Journal of Cleaner Production xxx (2016) 1–9

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Carbon management of infrastructure performance: Integrated big data analytics and pavement-vehicle-interactions

Arghavan Louhghalam, Mehdi Akbarian, Franz-Josef Ulm*

Massachusetts Institute of Technology, Cambridge, MA, United States

ARTICLE INFO

Article history:
Received 25 October 2015
Received in revised form
5 June 2016
Accepted 30 June 2016
Available online xxx

Keywords:
Pavement-vehicle-interaction
Greenhouse gas emissions
Network analysis
Power-law distribution
Big data analytics

ABSTRACT

As a crucial part of the transportation system, roadway network provides mobility to the society and is vital for the economy. At the same time it contributes significantly to the environmental footprint during its construction, operation and maintenance. Hence, the sustainable development of our Nation's roadway system requires quantitative means to link infrastructure performance to lifecycle energy use and greenhouse gas emissions. Recent developments in mechanistic models of roughness- and deflection-induced pavement-vehicle interaction aim at providing such engineering estimates. Herein, it is demonstrated that these models when implemented at a network scale are a powerful basis for big data analytics of excess-energy consumption and carbon dioxide emissions by integrating spatially and temporally varying road conditions, pavement properties, traffic loads and climatic conditions. A novel ranking algorithm is proposed, that allows upscaling of the local carbon dioxide emissions due to pavement vehicle interaction to the size of state-wide or national sustainability goals. Implemented for 5157 lane-miles of the interstate highway system in the State of Virginia, sections contributing significantly to carbon dioxide emissions are identified. It is shown that the proposed ranking algorithm based on the inferred emission that exhibits a power-law distribution, provides the shortest path for greenhouse gas emissions savings per maintenance at network scale. That is, maintaining a few lane miles allows for a significant synergetic improvement of both infrastructure performance and environmental impact of the interstate network and helps transportation agencies in making economic and environmentally sustainable decisions.

1. Introduction

Accounting for 28% of the total United States greenhouse gas (GHG) emissions, the transportation sector, was the second largest contributor to the GHG emissions in 2012 (EPA, 2012). With more than four million miles of public roads, and with generation of 6526 million metric tons of Carbon Dioxide (CO_2) and total fuel consumption of around 168 billion gallons (FHWA, 2012) the US roadway network has a significant impact on the environment. Pavement condition, design and characteristics affect vehicle fuel consumption and the relating CO_2 emissions (Gyenes and Mitchell, 1994; Chatti and Zaabar, 2012). Thus maintaining the Nation's roadway network at good conditions, besides enhancing roadways performance, results in a more sustainable transportation system. However, by some estimates (U.S. Department of Transportation, Federal Transit Administration, 2013) maintaining the national highways at their current condition requires spending annually $95 to $109 billion during 2014 and 2020 respectively. The cost would increase to $161.7 and $184.2 billion to improve the condition. Given the limited financial resources of federal and state transportation agencies for road maintenance along with the initiatives for sustainable development, it is critical to develop fast and accurate frameworks for identifying the roads with higher environmental footprint, and to establish strategies for selecting pavement sections for maintenance that maximize investment returns in terms of the total network-level environmental impact.

While the environmental impact of material production (Huntzinger and Eatmon, 2009) and pavement construction and maintenance phases (Turk et al., 2016; Huang et al., 2009; Fernández-Sánchez et al., 2015) are widely studied in Life Cycle Assessment (LCA) of pavements, the use-phase impact is generally omitted in most of pavement LCA tools (Santero et al., 2011). Considering the fact that the impact of use phase for high volume

* Corresponding author.
E-mail address: ulm@mit.edu (F.-J. Ulm).

http://dx.doi.org/10.1016/j.jclepro.2016.06.198

traffic roads is significant and can surpass other embodied emissions (Wang et al., 2012; Araújo et al., 2014) the need to close this gap is evident.

Rolling resistance − due to pavement roughness, texture (Sandberg et al., 2011) and deflection − can contribute 15%–50% to the total vehicle fuel consumption, depending on vehicle speed (Beuving et al., 2004), and is one of the main factors in pavement's use-phase environmental footprint. Although small for a single vehicle, the aggregated impact for pavement sections with high traffic volume can exceed other factors contributing to the lifecycle footprint of pavements (Wang et al., 2012; Noshadravan et al., 2013). Pavement-vehicle-interaction (PVI) models quantitatively assess this footprint by taking into account the impact of different pavement characteristics and designs, and existing climatic and traffic conditions in the roadway network, on the energy dissipation and the ensuing excess fuel consumption. These models are thus important components in evaluating pavement sustainability performance. Furthermore, when combined with information at the network level, they can serve as a means to guide carbon management policies aiming at reduction of CO_2 emissions in roadway networks.

Herein, an approach is proposed that integrates roughness- and deflection-induced PVI models with various databases, which are available to transportation agencies, to identify pavement sections with the greatest potential for CO_2 emissions reduction at the network scale. By way of example, using big data analytics, the spatial and temporal variation of CO_2 emissions in the network of Virginia interstate highways due to the change in road condition and design is investigated, while considering variation in climatic conditions and traffic loads. In addition, a ranking algorithm for network maintenance strategy is proposed that results in both maximum reduction of use-phase CO_2 emissions at the network scale and improvement of infrastructure performance simultaneously.

2. Pavement-vehicle-interaction (PVI) models

The first step in development of a framework for an optimal maintenance strategy is to quantify the impact of pavement characteristics, environmental conditions and vehicle properties on excess vehicle fuel consumption and the corresponding CO_2 emission. While empirical investigations highlight the existence of correlation between fuel consumption and pavement structural (Taylor, 2002; Taylor and Patten, 2006; Gschösser and Wallbaum, 2013), and surface properties (Taylor et al., 2000; Zaniewski et al., 1982), until recently the link between several pavement characteristics and vehicle fuel consumption was missing. Newly developed deflection-induced (Pouget et al., 2011; Louhghalam et al., 2013) and roughness-induced PVI models (Chatti and Zaabar, 2012; Velinsky and White, 1980; Louhghalam et al., 2015) aim at closing this gap by establishing a link between mechanical properties of pavements and vehicle fuel consumption.

The underlying concept behind the PVI models is that to maintain a constant speed, the dissipated energy due to rolling resistance must be compensated by extra engine power which results in excess vehicle fuel consumption and GHG emissions. Deflection- and roughness-induced PVI models respectively account for the dissipation of energy in pavement material and vehicle suspension system. The impact of pavement texture on vehicle fuel consumption has not taken into account in the network analysis due to lack of available information.

2.1. Deflection-induced PVI

The recently developed deflection-induced PVI (Louhghalam et al., 2013) provide a means to quantitatively assess the impact of pavement characteristics (e.g., subgrade modulus, pavement thickness, stiffness and viscosity) and climatic conditions on vehicle fuel consumption.

The key underlying principal behind deflection-induced PVI is: the energy dissipated within pavement material due to its viscoelasticity must be compensated by an external energy source, leading to excess fuel consumption. Using the first and second laws of thermodynamics, it is shown that the dissipated energy per distance travelled $\delta\varepsilon$ is directly related to the slope underneath the wheel in a moving coordinate system that is attached to and traveling with the tire with speed V, i.e. $\delta\mathscr{E} = -Pdw/dX$, where P is the axle load, dw/dX is the average slope at tire-pavement trajectory in the moving coordinate system $X = x - Vt$, with x and t denoting coordinates of space and time in a fixed coordinate system (Louhghalam et al., 2013). It is worth noting that in this coordinate system, the maximum deflection of an elastic material subjected to a moving tire occurs exactly under the tire. That means the average slope, thus the deflection-induced energy dissipation is zero for an elastic material, which is in agreement with the laws of thermodynamics.

The pavement is modeled as an infinite viscoelastic beam on an elastic foundation subjected to an axle load traveling with a constant speed V in steady-state condition. The constitutive relation between stress σ and strain ε of the viscoelastic material is described by a Maxwell model, $(\sigma + \tau\dot{\sigma})/E = \tau\dot{\varepsilon}$, with the Young's modulus E and relaxation time $\tau = \eta/E$, where η is the material viscosity and the superposed dot denotes time derivative. The differential equation of beam's displacement w in the moving coordinate system:

$$\frac{Eh^3}{12}\frac{d^4w}{dX^4} + mV^2\frac{d^2w}{dX^2} + kw = p \tag{1}$$

with h pavement thickness, k subgrade stiffness and m surface mass density, is solved in the frequency domain, by using the elastic-viscoelastic correspondence principle (Christensen, 1982). The average slope at the tire-pavement trajectory and ultimately the energy dissipation within the material is evaluated (see Louhghalam et al. (2013) for detailed solution).

Substituting this involving mathematical procedure with an accurate and computationally efficient expression is the next crucial task in developing models that are practical for big data analytics of network-scale analysis. This is achieved by rationalizing the problem through a dimensional analysis of physical quantities involved in the dissipated energy per distance travelled, $\delta\varepsilon$, namely subgrade stiffness k, pavement stiffness E, thickness h, width b, and relaxation time τ, as well as temperature T, vehicle axle load P and speed V. The analysis allows for further reduction of the problem to a 2-parameter relation between the dimensionless dissipation $\Pi = \delta\mathscr{E}Vbkl_s^2/V_{cr}P^2$ and dimensionless vehicle speed V/V_{cr} and relaxation time $\tau V_{cr}/l_s$ using Buckingham Π-theorem Buckingham (1914):

$$\Pi = \frac{\delta\mathscr{E}Vbkl_s^2}{V_{cr}P^2} = \mathscr{F}\left(\Pi_1 = \frac{V_{cr}}{V}; \Pi_2 = \frac{\tau V_{cr}}{l_s}\right) \tag{2}$$

with $V_{cr} = l_s k/m$, and $l_s = (Eh^3/12k)^{1/4}$ the Winkler length of the beam. The analysis above also provides scaling relationship of energy dissipation with different pavement mechanical properties, vehicle characteristics and temperature:

$$\delta\mathscr{E} \propto (V\tau)^{-1} \times P^2 \times E^{-1/4} \times h^{-3/4} \times k^{-1/4} \tag{3}$$

Note that the functional relation $\mathscr{F}$ in expression (2) cannot be evaluated using the Π-theorem and must be determined by numerical simulation. To this end for a wide range of practical dimensionless variables Π_1 and Π_2 ($0.03 < \Pi_1 < 0.5$ and $0.0001 < \Pi_2 < 12000$) in (2) the equation of motion (1) is numerically solved and the average slope and the dimensionless dissipations is evaluated. Ultimately a surrogate model is presented by fitting a 2-dimensional surface (with coefficient of variation $R^2 = 0.97$) to the exact numerical solution (see Louhghalam et al. (2014) for details):

$$\log_{10}\delta\mathscr{E} = 3 - \log_{10}\frac{Vbkl_s^2}{P^2V_{cr}} + \sum_{i=0}^{5}\sum_{j=0}^{3}p_{ij}\left(\frac{V}{V_{cr}}\right)^i \times \left(\log_{10}\frac{\tau(T)V_{cr}}{l_s}\right)^j \tag{4}$$

The regression coefficients p_{ij} along with the 95% confidence intervals are given in Table 1. Finally the instantaneous fuel consumption associated with this dissipation is evaluated as $\delta\mathrm{IFC}_D = \delta\mathscr{E}/\zeta_f$, with ζ_f the energy content of fuel equal to 34.84 and 38.74 Megajoules (MJ) per liter for gasoline and diesel respectively (EPA, 2004).

The temperature sensitivity of the dissipated energy is due to the temperature dependency of relaxation time $\tau(T)$ of the viscoelastic material leading to a variation of the complex stiffness. Time-temperature superposition principal is used to take into account this impact and to evaluate the relaxation time of the linear viscoelastic material at any given temperature T in terms of the relaxation time at a reference temperature T_0, i.e., $\tau(T) = \tau(T_0)a_T$. The shift factor a_T for bituminous and cementitious materials are respectively obtained from the empirical relationship of William-Landel-Ferry (Williams et al., 1955):

$$\log a_T = \frac{-c_1(T - T_0)}{c_2 + (T - T_0)} \tag{5}$$

with constants $c_1 = 34$, $c_2 = 203^\circ$ K and the reference temperature $T_0 = 283^\circ$ K (Pouget et al., 2011), and the Arrhenius law (Arrhenius, 1889):

$$\log a_T = U_c\left(\frac{1}{T} - \frac{1}{T_0}\right) \tag{6}$$

with $U_c = 2700^\circ$ K (Bazant, 1995). The characteristic relaxation time at the reference temperature T_0=10° C is obtained by calibration of the model against the results of a three-dimensional model reported by Pouget et al. (2011) and is equal to 0.0083 s (see Louhghalam et al. (2014) for the details of model calibration and validation).

2.2. Roughness-induced PVI

The impact of road roughness on excess CO_2 emissions is quantified using the Highway Development Management-4 (HDM-4) model, which is a vehicle operating cost model originally developed by the World Bank (Bennett and Greenwood, 2001) and later calibrated for the United States vehicle conditions by Chatti and Zaabar (2012). The HDM-4 model uses the International Roughness Index (IRI) as the metric for road roughness. IRI is defined as the accumulated suspension motion of the golden-car (a 2-degree of freedom quarter-car with specific inertial and stiffness properties) traveling at a speed of 80 km/h per distance traveled. IRI has unit of slope (m/km) (Sayers et al., 1986) and is usually evaluated from road roughness profile measurements. The HDM-4 model uses other input parameters such as vehicle class and speed in addition to IRI and provides an estimate for the increase in vehicle instantaneous fuel consumption $\delta\mathrm{IFC}_R$ with IRI for five different vehicle classes, namely medium car, SUV, van, light truck and articulated truck. Using the HDM-4 model, for the practical ranges of vehicle speed and pavement IRI values ($30 < V$ (Km/h) < 130 and $0 <$ IRI (m/Km) < 6), an expression is developed for the roughness-induced excess fuel consumption in liter per kilometer:

Table 2
Coefficients β_c and γ_c for medium cars and heavy trucks used in (7).

Vehicle type	β_c	γ_c
Medium car	1.2098e^{-3}	2.8190e^{-2}
Heavy truck	4.4461e^{-3}	1.9899e^{-2}

$$\delta\mathrm{IFC}_R = \beta_c\langle\mathrm{IRI} - \mathrm{IRI}_0\rangle\left(1 + \gamma_c\frac{V}{3.6}\right) \tag{7}$$

where $\langle x\rangle = x$ if $x > 0$, otherwise $\langle x\rangle = 0$, and the coefficients β_c and γ_c are given in Table 2 for the two vehicle classes – namely medium car and heavy truck – that are used in the network-scale analysis in Section 4. Similarly the coefficients can be evaluated for other vehicle classes used in the HDM-4 model. In the above equation, IRI_0 is the reference roughness index after maintenance. The magnitude of reference IRI_0 is a pavement management policy decision of the roughness of new pavements and is selected to be 1 m/km herein, to remain consistent with the baseline used in the calibrated HDM-4 model (Chatti and Zaabar, 2012).

Validation of the mechanics-based models discussed above using both controlled experiments and field measurements is part of authors' ongoing research efforts (Coleri et al., 2015) where it has been shown that the excess fuel consumption estimates obtained through these models are generally in agreement with other PVI models that are computationally intensive and thus not intended for integration with big data and network level analysis.

The CO_2 emissions associated with vehicle fuel consumption are evaluated from CO_2 content of fuel reported as 2.322 and 2.664 kg per liter by EPA for gasoline and diesel, respectively (EPA, 2005).

3. Databases

Data for the network-scale analysis comes from a variety of sources. Information on pavement condition and design in the state of Virginia was obtained from the Virginia Department of Transportation (VDOT) and the Virginia Center for Transportation

Table 1
Coefficients p_{ij} used in (4) with the 95% confidence intervals.

j	i					
	0	1	2	3	4	5
0	−1.918 (−1.922, −1.915)	4.487 (4.379, 4.596)	−19.54 (−20.64, −18.44)	59.58 (54.61, 64.55)	−92.51 (−102.6, −82.39)	56.23 (48.63, 63.83)
1	−0.4123 (−0.4135, −0.4111)	−1.802 (−1.824, −1.78)	4.014 (3.864, 4.163)	−4.628 (−5.04, −4.217)	1.375 (0.9895, 1.761)	–
2	−0.06942 (−0.06969, −0.06915)	0.2153 (0.2111, 0.2194)	−0.8618 (−0.8794, −0.8441)	0.7344 (0.7124,0.7563)	–	–
3	−0.009575 (−0.009656,−0.009495)	0.0203 (0.0196, 0.021)	0.04669 (0.04542,0.04797)	–	–	–

Table 3
Pavement types and their corresponding length in Virginia interstate highways.

VA labels	Pavement type	Lane-mile	Center-mile
BIT	Asphalt (AC)	3131	1416
JRCP	Concrete (PCC)	360	119
CRCP	Concrete (PCC)	382	143
BOJ	Composite (CMP)	854	294
BOC	Composite (CMP)	430	183

Innovation and Research (VCTIR). The data consists of structural, material and surface properties of pavement sections along with their mileposts for five pavement types comprising the interstate highways, namely Bituminous (BIT), Joint Reinforced Concrete Pavement (JRCP), Continuous Reinforced Concrete Pavement (CRCP), Bituminous over JRCP (BOJ) and Bituminous over CRCP (BOC). The corresponding length of each pavement type in the network of Virginia interstate highways is summarized in Table 3. For each pavement section the dataset includes section identifier, milepost, pavement thickness, pavement and subgrade moduli along with measured IRI values. Pavement and subgrade moduli provided by Virginia Center for Transportation Research are obtained by back-calculation using the results of Falling Weight Deflectometer (FWD) testing which has been implemented at the network level by VDOT (Galal et al., 2007; Diefenderfer, 2010). In addition to these pavement properties, the data set also includes the annual average daily traffic (AADT) and truck traffic (AADTT) for seven years (2007–2013) for the entire interstate system. To match this data with its geographical location via Geographical Information System (GIS) (ArcGIS 10.2.2), the basemap of VA interstate highways from Federal Highway Administration's National Planning Network (NHPN, 2013) is used along with pavement section mileposts (see the Supporting information for the maps of IRI, pavement type and traffic).

The temperature data is obtained from the dataset of National Oceanic and Atmospheric Administration (NOAA) in the form of average monthly temperatures for six different climatic regions comprising the state of Virginia. Pavement mileposts enable finding the climatic regions and thus temperature variations for all pavement sections in the interstate highway network.

The information on vehicle speed in VA interstate highways is inferred from the Weigh In Motion (WIM) data provided by VDOT. The dataset consists of axle weight, gross vehicle weight and vehicle speed. The measured vehicle speeds are used to estimate speed probability density function (PDF) in Virginia interstate system. It is observed that the vehicle speeds in the network follow a Gaussian distribution with a mean value of 103.93 km/h and a standard deviation of 7.52. The Gaussian PDF is later used for a Monte-Carlo simulation in the network-scale analysis.

4. Network-scale analysis

Fast and straightforward implementation of PVI models provides a convenient tool to upscale pavement section emissions to the network scale environmental impact. To this end, the component level PVI models are integrated with the datasets described above to perform a network-level analysis. The flowchart of the network analysis illustrated in Fig. 1 summarizes how the data sets described in the previous section provide the inputs to the PVI models. The indicator of pavement roughness (IRI) and vehicle speed are the inputs to the roughness-induced PVI model (Equation (7) and Table 2), whereas pavement structural and material properties, temperature and vehicle speeds are used to estimate the deflection-induced energy dissipation and the relating CO_2 emissions (Equation (4) and Table 1).

To take into account the uncertainty associated with vehicle speed and its impact on the excess fuel consumption due to pavement roughness and deflection, a Monte-Carlo Simulation is performed. For each road section inverse transformation sampling is used to generate 1000 samples of vehicle speed according to the Gaussian PDF obtained from the WIM data (i.e. a set of 1000 independent uniformly distributed random variables, $U = u[0,1]$ is generated and the inverse of the Gaussian cumulative distribution function (CDF) at U, $X = \Phi_V^{-1}(U)$, is calculated) and evaluate the 95 percentile of the CO_2 emissions.

The structural and material data for this study were available from the Virginia Department of Transportation. However for cases where data is not available, an approach similar to the above can be

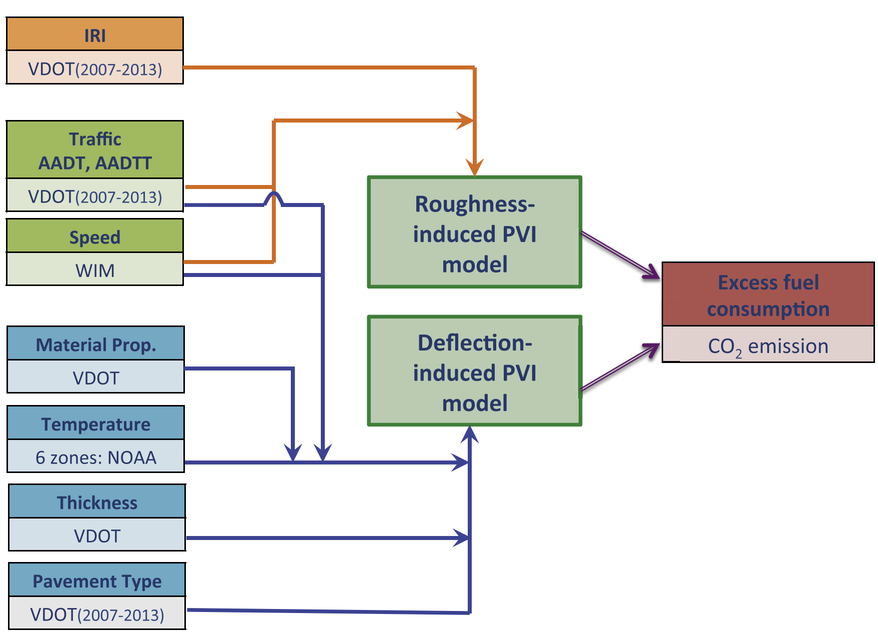

Fig. 1. Flow of network analysis; the inputs and the output of deflection- and roughness-induced PVI models.

Fig. 2. Spatial distribution of roughness- and deflection-induced excess CO_2 emissions in 2013 in the network of Virginia interstate highways.

used to find the confidence bounds of fuel consumption using the probability distributions of material and structural properties obtained either at the local level or at more global level, e.g., from the database of Long Term Pavement Performance (LTPP) program.

5. Results and discussion

The total annual contribution of roughness- and deflection-induced CO_2 emissions is studied separately for two classes of vehicles (passenger cars and five-axle trucks) and by aggregating the annual passenger-car and truck traffic volumes within the network. Distribution of the total excess CO_2 emissions in the roadway network in 2013 is shown in Fig. 2; the spatial variation of the excess CO_2 emissions in 2013 for medium cars and heavy trucks and for each of the dissipation mechanism are presented in the Supporting information. The results indicate high-concentration of excess CO_2 emissions around Washington DC and Richmond, which correspond to roads with both poor pavement condition and high traffic volume. Breakdown of the excess CO_2 emissions, based on different dissipation mechanisms (i.e. roughness- and deflection-induced PVI) and vehicle type, illustrated in Fig. 3, indicates that most of the PVI related emissions in Virginia interstate highways are due to roughness-induced car fuel consumption, and deflection-induced truck fuel consumption, whereas the contribution of deflection-induced car fuel consumption to the total GHG emissions is insignificant.

Upscaling of fuel consumption from pavement section to network-scale estimates provides a means for strategic maintenance planning when considering network-level carbon management. The challenge herein is to find the shortest path that results in maximum reduction of CO_2 emissions with minimum lane-mile of road maintenance. In this regard, an important feature emerges from ranking of total excess CO_2 emissions in Virginia interstate highways due to pavement deflection and roughness, with lowest ranking given to the section with highest excess CO_2 emissions. The rank-magnitude plot of the excess emissions exhibits a power-law behavior with the exponent of 0.36 for a wide range of sections with high CO_2 emissions (see Fig. 4). The inset in Fig. 4 shows the probability that CO_2 exceeds a particular value x, $P(CO_2 > x)$, which equates $1-$ CDF. The tail of the distribution, associated with high emission road sections, exhibits a power-law behavior akin to Zipf's law (Newman, 2005; Zipf, 1949), i.e. a probability distribution, where the probability $p(x)$ of measuring a particular value x varies inversely as a power function of that value, i.e. $p(x) = Cx^{-\alpha}$, with C a normalization constant, and α the power-law exponent, that is slope of the PDF in logarithmic scale. Power-law behavior appears in a wide range of phenomena such as magnitudes of earthquakes (Gutenberg and Richter, 1944), frequency of words (Zipf, 1949;

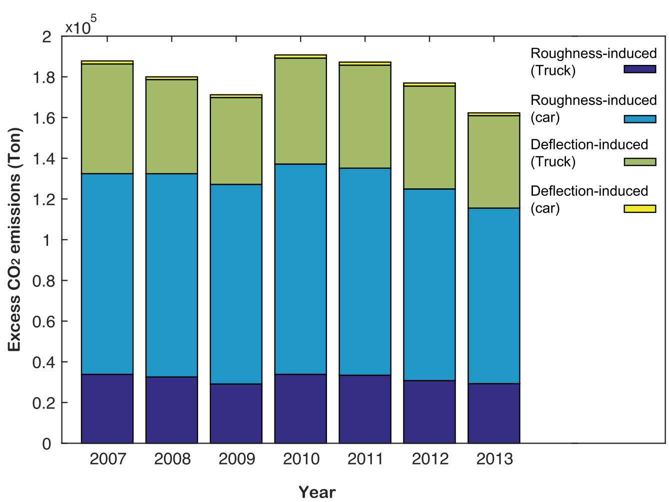

Fig. 3. Total annual excess CO_2 emissions (Tons) for a 7-year period (2007–2013) in Virginia interstate highways; different colors show the contribution of different vehicle classes (cars versus trucks) and dissipation mechanisms (roughness- versus deflection-induced pavement vehicle interaction). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

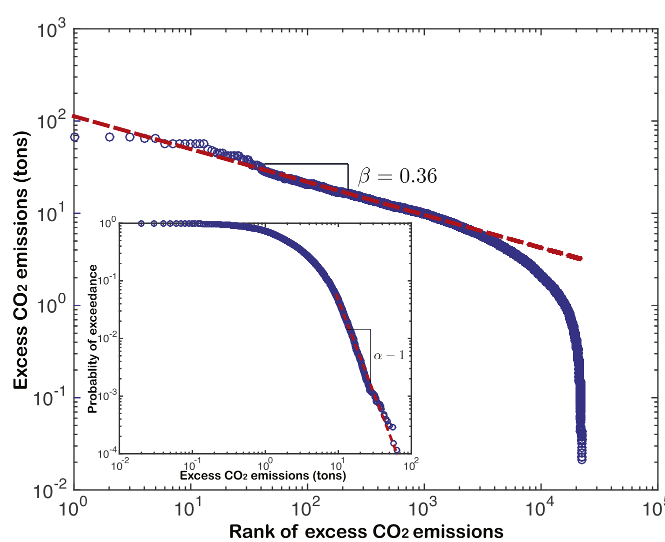

Fig. 4. Excess CO_2 emissions in function of its rank. Inset figure shows the probability that the excess CO_2 emissions exceeds a particular value, i.e. $1-$ CDF.

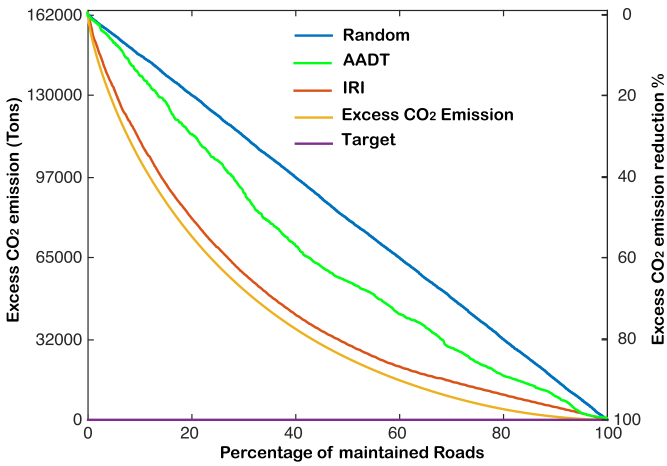

Fig. 5. Comparison of different road selection strategies for maintenance in terms of emission reduction potential. Selection strategies include random selection, selection based on annual average daily traffic (AADT), international roughness index (IRI) and fuel consumption.

Estoup, 1916), citation of papers (Redner, 1998; de S. Price, 1965) among others. For the network of Virginia interstate highways the exponent of power-law distribution at its tail is estimated using maximum likelihood as $\alpha = 4.32$. The head of distribution which deviates from power law corresponds to the road sections with negligible excess CO_2 emissions.

It can be shown that percentage reduction of CO_2 emissions r is related to the power-law exponent α (see Appendix A for the detailed derivations):

$$r = \left(\frac{m}{N}\right)^{\frac{2-\alpha}{1-\alpha}} \times 100 \tag{8}$$

where m/N is the ratio of maintained roads to total roads. Note that the above expression is valid when the phenomenon has a full power-law distribution. In case of the excess CO_2 emission for which only the tail follows a power-law behavior, the above expression provides a lower bound to the emission reduction and the reduction of CO_2 emission is greater that r.

Given the underlying power-law distribution of CO_2 emissions, ranking based on this metric enables separating the few road sections with high excess CO_2 emissions, from the many low impact ones. Hence, it provides the shortest path for the network-level CO_2 emission reduction and an optimal framework for maintenance management strategy. Such maintenance strategy maximizes the potential for excess fuel consumption and CO_2 emissions reductions for a constant given maintenance activity. Herein, the CO_2 emission reduction rate of selecting pavement sections based on this ranking scheme is compared with selection based on other criteria, such as randomly maintaining the roads, choosing the roads based on traffic volume and the current practice of selecting roads based only on their IRI values. The result of this comparison, shown in Fig. 5, reveals that an informed selection based on ranking PVI-induced emissions, which is an integration of road conditions, traffic loads and climatic conditions, leads to a maximum reduction rate of CO_2 emissions per lane-mile maintained. To further illustrate the significance of benefits that can be gained from ranking of total CO_2 emissions at network scale, the ranked road sections are categorized into ten groups, each representing 10% of the total excess CO_2 emissions and illustrated with different colors in Fig. 6. Combining such data with GIS technologies provides a tool to graphically highlight the locations with high potentials of emissions reduction. Note that maintaining respectively 1.59% and 4.24% of the total analyzed lane-miles in Virginia roadway network (sections represented respectively, by red and orange colors in Fig. 6) will result in 10% and 20% reduction of total excess CO_2 emissions. The same result would require maintaining 9.81% and 19.78% of the lane-miles when using random selection, 6.94% and 13.4% when using high traffic volume roads, and 2.36% and 5.52% when selecting road sections based only on the IRI values. The significance of improvement is more pronounced noting that while 1% of Virginia interstate highways include more than 500 lane-miles, for larger states with bigger roadway networks even 1% can translate to thousands of miles.

One should note that the above analysis does not take into account the environmental footprint associated with maintenance and rehabilitation, nor it includes the emission corresponding to maintenance-related congestions. Furthermore, the method herein is based on current pavement conditions, and provides a means to select the roads for maintenance. A comprehensive optimal maintenance strategy must also take into account the environmental footprint for different maintenance procedures to provide guidance not only for selection of roads for maintenance, but also for the maintenance procedure that results in minimum environmental impact over the full lifecycle of the pavement. This requires, in addition to the embodied emission of various maintenance procedures, models that can predict the time evolution of pavement properties such as material and structural durability models. However, if such information is available it can be included in the proposed ranking algorithm to

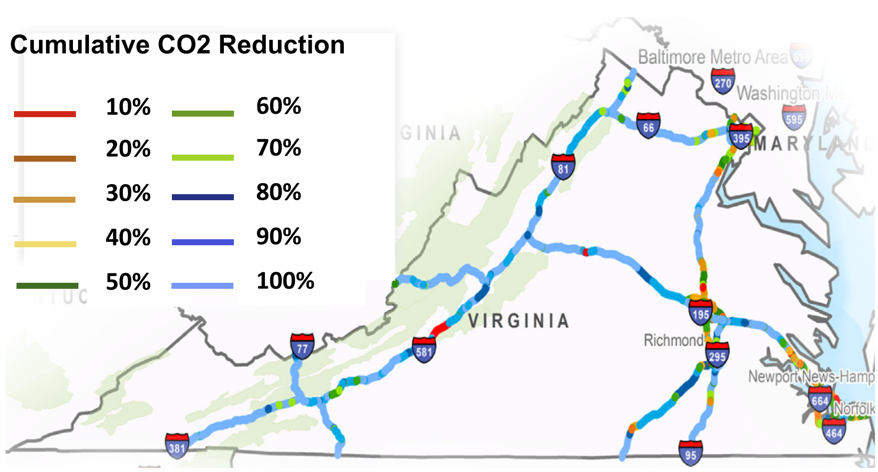

Fig. 6. Map of potential excess CO_2 emissions reduction in Virginia roadway network for 2013. Road sections represented by red color are the ones with highest potential for GHG reduction if selected for maintenance. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Please cite this article in press as: Louhghalam, A., et al., Carbon management of infrastructure performance: Integrated big data analytics and pavement-vehicle-interactions, Journal of Cleaner Production (2016), http://dx.doi.org/10.1016/j.jclepro.2016.06.198

arrive at an optimal maintenance strategy considering the full lifecycle emissions of roadway networks.

6. Conclusion

To conclude, a method is proposed that integrates data on pavement structural and surface condition, car and truck traffic, climatic condition, and weigh in motion measurements with computationally efficient PVI modeling to perform a comprehensive network-scale analysis that provides estimates of the total excess CO_2 emissions associated with pavement roughness and deflection. The models used in the network-scale analysis are easy to implement and require a minimum amount of input parameters, which are typically available to agencies. In case of missing data and to account for the uncertainty of input variables, it is shown that a Monte Carlo simulation scheme can be used to find the confidence bounds of excess fuel consumption and the corresponding CO_2 emissions. When applied at the network level, such an approach can guide the shortest path towards the reduction of excess CO_2 emissions by informed selection of roads for maintenance. As such, it can serve as an additional criterion for an optimal maintenance and rehabilitation and ideally as a tool to reduce CO_2 emissions in conjunction with a full lifecycle assessment (i.e. by including embodied emissions, maintenance emissions, and other lifecycle impacts necessary to fully capture the potential savings) and powerful available optimization algorithms. The proposed approach thus contributes to closing the gap by integrating the network level use-phase environmental impact in pavement LCA.

In addition, integration of pavement condition data and GIS provides a pavement management system with capabilities to graphically display pavement conditions and maintenance decisions through their lifetime. Finally using efficient and easy to implement model-based approaches for large data analytics, transportation agencies can go beyond the distress-based pavement management systems and go a long way in making economically and environmentally sustainable network-level decisions.

Acknowledgement

This research was carried out by the CSHub@MIT with sponsorship provided by the Portland Cement Association (PCA) and the Ready Mixed Concrete (RMC) Research & Education Foundation. Data for the Virginia interstate system analysis was provided by the Virginia Department of Transportation (VDOT) and the Virginia Center for Transportation Innovation & Research. The CSHub@MIT is solely responsible for content.

Appendix A. Impact of power-law exponent on effectiveness of ranking algorithm

A.1. Power-law distribution

The probability density function of a random variable X with power-law distribution with parameters $x_{\min}$ and α, $(\alpha > 2)$ can be expressed as:

$$f_X(x) = Cx^{-\alpha} = (\alpha - 1)\frac{x^{-\alpha}}{x_{\min}^{1-\alpha}} \tag{A.1}$$

where the constant C is determined by normalizing the area under the probability distribution function to unity. The exceedance probability which is one minus the cumulative distribution function is expressed as (Newman, 2005):

$$P(X > x) = 1 - F_X(x) = \frac{x^{1-\alpha}}{x_{\min}^{1-\alpha}} \tag{A.2}$$

A.2. Ranking Algorithm

Consider a roadway network with the total of N equal length road segments. The goal of ranking algorithm is to select $m < N$ road segments such that the total impact (e.g., CO_2 emissions) T is reduced by r percent.

Let the impact of each road section be represented by $X_i\{i = 1,2,\cdots,N\}$. One can write the total impact as $T = N \times E[X]$ (assuming $\alpha > 2$ ensures that $E[X]$ is finite). Let a new random variable $Y=\{X|X > x_m\}$ represent the maintained roads. Using conditional probability, the probability density function of Y can be expressed in terms of the probability density function of X:

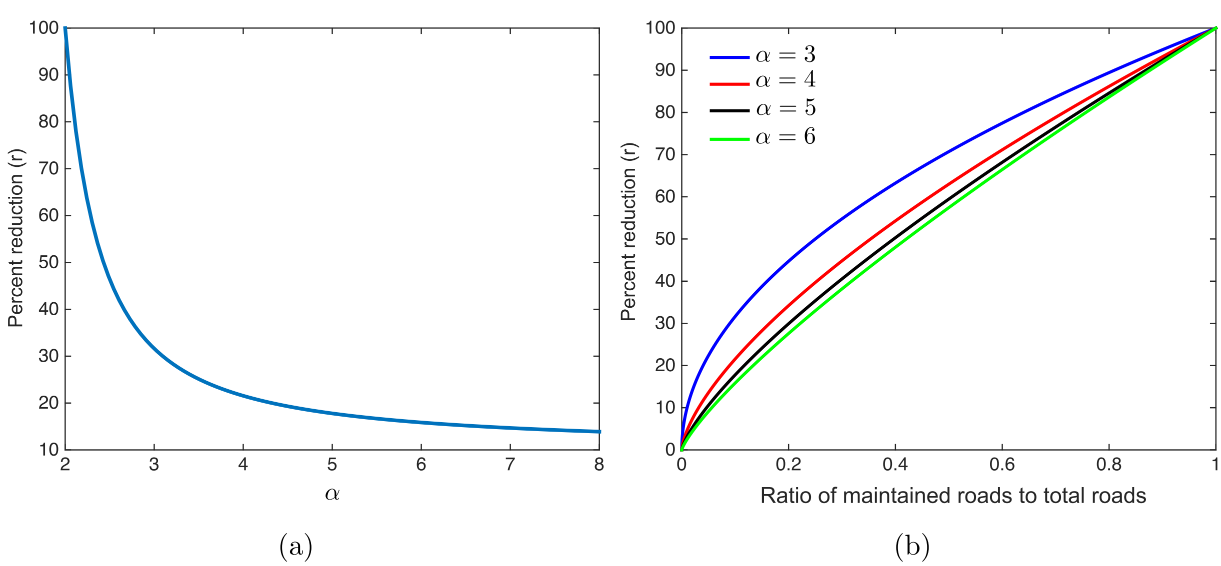

Fig. A1. Effectiveness of ranking algorithm in the form of percent impact reduction ($r \times 100$), (a) in function of α for 10% maintained roads; (b): in function of ratio of maintained roads and for different values of α.

Please cite this article in press as: Louhghalam, A., et al., Carbon management of infrastructure performance: Integrated big data analytics and pavement-vehicle-interactions, Journal of Cleaner Production (2016), http://dx.doi.org/10.1016/j.jclepro.2016.06.198

$$f_Y(y) = \frac{f_X(y)}{\int_{x_m}^{\infty} f_X(x)\mathrm{d}x} \tag{A.3}$$

Thus the expected value of Y is readily evaluated:

$$E[Y] = \frac{1}{\int_{x_m}^{\infty} f_X(x)\mathrm{d}x} \int_{x_m}^{\infty} y f_X(y)\mathrm{d}y \tag{A.4}$$

To determine the effectiveness of ranking algorithm it is necessary to obtain the relationship between r and the total number of maintained road segments m. To this end one needs to find x_m such that $m \times E[Y] = r \times N \times E[X]/100$. Also it is easy to show that $m = N \int_{x_m}^{\infty} f_X(x)\mathrm{d}x$. Thus using Equation (A.4) one can write:

$$\int_{x_m}^{\infty} y f_X(y)\mathrm{d}x = \frac{r}{100} \int_{x_{\min}}^{\infty} x f_X(x)\mathrm{d}x \tag{A.5}$$

Assuming the impact follows a power-law distribution with parameters $x_{\min}$ and α, the above expression can be written in terms of the exponent α:

$$\int_{x_m}^{\infty} y^{1-\alpha}\mathrm{d}y = \frac{r}{100} \int_{x_{\min}}^{\infty} x^{1-\alpha}\mathrm{d}x \tag{A.6}$$

For a fixed value of lane-mile maintenance m, the percent reduction in the impact is:

$$r = \left(\frac{m}{N}\right)^{\frac{2-\alpha}{1-\alpha}} \times 100 \tag{A.7}$$

Alternatively for a fixed percentage of impact reduction (r) one needs to maintain m road segments where:

$$\log m = \frac{1-\alpha}{2-\alpha} \log \frac{r}{100} + \log N \tag{A.8}$$

Fig. A1(a) shows the percent reduction in function of α for 10% road maintenance ($m/N = 0.1$). It can be observed that the effectiveness of the ranking algorithm decreases as α increases. Fig. A1(b) shows the effectiveness of ranking algorithm r in function of ratio of maintained roads to total roads m/N for different values of α>2. For instance to achieve 10% CO_2 reduction one needs to maintain 1%, 3.2%, 4.6% and 5.6% respectively if $\alpha = 3$, 4, 5, and 6.

It is worth noting that the above analytical expression is valid when a phenomenon follows a full power-law distribution. In case of the network-level CO_2 emissions, where only the tail of distribution has a power-law behavior, the above expression provides the lower bound for r and the real reduction percentage is more significant.

Appendix B. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jclepro.2016.06.198.

References

Araújo, J.P.C., Oliveira, J.R., Silva, H.M., 2014. The importance of the use phase on the lca of environmentally friendly solutions for asphalt road pavements. Transportation Research Part D: Transp. Environ. 32, 97–110.
ArcGIS 10.2.2,. Environmental Systems Research Institute (Esri), Geographical Information System. Accessed 2015.
Arrhenius, S., 1889. Über die reaktionsgeschwindigke it bei des inversion von rohrzuckerdurch säuren. Zeitsch. Phys. Chem. 4, 226–248.
Bazant, Z., 1995. Creep and damage in concrete. Mater. Sci. Concr. IV 355–389.
Bennett, C.R., Greenwood, I.D., 2001. Modelling road user and environmental effects in hdm-4. HDM-4 Highw. Dev. Manag. 7. www.hdm-ims.com. Website visited January 2, 2009.
Beuving, E., De Jonghe, T., Goos, D., Lindahl, T., Stawiarski, A., 2004. Fuel efficiency of road pavements. In: Proceedings of the 3rd Eurasphalt and Eurobitume Congress Held Vienna, May 2004.
Buckingham, E., 1914. On physically similar systems; illustrations of the use of dimensional equations. Phys. Rev. 4, 345–376.
Chatti, K., Zaabar, I., 2012. Estimating the Effects of Pavement Condition on Vehicle Operating Costs, Project 1–45. National Cooperative Highway Research Program, Report 720.
Christensen, R., 1982. Theory of Viscoelasticity: an Introduction. Academic Press.
Coleri, E., Harvey, J.T., Zaabar, I., Louhghalam, A., Chatti, K., 2015. Model development, field section characterization and model comparison for excess vehicle fuel use due to pavement structural response. accepted for publication in the transportation research record J. Transp. Res. Board.
Diefenderfer, B.K., 2010. Investigation of the Rolling Wheel Deflectometer as a Network-level Pavement Structural Evaluation Tool. Technical Report VTRC 10-R5. Virginia Transportation Research Council, Charlottesville, VA.
EPA, 2004. Unit Conversions, Emissions Factors, and Other Reference Data. Accessed 2015.
EPA, 2005. Average Carbon Dioxide Emissions Resulting Form Gasoline and Diesel Fuel. Accessed 2015.
EPA, 2012. Inventory of us Greenhouse Gas Emissions and Sinks: 1990-2010. Accessed 2015.
Estoup, J.B., 1916. Les Gammes Sténographiques. Institut Stnographique de France.
Fernández-Sánchez, G., Berzosa, Á., Barandica, J.M., Cornejo, E., Serrano, J.M., 2015. Opportunities for ghg emissions reduction in road projects: a comparative evaluation of emissions scenarios using co 2 nstruct. J. Clean. Prod. 104, 156–167.
FHWA, 2012. Highway Statistics (Washington, Dc: Annual Issues). U.S. department of transportation, federal highway administration. Accessed 2015.
Galal, K.A., Diefenderfer, B.K., Alam, J., 2007. Determination by the Falling Weight Deflectometer of the In-situ Subgrade Resilient Modulus and Effective Structural Number for I-77 in Virginia. Technical Report VTRC 07-R1. Virginia Transportation Research Council, Charlottesville, VA.
Gschösser, F., Wallbaum, H., 2013. Life cycle assessment of representative swiss road pavements for national roads with an accompanying life cycle cost analysis. Environ. Sci. Technol. 47, 8453–8461.
Gutenberg, B., Richter, C.F., 1944. Frequency of earthquakes in california. Bull. Seismol. Soc. Am. 34, 185–188.
Gyenes, L., Mitchell, C., 1994. The effect of vehicle-road interaction on fuel consumption. In: Vehicle-road Interaction. ASTM International.
Huang, Y., Bird, R., Heidrich, O., 2009. Development of a life cycle assessment tool for construction and maintenance of asphalt pavements. J. Clean. Prod. 17, 283–296.
Huntzinger, D.N., Eatmon, T.D., 2009. A life-cycle assessment of portland cement manufacturing: comparing the traditional process with alternative technologies. J. Clean. Prod. 17, 668–675.
Louhghalam, Arghavan, Akbarian, Mehdi, Ulm, Franz-Josef, 2013. Flügge's conjecture: dissipation-versus deflection-induced pavement–vehicle interactions. J. Eng. Mech. 140 (8), 04014053.
Louhghalam, A., Akbarian, M., Ulm, F-J., 2014. Scaling relationships of dissipation-induced pavement-vehicle interactions. Transp. Res. Rec. J. Transp. Res. Board 2457, 95–104.
Louhghalam, A., Tootkaboni, M., Ulm, F.J., 2015. Roughness-induced vehicle energy dissipation: statistical analysis and scaling. J. Eng. Mech. 04015046.
Newman, M.E., 2005. Power laws, pareto distributions and zipf's law. Contemp. Phys. 46, 323–351.
NHPN, 2013. United States Department of Transportation, Federal Highway Administration's National Highway Planning Network, Version 11.09. Accessed 2015.
NOAA,. Monthly or Seasonal Time Series of Climate Variables, National Oceanic and Atmospheric Administration. Accessed 2015.
Noshadravan, A., Wildnauer, M., Gregory, J., Kirchain, R., 2013. Comparative pavement life cycle assessment with parameter uncertainty. Transp. Res. Part D Transp. Environ. 25, 131–138.
Pouget, S., Sauzéat, C., Benedetto, H.D., Olard, F., 2011. Viscous energy dissipation in asphalt pavement structures and implication for vehicle fuel consumption. J. Mater. Civ. Eng. 24, 568–576.
Redner, S., 1998. How popular is your paper? an empirical study of the citation distribution. Eur. Phys. J. B Condens. Matter Complex Syst. 4, 131–134.
de S. Price, D., 1965. Network of scientific papers. Science 149, 510–515.
Sandberg, U., Bergiers, A., Ejsmont, J.A., Goubert, L., Karlsson, R., Zöller, M., 2011. Road Surface Influence on Tyre/road Rolling Resistance. Swedish Road and Transport Research Institute (VTI). Prepared as part of the project MIRIsAM, Models for rolling resistance In Road Infrastructure Asset Management systems. Available on the World Wide Web:¡. http://www.miriam-co2.net/Publications/MIRIAM_SP1_Road-Surf-Infl_Report20111231.
Santero, N.J., Masanet, E., Horvath, A., 2011. Life-cycle assessment of pavements. part i: critical review. Resour. Conserv.ation Recycl. 55, 801–809.
Sayers, M.W., Gillespie, T.D., Queiroz, A., 1986. The international road roughness experiment. Establishing correlation and a Calibration standard for

measurements. Technical Report HS-039 586. Word Bank.
Taylor, G., 2002. Additional Analysis of the Effect of Pavement Structure on Truck Fuel Consumption. Prepared for Government of Canada Action Plan 2000 on Climate Change. Concrete Roads Advisory Committee.
Taylor, G., Marsh, P., Oxelgren, E., 2000. Effect of Pavement Surface Type on Fuel Consumption-phase Ii: Seasonal Tests. Portland Cement Association, CSTT-HWV-CTR-041, Skokie, IL.
Taylor, G., Patten, J., 2006. Effects of Pavement Structure on Vehicle Fuel Consumption-Phase III. Technical Report CSTT-HVC-TR-068. Center for Surface Transportation Technology.
Turk, J., Pranjić, A.M., Mladenovič, A., Cotič, Z., Jurjavčič, P., 2016. Environmental comparison of two alternative road pavement rehabilitation techniques: cold-in-place-recycling versus traditional reconstruction. J. Clean. Prod. 121, 45–55.
U.S. Department of Transportation, Federal Transit Administration, 2013. 2013 status of the Nation's Highways, Bridges and Transit: Conditions and Performance. Accessed 2016.
Velinsky, S.A., White, R.A., 1980. Vehicle energy dissipation due to road roughness. Veh. Syst. Dyn. 9, 359–384.
Wang, T., Lee, I.S., Kendall, A., Harvey, J., Lee, E.B., Kim, C., 2012. Life cycle energy consumption and ghg emission from pavement rehabilitation with different rolling resistance. J. Clean. Prod. 33, 86–96.
Williams, M.L., Landel, R.F., Ferry, J.D., 1955. The temperature dependence of relaxation mechanisms in amorphous polymers and other glass-forming liquids. J. Am. Chem. Soc. 77, 3701–3707.
Zaniewski, J.P., Butler, B., Cunningham, G., Elkins, G., Paggi, M., 1982. Vehicle Operating Costs, Fuel Consumption, and Pavement Type and Condition Factors. Technical Report PB-82–238676. Texas Research and Development Foundation.
Zipf, G.K., 1949. Human Behavior and the Principle of Least Effort. Addison-Wesley, Menlo Park, CA.

Please cite this article in press as: Louhghalam, A., et al., Carbon management of infrastructure performance: Integrated big data analytics and pavement-vehicle-interactions, Journal of Cleaner Production (2016), http://dx.doi.org/10.1016/j.jclepro.2016.06.198