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Analysis of axle and vehicle load properties through Bayesian Networks based on Weigh-in-Motion data

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ABSTRACT

Weigh-in-Motion (WIM) systems are used, among other applications, in pavement and bridge reliability. The system measures quantities such as individual axle load, vehicular loads, vehicle speed, vehicle length and number of axles. Because of the nature of traffic configuration, the quantities measured are evidently regarded as random variables. The dependence structure of the data of such complex systems as the traffic systems is also very complex. It is desirable to be able to represent the complex multidimensional-distribution with models where the dependence may be explained in a clear way and different locations where the system operates may be treated simultaneously.

Bayesian Networks (BNs) are models that comply with the characteristics listed above. In this paper we discuss BN models and results concerning their ability to adequately represent the data. The paper places attention on the construction and use of the models. We discuss applications of the proposed BNs in reliability analysis. In particular we show how the proposed BNs may be used for computing design values for individual axles, vehicle weight and maximum bending moments of bridges in certain time intervals. These estimates have been used to advise authorities with respect to bridge reliability. Directions as to how the model may be extended to include locations where the WIM system does not operate are given whenever possible. These ideas benefit from structured expert judgment techniques previously used to quantify Hybrid Bayesian Networks (HBNs) with success.

1. Introduction

Weigh-in-Motion (WIM) systems are technologies that allow trucks to be weighed in the traffic flow without disruption of traffic operations. For a recent overview of WIM systems see [1]. The system has been developed since the 1950s with the purpose of reducing threats to roads transport operations from overloaded trucks. WIM aims at helping minimize problems related to the following:

- Avoiding accidents by detecting overloaded traffic for example due to increased truck instability, breaking faults, loss of movability and maneuverability or increased tire overheat.
- Damage to infrastructure by helping to prevent damage to pavement and bridges.
- Economic impact by helping to avoid distortions in freight transport competition, between transport modes (rail vs. waterborne or road) and between road transport companies and operators.

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WIM systems may be classified as Low Speed (LS) and High Speed (HS) systems. The LS-WIM is installed either outside the traffic lanes or on weighing areas, or in toll gates or any other controlled area. The operating speed is generally in the range of 5–15 km/h. The accuracy of the system can be 3–5%. For the HS-WIM, sensors are installed in one or more traffic lanes. They measure axle and vehicle loads while these vehicles are traveling at normal speed in the traffic flow. HS-WIM allows the weighing of almost all trucks crossing a road section. Their accuracy is 10–25% for approximately 95% of the gross weights [1]. In our applications this accuracy level has been accepted and treated in the results for advise to the authorities within model uncertainties.

In the Netherlands the Dutch Ministry of Transport, Public Works and Water Management has operated since 2001 the WIM system [2]. The system implements the Video WIM and automatic vehicle identification. This concept was originally developed in North America and the Netherlands itself. In the Netherlands, piëzo-quartz sensors are chosen for the WIM system. The WIM system is coupled to video cameras equipped with automatic license plate number recognition. The pictures and different measurements of all vehicles are recorded and stored in a database. Whenever no weighing area is available, warnings are sent to suspected violators which are most frequently cited. The database serves also for research purposes.

For every vehicle, variables recorded by the system in the Netherlands include vehicle speed, vehicle length, inter axle separation, axle weight and vehicular weight. With these variables, other may be inferred, for example, the total number of axles, the inter-vehicular separation or the average number of vehicles per unit time.

The nature of the overloaded traffic in time is evidently random. The data collected by the WIM system constitutes in general a complex probability distribution on the random variables listed above. It is desirable to represent the complex multidimensional-distribution with a model such that (a) the quantification can be made with a reduced number of parameters, (b) dependence may be explained in a more transparent way, (c) inference may be performed cost-efficiently in terms of computational time and (d) all locations over the Netherlands where the WIM system gathers information about traffic load may be treated simultaneously.

Bayesian Networks (BNs) offer an opportunity for a model with the four characteristics listed above. BNs are graphical models that attempt to represent a joint distribution in a compact way. They are increasingly gaining popularity as models for dependence [3]. They are also increasingly being used in reliability analysis (see for example [4]). The most popular version of BNs are those that handle exclusively discrete networks. However, recent developments in BNs have made it easier to handle discrete and continuous variables in a single network. These are most commonly referred to as Hybrid BNs (HBNs). An overview of some of the possibilities available for inference in hybrid BNs is presented in [5]. The class of Hybrid BN presented in this paper corresponds to Non-parametric BNs (NPBN).

In this paper we introduce NPBNs for the WIM system in the Netherlands. Our main objective is to discuss the type of BN models that may be constructed with WIM data. These models are discussed in the context of advise given to the Dutch authorities for bridge and road reliability. Alternative sources of data are discussed. The models presented are generic and may be quantified for other locations inside (if they become available) or outside the Netherlands where WIM systems (or other similar systems) operate. These models may also be used in combination with each other or with other techniques according to the question of interest. The models presented have been quantified with data from eight locations in the Netherlands. These are highways 04, 12, 15 and 16 in the left and right directions.

The remainder of this paper is divided as follows: in Section 2 we present the main concepts and definitions corresponding to the class of BNs to be used in this paper. In Section 3 we introduce four BN models quantified with WIM data. The first one corresponds to a model for individual axle loads (Section 3.2). The second one to a BN for traffic intensities as measured by the WIM system and compared with alternative data sources (Section 4.1). This comparison could be helpful when similar models need to be quantified through expert judgments. Section 4.2 presents a large scale BN consisting of 705 nodes representing one dimensional margins and more than 2300 arcs. This BN is discussed at length elsewhere [6]. Section 4.3 presents a dynamic BN used for combining traffic information with load variables. The networks are discussed in terms of their use in reliability analysis. As discussed before, our purpose is to give an overview of the models currently used to advise different infrastructure authority levels in the Netherlands.

2. Hybrid Bayesian Networks

We will understand *Bayesian Networks* as directed acyclic graphs (DAGs) whose nodes represent univariate random variables and whose arcs represent direct influences between nodes sharing an arc. A BN encodes the probability density or mass function on a set of variables $\mathbf{X}=\{X_1,\dots,X_n\}$ by specifying a set of conditional independence statements in the DAG associated with a set of conditional probability functions. It thus provides a representation of a high dimensional probability distribution on the set $\{X_1,\dots,X_n\}$. The *d-separation* criterion provides the criteria for reading conditional independence statements of the graph. The criteria center around the three possible network 'pieces':

(a) The structure $X_1 \rightarrow X_2 \rightarrow X_3$ states that without observing X_2, observing X_1 would say something about the distribution of X_3. That is X_1 is not marginally independent of X_3 ($X_1 \not\perp X_3$). However if X_2 is known, then X_1 would not add extra information to explain X_3, that is X_1 and X_3 are conditionally independent given X_2 ($X_1 \perp X_3|X_2$)
(b) The BN $X_1 \leftarrow X_2 \rightarrow X_3$ is similar as in (a), i.e. $X_1 \not\perp X_3$ marginally but $X_1 \perp X_3|X_2$.
(c) Finally $X_1 \rightarrow X_2 \leftarrow X_3$ indicates that $X_1 \perp X_3$ marginally however $X_1 \not\perp X_3|X_2$. That is, if we observe X_1 (X_3) without observing X_2 that would say nothing about X_3 (X_1). If on the contrary, we observe X_2 then observing $X_1(X_3)$ will say something additional about the distribution of X_3 (X_1).

A larger description of the semantics of a BN may be found in [7]. Examples in the context of reliability are given in [4]. The d-separation criterion implies that every variable is conditionally independent of its ancestors given its parents. Hence if every variable is associated with a conditional probability function of the variable given its parents $f_{X_i|Pa(X_i)}$ then the joint probability may be written as

$$f_{X_1,\dots,X_n}=\prod_{i=1}^{n} f_{X_i|Pa(X_i)} \tag{1}$$

If $Pa(X_i)=\varnothing$ then $f_{X_i|Pa(X_i)}=f_{X_i}$. Observe that whenever $\{X_1,\dots,X_n\}$ includes both discrete and continuous nodes we are in the class of HBNs.

One of the most powerful properties of BNs is their ability to perform inference. By inference in this paper we mean updating the marginal distributions of a subset of variables when evidence (observations) from a different subset is known. In general the problem of inference has been more studied in the context of discrete BNs. Performing inference in HBNs has proved to be more challenging. Inference may be exact or approximative. Approximative inference is most common in HBNs. In [5] five types of approximative inference for HBNs are presented. In [8] and [9] Enhanced BNs (eBNs) are introduced as another possibility to perform inference in HBNs. The references above do not consider NPBNs. A detailed comparison of the different techniques is out of the scope of this paper. Thus in the rest we focus only on NPBNs.

2.1. Non-parametric Bayesian Networks

Non-parametric Bayesian Networks were introduced in [10] and extended in [11]. The theory of NPBNs is built around bivariate copulas [12,13]. The *bivariate copula* or simply the *copula* of two continuous random variables X_i and X_j with $i\neq j$ is the function C such that their joint distribution can be written as

$$F_{X_i,X_j}(x_i,x_j)=C_\theta(F_{X_i}(x_i),F_{X_j}(x_j)). \tag{2}$$

Observe that the copula function in Eq. (2) is indexed by θ. This is because copulas are functions that allow naturally the investigation of association between random variables. For one parameter copula families, θ provides a relationship between the copula and measures of association such as the rank correlation (r) or Kendall's tau.