New Framework for Real-time Measurement, Monitoring, and Benchmarking of Construction Equipment Emissions

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Abstract

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The construction industry is one of the largest emitters of greenhouse gases and health-related pollutants. Monitoring and benchmarking emissions will provide practitioners with information to assess environmental impacts and improve the sustainability of construction. This research focuses on real-time measurement of emissions from non-road construction equipment and development of a monitoring-benchmarking tool for comparison of expected vs. actual emissions. First, exhaust emissions were measured using a Portable Emission Measurement System (PEMS) during the operation of 18 pieces of construction equipment at actual job sites. Second-by-second emission rates and emission factors for carbon dioxide, carbon monoxide, nitrogen oxides, and hydrocarbons were calculated for all equipment. Results were compared to those of other commonly used emission estimation models. Significant differences in emission factors associated with different activities were not observed, except for idling and hauling. Moreover, emission rates were up to 200 times lower than the values estimated using EPA and California Air Resources Board (CARB) guidelines. Second, the resulting database of emissions was used in an automated, real-time environmental assessment system. Based on videos of actual construction activities, this system enabled real-time action recognition of construction operations. From the resulting time-series of activities, emissions were estimated for each piece of equipment and differed by only 2% from those estimated by manual action recognition. Third, the actual emissions were compared to estimated ones using discrete event simulation, a computational model of construction activities. Actual emissions were 28% to 144% of those estimated by manual action recognition. Results of this research will aid practitioners in implementing strategies to measure, monitor, benchmark, and possibly reduce air pollutant emissions stemming from construction.

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Nomenclature and Abbreviations

CARB	California Air Resources Board
CO_2	Carbon Dioxide
CO	Carbon Monoxide
DES	Discrete Event Simulation
ECU	Engine Control Unit
EPA	Environmental Protection Agency
FRM	Federal Reference Method
HC	Hydrocarbon
MAP	Manifold Absolute Pressure
MLR	Model Linear Regression
MOVES	Motor Vehicle Emission Simulator
NO_x	Nitrogen Oxides
OBD	On-board Diagnostic System
PEMS	Portable Emission Measurement System
PM	Particulate Matter
RPM	Revolutions Per Minute

1 Introduction

Concerns about the environmental impacts, and specifically atmospheric emissions, generated by construction equipment call for action to ensure the construction industry is advancing toward improved sustainability. This research aims to establish a framework by which real-time construction equipment emissions can be measured, monitored, and benchmarked through a combination of techniques: direct measurement of exhaust emissions from construction equipment, vision-based technology, and computational simulation of construction activities.

1.1 Background

There are over two million pieces of construction and mining equipment in the US that consume over 6 billion gallons of diesel fuel per year (EPA 2005). The main environmental concern surrounding the use of construction and mining equipment is emissions of air pollutants that impact climate change and human health. According to the US Environmental Protection Agency (EPA), the construction industry is the third largest contributor of gas emissions among all sectors (EPA 2010). Emissions of GHGs and health-related pollutants, such as nitrogen oxides and particulate matter, from construction equipment account for more than half of the total emissions that result from construction activities (Guggemos and Horvath 2006). Therefore, there is a need for a framework by which emissions from heavy-duty construction equipment can be measured, monitored and benchmarked accurately.

The first requirement for such a framework is a comprehensive inventory of construction equipment emission rates. For this purpose it is necessary either to measure real-time construction equipment emissions or refer to emission estimation models. Several studies have been conducted in order to measure amounts of emissions from heavy-duty equipment (Gautan et al. 2002, May 2003, Lewis 2009). Some of these rely on a steady-state engine dynamometer test that may not be representative of real-world emissions during actual operation of the equipment (Charles and Springer 1973, Wang et al. 2000). Others lack quality assurance of data or are not available to the public (Gautan et al. 2002, May 2003). Because of these shortcomings, researchers have investigated other methods by which real-time emissions and duty cycles representing actual operating conditions can be measured (Kelly and Groblicki 1993, EPA 2002). The EPA has backed the development and use of Portable Emission Measurement Systems (PEMS), which are mounted on individual vehicles and measure concentrations of gases and particles in the exhaust (Fulper 2002). The EPA implemented this system to measure engine data and emissions from 50 pieces of construction equipment in 2002 (Constance et al. 2002). However that data is neither publicly available, nor quality assured. Therefore, there is a need for more efforts in this area in order to complete existing databases and propose new models by which real-time emissions can be estimated accurately (EPA 2002).

Researchers at North Carolina State University have used PEMS in order to measure real-time emissions from construction equipment (Abolhasani et al. 2008, Lewis et al. 2010). Based on these results, the researchers developed modal-based models (i.e., Modal Linear Regression (MLR)) to predict real-time emission rates (Lewis 2009). Furthermore, several different models for predicting emission rates from heavy-duty construction equipment have been proposed. One widely used approach to estimate emissions from non-road engines is the EPA’s NONROAD model, which is based on measurements from tests on a limited number of engines at steady-state conditions (EPA 1991, EPA 2004, EPA 2009). This model (EPA 2004, EPA 2009) has been implemented in many environmental assessment models for Nonroad equipment (Marr and Harley 2002, Zavala et al. 2006, Li and Lei 2010, Rasdorf et al. 2012, Hajji and Lewis 2013). The California Air Resources Board’s (CARB) guidelines for OFFROAD model are used to estimate emissions from individual pieces of equipment too (CARB 2010).

The second component of the framework is a method by which real-time emissions can be monitored and benchmarked. Controlling emissions from the construction industry has become a concern due to new and impending regulations (AGC 2010, Heydarian et al. 2012). Because regulations emphasize tighter controls on the equipment instead of improvement in efficiency during construction activities, they have resulted in costly upgrades. Controlling and monitoring air pollutant emissions during the construction phase through reasonable policies and practical tools may also be effective for reducing emissions. Monitoring technologies and techniques are important because without them, excessive emissions cannot be detected and minimized. Cost and accessibility of these technologies and techniques are two important factors which should be considered (Golparvar-Fard et al. 2009).

In recent years, various approaches have been introduced to estimate and monitor GHG emissions from construction operations. This information can be used to calculate the carbon footprint of the activity. Artenina et al. (2010) discussed using an intelligent and optimized GIS route planning system to reduce emissions from construction equipment. Shiftefar et al. (Shiftefar et al. 2010) introduced a system that enables visualization of construction emissions using a tree metaphor. In addition, Lewis et al. (2011) proposed a framework for quantifying the effect of operational efficiency on total emissions from construction. While these studies have advanced the idea of reducing emissions from construction activities, they have overlooked the possibility of automated monitoring and benchmarking of real-time emissions from construction equipment (Heydarian et al. 2012).

Other researchers have focused on several other techniques for monitoring real-time earthmoving operations by using techniques like RFID tags, GPS, and accelerometers in addition to on-site video cameras (Torrent and Caldas 2009, Gong and Caldas 2010, Moon and Yang 2010, Brilakis et al. 2011, El-Omari and Moselhi 2011, Gong et al. 2011, Yang et al. 2011, Ahn et al. 2013). These techniques mostly maneuver on tracking construction equipment and not on action recognition of videos, except in the study by Gong et al. (2010). Among all these possible solutions, using networks of cameras and recording activities has great potential for improving the understanding of the relationship between emissions and operational efficiency. Gong et al. (2010) introduced a vision-based tracking model for detecting and monitoring a bucket in construction operations; however, this model cannot detect location and action simultaneously. Zou and Kim (2007) also presented an image-processing approach that assesses idling time of an excavator based on image color space (hue, saturation, and value); however, this approach is susceptible to error due to change of scale and illumination (Heydarian et al. 2012). Recent developments have enabled researchers to overcome these deficiencies, resulting in accurate real-time emissions measurement. Timely and precise operational details empower researchers, managers, and practitioners to establish new corrective techniques, avoid delays, and minimize excessive environmental impacts (Golparvar-Fard et al. 2009). While embodied emissions, or those resulting from all activities associated with a construction project (e.g., production of building materials, transportation of crew and equipment to the site, heating sources on site) are important too, they fall outside the scope of the current study.

If idling time during construction activities can be minimized, then fuel usage, emissions, and cost will be reduced (SKANsKA 2011). To achieve this goal, a technique is needed to gather actual real-time data on activities performed at a construction site. Then, this time series of activities can be combined with fuel usage rates and emission rates in order to estimate total fuel usage, emissions of various pollutants, and carbon footprint. Developing an automated technique which is accessible and cheap will facilitate estimation of productivity and emissions for project managers, contractors, regulators, and investigators. Researchers can use the results from the monitoring system to determine the level of efficiency in construction activities and to propose new techniques to increase this efficiency. Practitioners can use the system to control the amount of resources being used and possibly reduce the amount that is wasted. Managers can use the system in support of sustainability certification, such as Leadership in Energy and Environmental Design (LEED), for a project. Currently, there are no available automatic measuring and monitoring techniques for real-time emissions assessment in the construction industry. Therefore, most certification organizations typically do not consider the construction phase in evaluation of environmental performance.

One possible solution is to use networks of cameras on construction sites and record videos from each piece of equipment in action. Through a network of cameras and an internet connection on site, videos are transferred to a computer which is able to remotely and easily analyze emissions and productivity (Golparvar-Fard et al. 2009). The technology can automatically recognize actions performed by construction equipment by extracting spatio-temporal features from video streams of construction operations. It enables real-time productivity and emission monitoring of construction equipment in an inexpensive and relatively accurate manner, which is a unique achievement in the construction environmental assessment domain. Once time-series of activities are generated, emissions associated with all equipment can be estimated. Reporting the emissions is not beneficial by itself. Rather, comparing them to a value set in the pre-construction phase, a benchmarked value, or one set by regulations will help practitioners in decision making. For this comparison, emissions should be estimated using other credible methods to identify if emissions may exceed calculated thresholds. Several researchers have used Discrete Event Simulation

(DES) to quantify construction-related emissions and have validated this tool in estimating the actual amount of emissions (Ahn et al. 2009, Ahn et al. 2010, Li and Lei 2010). Likewise, computational simulation of construction activities will be used as a benchmarking tool in this study (Ahn et al. 2009, Ahn et al. 2010, Li and Lei 2010). Therefore, emissions estimation using DES helps verify applicability of the proposed technology in assessing environmental impacts from construction activities. The results can be used to assess effects of construction operation configuration (i.e., schedule, type and number of pieces of in-use equipment, etc.) on total construction-related emissions. It can also lead to more sustainable construction operations with lower environmental impacts.

1.2 Objectives

The overall goal of this study is to present a framework by which construction equipment emissions can be measured, monitored, and benchmarked. The first specific objective is to expand and update the existing database of real-time emissions from construction equipment, validate existing approaches for off-road equipment emission estimation, and assess the relationship between emission factors vs. engine horsepower and tier. The second specific objective is to demonstrate real-time monitoring of emissions using vision-based technology. These results are compared to benchmarked emissions that have been determined via DES.

1.3 Thesis Outline

Chapter 2 reports real-time emission rates that were measured for 18 pieces of construction equipment and compares them to values estimated by EPA, CARB, and Lewis's MLR model. Differences in emission rates and emission factors by activity and engine size are also investigated. The database of emission rates is used in the monitoring and benchmarking emissions model presented in chapter 3.

Chapter 3 describes an extension of prior accomplishments in automated video processing to the real-time monitoring of emissions (Heydarian et al. 2012). The entire concept is presented, and the technology is demonstrated through a series of case studies. Vision-based technology, including an action recognition algorithm, is applied to case studies. From the resulting time-series of activities, productivity and amounts of emissions are assessed for each piece of equipment. Additionally, emissions for some case studies are predicted through simulation of construction operations using DES. For those specific case studies, emissions estimated using computational simulation, benchmarked values, and action recognition are compared.

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2 Comprehensive Study on Real-time Construction Equipment Emission: Using PEMS to Validate Existing Models

2.1 Abstract

The construction industry is one of the largest sources of greenhouse gases and health-related pollutants. Measuring and monitoring real-time emissions will provide practitioners with information to assess environmental impacts and improve the sustainability of construction. This research employed Portable Emission Measurement System (PEMS) for real-time measurement of emissions from non-road construction equipment to derive emission rates (mass of pollutant emitted per unit time) and emission factors (grams of pollutant emitted per unit volume of fuel consumed) from equipment under real operating conditions. Measurements were compared to emissions predicted by commonly used models: NONROAD, OFFROAD, and a modal statistical model. Measured emission rates agreed with the model predictions for some pieces of equipment but were up to 200 times lower for others. Idling and moving had significantly different emission factors compared to those of other activities, while there were no significant differences in emission factors between specific types of moving activities, such as digging and hauling. There were no significant relationships between emission factors and engine size and power for the equipment tested. Results of this research will aid researchers and practitioners in improving current emission estimation techniques, frameworks, and databases.

2.2 Introduction

There are over two million pieces of construction and mining equipment in the US that consume over 6 billion gallons of diesel fuel per year (EPA 2005). The main environmental concern surrounding the use of construction and mining equipment is emissions of air pollutants that impact climate change and human health. According to the US Environmental Protection Agency (EPA), the construction industry is the third largest contributor of greenhouse gas emissions among all sectors (EPA 2010). Therefore, there is a need to assess, monitor, and estimate emissions from heavy-duty construction equipment accurately.

Several studies have been conducted in order to quantify and predict amounts of emissions from heavy-duty equipment (Gautan et al. 2002, May 2003, Lewis 2009). Some of these rely on a steady-state engine dynamometer test that may not be representative of real-world emissions during actual operation of the equipment (Charles and Springer 1973, Wang et al. 2000). Others lack quality assurance of data or are not available to the public (Gautan et al. 2002, May 2003). One widely used model to estimate emissions from non-road engines is the EPA's NONROAD model (EPA 2004, EPA 2009). This model is based on measurements from tests on a limited number of engines at steady-state conditions (EPA 1991, EPA 2004). Because of these shortcomings, researchers have investigated other methods by which real-time emissions and duty cycles representing actual operating conditions can be measured (Kelly and Groblicki 1993, EPA 2002).

The EPA has backed the development and use of Portable Emission Measurement Systems (PEMS), which are mounted on individual vehicles and measure concentrations of gases and particles in the exhaust (Fulper 2002). Researchers have proved that this method can be practical and efficient in assessing real-time emissions from both light- and heavy-duty vehicles (Frey et al. 2003, Armos et al. 2009). Furthermore, Durbin et al. (2007), using PEMS, have shown that carbon dioxide (CO_2) and nitrogen oxides (NO_x) emissions measured from back-up generators agreed relatively well with values determined by the Federal Reference Method (FRM). The EPA implemented this system to measure engine data and emissions from 50 pieces of construction equipment in 2002 (Constance et al. 2002). However that data is neither publicly available, nor quality assured. Therefore, there is a need for more efforts in this area in order to complete existing databases and propose new models by which emissions can be estimated accurately (EPA 2002).

Researchers at North Carolina State University have used PEMS in order to measure real time emissions from construction equipment (Abolhasani et al. 2008, Lewis et al. 2010). Based on these results, the researchers developed a modal-based model (i.e., Modal Linear Regression (MLR)) to predict real-time emission rates (Lewis 2009). They also assessed dependency of emission rates on the type of fuel used for each piece of equipment (Frey et al. 2008). This approach has the advantages of better representing real-world conditions compared to an engine dynamometer test (Lewis et al. 2009) and providing sufficient data to support fleet management decision making (Lewis et al. 2009). Along the same lines, Fu et al. (2012) have applied PEMS to measure real-time emission from construction equipment in China and found that emissions were higher compared to other studies. Other approaches have also been used to measure real-time emissions from heavy-duty on-road vehicles (Yanowitz et al. 1999, Yanowitz et al. 2000, Yanowitz et al. 2002), and some studies have focused on idle emissions (Khan et al. 2006, Lewis et al. 2012), which differ considerably from non-idle emissions.

Several different models for predicting emission rates from heavy-duty construction equipment have been proposed. The NONROAD model (EPA 2004, EPA 2009) has been implemented in many environmental assessment models (Marr and Harley 2002, Zavala et al. 2006, Li and Lei 2010, Rasdorf et al. 2012, Hajji and Lewis 2013). The California Air Resources Board's (CARB) OFFROAD model is used to estimate emissions from individual pieces of equipment (CARB 2010). Melanta et al. (Melanta et al. 2013) have summarized tools by which emissions can be estimated from the scale of a single piece of equipment to nationwide.

Although several studies have focused on quantifying and estimating emissions from construction equipment, there is still a need to expand and update the database of emissions, to validate current models used to predict real-time emissions, and to assess the variability of emission factors with activity in order to improve environmental assessment models. In this study, we measured real-time emissions from 18 pieces of construction equipment and compared them to the values estimated by EPA, OFFROAD, and Lewis's MLR model. We also investigated differences in emission factors by activity and engine size. Results will enable more accurate estimation of emissions through environmental monitoring and assessment frameworks.

2.3 Methodology

We have measured emissions of carbon dioxide, the principal greenhouse gas, and health-related pollutants from excavators, backhoes, and loaders during actual operation at various construction sites. We tested 18 different pieces of equipment involved in earthmoving activities on Virginia Tech's campus and at other sites in Montgomery County, Virginia. Table 2-1 lists their engine specifications, and Table 2-2 describes the conditions during each test.

We measured concentrations of carbon dioxide (CO_2), carbon monoxide (CO), hydrocarbons (HC), and nitrogen oxides (NO_x) in the exhaust using a PEMS (AxionGO, GlobalMRV, Buffalo, New York). This system uses non-dispersive infrared (NDIR) absorption to measure CO_2, CO, and HC concentrations and an electrochemical cell to measure NO concentrations. We mounted the suitcase-sized device securely on the construction equipment and installed a probe inside the tailpipe to sample the exhaust. The PEMS recorded gaseous concentrations second by second and sent them remotely to a tablet which recorded and saved the data.

Engine data, such as speed in revolutions per minute (RPM) and intake air temperature, can be measured via sensor arrays installed around the engine or via the on-board diagnostic (OBD) system. Unfortunately, neither option was available in this study, nor was it possible to measure the fuel consumed during a test. Therefore, we estimated engine speed based on information from manufacturers. Emission factors (mass of pollutant emitted per mass of fuel consumed) could be calculated directly from exhaust gas concentrations, but emission rates (mass of pollutant emitted per unit time) required an estimate of engine speed or the rate of fuel consumption. We recorded a video of construction activities during each test to enable the assignment of emissions at any given time to a specific type of activity.

2.3.1 Quality assurance and quality control

We calibrated the PEMS against BAR 97 calibration standards and zero air according to the manufacturer's instructions within 2 days of each test. Before the actual construction activity began, we mounted the PEMS securely on a foam pad over the hood in order to minimize vibration and warmed it up for 15-30 min. We covered it with plastic to protect it from water and dust. Each test lasted between 15 and 120 min. After each test, we cleaned the probe.

We applied quality assurance and control measures to the data. After removal of data points when there were connection, power, or overheating problems or poor quality video, 16 hours of data remained for analysis. We also removed periods showing unnatural shifts or offsets in concentrations, and shifted the concentrations in time to synchronize the measurements with the video recordings.

2.3.2 Emission rates

The PEMS reported exhaust concentrations as volumetric mixing ratios (e.g., percent or parts per million). Given the estimated engine speed, ambient temperature, and ambient pressure, we calculated emission rates, or the mass of pollutant emitted per unit time, according to eq 2-1.

$$ER = Y * MW * D * \frac{RPM}{2} * \frac{1}{60} * \frac{P}{R * T} * 1000 \qquad \text{(Eq. 2-1)}$$

Y= Volumetric concentration of the pollutant of interest in the exhaust (unitless)
ER = Emission rate (g s^{-1})
MW= Molecular weight of pollutant (g mol^{-1})
D= Engine displacement (L)
RPM= Engine speed in revolutions per minute (min^{-1})
P= Ambient pressure (atm) [0.93 atm for Blacksburg]
R= Ideal gas constant (82.05×10^{-6} mol atm m^{-3} K^{-1})
T= Temperature inside tailpipe (K)
2= Accounting for the fact that exhaust emissions are vented during every other revolution in a 4-stroke engine
60= Conversion factor between minutes and seconds
1000= Conversion factor between cubic meters and liters

We assumed an engine speed equal to that reported by the manufacturer for the rated horsepower while the engine was in non-idle mode (Table 2-1) and an engine speed of 1000 RPM while the engine was in idle mode (Abolhasani et al. 2008). As the probe sampled at the exit of the tailpipe, we assumed pressure was equal to that of the ambient environment (Table 2-2). We assumed an exhaust temperature of 402˚C or 213˚C at the exit of the tailpipe depending on whether equipment is equipped with a diesel particulate filter or not (Gonzales 2008). All the sites were 594-655 m above sea level.

2.3.3 Emission factors

We calculated emission factors in terms of the grams of pollutant emitted per liter of diesel fuel consumed on the basis of carbon balance using eq 2-2 (Singer and Harley 2000). The equation assumes that all carbon in the fuel is emitted as CO_2, CO, or HC.

$$EF = \frac{\left(\frac{Y}{Y_{CO_2}}\right)}{\left(1 + \left(\frac{Y_{CO}}{Y_{CO_2}}\right) + 3 * \left(\frac{Y_{HC}}{Y_{CO_2}}\right)\right)} * MW * 840 * \frac{0.87}{12} \qquad \text{(Eq. 2-2)}$$

EF = emission factor (g L^{-1})
Y= Volumetric concentration of the pollutant of interest in the exhaust (unitless)
Y_{CO2}= Volumetric concentration of CO_2 in the exhaust (unitless)
MW= Molecular weight of the pollutant of interest (g mol^{-1})

840= Density of diesel fuel (g L^{-1})
0.87= Carbon content of diesel fuel (g C g^{-1} diesel fuel)
12= Atomic weight of carbon (g mol^{-1})
3= Adjustment for use of propane with three carbons as a calibration gas (unitless)

Table 2-1. Engine Specifications of Each Piece of Equipment Tested

Type	Make	Gross Power (hp)	Tier	Engine Displacement (L)	Model Year	Assumed Engine Speed (RPM)
Bulldozer	Komatsu-D31E	70	I	3.9	1993	2350
Loader	Komatsu-WA180	110	I	5.9	1998	2200
Excavator	John Deere-120C	89	II	4.5	2004	2200
Excavator	Kobelco-135SR	94	II	4.3	2002	2200
Backhoe	John Deere-410G	98	II	4.52	2004	2200
Excavator	Komatsu-PC228	110	II	6.69	2003	2000
Excavator	Caterpillar-320CL	138	II	6.37	2001	2000
Excavator	Hitachi-EX270LC	168	II	6.7	1997	2050
Excavator	Kobelco-SK250LC	176	II	5.9	2004	2100
Loader	John Deere-755C	177	II	10	2004	1800
Excavator	Volvo-EC240	180	II	7.1	2005	2000
Excavator	Kobelco-SK330LC	238	II	7.5	2008	2200
Excavator	Komatsu-PC300LC	242	II	8.3	2005	1900
Excavator	Komatsu-PC160-6	113	III	3.9	2009	2100
Excavator	Sany-SY215CLC	155	III	5.86	2012	2000
Excavator	Komatsu-PC200-8	155	III	6.7	2009	2000
Excavator	Caterpillar-308D	56	IV	2.83	2009	2000
Excavator	Volvo-EC250D	202	IV	7.8	2012	1800

Table 2-2. Conditions During Each Test

Test Date	Time	Equipment	Activity	Temperature[1] (˚C)	Humidity (%)	Operational Productivity (%)
5/17/2013	9:50 AM	Komatsu Bulldozer	Surface grading	22	78	98
10/4/2013	7:30 AM	Komatsu Loader	Equipment hauling	12	100	49
6/4/2013	1:15 PM	John Deere Excavator	Soil excavation	23	65	41
5/16/2013	9:15 AM	Kobelco Excavator	Soil excavation	22	60	87
8/20/2013	12:15 PM	John Deere Backhoe	Pipe laying	23	88	88
5/3/2013	9:45 AM	Komatsu Excavator	Soil excavation	35	77	84
10/1/2013	7:30 AM	Caterpillar Excavator	Soil excavation	12	100	90
9/19/2013	7:30 AM	Hitachi Excavator	Soil excavation	14	100	91
8/21/2013	11:40 AM	Kobelco Excavator	Soil excavation	23	88	99
9/4/2013	7:50 AM	John Deere Loader	Surface grading	14	100	71
8/1/2013	12:30 PM	Volvo Excavator	Soil excavation	23	88	97
9/11/2013	7:30 AM	Kobelco Excavator	Soil excavation	18	100	74
8/14/2013	11:50 AM	Komatsu Excavator	Soil excavation	19	60	97
9/16/2013	7:30 AM	Komatsu Excavator	Soil excavation	13	100	81
10/3/2013	7:30 AM	Sany Excavator	Soil excavation	12	100	75
9/5/2013	7:30 AM	Komatsu Excavator	Soil excavation	14	100	88
7/10/2013	12:45 PM	Caterpillar Excavator	Landscaping	29	74	85
9/10/2013	7:30 AM	Volvo Excavator	Soil excavation	18	100	38

1: temperature at beginning of each test

2.3.4 Emissions predicted by EPA guidelines

We compared our estimates of emission rates to those predicted by EPA guidelines for NONROAD (EPA 2004), which specify that emission rates for HC, CO, and NO_x can be calculated according to eq 2-3.

$$ER_{adjusted} = ER_{steady-state} * TAF * DF \qquad \text{(Eq. 2-3)}$$

$ER_{adjusted}$ = Final, emission rate after adjustment to account for transient operation and deterioration (g hp^{-1} hr^{-1})
$ER_{steady\text{-}state}$= Zero-hour (when the engine is brand new), steady-state emission factor (g hp^{-1} hr^{-1})
TAF = Transient adjustment factor (unitless)
DF= Deterioration factor (unitless)

The deterioration factor is a function of age of the equipment, as shown by eq 2-4.

$$DF = 1 + A * \left(\frac{Cumulative\ hours * load\ factor}{median\ life\ at\ full\ load, in\ hours}\right)^{b} \qquad \text{(Eq. 2-4)}$$

A= relative deterioration factor for a given pollutant and control technology (unitless)
b= constant for a given pollutant and control technology (equal to 1 for diesel engines)

The CO_2 emission rate is calculated according to eq 2-5.

$$ER_{CO_2} = ((BSFC * 453.6) - ER_{HC}) * 0.87 * \left({}^{44}/_{12}\right) \qquad \text{(Eq. 2-5)}$$

ER_{CO2}= adjusted emission rate for CO_2 (g hp^{-1} hr^{-1})
BSFC= Brake Specific Fuel Consumption or in-use adjusted fuel consumption
(lb hp^{-1} hr^{-1})
ER_{HC}= adjusted emission rate for HC (g hp^{-1} hr^{-1}) calculated using eq 2-3.

We used gross horsepower reported by the manufacturer to calculate emission rates in grams per hour. Since gross horsepower is much greater than actual horsepower while equipment is idling, we excluded idle emission rates from this comparison. Input values used to predict emission rates according to EPA guidelines for all equipment are shown in Table 2-3 (Lindhjem and Beardsley 1998, EPA 2004).

Table 2-3. Steady-state emission rates, transient adjustment times, relative deterioration factors, load factors and cumulative hours of the equipment tested, based on EPA guidelines

Make	BSFC (Ib $hp^{-1}hr^{-1}$)	Steady-State Emission Factor (g hp^{-1} hr^{-1})			Transiet Adjustment Factor			Relative Deterioration Factor			Load Factor	Cumulative Hours		
		CO	HC	NO_x	CO	HC	NO_x	CO	HC	NO_x		Hours Per Year	Years	Median Life (hr)
Komatsu-D31E	0.41	2.37	0.52	5.9	1.53	1.05	0.95	0.10	0.036	0.024	0.58	936	20	4000
Komatsu-WA180	0.37	0.87	0.34	5.65	2.57	2.29	1.1	0.10	0.036	0.024	0.21	1135	15	4000
John Deere-120C	0.41	2.37	0.37	4.7	2.57	2.29	1.1	0.10	0.034	0.009	0.21	1135	9	4000
Kobelco-135SR	0.38	0.75	0.31	4	1.53	1.05	0.95	1.53	1.05	0.95	0.53	859	11	4000
John Deere-410G	0.41	2.37	0.37	4.7	2.57	2.29	1.1	0.10	0.034	0.009	0.21	1135	8	4000
Komatsu-PC228	0.37	0.87	0.34	4.1	1.53	1.05	0.95	0.10	0.036	0.024	0.53	859	10	4000
Caterpillar-320CL	0.37	0.87	0.34	4.1	1.53	1.05	0.95	0.10	0.034	0.009	0.53	859	11	4000
Hitachi-EX270LC	0.37	0.87	0.34	5.65	1.53	1.05	0.95	0.10	0.034	0.009	0.53	859	17	4000
Kobelco-SK250LC	0.37	0.75	0.31	4	1.53	1.05	0.95	0.10	0.034	0.009	0.530	859	9	4000
John Deere-755C	0.37	0.75	0.31	4	2.57	2.29	1.1	0.10	0.034	0.009	0.21	1135	8	4000
Volvo-EC240	0.37	0.75	0.31	5.58	1.53	1.05	0.95	0.10	0.034	0.009	0.53	859	9	4000
Kobelco-SK330LC	0.37	0.75	0.31	4	1.53	1.05	0.95	0.10	0.034	0.009	0.530	859	5	4000
Komatsu-PC300LC	0.37	0.75	0.31	4	1.53	1.05	0.95	0.10	0.034	0.009	0.530	859	8	4000
Komatsu-PC160-6	0.37	0.87	0.18	2.5	1.53	1.05	1.04	0.15	0.027	0.008	0.530	859	4	4000
Sany-SY215CLC	0.37	0.87	0.18	2.5	1.53	1.05	1.04	0.15	0.027	0.008	0.53	859	1	4000
Komatsu-PC200-8	0.37	0.87	0.18	2.5	1.53	1.05	1.04	0.10	0.034	0.009	0.530	859	4	4000
Caterpillar-308D	0.41	2.37	0.18	3	1.53	1.05	1.04	0.15	0.027	0.008	0.530	859	4	4000
Volvo-EC250D	0.38	0.75	0.18	2.5	1.53	1.05	1.04	0.15	0.027	0.008	0.53	859	1	4000

2.3.5 Emissions predicted by CARB guidelines

According to CARB guidelines as a part of OFFROAD for emission estimation from a single piece of equipment, emission rates can be estimated according to eq 2-6(CARB 2007).

$$EF = Zh + Dr * CHrs \qquad \text{(Eq. 2-6)}$$

EF= emission factor, in grams per horsepower-hour (gr $bhp^{-1}hr^{-1}$)
Zh= Zero-hour emission rate or when the vehicle is new (g $bhp^{-1}hr^{-1}$)
Dr= deterioration rate or the increase in zero-hour emissions as the vehicle is used (g hp^{-1} hr^{-2})
CHrs= Cumulative hours or total number of hours accumulated on the vehicle, maximum value is equal to 12,000 hours (hr)

Zero-hour and deterioration rates for different models and horsepower are available as part of CARB's emission estimation documentation (CARB 2007).

2.3.6 Emissions predicted by the MLR model

Modal Linear Regression (MLR) is a statistical model developed by Lewis (Lewis 2009) to predict fuel consumption and emissions based on the normalized manifold absolute pressure (MAP) in the engine, as shown in eq 2-7.

$$MAP_{norm} = \frac{MAP - MAP_{min}}{MAP_{max} - MAP_{min}} \qquad \text{(Eq. 2-7)}$$

MAP_{norm} = Normalized MAP
MAP_{max} = Maximum MAP for a specific item of equipment
MAP_{min} = Minimum MAP for a specific item of equipment
MAP = Measured MAP

Normalized MAPs, ranging from 0 to 1, are categorized into 10 equal-sized subcategories, modes 1 to 10. In this classification, mode 1 represents idling and mode 10 represents the highest possible engine pressure during a working cycle. For each mode, a specific formula enables estimation of fuel usage and emissions. In this approach fuel consumption is a function of engine mode, horsepower, and tier, as shown in eq 2-8 (Lewis 2009).

$$Fuel\ [g/s] = a + b\ HP + c\ TIER\_0 \qquad \text{(Eq. 2-8)}$$

a, b, c= constants depending on engine mode and tier
HP= net horsepower rating of the engine (hp)
TIER_0= 0 if engine does not meet any tier regulations; otherwise 1

Fuel consumption and emission rates are calculated using eq 2-9 and 2-10.

$$Fuel_{\ wt.avg.} = \sum_{i=1}^{n} F_{time(i)} * A_i * CF \tag{Eq. 2-9}$$

$Fuel_{\ wt.\ avg.}$ = weighted-average fuel consumption rate (gal hr^{-1}) for a duty cycle with *n* engine modes
$F_{time(i)}$ = fraction of time spent in engine mode *i*
A_i = estimated fuel use rate for mode *i* (g s^{-1})
CF = factor (1.132) to convert (g s^{-1}) to (gal hr^{-1})

$$E_{j\ wt.avg.} = Fuel_{wt.avg.} * \sum_{i=1}^{n} F_{fuel(i)} * B_{ij} \tag{Eq. 2-10}$$

$E_{j\ wt.\ avg.}$ = weighted-average emission rate (g hr^{-1}) of pollutant *j* for a duty cycle with *n* engine modes
$Fuel_{\ wt.\ avg.}$ = weighted-average fuel use rate (gal hr^{-1}) for a duty cycle with *n* engine modes
$F_{fuel(i)}$ = fraction of fuel used in engine mode *i*
B_{ij} = emission factor (g gal^{-1}) for pollutant *j* and engine mode *i*

By analyzing real-time data from the engine control unit (ECU), one can calculate the time spent in each mode. Consequently, fuel consumption and emission rates for each mode and for the whole cycle can be estimated. As engine data were not available in this study, we used the same fractions of time spent in each mode as recommended in the original formulation of the model to calculate emission rates for moving materials, fine grading, and excavating soil (Lewis 2009).

2.3.7 Activity-based emission factors

We examined videos of each test manually to identify activities, such as idling, scooping, and dumping, second by second. In addition, we aggregated some of the specific activities into five more general categories and reported results according to these. Table 2-4 shows the types of specific activities detected as well as the general category to which they were assigned. We compared emission factors associated with each activity to determine whether they were significantly different by the Tukey test. If the emission factors were not normally distributed, we transformed them (i.e., log, log-log or inverse transformation depending on the dataset) in order to satisfy the assumption of normality for the Tukey Test. If the emission factors remained non-normally distributed, even after transformation, they were excluded from further analysis. We calculated a p-value for each comparison and defined the level of significance at 0.05. If emission factors from two different sets of activities were not significantly different from each other, we merged them together into a single category of activity. To investigate the relationship between emission factors and engine parameters, we plotted emission factors for a single category for engines meeting the same tier against engine horsepower and displacement and calculated the least-squares linear regression line.

Table 2-4. Types of activities detected

Specific activity	General activity
Idling	Idling
Scooping	Digging
Empty bucket in air	Idling
Empty bucket moving in air	Swinging
Full bucket in air	Idling
Full bucket moving in air	Swinging
Full bucket lifting	Swinging
Dumping	Dumping
Vehicle moving with empty bucket	Hauling
Vehicle moving with full bucket	Hauling

2.4 Results and Discussion

2.4.1 Emission rates

Tables 2-5 and 2-6 show emission rates and emission factors, respectively, for each piece of equipment averaged over all valid data points. Because the duty cycle, including operational efficiency (ratio of non-idle time to total time), and environmental conditions differed between tests, we expected considerable variability in emission factors (Bishop et al. 2001, Clark et al. 2002, Ahn and Lee 2013). On the other hand, parameters like site altitude, humidity, grade of terrain, and temperature can affect emissions from a single engine. Generally all equipment emitted relatively low amounts of CO and HC, as is expected for diesel engines. In some cases, the standard deviations of CO emission rates were larger than the mean value, implying that there were many instances in which the CO concentration was zero. Emission factors of CO_2 were much higher than for other pollutants, of course, as the majority of the fuel is oxidized to this product. The tier indicates the emissions standards that the engine must meet, with higher tiers having more stringent requirements; and in general, emissions of CO, HC, and NO_x decreased with higher tier number.

Standard deviations of emission factors were generally smaller than those of emission rates, indicating larger variability among emission rates, as has been found in other studies (Lewis et al. 2010). Generally, second-by-second emission factors, especially CO_2, were not normally distributed. The Hitachi-EX-270LC excavator and the Komatsu-PC200-8 excavator both had the same horsepower and met the same standards (tier), but their emission factors were significantly different from each other, meaning that emissions control technologies, differences in manufacturing technologies, engine duty cycle, and/or environmental conditions had a large effect on emissions.

As expected, CO_2 emission rates were orders of magnitude higher than those of health-related pollutants. Among the health-related pollutants, NO_x was emitted in the largest amounts, and CO and HC emissions were low, as expected for diesel-powered engines. In general, emission tier standards are effective in reducing emissions from construction equipment. For instance, health-related emission rates associated with engines meeting tighter emission tiers (III and IV) were lower than those from equivalent-size engines of lower tiers. Based on the assumptions made in this study, emission rates are not proportional to engine horsepower.

Table 2-6 shows measured emission factors for the 18 pieces of equipment. Among all emission factors, CO_2 was the least variable. NO_x emission factors for engines meeting tiers III and IV were generally lower than those of engines meeting tiers I and II.

Table 2-5. Estimated emission rates

Make	Gross Horsepower	Engine Tier	Estimated Emission Rates (g s^{-1})			
			CO_2	CO	HC	NO_x
Komatsu-D31E	70	I	2.9±0.7	0.022±0.006	0.0042±0.0011	0.032±0.011
Komatsu-WA180	110	I	2.0±1.2	0.013±0.010	0.0021±0.0008	0.044±0.029
John Deere-120C	89	II	5.8±0.5	0.001±0.002	0.0053±0.0035	0.052±0.005
Kobelco-135SR	94	II	4.7±1.6	0.003±0.003	0.0029±0.0016	0.035±0.012
John Deere-410G	98	II	1.8±0.7	0.011±0.023	0.0013±0.0003	0.023±0.007
Komatsu-PC228	110	II	4.5±2.5	0.010±0.005	0.0049±0.0024	0.056±0.023
Caterpillar-320CL	138	II	4.3±1.4	0.005±0.013	0.0013±0.0003	0.021±0.008
Hitachi-EX270LC	168	II	6.4±3.4	0.029±0.059	0.0028±0.0008	0.067±0.037
Kobelco-SK250LC	176	II	3.3±1.3	0.006±0.012	0.0014±0.0010	0.020±0.007
John Deere-755C	177	II	2.1±1.3	0.010±0.010	0.0013±0.0004	0.023±0.012
Volvo-EC240	180	II	5.7±1.0	0.002±0.002	0.0036±0.0020	0.041±0.010
Kobelco-SK330LC	238	II	1.7± 1.6	0.005± 0.006	0.0013± 0.0006	0.013±0.007
Komatsu-PC300LC	242	II	5.4± 1.3	0.009±0.004	0.0015±0.0003	0.027±0.007
Komatsu-PC160-6	113	III	1.4±0.7	0.006±0.003	0.0009±0.0004	0.010±0.010
Sany-SY215CLC	155	III	1.1±1.0	0.004±0.002	0.0007±0.0002	0.005±0.004
Komatsu-PC200-8	155	III	1.7±0.8	0.003±0.001	0.0007±0.0003	0.005±0.002
Caterpillar-308D	56	IV	1.6±0.6	0.002±0.004	0.0003±0.0003	0.007±0.003
Volvo-EC250D	202	IV	1.3±1.5	0.001±0.002	0.0005±0.0003	0.006±0.004

Table 2-6. Measured emission factors

Make	Gross Horsepower (hp)	Engine Tier	Measured Emission Factors (g L^{-1})			
			CO_2	CO	HC	NO_x
Komatsu- D31E	70	I	2628±74	23.0±24.0	5.2±12.3	30.1±13.6
Komatsu- WA180	110	I	2608±159	54.3±124.5	3.7±8.5	63.1±55.6
John Deere-120C	89	II	2671.5± 6	0.4±2.2	2.5±1.8	24.1±2.4
Kobelco- 135SR	94	II	2668±44	3.0±8.4	2.4±10.6	21.7±26.9
John Deere- 410G	98	II	2643±85	17.7±39.8	3.0±9.8	41.9±51.0
Komatsu- PC228	110	II	2654±16	9.5±7.1	3.8±2.9	36.4±8.7
Caterpillar- 320CL	138	II	2670±16	4.0±9.1	1.0±1.0	14.9±4.5
Hitachi- EX270LC	168	II	2650±43	15.9±26.4	1.5±1.0	23.7±7.1
Kobelco- SK250LC	176	II	2667±36	5.8±22.5	1.3±1.3	16.7±4.7
John Deere- 755C	177	II	2647±46	30.1±4.6	16.3±47.9	27.6±8.1
Volvo- EC240	180	II	2672±5	4.6±3.6	1.7±0.9	19.2±3.8
Kobelco- SK330LC	238	II	2669± 22	4.2±11.5	2.2±1.6	19.7±9.9
Komatsu- PC300LC	242	II	2669±11	5.2±5.3	0.9±1.0	14.1±9.6
Komatsu- PC160-6	113	III	2652±20	13.7±12.1	2.0±1.0	12.3±4.1
Sany- SY215CLC	155	III	2649±13	15.2±7.1	2.4±1.0	3.5±1.4
Komatsu- PC200-8	155	III	2667±8	5.7±4.5	1.3±0.7	8.6±2.6
Caterpillar- 308D	56	IV	2672±13	4.2±7.7	0.5±0.6	10.6±3.2
Volvo- EC250D	202	IV	2664±23	2.9±9.2	3.6±4.4	17.5±9.6

Figure 2-1 shows ratios of CO_2 emission rates estimated from our measurements to those calculated using EPA guidelines and the MLR model. A comparison to OFFROAD (CARB guidelines) is not shown because this model does not predict CO_2 emissions. A value of 100% means that the two values agree perfectly. The ratios associated with EPA's emission rates varied between 20% and 39%, meaning that the estimated emission rates were much lower than those predicted by EPA's methods in every case; while those for the MLR values varied between 16% and 180%. Emission rates were highly variable depending on the method used to estimate them. For engines meeting higher emission tiers, ratios for the two methods converged, except for the 56-hp Cat excavator. Both of the ratios associated with more recent engines were considerably less than 100%. Differences between our emission rates and modeled ones may be due to the relatively old database used to construct both models (EPA 1991, Lewis 2009).

Discrepancies associated with estimation of CO, HC, and NO_x emission rates were larger than for those of CO_2. Ratios fell well below 100% for engines meeting tighter emission standards (tier III and IV). All CO emission rates in this study were lower than those predicted by OFFROAD and EPA guidelines; the ratios varied from 0% to 31%. For HC, ratios associated with EPA's and OFFROAD's approaches varied between 5% and 59%, while those associated with the MLR model varied between 5% and 121%. Generally for same pieces of equipment, the largest and smallest discrepancies between different approaches were associated with CO and CO_2, respectively. As tier increased, discrepancies between the emission rates estimated in this study and those predicted by other approaches grew. It is possible that factors considered in existing emission estimation approaches are not sufficient to predict emissions accurately under actual operating conditions. It is likely that improved consideration of emission control technologies implemented in engines meeting tiers III and IV—particulate filters, selective catalytic reduction, exhaust gas recirculation—is needed. The MLR model is based on PEMS data (Lewis 2009), yet there are large discrepancies between its predictions and our measurements, which were also collected using PEMS, especially for tier III and IV engines. Differences may be due to the fact that the MLR model was based on measurements from older excavators which only met tier I standards.

Figures 2-2, 2-3, and 2-4 show ratios of emission rates estimated from our measurements to those calculated using EPA guidelines, the MLR, and OFFROAD for CO, HC, and NO_x, respectively. Ratios for these three pollutants were lower than those for CO_2, meaning that discrepancies between health-related emission by these estimation approaches are larger than those for CO_2.

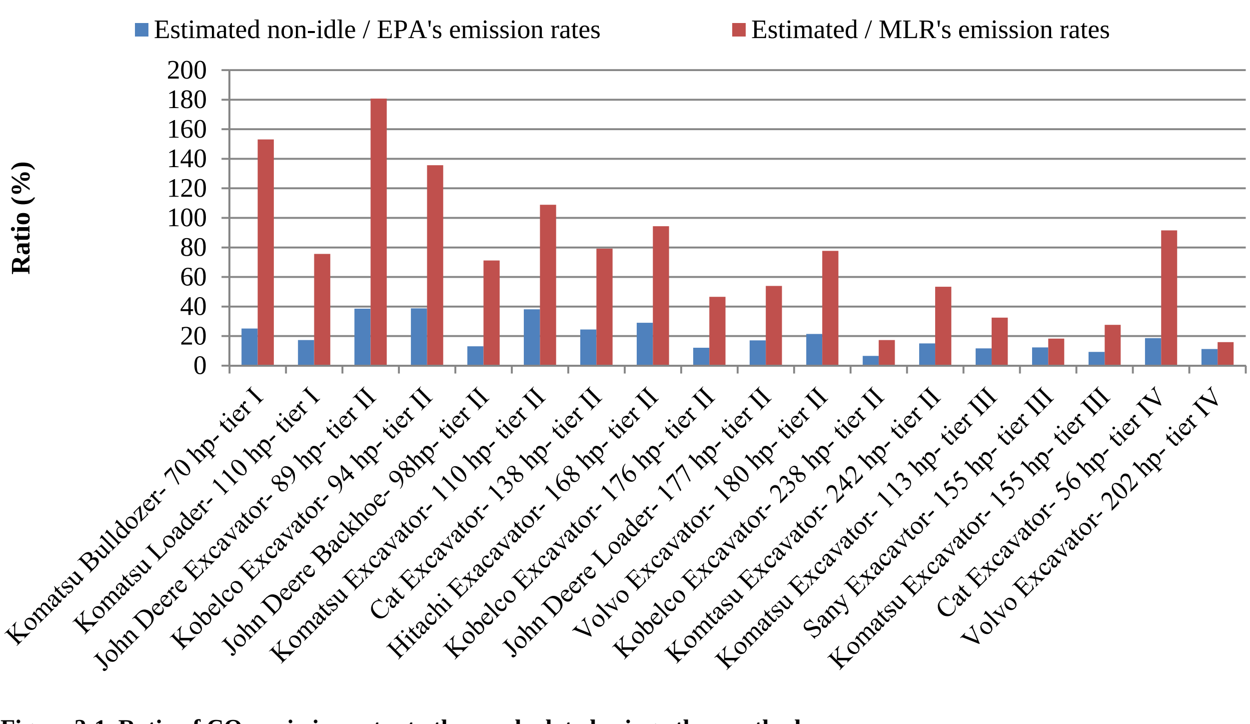

Figure 2-1. Ratio of CO_2 emission rates to those calculated using other methods

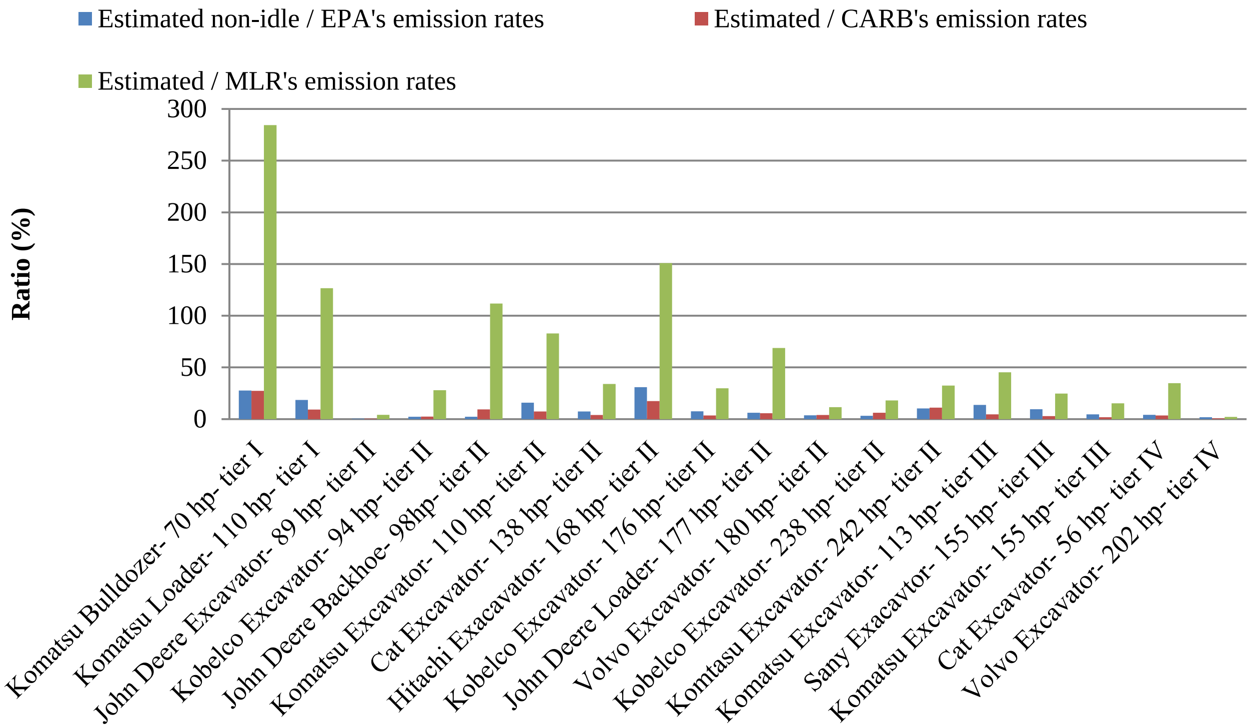

Figure 2-2. Ratio of CO emission rates to those calculated using other methods

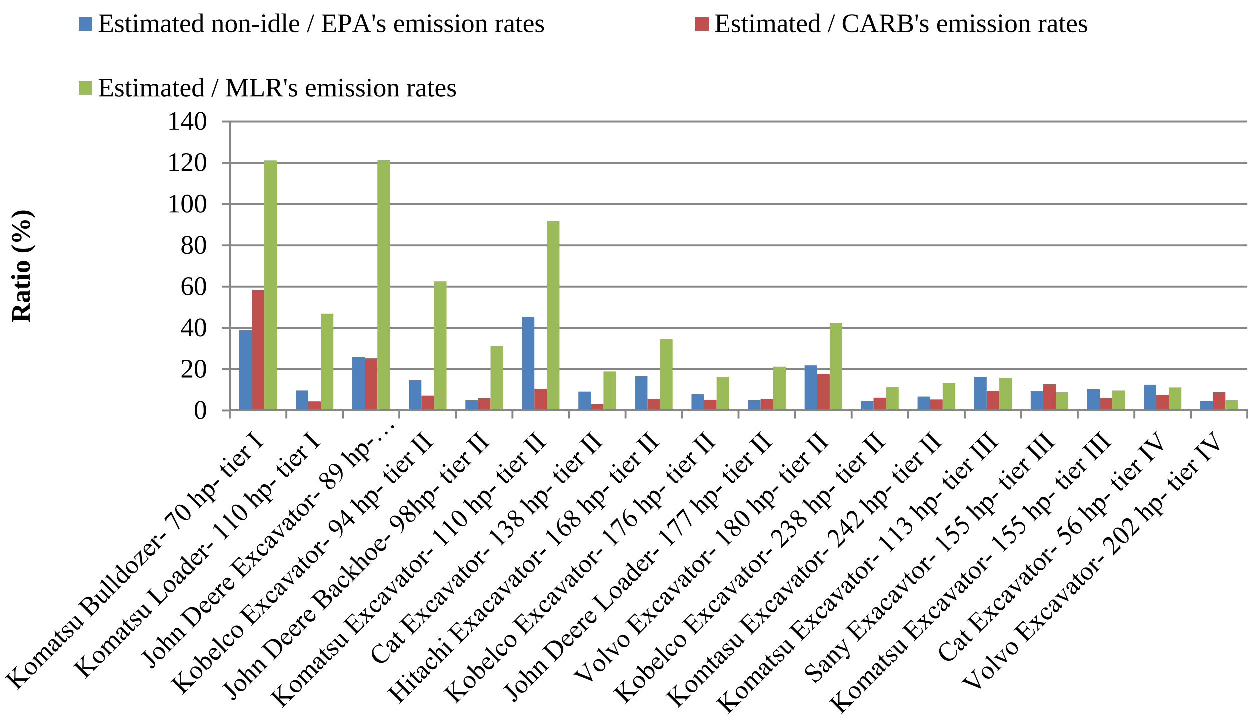

Figure 2-3. Ratio of HC emission rates to those calculated using other methods

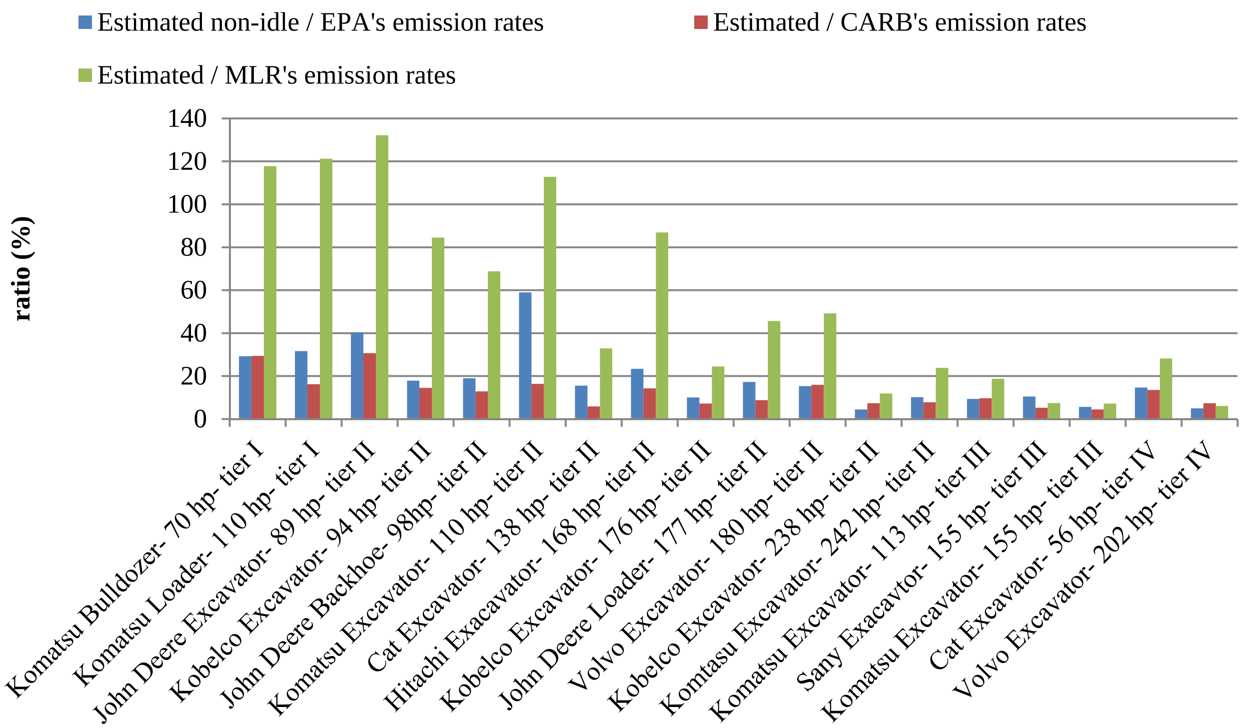

Figure 2-4. Ratio of NO_x emission rates to those calculated using other methods

We conducted a sensitivity analysis in order to quantify the possible error associated with the engine speed, pressure, temperature, and ambient conditions used to calculate the emission rates (Eq. 1). We consulted several practitioners who stated that the engine speed typically ranged from 1750 RPM to 2200 RPM. Humidity affects NO_x emission rates (Yanowitz et al. 2000) but was not parameterized here. In order to combine effects of these independent factors, we multiplied our emission rates by an aggregated correction factor. We calculated correction factors for NO_x emission rates based on ambient relative humidity for different tests. We assumed the engine speed to be 2200 RPM (maximum value suggested by practitioners in this domain) for all the tests. Temperature and pressure at the tailpipe, where concentrations were measured, may have varied from our initial assumptions as well. We considered a minimum temperature of 97˚C for the exhaust, the mean of observed exhaust temperatures in diesel engines (Gonzales 2008), and pressure up to 250 kPa (Lewis 2009). By applying all corrections mentioned above in a worst-case scenario, we estimated the highest possible emission rates compared them to those suggested by EPA and CARB guidelines.

Table 2-7 shows the resulting ratios of emission rates, corrected emission rates to those of EPA's, when the adjustment factors were applied. The table shows only the mean and standard deviation across all pieces of equipment rather than results for individual pieces of equipment (Figures 2-1 to 2-4). Even after we modified the input assumptions, the mean of ratios remained below 100%. Thus, the finding was robust that our PEMS-based emission rates, which required a number of assumptions about engine speed and exhaust parameters, were lower than those predicted by widely used models. This sensitivity analysis may not represent actual real-world conditions.

Table 2-7. Ratio of measured, non-idle emission rates to those calculated according to EPA's and CARB's approaches (%) after changing engine data assumptions

EPA (%)			
CO_2	CO	HC	NO_x
83 ± 32	39 ± 31	60 ± 38	73 ± 38
CARB (%)			
NA	25 ± 22	50 ± 42	57 ± 23

Emission factors at idling were also of interest because they differ from those under working modes and can have a large impact on average emission factors, which depend on the time spent in each mode. Table 2-8 shows the ratio of measured idling emission factors to those recommended by the MLR model for all 18 pieces of equipment. The MLR model assigns a constant emission factor that is independent of engine size, horsepower, and tier for mode 1, which represents idling. In contrast to ratios for emission rates (Figures 2-1 to 2-4), the values were larger than 100% in some cases. There were large differences for bulldozers and loaders, even though the testing procedure for both studies was similar. The ratios shown in Table 2-8 suggest that using a single idling emission factor for all construction equipment may not be ideal, especially for CO, NO_x and HC. Factors other than engine mode must also affect idling emission.

2.4.2 Differences between activity emission factors

Based on the videos of each piece of construction equipment's actions, we assigned emission factors to one of the specific activities in Table 2-3 on a second-by-second basis. Table 2-9 shows the number of tests for which a significant difference was observed in the emission factors between each combination of activities. For example, a value of 5/16 in Table 2-9 for CO means that in 5 out of 16 tests, there was a significant difference between digging and dumping in terms of their emission factors. Since emission rates were not directly measured (i.e., they required assumptions about engine speed and exhaust parameters), they were excluded from this analysis. Although there were 18 different pieces of equipment, not all of them performed all categories of activities defined in Table 2-4, nor were their emission factors normally distributed, and thus the total numbers of comparisons for a pair of activities was not the same for each combination.

Table 2-8. Ratio of idling emission factors to those recommended by MLR

	CO_2 (%)	CO (%)	HC (%)	NO_x (%)
Komatsu Bulldozer- 70 hp- tier I	82	1486	1481	250
Komatsu Loader- 110 hp- tier I	98	761	104	161
John Deere Excavator- 89 hp- tier II	102	4	45	59
Kobelco Excavator- 94 hp- tier II	101	87	137	79
John Deere Backhoe- 98 hp- tier II	101	145	71	115
Komatsu Excavator- 110 hp- tier II	102	28	43	77
Caterpillar Excavator- 138 hp- tier II	101	102	36	59
Hitachi Excavator- 168 hp- tier II	100	288	45	60
Kobelco Excavator- 176 hp- tier II	102	38	30	41
John Deere Loader- 177 hp- tier II	102	46	173	41
Volvo Excavator- 180 hp- tier II	102	42	38	46
Kobelco Excavator- 238 hp- tier II	101	145	67	71
Komtasu Excavator- 242 hp- tier II	101	118	45	72
Komatsu Excavator- 113 hp- tier III	101	155	44	38
Sany Excavator- 155 hp- tier III	101	148	49	10
Komatsu Excavator- 155 hp- tier III	102	82	33	27
Caterpillar Excavator- 56 hp- tier IV	102	44	8	26
Volvo Excavator- 202 hp- tier IV	102	29	84	49
Average	100	208	141	71

In general, there were significant differences between idling and other working modes. Differences in emission factors by activity were not consistent by pollutant. Table 2-9 suggests that using different emission factors for certain activities, as well as using fuel consumption specific to that activity, can help practitioners to estimate actual emission rates more accurately. Since fuel usage was estimated in this study—based on engine speed, pressure, and temperature—we can conclude that activity-specific emission rates follow the same trend. In other words, idling emission rates were different from non-idling emission rates.

Table 2-10 shows the results of linear regression of emission factors against engine characteristics, namely horsepower and displacement, separately for idling and non-idling modes. Only engines meeting tier II were considered because there were 10 of these and not enough meeting the other tiers for this analysis. For all pollutants, there was not a significant linear relationship between displacement, engine horsepower, and emission factors ($p > 0.05$). Under actual operating conditions, emission factors must have also been affected by factors other than engine size and power and tier, such as duty cycle, other engine parameters, and environmental conditions. Thus, these factors must be taken into account when predicting emissions from construction equipment activity.

Table 2-9. Numbers of significant statistical differences observed between activity-based emission factors

	Idling	Digging	Swinging	Dumping	Hauling
CO_2 emission factors					
Idling	–	2/4	4/4	3/4	4/4
Digging	–	–	3/4	2/4	2/4
Swinging	–	–	–	4/4	4/4
Dumping	–	–	–	–	4/4
Hauling	–	–	–	–	–
CO emission factors					
Idling	–	15/17	12/17	13/16	16/18
Digging	–	–	8/16	5/16	14/17
Swinging	–	–	–	8/16	12/17
Dumping	–	–	–	–	10/16
Hauling	–	–	–	–	–
HC emission factors					
Idling	–	15/17	14/17	12/16	15/18
Digging	–	–	11/16	4/16	11/17
Swinging	–	–	–	11/16	14/17
Dumping	–	–	–	–	7/16
Hauling	–	–	–	–	–
NO_x emission factors					
Idling	–	9/11	10/11	7/10	8/12
Digging	–	–	5/10	1/10	7/11
Swinging	–	–	–	5/10	7/11
Dumping	–	–	–	–	6/10
Hauling	–	–	–	–	–

Table 2-10. Analysis of linear relationships between emission factors for engines meeting tier II

Non-idling Emission Factor (g L^{-1}) vs. Horsepower					Idling Emission Factor (g L^{-1}) vs. Horsepower				
	CO_2	CO	HC	NO_x		CO_2	CO	HC	NO_x
Slope (m)	0.020	0.009	-0.001	-0.090	Slope (m)	-0.002	0.033	-0.008	-0.066
R^2	0.07	0.03	0.00	0.44	R^2	0.00	0.03	0.03	0.14
p-value	0.07	0.14	0.94	0.02	p-value	0.98	0.56	0.61	0.26
Non-idling Emission Factor (g L^{-1}) vs. Engine Displacement					Idling Emission Factor (g L^{-1}) vs. Engine Displacement				
	CO_2	CO	HC	NO_x		CO_2	CO	HC	NO_x
Slope (m)	0.359	0.825	0.757	-2.210	Slope (m)	1.76	0.30	0.43	-2.36
R^2	0.02	0.25	0.26	0.25	R^2	0.03	0.03	0.08	0.18
p-value	0.65	0.12	0.12	0.12	p-value	0.61	0.87	0.40	0.19

2.5 Conclusion

Due to the substantial contribution of the construction industry to emissions of GHGs and health-related pollutants, there has been an on-going need to quantify and predict emissions at scales ranging from a single piece of equipment scale to nationwide. The goals of this study were to augment the limited database of emission rates and emission factors for construction equipment, evaluate the ability of widely used models (EPA NONROAD, CARB OFFROAD, and MLR) to predict emissions, and investigate effects of activity and engine characteristics on emission factors under actual operating conditions.

Real-time emission rates varied more than did emission factors, confirming previous findings. Measured emission rates in this study were lower, from 0.5% to 59% and from 0.5% to 58%, than those predicted by EPA and CARB, respectively, and ranged from 2% to 284% of values predicted by the MLR approach. Differences in the two approaches—actual on-site emission measurement and those recommended by regulatory approaches—suggest that using a single emission factor for different engines, even for the same activity within each engine duty cycle, will result in noticeable discrepancies, from 4% to 1500%. Thus, depending solely on equipment, engine horsepower, and engine tier may not enable accurate prediction of emissions. Other factors may also influence emissions; MAP has been proposed to account for these, but it is not easily monitored. Emission control technology and time spent in each duty cycle may contribute greatly to overall emission rate and factor.

Emission factors associated with idling and hauling were significantly different from those for digging, swinging, and dumping. Therefore these two activities—idling and hauling—should be treated uniquely rather than lumped together under the umbrella of an overall emission factor. On the other hand, idling emission rates may vary between high-idle and low-idle modes. In the real-world conditions of this study, emission factors were not linearly proportional to engine horsepower and size. This outcome calls for future studies on the duty cycle and fuel usage of engines used in construction equipment. Since emission factors are less variable than emission rates, a thorough understanding of fuel usage by activity and duty cycle can enable more accurate estimation of emissions.

We found significant differences between emissions measured under real-world conditions and those predicted by widely used models. Results from this study might contribute to improving the accuracy of the models. There was a considerable difference between measured and modeled emission factors particularly for engines meeting higher tier standards. Thus, emissions databases and estimation models should be updated to account for advances in emission control and manufacturing technologies.

2.6 Recommendations and Future Work

The lack of real-time engine data was a limitation of this study, as we had to assume an engine speed in order to estimate emission rates from the measured exhaust gas concentrations. Development of a database on RPM, MAP, and temperature during equipment operation would be very useful. Doing so would require access to the ECU via an OBD port, which currently is not available on most construction equipment. Therefore, we encourage equipment manufacturers to install such ports.

The relationship between emissions and site and operational characteristics (e.g., type of soil hauled and traveled on, terrain grade, etc.) should be investigated further. This will help researchers to develop models to benchmark real-time construction emissions in the pre-construction phase and compare real-time performance to expected benchmarked values.

Although there have been recommendations on application of PEMS for construction emissions measurement, few studies have used this technique. Therefore there is a need for more work in this domain to measure real-time emissions. Calibration and validation of steady-state emission-related studies with real-time emission-related studies will possibly lead to better understanding of actual off-road diesel engine emissions.

Future research should focus on emissions of particulate matter (PM) because of its strong link to health effects and impact on climate change.

Since engine data and MAPs for each model of equipment are not usually available, emissions models should account for uncertainty and variability in emission factors by activity.

Finally, incorporation of results of studies such as this one should be incorporated into the development and refinement of emissions models, including the successor to NONROAD, MOVES (EPA 2010, Koupal et al.).

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3 Benchmarking and Real-time Monitoring of Construction Equipment Emission Using Discrete Event Simulation and Automated Vision-based Action Recognition

3.1 Abstract

This study reports recent advancements in vision-based technology for monitoring and predicting environmental impacts, specifically atmospheric emissions of greenhouse gases and health-related pollutants, resulting from construction operations. The technology can automatically recognize actions performed by construction equipment by extracting spatio-temporal features from video streams of construction operations. It enables real-time productivity and emissions monitoring of construction equipment in an inexpensive and relatively accurate manner, which is a unique achievement in the construction environmental assessment domain. In this study, vision-based technology and an action recognition algorithm have been applied to case studies. From the resulting time-series of activities, productivity and amounts of emissions were assessed for each piece of equipment. The automated technique produced results that were, on average, 98% of those estimated by manual recognition. Emissions from the total operations were very sensitive to in-use emission rates used in the model. Additionally, emissions for some case studies were predicted through simulation of construction operations using Discrete Event Simulation (DES). For those specific case studies, emissions estimated using computational simulation and action recognition agreed to within 14%. Emissions estimated using computational simulation were treated as a benchmark and were compared to actual values measured on-site. Actual emissions ranged from 28% to 144% of those predicted by DES, due to discrepancies between real-world practice and computational simulations. Results of this research will aid practitioners in implementing strategies to increase productivity and simultaneously reduce environmental emissions by using an inexpensive, robust, and user-friendly approach.

3.2 Introduction

The construction industry is the third highest emitter of GHGs among all industry sectors (EPA 2008). Emissions of GHGs and health-related pollutants, such as nitrogen oxides and particulate matter, account for more than half of the total environmental impacts that result from construction activities (Guggemos and Horvath 2006). The United Nations, many European countries, and the state of California are trying to reduce GHG emissions by 80% by the year 2050 (Luers et al. 2007, ENR 2010), and reductions from the construction industry will be required to meet this goal.

As a result of new and impending regulations, controlling emissions from the construction industry is a growing concern (AGC 2010, Heydarian et al. 2012). The often competing objectives of compliance with regulations and minimization of cost present a challenge for the industry. Because regulations emphasize tighter controls on the equipment instead of improvement in efficiency during construction activities, they have resulted in costly upgrades. Controlling and monitoring air pollutant emissions during the construction phase through reasonable policies and practical tools may also be effective for reducing emissions. Monitoring technologies and techniques are important because without them, excessive emissions cannot be detected and minimized. Cost and accessibility of these technologies and techniques are two important factors which should be considered (Golparvar-Fard et al. 2009).

In recent years, various approaches have been introduced to estimate and monitor GHG emissions from construction operations. This information can be used to calculate the carbon footprint of the activity. Several researchers have used Discrete Event Simulation (DES) to quantify construction-related emissions and have validated this tool in estimating the actual amount of emissions (Ahn et al. 2009, Ahn et al. 2010, Li and Lei 2010). Pena-Mora et al. (2010) presented a framework for managing emissions from construction activities and suggested using a Portable Emission Measurement System (PEMS) along with simulation tools to visualize construction operations. A PEMS is connected to the tailpipe to enable real-time measurement of emissions of certain gases, and sometimes particles, from any vehicle. However, because of cost and installation time, it is not feasible to implement this technology for all pieces of construction equipment on site (Ahn et al. 2013). Artenina et al. (2010) discussed using an intelligent and optimized GIS route planning system to reduce emissions from construction equipment. Shiftefar et al. (Shiftefar et al. 2010) introduced a system that enables visualization of construction emissions using a tree metaphor. In addition, Lewis et al. (2011) proposed a framework for quantifying the effect of operational efficiency on total emissions from construction. While these studies have advanced the idea of reducing emissions from construction activities, they have overlooked the possibility of automated monitoring and benchmarking of real-time emissions from construction equipment (Heydarian et al. 2012).

Other researchers have focused on several other techniques for monitoring real-time earthmoving operations by using techniques like RFID tags, GPS, and accelerometers in addition to on-site video cameras (Torrent and Caldas 2009, Gong and Caldas 2010, Moon and Yang 2010, Brilakis et al. 2011, El-Omari and Moselhi 2011, Gong et al. 2011, Yang et al. 2011, Ahn et al. 2013). These techniques mostly focus on tracking construction equipment and not on action recognition of videos, except in the study by Gong et al (Gong and Caldas 2010). Another innovative approach in practice since 2010 is telematics, which uses telecommunication tools in order to report location, action, and other useful pieces of information remotely (Sutton 2010, Zagoudis 2011). Although this technique has many useful applications, it is not able to monitor emissions and compare them to benchmarked values.

Among all these possible solutions, using networks of cameras and recording activities has great potential for improving the understanding of the relationship between emissions and operational efficiency. Gong et al. (Gong and Caldas 2010) introduced a vision-based tracking model for detecting and monitoring a bucket in construction operations; however, this model cannot detect location and action simultaneously. Zou and Kim (Zou and Hyoungkwan 2007) also presented an image-processing approach that assesses idling time of an excavator based on image color space (hue, saturation, and value); however, this approach is susceptible to error due to change of scale and illumination (Heydarian et al. 2012). Recent developments have enabled researchers to overcome these deficiencies, resulting in accurate real-time emissions measurement. Timely and precise operational details empower researchers, managers, and practitioners to establish new corrective techniques, avoid delays, and minimize excessive environmental impacts (Golparvar-Fard et al. 2009). Table 3-1 summarizes current techniques in emissions assessment and monitoring as well as strengths and limitations of each one.

While embodied emissions, or those resulting from all activities associated with a construction project (e.g., production of building materials, transportation of crew and equipment to the site, heating sources on site) are important too, they fall outside the scope of the current study. If idling time during construction activities can be minimized, then fuel usage, emissions, and cost will be reduced (SKANSKA 2011). To achieve this goal, a technique is needed to gather actual real-time data on activities performed at a construction site. Then, this time series of activities can be combined with fuel usage rates and emission rates in order to estimate total fuel usage, emissions of various pollutants, and carbon footprint. Developing an automated technique which is accessible and cheap will facilitate estimation of productivity and emissions for project managers, contractors, regulators, and investigators. Researchers can use the results from the monitoring system to determine the level of efficiency in construction activities and to propose new techniques to increase this efficiency. Practitioners can use the system to control the amount of resources being used and possibly reduce the amount that is wasted. Managers can use the system in support of sustainability certification, such as Leadership in Energy and Environmental Design (LEED) for a project. Currently, there are no available automatic measuring and monitoring techniques for real-time productivity and emissions assessment in the construction industry. Therefore, most certification organizations typically do not consider the construction phase in evaluation of environmental performance.

One possible solution is to use networks of cameras on construction sites and record videos from each piece of equipment in action. Through a network of cameras and an internet connection on site, videos are transferred to a computer which is able to remotely and easily analyze emissions and productivity (Golparvar-Fard et al. 2009). Once time-series of activities are generated, emissions associated with all equipment can be estimated. Reporting the emissions is not beneficial by itself. Rather, comparing them to a value set in the pre-construction phase, a benchmarked value, or one set by regulations will help practitioners in decision making. For this comparison, emissions should be estimated using other credible methods to determine if emissions may exceed calculated thresholds.

Table 3-1. Summary of Emission Assessment Techniques

Name	Characteristics	Deficiencies
EPA NONROAD / CARB OFFROAD model	• Widely used for emission estimation in pre-construction planning • Easy to be use	• Need to verify, and possibly, modify model outputs • Not able to monitor real-time emissions
Portable Emission Measurement System (PEMS)	• Real-time emission measurement • A portable laboratory needs to be installed on each equipment	• Expensive • Can monitor a limited number of pieces of equipment • Hard to install
Intelligent and optimized GIS routing	• Wide application of GIS • Easy to implement • Used for tracking equipment	• Not monitoring real-time emissions automatically • Not to detect activities and productivity
Tree metaphor	• Visualization of emissions in lay terms • Good for communicating environmental impact	• Not monitoring real-time emissions automatically • Not able to benchmark emissions
Radio Frequency Identification (RFID) tags	• Tracks equipment in real-time • Accurate	• Not able to detect activities • Not able to benchmark emissions
Electromechanical accelerometer	• Tracks equipment in real-time • Easy to implement • Accurate	• Not able to detect activities • Not able to assess productivity
Vision-based tracking model	• Tracks equipment in real-time	• Not able to detect actions, emissions, and productivity simultaneously
Vision-based approach using image processing	• Able to monitor and detect real-time actions	• Susceptible to errors due to illumination and scale change
Vision-based approach using spatio-temporal feature extraction	• Able to monitor real-time productivity and emissions • Able to handle noisy features arisen from dynamic background of construction	• Not applicable to horizontal construction activities • Need for comprehensive emission factor inventory
Telematics	• Telecommunicating engine and equipment data	• Not able to detect emissions • Not able to distinguish discrepancy between monitored and benchmarked emissions.

In this research, computational simulation of construction activities will be used as a benchmarking tool (Ahn et al. 2009, Ahn et al. 2010, Li and Lei 2010). Therefore, emissions estimation using DES helps verify applicability of the proposed technology in assessing environmental impacts from construction activities. The results can be used to assess effects of construction operation configuration (i.e., schedule, type, and number of pieces of in-use equipment) on total construction-related atmospheric emissions. It can also lead to sustainable construction operations with lower environmental impacts.

The objective of this work is to extend prior accomplishments in automated video processing to the real-time monitoring of emissions (Heydarian et al. 2012). The entire concept is presented, and the technology is demonstrated through case studies. Emissions monitored in real-time are compared to emissions that have been determined via two approaches: Discrete Event Simulation and manual action recognition approaches. In the latter, all the actions and emissions for each second of videos are manually assessed. Results will help researchers and practitioners to validate applicability of this technology and ultimately to implement it in practice.

3.3 Methodology

This monitoring and benchmarking framework is based on vision-based technology. Through a network of cameras installed at a construction site, the actions and locations of construction equipment can be recognized automatically. Then, productivity and atmospheric emissions can be monitored remotely and compared to the values that were established in the pre-construction phase using Discrete Event Simulation.

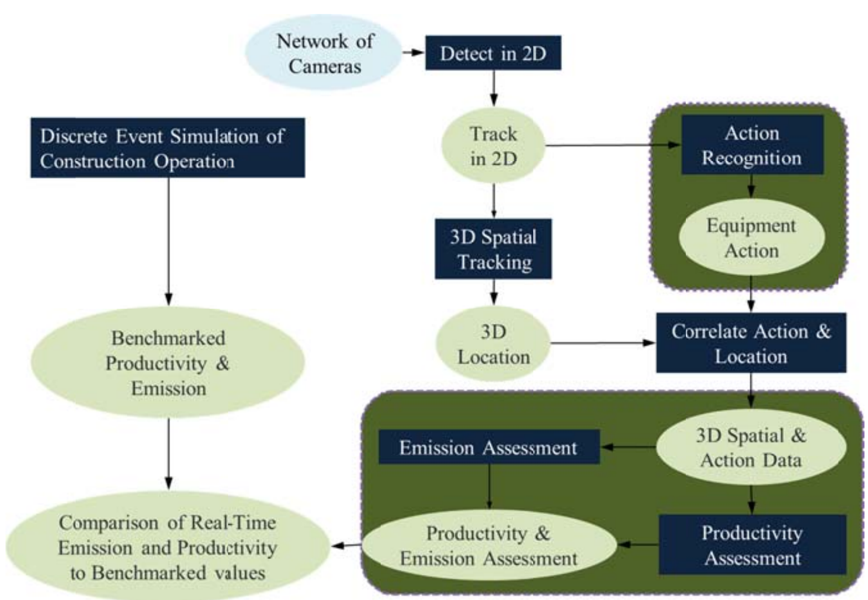

Figure 3-1. Framework for assessing productivity and emissions

Figure 3-1 shows the workflow of the model to assess productivity and emissions. Videos of construction activities are recorded and then analyzed to identify different types of activities. First, an integrated 3D reconstruction and recognition algorithm is introduced to model the construction site (Heydarian et al. 2012). This algorithm is based on extraction of spatio-temporal features from video frames. Space-time interest points, which have been proven to be useful for human action recognition, are extracted using Gaussian and Gabor filters. Gaussian and 2D Gabor filters are linear filters used for edge detection in image processing. They are proven to be useful in texture representation and discrimination (Mehrotra et al. 1992).

Then, each feature is described with a Histogram of Oriented Gradients (HOG) using K-mean clustering, which results in each video frame representing a set of spatio-temporal features (Heydarian et al. 2012). Histograms of Oriented Gradients are feature descriptors used in image processing in order to detect objects. This technique is based on counts of gradient orientations occurrences in localized sections of an image. K-mean clustering is a method in data mining used for vector quantization in cluster analysis. It partitions observations into clusters in which each observation belongs to the cluster with the nearest mean (Kanungo et al. 2002).

By clustering HOG descriptors, the probability distribution of the features in this algorithm is learned automatically. Therefore, histograms of spatio-temporal features are generated, and through application of a multiple binary Support Vector Machine (SVM) classifier, actions are recognized and located in 2D frames. SVM is a discriminative learning methodology founded on principles of structural risk minimization. It can analyze and recognize patterns for classification and regression analysis (Heydarian et al. 2012).

Videos are analyzed further in order to spatially recognize and locate equipment in 3D and register their location in D4AR, a 4-dimensional augmented reality environment (Golparvar-Fard et al. 2009). D4AR is a computational live view of physical, real-world construction site whose elements are augmented by images taken on-site. It enables the site to be monitored from long distances and managed in real-time.

Next, actions are recognized by an action recognition technique, which has to be applied to a long sequence of videos. For automatic recognition of the starting and ending point and duration of each activity, such as digging or dumping, a new temporal sliding window algorithm is introduced. Distributions of durations for all activities are calculated using a training dataset. Each temporal sliding window is divided into separate time frames. For each frame, the spatio-temporal features are extracted, and the probability of their distribution is learned by clustering their HOG descriptors. The histograms are placed into the classifier, and for each frame the action categories are stored. Durations of activities, and consequently starting points of the next subsequent activity in each video stream, are calculated based on using time frame stored previously in the video stream as the one with the highest score. For all the video frames within target video stream this process will be repeated (Heydarian et al. 2012).

Through integration of 4D building information models for each construction activity, measured productivity as well as operational emissions can be assessed (Golparvar-Fard et al. 2009). The output of this methodology is a time-series of activities performed by each piece of equipment.

The approach can handle noisy feature points that arise from typical dynamic backgrounds of construction sites.

Together with information about engine power, emission rates, and load factors, as well as site and weather conditions, emission rates can then be calculated. Multiplying the duration of each activity by the emission rate associated with the activity and adjusting for weather, site, and engine conditions enables estimation of total emissions via Equation 3-1.

$$E_T = \sum_p e_p * \Delta t_p \qquad \text{(Eq. 3-1)}$$

where e is the emission rate for activity p (e.g., digging, hauling, dumping, swinging or idling) (kg s^{-1}), Δt_p is the duration of activity p (sec), and E_T is the total amount of emissions of gas T while the equipment is working (kg).

Emission rates for construction equipment can be derived from various resources, such as the NONROAD model (EPA 2004) or Lewis's modal linear regression (MLR) model (Ahn et al. 2009, Ahn et al. 2010, Li and Lei 2010). Because none of these provide emission rates specific to all the activities identified by vision-based technology, field measurements were conducted to obtain these data (Heidari and Marr 2014). Briefly, emissions of carbon dioxide (CO_2), carbon monoxide (CO), hydrocarbons (HC), and nitrogen oxides (NO_X) from different pieces of equipment were measured using a PEMS (Axion Go, GlobalMRV) during earthmoving operations. Videos of the construction activities were recorded, and time series of five activities— digging, dumping, hauling, swinging, and idling— were generated by vision-based technology using the automated approach outlined above or by manual analysis. Action recognition by both automated means and manual analysis were applied to six videos representing two excavators (Caterpillar-320CL or Kobelco-SK330LC). Real-time emissions were calculated according to Eq. 3-1 using either EPA's emission rates (EPA 2004), which are not specific to the type of activity, or measured emission rates (Heidari and Marr 2014).

For prediction of emissions in the pre-construction phase, Discrete Event Simulation (DES) was used to model and simulate construction operations and develop an emissions benchmark. The STROBOSCOPE program (Martinez 1996) was used to implement DES for the six previously mentioned case studies (i.e., videos of two excavators) as well as three additional case studies: videos of a Volvo-EC250D, Sany-SY215CLC, and Komatsu-PC228. All the videos examined in this comparison were recorded from earthmoving activities in which excavators were dumping soils into trucks. Inputs to the model included details about the equipment and test characteristics, such as the number of pieces of equipment actually used on-site and their capacity, emission rates specific to the type of equipment, the duration of each activity, and the amount of work to be done (i.e., the volume of soil to be moved). Idling time was computed as part of the simulation. The code for the case study with the Sany excavator is presented in Appendix I. Model output was compared to emissions calculated according to manually generated time-series of activities and real-time emission measurements on-site. The comparison served two purposes: (1) validation of the model and (2) demonstration of case studies with the model output as the benchmark and results of the calculations described above as the actual project emissions. Analyzing deviations between the benchmark and actual emissions will enable real-time assessment of construction performance and possibly adjustment of operations to bring emissions more closely in line with pre-planned values.

3.4 Results and Discussion

Prior work has shown that vision-based technology is 86% accurate in recognizing activities (Heydarian et al. 2012). Using automated action recognition, a prior study produced time series of activities for excavators appearing in six videos (Heydarian et al. 2012). Figure 3-2 shows emissions of CO_2, CO, NO_x and HC estimated from the time series of activities in one video, which recorded an excavator (Caterpillar-320CL) digging soil and dumping it into a truck. CO_2 was emitted in much larger amounts than the other pollutants, as it is the main product of combustion. While emissions of the other pollutants were much lower, these have direct health effects at low concentrations, and dispersion modeling could be used to predict a worker's exposure to them (Turner 1994).

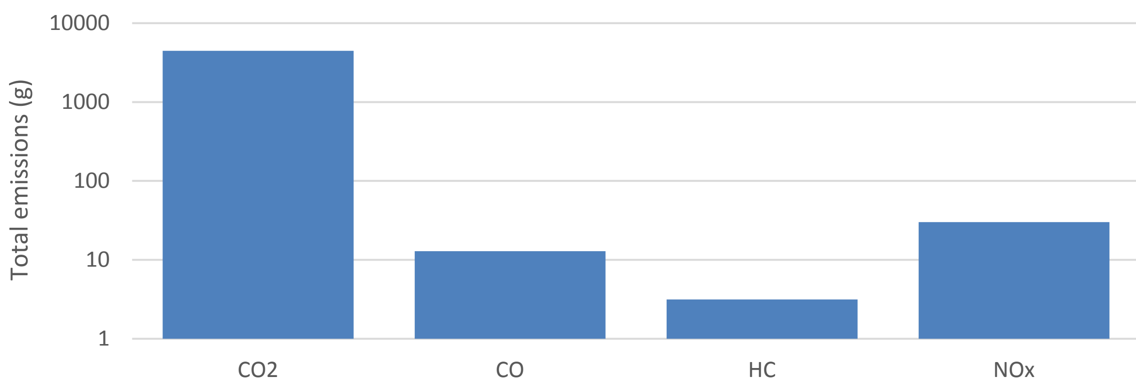

Figure 3-2. Emissions for a single video recorded during excavating and dumping activities over 283 s

Figure 3-3 shows CO_2 emissions, based on emission rates suggested by EPA guidelines, for different activities performed by the excavator along with the duration of each activity for the same video. Emissions were correlated with the duration of each activity. EPA recommends a single emission factor per horsepower for each pollutant. Since horsepower used in the emission rate calculation is the same regardless of the pollutant, ratios of emission rates between different activities are the same for all emitted gases.

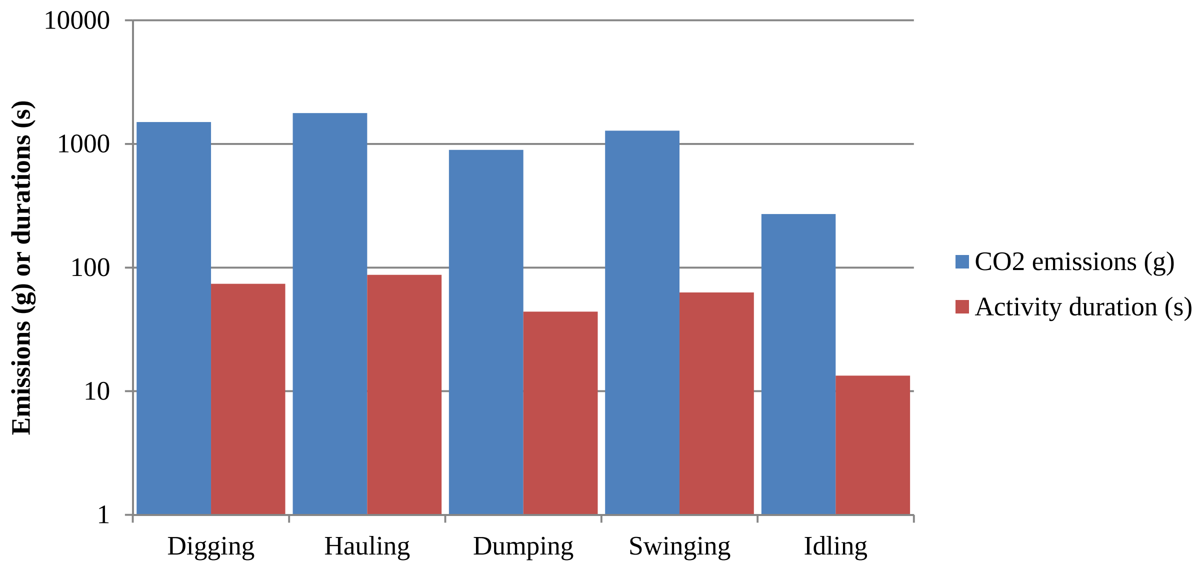

Figure 3-3. CO_2 emissions by activity and duration of each activity for an excavator working over 283 s

Table 3-2 shows ratios of estimated emissions using the action recognition approach to actual measured values for six videos. Actual measured values are sums over all activities of the activity-based emission rate times the duration of activity, assessed through manual action recognition. Estimated emissions using vision-based technology use activity durations determined by automated action recognition. Emissions estimated by vision-based technology were on average 98% of actual measured emissions. In all of these videos, which were not longer than 10 min, excavators were mostly active rather than idling and easily detectable for the entire video stream. The duration of each activity detected in a single video was independent of the pollutant, so differences in the ratio between different pollutants were due to differences in emission rates by activity. For example, CO_2 emission rates varied more by activity than did HC emission rates. These results are specific to excavators digging soil, swinging, and dumping it into trucks, and the outcome may differ for other types of equipment and activities.

Table 3-2. Ratio (%) of estimated emission to actual values for six different videos

Video	Model	Ratio of estimated emissions using vision-based technology to measured emissions (%)				Mean of ratio for each case study between different pollutants
		CO_2	CO	HC	NO_x	
1	Caterpillar-320CL	92	95	94	94	94
2	Caterpillar-320CL	91	100	79	91	90
3	Kobelco-SK330LC	98	111	95	97	100
4	Kobelco-SK330LC	100	100	100	100	100
5	Kobelco-SK330LC	97	102	98	98	99
6	Kobelco-SK330LC	103	118	104	103	107
Mean of ratio for each pollutant between case studies		97	104	95	97	98

As a complement to vision-based technology, earthmoving operations were modeled using DES in order to estimate and benchmark emissions during pre-construction planning. The modeling focused on earthmoving for nine cases studies involving five different types of excavator. Figure 3-4 shows conceptual design of the earthmoving simulation. The boxes represent activities and the arrows show the flow of resources, including excavated soil or haulers. Ovals represent the queues in which resources accumulate until the activity's starting condition is satisfied. For instance, excavators wait in the queue "Excavator idling" until the condition for starting the activity "Excavator loading" is satisfied. This condition is having at least one truck waiting in the queue "Trucks idling" and soil remaining that needs to be dumped by the truck. The simulation runs until the number of truck trips exceeds the number required to move the total volume of soil. In this simple case, the durations of various activities that the excavator performs determines the total amount of emissions, as well as the emissions per unit of soil moved. Emissions from the truck were not included in the results.

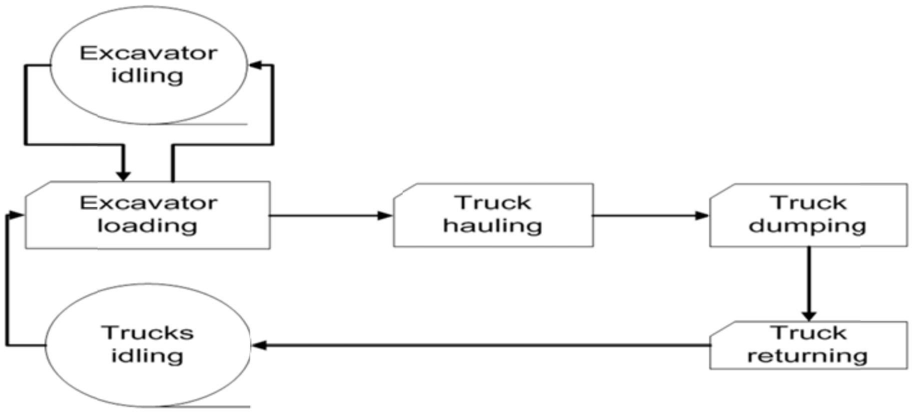

Figure 3-4. Conceptual design of earthmoving operation simulation

The model required assumptions about the duration of activities, duration of each cycle, and emission rates, and these were derived from observations and measurements of the excavators during actual use (Heidari and Marr 2014). The length of a cycle and duration of activities within a cycle, determined manually from videos of the excavators that were moving soil and dumping them into trucks, are summarized in Table 3-3. Each cycle comprises digging, swinging to the dump truck, dumping, and again swinging back to the dirt to be moved. The mean cycle duration varied between 18 and 26 s, and depended on the operator's skill, truck availability, type of soil excavated, and location of the truck relative to the excavator.

Table 3-3. Activity durations of different in-use excavators

Make and model	Duration (s)			
	Overall cycle	Digging	Swinging	Dumping
Caterpillar-320CL	25.8±2.5	6.7±1.1	7.2±1.4	4.5±0.7
Kobleco-SK330LC	18.6±2.9	6.1±2.7	5.2±0.8	2.1±0.5
Sany-SY215CLC	18.4±2.6	4.6±0.9	5.7±2.2	2.7±1.0
Komatsu-PC228	24.1±4.2	4.7±2.2	6.6±3.4	4.8±1.2
Volvo-EC250D	18.7±3.4	5.6±1.6	5.8±2.3	2.8±1.0

Results of measurements during actual operation of excavators have shown that emission factors, and consequently emission rates, for the various working (i.e., non-idling) modes are not significantly different from each other (Heidari and Marr 2014). Furthermore, there was no relationship between emission factors and soil density and type. Therefore, in the simulation model, emission rates for only idle and non-idle activities were used, where non-idling encompasses digging, swinging, moving, and dumping. Table 3-4 shows the emissions rates for CO_2, CO, HC, and NO_x that were used in the model.

Table 3-4. Non-idle and idle emission rates for excavators

Make and model	Tier	Gross power (hp)	Non-idle emission rate (g s^{-1})				Idle emission rate (g s^{-1})			
			CO_2	CO	HC	NO_x	CO_2	CO	HC	NO_x
Caterpillar-320CL	II	138	3.6	0.0031	0.0009	0.016	0.9	0.006	0.0006	0.002
Kobelco-SK330LC	II	238	2.3	0.0027	0.0010	0.011	0.5	0.005	0.0007	0.005
Sany-SY215CLC	III	155	2.8	0.0056	0.0008	0.012	0.6	0.004	0.0006	0.003
Komatsu-PC228	I	110	4.4	0.0057	0.0038	0.052	2.0	0.009	0.0033	0.028
Volvo-EC250D	IV	202	3.4	0.0012	0.0005	0.007	0.6	0.0002	0.0005	0.005

Simulation results were reported as the amount of emissions per unit productivity, where the productivity is quantified in terms of the volume of soil moved. Emissions from trucks were not included in this study. Table 3-5 shows the emissions, normalized by the amount of soil moved, predicted by DES and the ratio of monitored to predicted emissions. The monitored emissions were determined by manual recognition of activities and emission factors for idle or non-idle conditions. In practice, the ratios would represent how close actual emissions monitored by vision-based technology came to the benchmark (i.e., emissions predicted by DES). Differences would show the level of alignment between planned and actual operations.

Discrepancies in simulated vs. monitored emissions varied by case. The ratios were generally greater than 100% for all pollutants for the Caterpillar-320CL and less than 100% for all pollutants for the Sany-SY215CLC and Komatsu-PC228. Differences between excavators were mainly due to differences in emission rates, the configuration of earthmoving operations (number of pieces of equipment), and cycle duration. The latter two factors affect idling time and operational efficiency. For instance, the lower the ratio of excavators to trucks, the higher the idling time for excavators, and consequently there were higher emissions per volume of soil moved. Since ratios of idle to non-idle emission rates for different pollutants were not equal, the ratios reported in Table 3-5 differed by pollutant.

For case 1 listed in Table 3-5, the video lasted less than 5 min, and the excavator was active during the entire period, except for a few seconds. Therefore, reported emissions from different approaches agreed well. For case 2, operational efficiency was slightly higher (i.e., there was less idling). Thus, most of ratios associated with this case study converged to 100% even though it was the same type of excavator as in the first case study. In case 3, the excavator was idling while the model expected the equipment to operate, and therefore all ratios exceeded 100%. In case 4, the actual operational efficiency is higher than predicted by the computational simulation. Therefore, the ratio fell below 100%. For case 5 and 6, the simulation predicted the sequence to be over faster than actual operational time. As a result, monitored emissions exceeded simulated values. For case 7, 8, and 9, which lasted considerably longer than first six case studies, there were larger discrepancies between actual and planned operations. Thus ratios fell noticeably below 100%. For case 7, emissions per unit of soil moved were higher than for the cases 1 and 2 due to long idling times. Ratios for case 8 were significantly lower than for the other types of excavators mainly due to the fact that excavator was turned off while it was waiting for trucks to come to the site. However, emissions per unit of soil moved were much higher than for the other excavators due to higher emission rates. This excavator met less stringent tier I emissions standards. For case 9, CO emission rates dropped significantly during idling. This was possibly due to this excavator meeting more stringent emission standards (tier IV) and control technologies. However, this discrepancy was not observed for HC and NO_x. In real-world operations, excavators will perform different tasks while they are waiting, ranging from moving to turning off the engine completely. This variability will result in deviation of actual emissions from those expected through simulation.

Table 3-5. Excavator emissions predicted by DES compared to those monitored by vision-based technology

Case study number	Make and model	Amount of soil to move (m^3)	Number of trucks	Predicted emissions per volume of soil moved (g m^{-3})				Monitored emissions per volume of soil moved (g m^{-3})				Ratio of monitored to predicted emissions (%)			
				CO_2	CO	HC	NO_x	CO_2	CO	HC	NO_x	CO_2	CO	HC	NO_x
1	Caterpillar-320CL	13	1	100±3	0.087± 0.003	0.026± 0.001	0.47± 0.01	107	0.094	0.028	0.51	107	110	107	107
2	Caterpillar-320CL	26	2	91± 2	0.097± 0.002	0.025± 0.000	0.42± 0.01	94	0.095	0.030	0.44	104	98	122	105
3	Kobelco-SK330LC	9.8	1	36± 2	0.049± 0.002	0.017± 0.001	0.18± 0.01	39	0.051	0.019	0.20	107	97	114	111
4	Kobelco-SK330LC	9.8	1	32± 1	0.037± 0.001	0.014± 0.000	0.16± 0.01	29	0.035	0.013	0.15	94	93	93	94
5	Kobelco-SK330LC	10	1	28± 2	0.049± 0.002	0.014± 0.001	0.14± 0.04	39	0.046	0.017	0.20	140	81	115	136
6	Kobelco-SK330LC	18.2	2	52± 3	0.081± 0.003	0.025± 0.001	0.27± 0.01	65	0.078	0.029	0.33	122	87	112	118
7	Sany-SY215CLC	15	1	252±82	1.476± 0.565	0.211± 0.082	1.35± 0.46	221	1.322	0.153	1.10	88	69	72	82
8	Komatsu-PC228	76	2	1772±269	7.813± 1.325	2.74± 0.467	24.49± 3.82	815	1.503	0.947	10.3	46	28	35	42
9	Volvo EC 250	22	2	80±13	0.026± 0.004	0.039± 0.009	0.42± 0.10	115	0.004	0.032	0.44	144	18	81	105

Figure 3-5 to 3-9 show the time series of simulated vs. monitored emissions via automated action recognition for the case studies 1, 2, 3, 5, and 6 involving Caterpillar-320CL and Kobleco-SK330LC. Two different sets of emissions rates, measured emission rates (Heidari and Marr 2014) and those recommended by EPA (EPA 2004), were combined with the time series of activities. The purpose of this comparison was to demonstrate the sensitivity of the predictions to emission rates, for which large uncertainties and variability still exist (Abolhasani et al. 2008, Lewis et al. 2010). The simulated emission rates for cases 1 and 6 were constant because the excavators were working and not idling for nearly the entire simulation duration of these videos, and all non-idling activities had the same emission rate in the simulation. Since EPA does not recommend an emission rate for idling, the emission rates using EPA's data are all constant in time. Measured emission rates were approximately four times lower than those recommended by EPA.

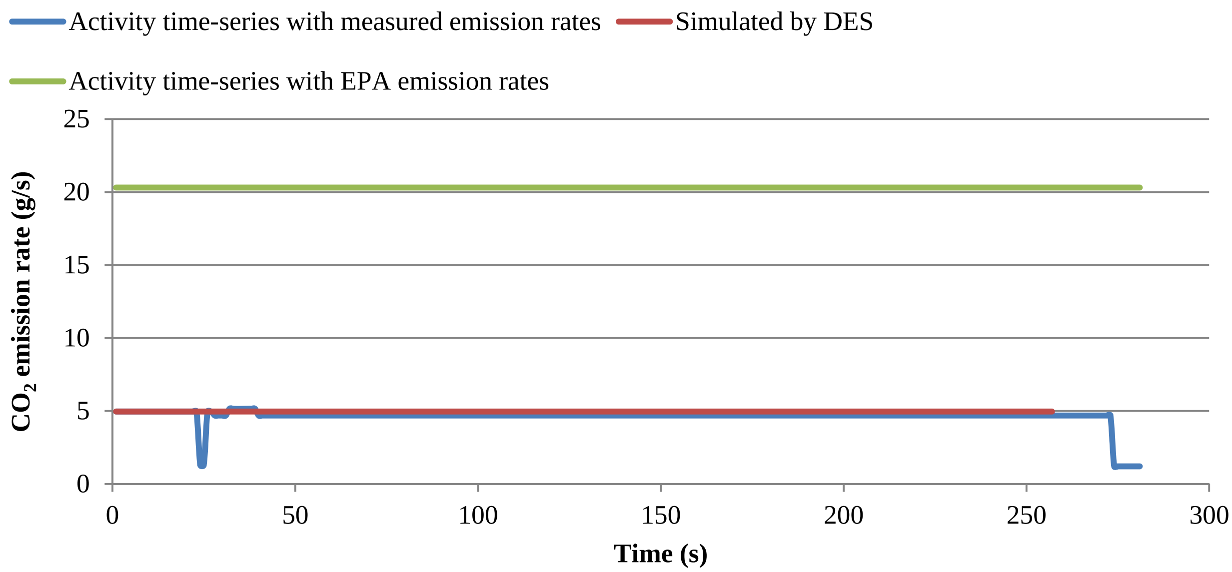

Figure 3-5. CO_2 emissions estimated for case 1 using different approaches

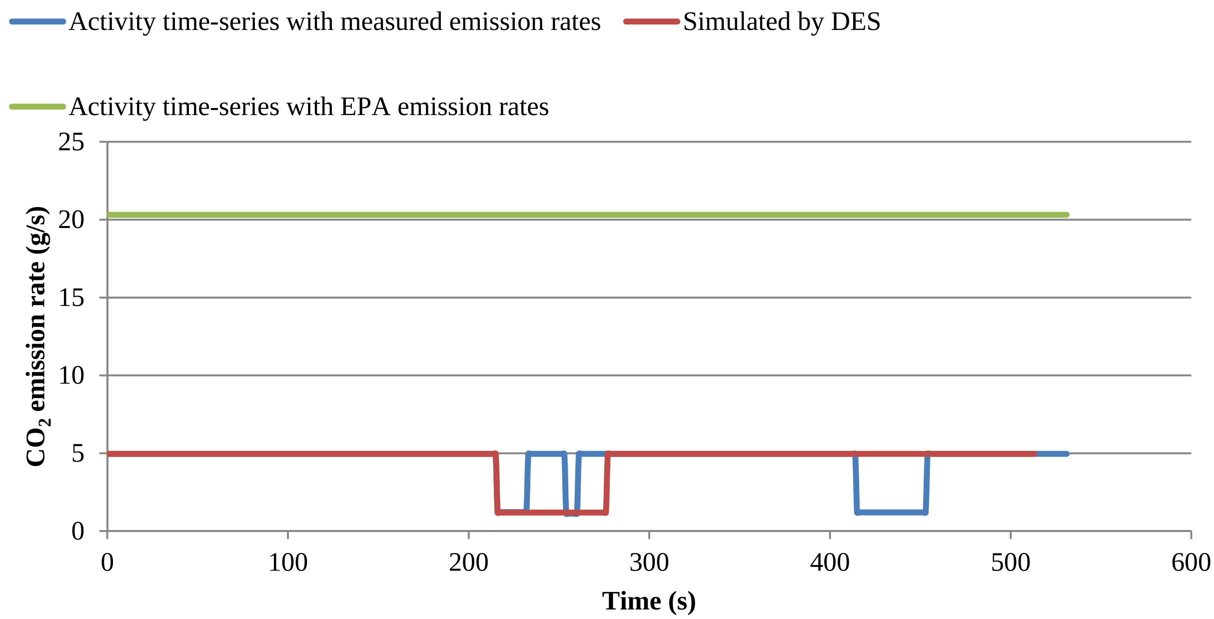

Figure 3-6. CO_2 emissions estimated for case 2 using different approaches

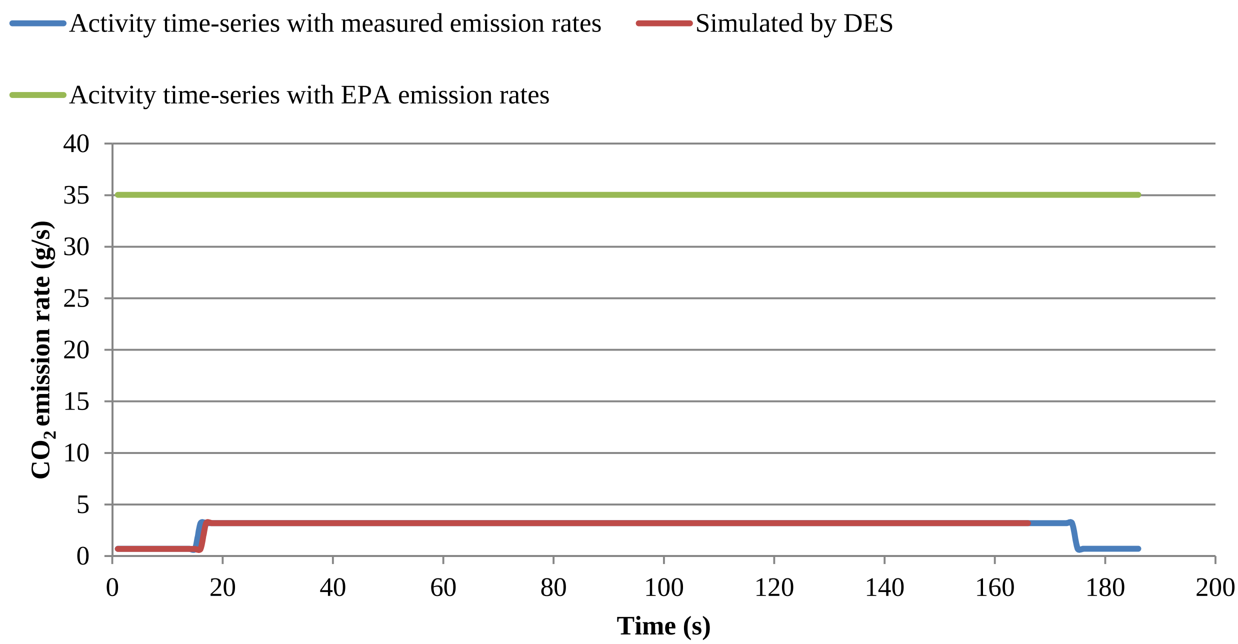

Figure 3-7. CO_2 emissions estimated for case 3 using different approaches

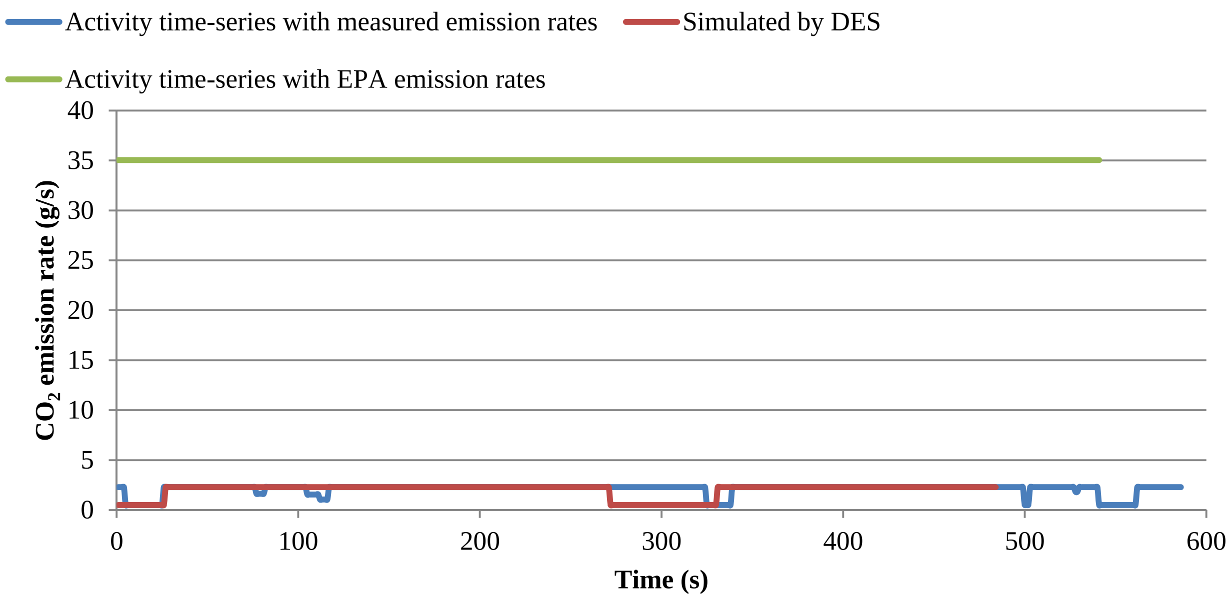

Figure 3-8. CO_2 emissions estimated for case 5 using different approaches

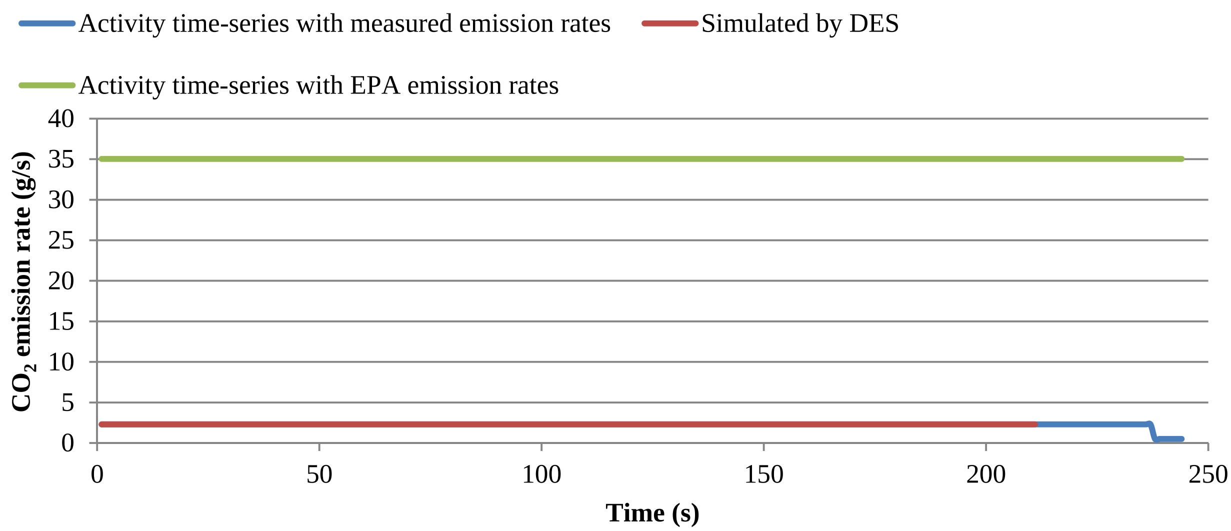

Figure 3-9. CO_2 emissions estimated for case 6 using different approaches

Figure 3-10 shows the cumulative emissions for the first case study. In application of the approach presented here, the simulated emissions would be prepared during the pre-construction planning phase, and the realized emissions would be monitored by vision-based technology. Comparison of the two could be used to determine compliance with sustainability goals. Estimated emissions using vision-based technology were higher than simulated ones for two reasons. First, the excavator was idling for 3 s, and emission rates were lower during idling than non-idling modes. Second, according to the simulation, after 258 s the soil was dumped into the truck and the excavator stopped while in actuality the activity lasted for 283 s.

This work examines a small set of case studies, and additional analysis of more videos with a higher number of activity classes will improve the accuracy of the technique. Discrepancies between actual and simulated emission have two main causes. First, actual operations are not as productive as expected by computational simulation. Second, actual operations are active, either productively or non-productively, while simulation results expect operations to be idle. Vision-based technology can be used to help identify the reason for missing the benchmark.

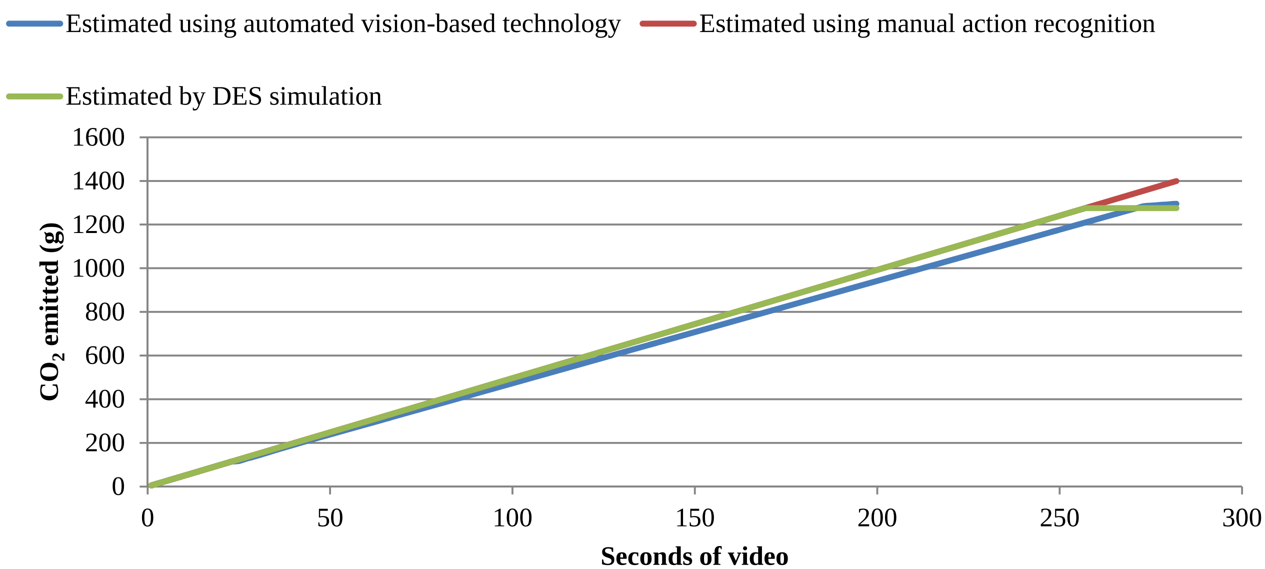

Figure 3-10. Cumulative CO_2 emissions for case 1

3.5 Conclusions

Concerns over environmental impacts from the construction industry have resulted in extensive research efforts to quantify, monitor, benchmark, and possibly control pollutant emissions. This research has introduced a framework employing automated visual action recognition using a network of cameras at a construction site. In this technique, real-time actions from construction activities and operations are recognized automatically from video streams by extracting spatio-temporal features from a sequence of video frames. Then, by integrating activity-based emission rates with the duration of activities, real-time emissions can be quantified. Furthermore, DES can be used to generate a benchmark for emissions, and then real-time emissions and productivity can be compared to expected values.

Emissions predicted using automated action recognition were on average 98% of those estimated by manual action recognition. On the other hand, total predicted construction emissions were very sensitive to emission rates used in the model. For instance, total CO_2 emissions estimated from earthmoving operation in a case study lasting 283 s were over four times higher with EPA's emission rates instead of on-site, measured emission rates.

Emissions and productivity were also predicted by DES. The ratio of actual emissions, which were measured on-site by PEMS for five different types of excavators, to those predicted by DES varied from 28% to 144% depending on the type of equipment, operational variables and emitted pollutant. Discrepancies may be due to the following factors: inconsistencies between actual and planned construction activities, errors in estimation of emission rates, recent control technologies applied to some pieces of construction equipment under which the equipment is turned off automatically after idling for a while, uniformity of construction simulations while actual construction operations are so dynamic and unpredictable in some cases, large fluctuations in real-time emission rates due to inter-engine or inter-equipment emissions control mechanisms (e.g., emission control technologies, fuel burning efficiency, and manifold absolute pressure within engine). If this discrepancy is due to inconsistency between actual and expected operations, whether the equipment was less productive or more active, vision-based technology can help identify the reason.

Therefore, this methodology appears to be promising for real-time monitoring and assessment of emissions. It also enables practitioners to assess the reason for the observed discrepancy between simulated and actual emissions. However, more research is needed in order to minimize the limitations of, as well as further develop, this real-time emission assessment technology.

3.6 Recommendations

The proposed technology, like all evolving technologies, is still in the completion process. Thus, there are still some technical limitations which must be overcome in future research efforts. The camera's power supply and location are should be considered in the pre-construction phase. An improved database of emission rates from construction equipment is needed in order to monitor and benchmark emissions more accurately. More detailed characterization of activities will probably result in more precise estimation of emissions. Defining different types of idling (low vs. high) is especially needed.

Combination of this technology with other techniques that can report engine MAP remotely and other sensing techniques in case equipment is not in the cameras' range of sight will be beneficial. For some activities, cameras are not able to detect activities due to their limited range of sight. In these cases, technologies such as an accelerometer, RFID, or Telematics will enable tracking of the equipment. However, detecting the specific activity in that case will become another challenge. Real-time measurement of engine data (speed, pressure, and temperature) will enable improved estimate of real-time emission rates.

One big benefit of using this technique is that it does not require technical training and is easy to use. Furthermore, it is cost effective. It can monitor and possibly help reduce unnecessary costs in an inexpensive manner. Therefore, by installing cameras and connecting them to the main server, operators can easily see the amount of emissions, compare them to the benchmarked values estimated in the pre-construction phase, and assess the reason for possible differences.

Furthermore, integration of emission database into fleet management tools, which can report real-time performance, can be of future practice and research.

3.7 Acknowledgments

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4 Conclusion

4.1 Summary

Due to the substantial contribution of the construction industry to emissions of GHGs and health-related pollutants, there has been an on-going need to quantify and predict emissions at scales ranging from a single piece of equipment scale to a nationwide scale. One research area is to quantify, monitor, benchmark, and possibly control pollutant emissions from a single piece of equipment in order to gear toward sustainable construction industry. This research has introduced a framework employing Portable Emission Measurement System, Automated Visual Action Recognition using a network of cameras at a construction site, and Discrete Event Simulation in order to benchmark emissions. In this framework, real-time emissions from construction equipment have been measured first. Then, activity-based emission rates are integrated into Automated Action Recognition and Discrete Event Simulation in order to monitor and benchmark real-time emissions. The general Framework is presented in Figure 4-1.

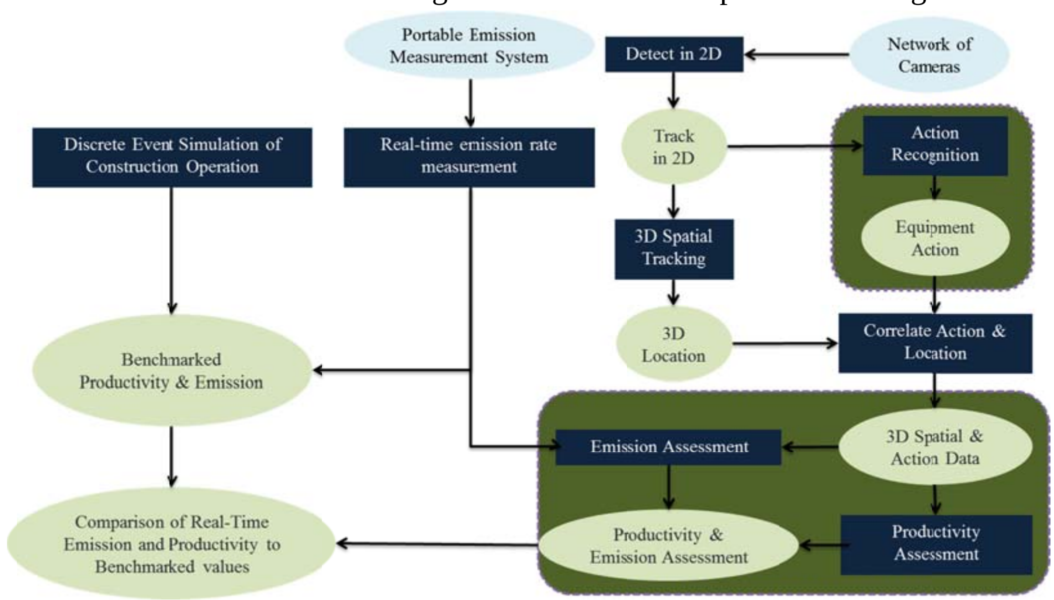

Figure 4-1. Overall framework for measuring, monitoring and benchmarking construction equipment emissions

Through actual emission measurement, the limited database of emission rates and emission factors for construction equipment were augmented, the ability of widely used models (NONROAD, OFFROAD, and MLR) to predict emissions were evaluated, and the effects of activity and engine characteristics on emission factors under actual operating conditions were investigated.

Real-time emissions from 18 different pieces of equipment were measured in this study. Associated emission rates and emission factors for different pieces of equipment were measured and compared to those of other widely used models. Real-time emission rates varied more than did emission factors, confirming similar previous findings. Measured emission rates in this study were lower, from 0.5% to 59% and from 0.5% to 58%, than those predicted by EPA and CARB, respectively, and ranged from 2% to 284% of values predicted by the MLR approach. Differences in the two approaches — actual on-site emission measurement and those recommended by regulatory approaches— suggest that using a single emission factor for different engines, even for the same activity within each engine duty cycle, will result in noticeable discrepancies, from 4% to 1500%. Thus, solely depending on equipment, engine horsepower and engine tier may not enable us to predict engine emission accurately. Other factors may contribute to emissions, of which some have been introduced as MAP. However, emission control technology and time spent in each duty cycle may contribute greatly to overall emission rate and factor. The database collected from emissions in this study might contribute to improving the accuracy of the models. There was a considerable difference between measured and modeled emission factors, particularly for engines meeting higher tier standards. Thus, emissions databases and estimation models should be updated to account for advances in emission control and manufacturing technologies.

Idling and hauling should be treated uniquely rather than lumped together under the umbrella of overall emission factors. On the other hand, idling emission rates may vary noticeably, resulting in a considerable difference between high-idle and low-idle emission factors. The same differences between activity–based emission rates can be claimed based on the assumptions made in this study. In the real-world conditions of this study, emission factors were not linearly proportional to engine horsepower and size.

As the next step, real-time measured emission rates were applied into the monitoring technique focused on in this study. In this technique, real-time actions from construction activities and operations were recognized automatically from video streams by extracting spatio-temporal features from a sequence of video frames. Then, by integrating activity-based emission rates with the duration of activities, real-time emissions were quantified. Furthermore, DES was used to generate a benchmark for emissions, and then real-time emissions and productivity can be compared to expected values.

Emissions predicted using automated action recognition were on average 98% of those estimated by manual action recognition. On the other hand, total predicted construction emissions were very sensitive to emission rates used in the model. For instance, total CO_2 emissions estimated from a earthmoving operation in a case study lasting 283 s were over four times higher using EPA’s emission rates instead of on-site measured emission rates.

Emissions and productivity were also predicted by DES. The ratio of monitored emissions, which were measured manually by detecting actual activities from videos for nine different types of excavators, to those predicted by DES varied from 28% to 144% depending on the type of equipment, operational variables and emitted pollutant. The following factors may potentially contribute to these differences: inconsistencies between actual and planned construction activities, errors in estimation of emission rates, recent emission control technologies applied to some pieces of construction equipment under which the equipment is turned off automatically after idling for a while, uniformity of construction simulations while actual construction operations are so dynamic and unpredictable in some cases, and large fluctuations in real-time emission rates due to inter-engine or inter-equipment emissions control mechanisms (e.g., emission control technologies, fuel burning efficiency, and manifold absolute pressure within engine). If this discrepancy is due to inconsistency between actual and expected operations, either excavator was less productive or more active, vision-based technology helps investigate the reason.

The vision-based methodology appears to be promising for real-time monitoring and assessment of emissions. However, more research is needed in order to minimize the limitations of, as well as further develop, this cost-effective real-time emission assessment technology.

4.2 Discussion, Recommendations and Future Work

The lack of real-time engine data was a limitation of this study, as we had to assume an engine speed in order to estimate emission rates from the measured exhaust gas concentrations. Development of a database on RPM, MAP, and temperature during equipment operation would be very useful. Doing so would require access to the ECU via an OBD port, which currently is not available on most construction equipment. Therefore, we encourage equipment manufacturers to install such ports.

The relationship between emissions and site and operational characteristics (e.g., type of soil hauled and traveled on, terrain grade, etc.) should be investigated further. This will help researchers to develop models to benchmark real-time construction emissions in the pre-construction phase and compare real-time performance to expected benchmarked values.

Although there have been recommendations on application of PEMS for construction emissions measurement, few studies have used this technique. Therefore there is a need for more work in this domain to measure real-time emission factors. Calibration and validation of steady-state emission-related studies with real-time emission-related studies will possibly lead to better understanding of actual off-road diesel engine emissions. Using this technique, it is impractical to measure real-time emissions from all of the equipment on-site. Therefore, new technologies which can measure emissions in an inexpensive and practical manner have to be proposed.

Future research should focus on emissions of particulate matter (PM) because of its strong link to health effects and impact on climate change.

The inventory of emission factors needs to be completed in order to monitor and benchmark emission more accurately. In order to complete and modify the current inventory, environmental agencies have to invest more to come up with a framework in which real-time emission factors can be estimated by specifying site and equipment characteristics.

Since engine data and MAPs for each model of equipment are not usually available, emission models should account for uncertainty and variability in emission factors by activity.

Finally, results of studies such as this one should be incorporated into the development and refinement of emission models, including the successor to NONROAD, MOVES.

Vision-based technology, like all evolving technologies, is still in the completion process. Thus, there are still some technical limitations which have to be overcome in future research efforts.
One big benefit of using this technique is that it does not require technical training and is easy to use. Therefore, by installing cameras and connecting them to the main server, operators can easily see the amount of emissions and compare it to the benchmarked values estimated in the pre-construction phase.

This technology is able to detect durations of specific pre-defined activities performed by construction equipment and consequently report the operational productivity and environmental emissions. It is capable of handling noisy features arisen from background, which are typical in construction sites. It can also handle blurry frames and camera movements to some extent.
As far as researchers who are involved in this project realized, there is still some work that needs to be done. Below are some areas which have to be worked on in future efforts.

Defining a higher number of activities will probably result in a more precise estimation of emissions. If activities are categorized further, estimations would become more realistic. Defining different types of idling activity (low vs. high) is especially needed.

This technology needs to be combined with other techniques that can report the pressure exerted on the engine remotely. This will help us distinguish between the activities that video processing is not able to discern. For some horizontal activities, cameras are not able to detect activities due to the limited range of sight they have. In these cases, tracking techniques, like accelerometers, RFIDs or Telematics will help in tracking the equipment. Thus, merging this technique with other sensing technologies will be beneficial in case of equipment going out of the cameras' range of sight. However, detecting their specific activity in that case will become another challenge.

Battery charging and replacement while cameras are set in construction sites has to be taken into account. Since supplying constant power for the cameras is a challenge, different ways to sustain battery energy become crucial. In addition, there should be communication between cameras and a main server by which cameras can inform mangers of the level of power they have used.

Placing the cameras, especially in complex construction sites, have to be considered in pre-construction phases. In addition, their locations have to be changed according to on-going progress in construction projects. Limited and non-blocked range of sight is a decisive factor for location planning. There is a possibility of a camera's range of sight being blocked while construction activities are under operation. This fact magnifies the importance of laborer training in order not to impede monitoring process.

If the networks of cameras are connected together and can simultaneously work with each other, possible errors will be minimized and possibility of videos being blocked will be decreased. This way energy consumption for cameras can be reduced as well. Therefore, the algorithm associated with this technology needs to be improved to the point in which if a piece of equipment goes off from a camera's sight, another camera can focus on the missed equipment and detect emissions from it.

Another interesting research area in this domain is to develop a neural network algorithm in which if the same piece of equipment appears in the sight of two different cameras, the interference will be realized. This way, one of the cameras will save energy by not detecting activities and emissions from the equipment.

The decisive factors for putting the technology into the market, cost and ease of use, have to be maneuvered on. Each camera will cost from $500-1000 initially and can monitor several pieces of equipment on a construction site. Depending on the scale of a project, the number of required cameras would vary. Assuming that 3 excavators are working simultaneously, 3 cameras are needed to monitor their activities. So it will cost $3000 to purchase the cameras at maximum. Assuming that 25% of idling activity can be shifted to non-idling using this technique, reduced cost associated with saved gasoline will be $9650 annually. On the other hand, it will increase productivity and possibly reduce the duration of a project.

Appendix I: Model for Earthmoving Operation of Sany Excavator

DISPLAY "Emissions from Exacavtor in earth Moving operation including excavator and trucks";

VARIABLE Numberofexcavators 1;

VARIABLE Numberoftrucks 1;

VARIABLE Volumeofsoiltomove 14.9;

VARIABLE Truckcapacity 7.5;

VARIABLE Excavatorcapacity 0.93;

VARIABLE ExcavatorCO2idleEmissionfactor 36.41;

VARIABLE ExcavatorCO2nonidleEmissionfactor 171;

VARIABLE ExcavatorCOidleEmissionfactor 0.25;

VARIABLE ExcavatorCOnonidleEmissionfactor 0.334;

VARIABLE ExcavatorHCidleEmissionfactor 0.0367;

VARIABLE ExcavatorHCnonidleEmissionfactor 0.0464;

VARIABLE ExcavatorNOxidleEmissionfactor 0.206;

VARIABLE ExcavatorNOxnonidleEmissionfactor 0.708;

VARIABLE Pessimisticloadtime 0.34;

VARIABLE Likelyloadtime 0.3;

VARIABLE Optimumloadtime 0.22;

VARIABLE Expectedhaultime 23.6;

VARIABLE Haultimevariability 1.05;

VARIABLE Dumptime 0.5;

VARIABLE Expectedreturntime 19.3;

VARIABLE Returntimevariability 1.05;

```
DISPLAY;
DISPLAY "Number of excavators          :"
Numberofexcavators;
DISPLAY "Number of trucks          :"
Numberoftrucks;
DISPLAY;
DISPLAY "Amount of soil to move      :"
Volumeofsoiltomove;
DISPLAY "Capacity of excavators         :"
Excavatorcapacity;
DISPLAY "Capacity of trucks         :"
Truckcapacity;
DISPLAY "Number of scoops per trucks :"
Truckcapacity/Excavatorcapacity;
DISPLAY;
DISPLAY;
DISPLAY "Duration of each scoop      : Normal["
Optimumloadtime ","
Likelyloadtime ","
Pessimisticloadtime "]min.";
DISPLAY "Duration of haul           : Normal["
Expectedhaultime  ","
Expectedhaultime*Haultimevariability
"] min.";
DISPLAY "Duration of dump           :"
```

```
Dumptime

"min.";

DISPLAY "Duration of return          :Normal["

Expectedreturntime ","

Expectedreturntime*Returntimevariability

"]min.";

DISPLAY;

GENTYPE Excavator;

GENTYPE Truck;

QUEUE Excavatorswait Excavator;

QUEUE Truckswait Truck;

COMBI Load;

NORMAL Haul;

NORMAL Dump;

NORMAL Return;

LINK LD1 Excavatorswait Load;

LINK LD2 Load Excavatorswait;

LINK HL1 Truckswait Load;

LINK HL2 Load Haul Truck;

LINK HL3 Haul Dump Truck;

LINK HL4 Dump Return Truck;

LINK HL5 Return Truckswait;

LINK HL6 Truckswait Load;

VARIABLE Scoopesrequiredperload Truckcapacity/Excavatorcapacity;

VARIABLE Truckloadsrequired Volumeofsoiltomove/Truckcapacity;
```

VARIABLE Truckloadsdumped Dump.TotInst-Dump.CurInst;

VARIABLE Dayssimulated SimTime/60/8;

VARIABLE Idletime Excavatorswait.AveWait;

VARIABLE Countexcavator Excavatorswait.TotCount;

VARIABLE TotalidleCO2emission Idletime*Countexcavator*ExcavatorCO2idleEmissionfactor;

VARIABLE TotalnonidleCO2emission ((SimTime*Numberofexcavators)-(Idletime*Countexcavator))*ExcavatorCO2nonidleEmissionfactor;

VARIABLE TotalCO2emission TotalidleCO2emission+TotalnonidleCO2emission;

VARIABLE UnitCO2emission TotalCO2emission/Volumeofsoiltomove;

VARIABLE TotalidleCOemission TotalidleCO2emission*ExcavatorCOidleEmissionfactor/ExcavatorCO2idleEmissionfactor;

VARIABLE TotalnonidleCOemission TotalnonidleCO2emission*ExcavatorCOnonidleEmissionfactor/ExcavatorCO2nonidleEmissionfactor;

VARIABLE TotalCOemission TotalidleCOemission+TotalnonidleCOemission;

VARIABLE UnitCOemission TotalCOemission/Volumeofsoiltomove;

VARIABLE TotalidleHCemission TotalidleCO2emission*ExcavatorHCidleEmissionfactor/ExcavatorCO2idleEmissionfactor;

VARIABLE TotalnonidleHCemission TotalnonidleCO2emission*ExcavatorHCnonidleEmissionfactor/ExcavatorCO2nonidleEmissionfactor;

VARIABLE TotalHCemission TotalidleHCemission+TotalnonidleHCemission;

VARIABLE UnitHCemission TotalHCemission/Volumeofsoiltomove;

VARIABLE TotalidleNOxemission TotalidleCO2emission*ExcavatorNOxidleEmissionfactor/ExcavatorCO2idleEmissionfactor;

VARIABLE TotalnonidleNOxemission TotalnonidleCO2emission*ExcavatorNOxnonidleEmissionfactor/ExcavatorCO2nonidleEmissionfactor;

```
;

VARIABLE TotalNOxemission TotalidleNOxemission+TotalnonidleNOxemission;

VARIABLE UnitNOxemission TotalNOxemission/Volumeofsoiltomove;

DURATION Load
'Scoopesrequiredperload*Pert[Optimumloadtime,Likelyloadtime,Pessimisticloadtime]';

DURATION Haul Expectedhaultime*Normal[1,Haultimevariability];

DURATION Return Expectedreturntime*Normal[1,Returntimevariability];

INIT Excavatorswait Numberofexcavators;

INIT Truckswait Numberoftrucks;

SIMULATEUNTIL 'Truckloadsdumped>=Truckloadsrequired';

DISPLAY

"**************************************************

    Emission Results from Simulation

";

DISPLAY "Idle Time  :"

Idletime

"minutes";

DISPLAY "Time required to move soil   :"

SimTime

"minutes";

DISPLAY "idle CO2 Emissions                 :"

TotalidleCO2emission

"g";

DISPLAY "non-idle CO2 Emissions                 :"

TotalnonidleCO2emission

"g";
```

```
DISPLAY "CO2 Emissions                :"
TotalCO2emission
"g";
DISPLAY "CO2 Emissions per unit of soil hauled     :"
UnitCO2emission
"g/m3";
DISPLAY "idle CO Emissions                :"
TotalidleCOemission
"g";
DISPLAY "non-idle CO Emissions                :"
TotalnonidleCOemission
"g";
DISPLAY "CO Emissions                :"
TotalCOemission
"g";
DISPLAY "CO Emissions per unit of soil hauled     :"
UnitCOemission
"g/m3";
DISPLAY "idle HC Emissions                :"
TotalidleHCemission
"g";
DISPLAY "non-idle HC Emissions                :"
TotalnonidleHCemission
"g";
DISPLAY "HC Emissions                :"
```

```
TotalHCemission
"g";
DISPLAY "HC Emissions per unit of soil hauled      :"
UnitHCemission
"g/m3";
DISPLAY "idle NOx Emissions                  :"
TotalidleNOxemission
"g";
DISPLAY "non-idle NOx Emissions                  :"
TotalnonidleNOxemission
"g";
DISPLAY "NOx Emissions                  :"
TotalNOxemission
"g";
DISPLAY "NOx Emissions per unit of soil hauled      :"
UnitNOxemission
"g/m3";
```