Identifying Road Sections with Similar Truck Axle Load Spectra Using a Commodity-Based Freight Demand Model and Vehicle Classification Count Data

Eradius E. Rwakarehe[1], Ming Zhong[2], James Christie[3] and Eric Hildebrand[4]

[1] Lecturer, Department of Transportation & Geotechnical Engineering, University of Dar es Salaam, P.O. Box 35131, Dar es Salaam, Tanzania; E-mail: eraddy2001@yahoo.co.uk

[2] ITS Research Center, Wuhan University of Technology, Wuhan, PR, China

[3] Honorary Research Professor, Department of Engineering, Faculty of Science, Applied Science & Engineering, University of New Brunswick, Saint John, NB, Canada

[4] Professor, Department of Civil Engineering, University of New Brunswick, Fredericton, NB, Canada.

Abstract

Introduction of the new pavement design method of the *Mechanistic-Empirical Pavement Design Guide (MEPDG)* developed under NCHRP project No. 37-A has brought about a significant challenge to pavement designers as well as highway authorities. In terms of data requirements, this method is more data hungry compared to the traditional standard axle-based method. Some of the data such as axle load spectra has to come from Weigh-In-Motion (WIM) devices, which are found at very few locations. Because of this challenge, extrapolation of axle load spectra data from WIM stations to other road sections is inevitable. However, prior to that, a set of appropriate criteria, for transferring data from one place to the other, needs to be developed. This paper proposes a methodology to be used for transferring such data.

In this study, truck weight data collected from 40 short-term weighing stations in the Province of Saskatchewan were analysed and clustered into groups with similar axle load spectra, so that they can be compared with groups generated through the proposed methodology. A commodity-based freight demand model, previously developed for the Province of Alberta, was blended with vehicle classification count data, followed by the formulation of a quantitative method that can be used for transferring data from one place to the other. The proposed methodology will enable transportation agencies to transfer data from the few existing WIM devices in a situation where they do not have Truck Weight Road Groups in place. This will also serve as an important tool required to migrate to the new method of pavement design - the MEPDG.

Key Words: Axle load spectra, Weigh-in-Motion, Freight demand model

1. INTRODUCTION

Traffic loading distribution is one of the major inputs for pavement analysis, design, maintenance and management. While much effort has been directed toward the development of more sophisticated and accurate design methods, like that of *Mechanistic-Empirical Pavement Design Guide (MEPDG)* developed under NCHRP project No. 1-37A (NCHRP, 2004), less has been devoted to enhancing techniques for acquiring more accurate traffic axle loading and distribution data required as an input. The MEPDG approach proposes using site-specific Axle Load Spectra (ALS) data for pavement design. By comparing it with previous methods, the use of these load spectra provides a more logical way for the estimation of the effects of traffic loading on pavement responses and distress, and therefore the optimal design of pavement structures. However, according to Haider *et al.* (2007), the demand for site-specific truck and axle-load related data makes the implementation of the MEPDG method a very complicated, costly, and labour-intensive undertaking.

According to a National Cooperative Highway Research Program report (NCHRP, 2004), because of these constraints, MEPDG has defined three levels of traffic input data as follows: Level 1 - very good knowledge of past and future traffic characteristics. This level requires the gathering and analysis of site-specific truck volume and loading data. The data measured at or near the site include counting and classifying the number of trucks traveling over the roadway by lane and direction and the axle loads for each truck class so as to determine the truck traffic for the first year after construction. This level is considered the most accurate because it uses actual data measured over or along the project site. Level 2 - modest knowledge of past and future traffic characteristics. This level requires collection of enough truck volume information at a site, in order to estimate it accurately including its seasonal variations. However, vehicle weights are not site-specific, but taken from regional Truck Weight Road Groups (TWRGs) summaries. Level 3 - poor knowledge of past and future traffic characteristics. In most cases, this level starts with Annual Average Daily Truck Traffic (AADTT) or from simple truck counts with no site-specific knowledge on the size of the loads carried by trucks traversing the link. At this point, it is recommended that regional average or national default values supplied together with the MEPDG software MUST be used.

Most highway agencies only have minimal coverage with Weigh-In-Motion (WIM) stations, and gathering enough weight data using portable scales is impractical; therefore, site-specific traffic loading data is typically limited. This forces the MEPDG method to be exercised at either Levels 2 or 3 in most cases. According to the Federal Highway Administration (FHWA) (2001), a minimum of 6 WIM stations per group is needed in order to develop TWRGs with acceptable homogeneity. The number of TWRGs usually ranges from two to fifteen depending on the size of the jurisdiction and the diversity of trucking characteristics. This means that, most of the transportation jurisdictions in the world cannot develop TWRGs as per the FHWA recommendations. If they decide to employ the new pavement design method, most of the traffic loading data to be used are likely to fall under Level 3. Unfortunately, the accuracy offered by Level 3 does not reflect the effort put into developing the MEPDG. At this level, the MEPDG approach may produce less optimal pavement structures than the traditional standard axle-load approach.

To work around the above dilemma, a good way of enhancing the accuracy of traffic loading in-put data at Level 2 is required. By looking at the current situation, it is even worse when it comes to Level 3, which uses default values supplied by the MEPDG software. A study by Romanoschi *et al.* (2011) shows that there is a high risk associated with the use of Level 3 traffic input data even in the US where the software was developed. This means that, a solution for reducing or getting rid of the reliance of Level 3 is needed.

According to Jablonski *et al.* (2010), due to the differences in regulations, Canadian trucks have different axle configurations and higher axle loads than those in the US, which means default values developed for the US cannot be directly applied in Canada. Further, in Canada, each province has its own weight and trucking regulations, which further complicates the matter. To address this non-transferability problem, it is recommended that each region develop its own specific factors that relate truck traffic volumes and loading distributions. In the same study, Jablonski *et al.* (2010) showed how Levels 2 (regional data) and 3 (default parameter values) input data specific to the Province of Manitoba can be compiled. In their study, the truck traffic volume and classification data is used in this regard. Axle weight inputs and TWRGs, which are more important for the MEPDG design method, were beyond the scope of their study. To address this deficiency, this paper presents a method for transferring ALS from the few WIM devices available elsewhere, as a substitute for TWRGs.

2. METHODOLOGY DEVELOPMENT AND DATA USED

2.1. Overview of the methods and data preparation

For the ALS data to be transferred, the truck loading and distribution on the section in question has to be compared with the data from the available WIM devices so as to choose the one with the most similar loading and distribution pattern. Two methodologies, traditional (existing) and quantitative (the one proposed in this study), can be used to identify a WIM device with the most similar loading and distributions pattern with a road section in question.

The existing method is only possible for those transportation agencies that have good TWRGs. To those agencies with no TWRGs, the proposed methodology in this paper is an appropriate alternative. To use this method, a Commodity-Based Freight Demand Model (CB-FDM) has to be in place so as to be blended with Vehicle Classification Counts (VCC). This study presents a brief description on how to blend the two and come up with a quantitative method. Development of a CB-FDM is beyond the scope of this paper[1].

In order to develop and validate the proposed methodology, the traditional approach, which can also be referred to as an intuitive method, was used. Under the traditional method, to allow two sites to be compared, at least Short-Term Weight Counts (STWC) for the two sites have to be available. From STWC, the ALS for each site is developed, and appropriate techniques, such as Pearson correlation analyses (Mai *et al.*, 2013), are used for identifying the site with an axle-loading pattern that is most similar to that of the road section in question.

Pearson correlation analyses generate coefficients, which indicate the degree of similarity between objects, in this case, the similarity of ALS between two stations. The generated coefficients range from 0.00 to 1.00, with the higher coefficients representing the high degree of similarity and vice-versa. However, it should be noted that, similar to any monitoring program, STWC data are also NOT ubiquitously available, and it is very expensive and challenging to acquire them. To solve the problem, this study has developed the alternative proposed method. This approach can be applied when a CB-FDM and VCC are available, as explained in the subsequent sections.

Unlike the traditional method where ALS data for the two sites to be compared have to be available, this approach does not require such data. The requirements are the net weight of commodities transported through the road sections to be compared and the VCC. As demonstrated in the subsequent sections, with several WIM devices available, the one that most closely matches the WIM device with the most similar ALS to that of the road section of interest is chosen.

To demonstrate the viability of using this proposed methodology, the vehicle weight count data collected at 40 short-term weight count stations in the Province of Saskatchewan were used (here the weight information is simply assumed not available). Figure 1 shows the geographical locations of the stations where the data were collected. Before starting to develop the ALS for all 40 stations, it was important to carry out the truck composition analysis in order to know the dominant truck classes. This helped to determine the dominant axle types to be included in developing the ALS. The data depicted in Figure 2 illustrate that the dominant truck classes are 9 (single trailer, 5 axles), 10 (single trailer, 6+ axles) and 13 (multi-trailer). The tandem axle was found to be the dominant in these truck classes. The use of the

[1] Development of a CB-FDM is presented in a separate paper, which is under review for publication.

tandem axle as representative of other axle types is supported by several studies carried out previously (Papagiannakis *et al.*, 2006; Mai *et al.*, 2013).

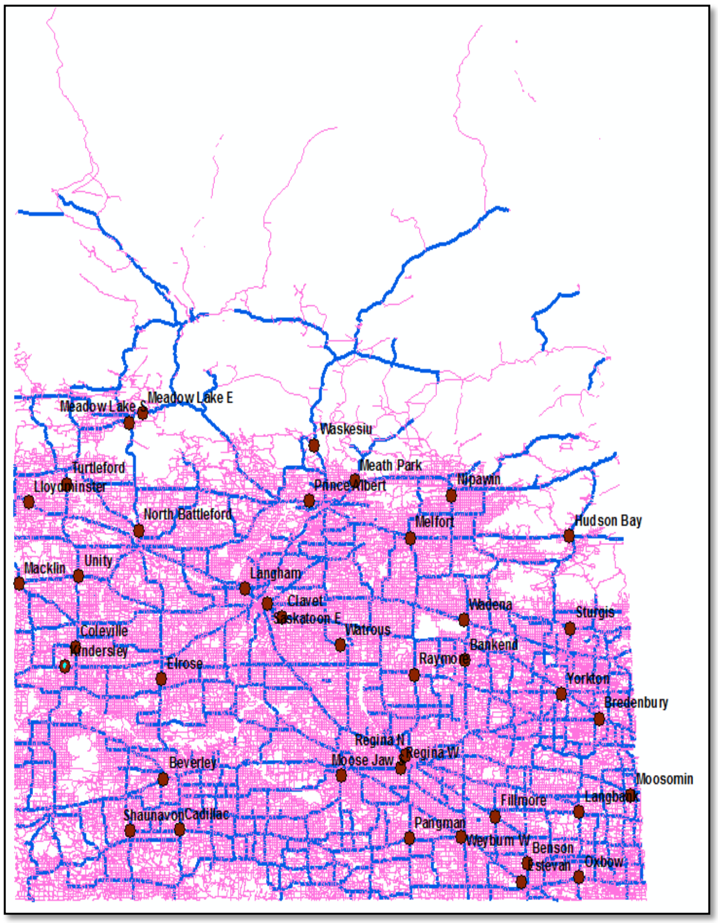

Figure 1: Locations of short-term weight count stations in Saskatchewan

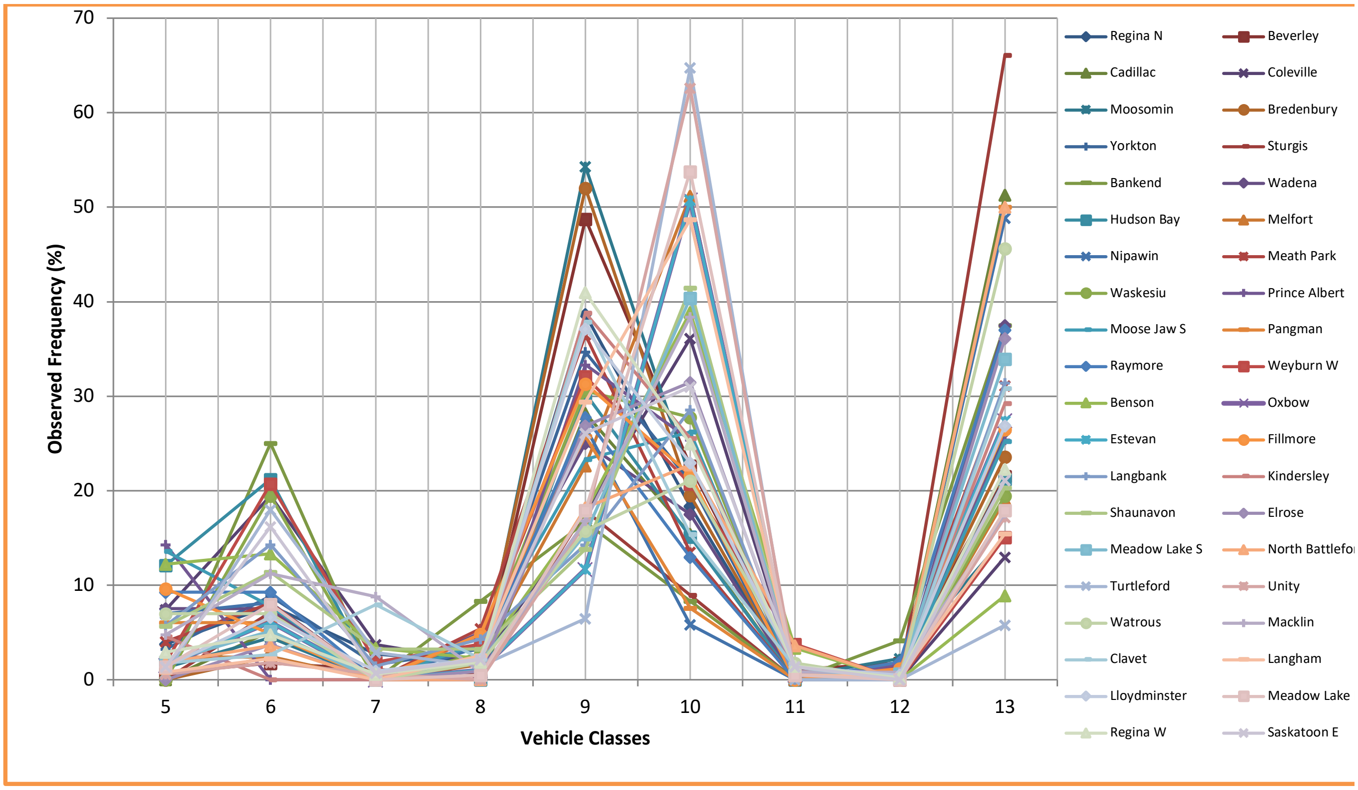

Figure 2: Truck composition for 40 short-term weight count data sites in Saskatchewan

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Having prepared the ALS, the short-term weight counting stations were clustered into four groups depending on their similarity in terms of the loading distribution patterns of tandem axle-loads. Taking into consideration that most of the Canadian Provinces have relatively few WIM stations (compared to the US), and the data collected did not cover many road functional classes[2], it was decided that at least four groups could be sufficient for this particular analysis.

The clustering analysis was completed in XLSTAT (a statistical analysis software) through an agglomerative hierarchical clustering method, whereby the ALS were used as input data and the number of clusters were pre-specified. The error sum of squares, which is also referred to as Ward's minimum variance method was used as a criterion for choosing two clusters to merge.

With the method used, the software treats the axle-load distribution numbers as vector points, and for each pair of objects, it calculates the euclidean distance to form a matrix D, which is also referred to as dissimilarity matrix. For *n* objects (in this case 40), the software initially assumes to have *n* clusters before it starts by searching the dissimilarity matrix D for the closest pair (*i, j*) of clusters. It then continues by replacing clusters *i* and *j* by an agglomerated cluster *h.* The software updates the matrix D to reflect the deletion of *i* and *j* clusters and to exhibit the revised similarities between *h* and the remaining clusters. The process continues until the last pair is grouped together to form a single cluster containing all objects. The process provides several output information including the resulting decision tree diagram (dendrogram) shown in Figure 3[3], the profile plot, which is basically the ALS for the four groups formed, shown in Figure 4 and the list of objects for each class.

[2] The department of transportation in the province of Saskatchewan collects STWC data on a highway if its AADTT is more than 80. Lower function classes including collector highways have AADTT below the threshold; as a result, do not qualify for the data collection.

[3] The clusters are numbered from left to the right

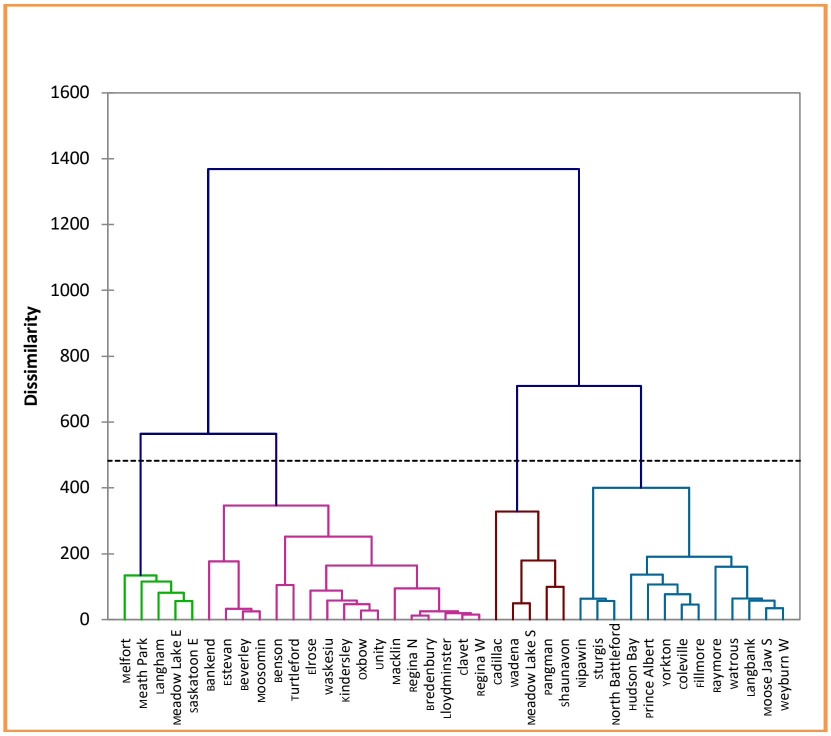

Figure 3: Dendrogram for the ALS clusters for the 40 sites of short-term weight count data in Saskatchewan

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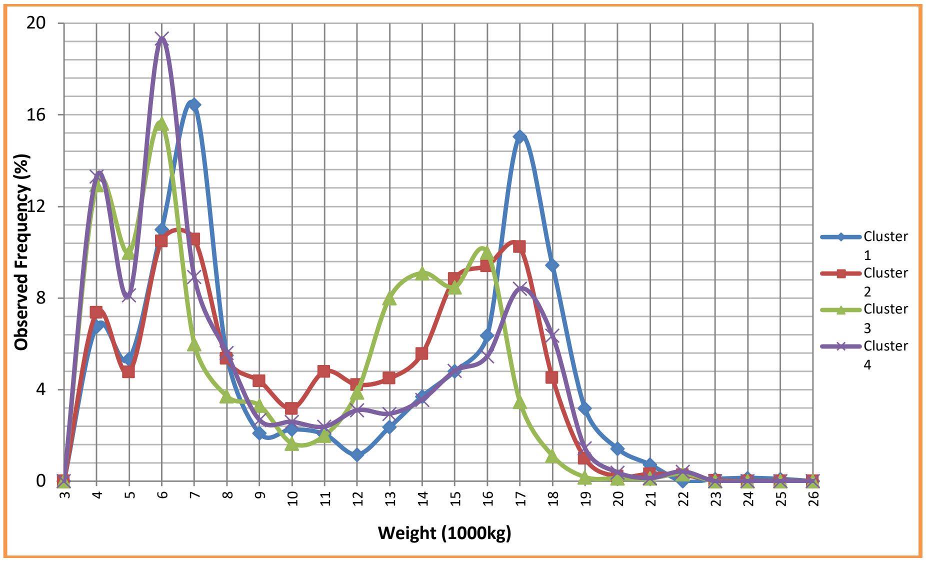

Figure 4: ALS for tandem axle for the four clusters developed using short-term weight count data collected in Saskatchewan

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The formed clusters were differentiated by the percentages of lightly and heavily loaded axles as well as the distributions of the axle loads. Cluster 4 represents the road sections that are generally lightly loaded. On average, 50% of the tandem axles within this cluster have loads below 7,000 kg. While the Clusters 1 and 2 have their peaks of heavily loaded axles at 17,000 kg, Cluster 3 has the same peak at 16,000 kg. Further, although Clusters 1 and 2 have the same peaks for lightly and heavily loaded tandem axles at the same load values, the distributions of Cluster 1 are more concentrated with low standard deviations, especially for the heavily loaded peak.

For comparison purposes, Pearson correlation analysis was done. This was done in order to confirm that stations within the same cluster are the most strongly correlated, compared to others; and this was proven to be correct.

2.2. Methodology development

The development of the proposed methodology began with the hypothesis that:

'If the ratio of the net weights of commodities transported through two road sections is equal to the ratio of the truck volumes traversing the same road sections, then the likelihood of the truck axle-loading patterns on the road sections to be similar or the same is very high'.

That is: If it is observed that

$$[1] \quad \frac{W_1}{W_2} = \frac{\mathrm{N}_1}{\mathrm{N}_2}$$

Then, the two road sections are more likely to have similar truck axle-loading distribution patterns.

Where W_1 and W_2 are the net weights of commodities transported through the two road sections
N_1 *and* N_2 are the truck volumes traversing the two road sections

Then, it followed testing the methodology by comparing its results with that of the traditional method. The net weights of commodities, which are the inputs in Equation [1] were computed using Equation [2]. The second term on the right hand side of Equation [2] represents the total weight of empty trucks.

$$[2] \quad W_{net} = W_{gross} - \sum_{i=5}^{14} W_i N_i$$

Where W_{net} is the net weight of commodities transported through the road sections of interest
W_{gross} is the total weight of all the trucks (including both the trucks and commodity carried) transported through the road sections of interest
W_i is the weight of a class *i* empty truck as they are shown in Table 1[4]
N_i is the number of trucks of class *i*

[4] The data used to establish the weights of empty trucks of different classes (in Table 1) were also collected in the province of Saskatchewan.

Table 1: Weight of empty trucks

Truck Class	Number of Empty Trucks Weighed	Total Weight (lb)	Average Weight per Truck (lb)	Average Weight per Truck (tonnes) - (W_i)
5	84	723,940	8,618	3.91
6	325	4,218,544	12,980	5.89
7	36	616,040	17,112	7.76
8	87	1,260,130	14,484	6.57
9	1,130	17,971,578	15,904	7.21
10	1,432	26,677,409	18,629	8.45
11	87	1,660,275	19,084	8.66
12	12	241,185	20,099	9.12
13	1,116	22,859,022	20,483	9.29

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Note: 1lb = 0.00045359237 tonnes

A typical/representative site from each group/cluster was identified by re-analyzing each cluster separately. This was achieved by forming an auxiliary ALS using the average for each load range (e.g. 2,000 kg-3,000 kg) for every cluster. Pearson correlation analyses between the auxiliary ALS and the rest of the sites (within the group) were done, and the site that showed the highest degree of correlation was chosen as the typical/representative site for that particular cluster.

Using Equation [1], the remaining 36 sites were re-assigned to the clusters. When this hypothesis was tested for the first time, it did not yield positive results. The hypothesized Equation was then modified to Equation [3] below.

$$[3] \qquad D = \left|\frac{W_1}{W_2} - \frac{N_{1,5}}{N_{2,5}}\right| + \left|\frac{W_1}{W_2} - \frac{N_{1,6}}{N_{2,6}}\right| + \dots\dots\dots\dots\dots.. + \left|\frac{W_1}{W_2} - \frac{N_{1,n}}{N_{2,n}}\right|$$

Where $N_{1,n}$ *and* $N_{2,n}$ are the truck volumes of class n traversing the road sections 1 and 2, respectively, while W_1 and W_2 follows the previous definitions.

Equation [3] yielded relatively convincing results as compared to the original premise. However, it was still lacking the consistency when data from one station were tested against data from other stations, one with low net weight of commodities and low truck volume, and the other with high net weight of commodities and high truck volume. Further examination of the results from the Equation revealed that the results could be improved by normalizing the data using the normalizing agent *(W_1/W_2)*. Applying the normalizing agent to Equation [3] yielded Equation [4] below, which gave consistent pairing results.

[4] $D = \frac{W_2}{W_1}\sum_{i=1}^{n}\left|\frac{W_1}{W_2} - \frac{N_{1,i}}{N_{2,i}}\right|$

Though Equation [4] gave consistent pairing results, it was still lacking the physical meaning that could be easily understood by most pavement engineers or other users. This led to further modification in the search for a more easily explainable physical meaning of the equation, which resulted in Equation [5] that was also re-arranged further to give Equation [6].

[5] $D = \sum_{i=1}^{n}\left|1 - \frac{W_2}{W_1} \times \frac{N_{1,i}}{N_{2,i}}\right|$

$$D = \sum_{i=1}^{n}\left|1 - \frac{W_2}{N_{2,i}} \div \frac{W_1}{N_{1,i}}\right|$$

Where

$$\frac{W_1}{N_{1,i}} = w_{1,i}$$

$$\frac{W_2}{N_{2,i}} = w_{2,i}$$

[6] $D = \sum_{i=1}^{n}\left|1 - \frac{w_{2,i}}{w_{1,i}}\right|$

Where $w_{1,i}$ is the weight per truck proxy for the truck class *i* on the road section 1
$w_{2,i}$ is the weight per truck proxy for the truck class *i* on the road section 2

Finally, Equation [6] was re-written in a general form as shown by Equation [7].

[7] $D = \sum_{i=1}^{n}\left|1 - \frac{w_{q,i}}{w_{w,i}}\right|$

Where $w_{q,i}$ is the weight per truck proxy for the truck class *i* on the road section in question
$w_{w,i}$ is the weight per truck proxy for the truck class *i* on the road section with a WIM device

While assigning the sites to their clusters, the following issues were observed: first, some stations that showed weak correlation in their clusters are likely to be assigned to wrong clusters. However, this was not considered a major problem, as the sites seem to have ALS that resembles that of either of the groups. Moreover, it should be noted that even by using the traditional method, the Pearson correlation analysis might yield slightly different results when compared to the least-sum of squares or other statistical methods. Therefore, slightly different results showed by the developed methodology is also seen when the traditional method is used with different statistical techniques for similarity comparison.

Secondly, the stations that had an ‘irregular distribution’[5] of trucks, such that one of the classes 9, 10 or 13 dominate, are also likely to be assigned to incorrect classes. It was found that, when a road section in question has such an irregular distribution' of truck classes 9, 10 and 13, this method might not give the proper results. However, it is possible that roads exhibiting such characteristics may be transporting special commodities, for instance, roads servicing the forestry industry for carrying logs or roads heading to places servicing agricultural activities, etc. Apart from the fact that these places are serviced by a particular class of trucks depending on the commodity to be carried, the trucks are either going there empty and returning loaded or vice-versa. It is recommended that such roads be identified and treated based on local experience or engineering judgement.

It should be noted that the vehicle classes with no significant number of vehicles should not be included in the computation process as they are likely to cause instability among the pairs being compared. In testing the viability of using the method, only trucks of classes 9, 10 and 13, which usually comprises 85-90% of all trucks, were used in the computation of the difference 'D'.

The parameters, $W_{q,i}$ and $W_{w,i}$ as defined before are found through a CB-FDM. Under the commodity-based modeling approach, a FDM development starts by converting commodity monetary values into tonnages, and then tonnages into numbers of trucks and assigning them onto the road network. Assigning trucks onto the road network is necessary for model calibration and validation. In this case, once the model is well calibrated and validated, the commodity weights (in tonnes) are assigned onto the road network. The product of the weight assignment onto the road network gives the parameters $W_{q,i}$ and $W_{w,i}$, which are required for computing the weight per truck proxies needed for one to execute the method (see Equation [7]). It is authors' opinion that other methods for acquiring the net weight of commodities transported along different road sections such as short-term weight counting are comparatively expensive.

However, it should be noted that a FDM used to estimate $W_{q,i}$ and $W_{w,i}$ may contain some errors that can significantly affect the results - the computations of weight per truck proxies. Whenever applicable, it is recommended that a ratio of the observed AADTT to the modeled AADTT ($AADTT_{observed}/AADTT_{model}$) should be used to adjust the values of $W_{q,i}$ and $W_{w,i}$ estimated through the model.

[5] An 'irregular distribution' means, by considering the three truck classes 9, 10 and 13, if any of these classes contributes more than 66% of the total, then the road section is considered to have an 'irregular distribution' of truck classes 9, 10 and 13.

3. VALIDATION OF THE METHODOLOGY

After the methodology was developed, it was necessary to test it on the ground for validation purposes. Despite the problem of data availability in Alberta, the six WIM stations available in the area were used. This section presents briefly how the validation exercise was carried out, the results as well as the discussion of the results.

3.1. Data preparation

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Using the CB-FDM that was developed in a separate study, and vehicle classification counts, the only step required was to obtain the net weights of commodities transported along the road network. Under the commodity-based freight demand modeling approach, truck assignment is preceded by truck trips estimation, which involves converting commodity tonnages into numbers of trucks. So, for this exercise, the data obtained after the mode split step, which is the weight of commodities (in tonnes), were assigned onto the road network without converting them into numbers of trucks. However, it should be noted that prior to this exercise, the model has to be fully developed to the point where traffic assignment is complete to allow for calibration and validation.

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Following the general practice for regional inter-zonal freight modeling, the All-or-Nothing traffic assignment technique was used to assign commodity tonnages onto the road network. It should also be noted that the same assignment technique that is used to assign trucks onto the road network during FDM development should be used for the sake of avoiding re-calibration. The product of the weight assignment exercise is the net weights of commodities transported through the road sections of interest. The net weights of commodities are used together with VCC for computing the weight per truck proxies required in Equation [7] (see page 12). The other data that are required from WIM devices were taken from the six WIM stations available in Alberta. The geographical locations of WIM stations in Alberta can be seen in Figure 5. The ALS similarities from the WIM stations were created using the traditional method so as to be compared with that of the methodology. Data from the CB-FDM were treated as per the procedures discussed under the Section 2- methodology development. Parameters such as vehicle classification data (N_i), weight per truck proxies (w_i) for classes 9, 10 and 13 that were seen to be dominant were processed. The results from the traditional method and the developed methodology were compared.

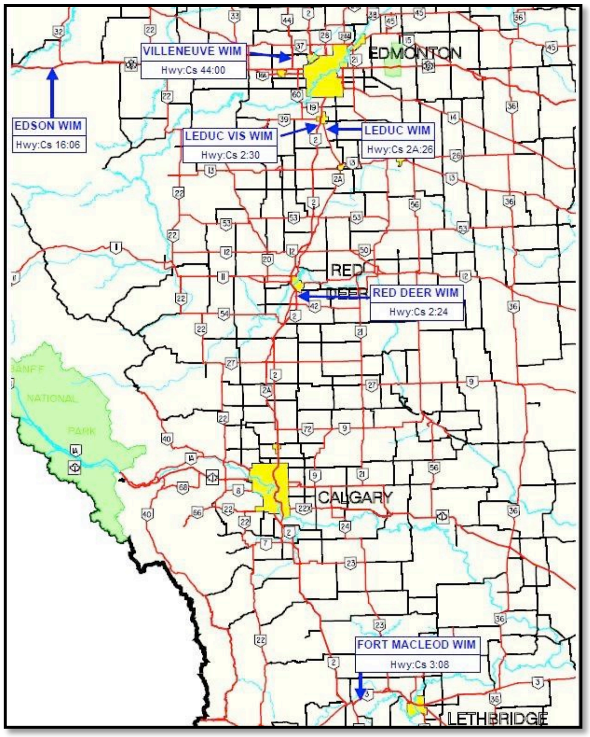

Figure 5: Geographical locations of the six WIM stations in Alberta

Source: Farkhideh (2012)

Before proceeding with the analysis, it was necessary to know the vehicle composition at each WIM station to assess the distribution of truck-classes 9, 10 and 13. Table 2 and Figure 6 show the composition of trucks at the WIM stations. From Table 2, it is noted that the dominant truck classes at all six WIM stations are 5, 9, 10 and 13, which account for about 90% or more. Similar to findings from previous studies, the tandem axle is used to represent other axles in evaluating ALS similarities among different road sections (Papagiannakis *et al.*, 2006; Mai *et al.*, 2013). For consistency, truck-class 5 was not considered in the computation of weight per truck proxies since it does not have any tandem axle.

Upon examining the trucks composition, it was revealed that at some stations such as Edson and Villeneuve, which are on highways #16 and #44 respectively, truck class 11 does not appear at all. It is also worthy to note that unlike the other stations, truck class 5 is the most dominant group at the Leduc (LED) WIM station, which is located on the old highway #2A. Another observation is that at the

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Villeneuve WIM station (VIL), the number of class 9 trucks is about one-third that of class 10, and also less than that of class 5, which is a bit unusual.

Table 2: Vehicle composition at WIM stations in Alberta

CLASSES\STATION	Edson (EDS)	Fort MacLeod (FTM)	Leduc - on #2A (LED)	Leduc - on #2 (LEV)	Red Deer (RDR)	Villeneuve (VIL)
4	53	32	25	145	218	28
5	349	172	113	588	929	189
6	57	35	30	72	186	112
7	23	5	4	13	25	11
8	11	17	10	37	48	33
9	353	322	74	962	1156	149
10	426	238	72	932	1027	504
11	0	1	1	2	4	0
12	6	5	1	17	17	1
13	579	131	58	670	685	397
TOTAL	1857	958	387	3438	4295	1424

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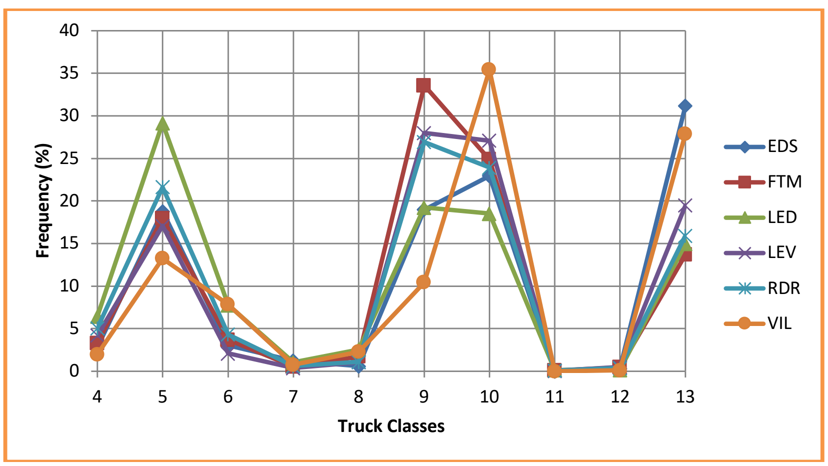

Figure 6: Vehicle composition at 6 WIM stations in Alberta

3.2. Results of the validation process

In a similar manner to that used for preparing the ALS for the 40 stations in Saskatchewan, the ALS data from all six WIM stations were prepared for the tandem axle as shown in Figure 7. As expected, this

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resulted in huge volumes of data that were not straightforward to analyse for identifying similarity among the WIM stations. In order to address this difficulty, Pearson's correlation coefficients (r_{ij}) were used to study the similarity between the above WIM sites, as shown in Table 3.

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A value of the coefficient r_{ij} close to 1.00 suggests a high degree of similarity between a pair of WIM stations, and a low r_{ij} value suggests a significant difference exists between the two. For instance, ALS for WIM stations at EDS and RDR are the most correlated with a correlation coefficient of 0.9687, followed by WIM stations at RDR and FTM with a coefficient of 0.9509. The ALS of WIM stations at VIL and LED, with a coefficient of 0.5417, are the least correlated among the sites presented in Table 3.

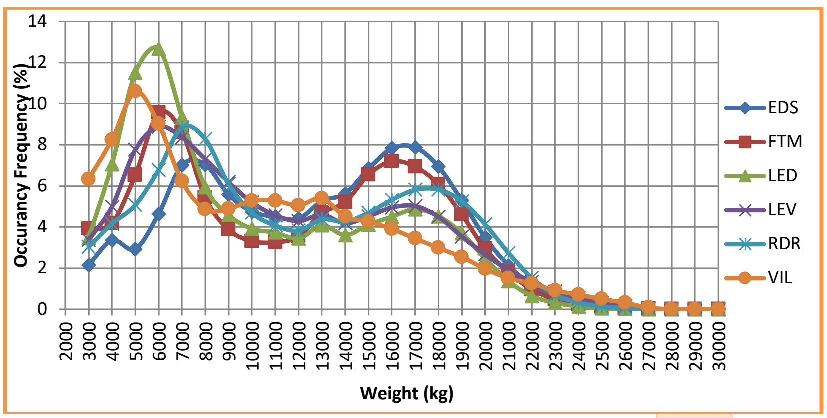

Figure 7: ALS for tandem axle at 6 WIM stations in Alberta

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Table 3: Pearson correlation coefficients for similarity ALS for 6 WIM stations in Alberta

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Sites	EDS	FTM	LED	LEV	RDR	VIL
EDS		0.9340	0.5883	0.9120	0.9687	0.7278
FTM	0.9340		0.7269	0.8950	0.9509	0.7960
LED	0.5883	0.7269		0.6364	0.6710	0.5417
LEV	0.9120	0.8950	0.6364		0.9199	0.8570
RDR	0.9687	0.9509	0.6710	0.9199		0.7478
VIL	0.7278	0.7960	0.5417	0.8570	0.7478	

The results from Table 3 were re-examined to arrange the WIM stations in the order of the similarity as shown in Table 4. This was very important as it allows for an easy comparison of the similarity generated using the ALS data from the WIM stations and the one generated by the developed methodology for identifying road sections with similar truck axle-loading pattern.

The next step was to compute differences - "D" using Equation [7]. This equation requires the weight per truck proxies and truck volumes for the truck-classes to be considered in the analysis - for this case, classes 9, 10 and 13. These parameters were computed as presented in Table 5.

Table 4: WIM similarities for six WIM stations in Alberta using Pearson correlation analysis of ALS

Site	Similarity Ranks				
	1	2	3	4	5
EDS	RDR	FTM	LEV	VIL	LED
FTM	RDR	EDS	LEV	VIL	LED
LED	FTM	RDR	LEV	EDS	VIL
LEV	RDR	EDS	FTM	VIL	LED
RDR	EDS	FTM	LEV	VIL	LED
VIL	LEV	FTM	RDR	EDS	LED

Table 5: Truck volumes and weight per truck proxies

	Truck Classes	WIM Stations					
		EDS	FTM	LED	LEV	RDR	VIL
Truck Volumes	9	353	322	74	962	1156	149
	10	426	238	72	932	1027	504
	13	579	131	58	670	685	397
Net Daily Commodity Weight (Tonnes)*		37,712	19,605	4,618	77,757	85,323	33,714
Weight Per Truck Proxies	9	107	61	62	81	74	227
	10	88	82	64	83	83	67
	13	65	149	80	116	125	85

* These values were extracted from the developed CB-FDM

The truck volumes and weight per truck proxies shown in Table 5 were used to compute the differences "D" as presented in Table 6. The similarity results from the difference "D" are presented in Table 7.

Table 6: Difference "D" calculated using Equation 7-6

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Sites	EDS	FTM	LED	LEV	RDR	VIL
EDS		1.4384	2.6368	1.0358	1.1155	1.6848
FTM	1.8692		2.7679	0.7130	0.6245	1.7996
LED	1.6763	1.5229		1.6723	1.4814	2.2650
LEV	1.2869	0.6989	3.0774		0.5846	1.3056
RDR	1.3884	0.5798	2.1018	0.4971		1.6234
VIL	3.2538	4.6403	4.9671	3.1180	4.1902	

Table 7: WIM similarities for six WIM stations in Alberta using the difference "D" from Equation 7

	Similarity Ranks				
Site	1	2	3	4	5
EDS	LEV	RDR	FTM	VIL	LED
FTM	RDR	LEV	VIL	EDS	LED
LED	RDR	FTM	LEV	EDS	VIL
LEV	RDR	FTM	EDS	VIL	LED
RDR	LEV	FTM	EDS	VIL	LED
VIL	LEV	EDS	RDR	FTM	LED

3.3. Discussion of the validation results

The WIM stations at Edson, Fort MacLeod, Leduc (on highway #2) and Red Deer are strongly correlated to the extent that they could be grouped under the same cluster. Interestingly, despite this strong correlation, the results from the developed methodology, to some extent could allow them to be arranged according to their similarity in the same order as that developed using the traditional method with data from WIM stations (refer to Tables 7-6 and 7-9). This occurred with the WIM stations at Fort MacLeod and Leduc (LEV). For the stations at Red Deer and Edson, because of the strong correlation, the other three stations could exchange the order of similarities. However, as explained earlier, even by using the traditional method, the Pearson correlation analysis might yield slightly different similarity order when compared to the least-sum of squares or other statistical methods. Therefore, a slightly different arrangement of the order of similarity shown by the developed methodology can also be seen when the traditional method is performed with different statistical techniques.

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In addition, the weak correlation on Villeneuve and Leduc (LED) shown by Pearson correlation using a traditional method was also confirmed, when the difference - "D" was calculated using the developed methodology. This also shows the strength and credibility of the developed methodology.

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From the above analyses, it clearly shows that the developed methodology for identifying road sections with similar truck loading patterns can provide credible results without requiring collection of axle loading data on the road sections of interest. It should be noted that in the absence of TWRGs, the only transparent way of deciding where to borrow the ALS is to compare the ALS data on the road section of interest, which is developed using short-term weight count data with that from the available WIM stations. With this methodology, the only requirements are a CB-FDM and VCC.

4. CONCLUSIONS AND RECOMMENDATIONS

One of the major problems inhibiting most transportation authorities from migrating from the traditional axle-based pavement design method to MEPDG is the lack of required truck ALS data. To acquire these data, extrapolating information from an existing WIM station with similar loading and distribution pattern is required given the limited number of installations. However, the problem has been how to identify a WIM device located along a road section with similar axle loading and distribution patterns. In this study, a quantitative methodology, which is capable of identifying road sections with similar ALS has been developed. The methodology serves as a proxy to having TWRGs in place. The requirement of the method are VCC at the study sites under consideration and a CB-FDM for supplying net weight of commodities transported along the study sections. The methodology is expected to serve as an alternative to transportation jurisdictions that do not have TWRGs in place, when adopting the new MEPDG. The methodology will also alleviate the problem of using default design data supplied with the software in a situation where there is no WIM data in place. Currently, most transportation authorities have not been able to develop a scientific method for transferring data from a few WIM devices available. The very few available WIM stations are not enough to develop credible TWRGs as per the FHWA guidelines. Prior to this study, it appears that the development of TWRGs and assigning road segments into the TWRGs is the only scientific way used for transferring ALS data from the WIM stations.

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