and $\theta_H = \theta_S = \theta_W = \theta_G = 1$. The first two elasticities, we assume that $D$ has a greater impact than $T$ on delays, while for the last three elasticities we assume that all contribute equally to delays with increasing returns to scale.

In all four scenarios, we load the road network with the same exogenous time-series of car accumulation shown in Figure 3a with a direct assignment. This series exhibits common distinct morning and evening peaks with a smaller lunch-time peak. We assume that the VRP results for each scenario in the number of UFVs shown in Figure 3b as well as UFV operation parameters given in Table 2. Note that the accumulation of UFVs is approximately two orders of magnitude smaller than the accumulation of cars. We simulate the effect of UFV operations in 60 time slices of 15 min duration, i.e. ranging from 6:00 AM to 9:00 PM. As seen in Figure 3b, the UFV operation hours in Scenarios 1, 3 and 4 range from 8:00 AM to 6:00 PM (e.g., as defined by the maximum work allowance of a single driver), the limited operation hours for Scenario 2 range from 9:00 AM to 4:00 PM. We follow a static accumulation-based perspective by considering the accumulation of cars and UFVs fixed in each simulation interval and predict the speeds of each mode based on the multi-modal MFD.

In Figures 3c-d we then show the resulting speeds of cars and UFVs, respectively. In Figure 3c we find the expected speed pattern resulting from the car accumulation pattern from Figure 3a with speeds dropping to more than half the network average space-mean speed in the morning and evening peak. In the congested time slots, we do not see an impact of the few UFVs (less than 20 UFVs compared to more than 4000 cars) as in congestion speeds of all modes typically converge. Contrary, in the less congested time slots, we find an impact of the UFVs with Figure 3’s inlay.
Network
- Total network length: 100 lane-km
- Average number of lanes per street: 3
- Blocks of 100 m length: 15

UFVs
- Total shipments: 10,000
- Number of stops per tour: 100
- Tour distance: 60 km
- Average stopping time per stop ($\bar{\tau}$): 4.5 min
- Tour per vehicle and day: 1
- Free-flow moving speed: 28 km/h
- MFD capacity: 0.1 veh/s
- MFD jam density: 0.1 veh/m

Cars
- Free-flow moving speed: 35 km/h
- MFD capacity: 0.149 veh/s
- MFD jam density: 0.145 veh/m

Interaction

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$H$</td>
<td>1</td>
</tr>
<tr>
<td>$W$</td>
<td>1</td>
</tr>
<tr>
<td>$S$</td>
<td>2</td>
</tr>
<tr>
<td>$G$</td>
<td>1</td>
</tr>
<tr>
<td>$\theta_T$</td>
<td>0.3</td>
</tr>
<tr>
<td>$\theta_D$</td>
<td>0.7</td>
</tr>
<tr>
<td>$\theta_H = \theta_S = \theta_W = \theta_G$</td>
<td>1</td>
</tr>
</tbody>
</table>

**TABLE 1**: Model parameters that are oriented towards European cities (cf. (2, 37)). As mentioned, this delay model uses the methodology by (35) that requires more interaction parameters. Those not listed above are similar to those given by (35) for cars and buses, except for $\lambda_{car} = \lambda_{UFV} = 0.01$.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Defining feature</th>
<th>Operation hours</th>
<th>Shipments per stop</th>
<th>Stops per hour</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Normal operations</td>
<td>10</td>
<td>2</td>
<td>10</td>
</tr>
<tr>
<td>2</td>
<td>Limited operation hours</td>
<td>7</td>
<td>2</td>
<td>10</td>
</tr>
<tr>
<td>3</td>
<td>More recipients at delivery stops</td>
<td>10</td>
<td>2</td>
<td>10</td>
</tr>
<tr>
<td>4</td>
<td>Cooperation</td>
<td>10</td>
<td>3</td>
<td>11</td>
</tr>
</tbody>
</table>

**TABLE 2**: UFV operation parameters for each considered scenario.
FIGURE 3: Results of the scenario analysis for UFV operations. a Car accumulation time-series for the simulation, b UFV accumulation time-series, c resulting changes in car journey speeds, d resulting changes in UFV journey speeds.
allowing to distinguish the four scenarios. The speed reduction is increasing from Scenario 4, Scenario 1, Scenario 3 to Scenario 2 and results from the impact of UFV accumulation and stops. The order is intuitive as Scenario 4 operations are optimized, while in Scenario 2 more stops per hour are required to deliver all shipments, increasing the delays for cars.

In Figure 3d we find that the network average space-mean speed of UFVs is substantially below its free-flow speed resulting from the interaction with car traffic. The speeds in Scenario 3 and 4 are even lower due to increased number of stops and stopping times. Importantly, this accumulation-based direct assignment does not consider whether shipments cannot be delivered due to delays or UFVs have to circulate longer in the network, but both have a negative impact on congestion and economics.

The results clearly emphasize the impact of bi-modal traffic of car and UFVs on car speeds as well as UFV speeds. Even when the number of UFVs is small compared to the car accumulation, an impact is seen which would be even amplified with more UFVs in the network. Nevertheless, the results also emphasize the need for calibration and specification for the many specific UFV operation systems that are in place in urban areas to capture the entire system dynamics.

DISCUSSION

In this paper, we presented a novel approach to model the interactions between cars and urban freight vehicles in urban areas based on the macroscopic fundamental diagram (MFD). Information on journey speeds that include interaction delays in multi-modal traffic are important not only for businesses to make better decisions, but also for cities in order to derive optimal strategies, e.g., for managing urban freight deliveries. The interactions are captured in the journey speeds using the two-fluid theory of town traffic (33) extended to the multi-modal MFD (35). We formulated the model abstractly to ensure transferability to as many problems for different delivery processes (e.g., vehicle routing or scheduling) as possible. When customizing the model for each specific application, the data required for calibrating the model is available to urban freight fleet operators (e.g., as an output of their fleet planning and vehicle routing problem calculations) and should be shared with municipal decision-makers in order to calculate network-optimal solutions as this will lead to long-term benefits (e.g., less congestion, higher journey speeds, higher delivery-trip productivity, higher profitability) for each involved fleet operator with their individual intentions (e.g., profit optimization) (16). Last, we showed the applicability of our proposed model to study urban freight regulation and management scenarios.

The proposed speed model can be included in many optimization problems where the number of vehicles and their journey speed are key variables. These problems are found on the UFV operator side, e.g., fleet management and routing, as well as on the municipal decision-maker side, e.g., parking regulations or traffic control. Thus, when properly calibrated and validated, the model and its resulting optimization problems allow to improve operations strategies in order to save costs and improve service quality. Future research, therefore, should build this speed prediction model as a module into applications relevant for fleet operators as well as municipal decision makers in order to exploit the benefits of an increased prediction quality (e.g., in vehicle routing problems of fleet operators or traffic volume and traffic flow predictions of municipal decision-makers).

The policy analyses in the previous section shows how the model applies for speed prediction associated questions, while it also emphasizes that data is required for the calibration and more importantly for deriving implications, but also for validation of the speed prediction model. Such data is already available for UFV fleet carriers, but usually not for cities. However, new data
collection methods using technologies such as drones (37) allow to measure all interactions and
trajectories required for the calibration of speed prediction models like ours. In addition, macro-
scopic traffic data is also becoming more widely available that help to define bounding boxes speed
prediction models’ parameters. Only the availability of such data then allows to identify when and
where this simplification of reality is adding value for decision making. Thus, future research could
engage in finding methods to obtain the model parameters, especially the interaction probability,
with high accuracy for improving decision making.

The fact that freight data availability outside private companies is still one central issue
for cities as well as researchers indicates an (ongoing) gap between research and practice. As al-
ready highlighted by (38) more than ten years ago, exploiting long-term benefits for the overall
(urban) transportation network with measures such as consolidation, cooperation, or route opti-
mization still seems to be a comparatively idealistic goal as the freight transport market is highly
competitive. Thus, incentives for data exchange between private companies and cities as well as
researchers are needed in order to bridge the gap of data availability. In this course, it will be par-
ticularly important for the incentive measures to quantify and communicate the potential benefits
of a data exchange to the involved private actors as this might, in the next step, enable them to eval-
uate their risks and recognize their potential individual benefits (e.g., saving costs through better
speed predictions) which could subsequently leverage them to cooperate. Future research could
therefore focus on laying the foundation for the data exchange, especially by developing technical
frameworks for the data exchange (ensuring data security) as well as for the data storage (ensuring
data anonymization).

In closing, the growing demand for mobility in urban areas together with growing demand
for shipments increase the load on the urban infrastructure and calls for improvement management
as well as regulation of multi-modal traffic. This proposed model can help to make better decisions
for businesses and society, thus could lead to make urban traffic more sustainable.

AUTHOR CONTRIBUTION STATEMENT
The authors confirm contribution to the paper as follows: AL and TO conceived and conducted the
study as well as wrote the manuscript. AL developed the code.

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