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# A STATISTICAL SPATIAL REPEATABILITY ALGORITHM FOR MULTIPLE SENSOR WEIGH IN MOTION



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## **Abstract**

The use of an array consisting of multiple WIM sensors is well established as a means of increasing the overall accuracy of in-motion axle weighing. This paper proposes a new algorithm for processing the outputs from such arrays and finding an improved estimate of the static axle weights. The mean pattern of forces from the axles of many vehicles are repeatable – this is the phenomenon of Statistical Spatial Repeatability (SSR). The recorded WIM force is therefore, on average, over- or under-estimating the static axle weight. Removing this bias and averaging the corrected measurements is the basis for the new algorithm. The newly developed SSR algorithm is assessed using experimental data from the WIM-Hand project test site near Arnheim in the Netherlands. The accuracy of the new algorithm was therefore assessed by applying the algorithm twice, once for each half of the multiple-sensor array, and comparing the calculated static weights. The difference was found to be small, which demonstrates that the calculation is accurate.

**Keywords:** Weigh-in-Motion, WIM, MS-WIM, multiple sensor, spatial repeatability, SSR.

**Résumé**

**Mots-clés:**

## **1.Introduction**

This paper proposes a new algorithm for the estimation of static axle weights from multiple WIM sensor readings in a multiple-sensor array. A number of algorithms have been proposed in the past for processing the outputs from such arrays. Two algorithms, Maximum Likelihood and Signal Reconstruction with Kalman Filtering were developed

in the 4<sup>th</sup> Framework *WAVE* project. However, it was concluded (Dolcemascolo 1999) that the results were not significantly more accurate than taking a simple average of the multiple measurements. Gonzalez et al (2003) proposed the use of Neural Networks but acknowledged that this approach requires a great deal of training (calibration) data which may be impractical in many situations.

This paper proposes a new Statistical Spatial Repeatability (SSR) algorithm. The phenomenon of SSR has been observed by a number of authors such as O'Connor et al (2000). There is considerable variation in the patterns of dynamic force applied by similar axles of the same rank from similar vehicles travelling at similar speeds. However, the mean pattern from the axles of many vehicles are repeatable – this is the phenomenon of SSR. In the context of multiple sensor WIM, SSR means that a bias is introduced by each sensor as the recorded WIM force is, on average, over- or under-estimating the static axle weight. Removing this bias and averaging the corrected measurements is the basis for the new algorithm.

Calibration using moving vehicles does not remove SSR as the pattern of force applied by a moving vehicle will vary considerably between runs and, in any event, is related to the pattern of spatial repeatability for that particular vehicle. For example, if a two-axle truck is used for calibration, it may, after many repeated runs, be used to remove the spatial repeatability bias of that two-axle truck. However, the spatial repeatability pattern for that truck may not be typical for trucks of that type and will certainly not be typical for other truck types such as those with 5 or more axles. In this paper, the SSR pattern for the class of target vehicles is identified and is used to improve estimates of static axle weights for vehicles of that class. MS-WIM data provided by the Dutch WIM-Hand research project is employed to assess the accuracy of the proposed method.

## **2. The WIM-Hand Project**

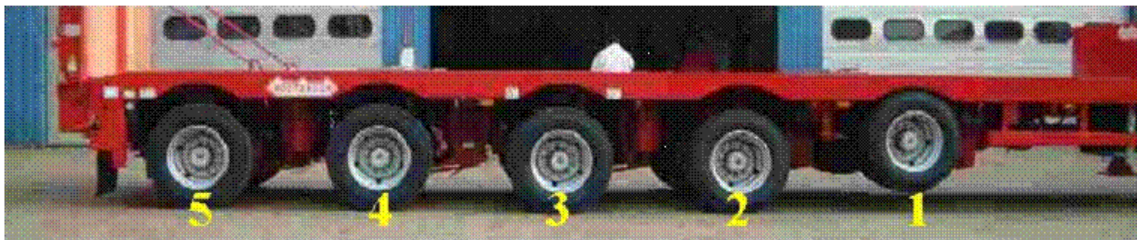
The WIM-Hand project was carried out as an element of the project ‘Overbelading’ (Overloading) by the Road and Hydraulic Engineering Division of the Ministry of Transport, Public Works and Water Management (DVS). The project was designed to investigate whether existing technology can be used to construct an axle load measuring system sufficiently accurate to carry out automatic enforcement of overloading by heavy goods vehicles. Unlike previous EU WIM projects, which focused mainly on the technological issues of WIM, WIM-Hand is focused on the harmonious implementation of WIM-technology within current enforcement strategies (van Loo and Henny 2005).

### **2.1 Field Testing**

The test site is located on the outer northern lane of the A12/A50 highway in Schaarsbergen, Arnhem. The multiple-sensor array comprises  $16 \times 4$  piezo-quartz electrical Kistler strip sensors. Each sensor is 1 metre long so at each of the 16 sensor

locations there is a 4-metre sensor consisting of 2×2 linked Kistler sensors. Thus, the total WIM sensor is longer than the width of the traffic lane, protruding by 30 cm into the emergency lane.

Longitudinally, the sensors are uniformly spaced at 1.5 m, bringing the total length of the sensor array to 22.5 m. The system also includes 4 induction loops to assist with vehicle classification. A MS-WIM system measures the dynamic axle load of passing vehicles using WIM sensors. Thus, calibration of the systems entails the dynamic calibration of each individual WIM sensor with an instrumented truck, illustrated in Figure 1. The figure shows the rear axles of the vehicle, which consists of a three-axle tractor with a five-axle trailer (VanLoo & Visser 2005).



**Figure 1** - Calibration vehicle trailer axles (van Loo 2004)

The first axle of the trailer is instrumented with strain gauges and accelerometers to calculate the dynamic wheel forces. These forces are measured with a maximum inaccuracy of 5% (Hoogvelt 2004). The calibration vehicle and the WIM sensors are synchronised using the exact time signal from GPS receivers. Four of the trailer axles are 'liftable' (axles no. 1, 2, 4 and 5 in Figure 1). By changing the axle configuration, several axle forces can be realised on the measurement axle without changing the mass of the trailer.

The WIM-Hand test system was calibrated using a large number of different runs by the instrumented vehicle over the WIM sensors. The runs varied in axle force on the measurement axle, speed, axle configuration of the vehicle and driving style, i.e., accelerating, braking and zigzagging.

A preliminary study of the data revealed that sensor no. 1 displayed significantly lower correlation with each left wheel (or odd-numbered) sensor measurement. Sensors 2, 6 and 8 from the right wheel sensor measurements did not deliver any data. Hence, the results from these four faulty sensors were removed from the dataset. Each left wheel was measured 15 times and each right wheel was measured 13 times giving complete axle load measurements at 13 of 16 sensor locations. This study investigates axle load measurements at these 13 working sensor locations.

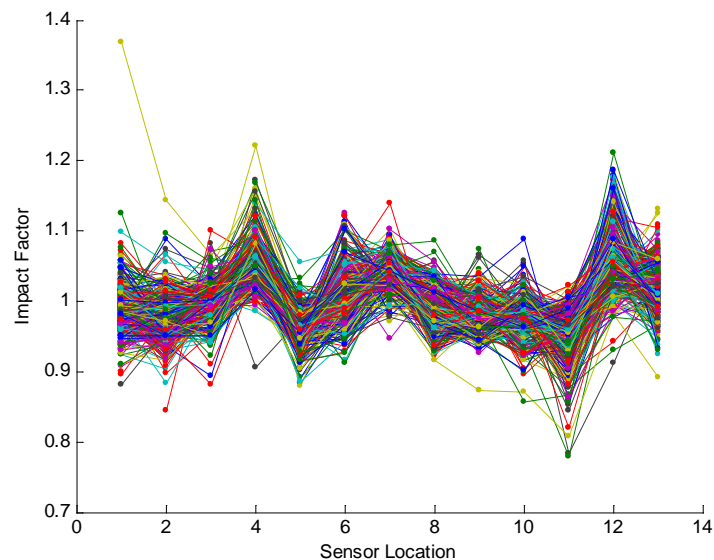
### 3. Identification of patterns within the data

The pavement profile was measured and for each individual vehicle, the WIM-Hand test system supplies the the number of axles, velocity, individual axle dynamic loads and the axle dynamic loading pattern over the 13 sensor locations.

Populations are classified according to the parameters above other than vehicle velocity. Velocity is not deemed a practical parameter for the definition of a population as a large portion of the vehicles travelled within a 10 km/h speed range. The WIM data obtained from the WIM-Hand project was normalised by dividing it by the mean of the 13 forces measured for each run, to allow the comparison of dynamic loading patterns.

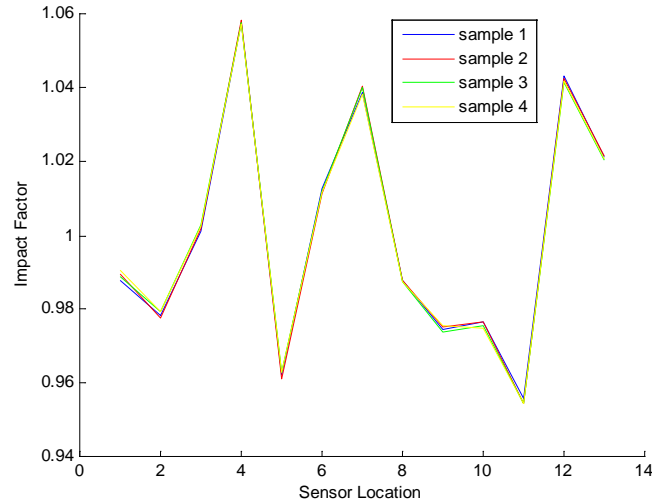
#### 3.1 Impact Factor Patterns of the Complete Data Set

Patterns of impact factors are calculated for the gross weight of each vehicle. The gross weight of a truck measured at each sensor location is determined by adding all measured axle forces at that particular location. Individual impact factor patterns are presented for a random set of vehicles in Figure 2. Variation in vehicle impact factors of approximately  $\pm 20\%$  is evident at each of the sensor locations.



**Figure 2** - Individual impact factors of gross vehicle weights for all vehicle types

The makeup of the population is then investigated. Two-axle and five-axle vehicles dominate the population; thus, the results seen in Figure 2 may be influenced by this dominance. To investigate the effect on the SSR pattern, a new 6000-vehicle population is created. This population is made up of four samples of 1500 trucks chosen at random from the data, one for each of two-, three-, four- and five-axle vehicles. The mean impact factor patterns are illustrated in Figure 3. It can be seen that the four patterns are almost completely overlapping, i.e., the SSR pattern is independent of the number of axles.



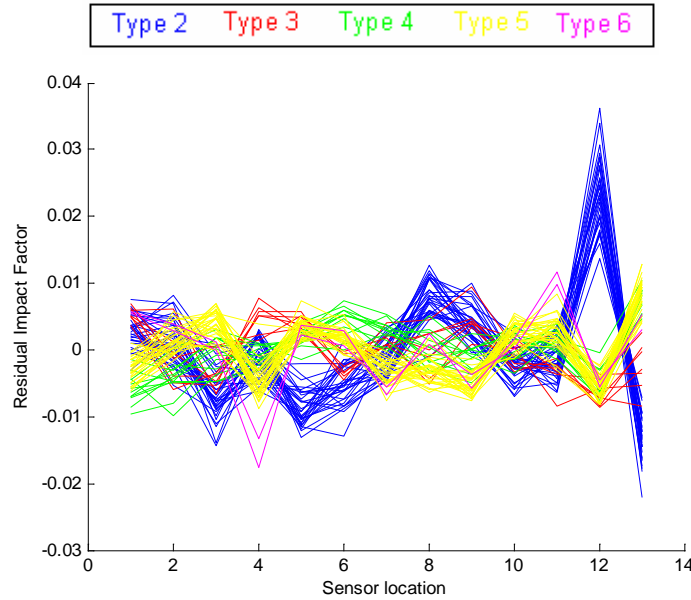
**Figure 3** - Mean impact factors of gross vehicle weights from a sample of 1500 vehicles (sample 1 = two-axle; sample 2 = three-axle; sample 3 = four-axle; sample 4 = five-axle)

This overall SSR pattern will be defined by the pattern obtained from this evenly distributed distribution of 6000 vehicles and will be referred to as the ‘pavement bias’.

### 3.2 Impact Factor Patterns of Populations defined by Vehicle Type

The complete data set of ‘parent population’ is then subdivided according to vehicle configuration. As axle spacing data was not collected at the WIM-Hand test system, a broad range of vehicle configurations could not be investigated. Vehicles are therefore classified simply by number of axles, from type ‘2’ to type ‘8’. This classification is somewhat crude, particularly in the case of larger vehicles, as there are many different axle configurations for vehicles with the same number of axles.

The SSR pattern defined as the pavement bias in Figure 3, is governing the SSR patterns of each vehicle type. The bias due to this pattern is removed from the measurement data set to enable a more direct comparison of the effect of vehicle type on the dynamic loading patterns. The mean residual impact factor patterns are calculated using equal sample sizes of 200 vehicles; the results are presented in Figure 4. Each truck type does not show the same high level of repeatability between patterns (this is essentially due to the smaller sample size); nevertheless, the distinction between vehicle types is clear. The pattern of vehicle type ‘2’ varies most from the others.



**Figure 4** – Residual impact factors of gross vehicle weight after removal of ‘pavement bias’

#### 4. Testing of Static Weight Estimation with Corrected Average Algorithm

This section investigates the effect of bias removal on static weight estimates using SSR patterns. Hereafter this method of estimating static weight will be referred to as the Corrected Average (CA) algorithm. It consists of removing both pavement bias (Figure 3) and mean residual impact factor (Figure 4) from each sensor reading and averaging the corrected values.

Static axle weights of vehicle type ‘5’ are estimated using this CA algorithm and compared to corresponding estimates using the standard Simple Average (SA) algorithm. The merit of the CA algorithm is tested against the current SA algorithm as follows: A total data set of 5881 five-axle trucks is split into a 2500-vehicle ‘learning set’ and a 3381-vehicle ‘test set’. The SSR pattern is defined as the mean impact factor pattern of a sample from the ‘learning set’ of vehicles. The dynamic load measurements of the ‘test set’ of vehicles is corrected according to the bias defined by the SSR pattern using Equation (1).

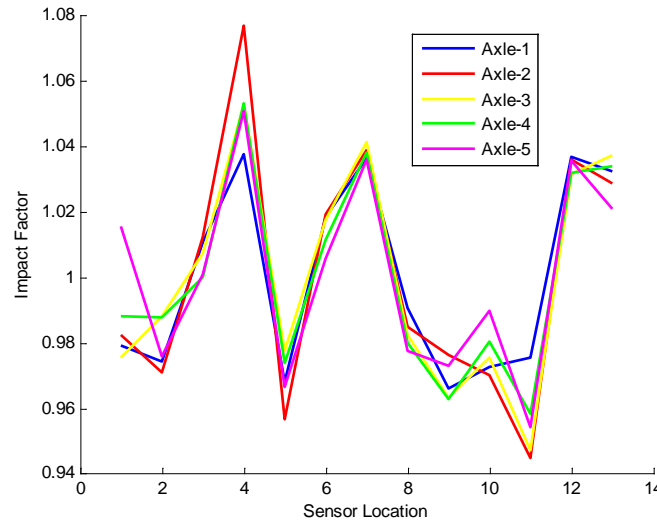
$$\text{Corrected measurement} = \frac{\text{WIM sensor measurement}}{\text{SSR impact factor}} \quad (1)$$

The mean of the WIM sensor measurements (SA) and the mean of the corrected measurements (CA) is then evaluated. Had static axle weights been obtained for this trial, both means would be compared directly to this. However, this data was unavailable so the

13 available WIM readings are used to form two separate MS-WIM systems and each algorithm employed to get two estimates of the same axle static weight from each MS-WIM sub-array. The relative difference between these two estimates is then used as a measure of accuracy for each algorithm.

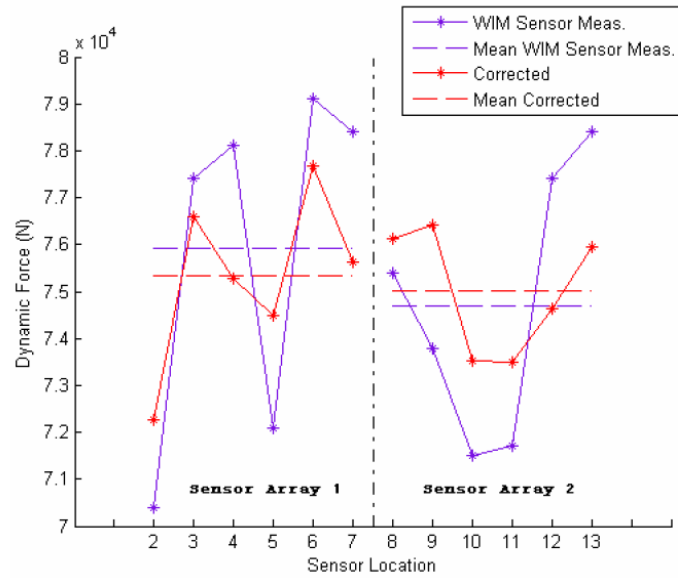
#### 4.1 Corrected Average Algorithm Based on Axle Rank Populations

The SSR patterns of the five-axle truck populations (Figure 5) are defined by the mean impact factor patterns of the 500 vehicles in the ‘learning set’.



**Figure 5** - Statistical spatial repeatable patterns of vehicle type ‘5’ axle populations

Vehicle type and axle rank are the only vehicle parameters required to associate the ‘test set’ data of 3381 vehicles with each of the five SSR patterns. The WIM sensor measurements for each axle are corrected to remove the bias defined by the associated pattern. If the population definition is appropriate and the SSR pattern is well defined, this correction will narrow the dynamic load range of individual axles. To test accuracy, two separate 6-sensor sub-arrays, ‘1’ and ‘2’, are identified in the total sensor array. For each algorithm, SA and CA, the difference between the estimates of sensor sub-arrays ‘1’ and ‘2’,  $E$ , is evaluated for all test axles. Figure 6 shows the differences between both approaches for a selected MS-WIM measurement. It can be seen that, as expected, the means of the corrected data for the two sensor arrays are much closer (at about 75 kN) while the means of the uncorrected data are significantly different (ranging from below 75 kN to below 76 kN). The considerable reduction in the differences after correction demonstrates that these results are more accurate.



**Figure 6** - Comparison of WIM sensor measurements and corrected measurements for 1<sup>st</sup> axle of a type ‘5’ vehicle on sensor array ‘1’ and ‘2’

The set of differences,  $\{E\}$ , is used as a measure of the inaccuracy of each algorithm. It is assumed that an ideal algorithm with unlimited data would return a normally distributed population of differences with mean zero. Two hypothesis tests,  $t$ -tests, are used to assess whether the mean of the SA and CA algorithms are statistically different from zero. Each  $t$ -test has a null hypothesis that the mean of the sample of errors is equal to zero. The associated  $t$ -statistic,  $T$ , is given in Equation (2).

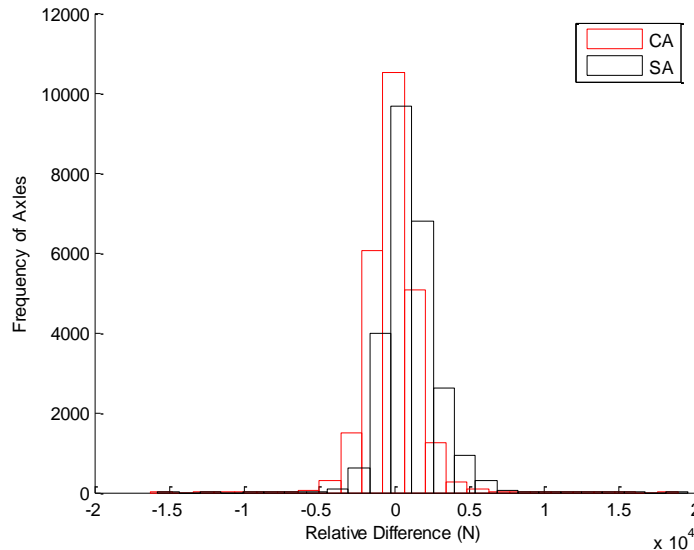
$$T = \frac{\bar{E} - m}{s/\sqrt{n}} \quad (2)$$

where  $\bar{E}$ ,  $s$ ,  $n$  and  $m$  are the sample mean, the sample standard deviation, the number of observations and the hypothesis error of zero respectively.

## 4.2 Results

The SA and CA algorithms are tested using each of the five axle populations separately. The five axle populations are also tested as a total group by combining the five individual  $\{E\}$  vectors as a complete set of  $E$ s. The total or complete relative error by SA and CA estimate populations,  $E$ , are displayed in Figure 7. It can be seen that there is a distribution of differences for the two sensor sub-arrays. For both algorithms, differences of up to about 5 kN (about 0.5 tonne) frequently occur. Notably, the CA differences are better centred about zero, i.e., the mean difference in results is closer to zero than the SA.

The standard deviation of the differences in the CA algorithm are also less than for the SA algorithm. This constitutes convincing evidence that the CA algorithm improves the accuracy of the calculation.



**Figure 7** - Comparison of total relative difference by SA and of CA static weight estimates of vehicle type ‘5’ axle population

McInerney (2007) carried out a number of theoretical simulations with sprung vehicle models of known static weight over a number of road profiles. From these studies, the improvement in accuracy of the CA algorithm over the SA algorithm is shown to be more significant as the number of array sensors decreased.

## 5. Conclusions

This paper has investigated the existence of SSR impact factor patterns within particular populations of data obtained from the WIM-Hand test system. A clear SSR impact factor pattern has been found in the parent population, and it has been deduced that the associated SSR pattern is primarily dependent on the pavement profile. The next set of sub-populations that has been investigated is classified by the number of axles per vehicle. Clear SSR impact factor patterns are observed. Types ‘4’ and ‘5’ populations have the most closely correlated patterns whilst type ‘2’ population is significantly different from the others.

A variation of the SA algorithm denoted as CA is used to remove the biases due to SSR. There were no available static load measurements to correspond to any of the dynamic load measurements available. Therefore, the CA and SA algorithms are compared by considering the differences between two estimates of the same axle weight from two

sensor sub-arrays. The CA algorithm was found to be more accurate than the SA algorithm for all populations.

## **6. Acknowledgements**

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