NEW DIRECTIONS IN PREDICTING AND MODELING TRUCK LOAD POPULATIONS INCLUDING OVERLOADS

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Overload trucks often appear as a sizeable portion of truck populations on highways. Within most transportation jurisdictions in the United States, overloads refer to truck weights in excess of 356 kN (80 kips). The load populations exhibit an inconsistent pattern—often with two or more distinct peaks. This paper represents new directions in modeling truck load patterns with capabilities to offer the continuity as well as the bimodal feature of the load data. The method presented is data-driven and uses a bimodal distribution function. The extension of the model to predict the truck load population when data are incomplete or not available is also presented. The parameters required in the model are estimated via the fuzzy regression analysis in the proposed method. The fuzzy regression analysis allows the utilization of subjective and limited information.

The Weigh-in-Motion (WIM) data obtained from several stations were used to quantify the parameters of this bimodal distribution function by employing the fuzzy regression analysis. The procedure on obtaining an appropriate distribution function for truck load population is explained along with illustrative examples.

\textit{Keywords}: Bimodal distribution, Fatigue damage assessment, Beta density function, Lognormal density function, Continuous probability box.

1 INTRODUCTION

In condition assessment and life-cycle management of transportation systems, such as pavements and bridges, truck load data play an important role. Methods used in condition assessment of these systems require a realistic estimation of damage accumulation as a result of the repeated application of truck loads. For a given transportation system, damage assessment can be done by using truck load data such as Weigh-in-Motion (WIM) statistics directly in a discrete format (Jang and Mohammadi 2021). Using this method, the frequencies of load occurrences can only be described with specific ranges. Each range in a discrete format has an upper and lower limit; and any other load value within the limits must be approximated as either an upper or lower value.

Load populations in the truck load data mostly exhibit an inconsistent pattern with two or more distinct peaks. This is because of a variety of reasons such as the prevalence of (1) the combination of loaded and empty trucks; (2) loads from vehicles with various axle configurations; and (3) loads from overloaded trailers and haulers. Within most transportation jurisdictions in the United States, the overload refers to vehicle weights in excess of 356 kN (80 kips). According to a recent report from the U.S. Department of Transportation, Bureau of Transportation Statistics (2018, 2020), truck overloads steadily increase over time. The data in Figure 1 shows a 38\% increase in the total...
overload permits issued from 2005 to 2018 although the number of permits temporarily dipped during the Great Recession of 2008-2009. Several studies on the effect of truck load on highway systems have shown that the load population frequently contains occurrences of overloads (Mohammadi and Shah 1992, Timm et al. 2005).

![Number of permits counted annually (U.S. Department of Transportation 2018, 2020).](image)

Vehicle with excessive heavy loads accelerate long-term damage to highways and bridges. In addressing the damage potentials of overloads, Jang and Mohammadi (2021) indicated that a more versatile and realistic approach in damage assessment can be achieved by using a theoretical model that best represents the truck load data such that the continuity in the load data can properly be represented in the load population. Accordingly, this paper presents results of a study with the objective of offering new directions in truck load populations with data continuity and with patterns capable of portraying all loads including overloads. Specifically, a bimodal distribution model is shown to offer these capabilities. In applications when damage estimation of facilities such as pavements and bridges is desired, theoretical models are useful. This is especially true if no WIM data is available. In such situations, the load distribution can be estimated with certain assumptions based on fuzzy regression using some basic information pertaining to the facility, such as for example, the average daily truck traffic and information on the truck load value that is the demarcation between the two distinct patterns in the bimodal function (i.e., the common load). To represent the truck load pattern in a distribution function, a combination of beta and lognormal distribution is used in this paper. The WIM data obtained from several stations were used to quantify the parameters of this bimodal distribution function by employing the fuzzy regression analysis. The fuzzy regression analysis allows the utilization of subjective information in cases where the data are incomplete or not available. The procedure on obtaining an appropriate function for truck load distribution is explained along with illustrative examples. Using the historical data such as annual daily truck traffic (ADTT) and the number of permit issued for overload trucks, the possible truck load population can be obtained with a probability box (P-box) of the cumulative probability function (CDF).

2 DESCRIPTION OF THE BIMODAL DISTRIBUTION MODEL

In situations when the WIM data is available, the theoretical distribution proposed in Jang and Mohammadi (2021) can be directly used to describe the entire truck load population. The truckload distribution for the gross vehicle weight is referred to a Bimodal distribution due to two distinctive peaks in the population. The Bimodal distribution uses two different continuous probability distributions ($f_1$ and $f_2$) with a common load, $S_c$, which is the demarcation value between the two functions. The common load can be selected subjectively by visual examination of the data through trial and error if the WIM data is available or by perceptions and judgment using expert opinions. Figure 2 describes the concept of mixed density function with consideration for the common load.
The probability density function for each part in the population will need to be adjusted since \( f_1 \) and \( f_2 \) are valid for \( s < S_L \) and \( s > S_L \), respectively (Mohammadi and Shah 1992). Then, the combined probability density function, \( g(s) \), is obtained to represent the entire truck load population.

Figure 2. Schematic of mixed density function with consideration for the common load (\( S_L \)).

In this paper, the Bimodal distribution is developed based on combinations of beta and lognormal distributions. These distributions only accept positive values. The common load \( S_L \) is taken as yet another parameter in the overall distribution function (see Fig. 2). The beta distribution is among a few distributions that are appropriate for bounded random variables. The combination of beta-lognormal distributions is decided for the proposed model based on a parametric analysis and the goodness-of-fit test, such as the Kolmogorov-Smirnov and the Anderson-Darling tests, to examine the validity of the proposed probability function to represent the data (Anderson and Darling 1954, Ang and Tang 2007). In the proposed model, the common load, \( S_L \), needs to be selected among several possible values (i.e., 200, 222, or 245 kN (45, 50, or 55 kips)) suggested for the truck load population.

In situations when no WIM data are available, the theoretical model is considered with certain assumptions based on the roadway traffic and other information related to the traffic. The number of overload permits and ADTT, issued by an agency for bridges along the roadway in a year, may be used as basic information in developing the model. As a first step, the minimum percentage of overloads in the entire truck load population, \( OL^* \), can be determined using the available information. Then using the fuzzy regression analysis, the parameters of the models are determined.

Figure 3 shows a flowchart on how the load population may be quantified and estimated for the two cases of (1) WIM data is available; and (2) no WIM data is available. In either case, the statistical parameters (i.e., \( \mu_1, \sigma_1, \mu_2, \sigma_2, \alpha_1, \) and \( \alpha_2 \)) should be estimated first to develop each part of probability density function using (1) WIM data for case 1 and (2) fuzzy regression model with limited information for case 2. The proposed model presented in this paper can be effectively used to predict or estimate the required truck load population for a given roadway as long as some preliminary information, such as the percentage of overload in the truck load population, is known.

3 STATISTICAL PARAMETERS USING LIMITED INFORMATION ON TRAFFIC

In situations where WIM data is not readily available, parameters (i.e., \( \mu_1^*, \sigma_1^*, \mu_2^*, \sigma_2^*, \) etc.) are estimated using fuzzy regression model. The fuzzy regression approach based on the fuzzy logic was developed by Tanaka et al. (1982) to treat the imprecise and uncertain phenomenon in a data set. Jang and Mohammadi (2021) suggested the use of fuzzy regression analysis in obtaining robust estimates for the statistical parameters of the model.
In the fuzzy regression analysis, for the defuzzification procedure, the \( \alpha \)-cut of membership function (\( \alpha \in [0,1] \)) is suggested to obtain the interval of confidence. The interval number for each parameter from selecting \( \alpha \)-cut to represent the bounded uncertainty of data. Then, the statistical parameters required in the bimodal distribution model (i.e., \( p, q, \xi, \) and \( \lambda \)) can be estimated as an interval number by using the interval arithmetic (Mazeika et al. 2007, Daumas et al. 2009). In the interval approach, it is noted that the interval arithmetic may induce the unexpected relationship between the bounded shape parameters in the beta and lognormal distributions, since they are correlated with each other. Especially, this correlation affects in adjusting the probability density function for each segment of the population function. Thus, after estimating statistical parameters \( (p, q, \xi, \) and \( \lambda) \), the interval number should be independently separated as upper and lower values for each parameter in developing the appropriate bimodal distribution model.
4 NUMERICAL EXAMPLE

As an illustrative numerical example, approximate values for the mean and standard deviation of the two portions of the load population (i.e., \( \mu_1^\ast, \sigma_1^\ast, \mu_2^\ast, \) and \( \sigma_2^\ast \)) and the parameters \( \sigma_{OL}^\ast \) can be estimated from the fuzzy regression analysis with a common load of 222 kN (50 kips). Figure 4 shows the fuzzy linear regression model for \( \mu_1^\ast \) for \( S_L=222 \) kN (50 kips) and an asymmetric triangular membership function for ADTT of 2624 and \( OL^\ast \) of 10.5 % as a representative parameter. The interval number for each \( \alpha \)-cut is directly determined from the membership function:

1. \( \mu_1^\ast \alpha=0.2=[37.57, 42.79] \),
2. \( \mu_1^\ast \alpha=0.5=[38.21, 41.47] \), and
3. \( \mu_1^\ast \alpha=0.8=[38.84, 40.15] \).

![Figure 4.](image)

Parameters \( p, q \) for beta and \( \xi, \lambda \) for lognormal distribution (see Figure 3) were calculated based on the interval arithmetic. These statistical parameters for the bimodal distribution were also estimated each as an interval number and were used to obtain the bounded theoretical distribution for predicting the truck load population including overloads. The P-box graphs shown in Fig. 5 were constructed using the upper and lower bounds of CDF to represent its possible boundaries.

![Figure 5.](image)

As the interval confidence for each parameter becomes narrow (i.e., the value of \( \alpha \) increases), the bounds for the P-box curves are decreased as shown in Fig. 5. This indicates that the selection of \( \alpha \)-cut in membership function of estimated parameters induces imprecise probabilities to predict the appropriate truckload population. In Fig. 6, the P-box of predicted CDF with the \( \alpha \)-cut of 0.5 are compared to a set of WIM data. For this case, as the outcome is expected, as the predicted
theoretical distribution reasonably matches the truck load population collected from WIM data. The bounds in the predicted CDF are able to account for uncertainties derived from the estimated statistical parameters in developing the theoretical distribution for truck load population.

![P-Box of Predicted CDF for α=0.5](image)

Figure 6. Comparison of CDFs from WIM data and prediction using bimodal distribution model.

5 CONCLUSIONS

In this study, a method to predict a truck load population including overloads without WIM data is introduced by estimating statistical parameters for the theoretical bimodal distribution using fuzzy regression analysis. The results obtained from the proposed model have a reasonable level of confidence by providing bounded predicted CDF to account for uncertainties in the estimated statistical parameters. This method needs further improvements to reduce the dependency on the shape of membership function, especially if it needs to be expanded to offer a more universal model.

References


