Mass Estimation of On-road Construction Equipment Based on Modelling Operational Parameters

K. Barati and X. Shen*

School of Civil and Environmental Engineering, the University of New South Wales, Australia
E-mail: khalegh.barati@unsw.edu.au, x.shen@unsw.edu.au

Abstract-

Earthmoving operations are considered as one of the main activities in the construction industry. These operations involve processing and moving soils and rocks from source site to dump destination using earthmoving equipment, such as trucks and haulers. Automated measurement of the payload carried by earthmoving equipment in each trip has been one of the main challenges in this field. Currently, different metric and volumetric methods including weighbridges, load volume scanners (LVS) and strain gauges have been used to estimate the mass of vehicles which can be costly, time-consuming and labor-intensive. This paper aims to develop an automated weight and mass estimation model for on-road construction vehicles based on modelling operational and engine parameters. Acceleration, speed and road slope are investigated as operational factors, while engine load is considered as engine attribute to estimate vehicles' weight. Field experiments on a broad range of in-use construction equipment have been carried out to collect real-world field data of the investigated parameters. GPS-aided inertial navigation system (GPS-INS) and engine data logger instruments are employed for collecting field data. The weight estimation model is then developed through performing ordinary least square (OLS) and multivariable linear regression (MLR) analyses on the collected field data using SPSS Software. The model validation process is finally conducted through comparing the weight estimated by the model with real measurement of vehicle's weight on the site.

Keywords-

Construction industry; mass; operational parameters; engine load; on-road equipment; data collection

1. Introduction

Construction sector is one of the main industries requiring a large number of different construction vehicles. Majority of construction activities associated with earthmoving operations including cut and fill activities require on-road heavy-duty vehicles (HDVs) for materials transportation. Such kind of activities are planned and paid based on the amount of materials, and the measurement of the mass and volume of materials carried by vehicles. As the main concern of contractors and equipment operators, a cost-effective, automated method is essential for accurately estimating the weight of vehicles' mass without scarifying field production. On the other hand, measuring gross vehicle weight (GVW) of vehicles is necessary in the transportation field. Overloading and increasing equivalent single axle load (ESAL) result in the difficulties of vehicle's manoeuvrability, heavy traffic accident and short vehicle life [1]. ESAL is determined based on pavement condition and its failure mode, and is one of the main parameters causing distress and damage of pavements [2]. Overweighting also causes serious damages to the bridges and increases the risk of overloading and failure of bridges. In this regards, many restrictions and regulations have been implemented by international organizations such as American Association of State Highway and Transportation Officials (AASHTO) and Federal Highway Administrations (FHWA) to reduce the ESAL of HDV vehicles.

This paper aims to develop an integrated framework to accurately estimate the weight and mass of on-road HDVs based on modelling operational parameters and engine attributes. To do so, the operational parameters affecting engine load are first investigated. Then, through instrumentation and field experimentation, field data are collected from on-road HDVs. Finally, field data are processed and analysed to quantitatively estimate the weight of vehicle at high level of accuracy. This paper starts with a comprehensive review on the current approaches used for measuring weight and mass of construction vehicles. An integrated methodology is then developed for data collection and data analysis. At the end, validation is conducted by comparing the predicted results of the model against the real weight measured by weighbridges on the site.

2. Literature Review

Governmental and international weight regulations and contractual payment arrangements are the two main incentives for measuring and controlling the weight of the construction equipment. Numerous theoretical and practical efforts have been conducted by academic scholars and industrial sectors to develop different approaches for weight and mass estimation of construction vehicles. Many devices and instruments have been also devised to measure the weight of various machineries.

Currently, numerous techniques and tools are employed in construction industry to measure the weight and mass of equipment and vehicles. On the whole, these methods can be classified into two volumetric and metric measurement systems. Volumetric techniques measure the volume of the materials inside the haul bed and bucket of vehicles through automatically scanning and comparing the empty and loaded equipment. Volumetric methods are non-contact and cost effective with low initial and maintenance cost, but not really accurate in weight measurement of bulk material [3]. In this process, vehicles need to move slowly under the load volume scanners (LVS) installed in the construction sites before and after loading.

Metric measurement systems are more common in construction sites, and directly weigh the mass and total weight of equipment using various instruments and sensors. At the moment, weighbridges are mostly used in construction industry to measure the total weight including the vehicle weight and the mass. Despite the high accuracy in weight measurement, this method has high initial, operation and maintenance costs and is time consuming. Axle hydraulic and pneumatic pressure controlling is another system invented by Bartlett [4] to automatically weigh the mass of HDVs through applying pressure sensors. Pressure modulation valves are needed for adjusting auxiliary axle pressures based on load distribution. The measured data are transferred from sensing devices to signal processing system for analysis. On-board pressure sensors are also extensively used to accurately measure the weight carried in the trucks body. This apparatus is embedded between the truck frames and haul bed. Proportional to the implemented pressure by the load, the electro-magnetic sensors generate electrical signals processed to calculate the load [2, 5]. As another metric technique, strain gauges have been pasted on the leaves of springs to measure suspension strain caused by the mass [6]. The weigh is then calculated through summing up the received voltage signals provided by gauges. Despite the applicability of the method for all vehicles, adopting the gauges to various types of vehicles is inconvenient accounted as its main drawback.

3. Methodology

As Figure 1 shows, this section aims to develop a comprehensive framework to estimate GVW and mass of the on-road HDVs based on operational parameters. The affecting operational variables and engine attribute are first identified and their relation is investigated. An integrated instrumentation system is then developed considering state-of-the-art technologies available in the market. Experimentation is conducted in the next step to collect laboratory and field data of considered operational and engine parameters using designed instruments. The collected raw data are then synchronized and processed to remove potential errors. In this study, OLS and MLR statistical methods are applied to analyse the processed data and develop the mass estimation model. The applied two regression methods have much more flexibility in comparison with other techniques and it is simple to add or remove some data after conducting initial analysis. Using these methods, it would be possible to compare data collected from different equipment type. Level of familiarity, assumption, and use of multiple variables are the other advantages of using these regression techniques. The model is finally validated through comparing the predicted weight of the model against the real weight measured by the weighbridge.

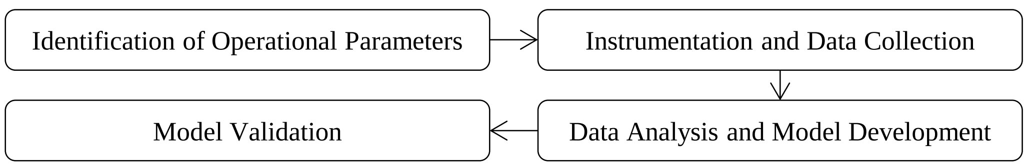

Figure 1. Integrated framework for developing weight estimation model of on-road construction equipment

3.1. Identifying Operational Parameters

In this study, the relation amongst operational variables and engine attribute has been investigated. Equipment’s weight, acceleration, speed and road slope are four main operational parameters considered in this research, which their effect are modelled on the used power of the engine. Engine load has been determined as an agent to quantify the produced power, and is defined as the ratio of the used power to the maximum power of engine as a percentage [7, 8]. Construction equipment rarely works with fully-loaded engine, and for most tasks, average engine load of equipment is approximately from 25% to 75% [9]. A few environmental variables such as ambient temperature and pressure influence the engine load value, but they are not take into consideration in this study due to their minor effects.

Acceleration is the major operational parameter which does have the highest effect on engine load. It is clear that the engine load has direct relation with vehicle’s speed and road of slope. The effect of slope can be interpreted as gravitational force resisting the movement of vehicle. As can be seen in Figure 2, weight of equipment is the main operational variable influencing the effect of other considered operational parameters. As initial analyses on the raw collected data show, weight parameter does not have direct effect on the engine load amount, but its influence is indirectly measured when the other operational parameters are modelled.

3.2. Instrumentation and Experimentation

As Figure 3 indicates, two major instruments have been applied to record required operational and engine data from experimented vehicles. GPS-INS is employed to measure real-world data of operational parameters. This devise is embedded inside the cabin and its antenna is installed on the roof of cabin to get the best signals from GPS satellites. Being an attitude and heading reference system, GPS-INS provides the highest accuracy in second-by-second data recording of acceleration, speed and orientation parameters in three dimensions. Also, engine data logger is an on-board diagnostics (OBD) device applied in this study to gather real-time engine load data. It is plugged into the J1939 port of the equipment's engine control unit (ECU) under the steering wheel. The collected data of these two instruments were transmitted and stored in an industrial Tough Pad to be synchronized, processed and analysed.

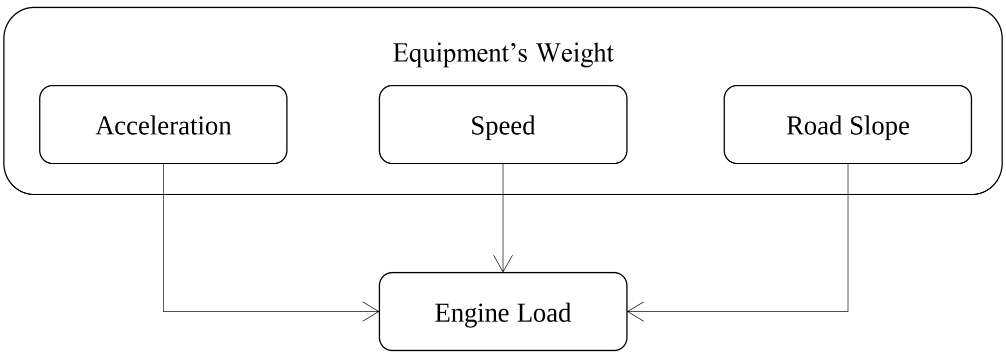

Figure 2. Investigated relation between operational parameters and engine load

(a) (b)

Figure 3. Instruments employed to collect real-world data, (a) GPS-INS and (b) engine data logger

Table 1. Specifications of equipment used for experimentation

Vehicle	Tier	Engine Size (kW)	Model	Empty Weight (ton)	Experiment Time (min)
Three-axle Granite	IV	345	2010	9.5	212
Three-axle Trident	V	400	2013	11	165
Six-axle Granite	IV	345	2010	14.5	272
Six-axle Trident	V	400	2014	17.7	120
Six-axle Vision	III	350	2005	17.6	265
Seven-axle Granite	IV	345	2010	16.6	205
Seven-axle Trident	V	400	2013	18.8	221

Experimentation process was conducted in two steps of laboratory and field data collection. The main aim of laboratory testing was verifying the performance of employed instruments and synchronizing the recorded data. The raw data from laboratory tests were also analysed for developing initial research framework. As Table 1 illustrates, seven on-road in-use HDVs were experimented, and more than 90.000 raw data points were collected from each instrument in the process of field data collection. The models of equipment varied between 2005 and 2014 with the engine sizes ranging from 345 kW to 400 kW. To precisely model the effect of different parameters, the vehicles were driven with much fluctuations and variations in the amount of acceleration rate, speed, road slope and equipment weight.

4. Operation-Based Weight Modeling

This section focuses on developing a technical method to estimate the weight of on-road HDVs based on measurable operational and engine parameters. As discussed, two GPS-INS and engine data logger were employed to record operational and engine data respectively. The raw collected data were transmitted to the industrial Tough Pad to be stored and processed. Through conducting data filtering and synchronization using Microsoft Excel software, potential errors were then identified and invalid data were removed, which approximately two-third of raw data (90.000 data points) were finalized. OLS and MLR statistical analysis techniques were carried out on the verified data by IBM SPSS Statistics V22.

As shown in Figure 2, weight parameter has indirect effect on engine load, and its influence is taken into consideration in the coefficients of other operational parameters. The conducted MLR analyses reveal that there is a highly-correlated linear relation between three parameters of acceleration rate, speed and road slope, and engine load in different loading conditions. Barati et al. [10] developed a linear relation to estimate the engine load presented in Equation (1). The weight factor (WF) has been defined as the combined weight of equipment (ton) that must be carried per 100 kW of engine size. Combined weight includes the weight of equipment, trailer and mas. In the designed model, C_{AC}, C_{SP} and C_{SL} are the coefficients of acceleration, speed and slope parameters respectively which are shown in Table 2.

$$EL = (C_{AC} * AC) + (C_{SP} * SP) + (C_{SL} * SL) + C \quad (1)$$

Where:
EL: Engine load of equipment (%)
AC: Acceleration rate of equipment (km/h.s)
SP: Speed of equipment (km/h)
SL: Slope of road (degree)
C: Engine load of equipment in idling mode which is around 15%.

Table 2. The coefficients of parameters in the engine load estimation model

Coefficients	Weight Factor				
	2.75	4.5	6.5	13	14.5
C_{AC}	22	30	36	50	56
C_{SP}	0.24	0.26	0.35	0.48	0.54
C_{SL}	2.4	4.3	6	8.2	9

It can be seen that with increase of WF, the effect of operational parameters on engine load rises. Conducted OLS analyses by Microsoft Excel software shown in Figure 3 indicate that there is a linear relation with high correlation and consistency (R^2 > 0.9) between WF and coefficients of investigated operational parameters. Based on truck configurations and loading conditions, WF varies from around 2.75 (ton/100kW) for empty truck without trailer to about 15 (ton/100kW) for fully-loaded truck with one trailer. Acceleration has the highest effect on engine load, varying from 22 (km/h.s) for WF of 2.75 to 56 (km/h.s) when WF increases to 14.5 (see Figure 4a and Equation (2a)). The analyses reveal that WF has less impact on the of speed and road slope parameters' coefficients ranging from just over 0.2 (km/h) to around 0.6 (km/h) for speed, and between about 3° to 9° for road slope. As the main limitation of the conducted research, due to the loading restrictions, a wide range of WF values could not be measured during experimentation process. The trucks were experimented in limited loading conditions of empty and fully-loaded trucks without or with one trailer.

$$C_{AC} = 2.67 * WF + 16.77,\ R^2 = 0.9849 \qquad (2a)$$
$$C_{SP} = 0.0252 * WF + 0.166,\ R^2 = 0.9848 \qquad (2b)$$
$$C_{SL} = 0.508 * WF + 1.79,\ R^2 = 0.9476 \qquad (2c)$$

In the next step of the study, WF is modeled by combining the Equations (1) and (2). As Equation (3) presents, WF is a function of operational parameters and engine load. Acceleration, speed and road slope are recorded by GPS-INS instrument in a second basis. Engine load is also measured with high accuracy using engine data logger connected to J1939 port of vehicle. So, having the real-world measured data, in each second, a value for WF can be estimated using Equation (3).

$$\mathrm{WF} = \frac{(\mathrm{EL} - \mathrm{C} - (16.77*\mathrm{AC} + 0.166*\mathrm{SP} + 1.79*\mathrm{SL}))}{(2.67*\mathrm{AC} + 0.0252*\mathrm{SP} + 0.508*\mathrm{SL})} \qquad (3)$$

As shown in Figure 5, conducted calculations using Equation (3) reveal that there is much variation in the value of WF due to many parameters including operator skill, engine condition and road type. Also, the performance of instruments in collecting raw data is one of the main sources of error affecting the accuracy of model in estimating WF. The variation of calculated WF indicates that the distribution of the data follows normal statistical function that the majority of the calculated WFs are around the average. The mean (M) representing the predicted WF, standard deviation and skewness can be calculated using Equation (4).

$$\mathrm{M} = \frac{1}{n} * \sum_{i=1}^{n} \mathrm{WF}_i \qquad (4a)$$
$$\sigma = \sqrt{\sum_{i=1}^{n} (WF_i - M)^2} \qquad (4b)$$
$$\gamma = \mu_3/\sigma^3 \qquad (4c)$$

Where:
M: Mean of the calculated WFs
σ: Standard deviation of the calculated WFs
γ: Skewness of distribution function
μ_3: Third moment of stochastic variables

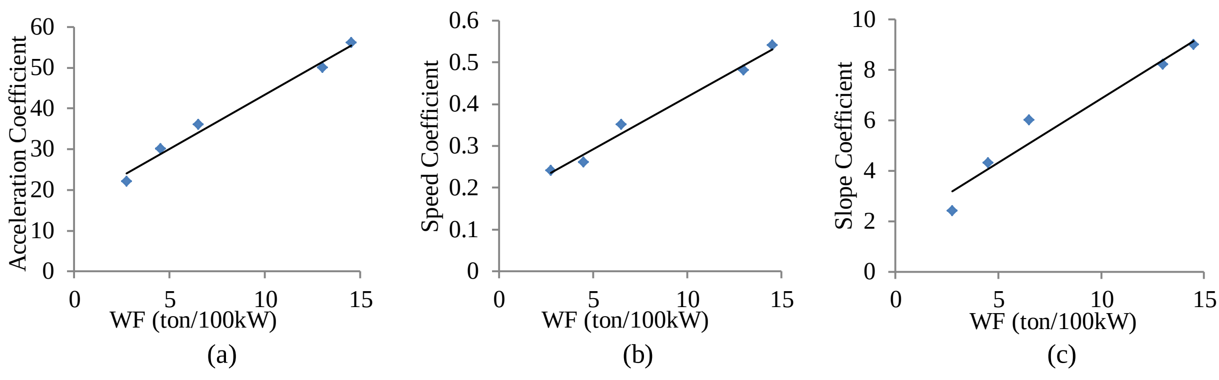

Figure 4. The effect of WF on the coefficients of (a) acceleration, (b) speed and (c) road slope parameters

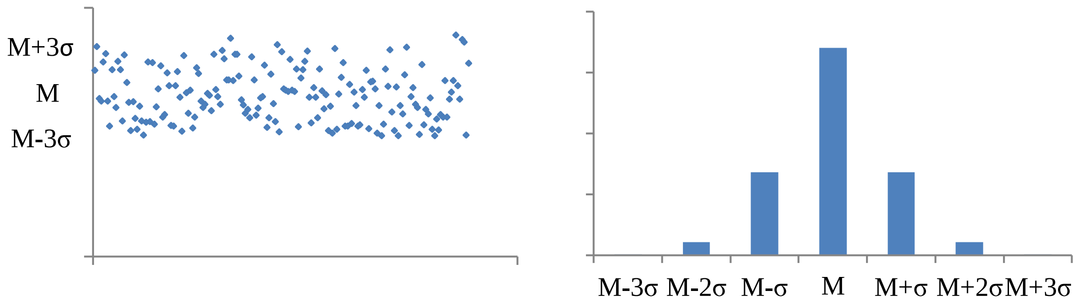

Figure 5. The distribution of calculated WFs using Eq. (3)

Using M as the final WF, total weight of HDVs can be easily calculated through Equation (5a). As defined before, WF is the amount of combined weight which is carried per 100 kW of engine. Having the weight of equipment itself and the weight of trailers if available, the mass can be calculated using Equation (5b).

$$TW = M^* PW/100 \quad (5a)$$

$$PL = TW - EW \quad (5b)$$

Where:
TW: Total weight of equipment (ton)
PW: Engine power (kW)
PL: mass of equipment (ton)
EW: Empty weight of equipment (ton)

5. Model Validation

This section focuses to verify the applicability of developed framework through conducting experimentation on seven different in-use on-road HDVs. The experimentation process took seven days, and more than 90.000 data points were collected to be analyzed. Figure 6 shows some sample photos of vehicles experimented as case study. As can be seen, a variety of trucks from three to seven axles with additional trailer were selected. Data processing and filtering were carried out on the raw collected data and invalid data were removed in the first step. Using Equation (3) developed in the previous section, the WF of the equipment was then predicted in different loading conditions. As achieved results show, there was much variation in the value of WF for each vehicle with specific condition. So, Equation (4) was applied to calculate the mean representing the predicted amount of WF and standard deviation according to normal distribution function. Having the specifications of experimented equipment such as engine size and empty weight of equipment, the total weight of vehicle and mass were finally estimated.

To verify and validate the developed model, the estimated weight of vehicles calculated by Equation (5) compared with the real weight measured using an industrial weighbridge available in the site. The analyzed data including M, σ and TW have been presented in Table 3. On the whole, data from 14 loading conditions with different trucks have been collected, but analyses were performed just on five conditions to validate the developed model. Figure 7 conducts validation through plotting the predicted TW using Equation (5) versus the real measured equipment's weight. As can be seen, there is high correlation between estimated and measured equipment's weight. As one of the main contributions of this study, it has been proven that the developed model has more than 90% accuracy in estimating the weight of on-road HDVs. Numerous sources of potential errors have also been identified in this study that can be improved to increase the accuracy of the developed model.

Table 3. The results of the analyzed data on five different vehicles for model validation

Equipment	Engine Size (kW)	M	σ	TW	Real Weight
Three-axle Granite	345	3.13	0.203	10.8	9.5
Six-axle Granite	345	3.65	0.242	12.6	14.52
Three-axle Trident	400	4.95	0.233	19.8	22.5
Six-axle Vision	350	12.77	0.390	44.7	48
Seven-axle Trident	400	13.55	0.367	54.2	50.5

(a) (b) (c)

Figure 6. Samples photos of on-road HDVs experimented, (a) a) three-axle vehicle without trailer, (b) six-axle vehicle with a trailer, and (c) seven-axle truck with a trailer

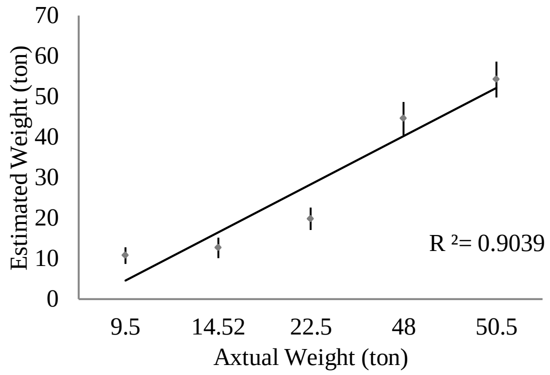

Figure 7. Validation of the developed weight estimation model by comparing the estimated and real equipment's weight

6. Conclusions

Earthmoving operations involve a large number of HDVs for material transportation. Monthly payment and scheduling of such projects are primarily based on the amount of soils and materials moved by the contractors. Numerous metric and volumetric techniques and devises have being applied in construction industry to estimate the weight of materials transferred by vehicles in each cycle. Despite the high accuracy of some existing methods, they are mainly costly, time-consuming and labor-intensive which could considerably increase the cost in construction projects.

This study developed an integrated framework to estimate the weight of on-road HDVs considering operational parameters and engine attributes. As the sources of data for developing the model, GPS-INS and engine data logger instruments were employed to collect real-world data from in-use construction equipment. More than 90,000 data points were collected during seven-day experimentation, and were analyzed after synchronization and data filtering. According to the model, WF is predicted based on acceleration rate, speed, road slope and engine load. By applying normal statistical distribution function, the mean value and standard deviation of WF were calculated. Comparing the predicted vehicle's weight with the real weight measured using weighbridge in the validation process reveals the high accuracy of developed model in weight estimation which is considered to be the main achievement of this study. Different sources of error were identified at the end such as instruments errors and operator's skill level that can be controlled to increase the accuracy of the model.

This model has considerable application potential in construction industry to automatically measure the weight of different haulers. In comparison with current weighting methods, this technique does not need high initial costs, and can save much time and money due to its automated process. In the future, this research will focus on extending this model to off-road equipment that is commonly used in civil and mining construction. Engine depreciation and tier can also be considered as new parameters for improving the accuracy of the current model.

Acknowledgements

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