Developing a Real-Time Energy and Environmental Monitoring System

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Developing a Real-Time Energy and Environmental Monitoring System

Final Report

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The objective of the research is to develop a framework for real-time emission modeling to improve eco-friendly intelligent transportation system (ITS) applications. The proposed framework can be utilized for real-time ITS applications such as eco-routing and applications for the environment: real-time information synthesis program. To develop a more efficient framework, a new interface to the motor vehicle emission simulator (MOVES) model is developed to enhance the computational performance. Additionally, a methodology using a probe vehicle equipped with onboard equipment is suggested for collecting operating mode distribution through the network to generate input for the MOVES model. Through virtual implementation using a simulation environment developed with the Python scripting language, this study demonstrates that the proposed framework generally works as designed. The study also investigates the effects of probe vehicle sampling size on estimation accuracy.
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Executive Summary

The objective of the research is to develop a real-time emission monitoring system. This study proposed a framework for real-time emission modeling to improve eco-friendly ITS applications. To conduct real-time modeling of automobile emissions at the roadway link level, a new interface to MOVES, designated NIM, was developed for enhancing its computational performance by directly accessing the MOVES database and retrieving relevant coefficients for computing the average emissions factors. The satisfactory computational performance of NIM was demonstrated through its average computation time of 0.001919 seconds for a single execution. Additionally, a methodology using prove vehicles (PVs) equipped with an OBE was suggested for collecting the OpMode distribution through the network to generate MOVES input.

A virtual implementation within the simulation environment developed using the Python scripting language demonstrated that the proposed framework generally works as designed. The simulation environment consists of the server for NIM execution, the component for communication between PVs and RSEs, the VISSIM model, and the main simulator. This study also investigated the effects of PV sampling size both at network and link levels on the accuracy of emissions estimation. It was found that the PV fraction needs be set to 10% using the two-standard deviation of relative errors between PV fuel consumption and all-vehicle fuel consumption if the relative error should be less than 15%. Also, it can be inferred that there should be more than 10 PVs in a link to maintain less than 10% relative error.

It is expected that the proposed real-time emission modeling system will make possible a variety of eco-friendly ITS applications, such as eco-routing, and may be used to develop environmentally conscious traffic operation strategies. Using MOVES through NIM, the proposed system has certain merits: first, it is easy to update the emission modeling tool because MOVES is periodically updated by EPA. Second, the system can easily be applied to any area in the US because area-specific data are already available in the MOVES database.
Chapter 1 Introduction

Real-time traffic monitoring is an essential component in the intelligent transportation system (ITS) domain, which is widely used to improve the mobility of vehicle traffic flow and to offer greater safety and comfort. This successful application has contributed to the remarkable development of telecommunication technologies. In recent years, the advent of greatly advanced telecommunication technologies, which enable vehicles to communicate with each other and with infrastructures, have inspired traffic engineers and professionals to invent more applications for fuel savings, safety enhancement, and emission reduction.

International research projects on eco-friendly ITS applications are actively ongoing in Europe and the US [1]. With three major projects named eCoMOVE, In-Time, and Freilot, research commitment is strong in Europe. The eCoMove project is the most noteworthy: the objective of this project is to construct a comprehensive roadmap for improving the efficiency of fuel use in road transport by systematically developing and evaluating the potential for eco-friendly applications. This project was structured with six sub-projects: SP1 through SP6. SP3, named ecoSmart Driving, developed eco-Pre-Trip Planning, ecoSmart Driving, and ecoPostTrip to assist drivers in reducing fuel consumption and carbon dioxide (CO₂) emissions by providing sufficient information [2]. The objective of the In-Time project was the generation and provision of multimodal real-time traffic and travel information to reduce energy consumption in urban transport [3]. Freilot aims to enhance the energy efficiency of urban freight by traffic management, vehicle control, driver assistance, and fleet management [4]. As is clear in the previously addressed projects, relevant information about the reduction of energy use and emissions is an essential component for success in application.

For the successful implementation of the eco-friendly ITS applications proposed in these projects, the timely estimation of fuel consumption and traffic flow emission is essential. For example, eco-routing is a promising application. Thus, eco-routing framework and its impacts have been studied and some auto manufacturers have developed and implemented eco-routing systems in their cars [5-7]. Given that an eco-routing system evaluates a set of potential routes between the same origin-destination pair and generates an optimal route with respect to the fuel consumed and emissions produced, the performance primarily depends on the accuracy of these estimates of fuel and emissions fed to the system. In particular, a dynamic eco-routing system requires real-time fuel consumption and emission estimations in a roadway link level, just as global positioning system (GPS) based navigation provides real-time travel information. However, it is difficult to estimate the fuel consumption and emissions of traffic flows in real time due to 1) the absence of relevant emission modeling tools, 2) the lack of collection methodologies for the distribution of forces exerted by vehicles as input for emission models.

Consequently, the objectives of this study are 1) to develop a methodology for improving the computational performance of a state-of-the-practice emission model, Environmental Protection Agency (EPA) the motor vehicle emission simulator (MOVES), because running the project level feature of MOVES is too slow for real-time emission modeling, 2) to design a data collection procedure using probe vehicles (PVs) for the preparation of input for MOVES, and finally 3) to construct a framework for real-time emission modeling by integrating the developed methodology and data collection technique into a modeling system. The significance of this study is that the proposed real-time emission modeling system would be utilized for eco-friendly ITS applications such as dynamic eco-routing and applications for the environment: real-time information synthesis (AERIS) program. Additionally this study is significant in the sense that the newly developed methodology enables MOVES users to easily use the project-level feature of MOVES with the enhanced computational performance.
Chapter 2 Automobile Emissions Modeling and Traffic Information

This section addresses the state-of-practice automobile emissions models to select an appropriate model for real-time modeling. Additionally, the collection methodologies for traffic information used as inputs for the emissions model are described to verify that the methodology proposed in this study is applicable for real-time modeling.

2.1 State-of-the-Practice Automobile Emissions Models

The potential automobile emissions model should satisfy the following requirements for real-time emissions modeling. First, it should be sensitive to vehicle acceleration because average speed-based automobile emissions models, such as the MOBILE6 and EMFAC, cannot fully capture the differences between two different trips if their average speeds are identical. For example, it is well known that stop-and-go conditions result in significant negative impacts on fuel use and emissions. However, the differences between one trip at a high-speed with frequent stops and one trip at moderate speed with no stops would not be captured if their average speeds are identical. This limitation was demonstrated by Rakha and Ding [8]. The potential model must have the capability to overcome this limitation for this study, given that one potential application for the results of this study is to provide link level emissions estimates representing speed and acceleration distributions aggregated at the roadway link level for certain eco-friendly applications such as eco-driving and eco-routing. Second, it should compute fuel consumption and emissions rates rapidly. The computation time in software modeling automobile emissions is critical to real-time emission modeling. Several factors affect the computation capability of the modeling system, such as the size of the modeled network, system update cycle, and performance of the computer systems. Given that most currently operating advanced traffic information systems (ATIS) update the traffic flow information during short periods, such as 5-minute, 10-minute, and 15-minute intervals, the modeling system proposed in this study should be adequate in this respect. Therefore, a sufficiently fast computation time is desirable. Finally, it should reflect changes in the emissions related characteristics of the fleet traveling on the roadway. The development of an automobile emissions model generally involves extensive vehicle testing to measure actual vehicle emissions under various engine load conditions. Additionally, it is necessary to periodically update the model. Therefore, it requires a significant amount of financial support. Consequently, it is common for the public sector, such as a federal or state agency, to take the lead in development. EPA developed its official automobile emission model (MOBILE) and has provided necessary updates. Since the first version of the MOBILE series of models was developed in 1978, MOBILE6.2 was finally developed in 2004. In 2010, EPA released MOVES as its official automobile emission model [9]. In this respect, the MOVES model is appropriate for the system proposed in this study.

A limited number of automobile emissions models are used in North America for evaluating transportation related environmental impacts. The state-of-practice automobile emissions models include VT-micro, comprehensive modal emissions model (CMEM), and MOVES. In terms of the previously mentioned requirements, MOVES is superior. All models are sensitive to vehicle acceleration, but MOVES is only expected to be updated periodically. This means that there is strong merit to using MOVES: it is only necessary to await its new release. However, it is difficult to determine
which model is superior in terms of computation time. Generally speaking, VT-micro and CMEM are more fine-grained models because they require vehicle-specific inputs, whereas MOVES requires link-specific inputs. Therefore, this study uses MOVES and proposes a new interface for fast computation.

2.2 Traffic Information for Real-Time Emissions Modeling

Several factors affect vehicle fuel consumption and emissions, which can be divided into the following categories: travel-related factors, driver-related factors, highway network characteristics, vehicle characteristics and other factors [10, 11]. Among those factors, the vehicle operating condition, represented by the vehicle speed and acceleration, is an essential factor to be used in fuel consumption and emissions modeling. This is because speed and acceleration instantaneously change depending on driving behavior and surrounding traffic conditions, whereas other factors such as roadway grade, engine size, and vehicle age are static at the roadway link level. Acceleration is particularly critical for accurate fuel consumption and emission estimations because sharp acceleration can exponentially increase vehicle emissions.

Providers of ATIS and advanced traffic management systems (ATMS) primarily disseminate not acceleration information but travel time and average speed information at the roadway link level. ATIS and ATMS have traditionally used loop detectors to measure average link speed. This classic data collection technology is not applicable for collecting vehicle acceleration. With the wide use of GPSs, PVs equipped with GPS devices were used specifically as moving detectors to collect their location and speed information for arterial link speed estimation. For example, more than 10,000 taxis equipped with differential GPS receivers have been used for the collection of average speed information in Singapore [12]. Likewise, an ATIS designated Urban Traffic Information System (UTIS) uses PVs equipped with GPS-integrated onboard equipment (OBE) to collect vehicle speed information in South Korea [13].

To date, the use of PVs for real-time traffic information collection has generally been limited to the collection of average speed information, as discussed in the previous examples. Recently, Boriboonsomsin et al. conducted a project that collected vehicle and engine operating parameters from electronic control units (ECUs) to accurately estimate the fuel consumption and emissions of heavy duty trucks’ (HDTs) [14]. They proposed real-time HDT emissions modeling architectures that use GPS and ECU data from HDT PVs in conjunction with CMEM. The authors of this project proposed a real-time HDT emission modeling system with a new methodology to collect more detailed engine load conditions and wirelessly transmit them to a server. Additionally, they addressed that the real-time emission modeling can make various eco-friendly applications possible with the connected vehicle technologies.

MOVES takes into account vehicle acceleration using vehicle specific power (VSP), which was developed by J. L. Jiménez [15]. VSP is a surrogate variable for instantaneous engine load that is expressed as engine power normalized by vehicle mass, as shown in Equation (1). In the development of MOVES, vehicle emissions are categorized into several homogeneous operating condition bins (designated OpModes) that are classified based on the VSP and vehicle speed. Consequently, this study proposes a methodology to compute instantaneous VSP and vehicle speed by using PVs equipped GPS devices and to determine OpModes.
Chapter 3 Framework of Real-time Emission Modeling System

The proposed framework consists of the following four components. The first is an OBE installed in a PV, which calculates the VSP from the speed and acceleration of the PV and determines the OpMode, generates the distribution of OpModes and wirelessly transfers this distribution to roadside equipment (RSE) when the PV is connected. The second component is a server-side module that receives the information packages at the predefined time interval from all RSEs installed in the network and transmits the data to a server. The third component is a new interface to MOVES (NIM), which computes the average emissions factors for the roadway links by using the distribution of OpModes as input. The final component is a module that estimates fuel consumption and emissions by using the average emissions factors estimated in MOVES and the traffic volumes collected from the existing ATIS. FIGURE 1 depicts the proposed framework.

FIGURE 1 Real-time modeling framework
3.1 Onboard Equipment for Probe Vehicle

An individual PV equipped with OBE acts as a moving detector that continuously collects speeds and acceleration from the GPS device and/or onboard diagnostics to produce the distribution of OpModes while the PV travels along the links. OpMode is an index that represents the ranges of vehicle speed and VSP in MOVES. An OpMode is determined based on the instantaneous vehicle speed and VSP. The collected OpModes are aggregated by the individual links of the network so that the emission modeling results can finally be displayed at the roadway link level.

OBE installed in a PV has the following functions. First, it determines the instantaneous OpMode and stores it in the memory. Then, it aggregates the OpModes by the individual links to produce the distribution of OpModes. Specifically, it first calculates the instantaneous VSP by using Equation (1) with the given vehicle-specific coefficients available in the "SourceUseType" table in MOVES database. More detailed descriptions about the parameters used in the VSP calculation are provided in [16].

\[
VSP = \frac{Av + Bv^2 + Cv^3}{\text{source mass}} + va + 9.81\sin(a \tan(G))v
\]  

where VSP is the vehicle specific power in kW/ton, source mass is the vehicle mass in ton, \( A \) is the rolling term, \( B \) is the rotating term, \( C \) is the drag term, \( v \) is the vehicle speed in m/s, \( a \) is the vehicle acceleration in m/s\(^2\), and \( G \) is the roadway grade in percent.

Given the calculated VSP and vehicle speed, the corresponding OpMode is determined. The number of OpModes changes based on the emission process and pollutant. This study only focuses on the real-time monitoring of running emission processes. There are a total of 23 OpModes for the running hydrocarbons (HC), carbon monoxide (CO), and oxides of nitrogen (NO\(_X\)) emissions and energy consumption processes. The definitions of the OpModes are provided in [16].

Roadway link level aggregation of OpModes can be achieved by utilizing the location information provided each second by typical GPS-based automobile navigation systems. Specifically, OBE continuously tracks the current link on which the PV is running by comparing its current location with the predefined link information. OBE generates a structured dataset for the current link that comprises travel time, link exit time, and distribution of OpModes of the PV when it leaves the current link and enters the next link. OBE stores these structured datasets in its memory until the PV transmits them to a RSE. Please note that the memory size allocated for storing an OpMode distribution is fixed regardless of the length of travel time of the PV, because OBE does not store the speed profile of the PV but continuously updates the numbers of OpModes in OpMode bins. This is a great advantage because the system requires less memory when compared to the collection of speed profile of the PV.

3.2 PV Data Collection Procedure

RSEs installed in the transportation network receive the data sets transmitted by the PVs and send them to the server. Specifically, the communication between the PV and RSE can be achieved via a short-range wireless communication protocol such as IEEE 802.11a. RSEs connect to the server via wired Ethernet and send the information to the server for aggregation. Additionally, the information processed in the server, including the average fuel consumption and emissions rates by roadway links and dynamic eco-routing information, can be disseminated to PVs and other vehicles via RSEs.
3.3 New Interface to MOVES

This study developed NIM to more rapidly produce link-level energy use and emission rates for real-time emissions modeling. Given that the project-level feature of MOVES is suitable not for modeling every single vehicle running on a link but for modeling the average condition on the link, MOVES is an appropriate tool for real-time emission modeling at the roadway link level. However, the project-level analysis using MOVES requires a significant amount of time for preparing the link-specific inputs and executing the emission rates. Thus, it is impossible to use MOVES unchanged for the purpose of this study.

To address the common procedure for creating a MOVES Runspec file for project level analysis, users prepare link-specific data and enter them into the software via a graphical user interface (GUI) designated the project data manager (PDM). Project-level inputs include links, off-network, link source types, age distribution, meteorological data, fuel supply, fuel formulation, fuel type and technology, inspection and maintenance (I/M), OpMode distribution, and link drive schedules. Among the inputs, the OpMode distribution is the most critical variable for real-time emissions modeling because it keeps changing, whereas the other inputs are constant during a short time interval or only available at the regional level. Consequently, for fast execution, NIM was designed to only use OpMode distribution as the only variable input.

Python scripting language was used to develop NIM to directly access the MOVES database and retrieve relevant coefficients for computing the average emissions factors. Because this study utilized MOVES version 2010b, NIM connects to the MOVES database designated “movesdb20121030”.

Users of MOVES 2010b can closely examine this database by using MySQL Query Browser.

The first function of NIM is to map source use types (vehicle types) to regulatory classes. There are a total of 13 source use types in MOVES [16]. The individual source use types include several vehicle groups that use different fuels and are categorized into different regulatory classes. For example, all passenger cars in a certain area are composed of certain percentages of gasoline, diesel, and electric light duty vehicles. In the MOVES database, the fuel engine and regulatory fractions are defined by vehicle model year. The fuel engine and regulatory class fractions can be retrieved from the “fuelengfraction” and “regclassfraction” tables of the MOVES database. For example, the passenger truck source type with the model year of 2000 can be divided into 98% gasoline and 2% diesel trucks based on the fuel engine fraction. Next, passenger trucks with gasoline engines are divided into 94% of light duty trucks and 6% of heavy duty trucks. The 2% diesel trucks are divided into 50% of light duty trucks and 50% of the heavy duty trucks with mileage less than 14,000 miles. This example is illustrated in [17].

The second function is to establish a query to retrieve the average emission rate from either the “emissionrate” or “emissionratebyage” tables, based on the pollutant of interest. Because the objective of this study is modeling fuel consumption and emissions while vehicles are running, only energy consumption, HC, CO, and NOx emissions are examined. Energy consumption rates are available in the “emissionrate” table and HC, CO, and NOx emissions rates are available in “emissionratebyage” table, respectively. NIM makes a string for establishing a query into the MOVES database by combining various strings representing fuel type, engine technology, regulatory class, model year group, pollutant type, process type, and age group.

The “emissionrate” table has eight fields (columns): “sourceBinID,” “polProcessID,” “opModeID,” “meanBaseRate,” “meanBaseRateCV,” “meanBaseRateIM,” “meanBaseRateIMCV,” and “dataSourceId.” The “emissionratebyage” table has eight identical fields and one more field designated “ageGroupID.” The “meanBaseRate” field includes the average emissions rates, which can be retrieved by the sourceBinID, polProcessID, opModeID, and ageGroupID fields. Detailed descriptions of the two tables are available in [16, 18]. FIGURE 2 shows the functions of NIM with the illustration of data transmission between NIM and the MOVES database and PVs.
Fuel consumption and CO\(_2\) emissions are not directly provided by the MOVES database, but are calculated from energy consumption. Specifically, the fuel consumption rate can be calculated by using the lower heating value and density of fuel consumed, as shown in Equations (2) and (3). Atmospheric CO\(_2\) emission in grams is calculated by using the oxidation fraction and carbon content of fuel consumed, as shown in Equation (4). The term of \(44/12\) is multiplied because the molecular weights of CO\(_2\) and C are 44 gram/mol and 12 gram/mol, respectively. The typical values of the lower heating value, densities, oxidation fraction, and carbon content of gasoline and diesel are available in the "fuelsubtype" table of the MOVES database and [19].

\[
FC_{\text{gram}} = \frac{EC}{LHV_t} \tag{2}
\]

\[
FC_{\text{gallon}} = \frac{FC_{\text{gram}}}{D_t} \tag{3}
\]

where \(FC_{\text{gram}}\) is the fuel consumption in grams, \(EC\) is the energy consumption in KJ, and \(LHV_t\) is the lower heating value of fuel type \(t\), \(FC_{\text{gallon}}\) is the fuel consumption in gallons, and \(D_t\) is the density of fuel type \(t\).

\[
CO_{2\text{atm}} = EC \times OF_t \times CC_t \times \frac{44}{12} \tag{4}
\]
where \( \text{CO}_2_{\text{atm}} \) is the atmospheric \( \text{CO}_2 \) in grams, \( EC \) is the energy consumption in KJ, \( OF_t \) is the oxidation fraction of fuel type \( t \), and \( CC_t \) is the carbon content of fuel type \( t \).

In addition to those previously addressed, other factors affect the calculation of energy consumption and criteria pollutant emissions. These primarily include the adjustment factors reflecting the impacts of different fuel types, temperature, humidity, I/M program, and air conditioning use. In this study, NIM does not consider these factors because some are constant across all of the vehicles traveling on a particular road link and are also easily added to the system by the manager.

By using the developed NIM, the fuel consumption rates of the EPA highway fuel economy test (HWFET) cycle were estimated for demonstration. A 1995 passenger car was selected as the source use type for demonstration and comparison to VT-micro and CMEM because it is similar to LDV1 of VT-micro and Category-11 of CMEM in terms of vehicle model year [20, 21]. FIGURE 3 shows the speed profile of HWFET, relative OpMode distribution, and instantaneous MOVES fuel estimates over an entire cycle, along with the VT-micro and CMEM estimates. As shown in FIGURE 3 (b), approximately 39% of OpModes were categorized in OpMode bin-1, which represents braking and deceleration maneuvers. The MOVES estimates appear discrete, whereas the VT-Micro and CMEM estimates are continuous. This confirms that the MOVES estimates using NIM are consistent with the VT-micro and CMEM estimates because the patterns of the peaks and valleys are generally similar. The total fuel consumption was estimated as 0.9383 liters, 1.0722 liters, and 0.9886 liters by NIM, VT-micro, and CMEM, respectively.
To assess the performance of NIM in terms of computation time, the execution time was measured on a typical personal computer (PC) system. The PC consists of an Intel(R) Core(TM) i5-2500 CPU running at 3.30 GHz with 4GB RAM and other components. The EPA HWFET cycle was used as a sample OpMode distribution input for NIM, which means that it was assumed to be a relative OpMode distribution for a roadway link collected from PVs. First, the average run time for a single execution was measured as 0.001919 seconds by iterating the computation 1000 times; thus, a total of 156,331 runs can be achieved during a collection interval of 300 seconds. To validate this result from a different approach, the execution of NIM for a period of 300 seconds was repeated 10 times. The results indicated that the average number of executions for a period of 300 seconds is 154,466. If the length of a typical link is assumed to be 0.5 km through 0.8 km, NIM can cover 77,233 km through 123,573 km of roadway over 5 minutes for a specific pollutant.

3.4 Data Manipulation in Traffic Management Center

The proposed framework can be implemented in an ATIS by means of adding one more layer to the existing system. An additional server receives OpMode distributions from all roadway links within the network and repeatedly executes NIM until the whole calculation is finished. Specifically, the OpMode distributions of all PVs passing an RSE are summed up to calculate the numbers of OpModes classified into the individual OpMode bins. Using Equation (5), these numbers are divided by the total travel time required by all PVs to complete their travel on the link of interest to calculate the fraction of individual OpMode bins.

\[
OPF_{i,j,l} = \frac{\sum_{k=1}^{n} OP_{i,k,l}}{\sum_{k=1}^{n} TT_{k,l}}
\]

\( \text{where } OPF_{i,j,l} \text{ is the fraction of OpMode } i \text{ for source use type } j \text{ and link } l, \ OP_{i,k,l} \text{ is the number of OpMode } i \text{ for PV } k \text{ and link } l, \ TT_{k,l} \text{ is the travel time of PV}_k \text{ for link } l, \ n \text{ is the number of PVs traversing link } l. \)

The average composite emission rate, reflecting the characteristics of link and traffic flow, is calculated by using NIM with the relative OpMode distribution. This single execution only calculates an average emissions rate for one specific pollutant, link, and source use type. Therefore, the number of executions of NIM varies depending on the source use types, links, and pollutants of interest. The total emissions for a link can be calculated by multiplying the average composite emission rates and traffic volumes measured by the existing ATIS.
Chapter 4 Demonstration of Proposed System

4.1 Virtual Realization Using Traffic Simulation Model

To demonstrate that the proposed system works in real time with the provision of reliable emission estimates, a simple network consisting of four intersections was modeled in VISSIM simulation software as shown in FIGURE 4. The reason of using VISSIM is because simulation models developed in VISSIM are externally controllable while the simulation is running by using the VISSIM component object model (COM). Multiple simulations were conducted under various traffic conditions by varying traffic volumes and PV fractions to investigate the relationship between PV population and estimation accuracy. This study referred to a previous work that analyzed PV population and sample size for estimation of speed [12]. The simulation environment was designed by combining the following components: the server for NIM execution, the component for the communication between PVs and RSEs, the VISSIM model, and the main simulator for combining the previous three components. Specifically, the main simulator runs the VISSIM COM for traffic simulation while collecting the relative OpMode distributions from the RSEs and transmitting them to the NIM server for real-time emission modeling. Please note that the installation of RSEs in the simulation model is just for demonstration. Therefore, the way for installation of RSEs in an intersection can be various in real-world applications. For example, a single RSE with multiple receivers can be installed at an intersection.
The VISSIM model has a total of 24 two-lane links and an RSE was installed at the end of each individual link. To mimic the RSEs, an VISSIM object, designated data collection point, was used. PVs transmit their relative OpMode distributions to the RSEs once they traverse the links. Please note that it was assumed that there are no errors in the communication between PV and RSE. The cycle length was set to 120 seconds and the traffic flow in each direction used a phase of 30 seconds, consisting of 1 second red, 26 seconds green, and 3 seconds yellow at each intersection. The left-turn, through, and right-turn movements of each approach used the same phase. The base case origin-destination (O-D) demand was set to 1000 veh/h to simulate a typical peak period because this is similar to the capacity under the given signal condition (1900 pcphpl × 2 lane × g/C = 824 pcph). The simulation result indicated that the level of service of the entire network is E, based on the average approach delay (74.5 s/veh). The O-D demand was evenly distributed among left-turn, through, and right-turn movements and was loaded to the network from each of the eight zones.

A total of 35 simulation runs was executed with the variations of five different traffic demand levels and seven different PV fraction levels in the O-D demand: 70%, 80%, 90%, 100%, and 110% in the base case OD demand; 3%, 6%, 9%, 12%, 15%, 18% and 100% of PV fractions in the total O-D demand. The simulation period was set to 1800 seconds for each simulation run: the first 900 second period was used as a warm-up period. The results of the real-time emission modeling were reported during a data collection interval of 300 seconds after this period.

The simulation runs confirmed that the framework for real-time emission modeling proposed in this study works as designed. TABLE 1 lists the simulation results for the period of 901-1200 second when the simulation was run with the base O-D demand and 12% of PVs in the network. Based on the results, the vehicles traversing Link 1 (RSE 1) consumed the most fuel and emitted the most air pollution, whereas the vehicles traversing Link 6 (RSE 6) consumed the least fuel and emitted the least air pollution. The information in TABLE 1 was generated in real time while the simulation was
running. Therefore, it is relevant to real-world implementation. Also, it may be applicable to various eco-friendly ITS applications when vehicle to vehicle (V2V) and vehicle to infrastructure (V2I) communication technologies become more popular and practical.

### TABLE 1 Average fuel consumption rate (L/km) and emissions rates (g/km) for 100% O-D demand and 12% PVs for the period of 901-1200 second

<table>
<thead>
<tr>
<th>RSE Index</th>
<th>Fuel</th>
<th>CO₂</th>
<th>HC</th>
<th>CO</th>
<th>NOₓ</th>
</tr>
</thead>
<tbody>
<tr>
<td>RSE-1</td>
<td>0.1923</td>
<td>452.8</td>
<td>0.0154</td>
<td>1.8025</td>
<td>0.0479</td>
</tr>
<tr>
<td>RSE-2</td>
<td>0.0986</td>
<td>232.1</td>
<td>0.0097</td>
<td>1.0864</td>
<td>0.0301</td>
</tr>
<tr>
<td>RSE-3</td>
<td>0.0568</td>
<td>133.7</td>
<td>0.0044</td>
<td>0.4587</td>
<td>0.0143</td>
</tr>
<tr>
<td>RSE-4</td>
<td>0.1292</td>
<td>304.3</td>
<td>0.0121</td>
<td>1.4185</td>
<td>0.0368</td>
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#### 4.2 Effect of Probe Vehicle Fraction on Estimation Accuracy

The average fuel consumption rate of all PVs (hereafter referred to as PV fuel consumption) within the collection interval was compared to the average fuel consumption of all vehicles (referred to as all-vehicle fuel consumption: 100% PV) to investigate the PV fraction effect. FIGURE 5 shows the linear regression line over the scatter plot with the equation and R² value. It is evident that the errors in average fuel consumption estimated from the PVs decrease as the PV fraction increases. This
confirms that the $R^2$ values of the regression lines increase as the fraction of PVs increases. The average fuel consumption rates estimated from the PVs were slightly overestimated: the slopes of the lines are marginally greater than 1. Additionally, the standard deviation of the errors between PV fuel consumption and all-vehicle fuel consumption decreases as the PV fraction increases, as shown in FIGURE 6 (a) and (b). The standard deviation of the errors significantly decreases when the PV fraction increases from 3% to 6%, and marginally decreases when the PV fraction increases from 12% to 18%. Specifically, the two-standard deviation of the relative errors drops 8.9% due to the increases in the PV fraction of from 3% to 6%, and decreases only 0.6% when the PV fraction increases from 12% to 15%. This reveals that introducing more than 12% of PV to the network only slightly improves the estimation accuracy. The two-standard deviation of the relative errors indicates that,95% of the time, the PV fuel consumption has relative errors of less than 15.8% for 9% of PV, and 12.7% for 12% of PV. The PV fraction needs be set to 10% by interpolation if the relative error should be less than 15%. In terms of the absolute error, the two-standard deviation is 0.013 L/km for 9% of PVs.

The previously addressed effects of PV fraction on estimation accuracy were about the network level. The factor affecting estimation accuracy in a specific link is the number of PVs that traversed the link. FIGURE 6 (c) and (d) show the absolute and relative errors between PV fuel consumption and all-vehicle fuel consumption as a function of PV sample size with the 95% confidence interval. As shown in FIGURE 6 (c) and (d), each link has at least one PV and at most 28 PVs. The 95% confidence interval in FIGURE 6 (d) indicates that there should be more than 10 PVs in a link to maintain the level of the relative error less than 10%. According to all simulation runs, 68.2% of the links have less than 11 PVs during the collection interval of 300 seconds. Therefore, one should consider the tradeoff between the size of collection interval and a confidence interval to determine the relevant number of PVs in a link.
FIGURE 5 Comparison between fuel consumption and of PVs and all vehicle
FIGURE 6 Relationship between errors and PVs
This study proposed a framework for real-time emission modeling to improve eco-friendly ITS applications. To conduct real-time modeling of automobile emissions at the roadway link level, a new interface to MOVES, designated NIM, was developed for enhancing its computational performance by directly accessing the MOVES database and retrieving relevant coefficients for computing the average emissions factors. The satisfactory computational performance of NIM was demonstrated through its average computation time of 0.001919 seconds for a single execution. Additionally, a methodology using PVs equipped with an OBE was suggested for collecting the OpMode distribution through the network to generate MOVES input.

A virtual implementation within the simulation environment developed using the Python scripting language demonstrated that the proposed framework generally works as designed. The simulation environment consists of the server for NIM execution, the component for communication between PVs and RSEs, the VISSIM model, and the main simulator. This study also investigated the effects of PV sampling size both at network and link levels on the accuracy of emissions estimation. It was found that the PV fraction needs be set to 10% using the two-standard deviation of relative errors between PV fuel consumption and all-vehicle fuel consumption if the relative error should be less than 15%. Also, it can be inferred that there should be more than 10 PVs in a link to maintain less than 10% relative error.

It is expected that the proposed real-time emission modeling system will make possible a variety of eco-friendly ITS applications, such as eco-routing, and may be used to develop environmentally conscious traffic operation strategies. Using MOVES through NIM, the proposed system has certain merits: first, it is easy to update the emission modeling tool because MOVES is periodically updated by EPA. Second, the system can easily be applied to any area in the US because area-specific data are already available in the MOVES database.
Acknowledgements

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15. Jimenez-Palacios, J.L., *Understanding and quantifying motor vehicle emissions with vehicle specific power and TILDAS remote sensing*. 1998, Massachusetts Institute of Technology.


