Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Mining urban sustainable performance: Spatio-temporal emission potential changes of urban transit buses in post-COVID-19 future

Yi Sui a,b,c, Haoran Zhang d,h,* , Wenlong Shang e, Rencheng Sun a,c, Changying Wang c, Jun Ji a,c, Xuan Song f, Fengjing Shao a,c,*

a College of Computer Science and Technology, Qingdao University, Ningxia Road No. 308, Qingdao 266071, China
b Center for Spatial Information Science, The University of Tokyo, 5-1-5 Kashiwanoha, Kashiwa-shi, Chiba 277-8568, Japan
c Institute of Smart City and Big Data Technology, Qingdao, Ningxia Road No. 308, Qingdao 266071, China
d School of Business, Society and Engineering, Mälardalen University, Västerås 721 23, Sweden
e Beijing Key Laboratory of Traffic Engineering, College of Metropolitan Transportation, Beijing University of Technology, Beijing 100124, China
f SUSTech-UTokyo Joint Research Center on Super Smart City, Department of Computer Science and Engineering, Southern University of Science and Technology (SUSTech), Shenzhen, China

HIGHLIGHTS

• Proposing a framework to analyze emission patterns of buses and changes in post-COVID-19.
• 2056 buses with 1.5 million ridership and 7589 taxis with 0.2 million trips are used for analysis.
• 224 social surveys are collected and show a 56.3% ridership reduction in post-COVID-19.
• We find buses cannot be “greener” travel modal than cars if ridership reduces by more than 40%.

ARTICLE INFO

Keywords:
Transit buses
Emission patterns
GPS trajectory
Ridership
COVID-19

ABSTRACT

Emission benefits of transit buses depend on ridership. Declines in ridership caused by COVID-19 leads uncertainty about the emission reduction capacity of buses. This paper provides a method framework for analyzing spatio-temporal emission patterns of buses in combination with real-time ridership and potential emission changes in the post-COVID-19 future. Based on GPS trajectory and Smart Card data of 2056 buses from 278 routes covering 1.5 million ridership in Qingdao, China, spatio-temporal emissions characteristics of buses are studied. 7589 taxis with 0.2 million passengers’ trips are used for acquiring private cars’ emissions to evaluate the emissions difference between buses and cars. Empirical results show that the average difference between buses and cars with 2 persons can reach up to 117 g/km-person during 7:00–8:59 and 115 g/km-person during 17:00–18:59. However, buses have various emission benefits around the city at different periods. A double increase in emissions during non-rush hours can be observed compared with rush hours. 224 online survey data are used to study the potential ridership reduction trend in post-COVID-19. Results show that 56.3% of respondents would decrease the usage of buses in the post-COVID-19 future. Based on this figure, our analysis shows that per kilometer-person emissions of buses are higher than cars during non-rush hours, however, still lower than cars during rush hours. We conclude that when ridership reduces by more than 40%, buses cannot be “greener” travel modal than cars as before. Finally, several feasible policies are suggested for this potential challenge. Our study provides convincing evidence for understanding the emission patterns of buses, to support better buses investment decisions and promotion on eco-friendly public transport service in the post-COVID-19 future.

* Corresponding authors at: School of Business, Society and Engineering, Mälardalen University, Västerås 721 23, Sweden (H. Zhang). College of Computer Science and Technology, Qingdao University, Ningxia Road No. 308, Qingdao 266071, China (F. Shao).
E-mail address: haoran.zhang@mdh.se (H. Zhang).

https://doi.org/10.1016/j.apenergy.2020.115966
Received 2 June 2020; Received in revised form 27 September 2020; Accepted 30 September 2020
Available online 9 October 2020
0306-2619/© 2020 Elsevier Ltd. All rights reserved.
1. Introduction

1.1. Background

COVID-19 pandemic has drastically changed energy demand and consumption patterns around the world, with expected impacts on greenhouse gas (GHG) emissions from the ground transport sector [1]. Due to mobility restrictions, a sharp reduction in transport demand has been seen in global public transit in the last few months. Faced with an epidemic of infectious disease, people would take precautionary actions to avoid public transportation [2]. Therefore, medium-long-term ridership reduction in public transit may be seen in the post-COVID-19 future. The decline in transit travel demand affected by COVID-19 poses a significant challenge to the role of public transit in reducing GHG emissions.

Transit buses, carrying large numbers of people with each trip, are widely considered as a “greener” alternative to reduce per-passenger emissions of GHG from the on-road transport sector compared with passenger cars [3]. It is estimated that a typical passenger car carrying one person emitted 89 lb of CO2 per 100 passenger miles, while a conventional bus at its capacity of 70 passengers emitted only 14 lb [4]. Emission benefits of transit buses were primarily realized during periods of high ridership [5]. It is important, however, on one hand, to note that urban residents’ travel demand was confirmed with a great difference in terms of built environment and time, which in turn caused ridership to vary at a different time of day (rush hours and non-rush hours) and city locations (downtown and suburb) [6]. It is inevitable, ridership of transit buses at certain periods is much lower than the capacity. For buses with low ridership, their per kilometer-person emissions could be higher than that generated by passenger cars [7]. Previous studies suggested there were at least 16 passengers in a diesel bus resulting in the same value of fuel consumption compared with a fully-loaded passenger car; to the emissions of CO, the number of passengers should be larger than 15; and from the aspect of NOx emission, diesel bus emitted more than fully-loaded passenger car [8].

On the other hand, people may take precautionary measures to reduce their risk of pandemic infection. 48% percent of Americans stated that riding public transport posed a high health risk due to COVID-19. With this concern, commute people may shift from public transit to passenger cars, which in turn results in road congestion and ridership reduction. Can transit buses be “greener” than private car on person emission basis in the post-COVID-19 future? To answer this question, it is important to understand spatio-temporal emission characteristics of transit buses in combination with real-time varying ridership and study potential emission changes between pre-COVID-19 and post-COVID-19 future.

Numerous studies have been conducted in recent years to study emissions of transit buses. All of these studies provide essential contributions and improve our understanding of emissions sourced from transit buses. Most previous studies used Portable Emission Measurement System (PEMS) to collect real-time tailpipe emissions data and arranged crew to record the number of passengers manually. These measures are effective, however, the amount of financial resources and labor required in the emissions data and ridership data collection limit their application [9]. As a result, previous studies mainly focused on a few buses running in a limited area and short period. Spatio-temporal characteristics of buses’ emission patterns with varying real-time ridership and locations at a metropolitan-wide scale remain largely unclear. Scenario analysis of emission changes of buses with potential ridership reduction caused by COVID-19 is unexplored. The goal of this study is to fill this gap by investigating buses’ emissions using GPS trajectory data and Smart Card ridership data of buses in Qingdao, China to answer the following research questions: what are the spatio-temporal characteristics of buses’ emissions at a metropolitan-wide scale? When and where can buses’ emissions on a per passenger basis be lower than passenger cars? In the post-COVID-19 future, compared with passenger cars, how will the emissions benefits of buses change? Answering these questions can help us understand emission patterns of buses and their capacity of emission reduction in different time periods and locations, so as to support better transit buses investment decisions and promotion of eco-friendly transit buses services in the post-COVID-19 future.

1.2. Literature review

Considerable efforts have been put into estimating bus emissions and understanding their relationship with driving operation (speed, acceleration/deceleration, road grade, air conditioner on/off), fuel types (conventional diesel, compressed natural gas (CNG)/liquefied natural gas (LNG) and electric buses) and passenger load.

Vehicle emissions during a trip were found to be sensitive to instantaneous speed. On-road tailpipe emissions measurement showed that low-speed operations resulted in higher emissions and fuel consumption [10]. Some studies confirmed average speed on the roadway link was a suitable parameter to estimate buses’ emissions at a fleet level when instantaneous speed data was unavailable [11]. Due to buses’ frequent stop-and-go operation, acceleration and deceleration operation around stops are inevitable. Roadway grades also have been found with a significant positive influence on buses’ emissions. Bus emissions increased with the increasing of grades under the same conditions of speed and passenger load [12]. Air conditioner is another important factor affecting bus emissions. Although diesel hybrid buses can decrease Nitrogen oxides (NOx) emissions with air conditioner on compared with CNG buses [13], the increase trend of NOx emissions and fuel consumption for conventional diesel buses in winter and summer implied the usage of air conditioning resulted in more emissions [14].

Urban buses are mainly divided into conventional diesel buses, buses fueled with CNG/LNG, and buses powered by electric. Emission characteristics were compared between diesel buses and CNG/LNG buses in the combination with different driving operations [15]. The general findings suggested CNG/LNG buses generated fewer emissions than diesel buses although their performance on emissions reduction and fuel consumption saving may be greatly influenced by driving conditions. With the advantages of not producing any pollutant emissions directly from the operation, electric buses have been widely promoted around the world, especially in China. China has more than 400,000 electric buses, about 99% of the world’s total [1]. Some studies highlighted that in order to maximize road transport emission reduction electrification of buses should be implemented in combination with strategies for increasing ridership [16] and optimizing operation schedule and route planning [17].

Ridership has a greater impact on energy consumption and emissions for transit buses. As the passenger load increased, energy consumption, and emissions for both diesel buses, CNG/LNG buses, and electric buses increased proportionally [18]. Whereas, for the per-person emissions, the passenger load is inversely proportional to the total emissions. A 20 percent increase in ridership resulted in a 1.1% increase in total emissions and a 13% decrease in per person emissions [19]. This result confirmed the advantage of buses in emissions reduction on a per person basis. Passenger load was found to have a significant effect on fuel consumption at middle and high-speed ranges but had almost no effect

https://www.masstransitmag.com/safety-security/article/21129378/survey-north-american-commuters-are-switching-commuting-habits-as-result-of-novel-coronavirus.

https://www.pri.org/stories/2019-10-08/china-dominates-electric-bus-market-us-getting-board.
on fuel consumption during idling or under very low speeds [12]. Emissions and fuel consumption at high speed and high Vehicle Specific Power (VSP) ranges were significantly underestimated when not considering passenger load [18]. However, bus ridership varies with periods (rush hours and non-rush hours) and locations (downtowns and suburbs), which in turn leads to a difference in emissions reduction capacity on a per person basis. Per passenger-kilometer fuel and emissions of bus during peak hours were half of non-peak hours [8]. Routes with high ridership and lower speed associated with the highest total emissions and the highest-emitting routes were those with the lowest ridership on a passenger-kilometer basis [7]. However, most literature studied emissions at a micro level, i.e. bus/route/corridor level. Emissions across a network of 200 bus lines in the city of Montreal, Canada were studied in [19], however, ridership data used in their study were simulated which cannot reveal real passenger load. Spatio-temporal characteristics of bus emissions in combination with real ridership during different periods and locations at a metropolitan-wide scale remain uncovered. With the negative impact of COVID-19, potential ridership reduction poses a significant challenge to the decarbonization capacity of buses. Existing studies emphasize bus emission estimation and affecting factors analysis based on limited buses and routes, however, the influence of potential ridership reduction caused by individual travel behavioral change in post-COVID-19 future on emissions reduction capacity of buses is not explored.

1.3. Contributions of this work

The main contributions of this study are three folds:

1. This paper provides a method framework for analyzing spatio-temporal emission patterns of transit buses in combination with real-time ridership and potential emission changes in the post-COVID-19 future. Power distribution and normalized entropy are adopted to measure the unbalanced distribution of emissions.

2. Compared with previous studies based on a few buses running in a limited area and short period, GPS trajectory data and Smart Card ridership data are utilized to measure spatio-temporal emission characteristics of buses at a metropolitan-wide scale. GPS trajectory data of taxis with passengers occupied are used for acquiring passenger cars’ emissions to evaluate emissions difference between buses and cars.

3. Social survey data are collected for analyzing passengers’ travel behavioral change in the post-COVID-19 future. Ridership reduction is observed. Comparative analysis between ridership reduction scenarios is given for exploring the potential change of emission reduction of buses.

The remainder of the paper is organized as follows: Section 2 provides our methodology. Study area and data preprocessing are given in Section 3. In Section 4, empirical analysis is provided. We discuss our findings and suggest feasible policies in Section 5. Finally, we conclude our study and discuss future research directions in Section 6.

2. Methodology

2.1. Preliminaries

Definition 1. ((bus route.)) A route \( r = (r_1, r_2, \ldots, r_n) \) is a sequence of bus stops, where \( n \) is the number of stops on route \( r \) and \( r_i, r_{i+1} \) are two consecutive stops (\( 1 \leq i \leq n-1 \)). Link \( r_i \rightarrow r_{i+1} \) is a road segment of route between stop \( r_i \) and \( r_{i+1} \).

Definition 2. ((ridership of route link.)) Ridership of route link \( r_i \rightarrow r_{i+1} \) at time \( t \) is expressed by \( R(r_i \rightarrow r_{i+1}, t) = F(r_i, r_{i+1}, t, \Xi) \), where \( f \) is a function mapping built environmental factors \( r_i, r_{i+1} \) and time factor \( t \) into an integer value representing regular ridership of route link \( r_i \rightarrow r_{i+1} \) at time \( t \). Parameters \( \Xi \) is a set of factors affecting regular ridership, such as weather condition, day of year, and event. \( \Xi = W \times D \times E \), where \( W = \{ \text{normal, rain, snow} \ldots \} \), \( D = \{ \text{weekday, weekend, holiday} \ldots \} \), \( E = \{ \text{noevent, emergencies} \ldots \} \). According to parameters \( \Xi \), function \( F \) maps the regular ridership \( f(r_i, r_{i+1}, t) \) into a real ridership. Let \( F(f(r_i, r_{i+1}, t), \{ \text{normalweather, weekday, noevent} \}) = f(r_i, r_{i+1}, t) \).

2.2. Framework

The framework of our methodology is shown in Fig. 1. In this paper, GPS trajectory data, Smart Card ridership data of buses, and GIS information of routes are used to infer the Origin-Destination (OD) trips of passengers. OD inferring method was proposed in our previous work [20, 21]. After this step, the real-time ridership of each bus can be obtained. Based on the emissions model, per-kilometer-person emissions of buses are calculated. Analysis of spatio-temporal emissions characteristics, including overall route links in the city and each route, is given by adopting power-law and normalized entropy. To understand the

![Fig. 1. Analysis framework of spatio-temporal emission patterns of buses and potential emission changes affected by COVID-19.](image-url)
emissions benefits of buses, we use taxi trips with passengers occupied to represent passenger car trips and compare their emissions difference with buses. Besides, 224 complete social surveys about individual’s travel behavior change after COVID-19 were collected by Tencent Survey⁴. Based on these surveys, comparative analysis between normal cases and post-COVID-19 cases is given. Emissions change analysis with potential ridership reduction and implications to transit buses are discussed.

For calculating exhaust emissions from buses and cars, we focus on carbon dioxide (CO₂) in this study. CO₂ emissions from urban surface transportation (passenger cars, bus transit, heavy rail/light rail transit, etc.) have become the leading and most-rapidly growing contributor to GHG emissions. In the European Union, cars alone account for 41% of total transport emissions of CO₂ [22]. In the U.S., cars contribute to 59% of total transportation greenhouse gas emissions in 2017 [23]. In China, more than 60% of the total carbon emissions of urban passenger transportation sources from private cars [24]. Therefore, we study CO2 emissions difference between transit bus and passenger cars in this study. It is worth mentioning that CO₂ emissions can be replaced by other pollutions, such as carbon monoxide (CO), nitrogen oxides (NOₓ), particulate matter (PM), which does not influence the framework.

2.3. Emission model

In this study, CO₂ emissions are estimated by MOVES (MOtor Vehicle Emission Simulator) model developed by EPA (United States Environmental Protection Agency). In general, road vehicles are classified into four groups: passenger cars, light commercial vehicles, heavy-duty vehicles and buses, mopeds and motorcycles. According to MOVES model, emission varies with vehicle categories, fuel type, weight and technology level of vehicles. Emission factors are further sub-divided according to different types of driving, such as highway, rural and urban. In the MOVES model, emissions are defined as a function of speed and vehicle-specific power (VSP) for light-duty vehicles, and speed and scaled-tractive power (STP) for heavy-duty vehicles and buses. VSP/STP is defined as the engine power output per vehicle unit mass. The VSP/STP-based modelling approach has been validated in previous work [18]. Second-by-second VSP/STP (KW/ton) are calculated as shown in Eq. (1) [25]:

\[
\text{VSP} = \frac{A}{M} \cdot v + \frac{B}{M} \cdot v^2 + \frac{C}{M} \cdot v^3 + \frac{m + n \times w}{M} \cdot (a + g \cdot \sin \theta) \cdot v
\]

where \( A \) is the rolling resistance coefficient (KW•s/m), \( B \) is the rotational resistance coefficient (KW•s²/m²), \( C \) is the aerodynamic drag coefficient (KW•s²/m²), \( m \) is the mass of vehicle (tonnes), \( M \) is fixed mass factor (tonnes), \( n \) is the number of passengers and \( w \) is the average passenger mass, default to 50 kg per person [18], \( v \) is instantaneous vehicle speed (m/s), \( a \) is instantaneous acceleration (m/s²), \( g \) is gravitational acceleration with the value 9.8 m/s², \( \theta \) is the fractional road grade. In this paper, \( \theta \) is set as 0. Parameters for VSP/STP are shown in Appendix A Table A1.

Inspired by [11], total link-based CO₂ emissions of bus are estimated as

\[
\text{TE} = \sum_{i=1}^{I} \text{TSTP}_i \times \text{ER}_i
\]

where \( i \) – VSP/STP mode index, 1, 2, · · ·; \( I \); \( \text{ER}_i \) is CO₂ emission rate for VSP/STP mode \( i \) (unit: g/s); \( \text{TSTP}_i \) is time spent in VSP/STP mode (unit: s).
s); and \(TE\) is total link-based CO\(_2\) emissions (unit: g). Per-kilometer-person CO\(_2\) emissions is calculated by Eq. (3):

\[
E_{km-per} = TE/(L \times n)
\]

where \(L\) is the length of link and \(n\) is the number of in-vehicle persons (including driver).

2.4. Evaluation of emission characteristic of route

Given \(r = (r_1, r_2, \ldots, r_n)\), \(E_{per-\text{km}}(r_{i \rightarrow i+1})\) is per kilometer-person CO\(_2\) emissions from \(r_i\) to \(r_{i+1}\). A probability distribution can be calculated as \(p(r_1 \rightarrow 2, \ldots, p(r_{i-1} \rightarrow i), \ldots, p(r_{n-1} \rightarrow n))\), where

\[
p(r_{i \rightarrow i+1}) = \frac{E_{per-\text{km}}(r_{i \rightarrow i+1})}{\sum_{i=1}^{n} E_{per-\text{km}}(r_{i \rightarrow i+1})}
\]

Distribution characteristic of per kilometer-person CO\(_2\) emissions of routes is evaluated by adopting normalized Shannon entropy [26] as Eq.5:

\[
\eta(r) = -\sum_{i=1}^{n} p(r_{i \rightarrow i+1}) \log_b\left(\frac{p(r_{i \rightarrow i+1})}{\log_b(n-1)}\right)
\]

where denominator \(\log_b(n-1)\) is the maximum value of Shannon entropy, \(b\) is a constant. \(\eta(r) \in [0, 1]\). Applying the basic properties of logarithm, constant \(b\) is eliminated and the Eq. (3) can be expressed as:

\[
\eta(r) = \log_b\left(\prod_{i=1}^{n} p(r_{i \rightarrow i+1})^{p(r_{i \rightarrow i+1})}\right)
\]

Based on metric \(\eta(r)\), emission characteristic of each route can be measured. When \(\eta(r)\) is close to 1, per kilometer-person CO\(_2\) emissions of links on route \(r\) present uniform distribution, which means that no link has very large or small emissions; whereas it comes approximately to 0 when there is fewer links with high/low emissions but most route links with low/high emissions. According to the value of \(\eta\), routes can be divided into four categories: (a) with a small value of \(\eta\), caused by most of the links associating with low emissions but fewer links with high emissions; (b) with a small value of \(\eta\), caused by most of the links associating with high emissions but fewer links with low emissions; (c) with a large value of \(\eta\), caused by all links associating with high emissions; (d) with a large value of \(\eta\), caused by all links associating with low emissions. Obviously, the category d is most ideal case. For route category a, efficient operation strategies, such as optimizing route links with high emissions might be a potential solution for reducing emissions. For route category b and c, getting rid of such routes or reducing the frequency of buses departure may contribute to mitigating environmental pollution.

3. Study area and data

3.1. Study area

Qingdao is a sub-provincial city in eastern Shandong Province on the east coast of China. With the rapid urbanization, the city is shifting from...
a monocentric structure along the southern coast towards a polycentric pattern extending to the north and west coast. This study focuses on five metropolitan districts in the city and divides them into two parts: downtown area (Shinan, Shibei, Licang) and suburb area (Chengyang, Laoshan), respectively. The downtown area owns a high population, in which peak population density reaches 18153.95/km² in Shinan district. Population density in the suburb is substantially lower than the downtown area. As shown in Fig. 2, the population density of the study area decreases from south to north, implying various ridership in spatial range. Therefore, the city is suitable as the case of this study.

3.2. Data source and preprocessing

GPS trajectory data and Smart Card data of buses are provided by Qingdao Public Transport Group. Buses have been equipped with GPS sensors and automated fare systems. GPS sensors record real-time trajectory information at an average time interval of 30 s, including route ID, bus ID, speed, timestamp, longitude, and latitude. There are three types of buses in the city: natural gas buses (CNG/LNG buses), electric buses, and diesel buses. As of 2017, natural gas buses and electric buses account for 88% of the total buses and the number of traditional diesel buses is less than 600. In this paper, we choose CNG buses from 278 routes (not including customized routes and tour routes) covering downtown and suburban areas, and their emissions have reached China’s Stage IV standards.

Passengers’ boarding information is recorded by swiping Qingdao Public Traffic Smart Card, including boarding time and bus’s route number. ‘One-vote system’ mode is used in Qingdao’s transit buses system. Passengers swipe the card when getting on the bus, but do not need swipe when getting off the bus. In our previous study [20,21], we proposed a method to estimate the number of alighting passengers at each stop. Based on this method, real ridership between two adjacent stops of each bus can be acquired. Due to September 2018, a total of 8 million Qingdao Public Traffic Smart Card has been issued, accounting for 86.1% of total residents in the city. Therefore, ridership of transit buses is well represented by the number of passengers swiping the card when getting on the bus, but not need when getting off the bus.

Taxi trajectories data is provided by Qingdao Hisense Network Technology Co., Ltd, covering about total of 8513 taxis in the study area. Information on each taxicab’s driver ID, longitude, latitude, status (i.e., ‘occupied’ or ‘vacant’), speed, and timestamp is automatically collected at an average time interval of 30 s. Considering the 8-year time limit for mandatory scrapping of taxis, without loss of generality, in this study taxi vehicles are regarded to comply with China’s Stage IV standards, and vehicle technologies are assumed as Passenger Cars and Petrol Small, respectively. In this paper, taxi trips with passengers occupied are used to represent passenger car trips and idle trips with no passengers are omitted.

Cubic Spline Interpolation (CSI) method is adopted to estimate second-by-second speed of buses and taxis as input for MOVES model. Although previous studies based on emissions data of light-duty gasoline vehicles suggested interpolation of sparse data sampled above 5-second interval may underestimate the emissions [27], this leads to little influence on comparative analysis between buses and taxis with the same sample frequency, which can be omitted.

GPS trajectory data of buses and taxis and Smart Card data of buses used in this study were collected from 14/03/2017 (Tuesday) to 18/03/2017 (Saturday). The weather was normal and no emergency occurred. According to Definition 2 in section 2.1, the estimated ridership can be regarded as regular ridership. Considering the real driving condition of buses, unreasonable records of buses are filtered out, such as those average travel speed more than 40 km/h (transit buses speed limit in Qingdao), a sudden distance deviation over 100 m (GPS error), and long idle condition more than 30 min for buses (probably caused by road accident). Unreasonable trips of taxis are also removed as shown in our previous study [28]. After these pre-processing steps, there are 2056 buses with an average 1.5 million passengers’ trips data and 7589 taxis with 0.2 million passengers’ trips data each day. Statistical features of weekdays are very similar. For obtaining higher statistical power, we focus on handling weekday datasets in this paper.

To estimate the potential impact of the COVID-19 pandemic on buses’ emissions, we designed a questionnaire for commuters (who use transit buses at least twice per day) and conducted social survey through Tencent Survey in Qingdao. 224 online complete surveys about an individual’s travel behavior change of transit buses in post-COVID-19 pandemic were collected. Respondents were mainly asked if they would reduce their usage of transit buses in post-COVID-19 future and the possible reasons, if so, which travel modal (private car, taxi, online-riding) they would choose. Based on analysis of survey data, the potential changes in bus ridership after the COVID-19 and their influence on transit bus emissions are discussed.

4. Results and analysis

4.1. Driving condition characteristics of buses

We analyze speed, acceleration and ridership characteristics. STP distribution is given in Appendix B Fig. B1.

(1) Speed and acceleration

![Fig. 7. Correlation between per kilometer-person CO\textsubscript{2} emissions, speed and passenger load.](http://www.qdtcn.com/qdtbus.net/views/402881ba236e195001236e5c040200072c-9282776835d401016859a68a30001.html)
The average speed of buses during morning rush hours (7:00–8:59), evening rush–hours (17:00–18:59), and non-rush hours are 11.0 ± 5.7 km/h, 10.6 ± 5.5 km/h, and 12.8 ± 5.8 km/h, respectively. Low speed of transit buses was also observed in other Chinese cities (Wuhan, Xiamen, Nanjing, Haikou, and Changzhou), in which share of speed range of 0–30 km/h was over 70% and even reached up to 80% in some months [14]. In general, the reason for such low speed mostly is heavy traffic volume caused by the growth of the number of private vehicles [29].

Percent of acceleration range between $0.5 \text{ m/s}^2$ and $0.5 \text{ m/s}^2$ accounts for 66.9% and 67.1% during morning and evening rush hours. The figure drops to 61.9% during non-rush hours. Appendix B Fig. B2 presents instantaneous speed-acceleration distribution (not including data pieces when stopping at stations), in which color indicates the percentage of pieces of speed-acceleration. The reddest area corresponds to drive mode with both speed and acceleration close to zero, suggesting a high percentage of travel time spent in idle mode. Percentages of idle mode during the morning, evening rush hours and non-rush hours are 26.7%, 25.3% and 21.2%, respectively. A high percentage of idle mode during rush hours indicates more traffic congestion during these periods.

Fig. 3 shows the spatial distribution of average speed on route links. Results show that routes in two regional hubs have obvious low travel speed. Increment of travel speed can be observed in the road links outside the two hub areas. The two hub areas are the economic centers of the city in downtown and suburban areas. Dense routes network in hub areas suggests high intra-traffic demand; and spares routes between the two hubs implies relatively low inter-traffic demand. Since average speed on route link had been confirmed to be closely related to emissions and fuel consumption [11], this unbalanced distribution of average speed could lead to a spatial difference in emissions.

(2) Ridership

We investigate percent changes in the number of boarding people by hour. Two obvious peaks are identified at 7:00–8:59 and 16:00–18:59 (Appendix B Fig. B3). These periods align with the hours with low traveling speed. Results show that nearly 1.5 million passengers were transported by buses, of which 47% of passengers boarding during two rush periods. Fig. 4 shows the distribution of ridership on route links during three periods. Histogram illustrates that the number of passengers transporting on most route links is substantially small, however, a few route links are handling large passenger flows both in rush hours and non-rush hours, implying non-uniform distribution characteristic. In the set of Fig. 4, the y-axis of the histogram is represented in log scale. Points in all subfigures appear to connect as straight lines. Maximum likelihood estimation (MLE) is used for obtaining a fitted distribution, and we apply the Kolmogorov-Smirnov test (KS-test) to the scaling parameter estimators. Results show that the number of passengers can be fitted well by exponential distribution $P(x) \propto e^{-x}$. The estimated parameters during morning, evening and non-rush hours are 0.06 (adjusted $R^2 = 0.95$), 0.075 (adjusted $R^2 = 0.98$), and 0.09 (adjusted $R^2 = 0.95$), respectively. This finding shows that ridership distribution in spatial structure presents an unbalanced distribution characteristic. This result, which is consistent with the finding from previous work [30], suggests trips of people have a high degree of spatial heterogeneity.

Fig. 5 illustrates the spatial distribution of the average number of passengers on route links. It can be seen that most of the bus routes that transport heavy volumes of passengers are located in downtown areas of the city. In previous work [31], passenger load factor was defined as the ratio of the actual number of passengers to the passenger capacity of the bus. The authors suggested when the passenger load factor was more
should add one person (bus driver).

and 4 persons, respectively. Similarly, for buses, estimated ridership study, the passenger capacity of bus is about 80

reaches up to 24% and 17% during morning and evening rush hours, crowded. The ratio of route links transporting more than 60 passengers respectively. The figure drops to 0.6% during non-rush hours. The result implies low emissions per person during rush hours can be obtained at busy-routes locating in downtown areas, however, this might be at the expense of undesirable in-vehicle crowding.

4.2. Emission characteristics

In the following analysis, we focus on running emissions which do not include emissions occurring at bus stops but do include emissions occurring during idling in traffic. Running emissions are calculated by Eqs. (2) and (3).

(1) Emissions comparison between buses and passenger cars

Taxi’s trip with passengers occupied are used to represent passenger car trip. No available data for the number of passengers in each taxi trip. Average number of passengers of each taxi trip is assumed as 1 pas-

gen, 2 passengers and 3 passengers, respectively. Considering the
driver, the number of persons in each taxi ride is 2 persons, 3 persons, and 4 persons, respectively. Similarly, for buses, estimated ridership should add one person (bus driver).

Fig. 6 compares the median value of per kilometer-person CO2 emissions of buses and taxis during different time periods, in which idle distance of taxis with no passengers occupied is omitted. Obviously per kilometer-person CO2 emissions of taxis decrease with the increase of ridership. It can be observed that per kilometer-person CO2 emissions of buses are lower than that of taxis with 2 persons or 3 persons at different periods (rush hours and non-rush hours). Compared with taxis with 2 persons, the maximum difference value between buses and taxis occurred at 7:00–8:59 (117 g/km-person), followed by 17:00–18:59 (115 g/km-person). Similar results can be observed between buses and taxis with 3 passengers, with 65 g/kilometer-person at 7:00–8:59 and 60 g/kilometer-person at 17:00–18:59.

However, when compared with taxis with 4 persons, per kilometer-

person CO2 emissions of buses are higher than taxis at 9:00–10:59 (1 g/kilometer-person), 13:00–14:59 (9 g/kilometer-person), and 19:00–20:59 (15 g/kilometer-person). This result suggests buses with high ridership during rush hours associate with lower per kilometer-

person CO2 emissions than private car, whereas during non-rush period buses could be as polluting as private cars with full occupancies on a per kilometer-person basis. Previous studies suggested that the average vehicle occupancy was 1.1 passengers per taxi ride [32]. Thus we can conclude buses have lower emissions on per kilometer-

person basis than passenger cars in most cases, implying that buses are more effective than passenger cars in reducing emissions. Emissions results in this case are defined as emissions in normal case. In the following section, emissions in normal case are set as baseline. We compare it with potential emissions change in post-COVID-19.

(2) Relation between emissions and driving conditions

We divide passenger load into 5 ranks, in which each rank represents the range of the number of passengers on bus. Rank 1, 2, 3, 4, 5 represent (0,20), [20,40), [40,60), [60,80), [80,100]) and > 100, respectively. And speed v is grouped into four ranges: v ∈ [0.1 m/s), [1 m/s,2m/s), [2m/
s,3m/s), greater than3m/s. For each load rank and speed group, the median value of per kilometer-person CO2 emissions is calculated.

As shown in Fig. 7, in each speed group, per kilometer-person CO2 emissions reach the maximum value when the number of passengers is the minimum value. Here, another interesting finding can be observed, that is, declining trend of per kilometer-person CO2 emissions is not obvious when passenger load becomes larger. This result is consistent with the findings of [15], in which authors suggested when the number of passengers exceeded the seating capacity of the bus, additional pas-

sengers no longer contributed noticeably to reduce per-person emis-
sions. This result implies increasing ridership can improve bus emission benefits, however, when ridership approaches or exceeds the capacity, the emission benefits of buses will reach upper limit.

On the other hand, an obvious decline trend of per kilometer-person CO2 emissions can be observed with the increase in travel speed during three periods. This result coincides with the findings of [18], indicating that when vehicle travels with low speed and carries a large number of passengers, per kilometer-person emissions are the highest.

(3) Spatio-temporal characteristics of emissions

Probability distribution of per kilometer-person CO2 emissions during different periods are summarized in Fig. 8 (a), in which a log–log scale representation is given. It can be observed that data points in each period group can be fitted by a straight line. MLE is used for obtaining a fitted distribution, and we apply the KS-test to the scaling parameter estimators. Results show that per kilometer-person CO2 emissions follow a power law $P(x) = x^{-k}$. The estimated scaling exponent k are shown in Fig. 8 (b), in which all fitted exponents associate with adjusted R2 greater than 0.9. Two peak values are observed during rush hours, suggesting a faster decline of probability with the increase of per kilometer-person CO2 emissions. This result implies per kilometer-

person CO2 emissions during non-rush hours present more obvious

Fig. 10. Passenger’s travel behavioral change in post-COVID-19 future.

Fig. 11. Emissions comparison between the normal case and the post-COVID-19 case.
unbalanced characteristics compared with during rush hours. As shown in Fig. 8 (b), during non-rush hours, i.e. during 9:00–16:59 and 19:00–20:59, there are more road links with high per-kilometer-person CO$_2$ emissions. Median value of per kilometer-person CO$_2$ emissions during 6:00–6:59, 7:00–8:59, 9:00–10:59, 11:00–12:59, 13:00–14:59, 15:00–16:59, 17:00–18:59, and 19:00–20:59 are 53.9 g/km-person, 44.3 g/km-person (lowest), 65.2 g/km-person, 60.3 g/km-person, 73.2 g/km-person, 65.1 g/km-person, 51.5 g/km-person and 83.4 g/km-person (highest), respectively. By comparison of the lowest emissions and highest emissions, approximately a twofold increase from rush hours to non-rush hours can be observed. This finding clearly shows that the emission benefits of transit buses have distinct characteristics during different periods.

According to Section 2.4, the emission characteristic of each route can be evaluated by normalized entropy $\eta(r)$. Fig. 9 compares all routes’ normalized entropy over time. The median value of all routes’ normalized entropy is larger than 0.8, approaching close to the maximum value 1. This result suggests per kilometer-person CO$_2$ emissions of links on route are very similar in general. However, median values of normalized entropy during 7:00–8:59 and 17:00–18:59 are smaller than during other periods, suggesting the difference in per-kilometer-person CO$_2$ emissions of links becomes larger. This result is mainly caused by a sharp increase of ridership on some hot stops during rush hours, leading to a decrease of per kilometer-person CO$_2$ emissions of some links.

The spatial distribution of per kilometer-person CO$_2$ emissions around the city is shown in Appendix B Fig. B4. Results show that during rush hours (7:00–8:59 and 17:00–18:59) most bus routes associate with low emissions and fewer bus routes in suburb area (North Jiaozhou Bay Park of Qingdao Hi-Tech Zone) with high emissions. The number of bus routes with high per kilometer-person CO$_2$ emissions increases during non-rush hours. An obvious expansion from the north-west area to the north area (Chengyang administrative government) can be observed. The unbalanced distribution of per kilometer-person CO$_2$ emissions, i.e., north area associating with high emissions and south area with low emissions is further worsened after 19:00. The reason for such difference in emissions between north and south areas is the heterogeneity spatial characteristic of ridership around the city. This finding suggests it would be difficult to reduce CO$_2$ emissions by simply promoting transit buses, such as expanding service areas of routes and increasing the frequency of bus departures. Investment in bus routes with low travel demand has little help decreasing CO$_2$ emissions per kilometer-person. Thus taking transit buses as a means of reducing emissions should be more selective rather indiscriminate use. Considering uncomfortable feelings caused by getting rid of such routes with low ridership, lowering fee, or a free transfer for longer periods (1 h currently in Qingdao) to attract more ridership may be a potential alternative solution, especially in the development of new districts area.

Fig. 12. Emissions comparison between buses in scenario cases and taxis in the normal case.
4.3. Potential emissions change in post-COVID-19 and scenario analysis

As shown in Fig. 10, according to our surveys, 56.3% of respondents stated that they would decrease the usage of transit buses in the post-COVID-19 future while 38.1% would use transit buses as before, only 5.6% would increase usage of transit buses. The proportion that would increase usage of passenger cars is 42.9% after COVID-19 and the figure for usage as before is 47.2%, only 9.9% of respondents would decrease the usage of passenger cars. 78.1% of respondents reported the reason for modal shifting from transit buses to private cars was caused by the concern of higher infection possibility in crowded buses. The result suggests the coronavirus will have medium-long-term impacts on individual’s travel modal choices.

Therefore, we assume ridership of normal case reduces by −56.3% as shown in our surveys and recalculate the emissions per kilometer-person of each bus. This result is defined as the post-COVID-19 case. Emissions comparison between the normal case and the post-COVID-19 case are shown in Fig. 11. Obviously, per kilometer-person emissions of buses during the post-COVID-19 case increased more than twice than the normal case. We further compare the emissions of buses in the post-COVID-19 case and that of cars with 2 persons. Results show that only during rush hours (7:00–8:59 and 17:00–18:59) per kilometer-person emissions of buses are lower than that of cars; while during other periods buses are more polluting than cars on a person basis, with the largest difference value (57 g/kilometer-person) occurring at 19:00–20:59.

We assume regular ridership declines by −10%, −20%, −30%, −40%, −50% and −60%, respectively. For each scenario, we compare the corresponding emissions of buses and cars with 2 persons. As shown in Fig. 12, even if ridership is reduced by −60%, during 7:00–8:59 and 17:00–18:59, buses’ emissions on a person basis are 50 g/kilometer-person and 39 g/kilometer-person lower than cars, respectively. During other periods, when ridership is reduced by −10%, −20% or −30%, buses are less polluted than cars on a person emissions basis. However, when ridership is reduced by −40%, −50% or −60%, buses could be as polluting as cars and even generate more emissions than cars, suggesting emissions benefits of buses during the post-COVID-19 may be uncertain. For illustrating which route links would have more emissions than taxis when ridership decreases, a simple comparison between rush hours and non-rush hours is given in Fig. B5. Ridership of buses is set to be reduced by −50%. It can be observed during non-rush hours more links associate with high emissions and links with emissions higher than the median value of emissions from taxis are concentrated in a suburban area (north part of the map).

5. Discussion and implications

Transit buses play a significant role in reducing GHG emissions sourced from on-road transportation. Compared with passenger cars, the emission benefits of buses can be acquired with high ridership. However, on one hand, ridership varies with different times and locations. On the other hand, with the negative effect of COVID-19, in the future, people’s travel behavior may change due to the fair of high health risks in crowded buses. Potential ridership decline poses significant uncertainty to the role of transit buses in emissions reduction.

In this paper, we adopted 2056 CNG buses from 278 routes with average of 1.5 million passengers’ trips data and 7589 taxis with 0.2 million passengers’ trips data per day in Qingdao, China to investigate spatio-temporal emissions characteristics of buses. Results in this case are regarded as the normal case. Based on that, 224 online survey data are used to study potential ridership reduction in the post-COVID-19 future, and several comparative analyses are given to explore emission benefits change of buses between the normal case and the post-COVID-19 case. Our main findings and related policy suggestion are presented as followed:

1. In the normal case, compared with passenger cars, buses associate with lower emissions on a person basis in most periods, except for cases when passenger cars with 4 persons during 9:00–10:59, 13:00–14:59, and 19:00–20:59 (the maximum difference is less than 15 g/kilometer-person). Considering the average number of passengers in a vehicle is 1.1, our finding confirms transit bus is an eco-friendly travel modal and outperforms passenger car in reducing emissions and air pollution on a person basis. In the study of [8], authors compared fuel consumption and emissions between diesel buses and passenger cars based on data collected from four buses of one route during limited periods in Shanghai. The passenger load threshold of buses was concluded. When the passenger load was smaller than this threshold, bus cannot be regarded as a greener travel mode compared with passenger cars. Different from diesel buses, we compare emissions of CNG buses and passenger cars based on data collected from thousands of buses and cars of one day. We analyze which periods buses associating with higher emissions on a person basis than passenger cars, which is complementary to their study.

Also our results show that although emission benefits of buses can be acquired with high ridership, when passenger load approaches or exceeds the capacity of the bus, there is no obvious decline trend of per-kilometer person CO₂ emissions. This result is consistent with the findings of [15], in which authors suggested when the number of passengers exceeded the seating capacity of the bus, additional passengers no longer contributed noticeably to reduce per-passenger emissions. This finding implies that retaining existing ridership in downtown areas with high ridership is crucial to maintaining the potential to operate with lower levels of emissions per passenger of transit buses. However, low emissions per person during rush hours come with undesirable in-vehicle crowding, which might greatly degrade the passengers’ experience and result in the possibility of ridership decrease [33]. The last decade has seen the decline of bus ridership in many megacities in the world. For example, transit ridership in the U.S. has declined steadily since 2014, with some of the largest urban areas, including Atlanta, Miami, and Los Angeles, losing more than 20% of their transit riders in the last few years [34]. As a result, bus agencies should improve the bus experience by providing a range of creature services in the downtown area, i.e., promoting customized bus along the busiest corridor which picks passengers up at only some stops, monitoring and releasing in-vehicle crowd index in real-time which help passengers planning travel.

2. Distribution of per kilometer person CO₂ emissions around the city can be fitted well by a power-law \( P(x) \propto x^{-k} \), suggesting most of the buses associating with low emissions but a few buses with high emissions. A smaller value of estimated parameters \( k \) is found during non-rush hours, implying there are more buses with high emissions during non-rush hours compared with rush hours, i.e., per-kilometer-person emissions having doubled during non-rush hours compared with rush hours. The area with high per-kilometer-person emissions can be firstly observed in non-hub areas of suburbs during non-rush hours and then the area gradually expands to the whole suburb including hub areas. Previous work studied the spatial distribution of emissions from diesel transit buses in one of the busiest routes in Vancouver, Canada, and concluded that emissions along the route exhibited significant variability [35]. Based on data collected from all the routes around the city, our study adopts power-law distribution to measure this variability and provides more clear illustrations of the spatial heterogeneity of emissions. Various emission benefits also are found between different links of the route. We adopted normalized entropy to evaluate the unbalanced degree of emission benefits of one route. Results show that routes during
rush hours present more unbalanced emissions characteristics compared with non-rush hours, suggesting although routes in downtown areas during rush hours associate with relatively low emissions per kilometer-person, there are still a few route links with high emissions.

These results provide convincing evidence on transit buses that have distinguishing spatio-temporal emission patterns around the city and their emission benefits in the suburb during non-rush hours are substantially low. We highlight that investment in transit buses should be more selective rather indiscriminate use. Our studies show that buses running in suburbs during non-rush hours have more emissions on a person basis. Therefore, it is important to note that investment in bus routes of areas with low travel demand has little help decreasing emissions per kilometer-person. In China, with fast urbanization and economic growth, more and more suburbs around the city are integrated into the urban area, followed by the extension of existing bus routes and operation of a large number of new transit routes. At the early development period, bus agencies are recommended to reduce departures frequency to avoid transit buses running significantly below capacity. With the growing number of residents, attracting more new riders by ride discount or a free transfer for long periods might be a potential alternative solution for reducing emissions per kilometer-person.

(3) potential ridership reduction has a significant negative effect on the emission benefits of buses. Our surveys show that 56.3% of people would decrease the usage of buses in the post-COVID-19 future. Based on this potential reduction figure, emissions of buses on a person basis increase more than double times than before, and buses cannot be “greener” travel modal than passenger cars except for rush hours. When ridership drops by 30%, buses can still perform better than passenger cars on a person emissions basis, however, when ridership is reduced by larger than 40%, buses could be as polluting as cars and even generate more emissions than cars. Although the medium-long-term influences of the novel coronavirus on ridership are still unknown, our result highlights the urgency for policy marker to plan effective measures for this upcoming crisis.

On one hand, in short term, people’s health risk concerns of transit buses may be alleviated by promulgating safe requirements for drivers and passengers, such as wearing a face mask when having a ride and opening a window for ventilation. Our results show that when ridership declines by fewer than 30% buses can generate less emissions on a person basis than passenger cars. Therefore, safe distance can be realized in-vehicle by limiting bus capacity to some extent. Regular disinfection of vehicles and equipment (such as handrails) with antimicrobial cleaners is essential to reduce infection risks. These measures can strengthen passengers’ confidence in safe transits and make ridership be attracted back to public transits. On the other hand, promoting the usage of low-carbon buses, such as hybrid, plug-in hybrid and electric buses can be an effective strategy for reducing emissions in the medium-long terms. The electrification of buses can help to reduce local air pollution. Although previous studies confirmed the performance of electric buses was sensitive to electricity mix, the battery-electric buses that use electricity from renewable sources were the best option when considering environmental benefits and operational advantages [36]. Besides, when considering limited funds, routes with low ridership and uneven emissions characteristics should be given priority to update electric buses.

6. Conclusion

This paper presents a method framework to study the spatio-temporal emission characteristics of buses and potential change analysis on emissions of buses caused by ridership reduction. Case study in Qingdao, China by adopting 2056 CNG buses from 278 routes with average 1.5 million passengers’ trips data and 7589 taxis with 0.2 million passengers’ trips data show that compared with passenger cars, buses associate with lower emissions on a person basis. There is no obvious decline trend of per kilometer-person emissions when ridership approaches or exceeds the capacity of bus. Transit buses are confirmed with distinguishing spatio-temporal emission patterns around the city and their emission benefits in the suburb during non-rush hours are substantially low. Our surveys present that in the post-COVID-19 future, buses cannot be “greener” travel modal than passenger cars as before. However, when ridership is reduced by less than 30%, buses can still perform better than passenger cars on a person emissions basis. Based on our findings, corresponding policy suggestions are provided to support better transit buses investment decisions and the promotion of eco-friendly public transport services.

Although this study provides a deeper and nuanced understanding of spatio-temporal emission characteristics of transit buses at a metropolitan-wide scale, there are several limitations. First, we only focus on weekdays in this study. Other periods, such as weekends and holidays have been omitted. In the future, we will attempt to obtain more available datasets to complement our study. Second, dead mileage, when a bus runs from/to a garage to begin/end its first/last trip of the day without carrying or accepting passengers, is not considered in this study. A more accurate analysis will be carried out by accounting for non-service miles and variations in ridership throughout the day. Third, mix mode of travel switching between bus and car will be studied for potential reduction of emissions from routes bridging downtown and suburban.

Declaration of Competing Interest

The authors declare no competing interest.

Acknowledgments

This research is supported by Young Scientists Fund of the National Natural Science Foundation of China (41706198), National Statistical Science Research Project of China(2017LY82), Shandong Province colleges and universities youth innovation technology plan innovation team project under Grant No.2020KJN011, and A Project of Shandong Province Higher Educational Science and Technology Program of China (J17KA056).

We would like to thank Qingdao Public Transport Group and Qingdao Hisense Network Technology Co., Ltd for access to the data on which the paper is based.

Appendix A

Table A1

Appendix B

Fig. B1 presents a comparative analysis of operation mode distribution based on all data and running operation modes distribution. Running
operation modes refer operations not occurring at bus stops (but do include operation mode occurring during idling in traffic). It can be observed that the most difference between Figs. B1 (a) and B2 (b) is the decrease in share of bin 1, and the increase in bin 11 and bin12. The share of bin1 drops from 64.2% to 24.3% for morning rush-hours; 62.9% to 23.2% for evening rush hours; and 62.9% to 17.9% for non-rush hours. This suggests dwell time during boarding and alighting of passengers at bus stations is substantially long. Average dwell time at station during morning, evening and non-rush hours are $72.9 \pm 29.5$ s, $70.0 \pm 27.3$ s and $47.0 \pm 11.8$ s, respectively. When bus stopped at station, vehicle’s engine often run but the vehicle was not in a motion. These idle emissions are mainly determined by emission rates and dwell time [37,38], suggesting longer dwell contributing to higher idle emissions. Average dwell emissions at station are $133.3 \pm 54.0$ g, $128.0 \pm 50.0$ g and $85.9 \pm 21.6$ g during morning, evening and non-rush hours, respectively, implying emissions sourced from dwell time at stops during rush hours are higher than during non-rush hours.

Fig. B1. Operation mode distribution of transit buses: (a) including data stopping at stations; (b) not including data stopping at stations.

Fig. B2. Joint distribution of speed and acceleration of transit buses group by different time periods (morning refers time period from 7:00am to 8:59am, evening refers time period from 17:00am to 18:59am, and non-rush hours refer other time periods).

Fig. B3. Hourly variation of percent of boarding people (each bar represents one hour).
Fig. B4. Spatial distribution of per kilometer-person CO$_2$ emissions (colored by natural breaks). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
Fig. B5. Spatial distribution comparison of emissions between buses with ridership reduced by – 50% and taxis in normal case. (a) morning rush hours; (b) non-rush period.

References

[1] Le Quéré C, Jackson RB, Jones MW, Smith AJ, Abernethy S, Andrew RM, et al. Temporary reduction in daily global CO2 emissions during the COVID-19 forced confinement. Nat Clim Change 2020;1–7.

[2] Sadique MZ, Edmunds WJ, Smith RD, Meerding WJ, De Zwart O, Brug J, et al. Precautionary behavior in response to perceived threat of pandemic influenza. Emerg Infect Dis 2007;13:1307–12.

[3] Cretazig F, Jochem P, Edelenbosch OY, Mattauch L, van Vuuren DP, McCollum D, et al. Transport: A roadblock to climate change mitigation? Science 2015;350:911–2.

[4] Lowe M, Aytekin B, Gereffi G. Public transit buses: A green choice gets greener. Center Global Governance Compet 2009.

[5] Naviaux JD. From Cars to Buses: Using OCTA Ridership to Analyze the Emission Benefits of Bus Transportation. The UCI Undergrad Res J 2011;11:25–33.

[6] Kim J, Corcoran J, Papamamalia M. Route choice stickiness of public transport passengers: Measuring habitual bus ridership behaviour using smart card data. Transport Res Part C: Emerg Technol 2017;83:146–64.

[7] Lau J, Hatzopoulou M, Wahba MM, Miller EJ. Integrated multimodel evaluation of transit bus emissions in Toronto, Canada. Transport Res Rec 2011;2216:1–9.

[8] Chen X, Shan X, Jia W, Ye J, Yi F, Wang Y. Evaluating the effects of traffic congestion and passenger load on feeder bus fuel and emissions compared with passenger car. Transp Res Proc 2017;25:616–26.

[9] Shan X, Chen X, Jia W, Ye J. Evaluating Urban Bus Emission Characteristics Based on Localized MOVES Using Sparse GPS Data in Shanghai, China. Sustainability. 2016;11:496.

[10] Wang A, Ge Y, Tan J, Fu M, Shah AN, Ding Y, et al. On-road pollutant emission and fuel consumption characteristics of buses in Beijing. J Environ Sci 2011;23:419–26.

[11] Zhai H, Frey HC, Rouphail NM. A vehicle-specific power approach to speed-and facility-specific emissions estimates for diesel transit buses. Environ Sci Technol 2008;42:7985–91.

[12] Frey HC, Rouphail NM, Zhai H, Farias TL, Gonzalves GA. Comparing real-world fuel consumption for diesel-and hydrogen-fueled transit buses and implication for emissions. Transport Res Part D: Transp Environ 2007;12:381–91.

[13] Zhang S, Wu Y, Hu J, Huang R, Zhou Y, Bao X, et al. Can Euro V heavy-duty diesel engines, diesel hybrid and alternative facility technologies mitigate NOX emissions? New evidence from on-road tests of buses in China. Appl Energy 2014;132:118–26.

[14] Yu H, Li M, Li J, Liu Y, Lv H, Ma K. Real-road NOx Emission and Fuel Consumption Characteristics of China IV Public Transit Buses. Energy Proc 2019;158:4623–8.

[15] Alam A, Hatzopoulou M. Investigating the isolated and combined effects of congestion, roadway grade, passenger load, and alternative fuels on transit bus emissions. Transport Res Part D: Transp Environ 2014;29:12–21.

[16] Xylia M, Leduc S, Laurent A-B, Patrizio F, Van Der Meer Y, Kraxner F, et al. Impact of bus electrification on carbon emissions: The case of Stockholm. J Clean Prod 2019;209:74–87.

[17] Lajunen A. Energy consumption and cost-benefit analysis of hybrid and electric city buses. Transport Res Part C: Emerg Technol 2014;38:1–15.

[18] Yu Q, Li T, Li H. Improving urban bus emission and fuel consumption modeling by incorporating passenger load factor for real world driving. Appl Energy 2016;161:101–11.

[19] Waraich AS, Anowar S, Tenaglia T, Sider T, Alam A, Minaei NS, et al. Disaggregate level simulation of bus transit emissions in a large urban region. Int J Sustain Transport 2019;1–10.

[20] Yu X, Shao F, Sun R, Sui Y. Boarding stations inferring based on bus gps and ic data. Asian Simulation Conference: Springer 2018;361–71.

[21] Sui Y, Shao F, Yu X, Sun R, Li S. Public transport network model based on layer operations. Physica A 2019;523:984–95.

[22] Todts W. CO2 emissions from cars: The facts. European Federation for Transport and Environment AISBL: Brussels, Belgium; 2018.

[23] Agency UEP. Inventory of US greenhouse gas emissions and sinks: 1990–2018. DC: US Environmental Protection Agency Washington; 2020.

[24] Li X, Yu B. Peaking CO2 emissions for China’s urban passenger transport sector. Energy Policy. 2019;133:110913.

[25] Agency UEP. Population and Activity of On-road Vehicles in MOVES2014. EPA-420-R-16-0032016.

[26] Shannon CE. A mathematical theory of communication. Bell Syst Tech J 1948;27:379–423.

[27] Li Z, Song G, Yu X, Yu L, He W. Developing Mode Change Options From Sparse Trajectories for Emission Estimation. Transp Res Res 2019;2673:137–48.

[28] Sui Y, Zhang H, Song X, Shao F, Yu X, Shibasaki R, et al. GPS data in urban online ride-hailing: A comparative analysis on fuel consumption and emissions. J Clean Prod 2019;227:495–505.

[29] Bureau QMS. Qingdao NSOi. Qingdao Statistical Yearbook: China Statistics Press; 2018.

[30] Gonzales MC, Hidalgo CA, Barabasi A-L. Understanding individual human mobility patterns. Nature 2008;453:799–802.

[31] Shen X, Feng S, Li Z, Hu B. Analysis of bus passenger comfort perception based on passenger load factor and in-vehicle time. SpringerPlus. 2016;5:1–10.

[32] Rayle L, Shaheen SA, Chan N, Dai D, Cervero R. App-based, on-demand ride-hailing: A comparative analysis on fuel consumption and emissions. J Clean Prod 2019;277:91–101.

[33] Haywood L, Koning M, Monchambert G. Crowding in public transport: Who cares and why? Transport Res Part A: Policy Prat 2017;100:215–27.

[34] O’Toole R. Charting Public Transit’s Decline. Cato Institute. Policy Anal 2018;10.

[35] Goube B, Ries FJ, Dowlatabadhi H. Spatial distribution of diesel transit bus emissions and urban populations: Implications of coincidence and scale on exposure. Environ Sci Technol 2010;44:7163–9.

[36] Mahmoud M, Garnett R, Ferguson M, Kanaroglou P. Electric buses: A review of alternative powertrains. Renew Sustain Energy Rev 2016;52:673–84.

[37] Yu Q, Li T. Evaluation of bus emissions generated near bus stops. Atmos Environ 2014;85:195-203.

[38] Armas O, Gomez A, Mata C, Ramos A. Particles emitted during the stops of an urban bus fuelled with ethanol-biodiesel-diesel blends. Urban Clim 2012;2:43–54.