

MODELLING THE DYNAMIC WHEEL FORCES OF THE HEAVY VEHICLE FLEET

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ABSTRACT

Pavement strength and durability design is generally based on the level of heavy vehicle loading that it is expected to withstand. Traditionally this loading has been expressed in Equivalent Standard Axles (ESA) or some similar measure. More recently pavement designers have started to design for actual wheel loads and using computer models apply a distribution of loads to their design. This approach still assumes that each location on the pavement "sees" the same distribution of wheel loads. However, several recent studies including research element 5 of the DIVINE project have demonstrated a spatial repeatability in the dynamic loads applied by the fleet. Each heavy vehicle responds to the unevenness in the pavement which excites the vehicle's dynamics and generates a wheel force distribution that is not constant as it travels along. Although each vehicle's wheel force response is different there is a degree of correlation and so when the wheel forces are combined the mean is not constant along the pavement.

In this paper we present a method for predicting this distribution of wheel forces from the pavement profile. Multi-body simulation models are used to simulate the response of individual vehicles to a profile with the appropriate roughness. The effects of variations in speed and suspension characteristics are determined. From these responses transfer functions are calculated. By combining the transfer functions for the different vehicles in the fleet a fleet transfer function is estimated which is then fitted with a simple model. This model can then be implemented in a pavement performance model.

The data from DIVINE element 5 have been used to validate the model and the results of the validation are presented.

INTRODUCTION

The loading applied to a section of road pavement consists of a sequence of applications of axles of various weights. Even for an individual axle these weights are not constant but vary as the vehicle suspension responds to the pavement unevenness. To simplify the task of designing pavements to have sufficient strength and durability this loading spectrum has, since the 1960s been simplified to an equivalent number of passes of some standard axle, the most common of which is the Equivalent Standard Axle (ESA) although a number of variants exist.

The ESA derives from the findings of the American Association of State Highway Officials (AASHO) road test conducted in the USA in the late 1950s and is based on the so-called fourth power law. The number of ESA applied by an axle is its load normalised by the reference axle load raised to the fourth power. Thus the ESA incorporates a model of pavement wear in its definition. Although the ESA is based on static loads, it was derived from full-scale practical experiments which included dynamics loading so it can be argued that dynamic effects are included in the ESA formulation.

From the late 1960s onwards a number of researchers undertook experimental studies to measure the dynamic wheel loads generated by heavy vehicles as they travel along the road. (Eisenmann, 1975) developed a dynamic load factor to account for the effect of dynamic wheel forces. This factor comes from the expected value of the fourth power and thus implicitly assumes that the distribution of dynamic wheel forces along the pavement is random. That is, when considering the whole vehicle fleet, every section of pavement would see the same distribution of wheel loads.

As dynamic loads are generated by the vehicle's response to unevenness in the pavement it seems likely that there some locations on the pavement will receive higher average loads than others. (Cebon, 1986) identified this issue and proposed several options for pavement wear models based on the accumulation of load applications at pavement locations. This phenomenon has been termed "spatial repeatability".

Measurements undertaken in the UK (Gyenes and Mitchell, 1994) and in France (Jacob, 1996) as part of the Organisation for Economic Cooperation and Development (OECD) DIVINE project confirmed the existence of spatial repeatability with some locations on the pavement experiencing average loads more than 10% higher than the average for the pavement as a whole.

Although over the years since the AASHO road test a number of studies have developed power law relationships for pavement wear with exponents ranging from 2 to 12 depending on the failure mechanism and the type of pavement construction, they have still tended to use ESA which has an embedded 4th power relationship as the means of determining the traffic loading. More recently there has been a trend to use direct calculation methods usually based on multi-layer linear elastic theory to calculate the stresses and strains within the pavement as the basis for design but again the ESA or some alternative is often used for simplifying the traffic.

At the research level whole life pavement performance models have been developed and some of these have used vehicle loading models which try to simulate the spatial repeatability that is observed in practice. (Cole and Cebon, 1992) developed a measure of spatial repeatability based on the correlation of wheel forces from different vehicles. (Collop et al., 1996) applied this measure by determining the wheel forces from a quarter vehicle model which they massaged by randomising the phase angle of the Fourier transform so that it provided a series of wheel force signals with correlations similar to those observed in the spatial repeatability. This approach is quite computationally efficient but it is not clear how well it represents the in-service spatial wheel force distribution. In this paper we address the same problem but with a different approach.

Analysis of the DIVINE Data

Research element 5 of the OECD DIVINE project was concerned with determining the level of spatial repeatability of dynamic loading that occurs on roads subjected to normal fleet traffic. The main experimental program consisted of measurements undertaken by Laboratoire Central des Ponts et Chaussées (LCPC) in France at a site on the RN10 motorway at Trappes. An array of 24 weigh-in-motion (WIM) sensors was placed in the right lane. The array spanned 36m with a pattern of spacing designed to capture typical wavelengths of vehicle dynamic response.

Specifically the array was laid out as follows:

- 7 sensors at 0.375m spacing
- 4 sensors at 1.125m spacing
- 13 sensors at 2.25m spacing

Three sets of vehicle measurements were taken. The first set consisted of a series of passes by instrumented test vehicles at a range of speeds and loads. As the instrumentation on the vehicles was also measuring wheel forces, these runs were aimed at calibrating the system and cross-checking between the two wheel force measurement methods. The second set of measurements involved measuring the response of the system to a set of pre-weighed vehicles. For these tests, vehicles were taken from the normal traffic stream and weighed axle-by axle on a weighbridge just prior to passing over the array. The third set of measurements recorded nearly 3000 trucks out of the normal traffic stream over a one week period. Full details of the measurements and the results are presented in several papers and reports (Dolcemascolo and Jacob, 1999, Jacob, 1996).

The first stage of analysis for this work involved re-analysing the data from the pre-weighed vehicles. Initially the analysis considered the different vehicle types independently and then the different axle types independently. It was found that the fundamental trends found for these individual categories were similar to those for the all vehicles types and all axle types grouped together as a single set of applied loadings. Considering all the axles together is much simpler and so this is the approach that was used.

The mean and standard deviation of the applied axle loads by WIM sensor was as shown in Figure 1. As noted earlier the variation is approximately $\pm 10\%$ from the mean value. Interestingly the standard deviation appears to be quite well correlated with the mean. The r^2 value for this correlation is 0.63. The typical distribution of axle loads at a sensor is illustrated in Figure 2. As can be seen the distribution is not Gaussian as it has an extended tail at the higher end.

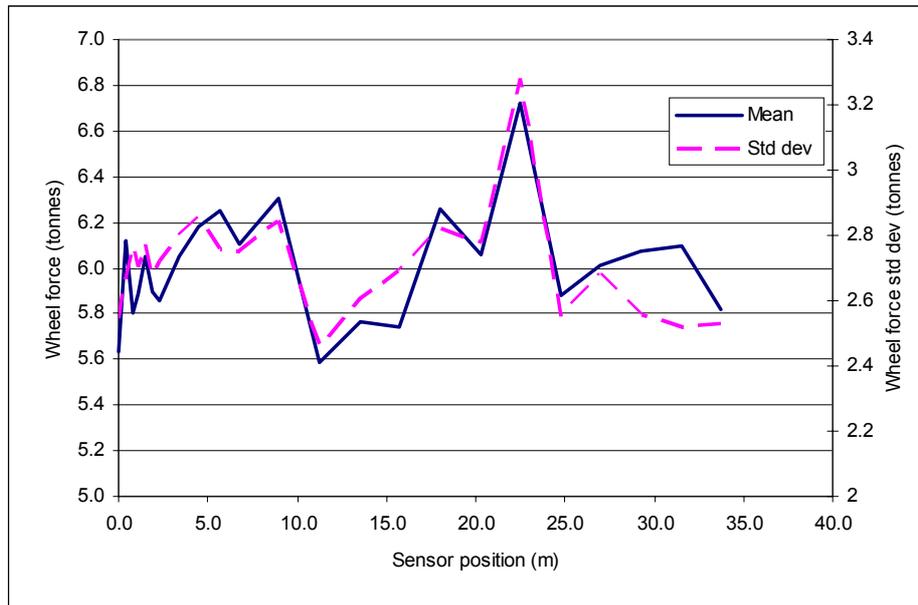


Figure 1. Mean and standard deviation of axle loads for pre-weighed vehicle set.

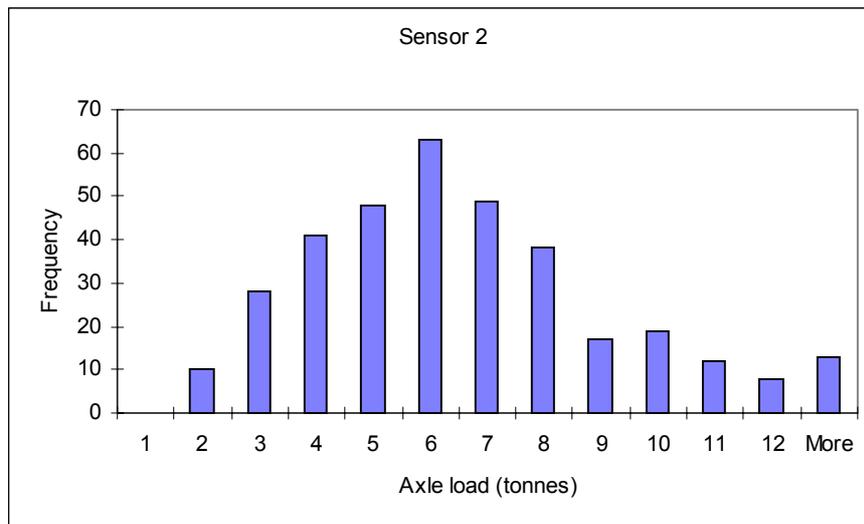


Figure 2. Distribution of axle loads at a sensor for re-weighed vehicle set.

The Box-Cox (1964) transformation is given by the equation:

$$T(Y) = (Y^\lambda - 1)/\lambda$$

where Y is the variable, $T(Y)$ is the transformed variable and λ is the transformation parameter. For $\lambda = 0$, the natural log of the data is taken instead of using the above formula. This provides a useful method for "normalising" distributions of this type. Although a λ value of 0.4 gives the best results for these data, $\lambda = 0.5$ gives a good fit and allows analytical relationships for the mean and standard deviation of the transformed data to be derived. Figure 3 shows the $\lambda = 0.5$ transformation on the data from sensor 2 which is displayed in Figure 2. Clearly the transformed data is now approximately Gaussian.

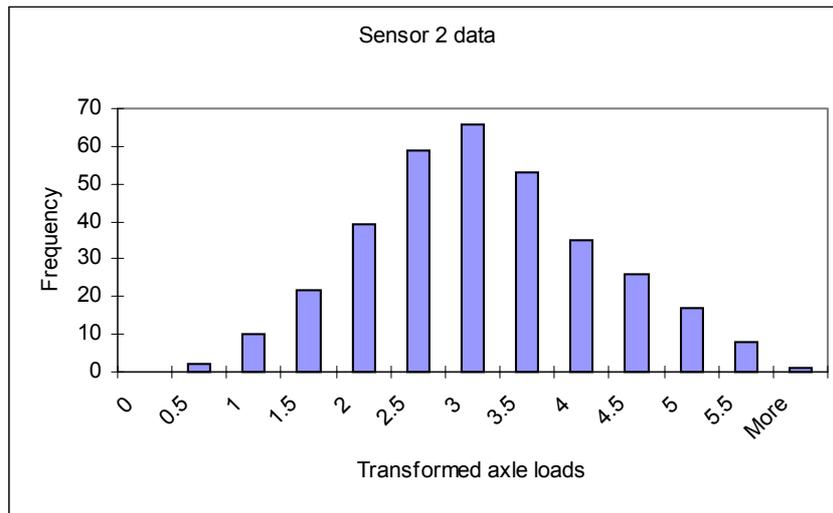


Figure 3. Distribution of Box-Cox transformed axle load data for sensor 2.

The previous analysis gives us the basis of a straightforward method for generating the applied axle load distribution at some location on the pavement providing we can predict the mean axle load at the location. The standard deviation is approximately proportional to the mean (as shown in Figure 1) and so this can be determined. For the $\lambda = 0.5$ Box-Cox transformation, the mean and standard deviation of the transformed distribution can be determined and so the appropriate normal distribution can be generated. The inverse Box-Cox transformation can be applied to this distribution to generate a prediction of the actual axle load distribution. Thus the only step still required is a method for predicting the mean axle load at a location.

Unfortunately when the full data set of vehicles is analysed these rather convenient distribution characteristics are not maintained. Figure 4 shows the mean and standard distribution by sensor for the full data set.

The mean and standard deviation are no longer correlated. The distribution of axle loads for the whole fleet by sensor now has at least two modes and so cannot be transformed into a Gaussian distribution using the Box-Cox transformation.

The mean axle load at a pavement location represents the average response of all the vehicles in the fleet to the pavement profile. Although 13 possible vehicle configurations were identified, the fleet was dominated by only three of these. The 2-axle rigid truck, the 2-axle tractor with a 2-axle semi-trailer and the 2-axle tractor with a 3-axle semi-trailer together made up about 90% of the traffic at the measurement site. If we consider the axle loads for each of these three vehicle types at a sensor we find that it is bi-modal and can be reasonably approximated by two Gaussian distributions. Using least squares best fit we can estimate the parameters of these two distributions at each sensor for each axle number. If the proportion of each distribution is optimised for best fit we get values that vary with axle number and sensor but are approximately half each. Forcing the distributions to be half each, the means and standard deviations for the average across all sensors for each axle are shown in Table 1 for the 2-axle tractor 3-axle semitrailer combination which was classified as type 5. This is the most common vehicle configuration and represents nearly 40% of the fleet.

Table 1. Parameters for bi-modal Gaussian fit to axle load distribution on type 5 vehicles.

	Axle 1	Axle 2	Axle 3	Axle 4	Axle 5
Mean 1	5.50	5.53	2.57	2.60	2.65
Std. dev. 1	0.49	1.45	0.87	0.80	0.84
Mean 2	5.87	10.44	6.28	6.32	6.35
Std. dev. 2	0.76	1.92	1.87	1.84	2.02

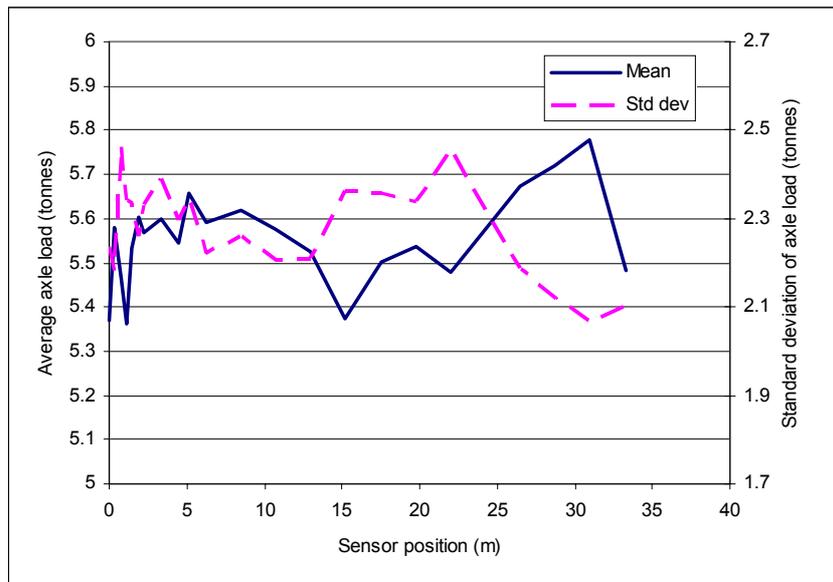


Figure 4. Mean and standard deviation of axle loads for general traffic vehicle set.

It can be seen that the two distributions represent empty and laden vehicles. The steer axle (axle 1) does not change much between empty and laden and, in fact, could have been represented satisfactorily with a single Gaussian distribution. Axles 3, 4 and 5 are part of a tridem group and as expected are very similar. For laden vehicles the standard deviations are higher and again this is as expected.

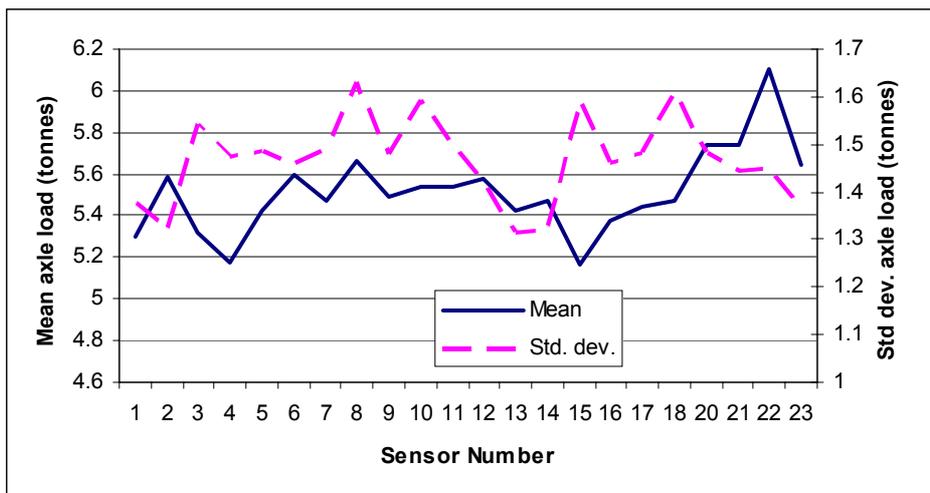


Figure 5. Mean and std. dev. by sensor for unladen axle 2 on type 5 vehicles.

Even at the individual axle and vehicle type level the mean and standard deviation are not correlated. Figure 5 shows, as an example, the variation in mean and standard deviation by sensor for axle 2 in the empty state. There is no reason why these should be correlated but it would simplify the prediction model.

From the dataset we can also extract, for each vehicle type, the speed distribution, and the axle spacing distribution.

Thus we have a relatively compact description of the fleet.

- three vehicle types each operating laden 50% of the time and unladen the other 50% of the time
- a speed distribution
- an average vehicle geometry (axle spacing) for each type. Apart from the rigid trucks, the variations in axle spacing within a vehicle type are quite small.

Computer simulation models

Research element 4 of the DIVINE project showed that the better performing multi-body vehicle dynamics simulation models could replicate the frequency content and magnitudes of the dynamic wheel force distributions generated by actual vehicles quite well. The match at the time domain level was not as good.

Of the various modelling packages tested the AutoSIM program from MSC Corporation was among the best performed. Thus AutoSIM models of the main vehicle types were built using the average vehicle geometry and typical suspension characteristics. The parameters of these models can be varied to build a fleet of vehicle models which can be "run" over the pavement at each level of roughness to generate the wheel force distribution. However, this approach is too computationally expensive and cumbersome to be included in Whole Life Pavement Performance Models where it would have to be repeated at every interval where there was a significant change in road profile.

The method used was to generate pseudo road profile data with a similar level of roughness to the pavement being modelled. The simulation models are then "run" over the pseudo-road profile and the transfer function matrices relating the input left and right road profiles to the resulting left and right wheel forces for each axle were determined. This effectively linearises the vehicle response. The process was repeated with axle loads at ± 1 standard deviation from the average. These variations had a relatively minor effect on the transfer functions. Similarly the effect of variations in speed was evaluated. This effectively smoothed and flattened the transfer functions. Figure 6 shows an example of an element of the transfer function matrix and shows how the speed distribution smoothes the response.

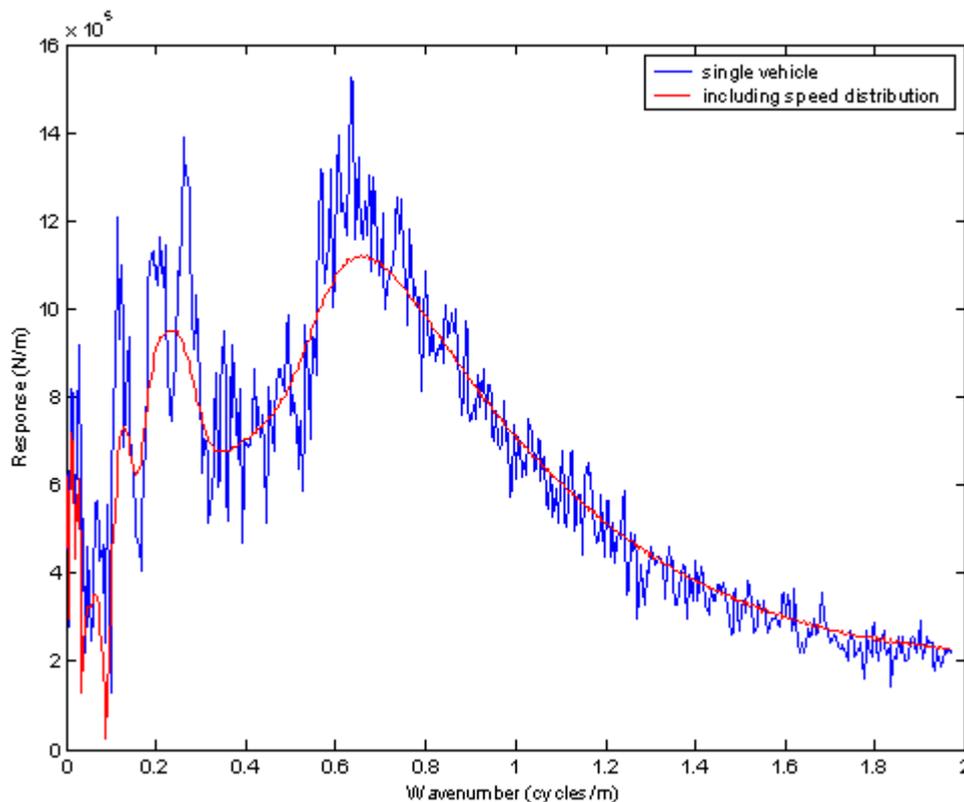


Figure 6. Transfer function magnitude for left profile to drive axle left wheel.

These transfer functions can then be applied to the actual road profile data at the site to estimate the mean dynamic axle load at each spatial location along the pavement. This needs to be done for each axle of the three main vehicle types and for both empty and full vehicles. For each vehicle type the distribution of axle loads is Gaussian and so is easily generated. Thus the overall distribution of axle loads by location can be generated.

The match between the forces predicted by the transfer function approach and those measured by the WIM system in DIVINE element 5 is fair at best. Figure 7 shows the predicted dynamic axle load distribution for a

particular axle on a particular vehicle compared with the WIM measurements for the same axle. Although the variations in wheel force are of the same order of magnitude and there is a similarity in the pattern one could not say there is a good match. Note that only the starred points on the WIM graph represent actual readings; the connecting lines have no physical meaning.

There are a number of possible reasons for the differences between the predicted and measured forces. The discrepancies could be from errors in either the measured or the predicted values or both. On the measurement side, the spatial variations in weight recorded by the WIM system are of the order of 10% of the mean weight. Thus if the calibration of the WIM sensors is accurate to, say, 2% of the total weight, the accuracy of the measurements of the variations are then accurate to 20%. Because the spatial repeatability findings are based on readings from 24 sensors this does not affect the overall findings on the magnitude of spatial repeatability but it does mean that the sensor by sensor readings may not be very accurate. On the prediction side the longitudinal coordinates of the road profile data are not necessarily accurate to the required resolution. For normal road roughness measurement this accuracy is not necessary. Similarly the lateral position of the profiler does not necessarily follow the centreline wheel paths precisely and this will lead to variations in the model response. However, it does appear that the model still has some limitations in generating an accurate spatial distribution of the fleet's dynamic wheel forces.

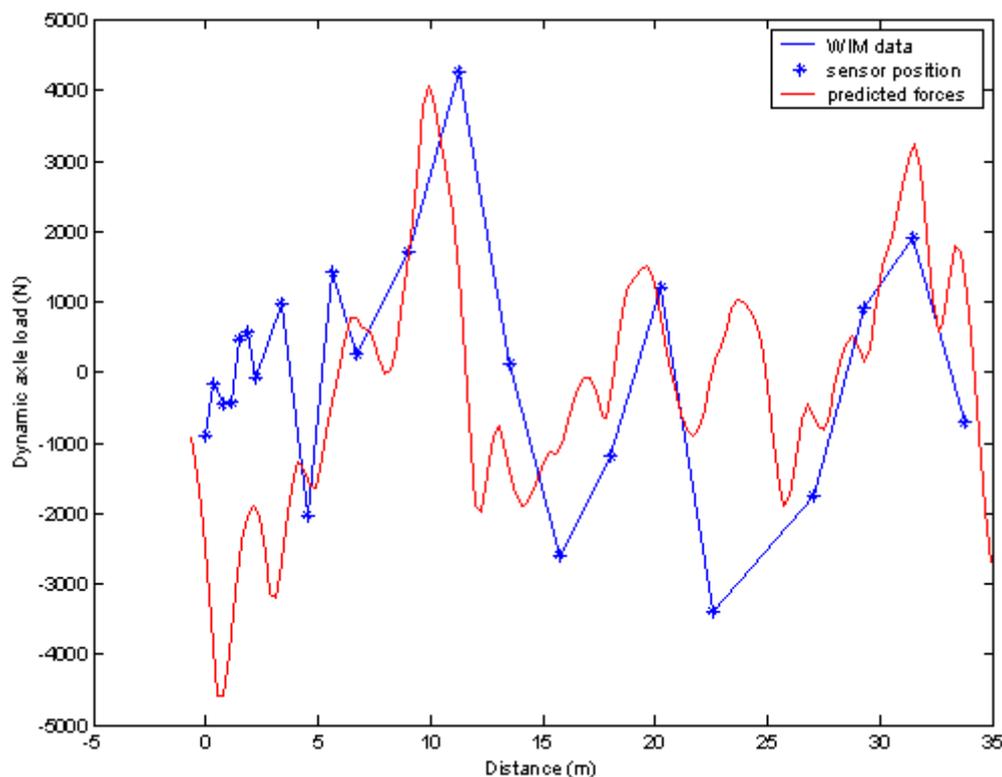


Figure 7. Comparison of predicted dynamic axle loads with WIM data for first trailer axle on laden type 5 vehicle.

CONCLUSIONS

The WIM data from DIVINE element 5 was re-analysed and it was shown that the vehicle fleet is dominated by three vehicle types. By fitting bi-modal Gaussian distributions to the axle load distribution for each axle on each vehicle type it was shown that the vehicles appeared to be 50% laden and 50% unladen. This then gives six characteristic vehicles (3 types, 2 load states) that constitute the fleet. For each of these characteristic vehicles each axle load distribution is approximately Gaussian and so can be characterised by its mean and standard deviation.

Multi-body simulation models of the characteristic vehicles were built. The wheel load response to road unevenness of these vehicle models was characterised by calculating the transfer function matrix for each axle. These transfer functions were adjusted to take into account the speed and load distribution for the

vehicles and these adjusted transfer functions were used to try to predict the spatial distribution of the dynamic axle load means.

Although the level of variation in the axle load means matched the WIM data, the point by point match was not very good. Whether this lack of match reflects the accuracy of the match between the profile data and the WIM data in the original data set or whether the method is inadequate requires further investigation.

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