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Development and application of a methodology to identify and rank the important factors affecting in-vehicle particulate matter

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ABSTRACT

The present study adopted a two-step approach in the development of a methodology to identify and rank the important factors affecting in-vehicle particulate matter (PM). Firstly, the important factors affecting the monitored vehicular PM were identified using regression trees, considering several factors (meteorology, time-related, indoor sources, on-road, and ventilation) that could impact the vehicular indoor air quality. Secondly, the analysis of variance was used as a complementary sensitivity analysis to the regression tree results to rank the significant factors affecting vehicular PM. In-vehicle PM concentrations and sub-micron particle numbers were mainly influenced by the monthly/seasonal changes. Visibility and ambient $PM_{2.5}$ additionally influenced the sub-micron particles. Furthermore, this study emphasized the variation of the monitored vehicular PM levels under different combinations of the ranked influential factors.

1. Introduction

Indoor air quality (IAQ) is one of the major environmental concerns, since people spend nearly 90% of their time indoors and about 7% of their daily time is spent commuting, mostly between the workplace and their residences [1]. People are exposed to higher levels of traffic contaminants when they drive in heavy traffic, stand near idling vehicles, and spend time at places near roads having high traffic, especially if the location is downwind of a road [2]. The degree of exposure to contaminants for people commuting in a bus is much higher than that of human exposure occurring at bus stops or during loading and unloading [3]. A number of studies observed the concentrations of carbon monoxide (CO), oxides of nitrogen (NO_x), and fuel-related volatile organic compounds (VOCs) significantly higher inside the vehicles than in the ambient air [4–11]. High concentrations of toxic contaminants, such as benzene and other aromatic VOC's were observed within the vehicle microenvironments that contribute to about 10–60% of a nonsmoker's total exposure [6,12]. Therefore, it is important to study the effect of particulate matter (PM) on in-vehicle air quality and determine the factors that influence the vehicular PM.

A study of exposure to PM less than 10 micrometers ($PM_{10.0}$), PM less than 2.5 micrometers ($PM_{2.5}$), metals, thirteen organic compounds, CO, fine particle counts and black carbon (BC) identified driving lane, roadway type, congestion level, time of the day, and exhaust from lead vehicles as the significant factors affecting in-vehicle contaminants [7]. Occupant exposure to in-vehicle PM and CO was influenced by the time of day, average vehicle speed, wind speed, and relative humidity (RH) [9]. Vehicle exhaust and self-intrusion predominantly affected in-vehicle BC, particle-bound polycyclic aromatic hydrocarbons (PAH), nitrogen dioxide (NO_2), particle counts, and $PM_{2.5}$ when the windows were closed; while ventilation settings played a major role when the windows were open [13]. Road type, following distance between the lead vehicle and follow vehicle, and exhaust location of the lead vehicle affected vehicular BC, ultrafine particles (UFP), NO_x, CO, carbon dioxide (CO_2), $PM_{2.5}$, PM size distribution, and PM-bound PAH [14]. In-vehicle $PM_{10.0}$ and UFP were mainly influenced by stop-and-go traffic predominantly found at signals [15]. Based on the route selected, there was considerable variation in the vehicular $PM_{2.5}$ exposure levels [16].

Lead vehicle affected vehicular BC, particle-bound PAH, and NO_2 when the windows were opened; while the type of test bus affected in-vehicle levels when the windows were closed [17]. In-vehicle CO_2, CO, sulfur dioxide (SO_2), NO, NO_2, and PM were influenced by the monthly and seasonal changes [18]. Route travelled and peak hours mainly influenced vehicular CO_2, CO, SO_2, and PM levels [19]. Mean 8-h occupant exposures to $PM_{2.5}$ were statistically similar in 20% grade biodiesel (BD20) and ultra low sulfur diesel buses [20]. There are limited studies that investigated the occupant exposure to in-vehicle contaminants on different transportation modes [21–24]. Outdoor concentrations and traffic had a

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Table 1
Average values of independent variables during different seasons and ventilation indicators.

Independent variables	Seasons			
	Spring (April 2007 to June 2007)	Summer (July 2007 to September 2007)	Fall (October 2007 to December 2007)	Winter (January 2008 to March 2008)
Ambient $PM_{2.5}$ ($\mu g/m^3$)	12.99	17.71	14.74	8.07
Indoor temp. (°F)	76.80	76.41	77.65	77.18
Indoor RH (%)	34.27	34.10	36.98	33.10
Ambient temp. (°F)	59.67	75.80	60.59	28.54
Ambient RH (%)	60.71	56.76	72.66	76.97
Wind speed (mph)	7.48	6.28	7.53	10.66
Visibility (statute miles)	8.93	8.92	8.30	6.69
Precipitation (inches)	0.04	0.17	0.07	0.05
Passengers per 5-min (per hour)	5.75 (69)	5 (60)	6 (72)	4.91 (59)
Light vehicles per minute (per hour)	0.23 (14)	0.27 (16)	0.35 (21)	0.28 (17)
Heavy vehicles per minute (per hour)	0.14 (9)	0.14 (9)	0.16 (10)	0.16 (10)
Run/close (minutes per hour)	42.32	39.49	38.13	36.88
Idle/open (minutes per hour)	8.10	10.17	9.15	7.82
Idle/close (minutes per hour)	9.58	10.34	12.72	15.30
Ventilation indicators				
Difference between indoor temp. and ambient temp.	17.13	0.61	17.06	48.64
Difference between ambient RH and indoor RH	26.44	22.66	35.68	43.87
Ventilation indicator ranking	2 (moderate)	1 (good)	3 (moderate)	4 (reduced)

significant impact on vehicular PM [21]. Low wind speed contributed to an accumulation of in-vehicle CO and $PM_{2.5}$ levels [22]. In-vehicle $PM_{2.5}$ and $PM_{10.0}$ were influenced by air conditioning [23]; the route selected significantly affected vehicular $PM_{2.5}$ [24]. All the above mentioned studies adopted regression analysis to identify the important factors affecting vehicular IAQ. Only one study used regression tree analysis to model vehicular IAQ and observed the regression tree method to outperform the regression method [25].

From the literature review, it can be observed that the contaminant level buildup inside a vehicle is due to a combination of different factors, and not a result of variation due to a single variable. Regression and regression tree methods were adopted to identify the important factors affecting vehicular IAQ. Prior studies quantified the in-vehicle contaminants in relation to a single influential variable. None of the vehicular studies quantitatively analyzed and characterized the IAQ as the simultaneous function of multiple influential variables. To fill the knowledge gap, this study proposed a two-step approach to overcome the problem of quantitatively analyzing and characterizing the vehicular IAQ, by using advanced methods of the regression trees and the analysis of variance (ANOVA). In the first step, the important factors affecting vehicular PM were identified by developing regression trees, using CART® software. Next, the identified important factors from regression tree were ranked (based on the statistical significance) by performing the ANOVA as a complimentary sensitivity analysis, using SPSS® software. The methodology of ranking the factors using the ANOVA as a complementary sensitivity analysis to the regression tree results was adopted from the sensitivity analysis study on food safety risk models [26]. Additionally, this study quantified (low, medium, high) in-vehicle PM relationships with the ranked influential factors.

2. Methodology

2.1. Study area

A BD20 bus was selected from the Toledo Area Regional Transit Authority (TARTA) 500 series fleet, which had all the cameras located inside the bus in working condition. It operated on a single preassigned daily route. The route selected for the study was Route 20, which runs between the TARTA garage and Meijer, on the Central Avenue Strip [27]. The locations of the bus, when on the run, were identified by the GPS unit located inside the bus. Continuous monitoring of the PM concentrations and numbers inside the BD20 bus were done using the GRIMM® 1.108 aerosol spectrometer [28]. Other in-vehicle gases (NO, NO_2, and SO_2) that can possibly influence indoor PM levels were monitored simultaneously with indoor temperature (temp.) and indoor RH, using the YES Plus® instrument [29]. The instruments were held in position within a wired mesh box using the velcro attachments, and the instruments drew power continuously from the adapters connected to the bus. A comprehensive description of the study area, instrumentation, experimental setup, and test protocol were documented elsewhere [20].

2.2. Database development

Data collection included downloading data from the instruments, obtaining meteorological data, designating time-related variables, and monitoring the real-time on-road variables. Data collected between 6:00 a.m. and 11:00 p.m. over a period of one year (April 2007 to March 2008) were used in this study. Data downloaded from both the instruments were set for 1-min intervals that were averaged to 1-h for analysis. More details on the instrument calibration and maintenance procedures were documented elsewhere [18,20]. Different factors that can possibly affect vehicular IAQ, such as the meteorological variables (ambient temp., ambient RH, wind speed, sky condition, visibility, weather type, precipitation, ambient $PM_{2.5}$), the time-related variables (month of the year, season of the year, time of the day), and the on-road real-time variables (passenger count, light vehicles [cars/SUVs] ahead, heavy vehicles [buses/trucks] ahead, bus status to represent ventilation) were considered in this study. Ambient $PM_{2.5}$ concentrations were requested and obtained from the United States Environmental Protection Agency. Other meteorological data were downloaded for the Toledo Express Airport station from the National Climatic Data Center [30]. The passenger data, vehicles in front of the bus, and

Table 2
Classification of independent variables.

Variables	Low	Medium	High
Passengers per 5-min	<5	5–7	>7
Indoor temp. (°F)	<40	40–72	>72
Wind speed (mph)	<10	10–20	>20
Indoor RH (%)	<33	33–67	>67

the bus status were monitored using the hard drive present in the bus that records the video during its run. Ventilation settings were representative of the bus door position. More details on monitoring the real-time on-road variables were documented elsewhere [18,20].

The database, referred to as the complete database included only the hourly averaged data points with no missing values for any of the variables. Missing values were found predominantly in the real-time on-road monitored variables category, as it was not possible to get the real-time on-road variable data for all the days on which vehicular PM and gaseous contaminants were monitored. Missing variables were also a result of camera error, hard disk problems, and the amount of time required to record the observations on a 1-min interval basis. Seasons used in this study are defined as spring (April 2007 to June 2007); summer (July 2007 to September 2007); fall (October 2007 to December 2007); and winter (January 2008 to March 2008). Table 1 presents a summary of the average values for independent variables and indicators for ventilation in different seasons. From Table 1, one can observe ventilation indicator rankings were provided for different seasons (considering the ambient comfort parameters (temp. and RH) to be more or less equivalent to indoor comfort parameters when there is sufficient ventilation). There is good ventilation in the summer, moderate ventilation in the spring and the fall, and reduced ventilation in the winter (based on the difference between indoor and ambient comfort parameters or idle/open conditions). The Toledo metropolitan area received a fair amount of snowfall in the winter, and passengers kept the windows closed to keep themselves warm. This observation was made from the video analysis. To better understand the relationships between the monitored vehicular contaminants and the dependent variables, some of the independent variables were further classified into three categories (estimated at one-third range approximation): low, medium, and high, as illustrated in Table 2.

2.3. Regression tree methods

Regression tree methods are based on a set of if-then logical split conditions developed by the tree building algorithms. These methods help predict the relations between variables when there is very little or no knowledge on any theories or predictions that relate the variables. The importance of an input variable is indicated by whether it is selected as the basis for splitting the tree at the highest branches, and whether it has been selected at multiple levels of the tree to further subdivide the data. The partitioned data under different nodes of the same branch have significantly different mean values. Once a regression tree is constructed, it can be used further for classification of new data. The regression tree method has numerous advantages that it is non-parametric, does not require variables to be selected in advance, is robust to the effect of outliers, can use different combinations of categorical and continuous variables, can use linear combinations of variables to determine splits, can adjust for samples stratified on a categorical dependent variable, can discover context dependence and interactions, can process cases with missing values, can handle data sets with complex structure, and results are invariant with respect to monotone transformation of the independent variables [31]. Kadiyala and Kumar [25] provided a complete step-by-step procedure on running the CART® software to determine the optimal regression tree model and to identify the influential factors based on data collected for one month. The procedure established by Kadiyala and Kumar [25] in determining the important factors affecting vehicular IAQ was used in this study.

2.4. Approach to data analysis

Firstly, the important factors affecting vehicular PM were obtained (short-listed) by developing an individual regression tree for each monitored contaminant. No restriction was specified for the number of nodes in the regression tree so that mean responses obtained accounts for all the variability in the output that can be captured by partitioning the dataset. Complete details of the developed vehicular PM regression trees were documented in the CART Report [32], available online at the Alternative Fuels Project website, maintained by the Air Pollution Research Group, of the Department of Civil Engineering, at The University of Toledo.

Secondly, the ANOVA was used as a complementary sensitivity analysis to the regression tree results, to gain additional insights into the sensitivity of model inputs for a particular partition of the original input data. Sensitivity analysis results obtained from the complementary analyses will be different for different nodal databases. Hence, the partitions of the original input data for each contaminant were based on the important (primary) splitting criterion (having considerable number of data points) obtained from developing the regression tree. Ranking of the important factors (short-listed in the first-step) with statistical significance (Sig.) less than 0.05 is done based on the *F* value of the ANOVA results.

3. Results and discussion

The following sections provide more information on ranking the important factors affecting vehicular PM and characterization of vehicular IAQ under different combinations of the ranked factors.

3.1. Particulate matter concentrations ($PM_{1.0}$, $PM_{2.5}$, and $PM_{10.0}$)

Table 3 presents a summary of the results for relative importance of the variables obtained from development of $PM_{1.0}$, $PM_{2.5}$, and $PM_{10.0}$ regression trees for the complete database. 'Score' in Table 3 is the relative importance of a variable in its role as a surrogate to the primary split. It can be observed from Table 3 that the important factors affecting vehicular $PM_{1.0}$ and $PM_{2.5}$ (strongly correlated, $r = 0.97$) are the same. One can also observe the month

Table 3
Relative importance of the variables for in-vehicle PM ($PM_{1.0}$, $PM_{2.5}$, $PM_{10.0}$) obtained from CART runs.

$PM_{1.0}$		$PM_{2.5}$		$PM_{10.0}$	
Variable	Score	Variable	Score	Variable	Score
Month	100.00	Month	100.00	Month	100.00
Visibility	37.65	Visibility	28.37	Ambient temp.	4.56
Ambient RH	27.48	Ambient RH	26.72		
Ambient temp.	10.05	Ambient $PM_{2.5}$	9.75		
Ambient $PM_{2.5}$	8.08	Ambient temp.	6.66		

Table 4
Sensitivity results for in-vehicle $PM_{1.0}$ obtained from the ANOVA.

Variable	F-value	Sig.	Significant	Rank	Variable	F-value	Sig.	Significant	Rank
Month = April 2007 to May 2007, July 2007 to March 2008					Month = June 2007				
Visibility	4.610	<0.0001	Yes	1	Visibility	1.456	0.153	No	–
Ambient RH	1.806	0.007	Yes	2	Ambient RH	2.994	<0.0001	Yes	1
Ambient temp.	1.560	0.031	Yes	4	Ambient temp.	1.474	0.121	No	–
Ambient $PM_{2.5}$	1.737	0.045	Yes	3	Ambient $PM_{2.5}$	0.349	0.981	No	–

and the ambient temperature to be consistently affecting vehicular $PM_{1.0}$, $PM_{2.5}$, and $PM_{10.0}$. Visibility did not have an impact on in-vehicle $PM_{10.0}$ (moderately correlated with $PM_{2.5}$ ($r = 0.71$) and weakly correlated with $PM_{1.0}$ ($r = 0.51$)). Ambient $PM_{2.5}$ aerosols are effective light scatters that reduce the visibility [33]; while $PM_{1.0}$ aerosols are the most efficient scatterers of visible light [34].

Month of the year was found to be the most important factor in all three cases, as it was the primary splitting criterion and was selected repeatedly throughout the lower nodes of the regression tree. Tables 4 and 5, and 6 present the complimentary sensitivity analysis results obtained using the ANOVA to rank inputs conditional on the month for $PM_{1.0}$, $PM_{2.5}$, and $PM_{10.0}$, respectively. Rankings for the ANOVA complimentary runs in Tables 4–6 were based on the magnitude of F value for Sig. less than 0.05. For $PM_{1.0}$ and $PM_{2.5}$, the first dataset included data with months April 2007 to March 2008 excluding June 2007, and the second dataset contained data with the month of June 2007. For $PM_{10.0}$, the first dataset included data with months April 2007 to March 2008 excluding May 2007 and June 2007, and the second dataset contained data from the months of May 2007 and June 2007. From Table 4, one can observe vehicular $PM_{1.0}$ to be influenced by the ambient RH in both cases; while the visibility, the ambient $PM_{2.5}$, and the ambient temperature were influential only on the first dataset. Similar observations were made from Table 5, with the exception that the visibility was not found to be influencing either of the datasets. From Table 6, one can note the ambient temperature to be significantly influencing the first dataset. At higher temperatures with low humidity, there is a generation of secondary particles by atmospheric photochemical reaction; and there is a positive and negative relation of atmospheric PM with ambient temperature and ambient RH, respectively [35–39]. Cloudy sky conditions have shown a positive relation to atmospheric PM [38].

Considering the complete database PM concentration regression trees and the results of the complimentary analysis, the month, the ambient RH, the visibility, the ambient $PM_{2.5}$, and the ambient temperature were ranked as the five important factors, in ascending order that influenced vehicular $PM_{1.0}$; while, the month, the ambient RH, the ambient temperature, and the ambient $PM_{2.5}$ were ranked as the first, second, third, and fourth, respectively that influence vehicular $PM_{2.5}$ Month and the ambient temperature were ranked as the first and second important factors that influence vehicular $PM_{10.0}$.

Based on the $PM_{1.0}$, $PM_{2.5}$, and $PM_{10.0}$ regression trees developed, vehicular PM concentrations were categorized into three classes: low (<20 $\mu g/m^3$), medium (20–45 $\mu g/m^3$), and high (>45 $\mu g/m^3$) levels, to better understand the consequences of different combinations of the influential factors.

3.1.1. Influence of the month on $PM_{1.0}$, $PM_{2.5}$, and $PM_{10.0}$ with varying ambient RH, ambient temperature, and visibility under different ventilation levels

Medium levels of $PM_{1.0}$ were observed in the month of June 2007, and low levels of $PM_{1.0}$ were observed during other months, with May 2007 having the second highest average $PM_{1.0}$ concentration. Similar trends were observed for vehicular $PM_{2.5}$ concentrations. Medium levels of $PM_{10.0}$ were observed in the months of May 2007 and June 2007; and low levels of $PM_{10.0}$ were observed in the remaining months. Relatively lower $PM_{1.0}$ concentrations were observed for the case of (a) June 2007 with (b) ambient RH > 60% as compared to the case with (b) ambient RH ≤ 60%. Similar trends were observed for vehicular $PM_{2.5}$. Relatively higher $PM_{1.0}$ concentrations were observed (a) during the month of June 2007 with (b) ambient RH > 60% for (c) visibility ≤ 1.13 as compared to the case with visibility > 1.13. The following observations were made based on consideration of the relatively higher ventilation during the summer months and considering visibility to be a function of cloudiness:

- Medium levels of in-vehicle $PM_{1.0}$ and $PM_{2.5}$ were observed during the month of June 2007 and low levels were observed in other months.
- Medium levels of in-vehicle $PM_{10.0}$ were observed during the months of May 2007 and June 2007, and low levels were observed during other months.
- The relatively higher in-vehicle PM levels observed during May 2007 and June 2007 could be accounted by accumulation of the relatively higher outdoor ambient PM (combination of higher photochemical activity on days with higher ambient temperatures and lower ambient RH) and, to some extent, by the leading vehicular traffic exhaust when there is moderate ventilation.
- Vehicular PM concentrations were inversely proportional to ambient RH when there was moderate/good ventilation.
- Lower levels of vehicular PM were observed at higher visibility (indicating less cloudiness). Vehicular PM levels were inversely proportional to visibility when there was sufficient ventilation in the summer.
- In-vehicle PM levels were mainly influenced by ambient PM levels and in-vehicle PM trends were found to be consistent with atmospheric PM variations.

Table 5
Sensitivity results for in-vehicle $PM_{2.5}$ obtained from the ANOVA.

Variable	F-value	Sig.	Significant	Rank	Variable	F-value	Sig.	Significant	Rank
Month = April 2007 to May 2007, July 2007 to March 2008					Month = June 2007				
Visibility	1.549	0.146	No	–	Visibility	1.335	0.212	No	–
Ambient RH	1.858	0.005	Yes	2	Ambient RH	2.917	<0.0001	Yes	1
Ambient $PM_{2.5}$	1.718	0.048	Yes	3	Ambient $PM_{2.5}$	0.436	0.949	No	–
Ambient temp.	2.088	0.001	Yes	1	Ambient temp.	1.363	0.175	No	–

Table 6
Sensitivity results for in-vehicle $PM_{10.0}$ obtained from the ANOVA.

Variable	*F*-value	Sig.	Significant	Rank	Variable	*F*-value	Sig.	Significant	Rank
Month = April 2007, July 2007 to March 2008					Month = May 2007 to June 2007				
Ambient temp.	3.571	0.008	Yes	1	Ambient temp.	1.381	0.071	No	–

Table 7
Relative importance of the variables for in-vehicle particle numbers (0.3–0.4 μm, 0.4–0.5 μm) obtained from CART runs.

Particle numbers (0.3–0.4 μm)		Particle numbers (0.4–0.5 μm)	
Variable	Score	Variable	Score
Month	100.00	Month	100.00
Season	32.26	Season	35.73
Ambient $PM_{2.5}$	13.92	Visibility	23.33
Visibility	11.37	Indoor RH	18.26
Indoor RH	10.94	Ambient $PM_{2.5}$	13.33
Ambient temp.	3.34	Indoor temp.	4.29
		SO_2	2.17

3.2. Sub-micron particle numbers

Over 95% of the in-vehicle particulates have a diameter less than 1 μm. In-vehicle $PM_{1.0}$ mass was observed to comprise of over 40% particles less than 0.40 μm that contribute close to 65–70% of the total measured particle count. Particles with aerodynamic diameter between 0.40 and 0.50 μm contributed approximately 25% to $PM_{1.0}$ mass and count concentration [19]. Table 7 presents a summary of the results for relative importance of the variables obtained from development of 0.3 μm to 0.4 μm and 0.4 μm to 0.5 μm sized particle regression trees with the complete database. It can be observed from Table 7 that the important factors affecting vehicular PM numbers, for both size ranges considered are more or less similar. It was interesting to note that vehicular SO_2 influenced only the particles with aerodynamic diameter 0.4–0.5 μm and there was no influence of vehicular SO_2 on particles sized 0.3–0.4 μm.

Month was found to be the most important factor in both the cases, as it was the primary splitting criterion and was selected repeatedly throughout the lower nodes of the regression trees. Tables 8 and 9 present the complimentary sensitivity analysis results obtained using the ANOVA to rank inputs conditional on the month for particles with aerodynamic diameter 0.3–0.4 μm and 0.4–0.5 μm, respectively. The classification criterion for both the particle size ranges are the same (refer Tables 8 and 9). The first dataset includes data from the months April 2007 to March 2008, excluding August 2007. The second dataset contains data with the month of August 2007. From Tables 8 and 9, one can observe the season, the visibility, and the ambient $PM_{2.5}$ to influence both the particles size ranges. Ambient temperature additionally influenced particles with size range 0.3–0.4 μm; while indoor RH and SO_2 additionally influenced particles with size range 0.4–0.5 μm. Accumulation mode atmospheric particles (size range: 0.1–1 μm) vary positively with ambient temperature [40].

Considering the complete database PM number regression trees and the results of the complimentary analysis, the month/season, the visibility, the ambient $PM_{2.5}$, and the ambient temperature were ranked as the first, second, third, and fourth important factors that influence vehicular PM numbers with size range 0.3–0.4 μm; while the month/season, the ambient $PM_{2.5}$, the visibility, the indoor RH, and the SO_2 were ranked as the five important factors, in ascending order that influence PM numbers with size range 0.4–0.5 μm.

Based on the complete database PM number regression trees developed, vehicular PM number levels were categorized into three classes: low (<100,000 particles/liter), medium (100,000–180,000 particles/liter), and high (> 180,000 particles/liter) levels, to better understand the consequences of different combinations of the influential factors.

3.2.1. Influence of the month/season on particles with varying indoor temperature with sufficient ventilation levels

For 0.3–0.4 μm sized particles, high and medium levels were observed in August 2007 and July 2007, respectively; and low levels were observed during other months. For 0.4–0.5 μm sized particles, medium levels were observed in August 2007 and low levels were observed during other months. In August 2007, high levels of particles were observed when indoor temperature > 78 °F and medium levels were observed when indoor temperature ≤ 78 °F. The high and medium in-vehicle particle numbers in the summer months (having the lowest average wind speed, refer Table 1) with good ventilating conditions could be the result of greater infiltration of the lead vehicular exhaust particles and the higher accumulation mode particles (normally associated with higher ambient temperatures). The following observations were made based on consideration of the relatively higher ventilation during summer months and considering indoor temperature to be a function of ambient temperature:

- Medium and high levels of particles were observed only during the summer months.
- With an increase in the indoor temperature (during summer with sufficient ventilation), there was an increase in the accumulation mode sized particles indoors.

3.3. Validation of the two-step approach

Results obtained from using the complete database were compared with the results obtained from using the test database (90% of the hourly data points from the complete database) in each stage to validate the two-step approach in ranking the influential factors affecting vehicular PM. More detailed information on the validation results were documented in the CART report [32]. The following

Table 8
Sensitivity results for in-vehicle particle numbers (0.3–0.4 μm) obtained from the ANOVA.

Variable	*F*-value	Sig.	Significant	Rank	Variable	*F*-value	Sig.	Significant	Rank
Month = April 2007 to July 2007, September 2007 to March 2008					Month = August 2007				
Season	767.894	<0.0001	Yes	1	Season	–	–	–	–
Ambient $PM_{2.5}$	2.141	<0.0001	Yes	3	Ambient $PM_{2.5}$	166.158	0.061	No	–
Visibility	11.769	<0.0001	Yes	2	Visibility	0.661	0.717	No	–
Indoor RH	3.360	0.062	No	–	Indoor RH	–	–	–	–
Ambient temp.	1.550	0.013	Yes	4	Ambient temp.	0.330	0.964	No	–

Table 9
Sensitivity results for in-vehicle particle numbers (0.4–0.5 μm) obtained from the ANOVA.

Variable	*F*-value	Sig.	Significant	Rank	Variable	*F*-value	Sig.	Significant	Rank
Month = April 2007 to July 2007, September 2007 to March 2008					Month = August 2007				
Season	505.904	<0.0001	Yes	1	Season	–	–	–	–
Visibility	17.974	<0.0001	Yes	2	Visibility	0.178	0.990	No	–
Indoor RH	4.006	0.041	Yes	3	Indoor RH	–	–	–	–
Ambient $PM_{2.5}$	1.960	<0.0001	Yes	5	Ambient $PM_{2.5}$	474.796	0.011	Yes	1
Indoor temp.	2.800	0.216	No	–	Indoor temp.	–	–	–	–
SO_2	3.083	<0.0001	Yes	4	SO_2	–	–	–	–

observations summarize the validation results for the two-step approach using both databases:

- Regression trees performed reasonably well, considering that the short-listed factors (primary variable included) determined using the complete database were also obtained using the test database (though with different scores).
- In addition to the complete database short-listed factors, more variables (with low scores) affected the test database for in-vehicle $PM_{2.5}$ and sub-micron particles.
- The regression tree primary splitting criterion remained unchanged, irrespective of the database considered.
- The ANOVA ranking results were consistent for both the databases, considering the same set of variables were determined statistically significant.
- Additional factors identified by the regression tree analysis, using the test database, were not statistically significant.

4. Conclusion

A two-step approach to identify and rank the important factors affecting in-vehicle PM was developed and successfully applied to an experimental field program. The influential variables affecting the monitored vehicular PM were obtained in the first step by performing regression tree analysis. The identified influential variables were then ranked, based on the ANOVA results that served as a complimentary sensitivity analysis to the regression tree results. An experimental field study was performed to collect IAQ data in public transport vehicles for a period of one year, to support the development of the methodology. Vehicular PM concentrations and sub-micron particles were mainly influenced by the monthly/seasonal changes; while the visibility and the ambient $PM_{2.5}$ additionally influenced sub-micron particles. This study also quantitatively analyzed and characterized the IAQ (low, medium, and high levels) as a function of multiple influencing variables, based on the observations from the complete database regression trees. The single limitation of this approach was that the ANOVA sensitivity results will be different for different nodal databases.

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