Modeling Fuel Use, Emissions and Mass of On-Road Construction Equipment through Monitoring Field Operations

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Modeling Fuel Use, Emissions and Weight of On-Road Construction Equipment through Monitoring Field Operations

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Abstract

Construction industry is considered as one of the largest contributors to fuel consumption and greenhouse gases (GHGs) emissions globally. Fuel use and emissions of construction equipment are normally estimated through simulation or conducting dynamometer tests in the laboratory which may not represent the real-world situations. In such models, fuel use and emissions rate are mainly estimated at macro scale, while the effect of operational conditions cannot be measured. There is also a lack of quantitative operational level fuel use and emissions reduction schemes in the construction industry despite the potential of significant cost saving by applying such strategies.

This thesis presents an integrated data monitoring framework including instrumentation and experimentation procedures to monitor operations of construction equipment. It develops operational level models to estimate fuel use and emissions rate of on-road construction equipment through investigating the effect of operational and environmental variables. Using the automated data sensing system, this study also develops a comprehensive model to predict the weight of on-road construction vehicles and their carried payload as crucial parameter affecting fuel use and emissions rate. Three types of devices, portable emission measurement system (PEMS), GPS-aided inertial navigation system (GPS-INS) and engine data logger were employed to collect emissions rates, operational parameters and engine data of on-road construction vehicles. Models are developed through performing statistical regression and artificial neural network (ANN) analysis on the filtered data. The proposed models consider the engine specifications, operational factors and environmental parameters for estimating fuel use, emissions rate and weight of the vehicles.

Based on the developed models, this study designs different schemes to improve fuel efficiency of construction equipment. As the main operational level strategy, optimal driving speed is proposed over other operational and environmental variables. Other factors, such as traffic conditions, effect of idling and equipment stop on fuel use and emissions production of equipment are also investigated. At equipment level, this thesis evaluates the impact of different engine tiers on fuel use and emissions rate through applying the developed models. It is found that adoption of high-tier engines leads to considerable savings on the operation costs of equipment.

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ABSTRACT

Construction industry is considered as one of the largest contributors to fuel consumption and greenhouse gases (GHGs) emissions globally. Fuel use and emissions of construction equipment are normally estimated through simulation or conducting dynamometer tests in the laboratory which may not represent the real-world situations. In such models, fuel use and emissions rate are mainly estimated at macro scale, while the effect of operational conditions cannot be measured. There is also a lack of quantitative operational level fuel use and emissions reduction schemes in the construction industry despite the potential of significant cost saving by applying such strategies.

This thesis presents an integrated data acquisition framework including instrumentation and experimentation procedures to monitor operations of construction equipment. It develops operational level models to estimate fuel use and emissions rate of on-road construction equipment through investigating the effect of operational and environmental variables. Using an automated data sensing system, this study also develops a comprehensive model to predict the weight of on-road construction vehicles and their carried payload as crucial parameter affecting fuel use and emissions rate. Three types of devices, including portable emission measurement system (PEMS), GPS-aided inertial navigation system (GPS-INS) and engine data logger, were employed to collect emissions rates, operational parameters and engine data of on-road construction vehicles. Models are developed through performing statistical regression and artificial neural network (ANN) analysis on the filtered data. The proposed models

consider the engine specifications, operational factors and environmental parameters for estimating fuel use, emissions rate and weight of on-road construction vehicles.

Based on the developed models, this study designs different schemes to improve fuel efficiency of construction equipment. As the main operational level strategy, optimal driving speed is proposed over other operational and environmental variables. Other factors, such as traffic conditions, effect of idling and equipment stop on fuel use and emissions production of equipment are also investigated. At equipment level, this thesis evaluates the impact of different engine tiers on fuel use and emissions rate through applying the models developed in the research. It is found that adoption of high-tier engines would lead to considerable savings on the operation costs of equipment.

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LIST OF ABBREVIATIONS

AADTT	Annual average daily truck traffic
AASHTO	American Association of State Highway and Transportation Officials
ADVISOR	Advanced vehicle simulator
AFR	Air flow rate
AGC	Associated general contractors
AHRS	Attitude and heading reference system
ANN	Artificial neural network
ASTM	American Society for Testing and Materials
AVI	Automatic vehicle identification
BSFC	Brake-specific fuel consumption
CAAAC	Clean Air Act Advisory Committee
C_{AC}	Coefficients of acceleration rate
CARB	California Air Research Board
CBWIM	Contactless bridge weight-in-motion
CEDST	Construction Environmental Decision Support Tool
CERA	Australian Clean Energy Regulator Agency
CMEM	comprehensive modal emission model
CO	Carbon monoxide
CO_2	Carbon dioxide
CPF	Catalyst pass friction
C_{SL}	Coefficients of slope
C_{SP}	Coefficients of speed

DES	Discrete-event simulation
DGV	Digitized Graze Model
DOC	Diesel oxidation catalysts
DPF	Diesel particulate filters
ECU	Engine control unit
EPA	Environmental Protection Agency
ESAL	Equivalent single axle load
EU	European Union
EW	Empty weight of equipment
FHWA	Federal Highway Administrations
FR	Fuel consumption rate
GHG	Greenhouse gas
GPS-INS	GPS-aided inertial navigation system
GVW	Gross vehicle weight
GVWR	Gross vehicle weight rating
HC	Hydrocarbons
HCNG	Hydrogen compressed natural gas
HDV	Heavy-duty vehicles
HOG + C	Histograms of Oriented Gradients and Colours
IPCC	Intergovernmental Panel on Climate Change
LDV	Light-duty vehicles
LVS	Load volume scanners
MAP	Manifold absolute pressure
MEMS	Microelectromechanical systems

MIP	Mixed integer programming
MLR	Multilinear linear regression
MOVES	Motor vehicle emission measurement simulator
NAAQS	National Ambient Air Quality Standard
NAASRA	National Association of Australian State Road Authorities
NAEI	National atmospheric emissions inventory
NCHRP	National Cooperative Highway Research Program
NDIR	Non-dispersive infrared
NO_x	Nitrogen oxides
O_3	Ozone
OBD	On-board diagnostics
OEE	Operating equipment efficiency
OLS	Ordinary least square
PEMS	Portable emission measurement system
PL	Payload
PM	Particulate matters
PW	Power of equipment
R^2	Correlation coefficient
SO2	Sulfur Dioxide
SSE	Sum of the square errors
TRB	Transportation Research Board
TRS	Truck recognition system
TW	Total weight of equipment
ULSD	Ultra-low sulfur diesel

UNFCCC	United Nations Framework Convention on Climate Change
USB	Universal serial bus
VSP	Vehicle specific power
WF	Weight factor
WIM	Weight-in-motion
WVWMS	Wireless vehicle weight measurement systems

PUBLICATIONS

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In progress

- **Barati K**., and Shen X., Operational-level Reduction Schemes for Delivering Greater Fuel Efficiency to Construction Vehicles, to be submitted to *Journal of Construction Engineering and Management*.

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- **Refereed Conference Proceedings**

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- Klein. J., **Barati. K**., and Shen. X., 2016, "Optimum Driving Pattern for Minimizing Fuel Consumption of On-road Vehicles", *33rd International Symposium on Automation and Robotics in Construction and Mining*, 18-21 July, United States.

- **Barati. K.**, and Shen. X., 2015, "Integrated Framework for Estimating Real-Time Emissions of Construction and Mining Equipment", *32nd International Symposium on Automation and Robotics in Construction and Mining*, 15-18 June, Finland. **(This paper was selected as one of the 10 best papers presented in ISARC 2015).**

Chapter 1

Introduction

The growth of global population and industrialization in all sectors has boosted the demands for different sources of energies, particularly conventional fossil fuels. Today, over one billion vehicles in operation around the world consume over five trillion litres of fossil fuels per year (Dargay et al. 2007). Considering the diminishing sources of fossil fuels, such a rate of fuel consumption deems to be extremely unsustainable (Khan et al. 2014). However, due to increasing demands for vehicles in both business and private sectors, it is predicted that the number of global on-road vehicles and machinery reaches two billions by 2050 (Sperling and Gordon 2014). On the other hand, fossil fuels are considered to be the main source of air pollutants like carbon dioxide (CO_2), carbon monoxide (CO), hydrocarbons (HC), nitrogen oxides ($NO_x = NO_1 + NO_2$) and particulate matters (PM) (Gonzalez and Echaveguran 2012). According to USA Environmental Protection Agency (EPA) report, 76% of the total CO_2 emission is produced from the fuels used by vehicles and machinery globally (EPA 2009). These contaminants present a serious risk to human health, ecosystem and environment (IPCC 2007). Around 200,000 deaths per year in USA alone are caused by irreversible health problems due to air pollutants, such as respiratory and cancer diseases (Lewis et al. 2009; Caiazzo et al. 2013). The studies conducted by EPA also showed that the contaminants exhausted from vehicles are the main cause of environmental problems such as ecosystem degradation, ozone depletion and global warming (EPA 2008).

The increasing concern on the non-compensable effect of fossil fuels consumption on climate change and public health has led to the development towards fuel measurement systems, regulations and guidelines of fuel reduction (Hasan et al. 2013). According to the United Nations Framework Convention on Climate Change (UNFCCC), all sectors in industrialized countries should follow regulations to reduce fossil fuel use and resultant pollutions (Kim et al. 2012). EPA and European Union (EU) have developed various standards to restrict the pollutions produced by on-road vehicles and off-road equipment involved in all industrial sectors (Barati and Shen 2015). Also, many restrictions have been imposed by the Intergovernmental Panel on Climate Change (IPCC) (2007) to minimize carbon footprints through reducing activities consuming large amount of energy resources including fossil fuels.

The construction sector plays a significant role in fossil fuels consumption so as to the production of greenhouse gas (GHG) pollutants. According to EPA (2009), construction sector accounts for 1.7% of total GHGs production and 6.8% of all industrial-related emissions which is ranked as the third largest GHG emitter after oil and gas, and chemical manufacturing industries (Azzi et al. 2015; Truitt 2009). In addition, it is estimated that construction industry produces more than 100 million tons of CO_2 annually, and contributes to around 5% of global CO_2 emissions which is ranked as the third CO_2 emitter per used unit of energy after cement and steel production sectors (Avetisyan et al. 2012). According to UNFCCC, GHG emissions from construction operations account for around 6.8% of total emissions produced by all industrial sectors.

The majority of energy consumption and emissions production in construction sector is related to equipment operations. Around 45-48% of total vehicular consumed fuel and emitted pollutions of all industries are associated with construction equipment (Lewis 2009). These construction machineries are mainly involved in numerous earthmoving operations in which their emitted pollutions are much more than other commercial vehicles. For example, the pollution production of a middle-sized loader is nearly 500 times more than that of a private car (Kaboli and Carmichael 2012). Based on the report prepared by EPA's Clean Air Act Advisory Committee (CAAAC) (2006), construction sector accounts for 6% of light-duty vehicles (LDVs) and 17% of heavy-duty vehicles (HDVs) while producing 32% of NO_x and 37% of PM of all mobile source emissions. In construction projects, equipment operations and material transportation account for the majority of energy consumption and consequently emissions production. Previous studies have demonstrated that the type, age and size of engine, and fuel kind are the most significant parameters affecting emission rate of equipment.

Developing reduction strategies for construction equipment can have significant effect on decreasing the total amount of emitted pollutions. For example, if the idling time of construction equipment reduces by 10%, the emission of CO_2 decreases for around 0.8 million tons per year (Truitt 2009). EPA estimates that if the fuel consumed by construction equipment decreases by 10%, around 5% of entire energy used in the construction sector will be saved resulting a reduction of 6,700 tons CO_2 production (EPA 2009). The Australian Clean Energy Regulator Agency (CERA) predicts that by decreasing the fuel consumed by on-road equipment involved in all industry sectors including construction, over 3 billion litres fuel can be saved and approximately 8 million tones CO_2 emission is reduced in Australia only (Klein et al. 2016). In addition, equipment compatibility and efficiency are two crucial parameters having considerable effect on produced emissions per unit of conducted work (Ahn and Lee 2013). Large construction projects normally involve a variety of type and number of equipment, and therefore hold flexibility in selecting equipment to work on a given activity.

1.1. Problem Statement

Construction industry is one of the main contributors to global fuel consumption and GHG emission production mainly due to the large number of heavy equipment involved. This issue shows the essentiality of having accurate models to predict fuel consumption and pollutants production of construction equipment at different level. Previous studies have indicated that total weight of vehicles has an important effect on their fuel consumption and emissions production. Therefore, it is desirable to devise a precise and efficient method to estimate the weight of equipment, and then investigate its impact on vehicles' fuel use and pollutants production. In addition, fuel reduction schemes and strategies are expected to improve fuel efficiency significantly, which can be used as a guideline by operators and managers to lower fuel use and emissions production of equipment.

There is a lack of accurate models and methods in construction sector to predict fuel consumption and emissions production of vehicles especially at operation level. Current models mainly focus on predicting fuel use and emissions production of vehicles at macro level, such as per nation, state, or project. For example, NONROAD model developed by EPA and OFFROAD model devised by California Air research Board (CARB) are applied for having rough estimation of fuel consumption and emissions rate of different construction equipment groups at national and state levels. On the other hand, numerous operational and environmental parameters influencing fuel use and emissions rate of construction vehicles have not been fully investigated yet. Also, engine specifications are the other factors having major impact on fuel efficiency of equipment which require further and comprehensive investigations.

Further, there are no comprehensive and quantitative operational level strategies and schemes in practice to reduce fuel used and emissions produced by construction equipment in spite of their significant impact on saving costs in construction operations. The current reduction strategies mainly focus on engine attributes and fuel types which can be applied to new construction vehicles only, while failing to cater for existing machinery globally. On the other hand, weight of equipment is a main factor impacting fuel use and emissions production requiring an accurate and fast model to predict the weight of vehicles and to investigate the effect of weight on fuel use and emissions rate. The current weighting systems in construction are time consuming or error prone, which typically come with high initial cost. As the most applicable technique, weighbridges are widely used on the construction sites which require high installation and operation costs. The weight measurement time in traditional methods has considerable impact on the production rate of the equipment and the cost of project execution. Despite high speed of new volumetric measurement methods, these systems may not yield sufficient accuracy due to volume to weight conversion analysis.

1.2. Research Objectives

Considering the problems and gaps identified in the field of fuel use and emissions estimation of construction equipment, this study aims to develop a comprehensive framework to predict instantaneous fuel use and emissions rate of construction vehicles at operation level. According to the report published by EPA (2009), dump trucks are the major source of energy consumption and consequently emissions production in the construction industry. Therefore, this study focuses on modeling fuel use and emissions production of on-road construction vehicles including dump trucks through investigating the effect of operational, environmental and engine variables. For emissions modeling, this research focuses on four pollutants as the main GHGs, namely CO_2, CO, HC and NO_x.

The weight of equipment is a crucial parameter impacting fuel use and emissions rate. It is required to have a system to easily measure this operational parameter in practice. This study purposes an integrated framework to predict the weight of on-road construction equipment including their payload considering operational, environmental and engine variables. Developed weight estimation model will be finally validated and verified, and can be used in practice for weight modeling of on-road construction vehicles.

After developing research framework, and fuel use, emissions rate and weight estimation models, this research also devises different fuel and emission reduction strategies and schemes to deliver greater fuel efficiency to construction vehicles and lower their emission production. The devised schemes predict optimal driving patterns and trailer configurations taking into consideration the effect of investigated operational and environmental parameters. The research methodology developed in this study would have many other applications in construction industry such as monitoring and tracking resources, predicting equipment's production and managing machinery.

1.3.Research Framework

This section presents the framework and methodology developed in this study. As mentioned above, this research concentrates on operational level fuel use and emissions modeling of on-road construction vehicles. This study is divided into three separated layers, as shown in Figure 1.1. As the main contribution of this research, an automated data sensing framework is developed to monitor field operations in layer one. State-of-the-art instrumentation system is employed to automatically collect required real-world field data from construction equipment through preliminary and field experimentation. The data sensing system can be used in different construction fields.

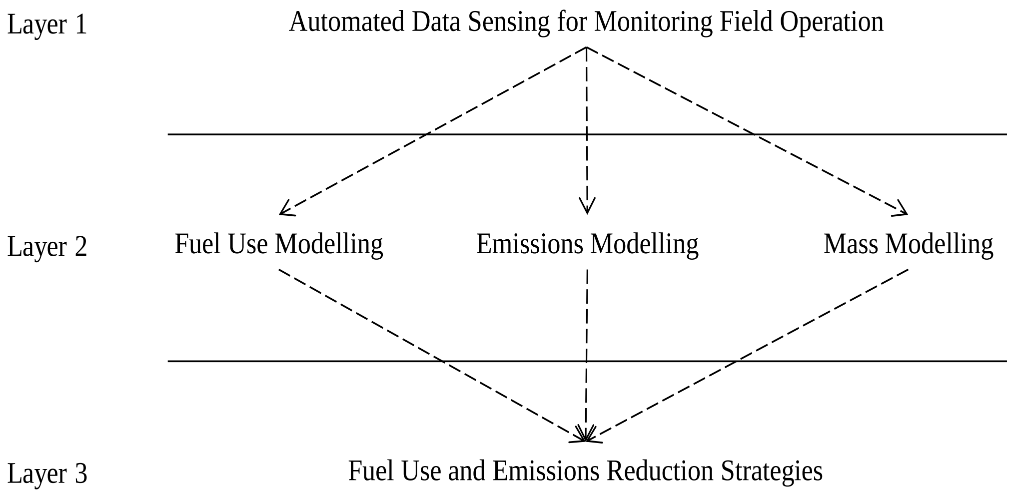


Figure 1.1. Different layers of the integrated research framework developed in this study

In the second layer, this study models fuel use, emissions rate and weight of on-road construction vehicles by applying the developed data monitoring method. This procedure is conducted through synchronizing and analyzing the data collected from field experimentation. Developed models have the capability of predicting the instantaneous fuel use and emissions rate based on the operational and environmental parameters. Those models are then validated through comparing the predicted results with the ground-truth values of fuel use, emissions rate and weight measured by independent instruments.

The estimation models on fuel use, emissions rate and weight are expected to have broad applications in the construction industry. By employing devised models in layer 2, the third layer of this study is focused to develop different reduction strategies and schemes to deliver greater efficiency to construction vehicles.

1.4.Thesis Structure

The thesis structure is illustrated in Figure 1.2. Chapter 1 introduces the topic of the thesis and justifies the significance and necessity of this study. This section also defines the current problems in modeling fuel use and emissions of equipment in construction sector, followed by research objectives of the study.

Chapter 2 reviews the previous studies in the field of fuel use, emissions rate and weight modeling in construction sector. Different models and techniques which are currently used in practice for measuring fuel use, emissions and weight of the vehicles are also investigated.

Chapter 3 develops an integrated data monitoring system as the primary research methodology of this study for developing models and strategies. Affecting parameters on fuel use and emissions rate of construction equipment are investigated. Suitable instruments for gathering real-world data from field experimentation are also evaluated. Data filtrating procedure is developed in this chapter for detecting and correcting potential errors.

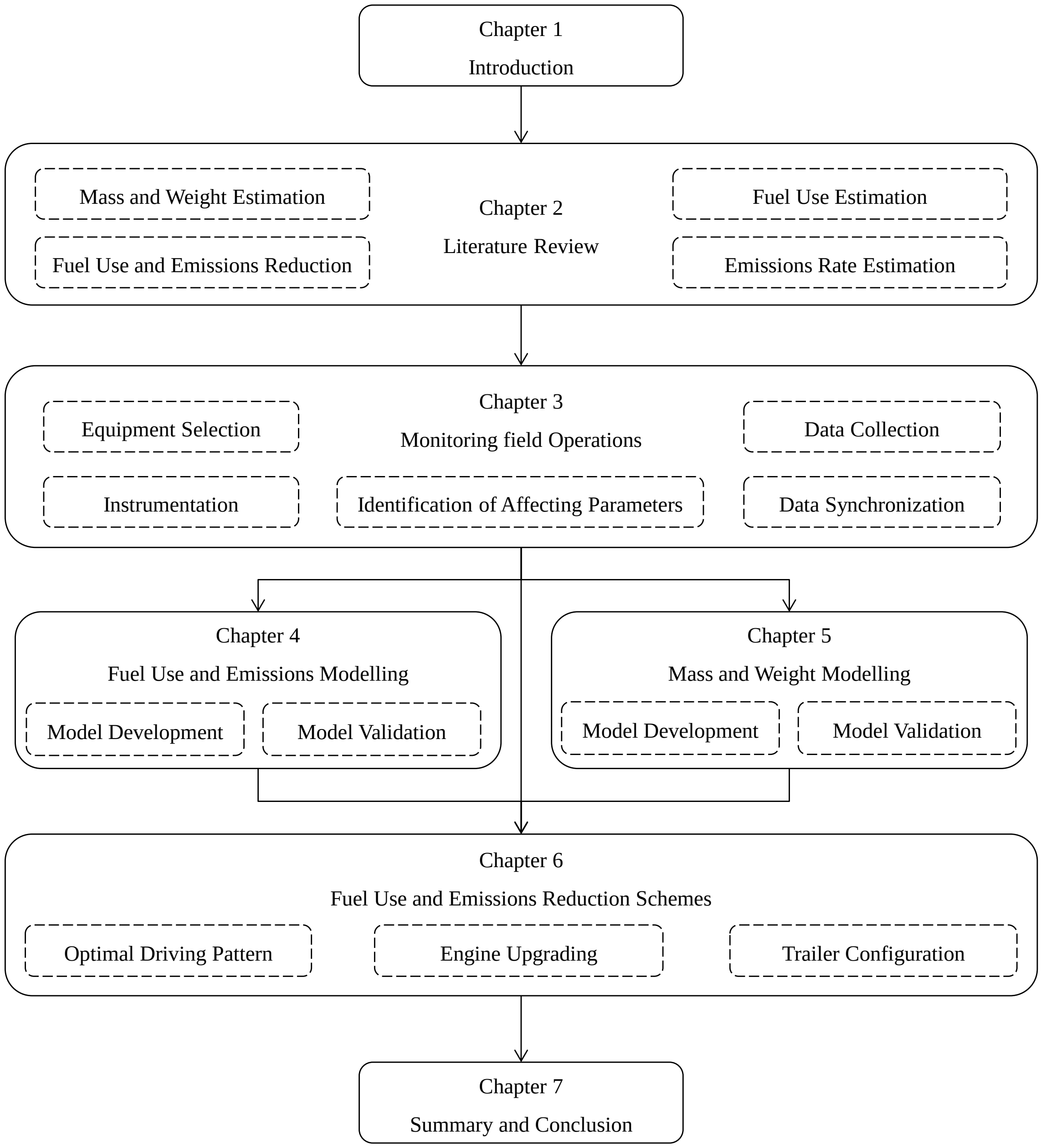


Figure 1.2. Structure of the thesis

Chapter 4 develops the operational level fuel use and emissions rate models for on-road construction equipment through conducting analysis on the filtered raw data. The emissions rate of CO_2, CO, HC and NO_x GHG pollutants are modelled. Validation process is finally performed on the developed models through comparing the predicted results with the ground truth data measured in the experimentations.

In Chapter 5, this study continues with devising a model to estimate the weight of equipment and their carried payload based on modeling the operational and environmental parameters, and engine attributes. ANNs are adopted for analyzing and configuring the model. Having the real weight of equipment and their carried payload using the weighbridges on the sites, weight estimation model is finally validated.

Applying fuel use and emissions rate models devised in this study, Chapter 6 develops several strategies to deliver greater fuel efficiency to construction vehicles and to reduce the emissions produced from construction operations. As the main scheme, optimal driving pattern is designed to predict the ideal driving speed based on monitoring the operational, environmental and engine variables. This chapter continues with considering the effect of engine tier and trailer configuration on fuel use and emissions production per transferred unit of weight. The effect of idling time and equipment stop on additional fuel use and pollutants production is finally modelled in this chapter.

Chapter 7 concludes the main findings of the thesis, discusses limitations of the study and provides suggestions for future research.

Chapter 2

Literature Review

2.1. Introduction

This chapter provides a comprehensive review of previous research that is relevant to this study. This research focuses on three main areas on construction equipment operations, namely (1) modeling fuel use and emissions, (2) developing schemes and strategies to reduce fuel use and emissions, and (3) estimating the total weight of equipment based on monitoring operational parameters. Accordingly, this chapter is divided into three sections to cover the background related to those research fields. At first, existing models and approaches for fuel use and emissions estimation of construction equipment are reviewed. Different fuel consumption and emissions reduction schemes applied in the construction industry are then investigated. Finally, current weight and payload measurement tools and techniques for weighing construction equipment are introduced.

2.2. Fuel Use and Emissions Modeling

This section reviews the background and previous studies in the field of fuel use and emission modeling of construction equipment. The current standards and regulations imposed by local governments and international agencies are found to be the key incentive and motivation to restrict fuel use and emissions of construction equipment.

The studies and efforts conducted by both academic scholars and professional sectors in the field of construction fuel use and emissions estimation are also summarized. This section continues with reviewing the modeling techniques and methodologies utilized for fuel use monitoring and emissions prediction of construction vehicles. The models commonly adopted for estimating fuel use and emissions of both on-road and non-road vehicles are then introduced and evaluated. Finally, the approaches and strategies which could be applied in reducing fuel use and emissions in the proposed study are reviewed.

2.2.1. Standards and Regulations

Regulations and standards are the main incentives and requirements for reducing fuel use and emissions rate of construction equipment. Current regulations can be classified into two broad categories of technological and air quality standards. The aim of the former is to restrict engine fuel use and emissions production, while the latter restricts the level of pollutants emitted into the atmosphere. These regulations impose restrictions on fuel use and emissions by focusing on the specifications of engines, fuel types and the combustion process (Lewis et al., 2009).

There are two main types of on-road and non-road emission standards. On-road regulations are applied for vehicles that can be driven on normal roads, which are significantly more stringent. The best known on-road standards were introduced by the European Union (EU) in the early 1970s and over the years, the EU standards have become more stringent. Currently, most countries around the world adopt and implement the EU in their own regulations (European Union, 2016). Table 2.1

summarizes the EU standards that have been implemented globally to restrict emission rate of four main pollutants for on-road heavy duty trucks and buses.

Table 2.1. EU emission standards of on-road diesel engines

Tier	Model	Emission standards (g/kWh)			
		CO	HC	NO_x	PM
Euro I	1992, < 85 kW	4.5	1.1	8	0.612
	1992, > 85 kW	4.5	1.1	8	0.36
Euro II	1996	4	1.1	7	0.25
	1998	4	1.1	7	0.15
Euro III	1999	1	0.25	2	0.02
	2000	2.1	0.66	5	0.1 0.13*
Euro IV	2005	1.5	0.46	3.5	0.02
Euro V	2008	1.5	0.46	2	0.02
Euro VI	2014	1.5	0.13	0.4	0.01

The first non-road emission regulation was introduced in 1994 by the EPA. This was implemented in 1998 as a Tier 1 regulation to restrict the emissions of main GHGs from engines with power lager than 37 kW. The power and model year of the engine were taken into consideration when making the tier classification for specific piece of construction equipment. In 2001 and 2006, the EPA implemented two more, and more stringent, regulations Tiers 2 and 3. The most stringent regulation so far, Tier 4, was released since 2008 from transitional (Tier 4t) to final phases (Tier 4f). Table 2.2 lists the standards that have been developed by EPA to restrict emissions of non-road diesel construction equipment over the last two decades.

Table 2.2. EPA emission standards of non-road diesel engines

Engine power	Tier	Model	Emission standards (g/kWh)				
			CO	HC	NMHC + NOx	NOx	PM
37 ≤ kW < 56	Tier 1	1998-2003	-	-	-	9.2	-
	Tier 2	2004-2007	5.0	-	7.5	-	0.4
	Tier 3	2008-2012	5.0	-	4.7	-	0.3
	Tier 4t	2008-2012	5.0	-	4.7	-	0.3
	Tier 4f	2013+	5.0	-	4.7	-	0.03
56 ≤ kW < 75	Tier 1	1998-2003	-	-	-	9.2	-
	Tier 2	2004-2007	5.0	-	7.5	-	0.40
	Tier 3	2008-2011	5.0	-	4.7	-	0.40
	Tier 4t	2012-2013	5.0	0.19	-	0.40	0.01
	Tier 4f	2014+	5.0	0.19	-	0.40	0.01
75 ≤ kW < 130	Tier 1	1997-2002	-	-	-	9.2	-
	Tier 2	2003-2006	5.0	-	6.6	-	0.3
	Tier 3	2007-2011	5.0	-	4.0	-	0.3
	Tier 4t	2012-2013	5.0	0.19	-	0.40	0.01
	Tier 4f	2014+	5.0	0.19	-	0.40	0.01
130 ≤ kW < 225	Tier 1	1996-2002	11.4	1.3	-	9.2	0.54
	Tier 2	2003-2005	3.5	-	6.6	-	0.2
	Tier 3	2006-2010	3.5	-	4.0	-	0.2
	Tier 4t	2011-2013	3.5	0.19	-	0.40	0.0

							1
	Tier 4f	2014+	3.5	0.19	-	0.40	0.01
225 ≤ kW < 450	Tier 1	1996-2000	11.4	1.3	-	9.2	0.54
	Tier 2	2001-2005	3.5	-	6.4	-	0.2
	Tier 3	2006-2010	3.5	-	4.0	-	0.2
	Tier 4t	2011-2013	3.5	0.19	-	0.40	0.01
	Tier 4f	2014+	3.5	0.19	-	0.40	0.01
450 ≤ kW < 560	Tier 1	1996-2001	11.4	1.3	-	9.2	0.54
	Tier 2	2002-2005	3.5	-	6.4	-	0.2
	Tier 3	2006-2010	3.5	-	4.0	-	0.2
	Tier 4t	2011-2013	3.5	0.19	-	0.40	0.01
	Tier 4f	2014+	3.5	0.19	-	0.40	0.01
kW ≥ 560	Tier 1	2000-2005	11.4	1.3	-	9.2	0.54
	Tier 2	2006-2010	3.5	-	6.4	-	0.2
	Tier 4t	2011-2014	3.5	0.4	-	3.5	0.1
	Tier 4f	2015+	3.5	0.19	-	3.5	0.04

In regard to air quality standards, the EPA established the National Ambient Air Quality Standard (NAAQS) to control the concentration of GHGs in the atmosphere and their effects on human health and the environment. The NAAQS is reviewed periodically and is becoming more stringent over time. The NAAQS includes primary and secondary emission regulations. The primary standards are more stringent, and focus on public health, including people with respiratory problems (EPA, 2006). The secondary standards limit pollutant concentrations to protect public welfare and prevent damage to the environment. As shown in Table 2.3, the EPA imposes restrictions on CO, NOx, PM, SO2, Ozone (O_3) and lead pollutants, which are known as criteria pollutants. Engines from construction equipment are the main contributors of CO, NOx, PM pollutants that are considered in this research. Hexane is also considered as a major source of HC emitted from equipment contributing to O_3 formation.

Table 2.3. NAAQS air quality standard developed by EPA

Pollutant		Primary/ Secondary	Averaging Time	Level	Form
(CO)		Primary	8 hours 1 hour	9 ppm 35 ppm	Not to be exceeded more than once per year
Lead		Primary and secondary	Rolling 3 months average	0.15 μg/m^3	Not to be exceeded
Nitrogen Dioxide (NO_2)		Primary	1 hour	100 ppb	98th percentile of 1-hour daily maximum concentrations, averaged over 3 years
		Primary and secondary	1 year	53 ppb	Annual Mean
Ozone (O_3)		Primary and secondary	8 hours	0.070 ppm	Annual fourth-highest daily maximum 8-hour concentration, averaged over 3 years
Particle Pollution (PM)	$PM_{2.5}$	Primary	1 year	12.0 μg/m^3	Annual mean, averaged over 3 years
		Secondary	1 year	15.0 μg/m^3	Annual mean, averaged over 3 years
		Primary and secondary	24 hours	35 μg/m^3	98th percentile, averaged over 3 years
	PM_{10}	Primary and secondary	24 hours	150 μg/m^3	Not to be exceeded more than once per year on average over 3 years

Sulfur Dioxide (SO_2)	Primary	1 hour	75 ppb	99th percentile of 1-hour daily maximum concentrations, averaged over 3 years
	Secondary	3 hours	0.5 ppm	Not to be exceeded more than once per year

2.2.2. Previous Studies

Many studies have been conducted by international agencies and academic scholars in the field of construction equipment's fuel use and emissions rate measurement. These studies include field experimentations to measure real data of in-use equipment for investigating the relationship between activity duty cycles and fuel consumption and emissions rate. Abolhasani et al. (2008) estimated fuel consumption and emission rate of excavators working in real operation condition. In this study, field operational data were collected from three different excavators through using a fuel and emission analyzer. Six operation modes of excavators were recorded, including idling, digging, loading, swing, dumping and moving. Fuel use and emissions rate under different operation modes of excavators were predicted after analyzing the data collected in the field. The results showed that excavators consume the highest rate of fuel in moving and using buckets modes, and consequently produce the highest amount of emissions in these two operation modes. Similarly, based on the field data collected from 34 pieces of non-road equipment, Lewis et al. (2012) quantitatively evaluated the effect of idling on fuel use and CO_2 emission rate of diesel vehicles. The total amount of used fuel and emitted CO_2 was calculated by considering the operational efficiency of equipment and the ratio of idling to non-idling mode.

Frey et al. (2008) conducted a comprehensive evaluation on the effect of different fuels including petroleum diesel and B20 biodiesel on emissions production on common construction equipment. Field experimentation was carried out on five backhoes, six graders and four front-end loaders. The analyzed results indicated that using B20 fuel instead of petroleum diesel decreases the opacity, HC and CO emission rates by 18%, 26% and 25%, respectively, but increases NO_x emission rate by around 2%. Guggemos and Horvath (2006) designed a Construction Environmental Decision Support Tool (CEDST) to evaluate the impacts of construction projects on the environment. The energy sources such as diesel and electricity, as well as produced emission and waste from construction phase were considered in CEDST. The total amount of used energy, fuel and produced emissions can be estimated at project level. It was found from this study that the use of equipment accounts for at least 50% of fuel used and pollution emitted in the execution of construction projects.

Avetisyan et al. (2012) proposed an optimization-based model for construction companies to evaluate their needs for equipment considering emissions and costs. Weighting technique was applied to investigate the effect of working conditions, equipment compatibility and availability, and regulatory constraints in minimizing project cost and emissions. The model developed in the study considered the effect of multiple variables such as site elevation, soil condition and geographic location on the operation and productivity of equipment. Kaboli and Carmichael (2012) investigated optimum fleet size of earthmoving equipment in order to achieve minimum unit cost and minimum unit emission in earthmoving operations. The impact of equipment heterogeneity, cycle time, truck size and payload was considered on emissions and costs of equipment (Kaboli et al., 2014; Kaboli and Carmichael, 2016). In this study, queuing theory was applied to theoretically calculate the production rate of earthmoving operations. The results verified that optimal fleet size coincides with minimum unit cost and minimum unit emission, while being independent of operational parameters (Carmichael et al., 2013; Kaboli and Carmichael, 2014).

Ahn and Lee (2013) developed operating equipment efficiency (OEE) criteria to control the operations of construction equipment. OEE was defined as the ratio of valuable operation time to total operation time. Emissions produced by equipment were then formulated by linking emission factors and generalized ratio of idling to operating emission rate. Case studies proved that by maximizing the OEE of equipment involved on the site, the emissions and operation cost will be minimized. Ahn et al. (2013) introduced different techniques and approaches to predict fuel use and emissions of equipment on construction sites.

2.2.3. Techniques for Estimating Fuel Use and Emissions

Several tools and techniques have been applied to estimate fuel use or emissions of equipment by monitoring site activities and operations. The commonly used methods and techniques are reviewed as below.

- **Statistical Analysis**

Statistical analysis is one of the most common techniques used to analyze statistical and stochastic data collected from field operations. Ordinary least square (OLS) and multilinear linear regression (MLR) methods are the two main statistical methods that have been used in different studies. In such analysis, correlation coefficient or coefficient of determination (R^2) show the closeness of the data to the fitted correlation line, and are defined as the percentage of the response variable variation that can be explained by the model. Lewis and Hajji (2012) presented a model to estimate the total fuel use, unit cost, activity duration, production rate and emissions of earthwork activities. Using MLR method, the impact of different affecting parameters including soil type and hauling distance was modelled on production rate and unit cost in the project. Abolhasani and Frey (2013) applied the OLS technique to develop a modal model and estimate the exhaust flow and normalized CO_2 and NO_x emissions in different modes of equipment operations.

- **Discrete-Event Simulation**

Discrete-event simulation (DES) is an effective technique for predicting different parameters related to construction operations and jobsite conditions without having access to real data. DES tool can model the operation as the discrete sequence of events. To have better accuracy, it is essential to develop DES to assess the impact of potential affecting variables (Ahn et al., 2013). Ahn and Lee (2013) developed a DES model to predict the operation efficiency of construction equipment through breaking down the resource's task to lower level. The operation efficiency was then used to estimate the amount of fuel use and emissions of each piece of equipment. This simulation technique was also applied in the pre-planning phase of tunnelling construction to estimate the carbon footprints produced during execution processes (Ahn et al., 2010).

- **Visual Computing Techniques**

Numerous researchers have applied visual computing techniques for monitoring and documenting construction operations, as well as affecting environmental parameters (Memarzadeh et al., 2013; Heydarian et al. 2012). The processes of tracking and localization of equipment, and activity recognition are required to estimate the fuel consumption and emission rate using predefined factors (Ahn et al., 2013). Memarzadeh et al. (2013) developed an algorithm to detect and localize the excavators, trucks and standing workers from video streams on the jobsites. They applied the Histograms of Oriented Gradients and Colours (HOG + C) to speed up the detecting process. The performance of this model was validated on around 8,000 video data sets containing equipment and vehicles with a wide range of scale, background, illumination and occlusion. Heydarian et al. (2012) presented a different visual method to automatically recognize actions of construction equipment from different camera viewpoints. Most of the recent works in this field focus on activity mode recognition within the dynamic construction environments (Golparvar-Fard and Niebles, 2013).

- **Mechanical Tools**

Electromechanical devices have been used in the construction industry for measuring different site and operational parameters. For example, accelerometer is a microelectromechanical systems (MEMS) based instrument that can be installed on the equipment and measure its three dimensional accelerate rate and force. Physical activities of the vehicles can be tracked through analyzing the data collected by the accelerometers. Ahn et al. (2013) determined the operation efficiency of the equipment involved in the construction operations through analyzing the acceleration data. The emission rate of vehicles was then estimated by predefining an emission value for idling mode. Ahn et al. (2012) investigated the feasibility of using MEMS device to identify the operation modes of construction equipment. They developed a method to monitor the operation status and efficiency through analyzing vibration information. The accuracy of the mechanical-based monitoring systems was found to be further improved by considering the features of MEMS devices (Ahn et al., 2013).

2.2.4. Approaches to Modeling Fuel Use and Emissions

Approaches in fuel use and emissions modeling can be classified into four main categories, namely aggregated, parametrized, modal and simulation-based studies, as shown in Figure 2.1. In the aggregated approach, the model is developed at the simplest level and emissions are estimated roughly based on the general specifications of the vehicle (Boulter el al. 2007). The NONROAD, OFFROAD and the national atmospheric emissions inventory (NAEI) models are examples of this approach. These approaches are mainly used by governments or international organizations to have a rough estimation of fuel consumption or pollution production at national or state level. Parametrized approaches, like MODEM and digitized graz (DGV), estimate emissions more accurately through considering driving patterns. These models are used mostly for estimating the fuel use rate and emissions of light duty vehicles in the urban areas (Barlow et al. 2001, Joumard et al. 1995). They are capable of distinguishing the effect of different fuel types and engine technologies on emissions production. So the effect of driving pattern and environmental parameters on the rate of fuel use and emissions can be investigated.

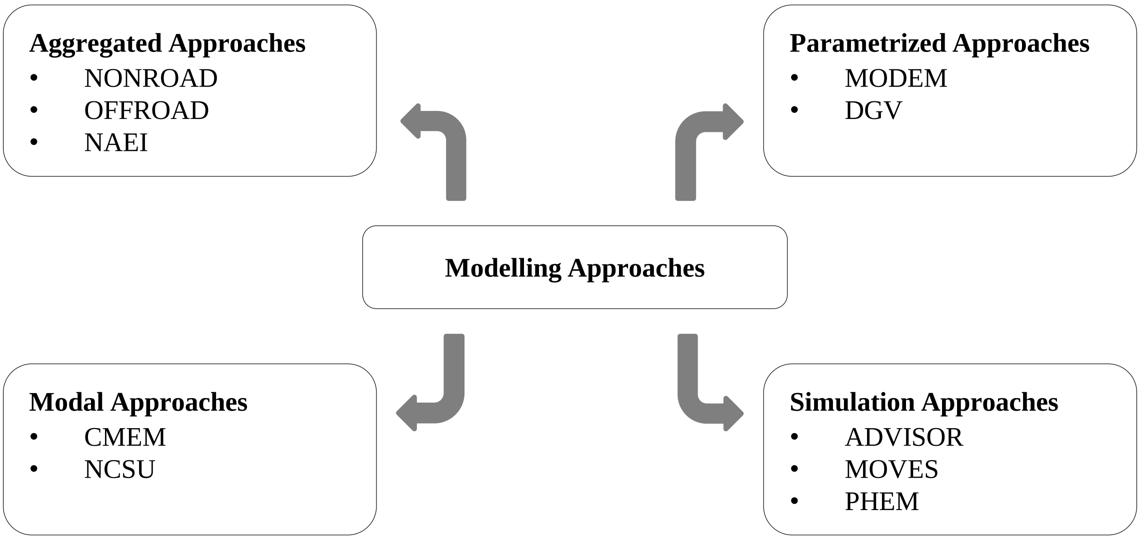


Figure 2.1. Fuel consumption and emissions modeling approaches

Modal models focus on predicting fuel consumption and emissions of vehicles in different operational modes. These models are relatively detailed and take into account the effects of engine size and engine power on energy consumption and exhaust emission rates. For instance, the model developed by Lewis (2009) in NCSU and CMEM estimates fuel use and emission rates of different equipment in idling, moving, dumping and scooping modes (Lewis et al. 2009, Boulter et al. 2007). These models consider the effect of operation features such as off-cycle driving and starting conditions. Simulation-based models such as the MOVES and the advanced vehicle simulator (ADVISOR) map different parameters, including emission rates and fuel consumption of vehicles according to driving pattern, fuel type and general engine specifications (Ahn and Lee 2013, Baulter et al. 2007). Two sets of data including vehicle definition and driving pattern are required for such models to simulate the fuel use and emissions rate. Considering different types of conventional, hybrid and electric engine technologies, these models have capability of estimating fuel economy and optimizing gear ratio to maximize the performance of the vehicle.

2.2.5. Selected Fuel Use and Emission Models

Numerous models have been developed by different international agencies and organizations to predict the fuel use and emissions rate of equipment involved in construction sites. In general, those models can be classified into two main categories of on-road and non-road models. On-road models are used to estimate fuel use and emission rates of construction vehicles that can be driven on normal roads, such as trucks, haulers and mobile cranes. By contrast, non-road models can only be applicable of off-road construction and earthmoving equipment such as loaders and bulldozers, which cannot be driven on the main roads.

Figure 2.2 shows typical fuel use and emissions models for both on-road and off-road equipment. The application of those on-road models is to estimate the GHG emission rates at vehicle, state and national levels by considering influencing variables, such as road conditions, fuel type and driving patterns. Off-road models can be used to roughly estimate the emissions at equipment, project and national level by factoring the engine power, average activity hours and equipment category and population. In the following sections, five commonly used on-road and off-road models are introduced, as shown in Figure 2.2.

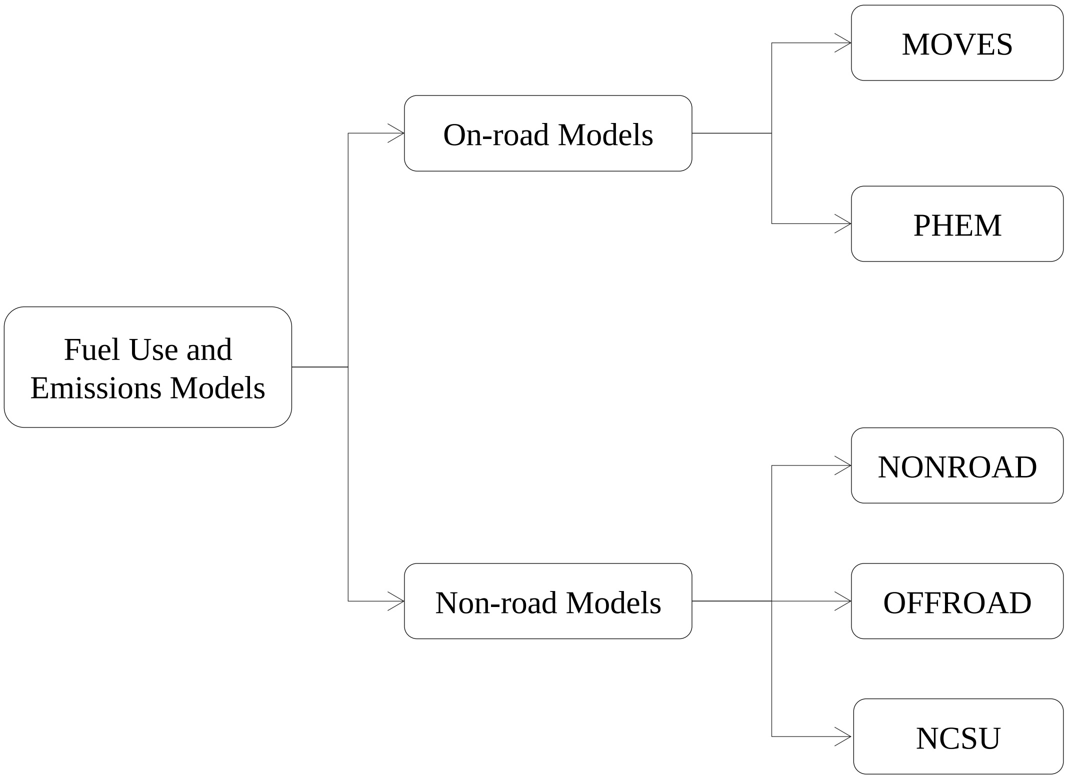


Figure 2.2. Classification of fuel use and emissions models

1) Motor Vehicle Emission Measurement Simulator Model

A motor vehicle emission measurement simulator (MOVES) model was developed by EPA in 2004 to estimate fuel use and different emissions (CO, NO_x, PM, CO_2, NH_3 and SO_2) of a variety of on-road motor vehicles (TRL, 2007). This model considers numerous parameters such as vehicle operation mode (idling, acceleration, cruising) and vehicle specific power (VSP), and derives second-by-second data from different programs such as US I/M240 and MOBILE6 (EPA, 2009). The MOVES model investigates the effect of different types of fuels on emissions, such as gasoline, diesel, CNG, LPG and also electricity. It is also adaptable to all engine technologies including internal combustion and hybrid electric engines. This simulator models the traffic condition and driving cycles in three ways of average speed, speed profile and distribution of operation mode (Oduro, 2016).

2) Comprehensive Modal Emission Model

A comprehensive modal emission model (CMEM) was developed by the cooperation of the University of California-riverside and the University of Michigan with the sponsorship of the National Cooperative Highway Research Program (NCHRP) in 1995. The main objective of designing this model is to estimate fuel use and emissions rate associated with operation modes of light-duty vehicles (Scora and Barth, 2006). CMEM simulates fuel use rate taking into consideration different readily-available parameters such as operating modes and specific vehicle factors, and calibrated parameters including fuel specifications and catalyst variables (Tate, Bell and Liu 2005, TRL 2007). As shown in Equation (2.1), the tailpipe emissions rate can be predicted by multiplying fuel consumption rate (FR), engine-out emission index ($g_{emission}/g_{fuel}$) and catalyst pass friction (CPF) (Bapat and Gao 2010).

$$\text{Tailpipe Emissions} = FR * (g_{emission}/g_{fuel}) * CPF \tag{2.1}$$

As the main limitation, this simulation-based approach is data intensive, and numerous parameters must be collected or simulated for different vehicle categories and engine technologies. Experimentation results showed that this model cannot be readily applied to the vehicle fleets in European countries prior to making some adjustments.

3) NONROAD Model

EPA (2005) developed NONROAD model to estimate the average fuel use and emission rate of different pollutants (CO_2, NO_x, SO_2, HC and PM) for more than 260 equipment pieces considering average engine power and equipment type (Lewis, 2009). NONROAD model takes into account the effect of four main parameters of equipment features i.e. load factor, engine power, average equipment activity hour and deterioration parameters on fuel consumption and emission rates (Rasdorf et al., 2012). Load factor is determined based on the operation conditions and equipment type, and presents the ratio of average used power relative to the rated power of engine. This parameter has been estimated to be 0.21 for backhoes and 0.59 for the majority of construction equipment including trucks and loaders (Caterpillar, 2015). In this model, brake-specific fuel consumption (BSFC) coefficient shows the fuel use of equipment operating at full power. BSFC varies from 0.198 to 0.22 L/hp.hr depending on engine power (EPA, 2010). Using Equation (2.2), this model estimates the emissions rate of different pollutants at state and national levels (ICCT, 2016).

$$\text{Emissions} = \sum AHP * EF * ACT * LF * POP \tag{2.2}$$

Where, AHP and LF are the average maximum rated horsepower and load factor of engine, respectively. EF is emission factor that is calculated based on deterioration or new standards. ACT and POP are the average activity hours and population of each equipment category. Table 2.4 ranks the contribution of non-road construction equipment types to GHG emissions in terms of three main pollutants of NOx, CO and PM10 using NONROAD model.

Table 2.4. EPA construction equipment ranking and contribution of NO_x, CO, PM_{10}

Equipment	NOx		CO		PM_{10}	
	Contribution	Ranking	Contribution	Ranking	Contribution	Ranking
Front-end loaders	14.5%	1	11.5%	3	11.2%	3
Bulldozers	12.5%	2	9.3%	4	9.1%	4
Excavators	11.4%	3	7.4%	5	8.6%	5
Trucks	11.0%	4	7.3%	6	6.6%	6
Backhoes	9.2%	5	16%	1	15.1%	1
Skid-steer loaders	6.2%	6	14.5%	2	13.6%	2
Generators	4.7%	7	5.1%	7	6.0%	7
Forklifts	3.9%	8	4.9%	8	4.6%	8
Scrapers	3.4%	9	2.7%	11	2.3%	12
Cranes	3.2%	10	1.5%	15	1.9%	14

4) OFFROAD Model

The California Air Research board (CARB) developed OFFROAD model to estimate emissions produced by non-road equipment at California state (OFFROAD 2007). Like NONROAD model, this model takes into consideration annual activity hours, BSFC, fuel type and engine load factors. It can predict emissions rate of 94 non-road equipment pieces in 17 classes of industry categories (CARB 2007, Lewis 2009). The OFFROAD model also considers the effects on emissions of such parameters as technology type, regulations, seasonal and temporal conditions, which were not considered in the NONROAD model (Lewis, Leming and Rasdorf, 2012). OFFROAD and NONROAD models have the similar basis and methodology in fuel use and emissions estimation. But the emission factors were developed based on dynamometer laboratory emission tests rather than field experiments, and therefore the results may not reflect the episodic nature of emissions in real-world working cycles (Barati and Shen 2015, Marshall et al. 2012).

5) North Carolina State University Model

Lewis (2009) developed a modal model to estimate fuel consumption and emissions of non-road construction equipment. The experimented equipment comprised loaders, bulldozers, backhoes, excavators, graders and off-road trucks with the engine power ranging from 70 to 306 hp. A manifold absolute pressure (MAP) parameter was developed in this model as the surrogate of engine load to investigate the effect of used power of engine on fuel consumption and emissions. Lewis (2009) divided MAP into 10 different modes and estimated average fuel consumption and emissions of CO, HC, NO_x and PM pollutants in each engine mode (Abolhasani et al. 2008). The fuel-based emission factors were developed for all investigated pollutants to estimate emissions rate based on used fuel. This model is capable of calculating the weighted-average fuel use and emissions rate factoring the fraction of time that equipment spends in each mode and engine power.

2.3. Fuel Use and Emissions Reduction Schemes

This section reviews the current strategies and schemes which have been employed in the construction sector to reduce the fuel use and emissions production of involved equipment. The previous studies in this field are first summarized. This section continues with classifying the current approaches in developing fuel use and emissions reduction strategies.

2.3.1. Previous Studies

Numerous efforts have been devoted by scholars and agencies to developing emission reduction schemes for the construction industry. Lewis et al. (2009) emphasized on mitigating GHGs emissions from construction activities due to resulting health problems and environmental damages. As the main incentive and requirement, they introduced emission taxes and governmental regulations for mandating such reductions. Many international agencies such as EPA have established technological and air quality standards to implement restrictions on the amount of emissions of non-road equipment. The technological standards impose limitations on emissions produced by equipment and engage manufacturers to build engine with higher performance level (Lewis et al. 2012, Ahn and Lee 2013). Air quality regulations are set to control the concentration of harmful pollutants in the atmosphere (Lewis et al. 2009, Kim et al, 2012).

A number of studies have sought for various means of emission reduction schemes, such as fuel changes, equipment upgrading and operator training. Frey et al. (2008) compared the emissions resulting from construction equipment running regular diesel and biodiesel fuels. Data from motor graders, loaders and backhoes performing real-world duty cycles and activities were collected in the comparative study. EPA and California Air Research Board (CARB) introduced ultra-low sulfur diesel (ULSD), and

B5 and B20 biodiesels as main alternative fuels for construction equipment. These fuels are the blend of renewable fuels made from crops with petroleum diesel which contains much lower amount of sulfur. Although these fuels may cost more up to 5%, they have contributed to a significant reduction in the emission rate of CO, HC and PM pollutants. It has been proved that the oil change interval of equipment using such biodiesel can be extended approximately 35% longer than that required for vehicles consuming normal diesel (EPA 2007).

Avetisyan et al. (2012) developed a decision model to reduce fuel use and GHG emissions from transportation construction projects. Using mixed integer programming (MIP), the optimization-based technique minimizes the emissions produced by the equipment by considering numerous parameters, e.g. machinery availability, project time, compatibility among equipment pieces and operation conditions. Kaboli and Carmichael (2014) explored the relationship between the operation cost and produced emission in the earthmoving activities using queueing technique. They concluded that by reducing emissions produced by machinery, the operation cost will decrease as well. It was also found that the minimal unit cost of emission and project cost are coincident, and this result is not dependent on operation conditions and equipment type (Carmichael et al. 2013).

EPA (2007) introduced different methods and techniques for decreasing fuel use and emissions of vehicles involved in the construction operations. In this report, the costs and benefits of implementing each strategy were evaluated in detail, and a guideline was provided to the construction firms. The case studies demonstrated that up to 45% of emissions can be decreased using the developed strategies. EPA (2008) published the results of a survey conducted by associated general contractors (AGC) on clean diesel strategies. As seen in Figure 2.3, around half of the 234 companies attended in the survey applied at least one reduction scheme on their equipment. Among those strategies employed, reducing idling time of equipment was the most common one due to not requiring any initial investment and not increasing operation cost and time.

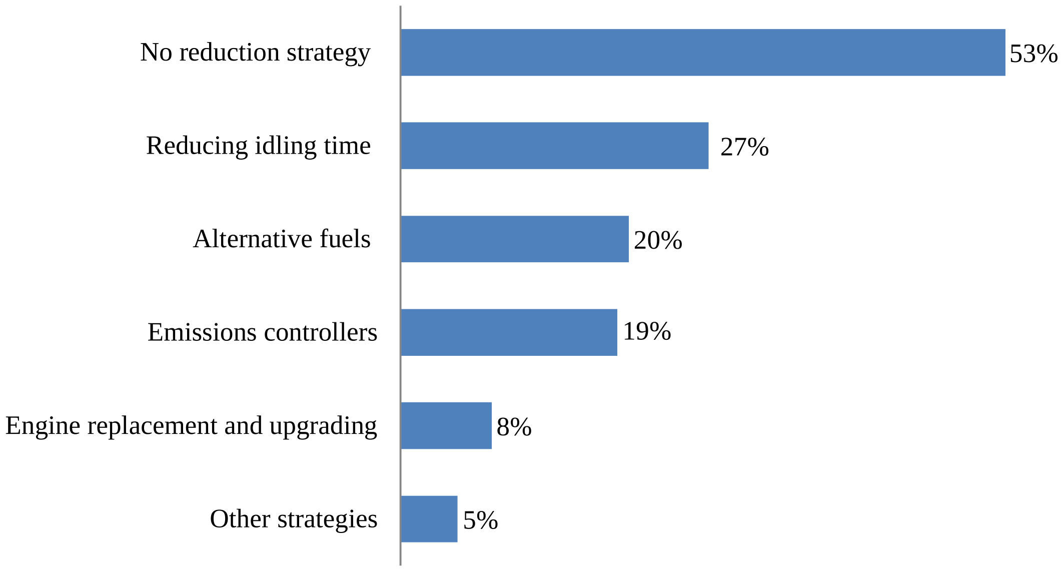


Figure 2.3. Reduction schemes applied by construction companies

2.3.2. Fuel Use and Emission Reduction Approaches

As shown in Figure 2.4, the current approaches employed in the construction industry to reduce the fuel use and emissions of equipment can be classified to four main categories of operation, engine, planning and fuel. As shown in Table 2.4, operation approaches mainly concentrate on operation and maintenance of equipment, including operator training, following optimal operation pattern, idling time reduction and regular maintenance to enhance operation efficiency and performance of equipment. These schemes rely on the skill level and experience of the operator, and noticeably decrease fuel consumption and lower emissions of machinery (Du et al. 2016). For example, by reducing one hour idling time of a middle-size construction equipment piece, approximately 3.8 litres diesel can be saved which could produce around 6.85 kg CO_2. The analysis of field experimentations conducted in real construction site indicated that around 15% of construction equipment's operation time is in idling mode (Hasan et al. 2013). Reducing idling time of equipment also leads to a significant reduction in maintenance costs and an increased engine life. Regular maintenance of machinery is another operational reduction strategy which systematically detects and corrects the potential problems of the engine. Although regular maintenance may incur some administrative costs, this strategy prolongs the equipment life and prevents engine major repairs in addition to reduced fuel use and emissions. Operator training considerably enhances the operation efficiency of equipment and reduces fuel use and emitted pollution for a specific job (EPA 2007).

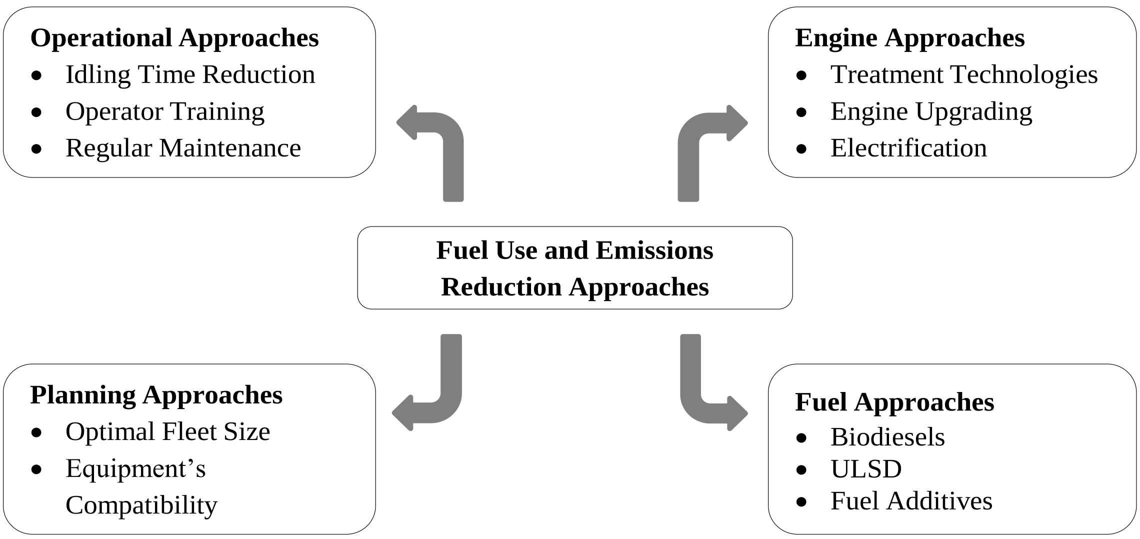


Figure 2.4. Classification of the fuel use reduction approaches in construction industry

Table 2.4. Operation strategies employed in construction sector

Strategy	Description
Idling time reduction	Causes significant reduction in fuel consumption and emissions. Increases engine life and decreases maintenance cost.
Engine regular maintenance	Reduces PM, NOx, CO, and HC emissions and lower fuel consumption. Increases equipment life and prevents high cost engine failure.
Operator training	Improves operation efficiency and reduces emissions and fuel consumption significantly.

Engine strategies consider engine replacing and upgrading schemes to reduce fuel use of equipment. These approaches improve the longevity and performance of engines, but normally need significant initial investment costs for engine modifications. These schemes include exhaust gas treatment, engine upgrading and electrification. Exhaust gas treatment devices such as diesel oxidation catalysts (DOC) and diesel particulate filters (DPF) are attached to the engine of equipment to improve the internal combustion and performance of engine (national clean diesel campaign 2007). Previous studies demonstrated that using DOCs can reduce the emissions of PM, HC and CO pollutants by 30%, 50% and 20%, respectively (EPA 2007). It is noteworthy that engine treatment technologies are applicable for all types of engines and fuels. Engine upgrading and replacement are the other strategies to repower the engines or replace older engines with more fuel-efficient ones having higher tiers (Diesel Technology Forum 2006). Electrification is another engine-related approach that employs hybrid or electric engines and uses electrical fuel cells to supply the required energy of the equipment instead of fossil fuel (Lin et al. 2010, Li et al. 2016). Also, supplying electricity from grid powers for stationary equipment like generators is a sound solution for reducing fuel consumption at construction sites (EPA 2007, Hampton 2007). In addition to substantial reduction in energy consumption, using electric engine makes site works less noisy. Table 2.5 summarizes the engine strategies used in the construction industry.

Table 2.5. Engine strategies employed in construction sector

Strategy	Description
Treatment Technologies	Physically traps diesel particulates and prevents their release into the atmosphere and can reduce PM emissions, but the total NOx emissions remain unchanged for diesel oxidation catalysts.
Engine upgrading and replacement	Reduces PM, NOx, CO, and HC emissions and lower fuel consumption. Improves engine reliability and lower maintenance costs.
Electrification	Reduces huge amount of PM, Nox, CO, and HC emissions. Hybrid electric vehicles have substantially lower energy use.

Planning strategies concentrate on management of resources and machinery so as to reduce total fuel consumed in construction projects, as listed in Table 2.6. Compatibility in the size and number of equipment involved on sites is one of the main areas of planning that has substantial effects on operation and fuel efficiency of equipment (Ahn and Lee 2013). The result analysis on case studies conducted in earthmoving operations indicated that the unit cost and unit fuel and emission are coincidently minimal at optimal fleet size of equipment involved in the construction sites (Kaboli and Carmichael 2014, Carmichael et al. 2013). Optimal selection of equipment considering the workload, job conditions and regulation restrictions is a primary planning scheme that considerably influences the fuel use, emissions and cost of the project (Avetisyan et al. 2012). This approach is a decision-making process to select the optimum size and number of equipment from the available machinery for a given construction project.

Table 2.6. Planning strategies employed in construction sector

Strategy	Description
Compatibility between equipment pieces	Increases the operation efficiency of equipment by decreasing idling time, and reduces emissions and fuel consumption. Less equipment pieces are needed for doing specific task.
Optimal equipment selection	Reduces the fuel use, emissions and costs of construction operations by selecting equipment pieces with higher engine tiers and increasing compatibility between involved equipment.

Fuel strategies also have considerable impact on reducing energy consumption and emitted pollutants of construction equipment without incurring any major investment. Changing fuel blends and alternative fuels are two most common practices for emissions reduction. Diesel fuel can be blended with components like Puri NO_x and Biodiesel rather than hydrocarbons to increase fuel performance. Biodiesels are the most common fuel blends that are made from renewable and biotic materials like cottonseeds and cooking grease. Natural gas, propane and hydrogen compressed natural gas (HCNG) are the alternative fuels can be used by construction equipment to reduce the amount of pollutants. Based on the research conducted in this field, using these types of fuels can dramatically decrease energy consumption and emission rates without incurring any significant extra cost (EPA 2007).

Table 2.7. Fuel strategies employed in construction sector

Strategy	Description
Biodiesel	Derived from renewable sources such as vegetable oil, animal fat, and cooking oil. Reduces HC, PM, and CO emissions but produces more Nox emissions. Compatible for use with high-efficiency catalytic emissions–reduction technology.
Ultra-low sulfur diesel	Reduces PM emissions and engine wear, corrosion and deposits. Enables the use of advanced technologies to reduce emissions.
Fuel additive	Can reduce Nox, HC, PM, and CO emissions and improve fuel economy. Some additives might increase one or more pollutant emissions while reducing other pollutant emissions and increasing fuel efficiency

2.4. Weight Estimation of Construction Equipment

Construction sector is one of the main industries requiring a large number of different construction vehicles. Majority of construction activities associated with earthmoving operations involve cut and fill activities and commonly employ heavy-duty vehicles (HDVs) for materials transportation. Since those activities are planned and paid based on the amount of materials moved, measurement of the payload and volume of materials carried by vehicles as payload is a necessary process. As the main concern of contractors and equipment operators, a cost-effective, automated method is essential to be developed to accurately estimate vehicles' payload.

Measurement of gross vehicle weight (GVW) is a crucial issue in the field of transportation. Overloading and increasing equivalent single axle load (ESAL) result difficulties in vehicle's maneuverability, heavy traffic accident and short vehicle life (Yang et al. 2008). ESAL is determined based on pavement condition and its failure mode, which is one of the main parameters causing distress and damage of pavements and bridges (Haidar and Harichandran 2007). Overweighting also causes serious damages to pavement conditions and increases the risk of overloading and failure of the bridges (Ojio et al. 2016). Three main parameters of annual average daily truck traffic (AADTT), percentage of trucks and ESAL are taken into consideration in designing and constructing pavements and bridges (Faruk et al. 2016). According to National Cooperative Highway Research Program (NCHRP), the distribution of weight over different axles is also a key factor in road and pavement design (NCHRP 2006). Therefore, the accurate and efficient weight estimation to minimize heavy vehicles' overweighting is essential in order to reduce the potential damages to infrastructures.

Previous studies found that HDVs account for 79% of damages to roadway pavement (Faruk et al. 2016, Refai et al. 2014). Many international agencies such as American Association of State Highway and Transportation Officials (AASHTO) and Federal Highway Administrations (FHWA) have implemented restrictions and regulations to reduce the ESAL of HDV vehicles (Vaziri et al. 2013, Fiorillo and Ghosn 2014).

Different guidelines have also been developed based on the bridge design formulas by several organizations, like American Transportation Research Board (TRB) and National Association of Australian State Road Authorities (NAASRA), to control the GVW and internal axle weight distributions of HDVs in order to prohibit overstressing of bridges (Moshiri and Montufar 2016).

However, despite the high demands for accurate and fast weight measurement methods, the current weighting systems used in construction sector are time consuming, error prone and typically associated with high initial and operational cost. As the most common practice, weighbridges are widely used in the construction sites which require high installation and operation costs. The time required for weight measurement would affect the production rate of the equipment and the cost of project execution. The state-of-the-art volumetric measurement methods provide fast measurement but fall short of accuracy due to conversion from volume to weight.

In this section, studies conducted in the field of weight and payload measurement of construction equipment have been comprehensively reviewed. The regulations and standards are also introduced as the main motivation and incentive for restricting the weight of on-road heavy duty vehicles. The previous investigations for measuring the vehicle weight are reviewed and evaluated. This section continues with introducing all techniques and methods currently used for estimating the weight of heavy machinery.

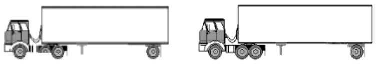
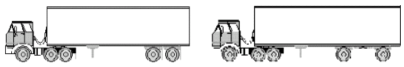
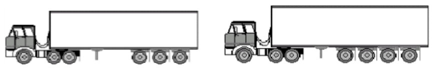
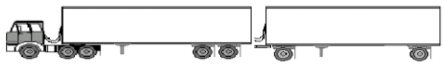
2.4.1. Weight Regulations

Governmental and international weight regulations are the main incentives for measuring and controlling the weight and size of construction equipment. Different countries may develop their own guidelines and standards based on their restrictiveness level to prevent highway infrastructures from excessive damages and to improve transportation productivity and safety (Moshiri and Montufar 2016, OECD 2011). The key parameters concerned by those regulations include GVW, ESAL, vehicle length, number of axles and spacing between axles. As shown in Table 2.8, based on axle configuration (single, tandem, tridem and quad) and number of trailers, FHWA categorized heavy vehicles into 9 different classes (Federal Highway Administration 2001). HDVs not fitting in those classes can be grouped in an additional Class 14. On the whole, FHWA categorizes all vehicles to 13 groups with classes' 1-4 for light vehicles. Based on the class, operators must follow gross vehicle weight rating (GVWR) which is the total vehicle weight plus payload and fuel weight. Also, considering axle configuration and spacing among axles, the ESAL should not exceed a certain amount in each class. Similarly, Austroads (2006) grouped HDVs into 10 categories based on the length and axle configuration parameters.

Bridge formulas are the other performance-based standard protecting bridges and pavements by calculating the maximum allowable weight of different axle series in order to limit the imposed stress and moment. Configuration of truck, axle series type, design load, maximum load rating and bridge design method are the criteria taken into account in the development of bridge formulas. Currently, six countries have implemented limitations on trucks' weight based on the bridge formulas, including

Australia, Canada, Mexico, New Zealand, South Africa and the United States (Moshiri and Montufar 2016). The devised formulas are different due to restrictiveness level of countries and type of vehicles, and can only be used for single-span bridges that need to be modified for the application in multi-span ones.

Table 2.8. List of FHWA classes for heavy vehicles

Class	Description	Vehicle Profile
5	Two-Axle, Six-Tire, Single-Unit Trucks	
6	Three-Axle Single-Unit Trucks	
7	Four or More Axle Single-Unit Trucks	
8	Four or Fewer Axle Single-Trailer Trucks	
9	Five-Axle Single-Trailer Trucks	
10	Six or More Axle Single-Trailer Trucks	
11	Five or Fewer Axle Multi-Trailer Trucks	
12	Six-Axle Multi-Trailer Trucks	
13	Seven or More Axle Multi-Trailer Trucks	

For the first time, U.S. Bridge Formula B was implemented in 1974 with the maximum allowable weight of 36.4 tons considering the number of axles and distance between them (Federal Highway Administration 2015). This formula received much criticism since introduction and has been revised and amended for several times. In 1994, Austroads proposed a bridge formula considering the overstressing limit imposed by the

Bridge Engineering Committee of the National Association of Australian State Road Authorities (NAASRA). The objectives of the formula were to optimize the distribution of longitudinal loads and to improve the design and operation of vehicles through limiting the internal weight, which considered length and class of vehicle, axle spacing, type of route and bridge.

2.4.2. Weight Measurement Techniques

Currently, several techniques and tools are employed in construction industry to measure the weight and payload of equipment and vehicles. These methods can be classified into metric and volumetric measurement systems.

Metric measurement systems are commonly used in construction industry, which directly weigh the payload or total weight of equipment using various instruments and sensors. Weighbridges are mostly used to measure the total weight including the vehicle weight and the payload. Despite the high accuracy in weight measurement, this method incurs high initial, operation and maintenance costs and is also time consuming. Axle hydraulic and pneumatic pressure controlling is another system for automatically weighing the payload of HDVs using pressure sensors (Faruk et al. 2016). 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 weight analysis.

Volumetric techniques measure the volume of the materials inside the tray or bucket of vehicles through automatically scanning and comparing the empty and loaded equipment. Volumetric methods are non-contact and cost effective with relatively low initial and maintenance cost, but may not be accurate enough in weight measurement of bulk material (Ojio et al. 2016). In this process, vehicles need to move slowly under the load volume scanners (LVS) installed on the construction sites before and after loading (Load Management Solutions 2017). Figure 2.5 illustrates the working process of load volume scanners. By having swelling factor and density of the loaded material, the weight and in-situ volume of the materials can be estimated.

Figure 2.5.Working procedure of load volume scanner (LoadScan, 2017)

On-board pressure sensors are also extensively used to accurately measure the weight carried in the truck tray. 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 which can be processed to determine the load (Haider and Harichandran 2007, NCHRP 2006). As another metric technique, strain gauges can be pasted on the leaves of springs to measure suspension strain caused by the payloads (Refai et al. 2014). The weigh is then estimated through summing up the received voltage signals output by the strain gauges. Despite the applicability of the method for all types of vehicles, installation of the strain gauges and sensing system to existing vehicles can be inconvenient and costly.

2.4.3. Recent Studies and Development

Some new techniques and tools have been devised by scholars and researchers to measure the GVW and payload of construction equipment in recent years. Normann and Hopkins developed a weight-in-motion (WIM) technology using reinforced concrete slabs and strain-gauge load cells (Vaziri et al. 2013). According to the American Society for Testing and Materials (ASTM) (Fiorillo and Ghosn 2014, ASTM 2009), WIM system is a set of sensors and instruments which are capable of measuring dynamic tire force, axle spacing, speed, time and wheelbase, and process the data without interrupting the regular traffic flow. The sensors and transducers can be attached to road surface as portable measures or permanently embedded within the pavement (Stergioulas and Ceban 2000). Currently, WIM systems are equipped with automatic vehicle identification (AVI) technology helping to identify overweight vehicles (Cambridge Systematic 2009, Huang and Chan 2012). Ojio et al. (2016) developed a contactless bridge WIM (CBWIM) system to weigh the vehicles without needing any instrumentation on the bridges. Two cameras and a telescope were applied to measure the deflection of bridge and monitor traffic flow and axle spacing. As the main advantages of this approach, the CBWIM system is portable and can be quickly implemented to a new bridge.

Strain gauges and wireless vehicle weight measurement systems (WVWMS) are the other techniques available for automatic vehicle weight estimation.. Yang et al. (2008) attached the strain gauges to the leaf springs of vehicle suspensions and calculated the payload of vehicle based on output voltages of circuits. As the main limitation, the resulting errors are quite large because the leaf springs may not fully recover to the original position before loading again. Xiao et al. (2006) instrumented the longitudinal ribs of a box-girder orthotropic bridge using strain gauges to estimate the ESAL of trucks. The weight of different axles was calculated by developing influence line of flexural stress and moment at two mid spans and supports in the length of bridge. Using WVWMS, Andrzejczak et al. (2014) designed a measurement board (DAW100) and truck recognition system (TRS) to be embedded on the pavement surface. Srinivas et al. (2006) simulated and modeled multivariate ESAL of common vehicle types based on copula approach which took into consideration the axle spacing and vehicle configuration.

2.5. Conclusion

In this chapter, a comprehensive review on studies and efforts relevant to this research has been presented. It starts with reviewing the fuel use and emissions regulations, monitoring techniques and estimation methodologies. The models applicable for estimating fuel use and emissions of different on-road and non-road vehicles were introduced. This chapter continued with categorizing different approaches in modeling fuel use and emissions. Current techniques and schemes used by construction firms to reduce fuel use and emissions were then introduced extensively.

The last section of the chapter reviews different methods and techniques employed for measuring or estimating payload and equipment’s weight. The current regulations and restriction imposed by the local governments were also introduced, followed by a critical review on various volumetric and metric weight estimation techniques. Finally, recent development in modeling the weight of equipment has been covered.

Limitations in the field of modeling fuel use and emissions rate of construction equipment have been identified after conducting the comprehensive literature review. The current models mainly focus on estimating fuel use and emissions at macro level, which fail to measure the fuel use and emissions at micro level or equipment level. As the other disadvantage of current models, they have low accuracy in measuring fuel use and emission production which may not be acceptable in construction applications.

There is also a lack of comprehensive schemes and strategies that can be used to reduce fuel use and emission production of construction vehicles at operation level. It is also found some qualitative guidelines developed so far are not sufficient for construction applications..

On the other hand, automatic weight measurement is still a challenging issue in earthmoving operations which needs further investigation. Currently, weighbridges are commonly used in construction sites which are considered to be time consuming and costly. They would slow down the production rate and increase operational cost of construction projects. The volumetric methods are available for weight estimation. Unfortunately, those solutions fall short of accuracy due to conversion of volume to weight by factoring average density of loose construction materials.

Chapter 3

Monitoring Equipment Operations through Instrumentation

3.1. Introduction

This chapter presents a comprehensive framework that has been devised in this study to monitor field operations of construction equipment through instrumentation. The methodology will be applied to model fuel consumption and emissions rate of on-road construction equipment at operation level. It is also used to develop an integrated model to estimate the weight of on-road construction trucks and haulers considering operational parameters. The proposed data monitoring system further facilitates developing operational level strategies to reduce fuel use and emissions of construction vehicles.

Figure 3.1 presents the proposed framework in this research. The experimental studies consist of two principal steps of real-world data collection and statistical data analysis. The operational and environmental parameters, and engine attributes affecting fuel use rate and emissions are first identified. Construction vehicles selected for experimentation are then described. This chapter continues with introduction to the instrumentation system that has been implemented to collect field data as required for the study. Data collection process is then explained followed by a discussion on the problems encountered in the field data collection. Data quality assurance is finally developed to validate the quality of gathered raw data and remove potential errors. The processed data are used in the next chapters to develop the fuel use, emissions and weight estimation models for on-road construction equipment.

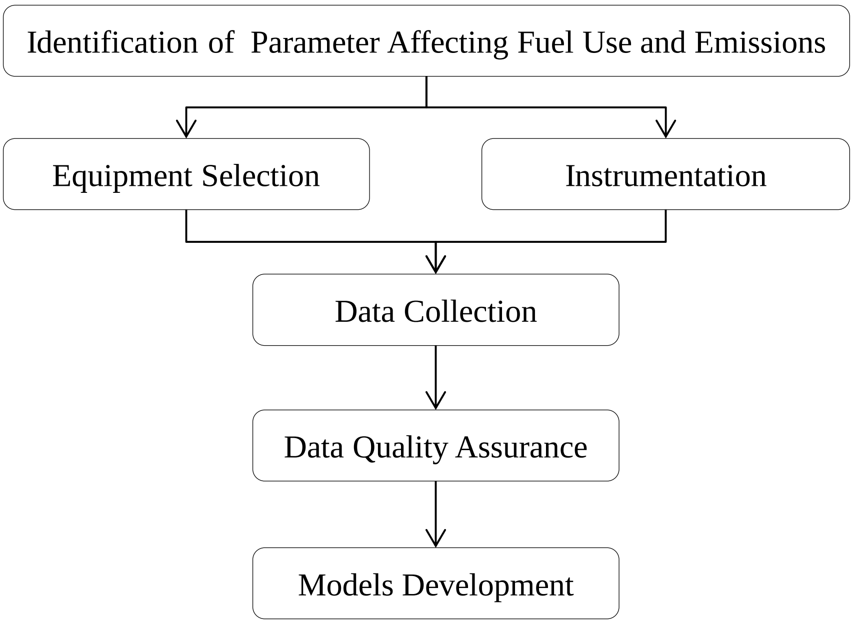


Figure 3.1. Developed data monitoring system for modeling fuel consumption, emissions and weight of construction vehicles

3.2. Identification of Parameters Affecting Fuel Use and Emissions

There are numerous parameters influencing fuel consumption of construction equipment. Lewis (2009) introduced engine parameters including size, load, age and tier of engine as the major affecting factors on fuel consumption and emissions. Oduro et al. (2015), through conducting extensive laboratory chassis dynamometer tests, determined acceleration, engine power, and ambient temperature as factors influencing fuel use and emissions rate of light duty vehicles. EPA (2005) considered the effect of average load factor, engine power and fuel type in the NONROAD model to estimate fuel use and emissions rate of different machinery types at equipment level. Similar to NONROAD model, CARB (2007) took into consideration the effect of fuel type, BSFC, annual activity hours and engine technology in OFFROAD model to estimate the emissions produced by 94 types of non-road equipment in the California state of the USA.

As illustrated in Figure 3.2, this study classifies the parameters investigated in the study into four main categories of operational parameters, engine attributes, environmental factors and fuel type. Each category of affecting factors is described in the following sections.

Figure 3.2. Classification of parameters considered in the process of monitoring field equipment operations

3.2.1. Operational Parameters

Acceleration rate, speed and vehicle's weight have been identified as operational parameters influencing fuel use and emissions rate of construction equipment. By accelerating the vehicle, more power of engine is used thus increasing the fuel consumption and consequently emissions production. The analysis indicated that compared to other operational parameters, acceleration rate has the highest influence. Instantaneous travel speed of vehicle is another operational variable having direct effect on fuel use and emissions rate.

The weight of vehicle was investigated as the other operational parameter impacting used power of engine and fuel consumption. Analysis on the field collected data demonstrated that this parameter does not have direct relationship with imposed load on engine and fuel use rate, but it indirectly impacts the effect of other investigated parameters on engine load and fuel use. In this study, weight of equipment is defined as total weight including the weight of vehicle itself plus the weight of payload and trailer(s).

3.2.2. Environmental Factors

Numerous environmental factors were identified to have impacts to fuel use and emissions rate of construction equipment. Slope of the road was considered as the main environmental variable in this study that affects the power of engine output significantly. The slope of roads varies in the flat areas between -5 and 5 degrees, but in mountainous regions, it can rise to over 15 degrees. The effect of road slope can be interpreted as gravitational force resisting or assisting the movement of vehicle.

Atmospheric pressure and ambient temperature are the other two environmental variables affecting fuel use rate of vehicles. The initial analysis on the data collected from construction sites in Australia and Iran with different ambient pressure and temperature indicated that the two parameters have negligible effect on fuel use rate which therefore were not considered in this study.

3.2.3. Engine Attributes

In this study, engine specifications were identified as the major parameters affecting fuel use and emissions of vehicles. The three main attributes of engine including load, size and tier of engine were investigated, with their effects on consumed fuel modelled. Engine load is the percentage of used power of engine and is defined as the ratio of the used power over the maximum available power of engine. Construction equipment rarely works at full engine load. Average engine load of equipment for most activities is between 25% and 75% (Nichols and Day 2005). Typically, the engine load for construction machinery varies from approximately 15% in idling mode to around 95% for most demanding activities.

Tier classification is defined based on the size and model year of the engine. Engines with higher tier should provide better performance thanks to the more stringent standards imposed. European Union has developed the EU I to VI standards for heavy duty on-road diesel engines which are also commonly adopted globally. The EU I standard was implemented in 1992, and all engines manufactured after this year must obey the specific emissions restriction. The EU VI, the latest tier for on-road vehicles was issued in 2014, but currently is imposed within European Union countries only. As was mentioned before, all non-road equipment including off road construction machinery should follow engine Tiers 1 to 4 developed by EPA.

Engine size is one of the main attributes that has significant effect on fuel consumption and consequently emissions rate. The size of engine is normally measured in horse power (hp) or kilowatts (kW) (1 hp = 0.7457 kW). kW has been selected as the standard unit of engine size in this study. The engine size of on-road construction vehicles typically ranges from 170 - 450 kW.

Engine age can be considered as another engine attribute affecting fuel use. As engines become older, they get more deteriorated with decreased efficiency. Therefore, old engines use more fuel to produce required force (Nichols and Day 2005; Lewis 2009). The experimental studies have shown that engine age does not have significant influence on fuel use. In this study, due to negligible effect of this parameter on fuel use, engine age was not investigated.

3.2.4. Fuel Type

As was discussed in the previous chapter, a variety of fuels can be used by construction vehicles. Based on the type of the fuel and its ingredients and additives, fuel use rate will be different. The emissions produced from burning the fuels are also different. For example, in comparison with diesel, biodiesel fuels produce less CO_2, CO and HC, but produce significantly more NO_x pollutant. Construction equipment mainly uses diesel fuel in their lifetime with minor changes made in the ingredient. Therefore, this research has focused on diesel fuel for experimentation and modeling development.

Figure 3.3 summarizes the groups of parameters investigated in this study in modeling fuel use, emissions rate and weight of construction equipment. Three engine attributes including load, size and tier were also taken into consideration in modeling fuel use and emissions of on-road construction vehicles. It is noteworthy that this study only investigates the effect of diesel fuel in developing the models, but the proposed research framework can be readily applicable for other fuel types in future studies.

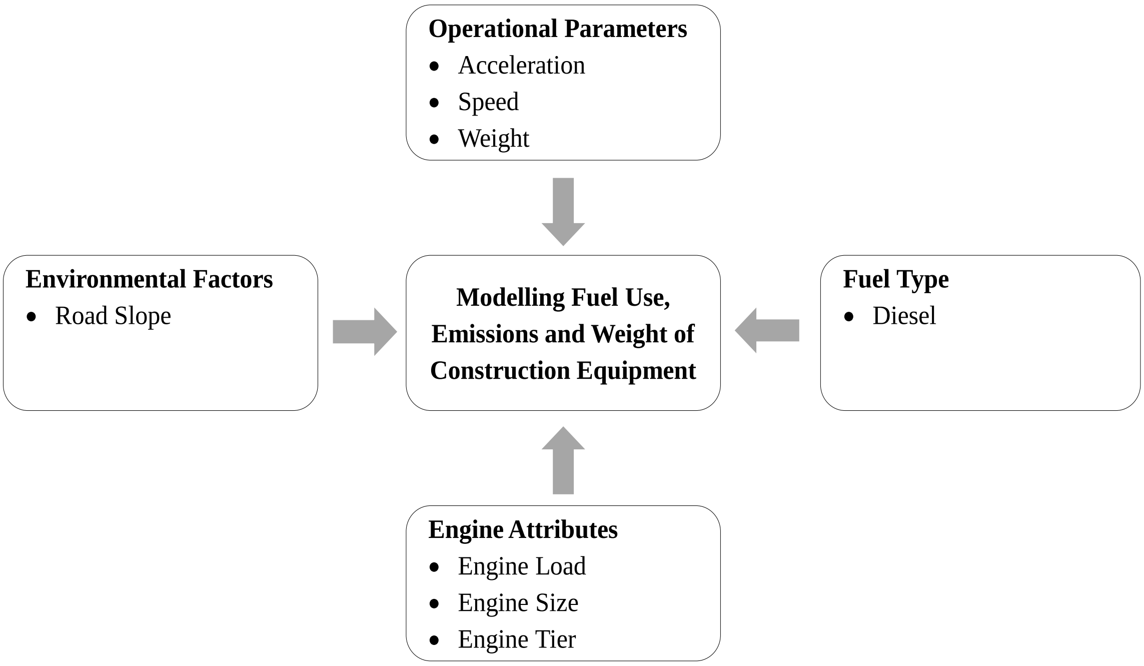
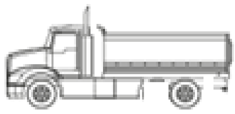
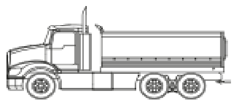
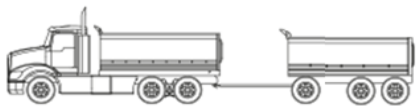
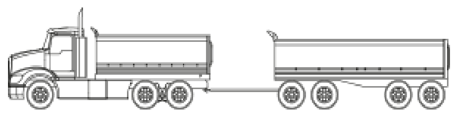


Figure 3.3. Parameters investigated in modeling fuel use, emissions rate and weight of on-road construction equipment

3.3. Equipment Selection

Earthmoving operations including transporting construction materials are one of the main sources of fuel consumption and emissions production in the construction industry. Due to the primary role of on-road vehicles in such operations, this study has focused on developing operational level fuel use model and fuel reduction schemes for on-road equipment. The report published by EPA shows that trucks are one of the major contributors to pollutants production in construction sector due to high use of energy and their high applicability on sites (EPA 2005). Based on classification performed by the FHWA, on-road vehicles can be categorized into 13 classes including all light-duty and heavy-duty vehicles (Maricopa Association of Governments 2007). As construction equipment is typically considered as heavy-duty vehicles, wide range of vehicles in different classes of 5, 6, 12 and 13 have been selected to be experimented in this study, as listed in Table 3.1.

Table 3.1. Class and description of vehicles used for experimentation

Class	Description	Vehicle Profile
5	Two-axle truck	
6	Three-axle truck	
12	Six-axle truck with a trailer	
13	Seven-axle truck with a trailer	

Currently, the engines of nearly all of the construction vehicles can be classified in three main tiers of Euro III, IV and V. A variety of construction equipment has been selected for the experimental studies which covers engines with all of the three different tiers. The equipment was also chosen from different model years from 2005 to 2013 considering different levels of equipment deterioration. Figure 3.4 and Table 3.2 present sample photos and specifications of the experimented equipment including tier, size and model of engine, and empty weight.

(a) (b) (c)

Figure 3.4. Vehicles selected for experimentation, (a) three-axle truck without trailer (Class 6), (b) six-axle truck with a trailer (Class 12), and (c) seven-axle truck with a trailer (Class 13)

Table 3.2. Specifications of equipment used for experimentation

Vehicle	Tier	Engine Size (kW)	Model (year)	Empty Weight (ton)
Two-axle Benz	III	180	2005	6.5
Three-axle Granite	IV	345	2010	9.5
Three-axle Trident	V	400	2013	11
Six-axle Granite	IV	345	2010	14.5
Six-axle Trident	V	400	2014	17.7
Six-axle Vision	III	350	2005	17.6
Seven-axle Granite	IV	345	2010	16.6
Seven-axle Trident	V	400	2013	18.8

3.4. Instrumentation

In the previous sections, different operational parameters and engine attributes were identified as affecting factors on fuel consumption and emissions rate. A wide range of equipment was also selected for the experimental studies. Different instruments are needed to collect required data of identified parameters from selected construction equipment. After reviewing state-of-the-art technologies available in the market, four instruments were developed in this study to collect real-world operational, engine and fuel use data from on-road construction vehicles.

As shown in Figure 3.5, portable emission measurement system (PEMS) is the main instrument used in this study. PEMS measured live emission rates of CO_2, CO, HC and NO_x pollutants from equipment. PEMS was installed inside the cabin of the equipment and measured pollutant emission rates using a sampling probe inserted into the exhaust. The sampling probe is connected to the main unit through the tube.

(a) (b)

Figure 3.5. The PEMS used to collect emissions data from equipment: (a) the main unit of instrument, and (b) sampling probe inserted into the exhaust

The PEMS utilized in this research is MEXA-584L automotive emission analyzer manufactured by HORIBA Ltd. This instrument has the capability of simultaneously measuring non-dispersive infrared (NDIR) gases and showing results in the LCD display. As the main advantage, this devise was compact, lightweight (approximately 4 kilograms), and efficient for all working conditions. PEMS provides different options to measure the engine speed, O_2 and oil temperature as well. To supply the required power (220 volt), an inverter was used to amplify the electricity of cigarette plug within the vehicle's cabin. Before conducting experimentation on the vehicles, the PEMS needed 5 minutes for warming up, and after each testing, the system should be calibrated and all filters need to be replaced.

GPS-aided inertial navigation system (GPS-INS) was the main instrument adopted in this research to collect operational and environmental parameters. This device is an attitude and heading reference system (AHRS) that provided accurate position, speed, acceleration and orientation under the most demanding conditions using accelerometers, gyroscopes and magnetometers. GPS-INS collected real-time data of three operational parameters of acceleration rate, speed and road slope. The GPS-INS employed in this study was SPATIAL-EK manufactured by the Advanced Navigation Pty Ltd. The accuracy of the utilized GPS-INS in position, speed and slope measurement is 2 m, 0.05 m/s and 0.2 degree, respectively. Figure 3.6 shows the GPS-INS instrument used in this study.

(a) (b)

Figure 3.6. GPS-INS instrument used in this study, (a) main unit, and (b) GPS antenna

This GPS-INS instrument is installed inside the cabin of equipment on a levelled surface. In order to increase the accuracy of measurement, the GPS-INS should be fixed on a surface with minimum vibration and without any lateral movement. GPS-INS measures the orientation of the vehicle in three different directions which are also known as Euler angles. The rotations around axes X, Y and Z are named as roll, pitch and heading, respectively. The GPS-INS instrument was installed in a way that X axis points to the direction of vehicle's movement, and pitch measured the slope of road.

The GPS antenna of the instrument is connected to the main unit via wire. For having better accuracy and satellite signal reception, the antenna was mounted on the roof of cabin. During experimentation, the data collected from inside the tunnels of city center areas were removed due to low performance of the GPS-INS instrument and potential measurement errors.

Engine data logger is an on-board diagnostics (OBD) instrument used in this study to collect real-time data of engine attributes, fuel use rate and air flow rate of exhaust, as shown in Figure 3.7. It was plugged into the J1939 port of the equipment's engine control unit (ECU) under the steering wheel and measured engine load and fuel use rate data on a second-by-second basis. This devise has the capability of measuring more than 30 variables related to engine attributes and operation modes. It is noteworthy that only two parameters of engine load and instantaneous fuel use rate have been used in this study. The engine data logger used in the research is Bluefire Data Adaptor 9 pin which was connected to the diagnostic plug of vehicle and sends equipment’s computer information to mobile phone or laptop via Bluetooth. Since majority of construction vehicles are equipped with the J1939 port, the engine data logger would be a suitable device for collecting engine data.

Figure 3.7. Engine data logger utilized for collecting engine and fuel data

An industrial tablet PC (shown in Figure 3.8) was used to store, synchronize and analyze the data collected by the other instruments. Using Microsoft Excel software, the data collected from different instruments were stored and compiled in the database at the same time. The model of utilized tough pad is Panasonic FZ-G1 running Windows 8 Operation System. This device was light, portable and rugged with long battery life which made it an appropriate PC for field experimentations.

Figure 3.8. Industrial tough pad used to store measured data

The data collected by PEMS were transmitted to the touch pad through the RS232 port. The tough pad was also used to activate, monitor and control the PEMS device. The MEXA communication software installed on the tough pad imported measured data as a CSV format file. The live data measured by GPS-INS instrument were transmitted through the universal serial bus (USB) data communication port to the tough pad. Spatial Manager V4.5 was installed on the tough pad to control the functionality of the GPS-INS, and convert the recoded raw data into CSV format file. The recorded data of the Bluefire engine data logger were transmitted to the tough pad through Bluetooth in each second. BlueFire for Truck Global Edition App was installed on the tough pad to communicate with the engine data logger and import the measured data. Figure 3.9 demonstrates the integration among different instruments and their communication types. The variables measured by each instrument were also indicated in Figure 3.9.

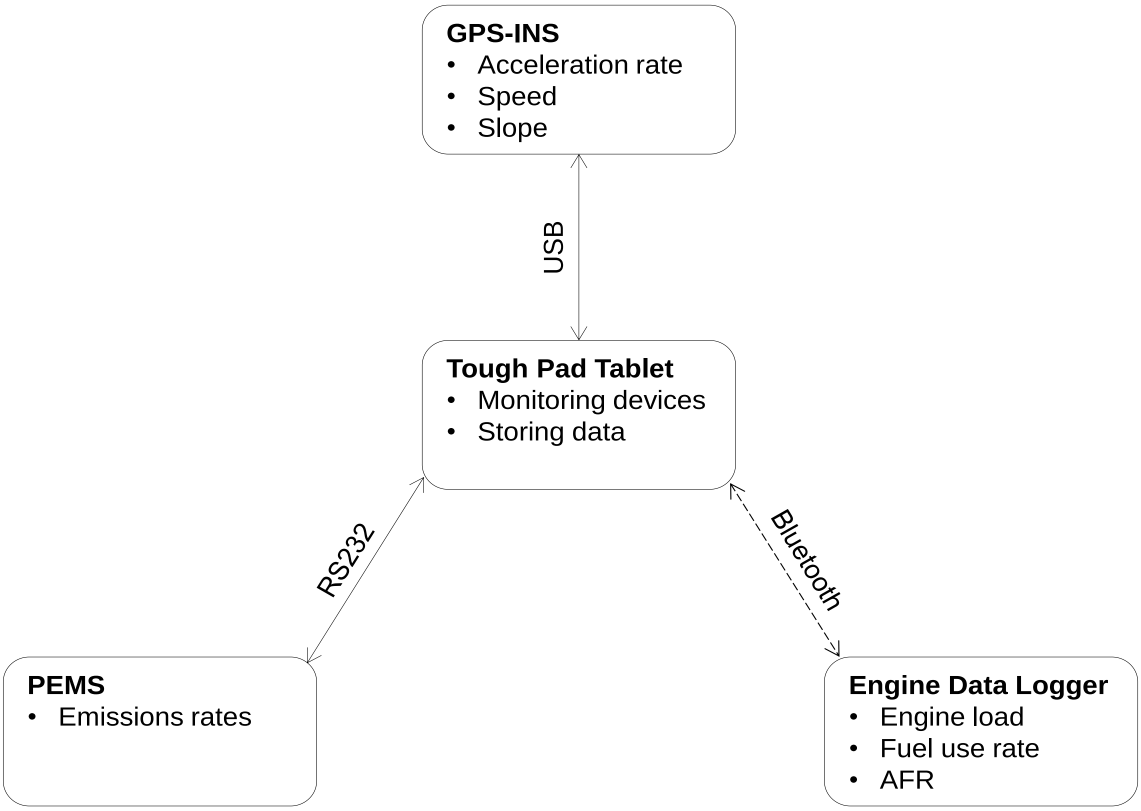


Figure 3.9. The integration and communication among various instruments

3.5. Data Collection

This section presents the procedures of data collection adopted in this study. This phase includes several steps of site observation, instrumentation, experimentation and vehicle data collection. It took around 30 minutes for system installation in each testing. The ECU port was first checked and the engine data logger was then plugged in the ECU port. In this step, all instruments were also set up and connected to the tough pad to collect, monitor and store the raw measurement data. Due to security concerns, the process of installation and data collection for one specific test were conducted in one day, and all instruments were decommissioned at the end of the day after experiments.

The procedures of site observation and experimentation were conducted at the same time. The equipment specifications including size, tier and model of engine and the empty weight were obtained from the vehicle’s catalogue. A video camera was also used to record the operation patterns, modes of experimented equipment and site conditions. In this study, the experimentation process was carried out in two stages of preliminary testing and field experimentation as explained below.

3.5.1. Preliminary Testing

Preliminary tests were carried out on selected light-duty construction trucks to verify the performance of instruments and to develop the methodology and framework of the study. Using the data collected from the testing, an integrated mechanism was developed for data processing and synchronization procedures. The results indicated that data measured by PEMS were delayed by around 8 seconds to engine data retrieved from the engine data logger. This could be caused by having a 5 m long sampling tube and the time required for gas analysis in PEMS. The data obtained from the preliminary experiments were also analyzed to develop the initial fuel use, emissions rate and weight models.

The preliminary field testing was conducted on in-use equipment involved in the construction sites to represent the real working conditions. Eight preliminary experiments were conducted on five construction trucks for collecting preliminary data. The model of vehicles varied from 2001 to 2012, and their engine size ranged between

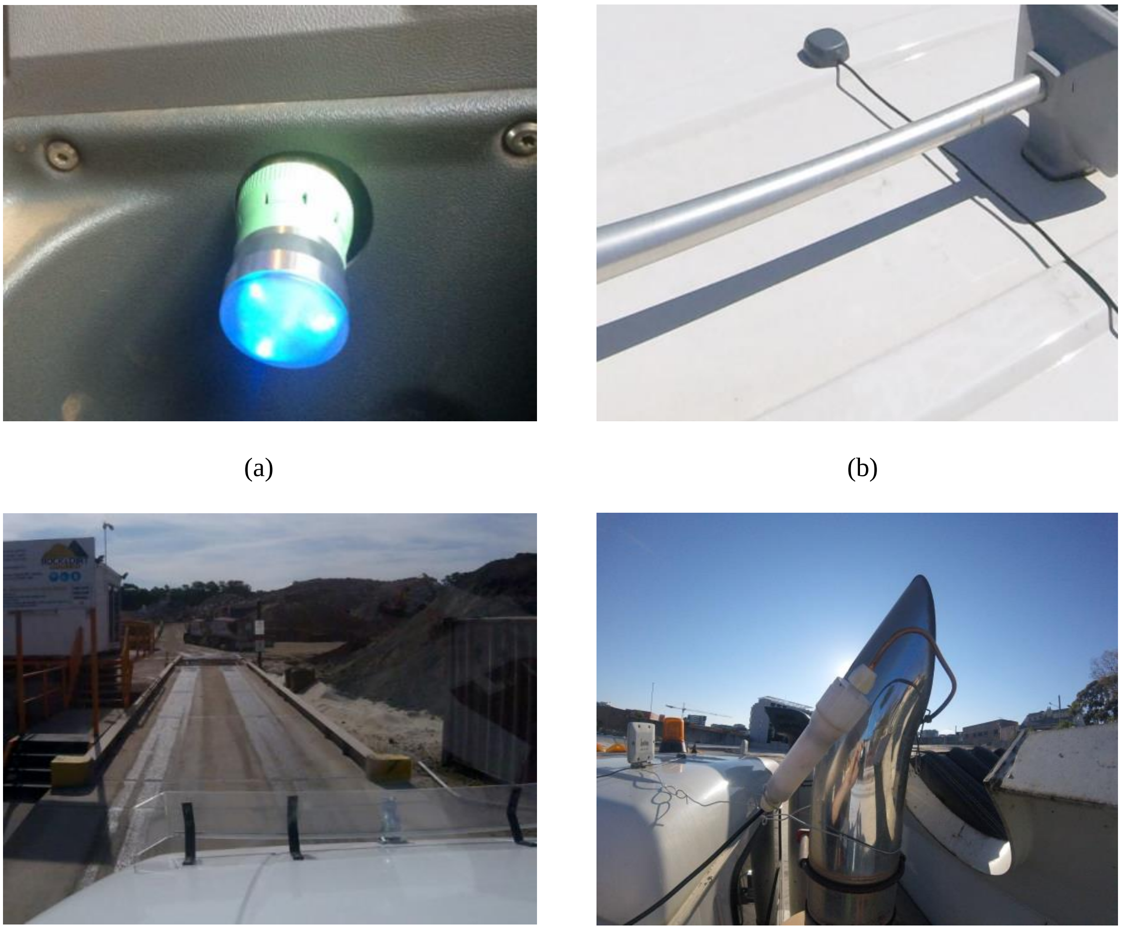
134 kW for Nissan Z24 and 240 kW for six-wheel Mercedes-Benz 1924 truck. On the whole, preliminary experiments took around ten hours and approximately 20,000 data points were collected. Table 3.3 presents the specifications of vehicles used for the preliminary experimentation.

Table 3.3. Vehicles used for preliminary experimentation

Truck Model	Engine Size (kW)	Model Year	Engine Tier	Empty Weight (ton)	Payload (ton)
Holden LX	147	2012	EU V	2.9	1.1
Nissan Z24	134	2008	EU V	1.75	2.1
Mercedes-Benz 808	147	2000	EU III	3.7	4.2
Mercedes-Benz 1513	166	2004	EU III	5.7	8.4
Mercedes-Benz 1924	240	2005	EU IV	6.8	11.5

3.5.2. Field Experimentation

Seven on-road heavy-duty construction trucks were experimented for field studies. As given in Table 3.4, the models of used equipment varied from 2005 to 2014 with the engine sizes ranging between 345 kW and 400 kW. The field experiments took around 35 hours with approximate 95,000 raw data points collected. For getting realistic data, trucks were drove at different speed, acceleration and slope during the experiments. On-road trucks were also tested with different payloads for determining the effect of payload on engine load. Figure 3.10 illustrates sample photos of instrumentation and experimental setup used in the field study. The payload of equipment was measured using an industrial weighbridge during the experiment.



(a) (b)

(c) (d)

Figure 3.10. Sample photos of field experimentation process: (a) engine data logger plugged in the J1939 port, (b) antenna of GPS-INS unit mounted on the roof of the cabin, (c) weighbridge used for weighing equipment, and (d) PEMS sampling probe inserted in the exhaust of vehicle

Table 3.4. Summary of field data collection process

Data Collection process	Vehicle	Model	Engine size (kW)	Engine tier	Empty Weight (ton)	Payload (ton)	Experimentation Time (min)	Collected Data Point
Day 1	Six-axle Trident	2014	400	Euro VI	17.7	30.3	235	9215
Day 2	Six-axle Vision	2005	350	Euro IV	17.6	30.9	340	16148
Day 3	Three-axle Granite	2010	345	Euro V	9.5	13	270	12662
Day 4	Seven-axle Trident	2013	400	Euro V	18.8	31.7	310	13365
Day 5	Seven-axle Granite	2010	345	Euro V	16.6	33.9	260	12147
Day 6	Six-axle Granite	2010	345	Euro V	14.5	33.5	410	21186
Day 7	Three-axle Trident	2013	400	Euro V	11	11.5	205	10067

3.5.3. Challenges in Instrument Installation and Equipment Monitoring

Several practical issues were encountered during instrumentations and equipment monitoring procedures, mainly due to the uncertainties and difficulties in construction environments. The main challenges faced in the field study include finding equipment and scheduling, data collection and unsuitable weather.

Finding suitable equipment and scheduling experimentation were the primary challenges encountered in this research. Many construction companies were contacted in Australia to get permission for experimentation and research cooperation in this study. After around three months since first contact, MOITS Geo-Civil Firm accepted to collaborate with this research and allowed the researchers to enter to the site for experimentation. The scheduling of equipment for experimentation was another issue. The experiments had to be scheduled in a way not affecting the site production and operation of equipment. For scheduling any experimentation, it was needed to get permission from the site managers and to check the loading and dumping locations, as well as closely collaborate with the equipment operators. We also tried to select different models of equipment for experimentation so as to acquire a wide range of field data which made experiment scheduling and field coordination even more difficult.

During equipment monitoring procedure, the research team had to stop experimentation and change the filters of PEMS once every half hour. This slowed down the progress of field data collection and potentially caused measurement errors in data collection. The other challenge in experimentation was the low accuracy of GPS-INS instrument in urban areas when measuring acceleration rate and speed. The engine data logger used in the research was found to function well in the field data collection process.

Adverse weather condition was the other critical issue which has caused significant delay and difficulties in the experimentation. During experimentation, three scheduled experiment days had to be cancelled and rescheduled due to adverse or rainy weather.

3.6. Data Processing and Synchronization

The affecting parameters for fuel use and emissions have been identified in the previous sections. The instruments were also employed to monitor and track selected equipment pieces involved in the construction operations. The process of data collection was designed to gather raw data of operational, engine and emissions parameters through preliminary and full-scale field experimentations. As discussed, the recoded data of each device were stored in a separate Excel file, and each experiment lasted for half an hour due to restrictions of PEMS operations. A data processing and synchronization procedure was needed to create a centralized database of all raw data gathered from separate instrument. Figure 3.11 demonstrates the framework developed in this study for data processing and synchronization.

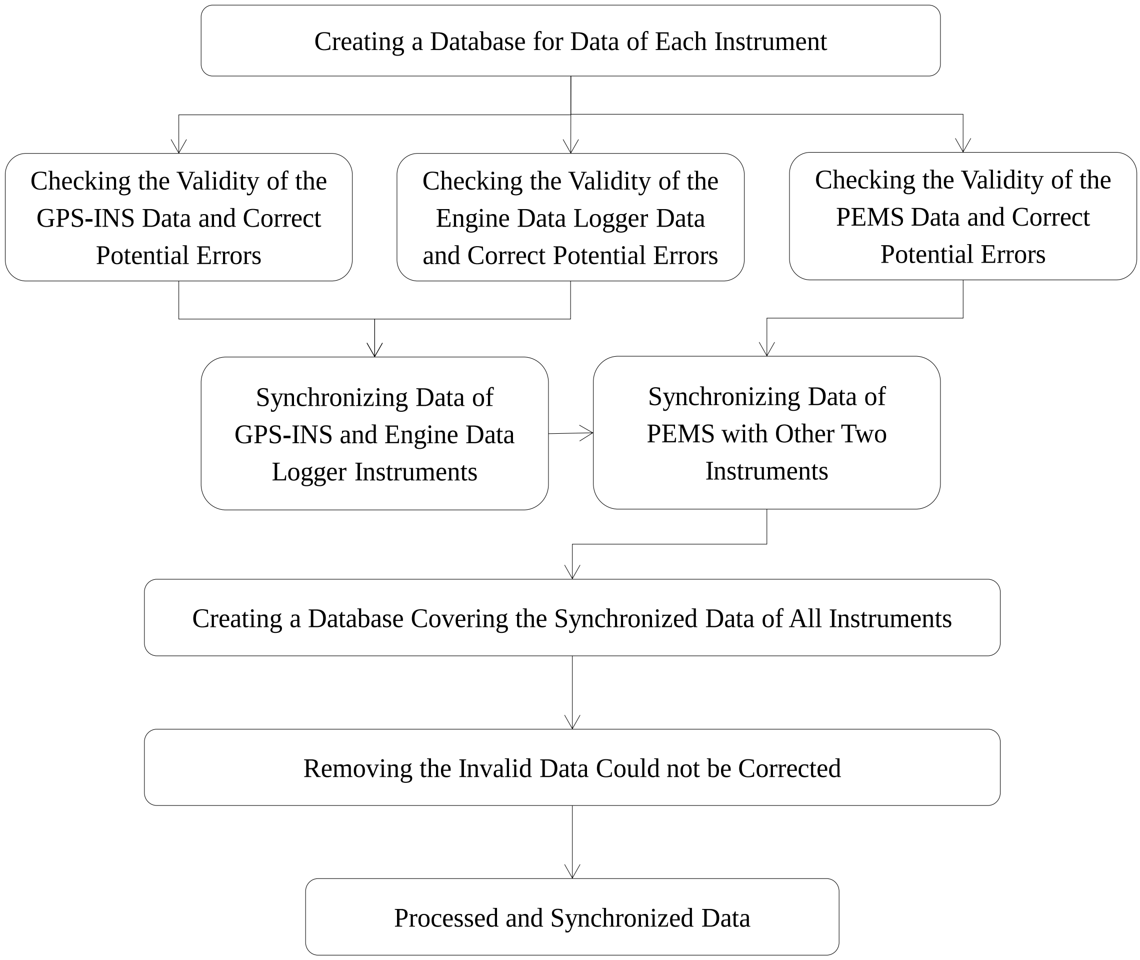


Figure 3.11. Developed framework for processing and synchronizing raw data

Several database files were first created for storing data collected from each piece of equipment. Data validation was then carried out to identify and correct potential errors in the raw data. In the next step, the data gathered by GPS-INS and engine data logger were synchronized. Since these two instruments did not have much delay in recording data, the simultaneous speed of vehicle measured by the both devices was used as a reference for data synchronization. The PEMS data were further processed to match with the data obtained from the other two instruments. One centralized database was then created with all field data of investigated parameters synchronized. The invalid data measured by each of the devices were finally detected and removed together with the corresponding data from other instruments. The field experiments were conducted on a total of 12 vehicles in this study, but only the data from seven on-road heavy-duty trucks were processed and synchronized, and the data of other 5 light-duty trucks were used for developing general research framework and distinguishing relationship among investigated parameters. Table 3.5 shows the total points of data collected from each vehicle as well as the percentage of validity after data processing.

Table 3.5. Results of data processing and synchronization procedure conducted on field data

Vehicle	Total data points	Valid data points	Validity (%)
Three-axle Granite	12,662	10,517	83%
Three-axle Trident	10,067	8,247	82%
Six-axle Trident	9,215	7,456	81%
Six-axle Granite	21,186	16,108	76%
Six-axle Vision	16,148	12,751	79%
Seven-axle Granite	12,147	10,452	86%
Seven-axle Trident	13,365	10,285	77%
Sum	94,790	75,816	80%

A total of 12 parameters were identified to be measured and post-processed in this study. Three of these were operational parameters recorded by the GPS-INS instrument. Engine data logger measured three engine-based variables of engine load, fuel rate and air flow rate (AFR) in each second. Emission rate of four main CO, CO_2, HC and NO_x pollutants were measured by the PEMS. Weight of equipment in each operation cycle was obtained through weighing vehicles by an industrial weighbridge on the site. Engine tier as one of the principal parameters was found in the document and catalogue of equipment. Figures 3.12, 3.13 and 3.14 show samples of synchronized data of investigated parameters for a three-axle Trident truck in the field experiments.

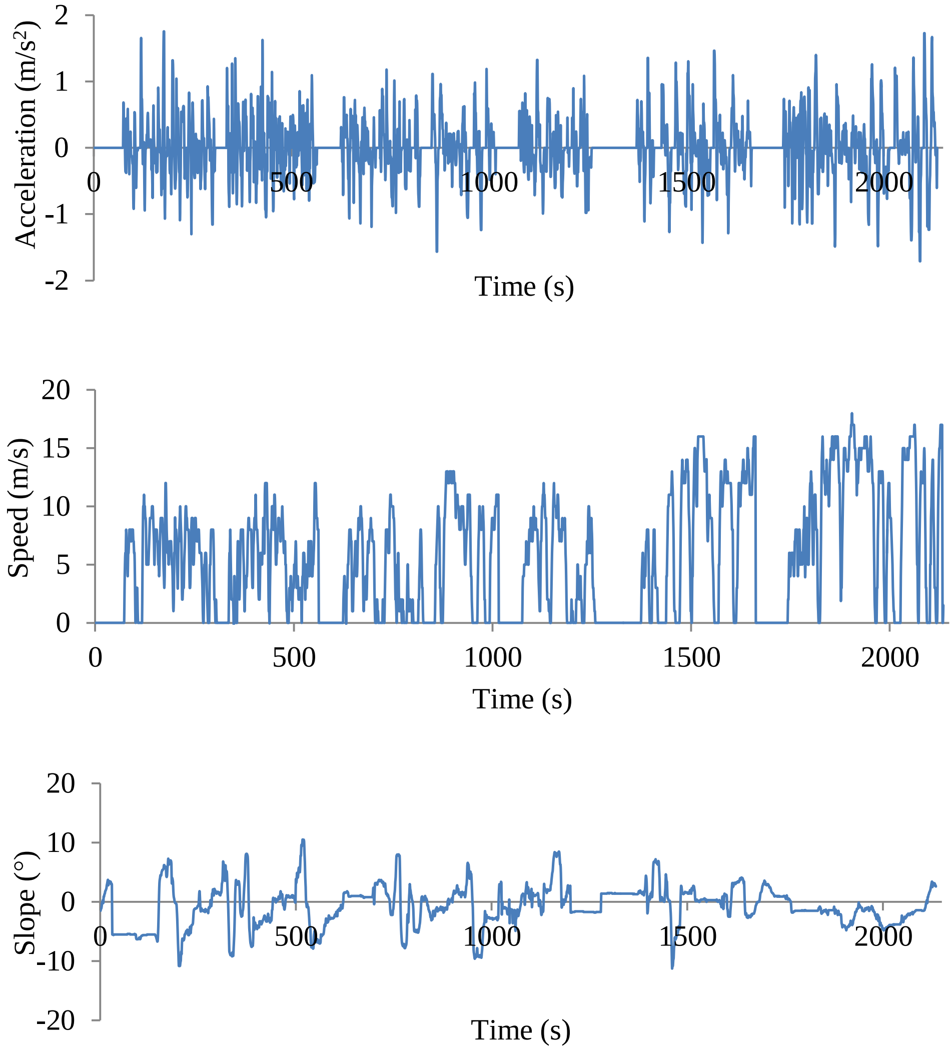


Figure 3.12. Samples of operational parameters data collected by GPS-INS instrument

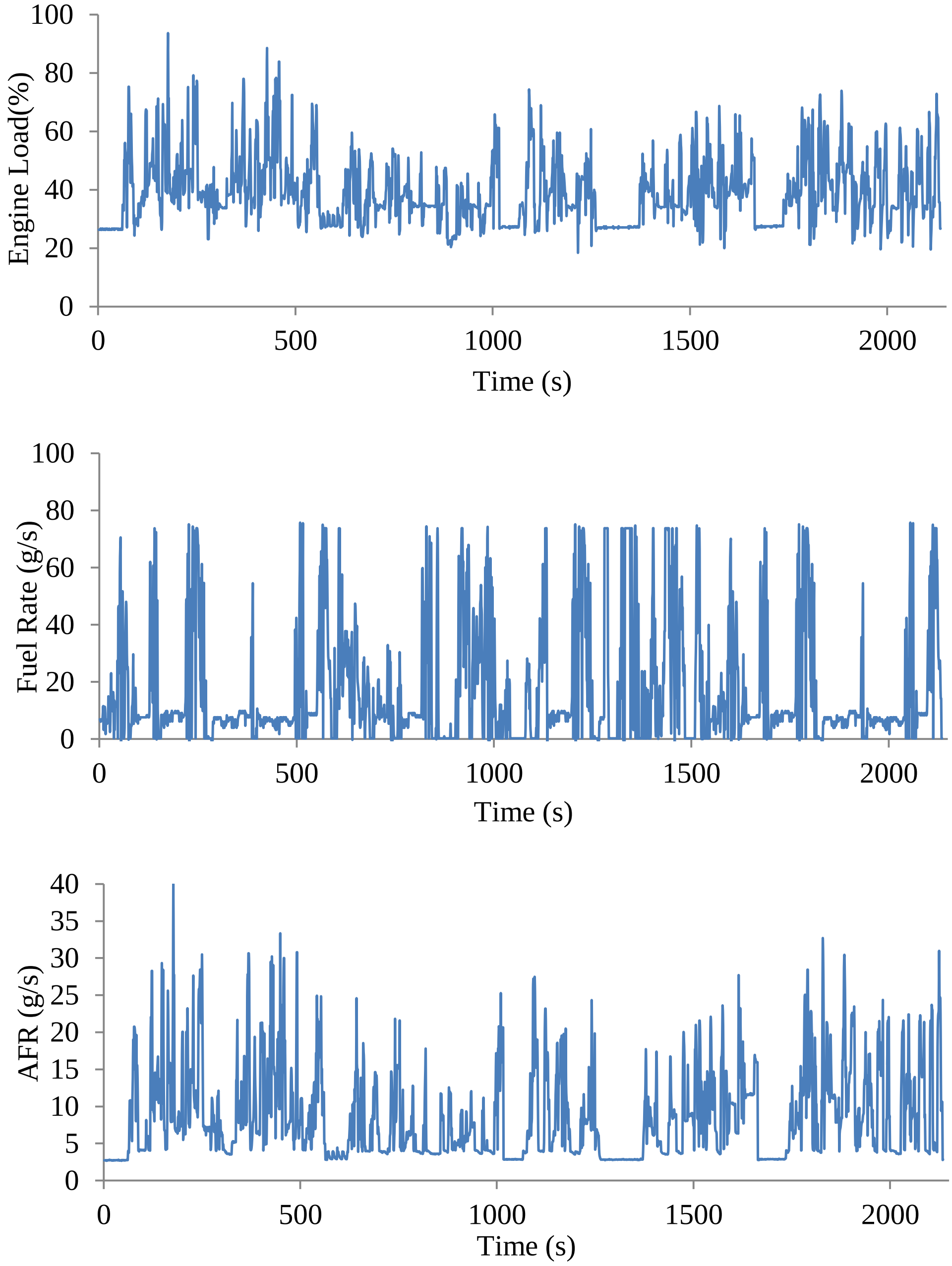


Figure 3.13. Samples of engine parameters data collected by the engine data logger instrument

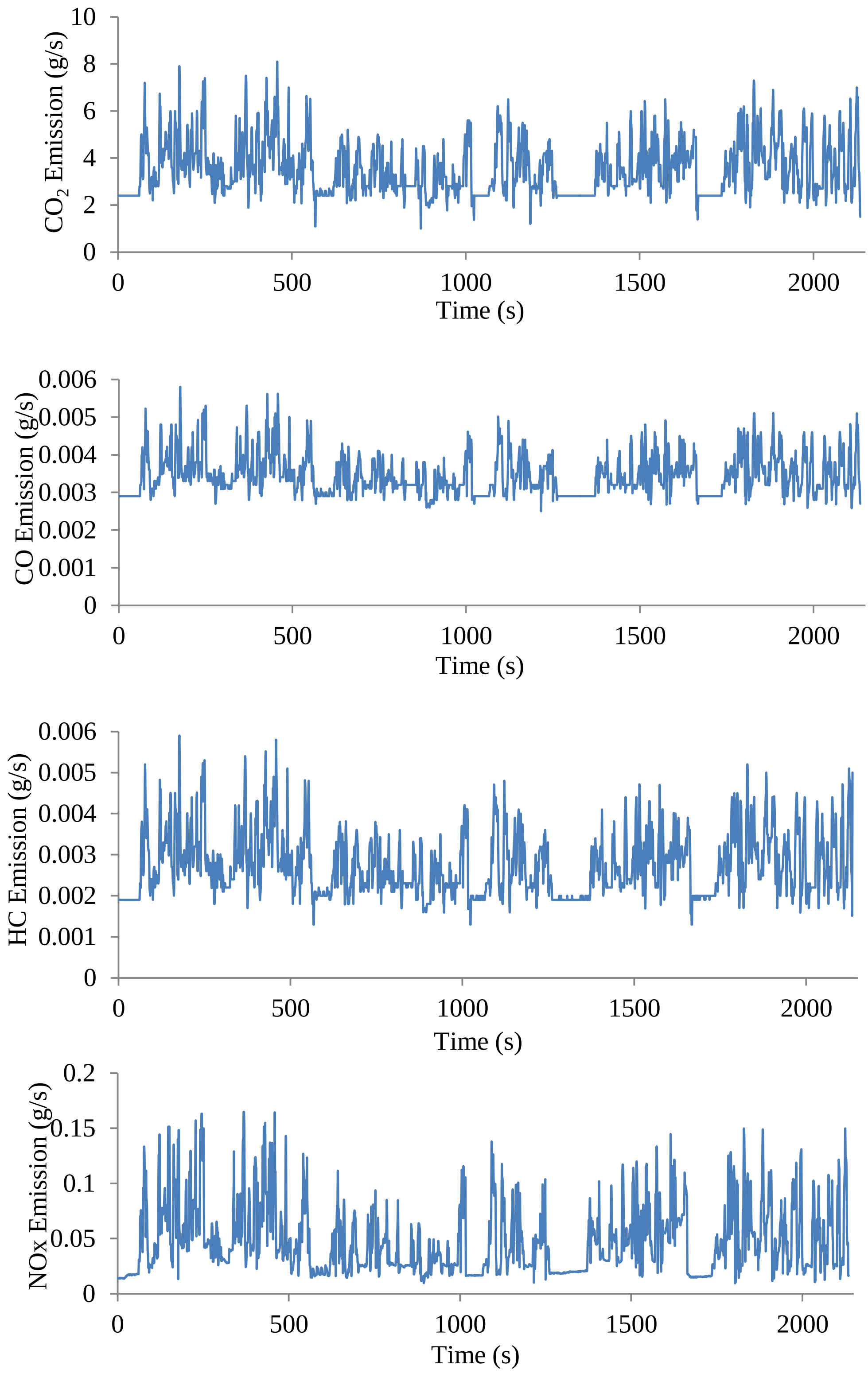


Figure 3.14. Samples of emissions data collected by the PEMS instrument

3.7. Conclusion

This chapter presented the methodology on monitoring field operations developed in this study. Twelve parameters on operation, engine and emissions were identified with their relationships investigated. The off-the-shelf instrumentation systems including GPS-INS, engine data logger and PEMS devices were employed and integrated to record field data and monitor field operations. Seven on-road construction vehicles were selected to be experimented for obtaining field data as required for the study.

The process of data collection was conducted through performing preliminary testing and full-scale field experimentation. Preliminary tests were carried out on eight light-duty construction trucks to verify the performance of the instruments and to develop the research framework. Extensive field experimentation took seven days with approximately 95,000 data points collected from seven in-use heavy-duty construction trucks. Several challenges including finding industrial partner, experimentation scheduling and adverse weather were encountered and overcame during the field study.

The field raw data recorded by three instruments were validated and synchronized to correct or remove potential errors occurred during data collection process. An integrated framework was finally developed in this chapter to create a centralized database for each experimented vehicle with all data synchronized and validated. The processed data are further analyzed in the next chapters to develop fuel use, emissions, and weight estimation models.

Chapter 4

Fuel Use and Emissions Modeling of Construction Equipment

4.1. Introduction

The growth of global population and industrialization in all sectors has boosted the demands for different sources of energies particularly for conventional fossil fuels. Today, over one billion vehicles in operation all around the world consume over five trillion litres of fossil fuels per year (Dargay et al. 2007). Considering the diminishing sources of fossil fuels, such a rate of fuel consumption deems to be extremely unsustainable (Khan et al. 2014). However, due to increasing demands for vehicles in both business and private sectors, it is predicted that the number of global on-road vehicles and machinery reaches two billions by 2050 (Sperling and Gordon 2014). On the other hand, fossil fuels are considered to be the main source of air pollutants including CO_2, CO, HC, NO_x (NO_1 + NO_2) and PMs (Gonzalez and Echaveguran 2012). According to EPA (2009) report, 76% of the total CO_2 emission is produced from the fuels used by vehicles and machinery globally. These contaminants present a serious risk to human health, ecosystem and environment (IPCC 2007). Around 200,000 deaths per year in USA alone are caused by irreversible health problems due to air pollutants, such as respiratory and cancer diseases (Caiazzo et al. 2013). The studies conducted by EPA also showed that those contaminants exhausted from vehicles are the main cause of environmental problems such as ecosystem degradation, ozone depletion and global warming (EPA 2008).

The construction sector plays a significant role in fossil fuels consumption as well as the production of GHGs pollutants. The sector is also ranked as the third highest contributing industry in energy consumption and emission production just behind the oil and gas, and chemical manufacturing industries (EPA 2008; Azzi et al. 2015). In particular, construction equipment accounts for 45% to 48% of total vehicular consumed fuel and emitted pollutions of all industries (Lewis 2009). Based on EPA's report, the fuel used by construction equipment produces over 100 million tons of CO_2 annually. EPA estimates if the fuel consumed by construction equipment decreases by 10%, around 5% of entire energy used in the construction sector will be saved, resulting in a reduction of 6,700 tons CO_2 production (EPA 2009). The Australian Clean Energy Regulator Agency (CERA) predicts that by decreasing the fuel consumed by on-road equipment involved in all industry sectors including construction, over 3 billion litres fuel can be saved and approximately 8 million tones CO_2 is emitted less in Australia only (Klein et al. 2016).

There is a lack of fuel use and emissions estimation models at operational level despite their considerable importance and their various applications. The fuel use and emissions prediction models currently applied in construction sector mainly focus on fuel use and emission production at macro level, such as per nation, state, project, or individual piece of equipment. As the most commonly used model, NONROAD developed by EPA is applied to roughly estimate fuel consumption and emissions rate of a group of construction equipment at both national and state levels. On the other hand, numerous operational and engine parameters effecting fuel consumption and emissions rate have not been fully investigated yet. As one of the main applications of operational level fuel use and emissions models, reduction schemes can be developed to be used by construction managers and equipment operators to lower fuel use and emission production. The current reduction strategies mainly focus on engine attributes and fuel types which are applicable to new construction equipment while failing to cater for existing machinery.

This chapter aims to model fuel use and emissions rate of on-road construction equipment by analyzing operational parameters. An integrated field operation monitoring framework was developed in the previous chapter to track construction vehicles and to collect field data of every parameter as required. State-of-the-art instrumentation system was also devised and the procedures of data collection and synchronization were developed. As one of the main applications of the research framework developed in the study, this chapter estimates fuel use and emission rate of four main pollutants from construction vehicles, including CO, CO_2, HC and NO_x. To do so, the following steps were taken in this chapter.

1. Creating a centralized database storing all validated data from each vehicle;
2. Investigating the relationship among operational parameters, environmental factors, engine attributes, fuel use and emissions;
3. Modeling the effect of operational and environmental variables on the used power of engine;
4. Quantifying the effect of engine attributes on fuel use rate;

5. Modeling emission rate of four pollutants of CO, CO_2, HC and NO_x considering engine attributes;
6. Validating the developed models through comparing the predicted results against real field data measured by instruments.

4.2. Database Creation

Having real-world data is the main necessity of such experimental studies. In the previous chapter, the data collection procedure was extensively explained, and an integrated framework was devised for processing the raw data to correct or remove potential errors. As the first step of data analysis, all collected data from each experimented equipment piece must be synchronized and entered into one Excel file to create a centralized database. This process was performed for seven vehicles experimented in field data collection process, and more than 75,000 validated data points were obtained to be analyzed. Table 4.1 shows sample data stored in the database for a seven-axle Trident truck used in the experiment.

Table 4.1. Sample of created database covering all field data collected by instruments

		GPS-INS				Engine Data Logger			PEMS			
Date (DD/MM/YY)	Time (H:M:S)	Acceleration (m/s^2)	Speed (m/s)	Road Slope (degree)	Weight (ton)	Engine Load (%)	Fuel Use (g/s)	AFR (g/s)	CO (%)	HC (ppm)	CO_2 (%)	NOx (ppm)
18/09/16	12:56:52	0.50	3.95	1.63	48	15	11.92	10	0.02	0	14.6	78
18/09/16	12:56:53	0.68	4.64	2.04	48	21	14.28	15	0.03	1	13.9	92
18/09/16	12:56:54	0.87	5.51	2.31	48	23	26.49	16	0.03	2	13.6	101
18/09/16	12:56:55	0.17	5.44	2.52	48	21	63.66	13	0.03	3	13.7	105
18/09/16	12:56:56	0.20	5.28	2.69	48	18	69.03	15	0.04	4	13.9	72
18/09/16	12:56:57	0.24	5.49	2.81	48	15	43.72	13	0.01	2	14.2	80
18/09/16	12:56:58	0.37	5.88	2.87	48	19	41.12	14	0.04	3	16.2	87
18/09/16	12:56:59	0.37	6.27	2.99	48	16	32.04	12	0.02	5	13.5	106
18/09/16	13:00:00	0.39	6.70	2.99	48	17	10.03	13	0.02	4	15.8	92
18/09/2016	13:00:01	0.27	6.98	2.54	48	19	11.27	12	0.03	2	17.2	81
18/09/2016	13:00:02	0.17	6.84	2.50	48	15	12.10	14	0.02	2	15.2	75

4.3. Relationships among Parameters

As discussed in the previous chapter, numerous parameters were identified, and required field data were collected. As the first step of data analysis process, the relationships among these parameters should be investigated. Identified parameters were divided into five categories of operational, environmental, engine, fuel type, and fuel use and emissions production parameters as given below.

- Operational category: acceleration, speed, and equipment's weight
- Environmental category: road slope
- Engine category: engine size, engine load and engine tier
- Fuel type category: diesel
- Fuel use and emissions production category: fuel use, CO, CO_2, HC and NO_x emissions

To determine the relationships amongst these parameters, initial data analysis was conducted on the data collected in preliminary testing process. The results showed that by increasing the acceleration rate, speed and weight of equipment, the used power of engine rises. The slope of road as an environmental factor has direct relationship with engine power use. The analysis also demonstrated that there is no direct relationship between weight of vehicle and used power of engine, but by increasing the equipment's weight, the effect of other operational and environmental parameters on engine power use is raised. In other words, the equipment weight affects the influence of other parameters on used power of engine. Developed relationship is shown in Figure 4.1.

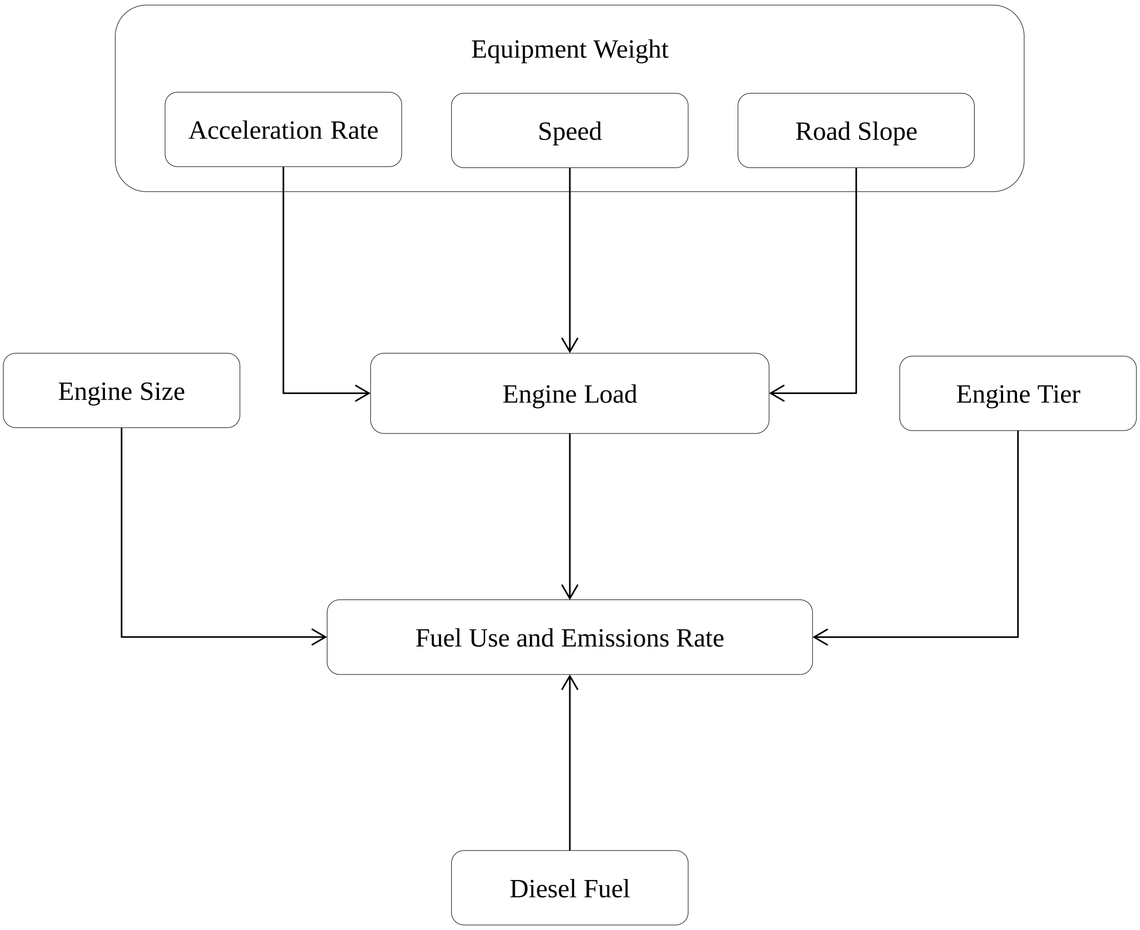


Figure 4.1. Parameters affecting fuel use and emissions rate of on-road construction equipment

Measurement of used power of engine in each second was essential in this study. In the initial data analysis phase, different engine parameters including engine speed, MAP and engine load were investigated as a surrogate for engine power use. The results achieved from preliminary testing on five light-duty construction trucks showed that in comparison with other aforementioned parameters, engine load value measured by engine data logger instrument has much more correlation and consistency with the real amount of engine power use in practice. Thus, the engine load parameter was selected in this study as the indicator of engine power use.

Considering engine load as used power of engine, three parameters of engine i.e. size, load and tier were investigated as engine category. Conducted analysis on the synchronized raw data indicated that there is highly-correlated linear relationship between size of engine, and fuel use and emissions rate. Thus, in this study, the fuel use and emissions of different pollutants are estimated for the unit of engine size (kW). The main advantage of this approach is that the developed models can be easily used to predict fuel use and emissions rate of equipment with different engine sizes.

Initial data analysis results demonstrated that engine load is one of the main variables influencing fuel use and emissions of construction equipment. This relationship is quantitatively modelled in the next sections. A comparison on the experiment results was conducted on equipment with three different engine tiers of Euro III, Euro IV and Euro V. It was found engines with higher tier use less fuel and consequently emit less pollution. Due to different ingredients, fuel type could be an important parameter affecting fuel consumption and emissions. Since construction equipment mainly uses diesel fuel in their lifetime, all analysis in this study are performed on diesel fuel data only. The relationships among different investigated parameters to model fuel use and emissions rate of on-road construction vehicles are summarized in Figure 4.1.

4.4. Models Development

This section aims to quantitatively investigate the relationships among parameters identified in the previous sections. As discussed, the initial analysis on the experimental data showed a strong relationship among operational parameters, engine load, fuel use and pollutants emission rate. The main source of data used to model the relationships is the database created from seven experimented construction vehicles.

The regression statistical method was applied to analyze the raw data and develop the fuel use and emissions estimation models. Regression analysis method has much more flexibility in comparison with other data analysis techniques. Using this statistical approach, it is simple to add or remove some data after conducting initial analysis. As one of the main advantages, this technique can distinguish the errors of data collection process which may have not removed from created database. Regression analysis method would make it much easier to find the differences among the developed relationships, and compare the results achieved from analyzing the data of different equipment pieces. There are some other advantages of using regression technique, such as level of familiarity, assumption, and use of multiple variables.

The initial data analysis demonstrated that there is highly-correlated linear relationship among engine factors, and fuel use and emission rate of different pollutants. It was also proven that the engine load can be linearly modeled based on the operational and environmental variables. The OLS and MLR analysis methods were used in this study to develop the fuel use and emissions models. IBM SPSS Statistics V22 and Microsoft Excel software were employed for conducting statistical analysis. In this research, the process of fuel use and emissions rate estimation is conducted in three steps: (1) engine load modeling with operational parameters (2) fuel use modeling based on engine attributes, and (3) emissions production modeling considering engine parameters.

4.4.1. Engine Load Estimation

This section investigates how the operational parameters affect the engine load of on-road construction equipment. As mentioned before, engine load is a function of acceleration rate, speed, road slope and equipment weight variables. In order to estimate engine load, all created databases for vehicles were analyzed using SPSS V22 and Microsoft Excel software. The highest recorded speed during the experiments was 120 km/h. Acceleration varied from -1.5 km/h.s to +1.2 km/h.s. The road slope measured in the experiments was between -12^{o} and $+13^{o}$ (-13.3% to 14.3%). The WF parameter was varied from 2.75 ton/100kW for an empty truck without trailer to 14.5 ton/100kW for a fully-loaded truck with a four-axle trailer.

Equation (4.1) predicts the engine load based on acceleration rate, road slope and speed under a certain WF. The parameter WF is defined as the combined weight of equipment (ton) carried per 100 kW of engine size. Combined weight refers to total weight of vehicle including equipment, trailers and payloads. The achieved results demonstrated that the developed model has a high accuracy ($R^2 > 0.85$) in estimating engine load of on-road construction vehicles. The coefficients of parameters in the developed engine load model are given in Table 4.2. Figure 4.2 presents the OLS analysis results, showing relationships of WF with acceleration, speed and road slope variables in the proposed engine load estimation model.

$$EL = (C_{AC}*AC) + (C_{SL}*SL) + (C_{SP}*SP) + C \qquad (4.1)$$

Where:

EL: Engine load of equipment (%)

AC: Acceleration of equipment (km/h.s)

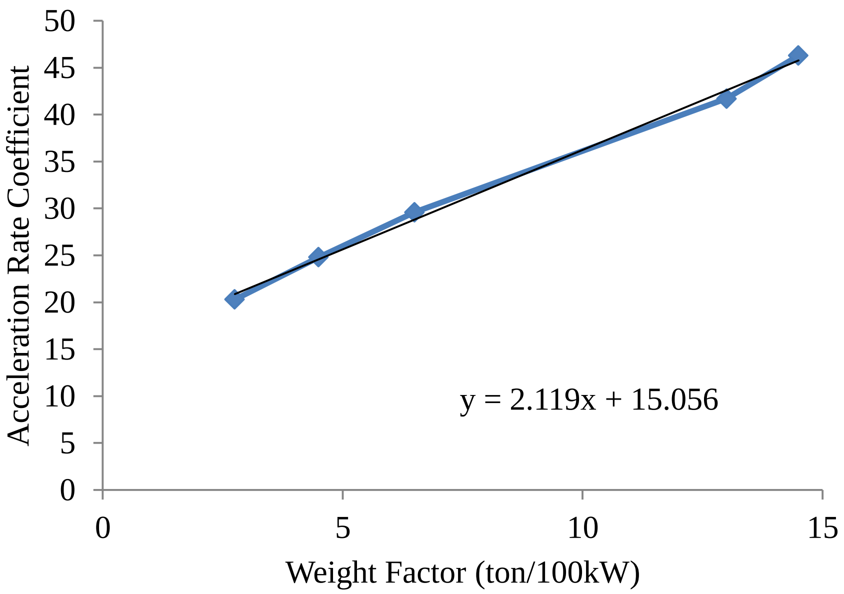
SL: Slope of road (degree)

SP: Speed of equipment (km/h)

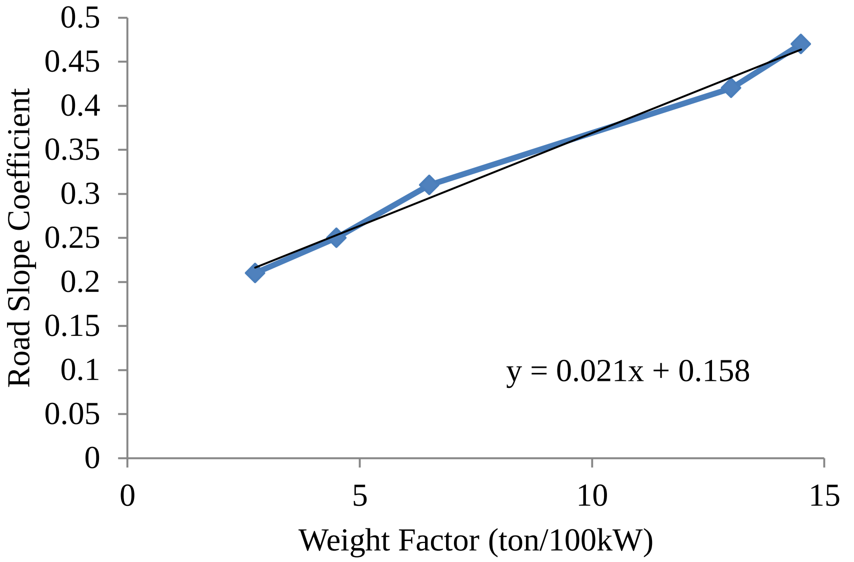
C: Engine load of equipment in idle mode which is around 20%.

Table 4.2. The coefficients of parameters in the engine load estimation model

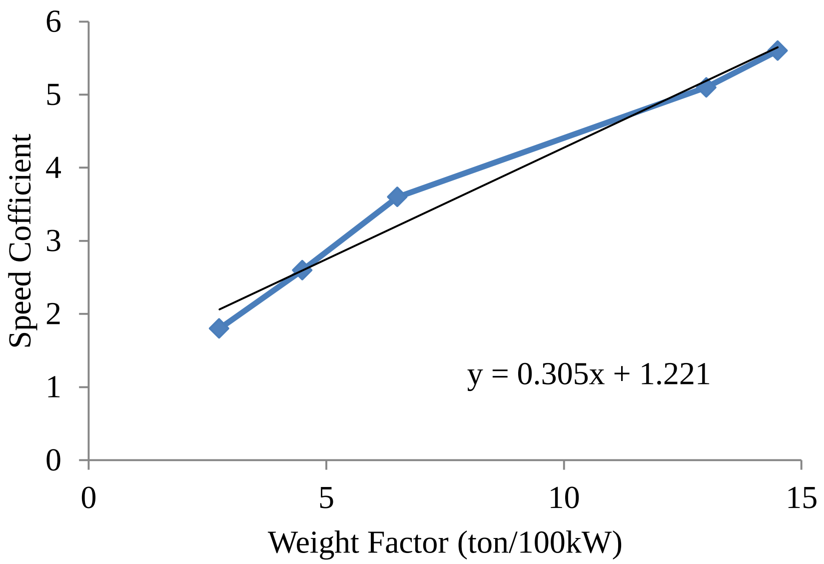
	WF				
Coefficients	2.75	4.5	6.5	13	14.5
C_{AC}	20.3	24.8	29.6	41.7	46.3
C_{SP}	0.20	0.25	0.31	0.42	0.47
C_{SL}	1.8	2.6	3.6	5.1	5.6



(a)



(b)



(c)

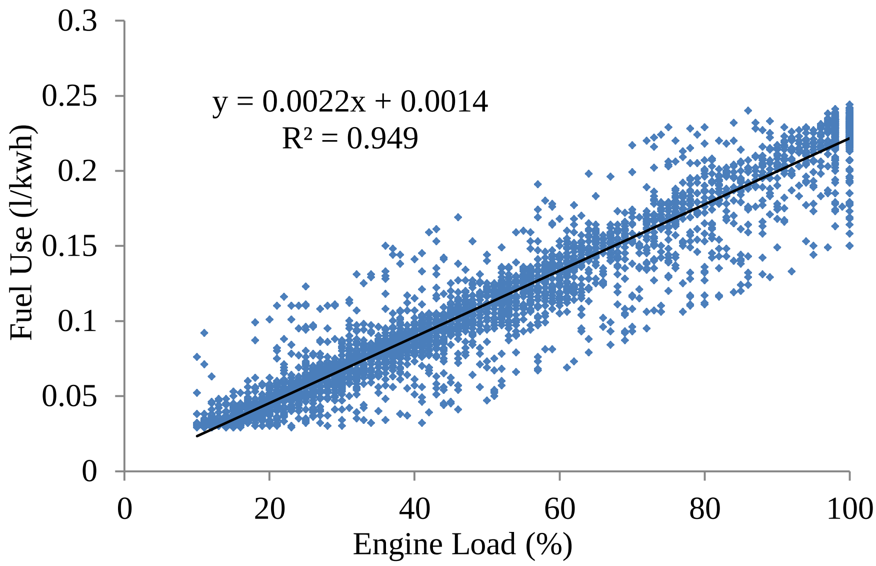
Figure 4.2. The influence of WF on the coefficients of a) acceleration rate, b) road slope, and c) speed parameters in the engine load estimation model

As indicated in the engine load estimation model, acceleration rate had the highest coefficient and is therefore identified as the most critical factor. As given in Table 4.1, the coefficient of acceleration rate parameter for an empty equipment without trailer

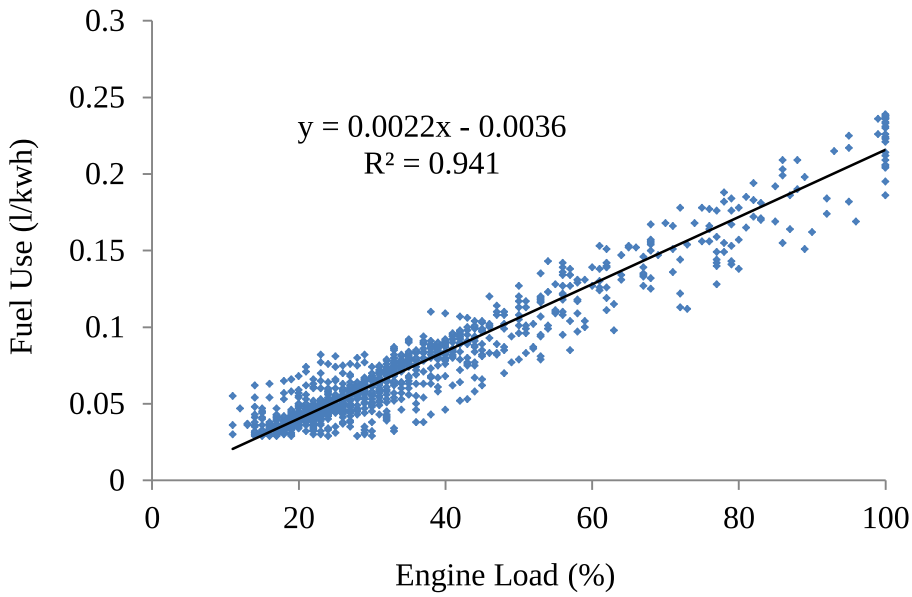
(WF = 2.75) is 20.3, which means that by accelerating such an on-road vehicle for 1km/h.s, engine load increases by about 20.3%. The acceleration coefficient has direct relationship with WF, reaching 46.3 for a fully-loaded vehicle with trailer (WF = 14.5). In addition, every one degree up or down in road slope changes the engine load of on-road equipment with WF of 2.75 by 1.8. The road slope coefficient for equipment with a full payload (WF = 14.5) increases to around 5.6. Of all the parameters considered, speed seemed to have a moderate effect on engine load with the coefficient being 0.20 for a vehicle with WF of 2.75 and 0.47 for a vehicle with WF of 14.5. The constant value can be explained as the amount of used power of the engine in idling mode, which is around 15% for on-road construction equipment.

4.4.2. Fuel Use Modeling

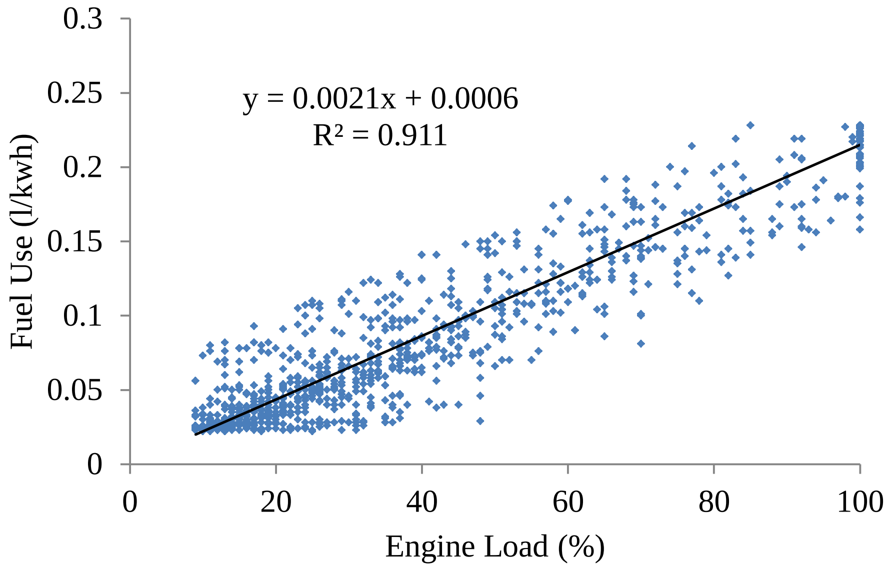
As mentioned before, load, tier and size of engine were identified as engine attributes affecting fuel use of construction vehicles. The engines of the majority of current on-road vehicles involved in the construction industry are categorized in Euro III, IV and V tiers which were manufactured in the period of 2000 to 2014. Normally, as estimated in the previous section, engine load of heavy construction equipment varies between 10% and 20% in idling mode, and is about 100% for the most demanding activities. Similarly, the fuel use is around 0.02 l/kWh in idling mode while reaching to approximately 0.12 l/kWh when engine is fully loaded. The conducted OLS statistical analysis showed there is a direct linear relationship between engine load and fuel use for all engine tiers. As shown in Figure 4.3, fuel use is highly correlated ($R^2 > 90\%$) with engine load for all engine tiers.


y = 0.0022x + 0.0014
R² = 0.949
Fuel Use (l/kwh)
0.3
0.25
0.2
0.15
0.1
0.05
0
0
20
40
60
80
100
Engine Load (%)

(a)


y = 0.0022x - 0.0036
R² = 0.941
Fuel Use (l/kwh)
0.3
0.25
0.2
0.15
0.1
0.05
0
0
20
40
60
80
100
Engine Load (%)

(b)



(c)

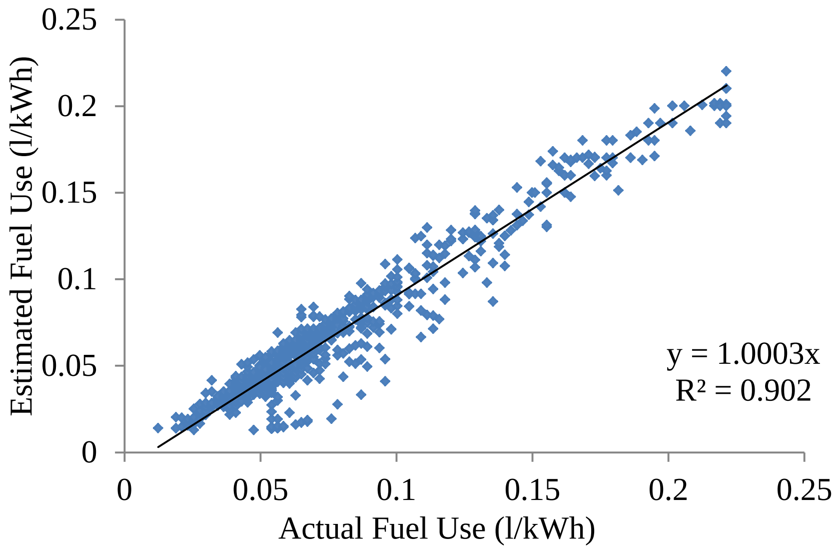
Figure 4.3. The OLS regression between engine load and fuel use for (a) Euro III engines, (b) Euro IV engines and (c) Euro V engines

As demonstrated in Figure 4.3, engines with higher tiers use less fuel. The comparison among Figures 4.3a, 4.3b and 4.3c shows there is big saving in fuel cost of equipment by using high tier engines. As an example, the fuel uses of engines with 400 kW in three different tiers of Euro III, Euro IV and Euro V when operating in 60% engine load are 53.36 l/h, 51.36 l/h and 50.68 l/h, respectively.

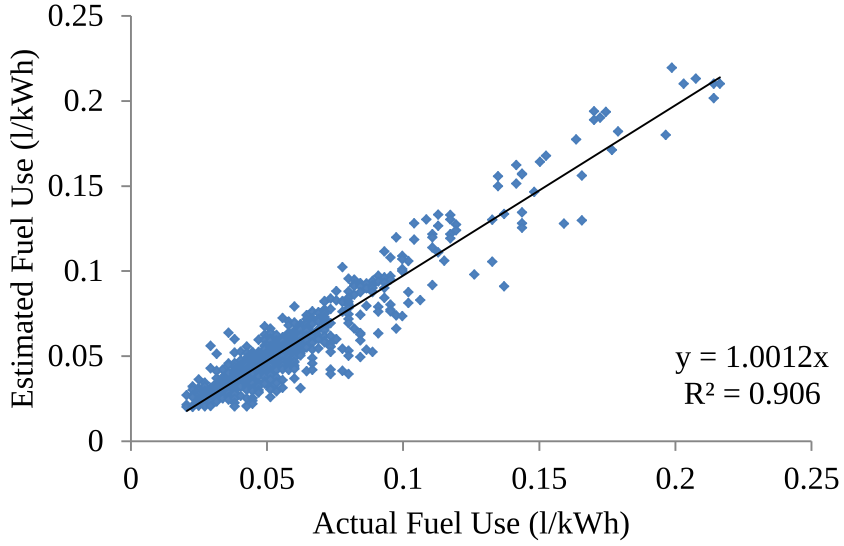
To validate the developed model, the estimated fuel use values are compared with the field data measured by engine data logger instrument. As shown in Figure 4.4, this process is performed by plotting estimated fuel use values versus the real field data. It is found there is high correlation and consistency between estimated and real values of fuel use for all considered engine tiers. The developed model has more than 90%

accuracy in fuel use estimation of on-road construction equipment which is one of the great achievements of this study.

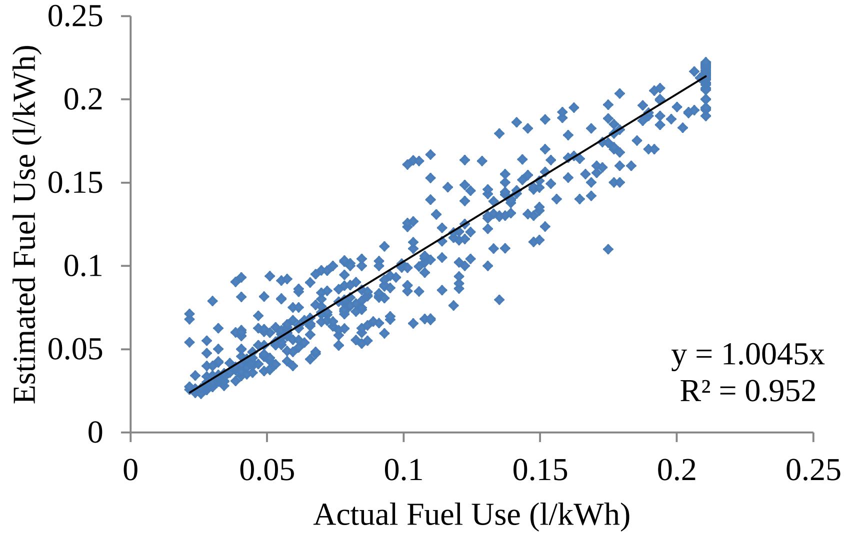
Various sources of errors affecting the accuracy of the model were identified as well. As the main cause of error, engine data logger did not function very well sometimes during measurement. Around 20% of the collected engine data were corrected or removed as outlier in data filtration process. The skill level of the operators is another factor influencing the accuracy of engine load estimation based on operational parameters collected. Using automatic transmission equipment could potentially decrease the effect of operator inaptitude on the accuracy of the model.



(a)



(b)



(c)

Figure 4.4. Validation of the fuel use model by comparing the estimated fuel use of the model with the actual fuel use for (a) Euro III engines, (b) Euro IV engines and (c) Euro V engines

4.4.3. Emissions Estimation Model

To quantify the relationship between emissions and engine load, exhaust air flow rate (AFR) is first investigated. The regression analysis on the field data of all vehicles shows a linear relationship with a high correlation coefficient ($R^2 = 0.94$) between engine load and AFR. As mentioned before, depending on the status of the engine when running, engine load value varies from around 15% to maximum 100%. At the same time, AFR is around 80 g/kWh in idle mode and reached about 1,200 g/kWh when the engine is running at full capacity. As shown in Figure 4.5, emission rates of CO_2, CO, HC and NO_x are found to be directly related to the changes in engine load. Equation (4.2) estimates the total emission rate of pollutants based on engine load, AFR and pollutants relative volume.

$$P_{ij} = 3600 * AFR_j * (1/PW) * (1/D_a) * V_{ij} * D_i \tag{4.2}$$

Where:

P_{ij}: Amount of pollutant I in engine load j (g/kWh)

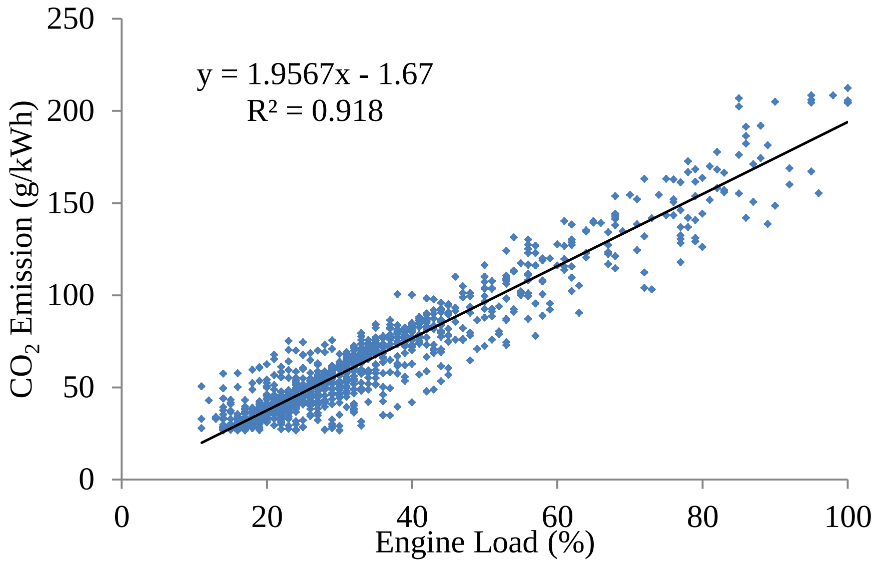
AFR_j: Air flow rate in engine load j (g/s)

PW: Power of equipment (kW)

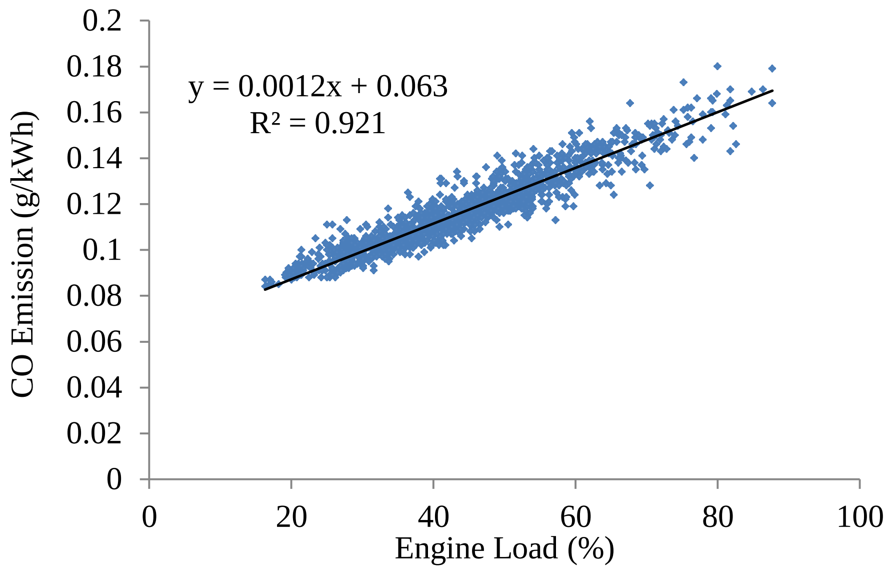
V_{ij}: Volumetric percentage of pollutant i in engine load j

D_a, D_i: Density of air and density of pollutant i in normal temperature and pressure (NTP) condition.

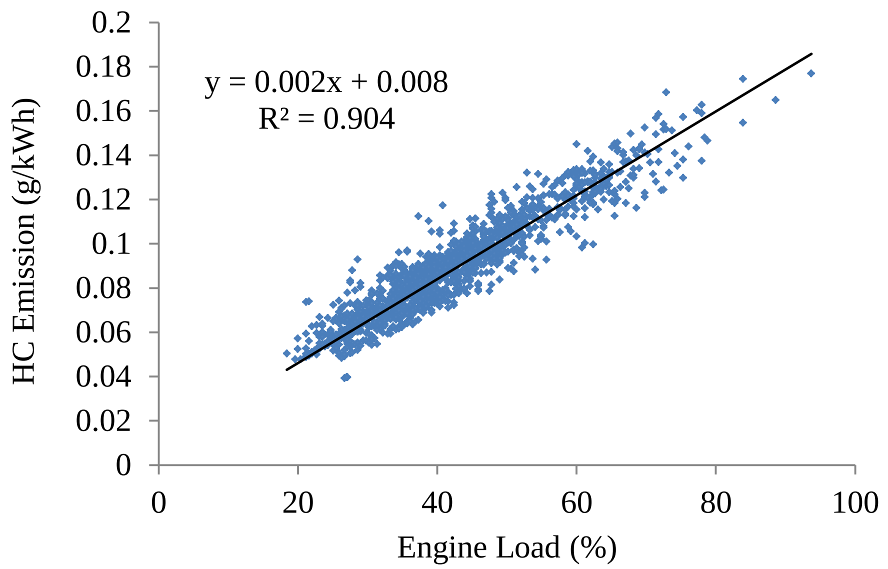
Figure 4.5 demonstrates total CO_2, CO, HC and NO_x emission rates based on engine load. The OLS regression method was used for statistical data analysis. As indicated in Figure 4.5a, CO_2 emission varied between 30 g/Kwh in idling mode to around 200 g/Kwh in full engine load mode. These results proved the high correlation of collected data while the R^2 value was around 0.918 for linear function. CO emission was minimum around 0.08 g/Kwh in idle mode, while increasing to 0.20 g/Kwh in fully-load engine mode (see Figure 4.5b). A linear relationship between CO emission and engine load was defined with the highest correlation coefficient being $R^2 = 0.921$. HC emissions increased from 0.05 g/Kwh to 0.20 g/Kwh when the engine load increased from 15% to 100%. As shown in Figure 4.5c, the R^2 value of the linear relationship between HC emissions and engine load was 0.904. Similarly, the linear relationship between the NO_x emission rate and engine load had the highest correlation coefficient, 0.954 (see Figure 4.5d).



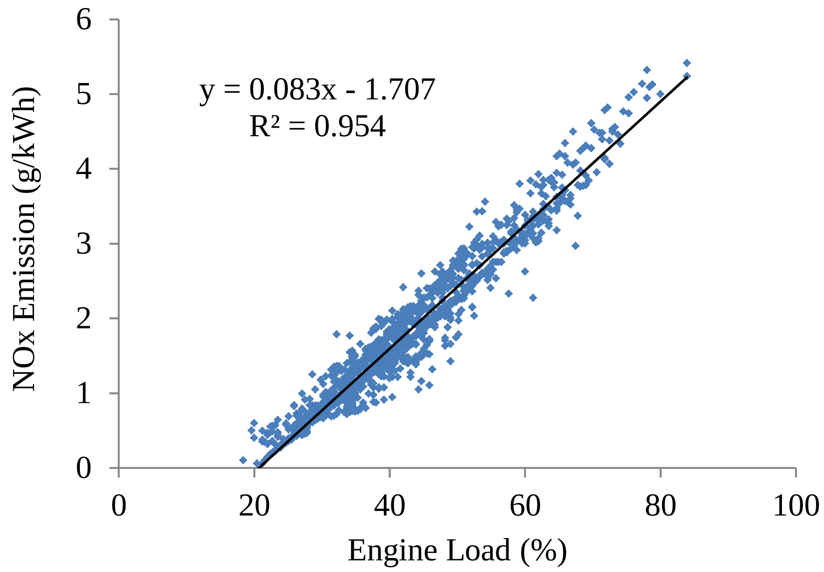
(a)


y = 0.0012x + 0.063
R² = 0.921
CO Emission (g/kWh)
Engine Load (%)
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
20
40
60
80
100

(b)


y = 0.002x + 0.008
R² = 0.904
HC Emission (g/kWh)
Engine Load (%)
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
20
40
60
80
100

(c)

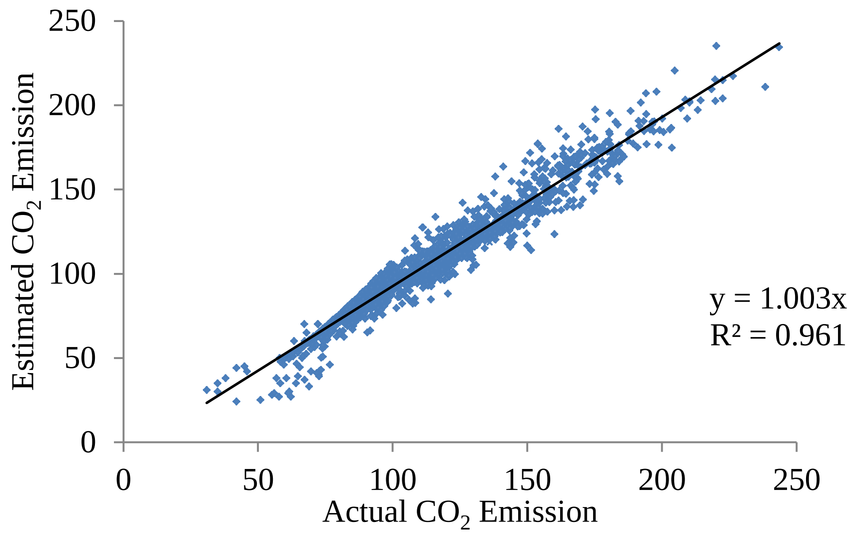


(d)

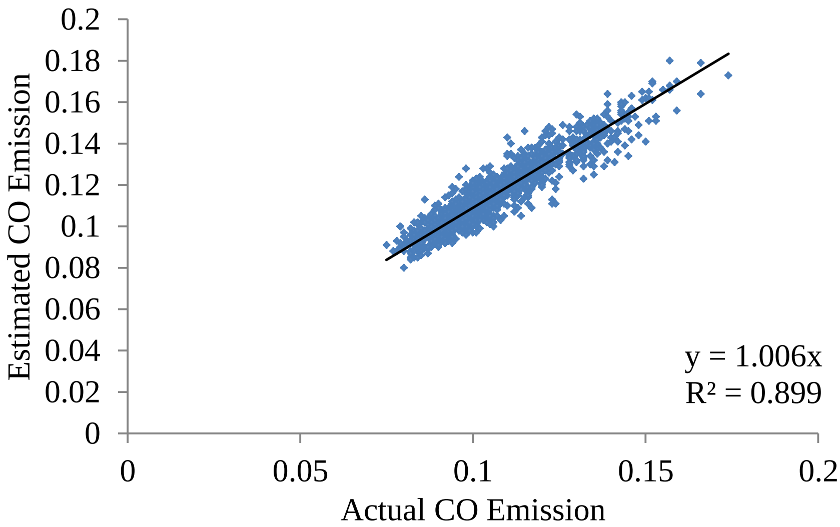
Figure 4.5. The OLS regression relationship among engine load and (a) CO_2 emission rate, (b) CO emission rate, (c) HC emission rate and (d) NO_x emission rate

Similar to fuel use validation process, to prove and validate the developed emissions estimation model, the estimated emissions rate were compared with the field data measured data by the PEMS. This process was conducted by plotting the predicted values produced by emission model versus the directly measured values of the emissions. As can been seen in Figure 4.6, for four investigated pollutants of CO_2, CO, HC and NO_x, there is high correlation (R^2> 0.90) between the estimated emissions and their corresponding actual values. This means that the accuracy of the developed model in estimating emissions of real-world operations is more than 90%. Based on some studies conducted to compare current emission models, the accuracy of the NONROAD and OFFROAD models is less than 70% at equipment-level or state-level emissions estimation (Abolhassani et al. 2008; Heidari and Marr 2015). So obtaining a level of accuracy over 90% in estimating emissions is considered to be one of the main achievements of this study.

There are various sources of error affecting the accuracy of the developed model. The main cause of error was the accuracy of the PEMS, which had at least 1.7% error in measuring emissions rate. The performance and internal combustion of the engine were other parameters affecting measurement accuracy of engine load and emission rates. The synchronization and filtering of the data collected from the different instruments were other factors that must be considered as possible sources of error in data analysis.



(a)



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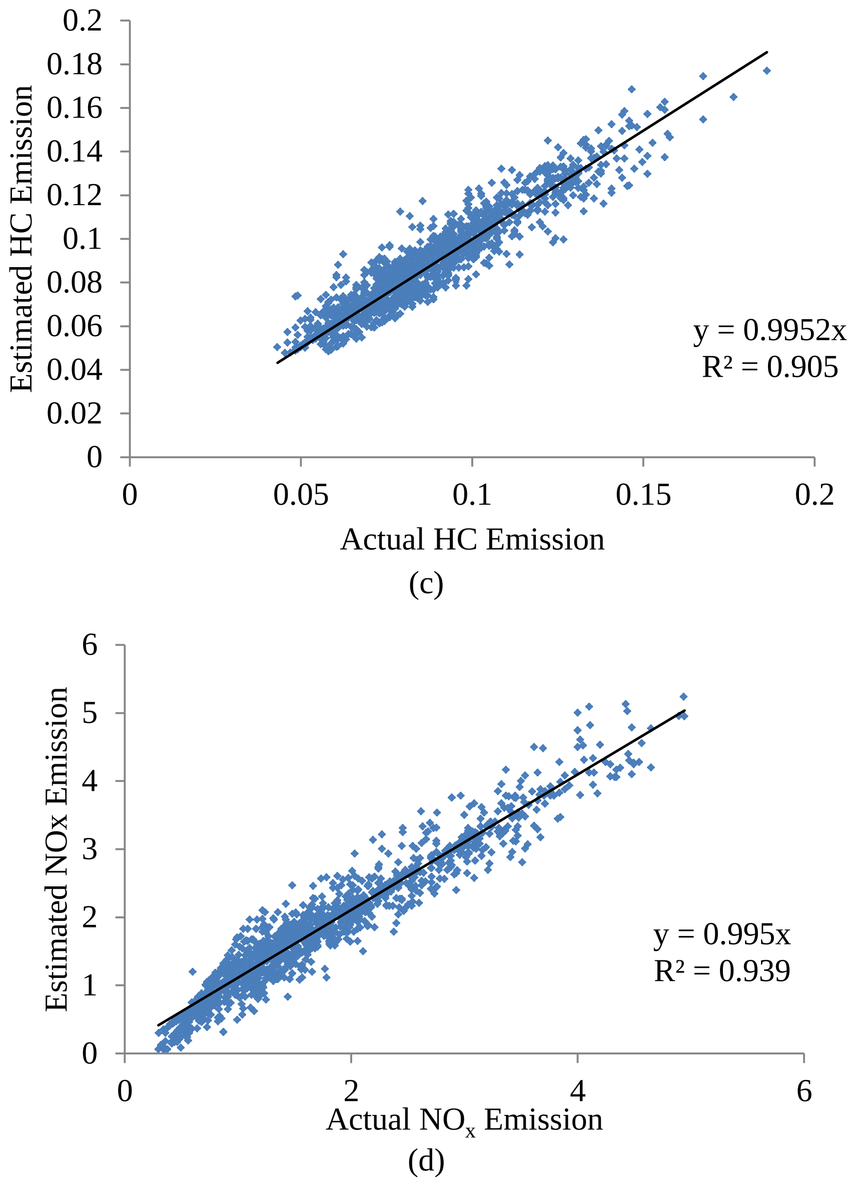


Figure 4.6. Validation of the developed emission model by comparing the estimated emissions rate of the model with the actual emissions for (a) CO_2, (b) CO, (c) HC, and (d) NO_x pollutants

4.5. Applications of Fuel Use and Emissions Models

The operational level fuel use and emissions estimation models were developed and validated in the previous sections. The effects of different operational, environmental and engine variables on fuel use and emissions rate were also investigated. As the main applications of the developed models, they can be used in the construction industry to improve the fuel efficiency of equipment and reduce their produced emissions. This can be done through quantitatively developing the optimal driving patterns considering the effects of investigated operational and environmental parameters. Using these devised models, the additional fuel use and emissions production due to equipment's stop and idling time can be predicted. These strategies and models can be used by construction managers and machinery operators to significantly reduce the fuel use and consequently emissions production of the equipment operated on the construction sites.

4.6. Conclusion

Construction industry is regarded as one of the main consumers of fossil fuels, and also has an important role in air pollutants production globally. In the construction sector, equipment and vehicles are the major contributors of fuel and energy consumption, and account for around 50% of total vehicular used diesel fuel of all industries. This study developed operational level fuel use and emissions estimation models for on-road vehicles involved in construction industry. Developed models have various applications in construction sector for devising practical strategies to improve the efficiency of fuel used by equipment including optimal driving speed, vehicle selection and trailer configuration.

The effects of acceleration rate, speed, slope and weight were investigated as operational and environmental parameters affecting fuel use and emissions rate. Engine load was identified as an intermediate parameter mapping the effect of operational parameters on fuel use and emissions rate. The data collected from all seven experimented heavy-duty trucks were used to develop the fuel use and emissions models. Through conducting statistical analysis on the filtered raw data, the effect of engine attributes was modeled on fuel use and emissions rate. It is found there is a highly-correlated linear relationship amongst engine tier, engine size, engine tier, and fuel use and emissions rate of vehicles. The effects of operational and environmental variables were also investigated on engine load through performing MLR regression analysis. The developed models were validated at the end through comparing the predicted results with the real value of the fuel use and emissions measured by instruments.

The results showed that the acceleration rate has the highest impact on used power of engine and this parameter was identified as the most crucial operational parameter. Also, it was proven that driving speed has a moderate influence on engine load. On the other hand, it was verified that there is a high consistency between engine load and fuel use and emissions (R^2> 90%). The sources of errors were also discussed for improving the accuracy of the devised models in the future. In the next chapters, these developed models were employed to develop operational level strategies and schemes to reduce fuel use and emission production of construction vehicles.

Chapter 5

Weight Modeling and Estimation of Construction Equipment

5.1. Introduction

Construction sector is one of the main industries requiring a huge number of construction vehicles. Majority of construction activities associated with earthmoving operations including cut and fill activities employ on-road HDVs for materials transportation. Such kind of activities are planned and paid based on the amount of materials transported. The precise measurement of the payload and volume of construction materials carried by vehicles as payload is necessary. As a main concern of construction contractors and equipment operators, a cost-effective automated method is essential to accurately estimate the payload carried by vehicles.

Measurement of total vehicle weight is vital in transportation field. Overloading and increasing ESAL result in difficulties of vehicle's maneuverability, traffic accident and short vehicle life (Yang et al. 2008). ESAL is determined based on pavement condition and its failure mode, and is one of the main parameters causing distress and damage of pavements and bridges (Haider and Harichandran 2007). Overweighting also causes serious damages to pavement conditions and increases the risk of overloading and failure of the bridges (Ojio et al. 2016). Annual average daily truck traffic, percentage of trucks and ESAL are the major parameters took into consideration in designing and constructing pavements and bridges (Faruk et al. 2016). According to NCHRP (2006), the distribution of weight on different axles is a key factor in road and pavement design. Therefore, the accurate and efficient weight estimation to minimize heavy vehicles' overweighting is essential to reduce the potential damages to infrastructures. Conducted studies indicated that HDVs account for 79% of roadway pavement damages (Faruk et al. 2016; Refai et al 2014). So, numerous international agencies such as AASHTO and FHWA have implemented restrictions and regulations to reduce the ESAL of HDVs (Vaziri et al. 2013; Fiorillo and Ghosn 2014). Different guiding principals have also been developed based on the bridge design formulas by several organizations like TRB and NAASRA to control the total vehicle weight and internal axle weight distributions of HDVs in order to prohibit overstressing of bridges (Moshiri and Montufar 2014).

However, despite the necessity of an accurate and fast weight measurement method, the current weighting systems used in construction sector are time consuming and error prone with high cost. As the most commonly used method, weighbridges are widely used in the construction sites which require high installation and operation costs. The weight measurement time would affect the production rate of the equipment and the cost of project execution. Also, in spite of high speed of volumetric measurement methods available in the market, these systems may fall short of accuracy due to volume to weight conversion analysis.

This chapter aims to develop a novel approach to accurately model and estimate the weight of on-road HDVs by analyzing operational parameters and engine attributes. To do so, the relationships among operational variables and engine factors are first investigated. Data analysis is then carried out on the raw data collected through experimentation to devise the models to estimate the total weight of HDVs. ANN analysis method was applied using MATLAB R2016b, IBM SPSS Statistics V22 and Microsoft Excel software. Developed framework holds various applications in construction and mining sectors, such as estimating the carried payload of trucks and haulers without stopping or requiring any specific site mobilization.

This model can also be employed in the transportation field to estimate the total weight of vehicles using operational and engine data. As the main advantage, using this weight estimation model requires minimal initial and operation cost. The weight can be estimated in real-time during normal site operation which leads to significant saving in project cost and considerable improvement in the production rate of equipment.

This chapter first starts with the introduction to the model framework developed in the study. The relationship between operational and environmental parameters including the equipment weight and engine attributes is quantitatively investigated. The weight estimation model is then devised through developing artificial neural network (ANN) methods and performing analysis on the processed raw data. In the end, validation process is conducted by comparing the predicted results of the model against the real weight measured by weighbridges on the construction site.

5.2. Model Framework

This research develops a new approach to estimate the weight of equipment (including its carried payload) based on the operational and environmental parameters. Four parameters of equipment weight, acceleration rate, speed and road slope were identified as operational and environmental variables affecting the engine load. The real-world data of all these parameters were measured in each second using GPS-INS and engine data logger instruments. Initial data analysis was performed to investigate the relationships among the considered factors, as shown in Figure 5.1. It is also found the equipment weight variable would affect the impacts of other investigated parameters on the engine load, like acceleration rate, speed and road slope.

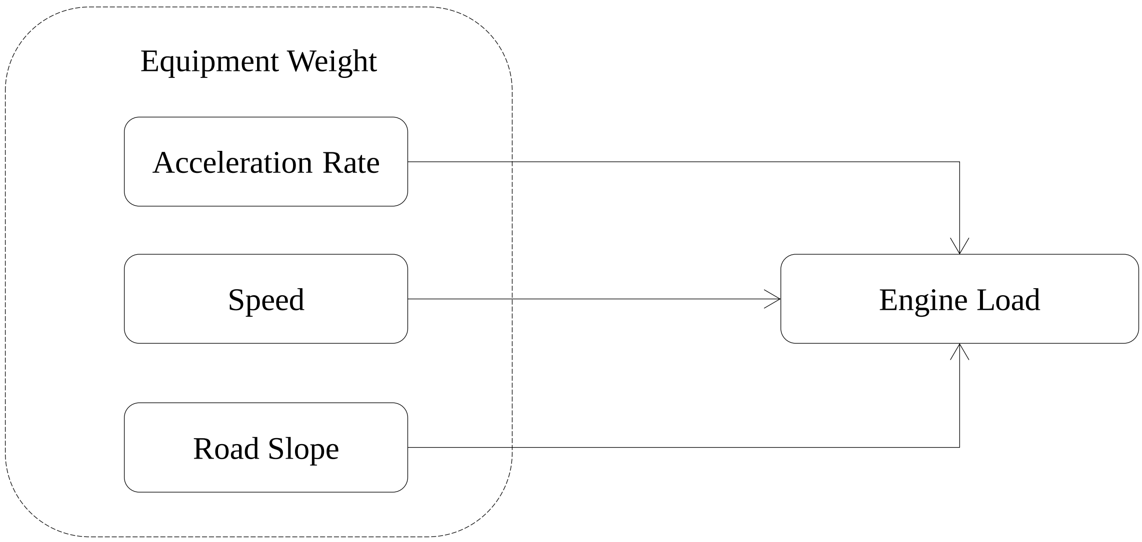


Figure 5.1. The relationship amongst equipment weight, operational parameters and engine load

This chapter focuses on estimating the value of weight which is interpreted as WF based on the operational and engine variables. As mentioned in previous chapters, the real operational and engine data can be readily measured through instrumentation. Weight of equipment is estimated based on monitoring live values of other operational and engine parameters.

5.3. Model Development

The processed field experiment data were analyzed in this section to develop weight estimation models. As discussed, four operational and environmental variables of acceleration rate, speed, road slope and vehicle weight affect engine load. The weight and consequently payload carried by equipment are predicted by monitoring the values of other parameters.

5.3.1. ANN Method for Data Analysis

ANN method was selected to analyze the collected data. ANN is a common analysis tool utilized to quantify and model the relationships between different parameters. ANN has many advantages compared to conventional methods. This tool is self-driven, self-adaptive, and has the ability of learning by itself to respond to incomplete and unknown data (Patel and Jha 2015). ANN is also capable of determining complicated relationships in data sets (Heravi and Eslamdoost 2015). It automatically adjusts the neuron weights after comparing the predicted output with the target to minimize errors, and consequently achieve accurate and reliable results (Boussabaine 1996; Wang and

Gibson 2010). On the whole, ANN method acts as human beings and can get experience from the trainings to improve its performance and adjust itself to changing situations (El-Gohary et al. 2017).

In this study, multilayered feedforward neural network trained with back propagation learning algorithm was selected as the architecture of the ANN. This design is efficient to conduct multivariable linear and nonlinear analysis, and can continue computation to acquire desired accuracy (Demuth 2000; Patel and Jha 2015). Multilayer feedforward neural network includes neurons sorted in outputs and hidden internal layers. Neurons are connected to each other in the network with different weights. In each layer, there is another neuron with the name of bias that is summed with other neurons to estimate output (Haykin 1999; Heravi and Eslamdoost 2015). According to Demuth et al. (2009), it is recommended to develop a two-layer network (one hidden layer) for the experimentation studies, as shown in Figure 5.2.

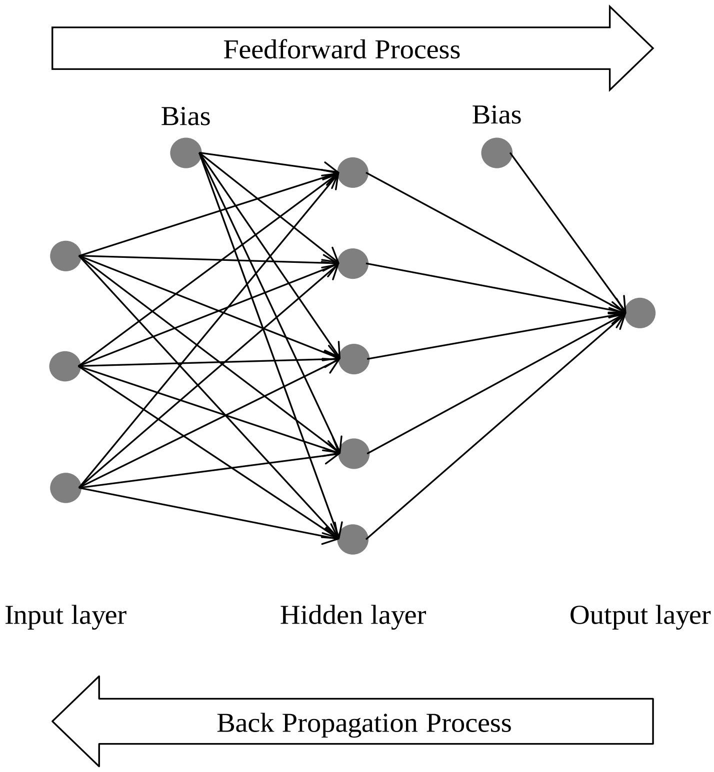


Figure 5.2. Design of the developed neural network model

The layers of ANN can be increased to three if the results of two layers were not satisfactory. Back propagation algorithm was then used to train the feedforward process. Back propagation technique repeats two cycles of propagation and weight update for several times which is known as epoch. The inputs are first fed forward layer by layer in the network to estimate the output. Through comparing the output with the target, the error is then calculated and propagated backward from output to inputs. This algorithm measures the gradient of function loss considering the weights in the network. The calculated gradient is then used to update the weights (Sarle 1995). Figure 5.3 shows the flowchart of the neural network algorithm developed in this study.

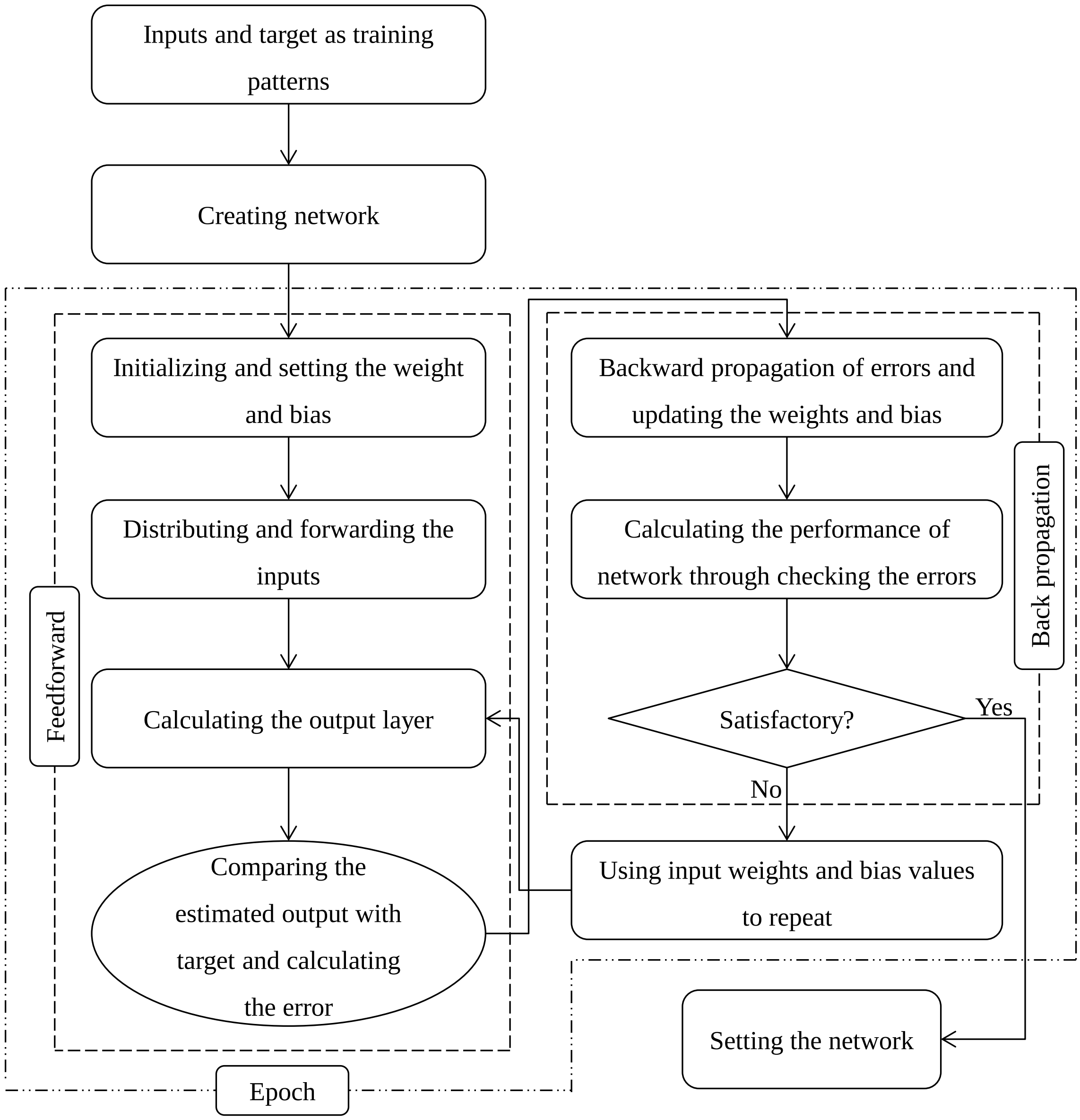


Figure 5.3. The algorithm of developed artificial neural network for training, testing and prediction processes

In the developed ANN network, 70% of the raw data were used for training, while 15% of the data were allocated to the validation process and 15% of data were employed for testing. Figure 5.4 shows sample outputs of a developed network considering three parameters of acceleration rate, speed and road slope as inputs. As can be seen, the perfect fit is the dashed line having 45 degree slope. For this shown sample, there is a good fit between output and target for all three processes of training, validation and testing. Also, the combination of all datasets yields the best fitting results.

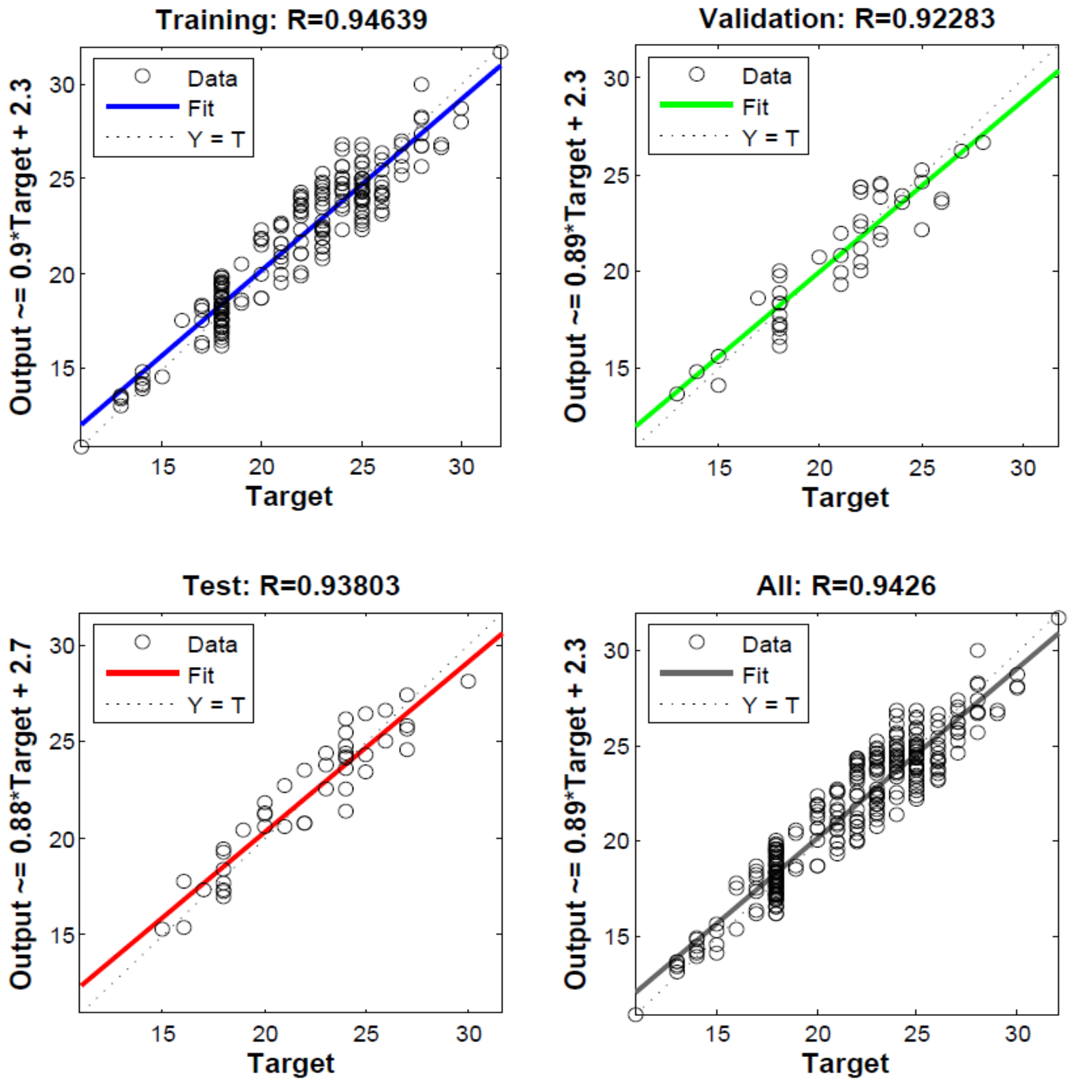


Figure 5.4. Sample results achieved by conducting analysis and validation on one of the developed networks

As mentioned before, ANN method is an iterative process to find the final answer through calculating the optimal weights for inputs and bias values, and reducing the sum of the square errors (SSE) to an acceptable level. Depending on the number of parameters, consistency of the relationships and acceptable error, the number of iterations (epoch) differs. In each epoch, the performance of the network is measured through calculating the SSE. Figure 5.5 shows a sample graph indicating the performance of a developed network and total number of epochs to acquire the best performance.

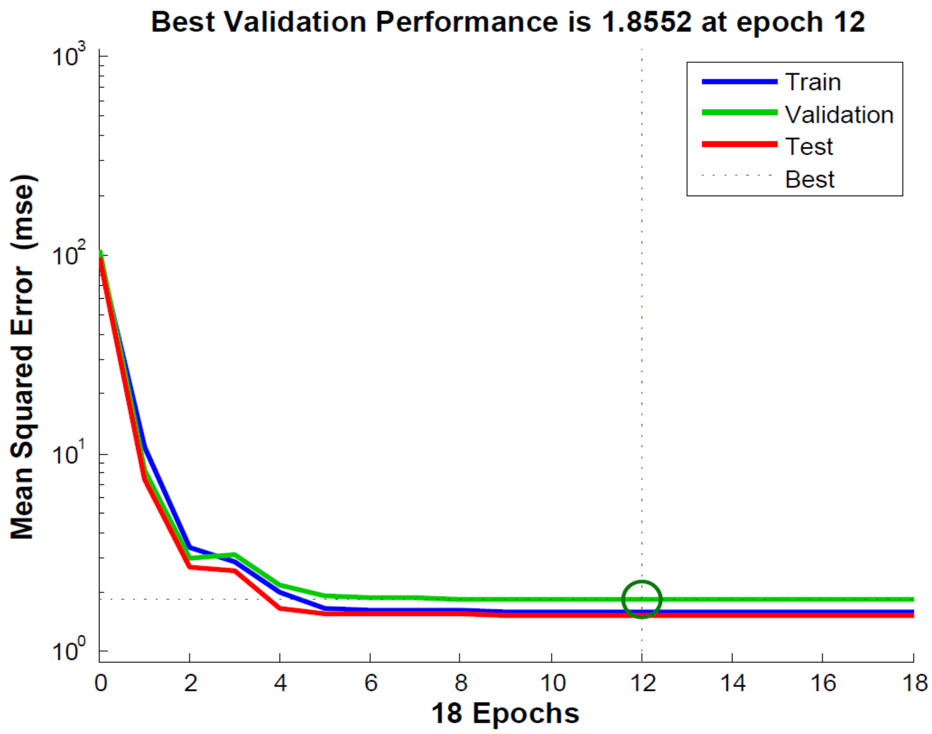


Figure 5.5. The performance plot of one developed networks showing the best validation performance is at epoch 12

As discussed in the previous sections, the total weight of equipment affects the influence of other parameters i.e. acceleration rate, speed and road slope on engine load. As the weight of equipment increases, more power of engine is used to accelerate vehicles or drive them in uphill roads. WF variable (combined weight of equipment carried per 100 kW of engine size) normally varies from 2.5 for empty vehicles without any trailer attached to around 15 for fully-loaded vehicle with a trailer. During seven days of field experimentations on the construction site, vehicles were tested in different WFs of 2.75, 4.5, 6.5, 13 and 14.5. As one of the major limitations of experimentation procedure, testing data were collected from five constant values of WF only due to loading conditions and vehicle configurations adopted in the experimental construction projects. WF values of 2.75 and 4.5 were collected from empty vehicles without and with a trailer respectively. WF of 6.5 is related to experimentation of fully-loaded truck without trailer, and 13 and 14.5 WF data were obtained from experimentation on fully-load equipment with three-axle and four-axle trailers, respectively.

As one of the main restrictions of weight modeling, ANN can have only one layer of input, as indicated in Figure 5.2. Three operational parameters of acceleration rate, speed and road slope could be entered to the network as inputs. To deal with this issue, ANN was developed for five times to consider the effect of five different values of WF on other operational parameters and engine load. In each developed network with a specific WF, the impact of the other three operational parameters was modeled on engine load through conducting sensitivity analysis. Then, by comparing the achieved results from the networks, the effect of the WF on the influence of the operational parameters on engine load can be determined.

5.3.2. Sensitivity Analysis

Sensitivity analysis investigates the effects on output of the developed model through varying the inputs, and determines the amount of an input contributing to the output. Interpreting the results achieved by ANN may not be easy to explain in all situations (Patel and Jha 2015). It can be mentioned that sensitivity analysis determines the cause-and-effect relations of inputs and output of the developed model. According to Sonmez and Rowings (1998), this analysis can be conducted by varying the value of an input and fixing the other inputs at their mean values.

In this research, sensitivity analysis was conducted on each of the investigated operational variables to determine their effects on engine load parameter, as shown in Tables 6.1 to 6.5. To do so, the mean (μ) and standard deviation (σ) of the collected data of the three parameters of acceleration rate, speed and road slope were identified for different investigated WFs. To investigate the effect of each operation parameter, we varied one specific parameter at a time, while other variables being fixed at their respective mean values. The varied data were then supplied to the developed network to analyze the effect of change in each unit of input to output.

It has been recommended to compute the correlation output network for three steps above and below the mean of each input in the interval of μ-σ and μ+σ (Patel and Jha 2015). In this study, the output was computed in respect to the variation of inputs for seven values of μ-σ, μ-0.67σ, μ-0.33σ, μ, μ+0.33σ, μ+0.67σ, and μ+σ. As illustrated in Table 5.1 to 5.5, this process was performed for 15 times to calculate the effect of all three operational parameters on engine load for all considered WFs.

Table 5.1. Result of the sensitivity analysis on the model for WF of 2.75

Parameters	Inputs Variation			Output Variation			Coefficient
	Min	Max	Swing	Min	Max	Swing	
Acceleration	0.03	0.48	0.45	28.21	37.36	9.15	20.33
Speed	20.89	77.90	57.01	29.03	38.90	9.87	0.21
Road Slope	-1.09	1.35	2.44	34.61	39.13	4.51	1.85

Table 5.2. Result of the sensitivity analysis on the model for WF of 4.5

Parameters	Inputs Variation			Output Variation			Coefficient
	Min	Max	Swing	Min	Max	Swing	
Acceleration	0.08	0.42	0.34	32.58	41.12	8.54	25.12
Speed	18.42	75.30	56.88	28.63	42.28	13.65	0.24
Road Slope	-0.89	1.15	2.04	38.36	43.52	5.16	2.53

Table 5.3. Result of the sensitivity analysis on the model for WF of 6.5

Parameters	Inputs Variation			Output Variation			Coefficient
	Min	Max	Swing	Min	Max	Swing	
Acceleration	-0.01	0.35	0.36	34.02	44.78	10.75	29.9
Speed	16.10	72.49	56.39	27.88	46.49	18.61	0.33
Road Slope	-1.05	1.21	2.26	36.69	44.56	7.86	3.48

Table 5.4. Result of the sensitivity analysis on the model for WF of 13

Parameters	Inputs Variation			Output Variation			Coefficient
	Min	Max	Swing	Min	Max	Swing	
Acceleration	-0.02	0.29	0.31	35.67	48.36	12.69	40.95
Speed	13.25	65.15	51.9	30.45	49.65	19.20	0.42
Road Slope	-1.12	1.08	2.20	36.06	47.62	11.53	5.24

Table 5.5. Result of the sensitivity analysis on the model for WF of 14.5

Parameters	Inputs Variation			Output Variation			Coefficient
	Min	Max	Swing	Min	Max	Swing	
Acceleration	-0.05	0.27	0.32	44.60	55.23	10.63	46.23
Speed	11.23	64.12	52.89	31.63	57.02	25.38	0.48
Road Slope	-0.75	1.11	1.86	44.71	55.35	10.64	5.72

The last columns in Tables 5.1 to 5.5 present the results of sensitivity analysis conducted on the developed networks. These coefficients were obtained through dividing the variations of the engine load as output to the variations of each investigated input. As discussed before, the effect of WF on engine load can be regarded as the variation in the coefficients of the other three operational parameters. The comparison of results in all five tables indicates that the WF has the highest impact on acceleration parameter by varying from 20.33 for WF of 2.75 ton/100kW to 46.23 for WF of 14.5 ton/100kW. WF parameter also has significant influence on the coefficient of road slope variable. As shown in Tables 5.1 and 5.5, for an empty vehicle (WF = 2.75 ton/100kW), the engine load increases by 1.85% for addition of each degree of road slope, but this value reaches the peak of 5.72% in the WF of 14.5 ton/100kW. It is also found that the WF has moderate effect on the driving speed coefficient, which varies from 0.21 for empty vehicle without trailer to 0.48 for fully-loaded vehicle with a large trailer.

5.3.3. Weight Modeling

The sensitivity analysis conducted on the developed networks indicates a linear relationship with high correlation ($R^2 > 90\%$) between the operational and engine load parameters for all WF values. As devised in the previous chapters, Equation (5.1) models the linear relationship between investigated factors and engine load.

$$\text{Engine Load (\%)} = (C_{AC} * AC) + (C_{SP} * SP) + (C_{SL} * SL) + C \qquad (5.1)$$

Where, C_{AC}, C_{SP} and C_{SL} are the coefficients of acceleration rate, speed and road slope, respectively. These coefficients were calculated as given in the last column of Tables 5.1 to 5.5. The parameters of acceleration rate, speed and road slope were measured with the units of km/h.s, km/h and degree in the experiments.. Engine load variable does not have any unit, and is measured as a percentage of the used power over the maximum power of engine. Through comparing the engine load value estimated by Equation (5.1) with the outputs predicted by ANN method, the value of C was measured for all data points. The value of C is relatively constant around 15 for all estimations which can be interpreted as the bias neuron with a fix value that can be added to the inputs in the hidden layer of ANN. In practice, the engine load in idling mode of construction vehicles is around 15%.

The comparison of results achieved by neural network analysis also confirms a highly-correlated linear relation among WF parameter and coefficients of the other operational and environmental variables. Equation (5.2) presents the results obtained by conducting regression analysis on data presented in Tables 5.1 to 5.5.

$$C_{AC} = 1.860 * WF + 17.48,\ R^2 = 0.94 \quad (5.2a)$$

$$C_{SP} = 0.019 * WF + 0.17,\ R^2 = 0.92 \quad (5.2b)$$

$$C_{SL} = 0.441 * WF + 1.79,\ R^2 = 0.92 \quad (5.2c)$$

WF parameter can be modeled by combining the Equations (5.1) and (5.2), as presented in Equation (5.3). WF is a function of operational parameters and engine load. Therefore, by having the real-world data of acceleration rate, speed and road slope parameters and engine load variable, WF parameter for on-road construction vehicles can be predicted using Equation (5.3).

$$WF = \frac{(EL - C - (17.48*AC + 0.17*SP + 1.79*SL))}{(1.86*AC + 0.019*SP + 0.441*SL)} \quad (5.3)$$

GPS-INS and engine data logger instruments have been employed in this study to record operational and engine data on a second by second basis. Therefore, a value for WF can be estimated by Equation (5.3) once a second, As shown in Figure 5.6, according to the conducted analysis, the resulted WFs are relatively the same with not much variation. The small variation in the value of WF is due to many factors including operator skill, engine condition and road type. It is also found the distributions of the estimated WFs in each operation cycle with a specific loading condition follow a normal statistical function. The mean of WFs determined by Equation (5.3) over a certain time period can be calculated as the final estimation of the vehicle weight. The mean and standard deviation of WF are calculated using Equation (5.4).

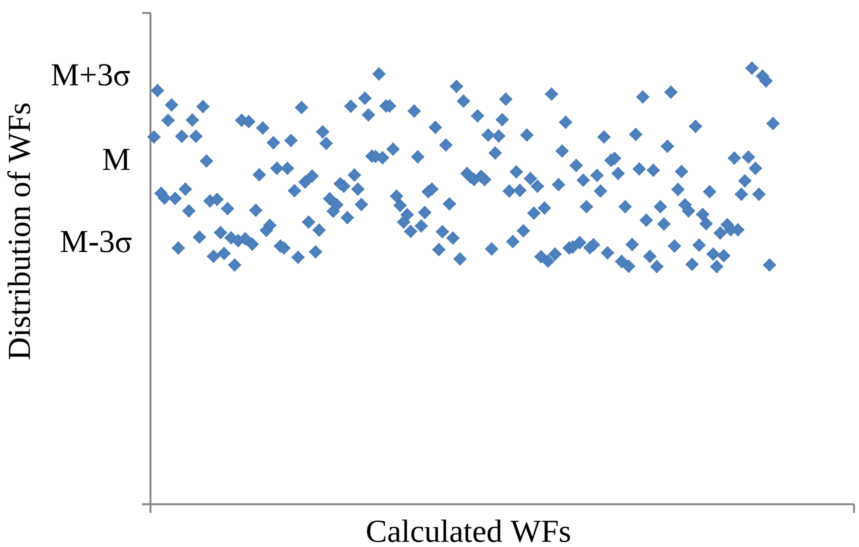
$$\mathrm{M} = \frac{1}{n} * \sum_{i=1}^{n} \mathrm{WF}_i \tag{5.4a}$$

$$\sigma = \sqrt{\sum_{i=1}^{n} (WF_i - M)^2} \tag{5.4b}$$

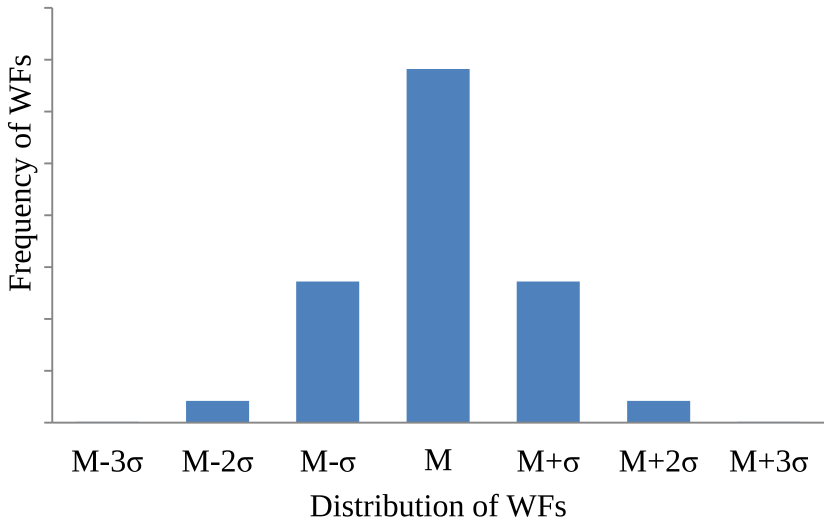
Where:

M: Mean of the calculated WFs

σ: Standard deviation of the calculated WFs



(a)



(b)

Figure 5.6. (a) and (b) The distribution of calculated WFs using Equation (5.3)

Using M as the final WF, total weight of HDVs can be calculated by Equation (5.5a). 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, the payload can be calculated using Equation (5.5b).

$$TW = M^* PW/100 \quad (5.5a)$$

$$PL = TW - EW \quad (5.5b)$$

Where:

TW: Total weight of equipment (ton)

PW: Engine power (kW)

PL: Payload carried by equipment (ton)

EW: Empty weight of equipment (ton)

5.4. Model Validation

In this section, the applicability of proposed weight estimation model is validated using field data collected during the seven-day experimentation. The estimated weights calculated by Equation (5.5) were compared with the real weight of vehicle measured by an industrial weighbridge employed on the site. A total of 14 different loading conditions of experimented trucks were considered for model development, while eight specific WFs were incorporated in the validation analysis. Figure 5.7 presents the predicted weight results versus the equipment's weight measured by the weighbridge. There is a high correlation and consistency amongst predicted and measured weight data with R^2 being 0.9843.

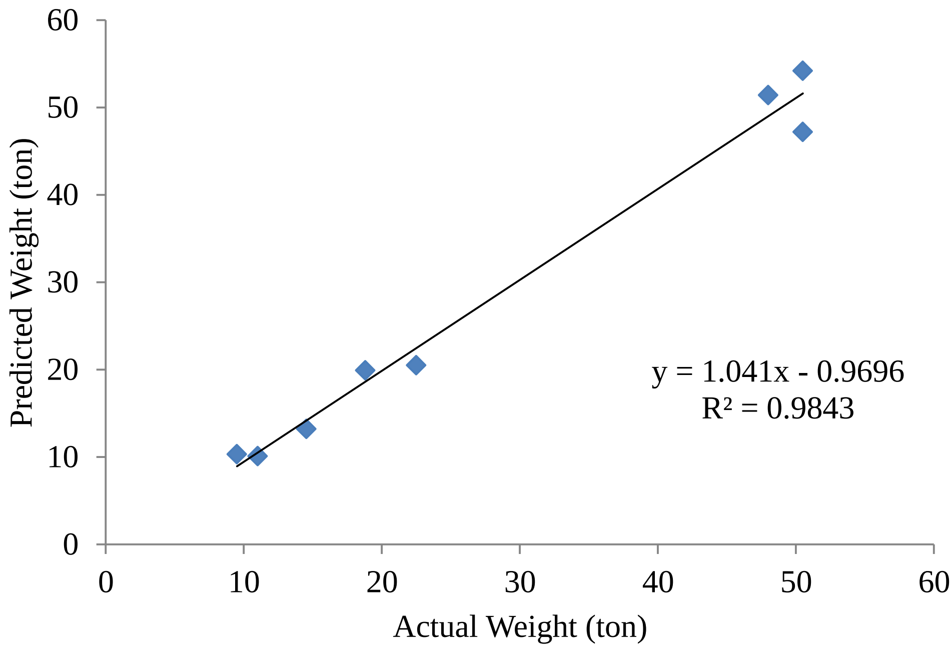


Figure 5.7. Validation of the developed weight estimation model by comparing the estimated and real equipment's weight

The accuracy of the developed weight estimation model was further investigated through dividing the predicted weight to the weight measured by the weighbridge. As shown in Figure 5.8, the accuracy of the model in estimating the weight of equipment in all eight case studies is more than 90%. For having higher accuracy, it is recommended to devise the model for each piece of equipment based on the developed methodology and calibrate its coefficients based on the performance and specifications of the engine.

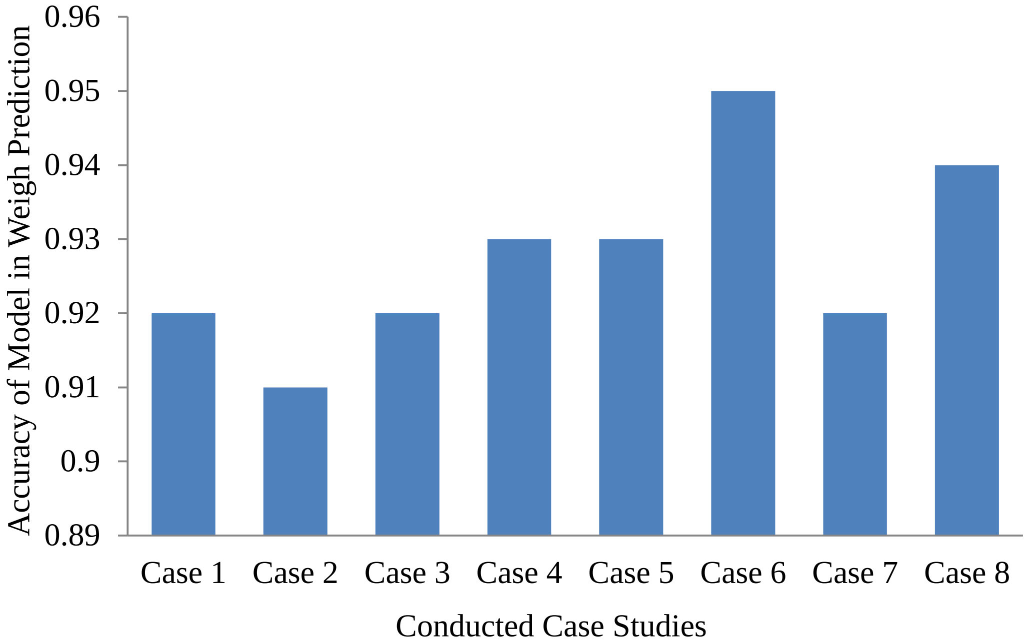


Figure 5.8. The accuracy of the developed model in predicting the weight of equipment

Various sources of potential errors were also identified which can be addressed to further increase the accuracy of the developed model. The main error source could be the accuracy of the engine data logger in measuring the engine load parameter. Also, the performance of GPS-INS instrument is another issue to study with. The driving skill of the equipment operators can cause potential errors in the modeling of weight based on operational parameters. The results showed that for aggressive drivers, the weight is normally overestimated. The engine performance and its internal combustion also affected the accuracy of the collected data. In this study, the quality of the analyzed data was assured through conducting data filtering and processing procedure.

5.5. Conclusion

Earthmoving operations as one of the major construction activities employ a large number of HDVs for material transportation. The planning and payment arrangements of such projects are normally based on the amount of transported construction materials. Different metric and volumetric methods and techniques have been employed to estimate the quantity of materials transported by haulers in each operation cycle on the construction sites. In spite of high accuracy of some current techniques in weight measurement, they are costly, time consuming and labor intensive which affect the production rate and cost in construction projects.

This chapter developed a comprehensive methodology to estimate the weight of on-road HDVs through quantifying the relations among operational parameters and engine load variable. To do so, the database was first created including all operational, environmental and engine raw data collected from field experimentations. ANN method was then devised to model engine load based on the four operational variables of vehicle weight, acceleration rate, speed and road slope. As one of the main limitations of this study, we could only have access to five WFs of 2.75, 4.5, 6.5, 13 and 14.5 due to the vehicle configurations and loading conditions. Through conducting sensitivity analysis on the developed networks, the effects of operational variables were computed on the engine load. The achieved results showed there is a linear relation with high correlation and consistency between operational parameters and engine load. WF, as the surrogate of equipment's weight, was then modelled based on the engine load variable and the other considered operational factors. Developed model was finally validated through comparing the predicted vehicle's weight with the weight measured using weighbridge. Validation process reveals the high accuracy (more than 90%) of the developed model in weight estimation which is considered to be one the great achievements of this study.

This model has numerous applications in practice to automatically estimate the weight of different on-road vehicles without requiring a full stop for measurement, which is also referred to as weigh-in-motion. In comparison with current weight measurement methods, this technique minimizes initial and operation costs, and can be realized automatically and in real time, leading to significant savings in operation time and cost in future applications.

Chapter 6

Fuel Use and Emissions Reduction Strategies

6.1. Introduction

The growth of population and industrialization has heightened demands on different sources of energies globally, which has increased the emissions of GHGs to the atmosphere. These contaminants have drawn serious concerns on human health, ecosystem and environment, which are also considered as potential causes of respiratory and cancer diseases (Klein et al. 2016). The awareness of the non-compensable effect of anthropogenic GHGs emissions on climate change and public health has brought global attention towards developing emission reduction regulations and guidelines. According to the UNFCCC, all sectors in industrialized countries should follow regulations to decrease GHGs emissions (Kim et al. 2012). EPA and EU have developed emission standards to restrict the GHGs emitted from on-road vehicles and non-road diesel equipment (Barati and Shen 2015). Also, many limitations have been imposed by the Intergovernmental Panel on Climate Change (IPCC) (2006) to minimize carbon footprints through reducing activities having produced large amount of emissions.

Construction industry is considered as one of the main contributors to energy consumption and GHGs production globally. According to EPA (2009), construction sector accounts for 1.7% of total GHGs production and 6.8% of all industrial-related emissions which is ranked as the third largest GHG emitter after oil and gas, and chemical manufacturing industries (Azzi et al. 2015; Thuitt 2009). Based on the report prepared by EPA CAAAC (2006), construction sector accounts for 6% of LDVs and 17% of HDVs while producing 32% of NO_x and 37% of PMs of all mobile source emissions. In addition, it is estimated that this industry produces more than 100 million tons of CO_2 annually, the most abundant GHG, which is around 7% of total CO_2 emitted across the world. The construction sector has also been ranked as the third highest CO_2 emitter per used unit of energy after cement and steel production industries (EIA 2009). The emissions on construction sites are mainly produced from on-site equipment operations. Developing reduction strategies for such equipment can have significant effect on total amount of emitted pollutions (Avetisyan et al. 2012). For example, if the idling time of construction equipment is reduced by 10%, the emission of CO_2 decreases for around 0.8 million tons per year (Truitt 2009). Furthermore, it is predicated if the fuel consumption of equipment involved in construction sites decreases by 10%, the corresponding CO_2 reduction in each year would be approximately 6.7 thousand tons (Lewis et al. 2012). In addition, equipment compatibility and efficiency are two crucial parameters having considerable effect on produced emissions per unit of conducted work (Ahn and Lee 2013). Large construction projects normally involve a variety of types and numbers of equipment, and therefore hold flexibility in selecting equipment to work on a given activity.

There is a lack of comprehensive strategy to reduce energy consumption and emissions resulting from the operations of equipment in construction projects. The current reduction schemes have mainly focused on engine and fuel attributes, and mechanical practices to decrease total amount of emitted pollutions. As a general guideline for construction firms, EPA (2007) introduced engine upgrading and retrofitting technologies to reduce emissions which could be costly and not readily applicable for the existing fleet of construction equipment. Cleaner and renewable fuels have been introduced as an alternative source of energy over traditional diesel which may not be economically feasible due to the high cost and power loss of equipment.

This chapter aims to develop different fuel use and emissions reduction schemes for on-road construction equipment using the models developed in the previous chapters. As the main strategy, this study devises an optimal driving pattern to reduce the fuel use and emissions through determining the optimum driving speed. At equipment level, this research also compares the fuel consumption and emissions rate of engines with different tiers. Several case studies were conducted to estimate the reduction in fuel use and emitted pollution using the proposed research framework. In next step, this study focuses on equipment selection and trailer configuration as a planning scheme to increase the fuel and emissions efficiency of construction vehicles. Finally, the effect of traffic condition on fuel use and emissions of on-road construction vehicles is investigated. The additional fuel use and emissions production due to vehicle stops happened in hauling and returning modes are estimated. The developed fuel use and emissions reduction schemes can be used as a guideline by construction managers and equipment operators under certain project settings.

6.2. Optimal Driving Pattern

As one of the main applications of developed fuel use and emissions models, optimal driving pattern can be devised to reduce fuel use and emissions of construction equipment. This scheme takes into consideration the effect of investigated operational and engine parameters, and can be used as a guideline by operators to increase fuel efficiency of heavy-duty construction equipment. In this operational level scheme, optimal driving speed can be determined based on weight of equipment and slope of road.

This operational level fuel use and emissions reduction scheme for on-road construction equipment is developed through analyzing the experimental data and using devised models in the previous chapters. The field collected data are classified into four main operational, environmental, engine, and fuel use and emissions categories. The results are achieved through conducting multivariable linear analysis on the operational, environmental and engine load parameters. OLS analysis is also performed to link engine attributes to the fuel use and emissions rate.

6.2.1. Effect of Weight on Optimal Speed

Like previous chapters, WF parameter is considered as an indicator of total equipment weight including equipment itself plus the payload and trailer. This parameter is defined as the amount of equipment's weight carried per 100kW of engine size. Due to restrictions in loading conditions and trailer configurations in the experimentation, the field data were collected on four WFs of 2.75, 4.5, 6.5, 13 and 14.5 only. The gathered field data showed that at limited time of operation, construction equipment is driven in acceleration or deceleration mode, resulting in much less speed changes when compared with passenger cars driven in urban areas. In spite of the effect of acceleration parameter on instantaneous fuel use and emissions rate, its influence on total used fuel and produced emissions in a trip can be negligible. Therefore, the effect of acceleration parameter has been ignored in developing optimal driving pattern. The engine load and engine size are the two main engine parameters considered in this study. As mentioned, engine load acts as an intermediate parameter bridging investigated operational and environmental parameters to fuel use and emissions rate.

Since CO_2 is the main GHG produced by construction equipment, the focus of this study is on the reduction of CO_2 emission. As the first step of data analysis, the effect of speed and WF parameters is concurrently investigated on fuel use and emissions rate. In this part, it is assumed that the equipment pieces are driven on a levelled route which slope parameter does not have any effect on engine load and fuel use. As shown in Figure 6.1, based on different WF values, on-road construction equipment can be driven at optimal driving speed to use minimum fuel and emit minimum emissions per travelled distance. As can be seen in Figures 6.1 to 6.5, by increasing the WF, the optimal driving speed decreases, but fuel consumption and CO_2 emission rate per travelled distance increase significantly. For example, for WF of 2.75 (empty vehicle), optimal driving speed and its corresponding fuel use and CO_2 emission rate are around 81 km/h, 6.5 l/100kW.100km, and 16.1 kg/100kW.100km respectively (Figure 6.1), while, these numbers are approximately 65 km/h,14.2 l/100kW.100km, and 38 kg/100kW.100km for WF of 14.5 (fully-loaded vehicle, see Figure 6.5). As shown in Figure 6.6, based on the experimentations conducted on five different WFs, there is a highly-correlated linear relationship among WF, optimal fuel use and minimal CO_2 emission.

As demonstrated in Figures 6.1 to 6.5, the minimum fuel use and minimum CO_2 emission rate coincide with each other. In other words, by driving at optimal speed, both fuel use and CO_2 emission can be minimized. The developed methodology and framework can be readily applied to estimate the optimal driving speed for the minimal emission rate of other pollutants, like CO, HC and NO_x.

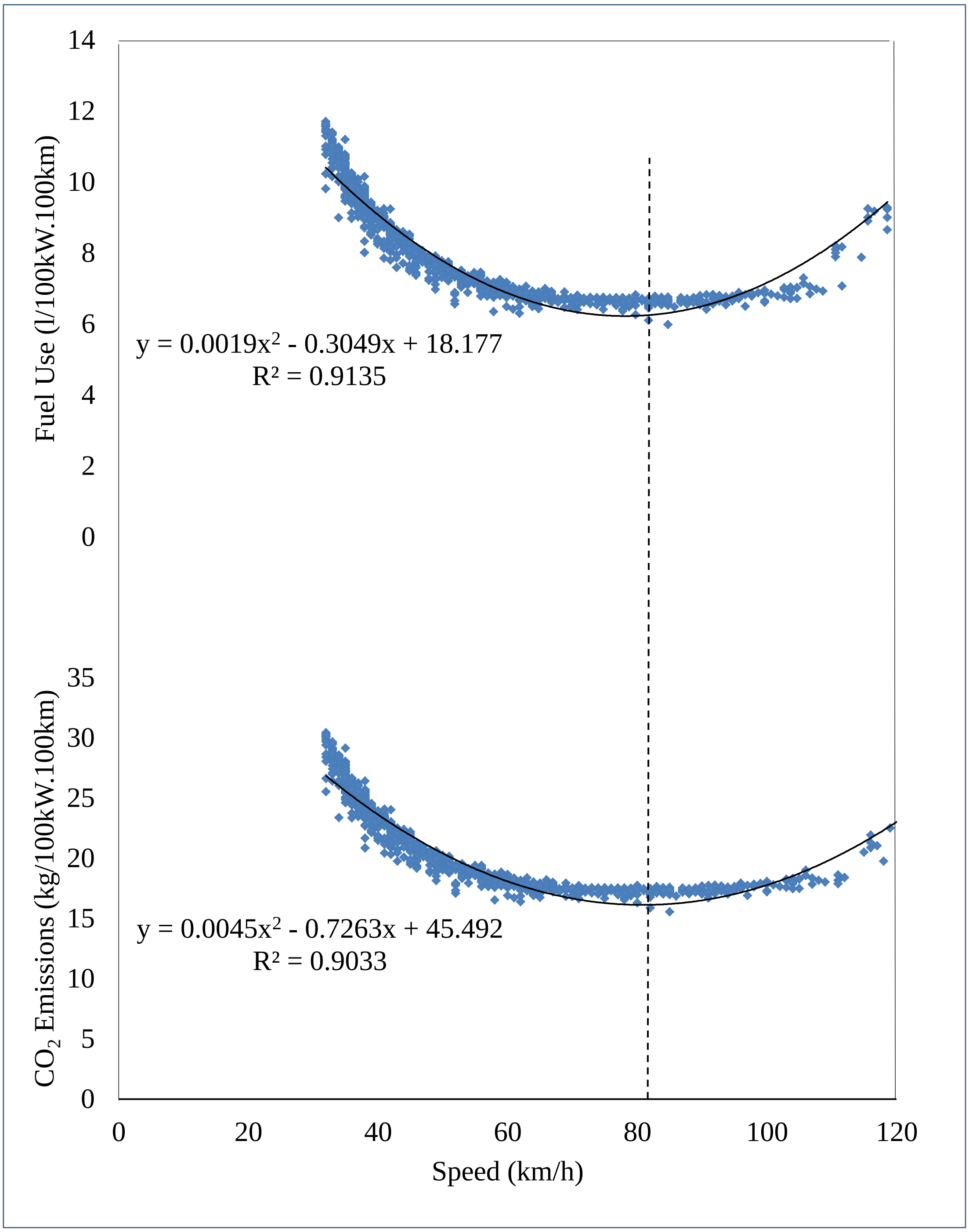


Figure 6.1. Fuel use and CO_2 emission rate of on-road construction equipment driven at a levelled road with WF of 2.75 (empty three-axle truck)

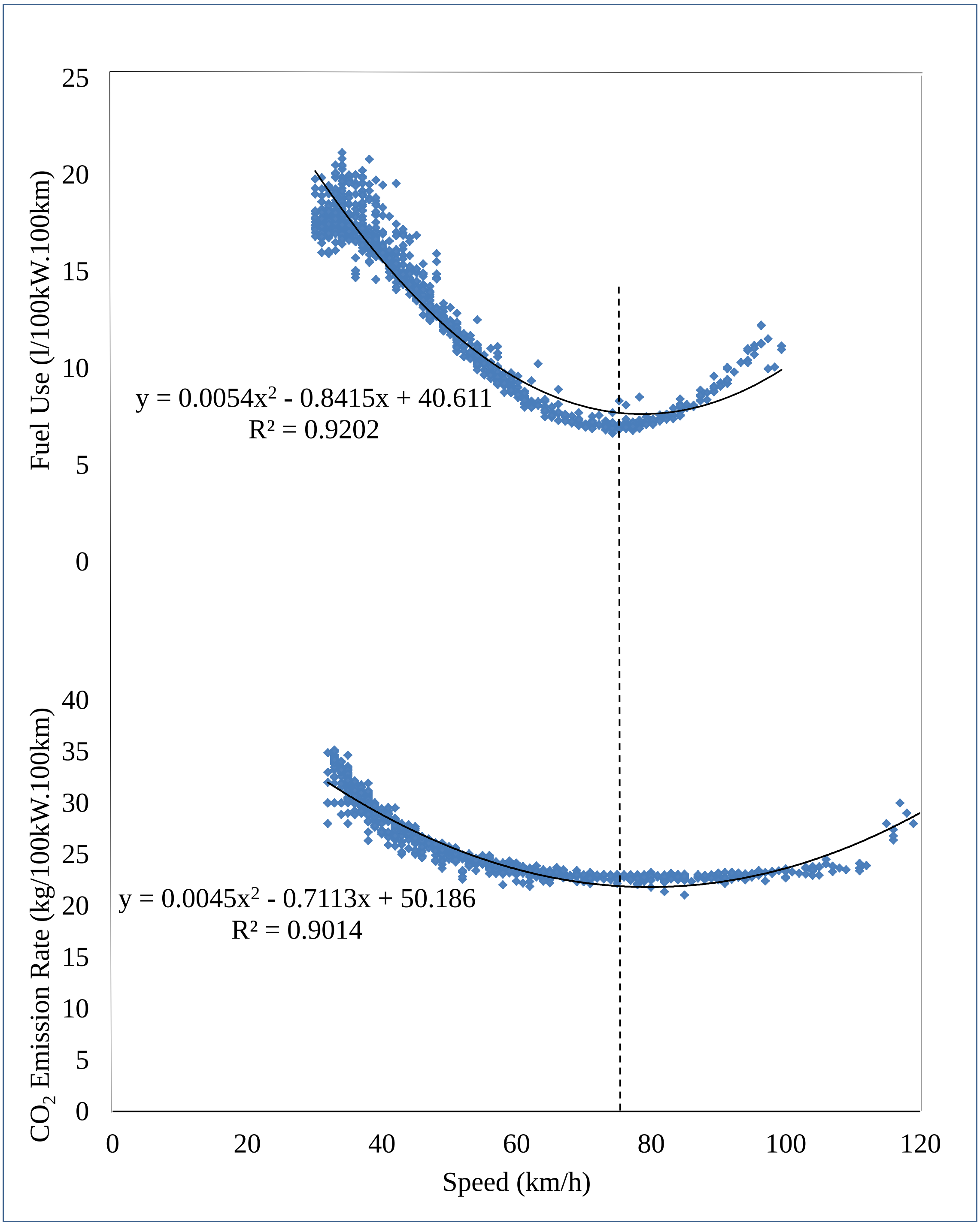


Figure 6.2. Fuel use and CO_2 emission rate of on-road construction equipment driven at a levelled road with WF of 4.5 (empty three-axle truck with a trailer)

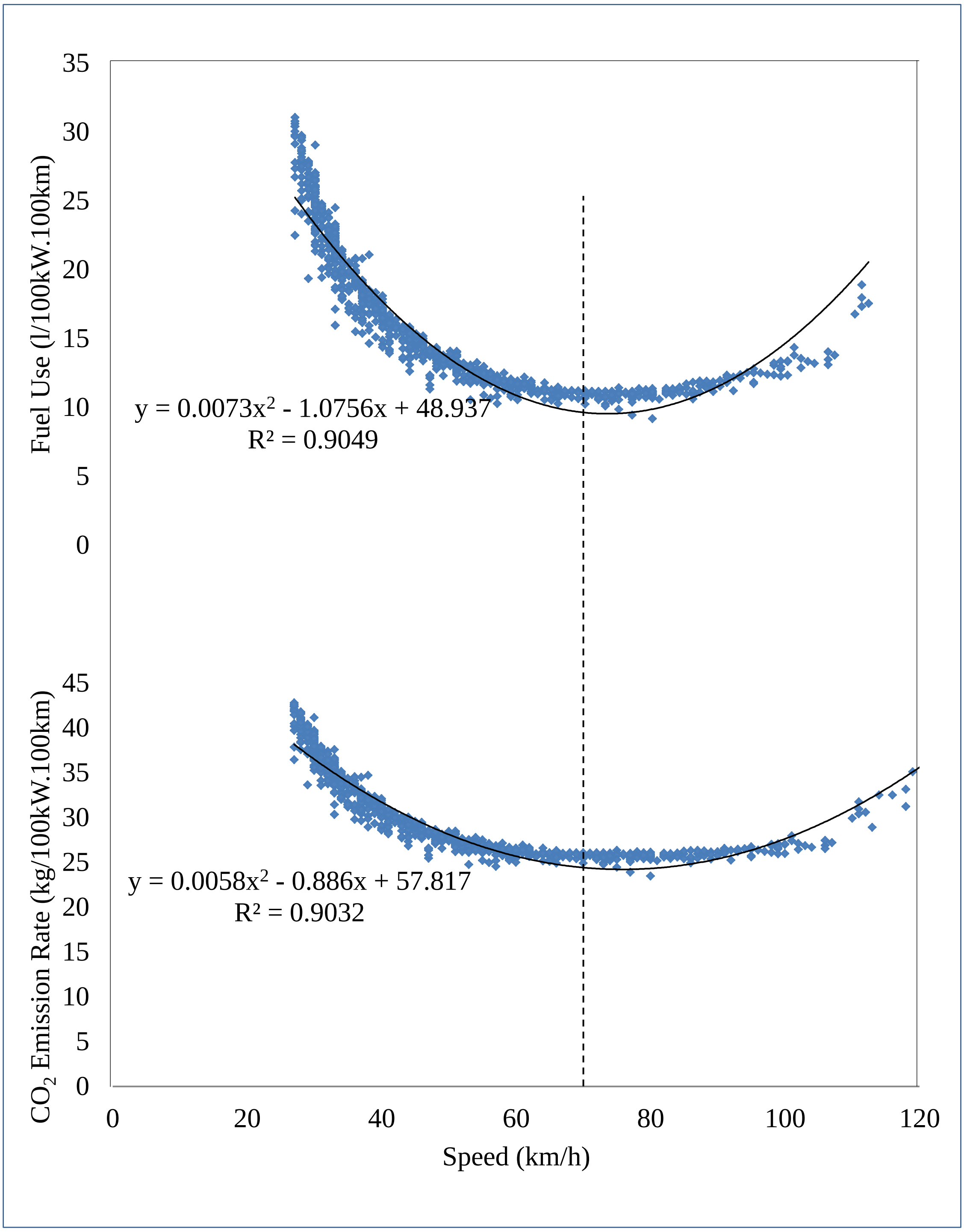


Figure 6.3. Fuel use and CO_2 emission rate of on-road construction equipment driven at a levelled road with WF of 6.5 (fully-loaded three-axle truck without trailer)

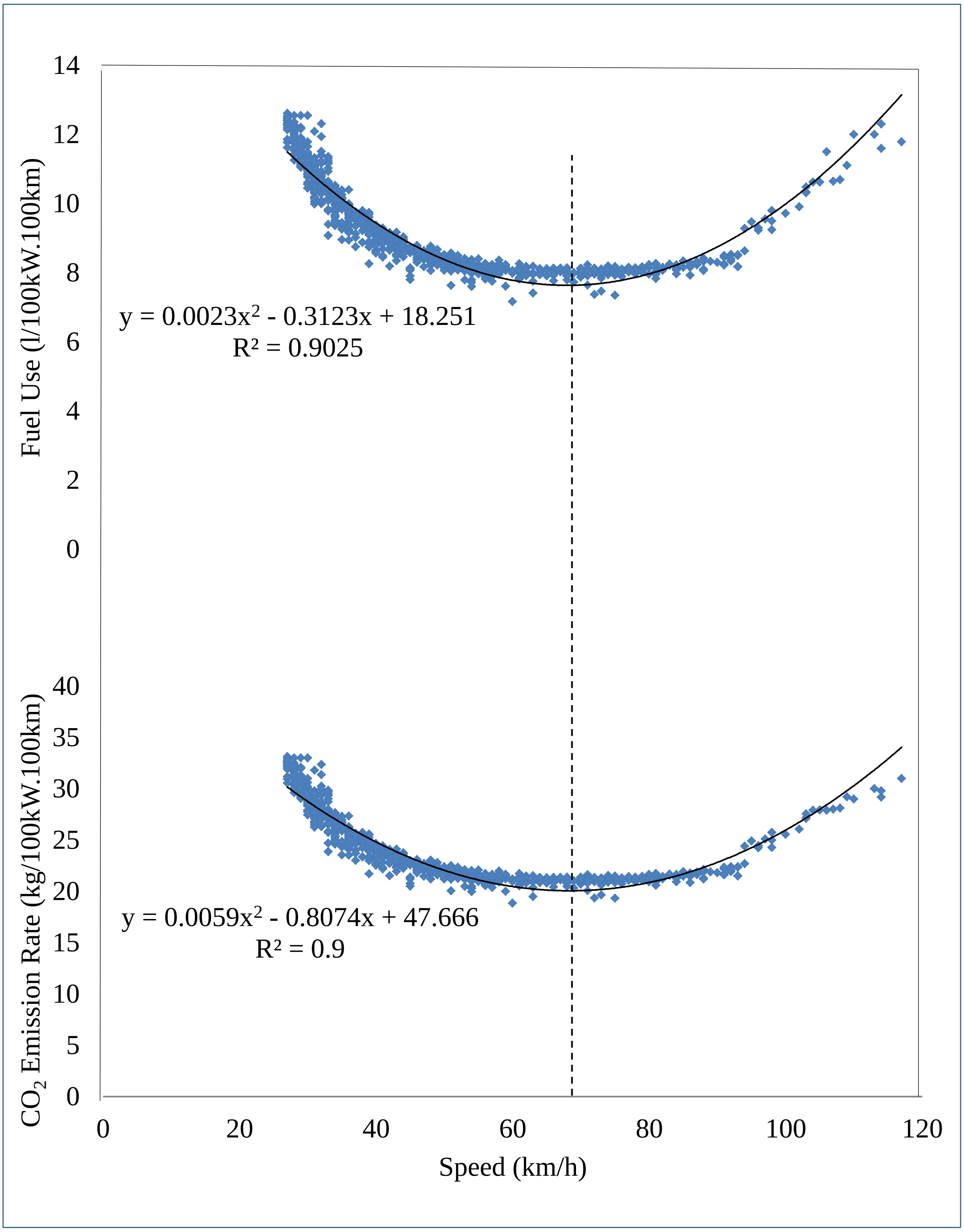


Figure 6.4. Fuel use and CO_2 emission rate of on-road construction equipment driven at a levelled road with WF of 13 (fully-loaded six-axle truck with trailer)

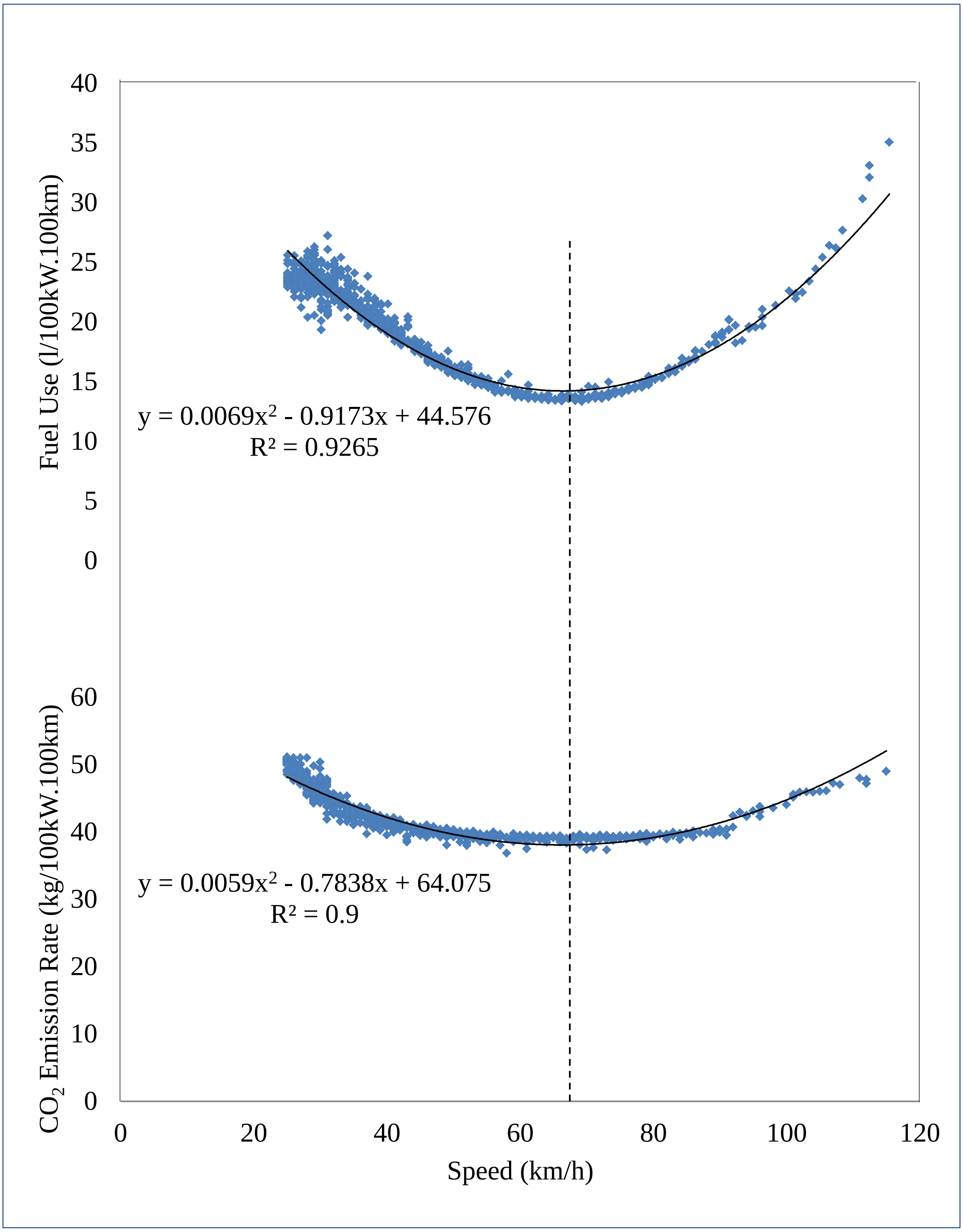


Figure 6.5. Fuel use and CO_2 emission rate of on-road construction equipment driven at a levelled road with WF of 14.5 (fully-loaded seven-axle truck with trailer)

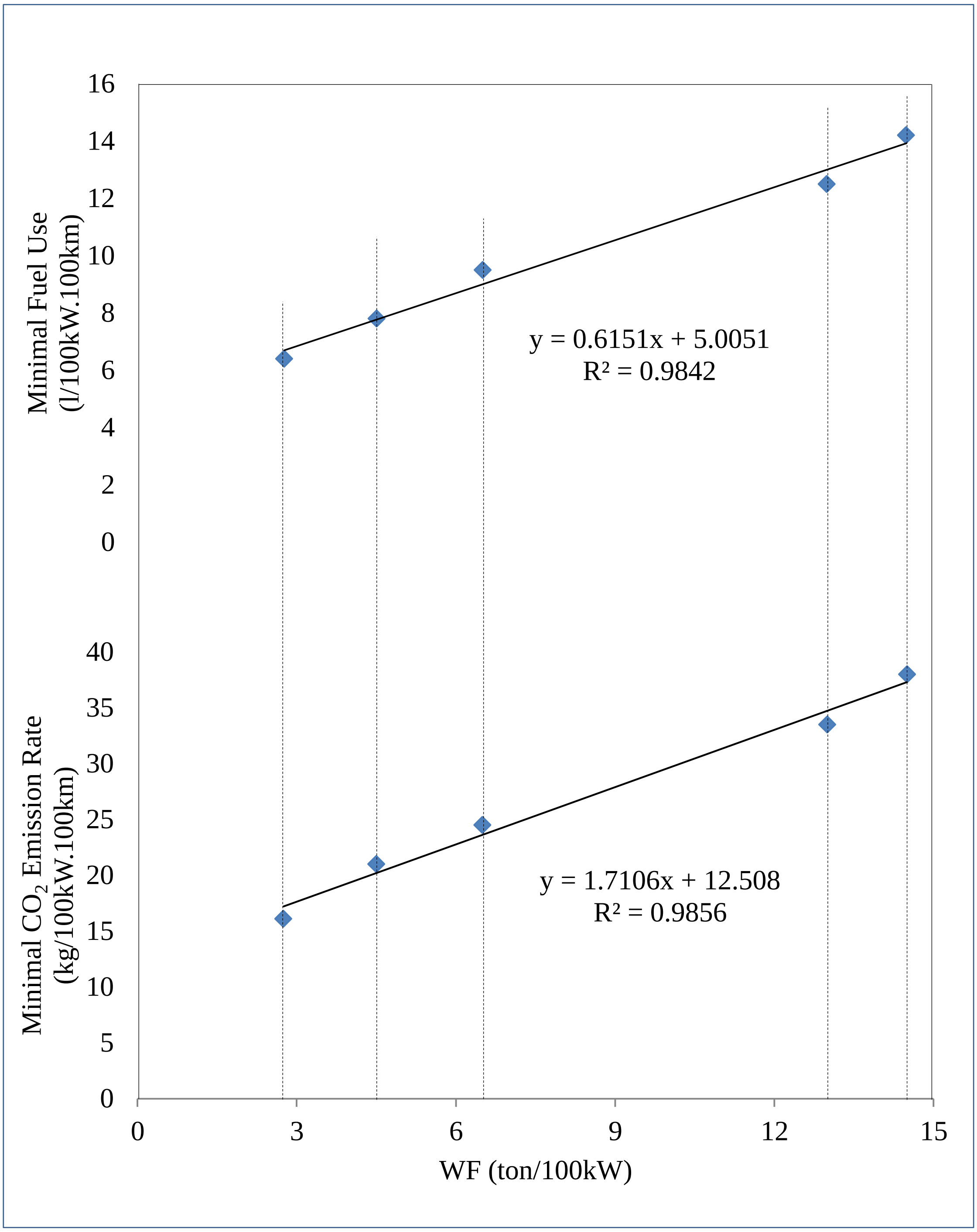


Figure 6.6. The minimal fuel use and CO_2 emission rate for different investigated WFs

6.2.2. Effect of Road Slope on Optimal Speed

Slope of road is a main environmental parameter affecting optimal driving speed, fuel consumption and emissions production of construction equipment. To investigate the effect of road slope on the optimal driving speed, the raw data collected from equipment pieces driven on the normal roads with different slopes were analyzed using the fuel use and emissions rate models developed in the previous chapters. Data from all experimented equipment pieces with different WFs were used in modeling the effect of road slope on optimal speed and its corresponding fuel use and emissions production.

Figures 6.7 to 6.10 demonstrate the effect of road slope on fuel use and CO_2 emission rate of equipment pieces driven with different speeds. It is found for different WF values, by increasing the slope of road, the optimal driving speed decreases, but there is significant increase in fuel use and CO_2 emission rate. For example, a piece of equipment with WF of 6.5 driven on a road with 4 degrees slope uses 14.4 l/100kW.100km fuel and produces 38 kg/100kW.100km CO_2 emission at optimal speed of 67 km/h and. If the slope of road increases to 8 degrees, the optimal speed, minimal fuel use and CO_2 emission for the same equipment would be 57 km/h, 20.8 l/100kW.100km, and 55 kg/100kW.100km, respectively.

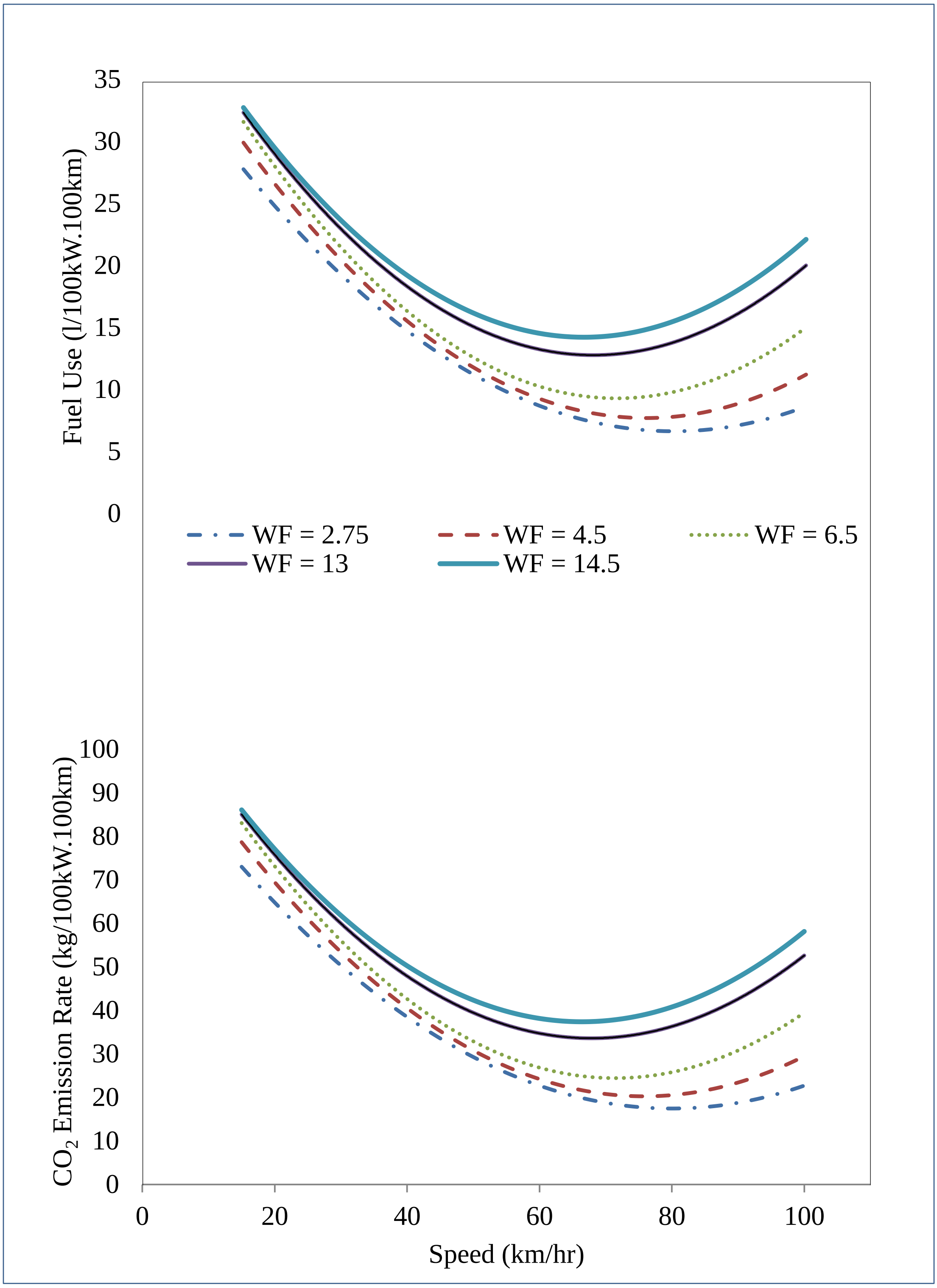


Figure 6.7. The optimal speed and it corresponding fuel use and CO_2 production for equipment with different WFs driven on a levelled road

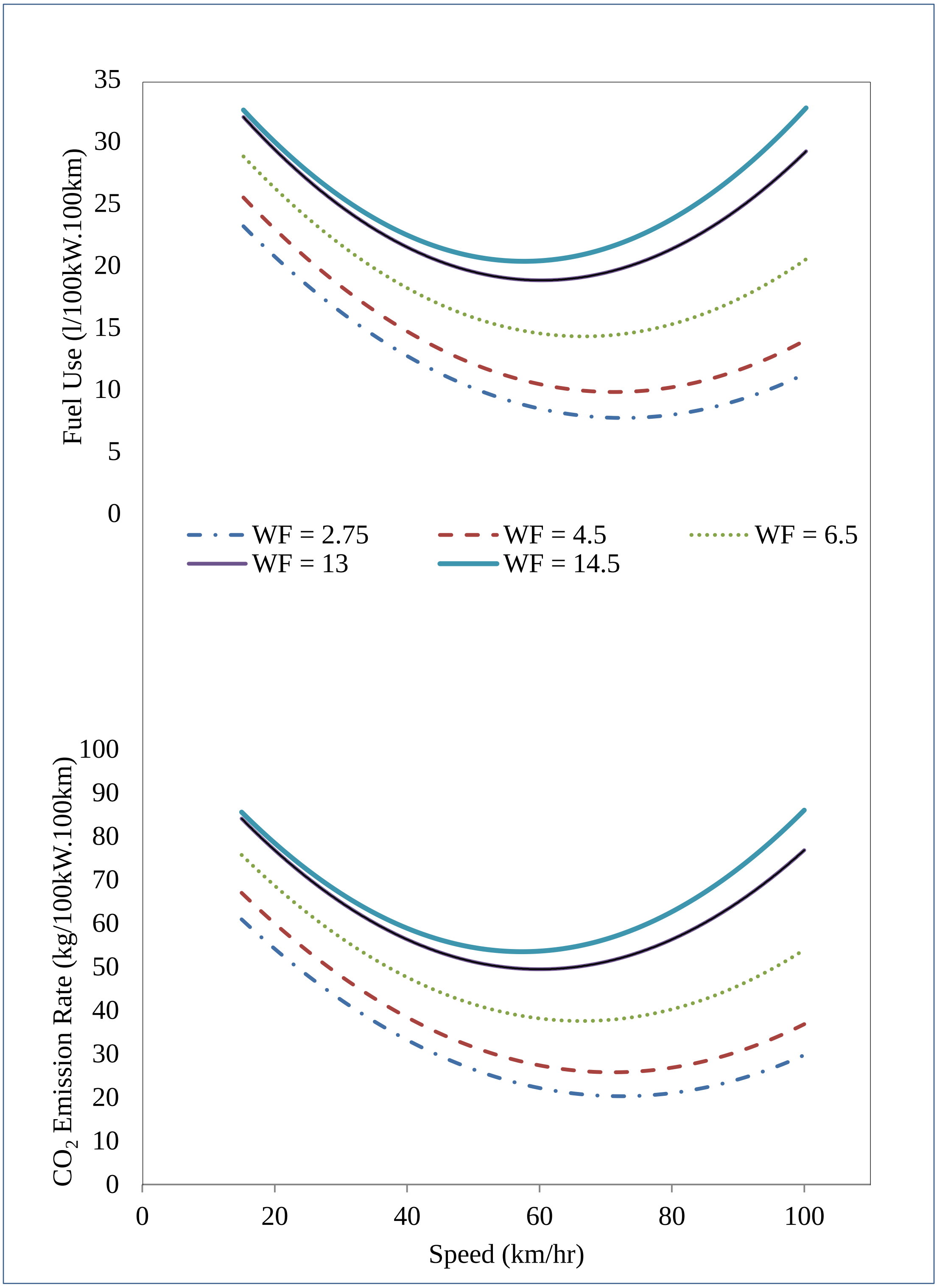


Figure 6.8. The optimal speed and it corresponding fuel use and CO_2 production for equipment with different WFs driven on a four-degree-slope road

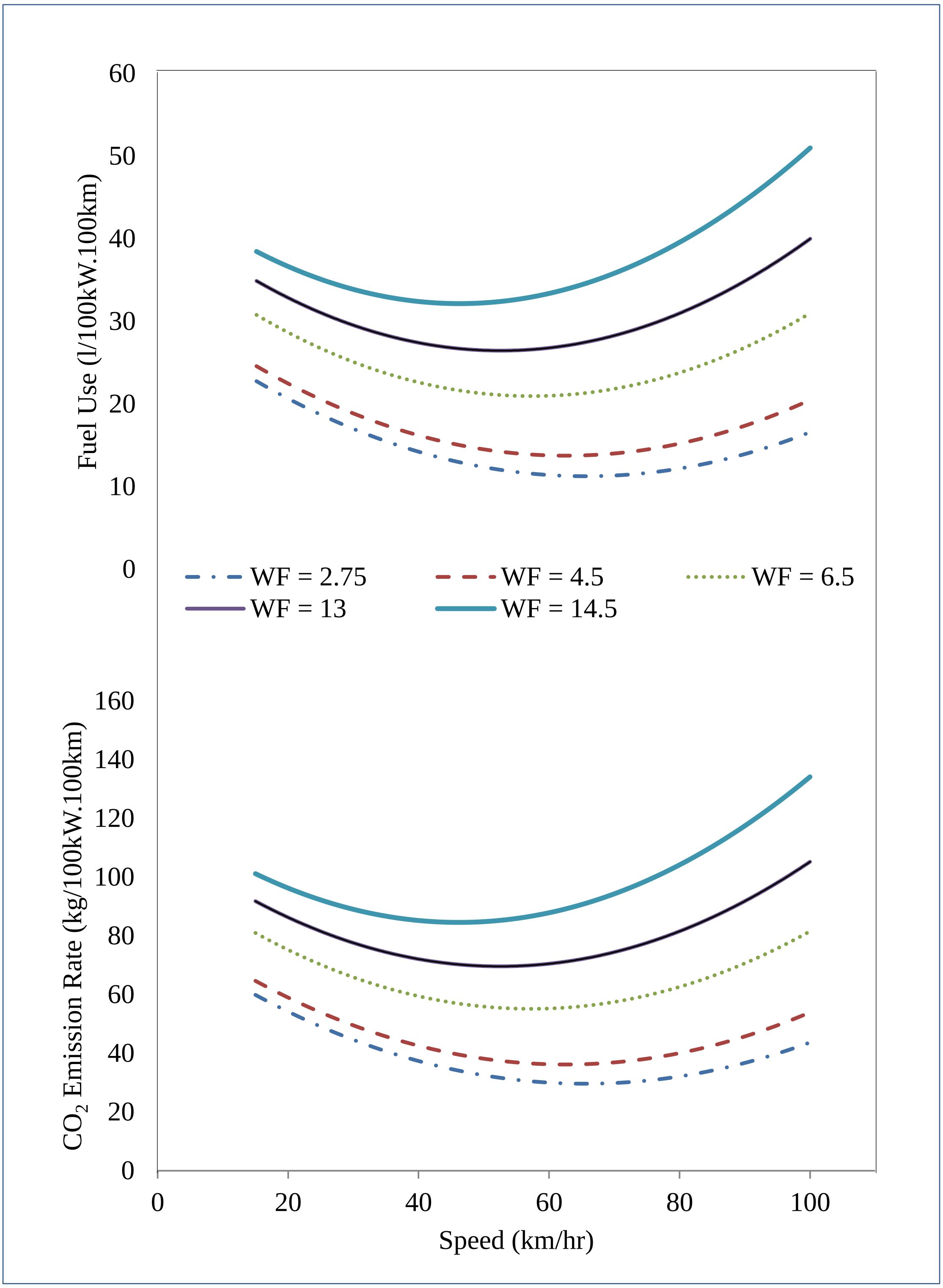


Figure 6.9. The optimal speed and it corresponding fuel use and CO_2 production for equipment with different WFs driven on an eight-degree-slope road

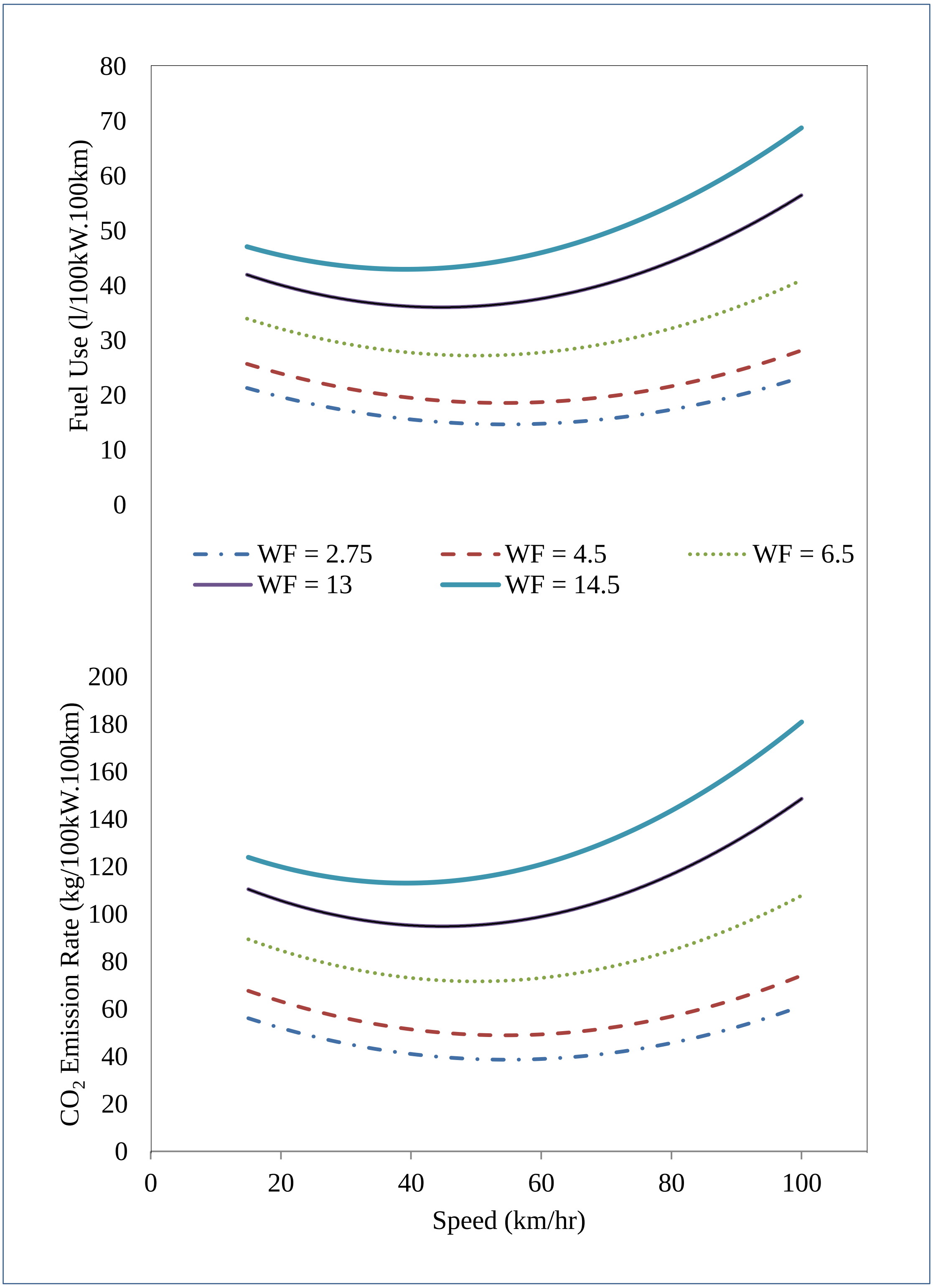


Figure 6.10. The optimal speed and it corresponding fuel use and CO_2 production for equipment with different WFs driven on a twelve-degree-slope road

As discussed, WF and road slope parameters are two main factors should be taken into consideration in developing optimal driving pattern. Figures 6.11 and 6.12 summarize the developed driving pattern in this section. As shown in Figure 6.11, there is a highly-correlated linear relationship between road slope and optimal driving speed for all five investigated WF values. Also, as Figure 6.12 indicates, by increasing the slope of road and WF parameters, fuel consumption and CO_2 emission of construction vehicles rise almost linearly.

The developed optimal driving pattern can be used as an operation guideline for construction contractors and equipment operators to achieve minimal fuel consumption and emissions per travelled distance by maintaining the optimal driving speed.

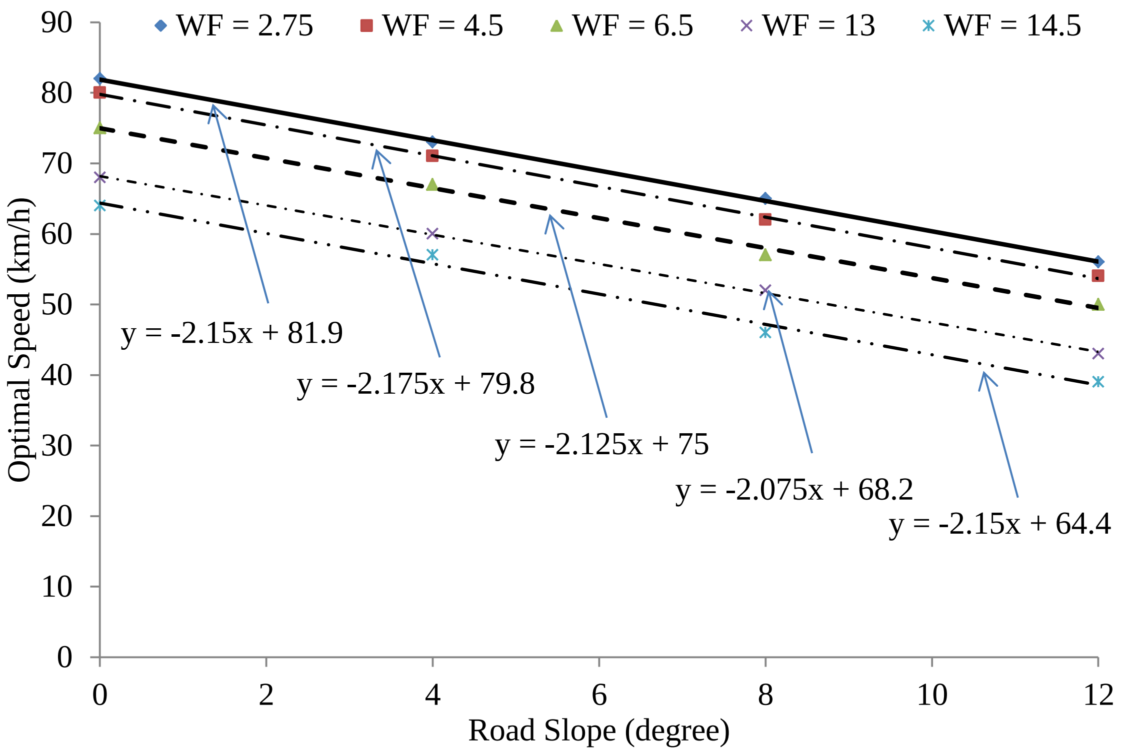


Figure 6.11. Optimal driving speed of construction vehicles based on the road slope and WF parameters

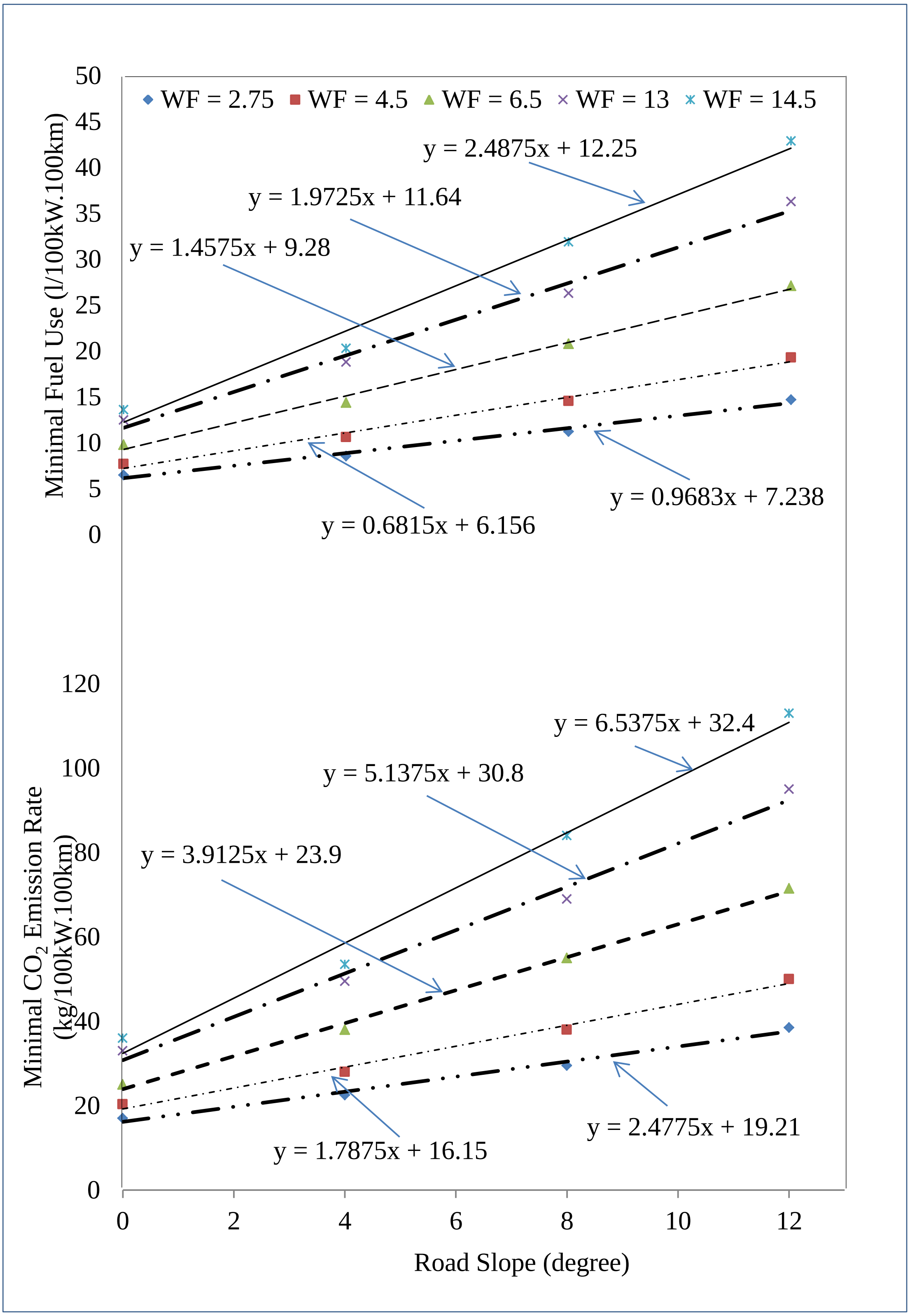


Figure 6.12. Developed relationship between road slope, minimal fuel use and minimalCO_2 emission of construction vehicles with different WF values

6.3. Engine Selection and Upgrading

As discussed in the previous chapters, engine specifications including tier, size and load are of the main parameters affecting fuel use and emissions production of equipment. In this research, the effects of engine load and engine size on fuel use and emissions rate were modeled in Chapter 4. The results showed that the fuel use and emissions production have a highly correlated linear relationship ($R^2 > 0.90$) with the load and size of engine.

Engine tier was also found to have significant influence on fuel use and emissions rate of construction equipment. As mentioned in Chapter 3, seven construction vehicles with different engine tiers were experimented. The analysis on the collected raw data was performed using the methodology developed in Chapter 4. Figure 6.13 shows the linear relationship among fuel use, CO_2 emissions and engine load for three investigated engine tiers. Also, Figure 6.14 compares fuel use and emissions with engine tiers of Euro III, Euro IV and Euro V.

In comparison with Euro IV engines which currently are the most common ones in construction industry, Euro III engines use fuel and emit CO_2 5% more, while the fuel consumption and CO_2 production of Euro V engines are 7% less. As the fuel cost is the main operational cost of construction equipment, engine tire can be considered as one of major criteria by machinery management teams for equipment selection or engine upgrading. The great saving in the operational cost of vehicles due to reduction in fuel use would be the main incentive for contractors to invest in or hire the equipment with higher engine tiers.

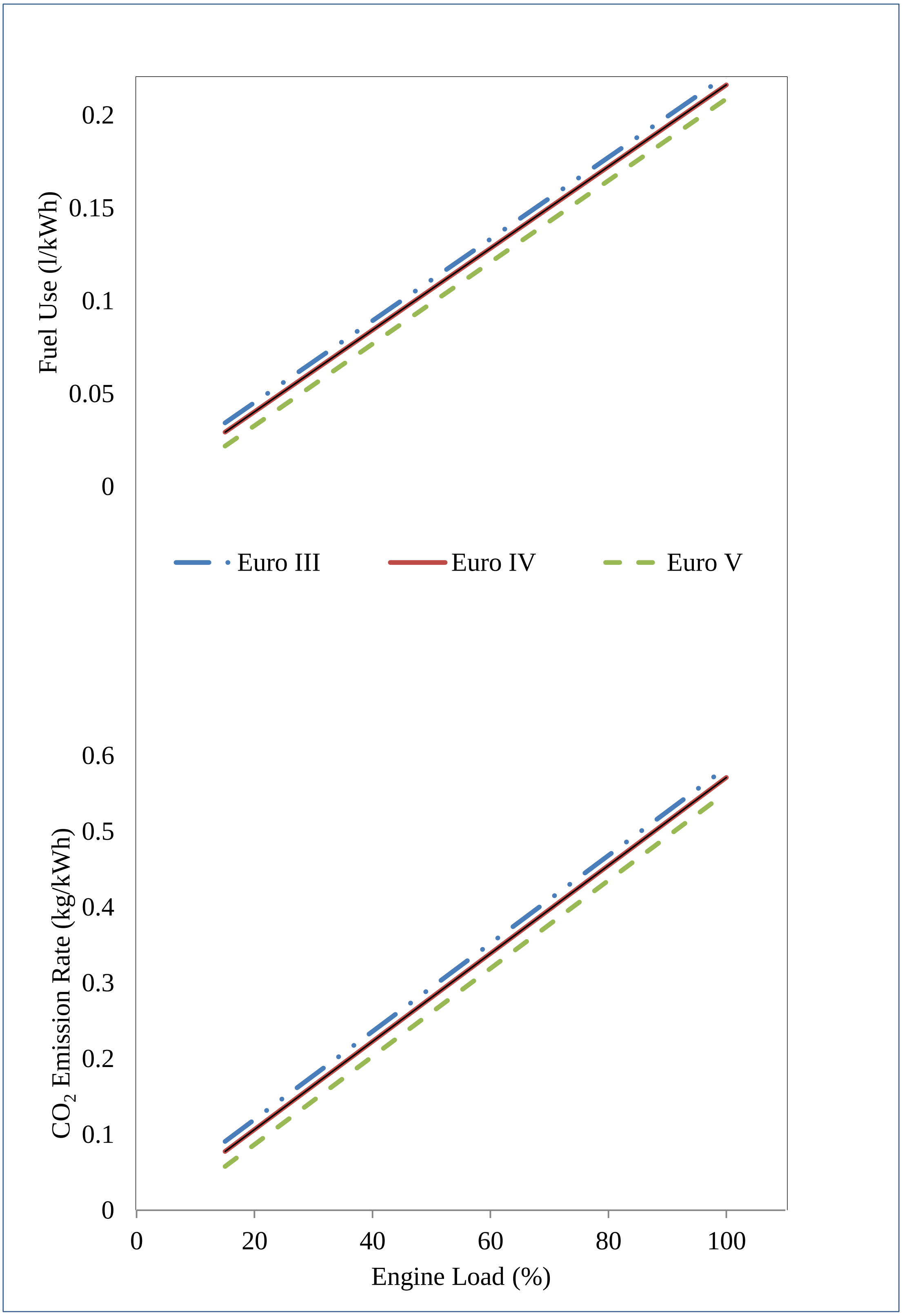
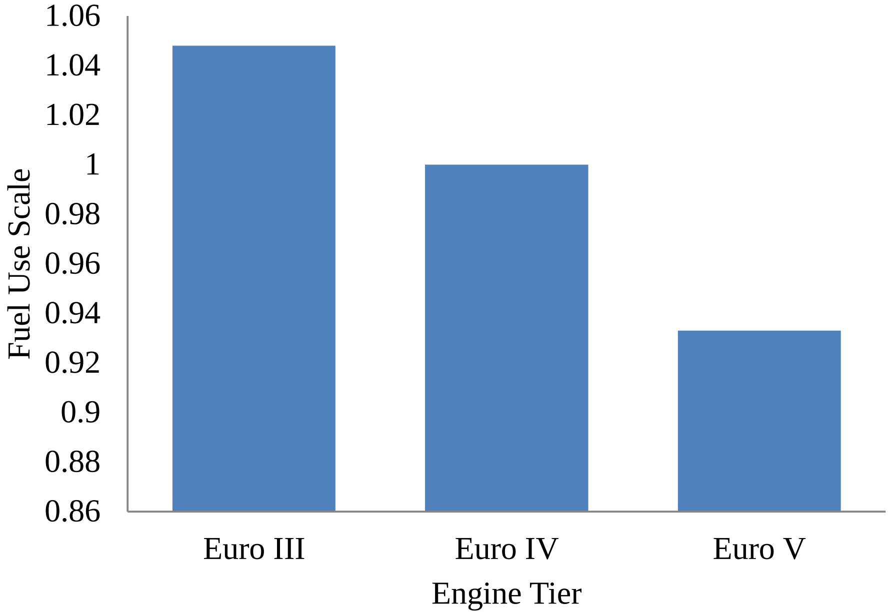
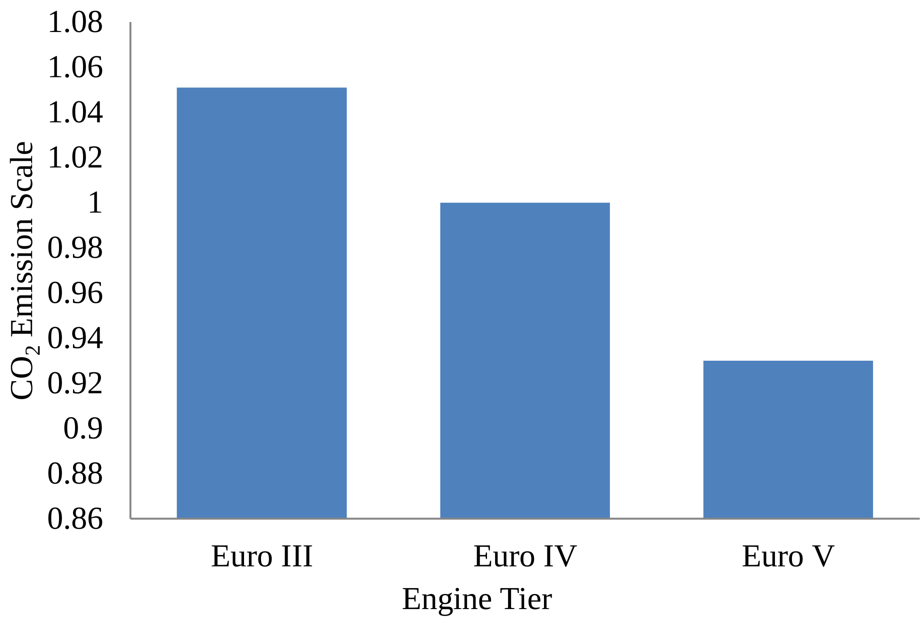


Figure 6.13. The effect of engine tier on fuel use and CO_2 emission of construction equipment



(a)



(b)

Figure 6.14. The comparison of (a) fuel efficiency and (b) CO_2 pollutant production of engines with different tiers

6.4. Equipment Selection and Trailer Configuration

Selecting equipment and configuring the trailers in an optimal way are planning-level approaches that should be taken into consideration by machinery managers to maximize the efficiency of fuel and minimize pollutants emission rates. Based on the type of load and road features such as slope, the optimal hauler and its trailer configuration can be recommended. Trucks are normally designed and manufactured in a way to have the capability of operation in all geographic and loading conditions. In order to increase the fuel efficiency, it is recommended to use extra trailers for light payloads, or to use high capacity of engine power when driving in relatively flat areas. According to the performance handbooks published by the equipment manufacturers, the average used power of engine is around 70% in the optimal operation conditions (Caterpillar 2015).

In this research, the effects of the operational and environmental parameters were modeled on engine load for different WFs. The effects of the road slope and WF variables have been considered in trailer configuration. As the road slope increases, the WF should be lowered. Assuming the road is levelled, the fuel use (l/ton.100km) and CO_2 emission (kg/ton.100km) are calculated for trucks with different trailer configurations driven at optimal speed. Figure 6.15 compares the fuel use and CO_2 production for three different trailer configurations experimented in this study. To compare the effect of different trailer configurations, it is assumed that all vehicles are driven at optimal speed. As shown in Figure 6.15, by employing trailers to transfer more payloads in each operation cycle, the fuel consumption and CO_2 production per unit of transferred weight decrease dramatically. Also, using large trailers to increase WF values can have significant influence on fuel use and CO_2 emission reduction.

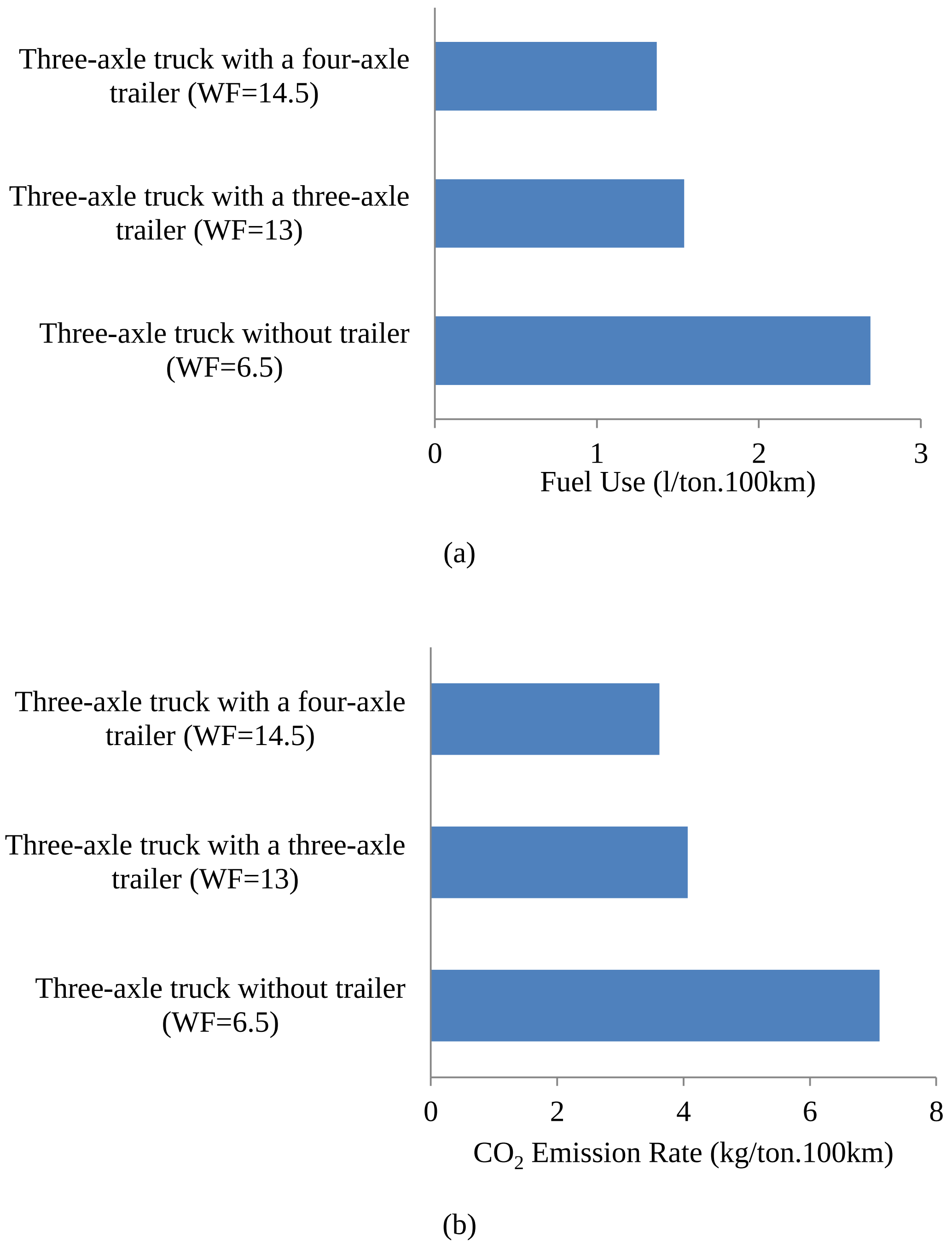


Figure 6.15. Comparison of fuel use and CO_2 production for different trailer configurations

6.5. Equipment Idling and Stop

A large amount of operation time of construction equipment is spent in idling mode. The equipment idling can be caused by traffic conditions, poor planning and low compatibility among different types of equipment involved in the construction projects. Reducing idling time of vehicles has considerable influence on their fuel consumption and emissions production. It was estimated if idling time of construction equipment involved in construction sites decreases by 10%, CO_2 emission reduces approximately 800 million tons per year (EPA 2009). In this section, the fuel use and CO_2 emission production in idling mode of construction equipment are first estimated using the models developed in Chapter 4. Then, the additional fuel use and emissions production due to stop of on-road construction vehicles caused by traffic conditions are calculated.

Figure 6.16 shows the fuel use and CO_2 emission rate of on-road construction vehicles in different operation modes. In comparison with other modes, vehicles consume much more fuel and produce much higher emission rate in hauling mode due to using more power of engine. The fuel use and CO_2 emission rate of construction vehicles in idling mode are 0.027 l/kWh and 0.073 kg/kWh, respectively. This proves the high significance of lowering vehicles' idling time to reduce fuel use and emissions production. For example, by reducing the idling time of an equipment piece with the engine size of 400 kW for one hour, 10.8 litres of fuel will be saved while resulting around 29 kg reduction in CO_2 production.

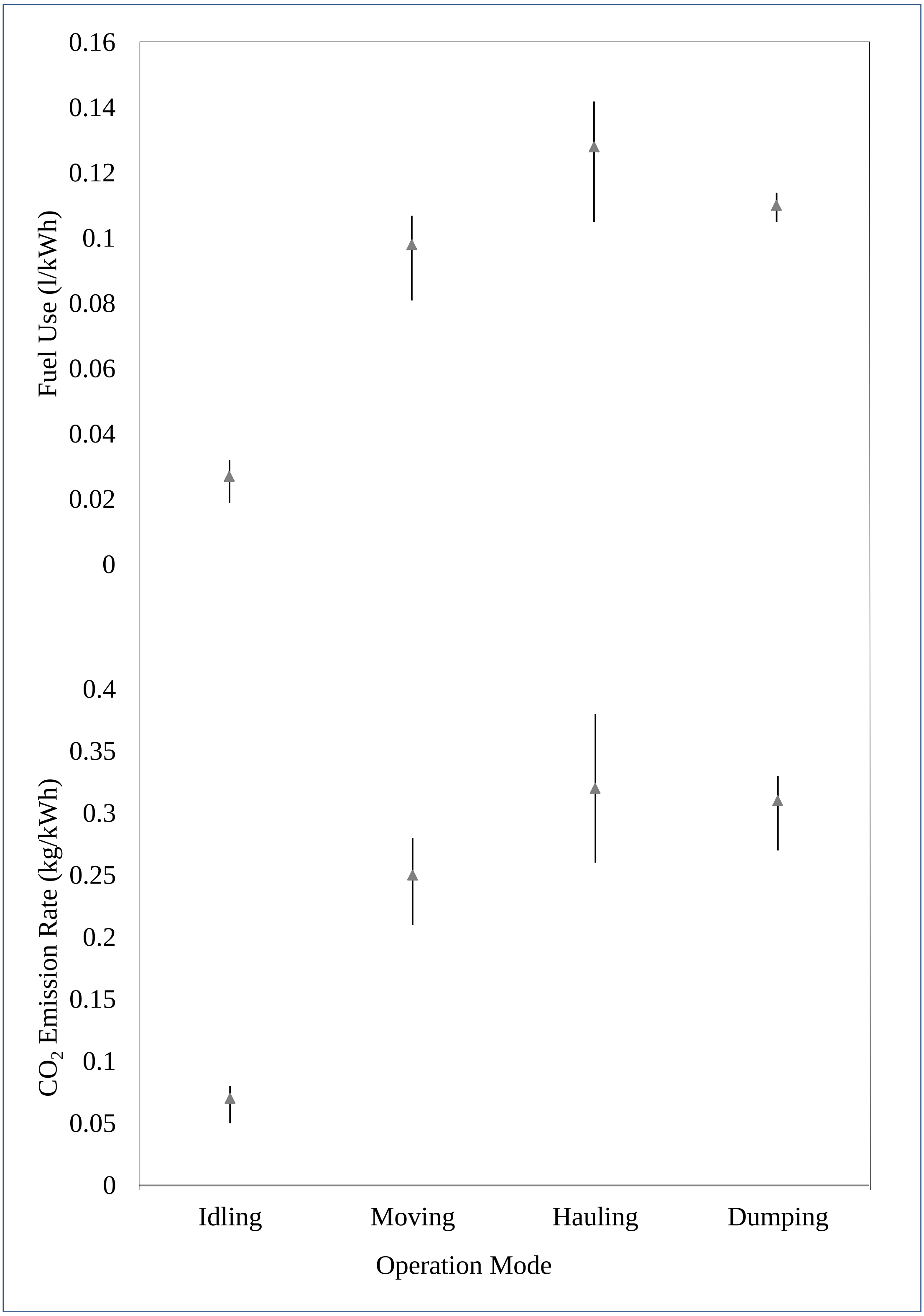


Figure 6.16. Comparison of fuel use and CO_2 emission rate of on-road construction vehicles in different operation modes

Figure 6.17 illustrates the average percentage of used fuel and produced CO_2 emission in different operation modes of on-road construction vehicles. These results were achieved through analyzing collected raw data and using fuel use and emissions models developed in Chapter 4. It is found approximately 9% of used fuel and produced emissions of construction vehicles is in idling mode. It is expected by having a better project planning, tasks scheduling and machinery managing, the fuel cost and emissions production can be reduced up to 9%.

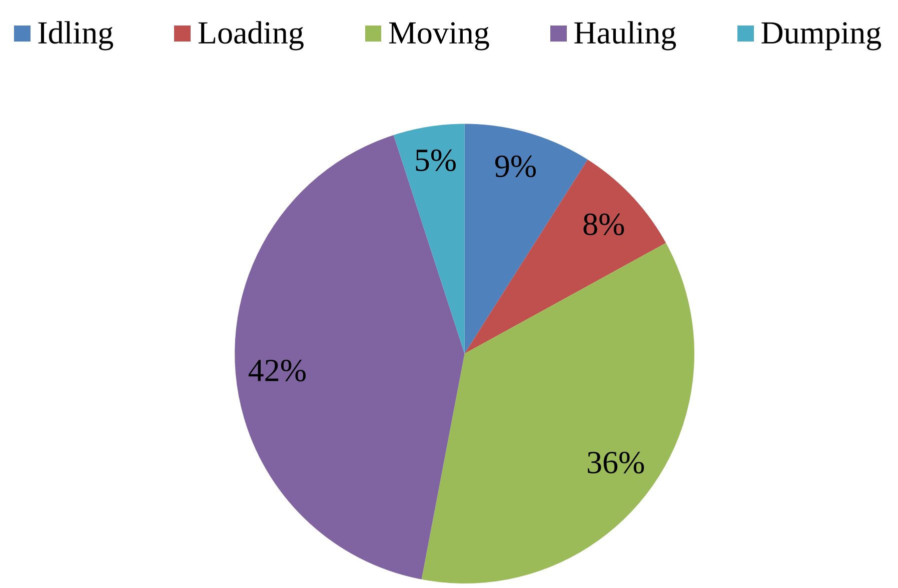


Figure 6.17. The average percentage of fuel use and CO_2 emission production in different operation modes of on-road construction vehicles

Stop of on-road construction vehicles due to traffic conditions would have a considerable influence on the fuel use and emissions production. In this step, it is focused to investigate the effect of equipment stop on the fuel consumption and CO_2 production of on-road construction vehicles. Figure 6.18 shows the additional fuel use and CO_2 emission due to a full stop of different construction vehicles.

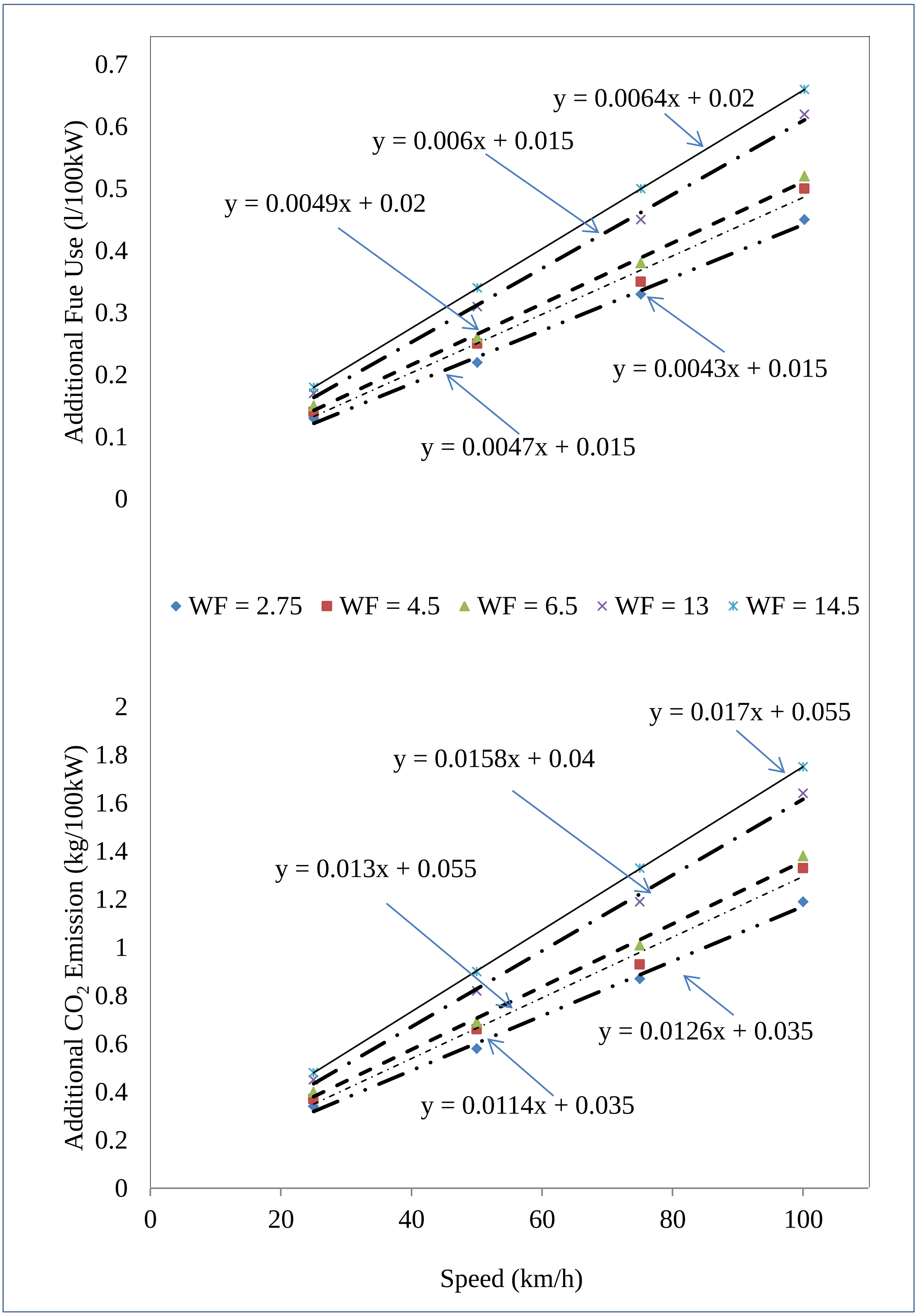


Figure 6.18. The additional fuel use and CO_2 emission due to stop of equipment with different WF values

The data analysis was conducted on all experimented equipment pieces. The effect of WF parameter was also taken into consideration in the process. It was assumed that during deceleration step to stop, gas pedal is not pressed while the engine load being around 15% (like idling mode). Also, vehicles have three minutes stop, and then start moving with the acceleration rate of 0.5 km/h.s until reaching the previous speed. These assumptions have been made based on conducted observations, and it has been tried to simulate normal stop conditions of construction vehicles. Changes in the assumptions such as stop time would result in slightly different results.

Equipment's speed and WF are the two main parameters influencing the additional fuel use and emissions production due to stop. As shown in Figure 6/18, there is a highly-correlated direct linear relationship among vehicles' speed, WF and fuel use and emissions production. The additional fuel consumption and CO_2 emission due to stop varies from 0.13 l/100kWh and 0.35 kg/100kWh for the vehicles with the speed of 25 km/h and WF of 2.75 to 0.66 l/100kWh and 1.75 kg/100kWh for equipment with the WF of 14.5 driven at 100km/h speed. It shows the significant effect of vehicles' stop that must be considered by equipment's operators as a reduction scheme to lower fuel use and emissions at operation level.

6.6. Conclusion

Construction industry is regarded as one of the main contributors to global energy consumption and GHGs emissions. There is a lack of comprehensive guideline to be used by construction managers and equipment operators to reduce the used fuel and emitted pollutions of construction vehicles. This chapter developed fuel use and emissions reduction schemes for on-road construction equipment by analyzing collected field data and using fuel use and emission models devised in Chapter 4. As the main reduction strategy, an optimal driving pattern can be followed by equipment operators to improve the fuel efficiency. The conducted analysis shows that the developed strategy has a high accuracy ($R^2 > 0.9$) in estimating optimal driving speed based on given operation conditions. The effect of road slope and WF operational parameters to the optimal driving speed was also investigated. In spite of the considerable effect of acceleration on instantaneous fuel use and emissions rate, this parameter was not considered in optimal driving pattern strategy as the percentage of time that construction equipment pieces are operated in acceleration mode is negligible.

As an equipment-level strategy, this chapter investigated the effect of engine tier on the fuel use and CO_2 production by analyzing the obtained raw data from engines with different tiers. The result demonstrated that by using engines with higher tiers such as Euro V in comparison with older engine with Euro III tiers, a reduction of 13% fuel consumption and emission production can be achieved. At project planning level, truck selection and trailer configuration were studied. It is found that the fuel efficiency can be increased up to approximately 50% by using large trailers to transport more construction materials in each operation cycle.

The fuel use and CO_2 emission production of vehicles in idling operation mode were also estimated using devised models. The analysis of raw data indicated that around 9% of used fuel and consequently produced emissions of construction vehicles is in idling mode. Lowering idling time of equipment was suggested as an operational level reduction scheme. Finally, the impact of stop of on-road construction vehicles on additional fuel use and CO_2 emission production was investigated. The achieved results confirmed that by trying to have fewer stops during moving and hauling operation modes, up to 0.66 l/100kW fuel can be saved and 1.7 kg/100kW CO_2 pollutant is produced less per stop.

Chapter 7

Conclusion and Recommendations

Construction industry is regarded as one of the major consumers of energy consumption (mainly fossil fuels), and has produced significant amount of air pollutants globally. As this sector is one of the main industries requiring a large number of heavy machinery, construction equipment is the major contributor to fuel and energy consumption, and accounts for around 50% of total vehicular used diesel fuel of all industries. Majority of construction activities associated with earthmoving operations including cut and fill activities require on-road heavy-duty vehicles for materials transportation. Such kind of activities are normally planned and paid based on the amount of materials transferred. The measurement of the mass carried by vehicles as payload is a necessary process.

In practice, there is a lack of models in construction sector to predict fuel consumption and emissions production of vehicles at operation level. The models currently applied in the construction field mainly focus on estimating fuel use and emissions production at macro level. NONROAD model developed by EPA and OFFROAD model devised by CARB are applied to roughly estimate fuel consumption and emissions rate of different construction equipment groups at both national and state levels. In addition, numerous operational and environmental parameters effecting fuel use and emissions rate have not been fully investigated yet.

Also, there is no comprehensive and quantitative scheme to reduce fuel use and emissions of equipment involved in the construction industry despite the considerable cost saving by applying such schemes. The current reduction strategies mainly focus on engine attributes and fuel types which are applicable to new construction equipment while failing to cater for existing machinery globally. On the other hand, weight of equipment is a major factor influencing fuel use and emissions production necessitating an accurate and fast weight measurement method. The traditional weighting systems available in the construction sector are time consuming, error prone and costly. As the most commonly used method in construction, weighbridges require high installation and operation costs. The time for weight measurement would affect the production rate of equipment as well as the cost of project execution. Meanwhile, alternative volumetric measurement methods may not have sufficient accuracy due to volume to weight conversion analysis.

7.1. Conclusion

This thesis was set to estimate the fuel use, emissions production and weight of on-road construction vehicles through monitoring field operations. Comprehensive methodology has been developed in the study to collect field data for mathematical model development. Three main instruments of GPS-INS, engine data logger and PEMS were employed to collect real-world data of investigated parameters. Seven heavy on-road vehicles were experimented, and for each vehicle, a database was created with all obtained raw data stored. The data synchronization process indicated that there were errors in the data measured by instruments due to technical problems during experimentation and engine malfunctions. A total of 94,790 data points were collected during seven days of experimentation in which 78,816 data points or around 80% of total data were validated in the data synchronization procedure.

The initial data analysis on the processed raw data demonstrated relationships amongst operational and environmental parameters, engine attributes, and fuel use and emissions rate. As one of the main contributions of this study, engine load was identified as an intermediate variable bridging the operational and environmental inputs to fuel use and emissions rate outputs. Different factors including MAP, engine load and engine speed were initially identified as the surrogate of used power of engine, but conducted analysis showed that engine load has the highest-correlated relationship with both operational parameters and fuel use and emissions rate outputs.

Regression statistical analysis including OLS and MLR were applied to develop the fuel use and emissions rate models using IBM SPSS Statistics V22 and Microsoft Excel software. It is found that there is high correlation and consistency (R^2> 85%) between engine load factor and four variables of acceleration rate, speed, road slope and WF. On the other hand, based on the achieved results, there is highly-correlated linear relationship (R^2> 90%) between engine load and fuel use and emissions rate. The operational level fuel use and emissions rate models were then developed through investigating the quantitative relationships among operational input parameters, engine attributes and fuel use and emissions rate outputs.

The engine load estimation with operational parameters showed that acceleration rate has the highest coefficient, and was therefore identified as the most critical factor. The impact of road slope and speed parameters was far less on used power of engine. Also, based on the devised fuel use model, fuel use of construction equipment varies from 0.03 l/kWh for idling mode (Engine Load ≈ 15%) to 0.25 l/kWh for most demanding activities (Engine load ≈ 100%). The emissions rates of CO_2, CO, HC and NO_x pollutants have direct linear relationship with engine load values. The developed fuel use and emissions rate models were finally validated through comparing the predicted fuel use and emissions rate values with the field data measured by engine data logger and PEMS devices. The models were found to have more than 90% accuracy in fuel use and emissions rate modeling of on-road construction vehicles at operation level.

WF parameter has indirect effect on the used power of engine, and influences the impact of other operational and environmental parameters on engine load value. Having access to real-world data of all investigated parameters, WF was modeled through developing neural networks among all variables. As one of the main limitations of modeling process, neural networks can have only one input layer. So, five networks were developed covering all five WF values of 2.75, 4.5, 6.5, 13 and 14.5. Through quantifying the effect of WF on the impact of other parameters on engine load and using developed engine load estimation model, WF was modeled as a function of operational and engine load variables. Having the weight of empty equipment, the total weight of equipment and carried payload were then predicted. To verify and validate the developed model, eight case studies were conducted. This process was performed through comparing the predicted weight to the real weight measured by weighbridge. It is found the accuracy of the model in predicting the total weight of vehicle is over 91%.

As one of the main applications of the developed fuel use and emissions rate models, different strategies and schemes were devised at operation and planning level to improve the fuel efficiency of equipment. As the major scheme, optimal driving speed was modeled based on two variables of WF and road slope. It was indicated that by increasing these two parameters, the optimal driving speed decreases significantly but fuel use and emissions rate per travelled distance and transferred weight increase considerably. The optimal speed and corresponding fuel use and CO_2 emission rate for a vehicle with WF of 2.75 driven on a levelled route are 82 km/h, 6.5 l/100kW.100km and 17 kg/100kW.100km, while these numbers would be 39 km/h, 42.9 l/100kW.100km and 113 kg/100kW.100km for a vehicle with WF of 14.5 driven on a route with slope of 12 degree. Engine tier was also recognized as one of the engine features affecting fuel use and emissions production. It was proven that in comparison with Euro IV engines which currently are most commonly used in the construction industry, Euro III engines use fuel and emit CO_2 5% more, while the fuel consumption and CO_2 production of Euro V engines are 7% less. It was also shown that selecting optimal trailer configuration based on the type of the road and geographical conditions, the fuel efficiency of equipment can be improved up to 50%. Finally, the effect of idling time and equipment stop was modeled on fuel use and CO_2 emission rate. It is found by trying to have fewer stops during moving and hauling operation modes, up to 0.66 l/100kWh fuel can be saved and 1.7 kg/100kWh CO_2 pollutant is produced less per stop.

7.2. Limitations and Suggestions

In the area of monitoring field operations, it is suggested to extend the experimentations to cover a wider range of on-road construction vehicles from numerous manufacturers with different engine capacities from 150 kW (light-duty vehicles) to 500 kW (heavy-duty vehicles). Also, as one of the limitations of the current study, only five WF parameter values were considered due to the types of the experimented vehicles and their trailer configurations. The obtained results can be improved by selecting various trailer configurations to collect real-world data from more values of WF variable. The accuracy of the used instruments was not high in some experimentation cases causing errors in the raw collected data. Although the data synchronization and filtering procedures were conducted on gathered raw data, it is highly recommended to employ more precise devices to improve the quality of data collected. For instance, the PEMS used in the study had at least 1.7% error in measuring emission rates.

The engine performance was identified as one of the main parameters affecting the accuracy of measured engine load and emission rates variables. To tackle with this issue, the functionality and performance of the engine should be checked before conducting experimentation. The skill level of the operators was recognized as another factor influencing the validity of engine load values. For example, , the engine load was normally overestimated for aggressive operators. It is recommended construction vehicles are driven by experienced operators in a conservative manner during experimentation. Automatic transmission vehicles can also be experimented to lower the effect of operator inaptitude on the accuracy of the models.

This thesis developed general fuel use, emissions rate and weight models to be used for all on-road construction vehicles. To have higher accuracy, these models can be devised for each specific vehicle separately following the developed methodology. The coefficients of investigated parameters can be calibrated based on the performance and specifications of each vehicle's engine. On the other hand, validation procedure can be extended by testing the developed models and strategies on more vehicles.

7.3. Recommendations on Future Research

This section discusses different directions for future studies in the field of energy and emissions modeling of construction equipment. This study focused on developing a comprehensive methodology to monitor construction operations and track involved equipment. As the application of the developed framework, the fuel use, emissions rate and weight of on-road construction vehicles were modeled. This integrated data-sensing methodology can be employed by scholars to model the energy consumption of all other off-road equipment on the construction sites. Devised framework can be used for many other applications in the construction field such as productivity measurement and equipment maintenance.

This research took into consideration the effect of four operational and environmental parameters of acceleration rate, driving speed, road slope and equipment weight as affecting variables on the engine load of equipment. It does not mean that there is no other factors affecting engine load value. The initial data analysis showed the other parameters do not have significant impact on the used power of engine, and can be ignored considering the desired accuracy of the models. This study can be extended by investigating the effect of more operational and environmental variables including atmospheric temperature, ambient pressure and road type on the used power of engine. Criteria can be developed as well to consider the skill level of the operator on average engine load value in a specific operation cycle. This study found that engine load value is normally overestimated for aggressive operators. The age of equipment can be another factor to be considered. In comparison with new engines, older ones are less efficient and consume more energy for delivering the same power.

In practice, brief guidelines can be prepared for training equipment operators to drive vehicles at optimal pattern to achieve greater fuel efficiency. Also, using devised frameworks and models, more practical reduction schemes and strategies can be developed to minimize fuel use and emissions of vehicles. Practical issues in using the weight model should be addressed, and engineering software can be developed for applying the weight model in real world.

As a new field of research, it is proposed to compare the efficiency of construction equipment using different sources of energy, including diesel, ULSD and electricity using the devised framework and models. Currently, some construction firms and equipment manufacturers have started developing or adopting new sources of energy which requires comprehensive studies from sustainability, productivity and financial perspectives.

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