## Development of a Cost Effective Wireless Vibration Weigh-In-Motion System to Estimate Axle Weights of Trucks

Ravneet Bajwa Iotera, Inc., CA, USA

Erdem Coleri<sup>\*</sup>

School of Civil and Construction Engineering, Oregon State University, Corvallis, OR, USA

Ram Rajagopal

Department of Civil and Environmental Engineering, Stanford University, CA, USA

Pravin Varaiya

Department of Electrical Engineering and Computer Science, University of California, Berkeley, CA, USA

Christopher Flores Advanced Technology, Sensys Networks, Berkeley, CA, USA

Abstract: Truck weight data plays an important role in weight enforcement and pavement condition assessment. This data is primarily obtained through weigh stations and weigh-in-motion stations which are currently very expensive to install and maintain. This paper presents results of the implementation of an inexpensive wireless sensor-based vibration Weigh-In-Motion (WIM) system. The proposed wireless sensor network (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 new method for speed compensation, an energy efficient algorithm (adaptive sampling method) to increase battery life, and a new modeling procedure to estimate gross vehicle weights. The system deployed near a conventional WIM system on I-80W in Pinole, CA passed the accuracy standards for WIM systems and outperformed a nearby commercial WIM station, based on conventional technology.

## 1. INTRODUCTION

Roads are valuable assets of the nation and contribute significantly to a nation's economy. However, construction and maintenance of road pavements is expensive. According to the U.S. Federal Highway Administration (FHWA), \$46 billion is spent annually on highway construction and maintenance but significant savings can be made by improving our pavement monitoring and management systems (FHWA, 2010). Pavement monitoring enables engineers to predict road deterioration and design an optimal repair (or rehabilitation) schedule to minimize costs and extend pavement lifetime. In the United States, the long-term pavement performance (LTPP) program collects data for pavement monitoring and management including traffic volume, truck weights, climate, structural and material properties for pavement sections, and other field testing data (FHWA, 2003).

Since heavy trucks cause significantly more pavement damage than passenger vehicles (TRB, 2007), accurate truck count and weight data must be collected. FHWA recognizes the importance of weight data and recommends an increase in the number of stations collecting such data. However, traditional static weigh stations are very expensive to install and operate, and also require trucks to be 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 costs of conventional bending plate and load cell type WIM

<sup>\*</sup>To whom correspondence should be addressed. E-mail: colerie@oregonstate.edu

system are very high, they are too expensive for widespread deployment. The main reasons for such high cost include the 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, an alternative system comprising an embedded wireless sensor network that measures pavement vibration, temperature and vehicle speed to infer the individual axle loads (weight) of moving vehicles is described. Unlike current WIM systems, the wireless WIM uses relatively inexpensive sensors and a much easier installation procedure to reduce the overall cost. Table 1 summarizes the estimated initial equipment and installation costs for the wireless WIM developed in this study and other WIM technologies. It is believed that this is the first wireless sensor network capable of weigh-inmotion in individual lanes at highway speeds.

	System(\$)	Lane Closure <sup>2</sup> (\$)	Labor(\$)	Total(\$)
Wireless WIM	19,500	2,000	2,000	23,500
Piezoelec. sensor <sup>1</sup>	13,500	10,000	6,500	30,000
Piezoquar. sensor <sup>1</sup>	29,000	20,000	12,000	61,000
Bending- plate <sup>1</sup>	21,500	40,000	13,500	75,000
Deep pit load cell <sup>1</sup>	50,500	60,000	20,800	131,300

Table 1.WIM system cost comparison(costs/lane)

Note: <sup>1</sup>: Hallenbeck and Weinblatt (2004) <sup>2</sup>: Herbsman and Glagola (1998)

#### 1.1. Current WIM technologies

The most widely used WIM systems consist of a pair of wired magnetic loops and a force sensor. The magnetic loops detect vehicles and estimate their speed. The force sensors [piezoelectric (Alavi et al., 2001) sensors (piezo-ceramic, piezo-polymer and piezo-quartz sensors) (Jiang et al., 2009), bridge WIM systems, load cells or bending plates] measure the instantaneous load applied by the tires of a vehicle. A major drawback of these technologies is that they require smooth pavement to be built around the force sensors to achieve the desired accuracy. Smooth pavement is required to minimize the difference between dynamic and

static loads by reducing the vertical dynamic movement of the vehicle. The force sensors are installed first and smooth concrete pavement is built around it. Pavement roughness excites the vehicle's suspension system, thus, 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 (asphalt or concrete pavement with lower surface texture) 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 (Cebon, 1999), but current technologies are too costly to make this approach practical.

While WIM technologies have not advanced much in the last decade, focus has shifted on using multiple WIM sensors to improve system accuracy as opposed to requiring special material pavement near the sensors (FHWA, 2001; Burnos et al., 2007; Kwon, 2016). A novel WIM sensor based on perturbation theory of microwave resonant cavities was presented in (Liu et al., 2007), and a special fiber optic sensor based on measuring light loss under mechanical stress was discussed in (Ramesh et al., 2008). However, both sensors were tested in a controlled laboratory setting, and challenges of road installation and sensor durability under heavy loads were not addressed.

#### 1.2. Problem statement and proposed solution: Wireless WIM

The system developed in this study addressed three main problems. The first problem involves building a wireless sensor network (WSN) to detect traffic and measure corresponding ultra-low elastic pavement vibrations. For detecting traffic, off-theshelf vehicle detection sensors, which can also estimate vehicle speed and length (Haoui et al., 2008), were used (Sensys Networks Inc., 2013).

Problem 1: A vehicle moves at an unknown speed, ranging from a few miles per hour to highway speeds. Design a wireless vibration sensor that can be embedded in the pavement to measure corresponding vertical pavement acceleration and temperature.

Once a capable WSN is available, it can be used to solve the following application-specific problems.

*Problem 2:* A vehicle of N axles moves at an unknown speed, ranging from a few miles per hour to highway speeds. Use the designed WSN to automatically detect axles of the vehicle and classify it using FHWA's vehicle classification scheme (Stevens et al., 1984).

*Problem 3:* Use the designed WSN to estimate the individual axle weights and the gross-weight of the truck. The above two applications can enable a cost-effective way of monitoring truck traffic for pavement design. The system can be calibrated once a year, utilizing a few pre-weighed vehicles.

important There are some additional requirements that any solution to this problem must meet. The system should weigh vehicles in lanes should be individual and 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. In addition, 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 (Table 1). Finally, sensor batteries should last at least 2 to 4 years to make the system an economical alternative.

Reducing cost of the WIM system requires rethinking the most critical component of the system: the force sensor. The force sensor in conventional bending plate WIM stations 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, in this study, utilizing the existing pavement itself as the transducer and estimating individual axle loads (referred to as modeled response in this study) from the measured vertical vibration response (referred to as measured response in this study) of the roadway is proposed. Small vibration and vehicle detection sensors are embedded in the pavement utilizing a convenient and low cost procedure. Multiple arrays of vibration sensors are used to average out the dynamic component of load and get equivalent of static weights. The vehicle detection sensors (TRB, 2007) 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 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 (GVW). Vehicle length, number of axles and axle spacing are estimated using the Axle Detection (ADET) algorithm described in (FHWA, 1992).

#### 1.3. Contributions

A prototype-easy to install embedded wireless vibration sensor system was developed by Bajwa et al. (2013) to measure truck weights. A novel load estimation procedure that relates individual axle load to pavement acceleration and calibrates for temperature, vehicle speed, and local pavement conditions developed. was However. implementation of wireless WIM system required overcoming additional testing, significant challenges in sensing and battery use, pavement modeling, signal processing and estimation. The main contributions of this paper are:

- Testing, calibration and validation of developed wireless WIM system with a larger dataset.
- A new method for speed compensation.
- An energy efficient algorithm (adaptive sampling method) to increase battery life from 5 months to 22 months.
- A new modeling procedure to estimate gross vehicle weights.
- Implementation and validation of developed wireless WIM system.

#### 2. Developed wireless WIM system

Figure 1 shows the schematic of the prototype system. There are four components: vibration sensors (2.5x2.5x2inches - 6.35x6.35x5cm), vehicle detection sensors (2.5x2.5x2 inches- 6.35x6.35x5cm), access point (AP) (4x7x6inches -

10x18x15cm), and a pan-tilt-zoom (PTZ) camera (not shown) connected to the AP. The vibration and vehicle detection sensors are installed in the pavement whereas the rest of the equipment is mounted on a 15ft (4.57 m) pole on the side of the road. The vibration and vehicle detection sensors follow a time division multiple access (TDMA) schedule to transmit their data to the AP. TDMA allows multiple sensors to use the same frequency channel by coordinating and using assigned time slots for each sensor's individual use. 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 24/7 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. The entire system can be monitored and controlled remotely. The network components and their communication protocol are described below.



**Fig.1.** Image showing a general setup of the system (Bajwa et al., 2013).

#### 2.1. Sensor network components

#### 2.1.1. Wireless vibration sensor

Figure 2 shows the block diagram for the sensor. Vibrations from the pavement are converted to analog voltage by a Micro-Electro Mechanical System (MEMS) accelerometer (Colibrys, 2010). 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 35µA in idle mode. Using a 7200 mAhr 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 (rather than transferring all data to AP without for processing) or adaptive sampling (described in section 3.4) can extend this for other applications. Wireless WIM system is expected to generate 6 megabytes (MB) of data every day, which can be remotely downloaded in about 10 to 20 seconds.



**Fig.2.** Block diagram of the vibration sensor (Bajwa et al., 2011).

Simulations reported in Rajagopal (2009) revealed that the sensor must have a resolution of 500 µg at a bandwidth of 50 Hz, and a range of ± 200 mg. The highway environment is extremely noisy, and noise from sound alone is a few mg if the sensor is not properly isolated. Filtering signals above 50Hz with a steep filter can eliminate sound noise significantly. It was shown by Bajwa et al. (2011) that a low pass filter with frequency response  $H(jw) = \frac{1}{\left(1 + \frac{jw}{50}\right)^2 \left(1 + \frac{jw}{500}\right)}$ 

sensor from most of the sound. Moreover, the sensor case attenuates sound before it reaches the accelerometer, providing additional 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 (Fehler, 2009). Center placement maximizes the distance of neighboring-lane vehicles from the sensors, thus minimizing lane-tolane interference.

#### 2.1.2. Vehicle detection sensor

The vehicle detection sensor measures changes in the local magnetic field to infer the presence of a vehicle. The sensors have been shown to be very accurate for vehicle detection and have a lifetime of 10 years (Haoui et al., 2008). Each sensor samples the on-board magnetometer at 128 Hz and uses an edge-detection algorithm to estimate the arrival time  $t_a$  and the departure time  $t_d$  of a vehicle. A pair of sensors (i,j) can be installed at a fixed distance  $d_{ij}$ apart from each other to estimate the speed and length of a vehicle. Given the arrival times  $t_{ai}$  and  $t_{aj}$ , and the departure times  $t_{di}$  and  $t_{dj}$  at sensor i and j, the speed v, length L, and the time window  $T_i$ corresponding to the vehicle at sensor i can be estimated as,

$$v = \frac{d_{ij}}{|t_{aj} - t_{ai}|} \tag{1}$$

$$L = v|t_{di} - t_{ai}| = v|t_{dj} - t_{aj}|$$
(2)

$$T_i = [t_{ai}, t_{di}] \tag{3}$$

#### 2.1.3. 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 3. The casing is then filled with fused silica and sealed airtight. This protects the electronics from rainwater, oil spills etc on the road and further attenuates interference from sound.



**Fig.3.** Packaging of a sensor in a sealed case (Bajwa et al., 2011).

#### 2.1.4. Access point (AP)

Figure 4 shows a block diagram for the access point. This equipment provides remote control and observation of the WSN. The AP contains: (i) a processor with attached radio transceiver and 2 TB 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; (v) a Wi-Fi bridge and an ethernet data port for local access to the system; and (vi) an optional pan-tilt-zoom (PTZ) camera for taking roadside images. Once a remote computer is connected to the AP, it can communicate with 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.



Fig.4. Access point (Bajwa et al., 2013).

#### 2.2. Communication protocol

The communication protocol followed by the wireless sensor nodes and the AP are described here. There are three major applications of this protocol: synchronization, sensor management, and firmware update.

### 2.2.1. 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 such as *change mode*, set RF channel, reset sensor.

## 2.2.2. 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 2. 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 the challenging environment of highways, sensors

frequently suffer from packet loses. To fix this problem, every packet is transmitted twice after a slight delay. Average packet loss was around 1% when data from all sensors are checked. It should be noted that in the final system, packet error rate is not important since the compressed data is transmitted until a confirmation/acknowledgement from the access point is received.

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 (heavy-light truck) 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, packet is retransmitted until each 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.

#### 2.2.3. Firmware update

This application allows reprogramming the entire ash 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.** System installation, data collection, and load estimation

#### 3.1. Wireless WIM system installation

A test system was installed on I-80 W (asphalt pavement) in Pinole, CA, about 300 ft (91.4m) away from an existing WIM station. This WIM station measures and records weights for every passing truck. A calibration truck was used to collect part of the ground truth data at different speed levels (16 passes). Since renting individual trucks to achieve a large calibration dataset was extremely expensive, research team collected ground truth data from a static weigh station in Cordelia, CA. However, collecting truck weight data from a static weigh station required extensive coordination with local and state agencies, and posed additional challenges. Each truck had to be stopped and weighed individually, and required the presence of a California Highway Patrol (CHP) officer. Moreover, the station is located about 25 miles upstream from the wireless WIM in Pinole, and some of the trucks take alternative routes and 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 (75 truck passes).

Figure 5 shows the detailed sensor layout. There are 4 arrays of vibrations sensors at a distance of 15 ft (4.57 m) from each other. Each array contains 5 sensors in the middle that are used for load estimation. Array 1 has additional sensors that cover the entire lane and can be used for estimating wheel locations along the array. The edge sensors can also be used to study the vibrations caused by vehicles in neighboring lanes.

In order to minimize the system cost, the installation procedure must be quick and simple. To install a sensor in the pavement, a 4-inch (10 cm) diameter hole, approximately 2.25 inches (5.7cm) deep is drilled at the desired location. The sensor is placed in the hole, properly leveled with the pavement's surface, and the hole is sealed with fast setting epoxy (sensors almost flushed with the surface since sensor height is 2inches-50mm). Each sensor can be installed in the road in less than 10 minutes. The AP and the PTZ camera are mounted on a 15ft (4.57 m) high pole on the side of the road, and do not require any lane closures.



**Fig.5.** Sensor layout at Pinole site (Lane width is 3.7m.) (Bajwa et al., 2011).

#### 3.2. Experiments

#### 3.2.1. Calibration truck runs

A 5-axle truck [one single axle at the front (2 tires) and two dual-tandem axles in the middle and at the back (8 tires on each axle)] loaded with lumber was run over the system 16 times at 15, 35, 55, and 65 mph (24, 56, 88.5, and 105 kph) to collect data. In addition to this, data were recorded for 525 random trucks during the same time period. The goal was to use the hired truck for system calibration, and compare load estimates of random trucks with the ground truth reported by the WIM station. Using the weight and classification data from the static weigh station, it was determined that the conventional WIM reported accurate vehicle classification data. However, it was also determined that the reported weight data were highly inaccurate and could not be used as ground truth.

## 3.2.1. Statically weighed trucks

To obtain accurate weight data, a static weigh station about 21 miles upstream from the sensors was used. Random trucks were stopped and weighed at the Cordelia weigh station on three separate days. Pictures of each truck were taken and matched with the road-side camera images in Pinole to extract the sensor data corresponding to these trucks. Since the station was far from the site, some of the trucks took alternative routes and only a subset of trucks that reached Pinole travelled in the sensor lane. Table 2 shows the number of trucks weighed on each day, the number of trucks that actually reached Pinole, and the number of trucks that were matched in the correct lane. Vibration data, pavement temperature, detection data and ground truth weights for 61 trucks were obtained this way.

Table 2. Summary of data collected from static weigh station in Cordelia.

Date (2012)	Trucks weighed	Trucks reaching Pinole	Trucks matched
May 29	47	29	18
July 3	60	32	18
Sept 10	50	37	25

Due to technical difficulties, weights from the WIM station were not available for one of our testing days. This leaded to a reduced dataset for comparison, containing 59 truck runs. Combining the 16 calibration truck runs with 59 statically weighed trucks, sensor data for 75 Class 9 (see Figure 6) trucks with reliable static weights were obtained. It should be noted that ASTM E1318-09 (2009) requires only 20 trucks for calibration. Corresponding data from the conventional WIM station was also obtained for comparison. This dataset included vehicle speed, length. classification, axle spacing, individual axle weights, and gross weight for each truck.

#### 3.3. Load estimation

In this section, a model for pavement-vehicle relates interaction that directly pavement speed, acceleration. vehicle and pavement temperature to applied axle load is proposed. Then the procedure used to extract pavement response due to individual axles from the measured response is described. The section is ended by describing how the model is calibrated for load estimation.

3.3.1. Pavement-vehicle interaction model The simplest pavement-vehicle interaction model is a composite one-dimensional Euler beam resting on an elastic Winkler foundation (Cebon, 1999; Rajagopal, 2009). The vehicle is modeled as a moving force modulated by its suspension system. As an axle approaches, 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  $y(t) = F\Phi(vt)$  (Rajagopal, 2009), 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 (Rajagopal, 2009).

Based on typical measured responses and theory developed in (Cebon, 1999; Rajagopal, 2009), it was assumed that the shape of pavement response due to a single axle load is closely approximated by a Gaussian function.  $\Phi(vt)$ , in our model, can be interpreted as the pavement response due to a unit force moving at speed v. Let  $\eta$  be the amplitude of pavement response for a unit force, then  $\Phi(t)$  and y(t) can be written as:

$$\Phi(t) = \eta e^{\frac{-t^2}{2\sigma_0^2}};$$

$$y(t) = F \Phi(vt) = F \eta e^{\frac{-v^2 t^2}{2\sigma_0^2}} = F \eta e^{\frac{-t^2}{2\sigma^2}}$$
(4)

The last step is obtained by assuming  $\sigma = \frac{\sigma_0}{v}$ , where  $\sigma_0$  is the width of pavement response due to a unit force, which depends on pavement properties. Since we measure acceleration and not displacement, model can be converted into a more appropriate form,

$$a(t) = \ddot{y}(t) = F\ddot{\varphi}(vt) = -F\eta \frac{v^2}{{\sigma_0}^2} \left(1 - \frac{t^2}{\sigma^2}\right) e^{\frac{-t^2}{2\sigma^2}}$$

Let 
$$\Psi(t,\sigma) = -\left(1 - \frac{t^2}{\sigma^2}\right)e^{\frac{-t^2}{2\sigma^2}}$$
 and  $\alpha = \frac{F\eta v^2}{\sigma_0^2}$ , and

the following relation for pavement acceleration due to a single load:

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

From the definition of  $\alpha$ , it can be observed that

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

$$y(t) = \alpha \frac{\sigma_0^2}{v^2} e^{\frac{-t^2}{2\sigma^2}} = \alpha \sigma^2 e^{\frac{-t^2}{2\sigma^2}}$$
(5)

The last step is obtained by combining Equations 4 and 5. The unknowns  $\alpha$  and  $\sigma$  can be estimated from the measured acceleration, but  $\beta$  depends on axle type and pavement properties, and needs to be calibrated using trucks of known weights. For a *K* axle truck, with the *i*<sup>th</sup> axle arriving at the sensor at time  $\mu_i$  and applying a force  $f_i$ , the response can be written as the superposition of individual axle responses  $(a_i(t))$  i.e.

$$a_i(t) = \alpha_i \Psi(t - \mu_i, \sigma_i) \tag{6}$$

$$a(t) = \sum_{i=1}^{K} \alpha_i \Psi(t - \mu_i, \sigma_i)$$
(7)

Using a non-linear curve fitting procedure,  $\alpha_i$ ,  $\mu_i$ , and  $\sigma_i$  for each axle can be estimated. 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,

$$F_{i} = \beta_{i} \frac{\alpha_{i}}{v^{2}},$$
  

$$y_{i}(t) = \alpha_{i} \sigma_{i}^{2} e^{\frac{-(t-\mu_{i})^{2}}{2\sigma_{i}^{2}}}$$
(8)

One of the simplifying assumptions that was made in our model was that the amplitude of the pavement displacement  $\eta$  is independent of vehicle speed v, see Equation (4). However, there is a dependency between  $\eta$  and v as peak displacement decreases with increasing vehicle speed (Cebon, 1999). This dependency was modeled as  $\eta$  (v)=  $\eta$  $v^{-\theta}$ . Substituting this into equation (4) and following the derivation for a(t) and F, the following equations are obtained:

$$y(t) = F \eta \upsilon^{-\theta} e^{\frac{-t^2}{2\sigma^2}},$$

$$a(t) = -F\eta \frac{v^{2-\theta}}{\sigma_0^2} \left(1 - \frac{t^2}{\sigma^2}\right) e^{\frac{-t^2}{2\sigma^2}},$$
  

$$\alpha = \frac{F\eta v^{2-\theta}}{\sigma_0^2} = \frac{F\eta v^{\rho}}{\sigma_0^2},$$
(9)

$$F_i = \beta_i \frac{\alpha_i}{v^{\rho}} \tag{10}$$

The updated model has an additional unknown parameter  $\rho$  that needs to be calibrated. This parameter can be estimated using a single truck of known weight. Equation (9) shows that  $\alpha$  for each axle increases with speed and follows a power law. Therefore, repeated runs of the same truck at different speeds can be used to estimate  $\rho$ . For this purpose, 16 runs of the calibration truck were used to calculate  $\rho$ . 4 passes out of 16 runs were at low speeds (less than 20mph) while 4 passes were at medium speeds (30 mph to 40mph). Rest was close to highway speeds.

Figure 6 shows the individual axle response plotted against the truck speed. A curve fit for the powerlaw is obtained using the data and  $\rho$  for Axle 2 is found to be 1.95. Similarly,  $\rho$  for Axle 1 and 3 were found to be 1.92 and 1.94 respectively.



Fig.6. Effect of speed on measured sensor response.

## 3.3.2. Temperature compensation procedure

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 the pavement at this site, a layered elastic theory (LET) model was developed to simulate the effect of temperature on the pavement response (Park et al., 2001). Details of the LET modeling procedure are available in Bajwa (2013). Pavement response can change by 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, all our measurements were normalized to the reference temperature of 25°C as  $a(t, T = 25^{\circ}C) = a(t, T) \tau(T)$ , where  $\tau(T)$  is calculated using the LET model. It can be seen from Equation (7) that  $\alpha_i(T = 25) = \alpha_i(T) \tau(T)$ , and accordingly:

$$F_i = \beta_i \frac{\alpha \tau(T)}{v^{\rho}} \tag{11}$$

#### 3.3.3. Extracting individual axle response

In order to extract individual axle response, a twostage process is followed. In the first stage, measurements from multiple sensors are combined to get an average pavement response for the whole vehicle. In the second stage, this response was fitted to the model described by Equation (7) and estimate  $\alpha_i, \mu_i$ , and  $\sigma_i$  for each axle.



**Fig.7.** Axle response (a) raw acceleration signal measured by the reference sensor (b) average pavement response  $a_m(t)$  (processed raw acceleration signal) and the fitted response a(t).

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. Let  $a_m^k(t)$  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:

$$a_m(t) = \frac{1}{I} \sum_{k=1}^{I} a_m^k(t)$$

Figure 7 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 7 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  $a_m(t)$ , the following algorithm is used.

*Curve fitting algorithm*: Let a(t) be the modeled response of a *K* axle truck, given by Equation (7). Let  $\in (t)$  be the error between the measured and modeled response for the truck at time t i.e.  $\in (t) = a_m(t) - a(t)$ . The measured response now can be written as:

$$a_m(t) = \sum_{i=1}^{K} \alpha_i \Psi(t - \mu_i, \sigma_i) + \in (t)$$
(12)

The unknown parameters  $\{\alpha_i\}_{i=1}^{K}$ ,  $\{\sigma_i\}_{i=1}^{K}$  and  $\{\mu_i\}_{i=1}^{K}$  are estimated by minimizing the mean square error:

$$\left(\alpha_{i}^{*},\sigma_{i}^{*},\mu_{i}^{*}\right) = arg \min_{\alpha_{i},\sigma_{i},\mu_{i}}\int_{-\infty}^{\infty}\left(a_{m}(t)-a(t)\right)^{2}dt$$

$$\begin{pmatrix} \alpha_i^*, \sigma_i^*, \mu_i^* \end{pmatrix} = \arg \min_{\alpha_i, \sigma_i, \mu_i} \int_{-\infty}^{\infty} \left( a_m(t) - \sum_{i=1}^{K} \alpha_i \Psi(t - \mu_i, \sigma_i) \right)^2 dt$$
(13)

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 (6) and (8). Figure 7 shows an example of how good the modeled response fits the measurements.

#### 3.3.4. Model calibration

Calibration method and requirements described in ASTM E1318-09 (2009) were used for system calibration. Before individual axle loads can be estimated using Equation (11), 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 preweighed trucks can be used to estimate it. Let *N* be the number of trucks used in the training data,  $\hat{f}_i^n$ be the load estimate for the *i*<sup>th</sup> axle of *n*<sup>th</sup> truck,  $f_i^n$ be the true weight,  $v_n$  be the speed,  $\alpha_i^n$  be the corresponding fitted parameter  $\alpha_i^*$ , and  $e_i^n$  be the percentage error associated with the load estimates. The optimal  $\beta_i$  can be calculated by minimizing the mean-square percentage errors for the load estimates,

$$\hat{f}_{i}^{n} = \beta_{i} \frac{\alpha_{i}^{n}}{v_{n}^{\rho}} \tau(\mathbf{T}), \qquad (14)$$

$$e_{i}^{n} = \frac{\beta_{i} \frac{\alpha_{i}^{n}}{v_{n}^{\rho}} \tau(\mathbf{T}) - f_{i}^{n}}{f_{i}^{n}} \times 100 = \left(\beta_{i} \frac{\alpha_{i}^{n}}{f_{i}^{n} v_{n}^{\rho}} \tau(\mathbf{T}) - 1\right) \times 100,$$

$$\beta_{i}^{*} = \arg \min_{\beta} \frac{1}{N} \sum_{i=1}^{N} \left(e_{i}^{n}\right)^{2} =$$

$$\arg \min_{\beta} \sum_{i=1}^{N} \left(\beta \frac{\alpha_{i}^{n}}{f_{i}^{n} v_{n}^{\rho}} \tau(\mathbf{T}) - 1\right)^{2} \qquad (15)$$

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 14.

Sensor calibration was done by following the procedure verified in Bajwa (2009). Figure 8 shows the calibration setup. The idea is to use gage blocks of different heights to change the inclination of the sensor, thus changing the component of gravity (g) along its sensing direction. The accelerometer output for approximately 10 seconds at each height is recorded, and the mean and standard deviation of the recorded signal for each height are calculated. The mean value is used for sensitivity estimation while the standard deviation is used to estimate the sensor resolution.



Fig. 8. Calibration set up for vibration sensors.

## 3.4. Energy-efficient algorithm for load estimation

The load estimation procedure described so far is very inefficient for a resource constrained wireless sensor network. All raw data is transmitted by the sensors; however, wireless data transmission is the most power consuming process and the amount of data transmitted should be minimized. This section discusses how adaptive rate sampling and the distribution of computation between the access point and sensors can lead to increased sensor lifetime while only minimally affecting the system accuracy.

One possible approach to compress data is to implement the curve-fitting procedure inside the wireless sensor and transmit just the fitted parameters. However, there are many drawbacks to this approach:

- It is not clear if the computationally intensive procedure can be implemented in a wireless sensor with limited processing power.
- The curve-fitting procedure is performed using acceleration for the entire truck but the vibration sensors do not know the time window for the truck's presence.

• The parameters for curve-fitting are initialized based on tire-on-top sensor data and speed of the vehicle, both of which are unknown at sensor level.

An alternative to the above approach is to perform the curve-fitting procedure at the AP level but reduce the sensor data required for the fitting procedure. The vibration sensor consumes an average current of 370  $\mu$ A without the radio transmissions and the required current consumption for a 2 year lifetime (using a single battery) is 410  $\mu$ A. Assuming that an axle arrives about every 4.5 seconds (based on Caltrans data) and the required average current consumption to be 410  $\mu$ A, a data budget of L<sub>0</sub>=72samples/axle is estimated for the vibration sensor.

### 3.4.1. Adaptive sampling

To reduce the amount of data transmitted, sensors should report data only when a loaded axle is detected. To detect an axle, the vibration sensor can filter measured data and look for any negative peaks that have magnitudes greater than a chosen threshold. The time period during which the axle pulse is "dominant" is called the pulse span (PS) and only the measurements that lie in this span should be transmitted. This change alone drastically reduces the amount of data being transmitted by the sensor. The conventional WIM at Pinole reports that the sensor lane, on average, receives a new axle after every 4.5 seconds. If just the pulse data from the time-series of measurements are transmitted, the corresponding average current consumption would have been 0.441 mA with an expected sensor lifetime of 1.86 years or 22 months.

The filtered acceleration corresponding to each axle (axle pulse) can be modeled as a Mexican hat function in the presence of additive random noise:

$$m(n) = -\alpha \left( 1 - \frac{n^2}{\sigma^2} \right) e^{\frac{-n^2}{2\sigma^2}} + \in (n)$$
 (16)

The amplitude  $\alpha$  is linearly proportional to axle load,  $\sigma$  is inversely proportional to axle speed, and the time of axle arrival  $\mu$  is assumed to be zero.

To further reduce the data transmitted, the axle pulse is subsampled such that the reconstructed signal is minimally affected. Since peak acceleration is very important for load estimation, the time and the magnitude of each axle peak is always retained. To calculate the PS, an important feature of the measured signal: the zero-crossings around each axle peak is used. It should be noted that the zero crossings of the noise-free function m(n) are at  $n=\pm\sigma$  and an estimate of the zero crossings of the measured signal can be found by setting m(n)=0. Let  $t_{z+}$ ,  $t_{z-}$  be the time of the positive and negative zero-crossings, the PS can be calculated as:

$$PS = [+3\sigma, -3\sigma] = \left[ +\frac{3}{2} \cdot 2\sigma, -\frac{3}{2} \cdot 2\sigma \right]$$
$$\approx \left[ +\frac{3}{2} \cdot \widehat{2\sigma}, -\frac{3}{2} \cdot \widehat{2\sigma} \right]$$
$$= \left[ +\frac{3}{2} \left| t_{z+} - t_{z-} \right|, -\frac{3}{2} \cdot \left| t_{z+} - t_{z-} \right| \right]$$
(17)

Now L points are selected around each axle peak with the peak being the central sample and with a sampling interval of:

$$\Delta T_L = \frac{3|t_{Z+} - t_{Z-}|}{L - 1} \tag{18}$$

To check the proposed procedure, we independently sample around each axle peak and use the samples corresponding to the entire truck to perform the curve fitting described in Section 3.3.3. Figure 9 shows an example fit for a class-9 truck. It can be observed that the proposed adaptive sampling worked well at even a low sampling rate of 9 samples/axle.



Fig.9. Adaptive sampling-Example for a truck.

Using the previously described cross-validation procedure, the accuracy of load estimates is evaluated using the compressed data. Table 4 lists the mean LTPP errors (ASTM E1318-09, 2009) for the individual axles and gross weight using L = 9samples/axle. For comparison, the results from Section 3.3.3 were provided where raw signals from all sensors are averaged first and the entire time

series of the average pavement response is used for curve-fitting. Comparing the first two columns, it can be observed that the errors in load estimates for the compressed dataset are slightly higher for Axle 1 but lower for the other axles and the gross weight.

The sensor lifetime after the adaptation of energy-efficient algorithm increased from 5 months to 28 months. While this does not achieve our target lifetime of 4 years, there are other alternatives available to achieve this. Two batteries can be used to double the lifetime; this will increase the sensor cost slightly and increase the sensor size. The other alternative is to use a lower current consuming accelerometer; the current consumption of the current MEMS accelerometer is about 300 µA by itself. While not available at the time of our sensor design, newer accelerometers are available in the market today that have similar noise density to our current sensor but lower current consumption. the datasheet. the According to current consumption of the newer accelerometer, Colibrys MS7002, is half of the current accelerometer (Colibrys, 2013). Using the new accelerometer is expected to provide a lifetime of about 4 years.

# 3.5. Separate regression for gross vehicle weight

Until now the estimate of gross weight was simply the sum of individual axle weights. In this section, a separate model is considered to estimate grossvehicle weight and calibrate this model by minimizing the LTPP error. Let the gross weight estimate for a truck be modeled as:

$$f_T = \sum_{i=1}^K \beta_{Ti} \frac{\alpha_i \tau(T)}{v^{\rho_i}}$$

where  $\alpha_i$  is the decoupled response for the i<sup>th</sup> axle and  $\beta_{Ti}$  is the corresponding scaling coefficient. The calibration factors ( $\beta_{Ti}$ ) can be estimated by minimizing the LTPP error for gross weights over the training set. 1000 different training and testing trials were simulated and it was determined that the mean LTPP error for gross weight estimation with the new method is about 2.8% higher than the previously adapted method (summing up individual axle weights). Thus, there is no improvement from doing a separate regression for gross weights. Data from all 75 truck passes are used to calibrate the model and examine how closely it explains the data. Figure 10 compares the axle weights estimated by the wireless WIM system with their true weights. The estimated loads track the true loads very closely, with a  $R^2$  value of 0.99 for the fit. The means and standard deviations associated with these bell-shaped curves are summarized in Table 3.

Figure 11(a) shows the percentage errors of load estimates at different temperatures. The errors are uncorrelated with temperature, implying that the compensation factor  $\tau(T)$  captures the effect of pavement temperature well. Figure 11(b) shows that the errors are much higher when no temperature compensation is used (i.e.  $\tau(T) = 1 \forall T$ ). The mean errors are negative for low temperatures and positive for high temperatures. Consistent with pavement models. without temperature compensation loads are overestimated at higher temperatures and underestimated estimated at lower temperatures. This is because pavement response for any load increases with temperature (Park et al., 2001). The error distributions for both scenarios are summarized in Table 3.

For the results in Figures 10 and 11 and Table 3, the entire dataset was used for training our system. In general, this leads to overfitting and overestimation of the predictive power of a model. For a more realistic evaluation of the system accuracy, the repeated random sub-sampling validation technique of cross-validation was used.



Fig.10. Model predictions - Estimated weights against the ground truth static weights. Note: 1 lbs = 0.45 kg.

	T <sup>1</sup> . compensation		No compensation	
	Mean of	Std <sup>2</sup> of	Mean of	Std of
	errors	errors	errors	errors
	(%)	(%)	(%)	(%)
Axle 1	-0.35	5.83	-0.18	6.41
Axle 2	-0.68	5.36	-0.22	6.15
Axle 3	-0.78	5.67	-0.41	6.26
Total	-0.63	4.46	-0.25	5.32

Table 3. Effect of pavement temperature on load estimation.

Note: <sup>1</sup>T: Temperature; <sup>2</sup> Standard deviation.



**Fig.11.** Percentage error in load estimates against pavement temperature (a) with temperature compensation (b) without temperature compensation.

1000 different training and testing trials were simulated. In each trial, 25 out of 75 trucks were selected for training the model and the calculated  $\beta_i$ 's were used for estimating truck weights in the testing set. Then LTPP errors ( $e_\lambda$ ), an error measure for WIM stations that assumes a normal distribution for measurement errors and calculates the error bound at a confidence level of 95%, are calculated for all 1000 test sets. LTPP errors are used as an evaluation metric for system accuracy (ASTM E1318-09, 2009).

Let  $\{e_i\}_{i=1}^N$  be the observed errors,  $\overline{e}$  be the mean error,  $\hat{\sigma}_e$  be the standard deviation of observed errors, and  $t_{N-I}$  be the critical value at 95% confidence level for a Student t-distribution with N - I degrees of freedom, then  $e_{\lambda}$  can be calculated as:

$$\mathbf{e}_{\lambda} = |\bar{e}| + t_{N-1}\hat{\sigma}_{e}$$

The maximum allowed LTPP errors for Axle 1 is 20% while the maximum allowed error for Axles 2 and 3 is 15%. Maximum allowed error for GVW (total) is 10%. Figure 12 shows the cumulative distribution for the LTPP errors for 1000 cross-validation trials. The wireless WIM errors for individual axles are below the LTPP allowed errors in every trial. The errors in gross weight are below the allowed limit for 95% of the trials.



Fig.12. Cumulative distribution of LTPP errors (in %) for 1000 random test sets.

#### 4.1. Comparison with the conventional WIM

A one-on-one comparison of wireless WIM with the nearby WIM station is provided in this section. Due to technical difficulties, weights from the WIM station were not available for one of our testing days. This leads to a reduced dataset for comparison, containing 59 truck runs, where 16 runs correspond to a single calibration truck and remaining 43 runs correspond to random trucks that were stopped and individually weighed at the static weigh station. While the weights reported for the calibration truck had low errors, the overall accuracy of the conventional WIM was below expectations. Table 4 compares the 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 Axle 1 and 2 but fails for Axle 3 and the gross weight.

Table 4. Comparison of mean LTPP errors between proposed system and the nearby convent. WIM.

$\mathbf{F} = \mathbf{F} = \mathbf{F} = \mathbf{F} = \mathbf{F}$		/ • • • • • • • • • • • • • • • • • • •		
	W-WIM <sup>1</sup>	W-WIM	Convent. <sup>4</sup>	Max.
	error BC <sup>2</sup>	error AC <sup>3</sup>	WIM	allowed
	(%)	(%)	error (%)	error (%)
Axle1	10.84	10.93	10.96	20
Axle2	12.01	11.79	14.53	15
Axle3	12.22	11.84	24.65	15
Total	9.48	9.10	13.13	10
$\mathbf{N}_{\mathbf{A}} = \mathbf{N}_{\mathbf{A}} $				

Note: <sup>1</sup>Wireless WIM; <sup>2</sup> Before compression; <sup>3</sup>After compression; <sup>4</sup>Conventional.

## 5. Conclusions and future work

Existing weigh-in-motion (WIM) technologies are too expensive for widespread deployment and there is insufficient data for pavement management, resulting in higher maintenance costs. The goal of this project was to develop an inexpensive but accurate wireless weigh-in-motion system that can be easily installed on new or existing roads. Current WIM systems have high costs because they use large, expensive load sensors and require special pavement construction around them. Motivated to reduce costs, the road pavement itself was used as the weighing scale. Multiple wireless sensors are embedded in the pavement to sense its response to passing vehicles and the measured response is then used to estimate the magnitude of applied axle loads.

The wireless vibration sensor designed for the developed wireless WIM 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 (GVW), and outperformed a nearby conventional WIM system. The use of multiple arrays of vibration sensors averaged out the dynamic component of load and provided

weight estimates that are close to static axle and gross vehicle weights. As part of load estimation, the system also estimates the pavement deflection, and therefore can be used for long-term pavement monitoring.

While the system outperformed a commercial WIM station in terms of accuracy, it needs improvement in other areas. The sensor lifetime, currently 2 years for this application, needs to be at least doubled. This can be done easily by doubling the sensor battery. An alternative is to replace the MEMS accelerometer with one that has a similar noise floor but a lower current consumption (Colibrys, 2013).

Some questions that need to be answered are:

- How does the system perform for other classes of vehicles? Is the calibration parameter different for different classes? If yes, this can make the calibration procedure more complex and expensive as more vehicles will be required.
- How would the pavement type (concrete or asphalt) affect the system errors?
- How does the system accuracy change with pavement deterioration? The answer to this question determines how often calibration is required for the system. The system was tested on 4 different days, spanning from February to September, and observed no significant change in accuracy.
- Can we improve the accuracy further by adding additional arrays of vibration sensors? Increasing the number of sensor arrays from 1 to 4 progressively reduces the errors in load estimates.
- Can we quantify the effect of vehicle wander (driving off the lane center) on load estimates? This requires a method to accurately determine the location of the wheels relative to the sensors. If possible, this can also help reduce the weight errors. In addition, straddling of vehicles needs to be captured and separated from the rest of the data sample.
- Can we develop specific installation and calibration protocols as would be needed by ASTM and/or AASHTO specifications?

The wireless WIM technology presented here has the potential to reduce the cost of WIM systems. The system can be used as a Prepass (screening) WIM near static weigh stations. Prepass stations estimate the weight of trucks in motion and direct them to the weigh station if they are likely to be overweight. If truckers can be incentivized to carry wireless tags for automatic identification, more intelligence can be added to the system. For example, anytime a truck with a tag is flagged for static weighing, the data obtained from the weigh station can be used to automatically re-calibrate the wireless WIM. In addition to weight, wireless WIM can also provide pavement temperatures, speeds, axle configurations, and vehicle classes.

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