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# Vehicular loads hazard mapping through a Bayesian Network in the State of Mexico

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Traffic counts collect information that is valuable, for example, in bridge and road design or maintenance processes. The average daily traffic volume is often the most collected measure of vehicular traffic, which is used in the design or assessment of major highways. Permanent control stations, situated in key locations of the highway network, gather data the entire year. However, one of the disadvantages of traffic count data is that most counters used, do not measure total vehicle weight and axle load data. Traffic counts display only the classification of vehicles, traffic volume, average daily traffic, and annual average daily traffic. Axle loads on the other hand are required, for example, as input in the design of pavement and new bridges, and the reliability assessment of existing ones. Weigh-in-motion (WIM) systems are usually used to collect vehicle load data. The State of Mexico (in central Mexico) has 115 permanent vehicle counting stations with 745 traffic counting points in its federally administered road network. However, due to the lack of WIM stations, it is not possible to obtain axle load data. In this paper, a Bayesian Network (BN) quantified with data from WIM stations in the Netherlands is used to describe the weight and length distribution of heavy vehicles registered in the permanent vehicle counting stations of the State of Mexico federal highways. The Dutch and Mexican vehicle types are matched according to similar characteristics. Later, synthetic WIM observations from the BN model are analysed through extreme value theory and vehicle loads with selected return periods are computed for all study counting points. The outcome is a mapping methodology with a linked database. The traffic volumes and extreme loads can then be easily found and compared with other highways in the network. This work shows that hazard maps can be implemented to provide importantly and summarized information to understand the risks of extreme traffic loads and to help in the reliability assessment and maintenance strategies of pavements and bridges.

*Keywords*: Traffic counts, Weigh in Motion, Bayesian Network, ,traffic loads, mapping, State of Mexico.

## 1. Introduction

The State of Mexico is one of the 32 states of Mexico, located in center of the country. Its road infrastructure, with around 1716 km of federal administered roads (IMT-SCT-INEGI, 2020), makes the entity one of the states with a strategic geographic position for the freight flow that circulates through the national territory. For this reason, there has been a significant increase in traffic loads on federal roads and bridges within the state's territory. Vehicular loads change over time presenting great uncertainty and increasing the safety concerns for the road infrastructure (OBrien et al., 2012). Additionally, because of the increase in traffic loads, accurate of mapping extreme traffic loads at the road network is relevant (Walubita et al., 2019).

Hazard maps can be constructed to provide importantly and summarized information to understand risks related to extreme traffic loads and to help in the design and implementation of maintenance strategies to improve the durability of pavements and bridges. Traffic loads maps, as described for example in Sprung et al. (2018); Li et al. (2012); Titi et al. (2014), have been developed to analyse oversize–overweight trucks for building optimal routes for priority loads and for investigating the pavement damage caused by permitted heavy trucks. de Leeuw, Rob and Newton Sean and Menist (2019) mapped trucks for establishing a safe and secure network of truck parking areas and. Although these maps are useful they are not focused on the computation of design loads and databases used are not for open access.

In order to map vehicular loads the most reliable source of information is WIM systems. This technology provided information about traffic volume, axle loads, inter-axle distances, and vehicle classification among others. This data is also required, for example, as input in the design of pavement, new bridges, and in the reliability

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assessment of existing ones. Several WIM-based traffic load models for bridge analysis have been formulated (see Mendoza-Lugo et al. (2019); Li et al. (2020); Anitori et al. (2017) for example). However, some of the limitations for the wide installation of permanent WIM stations on the road network are the high installation, operation, and maintenance costs. On the other hand, the cheapest alternative to "easily-obtained" traffic data is traffic counts through pneumatic traffic tubes. These types of counters are used to gather data such as the classification of vehicles, volume counts, and average daily traffic. However, data regarding inter-axle distances or individual axle loads is not provided by such devices (Beyer, 2015; Kusimo and Okafor, 2016).

There exist 115 permanent vehicle counting stations with 745 traffic counting points (CP) on the federally administered road network of the State of Mexico. However, in Mexico, the use of WIM systems is not common and public databases are not available. Consequently, no information regarding individual axle loads or inter-axle distances is available. A possible way to overcome this is through modeling data based on other available databases. Previous studies have done this by means of simple deterministic models, linear correlations, and copulas (see S. et al. (2006); Kim and Song (2019) for example). These studies focus only on modeling axle loads (and not inter-axle distances) or provide at best fixed inter-axle distances. In previous studies, such as Walubita et al. (2019); Papagiannakis et al. (2006); Sayyady et al. (2010), traffic load spectra are estimated by using clustering techniques where permanent WIM stations are not installed. Nevertheless, these models are used to obtain input data for the Mechanistic-empirical pavement design (MEPDG) method.

All things considered, a methodology is required for: (i) straightforward computation of similar WIM data by using other traffic data sources more "easy" to be obtained and (ii) compute and map extreme vehicle loads. Mapping extremes has been proved to be an essential engineering design tool in hydraulic engineering. Using similar techniques to analyse the road network vehicular loads can be useful for constructing or improving probability-based codes. The aim of this research is to estimate extreme traffic loads at the federally administered road network of the State of Mexico. Traffic counters data from the study area are used to compute synthetic WIM observations. This synthetic dataset is generated through a WIM data-based Non-parametric Bayesian Network (NPNB) of heavy vehicles (with a total weight above 3.5 tons). The outcome will be presented in maps of extreme vehicle loads processed through geographic information systems (GIS) based tools. The rest of the paper is organized as follows. In Section 2 the methods are described together with concepts regarding Bayesian Networks and extreme value theory. In Section 3 the results of applying the methodology are summarized. Next, in Section 4 the results are discussed. Finally, in Section 5 the conclusion of this work are drawn and some research lines for future work are proposed.

## 2. Methods

The method consists of different steps. First, the Mexican road database, *Datos Viales*, of traffic counts was collected (see subsection 2.1 for further details). The database was filtered and preprocessed to extract information about the State of Mexico's heavy vehicles, i.e, motorcycles and automobiles were left out. Mexican vehicle types were matched according to their silhouette with the Dutch NPBN WIM model (sub section 2.3). Simulated WIM observations, for each counting point (that is, every geographical point where data is available in the *Datos Viales* database), were computed by the NPBN WIM model with information of the Mexican traffic counts database as input. Daily maxima of total vehicle weight (Wmax) were derived with more than 6900 simulations. Wmax were fitted to probability distributions in order to calculate the return periods of extreme vehicular loads in all counting points of the State of Mexico federally administered roads. Finally, 50, 75, and 1000 year return period vehicular weight maps for main roads in the state of Mexico were produced. The method is explained in detail in the next sections.

### 2.1. *Data*

We use the *Datos Viales* (road data) 2018 database published by the Department of Infrastructure (IMT-SCT-INEGI, 2020). The database includes the following information: name of the road, name of the counting point (CP), lane direction, annual average daily traffic (AADT), and the proportion of vehicle types that form the traffic flow.

The data were filtered with the open-source GIS software QGIS to take into account CPs located at the federally administered road network of the State of Mexico. A total of 745 CPs were obtained, of which, we eliminate the duplicates and choose the ones in the lane direction with higher AADT. After these filters, 151 counting points were studied. Furthermore, vehicle types M and A corresponding to motorcycles and automobiles were left out of the records since the interest is in heavily loaded traffic. Subtracting the corresponding proportion of categories M and A to AADT we obtained the average daily truck traffic (AADTT). The codes of the Mexican vehicle types are given by the Ministry of Communications and Transport or SCT for its acronym in Spanish (SCT, 2008). The main heavy vehicles that conform to

the traffic of the database are buses (B), single unit vehicles of two and three axles (C2, C3), three-axle tractors plus two-axle semitrailer (T3S2), and three axles semitrailer (T3S3), three-axle tractors plus two-axle semitrailer plus four-axle trailer (T3S2R4) and, others (*Otros*).

### 2.2. *Bayesian Networks*

Bayesian Networks (BNs) are effective tools for modeling multivariate probability distributions (Pearl, 1988). BNs are directed acyclic graphs (DAG), consisting of nodes and arcs. The nodes of BNs represent random variables which for the case of non-parametric BNs (NPBN) can be either continuous, discrete (in an ordinal scale), or functional. The arcs represent probabilistic relations between the variables represented as nodes in the BN. The direct predecessors of a node are called the parents. The set of parents of node $X_i$ will be denoted $pa(X_i)$. The direct successors of a node are the children. For this work, a NPBN is applied.

A BN encodes the probability density or mass function on a set of variables $\boldsymbol{X} = \{X_1, ..., X_n\}$ by specifying a set of conditional independence statements in the DAG associated with a set of conditional probability functions (Morales-Nápoles and Steenbergen, 2015). In (Hanea et al., 2006), (Neil et al., 2000), Pearl (1988), and Marcot and Penman (2019) for example more information and overviews of applications of BNs may be found.

The theory of non-parametric Bayesian Network is built around bivariate copulas (Kurowicka and Cooke, 2005). Copulas are a class of bivariate distributions whose marginals are uniform on the (0,1) interval (Genest and MacKay, 1986). Zero correlation implies independence for the normal copula. Denote by $\Phi_\rho$ the bivariate standard normal cumulative distribution function with product-moment correlation $\rho$ and $\Phi^{-1}$ the inverse of the one dimensional (1D) standard normal distribution function, the normal copula, with $\rho$ as a parameter is:

$$C_\rho(u, v) = \Phi_\rho[\Phi^{-1}(u), \Phi^{-1}(v)]; \quad (u, v) \in [0, 1]^2 \tag{1}$$

The rank correlation is the product-moment correlation of the ranks of variables $X_i$ and$X_j$ and measures the strength of the monotonic relationship between variables. The conditional rank correlation is the dependence measure of interest because of its close relationship with conditional copulas. In a NPBN, every node is assigned with a one dimensional distribution and every arc with an (un)conditional rank correlation. For each variable $X_i$ with $m$-parents $X_1 = pa_1(X_i), ..., X_k = pa_m(X_i)$, associate the arc $pa_j(X_i) \to X_i$ with the rank correlation.

$$r[X_i, pa_j(X_i)]; j = 1$$
$$r[X_i, pa_j(X_i)|pa_1(X_i), ..., pa_{j-1}(X_i)]; \quad j = 2, ..., m \tag{2}$$

The assignment is empty if $pa(X_i) = \varnothing$. The indices $1, ..., m$ are the indices of the parents of variable i in the sampling order $(1, ..., n)$. This order may be different from the original labeling of variables and is not unique. More details may be found in Hanea et al. (2015). In order to find a given conditional distribution in a NPBN, it is a matter of computing the conditional distribution on the standard normal transformation of the corresponding NPBN, then transform back to the original units through the inverse of the 1D marginal distribution.

### 2.3. *NPBN WIM model*

WIM data corresponding to April 2013 for three Dutch locations in both right (R) and left (L) driving directions, were used. The measurements were taken on highways A12 (km 42), A15 (km 92), and A16 (km 41). Considering the database size it is not practical to examine the complete configuration of axle loads for each vehicle code. Therefore, 26 vehicle types were further considered. These are presented in Table 1, grouped per vehicle configuration and per number of axles. The codes used in the WIM system, consist of a letter and a number of digits that define the sequence of axle groups. The digits represent the number of axles. The letters represent vehicle configurations: buses (B), tractor plus semitrailer plus trailer (R), tractor plus semitrailer (T), and single-unit multi-axle vehicle (V). For example, a five-axle vehicle with the configuration tractor plus semitrailer with one axle at the front of the cabin and one at the rear and semitrailer with a group of three axles is coded as T11O3. The corresponding created vehicle type, of the previously mentioned configuration, is a T5 type (tractor plus semitrailer with five axles in total).

For each axle load of each vehicle type, a one-dimensional marginal distribution is approximated by a Gaussian Mixture (GM, McNicholas and Murphy (2008)). A GM is a weighted sum of $G$ Gaussian densities (each one referred to as a component) expressed as follows:

$$f(x) = \sum_{g=1}^{G} \pi_g \phi\left(\mathbf{x} \mid \boldsymbol{\mu}_g, \sigma_g\right) \tag{3}$$

Where $g = 1, ...G$, $\sum_g \pi_g = 1$ are the mixture weights and $\phi\left(\mathbf{x} \mid \boldsymbol{\mu}_g, \sigma_g\right)$ are components of Gaussian densities with parameters $\boldsymbol{\mu}_g$ and $\sigma_g$ .

Table 1. Created vehicle types with their corresponding WIM codes.

| Vehicle ($i$) | Type | No. Axles ($n_i$) | Code | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 1 | B2 | 2 | B11 | | | | | | |
| 2 | B3 | 3 | B11A1 | B12 | B21 | | | | |
| 3 | O3 | 3 | O3 | | | | | | |
| 4 | O4 | 4 | O4 | | | | | | |
| 5 | O5 | 5 | O5 | | | | | | |
| 6 | O6 | 6 | O6 | | | | | | |
| 7 | O8 | 8 | O8 | | | | | | |
| 8 | O9 | 9 | O9 | | | | | | |
| 9 | O10 | 10 | O: | | | | | | |
| 10 | O11 | 11 | O> | | | | | | |
| 11 | R5 | 5 | R11111 | | | | | | |
| 12 | R6 | 6 | R111111 | R11112 | R11211 | R1122 | | | |
| 13 | R7 | 7 | R111121 | R11113 | R11221 | R1123 | R1222 | | |
| 14 | R8 | 8 | R112121 | R12221 | R1223 | | | | |
| 15 | R9 | 9 | R121221 | | | | | | |
| 16 | T3 | 3 | T11O1 | | | | | | |
| 17 | T4 | 4 | T11O2 | T11O11 | T12O1 | | | | |
| 18 | T5 | 5 | T11O3 | T11O21 | T11O111 | T12O2 | T12O11 | T21O11 | |
| 19 | T6 | 6 | T11O4 | T11O1111 | T12O3 | T12O21 | T12O111 | | |
| 20 | T7 | 7 | T12O4 | T12O1111 | | | | | |
| 21 | V2 | 2 | V11 | | | | | | |
| 22 | V3 | 3 | V11A1 | V12 | V21 | V111 | | | |
| 23 | V4 | 4 | V11A2 | V11A11 | V13 | V22 | V211 | V1111 | |
| 24 | V5 | 5 | V11A12 | V12A2 | V12A11 | | | | |
| 25 | V6 | 6 | V12A12 | V22A2 | V22V11 | | | | |
| 26 | V7 | 7 | V22A12 | | | | | | |

The expectation maximization (EM) algorithm (McLachlan, G. J. and Peel, 2000) was used in the fitting procedure and the Akaike information criterion (AIC) was used to assess goodness-of-fit (Mutua, 1994). For the inter-axle distances fitting GM distribution may not be a good approach because, contrary to axle loads, there are a finite number of vehicle lengths based on vehicle makers. Therefore, for each inter-axle distance and for the total vehicle length, the empirical cumulative distribution function (ECDF) defined in Eq. (4) was used.

$$F_n(x) = \frac{1}{n+1} \sum_{i=1}^{n} \mathbf{I}\{X_i \leq x\} \tag{4}$$

Where $\mathbf{I}$ is the indication function, namely $\mathbf{I}\{X_i \leq x\} = 1$ if $X_i \leq x$ and $\mathbf{I}\{X_i \leq x\} = 0$ otherwise. Next, the dependence structure of the WIM observations was modeled with a NPBN. A representation of the NPBN for highway A12 in the left direction is presented in Figure 1. The arcs represent correlations between axle loads $X_{i,j}$, where $j = \{1...n_i\}$ and $n_i$ is the number of axles per vehicle type $i$ as specified in Table 1. Total vehicle length is node $X_{i,n_i+1}$ while the inter-axle distances are $X_{i,n_i+1+j}$. The model is implemented in MATLAB with the toolbox BANSHEE (Paprotny et al., 2020). The full model (Figure 1) consists of 324 nodes and 2136 arcs.

Next, to use the NPBN WIM model, the Mexican vehicle types were matched with the NPBN vehicles according to their visual representation and number of axles as can be seen in Figure 2. We omit the vehicle type "others" in the simulations since there is no visual representation corresponding to it or the number of axles specified. As a result, we have a sub-model of the NPBN with 6 of the 26 vehicle types available (according to

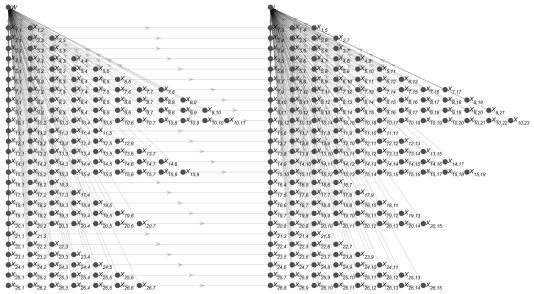

Fig. 1. NPBN model for A12-L highway of the WIM system in the Netherlands. The left side of the network represents the $X_{i,j}$ axle loads. The right side represents the vehicle length $X_{i,n_1+1}$ and the inter-axle distances $X_{i,n_i+1+j}$. Where $i = \{1, 2, ..., 26\}$ vehicle types.

Table 1) that represents the Mexican vehicle types presented in the traffic counts database.

| Number of axles | SCT | Silhouette | WIM NPBN | Silhouette |
|---|---|---|---|---|
| 2,3 | B | | B2, B3 | |
| 2 | C2 | | V2 | |
| 3 | C3 | | V3,03 | |
| 5 | T3S2 | | T5,05 | |
| 6 | T3S3 | | T6 | |
| 9 | T3S2R4 | | R9 | |
| --- | OTH | --- | --- | --- |

Fig. 2. Vehicle comparison between SCT vehicle types and NPBN WIM model vehicle types.

Once the vehicle types were selected and knowing the proportion of vehicle types from the *Datos Viales* database, we simulate with the NPBN the number of vehicles that match the AADTT vehicle amount for each one of the 151 counting points of interest. To clarify, when a SCT vehicle type has two equivalent WIM NPBN vehicle types, the corresponding vehicle for the simulation is randomly selected. Moreover, for the NPBN model we use the so-called "hypothetical highway" (HH) this HH is a combination of all six available WIM locations in the model. Therefore, each simulated vehicle is a realization of a randomly chosen location. In total, 6795 simulations and more than 20 million heavy vehicles were computed to obtain 45-day data. Figure 3 shows an example of the sub-NPBN model used for one simulation of the counting point *El dorado* to compute N = AADTT = 5812 vehicles with the proportions: B = B3 = 20.2%, C2 = V2 = 36.7%, C3 = V3 = 10.6%, T3S2 = T5 = 22.9%, T3S3 = T6 = 5.3% and T3S2R4 = R9 = 4.3%. As a result, the NPBN has 83 nodes

and 527 arcs.

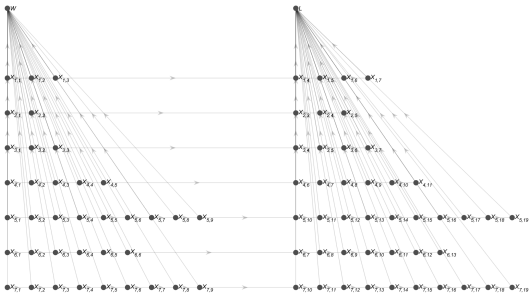

Fig. 3. NPBN model for one sumilation of *El dorado* CP.

The output of the NPBN is similar WIM observations describing the weight and the length of the simulated vehicles presented in a 26 columns table (see Table 2 and Table 3). The first column represents the number of observation, the second vehicle type, the third the total vehicle weight (W) in kN, columns 4th to 14th individual axle load (AW) in kN, column 15th vehicle length (L) in m, and columns 16th to 26th individual inter-axle distances (AD) in m. A Not a number (nan) notation is placed in fields where no data is computed.

Table 2. Exaple of the NPBN output for *El dorado* CP.

| Item | Type | W | AW1 | AW2 | AW3 | AW4 | AW5 | AW6 | AW7 | AW8 | AW9 | AW10 | AW11 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | T6 | 491.36 | 72.11 | 21.15 | 103.67 | 98.57 | 97.00 | 98.87 | nan | nan | nan | nan | nan |
| 2 | T5 | 246.97 | 54.96 | 71.70 | 44.27 | 34.85 | 41.20 | nan | nan | nan | nan | nan | nan |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 5812 | T5 | 410.35 | 92.22 | 108.14 | 96.08 | 48.99 | 64.92 | nan | nan | nan | nan | nan | nan |

Table 3. Table 2 (Continued).

| L | ADF1 | AD12 | AD23 | AD34 | AD45 | AD56 | AD67 | AD78 | AD89 | AD100 | AD111 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 13.26 | 1.66 | 2.76 | 1.30 | 1.30 | 1.31 | 1.29 | nan | nan | nan | nan | nan |
| 18.61 | 1.89 | 4.77 | 1.35 | 6.88 | 1.79 | nan | nan | nan | nan | nan | nan |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 19.47 | 1.73 | 4.79 | 1.40 | 6.27 | 1.35 | nan | nan | nan | nan | nan | nan |

### 2.4. *Extreme value analysis*

In this section, extreme value analysis is performed to obtain traffic loads corresponding to different return periods. The most common approach to describe the traffic loads and their effects is fitting the data to an Extreme Value (EV) distribution. As noted in previous studies regarding the precision of estimations, data quality is often more important than the extrapolation method (OBrien et al., 2015). In this study we use the Gumbel distribution with location parameter $\mu$ and scale parameter $\beta$ (see Eq. 5). The reason being that in general, based on the AIC, this was the best fit for the counting points included in this study.

Return periods of vehicle loads were calculated by obtaining the maximum total vehicle weight per day of the NPBN simulations per CP. The 45-daily maxima (Wd) obtained were fitted to a parametric probability distribution. We computed and compared extrapolated values obtained from daily maxima to the extrapolated values derived from the yearly maxima. The values obtained with daily maxima are on average 1.5% higher than those computed with yearly maxima. Hence, the use of one or another does not represent a significant difference in the results. Therefore, in this work and to reduce computational load we use the extrapolated values of the daily maxima distribution.

$$f(x,\mu,\beta) = \frac{1}{\beta} e^{-\left(z+e^{-z}\right)}; z = \frac{x-\mu}{\beta} \qquad (5)$$

## 3. Results

### 3.1. *Return periods*

In Mexico, the SCT and the Mexican Institute of transport (IMT, (Rascó-Chávez, 2004)) establish that the period of non-exceedance for the road bridge design loads should be 50 years. Similarly, in the United States of America, according to the Load and Resistance Factor Design (LRFD) of the American Association of State Highway and Transportation (AASHTO, (Grubb et al., 2015)) the serviceability criteria for bridges is 75 years. While, the traffic road models for road bridges, load model one (LM1), and load model two (LM2) (European Committee, 2010) specified the characteristic value of 1000-year return period for traffic on the main roads in Europe. Consequently, we computed the vehicle loads with 50 year return period ( $W50$) assuming 254 working days per year excluding weekends and holidays. Similarly, the total vehicle weight for a 75-year ($W75$) and a 1000-year return period ($W100$) were computed. The calculated $Wd$, $W50$, $W75$, and $W1000$ for all studied counting points are presented in Figure 4. Notice that there is not a significant difference between $W50$ and $W75$. There is a clear trench among three peak maxima, with a $Wd$, $W50$, $W75$, and $W1000$ high mean of about 1160 kN, 1192 kN, 1195 kN, and 1212 kN correspondingly. In general, the results show that $W75$ is at most 1% higher than $W50$. $W1000$ is 1% to 3% higher in comparison with $W75$ while, compared to $Wd$ it is 1% to 13% higher.

For illustration purposes, the results of the computations for $W50$ per counting point are presented in the main map in Figure 5. Likewise, the results for $W75$ and $W1000$ are presented in

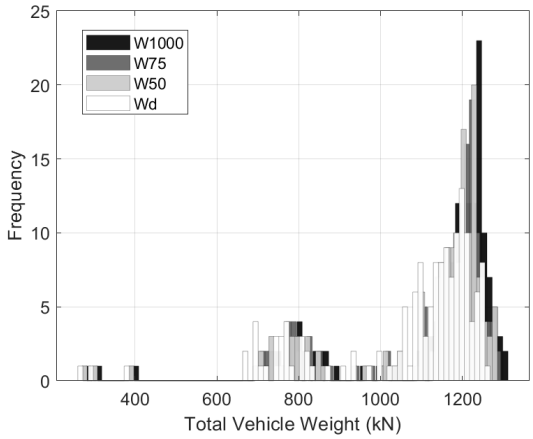


Fig. 4. Total vehicle weight maxima comparison.

Figure 6 and Figure 7 respectively. The smaller map in each one of the three main maps represents the computed daily maximum total vehicle weight in 2018. The maps were built in QGIS. In all cases, an increase of extreme $W$ is expected, especially in the north part of the state.

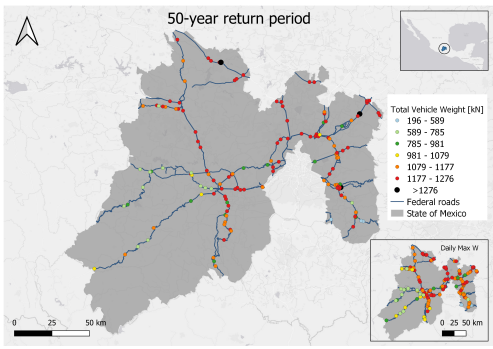


Fig. 5. Total vehicle weight [kN] for a 50-year return period.

## 4. Discussion

Although the extreme vehicular loads calculated here were based on Dutch WIM observations. To investigate, if the data generated with the NPBN model is capable of reproducing Mexican vehicular loads. We use the relative entropy ($I$) (Kullback and Leibler, 1951), which is a measure of how two probability distributions are different. The relative entropy of $W$ is estimated from data generated in the sub-model computed with the matched vehicle types (see Figure 2) and the observed distributions for the Mexican vehicles

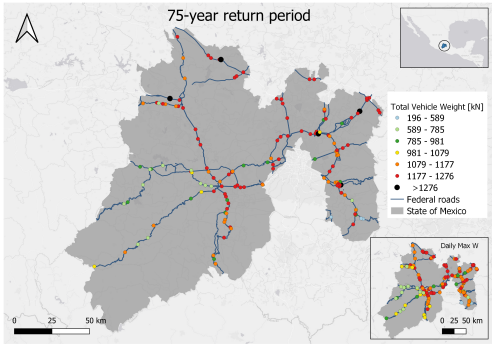


Fig. 6. Total vehicle weight [kN] for a 75-year return period.

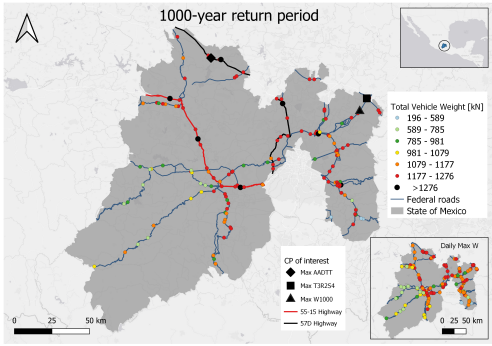


Fig. 7. Total vehicle weight [kN] for a 1000-year return period.

reported in Chavez Ayvar et al. (2013). This resulted in a relative entropy of 0.25. While fifth and 95th percentiles of the distribution of $I$ computed with a sample of 100 observations generated 500 times are 0.16, and 0.28, respectively. This shows that the difference is between the 5% and 95% differences for the Dutch WIM data. Seemingly, synthetic observations computed from the NPBN can be used as an alternative for Mexican data.

The results show that for $W50$ there are three CPs with total vehicle weight higher than 1276 kN (black CPs in Figure 5) while for $W75$ another two CP pass that threshold. For W100 the number of CPs with $W > 1276kN$ is doubled (10 black CPs in Figure 7) compared to $W50$. The CP with the highest $W75$ and $W1000$ can be found in the northeast part of the state (counting point *X. C. Tizayuca – Otumba*, black triangle in Figure 7). The CP is located in km number 37.5 of the road *Venta de Carpio - T. C. (Pachuca - Túxpam)* with a total vehicle weight of 1288 kN for $W75$ and 1309 kN for $W1000$. Additionally, as expected in the majority of the CPs, the heaviest vehicle is the

T3S2R4 type. The highest proportion of the nine axle vehicles T3S2R4 is located in the counting station *X. C. Venta de Carpio - T. C. (Pachuca - Tulancingo)*. The CP is located in km number 151.11 of the road *Libramiento Norte de la Ciudad de Mexico (Cuota)* with around 17.1% of T3S2R4 vehicles that compound the traffic (black square in Figure 7).

The highest AADTT can be found in the counting station *T. Izq. Aculco*. It is located in the km number 125 of the road *Mexico - Queretaro (Cuota)* with an AADTT of 11 207 trucks (black diamond in Figure 7). It is noted that the highway 57D *Mexico – Queretaro* has three of the ten CPs with $W > 1276$ kN, this can be explained because this highway connects the country's capital (Mexico City) with the city of *San Juan del Rio* which according to its geographical location, works as a commercial exchange hub between the center of the country, the *bajio* and the northern regions of the country. Another case of interest is federal highways number 15 and number 55 which are two of the fifteen of Mexico's main corridors, connecting Mexico City with the U.S.-Mexico border. These roads across the State of Mexico passing by the cities of Toluca, Ixtlahuaca, and Atlacomulco. As can be seen in Figure 7, the CPs near these cities have a $W$, for a 1000-year return period, over $1276kN$.

## 5. Conclusions

This paper presented the development of a methodology to compute and map extreme vehicle loads in the federally administered roads of the State of Mexico. The methodology uses one the one hand, non-parametric Bayesian Networks quantified with Weigh-in-Motion observations of six locations in The Netherlands. The model was employed to generate synthetic Weigh-in-Motion observations. The input for the non-parametric Bayesian Network was data obtained from traffic counters of the 115 permanent vehicle stations in the State of Mexico. On the other hand, extreme value theory analyses the synthetic observations for the State of Mexico to compute extreme vehicle loads with 50, 75, and 1000-years return periods. The results were presented in maps, using GIS, for each return period.

The methodology and results of this work have various applications for road design, bridge engineering, and road reliability analysis. For example, the methodology for computing synthetic WIM observations through NPBN can be applied virtually in any WIM location, using site-specific WIM records and site-specific vehicle types. This research shows that using data gathered by traditional traffic counts, such as pneumatic traffic counters, together with WIM observations of different locations it is possible to have an insight into the axle loads and inter-axle distance distributions.

The purpose of the methodology is to deliver a spatially explicit dataset of extreme vehicle loads with certain return periods for the federally administered roads of the State of Mexico. The results could be used in large-scale traffic loads analyses, serving as input for the reliability analysis of the existent road infrastructure from which optimal long-term road infrastructure maintenance plans can be derived. The next step of our research is to extend the results here presented nationwide while joining traffic count to the national inventory of bridges to better assess the reliability of existing infrastructure.

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