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ScienceDirect

Transportation Research Procedia 79 (2024) 29–35

Transportation Research Procedia

www.elsevier.com/locate/procedia

City Logistics 2023

The effect of vehicle load on urban freight emissions

Johan W. Joubert[a,b,*]

[a] Centre for Transport Development, Industrial and Systems Engineering, University of Pretoria, 0028, South Africa.
[b] KU Leuven Institute for Mobility, Centre for Industrial Management (CIB), 3001, Leuven, Belgium.

Abstract

Several city logistics initiatives focus on lowering last-mile deliveries' environmental impacts. And here, the *impact* is often the total (absolute) pollutants emitted by urban goods vehicles and the population's exposure to those pollutants. Some of these interventions include the conversion of traditional fleets to clean(er) fuels or imposing vehicle access restrictions, based on emission standards, in the form of (ultra) low emission zones. Many of these interventions rely on models to predict and evaluate, a priori, what the impact will be. But, like all models, assumptions must be made, resulting in predicted results underestimating actual emissions. For urban logistics, more than for private cars, the literature shows a substantial difference between the predicted and tail-pipe emissions for most pollutants. This paper builds on prior research and shows the cargo load's nonlinear effect on emissions in an urban environment.

Keywords: Urban transport; real driving emissions; portable emissions measurement system; PEMS; rigid body; vehicle load.

1. Introduction

There is consensus that we require drastic changes in our urban mobility to affect a reduction in its contribution to greenhouse gasses (GHGs). Various interventions cater to alternative fuels, electrification, modal shift, changes in consumption patterns, access restrictions, and more. And as cities' population increases and densifies, so do the consumption densities. To fulfill these increasing needs for goods and services, as well as collecting and removing the resulting waste and reverse flows, urban logistics faces the same pressures to reduce its environmental impact.

* Corresponding author. Tel.: +32 472 57 6264.
E-mail address: johan.joubert@kuleuven.be

10.1016/j.trpro.2024.03.006

But interventions are frequently costly and disruptive, so before embarking on them, decision-makers rely on a spread of models to anticipate the consequences of interventions. Since the impact is typically measured in large cities and urban regions, predictive models must simplify assumptions like deriving the vehicle fleet from socio-economic factors or assuming average speeds across road links and segments in the city network. Policy- and decision-makers are mostly comfortable with the trade-off.

Recently, literature has seen an increasing number of publications focusing on more advanced predictive models that can identify both the intended and the unintended consequences. For example, in their study of Munich, Germany, Hülsmann et al. (2011) showed that vehicle restriction might result in a higher total amount of vehicle kilometers traveled. While advances in, for example, agent-based transport models allow decision-makers to study environmental (emission) impacts at a very fine spatiotemporal resolution, the quality of models is rarely challenged.

In recent work, Gräbe and Joubert (2022) showed that even a state of art emission predictor underestimates the tailpipe pollutants of a typical city logistics vehicle: a rigid-body goods vehicle with a cargo capacity of 5–8 tonnes. And in their work, the freight vehicle was unladen. It is then natural to ask the follow-up question: *"If we get estimations wrong on an unladen city logistics vehicle, what is the effect of cargo?"* This paper aims to take the first step at answering this question. We present results of urban field tests that accurately measured the tailpipe emissions of the logistics vehicle used in Gräbe and Joubert (2022) using the exact Portable Emissions Measurement System (PEMS) equipment, but with zero, 1.5 and 3-tonne loads, respectively.

The paper is structured as follows. Section 2 reviews emissions measurement practices and the gap between predictive models and empirical findings. Section 3 presents the baseline predictive model and the field test setup. Section 4 compares the empirical emissions of the different cargo configurations to the baseline predictions. The paper concludes in Section 5 and suggests a way forward.

2. Prior research

Chossière et al. (2017) popularised the difference between emissions as formerly reported by vehicle manufacturers and measured using PEMS under typical driving conditions. As a result of what became known as the Dieselgate saga, Real Driving Emissions (RDE) testing is becoming a standard part of the homologation of road vehicles, including urban commercial vehicles. Homologation is the process and associated requirements to deem a vehicle fit in a specific market. Classifying a vehicle's emissions class more accurately is a step in the right direction. But precisely how much and where a vehicle emits exhaust pollutants in the real world, where it affects the population at large, is more complicated. Actual emissions can depend on the ambient environment, driver behavior, road grade, road conditions, the level of congestion, and the load on the vehicle and its associated burden on the vehicle's power train.

Trying to cater to all the variability sources when evaluating environmental interventions aimed at transport at the mezzo and macro city level, generally, and urban freight, more specifically, is overly ambitious. So, when predicting emissions using simulation, Nocera et al. (2017) note a common two-step approach: the first is a traffic model to estimate flow, and the second is using the former's output as input into the emissions model. This abstraction allows for aggregated emissions estimation at the city level (Nocera et al., 2018). Linton et al. (2015) review aggregate emission estimation approaches for transport and note many simplifying assumptions required to achieve the aggregate, including the reliance on fuel consumption averages and generic socio-economic factors. Average speed and traffic-situation models are the critical go-to assumptions in Europe and America (ERMES, 2021). Primarily based on aggregate trip-based transport models (McNally, 2007), such simplifications fail to account for the spatiotemporal and behavioral details one would expect for supporting decisions that affect real people in our urban environments.

The reader is directed to Rasouli and Timmermans (2013) and Gräbe and Joubert (2022) for a more comprehensive discussion of the need for and advances made in activity-based transport models. The latter reference argues for a disaggregate agent-based approach as each vehicle is modeled individually. Its movements are linked to the Handbook Emission Factors for Road Transport (HBEFA) to identify more accurate emission factors throughout the vehicle's journey.

Not only are most emission models used for evaluating interventions at urban and regional scales based on aggregate data, but the models are also rarely validated against empirical data. One recent exception is Gräbe and Joubert (2022). In the study, the authors compare the emission estimates from a state-of-the-art simulation model, the

Multi-Agent Transport Simulation (MATSim), with empirical results obtained using a PEMS unit. A PEMS unit is a high-precision device connecting directly to a vehicle's exhaust and measuring pollutant concentrations under natural driving conditions. The results shown in Figure 1 compare the actual CO_2 emissions, using a PEMS unit, against the simulation coupled with the HBEFA database along a 61.7 km standardized route in an urban setting.

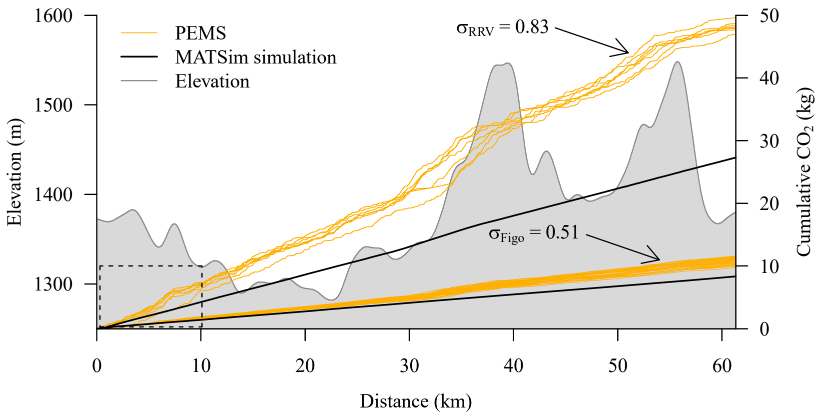


Fig. 1. Elevation profile with the heavy and light vehicle's cumulative CO_2 emissions (Gräbe and Joubert, 2022)

Gräbe and Joubert (2022) compared a light passenger vehicle, a 1.5 litre Ford Figo, and a typical urban delivery heavy goods vehicle.

Most emissions environmental research and policies focus on CO_2 and, more specifically, on passenger vehicles. Consequently, and also visible in Figure 1, the state-of-the-art simulation gets the pollutant for light passenger vehicles (a Ford Figo) reasonably accurate. This can be seen as the proximity of the lower solid grey line to the set of orange PEMS lines annotated with the variation, $\sigma_{Figo} = 0.51$, for the light vehicle. In fact, it closely mimics the pollutant levels reported by the Original Equipment Manufacturer (OEM).

Unfortunately, as is often the case, research focussing on Heavy Goods Vehicles (HGVs) lag of passenger vehicles. Even for CO_2, the HGV's pollutant predictions only account for just over 50% of the actual emissions. This is reflected in Figure 1 by the large gap between the upper solid grey line, representing the simulated HGV emissions in MATSim, and the set of orange PEMS lines annotated with the variation, $\sigma_{RRV} = 0.83$, for the HGV. Gräbe and Joubert (2022) report that the simulation only accounts for 25% of the CO_2 on steeper road sections when road grade is considered. Results on other pollutants measured are provided in Table 1.

Table 1. C-route emissions for the Isuzu FTR850 PEMS trip data, the simulated counterparts in MATSim and the applicable OEM emissions data as reference (adapted from Gräbe and Joubert (2022)).

Vehicle	**Pollutant (g)**				
	CO	**CO_2**	**NO**	**NO_2**	**NO_x**
PEMS	120.8	48 191	403.4	17.6	421.0
MATSim	71.8	27 308	0.5	10.9	11.4
OEM data*	≤58.1	18 570	-	-	≤48.3

* based on the per-km emission rates and Euro emission standards as published by Isuzu (2021). DieselNet (2021) is used as reference for emission standards. The HGV, weighing ±10 740kg (Joubert and Gräbe, 2022), is classified as an *N2*-category vehicle, having a total mass of between 3.5 and 12 tonnes.

The field tests conducted by Gräbe and Joubert (2022), over multiple trips of a standardised 61.7km test route, used a typical urban goods vehicle based on the popular Isuzu FTR850 AMT, a rigid body, a diesel-powered truck with a

Euro III emissions standard. Their results were conservative, as all test trips were conducted without cargo. It is this exact vehicle that is of interest in this current research.

3. Model and experimental setup

This paper builds directly on Gräbe and Joubert (2022) in two ways. Firstly, the same MATSim simulation model is used as the baseline against which RDE field tests are compared. Secondly, this paper benefits from access to the exact medium-heavy urban goods research vehicle. But in this paper, we report on the results of two additional field test configurations, each with a different cargo load added to the truck.

3.1 Baseline model

Li et al. (2021) argue that MATSim is a reliable activity-based transport model to simulate detailed vehicle movement. Even though the scope is at the city/metropolitan scale, it can still couple each vehicle with its associated emissions factors from HBEFA. The starting point is the trip-based model for the Gauteng province in South Africa (Robinson and Venter, 2019) that is converted into an improved (Fourie, 2010; Gao et al., 2010) agent-based counterpart (Joubert and Gräbe, 2021).

A daily activity sequence represents the vehicle's movement during the morning peak for each private and commercial vehicle. Each vehicle executes its schedule on a network derived from *OpenStreetMap*. The coevolutionary machinery of MATSim allows each vehicle to adjust its executed plan by changing the timing of activities (to avoid peak congestion) or by rerouting (to avoid heavily congested links). The resultant is a relaxed state of traffic flow that represents reality well. Still, with the added benefit that each vehicle's movement can be tracked along its entire route, one can also associate the detailed emissions factors with each vehicle. Joubert and Gräbe (2021) discuss the vehicles' profiles in more detail.

To estimate the baseline emissions profile for the Isuzu FTR medium heavy goods vehicle, one additional vehicle agent, called the probe vehicle, is created in MATSim and injected into the mobility simulation along with the entire population of vehicles. The only difference is that the probe vehicle is assigned the same predefined 61.7 km C-shaped route driven in the field tests. The probe vehicle is not allowed to change its route during the simulation. Gräbe and Joubert (2022) explain that the simulation model results in the emissions calculated per vehicle per road link basis, which can then be aggregated to any required level.

3.2 Field test setup

The SEMTECH DS+ PEMS unit was mounted onto the Isuzu FTR850 medium heavy goods vehicle according to the setup described in the public data set published by Joubert (2022) and its supporting article (Joubert and Gräbe, 2022). The following is a concise explanation of the equipment setup from Joubert and Gräbe (2022):

> "Spatial data is captured using a Garmin Global Positioning System (GPS) module integrated with the PEMS unit. A weather probe is also integrated into the unit and provides ambient readings… The PEMS unit has an integrated In-vehicle Control Module (ICM) that allows the driver to record event markers (flags) during a field test. The ICM also connects to and records the vehicles Onboard Diagnostics (OBDII) port while driving… Exhaust gasses pass through the 4-inch (±100 mm) Exhaust Flow Meter (EFM) tube, responsible for measuring the raw exhaust mass flows… The EFM operates under Bernoulli's principle using averaging pitot tubes and employing five dual-stage, differential pressure transducers. The gas analyser unit houses the analytical devices for the gaseous measurements of CO, CO_2, NO, and NO_2."

Once calibrated, the unit is switched

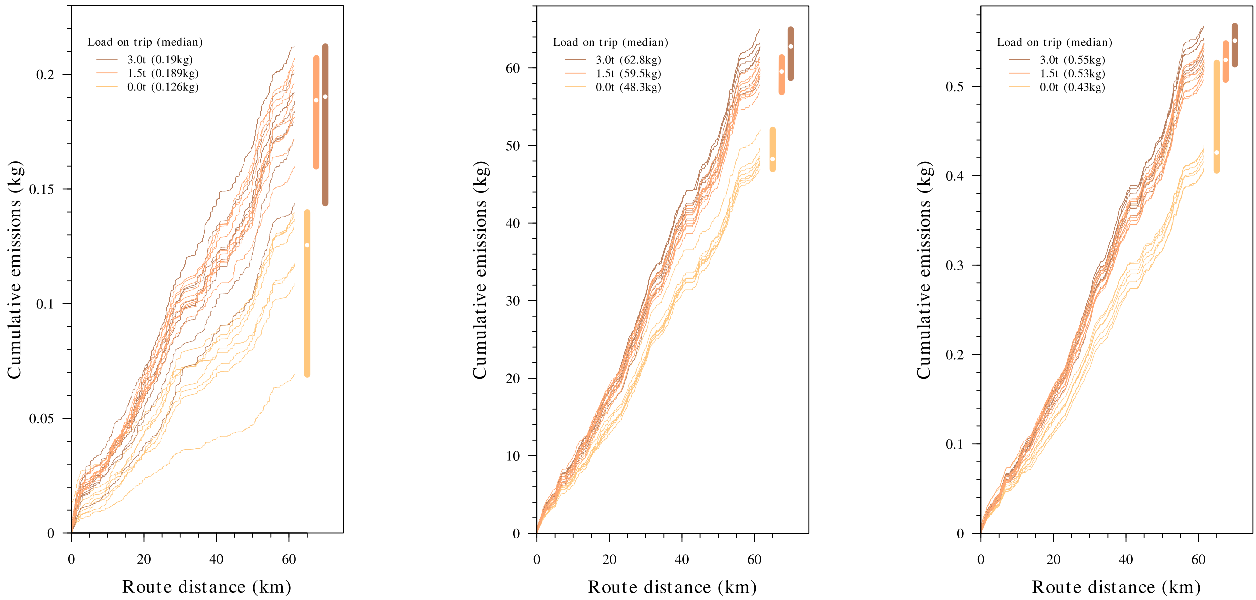
> "…from shore power to its dedicated power source: a 13 V Lithium Iron Phosphate (LiFePO4) battery with a 108 Ah capacity. The purpose of the power source independent of the vehicle's battery is not to place an additional burden on the vehicle's alternator to charge and power the DS+, potentially affecting fuel consumption and emissions. The (co)driver places a data marker in the field test recording, using the In-vehicle Control Module (ICM) unit, and the driver starts the vehicle."

The heavy goods vehicle has a 7.8-litre, common-rail diesel engine with a Euro-III emissions rating, Isuzu (2021). For each load configuration, the truck takes approximately two hours to complete one trip along the C-route in typical urban traffic conditions. For each configuration, the same driver aimed to perform ten test cycles. The benefit of using PEMS over multiple test cycles is that the variation we often attribute to driver behavior can be accounted for. Why is the variation significant? It allows us to also account for other unobserved factors, such as changes in daily traffic volumes, inherent driver behavior, and the weather.

4. Results and discussion

The field trips for the unladen truck were conducted from 2 February to 11 March 2021. There are eight trips in this field test set, as two trips' data were discarded because of a brake failure on the truck. It was decided not to consider those trips' data reliable. The field trips for the configurations with 1.5-tonne and 3.0-tonne cargo, respectively, were conducted from 5 to 10 December 2022, and there are ten trips each for the two configurations.

While the unladed trip data has already been curated and is in the public domain (Joubert, 2022), the laden trip data should appear within the foreseeable future. The cumulative emissions along the 61.7 km route for all the trips are shown in Figure 2. The order of magnitude might differ between the pollutants, but the reader should remember



a. CO. b. CO_2. c. NO_x.

Fig. 2. Comparing the cumulative emissions emitted over multiple trips with different load configurations. The vertical bars to the right of each graph show the spread across the load configuration's trips, with the circle on the bar representing the median over the trips

that their societal impact per concentration is also significantly different. Of interest in this paper is the increase in the median emission levels for the different load configurations.

Carbon monoxide (CO, Figure 2a) is an odorless, colorless, and poisonous gas that results from partial combustion when insufficient heat or oxygen produces carbon dioxide (CO_2). The unladen trips had a median total CO of 0.126 kg, which increased to 0.189 kg with a 1.5 t load, a significant increase of 50.4%. When the load doubled, the total increased to 0.190 kg, an increase of 51.5% over the unladen case but only 0.8% over the 1.5 t case. Applying a t-test to check if the difference between the 1.5 t and 3.0 t difference is statistically significant, it results in a p-value of 0.9445, so we cannot reject the null hypothesis that the two medians are the same.

A similar story unfolds for the other pollutants. In the context of emissions, CO_2 (Figure 2b) results from the (successful) combustion of fossil fuels — diesel in this case. As a greenhouse gas, it receives particular interest as a metric as it contributes to global warming. The unladen trips had a median total CO_2 of 48.3 kg, which increased to 59.5 kg with a 1.5 t load, a significant increase of 23.4%. When the load doubled, the total increased to 62.58 kg, an increase of 30.1% over the unladen case but only 5.4% over the 1.5 t case. In this instance, when applying a *t*-test to check if the difference between the 1.5 t and 3.0 t difference is statistically significant, it results in a *p*-value of 0.0015 < 0.01, so we can reject the null hypothesis with even a 99% confidence level: the two medians are different.

NO_x (Figure 2c) is the generic term that includes both nitric oxide (NO) and nitrogen dioxide (NO_2), and respiratory exposure can exacerbate (or even trigger over more extended periods) asthma symptoms. Its greenhouse effect is complex and neither strictly positive nor strictly negative, depending on the environment and the chemicals with which it reacts. The unladen trips had a median total NO_x of 0.43 kg, which increased to 0.53 kg with a 1.5 t load, a significant increase of 24.3%. When the load doubled, the total increased to 0.55 kg, an increase of 29.4% over the unladen case but only 4.1% over the 1.5 t case. Here, when applying a t-test to check if the difference between the 1.5 t and 3.0 t difference is statistically significant, it results in a p-value of $0.0001 \ll 0.01$, so we can again reject the null hypothesis with even a 99% confidence level: the two medians are different.

Why does this matter for city logistics? Gräbe and Joubert (2022) showed that actual emissions are already much higher than predicted, even when using a state-of-art and spatiotemporally sensitive model like MATSim. For CO, actual emissions were 1.7 times higher than predicted for the unladen case. This increases to 2.6 and 2.7 times higher for both partially and fully laden cases. For CO_2, the factors increase from 1.8 to 2.2 and 2.3. The most significant effect remains for NO_x, where the factors increase from a whopping 37.4 to 46.5 and 48.3. That is nearly two orders of magnitude.

5. Conclusion

Citizens are exposed to real and variable emissions, not simply the pollutants theoretically predicted by models with their inherent simplifications and abstractions. Even the most sophisticated models still do not do very well in supporting decision-making regarding environmental interventions.

This paper presented the first results of a novel study to compare empirical RDE for a typical urban logistics vehicle under different load configurations. The relationship is not linear. As expected, the emissions under load are higher than when the truck travels unladen. But whether the vehicle is partially or fully laden does not seem to make as significant a difference as claimed in earlier research that did not measure the actual emissions but instead used other proxy variables to estimate emissions.

Much research remains. Firstly, this paper only considered two load configurations: 1.5t and 3.0t. It might be valuable to add a finer resolution in increments of 0.5t, for example, if one wishes to establish a more precise relationship between load and emissions. But field tests using PEMS are not only expensive, but they are also very time-consuming.

Secondly, and echoing Gräbe and Joubert (2022), there is much improvement in the emission models we rely on. Since MATSim can model each vehicle uniquely, vehicle load can be inferred from a truck's route profile (and load schedule). Emission factors could be adjusted to account for the specific load. But for that to realize, researchers need to solve the first hurdle mentioned previously: vehicle-specific emissions as a load function.

Acknowledgements

Several funding sources contributed to the acquisition and use of the PEMS equipment. The author would like to acknowledge the University of Pretoria as the primary contributor, the Department of Science and Innovation through their Waste RDI Roadmap (Grant CSIR/BEI/WRIU/2019/028) and the National Research Foundation, South Africa (National Equipment Programme, Grant EQP180425324146). Also, thank you to Prof P.J. (Hannes) Gräbe for using the vehicle in this research. Data analyses and figures were prepared using R (R Core Team, 2022).

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