

Variations of Archived Static-Weight Data and WIM

C. James Elliott, LANL
Ralph Gillmann, FHWA
Perry M. Kent, Perry M. Kent and Associates, Inc.

ABSTRACT:

Using seven-card archived, static-weight and weigh-in-motion (WIM), truck data received by FHWA for 1966-1992, we examine the fluctuations of four fiducial weight measures reported at weight sites in the 50 states. The reduced 172 MB Class 9 (332000) database was prepared and ordered from 2 CD-ROMS with duplicate records removed. Front-axle weight and gross-vehicle weight (GVW) are combined conceptually by determining the front axle weight in four-quartile GVW categories. The four categories of front axle weight from the four GVW categories are combined in four ways. Three linear combinations are with fixed-coefficient fiducials and one is that optimal linear combination producing the smallest standard deviation to mean value ratio. The best combination gives coefficients of variation of 2-3% for samples of 100 trucks, below the expected accuracy of single-event WIM measurements. Time tracking of data shows some high-variation sites have seasonal variations, or linear variations over the time-ordered samples. Modeling of these effects is very site specific but provides a way to reduce high variations. Some automatic calibration schemes would erroneously remove such seasonal or linear variations were they static effects.

RECEIVED
DEC 21 1998
OSTI

DISTRIBUTION OF THIS DOCUMENT IS UNLIMITED

MASTER

DISCLAIMER

This report was prepared as an account of work sponsored by an agency of the United States Government. Neither the United States Government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof.

DISCLAIMER

Portions of this document may be illegible in electronic image products. Images are produced from the best available original document.

THE DATA WE USE:

USA truck weight data [1] of Class 9 (332000) vehicles from 1966-1989 and beyond have been grouped together in the form of a database. A portion of these data have been obtained on static scales throughout the United States and are regarded as being accurate to a fraction of a percent. Ground truth is exactly what these weight data files represent. There are no electronics involved to vary in signal strength. All of the axle spacings were done with tape measurements. All of the weights were obtained from wheel-load weighers exact enough to issue citations for weight violations. The WIM data was submitted to FHWA in the 7-card format .

All Class 9 7-card data from two Federal Highway Administration (FHWA) CD-ROMS have been aggregated and sorted (171.6 MB with duplicates removed and data made uniform) according to the following properties in order of importance

- state code,
- functional classification,
- station id,
- direction of travel,
- year of data,
- month of data,
- date of month,
- hour of day,
- vehicle type code,
- body type,
- engine type,
- (option open),
- registered weight,
- basis of registration,
- (option open),
- lane of travel,
- (commodity code),
- (load status code),
- total weight of truck or combination,
- 5 weights of axles in hundreds of pounds,
- 4 axle spacings in tenths of feet,
- total wheel base,
- record serial number,
- continuation indicator.

A two-character state code, a three character station identification, and a one digit direction of travel characterize a site referred to as a *directed site* for clarity. In this study a blank character was considered different from 0. A major change occurred in

data entered into the database after the introduction of the Traffic Monitoring Guide, July 1985[1]. It specified use of the Federal Information Processing Standards (FIPS 5-1 now 5-2) [2] alphabetically-ordered numerical code for designation of the state rather than the previous Traffic Weight Study [3] system which was based on sub-units of region (New England, Mid-Atlantic States, etc.). At this time, states such as Texas changed the designation system for sites from which data was collected. Tracking site data through this transition period requires more information than found in the 7-card data set.

GOALS OF THIS STUDY:

We are looking for a means of determining if the weights that would have been registered by a weigh-in-motion (WIM) device are sufficiently regular and predictable that a drift or sudden change in WIM calibration can be detected. To do so we examine a mix of static weight and WIM data. The criteria/approach that such a method will have for the purposes of this study are:

- (0) Conventional 7-card weight data [1] are used exclusively.
- (1) It is based on pools of a number of Class 9 truck observations.
- (2) Errors in WIM devices will be compared with old static weight variations.
- (3) The computation is straight forward and understandable.
- (4) The method involves determining a quantity that has dimensions of weight called the weight fiducial and watching variations of that fiducial over time.
- (5) Robust algorithm: it makes a prediction for each pooled set of data.
- (6) Methodology for establishing false positives, natural static weight variations that might be confused with WIM malfunction, can be established.
- (7) It utilizes the information of the data set efficiently.
- (8) Scheduled calibrated vehicles are implicit but beyond the scope of this study.

Additional notes:

- (0) Weight data as opposed to transponder information indicates a near-term concern.
- (1) Class 9 trucks are most numerous and are sufficiently heavy to be important in infrastructure maintenance. We use pools of 100 vehicles. Moving averages can also be used [4,5].
- (2) WIM errors depend on road roughness, tire quality, device mechanics, device electronics, and more. Vehicle dynamics contribute to significant differences between WIM and static weight. See WIM Errors Section.
- (3),(4) Suggest a linear combination of weights may be considered.

BACKGROUND/OTHER WORK:

A variety of metrics have been proposed [4-11] as a way of determining if a shift in the calibration of a WIM device occurs. Some of these are practical today and other methods could apply in the future. There is no absolute way to separate a calibration shift from a shift in vehicle weights without additional information as to calibration or

weight expectation. To do so practically, it must be sufficiently large to make a difference beyond normal fluctuation expectations. At that point, one expects a calibration shift and recalibrates. If the new calibration is the same as the old, the shift is considered a real-weight shift. Then procedures may be considered for modeling these shifts. Such a *posteriori* modeling is very site dependent. Although such modeling could in principal be done on a national scale *a priori*, it would require detailed information about shipping decisions, available fleet vehicles, information usually thought to reside in the private sector. It would also involve road quality and have other stochastic elements describing tire and rim non-uniformity, possibly king-pin location, and suspension wear for instance. After sufficient *a posteriori* modeling, it may be possible to guess most important factors that would go into an *a priori* model. Stochastic elements, for instance, may average away or be described by a few parameters. Important commercial parameters could conceivably have surrogate parameters that are observable. Before such a national model is constructed, however, it is likely that technology will change the very nature of the problem. In particular, individual vehicle identification technology and fluidity of that information will impact calibration. For instance, a measured-weight versus claimed-weight system could lead to a different type of WIM calibration-drift detection.

One existing technique under study is to determine the gross vehicle weights (GVW) at which peaks occur in the distribution of vehicles. The underlying assumption is that there are many nearly-full and nearly-empty Class 9 trucks but many fewer intermediately loaded trucks. The approach of this technique is similar to a Bayesian *a priori* expectation. A future version of the model might predict GVW and front axle weights at particular sites in the various directions and lanes. As it now stands, the Bayesian expectations are not always met and the method suffers from lack of robustness, criterion (5).

A second technique is to use the front axle weight of Class 9 vehicles; it meets criteria (1)-(6) but needs to be evaluated with respect to (7). It is one of four techniques evaluated in this study.

OUR APPROACH:

After we visually explored multi-dimensional data sets in projection space, classes of algorithms we consider promising for this study have the additional properties

- (1) They are site and direction specific, but lane is not considered.
- (2) They involve utilizing both GVW and front axle weight.
- (3) Quartile statistics capture relevant information and generalize front-axle-only information.
- (4) Solving linear equations as used in the best-fit technique is not overly complex.

METHOD:

We order the vehicles by state, road-site designation, direction, and then by time. A weight fiducial is formed by four techniques: front-axle weight, first-quartile front-axle weight, 0-quartile extrapolated front-axle weight, and a best percentage fit of the four quartile axle weights. The later measure involves taking a linear combination of the quartile values that have been accumulated for 5 to 100 100-vehicle sets at each directed site. The quartiles are 4 bins of 25 vehicles each, with respect to the total GVW. The bins may be thought of as lightweight, heavyweight, and two intermediate weights. The average front axle weights in each bin are the only four numbers we use to characterize the 100 vehicle samples.

Comment:

The statistical efficacy of the method depends weakly on the vehicle properties being independent of time of day; most of the samples occur at peak traffic hours. The sparsity of the static data prohibited a closer look at short-time dependent effects. Such a study could be undertaken, for instance by pooling all vehicles in the same functional class within a given state, but site-specific effects could impact the utility of this approach. The linear combination method looks at that linear combination of sets of quartile values which minimize the fractional standard deviation, for a particular state, road-site, and direction. (This method can be solved by linear algebra, see Appendix A.) A variation on this theme is to use fixed GVW boundaries between bins rather than determine the boundaries of the quartiles. Lane variations may be expected when trucks occupy a slow lane, for instance, but these effects are not treated here.

The extrapolation to zero GVW is based on assigning the centers of the quartile values to $1/8, 3/8, 5/8$, and $7/8$ and interpolating best linear fit to 0. We do not attempt to justify this method by an underlying model; it did, however, work well on an initial trial set of data. The method amounts to assigning fixed importance to the quartile bins.

RESULTS:

Computational results for directed sites having more than 500 vehicles are shown in Fig. 1 and Fig. 2 for the front axle weight (irrespective of GVW) and for the best linear combination method, respectively. There the percent standard deviation is the ordinate or y axis. The number of pools of 100 vehicles is the abscissa. When more than 100 pools were present, the excess were dropped from the study. Here we see that the best linear combination method does sufficiently better. What this means is that fewer samples of vehicles need to be used to get the same standard deviation. Figs. 3-6 show a summary of the results for all four techniques.

Extraordinarily good results occurred at a few sites. With the best-combination method, standard deviations as low as 0.02% occurred with the 100-vehicle-sample sets. However, standard deviation errors as large as 16%-50% depending on method

occurred at the worst-case site. Generally, the best-combination method gives about 2-3% as the fractional standard deviation. It should be noted that these values typically have raw data spanning a time interval of 5-6 years.

Often 0-quartile estimation does better than using the front axle weight of the first quartile group, though usually not as well. The 0-quartile method was developed by examining a subset of data on which it was ideally suited. The lack of good fit to all the data suggested that modeling of data is very site specific.

The best of these results are also very site specific. They involve combinations of weights that have no simple known method by which to justify them, e.g. the extrapolation to 0 method. One can imagine a set of vehicles over the years appropriate to one direction of traffic at a state site. What is it that governs whether a vehicle set appropriate to another site will or will not visit the site under study or will not turn around and go the other way? Assuming there is an answer, this question gets into the area of how one models the traffic flow of Class 9 vehicles. These vehicles exist in many configurations varying from bread trucks to gasoline tankers. The cargo they carry may vary or be relatively fixed. The distribution of their weight depends strongly on the position of the largely unobservable kingpin.

Large variations of static-weight data would give rise to false-positive WIM-calibration errors, were a WIM device measuring correctly. Unusually large errors will result in false positive assignment confusing it with WIM calibration errors. In Fig. 7 we show data from Texas Site N25 direction 5. The span of these data is from February 1989 to July 1990 and the variation suggests a seasonal change. Here an *a posteriori* site model would be useful. Insights from such a model could have application to other sites, even with less seasonal variation. These particular data are of the WIM variety.

Other less volatile data from Florida Site 004 directions 1 and 5 show in Figs. 8 and 9 that well established trends in one direction do not imply similar trends in other directions. Here again, a site model for the trend line could be useful if the explanation were simple and true, and not a calibration error.

WIM ERRORS:

The details of the road roughness hundreds of meters prior [5] and the orientation and condition of the tires as they cross a weigh-in-motion detector (WIM) are critical, having up to the 10% effect on a single-vehicle measurement. Other effects such as dynamic braking and release cycles by the driver can alter WIM measurements. The entrance onto the WIM platform should have no discontinuity in height. These WIM-specific effects have been removed in the study we have reported because the values we use are highly accurate static weights. Examination of the effects in the list below suggest that both extrinsic factors such as road roughness or entrance height and intrinsic factors such as fatigue may be cause for recalibration.

Extrinsic to WIM scale:

Tires out of round, road hop, off-centered mounting on rim [12,13],
Vehicle vibration-resonance enhancement by resonator Q [14],
Breaking/clutching/rolling resistance [15,16],
Aerodynamic effects/Wind [17-21],
Weight-distribution effects/ wheelies [22],
Road roughness condition/path on road [17],
Condition and entrance height to scale platform,
Concrete with water-pumping effects,
Asphalt rutting at scale,
Soil compaction and runoff,
Power conditioning.

Intrinsic to WIM scale:

Piezo-transducer transverse inhomogenities,
Equipment-flex fatigue,
Electronic malfunction,
Environmental dust/charge invasion,
Physical damage by lightning or impact.

The practical use of WIM data derives from plots such as that shown in Fig. 10. The time scale for this data is one month, considerably shorter than the static weight data. The question to ask is, "is the observed downward drift owing to calibration or natural causes?" Because these data from Washington are WIM data, we cannot answer the question as we could were they from static-weight data.

CONCLUSIONS:

The majority of sites have a static weight fiducial with standard deviations over periods of 5-6 years that is small compared to expected variations from single event WIM errors. For these sites, suspected WIM calibration error detection would have been feasible if it had been undertaken concurrently. The outliers in the static weight fiducial data have interesting seasonal behavior. The extreme outliers (>10%) are only from WIM sites. How tight the separation error is set and what false-positive performance can be achieved at each of the levels is a topic for future investigation. Models of site behavior such as periodic or linear may be useful providing the underlying cause of the variation can be identified or the behavior well established. Further characterization of the outliers may give more insights.

REFERENCES:

- [1] Traffic Monitor Guide, Federal Highway Administration, July 1985. Latest version is now on-line [www](http://www.fhwa.dot.gov/trafficmon/).
- [2] Federal Information Processing Standards Publication (FIPS) 5-2, NIST, available on [www](http://www.fips.gov/); note that FIPS 5-1, June 15, 1970 and FIPS 5, November 1, 1968 were earlier versions of the same standard with the same numeric values for state codes.
- [3] P. Kent, Traffic Weight Study; information also used in Appendix A of, R. Winfrey, P. D. Howell, and P. M. Kent, Truck Traffic Volume and Weight Data for 1971 and Their Evaluation, FHWA-RD-76-138, December, 1976.
- [4] C. Han, W.T. Boyd, and M. M. Marti, Quality Control of Weigh-in-Motion Systems Using Statistical Process Control, Transportation Research Record, 1501, 72-85.
- [5] J. E. Garner and C. E. Lee, Augmented Weigh-in-Motion System for Traffic Data Collection and Analysis, Transportation Research Record, 1501, 81-86. Clyde Lee et al, 3rd International Conference on weigh in Motion, Oct. 17-21, 1988, St. Paul, Minn. Also Wiley D. Cunagin and J. M. Zweiback et al, same conference
- [6] M. Hallenbeck, Seasonal Patterns of Truck Loads and Volume in the United States, TRAC, Washington University, Oct. 14 1944. Also M. Hallenbeck, Quality Assurance and Automated Error Detection for WIM and AVC Equipment in the Long Term Pavement Performance (LTPP) Project
- [7] A. T. Papagiannakis, K. Senn, A.T. Bergan, WIM System Evaluation/Calibration Progress of NCHRP Study 3-39(2), 74th Annual Transportation Research Board Meeting, Washington DC, January 21-26, 1995.
- [8] W. C. Ott, A. T. Papagiannakis, WIM Data QA Based on 3-S2 Steering Axle Load Analysis, Transportation Research Board, 75th Annual Meeting, January 7-11, 1996, Washington, D. C.
- [9] R. J. Henry, European Databases on WIM, First European Conference on Weigh-in-Motion of Road Vehicles, Zurich, 8-10 March 1995, 363-67.
- [10] Chaparral Systems, 7-Card Format: LTPP Quality Assurance Analysis Procedures, May 2, 1995.
- [11] SAIC, Chaparral Systems, TRAC, Researches Guide to the Long-Term Pavement Performance Traffic Data, June 1997
- [12] Society for Automobile Engineers (SAE) J332, August 1981; originally 1969; see also version of 1993. Additional details on http://EES-www.lanl.gov/EES5/trans/September_97.html
- [13] A. Lloyd Nedley and Deane M. Gearig SAE Transactions 700089, 1970.
- [14] See: http://EES-www.lanl.gov/EES5/trans/November_97.html,
- [15] Tarpinian, SAE Transactions 700462, 1970; SAE Transactions 700462, 1970.
- [16] G. Roussillon, Journal of Wind Engineering and Industrial Engineering, 9, 33-48, 1981
- [17] Sayers formula in Papaginnakis, Journal of Testing and Evaluation JTEVA , 25, 197-204, March 1997.
- [18] C. K. Yip et al, Total Vehicle Dynamics, pp. 11-23, Institution of Mechanical Engineers, London, Technical Papers of FISITA 1992.

[19] W. H. Rae, Jr. and A. Pope, Low-Speed Wind Tunnel Testing, 2nd Edition, John Wiley & Sons.

[20] H. Fessler, T. H. Hyde, and W. Sun, Industrial Mechanical Engineering, Part D: Journal of Automobile Engineering, 1995, 103-110.

[22] http://www.ees.lanl.gov/EES5/trans/September_97.html

A motorcycle wheelie stunt:

<http://www.niweb.com/sport/motorcycles/stunts/stunts.htm>,

[21] Aerodynamic Drag Mechanisms of Bluff Bodies and Road Vehicles, ed. G. Sovran et al, W. T. Mason, Jr. and P. S. Beebe of the General Motors Research Laboratory

<http://rothmedia.com/photos/chenet/rc003/buell.html>,

<http://www.racefan.net.au/images/scottwh2.jpg>,

<http://www.bayarea.net/~tohf/htdoc/images/coelho0702.jpg>,

<http://www.bayarea.net/~tohf/htdoc/images/geving.jpg>.

APPENDIX A

Here we describe a method to minimize the fractional standard deviation of a set of data. This is appropriate to a system that an error in calibration factor whose value is independent of the date range. In 4-vector notation, each fiducial weight, f_j , is a linear combination of the four quartile values, q_j , associated with pool j , where the linear combination 4-vector w is to be determined. This vector may be normalized in any number of ways: we require the components to add to unity; the magnitude is irrelevant; only the ratios of components are of interest. Thus,

$$f_j = w \cdot q_j.$$

The minimum ratio of the standard deviation to the mean is achieved by minimizing the ratio, S , of the sums-of-squares of the fiducials divided by the square of the mean fiducial.

$$S = \sum f_j^2 / (\sum f_j)^2.$$

This amounts to examining all possible choices for w and choosing that choice with least S . Without loss of generalization, we find the minimum of $\sum f_j^2$ subject to the unity constraint $\sum f_j = 1$. The solution of this problem is that linear-combination vector, w , which when taken with the dot product of the covariance matrix of the quartiles gives the mean of the quartiles. The linear combination can be solved for by robust linear algebra and can be normalized by multiplying each component by a constant without effecting S .

FIGURES:

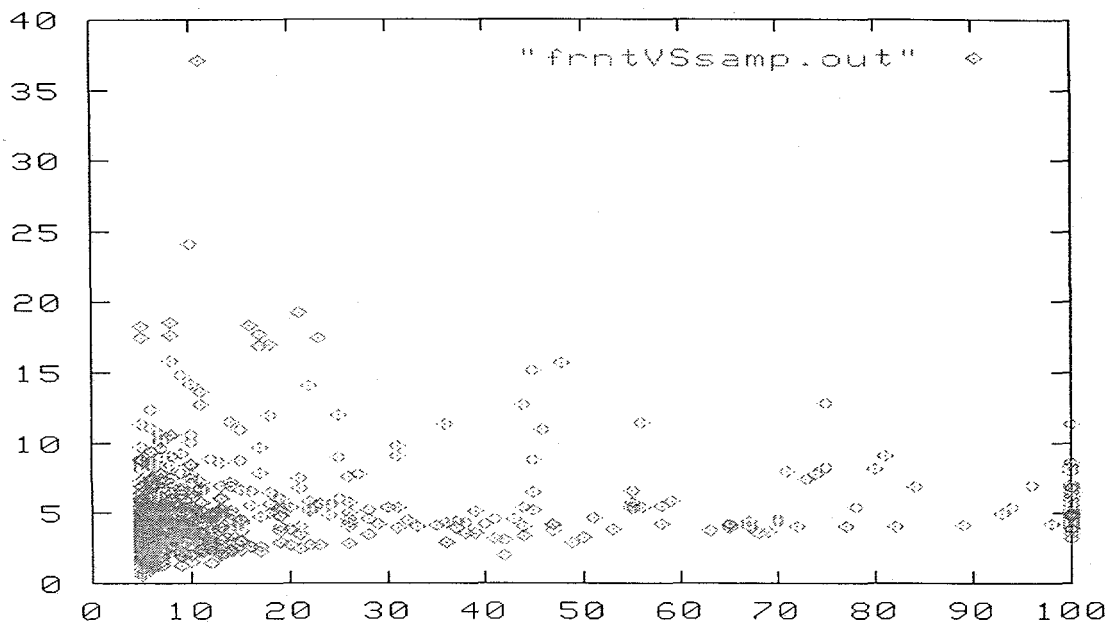


Fig. 1 Coefficient of variation in percent plotted against number of groups of 100 trucks: Front -axle weight in first GVW quartile.

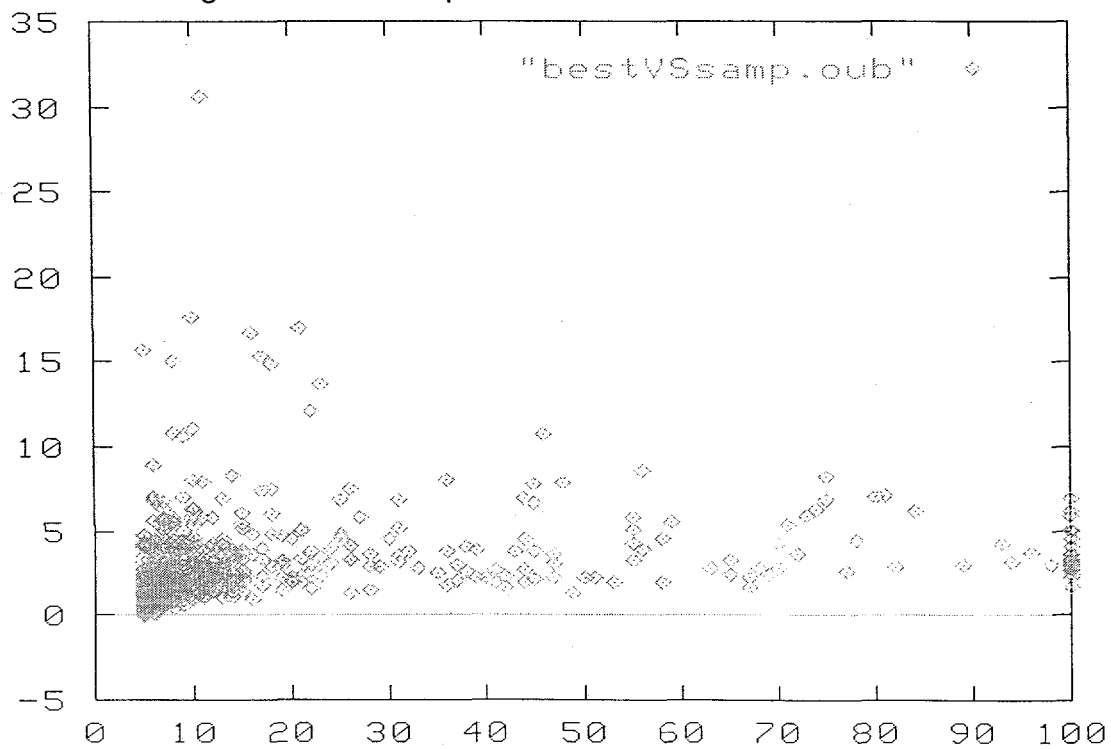


Fig. 2 Coefficient of variation in percent plotted against number of groups of 100 trucks: Best linear combination of front-axle-weight quartiles.

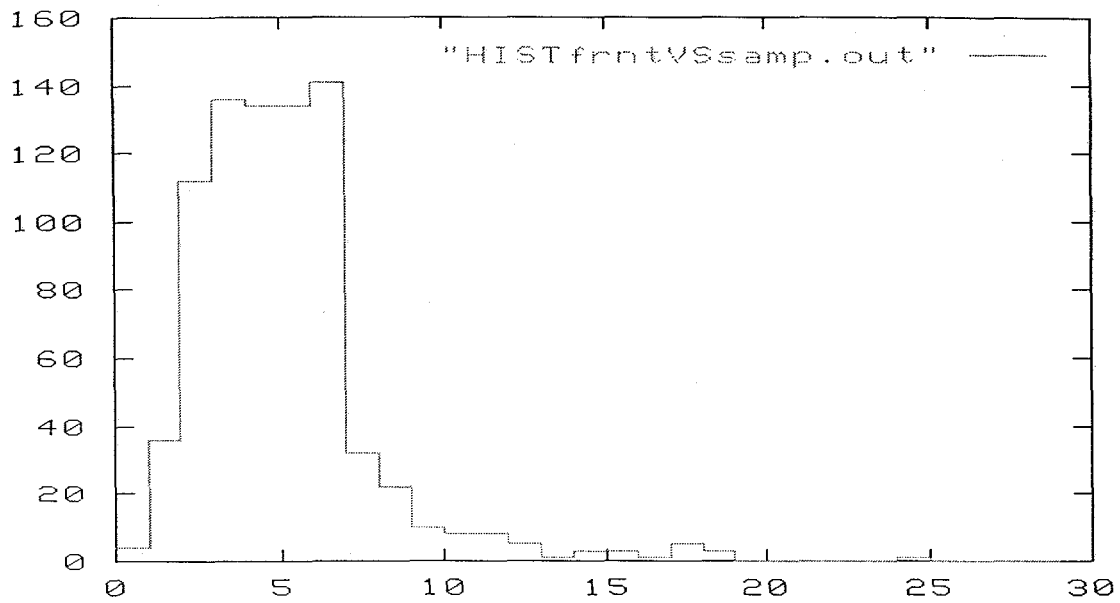


Fig. 3 Number of sample sets versus 1% bins of coefficient of variation:
Front-axle weight in first GVW quartile.

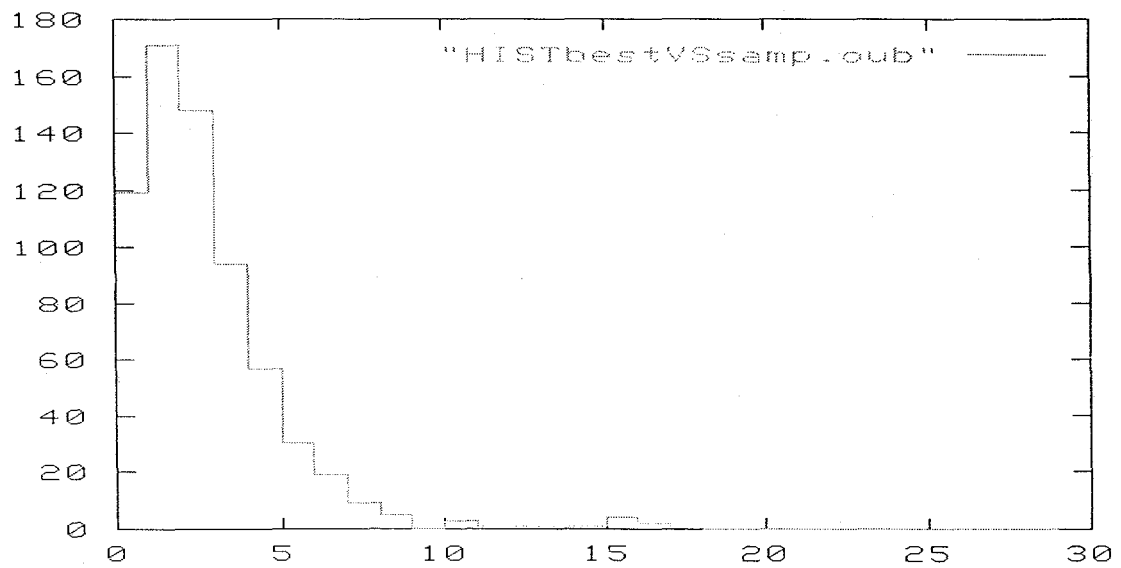


Fig. 4 Number of sample sets versus 1% bins of coefficient of variation:
Best linear combination of front-axle weights.

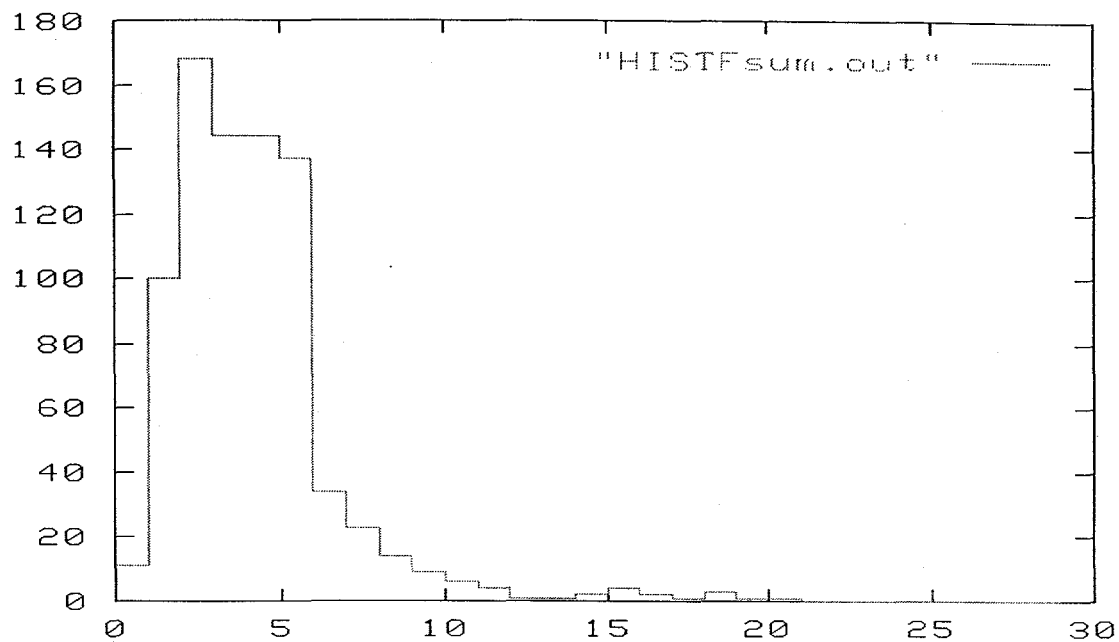


Fig. 5 Number of sample sets versus 1% bins of coefficient of variation:
Front -axle weights (irrespective of GVW).

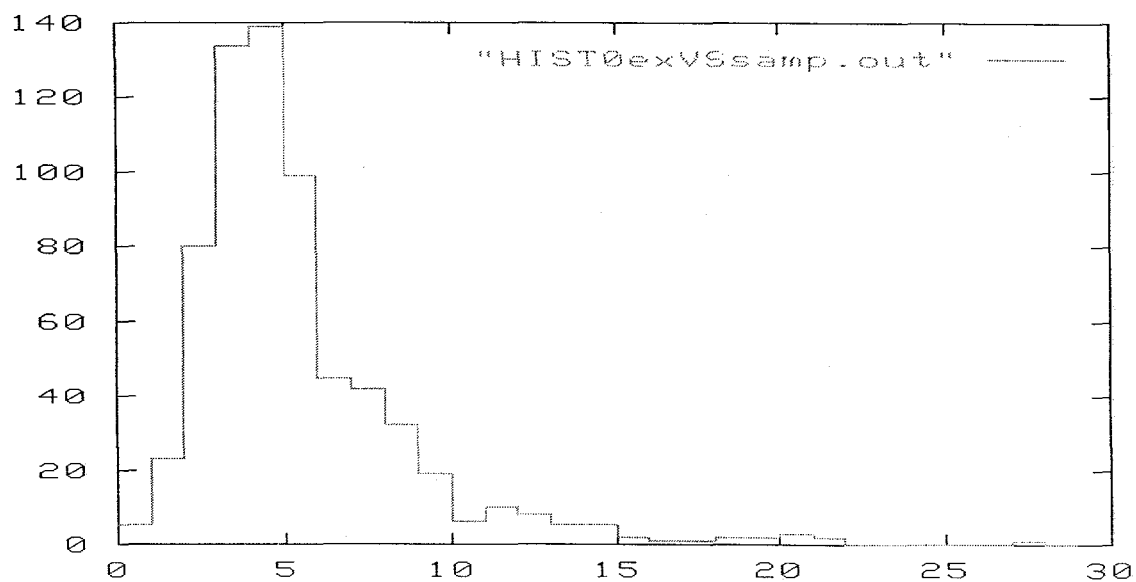


Fig. 6 Number of sample sets versus 1% bins of coefficient of variation:
Extrapolation to zero quartile of front -axle weights.

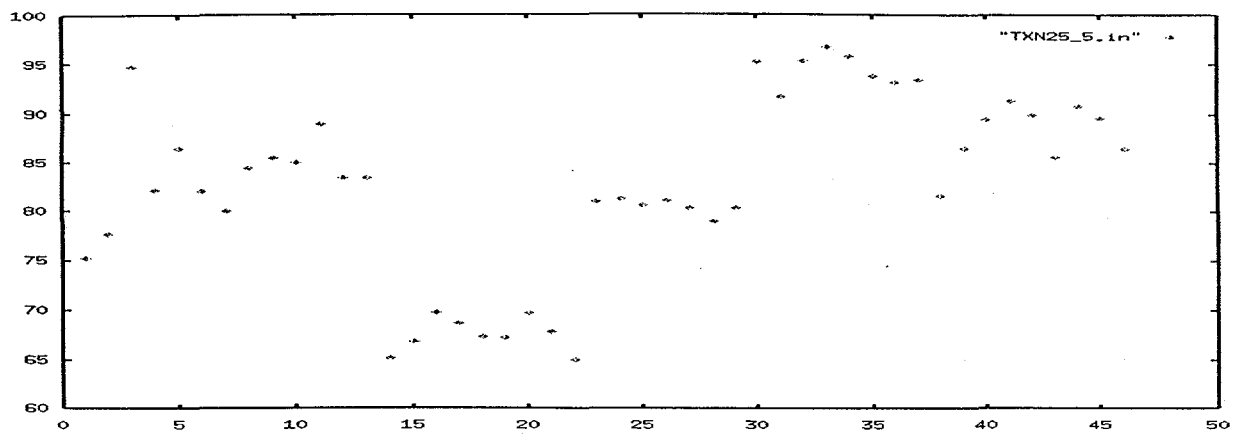


Fig. 7 Feb. 89 to July 90 front axle WIM weights on Texas road N25 south direction

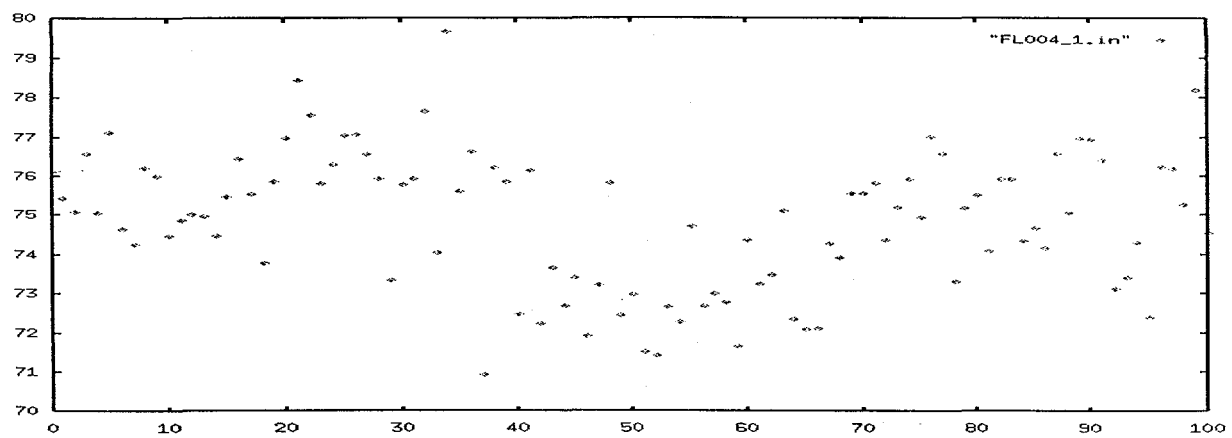


Fig. 8 Front axle WIM data on Florida road 004 (north direction) 1976-1985

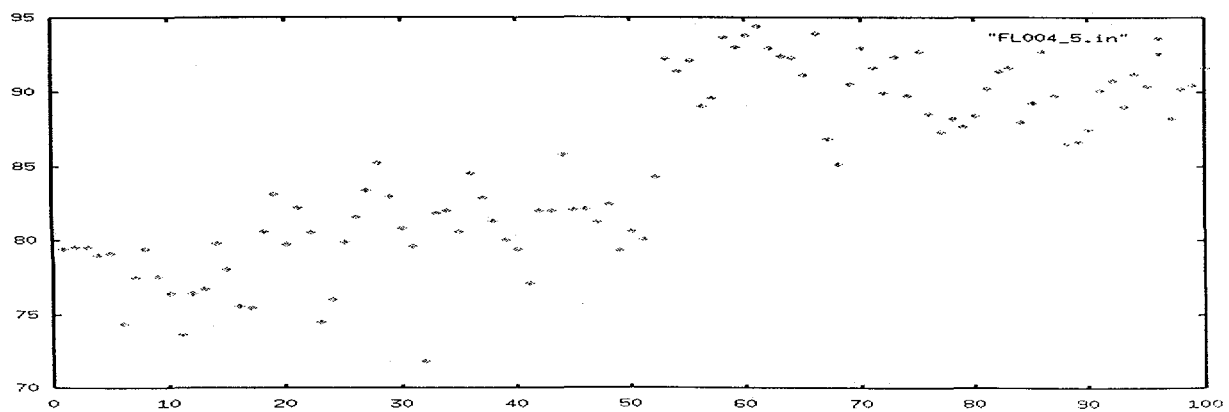


Fig. 9 Front axle WIM data on Florida road 004 (south direction) 1976-1985

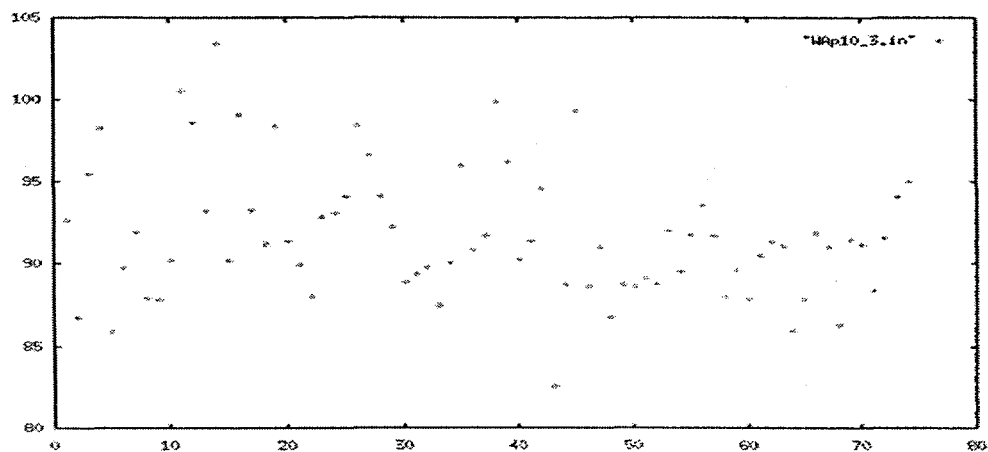


Fig. 10 LTPP weigh-in-motion data from Washington state.