In-Pavement Wireless Weigh-In-Motion

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ABSTRACT

Truck weight data is used in many areas of transportation such as weight enforcement and pavement condition assessment. This paper describes a wireless sensor network (WSN) that estimates the weight of moving vehicles from pavement vibrations caused by vehicular motion. The WSN consists of: acceleration sensors that report pavement vibration; vehicle detection sensors that report a vehicle’s arrival and departure times; and an access point (AP) that synchronizes all the sensors and records the sensor data. The paper also describes a novel algorithm that estimates a vehicle’s weight from pavement vibration and vehicle detection data, and calculates pavement deflection in the process. A prototype of the system has been deployed near a conventional Weigh-In-Motion (WIM) system on I-80 W in Pinole, CA. Weights of 52 trucks at different speeds and loads were estimated by the system under different pavement temperatures and varying environmental conditions, adding to the challenges the system must overcome. The error in load estimates was less than 10% for gross weight and 15% for individual axle weights. Different states have different requirements for WIM but the system described here outperformed the nearby conventional WIM, and meets commonly used standards in United States. The system also opens up exciting new opportunities for WSNs in pavement engineering and intelligent transportation.

Categories and Subject Descriptors
C.3 [Special-Purpose and Application-Based Systems]: Realtime and Embedded Systems, Signal Processing Systems; I.5.4 [Applications]: Signal Processing, Waveform Analysis

General Terms
Design, Measurement, Experimentation, Algorithms

Keywords
Weigh-In-Motion (WIM), traffic monitoring, pavement vibrations, pavement deflection, real-time pavement monitoring, structural health monitoring, pavement-vehicle interaction model, accelerometers

1. INTRODUCTION

Transportation agencies such as Caltrans use weigh stations to enforce weight limits, collect fees, and record truck weight data. For assessment of pavement life and pavement quality, it is critical to know the loads being applied to the pavement. The weight data is, therefore, used to make important decisions concerning road maintenance, pavement design, and transportation policy at both the state and national levels [10]. Federal Highway Administration (FHWA) recognizes the importance of weight data and recommends an increase in the number of stations collecting such data. However, traditional static weight stations are very expensive to install and operate, and also require that the trucks are stopped and weighed individually. An alternative to traditional weigh station is a weigh-in-motion (WIM) system that is installed on an existing highway lane and can estimate the weight of vehicles at highway speeds without disrupting the traffic flow. However, since the typical cost of a WIM system is around $0.5M, they are very expensive for widespread deployment. The main reasons for such high cost are: use of expensive force sensors; construction work required to embed the wired sensors in the road; and the prolonged road closures during installation and maintenance. In this paper we describe an alternative system comprising an embedded wireless sensor network that measures pavement vibration, temperature and vehicle speed to infer the individual axle loads of moving vehicles. Unlike current WIM systems, the wireless WIM uses relatively inexpensive sensors and a much easier installation procedure to reduce the overall cost. We believe this is the first wireless sensor network capable of weigh-in-motion in individual lanes at highway speeds.

Current WIM technologies. The most widely used WIM technologies consist of a pair of wired magnetic loops and a force sensor, as shown in Figure 1. The magnetic loops detect vehicles and estimate their speed. The force sensors (piezoelectric plates, load cells or bending plate sensors) measure the instantaneous force (or load) applied by the tires of a vehicle. A major drawback of these technologies is that they require smooth concrete pavement to be built around the force sensors to achieve the desired accuracy.
Pavement roughness excites the vehicle’s suspension system causing the instantaneous axle load to be different from the static load. The difference between the instantaneous and static load, known as the dynamic component of applied load, is reduced by having a smooth pavement. However, this construction increases the system cost and the installation time, typically requiring several days or even weeks of lane closure. As an alternative to this approach, the use of multiple force sensors on existing pavement has been suggested to improve the estimate of static load [5], but current technologies are too costly to make this approach feasible. The WSN described here uses a different sensing principle, and makes this multi-sensor approach much more cost effective.

**Contributions.** Enabling wireless WIM requires overcoming significant challenges in sensing, pavement modeling, signal processing and estimation. The main contributions of this paper to enable this concept are:

- An easy to install embedded wireless vibration sensor capable of measuring pavement acceleration in a very noisy environment (Section 3).
- Design and verification of the wireless WIM system comprising vibration, speed and temperature sensors, and an access point that can be used to compute loads in real-time (Section 3, 7).
- A simplified and novel model relating individual axle load to pavement acceleration (or displacement), temperature and speed of the vehicle (Section 5).
- A new algorithm to estimate pavement displacement from ground acceleration and to isolate individual axle responses from the combined response (Section 5).
- A novel load estimation procedure that calibrates for temperature, vehicle speed, and local pavement conditions (Section 5).
- Experimental testing of the system on a real highway, under different weather conditions, and a variety of axle load distributions (Section 6).

The paper is organized as follows. Section 2 describes the problem of weigh-in-motion, related work, proposed solution and its challenges. Section 3 describes the wireless WIM and associated components. Section 4 describes the experimental setup used to collect data for calibration and system evaluation. Section 5 proposes a simplified pavement-vehicle interaction model and describes the load estimation algorithm. Section 6 reports experimental results and Section 7 concludes the paper.

2. **WEIGH-IN-MOTION**

In this section, we state the problem of weigh-in-motion and propose a wireless solution. We list the challenges the system must overcome and conclude with a discussion of related work done in the field.

2.1 **Problem statement**

A vehicle with $K$ axles moves in a traffic lane at $v$ miles per hour. Axle $i$ weighs $f_i$ and the total vehicle weight is $f$ pounds. The goal of a WIM system is to detect the presence of a vehicle, measure its speed $v$, count the number of axles $K$ and measure inter-axle spacing, and provide estimates of $f_i$ and $f$ with a required statistical accuracy. The system can be calibrated once a year, utilizing a few pre-weighed vehicles.

There are some important additional requirements that any solution to this problem must meet. The system should weigh vehicles in individual lanes and should be accurate independent of time and weather conditions. It should also be able to account for vehicle wander, i.e., vehicles moving slightly off-center in a given lane. Finally, installation and maintenance costs should be kept at a minimum to enable widespread deployment. A significant portion of the cost is due to traffic disruption from lane closures during installation and maintenance. These costs are easily five to ten times more than the cost of measurement system.

2.2 **Proposed solution: Wireless WIM**

Reducing cost of the WIM system requires rethinking the most critical component of the system: the force sensor. The force sensor works by replacing part of the pavement with a platform that bears the full load of each axle, and providing signals to estimate it. In order to avoid replacing the pavement, we propose utilizing the existing pavement itself as the transducer and estimating individual axle loads from the measured vibration response of the roadway. Small vibration and vehicle detection sensors are embedded in the pavement utilizing a convenient and low cost procedure. The vehicle detection sensors [13] report the arrival and departure times of a vehicle which are used to calculate its speed and length. The vibration sensors report the pavement’s vertical acceleration and its temperature. Multiple arrays of vibration sensors are used to average out the dynamic component of load. The acceleration data is processed to extract the pavement’s response due to each individual axle. This, along with speed and temperature data are then used to estimate axle loads. The axle loads are simply added to get gross vehicle weight. Vehicle length, number of axles and axle spacing are estimated using the Axle Detection (ADET) algorithm described in [2].
2.3 Challenges

The system needs to overcome several challenges:

**Measurement:** The road pavement is designed to experience very small vibrations from vehicle movement [5]. The vibration sensor must measure these small vibrations while being immune to the high environment noise arising from vehicle sound and traffic in neighboring lanes.

**Modeling:** The relationship between applied axle load and pavement vibrations is not well-understood. Most pavement models relate pavement deflection to applied load, but estimating pavement deflection from acceleration is a challenging problem in itself. Moreover, the response is highly dependent on pavement temperature and speed of the vehicle, and these variables must be properly accounted for. Another challenge is to estimate static load from dynamic load, as discussed before.

**Signal processing:** The pavement response at any given time and location is an accumulated response due to all vehicles in the vicinity, therefore response due to other vehicles needs to be filtered out. An even harder challenge is to extract the pavement response due to each axle because at any given time, all the axles of a vehicle are affecting sensor measurements. Additionally, the signal processing algorithms have to be simple enough for real-time execution and efficient enough to conserve energy for a longer lifetime.

**Design:** The sensors should be well coupled to the pavement and robust enough to withstand the tire forces. The system should also be insensitive to vehicle wander. It should be cost-effective and convenient to install and maintain, and have a lifetime of at least 4 years [4].

2.4 Related work

We identify four areas related to this work: applications of wireless sensor networks (WSN) in transportation, applications of sensor networks in infrastructure monitoring, in-motion sensor technologies, and algorithms that estimate pavement displacement from acceleration.

Applications of WSNs in transportation have been growing. WSNs have been used for vehicle detection using magnetic sensors [7, 15, 23], classification of vehicles in different categories [2], and increasing road safety by intervehicular information sharing [22]. Much less has been done in terms of monitoring the response of road infrastructure itself.

Monitoring large infrastructures using accelerometer sensor networks has been studied for structural monitoring of bridges [14], buildings [6] and underground structures such as caves [16]. Wired embedded sensors in concrete structures have been investigated [19] but usually require complex installation procedures and have limited lifetime if used in roads.

WIM technologies have not advanced much in the last decade and focus has shifted on using multiple WIM sensors to improve system accuracy, as opposed to requiring special-material pavement near the sensors [10, 3]. A novel WIM sensor based on perturbation theory of microwave resonant cavities is presented in [17], and a special fiber optic sensor based on measuring light loss under mechanical stress is discussed in [18]. However, both sensors were tested in a controlled laboratory setting, and challenges regarding road installation and sensor durability under heavy loads were not addressed.

Estimating pavement deflection (or displacement) from acceleration is a challenging problem in itself. Simple double integration amplifies the low frequency noise leading to a large unpredictable drift [6]. Popular techniques for drift correction include fitting some polynomial during the silent periods to estimate drift, and subtracting it from the calculated displacement to correct it [12, 1]. However, corrected signals are highly sensitive to the choice of the drift polynomial, and these techniques do not perform as well for low SNR measurements.

3. **WIRELESS WIM SYSTEM**

![Figure 2: Wireless WIM system: The accelerometer and magnetometer sensors report data to the access point. The data is stored locally on hard drives and can be transferred remotely via a cellular modem [2].](image)

Figure 2 shows the schematic of the proposed system. There are four components: vibration sensors, vehicle detection sensors, access point (AP), and a pan-tilt-zoom (PTZ) camera (not shown) connected to the AP. The vibration and vehicle detection sensors are installed in the pavement as shown whereas the rest of the equipment is mounted on a 15ft pole on the side of the road. The vibration and vehicle detection sensors follow a TDMA schedule to transmit their data to the AP. The camera captures images of vehicles to validate that the sensor data corresponds to the correct vehicles. For accurate time stamps on the data, the sensors, the AP, and the camera are periodically synchronized to a common Network Time Protocol (NTP) server. Data from the site can be collected 24x7 and the AP saves all this data locally. The data can be retrieved through a local WiFi connection to the AP or remotely via a cellular connection. In fact, the entire system can be monitored and controlled this way. We now describe the network components and their communication protocol.

3.1 **Sensor network components**

**Wireless vibration sensor.** Figure 3 shows the block diagram for the sensor. Vibrations from the pavement are converted to analog voltage by a MEMS accelerometer on board [8]. The voltage signal is then passed through a filter stage. The output of the filter stage is sampled at 512 Hz by a 12-bit ADC included in MSP430 microprocessor. The collected samples are then transmitted via the radio transceiver using a TDMA based, low power consuming protocol. Along with each packet of acceleration data, the vibration sensor also sends out a temperature reading using the on-board
analog temperature sensor. The average current consumption of the vibration sensor is 1.96 mA in active mode and 35 µA in idle mode. Using a 7200 mAh battery, the respective lifetimes are around 5 months and 23 years respectively. For data collection purposes, lifetime is sufficient and techniques such as in-sensor processing (Section 7) can extend this for other applications.

Figure 3: Block Diagram of the vibration sensor [2].

Simulations reported in [21] revealed that the sensor must have a resolution of 500 µg at a bandwidth of 50 Hz. The highway environment is extremely noisy, and noise from sound alone is a few mg if the sensor is not properly isolated. Another problem is that vehicles in the neighboring lanes cause pavement vibrations and corrupt our measurements. In order to estimate the load of a given vehicle, we need the pavement vibrations corresponding to that vehicle alone. Any measured vibrations due to another vehicle will contribute to error in our load estimates.

Filtering signals above 50Hz with a steep filter can eliminate sound noise significantly. It was shown in [2] that a low pass filter with frequency response \( H(j\omega) = \frac{1}{(1 + \frac{j\omega}{50})^2(1 + \frac{j\omega}{500})} \) successfully isolates the sensor from most of the sound. Moreover, the sensor case shown in Figure 5 attenuates sound before it reaches the accelerometer, providing more isolation.

To provide isolation from traffic in neighboring lanes, the sensors are placed towards the middle of the lane. Pavement vibrations are maximum at the location of applied load and magnitude decreases exponentially away from that location [11]. Center placement maximizes the distance of neighboring-lane vehicles from the sensors, thus minimizing lane-to-lane interference.

Vehicle detection sensor. A wireless magnetic sensor is used to infer the presence of a vehicle by measuring changes in the local magnetic field. The sensor transmits the arrival time \( t_a \) and departure time \( t_d \) of a vehicle as it arrives at the sensor and traverses it. Multiple sensors are combined to estimate speed. These sensors have a lifetime of over 10 years [13].

Pan-tilt-zoom (PTZ) camera. The PTZ camera takes vehicle images from the side of the road and transmits them to the AP using a wired connection. The power to the camera and AP is provided through Caltrans controller box on the side of the road.

Access point (AP). Figure 4 shows the schematic of the access point. This equipment provides remote control and observation of the WSN. The AP contains: (i) A processor with attached radio and 2TB hard drive storage; (ii) a power controller that controls power to each connected device; (iii) an ethernet hub through which a local area network (LAN) is setup for devices to communicate with each other; (iv) a 3G modem that acts as a gateway to the wide area network (WAN) and enables remote access to the system; and (v) a Wi-Fi bridge and an ethernet data port for local access to the system. Once a remote computer is connected to the AP, it can communicate to any of the connected devices through the LAN. It can, for instance, use the power controller to turn on/off individual components in the box, send commands to the sensors via the radio, change the settings of the PTZ camera, and start collecting video and sensor data remotely.

Figure 4: Schematic of the access point.

3.2 Communication protocol

We focus on the communication protocol followed by the wireless sensor nodes and the AP. Other components follow widely used standard protocols and are not discussed here. The sensors follow a TDMA protocol that uses headers very similar to IEEE 802.15.4 MAC layer. Time is divided into multiple frames with each frame about 125 ms long. Each frame is further divided into 64 time slots, numbered 0 to 63, most of which can be used by the sensor nodes to transmit data. Timeslot 0 is used by the AP to send clock synchronization information and other commands to the sensors. The AP assigns every node unique time slots and a network address (or node ID) to communicate with it. This schedule enables individual nodes to stay awake for the minimum amount of time and prevents packet collisions. There are three major applications of this protocol: synchronization, sensor management, and firmware update.

Synchronization. This application ensures clock synchronization of all nodes within 60 µs. Sync packets are sent by the AP on a periodic basis with very low jitter. Nodes must first synchronize their clocks before transmitting. When a sensor node first starts, it listens to sync packets every 125 ms. It learns the difference between its clock and the AP’s clock, and over time improves its estimate of the AP’s clock. As the estimate improves, the node converges to a steady state in which it listens for a sync packet only once in 30
s. If a node loses sync, it repeats the above process to get synchronized again. In addition to sending clock information, the sync application is also used to send commands to individual sensors like change mode, set RF channel, reset sensor.

Sensor management. This is the most important application for both sensors. For the vibration sensor, the application controls when to turn on the accelerometer and related circuitry, when to sample, and when to wake up the radio to transmit the data collected. There are two main modes in this application: idle mode and raw data mode. In idle mode, the accelerometer and related conditioning circuitry are turned off by disabling the voltage regulator that powers this part of the circuit. Even the microcontroller and the radio transceiver are put in a low power consuming state most of the time. Once every 30 seconds, the microcontroller and the transceiver wake up and acquire the sync packet. In raw data mode, the accelerometer and related circuitry are turned on. The microcontroller wakes up every 1/512 seconds and samples the analog output from the accelerometer unit, as shown in Figure 3. In addition to waking up for the sync packet, the transceiver wakes up right before its allotted timeslots to send the sampled data. Due to challenging environment of highways, sensors frequently suffer from packet losses. To fix this problem, we transmit every packet twice after a slight delay.

For the detection sensor, the application is similar. The key difference is that instead of the raw data mode there is a vehicle detect mode. The magnetometer is constantly sampled at 128 Hz, followed by in-sensor processing to determine if the vehicle is present or not. Only in case of a detection is any data transmitted, as opposed to the vibration sensor which continuously transmits raw data. Since the data throughput from detection sensors is very small, each packet is retransmitted until an acknowledgement is received from the AP.

The AP receives data from each sensor, appends useful information such as the timestamp, Received Signal Strength Indicator (RSSI), the Link Quality Indicator (LQI), and records it into a file that can be processed offline.

Firmware update. This application allows reprogramming the entire flash memory of a sensor node over the air, via the AP. Using this mode, any future upgrades in the sensor firmware can be made remotely and since no lane closures are needed, it considerably reduces maintenance costs.

3.3 System design

In order to overcome the measurement challenges described in Section 2.3, sensor casing, system layout, and installation procedure need to be selected carefully.

Sensor casing. In order to withstand large forces in a harsh environment, the sensors must be packaged for durability before installation. The circuit board and the battery are placed in a hard plastic casing as shown in Figure 5. The casing is then filled with fused silica and sealed air tight. This protects the electronics from rain water, oil spills etc on the road and further attenuates interference from sound.

System layout. Figure 6 shows the selected layout. The vehicle detection sensors are set in the standard recommended configuration. There are four arrays of vibration sensors installed 15 ft apart, with five sensors in each array. The sensor layout is designed to minimize lane-to-lane interference and maximize the in-lane signal-to-noise ratio. The pavement response at the sensor location reduces exponentially with the distance between the sensor and applied force [11]. Thus we minimize the interference from neighboring lane vehicles by placing the sensors in the middle of each lane as this maximizes the distance between the sensors and neighboring lane vehicles. An additional important benefit is that this placement minimizes the effect of vehicle wander. The left and right wheels of a vehicle contribute additively to sensor measurements. Vehicles moving off-centered in the lane will have one wheel closer to the sensors than the other. Therefore, reduction in measurements from one wheel are compensated by the other to ensure that their sum remains almost constant.

Installation procedure. In order to minimize the system cost, the installation procedure must be quick and simple. 
To install a sensor in the pavement, we drill a 4-inch diameter hole, approximately 2\(\frac{1}{4}\) inches deep at the desired location. The sensor is placed in the hole, properly leveled with the earth’s surface, and the hole is sealed with fast-drying epoxy [23], as shown in Figure 7. Each sensor can be installed in the road in less than 10 mins. The AP and the PTZ camera are mounted on a 15ft high pole on the side of the road, and don’t require any lane closures.

4. EXPERIMENTAL SETUP

![Figure 7: Installation procedure for embedding the sensors in the pavement][2]

This section describes deployment challenges and data collection procedure used to test our system.

Deployment challenges. A test system was installed on I-80 W in Pinole, CA, about 300 ft away from an existing WIM station. This WIM station, operated by Caltrans, measures and records weights for every passing truck which we planned to use as ground truth for training and testing our system. However, the data provided by this station turned out to be inaccurate (Figure 18). Renting individual trucks to test our system is also very challenging, given the volume of trucks that go over the wireless WIM every day. The trucks also cannot be directed to drive in our installation lane and often never arrive at our site. Identification of trucks that reach our site is also very challenging, given the volume of trucks that go over the wireless WIM every day. The trucks also cannot be directed to drive in our installation lane and often traveled in neighboring lanes. All these factors limited the size of our final dataset.

Data collection. Randomly selected class 9 trucks were weighed individually at the static weigh station. These trucks have 3 axles, 1 single axle and 2 tandem axles. Class 9 trucks were chosen because these are the most common trucks on highways and other truck classes are made up of different combinations of these two axle types. For truck identification, pictures of each truck were taken at the station and matched with images collected by the road-side PTZ camera of the wireless WIM. Timestamps provided by the PTZ camera are then used to extract data reported by the sensors:

- Speed data. Timestamps from the camera images are matched with the detection sensor timestamps to get the data corresponding to the truck. Each vehicle detection sensor reports both the time of arrival and time of departure of the truck. A pair of sensors \((i, j)\) installed at a fixed known distance \((d_{ij})\) apart from each other are used to estimate speed. Given the arrival times \(t_{ai}\) and \(t_{aj}\) at the two sensors \(i\) and \(j\), the speed \(v\) is given by \(v = \frac{d_{ij}}{t_{aj} - t_{ai}}\). The speed can then be used to estimate the length \((L)\) of the vehicle as \(L = v(t_{dj} - t_{ai})\), where \(t_{dj}\) is the departure time reported by sensor \(j\). These measurements have been shown to be accurate in practice [13].

- Acceleration data. The arrival and departure times reported by detection sensors are used to estimate the time window during which the truck passed each array of vibration sensors. This time window is then used to extract the corresponding acceleration reported by each sensor.

- Temperature data. Temperature readings reported by vibration sensors around the time of vehicle’s arrival are averaged to get a single estimate of pavement temperature around that time.

The collected ground truth data is a very good representation of the distribution of loads, speeds, and pavement temperatures for this site. Axle weights range from 10,000 to 35,000 lbs, speeds vary from 15 to 65 mph, and pavement temperature from 15 to 40\(^\circ\)C. In fact, most common WIM standards use only a couple of pre-weighed vehicles at different speeds to verify WIM performance [10, 9]. In order to test the system under different environmental conditions, we collected data on three different days over a span of six months. Most WIM standards finish their testing on a single day. In addition to the ground truth from static weigh station, we also obtained loads reported by the nearby WIM station. This data provides a useful one-on-one comparison between our system and an operational WIM system currently used by the government.

![Figure 8: Euler beam model for vehicle-pavement interaction][5]

5. LOAD ESTIMATION

In this section, we propose a model for vehicle-pavement interaction that directly relates pavement acceleration, vehicle speed, and pavement temperature to applied axle load. We then describe the procedure used to extract pavement response due to individual axles from the measured response. We end the section by describing how the model is calibrated for load estimation.
5.1 Pavement-vehicle interaction model

We start by describing the model for pavement acceleration (and displacement) at a constant temperature, and then explain how measurements can be properly compensated for temperature variation. The simplest vehicle-pavement interaction model is a composite one dimensional Euler beam resting on an elastic Winkler foundation as shown in Figure 8 [5, 21]. The vehicle is modeled as a moving force modulated by its suspension system. A typical pavement response due to a moving load is shown in Figure 9. As an axle approaches the pavement the pavement is pushed down, but it returns to its original location after the axle has passed. The response of the pavement at any fixed location can be approximated as $y(t) = F\Phi(vt)$ [21], where $y(t)$ is the vertical displacement or deflection of the pavement, and the function $\Phi(\cdot)$ mainly depends on the structural and material properties of the pavement. The model is linear in $F$, and vehicle speed $v$ just scales the function $\Phi(\cdot)$ in time. This is a simplifying assumption, and in general $\Phi(\cdot)$ has some dependency on $v$ and unknown suspension frequencies of the vehicle [21].

Now, let $\Psi(t, \sigma) = -\left(1 - \frac{\sigma^2}{\sigma_0^2}\right)e^{-\frac{\sigma^2}{\sigma_0^2}}$ and $\alpha = \frac{F_{\text{axle}}}{\sigma_0^2}$, and we have the following relation for pavement acceleration due to a single axle load:

$$a(t) = \alpha \Psi(t, \sigma).$$

From the definition of $\alpha$, we see that

$$F = \frac{\sigma_0^2 \alpha}{\eta v^2} = \beta \frac{\alpha}{v^2};$$

$$y(t) = \alpha \sigma_0^2 e^{-\frac{\alpha^2}{\alpha^2}}.$$

The last step is obtained by combining Equations (2) and (1). The unknowns $\alpha$ and $\sigma$ can be estimated from the measured acceleration (Section 5.2), but $\beta$ depends on axle type (single or tandem) and pavement properties, and needs to be calibrated using trucks of known weights (Section 5.3). For a $K$ axle truck, with the $i^{th}$ axle arriving at the sensor at time $t_i$ and applying a force $f_i$, the response can be written as the superposition of individual axle responses $(a_i(t))$ i.e.

$$a(t) = \alpha \Psi(t - t_i, \sigma_i).$$

Using a non-linear curve fitting procedure, described in Section 5.2, we estimate $\alpha_i$, $\mu_i$, and $\sigma_i$ for each axle. Once these have been estimated, each axle can be treated separately to estimate quantities like individual axle loads ($F_i$) and pavement displacement ($y_i(t)$) due to each axle,

$$F_i = \beta \alpha_i \sigma_i,$$

$$y_i(t) = \alpha_i \sigma_i^2 e^{-\frac{(t-t_i)^2}{\sigma_i^2}}.$$

Temperature compensation. The above model is valid for a constant temperature but pavement response for asphalt-concrete layer is highly dependent on temperature. Using the thickness of different layers and material parameters for

![Figure 9: Example of pavement deflection due to two-axle truck moving at 50 km/h. Image taken from [1].](image)

![Figure 10: Percentage change in pavement response with temperature. For the same applied load, pavement acceleration (or displacement) increases with increasing temperature.](image)
the pavement at this site, we developed a layered elastic theory (LET) model to simulate the effect of temperature on the pavement response \[20\]. Figure 10 shows how the pavement acceleration changes with temperature according to the LET model. The plot shows that pavement response can change over 15% with changes in temperature alone and proper temperature compensation is needed for accurate load estimation.

Let \( \tau(T) \) be the ratio of the modeled response at 25°C and at temperature \( T \). To compensate for temperature, we normalize all our measurements to the reference temperature of 25°C as \( a(t, T = 25°C) = a(t)\tau(T) \), where \( \tau(T) \) is calculated using the LET model. It can be seen from Equation (4) that \( \alpha_i(T = 25) = \alpha_i(T)\tau(T) \), and accordingly

\[ F_i = \beta_i \frac{\alpha_i}{\tau^2}(T). \]  

(6)

5.2 Extracting individual axle response

In order to extract individual axle response, we follow a two-stage process. In the first stage, measurements from multiple sensors are combined to get an average pavement response for the whole vehicle. In the second stage, we fit this response to the model described by Equation (4) and estimate \( \alpha_i \), \( \mu_i \), and \( \sigma_i \) for each axle.

![Figure 11: Top plot shows the raw acceleration signal measured by the reference sensor. Bottom plot shows the average pavement response \( a_m(t) \) and the fitted response \( a(t) \). There are 3 mexican-hat functions in \( a(t) \) (at 0.6, 0.8, and 1.2 s resp.), each corresponding to an axle. The response due to last axle is well isolated from the others but the response for the first two axles is not isolated.](image)

**Average pavement response.** The average pavement response requires aligning the measurements from each sensor. Each signal is first passed through a low pass filter to filter out high frequency noise. The highest amplitude signal is then designated as the reference signal, and signals from all other sensors are time-shifted to align with the reference signal proper. Let \( a^{k,*}_m(t) \) be the time-shifted signal for the \( k \)th sensor, and \( I \) the number of available sensors. Then the average pavement acceleration \( a_m(t) \) can be estimated as:

\[ a_m(t) = \frac{1}{I} \sum_{k=1}^{I} a^{k,*}_m(t). \]

Figure 11 shows an example of the raw acceleration data from a sensor, and the average pavement response \( a_m(t) \). The improvement from filtering and combining signals can be easily seen in the plot. Figure 11 also highlights another important challenge in estimating individual axle loads. Response due to each axle needs to be decoupled and extracted from \( a_m(t) \). Because of high speeds and relatively short axle spacings, the trailing axles of a truck arrive at the sensor before the pavement has relaxed from the first axle’s load. To extract each \( a_i(t) \) from \( a_m(t) \), we use the following algorithm.

**Curve fitting algorithm.** Let \( a(t) \) be the modeled response of a \( K \) axle truck, given by Equation (4). Let \( e(t) \) be the error between the measured and modeled response for the truck at time \( t \) i.e. \( e(t) = (a_m(t) - a(t)) \). We can now write the measured response as:

\[ a_m(t) = \sum_{i=1}^{K} \alpha_i \Psi(t - \mu_i, \sigma_i) + e(t). \]  

(7)

We estimate the unknown parameters \( \{\alpha_i\}_{i=1}^{K}, \{\sigma_i\}_{i=1}^{K} \) and \( \{\mu_i\}_{i=1}^{K} \) by minimizing the mean square error i.e.

\[
(\alpha^*_i, \sigma^*_i, \mu^*_i) = \arg \min_{\alpha_i, \sigma_i, \mu_i} \int_{-\infty}^{\infty} (a_m(t) - a(t))^2 dt,
\]

\[
(\alpha^*_i, \sigma^*_i, \mu^*_i) = \arg \min_{\alpha_i, \sigma_i, \mu_i} \int_{-\infty}^{\infty} (a_m(t) - \sum_{i=1}^{K} \alpha_i \Psi(t - \mu_i, \sigma_i))^2 dt.
\]  

(8)

This is a non-linear least-squares problem that can be solved using standard techniques. Once the fit is performed, acceleration and displacement corresponding to each axle can be calculated using Equations (3) and (5). Figure 11 shows an example of how good the modeled response fits the measurements.

5.3 Model calibration

Before individual axle loads can be estimated using Equation (6), the parameter \( \beta_i \) needs to be calibrated. In general, \( \beta_i \) is site specific and can depend on axle type but a set of pre-weighed trucks can be used to estimate it. Let \( N \) be the number of trucks used in the training data, \( \hat{f}^n \) the load estimate for the \( n \)th axle of \( n \)th truck, \( f^w_n \) the true weight, \( v_n \) the speed, \( \alpha^*_n \) the corresponding fitted parameter \( \alpha^*_n \), and \( e^p_n \) be the percentage error associated with the load estimates. The optimal \( \beta \) can be calculated by minimizing...
the mean-square percentage errors for the load estimates,
\[
\hat{f}_n^i = \beta_i \alpha_{n}^\tau(T),
\]
\[
e_n^i = \frac{\beta_i \alpha_{n}^\tau(T) - \hat{f}_n^i}{\hat{f}_n^i} \times 100,
\]
\[
= (\beta_i \alpha_{n}^\tau(T) - 1) \times 100,
\]
\[
\beta_i^* = \arg \min_{\beta} \frac{1}{N} \sum_{i=1}^{N} (e_n^i)^2,
\]
\[
\beta_i^* = \arg \min_{\beta} \frac{1}{N} \sum_{i=1}^{N} (\beta_i \alpha_{n}^\tau(T) - 1)^2.
\]
Equation (10) is a standard linear least squares problem and can be solved for $\beta_i^*$. Once $\beta_i^*$ is known, individual axle loads can be estimated using Equation (9).

6. RESULTS AND DISCUSSION

The results discussed in this section serve three goals: verify that the proposed model fits the data well, evaluate the accuracy of wireless WIM, and understand the effect of dynamic component of load on system accuracy.

Model verification. We calibrate the model using the entire set of trucks and examine how closely it explains the data. Figure 12 compares the axle weights estimated by our system with their true weights. The estimated loads track the true loads very closely ($R^2 = 0.99$) but there is one interesting observation. The error in klbs\(^1\) increases as the true weight increases. This is, however, by design as percentage errors ($e_n^i$) are more important for WIM systems, and we calibrate the system to minimize the percentage errors. If error in klbs is minimized, the lighter axles will tend to have much higher percentage errors. Figure 13 shows the estimated probability distribution function of errors for each axle. The means and standard deviations associated with these bell-shaped curves are summarized in Table 1.

\(^1\)klb, also known as kip, is a non-SI unit of force and equals 1000 pounds-force.

Figure 13: Plot shows the probability distribution of percentage errors in load estimates for each axle and the entire vehicle.

Figure 12: Plot shows the estimated weights against the ground truth static weights.

Figure 14: Plot shows the percentage error in load estimates against truck speeds. Errors are statistically uncorrelated to speed.

Figure 14 shows the percentage errors in load estimates at different truck speeds. The errors are uncorrelated to speed, implying that the $\frac{1}{v^2}$ term in the model captures the speed dependence of the pavement response pretty well.

Figure 15 shows the percentage errors of load estimates at different pavement temperatures. The errors are uncorrelated to temperature and compensation $\tau(T)$ captures the effect of pavement temperature well. Figure 16 shows that the errors are much higher when no temperature compensation is used (i.e. $\tau(T) = 1 \forall T$). Consistent with pavement models [20], without temperature compensation loads are overestimated at higher temperatures and underestimated estimated at lower temperatures. This is because pavement response for any load is higher at higher temperatures. Quantitatively, the errors for both scenarios are provided in Table 1. Clearly, temperature compensation is a very crucial step in our load estimation algorithm.

Wireless WIM accuracy. For the results above, we use the entire dataset for training our system. For a more realistic evaluation of the system accuracy, we now run 1000
Table 1: Effect of pavement temperature on load estimation. Errors in total weight estimates are below 8.2% at a confidence level of 95% when temperature compensation is applied. When no temperature compensation is used, the 95% error bound on total weight estimate increases to 11.3%.

<table>
<thead>
<tr>
<th></th>
<th>Temperature compensation</th>
<th>No compensation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean Error (%)</td>
<td>Std of errors (%)</td>
</tr>
<tr>
<td>Axle 1</td>
<td>-0.27</td>
<td>5.25</td>
</tr>
<tr>
<td>Axle 2</td>
<td>-0.22</td>
<td>4.75</td>
</tr>
<tr>
<td>Axle 3</td>
<td>-0.33</td>
<td>5.81</td>
</tr>
<tr>
<td>Total</td>
<td>-0.19</td>
<td>4.09</td>
</tr>
</tbody>
</table>

Figure 16: Plot shows the percentage error in load estimates against pavement temperature when temperature compensation is not applied. Errors increase with increase in temperature.

Figure 17: Plot shows cumulative distribution for the LTPP errors from the 1000 trials. Majority of trials pass the LTPP specification for allowed errors.

**Effect of dynamic component.** Road roughness and the vehicle suspension system cause the applied load $F_d$ to be different from the static load $F_s$ that we are interested in estimating. In general, the instantaneous applied load can be written as $F = F_s + F_d \sum \cos(\omega_i t)$, where $\omega_i$ depends on the suspension system and $F_d$ is usually within 30% of $F_s$ [5]. To reduce the error $(F - F_s)$ or the dynamic component, we average measurements from multiple arrays. Figure 19 shows how the LTPP error decreases when the number of arrays increase. Each array essentially measures the static load with some uncertainty, and by averaging multiple measurements we reduce the amount of uncertainty in our load accuracy of both systems. The wireless WIM clearly outperforms the conventional WIM in every category. The conventional WIM meets the required LTPP accuracy levels for only axle 1, and fails in all other cases. It is worth noticing in Figure 19 that even a single lane of wireless WIM outperforms the conventional WIM (except for Axle 1).
Table 2: Comparison of mean LTPP errors between our system and the nearby conventional WIM. The errors for the conventional WIM are much higher than the errors allowed by the LTPP standard.

<table>
<thead>
<tr>
<th></th>
<th>Wireless WIM error</th>
<th>Conventional WIM error</th>
<th>Maximum allowed error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Axle 1</td>
<td>11.29</td>
<td>18.67</td>
<td>20</td>
</tr>
<tr>
<td>Axle 2</td>
<td>10.07</td>
<td>26.49</td>
<td>15</td>
</tr>
<tr>
<td>Axle 3</td>
<td>12.44</td>
<td>37.35</td>
<td>15</td>
</tr>
<tr>
<td>Total</td>
<td>8.76</td>
<td>23.23</td>
<td>10</td>
</tr>
</tbody>
</table>

Figure 18: Plot shows errors in load estimates for the nearby WIM system. These are much higher than expected and fail to meet the LTPP standard.

Figure 19: Plot shows that errors in static loads decrease as the number of arrays increase. The more the number of arrays, the better we filter out the dynamic component.

7. CONCLUSIONS AND FUTURE WORK

Conclusions. A wireless WIM system that uses pavement vibrations to estimate axle loads was built and tested in this study. The wireless vibration sensor designed for this system is capable of measuring very small pavement vibrations in an extremely noisy environment. A new pavement-vehicle interaction model that relates applied load to pavement vibrations, temperature, and speed of the vehicle was also developed and evaluated. The system was tested on a real highway and passed the WIM accuracy standards. The system achieved the required accuracy of 15% for individual axle loads and 10% for total load, and outperformed a nearby conventional WIM system. As part of load estimation, the system also estimates the pavement deflection, and therefore can be used for long-term pavement monitoring.

Future work. Even though we have provided a proof-of-concept for the wireless WIM, more work needs to be done before the system can be widely used. The following are some avenues for future work.

- In-sensor processing. As mentioned in Section 3.1, the lifetime of the vibration sensors is only 5 months because they continuously transmit all the raw data. One efficient way to reduce the current consumption of the sensor is to only send out processed data. This can be done by implementing a version of the fitting algorithm inside the sensor and only sending the fitted coefficients. This should immediately increase the lifetime of the sensor to a few years. The challenge, however, is to preserve the accuracy of the system while reducing the current consumption. To learn about the trade-off between current consumption and system accuracy, we simulated the in-sensor processing of data. Instead of combining the raw data from all sensors and then using the fitting algorithm, we apply the fitting algorithm to individual sensor data and average the fitted coefficients to get the average pavement response. The load estimates based on this procedure are shown in Figure 20. The LTPP errors were 10.33, 12.09, 12.36, and 9.45 percent respectively for axle 1, 2, 3, and the total weight. These are very similar to our previous results and still pass the accuracy levels defined by the LTPP specification. The in-sensor fitting algorithm needs to be implemented and tested.

- Testing on different pavements. Pavement response is highly dependent on pavement’s structural and material properties. More tests need to be done using different kinds of pavements to understand the effect of pavement properties on the load estimation procedure.

- Pavement monitoring. We plan on working with pavement engineers to use this system as a pavement monitoring tool. Long-term pavement monitoring systems are practically non-existent currently but many interesting problems can be studied using such systems.

8. ACKNOWLEDGEMENTS

We would like to thank the California Department of Transportation for letting us install the system near their oper-
Figure 20: Expected results of load estimation after in-sensor processing. The results are very similar to Figure 12

9. REFERENCES


[8] Colibrys, Inc, acceler.us@colibrys.com. MEMS Capacitive Accelerometers Datasheet MS9000.D.


