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Reducing air pollution exposure in a road trip

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Abstract

Air pollution is considered to be responsible for a variety of respiratory and cardiovascular diseases, and vehicle emission is becoming one of the dominant pollution sources. Travelers, especially occupational drivers, spend many hours in vehicles every day, but they lack the visibility of air pollution of the trips and the knowledge of how to prevent themselves from such exposure. In this paper, we first investigate the problem of air pollution on the road with extensive experimental research. Two corresponding methods are then proposed to reduce the in-vehicle air pollution: (1) car usage optimization to provide the drivers personalized real-time recommendations on how to achieve best possible in-vehicle air quality in specific circumstances via controlling the car window and air conditioner, and (2) filter maintenance advice notifying the drivers when to perform a filter maintenance for achieving significant purification efficiency improvement. Extensive experiments on real driving data from multiple cities worldwide have proved the efficiency of our proposed solution.

KEYWORDS

Air quality, Traffic pollution, In-vehicle

Introduction

The prevalence of urban air pollution raises serious concerns from the public in the past decades, especially in metropolitan cites of developing countries, such as China or India. High level of atmospheric pollutants is considered to be responsible for a variety of respiratory and cardiovascular diseases, and may cause cancer if human beings are exposed to such environment for long hours [1]. World Health Organization (WHO) reports that around 7 million people died as a result of air pollution exposure in 2012 only, and air pollution is now the world's largest single environmental health risk [2].

Due to the increasing number of vehicle ownership, vehicle emission has become the dominant source of air pollutants, which includes carbon monoxide (CO), carbon dioxide (CO2), volatile organic compounds (VOCs) or hydrocarbons (HCs), nitrogen oxides (NOx), and particulate matter (PM) [3]. Previous research [4] discloses that some illnesses, like childhood asthma and nonasthma respiratory symptoms, are specially related to traffic air pollution exposure. A recent work addresses the air pollution estimation problem via photography data [5].

Travelers, especially occupational drivers such as taxi drivers, spend hours of time in vehicles on the road every day. However, they are commonly not provided with the visualization of in-vehicle air quality, not to mention air pollution exposure statistics on the road. In addition, even though more and more attentions have been paid to the harm of air pollution exposure, drivers usually lack the knowledge of how to prevent themselves from the air pollution by utilizing the resources at hand.

To solve the above problem, we aim to learn the problem of air pollution on the road and provide specific methods for drivers to reduce air pollution in vehicles. We summarize our contributions as follows.

- We collect a large amount of in-vehicle air quality data based on a Cloud-based Internet of Things (IoT) platform.
- A comprehensive factor analysis of air pollution on the road is performed on the in-vehicle air quality dataset, together with an aggregated set of data sources, in order to learn the main factors affecting air quality on the road and how in-vehicle air quality changes with them.

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- Based on the factor analysis results, we utilize the Cloud-based IoT platform to provide two ways to improve in-vehicle air quality for drivers: car usage optimization and filter maintenance advice. The car usage optimization method provides the drivers personalized real-time recommendations of how to control the car window and air conditioner in specific circumstances to achieve best possible invehicle air quality. The filter maintenance method notifies the drivers when to conduct a filter maintenance to achieve significant purification efficiency improvement.
- Experiments on real driving data from multiple cities worldwide are provided to demonstrate the efficiency of our proposal.

Related Works

The urban air pollution problem has attracted a lot of attentions from both industrial and academic communities in recent years [6-9]. In addition, a large amount of measures are also been carried out to address the traffic related air pollution issues from different perspectives.

United States Environmental Protection Agency (EPA) has reduced pollution from new vehicles by establishing more stringent emission standards and cleaner fuel requirements. EPA also sets the health-based National Ambient Air Quality Standards (NAAQS) for pollutants that are emitted from on-road mobile sources and has recently required that air quality monitors shall be placed near high-traffic roadways for determining compliance with the NAAQS for NO2, CO, and PM2.5. Over the past years, EPA has also been conducting research to better understand the phenomenon of near roadway pollution, exposure and adverse health effects, and how to reduce air pollution near these high-traffic areas [10].

Zhang and Berkowicz explore physical modeling and simulation techniques to discover the traffic air pollution impact [3][11]. Devarakonda and Zhu have developed onboard mobile sensing system to measure air quality inside and outside of the vehicle [12] [13].

OpenSense, a project run by EPFL and ETH Zurich, Switzerland, aims to study the feasibility of installing sensors on the roofs of buses and trams, and take the advantage of the existing public transportation vehicles to form an extensive network of mobile air quality data collection sites [14].

Our previous paper introduced a solution for detecting in-vehicle air quality through a Cloud-based Internet of Things (IoT) platform [15]. Some early insights were also discussed. In this paper we illustrate results of the complete experimental research. Moreover, two specific methods are also proposed to reduce in-vehicle air pollution. To the best of our knowledge, no extensive study has been performed to understand the patterns of air pollution on the road before. In addition, no comprehensive solution has been proposed to reduce the exposure for drivers by taking systematic approaches and considering the related factors, such as weather, traffic, road structure, vehicle condition and car usage behaviors, like our paper does.

Intelligent In-vehicle Air Quality Management Solution

This work is based on our previous intelligent in-vehicle air quality management solution [15], the diagram of which is demonstrated in Figure 1. The overall solution consists three components: (1) an air quality sensing device in the vehicle measuring the in-vehicle air quality in real-time; (2) a mobile application offering drivers air pollution exposure situations; (3) a Cloud-based Internet of Things (IoT) platform for collecting, managing and analyzing the sensing data as well as other contextual information, such as weather, traffic, road-network structure, etc.

Air Quality Report/Forecast Weather Report/Forecast Road Network/Map (City data or GreenHorizon) Maintenance Data Eco-drive mobile app Air Condition/filter **Driving Context Fusion** Maintenance Advisor Targeted Driving behavior advisor Air Pollution Driver (journey: route/time; vehicle Alerts/air usage: window/air condition, Correlation Knowledge condition road structure: Learning (with traffic, control tunnel/underground) road structure, vehicle usage, weather) Vehicle usage condition IoT Data learning (window, air Knowledge Collection condition status) Base ADAS sensor/Air quality sensor

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Figure 1. Intelligent in-vehicle air quality management solution framework

Data Preprocessing

In our latest experiment, we have continuously collected data with a sampling interval of 3 seconds for three months on 500 floating cars cross 4 major cities in China. All the cars are equipped with an air quality sensing device, a mobile application, and supported by our Cloud-based IoT platform. We have collected over 1.3 million kilometers mileages sensing data in total, which corresponds to around 2.41 driving hours per day per driver. The entire volume of sensing data (including in-vehicle air quality related data and GPS data) we collected are over 9 GB on disk.

Note that although our experiment objects are cars, our platform and methods proposed in this paper are suitable for all kinds of vehicles. In the followings of this paper, we use the terms *car* and *vehicle* interchangeably.

Data preprocessing on the collected data is non-trivial work. The overall data preprocessing procedure is demonstrated in Figure 2. In particular, in order to understand the impact of environment on the air quality on the road, not only the time-series sensing data from floating cars are collected, we also build an augmented set of data from other spatiotemporal data sources, which includes weather information, city air pollution information, road network structure attributes, traffic, etc. The augmented data are denoted as *context information*, which is then fused with the sensing data utilizing spatiotemporal data fusion algorithms and efficient spatial and temporal indexing algorithms [16] [17], shown as the first step in Figure 2.

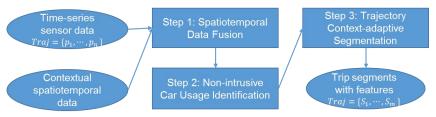


Figure 2. Data preprocessing procedure

In addition, based on our practical experience and a preliminary data analysis, we find out that the usage of the car window as well as the air conditioner is one of the major factors that affects in-vehicle air quality. Note that the status of the car window and air conditioner cannot be directly obtained from the existing data collection system. To deal with this problem, we have designed and implemented an non-intrusive car usage identification algorithm (Step 2 in Figure 2), which can automatically label the car window and air conditioner statuses, based on the varying trends of real-time sequential sensor readings, such as invehicle PM2.5, TVOC and humidity, as well as environment information.

Note that the trajectory of a driving trip consists of a set of data points ordered by time. In addition, the context information and car usage label are corresponding to each data point. In order to eliminate the disturbance of outlier data points, we split each trajectory into several segments, so that each segment consists of successive data points with the same car usage label and similar context information. We call this process the Trajectory Context-adaptive Segmentation, as shown as the last step in Figure 2. A rich set of features are then calculated for each segment, including average in-vehicle air quality, best and worst in-vehicle air quality, average environment information, average city air pollution, average car speed, etc. The segment is the smallest data unit in our experiments.

Factor Analysis

We perform factor analysis to learn what are the main factors affecting air quality on the road and how the in-vehicle air quality changes along with them. We classify the affecting factors into four categories: environment factors, traffic factors, car usage factors, and vehicle-related factors. The key findings of each category are presented in the following sections.

Environment factors

We first analyze the correlation between the in-vehicle air quality and the environment factors. Some interesting observations are found. For example, a piece of our results is shown in Figure 3, where we demonstrate the correlation matrix between the in-vehicle PM2.5 and the environment factors, such as temperature, humidity, wind speed and pressure, under two car usage statuses---*car window open* (Figure 3(a)) and *car window close and air conditioner on* (Figure 3(b)). As we can see from the second column and first row in Figure 3, high PM2.5 pollution usually happens when outside humidity is very high, especially when outside temperature is also high.

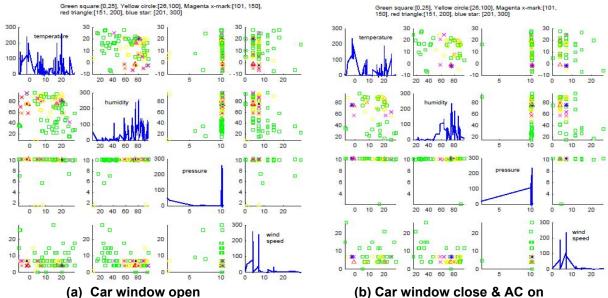


Figure 3. Correlation between environment factors and in-vehicle PM2.5

Another observation is that according to the rightmost column of Figure 3, when wind speed is high, invehicle PM2.5 tends to be low. In addition, this trend is more obvious when the car window is open---as shown in Figure 3(a), compared to the status of car window close and air conditioner on as shown in Figure 3(b).

Correlation analysis for other environment factors and other air pollutants are performed in the same way. We find out some other interesting observations. For example, in-vehicle PM2.5 nearly linearly increases as outside PM2.5 increases when the car window is open. Also, in-vehicle TVOC is averagely lower when car window is open.

Traffic factors

We perform correlation analysis to learn how traffic status affects air pollution on the road, and the results indicate that traffic congestion has direct impact on the in-vehicle TVOC level. As illustrated in Figure 4, generally the in-vehicle TVOC increases in congestion situation, especially when the car window is open.

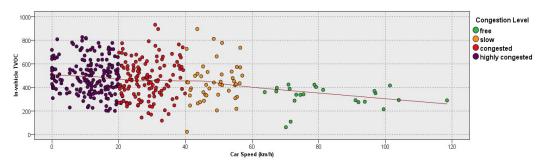


Figure 4. Impact of traffic congestion on in-vehicle TVOC when the car window is open

The factor analysis results of environment factors and traffic factors provide us important clues about in what circumstances the in-vehicle travelers are suffering from air pollution on the road the most.

Car usage factors

Besides external factors (environment factors and traffic factors), how drivers use their car window and air conditioner (recirculation or out circulation modes) will also significantly affects the in-vehicle air quality. Figure 5 shows the daily purification efficiency of two drivers in the same city but with quite different car usage habits. Driver A (shown in blue line) usually closes the car window and turns on the air conditioner and recirculation during driving. Driver B (show in red line) randomly uses the car window and air conditioner, without paying attention to in-vehicle air quality. As we can see in Figure 5, the average purification efficiency of Driver A is around 60% and the purification efficiency could reach to more than 90% in days of high pollution (for example, Sep 5th,). However, Driver B only achieved purification efficiency with average value of around 30% and maximum value of 50%.

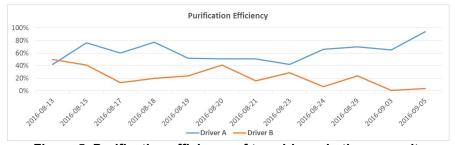
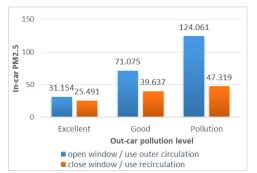


Figure 5. Purification efficiency of two drivers in the same city

We further study the impact of car usage on in-vehicle air quality based on our data of all 500 drivers. For the sake of clear comparison, in this set of experiments we classify car usages into two categories: *open* actions and *close* actions. Open actions include (1) opening the car window or (2) closing the car window and using outer circulation. Close action means closing the car window (using or not-using recirculation both included). We compare the results of these two car usage categories in different environment conditions. Figure 6 shows the impact of the car usage on in-vehicle PM2.5 in days of different pollution levels. The blue bars and red bars represent the results of open actions and close actions respectively. As we can see in Figure 6(a), the average in-vehicle PM2.5 readings under close actions are always lower than open actions. The advantage of close actions is more obvious in polluted days. The PM2.5 improvements in Figure 6(b) mean the difference between outside PM2.5 and in-vehicle PM2.5 readings. In polluted days, the PM2.5 improvement achieved by close actions is 6.66 times compared to open actions in our experiments.



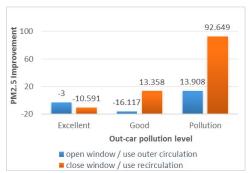


Figure 6. Impact of car usage on in-vehicle PM2.5 pollution

Moreover, we analyze the differences among individual drivers. In particular, for each driver, we compute a percentage of time of their open actions in days with high pollution. Results in Figure 7 show that generally the purification efficiency decreases as the percentage of open actions increases in polluted days. If one driver keeps using close actions in polluted days, he could achieve a purification efficiency up to 90%.

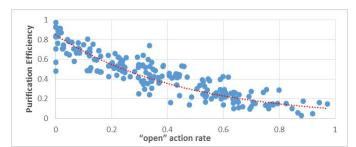


Figure 7. Impact of car usage on purification efficiency in polluted days

Based on the experimental study, we conclude that in-vehicle air quality, especially for the PM2.5, is benefit from the close actions in polluted day. This is because closing the car window will prevent invehicle air from outside PM2.5 pollution to a certain extent and using recirculation will take full advantage of the car filters to further reduce in-vehicle PM2.5 pollution.

Vehicle-related factors

As we mentioned above, the reason why using recirculation has positive impact of in-vehicle air quality is that the car filters can help to absorb in-vehicle air pollutants. Therefore, the status of the car filters is also a key factor deserving a further study.

We measure the efficiency of the car filters using the *stable in-vehicle PM2.5*, which equals to the invehicle PM2.5 value when: (1) the car window is close, and (2) car filters already work to their limitations against outside air pollution and therefore cannot decrease the in-vehicle PM2.5 value further more. Intuitively, if the car filter of one vehicle is efficient, the corresponding stable in-vehicle PM2.5 value should be small and then the PM2.5 improvements (outside PM2.5 minus stable in-vehicle PM2.5) at the stable moment should be large. Results as shown in Figure 8 are consistent to our assumptions. In Figure 8, each dot in the figure represents one driver. The results show that the purification efficiency of each individual driver increases as the PM2.5 improvement increases, which indicates that more efficient car filters tend to lead to a higher purification efficiency.

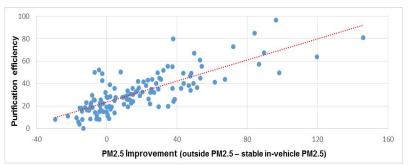


Figure 8. Impact of car filters on purification efficiency

Improving In-vehicle Air Quality

The experiments in above sections show that a complex set of factors, such as environment factors, traffic factors, car usage factors and vehicle-related factors, together affect the in-vehicle air quality. Therefore, when we try to reduce the in-vehicle air pollution, lack of the considerations of any of these factors could lead to unexpected or even opposite outcomes.

Based on our factor analysis results and powered by our Cloud-based IoT platform, which provides a wide range of aggregated real-time data sources, we propose two methods to improve in-vehicle air quality in a road trip: car usage optimization and filter maintenance advice. Experimental studies of the efficiency of our methods are also shown in this section.

Car usage optimization

Although we cannot change the uncontrollable external factors (environment factors and traffic factors), we can recommend each driver the optimized way to control the car window and air conditioner (recirculation or outer circulation modes) in different circumstances to achieve the best possible in-vehicle air quality for him, by learning from a complex set of real-time data sources about the environment and traffic status. We denote this process as the car usage optimization.

More specifically, for each vehicle, sensing data of the in-vehicle air quality---mainly including PM2.5, TVOC, humidity and temperature as well as GPS locations---are continuously collected and sent back to the Cloud-based IoT platform. Based on the real-time GPS locations of these vehicles, a Context Map component of the platform provides a complex set of information on top of the map, such as weather information (outside temperature, humidity, weather type, wind speed and so on), city air quality (PM2.5, PM10 and so on) published by local government and traffic status of that location.

Additionally, we analyze the circumstances for the vehicle. If one vehicle is in a circumstance that has obvious negative impacts on the in-vehicle air quality, for example if the outside air is polluted by gas emission of nearby trucks or traffic jams, we tend to recommend the driver to take close actions, such as closing the car window and using recirculation. Otherwise, if the circumstances of one vehicle have more positive impacts on the in-vehicle air quality, for example when the outside air quality is good and the

environment has perfect humidity and temperature for a comfortable drive, we recommend the driver to take open actions, such as keeping the car window open. The personalized recommendations of the car usage are then sent back to the drivers through our mobile application.

Note that all above processes, including collecting data from the mobile side, merging with aggregated information from Context Map, analyzing underlying circumstance, optimizing car usage actions and sending back personalized recommendations to the drivers through mobile application are performed in real-time. Only millisecond-level latency is required by all processes in our platform except the first and last ones, which regard to the mobile application and are sometimes affected by the speed of the telecommunication network that is beyond our control.

Furthermore, we show experiment results which prove the efficiency of the car usage optimization. For the sake of intuitive comparison, in this set of experiments, we classify the car usage behaviors into appropriate behaviors and inappropriate behaviors. More specifically, we consider the driving behaviors opposite to our optimized recommendations in circumstances that have obvious negative impacts on the in-vehicle air quality as inappropriate behaviors. And all the other behaviors are considered as appropriate behaviors.

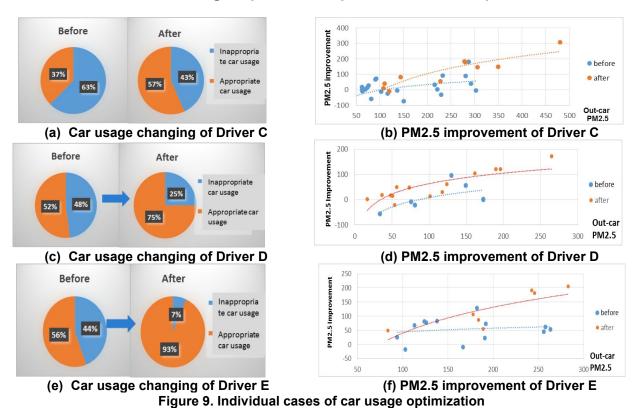
At the beginning stage of the whole experiment period, we detected 50 drivers with top percentages of inappropriate behaviors, and then started to send them personalized real-time car usage recommendations through our mobile application. Even though occasionally some recommendations may not be followed by the drivers due to some reasons, for example, their mobile phones are muted and the recommendation voices cannot be heard, this is rare in our experiments, especially after a little bit of training to the drivers. In the following experiments, we only consider the drivers who follow most of the recommendations.

Table 1 shows the overall experiment results before and after enabling the car usage recommendations to the selected drivers. As we can see in Table 1, the rate of inappropriate car usage behaviors decreases from 53.9% to 25.4% in polluted days, which consequently leads to a PM2.5 improvement increasing by 132.9% and purification efficiency increasing by 67.1%.

Table 1. Comparison experiments on car usage optimization.

Average values in polluted days	Before	After	Trend
Inappropriate car usage behavior rate	53.9%	25.4%	Decrease 52.9%
Outside PM2.5	129.76 µg/m ³	174.43 µg/m ³	
In-vehicle PM2.5	84.26 µg/m ³	68.47 µg/m ³	Decrease 18.7%
Improvement of PM2.5	45.50 μg/m ³	105.97 µg/m ³	Increase 132.9%
Purification efficiency	34.6%	57.8%	Increase 67.1%

Figure 9 further illustrates the detailed results of three typical individual drivers in polluted days. As shown in Figure 9, car usage optimization leads to significant decreasing of inappropriate car usage behaviors. Driver E, shown in Figure 9(e), uses the car window and air conditioner appropriately during 93% driving time after following our car usage recommendations. In addition, due to car usage optimization, all the three drivers achieve significant improvement with respect to the in-vehicle air quality. As shown in Figure 9(b), 9(d) and 9(f), the in-vehicle PM2.5 improvement after car usage optimization is clearly higher than those without optimization.



Filter maintenance advice

The second method is called *filter maintenance advice*. We analyze the data streams that are constantly being collected from the vehicle, and identify those vehicles which are impaired due to inefficient car filters. More specifically, we identify a list of candidates whose car filters work at a lower speed than others, and those whose car filters cannot purify in-vehicle air to a level as clear as others. A reminder of filer maintenance is then automatically sent to corresponding drivers.

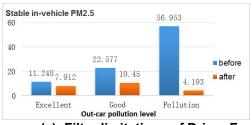
In our experiments, we sent reminders to 52 drivers and 7 of them replaced their car filters within two weeks. We analyze the average improvement of these drivers, achieved by filter maintenance, and show it in Table 2, where we only consider the trip segment when the car window is closed and drivers are using recirculation. As we can see in Table 2, new car filters averagely reduce the in-vehicle PM2.5 to 18.215µg/m³ to their limitations in polluted days, while the old ones are with an average limited value of 57.281µg/m³. The purification efficiency increases by 79.75% after filter maintenance.

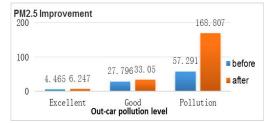
Table 2. Comparison experiments for filter maintenance advice.

Average values in polluted days	Before	After	Trend
Outside PM2.5	112.699 µg/m ³	127.125 µg/m ³	-
Stable in-vehicle PM2.5	57.281µg/m ³	18.215 µg/m ³	Decrease 68.2%
Improvement of PM2.5	55.418 µg/m ³	108.909 µg/m ³	Increase 96.52%
Purify efficiency	46.91%	84.32%	Increase 79.75%

Figure 10 further demonstrates the detailed results of a typical driver, Driver F, where only closing the car window and using recirculation cases are considered. The limitation of car filters improves up to 13 times in polluted days after filter maintenance as shown in Figure 10(a). Accordingly, the in-vehicle PM2.5

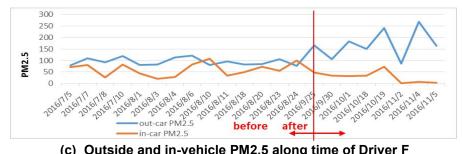
improvement increases to nearly 3 times (Figure 10(b)). Figure 10(c) shows the daily average outside PM2.5 and in-vehicle PM2.5 readings. Before filter maintenance, the in-vehicle PM2.5 readings are similar to outside PM2.5 values, which indicates that Driver F's old car filter was functioning really poorly. After car filter replacement (on Sep 25th), the new car filter immediately reduces the in-vehicle PM2.5 to a low value even when outside air is highly polluted.





(a) Filter limitations of Driver F

(b) PM2.5 improvement of Driver F



(c) Outside and in-vehicle PM2.5 along time of Driver F Figure 10. Individual cases of filter maintenance

It is worth mentioning that the efficiency of the two proposed methods depends on each other. For example, an appropriate car usage behavior, like closing the car window and using recirculation in polluted days, cannot function well with a poor car filter. In addition, a worn car filter itself can even become a polluting source. On the other hand, it is hard for a new car filter to play its role in improving the air quality if the driver does not use it and always keeps the car window open. Therefore, these two methods are suggested to work simultaneously as an integrated solution in practice.

Conclusion

In this paper, we investigate the problem of air pollution on the road based on an extensive experimental study. The experiment results show that a complex set of factors, including environment factors, traffic factors, car usage factors and vehicle factors, combined together affect the in-vehicle air quality. Consequently, when we try to reduce the in-vehicle air pollution, lacking of consideration of any of these factors could lead to unexpected or even opposite outcomes.

Utilizing our improved understanding of the problem and powered by our Cloud-based IoT platform, which provides a wide range of aggregated real-time data sources, we propose two methods to improve the invehicle air quality in a road trip: car usage optimization and filter maintenance advice. We also show extensive experiments on real driving data to prove the effectiveness and efficiency of these two methods.

Moving forward, we plan to develop fine-grained air quality prediction models with respect to road, traffic and weather conditions, and explore physical air flow and chemical simulation models, to discover more traffic pollution insights and support sustainable traffic management as well as green mobility experiences for travelers by taking appropriate measures. In particular, recent advances in machine learning for stochastic point processes [18,19,20] can be a potential tool for modeling such interactions.

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