An Empirical Study on Low-cost, Portable Vehicle's Weight Estimation Solution using Smartphone's Acceleration Data for Developing Countries

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Keywords: Accelerometer, Speed, Smartphone Sensor, Vehicle Weight Estimation, Intelligent Transportation System.

Abstract: One in every three trucks in developing countries are overloaded, causing damage to roads and susceptible to accidents. Conventionally, vehicle's weight is measured at fixed weigh stations and result in high traffic congestions at toll booths. To improve highway traffic and enhance regulation, we propose a low-cost, portable sensor-based system viable for continuous real-time assessment of vehicle's weight. A smartphone-based sensing device is installed in vehicle and weight is estimated by applying multiple linear regression model on acceleration data. In this paper, we include statistical features having relationship with target variable. A consistent model performance of vehicle's weight estimated at all speed ranges is established; we also evaluate the improvised model under engine idling state. An increased accuracy is obtained with error of 2% in engine idling state and overall system error of 6% with vehicle in motion. A heterogenous data source (such as vehicle class, load condition, goods, sensor locations, etc.,) of vehicle operating on Indian highway segment are collected to evaluate model robustness. With exploitation of big data and advanced analytics; advent of this solution will leverage contribution in Intelligent Transport System, focused towards smart and sustainable transportation for ASEAN region.

1 INTRODUCTION

Logistics is one of the important sectors for a country's economy. Efficiency improvement in this area can boost economic growth, increasing export through global supply chains and helps in generating employment. The robust growth in manufacturing envisioned in developing countries like India is through Government initiatives like "Make in India", which demands high level of logistic efficiency. It has been reported, due to poor logistics, management has led to unsafe practices such as overloading of trucks, compromising road safety both for truck drivers and other road users. In reports from developing countries such as India, it is stated that National highways connecting the major corridors to metro cities like Delhi, Kolkata, Chennai, Kochi, Mumbai account for less than 0.5% of the road network capacity but still carry more than 40% of the freight movement by road (NITI Aayog, 2018). Trucks spend just 40% of their time moving on the road. The rest of the time is taken up at checkpoints and tollgates. India Government in July 2018 announced the increase in axle load limit to 25%. While experts feel overloading will continue, and industry players expect the "life of roads" to decrease. With the revised permissible weight for the transport vehicles, the state enforcement authorities are requested to rigorously enforce the regulations and take strict action against overloading by goods vehicles on roads. Similar issue exists in other developing countries too, for example according to a case study of Indonesia as provided by (APEC Vietnam, 2017), 22% of trucks exceed the legal 10 tonne single axle dual tyre limit. In Central Java, 38% of trucks exceed pavement design limit. 6.5% of the axle loadings that exceeded the 10-tonne limit caused 90% of pavement damage.

Overloaded trucks also add to air pollution in the city as well, as emissions from such vehicles is significantly higher than trucks weighing within the prescribed limits.

Challenges associated with Weigh-in-Motion (WIM) system is installing sensors in the roadway pavement. They require temporary roadway closure, pavement cuts for placing the sensors. Pavement at the site must be sufficiently smooth for a minimum

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distance before and after the location of the weight sensor to minimize the influence of vehicle dynamics on the weight measurements as mentioned in (Weigh-in-motion, Pocket Guide, 2018). A huge maintenance and rehabilitation cost of WIM is required to increase lifespan of WIM installation.

As a potential use case of ITS solution for Traffic Safety on highways serving central and state requirement to curb overloaded vehicle on national and state highways, we propose a smart IoT sensor-based technology. This system is easy to handle by its users, portable, and requires minimum cost to maintenance, difficult to defeat and provide reliable information to the concerned regulators by continuously monitoring and estimate weight from moving vehicles on road.

Vehicle's weight and its relationship to road management is been identified as an important topic of research in Transportation Engineering. In this paper, we brief accelerometer-based sensing techniques that are being used to determine behaviours of vehicle dynamics in real-world scenario of heavy-duty vehicles. The state-of-the art Vehicle's Weight Estimation by (Phong X. Nguyen et al., 2018) uses smartphone's acceleration data with statistical features to predict the weight. However, the method requires the vehicle to be at certain speed range of 20-22 kmph to estimate vehicle's weight accurately and inconsistent for other speed ranges. In real-time scenarios the vehicle's weight requires to be monitored continuously for violations, which limits above method for such deployment.

In this paper, we aim to extend the method to overcome the mentioned challenges, (a) evaluate model performance consistency at different vehicle speed profiles while vehicle is in motion on road, also including vehicle in static state i.e., engine idling condition; and (b) assess the optimal sensor location for deployment on vehicle by evaluating with heterogenous vehicle data.

Initially, a feasibility study was conducted to estimate the vehicle's weight method on data obtained from different sources. The method failed to provide a stable result due to variability of data source as identified in Table 1. We then study in detail different speed profiles of vehicle undergone during the journey and propose an improved multiple linear regression model by extracting more statistical features from linear acceleration data which shows high significance with load factor. The improved method estimates vehicle's weight with an average error of 1800 kg, which accounts for 5.5% of true average vehicle's weight with vehicle in idling condition; and 1932 kg, which accounts for 5.7% with vehicle under constant speed range. We also compare the model performance with other speed profile. We extend the validation of our improvised method on Indian road segment considering variability of data with combinations of vehicle factors such as vehicle class type, manufacture make, load, and goods. The results obtained confirm the validity of applying the improved method for determining the weight of vehicle across vehicle class types and for all speed ranges.

As a pilot project we likewise mount sensors on three different locations in each vehicle to evaluate the performance of our proposed solution and assess which sensor location mount is ideal for our solution considering as a system.

The rest of the paper is organized as follows. Section 2 discusses related work on vehicle's weight estimation. Section 3 presents our proposed method. In Sections 4 and 5 we present our experimental setup and evaluation of the experimental results. In Section 6, we discuss the strengths and weaknesses of our method. We conclude in Section 7 with a summary and details on future work.

2 RELATED WORK

We identify that Weigh-in-Motion (WIM) technology (Magdalena et al., 2020) is the closest competitor to the technology under development, some of which have accuracy more than 95%. However, the technology is based on static sensors over which the vehicle moves at low speed (LTBP, 2016). This solution however is limited to toll way deployment. (Kadlecek et al., 2005) describes a weight estimation method that measures the energy output from engine of a given vehicle and measures the acceleration derived of it. Here, we take the inspiration of including energy as one of the explanatory features to our model. (Jyotishman Ghosh et al., 2017 and Nan Lin et al., 2019) describes a real-time vehicle mass estimation from CAN data and drivetrain torque observation. This technique considers different driving forces acting on longitudinal motion, where majority of contribution is due to traction and braking forces. (Viengnam Douangphachanh et al, 2014), describes collecting sensing data from android smartphone. They find a relationship of acceleration data with road roughness condition and its significance partially dependent on speed. This work is being investigated in frequency domain to analyse the behaviour of road roughness on an average speed. (Joshua E. Siegel et al., 2015), explore a novel application of fault detection in wheels tires and related suspension components in vehicles. The smartphone is mounted vertical on dashboard of a vehicle and validation is performed on at least two different vehicle model. The approach mentioned in this research, is referred for further analysis in our proposed development. (Phong X. Nguyen et al., 2018), uses smartphone-based sensor to estimate vehicle overloading, and claims to achieve an average 5.89% error on true vehicle's weight, however the model requires the vehicle to run at certain speed range only. For other speed ranges, the model error is high, and smartphone is placed on truck chassis within an encapsulated box. These two factors inspire us to derive at a more robust solution experimenting on different vehicle model and roads of Indian highways.

The benefit with the proposed method is, we will be able to assess at what speed zone the model performance is high; and which placement of mobile sensor on vehicle gives least accuracy error against its actual weight. For vehicle overload detection as a system, one can further make use of the classification method, provided, payload weights are known prior; and included as an exploratory variable to model as described by the author, which is currently not in scope of this work.

3 IMPROVISED VEHICLE'S WEIGHT ESTIMATION METHOD

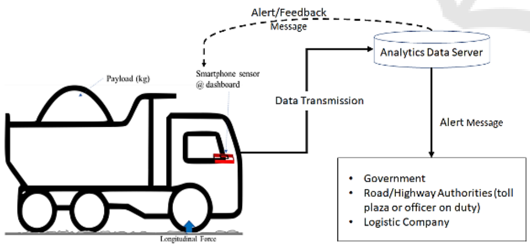


Figure 1: Vehicle Overloading Control System (Phong, 2018).

Described in Figure 1, is the proposed ubiquitous system for detecting suspicious overloaded vehicle running on highway and send notification to concerned authorities in real-time. A smartphone mounted on the vehicle is enabled for capturing the vehicle registration, driver information and transmit along with data collected by sensors via cellular network to the centralized server. The capture of data is enabled batch-wise, which is received at analytics data server where our proposed model is deployed for prediction of weight as part of backend process. The estimated weight is compared with legal permissible weight to determine if vehicle is overloaded in the system. If vehicle is determined to be overloaded, the vehicle and driver information are notified to the road authorities, traffic police, and logistic company. Based on the event information shared to the authorities a penalty will also be processed and sent to the driver of vehicle. All these processes are automated, and remotely monitored with high efficiency.

Table 1: Comparison of data specifications from two different sources.

Features	Vehicle Source 'A'	Vehicle Source 'B'
Sensor placement	Truck chassis (near rear axle)	Truck cabin (dashboard)
Sensor mounting	In synchronization with vehicle frame of reference	Placed at a degree of tilt on dashboard
Insulation	Tightly bound to chassis Additional casing to protect from dust, moist and arrest free fall vibration	Loosely placed on dashboard
Phone model	Nexus S	Samsung GT-19300
Sampling rate	50 Hz	50 Hz
Number of Trips	10	1
Number of Trucks	2	1
Road condition known	Yes (analysed from another research work)	No

To improve the accuracy of Vehicle's Weight Estimation (VWE), our methodology is based on the significant correlation of vehicle's payload on vertical acceleration got from smartphone's acceleration sensor data. Heavier the payload lesser dispersed are the vertical acceleration and vice versa for vehicle with no payload or partial payload. The payload material also significantly plays a role which can be considered as a future work considering the amount of data availability. Along with the statistical features being considered from the baseline method, we propose more features considering the higher order analysis and frequency analysis of vertical acceleration data. We continue to improve the multiple linear regression model to improve accuracy of VWE solution. The model is evaluated on 75-25 % ratio of dataset. In our observation, the vehicle at static i.e., idling condition and vehicle with constant speed profile shows stable response of vehicle's vertical acceleration. Due to minimum impact from road surface condition; and engine response on acceleration/deceleration event.

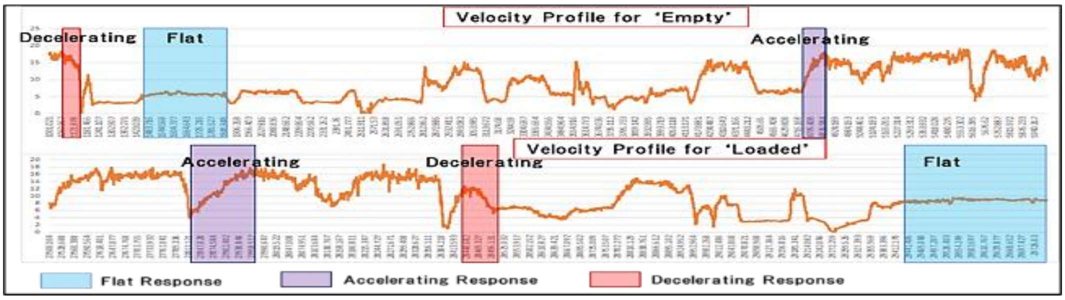


Figure 2: Depiction of random pair of velocity profile segments 'Flat', 'Accelerating', and 'Decelerating' for 'Empty' and 'Loaded' vehicle.

Therefore, it is essential to consider the influence of such statistical factors including the vehicular velocity while considering a generic estimation model to predict weight.

In this section, a comparison of data specification got from two different sources; observations of data analysis with vehicle under 'Empty' and 'Loaded' conditions; identification of vehicular speed category; and construction of estimation model are described below. Here, we do not consider the different load category within the class of vehicle model, since it is already proved in baseline model (Phong X. Nguyen et al., 2018). The supervised classification model result for identifying different vehicle load category, can be included as an encoded exploratory variable to improve estimation accuracy of multiple linear regression model.

As indicated in Table 1 the accelerometer data received from vehicle source 'A' is compared with accelerometer data got from vehicle source 'B'. It is observed, the sensor placement, mounting, insulation and vehicle trip parameters as mentioned are different; and thus, sets the challenge to existing baseline model to predict accuracy with high precision. Here, we compare the results and propose features which can be utilized for prediction of vehicle weight at different speed categories and smartphones positioned at different locations.

3.1 Velocity Profile Analysis

We observe in total the trip information has had varied range of speed pattern, which may be due to (a) terrain, (b) traffic conditions, and (c) road conditions. To evaluate the obtained data for feasibility study, we investigate the response of baseline VWE model with different patterns of velocity profiles. The different velocity profile is as presented in Figure 2.
From the velocity profile, we consider sub-portion(s) of raw data as indicated in different colours in Fig. 2 comprising off and classified to categories such as:

i. Flat response (same range of speed)
ii. Accelerating response (velocity ramp up)
iii. Decelerating response (velocity ramp down)

3.2 Feature Extraction

The single trip vertical acceleration sensor data is investigated both in time and frequency domain. In time domain, we explore the relevance of statistical features derived from 'Empty' and 'Loaded' dataset to estimate vehicle weight. The details of time-domain analysis are as mentioned in 3.2.1. In frequency domain, we analyse the spectral information of measured raw acceleration data, details are as mentioned in 3.2.2.

3.2.1 Time Domain Analysis

Considering z-axis of tri-axial accelerometer i.e., linear accelerometer; the vertical acceleration captures effect of longitudinal movement of a body i.e., vibration from road with effect of mass. From each dataset 'Empty' and 'Loaded', a defined length of window sample (here we consider 5 second), non-overlap in nature; from which '*N*' number of segmented outputs are generated. These segmented raw data are further used for feature extraction.

To analyse in detail, we consider the vertical acceleration (z-axis) data, with an average response of 10 segmented data for a defined window size (5 seconds) is as shown in Figure 2.

The features derived are further described below.

i. Average of Upper and Lower Acceleration.
The upper and lower acceleration threshold value is set +/- 1 of median value of vertical acceleration for each window sample computed. The mean of data points satisfying the condition is calculated. Acceleration value along z-axis of source 'B' data is different from z-axis acceleration value of source 'A'

dataset; this is due to change in sensor placement, orientation and vehicle model, refer Table 1. In case of such variations, a possible method to rectify can be by applying Euler transformation. To negate the effect of different orientation with placement of sensor, one possible solution is to consider the transformation in android application interface. In this experiment, we have considered the transformation matrix to be included for sensor axis correction in our second phase of evaluation where we consider different sensor position.

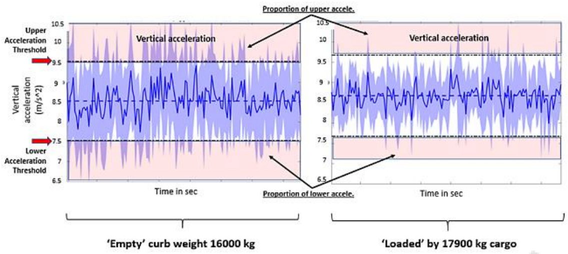


Figure 3: Average response of z-axis vertical acceleration profile for 'Empty' and 'Loaded' dataset.

ii. Proportion of Upper and Lower Acceleration.
Based on the upper and lower acceleration threshold value set, we consider the ratio of data points in upper & lower proportion range to total number of samples in the window (refer Figure 3, red highlighted portion).

iii. Standard Deviation.
Is measured to quantify the amount of variation in signal. Consider the random time-series signal X_i Number of variables available in the data distribution and denoted by N.
The standard deviation is calculated as shown in Equation 1.

$$\sigma = \sqrt{\frac{\sum_i^N (X_i - X)^2}{N}} \quad (1)$$

iv. Mean Absolute Difference.
Is measured to compute the average absolute difference of discrete values within a window sample. From Figure 3, it is observed the number of data points considered in Proportion of upper and lower acceleration (within highlighted red box), is lower in 'Loaded' set when compared to 'Empty' set. This constitutes the relationship between mass and acceleration. The magnitude information got from continuous time-series data alone is in-sufficient for a model to predict the vehicle's weight.

Henceforth, in this feasibility study, in addition to already considered baseline features, we explore the influence of statistical features derived from higher order moment of probability distribution of each dataset.

The primary hypothesis of this research is that the accelerometer data parameters both unique and derived has significant impact on the weight estimation of a vehicle. To validate the hypothesis, we consider the probability distribution of sample of data from each 'Empty' and 'Loaded' cases, respectively. The statistical hypothesis considered to evaluate the relation of histogram to weight is;

Null Hypothesis H_0:
Histogram has no relation to weight

Alternative Hypothesis H_1:
Histogram has relation to weight

The formulation of test statistic is to compute the measure of significance of feature set and weight. We use p-value to weigh the strength of evidence against the null hypothesis. One-sample T-test in R is considered for the features mentioned here after, whose p-value <2.2e-16, indicates strong evidence against the null hypothesis.

Probability distribution function (PDF) is a statistical function that describes all the possible values and likelihoods that a random variable can take within a given range. Here, we normalize the relative probabilities by a number N (number of elements in the input data) as shown in Equation 2:

$$v_i = \frac{c_i}{N} \quad (2)$$

where, v_i is the bin value
c_i is the number of elements in the bin

From PDF of 2 consecutive segmented data of 'Empty' and 'Loaded' datasets (refer Figure 4), the corresponding 'Median and 'Standard Deviation' are plotted. The green dotted line plotted in Figure 4, marks the median for (a) Empty (8.25 g) and (b) Loaded (8.65 g). The red dotted line indicates the Standard deviation (Sd) computed for (a) Empty (1.31) and (b) Loaded (0.52).

The Standard deviation (Sd) has reduced for 'Loaded' case, but not sufficient to validate null hypothesis H_0.

Henceforth, we consider alternative indicators of distribution, i.e., third and fourth order moment of distribution Skewness and Kurtosis.

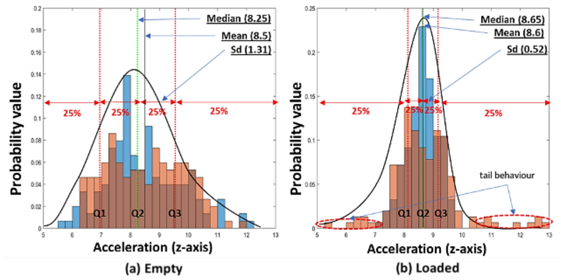


Figure 4: An example of Probability density with quartiles, Sd, Median, and Mean for (a) 'Empty' and (b) 'Loaded' case.

v. Skewness and Kurtosis.

Skewness, measures the degree of distortion from the symmetrical bell curve or normal distribution. It is measured as the third moment of probability distribution as indicated in Equation 3.

$$Skewness = \frac{\sum_i^N (X_i - \overline{X})^3}{(N-1) * \sigma^3} \tag{3}$$

In general terms, a normal distribution will have a skew of zero under a bell curve; in our experimentation for Flat Response of velocity profile, on an average shows positive skewness; 'Empty' (on an average = 0.13) case being more skewed than 'Loaded' (on an average = 0.037). This response is subject to vary case to case.

Kurtosis is measured as the fourth moment of probability distribution as indicated in Equation 4.

They measure extreme values in either tail, here in Figure 4(b), it is observed persistence of tail behaviour highlighted in red as an example; and narrow Peakiness of distribution for 'Loaded' (-0.02), when compared to 'Empty' (0.02) as seen in Fig. 4(a).

$$Kurtosis = \frac{\sum_i^N (X_i - \overline{X})^4}{(N-1) * \sigma^4} \tag{4}$$

vi. Quantiles.

Is statistical measure with cut points dividing the range of a probability distribution into continuous intervals with equal probabilities. In our experiment, it was observed the Standard deviation (σ) for normal distribution is not sufficient; hence Quantiles (2σ, 3σ) i.e., Q1, Q3 are considered.

vii. Energy.

From Figure 5, it is observed there is high significance of vehicle weight with amount of energy dissipated from vehicle. Heavier the load, higher the range of energy. Hence, in consideration to improvement of baseline model we include 'energy' variable in final regression equation.

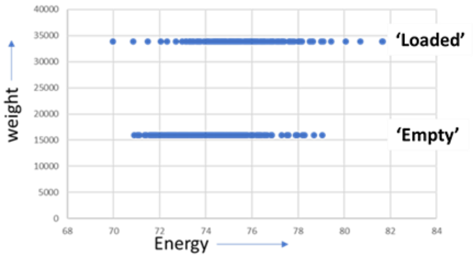


Figure 5: Relationship of Energy with weight of vehicle.

Thus, in this experiment, with measure of Kurtosis, Skewness, Quantiles, and Energy derived from sample windows; we can validate the rejection of null Hypothesis H_0.

3.2.2 Frequency Domain Analysis

In this research, the frequency response of acceleration measured under two conditions with vehicle Engine in ON state and with payload (kg) are (a) vehicle idling and (b) vehicle in motion. For data measurement, the assumption is as the vehicle's engine is ignited (ON), the sensor recording begins, by which the accelerometer measurement starts recording the vibration due to throttling of engine and chassis; and with payload added to empty vehicle, there is expected longitudinal force acting against the mass lowering the vibration amplitude when compared to information gathered from empty vehicle alone. Further to this, our proposition is, overload of vehicle occurs with payload added when vehicle is brought to a halt and idling (stationary with engine ON). Henceforth, we analyse for both vehicle in idling state along with vehicle in motion. We consider the Welch's power spectral density (PSD) method, also called the periodogram method for estimating power of a signal at different frequencies. The PSD is computed for (a) Vehicle at Rest/Idle, and (b) Vehicle in motion with signals sampling frequency at 50 Hz. From power spectrum in Figure 6, it is observed for (b) Vehicle in motion, there appears presence of prominent signal strengths as highlighted in red arrow in frequency range [5 to 20] Hz infused due to certain external factors unknown to trial. Whereas, in (a) Vehicle at Rest/Idle, the signal has a smoother roll-off when compared to PSD in (b); which indicates the signal is free from influence of other external factors except that of vehicle's engine; and suitable for extracting information from vehicle's linear accelerometer sensor data and its relationship with mass.

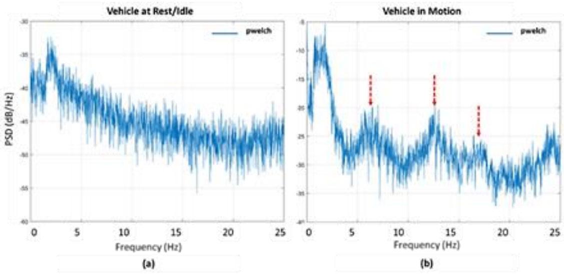


Figure 6: Power spectral density response of (a) Vehicle at Rest/Idle and (b) Vehicle in motion with sampling frequency of 50 Hz.

viii. FFT Function.

In addition, since the vibration component in this test experiment is unknown, we limit ourselves to compute amplitude and phase response of the signal only from each sample window; and add to the feature set list.

The additional indicator features of accelerometer data derived from time-frequency analysis as detailed in 3.2 are listed in Table 2. This table contains features considered apart from time domain features considered in baseline solution.

3.3 Estimation of Vehicle's Weight

During the evaluation process, stepwise bi-directional Akaike information criterion (AIC) regression algorithm is used to derive the best features from the accumulated feature set list (Total of 20 in number) as mentioned in 3.2. The final model may contain smaller number of features to reduce the complexity but maintain same level of accuracy or better. For evaluation purpose, 75% of data sample created are used for Training and remaining 25% for Testing. AIC regression algorithm was implemented over a batch of data samples considering the new set of feature list; a set of best features were provided as output and referred as final model.

Table 2: Summary list of additional time-frequency statistical indicators considered.

Features	Description
Skewness	in statistics, is the degree of distortion from the symmetrical bell curve in a probability distribution. considers the extremes of the data set rather than focusing solely on the average.
Kurtosis	is a statistical measure that is used to describe the distribution. measures extreme values in either tail of distribution.
Variance	is a measurement of the spread between numbers in a data set.
Quantile	Quintiles are used to create cut-off points for a given population of data set. Probabilities (0.025,0.25, 0.5, 0.75, 0.095) are considered
Amplitude of signal	Compute the Mod (magnitude of each complex number) of fast fourier transform (FFT); and select only first half of vector length
Phase of signal	Compute phase of FFT and first half of vector length.

Results of evaluation on improvised method and its comparison with baseline model is presented in section 4 for further discussion.

4 FEASIBILITY STUDY AND PRELIMINARY RESULTS

Based on the input shared as ground truth, we identify the trip begin and end time-stamp in seconds for 'Empty' and 'Loaded' vehicle trip respectively; here a continuous 2 hour sensor inputs of vehicle running with and without load condition are extracted from raw data for experiment evaluation. The sensor inputs extracted are GPS, 3-axis accelerometer, and gyroscope data information. The data is processed at a sampling rate of 50 Hz. As ground truth, for example, Empty refers to vehicle (truck) curb weight of 16000 kg; and Loaded refers to vehicle (truck) gross weight of 33900 kg after loaded with goods weighing 17900 kg. The reference to time of vehicle running with and without load are also captured. The afore mentioned analysis is conducted offline. We are currently in final phase on development of system that can automatically capture the above-mentioned sensor information in real-time.

4.1 Baseline Evaluation

We evaluate the vertical acceleration with baseline model considering the null hypothesis that velocity has no relationship with weight of vehicle. In Table 3, in 2nd and 3rd column we project results of VWE's mean absolute percentage error (MAPE) for baseline solution with and without velocity condition respectively; in 4th column VWE response with improved model without any velocity conditions, and in 5th column i.e., last column we represent the results obtained of improved VWE model considering a flat response pattern of vehicle velocity. Note: In this vehicle data, the highest speed range observed is 15.0 to 20.0 m/s.

Table 3: Baseline vs Proposed model with and without velocity condition.

Window sample length 5 sec	Baseline (15.0 to 20.0 m/s) Error rate %	Baseline (all speed range)* Error rate %	Proposed Model (all speed range)* Error rate %	Proposed Model Flat Response Error rate %
Vehicle 'Empty'	43.20	34.72	30.10	3.75
Vehicle 'Loaded'	32.13	34.48	25.88	7.73
VWE Overall	37.67	34.60	27.99	5.74

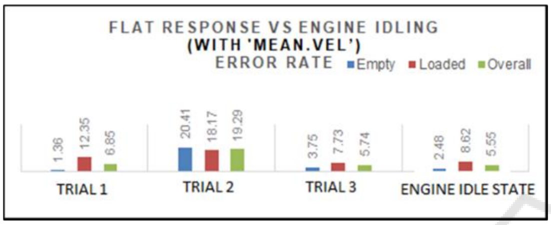
** Speed range condition removed while sampling of measurement (segmentation phase)*

Table 4: Error rate (MAPE) of different velocity profile vs engine idling state.

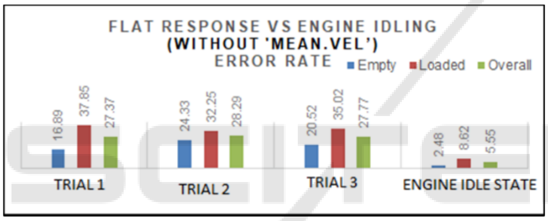
Window sample length 5 sec	Accelerating Response Error rate %	Decelerating Response Error rate %	Flat Response (Trial 3) Error rate %	Engine Idle State Error rate %
Vehicle 'Empty'	14.47	23.65	3.75	2.48
Vehicle 'Loaded'	26.87	9.38	7.73	8.62
VWE Overall	20.67	16.52	5.74	5.55

4.2 Evaluation on Velocity Profiles

Considering the improved model to efficiently predict vehicle's weight we continue to evaluate data for possible different scenarios.



(a)



(b)

Figure 7: Error rate measure of flat response trials vs Engine idle state (a) with 'mean.vel'; (b) without 'mean.vel' variable.

As described in Figure 2, section 3.1, different velocity profile of vertical acceleration is considered, and their respective MAPE (error rate) are tabulated in Table 4. We also compare results against the Engine Idle state as explained in frequency domain analysis in 3.2.2. For this experiment, a 5 sec window size for each of the responses are considered; the prediction performance is gathered individually for 'Empty' and 'Loaded' case and an overall error rate of model against each of the response is tabulated in last row in Table 4.

Additionally, we evaluate the VWE model and its dependency with velocity for various random pair of flat response segments as shown in bar graph in FigureFigure 7. The error rate results are projected where (a) refers to VWE response considering its dependency with velocity within the segment, and (b) without considering velocity variable in improvised model.

5 RESULTS OF ACTUAL DATA

After the feasibility study of improved VWE method, we evaluate this model on actual data collected from Indian road segment. Here, the smartphones are mounted at three different locations on to the chassis of each vehicle as shown in Figure 8. The smartphones in Placement 2 &3 are put in a case to restrict any free movement of smartphone within the case during the journey as shown in Figure 9. The smartphone in Placement 1 is placed over the dashboard of the vehicle and tapped to avoid any lateral shifts or any accidental fall-off. We do not make use of mobile holders here, as it may lead to additional vertical vibration infused to the acceleration data.

The process flow considered for VWE model is as shown in Figure 10. Each of the steps are explained in detail in below sub-section.

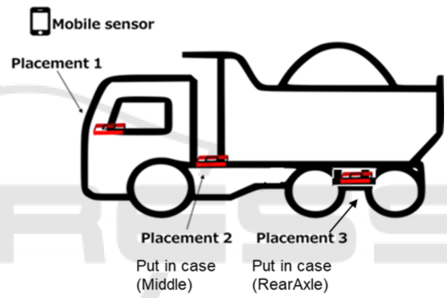


Figure 8: Illustration on placement positions of mobile sensor on vehicle planned for data collection.

Figure 9: Examples of smartphone placements on vehicle.

5.1 Data Collection

The data collection method is carried out based on the below mentioned conditions and were collected from Indian roads.

- To confer two or more reference vehicles from target vehicle group with repeated runs (trips).
- The reference vehicles will be driven on its regular routes, with different load condition, thus

study is conducted under dynamic vehicle environment unlike in a controlled setup.

- Details of each vehicle regarding their manufacture make, age, suspension types, number of axles, goods being carried, route(s) considered, running start and end time, and goods loading factor are gathered in a checklist and referred as ground truth information per trip.
- The actual gross weight (GVW) of vehicle are also recorded for each vehicle trip as ground truth to evaluate the model.

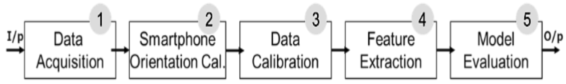


Figure 10: Process flow of VWE project.

5.2 Smartphone Orientation Calculation

Knowledge of smartphone's placement on vehicle at three different position is important to assess the reliability of collected data. On vehicle's placement-1 position, a mobile phone is installed on dashboard secured with double tape. In placement-2 and placement-3 the smartphones are packed inside an insulated case and secured at the bottom of the vehicle chassis at around centre of gravity (CoG) and near rear axle suspension. The two smartphones are restricted of free movement inside the box. However, it is observed, with different vehicle make, the provision for tying the insulated case with smartphone would need to be different (as shown in Figure 11); which in turn results in rotation of sensor axis with reference to vehicle's reference frame (x-axis, y-axis, and z-axis).

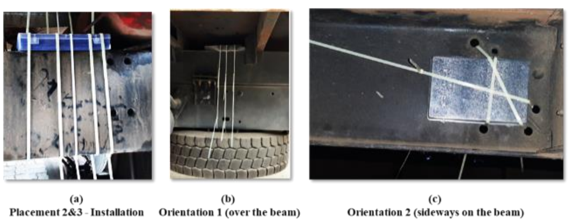


Figure 11: Smartphone installation under vehicle chassis and their different orientations.

In order to acknowledge the relation between smartphone-to-vehicle orientation as referenced by (Johan et al., 2019), in their study on "Smartphone placement within vehicle" and the smartphone's placement in the vehicle, we compute a 3-axis Euler rotation in Equation 5, as a pre-liminary step to correction.

$$v' = Av = R_z(\gamma)R_y(\beta)R_x(\alpha) \tag{5}$$

where, $R_x(\alpha)$ refers to counter clockwise rotation around x-axis;
$R_y(\beta)$ refers to counter clockwise rotation around y-axis and
$R_z(\gamma)$ refers to counter clockwise rotation around z-axis.

5.3 Data Calibration or Conditions

It is observed the model performance alters for varying input sets such as (i) speed zone (very low, low, medium, high to very high); and (ii) sample window size (1 sec to 5 sec of epoch size).

For automating the process of computation, we consider the following sequence combination of parameters of input vertical acceleration data i.e., sensor location, load condition (vehicle is loaded or empty), window size and speed zone.

Initially, we considered the model performance evaluation, with varying non-overlapping sampling window ranging from 1sec to 5sec, at a sampling rate of 50 Hz. However, it was observed, as the sampling window increases the performance of model drops due to lack of continuous data; hence, for analysis purpose we resort to minimum 1sec sampling window with an assumption that each segment holds continuous datapoints.

Additionally, we consider the average speed of each segmented dataset as an independent feature to regression model considered.

5.4 Feature Extraction

To evaluate the model, we make use of all the time and frequency domain features mentioned in section 3.2.

5.5 Model Evaluation

We confer to two or more reference vehicles availability for this experiment. From 21 vehicle trips data available, four of the trip information had to be discarded due to loss of data. For model evaluation, from 17 trips, we identify three vehicle class dataset and their use cases defined are as indicated in Table 5. The results of considered cases 1, 2 & 3 as mentioned are evaluated considering the statistical features derived from vertical acceleration data, including the average of speed considered per segment. Evaluation is represented in three different conditions of data sample.

Table 5: Test cases with varying vehicle and load conditions.

Test Cases	Vehicle Criterion	Load Capacity	Load Condition	Goods	Route
Case1	Single	Single	Different	Different	Different
Case2	Different	Different	Single	Single	Different
Case3	Different	Single	Single	Single	Different

5.5.1 Vehicle Running State

We fit a multiple linear regression model which minimize sum of the squared residuals using accelerometer features. In this section, each of the smartphone placement results are presented for running condition of vehicle. We compare estimated results with actual weight as ground truth to evaluate the model. For error determination, we consider MAPE as before. This defines on an average what is the error of the model trained.

<u>Case 1</u>: Light Duty Vehicle – Evaluation of single vehicle (12T capacity), with varying load condition (<50%, 75%, 100%), carrying different goods material. Consider all four loaded datasets; a k-fold cross-validation based evaluation method is carried out as the given number of data sample to split is limited with varying load condition.

<u>Case 2</u>: Heavy Duty Vehicle – Evaluation of different vehicles, carrying different goods and load condition.

For training we consider trips all loaded with same material, for example, cement on vehicle having tonnage capacity of 49T, 43T and 35T respectively. For testing, we consider unseen trips loaded with capacity of 49T, 31T, 36T and 43T carrying similar/same material.

<u>Case 3</u>: Over Dimensional Cargo – Evaluation of Trailer type truck. Dataset comprises of different vehicle, same manufacture makes, with full load condition (100%), carrying same goods material, but comprises of only 3 instances.

Considering the above cases, on an average the accuracy of different vehicle classes considered are as listed in Table 6.

5.5.2 Vehicle Idling State

Additionally, we also analyse the data for idling condition of vehicle. For comparison, we consider the vehicle running and idling state of Case1: Light Duty vehicle, since a single vehicle is being used for multiple trips. The accuracy measure of vehicle in idling state is as indicated in Table 7; however, the number of datapoints available are less.

Table 6: Summary of VWE for different use cases.

Use case	Smartphone Placement	Error rate %
Case 1: Light Duty Vehicle	**Dashboard**	**9%**
	CoG	19%
	Rearaxle	27%
Case 2 : Heavy Duty Vehicle	**Dashboard**	**5%**
	CoG	7%
	Rearaxle	7%
Case 3: Over Dimensional Cargo	**Dashboard**	**4.16%**
	CoG	4%
	Rearaxle	4.11%

We then consider evaluating VWE with different speed condition of vehicle. The speed calculated from smartphone's GPS feeds are divided into 5 different speed zones such as, speed zone1 range 0 to 3 m/s (0 – 10 km/h); speed zone2 range 3 to 6 m/s (10 – 20 km/h); speed zone3 range 7 to 10 m/s (20 – 40 km/h); speed zone4 range 11 to 14 m/s (40 – 55 km/h); and speed zone5 range 15 to 20 m/s (55 – 80 km/h).

Table 7: Summary of VWE for Case1 with Vehicle Running and Idling State.

Use case	Smartphone Placement	Vehicle Running State Error rate %	Vehicle Idling State Error rate %
Case 1: Light Duty Vehicle	**Dashboard**	**9%**	**2%**
	CoG	19%	13%
	Rearaxle	27%	19%

Since, speed is considered as a feature, and to assess robustness of model, we further examine if model's accuracy is consistent across different driving speed zones identified. Here, we consider all loaded data Placement1-Dashboard position of Light Duty vehicle only, to verify the variability or relationship of VWE with vehicle speed information as referenced in Figure 12.

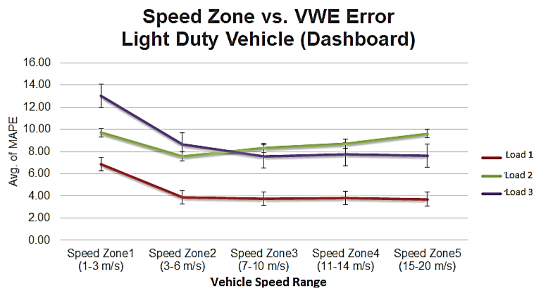


Figure 12: Graph of speed zone vs model error for all loaded conditions of Light Duty vehicle case.

6 DISCUSSION

VWE technology based on acceleration and GPS data collected by smartphone in logistics vehicle is validated using multiple linear regression model. We identified additional statistical features derived from vertical acceleration whose response shows significant importance pertaining to vehicle vibration information.

- Considering the improvised multiple linear regression model, we evaluate real data with different velocity profile. From table 4, it indicates that (i) ‘Flat response’ shows better performance i.e., reduced error rate when compared to (ii) Accelerating response and (iii) Decelerating response.
- Flat response shows reduced error rate of 6%.
- To test further, we conducted few more trials by selecting random pairs of flat response segment. It is observed, vehicle speed responses with flatter (constant) velocity profile shows reduced error rate in prediction of VWE, when compared to trials which shows some amount of variation in vehicle speed. These variations can be attributed due to road surface condition and/or traffic conditions.
- In this experiment, we confirm that in moving vehicle scenarios the “velocity of vehicle” has high influence in accurate prediction of vehicle’s weight.

- Case 1: Light Duty Vehicle placement1-Dashborad, sensor location shows on an average accuracy error of 6.87% for vehicle data comprising of 12T and 10T.
- Since, single vehicle was used for to-and-from trips, we validate with assumption that vehicle is being driven by a single driver; hence, assuming driving pattern influence on vibration data to be unchanged. Stats from Figure 12, shows consistent model performance across varying speed zone, whereas, in (Phong et.al., 2018) research work it is observed model performs best under speed zone of 20 – 22 km/h.
- We also validate results with vehicle in idling state, under the assumption, external factors such as vehicle dynamics, road condition, and other environmental parameters will not affect vibration data captured from sensors. We observe the idling values of data got from Light Duty vehicle class, shows improved accuracy by at least 5 % from its running state, i.e., with overall highest accuracy of 98% when compared to state of vehicle in motion as referenced from Table 7.
- Case 2: Heavy Duty Vehicle from Table 6, considering model accuracy error on an average across all trips, shows that placement1 – Dashboard has an MAPE value of 5% lower error rate when compared to the other two sensor location.
- When vehicle trip carrying different goods material was tested against Heavy Duty vehicle class model, the performance drops. This indicates the carrying goods material also has an inference on feature engineering during model learning process. However, it requires to be confirmed with exploratory data approach.

- Case 3: Over dimensional cargo the configuration of vehicle regarding its design, axle distribution, number of wheels are different and require further studies.

7 CONCLUSIONS

A machine learning model considering statistical parameters of vertical acceleration applied for evaluation of overloaded vehicle using Indian vehicle dataset is introduced in this paper. The developed VWE model shows improved and consistent accuracy considering vehicle engine idle state and flat response of velocity for both ‘Empty’ and ‘Loaded’ dataset scenario. It is observed from our studies moving vehicle’s acceleration response is highly influenced by velocity measure of vehicle. For validation on installation location, three sensor placements on the vehicle are considered to determine the feasible sensor position for system integration. For which, the developed model was evaluated considering different vehicle class type based on their tonnage. It is observed, on an average, model performance gives low MAPE error on dashboard, for vehicle carrying same goods to full capacity. The model accuracy is observed to be consistent at all speed range of vehicle motion, which makes our technology reliable for real-time assessment of vehicle’s weight.

As a continued research we are investigating deep learning-based regressor model on time series data considering different rate of load filling on vehicle. Other candidates for research improvements are:

- To study the impact of different axle configuration and vehicle’s suspension type on accelerometer data.
- The impact of road grade condition, driving behaviour pattern, which in-turn influences vibration on vehicle.

As a system, we propose integration of VWE technology to on-board unit alike AIS-140 vehicle system which abides to the law enforcement regulation mandated by the government.

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