

Dynamic Load Estimation for Heavy Trucks on Bridge Structures

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ABSTRACT

As part of a system for structural health monitoring, it is required to determine the spatial and temporal distributions of vertical loads arising from heavy trucks driven on flexible bridge structures. An instrumented truck is used to generate the input loads and estimate the load time histories. The truck can carry a range of sensors; however direct measurement of vertical tire loads between the tires and the structure is not considered realistic. The dynamic loads are to be estimated from the sensor outputs. These are affected by both truck and bridge dynamics and these must be accounted for within the load estimation process. Estimation may be susceptible to many factors including static mass distribution, vehicle longitudinal motion, variations in lateral position on the bridge, as well as any surface unevenness. The focus of this paper is on using high fidelity simulation models to develop appropriate methodologies for load estimation which optimize the use of sensors on the truck. The estimation methods are evaluated in the context of any loss of accuracy in the predicted bridge response and in particular the coherency between inputs and outputs. It is proposed that using only static tire load data, GPS satellite data, string-potentiometers and accelerometer measurements, a robust measurement system can be constructed. The goal is to use near real-time processing of truck sensor data so that dynamic truck loads are available; when combined with data from separate bridge-mounted sensors, the structural performance of the structure can be evaluated.

CITATION: Gordon, T. and Mitra, M., "Dynamic Load Estimation for Heavy Trucks on Bridge Structures," *SAE Int. J. Commer. Veh.* 6(1):2013, doi:10.4271/2013-01-0626.

INTRODUCTION

The prediction or estimation of dynamic axle loads of a vehicle is a well-researched problem. Earliest attempts at force identification involved using simulation and model calibration [1]. With the development of more accurate sensors and improvement in the computation techniques of filtering and system identification it was possible to observe the dynamics of the vehicle from sensor readings and some knowledge of environmental parameters such as road roughness [2]. The vertical tire loads are usually expressed as a function of states of a linear or non-linear dynamic model of the vehicle, and some known inputs. Filtering and estimation procedures are then used to estimate the assumed states and calculate the dynamic loads. An extended Kalman filter is used in [3] and a sliding mode observer is employed by [4], [5] and [6]. These use relatively complex models to estimate not only the vertical tire loads but the longitudinal and lateral tire forces as well. Also these methods were developed for estimation of forces on a rigid pavement and therefore could not exploit the information available from the response of a dynamic structure when subjected to these

loads. The identification of axle loads purely by studying the bridge response has also been developed in [7], [8], [9], [10] and [11] using improvements on standard weigh-in-motion techniques. Although these methods can identify the dynamic axle loads, they are sensitive to parameter values used for estimation, vehicle and bridge properties. On-board tire-embedded sensor modules specific to the purpose of direct measurement of tire-pavement interaction forces have been attempted in [12] and [13]. However, accurate measurement of the vertical forces using such a direct method is especially difficult in heavy vehicles due to chassis flexibility, high dynamic change of some system parameters such as tire stiffness and inexact knowledge of others such as the payload [12]. Effective calibration of the estimation parameters for the required accuracy may not be possible and the cost of such a system prevents it from being widely deployed.

In this paper we propose a system of vertical tire load estimation for heavy vehicles based on combined information from on-board sensors and bridge response measurements. A reduced order (7-DoF) linear vehicle model is used in conjunction with a Kalman Filter to obtain an estimate of the

tire-force history at each axle or group of axles. The effect of this estimated force on the bridge response is then compared with the actual response. A coherence measure to quantify the estimated bridge response error in various modes is also proposed. Overall, this enables us to study the vertical load estimation problem in the context of vehicle-structure interaction and hence in a way that is directly applicable to structural health monitoring. It is also observed that information from all the on-board sensors, called the sensor-superset is sometimes superfluous and that it is possible to reduce the number of sensors without losing any significant accuracy in the estimated bridge response. The study includes a detailed analysis of sensor combinations on the vehicle and their performance relative to the simulated wheel loads. To help extend this work to experimental data in the future, where the actual wheel loads are unavailable, additional criteria are also considered in this work, specifically the coherency of force estimates to the bridge dynamic response, the effect of vehicle speed and also the spectral uniformity (whiteness) of the Kalman filter innovations process.

The work presented provides a ranking method for best choice of the “minimal vehicle sensor set” used to predict the axle loads in the context of bridge response. While the study is based on simulation, in future research the results and methods are to be applied to real-world data for vehicle-structure interaction.

SIMULATION MODELS

High-Fidelity Models

Although the methods used in this study are being developed to be used with data from real trucks for an in-situ application, a more controlled and reliable simulation scenario was required for mutual comparison and determination of their effectiveness. A high-fidelity simulation of a highly instrumented five axle tractor-trailer combination modeled in TruckSim on a non-linear bridge model in ADINA was carried out in a previous study [14]. The combined vehicle-bridge simulation captures many effects present in real world vehicle-structure interaction such as non-linearities in suspension elements and bridge, multiple-degrees of freedom of rigid bodies connected through flexible elements and is considered representative of the real truck-bridge dynamics. The truck modeled in Trucksim is a 3-axle Tractor connected to a 2-axle loaded flatbed trailer by a 5-th wheel. The axles are numbered 1 to 5 from front to rear. The wheel numbering scheme is from left to right and front to rear as shown in Figure 1a). Non-linearities present in dampers and leaf springs include nonlinear force vs. displacement and velocity response behavior as well as saturations such as suspension travel.

Analyzing the effect of estimated vehicle axle forces on the non-linear bridge model is computationally expensive and time-consuming. As an alternative, a linearized bridge model was developed in the same study and again coupled with the nonlinear TruckSim model; the results and trends were shown

to be similar to those of using a nonlinear bridge model. Hence the coupled linear bridge model and nonlinear TruckSim vehicle model are used as a baseline for estimation throughout this study. This baseline simulation consists of data of the dynamic wheel loads and of bridge deflections and accelerations at certain nodal points. The truck is considered to have a constant longitudinal velocity of 45mph over the bridge for most of the results presented in this study. We shall also analyze the effect of variation of this constant velocity towards the end of the study.

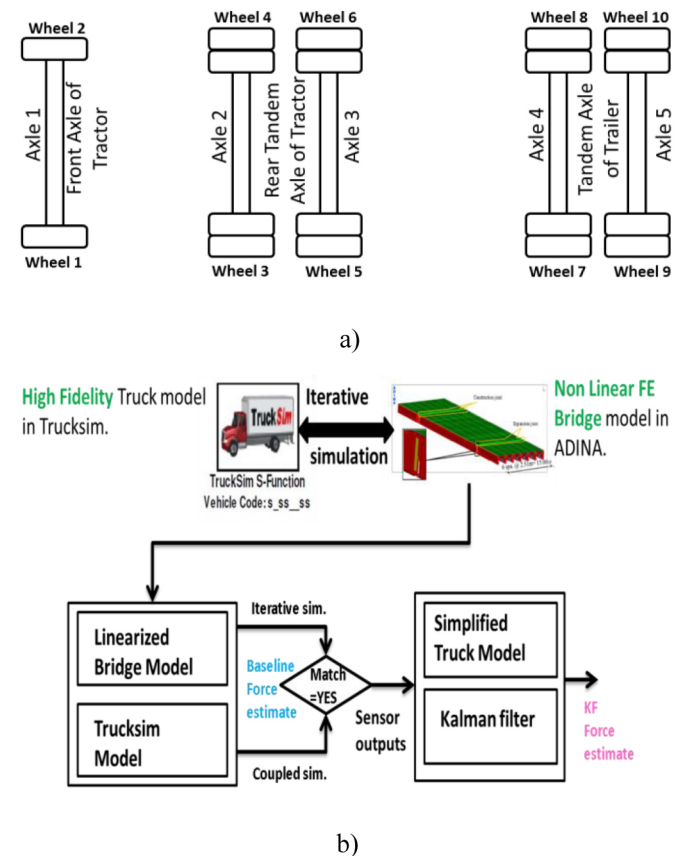


Figure 1. a) Wheel numbering scheme b) Simulation of High-fidelity Truck and Bridge models and development of Baseline with Linearized Bridge model

Linearized Bridge Models

The linearized reduced order model of the bridge [14] extracted from the high-fidelity model used in the baseline simulation in state-space form is as follows:

$$\dot{\mathbf{x}}_B = \begin{bmatrix} \mathbf{0} & \mathbf{I} \\ -\mathbf{M}_r^{-1}\mathbf{K}_r & -\mathbf{M}_r^{-1}\mathbf{C}_r \end{bmatrix} \mathbf{x}_B + \begin{bmatrix} \mathbf{0} \\ \mathbf{B}_v \end{bmatrix} \mathbf{u}_B \quad (1)$$

$$\begin{bmatrix} \mathbf{y}_B \\ \dot{\mathbf{y}}_B \end{bmatrix} = \begin{bmatrix} \mathbf{C}_d & \mathbf{0} \\ -\mathbf{M}_r^{-1}\mathbf{K}_r & -\mathbf{M}_r^{-1}\mathbf{C}_r \end{bmatrix} \mathbf{x}_B \quad (2)$$

where, $\mathbf{x}_B$ is a vector of the bridge states consisting of displacements and velocities of nodal points on the bridge. Further:

$\mathbf{M}_r$ is the mass matrix associated with the bridge model.

$\mathbf{K}_r$ is the stiffness matrix associated with the bridge model.

$\mathbf{C}_r$ is the damping associated with the bridge model.

$\mathbf{y}_B$ is a vector of the displacements at the nodal points on the bridge.

$\dot{\mathbf{y}}_B$ is a vector of the accelerations at the nodal points on the bridge.

$\mathbf{u}_B$ is a vector of forces applied on the nodal points of the bridge.

The axle forces obtained from the Kalman filter are interpolated to the nearest nodal points of the bridge at every time step of simulation and used to construct the input vector to the model $\mathbf{u}_B$. The response of the bridge in terms of acceleration and displacement are obtained.

Simplified Truck Model for Estimation

For the purposes of estimation, a linear pitch-plane model of the truck is considered. The dual rear axles of the tractor (axles 2 and 3) and the dual trailer axles (axles 4 and 5) are combined into single axles (axles 23 and 45 respectively) for the model. Wheel hop at each of the 3 axles, and tractor and trailer body pitch and bounce constitute the degrees of freedom in the model. The states and inputs are shown in Figure 2.

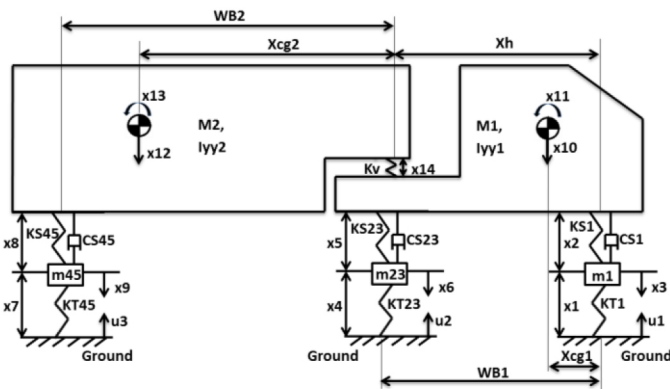


Figure 2. Simplified Linear 7 Degree of Freedom 3-axle Pitch-plane model of Truck for use with Kalman filter

The pitch plane model consists of 14 states:

x_1, x_4, x_7 = Effective Tire deflections at axles 1, 23 and 45 respectively

x_2, x_5, x_8 = Effective suspension deflections at axles 1, 23 and 45 respectively

x_3, x_6, x_9 = Effective vertical unsprung mass velocities at axles 1, 23 and 45 respectively

x_{10}, x_{12} = Vertical velocities of centre of mass of tractor and trailer respectively

x_{11}, x_{13} = Pitch velocities of tractor and trailer respectively

x_{14} = Effective vertical deflection at the 5th wheel

The inputs to the model are:

u_1, u_2, u_3 = Road vertical velocities at axles 1, 23 and 45 respectively

u_4, u_5, u_6 = Non-linear suspension force inputs at axles 1, 23 and 45 respectively (Not shown in Figure 2.)

The outputs of the model which constitute the sensor-superset for the Kalman filter are:

y_1 = Accelerometer measuring vertical acceleration mounted on tractor body

y_2, y_3, y_4 = String potentiometer used to measure suspension deflection at axles 1, 23 and 45 respectively

y_5, y_6, y_7 = Wheel accelerometers used to measure vertical acceleration of unsprung mass at axles 1, 23 and 45 respectively

y_8, y_9, y_{10} = Chassis accelerometers used to measure vertical acceleration of chassis points directly above axles 1, 23 and 45 respectively.

The model takes the standard form in the linear state space in discrete time:

$$\mathbf{x}_{k+1} = \mathbf{A}\mathbf{x}_k + \mathbf{B}\mathbf{u}_k + \mathbf{B}_w\mathbf{w}_k \quad (3)$$

$$\mathbf{y}_k = \mathbf{C}\mathbf{x}_k + \mathbf{D}\mathbf{u}_k + \mathbf{D}_w\mathbf{w}_k + \mathbf{v}_k \quad (4)$$

Where,

$\mathbf{x}_k = [x_1(k) \dots x_{14}(k)]^T$ is the vector of states at the k-th time instant.

$\mathbf{y}_k = [y_1(k) \dots y_{10}(k)]^T$ is the vector of sensor outputs at the k-th time instant.

$\mathbf{u}_k = [u_1(k) \dots u_6(k)]^T$ is the vector of inputs at the k-th time instant.

$\mathbf{w}_k$ is the vector of disturbances at the k-th time instant corresponding to the errors in $\mathbf{u}_k$.

$\mathbf{v}_k$ is the vector of sensor noise in various channels at the k-th time instant corresponding to the errors in $\mathbf{y}_k$.

Both $\mathbf{w}_k \sim (0, \mathbf{Q})$ and $\mathbf{v}_k \sim (0, \mathbf{R})$ are assumed to be zero-mean white noise signals with constant covariance matrices.

Since the TruckSim model has many more degrees of freedom (e.g. 5 axles, roll dynamics) each "sensor" used in the pitch-plane model may correspond to several sensors in the real system. Hence a mapping is required to calculate the values of $\mathbf{y}_k$; the simplest and most obvious choices are made, for example vertical axle accelerations at axle 23 is obtained by averaging the four acceleration measurements in the detailed vehicle model i.e. left and right accelerations at axle 2 and axle 3.

FORCE ESTIMATION USING SENSOR SUPERSET

With the given sensor superset various methods of force estimation might be employed. It is desired that these estimated loads be evaluated not only in terms of their

deviation from the actual baseline force values, but also with regard to the predicted response they cause when applied on a bridge and how these differ from the baseline responses. The overall objective is to determine the simplest force estimation method which in conjunction with the fewest possible sensors is able to estimate the truck loads sufficiently accurately such that the predicted bridge responses due to these estimated forces are within tolerable limits of those seen in the baseline. With this as a motivating factor a Kalman filter [15] is developed and tuned according to the noise levels assumed. In the real application these noise matrices must also be estimated [16].

Kalman Filter

To estimate the states of the simplified truck model a linear Kalman filter is used, whose update equations are as follows:

The a-priori estimates are calculated as follows:

$$\hat{\mathbf{x}}_{(k+1|k)} = \mathbf{A}\hat{\mathbf{x}}_{(k|k)} + \mathbf{B}\mathbf{u}_k \quad (5)$$

$$\hat{\mathbf{y}}_{(k+1|k)} = \mathbf{C}\hat{\mathbf{x}}_{(k+1|k)} + \mathbf{D}\mathbf{u}_{k+1} \quad (6)$$

$$\begin{aligned} \tilde{\mathbf{y}}_{(k+1|k)} = \mathbf{y}_{k+1} - \hat{\mathbf{y}}_{(k+1|k)} = \mathbf{C}\mathbf{x}_{k+1} + \mathbf{D}_w\mathbf{w}_{k+1} + \mathbf{v}_{k+1} \dots \\ \dots - \mathbf{C}\hat{\mathbf{x}}_{(k+1|k)} \end{aligned} \quad (7)$$

$$\mathbf{P}_{k+1|k} = \mathbf{A}\mathbf{P}_{k|k}\mathbf{A}^T + \mathbf{B}_w\mathbf{Q}\mathbf{B}_w^T \quad (8)$$

where,

$\hat{\mathbf{x}}_{(k+1|k)}$ is the a- priori state estimate at the $k+1^{\text{th}}$ time instant.

$\hat{\mathbf{y}}_{(k+1|k)}$ is the a- priori output estimate at the $k+1^{\text{th}}$ time instant.

$\tilde{\mathbf{y}}_{(k+1|k)}$ is the innovation at the $k+1^{\text{th}}$ time instant.

$\mathbf{P}_{k+1|k}$ is the a-priori state error covariance matrix.

The Kalman filter is not directly provided with any information regarding the inputs to the truck $\mathbf{u}_k$ - in reality this is unavailable. Instead information is provided in the form of the covariance matrices for the disturbance inputs. The noise co-variance matrix $\mathbf{R}$ used in the Kalman filter is obtained by assuming that the variances of the noise outputs are proportional to the variance of the signals themselves by assuming a constant noise to signal ratio in all channels. The variance terms in the disturbance co-variance matrix $\mathbf{Q}$ correspond to disturbances from road roughness and from suspension non-linearities. The road profile and suspension forces are known from simulation and its variance is readily calculable. No cross-covariance terms are used in $\mathbf{R}$ or $\mathbf{Q}$ and both are purely diagonal.

The a-posteriori estimates are calculated as follows:

$$\hat{\mathbf{x}}_{(k+1|k+1)} = \hat{\mathbf{x}}_{(k+1|k)} + \mathbf{K}_{k+1}\tilde{\mathbf{y}}_{(k+1|k)} \quad (9)$$

$$\hat{\mathbf{y}}_{(k+1|k+1)} = \mathbf{C}\hat{\mathbf{x}}_{(k+1|k+1)} + \mathbf{D}\mathbf{u}_{k+1} \quad (10)$$

where,

$\tilde{\mathbf{y}}_{(k+1|k)}$ are the innovations at the $k+1^{\text{th}}$ time instant

$\mathbf{K}_{k+1}$ is the Kalman filter gain at the $k+1^{\text{th}}$ time instant given by

$$\mathbf{K}_{k+1} = \mathbf{P}_{k+1|k}\mathbf{C}^T(\mathbf{C}\mathbf{P}_{k+1|k}\mathbf{C}^T + \mathbf{D}_w\mathbf{Q}\mathbf{D}_w^T + \mathbf{R})^{-1} \quad (11)$$

It is assumed that the static axle loads are measured when the truck is at rest or using weigh in motion (WIM) sensors. Accurate methods of measuring static weights from moving vehicles on static pavements have been developed and are used widely [8]. The static weights may be measured on a rigid pavement ahead of the bridge. The dynamic variations in the axle loads are estimated as a function of some of the states estimated by the Kalman filter.

The total dynamic axle wheel force is given by :

$$\hat{\mathbf{F}}_{i \text{ total}}(t) = \hat{\mathbf{F}}_{i \text{ static}} + \mathbf{K}\mathbf{T}_i * \hat{\mathbf{x}}_j(t) \quad (12)$$

where, $i = 1, 2, 3, 4, 5$ and $j = 1, 4, 7$ respectively

Alternative Methods

Although, the Kalman filter is the anticipated method of choice for this study two simpler methods are considered for comparison.

Static Loads

The relevance of dynamic contributions to input loads on bridges, both for dynamic response and structural health monitoring, is already well-established [17]. However, for comparison purposes, we start with the case where such contributions are neglected, and consider the static axle loads as crude estimates of the dynamic axle loads.

The total dynamic force at a wheel in this wheel is in this case estimated as the constant vertical force exerted by the wheel when it is at rest.

$$\hat{\mathbf{F}}_{w \text{ total},i}(t) = \hat{\mathbf{F}}_{w \text{ static},i} \quad (13)$$

where $i=1, \dots, 10$. $\hat{\mathbf{F}}_{w \text{ total},i}(t)$ is the total load at wheel i and $\hat{\mathbf{F}}_{w \text{ static},i}(t)$ is the static load at wheel i .

Quarter-Car Models

One of the simplest ways to include dynamic effects in the analysis is to represent each wheel of the truck as a