Calibration and Adjustment of Weigh-in-Motion Data

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Several methods have been used for calibrating weigh-in-motion (WIM) systems. One difference between the methods is in the formula used to make the calibration. A systematic approach is taken here in deriving and comparing four calibration methods. Adjustments of WIM data beyond calibration may be used to more closely emulate the properties of static weight data, such as in equivalent axle load calculations. Several adjustments of WIM data are also derived. Examples are given of the various methods of calibrating and adjusting WIM data.

The accuracy of weigh-in-motion (WIM) data depends on many factors, including calibration of the WIM system. The many reports received at FHWA show a variety of approaches to WIM system calibration. One way in which they differ is in the formula used to make the calibration. It does not seem to be appreciated how calibration affects the accuracy of the WIM data. The underlying criteria for four different calibration methods are examined and guidelines in their application are given. One of the main points is that the way in which WIM is evaluated should guide the selection of a calibration method.

WIM data are often used in place of static weight data because of their relatively low cost and convenience. What is then desired is to minimize the differences between WIM and static weight data. In particular, ways in which WIM data can be made to approximate static data in the determination of equivalent axle loads are examined here. Although other approaches are briefly mentioned, the main approach taken is to adjust the WIM data. The results of calibrating and adjusting three data sets are shown as examples of the methods.

ASTM standard specification E 1318-90 states that WIM is "the process of measuring the dynamic tire forces of a moving vehicle and estimating the corresponding tire loads of the static vehicle" (*1*). Note that WIM measures dynamic weights and estimates static weights. All too often these two aspects have been combined or confused. One reason for this is that static weights are the reference standard for WIM data. Another reason is that WIM weights are often taken as a proxy for static weights.

The purpose of WIM data collection determines whether static or dynamic weights are desired. For weight enforcement purposes, WIM is only a proxy for static weights. Weight regulations are aimed at the static weight of individual axles, axle groups, and vehicles. For most other purposes, such as pavement design and management, however, dynamic weights may be acceptable, if not preferred. The actual forces of moving vehicles that affect the roadway are more meaningful than the static weights.

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CALIBRATION METHODS

A WIM sensor produces a signal whose value depends on the instantaneous dynamic wheel loads of a moving vehicle. When the output for the sensor is properly calibrated, a dynamic load measurement is produced. This dynamic load may then be used to estimate a static weight. Calibration is the process of adjusting the outputs of a WIM sensor to match the measurements of a static scale.

Some devices can function as both static scales and WIM systems, and thus can be calibrated statically. However, WIM systems usually have to be calibrated with moving vehicles. If a test vehicle could be instrumented in such a way as to record the dynamic wheel forces as it moves, than a WIM system could be calibrated to these dynamic weights. But in the absence of any dynamic weight measurements to compare with, the static weights derived from a nearby scale are the only standard for comparison.

One calibration method involves passing the same vehicle or group of vehicles over the WIM sensor repeatedly. Then an average WIM measurement for each vehicle can be calculated and related to the static weight. The problem with this approach has been that it is costly to get appropriate test vehicles, and the calibration is keyed to a small group of vehicles that may not be representative of the general traffic stream.

The calibration methods examined here use the gross vehicle weight from a sample of vehicles that have been weighed with both a static scale and a WIM system. The vehicles may include test vehicles as well as the general traffic stream (*1*) but should be representative of the heavy vehicle traffic at the WIM site. The vehicles should also cover the range of weights expected to avoid extrapolating the calibration.

INVERSE PREDICTION

Regression analysis determines a functional relationship between independent and dependent variables that expresses their statistical relationship. A particular regression function is chosen according to given criteria that evaluate the difference between the dependent variable and its estimate by the regression function. Once it is determined, the regression function may be used to predict values of the dependent variable for new values of the independent variable.

For calibration, inverse prediction is needed (*2,3*). The inverse of the regression function is used to predict values of the independent variable given new values of the dependent variable. This is done because the independent variable repre-

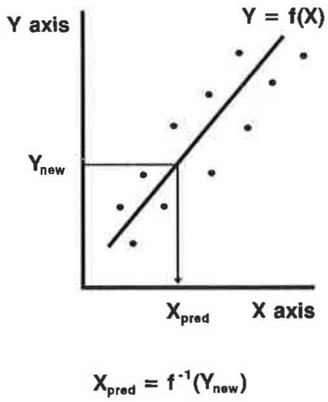

FIGURE 1 Inverse prediction.

sents the reference values that need to be estimated from the dependent variable that is being calibrated.

Let X_i be the reference values, Y_i the measured values to be calibrated, and $f(X)$ the regression function, where the index i ranges from 1 to n, the size of the data set (this same index will be used throughout). Then fit $Y = f(X)$ according to the regression criteria (see Figure 1). Finally, use the inverse of the regression function for the inverse prediction of X given a new value of Y:

$$X_{\text{pred}} = f^{-1}(Y_{\text{new}}) \tag{1}$$

For WIM calibration, static weights are the reference values X_i, and WIM weights are the measured values Y_i. Through inverse prediction, the static weight corresponding to a WIM weight may be estimated. The WIM system may then be adjusted to automatically produce these static weight estimates.

REGRESSION MODELS

A regression model specifies the type of function to be fitted and the criteria to be used to select the particular regression function. The functional form of the regression function may be determined by examining the way in which it is used. WIM calibration involves transforming the original WIM values of a sample data set, Y_i, into the calibrated values in a way that depends on the relation of WIM data to static weight data as defined by the regression model.

The gross vehicle weight is normally used for calibration because it varies less than the dynamic axle or wheel loads. The calibration is then applied to the wheels, axles, and axle groups. Thus the transformation that arises from calibration must be the same whether it is applied to the gross vehicle weight or the individual wheels, axles, or axle groups. That means the regression function must satisfy the functional equation

$$g(y_1) + g(y_2) = g(y_1 + y_2) \tag{2}$$

where y_1 and y_2 represent, for example, WIM axle weights, and $(y_1 + y_2)$ represents the gross weight. The general solution of this equation for nonnegative functions is

$$g(y) = k \cdot y \tag{3}$$

where the coefficient k is a nonnegative constant (*4*, p. 8). This constant is called the calibration factor (CF). This calibration function is the inverse of the regression function:

$$g(y) = \text{CF} \cdot y = f^{-1}(y) \tag{4}$$

so that

$$f(x) = \frac{x}{\text{CF}} = A \cdot x \tag{5}$$

where A is the coefficient derived from the regression analysis. The CF is thus the inverse of the regression coefficient A. We seek to minimize the error of the equation

$$Y_i = A \cdot X_i \tag{6}$$

by an appropriate choice of A. The errors are supposed to be in the WIM weights, not the static weights, so the regression of WIM on static data is used.

The CF is applied to the original WIM values Y_i to yield calibrated values Z_i:

$$Z_i = \text{CF} \cdot Y_i \tag{7}$$

which approximate the static weights X_i for each vehicle i in the data set.

To derive the CF, there must be some criteria for determining the particular regression function. The regression criteria should match the criteria that will be used to evaluate the accuracy of the WIM system. The type of calibration will be determined by the regression criteria employed. If the calibration criteria are inconsistent with the evaluation criteria, then the calibration will be inaccurate.

A particular regression function is chosen by optimizing a property of the residuals, which are the differences between the uncalibrated WIM and the regression estimate:

$$Y_i - A \cdot X_i \tag{8}$$

We will consider two approaches here: making the sum of the residuals equal zero, and minimizing the sum of the squares of the residuals. We will also apply these two approaches to the relative residuals, which are the residuals divided by the regression estimates:

$$\frac{Y_i - A \cdot X_i}{A \cdot X_i} \tag{9}$$

The mean of the differences between calibrated WIM and static weights is called the systematic difference and the standard deviation is called the random difference. This difference may be an absolute or relative difference as we shall see.

Evaluating a WIM system for accuracy and ensuring that it is within tolerance are two approaches to WIM evaluation. For accuracy the systematic difference is the most important consideration, but for tolerance the random difference may be more important. This is because accuracy is usually measured by an average value, whereas tolerances are concerned with keeping within a certain range of values.

A WIM regression model implicitly answers the question whether WIM deviations from static weights are considered measurement errors or dynamic differences. That is, does WIM measure static weight or dynamic weight? If WIM weights are expected to match static weights, then any differences are errors that should not be allowed to cancel one another. The first calibration approaches the residuals as errors.

LEAST-SQUARES CALIBRATION

A least-squares (LS) regression model focuses on the squares of the residuals and seeks to minimize their sum by an appropriate choice of the regression coefficient A:

$$LS_i = (Y_i - A \cdot X_i)^2 \tag{10}$$

All errors in the LS model are nonnegative, so negative errors cannot cancel out positive errors. To derive the LS calibration factor, take the derivative with respect to A of the total LS error and set it equal to zero:

$$\frac{d}{dA} \sum (Y_i - A \cdot X_i)^2 = 0 \tag{11}$$

or

$$\sum X_i Y_i = A \cdot \sum X_i^2 \tag{12}$$

so that A is (*3,5*)

$$A = \frac{\sum X_i Y_i}{\sum X_i^2} \tag{13}$$

Since the coefficient A is the inverse of the CF,

$$CF = \frac{1}{A} = \frac{\sum X_i^2}{\sum X_i Y_i} \tag{14}$$

In other words, the LS calibration factor is the sum of the squared static weights divided by the sum of the product of static and WIM weights.

When the errors are assumed to be uncorrelated and normally distributed with mean zero, the least-squares method gives the maximum likelihood estimator (*3*). However, several of the desirable properties of the least-squares estimator with intercept do not apply when there is no intercept. The sum and mean of the residuals do not equal zero. The sum of the observed values does not equal the sum of the fitted values. The regression line does not go through the center of the data points. LS calibration minimizes the variance, not the mean, of the residuals. When the sum or the mean of the residuals is made to equal zero, a different calibration method results.

ABSOLUTE DIFFERENCE CALIBRATION

If WIM is considered as a measurement of dynamic weight, then differences with static weights will be expected. WIM values will vary about the corresponding static values, but WIM should vary as much above static weights as below static weights. Thus, an average of the differences would be expected to equal zero as positive and negative differences cancel each other. Two models result from this approach, depending on which type of difference is used.

An absolute difference (AD) model evaluates WIM using the difference between the WIM and static weights (*6,7*):

$$AD_i = Y_i - X_i \tag{15}$$

This means that the regression line uses the residuals, not their squares. The sum of residuals is made to equal zero, which means that the sum of WIM and WIM estimates are equated. Thus

$$\sum Y_i = \sum A \cdot X_i \tag{16}$$

so that

$$A = \frac{\sum Y_i}{\sum X_i} \tag{17}$$

and the CF is the ratio

$$CF = \frac{1}{A} = \frac{\sum X_i}{\sum Y_i} \tag{18}$$

The AD calibration factor is the ratio of the sum of the static weights and the sum of the WIM weights. Geometrically, the AD calibration line goes through the origin and the center of the data points. The mean of AD-calibrated WIM equals the mean static weight, and the mean AD is zero. This calibration has the properties mentioned above that least squares without an intercept lacks.

PERCENT DIFFERENCE CALIBRATION

Instead of the absolute difference, the relative difference (RD) between WIM and static weights may be more important (*8*):

$$RD_i = \frac{Y_i - X_i}{X_i} \tag{19}$$

The relative difference is usually expressed as a percent difference (PD) (*1,6,7*):

$$PD_i = 100 \cdot RD_i \tag{20}$$

The RD and PD are related to the impact factor (IF), which is the ratio of corresponding WIM and static weights (*6,9*):

$$IF_i = \frac{Y_i}{X_i} = RD_i + 1 = \frac{PD_i}{100} + 1 \tag{21}$$

In this case, the regression line uses the relative residuals. The sum of the relative residuals is made to equal zero

$$0 = \sum \frac{Y_i - A \cdot X_i}{A \cdot X_i} = \frac{1}{A} \sum \mathrm{IF}_i - n \quad (22)$$

which implies that A equals the mean impact factor. Since the CF is the inverse of A,

$$\mathrm{CF} = \frac{1}{A} = \left(\frac{1}{n} \sum \frac{Y_i}{X_i}\right)^{-1} = (\overline{\mathrm{IF}})^{-1} \quad (23)$$

the CF is the inverse of the mean impact factor (*8*). The mean of the impact factor for PD-calibrated WIM equals 1 and the mean PD is zero.

RELATIVE LEAST-SQUARES CALIBRATION

The relative least-squares (RLS) calibration is derived in a manner similar to LS calibration, except that the relative residuals are used instead of the residuals. First, the derivative of the sum of the squares of the relative residuals is set equal to zero:

$$\frac{d}{dA} \sum \left(\frac{Y_i - A \cdot X_i}{A \cdot X_i}\right)^2 = 0 \quad (24)$$

or

$$\sum \frac{Y_i}{X_i} = \frac{1}{A} \cdot \sum \frac{Y_i^2}{X_i^2} \quad (25)$$

Therefore,

$$\mathrm{CF} = \frac{1}{A} = \frac{\sum Y_i/X_i}{\sum Y_i^2/X_i^2} = \frac{\sum \mathrm{IF}_i}{\sum \mathrm{IF}_i^2} \quad (26)$$

That is, the RLS calibration factor is the sum of the impact factors over the sum of the squares of the impact factors. This calibration method appears to be new.

EXAMPLES

Examples of these calibration methods are given in Table 1, which is based on data sets provided to FHWA from Kansas and Utah plus a test data set that we generated. Only five-axle tractor trailers (3S2s) were selected from the data. There are 81 trucks in the resulting Kansas data set, 327 in the Utah data set, and 21 in the test data set. The tolerance levels used in Table 1 are plus or minus 5,000 lb and 10 percent for the test data and Kansas data and plus or minus 15,000 lb and 25 percent for the Utah data.

TABLE 1 Examples of Weigh-in-Motion Calibrations

Type of Calibration	Data Set	Mean Absolute Difference	Mean Percent Difference	Percent Outside Absolute Tolerance	Percent Outside Percent Tolerance
None	Kansas	-0.26	-1.17	3.70	4.94
	Utah	6.06	10.24	18.04	16.82
	Test	-0.23	4.81	0.00	19.05
Absolute Difference	Kansas	0.00	-0.68	4.94	4.94
	Utah	0.00	0.42	6.73	8.26
	Test	0.00	5.23	4.76	23.81
Percent Difference	Kansas	0.36	0.00	4.94	6.17
	Utah	-0.26	0.00	6.42	8.26
	Test	-2.98	0.00	38.10	14.29
Least Squares	Kansas	-0.29	-1.22	3.70	4.94
	Utah	0.21	0.76	6.73	8.26
	Test	1.20	-7.33	4.76	23.81
Relative Least Squares	Kansas	0.24	-0.24	4.94	4.94
	Utah	-1.59	-2.14	7.65	7.03
	Test	-3.85	-1.52	42.86	23.81

The good news is that the accuracy of various calibrations with the two "real world" data sets varied less than 2 percent. The bad news is that it is not hard to generate a data set in which the difference is 5 to 7 percent as the test data set illustrates. Table 1 also shows that LS calibration does the best for two of the three data sets with an absolute tolerance. Similarly RLS calibration does the best for two of the three data sets with a percent tolerance.

Supposing that the best approach for calibration with a tolerance level is the direct approach, find the CF with the most points within tolerance. The problem is that there may be more than one CF that does this. An algorithm that picked one would be arbitrary. The particular tolerance level chosen would also have a significant effect on the CF.

Another approach is to minimize the variance of the residuals. For an AD tolerance level this leads to LS calibration. For PD tolerance levels this leads to RLS calibration. However, minimizing the variance without minimizing the mean of the residuals can produce skewed results. The systematic difference should be minimized before the random differences are addressed. That is why AD calibration is best for absolute tolerances and PD calibration is best for percent tolerances.

By choosing an inappropriate calibration method, accuracy may be needlessly lost. The calibration should at least work right on the calibration data set. It is the WIM regression model that determines what "right" means. This in turn depends on what criteria are used to make the evaluation of accuracy. For slow-speed WIM where high accuracy is expected, choosing the right calibration method is critical.

CALIBRATION STANDARDS

ASTM E 1318-90 specifies the evaluation of a WIM system in terms of tolerance levels for a test data set (*1*). A given percentage (95 percent) of the data must have an error within the tolerance interval. For most cases, the tolerance level is defined as plus or minus a certain percentage difference. For some cases, the tolerance is plus or minus an absolute value.

Standard E 1318-90 has much detail about the calibration sample and tolerance level but little about calibration calculations, simply (*1*),

> Make the necessary adjustments to the WIM-system settings which will make the mean of the respective differences for each basic measurement equal zero.

Earlier in E 1318-90 "difference" is defined as percent difference. This would imply that the recommended calibration is based on percent differences. However, for absolute tolerances a calibration based on absolute differences makes more sense.

ADJUSTMENTS WITH INTERCEPT

If wheels or axles are calibrated separately, then Equation 2 does not apply. In that case the intercept term need not equal zero. Although it is just possible that the dynamic weight of an axle could be zero, a WIM system reading of zero should mean that no axle is present. But by allowing a nonzero intercept within a certain range, another condition may be included with the calibration criteria. In this way, both the systematic difference and the random difference may be minimized.

Let Z_i be the adjusted data, AF the adjustment factor, and AI the adjustment intercept. Adjustments may be derived by inverting the regression equation:

$$f(x) = A \cdot x + B \quad (27)$$

(compare Equation 5) so that

$$\mathrm{AF} = \frac{1}{A} \quad (28)$$

and

$$\mathrm{AI} = \frac{B}{A} \quad (29)$$

If the mean absolute difference is made to equal zero and the standard deviation of the AD distribution is minimized, the result is the standard least-squares regression line with intercept. Because of the intercept term, the adjustment is applied either to the individual axles or to the gross weights but not to both. If the mean percent difference is made to equal zero and the standard deviation of the PD distribution is minimized, a different adjustment results.

There are other approaches to reducing the random difference. One may try to control the factors that give rise to the random difference in the first place. These are factors that make the dynamic weights differ from static weights, such as pavement condition and vehicle speed. If these can be avoided or limited at the WIM site, then the systematic difference should be reduced.

A list of factors causing dynamic weight to differ from static weight has been compiled by Lee (*10*). These include the vehicle factors of gross vehicle load, distribution of gross vehicle weight, suspension, tires, and aerodynamic characteristics. However, control of these variables and, hence, of the random difference, is limited.

Other approaches to reducing random differences involve the postprocessing of WIM data. We briefly look at the use of multiple calibration factors and then examine adjustments to WIM data.

MULTIPLE CALIBRATION FACTORS

Another approach to minimizing both systematic and random differences is the use of multiple calibration factors. Known sources of random difference can be accounted for by separate calibration factors. Different vehicle types, for example, might have their own calibration factor. Since WIM is normally used in conjunction with automatic vehicle classification (AVC) devices, the vehicle type should be known.

Standard E 1318-90 notes that some WIM systems allow various calibration factors for each wheel, axle, or axle group on a vehicle (*1*). For example, the steering axle usually weighs light with WIM systems because of the torque associated with the drive train (*11*, p. 340). A calibration that includes the steering axle weights will therefore be too high, making the other axles weigh heavier than they should. Having a separate CF for the steering axle would compensate for this. The CF derived from the other axles' weights would then be lower. There is also evidence that drive tandems and trailer tandems have different dynamic properties (*12*) and so might have separate calibration factors. In any case, more research needs to be done to separate out the sources of random difference.

ADJUSTMENT FOR ESALs

The calculation of equivalent single axle loads (ESALs) from WIM data requires special treatment. Unadjusted WIM data in ESAL calculations usually will overestimate ESALs because the standard deviation of WIM data is usually greater than that of the corresponding static weight data, and ESAL calculations are related approximately as a fourth-power function of the static axle weights (*13*). (This is also addressed in an unpublished paper by Tony Esteve of FHWA entitled *An Analysis of WIM versus Static Truck Weight Data*.) Minimizing both systematic and random differences should help alleviate this problem. Multiple calibration factors would be better than an adjustment with intercept because various adjustments would be needed for the axles and axle groups used in ESAL calculations because of the adjustment intercept. A more direct approach is to use ESALs calculated from static and WIM data instead of gross vehicle weights in a manner similar to calibration. Then the adjustment factor is defined in a manner similar to the calibration factor and is applied to the WIM ESALs instead of the weights:

$$\mathrm{ESAL}(Z_i) = \mathrm{AF} \cdot \mathrm{ESAL}(Y_i) \quad (30)$$

(compare with Equation 7). Since ESALs are added together, it would seem appropriate that the AD criteria be used. In that case the AD ESAL adjustment factor is similar to the AD calibration factor:

$$\mathrm{AF} = \frac{\sum \mathrm{ESAL}(X_i)}{\sum \mathrm{ESAL}(Y_i)} \quad (31)$$

(compare with Equation 18). If one uses the PD criteria, then the PD ESAL adjustment factor is similar to the PD calibration factor:

$$\mathrm{AF} = \left[\frac{1}{n} \sum \frac{\mathrm{ESAL}(Y_i)}{\mathrm{ESAL}(X_i)}\right]^{-1} \quad (32)$$

(compare with Equation 23). Since the ratio of ESALs is approximately as the fourth power of the ratio of the corresponding axle weights (*14*), a PD adjustment factor may be derived that is applied to the axle weights:

$$1 = \frac{1}{n} \sum \left(\frac{Z_i}{X_i}\right)^4 = \frac{1}{n} \sum \left(\frac{\mathrm{AF} \cdot Y_i}{X_i}\right)^4 \quad (33)$$

TABLE 2 Examples of Weigh-in-Motion Adjustments

		Equivalent Single Axle Load		
Type of Adjustment	Data Set	Mean	Mean Absolute Difference	Mean Percent Difference
Unadjusted Static Weight	Kansas	0.929	—[a]	—[a]
	Utah	1.426	—[a]	—[a]
	Test	1.979	—[a]	—[a]
Unadjusted WIM	Kansas	0.984	0.054	-0.86
	Utah	2.328	0.902	59.66
	Test	3.366	1.380	85.65
AD ESAL Adjusted WIM	Kansas	0.929	0.000	-6.35
	Utah	1.425	0.000	-2.22
	Test	1.979	0.000	9.37
PD ESAL Adjusted WIM	Kansas	0.992	0.063	0.00
	Utah	1.460	0.032	0.00
	Test	1.809	-0.170	0.00
PD Axle Adjusted WIM	Kansas	0.949	0.020	-4.33
	Utah	1.339	-0.086	-8.00
	Test	1.504	-0.475	-13.17

[a] Not applicable

so that

$$AF = \left[\frac{1}{n} \sum \left(\frac{Y_i}{X_i}\right)^4\right]^{-1/4} \quad (34)$$

which is the inverse of the fourth power mean of the impact factor. The adjusted axle weights would then be used to estimate the ESALs.

The data set used for deriving the ESAL adjustment factors that are applied to the WIM ESALs should be representative of the ESALs experienced at the WIM site. Because making adjustments is difficult to do in practice, it may be preferable to adjust the WIM axle weights instead of the WIM ESALs.

Table 2 gives examples of WIM adjusted for ESALs for the same data sets used in Table 1. This was done using a sensitivity index of 2.5 and a structural number of 3 on flexible pavement. The second and third axles as well as the fourth and fifth axles were combined into tandems since only 3S2s were included in the data set.

The 60 percent average percent difference in the unadjusted Utah data set shows the need for adjusting WIM ESALs. The form of the PD adjustment applied to the WIM axle weights is less accurate than the other adjustments. Further research is needed in this area. The calculation of ESALs directly from dynamic, rather than static, loads may be the best solution.

CONCLUSIONS

- The WIM calibration method should correspond to the following evaluation criteria:
  - –AD calibration should be used for WIM when the evaluation is based on absolute differences;
  - –PD calibration should be used for WIM when the evaluation is based on percent differences;
  - –AD calibration is preferable for slow-speed WIM with absolute tolerances;
  - –PD calibration is preferable for WIM with percent tolerances; and
  - –LS and RLS calibrations should be used with caution.
- Adjustment of calibrated WIM data may be useful for the following special purposes:
  - –To minimize both systematic and random differences; and
  - –To approximate static ESALs.
- Further research is needed
  - –To quantify the factors that make dynamic weights differ from static weights;
  - –To determine the advantages of using multiple calibration factors; and
  - –To use dynamic weights directly in ESAL calculations.

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