Deriving Traffic-Related CO_2 Emission Factors with High Spatiotemporal Resolution from Extended Floating Car Data

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Abstract Despite the deployment of more efficient vehicle technologies, global CO_2 emissions related to transportation have increased by 250 % between 1970 and 2010 due to a rise of vehicle ownership, traffic volumes and congestion. CO_2 is the most common of the anthropogenic greenhouse gas emissions and is a main contributor to climate change. Fine-scaled information on the spatial and temporal distribution of traffic-related CO_2 emissions can support decision making processes with regard to emission mitigation measures. For the purpose of providing such information, commonly traffic emission models are applied. However, such models are often restricted in their spatiotemporal resolution due to a lack of adequate input data. A potential data source could be provided by the extended floating car data (xFCD) approach, where vehicle operation parameters like fuel consumption are read out on-trip via the vehicle's onboard diagnostic system and get correlated with vehicle positions and timestamps at short recording intervals. In this work, the potential of fuel consumption recordings from xFCD for quantifying traffic-related CO_2 emissions is evaluated. For this, an extensive database of GNSS-trajectories from vehicles (FCD) and xFCD fuel consumption measurements were recorded in the city of Salzburg, Austria. Using this input data, a set of averaged driving patterns for road segments, 15-min intervals and weekdays was derived. A similarity measurement algorithm was performed on these patterns, so that the most representative vehicle speed profile with fuel consumption recordings could be identified. The results indicate that the elaborated methodology can be applied for calculating representative, plausible and consistent CO_2 emission factors from xFCD fuel consumption recordings with high spatial and temporal resolution. This shows the potential of the systematic usage of xFCD for the purpose of estimating traffic related CO_2 emissions.

Keywords Traffic emission models · CO_2 emissions · Extended floating car data · Vehicle probe data

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1 Introduction and Objectives

In the year 2011, 600 million motorized passenger cars were traveling on the roads worldwide and a further significant rise of vehicle ownership is expected in the future, particularly in emerging countries such as China or India (Annema et al. 2011). Although this motorization has led to a significant rise of individual mobility over the century (Dargay et al. 2007), it negatively effects the natural and built environment as well as human health. The transportation sector contributes significantly to the anthropogenic emission of carbon monoxide (CO), nitrogen oxides (NO_x), volatile organic compounds (VOC) and carbon dioxide (CO_2). In most motorized vehicles, fossil fuels are used as energy for propulsion due to their high energy content. Emissions are formed as unwanted byproducts of the imperfect combustion of hydrocarbons of fossil fuels (Van Wee et al. 2013).

While CO_2 is not directly harmful to human health, anthropogenic CO_2 emissions are considered to be the major contributor to climate change (IPCC 2013). CO_2 is a common greenhouse gas, which absorbs thermal radiation from the earth's surface and thus causes the heating of the atmosphere. Although advancements in vehicle technology have led to the propagation of more fuel efficient and low-emission vehicles, transportation is the major sector with the strongest continuing growth in CO_2 emissions. The correlation of improvements in energy efficiency with increases of energy consumption is commonly described as 'rebound-effect', as the enhanced efficiency sets incentives for an intensified energy consumption (Brookes 1990). In the case of transportation, this results in a rise in vehicle ownership and a tendency to buy larger cars. Moreover, also continuing traffic growth and resulting traffic congestions contribute to an intensified emission of CO_2, as vehicles need more energy for propulsion during stop-and-go driving patterns (Capiello 2002). As a result, global CO_2 emissions caused by transport have increased by 44 % between 1990 and 2008, with motorized road traffic being responsible for 74 % CO_2 emissions from transport. In 2010, the transportation sector released 14 % of anthropogenic GHG emissions (Kok et al. 2011).

The availability of fine-scaled information on emissions related to traffic could support policy makers to set up effective emission mitigation measures. Knowing the spatial distribution and temporal shift of emissions within a road network, it is possible to efficiently target problematic areas and thus maximize impact and minimize costs of operational efforts (Gurney et al. 2012). However, most current emission models are applicable rather on a national or regional scale than on the microscopic level of single roads. The exact localization of traffic emissions is mainly limited due to the restricted availability of appropriate data at the local scale (Gately et al. 2013; Smit et al. 2008).

With the proliferation of communication and information technologies and their use in road transportation, new services came in use, which are commonly summarized under the term 'Intelligent Transport Systems' (ITS) (Ezell 2010).

Widespread examples of ITS applications are onboard navigation systems, which determine a vehicle's position in a road network based on GNSS coordinates. GNSS (Global Navigation Satellite Systems) has become the primary technology for the determination of a vehicle's position. Satellites are sending signals to the earth with information on the exact time the message was sent (every satellite is equipped with at least 4 atomic clocks, the time is annotated in the Universal Time Coordinated, UTC) and the satellite position. Through receiver devices, the geographic longitude and latitude as well as the altitude on a specific point on earth can be determined with an accuracy between around 12 m and 1 mm (Zogg 2011). GNSS devices are also used in the 'Floating Car Data' (FCD) approach, where vehicles which participate in regular road traffic, serve as mobile sensors for the collection of on-trip movement data. In this way, it is possible to determine a vehicle's speed and direction on the travelled road segment during a specific time. This information is for example used for dynamic traffic management or for the traffic-sensitive routing of navigation systems (Messelodi et al. 2009).

The concept of FCD, where usually only timestamps, coordinates and GNSS-specific quality parameters are transmitted in a specific recording interval, is further enhanced by the approach of 'extended Floating Car Data' (xFCD). Data collected on-trip are extended by additional parameters, including for instance fuel consumption or engine revolutions per minute. These parameters are sourced directly from the vehicle electronics through reading out data from a vehicle's onboard diagnostic system (OBD) using standardized message protocols like CAN-bus (Breitenberger et al. 2004). From fuel consumption, which is calculated from the mass air flow (MAF) of the engine, on-trip CO_2 emissions can be determined and related to the respective coordinates and timestamps of the recording interval. This enables a microscopic localization of vehicle CO_2 emissions both in space and time. The application of xFCD in traffic emission modeling could therefore potentially contribute to overcome current limitations due to restricted availability and resolution of input data. Thus, the main objective of this work is to develop, implement and evaluate a methodology to derive plausible and consistent emission factors from onboard fuel consumption recordings of passenger vehicles (xFCD) for the quantification of traffic induced CO_2 emissions on the level of road segments and short time intervals.

2 Current State of Research

Li et al. (2010) developed a road segment centered vehicle emission model for the estimation of greenhouse gases on highways in Beijing using FCD from more than 20,000 taxis as well as stationary detector data as primary inputs. Emission factors were calculated based on vehicle specific power (VSP) and engine stress (ES) of the vehicles. Through the use of FCD, spatiotemporal patterns of daily greenhouse gases could be estimated in the road network of Beijing.

Bert et al. (2007) conducted a study comparing results from CO_2 emission calculations based on FCD and traffic sensor data. The study area was the road network of the city center of Lausanne, Switzerland. CO_2 emission factors were calculated based on driving state (accelerating, decelerating, idling and cruising) and vehicle speed. The results showed a tendency that FCD-based emissions were more similar to simulation results the higher the penetration rate of probe vehicle was.

In a study by Yu et al. (2012), taxi emissions in the urban area of Shenzhen, China, were observed based on FCD. Detailed taxi operation information is derived from taxis equipped with GNSS receivers. The emission model comprehensive modal emission model (CMEM) was used to calculate emissions from the taxi FCD at each implemented speed and acceleration category. Through FCD, it was also possible to relate amount of emissions to specific driving pattern (idling, cruising) and to a specific time of day.

Several further studies focus on evaluating eco-driving and eco-routing recommendations through onboard fuel consumption data (Jakobsen et al. 2013; Marquette et al. 2012; Litzenberger et al. 2014). Crowd sourcing approaches towards collecting fuel consumption and corresponding emission data were pursued in the two projects ‘Fueoogle’ and ‘EnviroCar’. Vehicles participating in the data collection process are equipped with Bluetooth adapters, which are connected to the OBD-2 interface, reading out vehicle sensor data. These data then get transmitted to a smartphone and to a central processing server. Further analyses are made using these data, including a fuel-efficient routing application (Pham et al. 2009).

Based on literature review, it can be concluded that data from mobile sources have already been used in several studies to support the estimation of traffic emissions or evaluate driving patterns with regard to emissions. However, a systematic approach to utilize xFCD-based fuel consumption data to derive valid emission factors for quantifying traffic emissions on the level of road segments and in their temporal variation has not been undertaken so far (Krampe et al. 2013).

3 Data Sources

The collection of on-trip fuel consumption data from vehicle sensors (xFCD) was conducted with a gasoline-driven BMW MINI Cooper R56. For reading out data from vehicle sensors, the device tinxi® Bluetooth EOBD OBDII was used. It is a low-cost vehicle diagnostics system, which is attached to the OBD-2 interface of a vehicle. It reads out 15 different kinds of sensor data, including engine speed (rpm), vehicle speed (km/h) and fuel consumption (l/100 km). Via Bluetooth, the device was connected to a smartphone or a computer and reads out fuel consumption, timestamps and coordinates on-trip at a transmission rate of 1 s. The data recording process was conducted between November 2013 and October 2014 in the city of

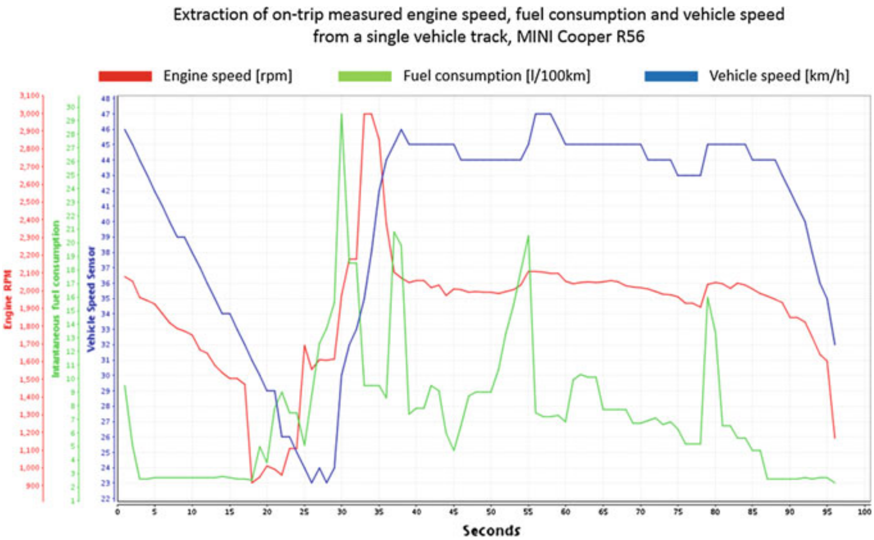

Fig. 1 Extraction of on-trip measured vehicle sensor parameters, MINI Cooper R56, gasoline fuelled

Salzburg and surroundings, resulting in 128 single vehicle trajectories recorded at 1 Hz, with overall 513 km of road covered. Figure 1 shows an exemplary extraction from a vehicle trajectory with recorded vehicle sensor parameters. In this case, vehicle speed (km/h), engine speed (rpm) and fuel consumption (l/100 km) are depicted. It can be observed that a plausible, correlated behaviour exists between these parameters: During a phase of deceleration, fuel consumption and engine speed are low or decline. While vehicle speed rises, also the other parameters incline. Also the effect of gear shifting is recognizable, with sharply falling engine speed and fuel consumption despite increasing speed.

The following Fig. 2 shows a plot of vehicle speed in km/h and engine speed in rpm. The colour gradient of the data points is based on fuel consumption in l/100 km, with blue colour for 0 or no fuel consumption to red colour for the highest measured values. It can be seen that data points with high fuel consumption have a tendency to cumulate especially during high engine speeds, as it would be expected. Also, the influence of gear shift behaviour and vehicle speed on engine speed and thus on fuel consumption can be observed.

For the further quantification of CO_2 emissions, also cross-section traffic volume counts from stationary road-side detectors, data on registered vehicles in Salzburg from 'Statistics Austria' representing traffic composition as well as GNSS trajectories from vehicles participating in regular traffic were used.

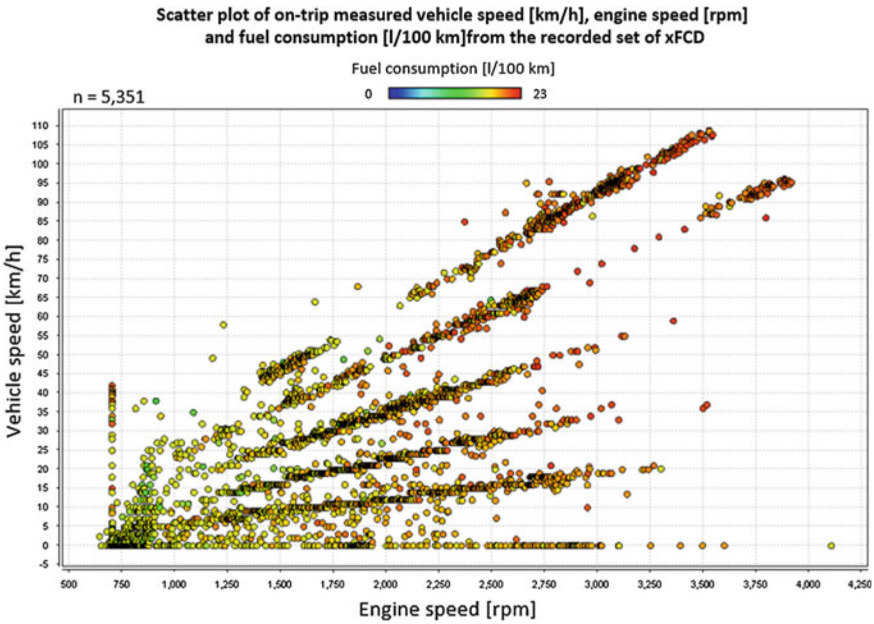

Fig. 2 Plot of vehicle speeds (km/h), engine speeds (rpm) and fuel consumption (l/100 km) of an extract of the recorded set of xFCD

4 Methodology

Various factors have impact on the amount of fuel combusted on-trip by a vehicle. Driving kinematics and the resulting driving patterns are among the most significant factors (Alessandrini et al. 2012). Especially patterns with repeating phases of acceleration and deceleration during low engine load cause higher fuel consumptions. Such patterns are for instance typical for urban driving or during limited traffic flow quality. Various studies elaborating real world or laboratory fuel consumption tests further show the influence of driving patterns on the amount of combusted fuel. Fuel consumption values tend to be distinctively higher during stop-and-go traffic, and the acceleration pattern has a much higher influence than average speed values. Fuel consumption can increase by about 80 % during stop-and-go traffic compared to free flow traffic conditions. This is due to the dependence of fuel consumption on the effective motor pressure and the revolution rate of a vehicle's crankshaft (Treiber et al. 2007).

Because of the obvious correlation between driving patterns, it is assumed that through the definition of a representative driving pattern with fuel measurements for a road segment and a time interval, also a representative emission factor can be obtained. In this way, the dynamics of driving are incorporated as main determinant for calculated emission factors. Here, the term 'driving pattern' describes the sequence of acceleration, deceleration as well as the resulting course of vehicle velocity over time. A driving pattern on a road segment can also be regarded as time series. A time series $T = t1, \ldots,$ is defined as an ordered set of p real-valued variables.

For determining the similarity of time series, usually statistical distance measures are applied. Given two time series $T1$ and $T2$, the distance $D(T1, T2)$ between them is calculated as a similarity function. Various distance measures haven been proposed in literature, with the Euclidean distance being the most frequently used one. The Euclidean distance aligns time series in point-to-point manner. In this way, point i in time series X is compared with point in time series Y (Lin et al. 2009). The Euclidean distance is easy to compute, is parameter-free and performs generally well compared to more complex methods, especially for shorter time series data. However, the accuracy of this approach diminishes in case local time shifting is observed between sequences, as the points of the compared sequences are regarded as fixed. For this reason, time series which might appear to have similar shapes but are slightly shifted in terms of time, might have a high measured distance (Ding et al. 2008). Such time shifts can be expected between driving patterns of different vehicles, as phases of acceleration and deceleration, for example at highway ramps, might set in at different points in time due to individual driving behaviors.

This limitation of the Euclidean distance approach for similarity measurement can be overcome by applying a dynamic time warping (DTW) algorithm, which is used especially in speech recognition (Müller 2007). In DTW, a potential time shift between two or more time series is considered by stretching or compressing locally until the minimum distance between them is obtained. The similarity function is then calculated by summing the heights of the aligned points of the compared time series, resulting in a real number which quantifies their similarity. Formally, DTW is computed as follows (Petitjean et al. 2012):

$$D\left(A_i, B_j\right) = \delta\left(a_i, b_j\right) + \min \left\{ \begin{array}{c} D\left(A_{i-1}, B_{j-1}\right) \\ D\left(A_i, B_{j-1}\right) \\ D\left(A_{i-1}, B_j\right) \end{array} \right\}$$

where:

A_i Sequence with ⟨a_1, …, a_i ⟩
B_j Sequence with ⟨b_1, …, b_i ⟩
δ Distance between elements of the sequence.

In the developed approach, the similarity search is conducted between all xFCD driving patterns on a road segment and a typical driving pattern, which is representative for the road segment at the observed time interval. In order to define this representative driving pattern, a single driving pattern out of all available driving patterns for the specific spatio-temporal context is calculated. For this, the global averaging strategy 'DTW Barycenter Averaging' (DBA) for multiple time series is applied. The sequences are averaged all together, hence obliterating the effects of order on the calculation outcomes. The DBA algorithm minimizes the sum of

DTW-calculated squared distances of an average times series to the set of all incorporated time series. It is computed as the sum of Euclidean distances between a point and points of the sequences aligned to it according to the DTW calculation. This partial sum is minimized for each point by calculating the barycenter of the associated set of points. The average sequence is the result of the computation of a barycenter for each data point in the sequence. The DBA is defined as follows (Petitjean et al. 2011):

$$C_T^{'} = barycenter(assoc(C_T))$$

$$barycenter\{X_l, \ldots, X_\propto\} = \frac{X_l + \cdots + X_\propto}{\propto}$$

C_T The average sequence with ⟨C_l, …, C_T ⟩ at iteration i
$C_T^{'}$ The average sequence with ⟨C_l^′, …, C_T^′⟩ at iteration i + 1

assoc Association of each point of the average sequence to one or more points of the set of sequences.

As stated before, the xFCD vehicle trajectories are constituted by sequences of points, which bear both spatial (latitude, longitude) and temporal (timestamp) information. However, recorded values from single vehicle tracks can't be simply adopted as representative for the identified spatio-temporal dimension due to the influence of individual driving behaviour. Thus, a broader set of vehicle trajectories have to be aggregated spatio-temporally in order to decrease the impacts of individual, non-representative patterns (Jackson et al. 2009). Another reason for the aggregation of xFCD is the resulting smoothing effect, which further contributes to reduce the influence of potentially erroneous data points (Lou et al. 2009). As basic spatial aggregation unit, road segments of the digital OpenStreetMap road network graph are used. To reference data points to the road segments, a 'map-matching' procedure is applied. Temporal similarity of xFCD is commonly determined by grouping the data into daily time intervals (Krampe 2006). Accordingly, data points of all incorporated vehicle trajectories, which were recorded at 1 Hz, are assigned to 15-min intervals based on the GNSS-timestamps, resulting in 96 daily intervals. All calculations for deriving representative emission values were conducted based on the described spatio-temporal reference units.

As emission factors from xFCD fuel consumption data are only representative for the specific vehicles which conduct the recordings, further adjustment factors have to be incorporated in order to make assumptions about the emission output of an entire traffic system per observed spatio-temporal unit. The vehicle specific emission factor from fuel consumption has to be transformed in such a way that it is representative for the expected overall traffic composition on a road network. As no thoroughly empirical on-site measurements of traffic composition were available, data from the annual report of the year 2012 on automobile stocks per county and make of car published by the national statistics authority is used. The calculated vehicle specific emission factor is correlated with the expected mix of passenger vehicles in the traffic composition on a road network by applying a rule of three. For this, standardized fuel consumption values from the measuring procedure determined in European Community regulation 715/2007 of the vehicle used for recording xFCD and the assumed statistical average of the traffic composition of passenger vehicles in Salzburg, Austria, is incorporated. Another utilized adjustment factor is the absolute traffic volume, which are derived from detector measurement at road cross sections.

5 Results

The developed methodology is applied and evaluated based on two case studies of road stretches in Salzburg, Austria. The first case study represents an inner-urban road stretch, while the second case study is conducted on an important artery road to the inner-city of Salzburg. In this paper, the results of the second case study are introduced.

The observed road stretch is a 1.68 km long part of the Alpenstraße between Anif and the administrative city boundary of Salzburg, Austria (see Fig. 3). The driving direction is northbound towards the city of Salzburg, with an allowed driving speed of 70 km/h. The road side detector, which is situated near the exit of the administrative limits of Anif, measures 5705 cars passing by on average on a weekday, with peaks during morning and especially evening traffic. Unlike the road in case study 1, the pattern of the average travel time shows a distinct peak during morning traffic, with the highest travel times of 157 s in average between 07:30 and 08:15 am. It can be seen that the number of vehicles passing the detector cross section declines during this morning peak, the traffic volume is less due to a restricted traffic flow. Another peak can be observed during evening traffic between 04:00 and 05:15 pm, with an average travel time of 120 s. Unlike during the morning peak, this does not lead to a significant decline of traffic volume. In the daily average, the time to pass this road stretch is 84 s. It can be seen that during night phases, low traffic volume and short travel times occur. Thus, the traffic quality on the observed road stretch of the Alpenstraße varies highly in the course of a weekday, which is assumed to have also impact on computed emissions. For the studied road stretch, 5803 FCD vehicle trajectories recorded at 1 Hz with information on acceleration and vehicle speed are available in the data basis, with an average number of 60 trajectories per aggregated 15-min interval for weekdays. The data basis of xFCD trajectories with fuel consumption recordings comprises 38 trips.

In Fig. 4, the daily course of predicted fuel consumption per calculation method for a MINI Cooper R56 on the road stretch of case study 2 per 15-min intervals on weekdays is depicted. A morning peak of fuel consumption can be observed, with increasing values around 6:30 am. The maximum fuel consumption for traveling over the road segment is predicted between 08:15–08:30 am, with 8.64 l/100 km.

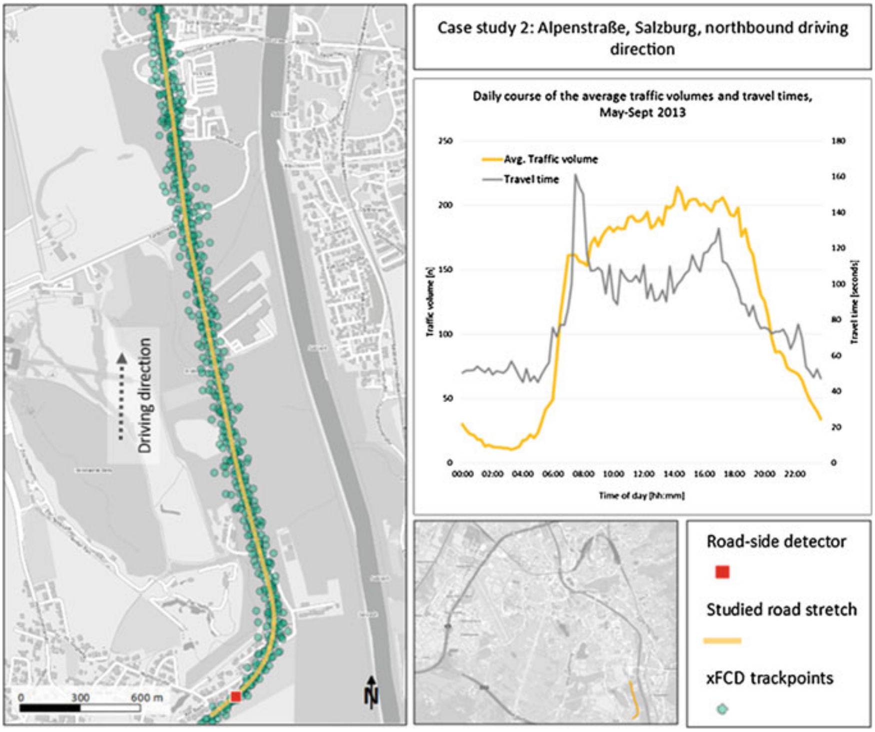

Fig. 3 Road segment of the inter-urban case study of Alpenstraße, Salzburg, Austria

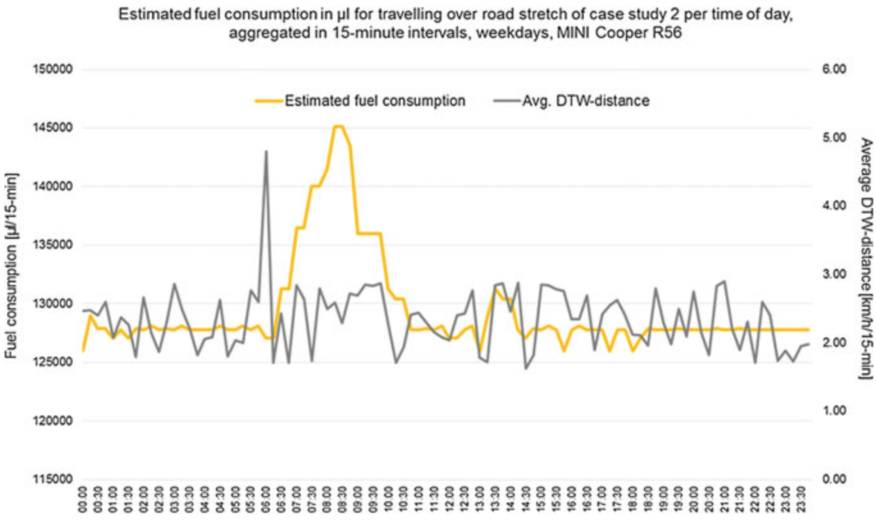

Fig. 4 Fuel consumption in µl for passing through road stretch of case study 2 per time of day, aggregated in 15-min intervals, weekdays, MINI Cooper R56

This peak in fuel consumption corresponds to the highest travel time derived from the FCD recordings. This indicates that the reduced traffic flow, which leads to more dynamic driving patterns, causes increasing calculated fuel consumptions. However, the smaller evening peak in travel time around 17:00 does not show any effects on the curve of predicted fuel consumption values. The average daily fuel consumption for traveling over the observed road stretch on weekdays is predicted highest with 7.70 l/100 km by the developed methodology.

For the evaluation of the driving pattern approach, the DTW-distances are utilized. It gives the difference in km/h per recording (conducted in 1 Hz frequency) of a matched driving pattern with fuel consumption to the representative driving pattern on a road segment and 15-min interval. For the case study, the minimum DTW-distance is derived at 14:30–14:45 (1.62 km/h per second), the maximum at 06:00–06:15 (4.80 km/h per second). For all 15-min intervals, the average distance between a reference driving pattern and the matched fuel consumption pattern is 2.34 km/h per second. The obtained distance is considered to be tolerable and it is assumed that for the observed road segment, the fuel consumption patterns do adequately match the representative driving patterns.

Based on the derived emission factors from fuel consumption, the absolute CO_2 emission values are calculated. This is done by introducing a traffic composition adjustment factor for fuel consumption, so that the values from the vehicle used for recording are adjusted according to the general traffic composition. Data on traffic composition is derived from vehicle ownership statistics in Salzburg. Moreover, the overall traffic volume is incorporated by using traffic volume data from a stationary road side detector. The resulting predicted daily course of CO_2 emissions is depicted in Fig. 5. As it can be expected, the extent of CO_2 emissions are highly

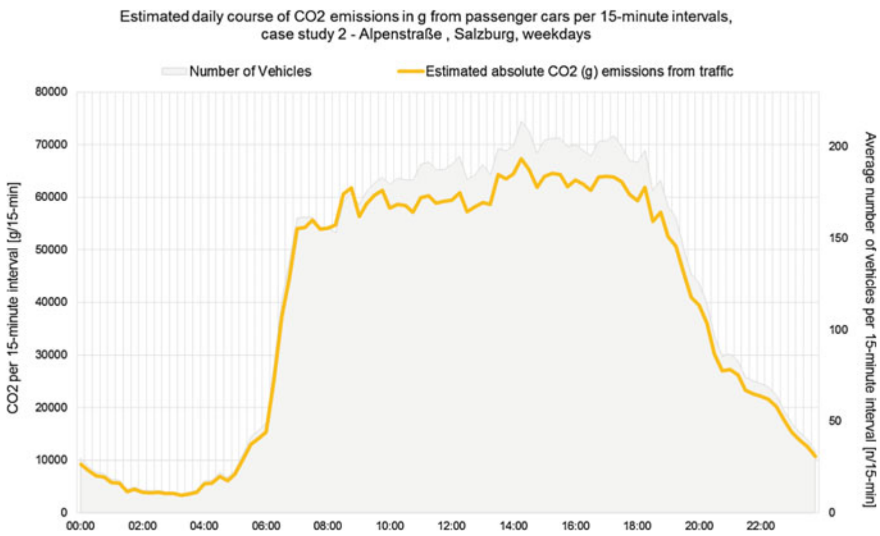

Fig. 5 Estimated daily course of CO_2 emissions in g from passenger cars per 15-min time intervals, case study 2—Alpenstraße from Anif to Salzburg, weekdays

coupled with the traffic volume, which usually starts to increase steeply from 05:45 on and declines again around 19:30. The level of CO_2 emissions is estimated to be between 50,100 and 67,300 g/15-min during daytime. The peak is predicted for 14:15–14:30 with 67,264.5 g of CO_2 emissions. Another peak can be observed between 08:45–09:00, with 63,613.8 g of CO_2 emission. The overall daily amount of CO_2 emitted on the observed 1.68 km long road stretch on regular weekdays is predicted to be 3,713,806 g. From a typical vehicle traveling over this road stretch, 191 g/km of CO_2 are emitted on daily average.

6 Conclusion

Based on the evaluation of the developed methodology in the case studies, the elaborated driving pattern approach is considered to have high potential for calculating representative, plausible and consistent CO_2 emission factors from xFCD fuel consumption recordings with a high spatial and temporal resolution. In general, the obtained CO_2 emissions showed values within plausible ranges and are closely correlated to the traffic flow quality in the respective interval, as it would be expected. Moreover, the daily profile of estimated CO_2 emissions and the fluctuations of values between subsequent 15-min intervals appeared to be reasonable. However, to further determine the validity and feasibility of the developed methodology, also additional case studies would have to be conducted, involving larger and diverse vehicle fleets for the recording of fuel consumption data, as well as a wider study area. A suitable framework for this could be a field operational test (FOT).

Nevertheless, the potential of the systematic usage of xFCD for the purpose of estimating traffic related CO_2 emissions could be shown. A better understanding of the spatio-temporal occurrences of CO_2 emissions through the provision of fine-scaled information based on mobile fuel consumption measurements can thus be a valuable building block for implementing dynamic and more efficient ecologically-orientated traffic management strategies. Besides the intended purpose of quantifying traffic-related CO_2 emissions, the developed methodology could also be used for evaluating the energy efficiency of road segments at specific times of the day. Provided the development of respective software modules, this could contribute to enhance existing in-vehicle ITS solutions, like eco-friendly routing alternatives for navigation units or a more realistic calculation of kilometers left for traveling using the current fuel level and the appointed route of a vehicle's navigation system.

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