Abstract—In this paper, a bottom–up vehicle emission model is proposed to estimate real-time CO$_2$ emissions using intelligent transportation system (ITS) technologies. In the proposed model, traffic data that were collected by ITS are fully utilized to estimate detailed vehicle technology data (e.g., vehicle type) and driving pattern data (e.g., speed, acceleration, and road slope) in the road network. The road network is divided into a set of small road segments to consider the effects of heterogeneous speeds within a road link. A real-world case study in Beijing, China, is carried out to demonstrate the applicability of the proposed model. The spatiotemporal distributions of CO$_2$ emissions in Beijing are analyzed and discussed. The results of the case study indicate that ITS technologies can be a useful tool for real-time estimations of CO$_2$ emissions with a high spatiotemporal resolution.

Index Terms—Air pollution, carbon dioxide (CO$_2$) emissions, intelligent transportation systems (ITSs), International Vehicle Emissions (IVE) model.

NOMENCLATURE

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>Index of a lane.</td>
</tr>
<tr>
<td>$\theta$</td>
<td>Slope of a road segment.</td>
</tr>
<tr>
<td>$\phi$</td>
<td>Index of a road segment.</td>
</tr>
<tr>
<td>$\varphi$</td>
<td>Traffic flow of a lane.</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>Length of a lane.</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Index of a vehicle type.</td>
</tr>
<tr>
<td>$\omega$</td>
<td>Number of vehicles.</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>Number of lanes within a road segment.</td>
</tr>
<tr>
<td>$b$</td>
<td>Vehicle acceleration (in square meters per second).</td>
</tr>
<tr>
<td>$e_{\text{sampling}}$</td>
<td>CO$_2$ emission error due to the GPS sampling error.</td>
</tr>
<tr>
<td>$f_{[b]}$</td>
<td>Percentage of vehicles in technology category $k$.</td>
</tr>
<tr>
<td>$f_{[\lambda,\phi,t]}$</td>
<td>Percentage of type-$\lambda$ vehicles in road segment $\phi$ during time period $t$.</td>
</tr>
<tr>
<td>$f_{[k,\phi,t]}$</td>
<td>Percentage of vehicles in technology category $k$ in road segment $\phi$ during time period $t$.</td>
</tr>
<tr>
<td>$f_{[\lambda,k,\phi,t]}$</td>
<td>Ratio of the number of vehicles in technology category $k$ to that of vehicles in type $\lambda$.</td>
</tr>
<tr>
<td>$i$</td>
<td>Index of a correction factor.</td>
</tr>
<tr>
<td>$k$</td>
<td>Index of a vehicle category.</td>
</tr>
<tr>
<td>$p$</td>
<td>Number of correction factors.</td>
</tr>
<tr>
<td>$t$</td>
<td>Index of a time period.</td>
</tr>
<tr>
<td>$v$</td>
<td>Vehicle speed (in meters per second).</td>
</tr>
<tr>
<td>$w$</td>
<td>Weighting parameter determined by the quality of floating-car and loop detector data.</td>
</tr>
<tr>
<td>$D$</td>
<td>Travel distance by a vehicle.</td>
</tr>
<tr>
<td>$\overline{D}$</td>
<td>Average travel distance by a vehicle.</td>
</tr>
<tr>
<td>$B_{[k]}$</td>
<td>CO$_2$ base emission rate for vehicle technology $k$ (in gallons per kilometer).</td>
</tr>
<tr>
<td>$C_{[i,k]}$</td>
<td>$i$th correction factor for vehicle technology $k$.</td>
</tr>
<tr>
<td>$N$</td>
<td>Total vehicle kilometers traveled (in kilometers).</td>
</tr>
<tr>
<td>$\overline{P}$</td>
<td>Fuel economy of a vehicle (in liters per 100 km or cubic meter per 100 km).</td>
</tr>
<tr>
<td>$Q_{[k]}$</td>
<td>CO$_2$ production rate by unite of fuel (kilograms per liter of kilograms per cubic meter).</td>
</tr>
<tr>
<td>$Q_{\text{running}}$</td>
<td>Number of correction factors.</td>
</tr>
<tr>
<td>$\hat{Q}_{\text{running}}$</td>
<td>Average vehicle power load over the last 20 s (in kilowatts per ton).</td>
</tr>
<tr>
<td>$\hat{Q}_{[\phi,t]}$</td>
<td>Adjusted CO$_2$ base emission rate for vehicle category $k$ (in gallons per kilometer).</td>
</tr>
<tr>
<td>$\hat{P}_{\text{running}}$</td>
<td>CO$_2$ emission amount on road segment $\phi$ during time period $t$ (in kilograms).</td>
</tr>
<tr>
<td>$\hat{P}_{[\phi,t]}$</td>
<td>Adjusted CO$_2$ emission amount on road segment $\phi$ during time period $t$ (in kilograms).</td>
</tr>
<tr>
<td>$\omega_{\text{VSP}}$</td>
<td>Engine revolutions per minute.</td>
</tr>
<tr>
<td>$U_{\text{c}}$</td>
<td>Local average velocity (in kilometers per hour).</td>
</tr>
</tbody>
</table>

Manuscript received February 22, 2012; revised June 6, 2012; accepted September 10, 2012. Date of publication October 5, 2012; date of current version February 25, 2013. This work was supported in part by the National Natural Science Foundation of China under Grant 41071285, Grant 40830530, and Grant 21201466 and by the U.S. Department of Energy under Contract DE-AC05-00OR22725. The Associate Editor for this paper was S. Tang.

X. Chang, B. Y. Chen, Q. Li, and L. Tang are with the State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, Wuhan 430079, China (e-mail: changxiaomeng@gmail.com; chen.biyu@gmail.com; qqli@whu.edu.cn; tll@whu.edu.cn).

X. Cui and C. Liu are with the Computational Sciences and Engineering Division, Oak Ridge National Laboratory, Oak Ridge, TN 37831 USA (e-mail: cuix@ornl.gov; liuc@ornl.gov).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TITS.2012.2219529
\( U_{FTP} \) \hfill Average velocity of the LA-4 driving cycle (in kilometers per hour).

\( U_{GPS}^{\phi,t} \) \hfill Travel speed estimated by GPS data from the floating-car system.

\( U_{\text{Loop}}^{\phi,t} \) \hfill Travel speed estimated by GPS data from the loop detector system.

\( \text{VKT}^{\phi,t} \) \hfill Vehicle kilometers traveled on road segment \( \phi \) during time period \( t \) (in kilometers).

\( X \) \hfill Longitude of a node.

\( Y \) \hfill Latitude of a node.

\( Z \) \hfill Altitude of a node.

I. INTRODUCTION

NOWADAYS, global-climate-change-induced problems have become major critical threats to humanity. Reducing greenhouse gas emissions and keeping the anthropogenic CO\(_2\) emission rate at a reasonable level is a great challenge for mankind. In recent years, CO\(_2\) emissions from the transport sector have received much attention [1]–[3]. It has been estimated that 23% of the world’s energy-related CO\(_2\) emissions were coming from the transport sector and road transport accounted for 74% of the total transport CO\(_2\) emissions [4]. Moreover, CO\(_2\) emissions from road transport are continuously rising, with the remarkable development of urban economy and population expansion. It is therefore important to continuously monitor CO\(_2\) emissions from road transport to manage the road transport development in a sustainable way.

To monitor CO\(_2\) emissions from road transport, “top–down” and “bottom–up” approaches are two commonly used methods in the literature [4]–[6]. The top–down approach is to estimate the CO\(_2\) emissions from aggregate fuel-used data at a large spatiotemporal scale (e.g., national annual level). The emissions at a detailed spatiotemporal level (e.g., daily emissions of a city) are roughly approximated by socioeconomic or population data [7].

The bottom–up approach is to estimate the CO\(_2\) emissions by each individual vehicle. The detailed vehicle technologies (i.e., vehicle types, engine sizes, fuel types, vehicle ages, transmission types, and air conditioning systems) and driving patterns (i.e., speed, acceleration, and road slope) are explicitly considered in this bottom–up approach. Compared with the top–down approach, the bottom–up approach can provide much more accurate estimations with a higher spatiotemporal resolution, but more detailed data are required [6].

In the literature, many research efforts have been given to develop accurate vehicle emission models using the bottom–up approach, including MOBILE, COPERT, Emission FACTors (EMFAC), Comprehensive Modal Emission Model (CMEM), International Vehicle Emissions (IVE) model, and Motor Vehicle Emission Simulator (MOVES) [8]–[10]. To obtain detailed vehicle technology and driving pattern data, a large-scale survey at the area of interest should be carried out [11]. Such a large-scale survey, however, is generally time consuming and labor intensive. As an alternative to obtain vehicle technology and driving pattern data, dynamic traffic simulation models are employed [12], [13]. Several commercial software packages using the dynamic traffic simulation models have been developed, including INTEGRATION [13], TRAnsportation ANalysis SIMulation System (TRANSIMS) [14], and Visual Traffic Simulation (VISSIM) [15]. These simulation-based emission models can be a valuable tool for evaluating the effects of various policies on traffic CO\(_2\) emissions [16], [17]. Nevertheless, the dynamic traffic simulation models are only a simple representation of traffic conditions and cannot generate real driving patterns of all vehicles. Thus, such simulation-based emission models are not suitable for estimating accurate CO\(_2\) emissions in real time.

With the recent development of intelligent transportation systems (ITSs), acquiring real-time high-quality traffic information becomes feasible [18]–[22]. Among various traffic detectors, fixed embedded loop detectors are one of the most commonly used techniques in many nations and regions across the world [23], [24]. Using the magnetic technique, the loop detectors can detect vehicles that pass through the road according to the changes of the magnetic field. Useful information can be obtained from loop detectors, such as traffic flow, average travel speeds, and vehicle types. With the advances in positioning and wireless communication techniques, the floating-car system has become popular in recent years due to its low cost and large spatial coverage [25], [26]. Floating-car data are typically collected from a fleet of probe vehicles (e.g., taxis) that are equipped with Global Positioning System (GPS) receivers and wireless communication devices. The location (longitude, latitude, and altitude) and speed of these probe vehicles are usually collected in low frequency (e.g., 20 s).

The real-time traffic information that is collected by ITS is mainly for monitoring network traffic conditions [27] and providing route guidance services to road users [28], [29]. In fact, the ITS traffic data can be very useful data sources for estimating CO\(_2\) emissions. To our knowledge, few research work has been carried out to utilize the ITS traffic data for monitoring real-time CO\(_2\) emissions. This paper attempts to fill the gap by devising an effective method for using ITS traffic data in real-time estimations of CO\(_2\) emissions. This paper extends the previous work in the following aspects.

1) A bottom–up vehicle emission model is proposed based on the ITS technologies. In the proposed model, the ITS traffic data are fully utilized to estimate detailed vehicle technology and driving pattern data. The traffic data, collected by loop detectors, are employed to estimate vehicle technology distribution and vehicle kilometers traveled data. The low-frequent GPS data collected by the floating-car system are interpolated into second-by-second speed profiles to estimate speeds and accelerations of all vehicles. The road slope data are generated by the digital elevation model (DEM). This way, vehicle technologies and driving patterns of all vehicles could be estimated in a short time interval. Accordingly, the CO\(_2\) emissions from the road transport can be estimated on a real-time basis by using the IVE model. In addition, the CO\(_2\) emission error due to the low-frequent GPS sampling is explicitly considered.

2) In the proposed model, the transport road network is divided into a set of small road segments to consider the effects of heterogeneous speeds within a road link. In
the congested urban road network, the travel speeds of vehicles are generally not uniform within the road link. For example, drivers tend to decelerate when they are approaching to signalized intersections. Then, an acceleration process can usually be observed after vehicles have passed the intersections. Compared with the link-based approach, the proposed road-segment approach can explicitly consider the heterogeneous speed effects to improve the estimation accuracy of CO₂ emissions. In addition, this segment-based approach can take into account uneven links with various road slopes.

3) A real-world case study is carried out to demonstrate the applicability of the proposed model using real ITS traffic data that were collected in Beijing, China. The spatiotemporal distribution of CO₂ emissions in Beijing is analyzed and discussed. A comparison study is also carried out using a top-down approach. The results of the case study indicate the usefulness of the proposed model in the real-time estimation of CO₂ emissions for large-scale road networks.

This paper is organized as follows. Section II briefly introduces the IVE model. Section III presents the proposed vehicle emission model. Section IV reports the results of the case study using real ITS traffic data in Beijing. Conclusions, together with further studies, are given in Section V.

II. INTERNATIONAL VEHICLE EMISSIONS MODEL

To facilitate the presentation of the essential ideas in this paper, the IVE model is briefly introduced in this section. The IVE model was funded by the U.S. Environmental Protection Agency (EPA) and jointly developed by the International Sustainable Systems Research Center and the University of California, Riverside (UCR). It was designed and calibrated to estimate CO₂ emissions from motor vehicles, particularly for developing countries [30], [31].

In the IVE model, vehicles with various technology factors (i.e., engine sizes, fuel types, vehicle ages, transmission types, and air conditioning systems) are classified into 1372 categories. For each category, LA-4 driving cycle tests 1 were conducted in the laboratory to estimate vehicle CO₂ emission rates. \(^2\) Let \( k \) be the index of the vehicle technology category. For each vehicle category \( k \), a base CO₂ emission rate, which is denoted by \( B_{[k]} \) (in grams per kilometer), is provided. Several correction factors (i.e., temperature correction factor, humidity correction factor, fuel quality correction factor, inspection/maintenance correction factor, and country correction factors), which are denoted as \( C_{[i,k]} \), are also provided to adjust the base emission rate \( B_{[k]} \) by

\[
Q_{[k]} = B_{[k]} \cdot \prod_{i=1}^{N} C_{[i,k]} \tag{1}
\]

where \( Q_{[k]} \) (in gallons per kilometer) is the adjusted base emission rate for vehicle category \( k \), \( N \) is the number of the correction factors, and \( i \) is the index of the correction factor.

The vehicle-specific power (VSP) bin technology is adopted in the IVE model to consider the effects of various vehicle driving patterns on CO₂ emissions. The VSP bin technology uses the VSP and engine stress (ES) to depict different driving patterns. The concept of VSP (in kilowatts per ton), was developed by Jimenez [32]. It describes the instantaneous power per unit mass of a vehicle and can directly be related to vehicle instantaneous driving patterns such as travel speed, acceleration, and road slope. The VSP can be calculated by

\[
VSP = v (1.1 a + 9.81 \cdot \text{Sin} (A \tan(\theta)) + 0.132) + 0.000302 \cdot v^3 \tag{2}
\]

where \( v \) is the vehicle speed (in meters per second), \( a \) is the acceleration (in square meters per second), and \( \theta \) is the road-segment slope. For each technology category \( k \), the calculated VSP value is classified into 20 VSP bins. The index of VSP bin is denoted by \( b_{VSP} \in \{1, \ldots, 20\} \).

Using the aforementioned calculated VSP, the ES could be calculated by

\[
ES = \frac{\text{RPM}}{1000} \cdot 0.08(\text{ton/kW}) \cdot \mathcal{P} \tag{3}
\]

\[
\mathcal{P} = \frac{1}{20} \sum_{t=19}^{60} \text{VSP}_t \tag{4}
\]

where \( \mathcal{P} \) is the average vehicle power load over the last 20 s (in kilowatts per ton), and RPM is the engine revolutions per minute. Similarly, the calculated ES value is divided into three ES bins for each technology category \( k \). The index of the ES bin is denoted by \( b_{ES} \in \{1, \ldots, 3\} \).

By combining VSP and ES bins, the driving pattern of a vehicle can be defined as one of the 60 driving patterns (or 60 power bins) for each vehicle category \( k \). Let \( b \in \{1, \ldots, 60\} \) be the index of a driving pattern. It can be calculated as

\[
b = b_{VSP} \cdot b_{ES}. \tag{5}
\]

To take into account CO₂ emissions by vehicles at different driving patterns, a vehicle driving pattern correction factor, denoted as \( C_{[b,k]} \), is provided in the IVE model to adjust base CO₂ emissions. Consequently, given vehicle \( c \) in technology category \( k \), its CO₂ emissions \( Q_{\text{running}}^{c} \) (in gallons per kilometer) can be then calculated by

\[
Q_{\text{running}}^{c} = \frac{\mathcal{U}_{FTP} \cdot D}{\mathcal{U}_c} \cdot Q_{[k]} \cdot \sum_{k=1}^{60} (f_{[k]} \cdot C_{[k,h]}) \tag{6}
\]

where \( D \) is the travel distance, \( f_{[k]} \) is the percentage of vehicles traveling at driving pattern \( b \), \( \mathcal{U}_{FTP} \) is the average velocity of the LA-4 driving cycle (in kilometers per hour), and \( \mathcal{U}_c \) is the local average velocity (in kilometers per hour).

Given an area of interest, the number of vehicles in this area is denoted by \( \mathcal{N} \), and the percentage of vehicles in technology category \( k \) is denoted by \( f_{[k]} \). The total traffic CO₂ emissions
in this area, which are denoted by $Q_{\text{running}}$ (in gallons per kilometer), can be calculated by

$$Q_{\text{running}} = \frac{U_{\text{FTP}} \cdot VKT}{U_c} \cdot \sum_{k=1}^{1372} \sum_{b=1}^{60} (f[k] \cdot f[k,b] \cdot C[k,b] \cdot Q[k])$$

(7)

where $VKT = \omega \cdot D$ (in kilometers) is the vehicle kilometers traveled by all vehicles, and $D$ is the average travel distance by a vehicle.

According to (7), to obtain an accurate estimation of traffic CO$_2$ emissions, second-by-second speed profiles of all vehicles with detailed vehicle technology information are required. Intuitively, these second-by-second speed profiles can be obtained by GPS records of all vehicles. Such high-frequency GPS data for all vehicles, however, are not available in practice. In real ITS applications, only some probe vehicles (e.g., taxis) are equipped with GPS detectors. In addition, the GPS records of probe vehicles are generally collected in low frequency (e.g., 20 s). In view of this, the next section presents a method of calculating CO$_2$ emissions by using GPS and loop detector data that were collected by real ITS applications.

III. ESTIMATION OF CO$_2$ EMISSIONS USING INTELLIGENT TRANSPORTATION SYSTEM TECHNOLOGIES

In this section, an ITS-based bottom–up vehicle emission model is proposed for estimating real-time traffic CO$_2$ emissions. In the proposed model, the transport road network is divided into a set of small road segments. For each road segment, the road slope is generated by DEM. The low-frequency GPS data that were collected by the floating-car system are interpolated into a second-by-second speed profile to obtain the driving pattern distribution [i.e., $f[k,b]$ and $C[k,b]$ in (7)] in the road segment. The traffic flow data, collected by loop detectors, are employed to calculate the vehicle kilometers traveled [i.e., $VKT$ in (7)]. The vehicle technology distribution [i.e., $f[k]$ and $Q[k]$ in (7)] is estimated by vehicle-type data that were collected by loop detectors. The detailed method is given in the following sections.

A. Road-Segment Structure

In most ITS applications, a road network is typically represented by a set of links and nodes [26], [29]. Each node represents a network intersection, whereas each link represents a one-way street that connects each two intersections. Note that a two-way street is represented as two directed links. In this paper, a road link is further divided into a set of road segments, and the road segment is used as a basic spatial unit for calculating CO$_2$ emissions.

The slope value is calculated for each road segment using DEM data. DEM data are an important GIS data source. These are a digital representation of a land surface by a sample of elevation points, for which the longitude, latitude, and altitude values are recorded [33]. Given a road segment AB, the slope of AB could be calculated by

$$\theta = \frac{|Z_B - Z_A|}{\sqrt{(X_B - X_A)^2 + (Y_B - Y_A)^2}}$$

(8)

B. Road-Segment Driving Pattern Distribution

Due to inevitable positioning errors caused by GPS receivers and geometric errors of the digital road network, the GPS data that were collected by the floating-car system could not directly be matched onto the real road network [26]. Therefore, raw GPS data need to be processed before being further used. In this paper, a probabilistic analysis-based map-matching algorithm is employed to match the low-logging GPS data onto the road network [34].

As aforementioned, the GPS data collected by the floating-car system tend to have low frequency (e.g., 20 s). In this paper, available low-frequency GPS data are interpolated into second-by-second speed profiles to calculate the VSP and ES bins in (2)–(5). A cubic spline interpolation method is adopted. Fig. 1 gives an illustrative example of this GPS data interpolation. In this figure, the black line refers to the actual high-frequency GPS data, whereas the red line refers to the interpolated GPS data. It is shown that the cubic spline interpolation method can provide a reasonable approximation of the actual high-frequency GPS data. It is also shown in Fig. 1 that, using this cubic spline interpolation method, some detailed acceleration or deceleration information may be missed, thus resulting in an underestimation of CO$_2$ emissions. The estimation error due to low-frequency GPS data should be taken into account in the proposed model (refer to Section III-D). The second-by-second GPS data of all probe vehicles are then matched to road segments. For each road segment and each probe vehicle, VSP and ES bin values be calculated using (2)–(5). It is assumed in this paper that the driving patterns (speed, acceleration, and road slope) of probe vehicles can represent those of all vehicles on the same road segment during a short time interval. This assumption seems valid in the congested urban road network, where vehicles do not have much freedom to change their travel speeds. Using this assumption, the driving pattern distribution, which is denoted by $f_{[k,b,\phi,t]}$, could be obtained for each road segment $\phi$ and time period $t$.

C. Road-Segment Vehicle Kilometers Traveled

In the proposed model, the traffic flow data (i.e., total number of passing vehicles) collected by loop detectors are employed to
calculate the vehicle kilometers traveled (denoted by $VKT_{[\phi,t]}$) for road segment $\phi$ and time period $t$.

The loop detectors can observe the traffic flows for each lane. Because the lane lengths for some links with a horizontal curve are not identical, the vehicle kilometers traveled are calculated by lanes in this paper. Let $\theta_{[\phi]}$ be the number of lanes within the road segment $\phi$ and $\gamma_{[\phi]}^\alpha$ be the length of its $\alpha^{th}$ lane. $VKT_{[\phi,t]}$ can be calculated by

$$VKT_{[\phi,t]} = \sum_{\omega_{[\phi]}} \left( \phi_{[\omega,\phi,t]} \cdot \gamma_{[\phi]}^\alpha \right)$$  \hspace{1cm} (9)

where $\phi_{[\omega,\phi,t]}$ is the traffic flow of the $\alpha^{th}$ lane within segment $\phi$ during time period $t$.

D. Road-Segment Vehicle Technology Distribution

Let $f_{[k,\phi,t]}$ be the vehicle percentage in technology category $k$ in road segment $\phi$ during time period $t$. To obtain this vehicle technology distribution parameter, detailed vehicle technologies (e.g., vehicle type, engine sizes, fuel types, and vehicle ages) for all vehicles in the road segment are required. The loop detector data can be very useful for identifying the types of vehicles that pass through the road segment, including private cars, buses, trucks, and motorcycles [35]–[37]. In this case, the percentage of type $\lambda$ vehicles in road segment $\phi$ during time period $t$ (denoted by $f_{[\lambda,\phi,t]}$) can be obtained from the loop detector data. Then, $f_{[k,\phi,t]}$ can be calculated by

$$f_{[k,\phi,t]} = f_{[\lambda,\phi,t]} \cdot f_{[k,\lambda,\phi,t]}$$  \hspace{1cm} \forall k \in \{\text{private cars, buses, trucks, motorcycles, etc.}\}$$  \hspace{1cm} (10)

where $f_{[\lambda,\phi,t]}$ is the ratio of the number of vehicles in technology $k$ to that of vehicles in type $\lambda$. The $f_{[k,\lambda,\phi,t]}$ parameter can be obtained by the roadside survey, which can be conducted on a regular period (e.g., each year).

E. Segment-Based Vehicle Emission Model

According to the aforementioned road-segment formulation, the CO$_2$ emissions by road segment (denoted by $Q_{[\phi,t]}^{\text{running}}$) can be calculated by

$$Q_{[\phi,t]}^{\text{running}} = \frac{\bar{U}_{\text{FTP}} \cdot \chi_{[\phi,t]}^{\alpha}}{\chi_{[\phi,t]}^{\alpha}} \cdot \sum_{\lambda} \sum_{k=1}^{1372} \sum_{b=1}^{60} \left( f_{[\lambda,\phi,t]} \cdot f_{[k,\lambda,\phi,t]} \cdot f_{[k,b,\phi,t]} \cdot C_{[k,b]} \cdot Q_{[k]} \right)$$  \hspace{1cm} (11)

where $\bar{U}_{[\phi,t]}$ is the average speed in road segment $\phi$ during period $t$. This $\bar{U}_{[\phi,t]}$ value can be calculated by fusing the travel speed that was estimated by both floating-car and loop detector data by

$$\bar{U}_{[\phi,t]} = \left( 1 - w \right) \cdot U_{[\phi,t]}^{\text{GPS}} + w \cdot U_{[\phi,t]}^{\text{Loop}}$$  \hspace{1cm} (12)

where $U_{[\phi,t]}^{\text{GPS}}$ is the travel speed that was estimated by GPS data from the floating-car system, $U_{[\phi,t]}^{\text{Loop}}$ is travel speed that was estimated by loop detector data, and $w$ is the weighting parameter that was determined by the quality of floating-car and loop detector data [24], [38].

As mentioned in Section III-B, the interpolation of low-frequency GPS data could underestimate CO$_2$ emissions; and thus, this GPS sampling error, which is denoted by $e_{\text{sampling}}$, should be taken into account. Then, the CO$_2$ emissions can be adjusted by

$$\hat{Q}_{[\phi,t]}^{\text{running}} = (1 + e_{\text{sampling}}) \cdot Q_{[\phi,t]}^{\text{running}}$$  \hspace{1cm} (13)

where $Q_{[\phi,t]}^{\text{running}}$ and $\hat{Q}_{[\phi,t]}^{\text{running}}$ are the unadjusted and adjusted emission amounts of road segment $\phi$ during time period $t$, respectively.

IV. CASE STUDY

This section presents two experiments to demonstrate the applicability of the proposed model. The first experiment aims at calibrating the GPS sampling error ($e_{\text{sampling}}$) using real GPS data. The second experiment aims at estimating CO$_2$ emissions in Beijing using real-time traffic information collected by a real ITS system. A top–down approach was also carried out for comparison.

A. Calibration of the GPS Sampling Error

To quantify the GPS sampling error (i.e., $e_{\text{sampling}}$), the 137 km of second-by-second GPS data were collected in Beijing during both traffic peak and nonpeak hours on December 9–15, 2008. Because the GPS sampling error is mainly affected by the sampling time interval, these collected second-by-second GPS data were resampled into different time intervals from 2 s to 40 s. The cubic spline interpolation method was applied to interpolate these resampled GPS data into 1-s intervals. Then, the IVE model was applied to estimate the CO$_2$ emissions from both original and interpolated second-by-second GPS data. Consequently, the $e_{\text{sampling}}$ values in different sampling time intervals were obtained.

Fig. 2 illustrates the calculated $e_{\text{sampling}}$ under different sampling time intervals. In Fig. 2, the $x$-axis represents the sampling time intervals, whereas the $y$-axis represents the...
average $e_{\text{sampling}}$ values. Based on the collected data, the $e_{\text{sampling}}$ values were fitted as a function of sampling time intervals as

$$e_{\text{sampling}} = 0.19835 - 0.19532e^{-(x-0.72427)/7.33568}$$  \hspace{1cm} (14)

where $x$ is the sampling time interval (in seconds). The $R^2$ value of this fitting is 0.955, indicating the significance of the fitted function for this typical set of data.

B. Real-Time CO$_2$ Emissions in Beijing

This section reports the results of CO$_2$ emissions estimations using the real ITS traffic data. In Beijing, real-time traffic information is provided by an advanced travel information system (ATIS) (http://www.bjjtw.gov.cn/bmfw/sslk/) that was sponsored by the Beijing Municipal Committee of Transportation. As shown in Fig. 3, the highway system of Beijing consists of four major ring roads and arterial radial roads that connect these ring roads. AITS in Beijing can provide the real-time traffic information of such a highway system in every 2 min.

In this ATIS, the fixed embedded loop detectors and floating-car detectors are deployed to generate the real-time traffic information. The locations of 390 deployed loop detectors are illustrated in Fig. 3. It is shown in the figure that the average distance between the adjacent loop detectors is about 940 m. More than 20,000 taxis in Beijing are used as probe vehicles in the floating-car system. Most GPS data are collected within 1-min intervals. Trajectories of occupied taxis are recorded every 40 s, whereas trajectories of unoccupied taxis are collected every 20 s. In this case study, real-time traffic information that was collected by these loop detectors and floating-car system on December 9, 2008 (Tuesday) was obtained to estimate real-time CO$_2$ emissions.

The detailed vehicle technologies distribution profile in Beijing (i.e., vehicle distributions of various engine sizes, fuel types, air conditioning system usages, transmission types, vehicle ages, and catalytic converter usages) and adjusted vehicle emission rates $Q_k$ and $f_{\lambda,k,\varphi,t}$ in (11) were obtained from a technology report [39] and the IVE official website (http://www.issrc.org/ive/).

Based on the collected data, the CO$_2$ emissions were calculated using our proposed method. It was found that the total CO$_2$ emissions in the Beijing highway system on this typical day were 7341 tons. The detailed hourly CO$_2$ emissions are given in Fig. 4.

It is shown in Fig. 4 that there were two emission peaks in the diurnal time and one clear trough in nocturnal time. The two emissions peaks were during traffic peak hours around 8–10 A.M. (morning peak) and 5–7 P.M. (evening peak). The CO$_2$ emissions during these peak hours were about 500 (12.9%) and 550 (13.6%) tons, respectively. It is clearly shown in the figure that the hourly CO$_2$ emission rate was very low from 10 P.M. to 7 A.M. and was only 99 tons (12.2%). The lowest hourly emission rate was 45 tons during the 3–4 A.M. period.
Based on these observations, results of the calculated CO$_2$ emissions seem to be consistent with the daily traffic pattern of the Beijing highway system.

The spatial distributions of CO$_2$ emissions were also investigated. Because road segments in this case study had different lengths, the CO$_2$ emissions at road segments were normalized by their lengths. Fig. 5 illustrates the spatial distribution of CO$_2$ emissions during a peak hour (5–6 P.M.). Note that each road in this figure is represented into two directed roads (i.e., northbound and southbound). It is shown in the figure that the CO$_2$ emissions were spatially unbalanced. Basically, the nearer the road is to the geographic center of the city, the higher the emission rate (in kilograms per kilometer per hour) becomes. The emissions on inner ring and radial roads (connecting the inner ring roads) were much higher than the outer ring roads. The highest normalized emission rate could reach 5000 kg/km/h at the areas around Beijing West Railway Station (A) and Xidan Commercial District (B), and Zhongguancun Commercial Center (C) and Chaoyang Business District (D) due to their high traffic demands. The lowest normalized emission rate at the Fifth Ring Road was only 50 kg/km/h. This indicates that the inner ring and radial roads were facing more pressure on reducing CO$_2$ emissions.

**C. Comparison Study**

A well-known top–down approach that was introduced by the Intergovernmental Panel on Climate Change (IPCC) was adopted in this paper to make a comparison with our proposed approach. The IPCC approach is based on fuel used data to estimate the CO$_2$ emissions [40]. Detailed data for the IPCC approach is shown in Tables I–III. The CO$_2$ emissions from the road transport can be estimated by

$$\text{Emissions}_{\text{CO}_2} = \left( \frac{\text{Liters}}{\text{Kilometer}} \right) \cdot \left( \frac{\text{Mass CO}_2}{\text{Liter}} \right) \cdot (\text{KilometersTraveled}) \quad (15)$$

where Liters/Kilometer is the vehicle-technology-related parameter used to describe the fuel economy of a vehicle, Mass CO$_2$/Liter is the fuel-related parameter for estimating the amount of CO$_2$ emission produced by each unit of fuel, and KilometersTraveled is the traffic activity parameter for representing the travel distance of total vehicles.

In this case study, the fuel-related parameter Mass CO$_2$/Liter was obtained from the U.S. EPA. According to the EPA, 1 L of gasoline and diesel can approximately produce 2.325 and 2.66 kg of CO$_2$, respectively [41]. The CO$_2$ emissions generated by natural gas can approximately be estimated by 1.922 kg of CO$_2$ per cubic meter [42].

To obtain the Liters/Kilometer parameter in (15), the survey results, as reported by the China Association of Automobile Manufactures (CAAM) and China Automotive Technology and Research Center (CATARC) in 2009, were adopted in this paper [43]. In this survey, the average fuel consumption rates for all categories of vehicles in Beijing were obtained. The percentage and average vehicle fuel economy data in terms of four major vehicle types (i.e., private cars, taxis, buses, and trucks) were given in Table I.

The KilometersTraveled parameter in (15) was adopted from a recent survey that was conducted in major highways of Beijing. In 2004, Tsinghua University, Beijing Technology, Business University, and the International Sustainable Systems Research Center (ISSRC) in cooperation with the UCR conducted a survey to obtain the vehicle kilometers traveled for vehicles in different vehicle types [39]. The average travel distance per vehicle per day on the highway in Beijing and the distributions of highway vehicle traveled distance for each hour were also given in Tables II and III.

Based on the aforementioned collected survey data, the CO$_2$ emissions in 2004 were calculated using the IPCC approach and shown in Fig. 6. Because of the lack of KilometersTraveled survey data in 2008, a simple adjustment factor was calculated. It was reported that the volume of vehicles increased from 22,960,000 in 2004 to 35,040,000 in 2008. Accordingly, the CO$_2$ emissions in 2008 were also obtained and shown in Fig. 6.

The aforementioned results of the IPCC approach were used to validate the CO$_2$ emissions generated by our proposed approach. As shown in Fig. 6, the solid blue line refers to the CO$_2$ emissions generated by our proposed approach in 2008, whereas the green and orange dot lines, respectively, refer to the CO$_2$ emissions generated by the IPCC approach in 2004 and 2008.

It can be observed in Fig. 6 that the CO$_2$ emissions calculated by the IPCC approach and our approach have a similar pattern. For example, the peak CO$_2$ emissions were around 9 A.M. and 5 P.M. The hourly CO$_2$ emissions rapidly increased from 6 A.M. to 7 A.M. but quickly dropped from 6 P.M. to 7 P.M. The lowest hourly emissions occurred during 3–4 A.M. In addition, the CO$_2$ emissions calculated by these two methods were very close in off-peak hours (i.e., from 9 P.M. to 7 A.M.).

A significant distinction, however, can also be found between the results generated by these two approaches for peak hours of the year 2008 (i.e., from 8 A.M. to 10 P.M.). For example,
Fig. 5. Spatial distribution of CO$_2$ emission rate (in kilograms per kilometer per hour) of the Beijing highway system during a peak hour (5:00–6:00 P.M., December 9, 2008).

According to the IPCC approach results, the average hourly CO$_2$ emissions during 8–9 A.M. were 715 tons. According to our proposed approach, the CO$_2$ emissions at the same time period were only 459 tons. This result was 28.1% lower than that of the IPCC approach.

This distinction may be due to several reasons from different aspects. First, the result calculated by the IPCC approach was the average hourly CO$_2$ emissions for the whole year. The result generated by our approach was the hourly CO$_2$ emissions of a typical Tuesday. The seasonal and daily variations may lead to this distinction. Second, a simple adjustment parameter was used to calculate the CO$_2$ emissions in 2008 from that generated by the IPCC approach in 2004 due to the lack of updated survey data. This simple treatment may contribute to such result distinction. Last but not least, the IPCC results were
obtained from the different sources of survey data conducted at different time periods and with various levels of data quality. The survey errors of these collected data may also contribute to the result distinction. Therefore, such result distinction, to some extent, reflects the lack of capabilities of the top–down approach (similar to the IPCC) in monitoring real-time CO$_2$ emissions.

V. CONCLUSION

In this paper, a bottom–up vehicle emission model has been proposed to estimate real-time CO$_2$ emissions using ITS technologies. In the proposed model, the road segment was adopted as a basic spatial unit to estimate CO$_2$ emissions to explicitly consider the effects of heterogeneous speeds within the road link. The GPS and loop detector data that were collected by ITS applications were employed to generate detailed vehicle technology and driving patterns for all vehicles in the road network. The low-frequent GPS data were matched onto the road network and interpolated into second-by-second speed profiles to calculate the vehicle driving pattern data (i.e., travel speed and acceleration) for each road segment. The traffic flow data that were collected by loop detectors were processed to calculate the vehicle kilometers traveled data for each road segment and to estimate the vehicle technology data based on the identified vehicle-type data. Based on these calculated detailed vehicle technology and driving pattern data, the CO$_2$ emissions were estimated using the IVE model.

A real-world case study was carried out in Beijing to demonstrate the applicability of the proposed model. The CO$_2$ emission error due to low-frequent GPS data was investigated and calibrated. The spatiotemporal distributions of CO$_2$ emissions from the Beijing highway system were analyzed and discussed. It was found that the CO$_2$ emissions in Beijing are spatially unbalanced. An effective traffic measure is required to reduce high CO$_2$ emissions on inner ring roads and the radial roads that connect the ring roads. The results of the case study indicated that the proposed model can be a valuable tool for monitoring real-time CO$_2$ emissions in a large-scale city (such as Beijing) with a high spatiotemporal resolution.

In this paper, traffic data that were collected by two popular ITS technologies (i.e., floating-car system and loop detectors) have been employed. The proposed model can be extended to other types of ITS traffic data. For example, traffic flows and travel speeds can also be obtained by video detectors. In addition, the proposed model relies on ITS traffic data to estimate CO$_2$ emissions, and thus, the applicability of the proposed model depends on the availability of ITS infrastructures. Great strides have recently been made in ITSs toward a data-rich era (called data-driven ITS systems) [18]. For example, in Shanghai, China, the loop detectors have been installed at every network intersection [24]. With such data-driven ITS systems, the proposed method can be useful for monitoring real-time CO$_2$ emissions. In the proposed model, the estimation accuracy depends on the quality of collected ITS traffic data. In reality, inferior ITS traffic data may be caused by measurement errors (e.g., errors due to loading or unloading taxi passengers), sensor failures, and transmission failures. How we can quantify the CO$_2$ emission accuracy is required for further study. A roadside survey of CO$_2$ concentration is also needed to directly validate the proposed method.

REFERENCES

Bi Yu Chen received the B.S. degree in surveying and mapping engineering and the M.S. degree in geographical information science from Wuhan University, Wuhan, China, in 2003 and 2006, respectively, and the Ph.D. degree in transportation engineering from the Hong Kong Polytechnic University, Kowloon, Hong Kong, in 2012. He is currently a Lecturer and a Postdoctoral Fellow with the State Key Laboratory of Information Engineering in Surveying Mapping and Remote Sensing, Wuhan University. His research interests include intelligent transportation systems, transport geography, network reliability, and vulnerability modeling.

Qingquan Li received the M.S. degree in engineering and the Ph.D. degree in photogrammetry and remote sensing from Wuhan University, Wuhan, China, in 1988 and 1998, respectively. From 1988 to 1996, he was an Assistant Professor with Wuhan University, where he became an Associate professor from 1996 to 1998 and has been a Professor with the State Key Laboratory of Information Engineering in Surveying, Mapping, and Remote Sensing since 1998. He is currently the Executive Vice President of Wuhan University and the Director of the Engineering Research Center for Spatiotemporal Data Smart Acquisition and Application, Ministry of Education of China. He is an expert in Modern Traffic with the National 863 Plan and an Editorial Board Member of the *Surveying and Mapping Journal* and the *Wuhan University Journal—Information Science Edition*. His research interests include photogrammetry, remote sensing, and intelligent transportation systems.

Xiaohui Cui (M’02) received the B.S. degree from Wuhan Technical University of Surveying and Mapping, Wuhan, China, in 1992, the M.S. degree from Wuhan University in 2000, and the Ph.D. degree from the University of Louisville, Louisville, KY, in 2004. He is currently an Assistant Professor with the Computer Science Department, New York Institute of Technology. Meanwhile, he has served as a Staff Scientist with the Oak Ridge National Laboratory of the Department of Energy, Oak Ridge, TN. His research interests include swarm intelligence, GPU computing, agent-based modeling and simulation, cyber security, GIS and transportation, emergent behavior, complex systems, high-performance computing, social computing, and information retrieval. Dr. Cui is a member of the Association for Computing Machinery and the North American Association for Computational Social and Organizational Sciences.

Luliang Tang received the B.S. degree from Wuhan Technical University of Surveying and Mapping, Wuhan, China, in 1998 and the M.S. and Ph.D. degrees from Wuhan University in 2003 and 2007, respectively. He is currently an Associate Professor with the State Key Laboratory for Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University. His research interests include intelligent transportation systems, Geographic Information Systems for transportation, and spatial data change detecting.

Cheng Liu received the B.S. degree from the Chinese Cultural University, Taipei, Taiwan, in 1974, the M.S. degree from Taiwan Normal University, Taipei, in 1976, and the Ph.D. degree from the University of Tennessee, Knoxville, in 1986. He is currently an Adjunct Associate Professor with the Department of Geography, University of Tennessee and has served as a Staff Scientist with the Oak Ridge National Laboratory, Oak Ridge, TN. His research interests include geographic information systems, operations research, transportation modeling, algorithm design, supply chain management, software development, and high-performance geocomputing.