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Travel Time Differences between Cargo Cycles and Cars in Commercial Transport Operations

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1 Introduction

Approximately every third journey undertaken in Germany falls into the category of commercial transport, that is, freight deliveries or service trips (Menge & Horn 2014), with the proportion being even higher in the dense city cores. According to forecasts, freight traffic on German roads will continue to rise in the coming years: in 2030, Germany will experience 39% more volume (in ton-miles) compared to 2010 (BMVI 2014). There is a clear political and societal will to develop countermeasures to cope with the negative externalities that coincide with increasing commercial transport operations, such as air and noise pollution, greenhouse gases, congestion, safety hazards, and less urban liveliness. More than 500 European municipalities have imposed vehicle access restrictions (Kassyda 2016), and the first cities have imposed driving bans for diesel-driven vehicles, with Stuttgart (where Daimler and Porsche have their headquarters) being a prominent example (Bennhold 2018). In May 2018, the European Commission sued Germany, the UK, France, Italy, Romania, and Hungary, stating that these countries had failed to meet NO_x and PM limits (European Commission 2018). Furthermore, the European Commission set the goal to "achieve essentially CO_2-free city logistics in major urban centers by 2030" (European Commission 2011).

To minimize the environmental burden of commercial trips, using cleaner and smaller vehicles such as electric cargo cycles for freight operations and service trips is seen as one promising solution (Schliwa et al. 2015). A substantial substitution potential for cargo cycles was found for Germany: 8-23% of commercial trips and 1-4% of the corresponding mileage could technically be shifted to cargo cycles (Gruber et al. 2016). Successful commercial use cases for cargo cycles have been found throughout Europe (Schliwa et al. 2015, Lenz & Riehle 2012).

There are diverging results when it comes to assessing operative feasibility. Some authors use (micro) simulation approaches for concept assessments. For Porto (Portugal), a replacement potential of 10% of conventional vans for distances up to 2 km (1.2 miles) was found to be economically viable (Melo & Baptista 2017). For Berlin (Germany), results show a potential 22% reduction in emissions, and cost savings of 28% for parcel providers, if the use of cargo cycles is implemented (Zhang et al. 2018). On the other hand, a similar approach for Seattle, WA, finds that cargo cycles are hardly a cost-efficient solution for last-mile logistics (Butrina et al. 2018). Data from Austin, TX, was used to compare the costs of cargo cycles with the trucks used by the US Postal Services, and this showed the cost competitiveness for e-trikes, especially in CBD areas and during congested traffic conditions (Choubassi et al. 2016).

While diversification and performance increases in available cargo cycle models have been noticeable in recent years, many businesses are still reluctant to implement the use of this type of vehicle. Fleet decision-makers and the customers of logistics operators show reservations about using cargo cycles (Melo & Baptista 2017), while the prevalent conditions and cultures of many small-sized cycle freight companies prevent a professionalization of the sector, as has been found in the UK (Schliwa et al. 2015).

Many consider the load-carrying capacity of cargo cycles to be a deterrent to their application. Though it is unrealistic to consider cargo cycles replacing all forms of motorized commercial transport in urban areas, findings show that a substantial amount of commercial trips being carried out by motorized vehicles can be taken over by cargo cycles in terms of load capacity, as has been shown for point-to-point shipments (Gruber et al. 2014).

Another major factor affecting the successful application of cargo cycles is their travel time performance in comparison to cars. As was hinted in the literature (Melo & Baptista 2017, Choubassi et al. 2016), the travel times of cargo cycles might be one of the operative limits as they are said to only be suitable for short travel distances. Time is arguably the most precious asset within commercial transport operations; hence, we want to focus on this important issue: the (potential) increase in travel time when switching to a smaller and cleaner vehicle. By looking at cargo cycles' travel time differences compared to cars, we would like to contribute to the assessment of the cargo cycles' substitution potential within commercial transport operations.

The two main research questions addressed are:

1. What are the differences in travel times between cargo cycles and cars when used for commercial transport operations?
2. Which factors, including but not limited to trip distance, payload utilization, time of day, and vehicle type, affect these travel time differences?

The rest of this paper is organized as follows: after a summary of the existing literature, the research setting and methods will be described, followed by descriptive statistics of the cargo cycle trips sample and the model results. Subsequently, an application of the model and a scenario analysis will be presented. After discussing our findings, this paper ends with a conclusion.

2 State of the Art

This section consists of literature findings concerning speed and travel time differences between bicycles or cargo cycles and cars as well as macroscopic factors affecting bicycle and car speed. Generally, the literature concerning cargo cycles and relating to the current research focus is limited; hence, literature findings from both commercial and passenger transport were considered.

One contribution presents an in-depth analysis of two cycle freight operators in New York City using human-powered vehicles (Conway et al. 2017). It was shown that cargo cycles can be competitive in terms of speed compared to conventional vehicles in congested situations. Results from Porto (Melo & Baptista 2017) indicate that the implementation of cargo cycles can lead to better traffic performance (with lesser delay times being one indicator), yet only up to a replacement rate of 10% of conventional vehicles.

Concerning passenger transport, speed ranges of electric bicycles and cars show some overlap, as shown for Europe (BMVIT 2016) and the United States (Tranter 2012), which can be seen as an indicator of the potential for competition between these modes, even in commercial transport operations. One analysis compares hailing a taxi to taking a rental bike in New York City for trip distances of up to 6 km (3.7 miles) (Faghih-Imani et al. 2017). While this study doesn’t address freight movement, some findings might be comparable. The results show that, on average, taxi trips were slightly faster than bicycle trips. However, some influencing factors can cause substantial deviations in the travel time differences between bicycle and taxi. In the following, spheres of influence are grouped into spatial context, time, vehicle, and trip conditions.

Concerning spatial context, it was found for New York City that greater trip distance was a factor favoring trucks over cargo cycles without electric assist (Conway et al. 2017), as well as taxi travel times compared to bicycles for private mobility (Faghih-Imani et al. 2017), i.e., one can expect higher travel time difference between cycles and cars as the trip distance increases. Comparing trip distances between identical origin-destination relations for bicycles and cars, bicycles have the option of taking shortcuts, e.g. through parks or along one-way streets that are bidirectional for bicycles, which renders travel time savings (Tranter 2012); hence, cycles can achieve reduced travel time compared to cars. Different elevation levels of origin and destination have an effect on bicycle speed, the speed declining with increasing road grade due to grade resistance (Tengattini & Bigazzi 2017). On a disaggregate level, a positive influence on cycling speed was found within Montreal’s road network due to the availability of good/dedicated bicycle infrastructure (Strauss & Miranda-Moreno 2017).

Furthermore, temporal aspects play a role: bicycles have an advantage in terms of speed during times of greater congestion such as morning rush hour periods, as was found for freight (Conway et al. 2017) and passenger transport (Strauss & Miranda-Moreno 2017). On the other hand, empty network conditions that would more likely happen on weekends or during the night would favor increased car speeds (Laflamme & Ossenbruggen 2017).

When it comes to type of vehicle, the presence and type of electric assist plays a role. The speed gains of electrically assisted bicycles (predominantly used for private mobility) in Germany are 2-9 km/h (1.2-5.6 mph), due to the lower level of effort required to achieve a higher speed (Schleinitz et al. 2017). When it comes to cargo cycles, two-wheelers are generally seen as faster than three-wheelers because of the extra effort required to ride three-wheelers. This effect is strengthened by the fact that the usual payloads are higher for three-wheelers (Tab. 1).

Finally, specific trip conditions could change travel speeds. Several studies look at the influences of weather variables on cycling behavior such as modal share, frequencies, and use duration per day (Böcker & Thorsson 2014). However, results concerning influences on cycling speed and travel time have not been found. For combustion engine vehicles, analyses found significant speed reductions caused by precipitation and inclement weather (Akin et al. 2011).

Literature findings concerning speed and travel time differences between bicycles and cars show that cycles are promising in terms of speed and travel time. However, it should be noted that an analysis consisting of users from different sectors of commercial transport is still missing and the current study has been designed to fill this gap. Though an in-depth analysis on cargo cycle speed is conducted in (Conway et al. 2017), it should be noted that the findings were generated based solely on freight operators in Manhattan and one distinct cargo cycle model. Given the diverse needs of different organizations, results based on CBD delivery operators and a single cycle model might not be sufficient, and large-scale research comprising different types of cargo cycles and a wide variety of users and contexts is warranted.

Major factors that should be explored during this research include trip distance, shortcuts available for cycles, road grade, network load (peak and off-peak hours), cargo cycle type (number of wheels and presence of electric assist), and weather conditions (temperature and precipitation). Although, to the best of the authors' knowledge, there is no existing literature on this, the authors would like to explore the effect of payload utilization and car ownership per capita in the cities where the trips were carried out. One would assume that increased payload utilization would result in decreased cycle speed. The authors believe that this decrease might not be substantial until a certain threshold (e.g. ¾ of maximum) of payload utilization has been reached and would like to analyze this in this research. Regarding car ownership per capita, it can be assumed that higher car densities would increase the probability of congestion and hence lead to an increase in travel time for cars.

3 Research Setting

3.1 Project Background: "Ich entlaste Städte" – The German Cargo Cycle Testing Scheme for Commercial and Public Users

Despite their great potential, to date cargo cycles have rarely been used in commercial operations. The project "Ich entlaste Städte" ("Taking the load off cities"), managed by the Institute of Transport Research within the German Aerospace Center (DLR), aims to decrease barriers built on uncertainty or a lack of knowledge about the operative feasibility of cargo cycles. Therefore, private companies and public organizations across Germany are being given the opportunity to test a cargo cycle for three months at a very low cost (roughly US$ 30 monthly). The project is specifically targeted at companies without cargo cycle experience, irrespective of business sector, size, or location. Participating organizations can choose between 18 different cargo cycle models, of several construction types, in order to cope with heterogeneous demand and use patterns.

3.2 Data Collection

3.2.1 Cycle Trip Details

During cargo cycle testing, the participating organizations are required to use a smartphone app which was developed for the purpose of obtaining data. Users manually start and stop GPS track recording and answer trip-related questions, such as trip purpose, payload capacity utilization, or substituted type of vehicle. Trips with inconsistencies (e.g. 'jumps' due to insufficient GPS coverage) and round trips were removed. The sample contains 1,421 cargo cycle trips.

3.2.2 Car Trip Details

Equivalent data for the mode 'car' was obtained from Google Maps using the latitude and longitude values for the origins and destinations of the cargo cycle trips, day, and starting time (Melo & Zarruk 2016). The potential of Google Maps' API for travel time estimation has been shown in Wang & Xu (2011) and Dumbliauskas et al. (2017). Two estimates of travel times were obtained, namely 'best guess' and 'pessimistic'. Best guess is the best estimate (most likely value) for travel time and pessimistic value is a value longer than the actual travel time on most days (a value representing the upper end of the travel time distribution, representative of the congested scenario for cars). While ‘best guess’ values were used for model estimation, pessimistic travel times were used for scenario analysis in order to evaluate the effect of congestion.

3.2.3 Other Variables and Data

Further data was collected concerning city size (BBSR 2015), car ownership (Kraftfahrt-Bundesamt 2018), altitude of the trip origins and destinations (Cooley 2017), air temperature and precipitation for all involved locations on an hourly basis (DWD n.d.), and perceived bicycle infrastructure quality (ADFC 2016).

Furthermore, data from the most recent national travel survey focusing on commercial transport (KiD2010) was used (BMVBS 2012) to create a subsample of trips that are feasible for cargo cycles. Filter criteria: Vehicle type: motorcycles, cars, or light commercial vehicles with up to 3.5 metric tons (3.2 T) of payload, trip length ≤ 20 km (12.4 miles), trip payload ≤ 50 kg (110.2 lbs.), trip purpose: commercial transport or service trips. Within these criteria, a total of 2.37 billion commercial trips are carried out each year in Germany.

3.3 Sample Descriptive Statistics

3.3.1 Geographic Background

This analysis sample contains 1,421 cargo cycle trips. These trips were carried out by 84 users located in 44 German municipalities in 14 out of the 16 German states. Naturally, large cities proved to be a favorable setting for alternative vehicle concepts, with 11 users from Berlin and seven users in Munich. While three out of four participating organizations are located in cities with 100,000 or more inhabitants, medium-sized cities and rural areas were also involved.

3.3.2 Organizational Background

Almost half of the users are self-employed or work as freelancers, underlining that low-cost cargo cycle testing is highly attractive for this professional group. Participation in the project is not limited to companies; consequently, approximately every fourth user was a public institution, an association, or another type of organization. The sample contains a very diverse collection of business areas, including: café, carpenter, chimney sweep, construction firm, copy shop, courier logistics, facility management, flower delivery, gardener, movie production, municipal agency, pharmacy delivery, and photographer. Concerning turnover, 88% of the organizations are considered micro enterprises (turnover < € 2 million), while the remainder is quite evenly distributed among small (€ 2-10 million), medium-sized (€ 10-50 million), and large enterprises (> € 50 million). More than four out of five organizations hadn’t had any cargo cycle experience prior to the test.

3.3.3 User Characteristics

It was not possible to collect socio-economic data for all the users due to data privacy concerns. Only 38 users registered their socio-economic data (less than half the number of users in the sample). Exploring the data of the 38 users shows that their ages range from 26 to 61. Among the 38 users, 34 are male and four are female. Nine users earned a net income of below € 1,750, 10 above € 3,000 and the rest in between. Only two of the 38 users had experience with cargo cycles before this project.

In summary, looking at geographic background, organizational background, and characteristics of the users, it is certain that the sample includes a broad variety of users.

3.3.4 Vehicle Characteristics

Participating organizations were offered a selection of 18 different vehicles, which can be grouped into five construction types (Tab. 1). Parts of the fleet are two-wheelers and targeted towards more time-critical operations, while tricycles have higher payload capacity and therefore rather lower speed profiles. Most of the models had electric assist up to 25 km/h (15.5 mph), known as ‘Pedelec-25,’ as these vehicles are classified as non-motorized bicycles by EU law. Two models had no electric assist, and one model had electric assist up to 45 km/h (28.0 mph), known as 'Pedelec-45'. All models were able to carry a minimum payload of 50 kg (110.2 lbs.).

3.3.5 Trip Characteristics

Fig. 1 shows the sample's trip distance distribution compared to the KiD2010 survey, which is representative for commercial transport in Germany (see 'Data Collection'). While for trip distances between 9 and 20 km (5.6-12.4 miles), the sample contains substantial smaller shares of the total amount of trips, it is still the case that, both in the sample and in KiD2010, the vast majority of commercial trips are below 10 km (6.2 miles): 89% of the sample trips and 76% of the KiD2010 trips, respectively.

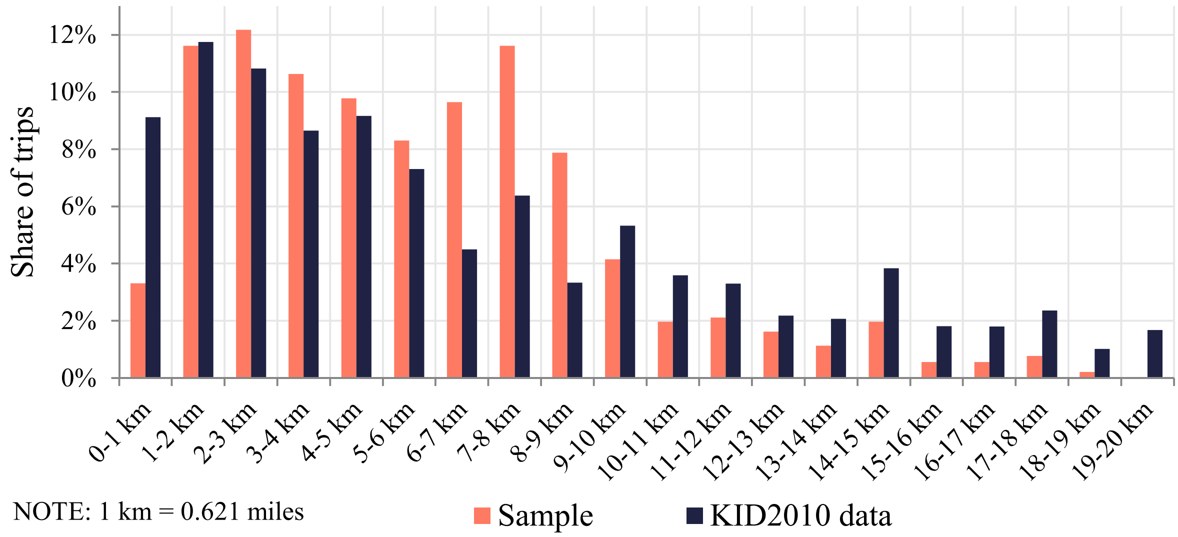

Fig. 1: Distribution of trip distances in sample (n=1,421) and KiD2010 (n=2.37 billion).

Tab. 1 presents in-depth descriptive statistics of the analyzed sample. From the table, one can ascertain that the dataset consists of a good representation of trips throughout the day (intra-day variation) and also for each day of the week (inter-day variation).

As can be seen in Fig. 2, the travel times by cargo cycles and cars overlap, especially for lower distance trips. As trip distances increase, cars become more advantageous in terms of speed. However it should be noted that, even for longer trips, there are some cases where cargo cycles are faster.

Tab. 1: Fleet and Trip Characteristics

Cargo Cycle Fleet Used							
No. of wheels	**Construction type**	**Side view of typical model**	**No. of models**	**Models with electric assist**	**No. of vehicles**	**Mean cargo box volume (L)**	**Share of trips (n=1,421)**
2	Pizza delivery bike		1	1x without	8	131	6.1%
	Long John bike		9	1x without 7x Pedelec-25 1x Pedelec-45	56	187	67.8%
	Longtail bike		2	1x without 1x Pedelec-25	4	*no cargo box*	11.7%
3	Tricycle, front load		5	5x Pedelec-25	15	304	13.7%
	Heavy-load tricycle		1	1x Pedelec-25	1	1300	0.8%

Trip Characteristics (n=1,421)					
Cycle trip distance (km)	Min	0.3	Car trip distance (km)	Min	0.3
	Mean	5.8		Mean	5.9
	Median	5.3		Median	5
	Max	18.6		Max	21.5
Cycle trip travel time (min)	Min	1.3	Car trip travel time (min)	Min	1.2
	Mean	21.5		Mean	12.8
	Median	19.7		Median	12.2
	Max	69.9		Max	39.4
Cycle trip speed (km/h)	Min	7.9	Car trip speed (km/h)	Min	10.6
	Mean	15.9		Mean	26.9
	Median	15.7		Median	24.7
	Max	32.7		Max	67.1
Elevation difference between destination and origin (m)	Min	-132.8			
	Mean	1.1			
	Median	0.2			
	Max	137.8			
Temperature (°C)	Min	-9.5	Precipitation (mm/hour)	Min	0
	Mean	9.5		Mean	0.1
	Median	8.8		Median	0
	Max	27.4		Max	5.2
Intra-day variation (share of trips)	12-6 a.m.	1.2%	Inter-day variation (share of trips)	Mon	15.1%
	6-7 a.m.	1.0%		Tue	17.7%
	7-8 a.m.	5.5%		Wed	20.6%
	8-9 a.m.	6.0%		Thu	16.9%
	9-10 a.m.	6.6%		Fri	16.6%
	10-11 a.m.	7.7%		Sat	8.3%
	11 a.m.-12 p.m.	7.4%		Sun	4.8%
	12-1 p.m.	6.2%	Utilization of available loading capacity (share of trips)	Almost empty	21.2%
	1-2 p.m.	6.2%		One quarter	30.1%
	2-3 p.m.	6.9%		Half	19.5%
	3-4 p.m.	6.1%		Three quarter	10.2%
	4-5 p.m.	5.6%		Full	18.2%
	5-6 p.m.	7.5%		Overloaded	0.7%
	6-7 p.m.	8.8%	Trip purpose return trip (share of trips)	Yes	29.5%
	7-8 p.m.	6.9%			
	8-9 p.m.	3.8%	Three-wheeled cargo cycle (share of trips)	Yes	14.4%
	9-10 p.m.	2.8%			
	10-11 p.m.	2.5%	Electric assist (share of trips)	Yes	81.3%
	11 p.m.-12 a.m.	1.3%			
NOTE: 1 L = 0.0353 ft³; 1 km = 0.621 miles; 1 m = 1.094 yd; Fahrenheit temperature F = 1.8*C + 32					

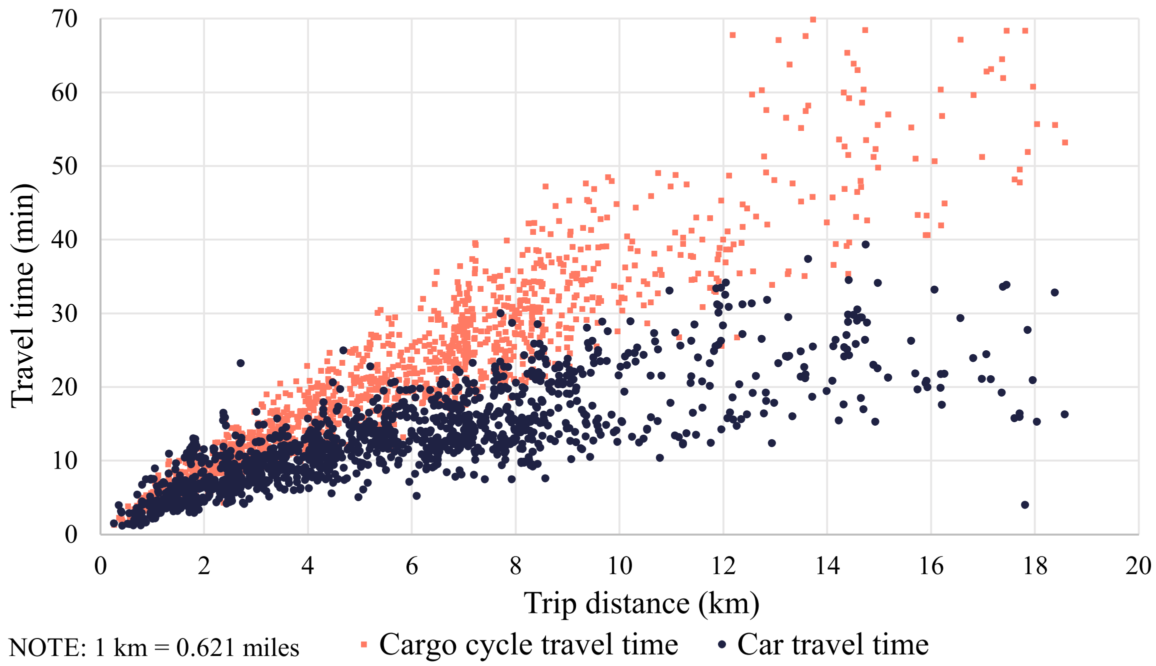

Fig. 2. Travel times of cargo cycles and cars versus trip distance.

4 Model Estimation

As mentioned earlier, the travel time for the mode 'cargo cycle' was taken from the trip details recorded through the official smartphone app while, for the mode 'car', the data was obtained from Google Maps. A regression model will be estimated since the factors are easily interpretable and the model is readily usable. The difference between the travel times of the modes 'cargo cycle' and 'car' (in min) was considered as the dependent variable for the model.

Regression models based on an ordinary least squares (OLS) approach were tried out initially. Attributes for the model were selected based on the literature. The decision to keep an independent variable was based on the p-value (significance level 0.10) of the corresponding variable and the adjusted R^2 value of the model obtained upon adding the new variable.

Since the route options available to the mode 'car' could increase for longer trips and hence there could be a wider distribution of travel time difference, it was expected that the variance of the residuals would increase as the trip length increases, i.e. the residuals were expected to be heteroskedastic. To account for the heteroskedasticity, it was decided to apply weights to the residual variance based on the trip length (υ; variance covariate), as shown in Equation 1 (Pinheiro & Bates 2000). To implement this, a generalized least squares approach (GLS) was implemented with the same model specification as that of the final OLS model. GLS is efficient over OLS in the presence of heteroskedasticity (Greene 2012). ANOVA test was used to ascertain the significance of the GLS model.

$$Var(\epsilon) = \sigma^2 \upsilon \qquad (1)$$

Given that there are multiple observations from individual users, observations would be correlated. The estimated standard errors are biased if this fact is ignored (Dupont & Martensen 2007, Moulton 1986), especially when the model does not contain user-specific attributes. Hence, a random intercept model was used to capture the influences of the user on the dependent variable. The suitability of a random intercept model for a dataset containing correlated observations is made obvious in (Dupont & Martensen 2007), which shows the application of mixed models in the field of traffic safety. Following the estimation of a random intercept model, the intraclass correlation (ICC) was computed based on Equation 2 (Dupont & Martensen 2007, Moulton 1986) to substantiate the necessity for a random intercept model.

$$ICC = \frac{Variance\ of\ the\ random\ effect\ of\ the\ intercept}{Total\ variance} = \frac{(\sigma_u)^2}{(\sigma_u)^2 + (\sigma_e)^2} \tag{2}$$

Further, 5-fold cross-validation (James et al. 2013) was carried out to compare the predictive performance of the three model types: OLS, GLS, and the random intercept model. The validation process involves dividing the sample set into five groups of equal size. Estimation is done using four groups while the remaining set is used as a validation set. The estimation is repeated four more times, and each time a different group is considered as the validation set. The process results in five Mean Squared Error (MSE) values, with the final MSE being calculated by averaging the five values. MSE values for each model are computed and compared to assess the predictive performance of the models.

5 Model Results

The estimation results from the OLS models show that all the independent variables tested have the expected sign. The OLS model with the variable 'cycleTripDistance' had an adjusted R^2 value of 0.648, proving that this variable is the most significant one. The second most significant variable was 'distanceDifferenceCarAndCargoCycle,' which improved the adjusted R^2 value from 0.648 to 0.697. Followed by this, log(carOwnership) improved the adjusted R^2 value to 0.727. Adding the rest of the significant variables resulted in a minor improvement of the adjusted R^2 value, reaching 0.755 in the final OLS model.

As expected, the residuals from the OLS model were heteroskedastic (Fig. 3A). A visual inspection of the fitted vs residuals plot of the GLS model (Fig. 3B) showed that the heteroskedasticity issue has been nullified. The change in significance level of some of the variables in the GLS model reflects the correction applied to heteroskedasticity. In the initial estimation of the random intercept model, the variable 'isTemperatureAbove5' was insignificant (t-value: -1.405 and p-value: 0.160), and hence this variable was removed. As mentioned in the methodology section, a model without random intercept could result in inflation or deflation of the t-values, and the significance of the temperature dummy variable in models without random intercept is an example of this. The intraclass correlation value obtained for the current dataset is 0.33, with a value of 0.20 and above being considered a large value (Kreft & de Leeuw 1998). Hence, it is certain that the clustering effect of the users cannot be disregarded, and a random intercept model must be used. Fig. 3C shows the fitted vs residuals plots of the random intercept model and Fig. 3D shows the cumulative distribution of travel time difference in the sample and the fitted values from the model.

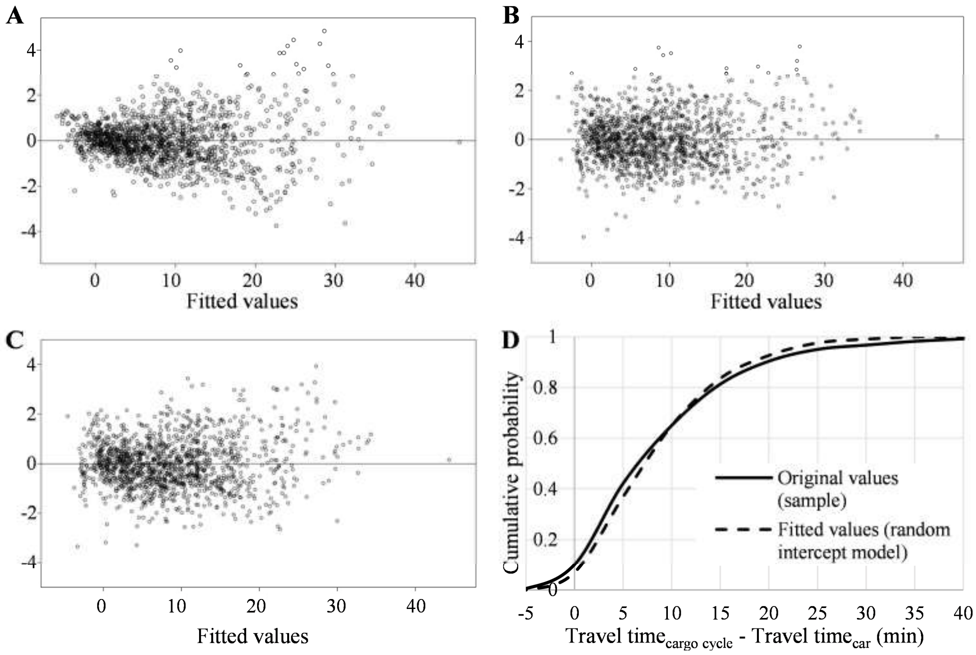

Fig. 3. Residual distribution from OLS (A), GLS (B), and random intercept Model (C); Cumulative distribution of original and fitted values of dependent variable (D).

Comparing the values of the goodness of fit indicators between the GLS model and the final random intercept model clearly showed that the random intercept model is statistically superior. Hence, this model will be used for further analysis. Variables that were insignificant in the OLS model remained insignificant in the random intercept model. The random effect, which represents the variation between the users, is normally distributed with a mean of 0. Though there is no substantial difference in the mean squared error value obtained for the three models through 5-fold cross-validation, the random intercept model performs slightly better than the other two.

In Tab. 2, below, the estimates are presented from the final OLS model, the GLS model, and the random intercept model along with the result of the cross-validation and goodness of fit indicators.

Tab. 2: Estimation Result

Coeff.	**OLS Model**			**GLS Model**			**Random Intercept Model**		
	Estimate	Std. err.	t. Statistic	Estimate	Std. err.	t. Statistic	Estimate	Std. err.	t. Statistic
β_{CON}	3.160	0.593	5.332 (***)	1.760	0.424	4.339 (***)	2.318	0.596	3.889 (***)
β_{TD}	1.846	0.033	55.699 (***)	1.747	0.030	57.129 (***)	1.696	0.032	53.279 (***)
β_{ED-M}	0.132	0.027	4.856 (***)	0.131	0.027	4.843 (***)	0.129	0.026	5.017 (***)
β_{ED-E}	0.025	0.005	4.845 (***)	0.022	0.005	4.763 (***)	0.020	0.004	4.513 (***)
β_{DD}	-1.657	0.104	-15.927 (***)	-1.784	0.103	-17.110 (***)	-1.665	0.109	-15.308 (***)
β_{CO}	-0.609	0.071	-8.575 (***)	-0.342	0.052	-7.956 (***)	-0.512	0.106	-4.848 (***)
β_{6-10}	-2.008	0.447	-4.492 (***)	-1.824	0.360	-4.637 (***)	-1.318	0.357	-3.692 (***)
β_{10-19}	-1.128	0.375	-3.007 (**)	-1.217	0.300	-3.987 (***)	-0.993	0.296	-3.352 (***)
β_{3W}	1.779	0.360	4.946 (***)	2.025	0.273	7.872 (***)	2.066	0.504	4.100 (***)
β_{P45}	-2.359	0.342	-6.889 (***)	-0.930	0.245	-3.800 (***)	-1.292	0.632	-2.044 (*)
$\beta_{T>5}$	-0.865	0.258	-3.358 (***)	-0.290	0.172	-1.686 (.)	-		
σ_{CON}	-			-			1.126		
5-fold Cross-validation	MSE: 20.441			MSE: 20.669			MSE: 20.114		
Goodness of fit indicators	Adj. R^2: 0.755 AIC: 8196.194 BIC: 8259.278 Log likelihood: -4086.097			AIC: 7711.662 BIC: 7774.746 Log likelihood: -3843.831			AIC: 7617.105 BIC: 7680.189 Log likelihood: -3796.553		

NOTE: For coefficient names and description, please refer to

Tab. 3.

Negative coefficients indicate travel time advantages for cargo cycles.

(.) - p<0.10 | (*) - p<0.05 | (**) - p<0.01 | (***) - p<0.001

In the following, we describe the magnitude of the variables. The estimates from the random intercept model show that with every km (0.6 miles) increase in cycling trip distance one can expect the time difference value to increase by 1.70 minutes. While one meter (1.1 yd) difference in elevation between the origin and destination can change the dependent variable value by 0.13 minutes when using a manual cycle, the effect is much less when using an electric cycle, ranging around 0.02 minutes per meter. A 1 km (0.6 miles) difference in trip distance between car and cargo cycle (trip distance of car being higher) can, on average, reduce the travel time difference by 1.66 minutes. This shows the advantage of the shortcuts available for cycles. When a trip is done during the morning peak hour, one can save around 1.32 minutes if a cargo cycle is used instead of a car, and the saving in travel time during the afternoon and the evening peak is around one minute. Using a three-wheeler instead of a two-wheeler cycle can delay the trip by, on average, 2 minutes. Using a 'Pedelec 45' electric cycle can reduce travel time by 1.29 minutes.

Besides giving more detailed information about names and types of variables, Tab. 3 below depicts the directions of effects along with the interpretation of the effect, both for significant and insignificant variables.

Tab. 3: Effects of the Independent Variables

Var. Group	Variable Name	Description	Coeff.	Coeff. Sign	Interpretation & Comparison with Literature
Significant variables (in random intercept model)					
	Intercept	Model constant	β_{CON}	+	The positive sign is interpreted as indicative of the superiority of the car in general.
Spatial context	cycleTrip Distance	Cargo cycle trip distance recorded by smartphone app (km)	β_{TD}	+	With increasing trip distance, one can expect cars to be advantageous. In line with (Gruber et al. 2014).
	elevation Difference ManualCycle	Elevation difference between destination and origin (m) – when cargo cycle without electric assist was used	$\beta_{ED\text{-}M}$	+	Increasing upward gradient results in increasing grade resistance, which in turn results in increasing travel time for cycles. In line with (Tengattini & Bigazzi 2017).
	elevation Difference ElectricCycle	Elevation difference between destination and origin (m) – when cargo cycle with electric assist was used	$\beta_{ED\text{-}E}$	+	Similar interpretation as for $\beta_{ED\text{-}M}$.
	distance Difference CarAnd CargoCycle	Difference in trip distance between car and cargo cycle ($Dist_{car} – Dist_{cargo\ cycle}$; km)	β_{DD}	–	With car trip distance higher than the cycle trip distance, travel time for car increases and hence the travel time difference decreases. This shows the effects of shortcuts. In line with (Tranter 2012).
	log(car Ownership)	Car ownership per 1,000 inhabitants in the city where the trip was done	β_{CO}	–	In cities with high car density, the probability of congestion is higher, hence travel time for car increases.
Time	is MorningTime	Dummy variable: trip started between 6 a.m. and 10 a.m.	$\beta_{6\text{-}10}$	–	During the morning peak, the travel time for car is generally higher, hence travel time difference decreases. Also, cyclists travel faster during this time compared to night and early morning (Strauss & Miranda-Moreno 2017).
	is DayTime	Dummy variable: trip started between 10 a.m. and 7 p.m.	$\beta_{10\text{-}19}$	–	Trips other than home-based work and school trips are usually done in the afternoon after the morning peak, and in the evening, all kinds of trips are seen. Hence, travel time for car is generally higher during this time because of congestion. Also, cyclists travel faster during this time compared to night and early morning (Strauss & Miranda-Moreno 2017).
Vehicle	is ThreeWheeler	Dummy variable: three-wheeled cargo cycle was used	β_{3W}	+	Three wheelers are slower because of higher payload capacity and the extra effort required to ride them compared to two wheelers (see Tab. 1).
	is Pedelec45	Dummy variable: trip was done using cargo cycle with 'Pedelec-45' electric assist (Tab. 1)	β_{P45}	–	Higher speed achievable with less effort, hence reduction in travel time difference.

Var. Group	Variable Name	Description	Coeff.	Coeff. Sign	Interpretation & Comparison with Literature
		Insignificant variables (in random intercept model)			
Spatial context	isCitySize Large / isCitySize Medium / isCitySize Small	Dummy variable: Population of the city/municipality where the trip was done		– + +	Due to higher possibility of congestion (as shown by (Chang et al. 2017) for US cities), cargo cycles are advantageous in larger cities.
	bikeInfra Quality Index	Perceived bicycle infrastructure quality index (ADFC 2016) of the city where the trip was done		–	Better cycling infrastructure supports higher cycling speed, hence reduction in travel time difference (Strauss & Miranda-Moreno 2017).
Time	isWeekEnd	Dummy variable: trip was done on Saturday or Sunday		+	Less congestion on main roads and therefore higher driving speed possible for cars.
Vehicle	isElectric	Dummy variable: trip was done using cargo cycle with 'Pedelec-25' or 'Pedelec-45' electric assist (Tab. 1)		–	Same interpretation as that of isPedelec45 applies here.
Trip condition	isFullyOrOver Loaded	Dummy variable: cargo cycle was fully or overloaded during trip (stated by rider within smartphone app)		+	Loading more than three quarters of the available loading capacity significantly reduces cycling speed, hence increasing the travel time difference.
	isReturnTrip	Dummy variable: trip purpose is return to point of origin (stated by rider within smartphone app)		+	Users tend to cycle slowly for return trips as there is no time pressure.
	is Temperature Above5	Dummy variable: temperature during the trip is above 5°C (41°F)	$\beta_{T>5}$	–	Air becomes denser at lower temperatures; hence air resistance and tire rolling resistance increases. Therefore, as temperature increases, cyclists can achieve faster speeds and hence a reduction in travel time difference.
	Temperature	Temperature during the trip (°C)		–	Same interpretation as for isTemperatureAbove5 applies here.
	Precipitation	Quantity of precipitation (mm/h) at departure time		–	Reduction in car driving speed due to rain (to avoid skidding and other similar problems), hence reduction in travel time difference.

6 Model Application

The results from the random intercept model were applied to an out-of-sample prediction of 9,821 car trips taken from the IeeA database (Gruber et al. 2014), a database of point-to-point shipments collected by DLR during the current project's predecessor "Ich ersetze ein Auto" ("I substitute a car"). All 9,821 trips were made by car in March 2014 by 205 individual (self-employed) messengers in eight German cities. Actual car delivery origins, destinations, and time stamps of the trips from the IeeA database were used. A comparison of the distributions of trip distances from the main sample and the IeeA dataset is shown in Fig. 4.

The s-curve in Fig. 5 is constructed based on the predictions for the IeeA dataset. The figure shows that around 50% of the trips can be done with a maximum delay of around 10 minutes if the users use a two-wheeled cargo cycle with 'Pedelec-25' electric assist, and in the case of a three-wheeled 'Pedelec-25' cargo cycle, the median value is around 12 minutes. If the user uses faster electric assist ('Pedelec 45') on a two-wheeler, 50% of the trips can be done with a maximum delay of 8 minutes. The maximum delay that can be expected for all the trips is less than 40 minutes. Hence, even during time-critical situations, cargo cycles are viable alternatives to cars, though not in every case. This result shows that the range of expected travel time difference is consistent.

Fig. 6 shows the plot between car trip distance and predicted travel time difference for a two-wheeled cargo cycle with 'Pedelec-25' electric assist and a car. This type of cargo cycle is highlighted because of its common usage, both in the sample (Tab. 1) and in commercial operations in general (Gruber et al. 2016). The plot clearly shows that there are a few cases wherein a cargo cycle is faster in terms of travel time, even for trips longer than 10 km (6.2 miles). A look into those data points reveals that this is mainly due to the difference in distance between cycle route and car route. This serves as evidence that cycles are better able to compete with cars in cities where shortcuts are available for cycles.

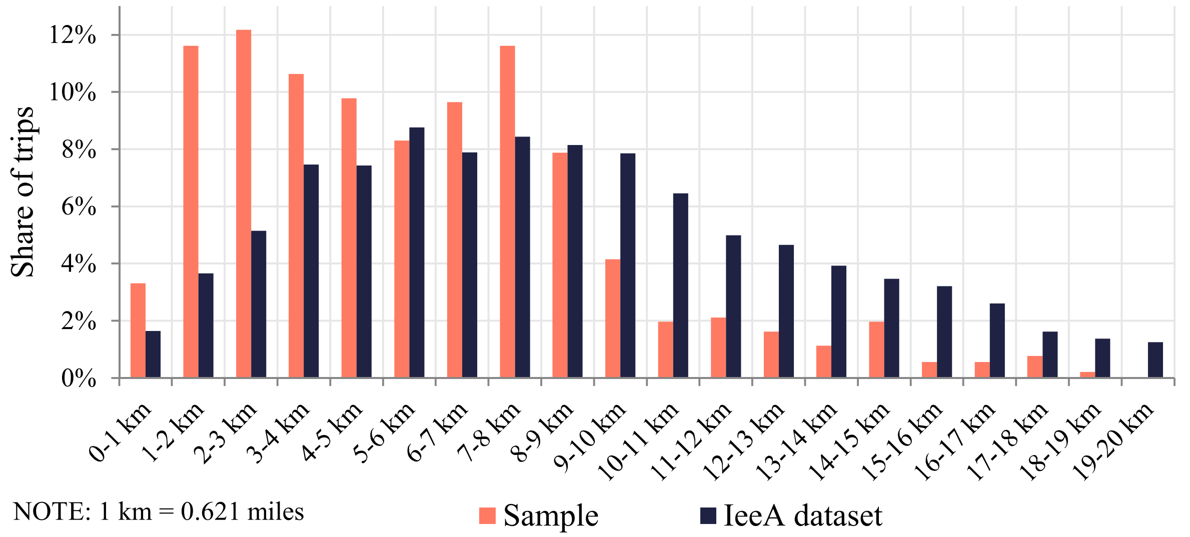

Fig. 4. Distribution of trip distances in sample (n=1,421) and IeeA dataset (n=9,821).

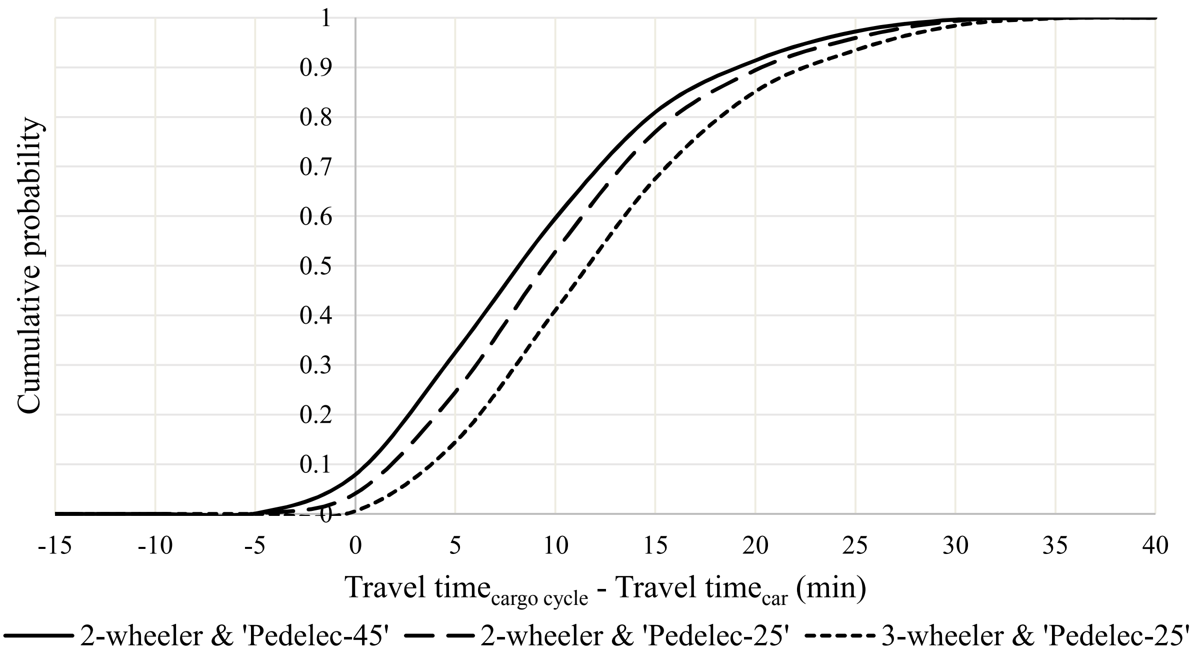

Fig. 5. Cumulative probability distributions for travel time difference between cargo cycles and cars for the trips collected from the IeeA database.

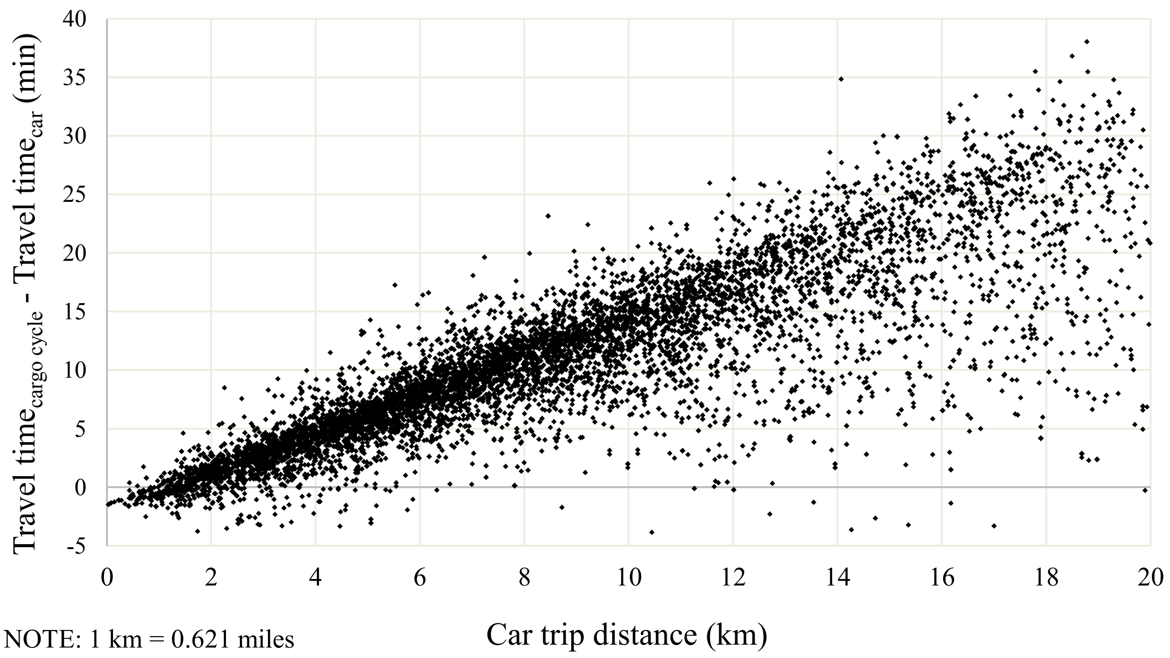

Fig. 6. Travel time difference between cargo cycle and car versus trip distance for two-wheeled cargo cycles with 'Pedelec-25' electric assist.

7 Scenario Analysis

Many cargo cycle trips in the sample dataset were conducted through suboptimal routes (not the shortest route in terms of trip distance; decided based on comparison with Google's bicycle routing). In order to help practitioners get a feel of what could happen if the users take the optimal cycle route and the situation for cars is worse (highly congested), a scenario analysis was added.

A correction factor was generated based on the formula in Equation 3. This correction factor was applied to the trip distance for the trips in the sample, allowing the corrected trip distance and the average speed of the trips from the sample to be used to generate new travel times for each trip. Further, one minute will be subtracted from the travel time for starting and ending the smartphone app at origin and destination. Google's 'pessimistic values' would be considered as the travel times for cars as they are representative of a congested scenario for cars.

$$correctionFactor = mean(Trip\ distance_{Google\ bicycle\ routing}) \ / \ mean(Trip\ distance_{cargo\ cycle}) \quad (3)$$

The value of correctionFactor obtained is 0.95, meaning that the users have not chosen an optimal bicycle route but rather used familiar streets accepting (smaller) detours. The scenario analysis s-curve in Fig. 7 was constructed based on the new travel time difference, cyclists taking an optimum route and the cars facing above normal congestion. The other two curves represent the original travel time difference value used for model estimation (curve 'Sample') and the predicted travel time difference value for the IeeA dataset (curve 'Model application').

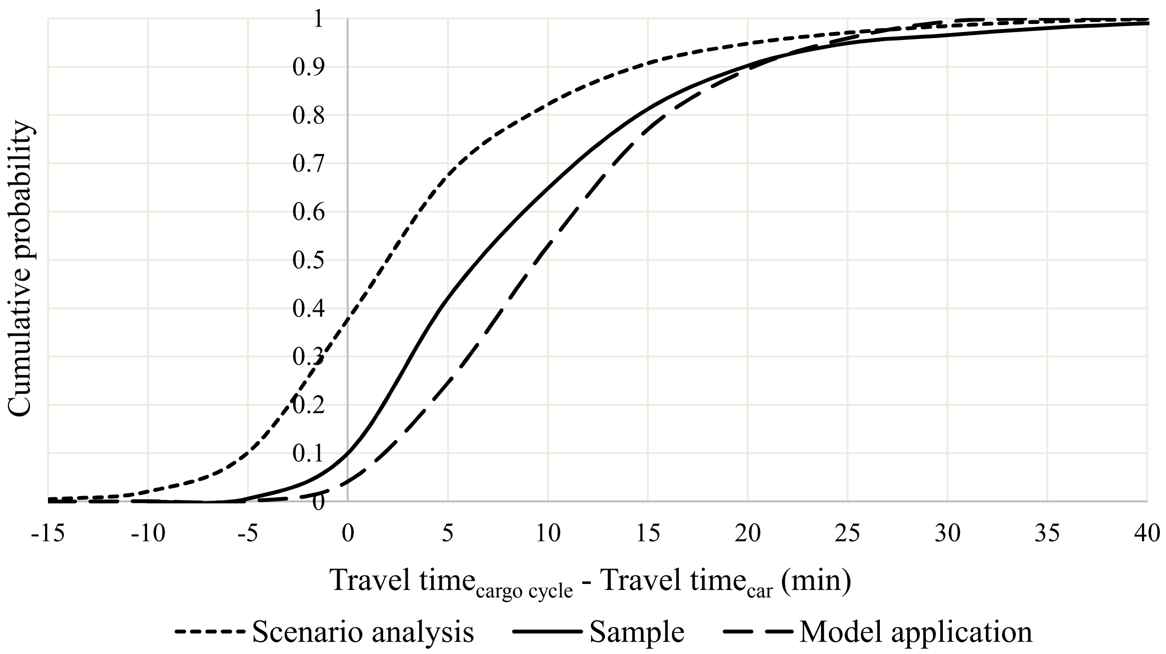

Fig. 7. Cumulative probability distributions for travel time differences between cargo cycles and cars.

As can be interpreted from the figure, though the trip length distribution can change the steepness of the s-curve, the range of values remains almost consistent. However, a change in traffic conditions would change both the steepness and the range of values.

8 Discussion

The findings from this study show that about half of the commercial transport trips switched from cars to cargo cycles wouldn't be delayed more than 2-10 minutes and 90% of the trips could be switched with less than 20 minutes delay. It should be noted that the current study did not consider other possible extra trip times for cars such as time for parking or walking to the exact spot of destination, the inclusion of such would decrease the expected travel time gap. There are, surprisingly, quite a few examples of cargo cycles having travel time advantages over cars, even at longer trip distances. While it is unfortunate not to offer a precise value for the travel time differences between cargo cycles and cars, the presented results should allow most commercial transport operators to make a reliable individual assessment. To achieve planning security in terms of delays, a relatively high travel time surplus per trip must be taken into account. However, the authors believe that operators are willing to accept a certain level of delay in return for the positive effects of switching to a cleaner vehicle.

As the scenario analysis shows, greater congestion on the road network could result in a different range of travel time delays. With cities becoming more and more congested and the government banning the entry of cars into certain streets, the possibility of an increase in travel time for cars is high, and hence it is expected that the travel time difference between cargo cycles and cars will be greatly reduced in future. This suggests that companies may benefit from using cargo cycles instead of cars.

Our findings quantify the influences of spatial context, time, vehicle-based attributes, and specific trip conditions. Concerning spatial attributes, while trip distance and the elevation favor the car, higher numbers of cars per capita in the respective city favors cargo cycles. Both in the morning and during the day up to 7 p.m. showed advantages for cargo cycles, mainly due to higher road network occupation and congestion delays for cars. Benefitting from the large variety of cargo cycle models involved in the sample, it was possible to show that two-wheelers are faster than three-wheelers and, as expected, cargo cycles are faster with electric assist. Loading more than three quarters of the available loading capacity will substantially decrease the cycling speed.

The novel aspect to our findings is that they were obtained using a large dataset of diverse real-life cargo cycle operations. Furthermore, the collected data is not too skewed compared to lightweight commercial transport up to 20 km (12.4 miles) trip distance in general. A further strength of this study is that it is including greater trip distances (up to 20 km) than other studies, which stop at 2 km (1.2 miles) (Melo & Baptista 2017) or 6 km (3.7 miles) (Faghih-Imani et al. 2017). This broader range increases the practical relevance of the results, as predictions for travel time differences between cargo cycles and cars can be made for a larger set of commercial trips.

This study also has its limitations. Our work is based on a comparison of real-life cargo cycle trips with fictitious car trips that represent not the true value but rather historic averages. However, Google's routing data has been shown to be reliable in this regard. Naturally, there are more factors that could potentially affect travel time differences between cargo cycles and cars, two of which being socio-demographic attributes and attributes of the built environment such as type of bicycle infrastructure. The authors suggest future researchers explore such attributes. Further, a regression model is proposed because of the lower level of effort required to interpret and use this model. The model is meant to be readily used by the individual operators and business entities involved in commercial transport operations. However, the calibration of an existing simulation system could be tested in the future, which might be useful for large-scale business organizations.

9 Conclusion

Cargo cycles are a viable potential alternative to combustion engine vehicles for many commercial transport operations, supporting cities to achieve air quality and carbon emission reduction goals. However, it was unclear whether cargo cycles are competitive enough in terms of travel time to replace existing vehicles. Building on cargo cycle trip data from 84 organizations throughout Germany, the estimated model can be used to predict the travel time differences between cargo cycles and cars. It is an important tool to assess travel time competitiveness of cargo cycles and to break down the reservations that currently exist among many operators. Values for the variables included in the model can easily be obtained, and hence this model can be readily used by a company's decision-maker.

The travel time differences from both the sample and IeeA dataset show that a range of values can be expected based on the trip context. However, it is certain that the maximum travel time difference expected is around 40 minutes, even for a trip distance of 20 km (12.4 miles), with encouraging median delay values of 2-10 minutes. An explanation was discussed as to why this can serve as orientation for operators determining the feasibility of switching to cargo cycles. In conclusion, though a range of travel time differences can be expected based on the context of a trip, the application of cargo cycles is still promising.

Overall, our findings should give companies the confidence to try out cargo cycles and allow policy-makers to support the transition to smaller vehicles in commercial transport operations, given the potential to reduce transport-related emissions.

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11 Author Contribution Statement

The authors confirm contribution to the paper as follows: study conception and design: J. Gruber; data collection: J. Gruber, S. Narayanan; analysis and interpretation of results: J. Gruber, S. Narayanan; draft manuscript preparation: J. Gruber, S. Narayanan. All authors reviewed the results and approved the final version of the manuscript.

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