Formulation of Traffic Inputs Required for the Implementation of the M-E PDG in Data-Scarce Regions: Lebanon Case Study

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Abstract: The implementation of the *Mechanistic-Empirical Pavement Design Guide* (M-E PDG) in regions outside the United States and Canada, such as the Middle East and North Africa region (MENA), is still in its early stages due to the scarcity of the design input data required for its use at high reliability levels. Several studies have been carried out to present correlations for obtaining material properties as well as exploring the use of M-E PDG embedded climate files to account for the missing inputs and different environmental conditions. Yet, the main challenge resides in obtaining adequate traffic data and adapting local traffic inputs for M-E PDG default values. This paper presents guidelines for developing truck classification and growth factors from short-term traffic count surveys for countries where historical traffic data are unavailable or insufficient. The case of Lebanon is tackled as a case study for demonstration. The sensitivity of the pavement response to the variation of the extrapolated traffic input data is studied under different climatic and material conditions and validated against recent characterized and categorized traffic data. The results reveal that highway design agencies can process traffic count surveys to convert them into traffic input data as elaborated in the methodology, as the pavement's performance is not majorly affected by the variations and assumptions used in the calculations of the truck classes. However, the variation in the truck traffic volume, i.e., growth factor, significantly influences the predicted pavement distresses, which necessitates the continuous collection of traffic data to have more representative values for the growth rate estimation. Based on the obtained results, final recommendations are presented for the implementation of the M-E PDG in regions lacking traffic records. **DOI: 10.1061/(ASCE)MT.1943-5533.0002279.**

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Introduction

Background

For decades, extensive efforts have been exerted to come up with simple yet effective and reliable methodologies for flexible pavement design. As of late, the *Mechanistic-Empirical Pavement Design Guide* (M-E PDG), applied through the use of the AASHTOware Pavement ME software, is being used by some highway agencies in the United States (Roesler and Hiller 2013). A recent survey found that, in the United States, 46 states are working toward the implementation of the M-E PDG (Robins et al. 2014) and only three states—Oregon, Missouri, and Indiana—have fully adopted the mechanistic-empirical method as their pavement design procedure. The others still use the empirical design methods (Pierce and McGovern 2014).

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Currently, significant research is being carried out to facilitate the adoption of the M-E PDG as it requires thorough input from the designer (Li et al. 2011). In the United States, the Indiana Department of Transportation (Galal and Chehab 2005) and Maricopa transportation department in Arizona adopted an implementation plan based on a series of sensitivity analysis studies. The studies underline the necessity of collecting design input data, establishing a suitable database, and developing guided methodologies on the collection of the needed input parameters for the practical implementation of the M-E PDG according to local conditions (Robins et al. 2014; Souliman et al. 2011). The same was proposed for New England states (Ayyala et al. 2010).

Similarly, in Romania, efforts have been focused on evaluating the implementation of the M-E PDG to obtain reliable and cost-effective pavement design (Plescan and Plescan 2014). The study concluded that the adoption of the M-E PDG requires a great quantity and quality of input data, mainly traffic and material characterization.

In addition to the above, a study was carried out on the implementation of the M-E PDG in Latin American countries (Delgadillo et al. 2011). Local input axle-load distributions, weather, and material data were collected for Chile, and the distress prediction models were calibrated based on preliminary calibration factors for the region. The pavement designs obtained were compared upon using M-E PDG versus the local design methods, namely, the AASHTO (1993, 1998) methods. The study highlights the importance of switching to the implementation of the M-E PDG for pavement design and reveals that the local load spectra vary significantly from the default load spectra. Yet, M-E PDG can be implemented in Latin America if efforts are put into data collection.

As for the MENA region, road authorities in Saudi Arabia have been considering the use of the mechanistic empirical methods in pavement design. As such, research has been conducted to collect the required data for the calibration and implementation of the M-E PDG (Alqaili and Alsoliman 2017), in which the materials' properties were obtained from the Materials and Research Department of the Saudi Ministry of Transportation; climate files were developed from records of meteorological stations and corresponding correlations; and traffic characteristics were developed from traffic counts such as annual average daily traffic (AADT), hourly distribution factors, percentage of vehicle types, and vehicle classification.

Besides the full implementation plans and methodologies explored, numerous studies have been developed to target the necessary materials and climate data specifically from laboratory testing and the correlations available in the literature. A recent study in Qatar promoted the use of the mechanistic-empirical methods in the country and the region by underlining the significance of investing in the calibration of material and damage prediction models for more accurate results of pavement performance (Sadek et al. 2014). Likewise, efforts have been focused on the development of new approaches to tackle the scarcity of climatic data and to create reference files for local climatic conditions outside of the United States and Canada. An up-to-date study concluded that it is possible to rely on M-E PDG embedded climate files with matching climate for their use as climatic input in cases where records from meteorological stations are unavailable (Chehab et al. 2017).

Nevertheless, the major challenge remains in obtaining adequate traffic data suitable for the implementation of the M-E PDG. Unlike the 1993 AASHTO design guide that is based on the cumulative expected 80 kN (18-kip) equivalent single axle loads (ESALs) (AASHTO 1993), the M-E PDG requires very detailed and site-specific traffic load spectra and truck configuration inputs, which are typically recorded by weigh-in-motion (WIM) stations (MDOT 2015). Since this type of data is not available in several regions and is expensive to acquire, alternatives for developing and acquiring suitable traffic data from rather simplistic methods and assumptions are being explored.

A study in Virginia investigated the effect of using the M-E PDG default traffic inputs for flexible pavement design versus using site-specific data by comparing the differences in pavement response (Smith and Diefenderfer 2010). Traffic data were analyzed from records of eight interstate weigh-in-motion sites in Virginia. The results revealed that the variation in the distress models was not statistically significant. However, using the site-specific developed axle-load spectra resulted in an increase in the predicted time to failure as compared to the default traffic inputs. Therefore, it was recommended to collect site-specific axle-load spectra data for analysis of flexible pavements; nevertheless, default inputs can be taken for the remaining traffic parameters.

Another methodology was developed for creating traffic input data from raw records of WIM stations in Michigan when site-specific records are not available for the M-E PDG implementation (Haider et al. 2011). Vehicle classifications and axle-load data were obtained from records of WIM from different sites in Michigan stations to obtain Level 1 data, and cluster analysis was used to group the different sites into broader regions in the state for Level 2 analysis. Finally, the traffic data for the different sites was averaged to obtain a database for a statewide traffic characterization (i.e., Level 3). A sensitivity analysis was done to study the influence of the three input levels on the predicted performance. The results revealed that it is recommended to use the Level 1 analysis for pavement design in case of availability of the required detailed inputs. If site-specific data are not available, a sensitivity analysis should be carried out to assess whether Level 2 or Level 3 data are acceptable and to determine the minimum quantitative data requirements for different traffic characteristics.

On the other hand, accurate estimation of truck flow and growth rate are crucial for the design of new pavements and predicting the behavior of existing pavements. According to a study carried out on the effect of time coverage of traffic data collection on pavement M-E Design in Oklahoma, a minimum of 48-h site-specific truck class count data are needed to obtain acceptable vehicle class distribution inputs (Li et al. 2016). Different traffic input data scenarios collected from records of 20 WIM stations were created and used to simulate different lengths and times of coverages of traffic data, and the variations in the pavement response for each scenario were compared. Findings revealed that it is necessary to collect site-specific traffic input data as the variations in truck volumes and weights variations affect the pavement response. Therefore, relying on regional or national default inputs would result in errors in the pavement response.

Another research study conducted in California illustrated the importance of careful selection of parameters used in truck traffic growth models (Li et al. 2009). It revealed that state departments of transportation (DOTs) cannot rely on small number of observations to estimate growth rates; instead, it is recommended to have at least 6 years of traffic data to be used for parameter estimations. In addition, the use of socioeconomic factors to directly predict truck traffic growth rates resulted in inaccurate performance predictions, yet some factors such as population density and growth, land use, and highway functional classifications can be associated with traffic growth and can be of significant help for pavement engineers when selecting appropriate defaults for traffic growth rates.

Objectives

This paper focuses on obtaining traffic inputs for the implementation of the M-E PDG in countries with insufficient data. The main objectives of this study are as follows:

1. Outline current challenges and constraints in implementing the M-E PDG in countries with insufficient data, mainly of traffic, with a focus on Lebanon that is tackled as a case study;
2. Offer guidelines for developing traffic data suitable for the M-E PDG implementation from traffic count surveys in countries lacking a traffic classification database; and
3. Validate the proposed methodology and the assumptions carried to obtain the traffic data by studying the predicted performance of pavement using these data across different climatic and material conditions.

Methodology

In order to meet the stated objectives of this study, traffic input data were first collected from the concerned agencies and firms. The acquired data were evaluated and analyzed, and estimations of truck classification and growth factors were suggested based on site-specific conditions and assumptions. Sensitivity analysis runs—in which the traffic design inputs were varied within the typical ranges for Lebanon—were performed to test the validity of the proposed traffic data acquirement methodology. This methodology was also tested by varying the climatic and material conditions to include its application for the implementation of the M-E PDG in other countries in and outside of the MENA region. The analysis focused on performance measures such as longitudinal cracking, alligator cracking, total rutting, and international roughness index (IRI).

Finally, based on the sensitivity of the pavement response to the variations in the traffic input data, a final plan for the implementation has been proposed to address the problem of traffic data unavailability and incompatibility with the requirements of the M-E PDG.

Traffic Data Collection and Processing

For the case of Lebanon, the available traffic data originate from surveys conducted for geometric highway design and traffic analysis. There are no traffic data available for the purpose of pavement design in Lebanon, such as vehicle classification and categorization or vehicle weights. The Ministry of Public Works and Transport in Lebanon does not provide any systematic approach to monitor and classify registered vehicles, trucks in particular, as per the Federal Highway Administration classification system. It only classifies vehicles according to their weight, of which it distinguishes two types: vehicles that weigh less than 10 t and those that weigh more than 10 t (El Hajj Chehade 2016). This poor characterization and categorization of vehicles does not serve for the implementation of the new pavement design procedures.

For this study, traffic data were gathered from traffic count surveys conducted in 2002 for the National Physical Master Plan of the Lebanese Territory (DAR, IAURIF 2002). The aforementioned surveys were executed to obtain a database of the national and regional strategic trip-making characteristics in Lebanon. The results of the surveys provided traffic counts on different major routes in Lebanon. Nevertheless, in this paper only data from selective stations located on major coastal highways were considered for the sensitivity analysis.

Description of the 2002 Traffic Surveys

The data stem from short-duration traffic counts conducted over the course of 1 day from 6:00 a.m. to 7:00 p.m. and in 30-min intervals in 2002. Also, the counts were divided according to the vehicle type (passenger cars, SUVs, pickup trucks, vans, minibuses, buses, trucks, motorcycles, and other types) and not by the vehicle's class. The trucks were categorized into large goods vehicles (LGVs), medium goods vehicles (MGVs), and heavy goods vehicles (HGVs) according to the European Union Descriptions (European Commision 2016).

The software requires traffic characterization, including site-specific vehicle class distribution characterization, which was not available in the surveys. However, having these surveys as the sole available source of traffic data in Lebanon, it was deemed necessary to carry and apply assumptions to adjust the input data to serve as a reference for any future use for pavement design purposes. The underlying assumptions, as elaborated hereafter, were based on several factors that can be adjusted depending on the type of traffic counts and their accuracy and on the country's needed information and guidelines for pavement design.

Estimation of the Annual Average Daily Truck Traffic

Two-way annual average daily truck traffic (AADTT) is defined as the total volume of truck traffic passing through a segment of a road in both directions during a 24-h period. Since the data are not collected over the entire 24-h period, the available daily truck traffic is assumed to be representative of that period. In Lebanon, truck traffic volume is very minimal during the late hours of the night (after 8:00 p.m.) and early mornings (before 6:00 a.m.) (DAR, IAURIF 2002); therefore, the missing counts during these time intervals are taken as null values. The AADTT computed from the surveys corresponds to 2002 as mentioned earlier. Many political events happened in nearby regions, such as the ongoing war in Syria, which entailed a variation in the annual average truck traffic volume (Al-Monitor 2016). Thus, in order not to obtain underdesigned pavement, the design should be based on recent traffic volumes representing the actual situation and the base year in which the construction of a pavement will happen; consequently, a projection of the AADTT from 2002 to predict the traffic volumes foreseen in the present time (i.e., 2016) is needed. This projection is based on a compound growth factor applied to each truck class (Table 1).

Characterization of Truck Traffic

Typically, vehicle class distribution is computed using vehicle-classifying counting programs such as automatic vehicle classifi-

Table 1. Truck traffic growth factors used to calculate the expected number of trucks in 2016 from the 2002 survey counts

Vehicle class	Growth rate (%)	Growth function
Class 4	1.46	Compound
Class 5	1.62	
Class 6	0.56	
Class 7	0.56	
Class 8	0.56	
Class 9	0.56	
Class 10	0.56	
Class 11	2.89	
Class 12	2.89	
Class 13	2.89	

Table 3. Sensitivity analysis over the MGV/HGV truck categories

Truck categories adopted in the 2002 survey	Buses	LGV	MGV/HGV
Available truck counts in each category from the 2002 survey	300	728	546
Scenario 1	300	728	30% are MGV 70% are HGV
Scenario 2 (control values)	300	728	40% are MGV 60% are HGV
Scenario 3	300	728	50% are MGV 50% are HGV
Scenario 4	300	728	60% are MGV 40% are HGV
Scenario 5	300	728	70% are MGV 30% are HGV

Table 2. Available truck counts and categorization from the 2002 survey with the suggested corresponding FHWA classification

Truck categories adopted in the 2002 survey	Buses	LGV	MGV/HGV
Available truck counts in each category from the 2002 survey	300	728	546
Corresponding FHWA truck classes	Class 4	Classes 5 and 6	• MGV: Classes 7, 8, and 9 • HGV: Classes 10, 11, 12, and 13

Table 4. Distribution of truck classes within each category

Truck categories adopted in the 2002 survey	Buses	LGV	MGV	HGV
Truck counts in each category from the 2002 survey (assuming control scenario from Table 3)	300	728	218 (40% of 546)	328 (60% of 546)
Corresponding FHWA truck classes	Class 4	Classes 5 and 6	Classes 7, 8, and 9	Classes 10, 11, 12, and 13
Assumed percentage of each class within each category (control values)	100% of buses are Class 4	• 70% of LGV are Class 5 • 30% of LGV are Class 6	• 80% of MGV are Class 7 • 10% of MGV are Class 8 • 10% of MGV are Class 9	• 98% of HGV are Class 10 • 2% of HGV are Class 11 • 0% of HGV are Class 12 • 0% of HGV are Class 13

Note: The assumed percentage of each class within each category are changed for the sensitivity analysis as shown later in Table 12.

Table 5. Truck counts within each truck class according to the 2002 survey and their projection to 2016

FHWA truck classes	Class 4	Class 5	Class 6	Class 7	Class 8	Class 9	Class 10	Class 11	Class 12	Class 13
Truck count in each class within each category (control values) 2002	300 (100% of buses)	509 (70% of LGV)	219 (30% of LGV)	174 (80% of MGV)	22 (10% of MGV)	22 (10% of MGV)	321 (98% of HGV)	7 (2% of HGV)	0 (0% of HGV)	0 (0% of HGV)
Compound growth factor (%)	1.46	1.62	0.56	0.56	0.56	0.56	0.56	2.89	2.89	2.89
Projected truck counts to 2016	367	638	638	189	24	24	347	10	0	0

cation, weigh-in-motion, and automated traffic counts (ATC) or through manual counts. The Federal Highway Administration (FHWA) and the US Census Bureau categorize vehicles as medium duty (Classes 3–5) with gross vehicle weight rating (GVWR) between 4,536 kg (10,001 lbs) and 8,619 kg (19,001 lbs), light heavy duty (Class 6) with GVWR between 8,619 kg (19,001 lbs) and 11,793 kg (26,000 lbs) and heavy duty (Classes 7 and 8) with GVWR over 11,793 kg (26,000 lbs) (DOE 2016). According to the European Union terms, any truck with gross vehicle weight over 3,175 kg (7,000 lbs) is referred to as a heavy goods vehicle (also a large goods vehicle and medium goods vehicle) (European Commission 2016).

The lack of resources in Lebanon made it necessary to process the data available from the ATC surveys and assign classes to vehicles based on visual observations and typical types of trucks available in the country. In this paper, the following distribution is adopted: all buses are considered Class 4 vehicles; the LGVs are divided into Classes 5 and 6; the MGVs into Classes 7–9; and the HGVs into Classes 10–13. Table 2 shows an example of the available truck counts obtained from the 2002 survey as well

Table 6. Design input parameters of the base layer of type "crushed stone"

Sieve	Percent passing minimum–maximum
#200	5–20
#40	15–30
#10	20–45
#4	30–60
9.525 mm (3/8 in.)	40–75
25.4 mm (1 in.)	75–95
50.8 mm (2 in.)	100–100
Plasticity index	6
Liquid limit	25
Maximum dry unit weight	20 kN/m^3 (128.1 pcf)

Table 8. Dynamic shear modulus $|G^*|$ and phase angle of the unmodified binder

Temperature [°C (°F)]	$\lvert G^*\rvert$ (Pa)	Delta (degrees)
52 (125.6)	5,940	86.3
58 (136.4)	2,578	87.5
64 (147.2)	1,176	88.4
70 (158)	569	88.9
76 (168.8)	294	89.1

Table 7. Dynamic modulus E* of the asphalt concrete mix with unmodified binder

Temperature [°C (°F)]	$\lvert E^*\rvert$ [kPa (psi)]					
	20 Hz	10 Hz	5 Hz	1 Hz	0.5 Hz	0.1 Hz
−6.89 (19.6)	33,034,899 (4,791,307)	31,892,782 (4,625,657)	30,661,765 (4,447,113)	27,463,735 (3,983,278)	25,947,716 (3,763,398)	22,158,019 (3,213,749)
4.44 (40)	23,041,134 (3,341,834)	21,345,514 (3,095,905)	19,610,634 (2,844,282)	15,534,233 (2,253,050)	13,808,834 (2,002,802)	10,037,071 (1,455,754)
21.11 (70)	8,893,203 (1,289,850)	7,511,011 (1,089,380)	6,256,137 (907,376)	3,873,544 (561,810)	3,077,344 (446,331)	1,712,299 (248,348)
37.78 (100)	2,707,144 (392,638)	2,107,445 (305,659)	1,619,827 (234,936)	842,629 (122,213)	626,878 (90,921)	310,333 (45,010)
51.67 (125)	1,269,752 (184,162)	956,420 (138,717)	713,773 (103,524)	353,274 (51,238)	259,953 (37,703)	129,435 (18,773)

Table 9. Dynamic modulus $|E^*|$ of the asphalt concrete mix with modified binder

Temperature [°C (°F)]	$\|E^*\|$ [kPa (psi)]					
	25 Hz	10 Hz	5 Hz	1 Hz	0.5 Hz	0.1 Hz
−10 (14)	28,527,099 (4,137,506)	27,666,296 (4,012,657)	26,962,238 (3,910,542)	25,147,035 (3,647,269)	24,287,465 (3,522,599)	22,119,064 (3,208,099)
4.44 (40)	23,091,363 (3,349,119)	21,812,702 (3,163,665)	20,799,304 (3,016,684)	18,319,922 (2,657,080)	17,211,893 (2,496,374)	14,599,800 (2,117,522)
21.11 (70)	14,514,698 (2,105,179)	13,026,706 (1,889,364)	11,920,436 (1,728,913)	9,470,694 (1,373,608)	8,486,902 (1,230,921)	6,416,516 (930,637)
37.78 (100)	6,294,417 (912,928)	5,263,527 (763,410)	4,561,889 (661,646)	3,191,597 (462,902)	2,708,240 (392,797)	1,808,322 (262,275)
54.44 (130)	1,726,344 (250,385)	1,346,346 (195,271)	1,109,215 (160,878)	695,943 (100,938)	566,060 (82,100)	399,896 (58,000)

Table 10. Dynamic shear modulus $|G^*|$ and phase angle of the modified binder

Temperature [°C (°F)]	$\|G^*\|$ (Pa)	Delta (degrees)
76 (168.8)	1,948	66.0
82 (179.6)	1,212	64.1
88 (190.4)	808	60.9

Table 11. Design input parameters for the subgrade of type A-2-6

Sieve	Percent passing
#200	21.5
#100	29
#60	36
#40	41
#20	54
#10	69
#4	81.5
9.525 mm (3/8 in.)	93
19.05 mm (3/4 in.)	97
38.1 mm (1 1/2 in.)	100
Plasticity index	21
Liquid limit	43
Maximum dry unit weight	19.37 kN/m^3 (123.3 pcf)

as the assigned FHWA truck classes within each category (buses, MGV, LGV, HGV).

The most common load type carried by pickup trucks and MGVs is food, while HGVs are mostly seen to carry building construction materials and are the predominant category of trucks in Lebanon (DAR, IAURIF 2002). Therefore, based on frequently observed trucks maneuvering the Lebanese highways, it is only logical to allocate a higher percentage of the total count of MGV/HGV for HGVs (60% for HGV and 40% for MGV), while leaving the LGVs and buses categories as 100% each (Table 3). After obtaining the counts for each category, the subcategories (classes) were also assigned a percentage of the counts obtained based on the frequency of the observed classes on the Lebanese highways under consideration. For example, Class 4 under the buses category was given 100% of the counts; Classes 5 and 6 that were assigned to the LGVs category were given values of 70% and 30%, respectively, because it is more probable to observe Class 5 trucks; Classes 7–9 that are under the MGVs category were distributed into 80, 10, and 10%, respectively; and Classes 10–13 that are part of the HGVs category were assigned values of 98, 2, 0, and 0%, respectively. These percentages are illustrated in Table 4. Finally, Table 5 represents the projection of the 2002 truck counts (obtained in Table 4) to the year 2016 using the growth factors from Table 1. These 2016 truck counts are used later in the M-E PDG runs.

Effect of Varying Truck Classification Percentages on the Performance of Pavements

M-E PDG Runs

A sensitivity analysis was done to test the validity of the approach presented to convert from the truck categorization adopted in the survey (LGV, MGV, and HGV) to the classification required by the M-E PDG software (Classes 4–13), by:

1. Varying the percentages of different categories of trucks (MGV and HGV), and
2. Trying different combinations of realistic percentages of classes within each category (LGV, MGV, and HGV). These combinations

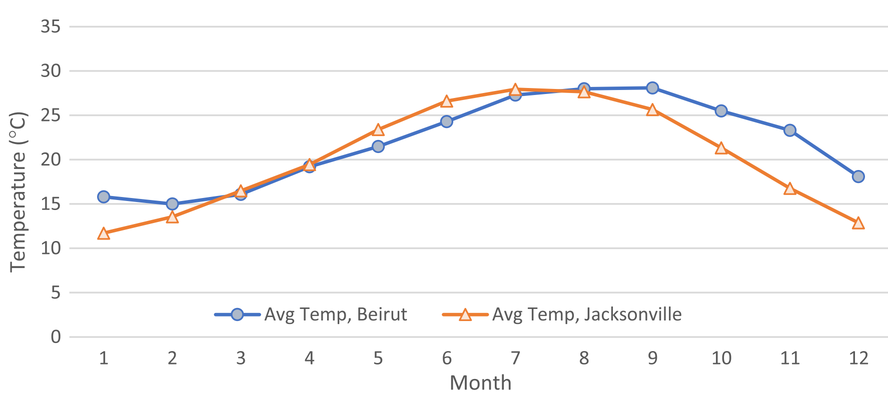

Fig. 1. Average monthly temperatures for Beirut and Jacksonville.

Table 12. Input variables for the sensitivity analysis runs corresponding to Phase 1

Parameter under study	Input percentages	Run number: Jacksonville, unmodified binder, A-2-6 subgrade	Jacksonville, modified binder, A-2-6 subgrade	Texas, unmodified binder, A-2-6 subgrade	Jacksonville, unmodified binder, A-4 subgrade	Jacksonville, unmodified binder, A-7-6 subgrade
Distribution of truck categories (MGV, HGV)	30, 70	1	15	29	59	73
	40, 60	**2**[a]	**16**[a]	**30**[a]	**60**[a]	**74**[a]
	50, 50	3	17	31	61	75
	60, 40	4	18	32	62	76
	70, 30	5	19	33	63	77
Distribution of LGV classes (Class 5, Class 6)	70, 30	**2**[a]	**16**[a]	**30**[a]	**60**[a]	**74**[a]
	60, 40	6	20	34	64	78
	50, 50	7	21	35	65	79
	40, 60	8	22	36	66	80
Distribution of MGV classes (Class 7, Class 8, Class 9)	80, 10, 10	**2**[a]	**16**[a]	**30**[a]	**60**[a]	**74**[a]
	60, 20, 20	9	23	37	67	81
	50, 25, 25	10	24	38	68	82
	40, 30, 30	11	25	39	69	83
Distribution of HGV classes (Class 10, Class 11, Class 12, Class 13)	98, 2, 0, 0	**2**[a]	**16**[a]	**30**[a]	**60**[a]	**74**[a]
	90, 10, 0, 0	12	26	40	70	84
	80, 10, 5, 5	13	27	41	71	85
	60, 20, 10, 10	14	28	42	72	86

Note: The bold values are control/reference values.
[a]Reference/control.

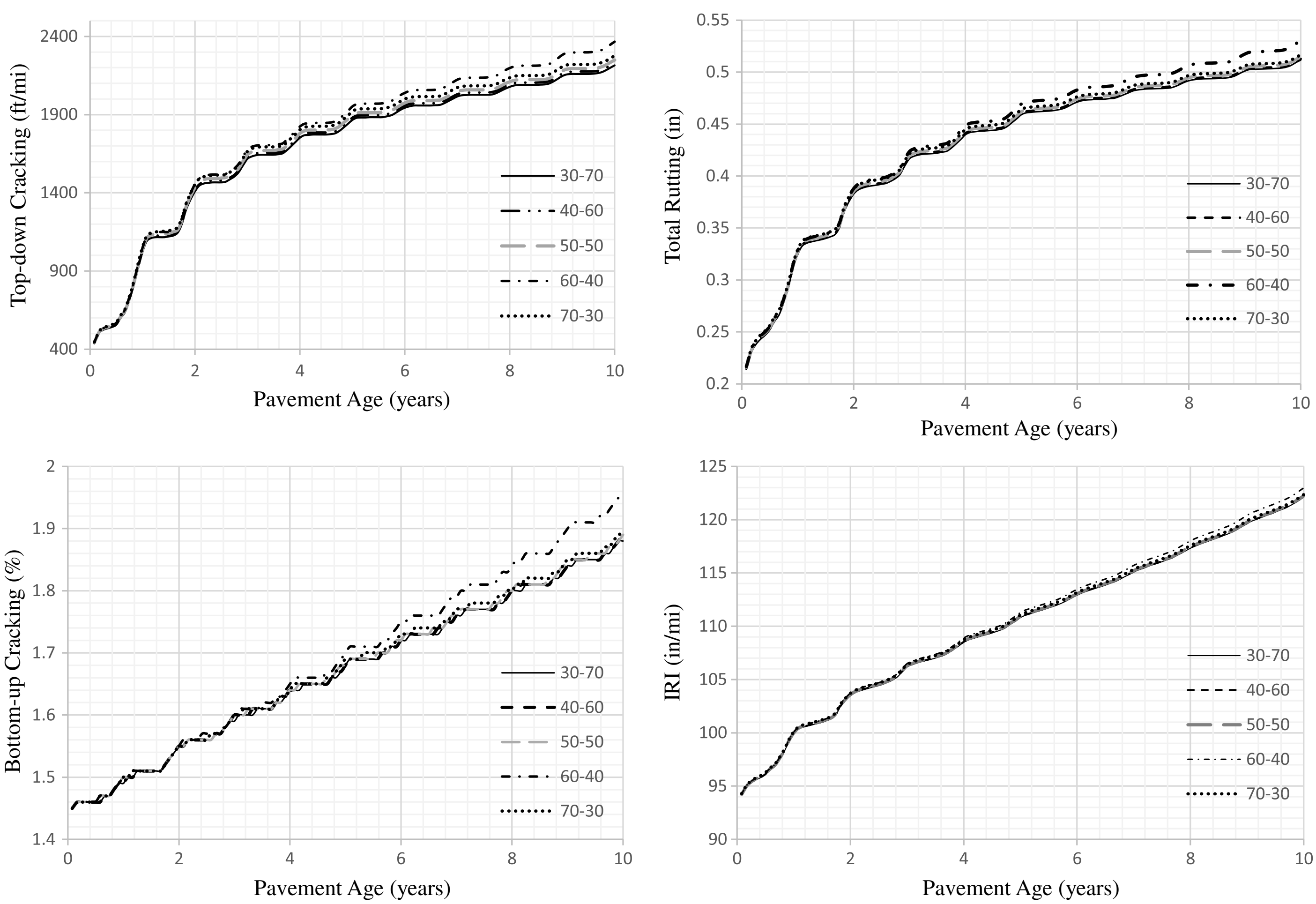

Fig. 2. Distress plots for the sensitivity of distribution of trucks (MGV and HGV) for unmodified binder in the Jacksonville climate for subgrade type A-2-6.

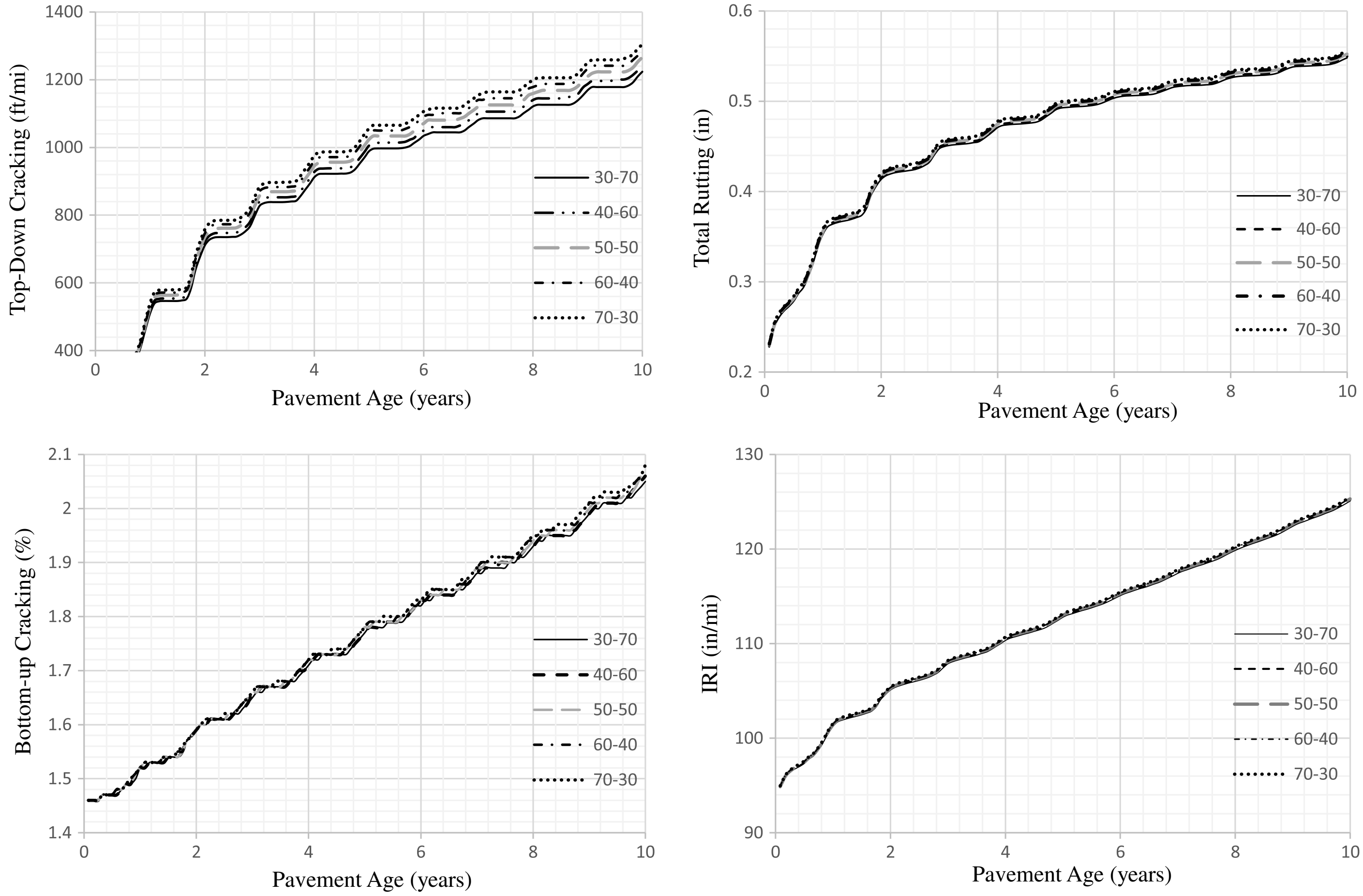

Fig. 3. Distress plots for the sensitivity of distribution of trucks (MGV and HGV) for unmodified binder in the Jacksonville climate for subgrade type A-7-6.

were based on visual observations as well as recommendations from different concerned parties such as pavement consultants well aware of traffic behavior in Lebanon.

Furthermore, the validity of the proposed methodology was assessed by trying different combinations of climatic and material conditions as elaborated hereafter.

To perform the runs, a typical three-layered flexible pavement structure was considered for this study: the asphalt concrete layer, the granular base, and the semi-infinite subgrade. For the granular base and the subgrade, design inputs for Level 2 analysis were obtained from the database of design consulting companies and the Lebanese Construction Specifications. For the asphalt concrete layer, a Level 1 analysis was selected and the required inputs were obtained from the American University of Beirut's material and structural laboratory database for mixes used in Lebanon (Chehab et al. 2017).

Design input data of the base layer, shown in Table 6, were kept the same for all the runs. However, two different asphalt concrete mixes—a mix with unmodified binder and another with modified binder—were adopted to study the effect of changing the properties of the mix on the validity of the proposed traffic classification methodology. Design parameters for both types of asphalt concrete mixes are shown in Tables 7–10. Furthermore, the approach adopted for truck categorization was tested against three subgrade types with different stiffnesses that are commonly available in Lebanon: A-2-6, A-4, and A-7-6. Input parameters for the subgrade of type A-2-6 are provided in Table 11. The gradations of subgrade types A-4 and A-7-6, available as a default in the software, were considered in the runs.

As for the climate, data for regions outside the United States and Canada were not included in the climatic database of the M-E PDG software. Therefore, one approach is to match, to the extent possible, cities in the United States and Canada for which climatic data exist in the M-E PDG database, with similar climatic conditions to those in the region under study (Chehab et al. 2017). For this study, the climate file corresponding to Jacksonville, Florida, was selected because it resembles Beirut with respect to average monthly temperatures, as can be seen in Fig. 1.

Additional sensitivity analysis runs were done using the climate file corresponding to Dallas, Texas, to test the validity of the proposed traffic data collection and analysis methodology in regions with hot climates. The values of the input parameters used for the sensitivity analysis are summarized in Table 12.

Sensitivity Analysis of Truck Categorization and Classification

Fig. 2 shows that the variations in the percentages of truck distribution for each category, i.e., MGV/HGV, using an unmodified binder asphalt mix under Jacksonville climatic conditions with a subgrade of type A-2-6, have a slight influence on the predicted performance of the pavement in terms of various distresses. A similar behavior was observed upon performing runs using modified and unmodified binders along with Jacksonville and Dallas climate files, respectively. In addition, changing the subgrade type to account for different stiffness resulted in the same behavior; an example of the distress plots is shown in Fig. 3.

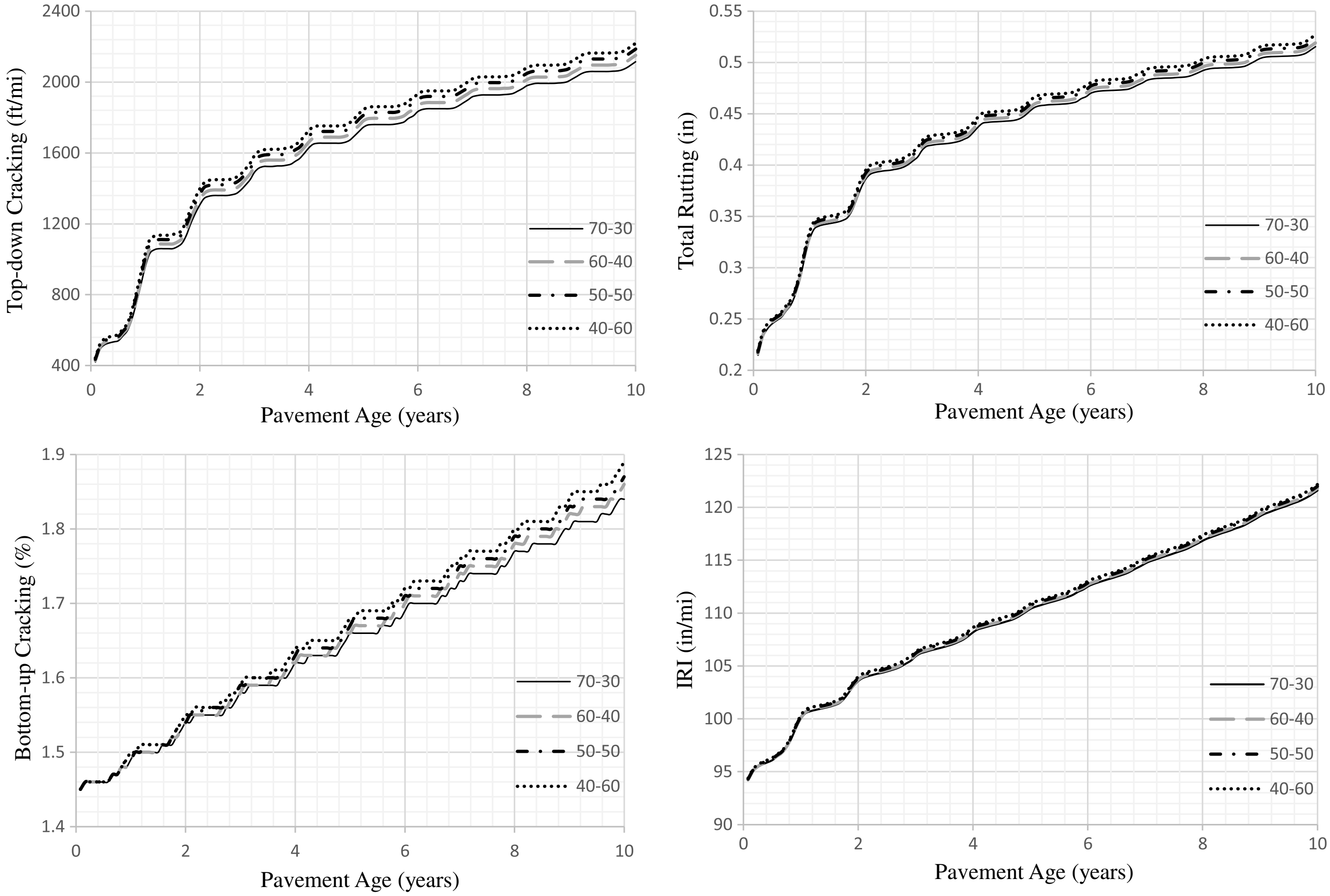

Fig. 4. Distress plots for the sensitivity of distribution of trucks (Classes 5 and 6) for unmodified binder in the Texas climate for subgrade type A-2-6.

Furthermore, varying the percentage of each class within each category resulted in a similar behavior. Examples of corresponding results for Classes 5 and 6 within LGV; Classes 7–9 within MGV; and Classes 10–13 within HGV are shown in Figs. 4–6, respectively. A similar behavior was observed for the other runs, where different combinations of truck classes, binder properties, subgrade types, and climate files were used. Thus, this observation remains true when varying the climatic conditions from moderate climate to a hot climate, the asphalt concrete mix's properties from unmodified asphalt binders to modified asphalt binders, and the subgrade from weaker to stiffer types. Therefore, reasonable errors in approximating the percentages of truck classes, as well as a mild variability in the truck distributions, are tolerable upon collecting traffic input for the design of pavement using the M-E PDG. Hence, to design pavement sections in regions with insufficient data, one can rely on the data from the automated traffic counts, as well as rational approximations of truck class distributions based on observations and vehicle records of governmental departments and agencies.

Validation of the Proposed Methodology Using Recent Traffic Counts

Description of the 2016 Traffic Surveys

Unlike the traffic surveys from 2002, the obtained traffic data for 2016 are more informative with respect to the characterization of the traffic. They are gathered from short-duration traffic counts conducted over the course of an entire week for 24 h per day in 15-min intervals. In addition, accurate hourly speed counts and measurements are recorded during the survey, which are of important added value to the study. To validate the carried assumptions and the methodology discussed above, the automatic vehicle classifications obtained from the 2016 surveys were taken as input parameters for the software runs as discussed in the following section. Three roads were selected from the new survey that best suit the roads that were analyzed during the previous survey data in 2002 for a parallel sensitivity approach, namely Dbayeh to Beirut (road 51), Jamhour to Beirut (road 30), and Jbeil to Jounieh (road 51).

Given the number of assumptions, it is important to note that the inaccuracy of the compiled traffic data used for the analysis runs using M-E PDG will most definitely lower the reliability of performance predictions. Results from the sensitivity analysis are important to assess implications of traffic data quality.

M-E PDG Runs

The sensitivity analysis study tackled three main traffic input parameters: AADTT, growth factor, and truck classification. The adopted procedure is elaborated in Table 13. Different sets of runs were performed with different combinations of traffic input data collected from both surveys. A comparison between the first

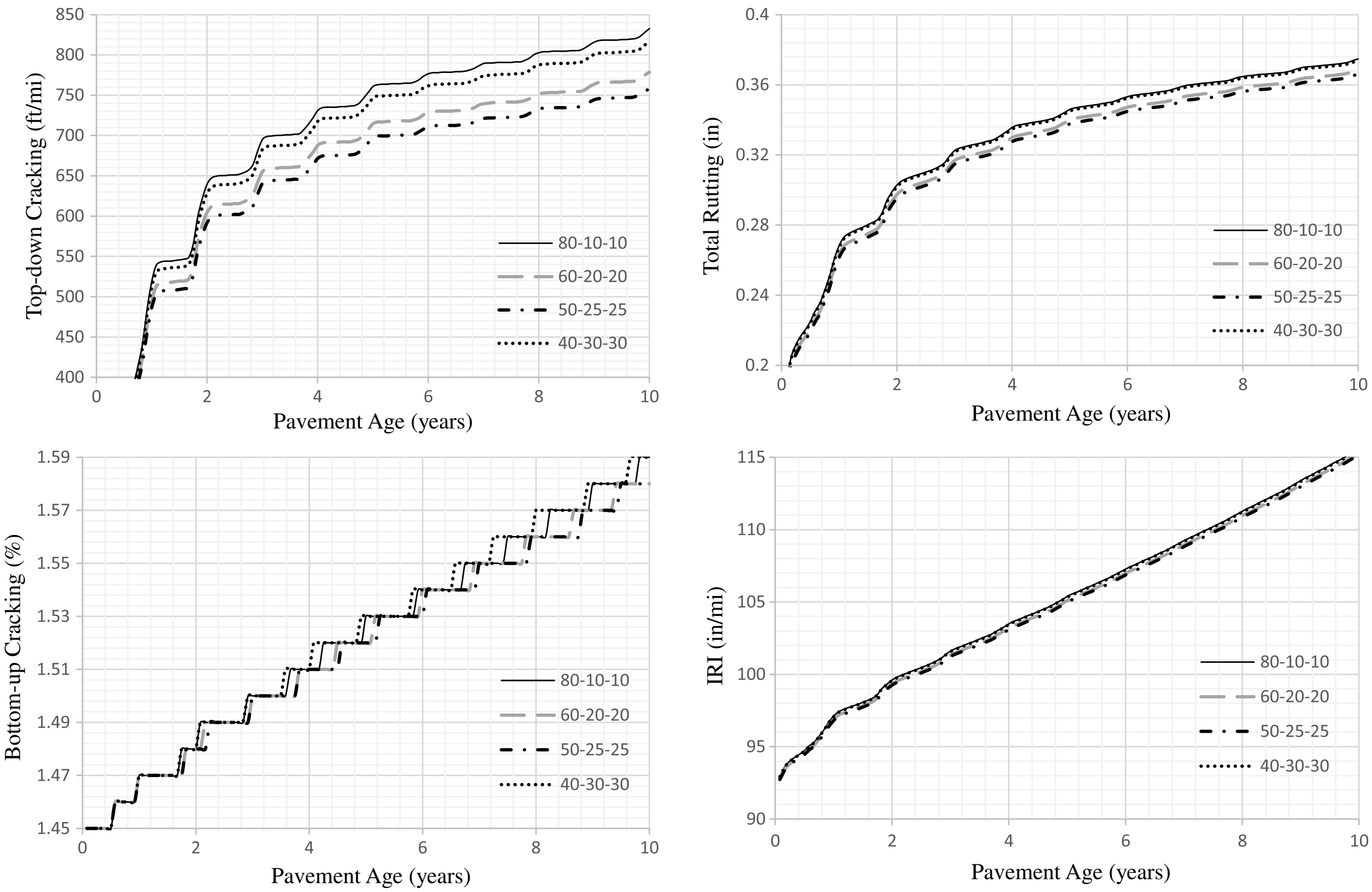

Fig. 5. Distress plots for the sensitivity of distribution of trucks (Classes 7–9) for modified binder in the Jacksonville climate for subgrade type A-2-6.

two sets of runs and Sets 1 and 3 was deemed necessary to recognize respectively the effect of truck classification groups and accurate AADTT on the performance of pavement.

Furthermore, the main objective of this study was to consider the efforts needed to collect traffic data in countries with insufficient resources and evaluate whether this extensive effort is reflected in the performance prediction of asphalt pavements. Therefore, a comparison between the two sets of data available as a whole (2002 in Set 1 and 2016 in Set 4) was essential. The predicted performance dictates whether state agencies in Lebanon are required to allocate funds and effort to collect traffic data continuously or whether collecting data once every few years is sufficient for pavement design.

Finally, the design guide defines three broad levels of analysis (Levels 1–3) where Level 3 is the least accurate and reliable for pavement design. To ensure the consistency of the results, a sensitivity analysis over the hierarchal levels in the M-E PDG was also conducted. The analysis targeted the two traffic scenarios (2002 in Set 5 and 2016 in Set 6) under all three different levels of asphalt concrete (AC) material data.

For the Level 2 analysis, the values of the dynamic shear modulus of the asphalt binder were kept the same as those of the unmodified binder used for Level 1, and the aggregate gradation of the considered asphalt mix was obtained from sieve analysis testing. This same aggregate gradation was used for Level 3 analysis along with the corresponding value of the performance grade (PG) grade (PG 64-20).

Effect of Actual versus Estimated Truck Classification

Fig. 7 shows the predicted pavement distresses obtained when using the AADTT of 2002 along with the various assumptions on the distribution of the truck counts (Set 1) almost overlap with those obtained when performing runs using the AADTT of 2002 yet with accurate classification found from ATC in 2016 (Set 2). This observation is true over the course of the 10-year pavement design life considered. Therefore, the assumptions of vehicles classification that were adopted in the first phase of the study are valid for use when no reliable traffic characterization and categorization are available.

Effect of Actual versus Estimated AADTT

The results show that the predicted distresses generated from the input data with the AADTT projected from 2002 to 2016 according to an assumed growth factor are significantly different from those generated from the input data with the actual AADTT collected from the traffic counts in 2016 (Fig. 8). This is due to the inaccuracy of the growth factor assumption, which yielded an AADTT of 7,953 for Dbayeh, Beirut; 3,492 for the Jamhour, Beirut, segment; and 5,292 for the Jbeil, Jounieh, section, while the actual AADTT recorded in 2016 for the three road sections were 25,000; 5,407; and 12,032 respectively. This behavior was expected since the country exhibited dramatic changes concerning population growth affected by the beginning and end of wars in neighboring countries during these 14 years. Therefore, the accuracy of AADTT

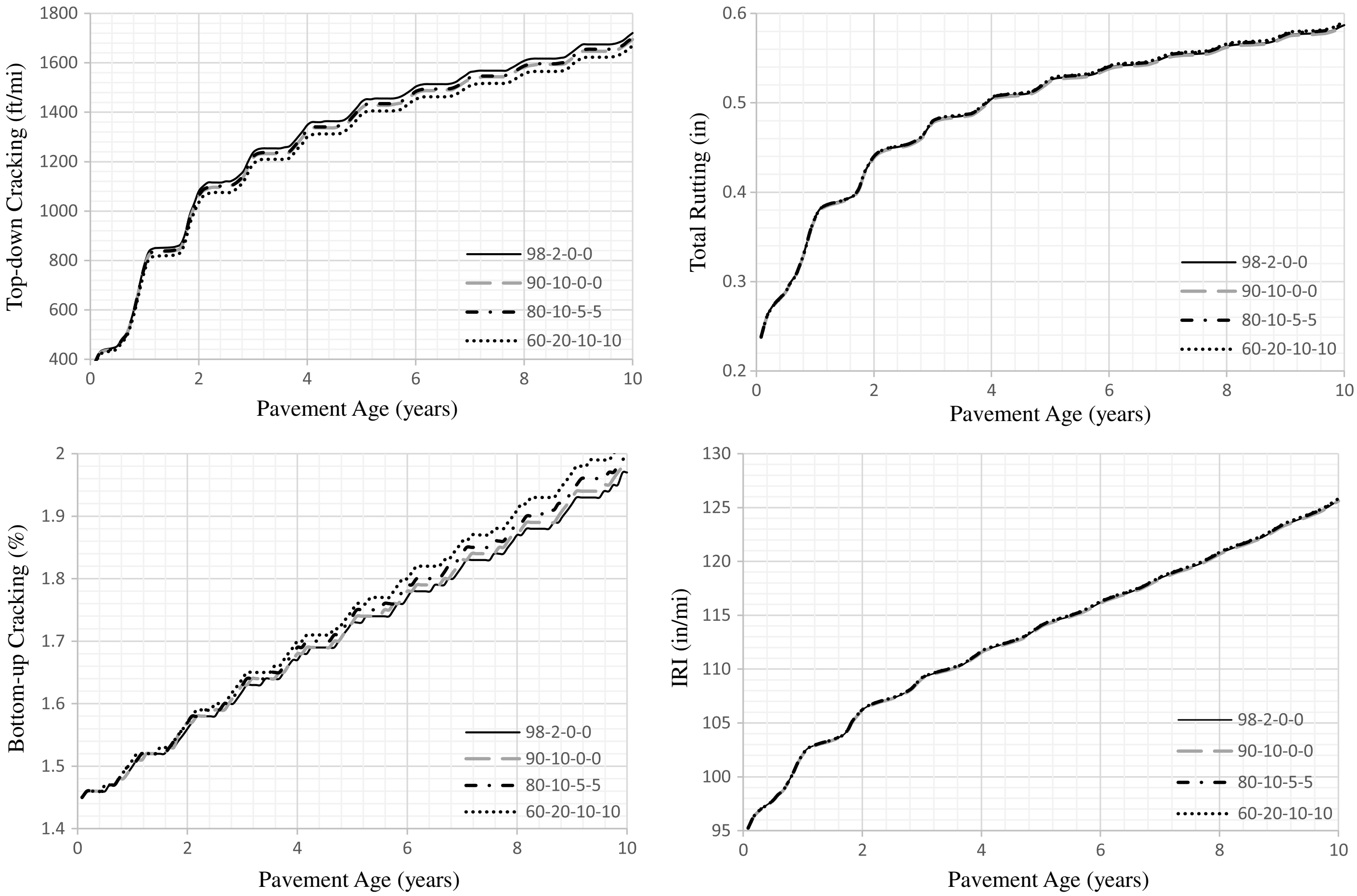

Fig. 6. Distress plots for the sensitivity of distribution of trucks (Classes 10–13) for unmodified binder in the Jacksonville climate for subgrade type A-4.

Table 13. Input variables for the sensitivity analysis runs corresponding to Phase 2

Set number	Run number	Road segment under consideration	Description
1	43 44 45	Dbayeh, Beirut Jamhour, Beirut Jbeil, Jounieh	The average annual daily truck traffic of 2002 is considered, along with the anticipated classification from previous work.
2	46 47 48	Dbayeh, Beirut Jamhour, Beirut Jbeil, Jounieh	The average annual daily truck traffic of 2002 is considered along with the accurate classification that was collected from the field in 2016.
3	49 50 51	Dbayeh, Beirut Jamhour, Beirut Jbeil, Jounieh	The average annual daily truck traffic from 2016 is considered with the anticipated truck classification from previous work.
4	52 53 54	Dbayeh, Beirut Jamhour, Beirut Jbeil, Jounieh	The average annual daily truck traffic traffic from 2016 is considered with the accurate classification that was collected from the field in 2016.
5	55	Dbayeh, Beirut	The overall traffic data gathered in 2002 in line with all the assumptions input as Level 2 for asphalt concrete materials.
	56	Dbayeh, Beirut	The overall traffic data gathered in 2002 in line with all the assumptions input as Level 3 for asphalt concrete materials.
6	57	Dbayeh, Beirut	The overall traffic data gathered from the new ATC collected in 2016 and simulated in Level 2 analysis for asphalt concrete materials.
	58	Dbayeh, Beirut	The overall traffic data gathered from the new ATC collected in 2016 and simulated in Level 3 analysis for asphalt concrete materials.

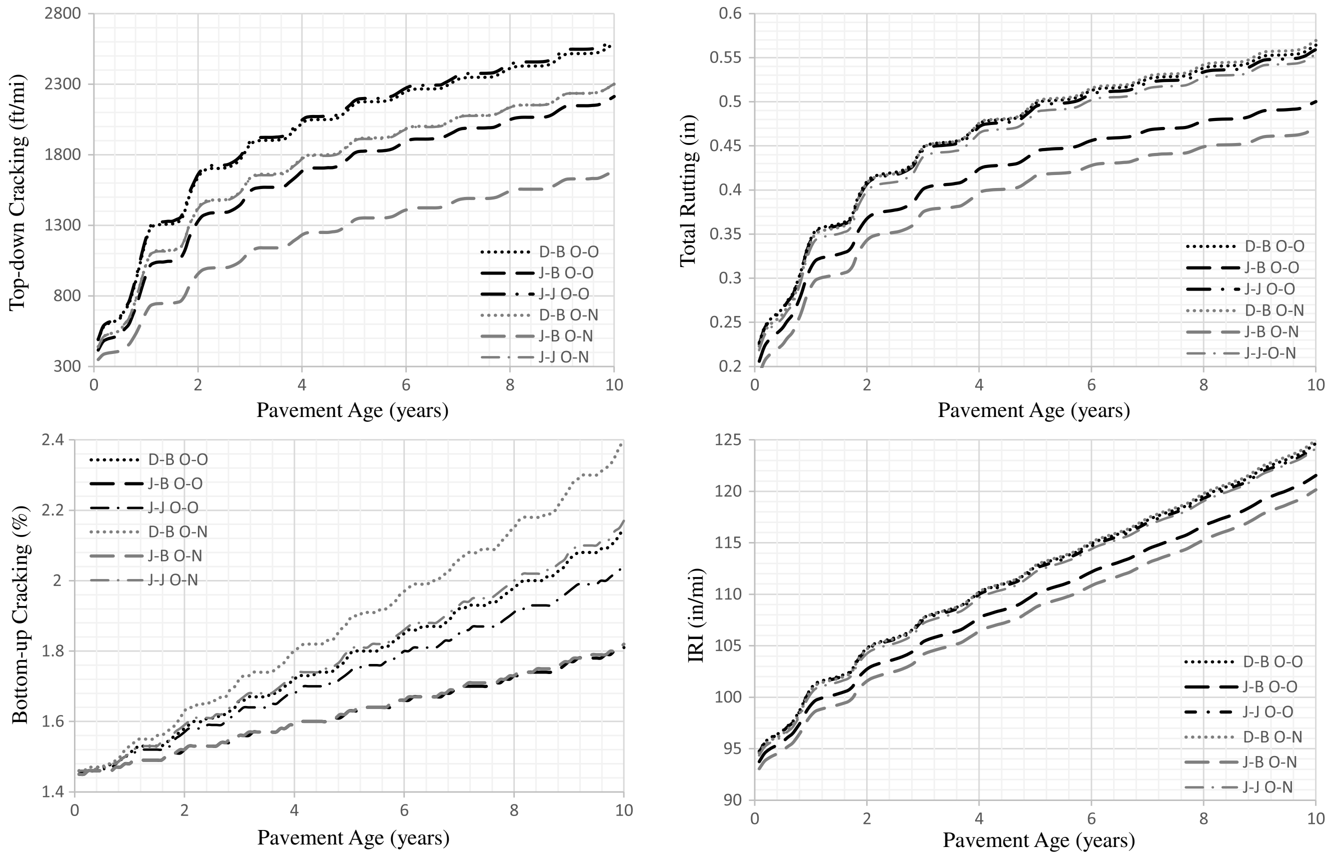

Fig. 7. Distress plots, Phase 2, for the sensitivity of truck traffic distribution (D-B = Dbayeh, Beirut; J-B = Jamhour, Beirut; J-J = Jbeil, Jounieh; O-O = old AADTT and old classification; O-N = old AADTT and new classification).

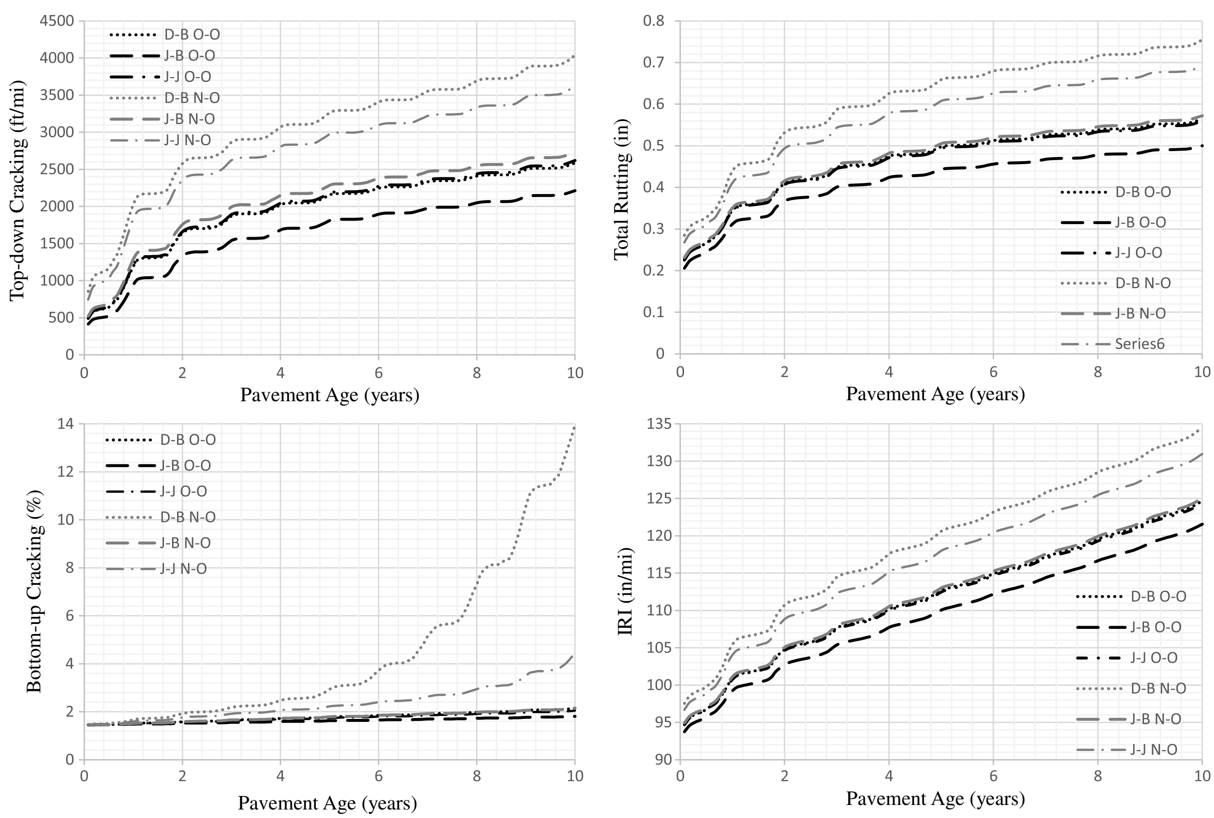

Fig. 8. Distress plots, Phase 2, sensitivity of AADTT (N-O = new AADTT and old classification).

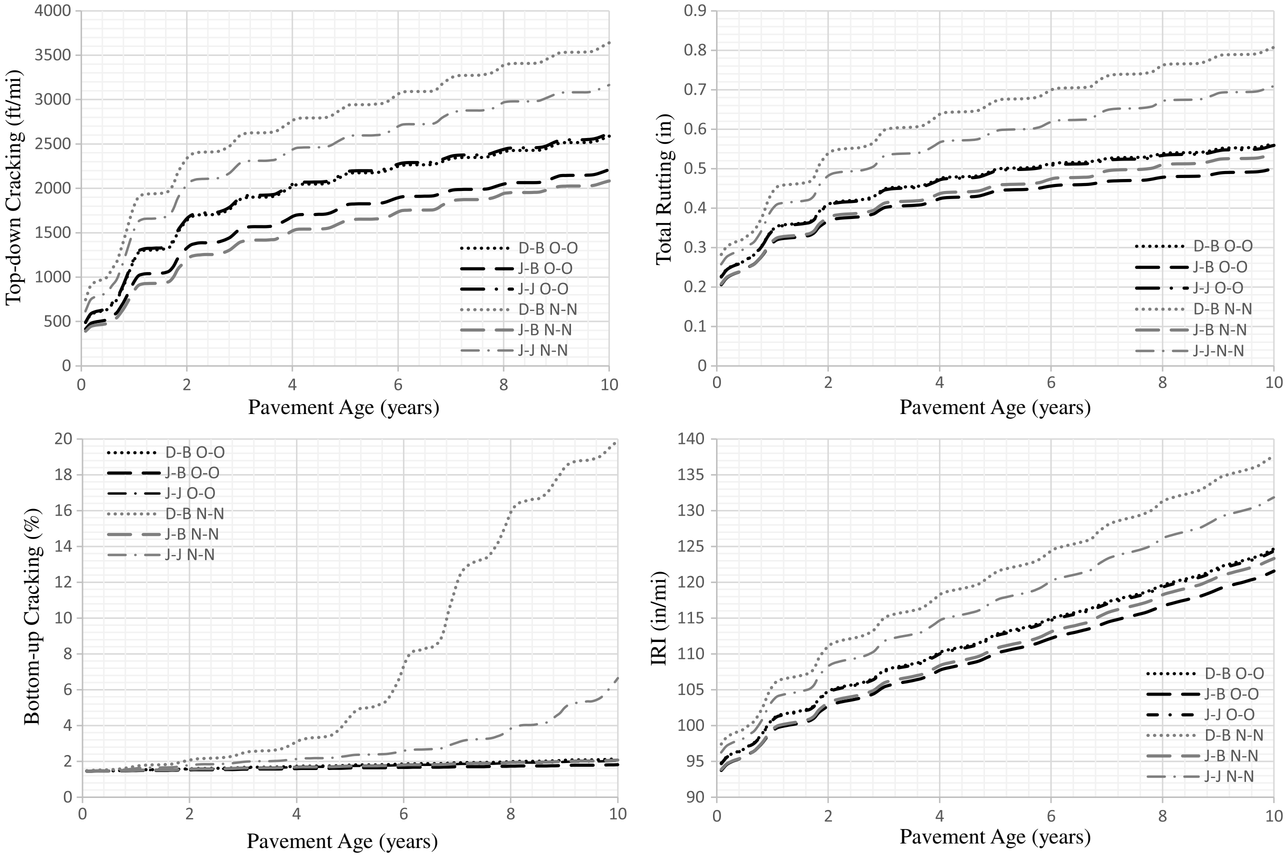

Fig. 9. Distress plots, Phase 2, sensitivity of the overall traffic data collected (N-N = new AADTT and new classification).

prediction is very crucial for the design of pavement because its underestimation can cause severe damage earlier than predicted.

Effect of Actual versus Estimated AADTT and Truck Classification

The distresses of the pavement structure under different conditions of traffic loading and truck configurations all together show a substantial change in magnitudes (Fig. 9). Asphalt is a viscoelastic material that is affected by physical changes, including temperature, traffic volume, and time of loading. However, it can be concluded that this difference is due to the huge increase in truck volumes (AADTT) that happened during these years.

Effect of the Material Properties Input Level

Predicted distresses generated from simulations over different levels of material input data for the Dbayeh, Beirut, road (Fig. 10) show a huge difference. The use of higher levels of input parameters resulted in a higher level of reliability over the design life of the pavement. Eventually, this was already accounted for by the mechanistic-empirical guide and hence the hierarchal levels that it contains. Nonetheless, for the purpose of comparisons between the different combinations of traffic input data only, a consistency in the results was noticed in terms of predicted distresses and, therefore, it can be concluded that the proposed methodology is valid under different reliability levels.

Conclusions

A methodology was presented to create traffic input data for the implementation of the *Mechanistic-Empirical Pavement Design Guide* in countries lacking the required data, while tackling Lebanon as a case study. The methodology presents guidelines for acquiring the missing parameters, mainly truck counts and traffic characterization and categorization. Afterward, the methodology was validated by comparing the pavement performance upon varying the input parameters within tolerable and reasonable ranges and under different environmental and material conditions.

The findings reveal that highway design agencies can rely on available automated traffic counts surveys and apply various assumptions based on their own observations and records of vehicles types to create a reliable truck categorization in accordance with the FHWA vehicle classification system. On the other hand, using typical values or estimating the growth factor for traffic prediction in cases where continuous data is not available might result in erroneous results, as mild variation in the growth factor significantly affects the predicted pavement distresses. Thus, it is recommended to allocate efforts in the continuous collection of traffic data to accurately forecast truck volumes (AADTT), since it has major impact on the predicted pavement performance.

Future Work

The analysis in this paper was based on the limited traffic data available for Lebanon. Thus, the results may not be applicable to other regions, where heavier traffic in terms of truck classes or volume is encountered. Thus, users and agencies are encouraged to carry out similar studies using their particular combination of traffic, materials, climate, and pavement structures, to decide on the required efforts for traffic data collection.

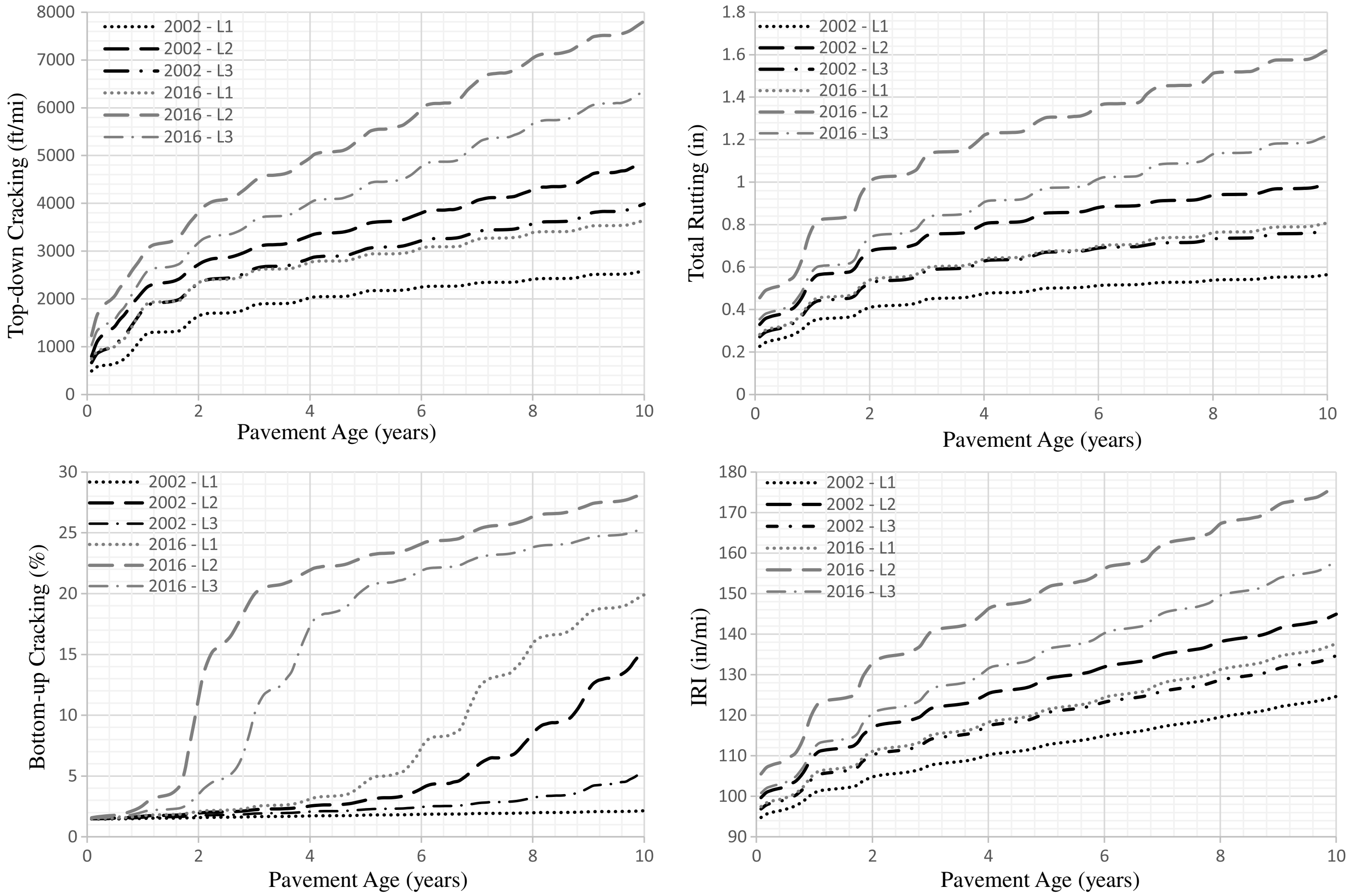

Fig. 10. Distress plots, Phase 2, sensitivity over the hierarchal approach in materials (2002 = AADTT and truck classification projected from the 2002 survey to 2016; 2016 = AADTT and truck classification from the 2016 survey; L-1, L-2, and L-3 = Levels 1, 2, and L3 input data, respectively, for the asphalt concrete layer).

In addition, it is necessary to consider the variation of traffic among different seasons and assess the effect of the different time coverages of traffic data collection on the pavement response.

Finally, research reveals that it is necessary to create site-specific traffic load spectra instead of relying on the default traffic values incorporated in the M-E PDG, as it turns out that relying on regional or national default inputs results in errors in the predicted pavement response (Smith and Diefenderfer 2010; Zofka et al. 2014; Ishak et al. 2010; Li et al. 2016). Therefore, governments and authorities should consider installing permanent WIM stations to collect continuous and site-specific traffic input data, to obtain accurate traffic input data and truck axle-load spectra and to obtain the actual variations in traffic over time.

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