

DEVELOPMENT OF A PRODUCTIVITY-BASED  
ECONOMIC, ENERGY, ENVIRONMENTAL MODEL  
FOR HEAVY DUTY DIESEL CONSTRUCTION  
EQUIPMENT

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ABSTRACT:

The use of heavy duty diesel (HDD) equipment in infrastructure projects accounts for a large quantity of fuel consumption, pollutants emissions and the majority of the total cost of the project compared to others. Construction professionals need a tool that can be used to estimate not only the cost, but also the fuel use and emissions footprint of construction projects, particularly HDD equipment activities. The main purpose of this research is to develop an E3 tool to estimate the economic, energy, and environmental impact of bulldozers, scrapers, excavators, and dump trucks. The tool was developed by combining the multiple linear regression (MLR)-based productivity rate model of selected HDD equipment from RSMMeans Heavy Construction Data with the US EPA's NONROAD model. The results showed that the overall productivity prediction models accounted for high percentage of variability in its respective data source; 95% for bulldozer, 99% for scraper, 92% for excavator, and 94% for dump truck. While the cost models also accounted for high percentage of variability, which are 97% for bulldozer, 99% for scraper, 70% for excavator, and 88% for dump truck. Since the the productivity and cost models had high precision and accuracy with low bias, it can be used as the basis for estimating the total cost and fuel quantities that will be required and the total expected pollutant emissions for the project. The total fuel use and emissions estimates resulted from E3 model are also useful to observe its relationship with HDD equipment performance attributes, such as engine size and the attachments set up to the equipment (buckets or blades), and with various earthwork working conditions, such as type of soil, distance, depth, and cycle time. This tool can also be used to estimate emissions for various construction sectors. By using construction plans and specifications, the methodology and tool presented in this research can be used to estimate cost, fuel use, and emissions from commercial, residential, industrial, or heavy highway. Once all types of construction can be covered by this methodology, it is possible to develop new fuel use and emissions inventories for the construction industry in general.

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## **CHAPTER I**

### **INTRODUCTION**

#### **1.1 Background**

Air pollutant emissions, which have serious effects on both the environment and human health from the use of heavy duty diesel (HDD) construction equipment, have become a major concern at the national level (Hendrickson & Horvath, 2000). According to the Environmental Protection Agency (EPA, 2005a), it is estimated that this type of equipment will consume over six billion gallons of diesel fuel and produce approximately 643,000 tons of nitrogen oxides (NO<sub>x</sub>), 63,000 tons of hydrocarbons (HC), 339,000 tons of carbon monoxide (CO), 71,000,000 tons of carbon dioxide (CO<sub>2</sub>), and 60,000 tons of particulate matter (PM) (Rasdorf et al., 2010). Construction and mining equipment account for 45-48% of the overall totals of each pollutant emitted by the nonroad equipment. The pollution emissions from major U.S. construction sectors are shown in Table 1.1. According to EPA's 2001 National Emission Inventory, main pollutants from nonroad diesel engines (including construction, and agricultural equipment,

marine vessels, and locomotives) are NO<sub>x</sub> and PM. These pollutants and ozone adversely affect the environment in various ways including visibility impairment, crop damage, and acid rain. The construction sector is a significant contributor to these emissions, creating 32 percent of all mobile source NO<sub>x</sub> emissions and 37 percent of PM emissions (EPA, 2007).

Nonroad diesel engine is responsible for 16 percent of NO<sub>x</sub> emissions nationally (3,600 tons per year) and 29 percent of NO<sub>x</sub> emissions come from mobile sources. NO<sub>x</sub>, which contributes to the formation of ground-level ozone, can cause respiratory problems. Ozone can trigger asthma and other respiratory diseases, as well as inflame and damage the lining of the lungs, which may lead to permanent changes in lung tissue and to irreversible reductions in lung function if the inflammation occurs repeatedly over a long time period (EPA, 2007).

Nationally, PM emissions are dominated by fugitive dust sources (mostly from farming and unpaved roads. Non-road diesel engines are responsible for eight percent of fine particulate emissions (PM-2.5) nationally (222 tons per year) and half of PM-2.5 emissions from mobile sources. PM has been associated with an increased risk premature mortality, hospital admissions for heart and lung disease, and increased respiratory symptoms. Long-term exposure to diesel exhaust is likely to pose a lung cancer hazard (EPA, 2007).

Earthwork is one of the fundamental activities of construction projects. Most earthwork activities are completed by HDD construction equipment, which consumes mass quantities of energy (diesel fuel) and subsequently emits large quantities of air pollutants and greenhouse gases. Although recent engine technology has greatly

improved emission rates for new equipment, this technology has not specifically addressed fuel use and greenhouse gas emissions, and has focused primarily on National Ambient Air Quality Standards (NAAQS) criteria pollutants including NO<sub>x</sub>, PM, CO, and HC (EPA, 2011). Furthermore, most HDD equipment currently in use was manufactured prior to the new engine standards and can last for over 30 years; thus, it is necessary to accurately estimate production rates of HDD equipment for economic, energy, and environmental purposes.

Table 1.1. Pollution Emissions from Major U.S. Construction Sectors (Hendrickson & Horvath, 2000)

Pollutant	New highways, bridges, and other horizontal construction			New office, industrial, and commercial building construction		
	Per \$100,000,000	Per total sector output	Percentage of US total	Per \$100,000,000	Per total sector output	As percentage of US total
SO <sub>2</sub> (tons)	258	86,678	0.4	197	181,017	1
CO (tons)	419	141,767	0.2	367	337,225	0.4
NO <sub>x</sub> (tons)	373	125,313	-	281	260,000	-
VOC (tons)	67	22,509	0.1	59	54,000	0.3
PM (tons)	402	135,056	-	394	368,000	-
CO <sub>2</sub> (tons)	84,485	28,383,581	2	63,949	58,760,818	3
Pollutant	New residential one-unit structures construction			Other new construction		
	Per \$100,000,000	Per total sector output	As percentage of US total	Per \$100,000,000	Per total sector output	As percentage of US total
SO <sub>2</sub> (tons)	216	249,372	1	178	253,460	1
CO (tons)	413	476,809	0.6	363	516,887	0.7
NO <sub>x</sub> (tons)	325	375,213	-	305	434,299	-
VOC (tons)	76	87,742	0.4	50	71,197	0.4
PM (tons)	466	537,997	-	57,900	757,531	-
CO <sub>2</sub> (tons)	69,388	80,108,446	5	2,013	82,445,547	5

## 1.2 Problem Statement

Developing fuel use and emissions inventories based on production rate can help design and construction professionals forecast the economic, energy, and environmental impact of a project based on a quantity takeoff using a set of construction documents,

including plans and specifications. Estimating emissions from project unit costs can be used with a project cost breakdown to assess the overall financial and environmental impacts of the project. It will also be possible to assign a dollar value to construction emissions (Rasdorf, Lewis, & Frey, 2010). Construction estimators have long been able to estimate the costs associated with construction equipment and the earthwork activities that they perform. Moreover, most construction estimators seldom concern themselves with the environmental impact, specifically air pollutant emissions, of the equipment that they use. As new environmental regulations, such as cap-and-trade and carbon taxes, appear on the horizon in other industries, construction professionals can no longer afford to disregard the environmental aspects of their work. They need a tool that can be used with their existing expertise to quantify the total cost, fuel consumption, and emissions of earthwork activities. A model is needed to estimate the emissions footprint of earthwork construction projects in order to assess their overall environmental impact. Reliable emission factors based on commonly accepted construction estimating techniques are required for the methodology to be useful. Although there are existing models that estimate emissions inventories of construction equipment, these tools typically do not address construction costs because their focus is on environmental issues. Conversely, most construction cost estimating tools accurately address equipment production rates and unit costs, but not equipment emissions.

### **1.3 Objective**

The main goal of this research is to develop a sustainability quantification tool for construction infrastructure projects, with particular focus on earthwork activities. To

achieve this goal, the primary objective is to build a model for estimating fuel use and emission rates of air pollutants from HDD construction equipment and link them to the costs of performing these earthwork activities, thus addressing three pillars of sustainability – economy, energy, and environment. This model will utilize cost, fuel use, and emission factors based on units of production, such as dollars of equipment operating cost per cubic yard of earth moved, gallons of fuel consumed per cubic yard, and grams of pollutant emitted per cubic yard. The productivity-based cost, fuel use, and emission factors can be used with construction plans and specification to estimate the fuel use and emissions footprint for a construction activity or an overall project during the planning phase, or it may be used to monitor, track, and control cost, fuel use, and emissions during the construction phase.

As shown in Figure 1.1., to achieve the objective of this research, the following tasks will be completed:

### **1. Develop Economic, Energy, and Environmental Models**

In order to estimate the economic, energy, and environmental impact of earthwork activities, a model will be developed for each impact.

#### *a. Economic Model.*

The data from two reliable sources, RS Means Building Construction Cost Data 2010 and Caterpillar Performance Handbook 38<sup>th</sup> Editio, will be the basis for predicting productivity and cost. Productivity and cost rates will be predicted by using Multiple Linear Regression (MLR) analysis, resulting in productivity rates in terms of volume of soil per time (hour or day) and a cost rate in terms of dollars per volume of soil moved.

b. *Energy Model.*

The energy model will link with the brake specific fuel consumption (BSFC) rates from EPA's NONROAD model (EPA, 2010b) to estimate the total fuel consumed in terms of total gallons per volume soil moved.

c. *Environmental Model.*

The environmental model will link with the mass per time emission rates of NO<sub>x</sub>, HC, CO, PM, and CO<sub>2</sub> from EPA's NONROAD Model in order to estimate the total mass of pollutants emitted in terms of grams per volume of soil moved.

**2. Validate and Calibrate Models**

Each models will be validated and calibrated by using field testing procedures and data, including a portable emissions measurement system (PEMS).

**3. Develop the Economic-Energy-Environmental (E3) Decision Support Tool**

Using the economic, energy, and environmental model, a spreadsheet-based tool with a graphical user interface will be developed. The purpose of this tool is to integrate the economic, energy, and environmental models into a user-friendly estimating tool that can be used to predict, monitor, track, and control costs, fuel use, and emissions from HDD construction equipment performing earthwork activities. The outputs from this tool are productivity rate, total cost, total fuel use, and total pollutants emitted for a specified construction activity.

**4. Conduct Sensitivity Analyses for Earthwork Activities using the E3 Model**

In order to quantify the economic, energy, and environmental impact of earthwork activities, the E3 tool will be used to conduct sensitivity analyses under various conditions. The resulting costs, fuel use, and emissions for each condition will be compared.

#### **1.4. Scope of the Research**

This research focuses on analyzing the productivity and economic, energy, and environmental impacts of earthwork activities performed by HDD equipment. A group of heavy equipment can work together to perform earthwork activities and each item of equipment in the group plays a specific role in the series of activities required to perform the task efficiently and effectively. Type of equipment used in the activity will vary based on the volume of work, desired productivity, equipment availability, and specific work conditions. Table 1.2 lists common earthwork activities and the types of equipment typically included. The specific equipment and activities selected for the purpose of the research are:

1. *Bulldozer* performing heavy ripping, topsoil removal, rough cutting, rough filling, road base construction, temporary road construction, dam construction, hauling soil less than 500 ft, soil windrowing, soil spreading, trench backfilling, rock removal, and side sloping.
2. *Scraper* performing below grade excavation, topsoil removal, rough cutting and filling, hauling soil 500 ft to 2 miles, and soil spreading.
3. *Dump truck* performing soil hauling over 2 miles.



4. *Excavator* performing below grade excavation, grubbing, foundation excavation and backfilling, footing excavation, ditch maintenance, deep trench excavation and backfilling, and small and large pipe installation.

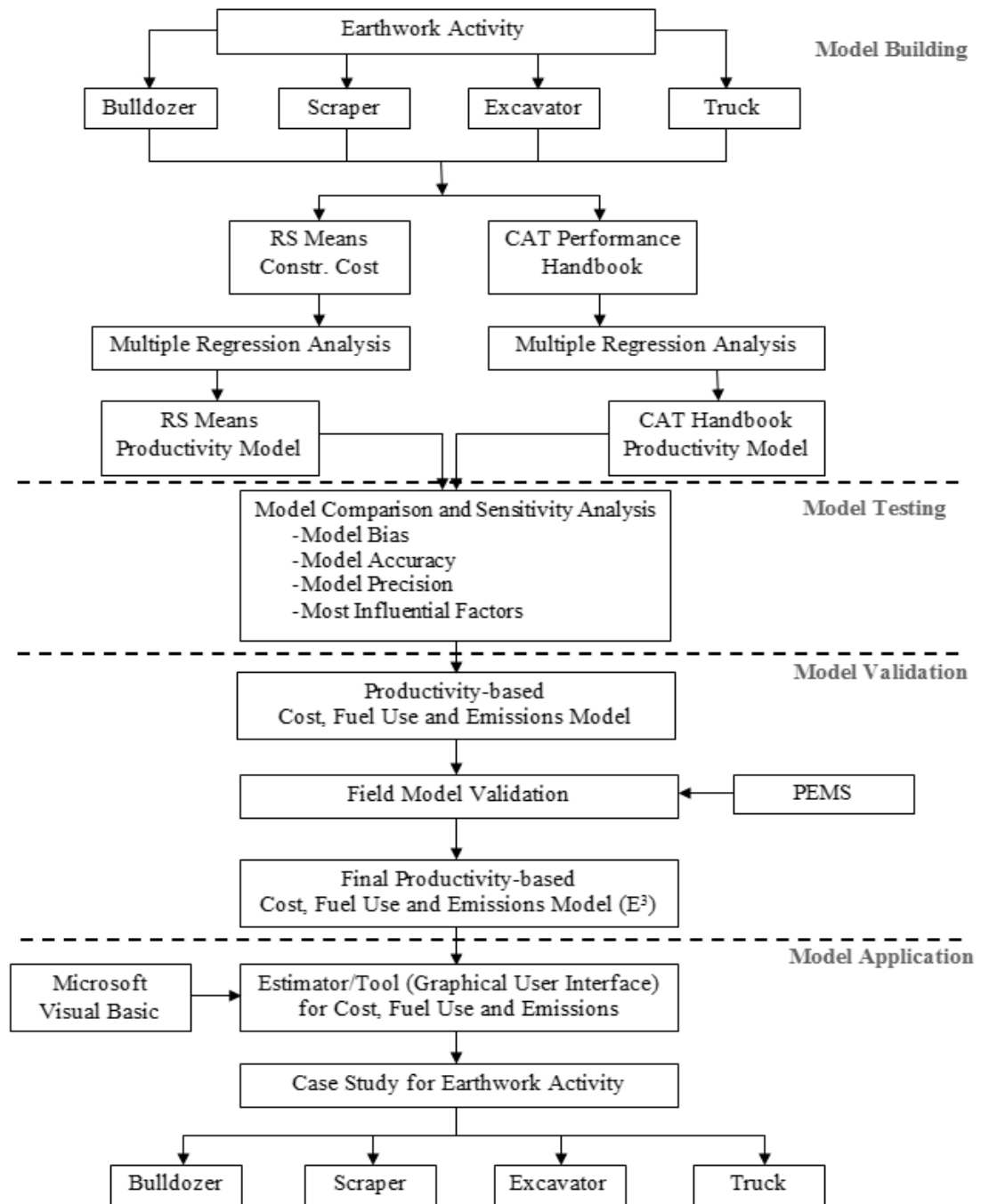


Figure 1.1. Flowchart of research tasks

Table 1.2. Common earthwork activities and types of equipment (Gransberg, et al., 2006)

Activity	Dozer	Loader	Grader	Scraper	Truck	Backhoe	Excavator	Shovel
Excavating above grade								X
Excavating below grade	X			X		X		
Grubbing	X						X	
Heavy ripping	X							
Light ripping			X					
Tree stump removal	X						X	
Topsoil removal	X		X	X				
Rough cutting	X			X			X	
Rough filling	X	X		X	X			
Finish grading			X					
Foundation excavation						X	X	
Foundation backfilling		X				X	X	
Footing excavation						X	X	
Road base construction	X	X	X		X			
Temporary road construction	X	X	X		X			
Haul road maintenance			X					
Culvert placement	X		X		X	X	X	
Dam construction	X		X		X			
Drainage ditch maintenance						X	X	
Haul less than 500 ft	X	X						
Haul 500 ft to 2 miles				X				
Haul over 2 miles					X			
Soil windrowing	X		X					
Soil spreading	X	X	X	X	X			
Soil removal		X			X			
Deep trench excavation							X	
Shallow trench excavation						X		
Trench backfilling	X	X				X	X	
Small utility pipe placement						X	X	
Large utility pipe placement							X	
Trench box placement						X	X	
Trash removal		X			X		X	
Rock removal	X	X			X		X	
Asphalt paving removal	X	X			X		X	
Concrete removal	X	X			X		X	
Assisting scraper	X			X				
Towing other equipment	X	X						
Concrete placement							X	
Side sloping	X							

## **CHAPTER II**

### **REVIEW OF LITERATURE**

#### **2.1 Methods in Estimating Emissions from HDD Construction Equipment**

Various methods have been employed to quantify emissions from HDD equipment. Real-world, in-use emission measurement is used to measure emissions from HDD equipment by using an on-board instrument. Other studies have tried to simulate or create models to estimate emissions. Government or agencies, like EPA or California Air Resource Board (CARB) have their own models to estimate emissions from HDD construction equipment. The section provides an overview of the major studies which have been conducted to measure emissions from HDD construction equipment.

##### **2.1.1 Real-World In-Use Emissions Measurement**

One alternative method for measuring emissions is to collect data in the field during actual operations. Real-World In-Use measurement is the methodology for

collecting real world air pollutant emissions from in-use diesel construction equipment. The methodology consists of second-by-second measurements of in-use equipment using a Portable Emissions Measurement System (PEMS) (Choi, 2009; Lewis, 2009; Rasdorf et al., 2010). The PEMS instrument, such as AXION RS (Global MRV, 2012) or SEMTECH (Sensor-Inc. 2011), collects both engine and emissions data on a second-by-second basis, so the relationship between engine performance and emissions may be determined. The PEMS uses non-dispersive infrared (NDIR) detection to measure CO<sub>2</sub>, CO, and HC, and uses electrochemical cells to measure NO and oxygen (O<sub>2</sub>). PM measurement is obtained by a light scattering laser photometer detection method. There are two ways that the PEMS collects engine data. First is through the use of an electronic control unit (ECU) to collect and report engine parameter. Second is through a sensor array that attaches to the equipment's engine to measure intake air temperature (IAT), manifold absolute pressure (MAP), and rotation per minute (rpm).

The results of emissions measurement from PEMS have been used to develop real-world emissions inventories of various types of diesel construction vehicles. Lewis et al. (2009) presented a new methodology for developing an emission inventory for construction vehicles on the basis of real world data from backhoes, front-end loaders, and motor graders. This study established three primary components of emission inventory: average emission rates, average annual fuel use, and estimated average annual emission. The emission inventory was used to compare vehicle types, fuel types, engine tiers, and to evaluate emission reduction strategies.

Meanwhile, Abolhasani et al. (2008) suggested the critical need to develop emissions inventories to understand the relationship between construction equipment

duty cycles with respect to energy use and emissions. This study laid its basis to a hypothesis that the variability in in-use duty cycle of construction equipment leads to variability in energy use and emissions that should be accounted for when developing an energy and emissions assessment framework. By using a PEMS for three excavators, this study demonstrated the episodic nature of the vehicle activity and emissions data and the influence of vehicle duty cycle on the average emissions rate. Since fuel use and emission rates typically have a strong linear association with MAP compared to other engine variables, such as IAT and RPM, the engine modal analysis is very useful to determine whether there are consistent trends in the relationship between fuel consumption or emission rates and engine activity. Engine modal analysis is the method of observing fuel use and emissions rates based on engine modes, which is represented by MAP. This study also found that the emission rates per gallon of fuel consumed were highest at idle for NO<sub>x</sub>, HC, and CO.

Frey et al. (2010) reported and assessed trends in nonroad construction equipment field data including engine size, model year, engine tier level, engine load, duty cycle, fuel use and emission rates (NO<sub>x</sub>, HC, CO, CO<sub>2</sub>, and PM). By using PEMS to measure the emissions, this study gave the basis for developing diesel emission inventories, evaluating diesel emission reduction programs, modeling diesel equipment fuel use, assessing air quality impact of alternative fuel, and estimating CO<sub>2</sub> emissions. For measuring emission rates, this study used representative duty cycles, which were divided into activity modes (idling, moving, working with attachment, such as blades or buckets) to evaluate relationships among equipment activity, engine performance data, and fuel use (Figure 2.1 and Figure 2.2).

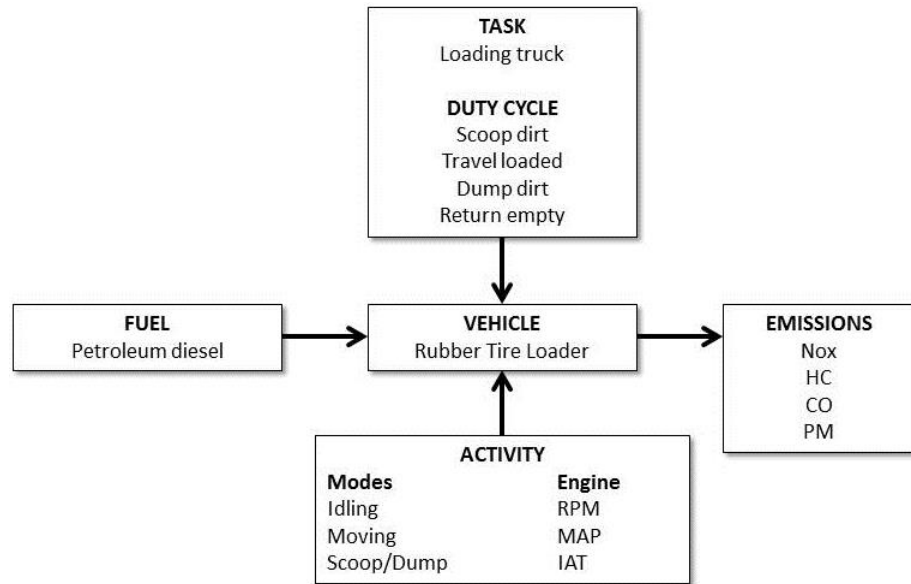


Figure 2.1. Real world-based emission inventory from construction vehicles (Lewis et al., 2009)

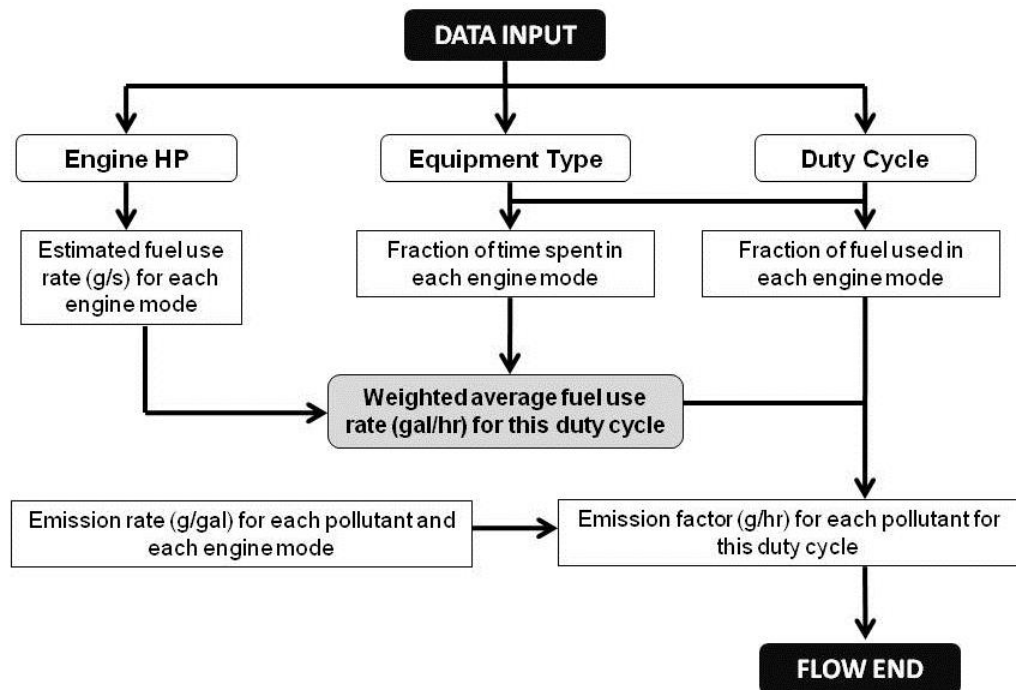


Figure 2.2. Equipment data to measure the emission rate (Lewis, 2009)

The PEMS results are also used for comparing different emissions characteristics from different types of fuel. Frey & Kim (2007) used PEMS to study the characteristics of real-world fuel use and in-use on-road emissions from dump trucks using B20 biodiesel and petroleum diesel. This study identified factors responsible for variability in emissions and fuel use, including the effects of different types of fuel. The emissions of HC, CO, NO<sub>x</sub>, PM, and CO<sub>2</sub> are measured by PEMS, which was attached to Tier 1 and Tier 2 single and tandem axle of dump trucks. The fuel use and emissions are measured during the following modes: idle, three level of acceleration, three levels of cruise, deceleration, and dumping. The results showed that the highest mass emission rates typically occur in the high acceleration mode.

Frey et al. (2008a) characterized the real world activity, fuel use, and emissions for selected motor graders fueled with petroleum diesel and B20 diesel. The study found that the idle mode is associated with the lowest mass per time fuel use and emissions in all cases. MAP is highly correlated with variability in fuel use and emission rates and thus is a practical basis for developing modal emission rates on a mass per time basis. Concerning the type of fuel, this study found that the emission rates for B20 biodiesel versus petroleum diesel were approximately the same for NO<sub>x</sub>, but decreased significantly for PM, HC, and CO. The overall comparison of emission estimates from different fuel use is shown in Figure 2.3.

Frey et al. (2008b) presented the PEMS-assisted benchmark comparison of average emission factors from selected construction equipment using B20 biodiesel and petroleum diesel. The equipment included backhoes, front-end loaders, and motor graders. By using PEMS for measuring HC, CO, CO<sub>2</sub>, NO<sub>x</sub>, and PM, this study analyzed

the effect of engine activity on fuel use and emissions and its correlation to the engine's manifold absolute pressure (MAP). It provided a time series plot to represent the variation of fuel use and emission rate in different real-world activities.

The PEMS results are also useful for comparing emissions rates with those from modeling tools such as NONROAD model. Lewis et al. (2009b) presented the comparison between real world emissions measurement using PEMS with the steady-state emissions estimates using EPA's NONROAD model. The equipment used in this study were backhoes, bulldozers, excavators, front-end loaders, generators, motor graders, off road trucks and skidsteers.

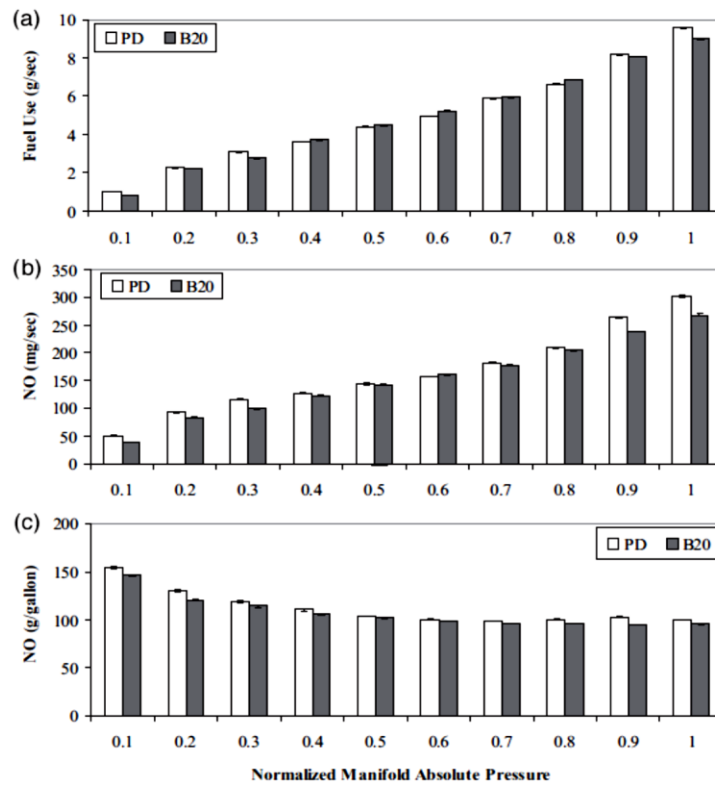


Figure 2.3. Comparison between petroleum diesel and B20 biodiesel from motor grader (Frey et al., 2008a)



The emission measurements from PEMS are based on actual in-use vehicle performing its duty cycles while the NONROAD model results are based on engine dynamometer results. PEMS uses actual engine load measurement whereas NONROAD uses various load factor adjustments to estimate emissions. The data obtained from PEMS can be used to characterize the episodic variation in fuel use attributable to specific activity, while outputs from NONROAD cannot. The available data on the NONROAD model provides only average emission rates, in contrast, real-world data from PEMS can be used to quantify real-world duty cycles and the influence of episodic events on fuel use and emission rates.

### **2.1.2 Modeling and Simulations**

An emission inventory can also be developed by using models or simulations. This method does not require a specific instrument to be attached to the construction equipment. Some studies used engine parameters, fuel characteristics, or the type of equipment activities to estimate the emissions rates.

Discrete-Event Simulation (DES) has been used as an approach to estimate emissions (Ahn, Pan, Lee, & Pena-Mora, 2010). DES can simulate a project or operation by running chronological occurred events. By calculating durations of work package, DES will estimate the emissions (Pan, 2011). Li & Lei (2010) studied the use of Discrete-Event Simulation (DES) in estimating and analyzing CO<sub>2</sub> emission during earthwork construction. The model can be used in the project pre-planning phase for assessment of pollutant emissions. One of the significant advantages of DES compared with other

existing methods is that the model is capable of estimating emissions from individual project-specific construction at a micro level.

Ammouri et al. (2011) proposed a model capable of estimating the total carbon footprint of a construction project taking into consideration the size, landscape, and material of construction. The proposed model, which is called as Carbon Footprint Calculator for Construction Project (CFCCP), utilized the detailed project bill of material quantities and schedule to produce a precise calculation of the total footprint. The data for the model building are collected from the construction material supplier, and coded to classify the general project information such as site work, concrete work, metal work, wood work, windows and doors, finishes, mechanical work, and electrical work. The expected outputs from this model are total carbon footprint that includes carbon embodied in raw material, transportation carbon footprint, and workforce carbon footprint.

Rasdorf et al. (2010) proposed an approach to estimate emission footprint of construction equipment. The estimate was based on the type of activity and takes the production rate into account. The estimate, which was called productivity emission rates and cost emission rates, was the total mass of pollutants emitted from construction activity (and ultimately the entire project) based on the quantity takeoff and cost estimate of construction plans and specifications. To estimate the productivity and cost emission rates, the following are required: construction activity, type of equipment to complete the activity, production rate of the equipment, the unit cost of the activity, and air pollutant emission rates of the equipment. The production and unit cost were obtained from RS Means Heavy Construction Data, which has been widely accepted and used. The

emission rates of each equipment type for HC, CO, NO<sub>x</sub>, PM, CO<sub>2</sub> and SO<sub>2</sub> were obtained by using EPA's NONROAD model. Studying topsoil stripping activities performed by 200 and 300 hp of bulldozers, this research expressed the production emission rate in term of grams pollutant emitted per cubic yard soil, while the cost emission rate in term of grams pollutant emitted per dollar amount spent. This approach can help design and construction professionals forecast the emission footprint of a project based on a quantity takeoff using a set of construction documents, including plans and specification.

Some studies approached emissions estimating by using Artificial Neural Networks (ANN). The ANN methodology is a modeling technique that produces mathematical expressions using a set of input-output data (Karonis et al., 2003). Artificial neurons are the elements that constitute the input, output, and hidden layers of the ANN models. Thompson et al. (2000) used ANN modeling to predict the relationship between the output torque and exhaust emissions from heavy duty diesel engines with limited use of dynamometer testing. The results showed that ANN was able to predict the instantaneous emissions of HC, CO, CO<sub>2</sub>, NO<sub>x</sub>, and PM and opacity for a heavy duty diesel engine. In concern with fuel properties, Karonis, et al. (2003) used ANN to model the exhaust emissions from a single-cylinder diesel engine with some of the most important properties of fuels. Using 29 fuels for training and 30 fuels for validating, the predictions of CO, HC, NO<sub>x</sub>, and PM emissions were very good. The fuel parameters affecting most significantly the emissions from diesel engines are density and backend volatility. Nagendra & Khare (2004, 2006) described a methodology consisting of step-by-step procedures involved in the development of ANN-based vehicular exhaust

emissions (VEE) model for urban roadways. The model was used to predict CO and NO<sub>x</sub> emissions for the purpose of air quality prediction at a traffic intersection and arterial road.

Some studies tried to estimate the emissions by using fuel-based method, where emission factors are normalized to fuel consumption and vehicle activity is measured by the amount of diesel fuel consumed. Dreher & Harley (1998) applied the fuel-based method for estimating heavy duty truck exhaust emissions of fine black carbon (BC) particles and NO<sub>x</sub>. The results showed that the heavy duty diesel truck emits 110,000 kg/day of NO<sub>x</sub> and 3,700 kg/day of fine BC during weekdays, and the emissions decline by 70-80% on weekends. Kean et al. (2000) described a fuel-based method for determining NO<sub>x</sub> and PM emissions from off-road diesel engines. The emission inventory from this model was obtained by multiplying the diesel fuel consumed by off-road engines by emission factors that normalized by fuel consumption (i.e. mass of pollutant emitted per unit of fuel consumed).

### **2.1.3 EPA NONROAD Model**

The emissions from construction activities, particularly from HDD equipment, can also be estimated by using some models developed by government agencies. The U.S. EPA has developed and published the EPA's NONROAD Model for estimating emissions from nonroad vehicles. Meanwhile, state governments including California, through the California Air Resource Board (CARB), also developed models such as OFFROAD and EMFAC2007 Model to estimate the emissions from construction projects and its heavy duty equipment in particular (CARB, 2007a & 2007b ). Some local

authorities, such as the city of Sacramento, California has also been developed a model to address emissions from construction.

The NONROAD model estimates air pollution from various types of diesel compression ignition (CI) and gasoline spark ignition (SI) nonroad sources. By using information such as equipment populations, equipment use, and emission factors, the NONROAD model estimates emissions of HC, CO, NO<sub>x</sub>, SO<sub>2</sub>, PM, and CO<sub>2</sub> (EPA, 2010b). The estimates rely on emission factors – estimates of the amount of pollution emitted by a particular type of equipment during a unit of use. Typically, emission factors for nonroad sources are expressed in terms of grams per horsepower-hour (gr/hp-hr), but they also may be reported in grams per mile, grams per hour, and grams per gallon. The CI emission factors in the NONROAD model are expressed in gr/hp-hr and are based on emissions test data where available, adjusted when necessary to account for in-use operation that differs from the typical test conditions. The process of obtaining the emission factors from off-road diesel equipment is shown in Figure 2.4.

For HC, CO, and NO<sub>x</sub>, the emission factor for a given diesel equipment type in a given year or age is calculated as follows:

$$EF_{adj}(HC, CO, NO_x) = EF_{ss} \times TAF \times DF \quad (2-1)$$

where:

EF<sub>adj</sub> = final emission factors used in model, after adjustments to account for transient operation and deterioration (gr/hp-hr)

EF<sub>ss</sub> = zero-hour, steady-state emission factors (gr/hp-hr)

TAF = transient adjustment factor (unitless)

DF = deterioration factor (unitless)

The zero-hour, steady-state emission factors (EFss) are mainly a function of model year and horsepower category, which defines the technology type. The transient adjustment factors (TAF) vary by equipment type. The deterioration factor (DF) is a function of the technology type and age of the engine.

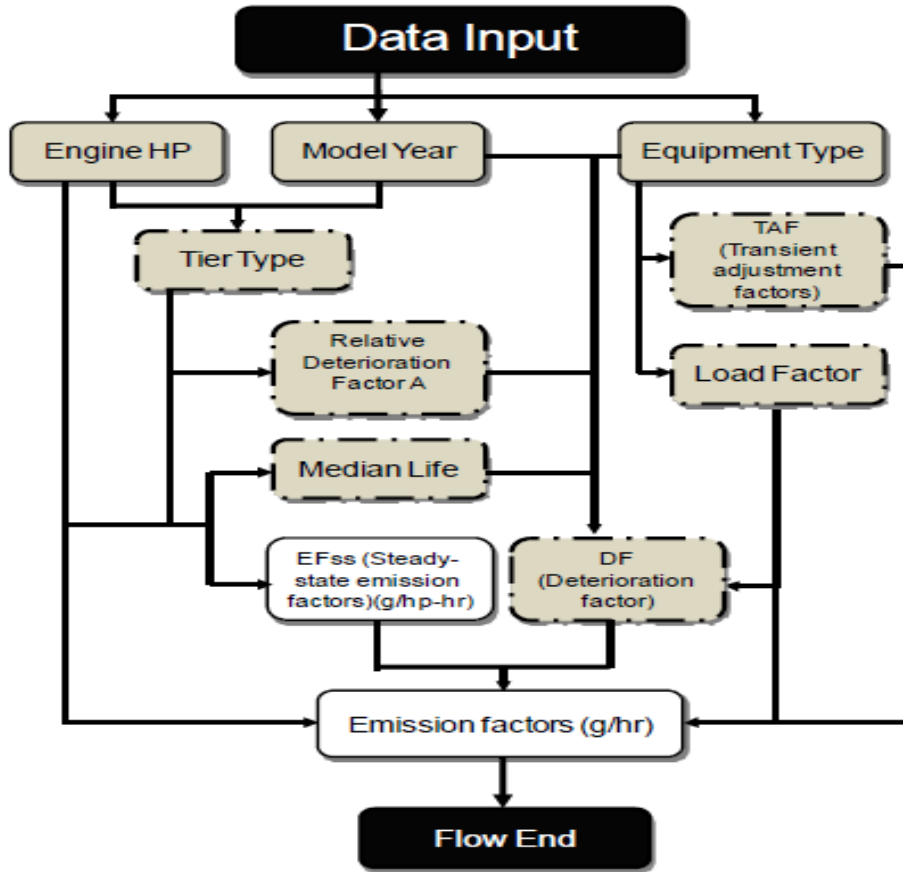


Figure 2.4. The NONROAD process of obtaining emission factors (Lewis, 2009; Pan, 2011)

Since PM emissions are dependent on the sulfur content of the fuel, the equation is as follows:

$$EF_{adj}(PM) = (EF_{ss} \times TAF \times DF) - SPM_{adj} \quad (2-2)$$

where:

- EFadj = final emission factors used in model, after adjustments to account for transient operation and deterioration (gr/hp-hr)
- EFss = zero-hour, steady-state emission factors (gr/hp-hr)
- TAF = transient adjustment factor (unitless)
- DF = deterioration factor (unitless)
- SPMadj = adjustment to PM emission factor to account for variations in fuel sulfur content (gr/hp-hr)

Emission factors for CO<sub>2</sub> and SO<sub>2</sub> are calculated based on brake-specific fuel consumption; therefore, the equation is as follows:

$$EF_{adj}(BSFC) = EF_{ss} \times TAF \quad (2-3)$$

To develop an emission inventory using EPA's NONROAD model, the construction equipment have to be categorized in the engine's tier level. The tier level is the emission standard that corresponds to the equipment model years and technology types (represented by engine horsepower) (EPA, 2005a). EPA has regulated emissions from non-road engines used in most construction and port cargo handling equipment since 1999. As shown in Table 2.1, these regulations continue to be phased in under a four-tier system, with emission standards based on engine horsepower (hp) and equipment model year.

Tier 1, 2, and 3 standards are largely being met by enhanced engine design and manufacturing improvements; they require little or no exhaust after-treatment, and do not address fuels. The Tier 4 standards require dramatic reduction in NO<sub>x</sub> and PM emissions. The off-road NO<sub>x</sub> and PM standards under Tier 4 are approximately 10 times lower than the Tier 3 standards for most engines. They will be phased in between 2008 and 2015. To comply with this rule, engine manufacturers will need to produce engines with advanced emissions control technologies similar to those that will be used for on-road trucks (Berg,

2010). This ruling also requires fuel producers to reduce the sulfur content of diesel fuel used in non-road engines. Reducing the level of sulfur in diesel fuel is necessary to prevent damage to emission control systems. The summary of all methods used to estimate and measure emissions from off-road vehicles are shown in Table 2.2, 2.3, and 2.4.

Table 2.1. General Guide to EPA Tier Level for Off-Road Diesel Engines (EPA, 2010a)

<b>Engine Power</b>	<b>Tier</b>	<b>Years</b>	<b>Engine Power</b>	<b>Tier</b>	<b>Years</b>
<b>HP &lt; 11</b>	1	2000-2004	<b>100 ≤ HP &lt; 175</b>	1	1997-2002
	2	2005-2007		2	2003-2006
	4	2008+		3	2007-2011
				4	2012+
<b>11 ≤ HP &lt; 25</b>	1	2000-2004	<b>175 ≤ HP &lt; 300</b>	1	1996-2002
	2	2005-2007		2	2003-2005
	4	2008+		3	2006-2010
				4	2011+
<b>25 ≤ HP &lt; 50</b>	1	1999-2003	<b>300 ≤ HP &lt; 600</b>	1	1996-2000
	2	2004-2007		2	2001-2005
	4	2008+		3	2006-2010
				4	2011+
<b>50 ≤ HP &lt; 75</b>	1	1998-2003	<b>600 ≤ HP &lt; 750</b>	1	1996-2001
	2	2004-2007		2	2002-2005
	3	2008+		3	2006-2010
				4	2011+
<b>75 ≤ HP &lt; 100</b>	1	1998-2003	<b>HP ≥ 750</b>	1	2000-2005
	2	2004-2007		2	2006-2010
	3	2008		4	2011+
	4	2008+			



Table 2.2. Summary of methods of measuring emissions from off-road vehicles

Research/Institution	Year	Methods		
		Simulation / Model	Laboratory Test (Dynamometer)	In-Use Operation (Real-World)
Rasdorf, Lewis, Frey	2010			√
Li and Lei	2010	√		
Frey, Rasdorf, Kim, Pang, Lewis	2008			√
Frey, Kim	2006			√
Lewis, rasdorf, Frey, Pang, Kim	2009			√
Frey, Rasdorf, Lewis	2009			√
Abolhasani, Frey, Kim, Rasdorf, Lewis, Pang	2008			√
Frey, Kim, Pang, Rasdorf, Lewis	2008			√
Lindgren, Larsson, Hansson	2010		√	
Rasdorf, Frey, Lewis, Kim, Pang, Abolhasani	2010			√
Ammouri, Srouf, Hamade	2011	√		
Ahn, Pan, et al.	2010	√		
Pan	2011	√		
Karonis, Lois, et al.	2003	√		
Thompson and Atkinson	2000		√	
Nagendra and Khare	2006	√		
Dreher and Harley	1998	√		
Kean, Sawyer, et al.	2000	√		
The U.S. Environmental Protection Agency (EPA)	2003		√	

Table 2.3. Summary of type of pollutants measured from off-road vehicles

Research/Institution	Year	Type of Pollutants					
		HC	CO	NOx	PM	CO2	SO2
Rasdorf, Lewis, Frey	2010			√	√		
Li and Lei	2010					√	
Frey, Rasdorf, Kim, Pang, Lewis	2008	√	√	√	√	√	√
Frey, Kim	2006	√	√	√	√	√	√
Lewis, rasdorf, Frey, Pang, Kim	2009	√	√	√	√	√	√
Frey, Rasdorf, Lewis	2009	√	√	√	√	√	√
Abolhasani, Frey, Kim, Rasdorf, Lewis, Pang	2008	√	√		√		
Frey, Kim, Pang, Rasdorf, Lewis	2008	√	√	√	√	√	√
Lindgren, Larsson, Hansson	2010	√	√	√	√	√	√
Rasdorf, Frey, Lewis, Kim, Pang, Abolhasani	2010	√	√	√	√	√	√
Ammouri, Srouf, Hamade	2011					√	
The U.S. Environmental Protection Agency (EPA)	2003	√	√	√	√	√	√

Table 2.4. Summary of types of vehicle as source of off-road emissions

Research/Institution	Year	Type of Vehicle/Equipment							
		Backhoe	Excavator	Bulldozer	Motor grader	Offroad Truck	Loader	Skidsteer	Generator
Rasdorf, Lewis, Frey	2010			√					
Li and Lei	2010		√	√		√	√		
Frey, Rasdorf, Kim, Pang, Lewis	2008	√			√		√		
Frey, Kim	2006					√			
Lewis, rasdorf, Frey, Pang, Kim	2009	√	√	√	√	√	√	√	√
Frey, Rasdorf, Lewis	2009	√	√	√	√	√	√	√	√
Abolhasani, Frey, Kim, Rasdorf, Lewis, Pang	2008		√						
Frey, Kim, Pang, Rasdorf, Lewis	2008				√				
Lindgren, Larsson, Hansson	2010			√					
Rasdorf, Frey, Lewis, Kim, Pang, Abolhasani	2010	√	√	√	√	√	√	√	√
The U.S. Environmental Protection Agency (EPA)	2003	√	√	√	√	√	√	√	√

## 2.2 Estimating Productivity in Earthwork Construction Activities

Productivity in earthwork construction activities, particularly for the equipment which performs it, has been studied and approached by various methods and techniques. Some researchers have tried to estimate the productivity of construction equipment performing earthwork projects. Some mathematical or statistical models both deterministic and probabilistic have been developed to explain factors influencing productivity. Productivity estimation is also provided by professional references such as RSMMeans Construction Data to comply with the standard classification system from Construction Specification Institute (CSI). This data is widely accepted by most construction professionals since it provides technical data required to prepare quantity takeoffs and complete construction estimates for major construction projects. Some construction equipment manufacturers such as CAT, John Deere, or Komatsu also

provide and recommend off-the-job productivity predictions in their performance handbooks.

### **2.2.1 Methods and Models for Estimating Productivity in Earthwork Construction Activities**

Productivity is defined as the rate of product output per unit time for a given production system (Parsakho et al., 2008). Productivity in earthwork activities have been conducted by several studies. The use of deterministic multiple regression (MR) analysis is well established in construction management research, particularly in predicting construction productivity (Akinsola, 1997; Akintoye & Skitmore, 1994; Edwards, Holt, & Harris, 2000; Smith, 1999). Smith (1999) outlined the development of a deterministic model that can be used to estimate earthmoving productivity. This study examined the excavator/dump truck earthmoving system that consists of a truck loading cycle, haulage of trucks to the planned fill or disposal point, dumping of the material and a return haul to queue and commence the cycle again. The model was based on data obtained from four United Kingdom (U.K.) highway construction projects and was developed using stepwise multiple regression techniques. The regression model provided an equation that describes over 90% of the variance in a large set of data. The significant factors of this model are: number of trucks, bucket per load and volume, truck travel time, and haul length. David & Gary (1993) used deterministic multiple regression to propose ESTIVATE, a model for calculating excavator productivity and output cost. The model was developed for calculating the cycle time of hydraulic excavators operating within the construction project. With machine cycle time, swing angle, machine weight, and digging depth as

predictor variables for cycle time, the resulted model can explain 88% variability of the excavator's cycle time. Parsakho, et al., (2008) studied the effects of soil moisture, soil porosity, soil bulk density, stump diameter in grubbing operations and terrain side slopes on hourly productivity of hydraulic excavator. By using multiple regression analysis, it was shown that grubbing time depends on the number of stumps, tree species, stump diameter, soil moisture, soil compaction, rooting system, rooting depth, and grubbing machine power. There were no significant effects from the slope classes treatment on productivity.

ANN was also used to predict heavy construction equipment productivity. Schabowicz & Hola (2007) applied the artificial neural network (ANN) to design sets of earthmoving machinery and used the results to predict productivity of collaborating earthmoving machines, which consisted of excavators and haulers. With low network training and testing RMSE values and high values of correlation coefficient R for testing, this study concluded that by having a set of such data as hauler capacity, excavator bucket capacity, hauling distance, road class, number of excavators and number of haulers in the earthwork operating system, productivity rate of can be predicted. Hola & Schabowicz (2010) presented a methodology for selecting an optimum set of collaborating earthmoving machines (excavators and haulers). The selection criterion is the minimum time needed to carry out the earthworks of the minimum cost of carrying them out. The main parameter having the bearing on the time and cost by the excavators and haulers is the productivity of the set of machines, measured by the number of cubic meters of soil loosened and transported to the place of unloading in a unit time. This study employed the ANNs to predict the productivity of such machines. The results

showed that the selected feed-forward multilayer error back propagation neural network with a conjugate gradient algorithm (BPNN-CGB), having five neurons in the input layer, eight neurons in the hidden layer, and one neuron in the output layer, is useful for predicting productivity of machinery sets made up of excavators and haulers.

In predicting the productivity rate in earthwork construction activities, some studies tried to compare the model built by using regression analysis with the model resulted from the ANN. Han et al. (2011) suggested new methods for productivity prediction with the use of construction simulation as a tool for data generation, and a multiple regression (MR) analysis and an ANN as tools for prediction. The results showed that a predictive model using ANN was better fitted to the actual data than using MR. However, the ANN model requires a specific skill for running the MATLAB program, while MR model was relatively easier since the user can obtain predictive results by merely inputting the information for each factor or explanatory variable. The predictive models from this study can help planners to carry out reliable productivity prediction while facing insufficient actual datasets. Ok & Sinha (2006) developed and compared two methods for estimating dozer's productivity. This study hypothesized that the neural network model may improve dozer's productivity estimation because of the neural network's inherent ability to capture non-linearity and the complexity of the changeable environment of each construction project. The parameters of this study included predicting dozer's productivity for earthmoving tasks, which consists of different type of dozers, blades, soil types, weather conditions, dozing grades, and distance. The mean-square errors results revealed that the non-linear neural network results have lower explained variation than the multiple regressions.

Keckojevic & Mrugala (2003) developed a tool that can be used for estimating bulldozer's purchase and evaluating the costs of performance. This tool was called as a Dozer Productivity and Cost (DPC) and capable of determining the productivity and economics of dozer units, using the logic that models simulate real situations. The DPC program includes the features such as: calculation of dozer production, estimation and comparison of dozer's ownership cost (residual value, cost per hour, interest, insurance and taxes, and operating costs). By using equipment database models, the dozer's production is defined by selecting a dozer from the existing database and specifying the cycle elements. The ownership cost is calculated by using parameters such as delivery price, time period, annual operating hours, interest rate, and insurance and taxes. The operating cost is defined by fuel cost, lubricants cost, undercarriage, repair reserve, and labor. Han & Halpin (2005) provided a methodology to establish a productivity estimation model combining actual data collection, input data generation using experimental designs and multiple regression analysis. This research suggested the use of a simulation methodology as an alternative to resolve the limitations of actual data: WebCYCLONE as one of simulation programs in order to generate datasets. A large number of datasets were generated by WebCYCLONE using sensitivity analysis, and the datasets were used as constant, precise, and abundant resources that provide input datasets to a multiple regression model.

### **2.2.2 Cost and Productivity Data from RSMeans Heavy Construction Data**

RSMeans Heavy Construction Data is a part of RSMeans estimating references, which is widely accepted and used by most construction professionals. This data provides

technical information required to prepare quantity takeoffs and complete construction estimates for major construction projects (RSMeans, 2010). It helps design and construction professionals compare the estimates of design alternatives, perform cost analysis and value engineering, and review estimates quotes and change orders prepared by others. The data also includes information in sizing, productivity, equipment requirements, design standards, and engineering factors – all organized according to the latest 2004 Construction Specification Institute (CSI) Master Format classification system, which has 48 divisions ranging from General Requirements to Electrical Power Generation.

Earthwork construction is provided in this data on Division 31: ‘Earthwork’. This division has sections representing major earthwork activities: clearing and grubbing, tree and shrub removal and trimming, stripping and stockpiling, grading, excavation and fill, erosion and sedimentation controls, soil treatment and stabilization, shoring, underpinning, dams, and tunnel construction. For the purpose of this research, sub-division 31.23 – Excavation and Fill is selected. This sub-division has two sections: 31.23.16 – Excavation, 31.23.19 – Dewatering, and 31.23.23 – Fill. For building the productivity and cost models of construction equipment, this research selected three sub-sections from Excavation section: 31.23.16.13 – Excavating Trench for excavators, 31.23.16.46 – Excavating Bulk Dozer for bulldozers, 31.23.16.50 – Excavating Bulk Scraper for scrapers, and one sub-sections from Fill section: 31.23.23.20 – Hauling for hauling trucks.

The productivity rate in RSMeans is listed as Daily Output; the number of units of a defined task that a designated crew or equipment will produce in one eight-hour

workday (RSMeans & Mubarak, S.A., 2006). Daily output represents an average figure, which varies with job conditions and measured in the units specified for related type of activities. For earthwork activities, the units are mostly in loose cubic yard (lcy) or bank cubic yard (bcy). The unit costs in RSMeans for each type of construction are broken down into the components of material, labor, equipment, and overhead-profit. The data also provides square foot costs by project type, which must be adjusted to fit with the specific location, size, and conditions of particular project.

### **2.2.3 Off-the-Job Productivity Estimates from CAT Performance Handbook**

CAT Performance Handbook provides machine performance information released by Caterpillar Inc. for their equipment. The information includes current specifications of all types of equipment and off-the-job measurement of both productivity and cost. The HDD equipment covered in this handbook includes track-type tractors, motor graders, skid steer loaders, excavators, backhoe loaders, forest equipment, pipelayer equipment, wheel tractor-scrappers, construction and mining trucks, wheel dozers and loaders, compactors, track loaders, and other hydro-mechanical work tools.

In estimating productivity, this handbook uses bearing factors such as weight to horsepower ratio, capacity, type of transmission, speeds, and operating costs. Some sections also include tables or charts showing cycle times or hourly production rate under certain conditions. The data provided are based on field testing, computer analysis, laboratory research. The methods for estimating productivity and machine owning-operating costs are based upon 100% efficiency in operation, which cannot be achieved continuously even under ideal conditions. For the purpose of this research, the following



sections are used: track-type tractors/bulldozers, wheel tractor-scrappers, excavator, and construction trucks.

## **CHAPTER III**

### **RESEARCH METHODOLOGY**

#### **3.1 Productivity and Cost Models**

As a basis for the emission model, the productivity and cost models will be developed from the selected vehicles. This section will describe the methodology used to develop the model: organizing the data from construction equipment and earthwork activity, analyzing the data by using multiple linear regression method, and applying the results from productivity models to build fuel use and emission models.

##### **3.1.1 Construction Equipment and Earthwork Activity Data**

The data for developing the productivity and cost models are collected from two sources: RSMeans Heavy Construction Cost Data 2010 and Caterpillar (CAT) Performance Handbook 38<sup>th</sup> Edition. RSMeans data is the most powerful and widely accepted construction tool available to construct an estimate and as reference for key

costs, current construction cost and productivity rates for any types of project (RSMeans, 2010). In constructing the costs, RSMeans takes some elements into consideration: material costs, labor costs, equipment costs, general conditions, overhead and profit, and factors affecting costs: quality, overtime, productivity, size of project, and location. RSMeans has updated its database from Construction Specifications Institute's 16-division Master Format 95 to the 48-division Master Format 2004.

In RSMeans data, earthwork activities are provided in Division 31 – Earthwork. For the purpose of this research, sub-division 31.23 – Excavation and Fill is selected. This sub-division has two sections: 31.23.16 – Excavation, 31.23.19 – Dewatering, and 31.23.23 – Fill. For building the productivity and cost models of construction equipment, this research selected three sub-sections from Excavation section: 31.23.16.13 – Excavating Trench for excavators, 31.23.16.46 – Excavating Bulk Dozer for bulldozers, 31.23.16.50 – Excavating Bulk Scraper for scrapers, and one sub-sections from Fill section: 31.23.23.20 – Hauling for hauling trucks. Therefore, the productivity and cost models will be based on four types of construction equipment: bulldozer, scraper, excavator, and hauling truck.

CAT Performance Handbook is used to measure the performance of heavy construction equipment manufactured by Caterpillar. The performance of each type of equipment is measured by its productivity rate and its affecting factors, such as weight to horsepower ratio, capacity, type of transmission, speeds, or operating costs (Caterpillar, 2008). Some tables and charts are also provided for calculating off-the-job productivity estimates. For the purpose of this research and to compare the productivity rate obtained

from RSMMeans data, the selected construction equipment are track-type tractors (bulldozer), wheel-tractor scraper (scraper), excavator, and construction truck.

### 3.1.2 Multiple Linear Regressions (MLR) Analysis

Regression analysis is a powerful tool to learn more about the relationships within the data being studied and has widely been used by many researchers (David J & Gary D, 1993; Dunlop & Smith, 2003; Han & Halpin, 2005; Lowe et al., 2006; Smith, 1999). It is one of the most widely used statistical tools because it provides a simple method for establishing a functional relationship among variables. Productivity in earthwork activities has been conducted by several studies. The use of ‘deterministic’ multiple regression regressions (MLR) analysis is well established in construction management research, particularly in predicting construction productivity (Akinsola, 1997; Akintoye & Skitmore, 1994; Edwards, et al., 2000; Smith, 1999). In this research, multiple linear regressions will be used to determine the statistical relationship between a response (i.e. productivity rate or unit cost) and the explanatory variables (e.g. engine horsepower, dozing distance, and type of soil).

The multiple linear regression model is written in the following form:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_p x_{ip} + \varepsilon_i \quad (3-1)$$

where:

1.  $y_i$  is the response that corresponds to the levels of explanatory variables  $x_1, x_2, \dots, x_p$  at the  $i$ th observation
2.  $\beta_0, \beta_1, \beta_2, \dots, \beta_p$  are the coefficients in the linear relationship. For a single factor ( $p=1$ ),  $\beta_0$  is the intercept, and  $\beta_1$  is the slope of the straight line defined

3.  $\varepsilon_1, \varepsilon_2, \dots, \varepsilon_n$  are errors that create scatter around the linear relationship at each of the  $i=1$  to  $n$  observations. The regression model assumes that these errors are mutually independent, normally distributed, and with a zero mean and variance  $\sigma^2$ . To make estimates of the coefficients in the regression model, the method of least squares is used.

Table 3.1. Equipment data from RSMMeans Heavy Construction Data

Type of Equipment	Activity Input	Unit/type/range
Bulldozer	Engine size	Horsepower (80-700 hp)
	Excavating distance	50-300 ft
	Type of soil	Sand and gravel
		Sandy clay and loam
Scraper	Soil quantity	Common earth
	Engine size	Clay
	Excavating distance	cy
	Type of soil	Horsepower (hp)
Excavator	Excavating distance	1500-5000 ft
	Type of excavation	Sand and gravel
		Common earth
		Sandy clay and loam
	Excavating bucket	Clay
		Elevated scraper
	Soil quantity	Self-propelled scraper
Towed		
Hauling Truck	Excavating bucket	11-21 cy
	Engine Size	Horsepower (HP)
	Capacity	0.5-3.5 cy
	Cycle distance	1-6 ft (shallow), 6-14 ft (medium), 16-24 ft (deep)
	Soil type	Sand and gravel
		Sandy clay and loam
		Common earth
Excavating type	Clay	
	Excavator	
	Excavator with truck mounted	
Hauling Truck	Excavator with trench box	
	Soil quantity	cy
	Engine Size	Horsepower (hp)
	Capacity	22-60 cy
	Cycle distance	2,000 ft – 4 miles
	Average hauling speed	5-25 mph
Average	15-25 minutes	
	Waiting/loading/unloading time	

The main purpose of carrying out a regression analysis on diesel construction equipment data is to obtain a model that will estimate productivity rates and unit cost of earthwork activities. The explanatory variables used to predict or estimate the productivity rates are obtained from the data available in two sources: RSMMeans Heavy Construction Data 2010 and Caterpillar (CAT) Performance Handbook 38<sup>th</sup> Edition. The explanatory variables are shown in Table 3.1 and 3.2.

Table 3.2. Equipment data from CAT Performance Handbook

<b>Type of Equipment</b>	<b>Activity Input</b>	<b>Unit/type/range</b>	
Bulldozer	Engine size	Horsepower (HP)	
	Blade capacity	7.53-45 cy	
	Distance	100-500 feet	
	Efficiency	67-83%	
	Soil grade	0.2-1.8	
	Operator's skill	Excellent	
		Average	
	poor		
	Soil type	Loose stockpile Hard to cut Hard to drift Rock/ripped/blasted	
	Dozing techniques	Slot dozing Side-by-side	
Scraper	Engine size	Horsepower (HP)	
	Material density	lbs/cy	
	Capacity (payload)	8.8-34.6 cy	
	Empty weight	lbs	
	Distance	100-5200 ft	
	Cycle time	0-16 min.	
	Rolling resistance	%	
Excavator	Engine size	Horsepower (HP)	
	Bucket capacity	cy	
	Cycle time	min.	
	Depth	ft	
	Load factor	%	
	Type of soil	Moist loam (sandy clay) Sand-gravel Hard-tough clay Rock-well blasted Rock-poorly blasted	
Hauling Truck	Engine size	Horsepower (HP)	
	Capacity	cy	
	Loading time	Min.	
	Hauling time	Min.	
	Dump time	Min.	
	Return time	Min.	

### **3.1.3 Total Cost, Total Fuel Use, and Total Emissions Models**

The models for cost, fuel use and emissions from diesel construction equipment will be built based on the productivity model and the EPA's NONROAD Model. For each type of equipment, all observed data will be categorized into two groups: Activity Input and Engine Property Input.

The activity inputs, such as soil type, dozing distance, and engine horse power will be used to build models for productivity and unit cost by using regression analysis. The projected results from this analysis are the productivity rate (soil volume per unit time), activity duration (time), and unit cost (dollar amount per soil volume). By using the information of engine horsepower, activity duration, total soil quantity, and EPA's fuel consumption rate (brake-specific-fuel-consumption or BSFC), the result will also have the rate of fuel use in term of gallons per soil quantity.

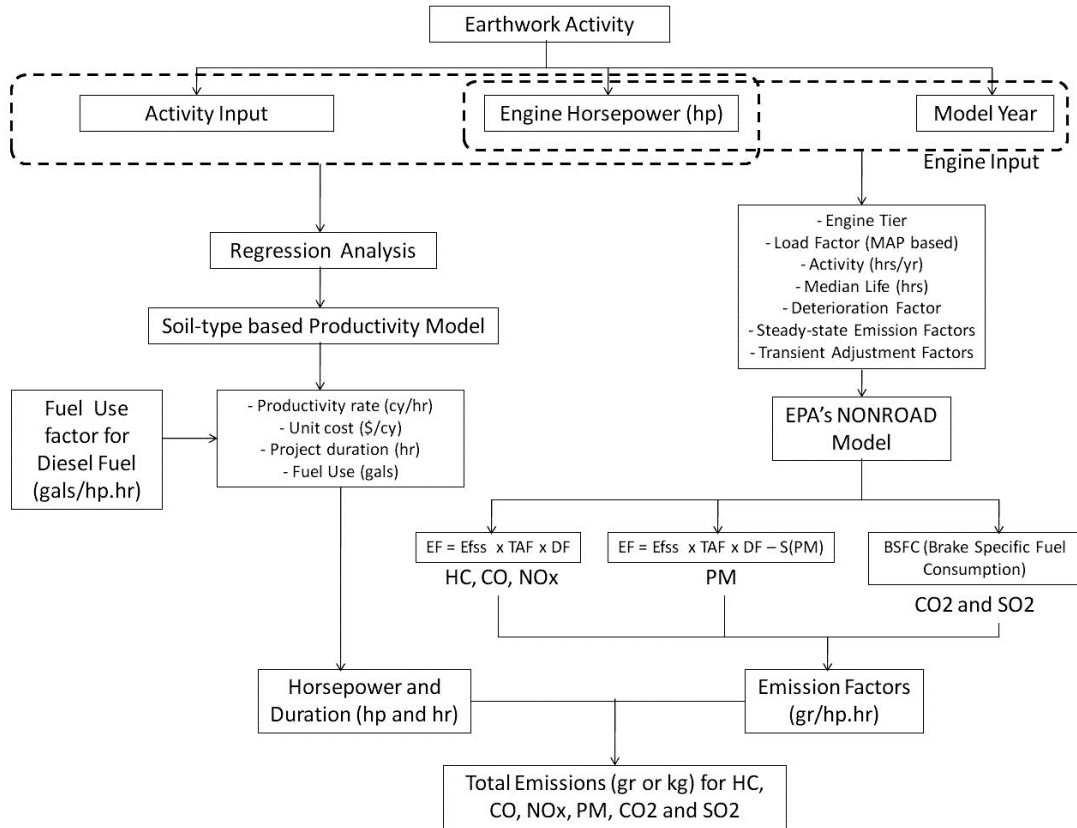


Figure 3.1. Productivity and emission model development chart

The engine property input –engine horsepower and engine model year, will be used to determine the engine tier level. The information of engine tier level will then be used to calculate deterioration factor (DF), transient adjustment factor (TF), and zero-hour steady state emission factors for all gas pollutants (HC, CO, NO<sub>x</sub>, CO<sub>2</sub>, and SO<sub>2</sub>) and PM. Meanwhile the type of equipment will define the load factor (LF) and annual activity, and the engine horsepower will determine the engine median life.

Since the projected results from engine property input will be emission factors of all pollutants in mass per horsepower-hour (g/hp-hr), the total mass emissions from an earthwork activity will be obtained by multiplying the emission factors with engine rated horsepower and total activity duration (as results from productivity model). The total



mass emissions per dollar amount spent on the earthwork activity will be obtained by dividing the total emissions with total cost (as results from cost model). The chart showing the productivity-based cost, fuel use, and emission model for all four studied equipment –bulldozer, excavator, scraper, and truck, is displayed in Figure 3.1.

### **3.1.4 Model Validation and Calibration**

The estimated total fuel use and emissions acquired by using the model will be validated with on-vehicle instrument in the field. The instrument used in this study is Portable Emissions Measurement System (PEMS) manufactured by Axion. Using the Clean Air Technologies International (CATI) system, the PEMS measures second-by-second mass emissions released from vehicle's exhaust and some other information associated with the engine, such as manifold absolute pressure (MAP), rotation per minute (RPM), and intake air temperature (IAT) (Frey et al., 2008).

For diesel construction vehicle, the PEMS collects emissions by using sample probe inserted into the tailpipe for the gas pollutants (HC, CO, NO<sub>x</sub>, CO<sub>2</sub>) and PM and connected to gas and PM analyzers. In order to collect emissions from the vehicle, the PEMS has to be installed and attached on the vehicle with the following procedures:

1. placing/mounting the PEMS safety case on the vehicle
2. connecting the emissions sample probes from the tailpipe to the gas and PM analyzer input lines
3. connecting the sensor array lines from vehicle's engine the PEMS
4. starting the PEMS

The PEMS uses non-dispersive infrared (NDIR) detection to measure CO<sub>2</sub>, CO, and HC, and uses electrochemical cells to measure NO and O<sub>2</sub>, while PM measurement is acquired by a light scattering laser photometer detection method (Rasdorf, Frey, et al., 2010). The PEMS is also equipped to detect vehicle location coordinate from a GPS. This will allow the vehicle to be tracked for providing data on the position, speed, and working distance of the vehicle. The illustration of installing PEMS instrument is shown in Figure 3.2.

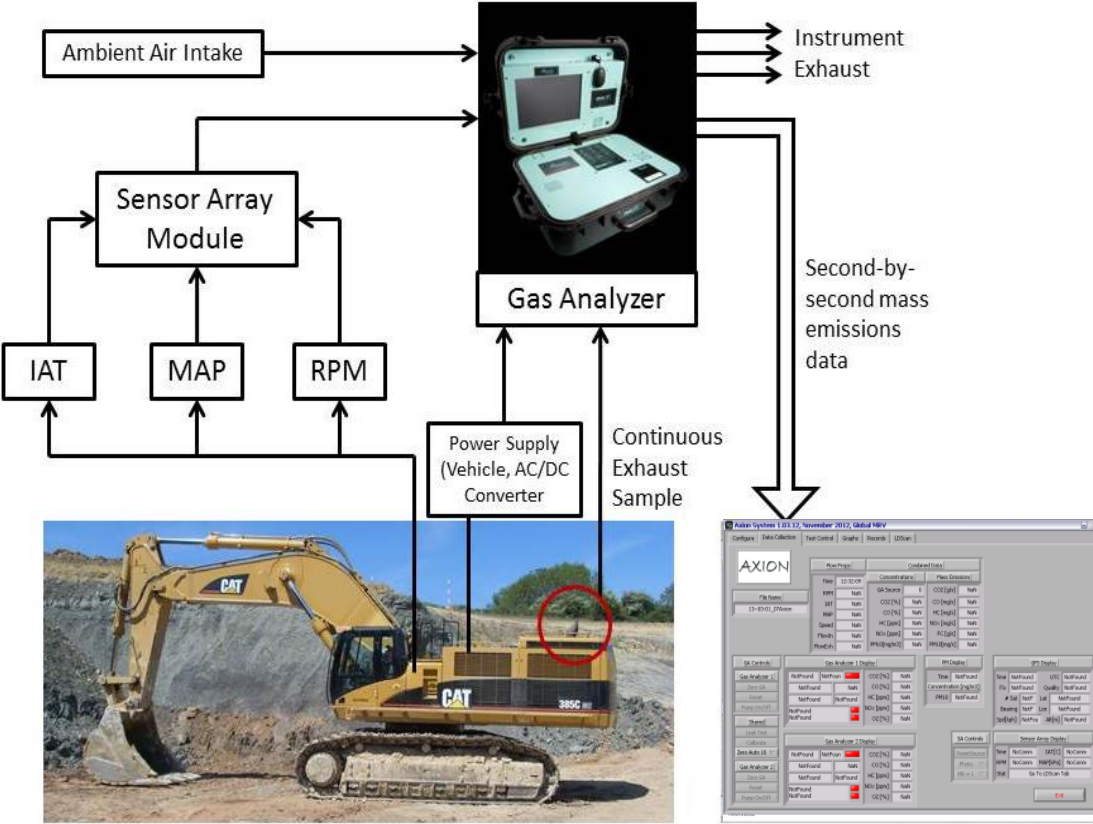


Figure 3.2. Installation of PEMS on construction equipment

### **3.1.5 Model Application and Sensitivity Analysis**

Model application and sensitivity analysis is conducted to analyze the effect of changes in explanatory variables against the output; cost, fuel use, and emissions. The analyses are useful to understand the economic, energy, and environmental impact of a certain earthwork activity performed by HDD equipment in different set of conditions.

The economic impact of the activity is determined by the total cost (including labor, equipment, overhead, and profit) to complete the activity. The energy impact of the activity is based on the amount of diesel fuel consumed by HDD equipment in terms of total gallons. The environmental impact of the activity is based on total emissions of each pollutant (HC, CO, PM, NO<sub>x</sub>, and CO<sub>2</sub>) in terms of grams.

### **3.2 Economic-Energy-Environmental (E3) Model User's Interface**

The Economic-Energy-Environmental (E3) decision support tool is a user interface developed from the regression model results by using Visual Basic program (VBA) for Microsoft Excel 2007. With a spreadsheet-based *UserForm* which is a custom-built dialog box, the interface was built by codes in the Visual Basic Editor. All input filled in the interface will automatically be executed when the spreadsheet is opened. UserForms are similar to other VBA objects in that they have properties, methods, and events used to control the appearance and behavior of the interface window.

## **CHAPTER IV**

### **RESEARCH RESULTS**

#### **4.1 Productivity Models**

Productivity models for bulldozer, scraper, excavator, and truck are built by using data from two sources: RSMeans Heavy Construction Data and CAT Performance Handbook. The productivity models are built, analyzed, and validated by using multiple linear regression (MLR) methods. The productivity models for each type of HDD equipment will be compared based on the source of data; models built by using RSMeans data and models built using CAT performance data. The comparisons of these two productivity models will be based on some key factors or predictors, such as engine size, working distance, soil types, or bucket/blade capacity. The comparison of estimated fuel use is also presented to show the magnitude of working duration of each type of equipment.

### 4.1.1 Model Building and Validation

Since the data collection has been done by using the RSMeans Heavy Construction Data and the CAT Performance Handbook, the next step for the building of a regression model involves three following phases: model building, model selection, and model validation. During the model building process, we need to examine whether all of the potential 'X' variable are needed or whether a subset of them is adequate (Kutner et al, 2004). A number of useful measures have been developed to assess the adequacy of various subsets of 'X' variables. For the purpose of this research, one manual selection method: Mallow's Cp, and an automatic model selection method: stepwise regression selection are used to develop best subset of 'X' variables

Mallow's Cp criterion considers the total mean squared error of the fitted values for each subset regression model. This value indicates a good model when it is small and ideally close to the number of regression parameters, p. It is calculated as:

$$C_p = \frac{SSE_p}{MSE(X_1, \dots, X_{p-1})} - (n - 2p) \quad (4-1)$$

Stepwise model selection uses an automatic search procedure to develop and identify a single regression model as 'best'. This research used a forward stepwise regression procedure. Essentially, this search method develops a sequence of regression models, at each step adding or deleting an 'X' variable. The criterion for adding or deleting an 'X' variable can be stated equivalently in terms of error sum of square reduction, coefficient of partial correlation, *t* statistic, or *F* statistic (Kutner et al, 2004).

The final step in the model building process is the validation of the selected regression model. The productivity models in this research are validated by using two

methods: data splitting and a plot showing a comparison of predicted and actual data. In data splitting method, the original data set are split into a model-building set and a validation set (Kutner et al, 2004). If the number of data is within 6 to 10 times the number of predictor variables, it is enough for making an equal data split. If the entire data is not large enough under these circumstances, the validation set will need to be smaller than the model building data set.

The model-building set is used to develop the model. The validation set is used to evaluate the reasonableness and predictive ability of the selected model. A means of measuring the actual predictive ability is to use the model to predict each case in the validation data set and then to calculate the mean of the squared prediction errors, denoted by MSPR or *mean squared prediction error*. The MSPR is calculated as:

$$\text{MSPR} = \frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{n} \quad (4-2)$$

where:

$Y_i$  = the value of the response variable in the *i-th* validation case

$\hat{Y}_i$  = the predicted value for the *i-th* validation case based on the model from using the model building data set

$n$  = the number of cases in the validation data set

If the MSPR is fairly close to the MSE based on the regression fit to the model-building data set, then MSE for the selected regression model is not seriously biased and gives an appropriate indication of the predictive ability of the model.

The plot showing the predicted versus the actual result of productivity model is used to identify the accuracy, precision, and bias of the model. Ideally, a plot of the

predicted versus the actual results will produce a line with a slope of 1.0 (accurate),  $R^2 = 1.0$  (precise), and y-intercept = 0 (no-bias).

Since some the productivity models have two or more qualitative predictors such as types of soil, types of excavator, or types of scraper, the regression functions need to be written in such way to consider the number of qualitative variables included in the model (Kutner et al, 2004). A bulldozer productivity model on four types of soil for example, has to be written for each type of soil. If engine size and distance are included in the productivity model as  $X_1$  and  $X_2$ , and for types of soil are defined as  $X_3$ ,  $X_4$ ,  $X_5$ , and  $X_6$  respectively, the response function for regression model will be:

$$Y = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \beta_5X_5 + \beta_6X_6 \quad (4-3a)$$

To understand the meaning of the regression coefficients, it is defined that when:

$X_3 = 1$  for soil type *a*, or  $X_3 = 0$  for otherwise,

$X_4 = 1$  for soil type *b*, or  $X_4 = 0$  for otherwise,

$X_5 = 1$  for soil type *c*, or  $X_5 = 0$  for otherwise.

For soil type *d*, since  $X_3 = X_4 = X_5 = 0$ , the response function becomes:

$$Y = \beta_0 + \beta_1X_1 + \beta_2X_2 \quad (4-3b)$$

Similarly, response functions for soil type *a*, *b*, and *c* becomes:

$$Y = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3 \quad (4-3c)$$

$$Y = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_4, \text{ and} \quad (4-3d)$$

$$Y = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_5 \quad (4-3e)$$

Thus, response functions imply that the regression models of each soil type on engine size and distance are linear.

#### 4.1.1.1 Bulldozer

The RSMeans productivity model for bulldozer was based on 72 observations taken from the ‘excavation bulk-dozer’ activity. The response variable of productivity was based on the daily output values for each observation, which was converted to hourly output values based on an eight hour work day, and reported in units of bank cubic yards per hour (bcy/hr). The predictor variables included a range of engine sizes (80-700 horsepower), dozing distance (50-300 feet), and soil types (sand-gravel, sandy clay-loam, common earth, and clay). Soil type was treated as a categorical variable with a value of 0 or 1, depending on the type of soil under consideration.

To build the productivity model, the data is split into two parts; model building data set and model validation data set. Since the number of data is more than 10 times of the number of predictors, the data can be equally splitted. From the results of original regression function, it was found that the plot of residuals against the predicted values showed evidence of unequal variance. The unequal error variances and non-normality of the error terms frequently appear together.

A Box-Cox analysis has been conducted and the result recommended the best lambda ( $\lambda$ ) for transforming the response variables (Y) is 0.2. Based on the transformed regression equations, the value of  $R^2 = 0.9534$  showed that the productivity model for bulldozer accounts approximately 95% of the variability of the RSMeans data. With  $\alpha = 0.05$ , all parameters (including the intercept) in the transformed model had p-values  $< 0.0001$  and were statistically significant.

The model selection result by using Mallows’ Cp method shows that with  $C(p)$  value of 4.296 and R-square of 0.9530, engine horsepower, dozing distance, and soil type



can be included in the model. Meanwhile, after fourth step in stepwise selection method, engine horsepower, dozing distance, and soil type were included in the model, and gave the R-square value of 0.9474. From these two methods, the final regression model for productivity can include bulldozer horsepower (hp), dozing distance (feet), and type of soil.

With the form of transformed regression function which can be written as:

$$Y^{0.2} = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_p x_{ip} + \varepsilon_i \text{ or,} \quad (4-4a)$$

$$Y = (\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_p x_{ip} + \varepsilon_i)^5 \quad (4-4b)$$

the overall productivity models of bulldozer for all types of soil are shown in the Table 4.1.

Table 4.1. Productivity models for bulldozer – RSMeans

Soil Type	Productivity Model	
Sand-gravel	$Y = (2.117 + 0.0035X_1 - 0.0024X_2)^5$	(4-5)
Sandy clay-loam	$Y = (2.097 + 0.0035X_1 - 0.0024X_2)^5$	(4-6)
Common earth	$Y = (2.046 + 0.0035X_1 - 0.0024X_2)^5$	(4-7)
Clay	$Y = (1.878 + 0.0035X_1 - 0.0024X_2)^5$	(4-8)

where:

Y = bulldozer productivity (bcy/hr)

X<sub>1</sub> = engine horsepower (hp)

X<sub>2</sub> = dozing distance (feet)

To validate the model, a plot in Figure 4.1 showing the predicted versus the actual results for the productivity model was made. The plot from the model shows the slope of 0.9763, R<sup>2</sup> = 0.9478, and intercept = 0.2338 bcy/hr, thus, the model was considered to be accurate, precise, and had small bias. In cross-validation procedure, the data were split to two: 36 data for model building and 36 data for model validation. The calculation result of mean squared prediction error (MSPE), by dividing the errors sum of squares with number of data in validation data set, is 0.084/36 = 0.0023. This result is fairly not too far

compared to mean square error (MSE) in model building data set, which is 0.0061. It can be concluded that the regression model for bulldozer productivity is not seriously biased and gives an appropriate indication of the predictive ability of the model.

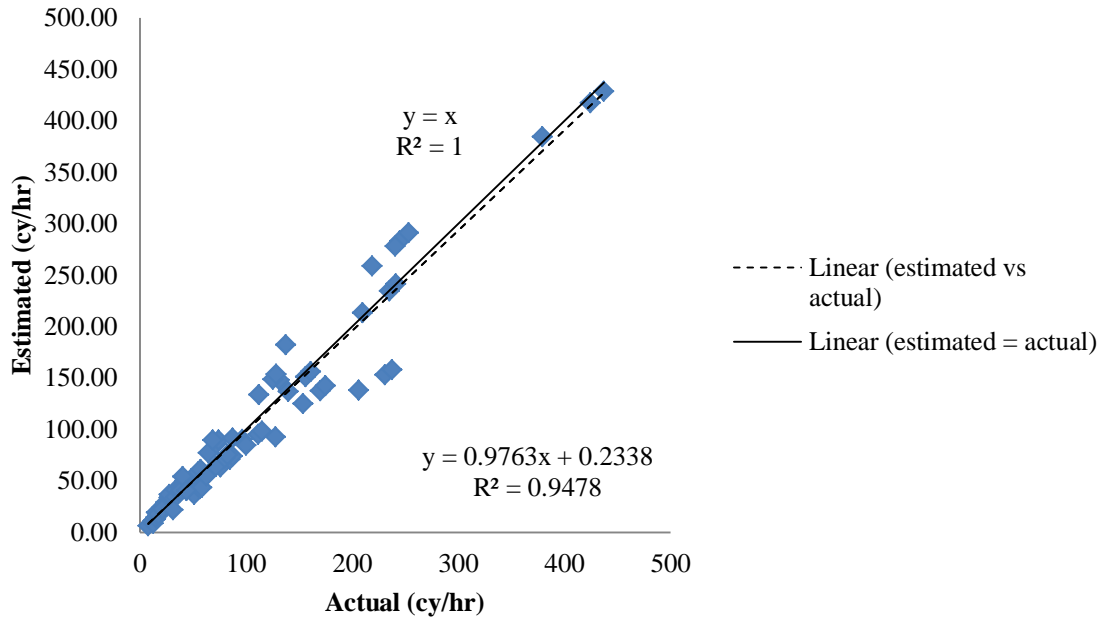



Figure 4.1. Actual and estimated productivity for bulldozer - RSMeans

The CAT productivity model for bulldozer was based on 2,880 observations taken from chart estimating off-the-job productivity rate and using correction factors such as operational efficiencies, site slope, operator skill, soil type, and dozing techniques. The estimated off-the-job productivity rates are obtained by using chart showing different types of bulldozer productivity as the function of dozing distance (Figure 4.3). All types of bulldozer in the chart using the same type of blade; universal blade, which provides high volume movement of light non-cohesive materials and other reclamation works. The bulldozer models used in the chart are listed in Table.

The response variable of productivity was based on the hourly productivity rate in loose cubic yard per hour (lcy/hr) by using the combination of bulldozer models or types and all possible correction factors configurations. The predictor variables included a range of engine size (202-850 hp), blade capacities (7.5-45 lcy), dozing distances (100-500 feet), operational efficiencies (67-83%), site slope (0.2-1.8%), operator skill (excellent, average, poor), soil types (loose stockpile, hard to cut, hard to drift, and blasted/ripped rock), and dozing techniques (slot and side-by-side).

Operator skill, soil type, and dozing techniques were treated as categorical variable with a value of 0 or 1 depending on the type under consideration; poor operator skill, blasted/ripped rock, and side-by-side dozing were considered to be the base cases. From the results of original regression function, it was found that the plot of residuals against the predicted values showed evidence of unequal variance. The unequal error variances and non-normality of the error terms frequently appear together. However, since the number of data is large ( $n = 2,880$ ), the normality issue is not important anymore, and the regression model for bulldozer can be used without using transformation. Based on the value of  $R^2 = 0.6421$ , the regression function for predicting productivity accounts for approximately 64% of the variability in the CAT data. With  $\alpha = 0.05$ , almost all parameters (including the intercept) in the transformed model had p-values  $< 0.0001$  and were statistically significant, except for blade capacity and dozing techniques.

Table 4.3. Types of CAT bulldozer used to develop productivity model

Bulldozer model	Type of blade	Blade capacity (lcy)	Engine size (hp)	Picture
CAT D11-U	Universal	45	850	
CAT D10-U	Universal	28.7	580	
CAT D8-U	Universal	15.5	305	
CAT D7-R	Universal	7.53	202	

The blade capacity is technically designed as function of engine size; bigger engine size has bigger blade capacity. From the result of Pearson Correlation Coefficients tests, it was also found that there is strong linear correlation between engine horsepower (hp) and blade capacity (0.998 with p-value <0.0001). Based on the result of correlation test, engine size or blade capacity has to be taken out from the regression model. Concerning the dozing techniques, since the p-values of dozing techniques is 0.1454 and is bigger than  $\alpha = 0.05$ , it can be concluded that different dozing techniques do not significantly lead to different rate of productivity. However, since the dozing technique is

categorical variable, it can be used to represent the categories of a qualitative explanatory variable in the regression model.

The model selection result by using Mallows' Cp method shows that with C(p) value of 11.122 and R-square of 0.642, engine horsepower, dozing distance, operational efficiency, site slope, operator skill, soil type, and dozing techniques can be included in the model. Meanwhile, after tenth step in stepwise selection method, dozing distance, engine horsepower, site slope, soil type, operator skill, and operation efficiency were included in the model, and gave the R-square value of 0.6417. From these two methods, the final regression model for productivity can include bulldozer horsepower (hp), dozing distance (feet), site slope (%), operational efficiency (%), soil type, operator skill, and dozing technique.

With the form of transformed regression function which can be written as:

$$Y = \beta_0 + \beta_1x_{i1} + \beta_2x_{i2} + \dots + \beta_px_{ip} + \varepsilon_i \quad (4-33)$$

the overall CAT productivity models of bulldozer for all types of soil are shown in the Table 4.4.

To validate the model, a plot in Figure 4.2 showing the predicted versus the actual results for the productivity model was made. The plot from the model shows the slope of 1.0204,  $R^2 = 0.9357$ , and intercept = 12.535 lcy/hr, thus, the model was considered to be accurate, precise, and had no bias.

Table 4.4. Productivity models for bulldozer – CAT

Dozing Technique	Operator skill	Soil type	Productivity model	
Slot	Excellent	loose stockpile	$Y = -158.1 + 1.5X_1 - 1.65X_2 + 628X_3 + 471X_4$ (4-9)	
		hard to cut	$Y = -443.62 + 1.5X_1 - 1.65X_2 + 628X_3 + 471X_4$ (4-10)	
		hard to drift	$Y = -368.5 + 1.5X_1 - 1.65X_2 + 628X_3 + 471X_4$ (4-11)	
		blasted/ripped rock	$Y = -500.7 + 1.5X_1 - 1.65X_2 + 628X_3 + 471X_4$ (4-12)	
	Average	loose stockpile	$Y = -308.4 + 1.5X_1 - 1.65X_2 + 628X_3 + 471X_4$ (4-13)	
		hard to cut	$Y = -593.9 + 1.5X_1 - 1.65X_2 + 628X_3 + 471X_4$ (4-14)	
		hard to drift	$Y = -536.8 + 1.5X_1 - 1.65X_2 + 628X_3 + 471X_4$ (4-15)	
		blasted/ripped rock	$Y = -651 + 1.5X_1 - 1.65X_2 + 628X_3 + 471X_4$ (4-16)	
	Poor	loose stockpile	$Y = -398.6 + 1.5X_1 - 1.65X_2 + 628X_3 + 471X_4$ (4-17)	
		hard to cut	$Y = -684.1 + 1.5X_1 - 1.65X_2 + 628X_3 + 471X_4$ (4-18)	
		hard to drift	$Y = -627 + 1.5X_1 - 1.65X_2 + 628X_3 + 471X_4$ (4-19)	
		blasted/ripped rock	$Y = -741.2 + 1.5X_1 - 1.65X_2 + 628X_3 + 471X_4$ (4-20)	
	Side-by-side	Excellent	loose stockpile	$Y = -178.1 + 1.5X_1 - 1.65X_2 + 628X_3 + 471X_4$ (4-21)
			hard to cut	$Y = -463.6 + 1.5X_1 - 1.65X_2 + 628X_3 + 471X_4$ (4-22)
			hard to drift	$Y = -406.5 + 1.5X_1 - 1.65X_2 + 628X_3 + 471X_4$ (4-23)
			blasted/ripped rock	$Y = -520.7 + 1.5X_1 - 1.65X_2 + 628X_3 + 471X_4$ (4-24)
Average		loose stockpile	$Y = -328.4 + 1.5X_1 - 1.65X_2 + 628X_3 + 471X_4$ (4-25)	
		hard to cut	$Y = -613.9 + 1.5X_1 - 1.65X_2 + 628X_3 + 471X_4$ (4-26)	
		hard to drift	$Y = -556.8 + 1.5X_1 - 1.65X_2 + 628X_3 + 471X_4$ (4-27)	
		blasted/ripped rock	$Y = -671 + 1.5X_1 - 1.65X_2 + 628X_3 + 471X_4$ (4-28)	
Poor		loose stockpile	$Y = -418.6 + 1.5X_1 - 1.65X_2 + 628X_3 + 471X_4$ (4-29)	
		hard to cut	$Y = -704.1 + 1.5X_1 - 1.65X_2 + 628X_3 + 471X_4$ (4-30)	
		hard to drift	$Y = -647 + 1.5X_1 - 1.65X_2 + 628X_3 + 471X_4$ (4-31)	
		blasted/ripped rock	$Y = -761.2 + 1.5X_1 - 1.65X_2 + 628X_3 + 471X_4$ (4-32)	

Where:

Y = productivity rate (lcy/hr)

- X<sub>1</sub> = engine horsepower (hp)
- X<sub>2</sub> = dozing distance (feet)
- X<sub>3</sub> = Job efficiency (%)
- X<sub>4</sub> = site slope (%)

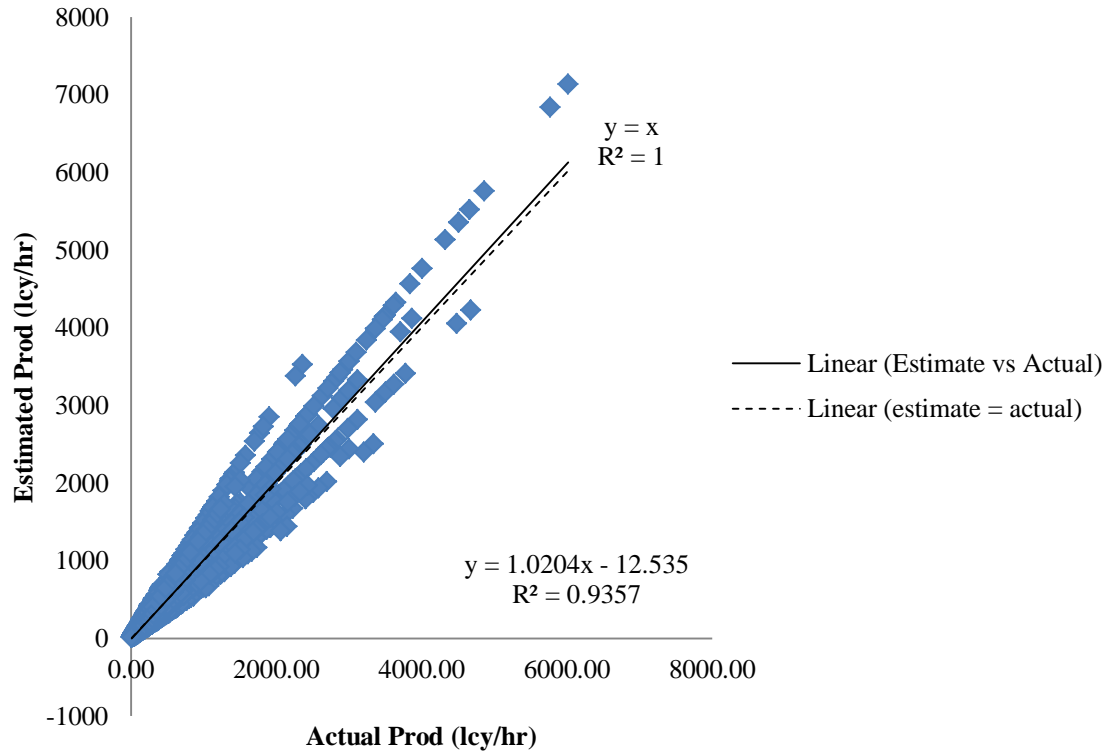


Figure 4.2. Actual and estimated productivity for bulldozer - CAT

#### 4.1.1.2 Scraper

The RSMeans productivity model for scraper was based on 60 observations taken from the ‘excavation bulk-scraper’ activity. The response variable of productivity was based on the daily output values for each observation, which was converted to hourly output values based on an eight hour work day, and reported in units of bank cubic yards per hour (bcy/hr). The predictor variables included a range of bucket size (11-21 cy), distance (1500-5000 feet), type of scraper (elevated scraper, self-propelled scraper, and towed), and soil types (sand-gravel, sandy clay-loam, common earth, and clay). Soil type

and type of scraper were treated as a categorical variable with a value of 0 or 1, depending on the type of soil under consideration. To build the productivity model, the data is split into two parts; model building data set and model validation data set. Since the number of data is more than 10 times of the number of predictors, the data can be equally.

From the results of original regression function, it was found that the plot of residuals against the predicted values showed evidence of unequal variance. The unequal error variances and non-normality of the error terms frequently appear together. To remedy the non-normality in the data, a Box-Cox analysis has been conducted and the result recommended the best lambda ( $\lambda$ ) for transforming the response variables (Y) is 0. After transformation, the regression model for productivity is formulated as:

$$\log Y = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_p x_{ip} + \varepsilon_i, \text{ or} \quad (4-34)$$

$$Y = e^{(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_p x_{ip} + \varepsilon_i)} \quad (4-35)$$

Based on the transformed regression equations, the value of  $R^2 = 0.9936$  showed that the productivity model for bulldozer accounts approximately 99% of the variability of the RSMMeans data. With  $\alpha = 0.05$ , all parameters (including the intercept) in the transformed model had p-values  $< 0.0001$  and were statistically significant for the model.

The model selection result by using Mallows' Cp method shows that with  $C(p)$  value of 7.000 and R-square of 0.9936, type of scraper, soil type, bucket size, and distance can be included in the model. Meanwhile, after seventh step in stepwise selection method, bucket size, soil type, distance, and type of scraper were included in the model, and gave the R-square value of 0.9936. From these two methods, the final regression model for productivity can include bucket size (cy), distance (feet), type



scraper, and type of soil. The overall productivity models for scraper are shown in Table 4.5.

Table 4.5. Productivity models for scraper – RSMeans

Type of scraper	Soil type	Productivity models	
Elevated scraper	Sand-gravel	$Y = e^{(1.878 + 0.0107X_1 - 0.000045X_2)}$	(4-36)
	Common earth	$Y = e^{(1.817 + 0.0107X_1 - 0.000045X_2)}$	(4-37)
	Sandy-clay loam	$Y = e^{(1.853 + 0.0107X_1 - 0.000045X_2)}$	(4-38)
	Clay	$Y = e^{(1.613 + 0.0107X_1 - 0.000045X_2)}$	(4-39)
Self-propelled scraper	Sand-gravel	$Y = e^{(1.853 + 0.0107X_1 - 0.000045X_2)}$	(4-40)
	Common earth	$Y = e^{(1.792 + 0.0107X_1 - 0.000045X_2)}$	(4-41)
	Sandy-clay loam	$Y = e^{(1.828 + 0.0107X_1 - 0.000045X_2)}$	(4-42)
	Clay	$Y = e^{(1.587 + 0.0107X_1 - 0.000045X_2)}$	(4-43)
Towed	Sand-gravel	$Y = e^{(1.965 + 0.0107X_1 - 0.000045X_2)}$	(4-44)
	Common earth	$Y = e^{(1.904 + 0.0107X_1 - 0.000045X_2)}$	(4-45)
	Sandy-clay loam	$Y = e^{(1.940 + 0.0107X_1 - 0.000045X_2)}$	(4-46)
	Clay	$Y = e^{(1.717 + 0.0107X_1 - 0.000045X_2)}$	(4-47)

Where:

Y = productivity rate (bcy/hr)

X<sub>1</sub> = bucket size (bcy)

X<sub>2</sub> = distance (ft)

To validate the model, a plot in Figure 4.3 showing the predicted versus the actual results for the productivity model was made. The plot from the model shows the slope of 0.9488, R<sup>2</sup> = 0.9711, and intercept = 3.34 bcy/hr, thus, the model was considered to be accurate, precise, and had small bias. In cross-validation procedure, the data were split to

two: 30 data for model building and 30 data for model validation. The calculation result of mean squared prediction error (MSPR), by dividing the errors sum of squares with number of data in validation data set, is  $0.01474/30 = 0.00049$ . This result is fairly not too far compared to mean square error (MSE) in model building data set, which is 0.00018. It can be concluded that the regression model for scraper productivity is not seriously biased and gives an appropriate indication of the predictive ability of the model.

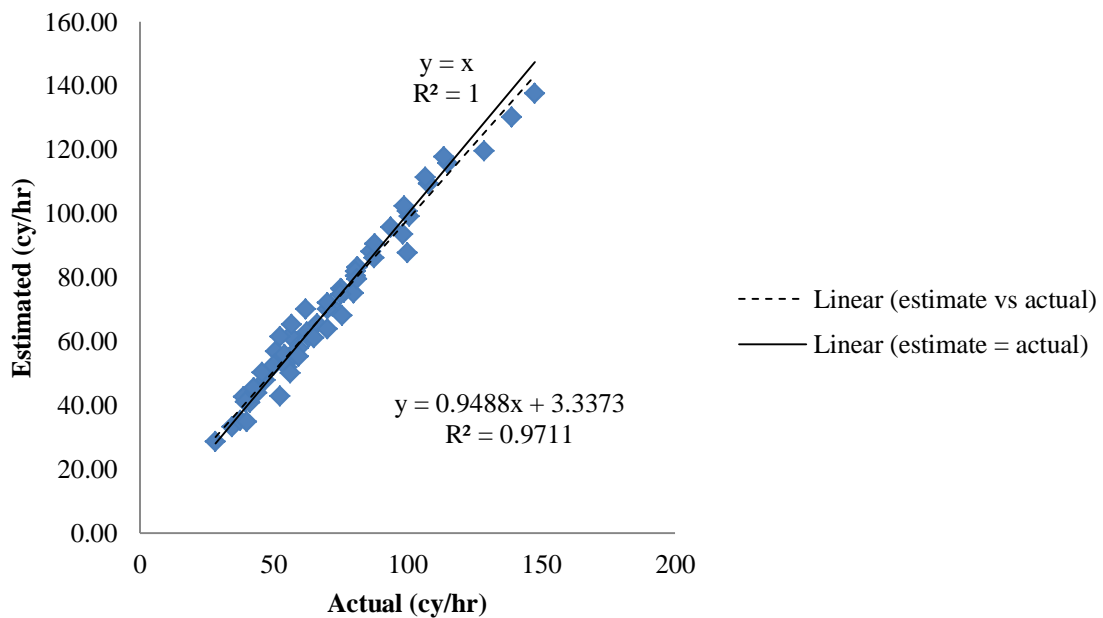


Figure 4.3. Actual and estimated productivity for scraper - RSMMeans

The CAT productivity model for scraper was based on 358 observations taken from chart estimating off-the-job productivity rate and assumed the flat haul condition with 100% operating efficiency of 60 minutes per hour. The scraper performs works on soil material with 3,000 pounds per cubic yard (lb/cy) of density. The estimated off-the-job productivity rates are obtained by using chart showing different types of scraper models and its productivity in bank cubic yard per hour (bcy/hr) as the function of

hauling distance in feet. Each model of scraper has productivity chart with information about its payload or bucket size in bank cubic yard (bcy), empty weight in pounds (lb), and material rolling resistance. The bucket capacity and empty weight will determine the size of the engine (horsepower), which can be found in the specification chart. The scraper models used in the chart are listed in Table 4.6.

The response variable of productivity was based on the hourly productivity rate in loose cubic yard per hour (bcy/hr). The predictor variables included a range of engine size (175-564 hp), bucket capacities (8.8-34.6 bcy), rolling resistance (0.02-0.1), and hauling distances (200-3600) feet. From the results of original regression function, it was found that the regression function for predicting productivity accounts for approximately 90% of the variability in the CAT data ( $R^2 = 0.9053$ ). With  $\alpha = 0.05$ , almost all parameters (including the intercept) in the transformed model had p-values  $< 0.0001$  and were statistically significant, except for engine size (hp).

The engine size is technically related to bucket capacity or size; bigger engine size has bigger bucket capacity. From the result of Pearson Correlation Coefficients tests, it was also found that there is strong linear correlation between engine horsepower (hp) and bucket capacity (0.989 with p-value  $< 0.0001$ ). Based on the result of correlation test, the regression model has to exclude whether the engine size or bucket capacity.

The model selection result by using Mallows' Cp method shows that with  $C(p)$  value of 5.000 and R-square of 0.9053, engine horsepower, bucket capacity, rolling resistance, and hauling distance can be included in the model. Meanwhile, after fifth step in stepwise selection method, bucket capacity, hauling distance, rolling resistance, and engine size were included in the model, and gave the R-square value of 0.9053 (Table 4).

From these two methods, the final regression model for productivity can include bucket capacity (bcy), hauling distance (ft), and rolling resistance.

Table 4.6. Types of CAT scraper used to develop productivity model

Scraper model	Bucket capacity (lcy)	Engine size (hp)	Picture
CAT-613C	8.9	175	
CAT-615C	13.6	265	
CAT-623G	17.6	330	
CAT-623G	18.3	365	
CAT-637G	27.4	462	
CAT-657G	34.6	564	

With the form of transformed regression function which can be written as:

$$Y = \beta_0 + \beta_1x_{i1} + \beta_2x_{i2} + \dots + \beta_px_{ip} + \varepsilon_i \quad (4-48)$$

the CAT productivity models of scraper for all types of soil are shown as:

$$Y = 263.97 + 9.518X_1 - 1556.28X_2 - 0.092X_3 \quad (4-49)$$

Where:

Y = productivity rate (bcy/hr)

X<sub>1</sub> = bucket capacity (bcy)

X<sub>2</sub> = rolling resistance

X<sub>3</sub> = hauling distance (ft)

To validate the model, a plot in Figure 4.4 showing the predicted versus the actual results for the productivity model was made. The plot from the model shows the slope of 0.662, R<sup>2</sup> = 0.8611, and intercept = -13.815 bcy/hr, thus, the model was considered to be accurate, precise, and had no bias.

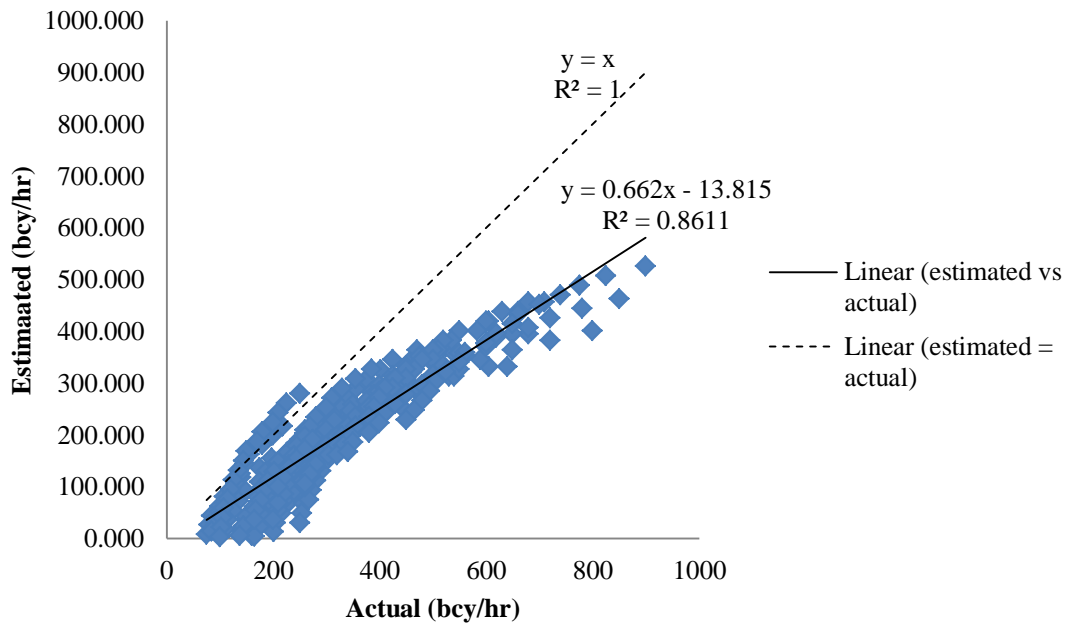


Figure 4.4. Actual and estimated productivity for scraper - CAT

#### 4.1.1.3 Excavator

The RSMeans productivity model for excavator was based on 195 observations taken from the 'excavation trench' activity. The response variable of productivity was based on the daily output values for each observation, which was converted to hourly output values based on an eight hour work day, and reported in units of loose cubic yards per hour (lcy/hr). The predictor variables included a range of trench depth (2.5-22 feet), bucket size (0.375-3.5 cy), type of excavator (excavator, excavator-truck mounted, and excavator-trench box), and soil types (common earth, loam-sandy clay, sand-gravel, and hard clay). Soil type and type of excavator were treated as a categorical variable with a value of 0 or 1.

From the results of original regression function, it was found that the plot of residuals against the predicted values showed evidence of unequal variance. The unequal error variances and non-normality of the error terms frequently appear together. However, since the number of data is large ( $n = 195$ ), the term of normality is not important, and the transformation to remedy the non-normality is not needed.

The regression function has the value of  $R^2 = 0.9195$ , and give the ability of predicting productivity accounts for approximately 92% of the variability in the RSMeans data. With  $\alpha = 0.05$ , almost all parameters in the transformed model had p-values  $< 0.0001$  and were statistically significant, except for type of excavator. Concerning the type of excavator, since the p-values of excavator and excavator-truck mounted were 0.1676 and 0.4743 respectively, bigger than  $\alpha = 0.05$ , they can be concluded that different type of excavator do not significantly lead to different rate of

productivity. However, since the type of excavator is categorical variable, it can be used to represent the categories of a qualitative explanatory variable in the regression model.

The model selection result by using Mallows' Cp method shows that with  $C(p)$  value of 4.297 and R-square of 0.9194, soil type, trench depth, bucket size, and type of excavator can be included in the model. Meanwhile, after fifth step in stepwise selection method, bucket size, trench depth, and soil type were included in the model, and gave the R-square value of 0.9185. From these two methods, the final regression model for productivity can include bucket size (cy), trench depth (feet), soil type, and type of excavator.

With the form of transformed regression function which can be written as:

$$Y = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_p x_{ip} + \varepsilon_i \quad (4-50)$$

the overall RSMeans productivity models of excavator for all types of soil and types of excavator are shown in the Table 4.7.

To validate the model, a plot in Figure 4.5 showing the predicted versus the actual results for the productivity model was made. The plot from the model shows the slope of 0.9195,  $R^2 = 0.9195$ , and intercept = 6.2632 lcy/hr, thus, the model was considered to be accurate, precise, and had no bias. Because the data set is large enough ( $n=195$ ), the model was also validated by using cross-validation procedure or data splitting. 101 observed data were used for model building, and 94 data were used for model validation. The calculation result of mean squared prediction error (MSPE), by dividing the errors sum of squares with number of data in validation data set, is  $20205/94 = 214.5$ . This result is fairly not too far compared to mean square error (MSE) in model building data set, which is 225.52. It can be concluded that the regression model for excavator

productivity is not seriously biased and gives an appropriate indication of the predictive ability of the model.

Table 4.7. Productivity models for excavator – RSMMeans

Type of excavator	Soil type	Productivity models	
Excavator	Common earth	$Y = 7.832 - 2.069X_1 + 55.131X_2$	(4-51)
	Loam-sandy clay	$Y = 14.274 - 2.069X_1 + 55.131X_2$	(4-52)
	Sand-gravel	$Y = 15.779 - 2.069X_1 + 55.131X_2$	(4-53)
	Hard clay	$Y = -0.633 - 2.069X_1 + 55.131X_2$	(4-54)
Excavator-truck mounted	Common earth	$Y = 8.681 - 2.069X_1 + 55.131X_2$	(4-55)
	Loam-sandy clay	$Y = 15.123 - 2.069X_1 + 55.131X_2$	(4-56)
	Sand-gravel	$Y = 16.628 - 2.069X_1 + 55.131X_2$	(4-57)
	Hard clay	$Y = 0.216 - 2.069X_1 + 55.131X_2$	(4-58)
Excavator-trench box	Common earth	$Y = 4.515 - 2.069X_1 + 55.131X_2$	(4-59)
	Loam-sandy clay	$Y = 10.957 - 2.069X_1 + 55.131X_2$	(4-60)
	Sand-gravel	$Y = 12.562 - 2.069X_1 + 55.131X_2$	(4-61)
	Hard clay	$Y = -3.946 - 2.069X_1 + 55.131X_2$	(4-62)

Where:

Y = productivity rate (lcy/hr)

X<sub>1</sub> = trench depth (feet)

X<sub>2</sub> = bucket size (cy)

The CAT productivity model for excavator was based on 1260 observations taken from two charts estimating cycle time and off-the-job productivity rate with various operation efficiency. The chart for estimating cycle time gives the estimation of total cycle time from loading, swinging (loaded and empty), and dumping. The total cycle time were accounted for different type/model of excavator, bucket size, soil type, and digging depth. This total time and bucket size information were then projected to the chart estimating productivity to obtain the estimated productivity rate in loose cubic yard per hour (lcy/hr). The bucket size information can also be used to determine the engine size



of the excavator by using specification chart. The selected excavators used in generating productivity model are shown in Table 4.8.

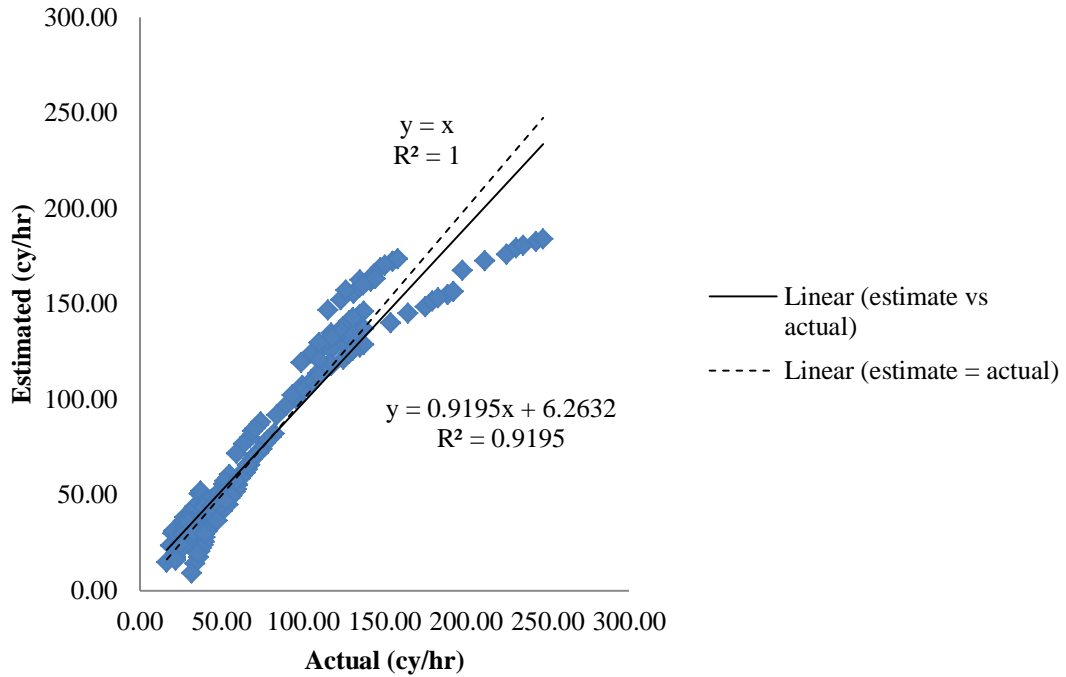


Figure 4.5. Actual and estimated productivity for excavator - RSMeans

The response variable of productivity was based on the hourly productivity rate in loose cubic yard per hour (bcy/hr). The predictor variables included a range of engine size (54-523 hp), bucket size (0.48-6.1 cy), cycle time (13.3-45 second), operational efficiency (0.67-1), and soil type (sandy clay, sand-gravel, hard clay, rock well-blasted, and rock poor-blasted).

Table 4.8. Types of CAT excavator used to develop productivity model

Excavator model	Bucket capacity (lcy)	Engine size (hp)	Picture
CAT-307C	0.48	54	
CAT-311C	1.33	79	
CAT-312C	0.98	96	
CAT-315C	1.13	115	
CAT-318C	1.8	125	
CAT-320D	1.96	138	
CAT-324D	2.6	166	
CAT-325D	2.6	204	
CAT-330D	3	268	
CAT-365C	4.29	404	

From the results of original regression function, it was found that the regression function for predicting productivity accounts for approximately 90% of the variability in the CAT data ( $R^2 = 0.8981$ ). With  $\alpha = 0.05$ , all parameters (including the intercept) in the transformed model had p-values  $< 0.0001$  and were statistically significant. The model selection result by using Mallows' Cp method shows that with  $C(p)$  value of 9.000 and R-square of 0.8527, engine size, bucket size, soil type, cycle time, and operational efficiency can be included in the model. Meanwhile, after ninth step in stepwise selection method, bucket size, cycle time, soil type, operation efficiency, and engine size were included in the model, and gave the R-square value of 0.8527 (Table 4). From these two methods, the final regression model for productivity can include engine size (hp), bucket size (cy), soil type, cycle time (second), and operation efficiency.

With the form of transformed regression function which can be written as:

$$Y = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_p x_{ip} + \varepsilon_i \quad (4-63)$$

the CAT productivity models of excavator for all types of soil are shown in Table 4.9.

Table 4.9. Productivity models for excavator – CAT

Soil type	Productivity models
Sandy clay	$Y = 67.5 - 0.521X_1 + 141.50X_2 - 10.23X_3 + 290.73X_4$ (4-64)
Sand-gravel	$Y = 52.64 - 0.521X_1 + 141.50X_2 - 10.23X_3 + 290.73X_4$ (4-65)
Hard-tough clay	$Y = 38.24 - 0.521X_1 + 141.50X_2 - 10.23X_3 + 290.73X_4$ (4-66)
Rock well-blasted	$Y = -4.97 - 0.521X_1 + 141.50X_2 - 10.23X_3 + 290.73X_4$ (4-67)
Rock poor blasted	$Y = -76.986 - 0.521X_1 + 141.50X_2 - 10.23X_3 + 290.73X_4$ (4-68)

Where:

Y = productivity rate (lcy/hr)

X<sub>1</sub> = engine size (hp)

X<sub>2</sub> = bucket size (lcy)

$X_3$  = cycle time (seconds)  
 $X_4$  = operation efficiency

To validate the model, a plot in Figure 4.6 showing the predicted versus the actual results for the productivity model was made. The plot from the model shows the slope of 0.8198,  $R^2 = 0.8629$ , and intercept = 49.69 lcy/hr, thus, the model was considered to be accurate, precise, but had bias. The estimated productivity has 49.69 lcy/hr more than the actual, when the actual productivity has 0 lcy /hr. It equals to approximately 8 buckets loaded with maximum capacity (6.1 lcy). The lowest bias occurred when the actual productivity is around 400 lcy/hr, and the estimated productivity departed gradually from ideal estimation as the actual productivity increase from 500 lcy/hr to 1500 lcy/hr.

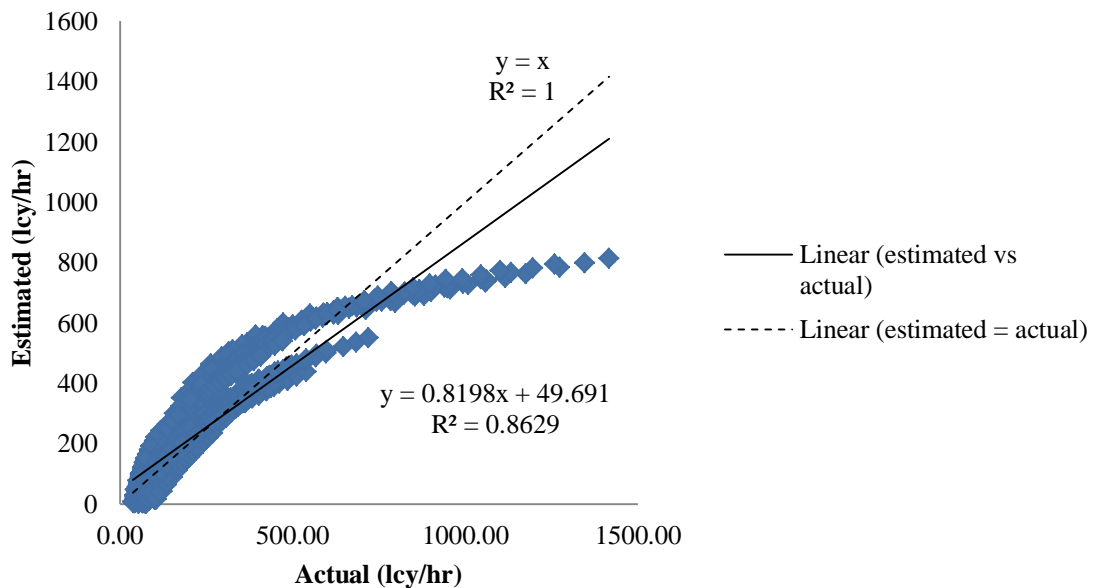


Figure 4.6. Actual and estimated productivity for excavator - CAT

#### 4.1.1.4 Truck

The RSMeans productivity model for truck was based on 240 observations taken from the 'hauling' activity. The response variable of productivity was based on the daily output values for each observation, which was converted to hourly output values based on an eight hour work day, and reported in units of loose cubic yards per hour (lcy/hr). The predictor variables included a range of loading capacity (22-60 lcy), average hauling speed (5-25 miles per hour), cycle distance (0.38-2 miles), and cycle time (15-25 minutes).

From the results of original regression function, it was found that the plot of residuals against the predicted values showed evidence of unequal variance. The unequal error variances and non-normality of the error terms frequently appear together. However, since the number of data is large ( $n = 240$ ), the term of normality is not important, and the transformation to remedy the non-normality is not needed.

The regression function has the value of  $R^2 = 0.9432$ , and give the ability of predicting productivity accounts for approximately 94% of the variability in the RSMeans data. With  $\alpha = 0.05$ , all parameters in the transformed model had p-values  $< 0.0001$  and were statistically significant in predicting productivity. The model selection result by using Mallows' Cp method shows that with  $C(p)$  value of 5.000 and R-square of 0.9432, loading capacity, average speed, cycle distance, and cycle time can be included in the model. Meanwhile, after fifth step in stepwise selection method, loading capacity, cycle distance, cycle time, and average speed were included in the model, and gave the R-square value of 0.9432. From these two methods, the final regression model for

productivity can include loading capacity (lcy), average hauling speed (mph), cycle distance (miles), and cycle time (minutes).

With the form of transformed regression function which can be written as:

$$Y = \beta_0 + \beta_1x_{i1} + \beta_2x_{i2} + \dots + \beta_px_{ip} + \varepsilon_i \quad (4-69)$$

the RSMeans productivity models of truck is written as:

$$Y = 58.799 + 2.079X_1 + 1.625X_2 - 12.056X_3 - 2.789X_4 \quad (4-70)$$

where:

Y = productivity rate (lcy/hr)

X<sub>1</sub> = loading capacity (lcy)

X<sub>2</sub> = average speed (mph)

X<sub>3</sub> = cycle distance (miles)

X<sub>4</sub> = cycle time (minutes)

To validate the model, a plot in Figure 4.7 showing the predicted versus the actual results for the productivity model was made. The plot from the model shows the slope of 0.9432,  $R^2 = 0.9432$ , and intercept = 4.528 lcy/hr, thus, the model was considered to be accurate, precise, and had no bias. Because the data set is large enough (n=240), the model was also validated by using cross-validation procedure or data splitting. 120 observed data were used for model building, and the remaining 120 data were used for model validation. The calculation result of mean squared prediction error (MSPE), by dividing the errors sum of squares with number of data in validation data set, is  $5913/120 = 49.28$ . This result is fairly not too far compared to mean square error (MSE) in model building data set, which is 46.79. It can be concluded that the RSMeans regression model for truck productivity is not seriously biased and gives an appropriate indication of the predictive ability of the model.

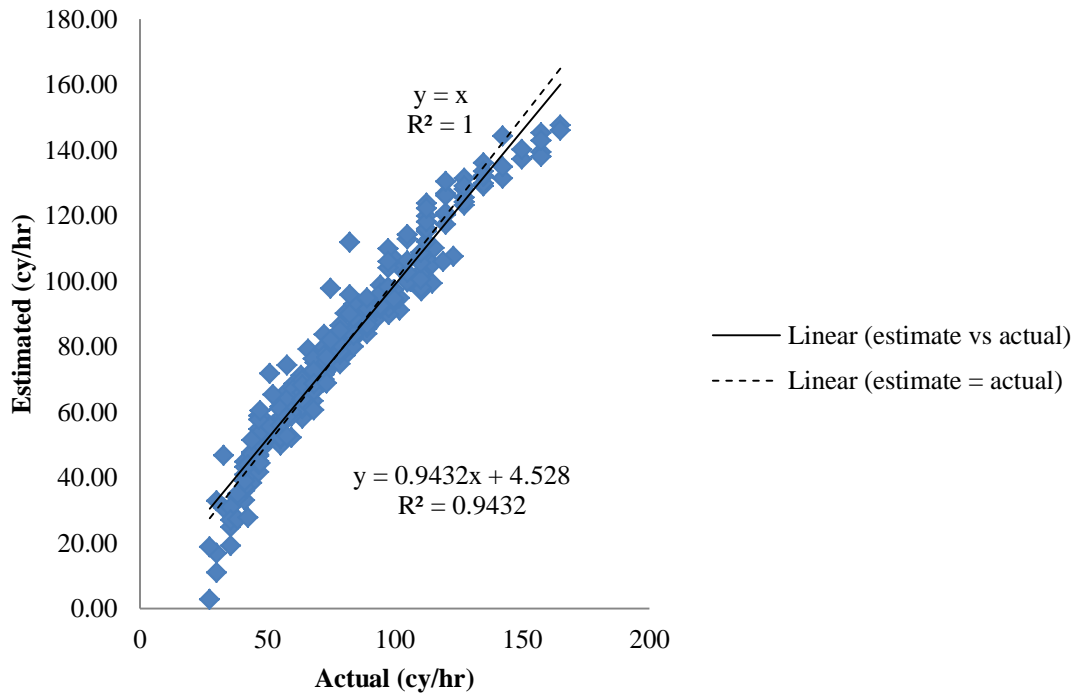


Figure 4.7. Actual and estimated productivity for truck - RSMMeans

The CAT productivity model for truck was based on 4800 possible estimated productivity, which were projected from truck specifications and other information such as supporting excavator activity and operation efficiency. CAT performance handbook only provides the information about truck specification that includes engine size, loading capacity, average hauling speed, dump time, and operation efficiency. To obtain productivity rate, it is assumed that truck has to be dependent on other supporting equipment, such as excavator, to determine the cycle time, especially for loading. Truck cycle time includes loading time, hauling-returning time, and dumping time. The loading time for truck equals to the time that is needed by an excavator to complete the task: to load material fulfilling the truck capacity. For example, to load 21.5 cy soil on truck, a 6.1cy-bucket-size excavator with average cycle time of 0.22 minute, will need 4 full material of buckets or equals to 0.775 minute. Thus, the loading time for truck is 0.775






minute. Since the average hauling speed is given in the specification, and the cycle distance of an off-road truck is in range of 0.22 to 2 miles, the average hauling time for truck can be calculated accordingly.

To generate the regression model for CAT productivity of truck, the predictor variables used includes a range of engine size (476-740 hp), loading capacity (21.5-43.3 cy), average hauling speed (38.6-49.5 mph), cycle distance (0.38-2 miles), cycle time (3.36-33.4 minutes), operation efficiency (0.67-1), excavator's bucket size (1.13-6.1 cy), and excavator's cycle time (0.22-0.67 minutes). The models of truck used in generating the productivity model are shown in Table 4.10. From the results of original regression function, it was found that the regression function for predicting productivity accounts for approximately 85% of the variability in the CAT data ( $R^2 = 0.8465$ ). With  $\alpha = 0.05$ , almost all parameters (including the intercept) in the transformed model had p-values < 0.0001 and were statistically significant, except for engine size (hp).

The engine size is technically related to loading capacity or size; bigger engine size has bigger loading capacity. From the result of Pearson Correlation Coefficients tests, it was also found that there is strong linear correlation between engine horsepower (hp) and loading capacity (0.641 with p-value < 0.0001). Based on the result of correlation test, the regression model has to exclude whether the engine size or loading capacity.



Table 4.10. Types of CAT truck used to develop productivity model

Truck model	Loading capacity (lcy)	Average speed (mph)	Engine size (hp)	Picture
CAT-770	21.5	46.5	476	
CAT-772	30.5	49.5	535	
CAT-773E	34.8	38.6	671	
CAT-773F	35	41.9	703	
CAT-775F	43.3	41.9	740	

The model selection result by using Mallor’s Cp method shows that with C(p) value of 7.474 and R-square of 0.8510, loading capacity, hauling speed, cycle distance, bucket size, excavator’s cycle time, truck’s cycle time, and operation efficiency can be included in the model. Meanwhile, after eight steps in stepwise selection method, truck’s cycle time, loading capacity, operation efficiency, bucket size, excavator’s cycle time, cycle distance, and hauling speed were included in the model, and gave the R-square

value of 0.8510. From these two methods, the final regression model for productivity can include loading capacity (cy), hauling speed (mph), cycle distance (miles), excavator's bucket size (cy), excavator's cycle time (minutes), truck's cycle time (minutes), and operation efficiency.

With the form of transformed regression function which can be written as:

$$Y = \beta_0 + \beta_1x_{i1} + \beta_2x_{i2} + \dots + \beta_px_{ip} + \varepsilon_i \quad (4-71)$$

the CAT productivity models of dump truck for all types of soil are shown as:

$$Y = -89.111 + 3.35X_1 + 1.01X_2 - 23.02X_3 + 18.36X_4 - 133.03X_5 - 3.94X_6 + 202.96X_7 \quad (4-72)$$

Where:

Y = productivity rata (cy/hr)

X1 = loading capacity (cy)

X2 = hauling speed (mph)

X3 = cycle distance (miles)

X4 = bucket size (cy)

X5 = excavator's cycle time (minutes)

X6 = truck's cycle time (minutes)

X7 = operation efficiency

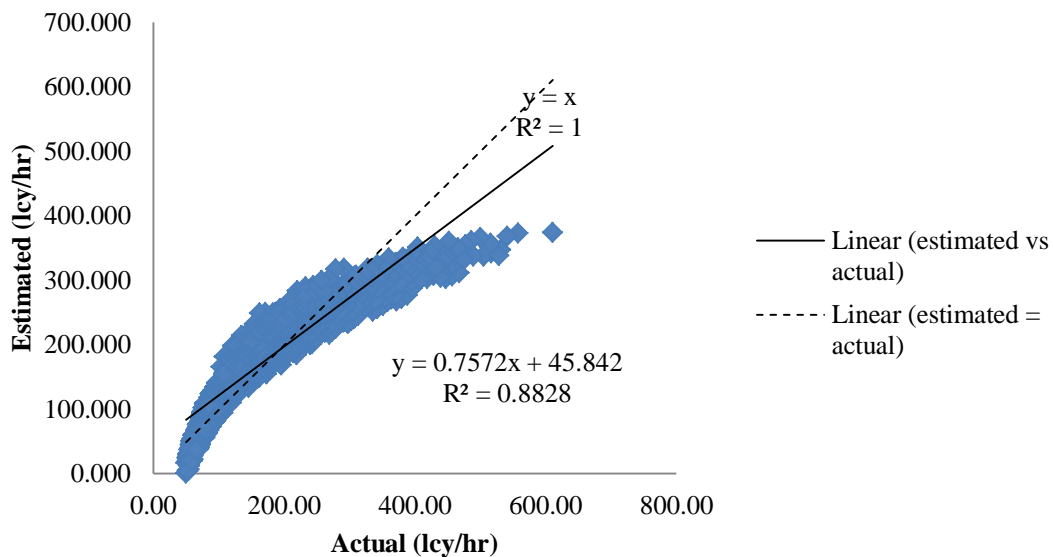


Figure 4.8. Actual and estimated productivity for truck - CAT

To validate the model, a plot in Figure 4.8 showing the predicted versus the actual results for the productivity model was made. The plot from the model shows the slope of 0.7572,  $R^2 = 0.8828$ , and intercept = 45.84 lcy/hr, thus, the model was considered to be accurate, precise, but had bias.

#### **4.1.2 Model Comparison**

The purpose of this part is to evaluate how the regression models of productivity from two data sources; RSMMeans Data and CAT Data, predict the productivity rate for the activities based on each data source. The comparisons of these two productivity models will be based on some key factors or predictors, such as engine size, working distance, soil types, or bucket/blade capacity, are presented. The comparison of estimated fuel use is also presented to show the magnitude of working duration of each type of equipment.

As an initial step towards developing the emissions estimating tool, modeling the productivity rate of HDD equipment is important. Air pollutants and greenhouse gas emissions are direct by-products of fuel consumption, and fuel consumption is dependent upon equipment productivity. Productivity is simply defined as the ratio of the quantity of work completed to the duration of time for completing the work. This definition also reveals that the duration of an equipment activity is inversely proportional to productivity; as productivity increases, the duration decreases or vice versa. The duration has the key role in estimating fuel use, cost, and emissions from a HDD equipment. The

increase of duration typically results in higher cost, higher fuel consumption, and higher emissions.

#### **4.1.2.1 Bulldozer**

Although in the previous sections both models were proven statistically accurate, precise, and had no bias, there are obvious differences between the two. For example, the RSMMeans model is based only on three input variables whereas CAT model is based on eight input variables. Both models included engine size, dozing distance, and soil type, but CAT model included additional information, such as blade capacity, operational efficiency, site slope, operator's skill, and dozing technique. At this analysis, it is difficult to conclude that the RSMMeans model is simpler because it has fewer input variables to consider.

The comparison of the two models is based on similar range of input or predictor variables. Since the range of RSMMeans model predictor variables is lesser than CAT model, the input variables for the comparison are selected as fit as possible to the RSMMeans predictor's range. The comparison used 80-700 hp of engine size, 50-300 feet of distance, and all the same type of soil. The blade capacity from CAT model is applied by using the nearest related engine size from the CAT bulldozer specification. For comparison, average skill operator slot dozing technique were used. For the unit of productivity, bank cubic yard per hour (bcy/hr) from RSMMeans model had to be converted first to loose cubic yard per hour (lcy/hr) as used in CAT model.

As shown in Figure 4.9 and 4.10, the difference in the two models is the magnitude of the productivity results; it is apparent that the CAT model produces much

higher results than the RSMeans model. It means that using RSMeans model gives more duration for the same quantity of soil comparing to CAT model. As the function of either engine size or dozing distance, the CAT model gives the productivity three or four times higher than RSMeans model. Furthermore, in a relation to dozing distance, there is an inverse relationship (Figure 4.9), where the productivity rates of bulldozer from both models decrease as the dozing distance increases. For different soil types, the estimated productivity curves for each soil type has the same general shape. For both models, based on dozing distance, sand-gravel type of soil gives highest productivity for bulldozer, while clay has the lowest productivity rate.

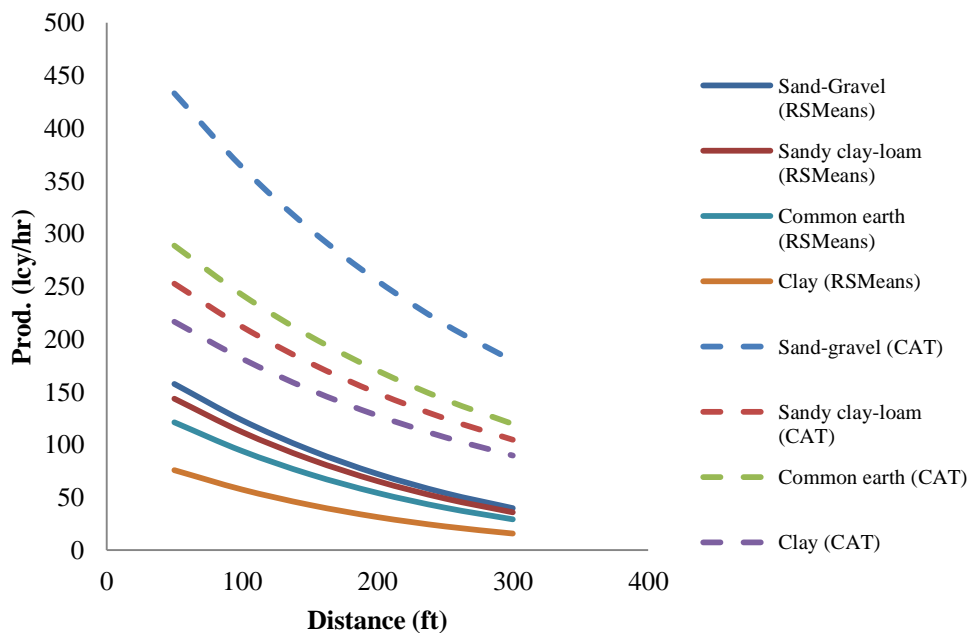


Figure 4.9. Bulldozer productivity comparison based on distance

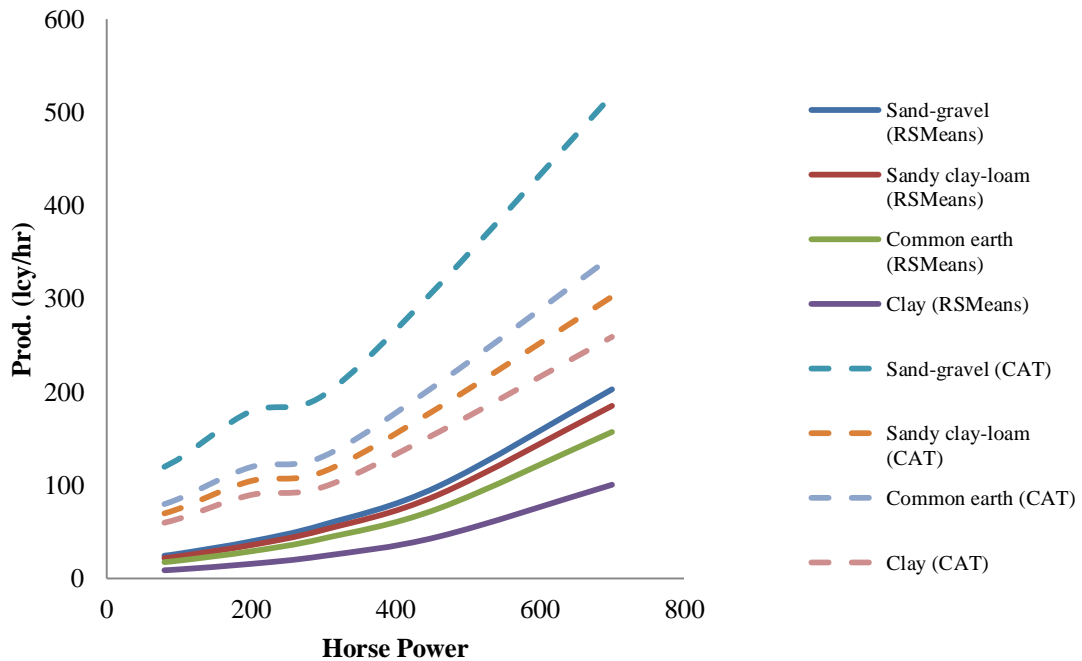


Figure 4.10. Bulldozer productivity comparison based on horsepower

As the function to engine size, there is a positive relationship between productivity rate and bulldozer horsepower for both models (Figure 4.10). The productivity increases as the engine size increases. For different type of soil, sand and gravel gives the highest productivity, while clay gives the bulldozer the lowest productivity. There is little difference or virtually no difference in RSMeans productivity rate with respect to engine size for sand-gravel, sandy clay, and common earth. The similar productivity rate also happened to sandy clay, common earth, and clay for CAT productivity rate.

#### 4.1.2.2 Scraper

The differences between two productivity models for scraper are that the RSMeans model for scraper is based on the type of scraper, type of soil, bucket size, and distance, while the CAT model is based only on numerical variables; engine size, bucket size, rolling resistance, and distance. Both models have distance and bucket size in the productivity model.

To compare these two models, some range of predictor variables are selected to fit with both models' range. For example, the bucket size is selected in the range of 10-21 cy, and the distance is selected within the range of 2000-3500 feet. Types of soil used in the RSMeans model are converted to nearest related rolling capacity in the CAT model. For example, sand-gravel is substituted with 0.02 rolling resistance, common earth with 0.06, and clay with 0.1. The comparison of productivity is based on various bucket capacity and distance.

Figure 4.11 shows that there is a positive relationship between bucket size or capacity with the productivity rate for both models. As the bucket used is bigger, then the productivity rate is higher. Generally, it can be said that the average estimated productivity from CAT model is higher than those from RSMeans model. However, for 10 to 14 cy of bucket size, RSMeans model estimates the productivity model for clay higher than CAT model. The productivity of different type of soil in CAT model looks more considerable compared to those from RSMeans model, and showed that the change in bucket size affects the productivity more intense. It also showed that sand-gravel gives highest productivity rate, while clay gives lowest productivity rate for both scraper productivity models.

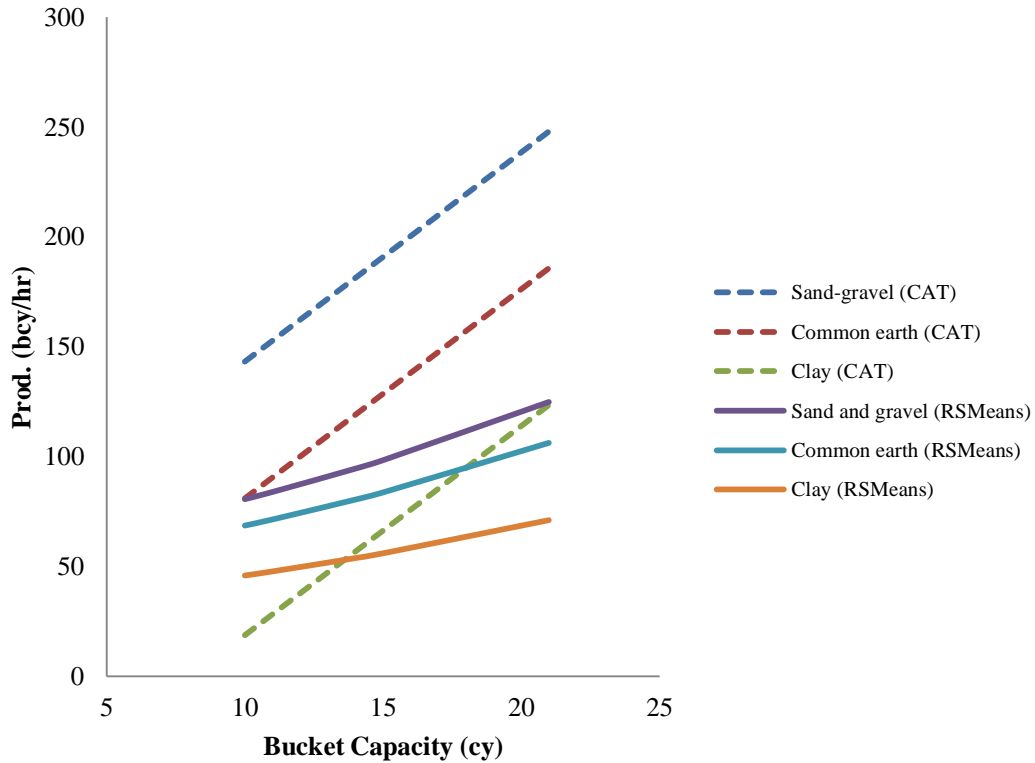


Figure 4.11. Scraper productivity comparison based on bucket capacity

Figure 4.12 shows that there is an inverse relationship between distance and the productivity rate. As the hauling distance increases, the productivity rate decreases. A special case occurred when scraper has to haul sand-gravel within range of 1500 to 2000 feet; the productivity rate increases and then decrease after 2000 feet. Again, the CAT model estimates the productivity higher than the RSMeans model with more significantly different productivity rate among different types of soil. However, when the scraper hauls clay for more than 3200 feet, RSMeans estimates higher productivity than CAT model. For both models, sand-gravel gives highest productivity, while clay has the lowest productivity rate for scraper.



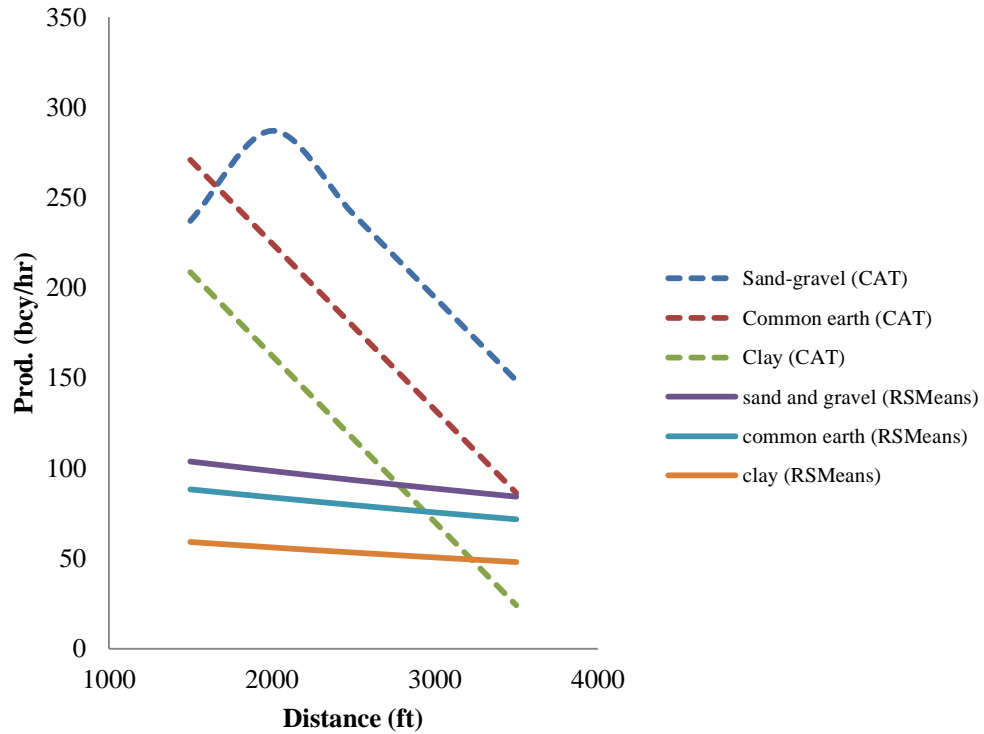


Figure 4.12. Scraper productivity comparison based on distance

#### 4.1.2.3 Excavator

The comparison of RSMMeans and CAT model for scraper is only based on the relationship between the productivity rate and the bucket size for different types of soil. It is because only bucket size which is included in both models. For the purpose of comparison, both models used the range of 1 to 3.5 cy of bucket size. The CAT model used 20 seconds of cycle time with 100% of efficiency, which are assumed to apply on the excavator on RSMMeans model. Since the soil quantity to excavate on CAT model is 1000 lcy, the bank cubic yard volume of soil used in the RSMMeans has to be converted to loose cubic yard by using appropriate swell factors.

Figure 4.13 shows that generally, the estimated productivity from CAT model is higher than those from RSMMeans model. It also shows that there is a positive relationship between the bucket size and the productivity rate. As the excavator uses bigger size of bucket, the productivity will increase. Although there is no significant difference of productivity among all types of soil, both models have different facts about which type of soil made the excavator more productive. Using CAT model, the excavator has highest productivity while digging sandy clay, and lowest in hard-clay. Meanwhile, the RSMMeans model shows that the lowest productivity occurred in hard-clay, and both sandy-clay and gravel are about the same.

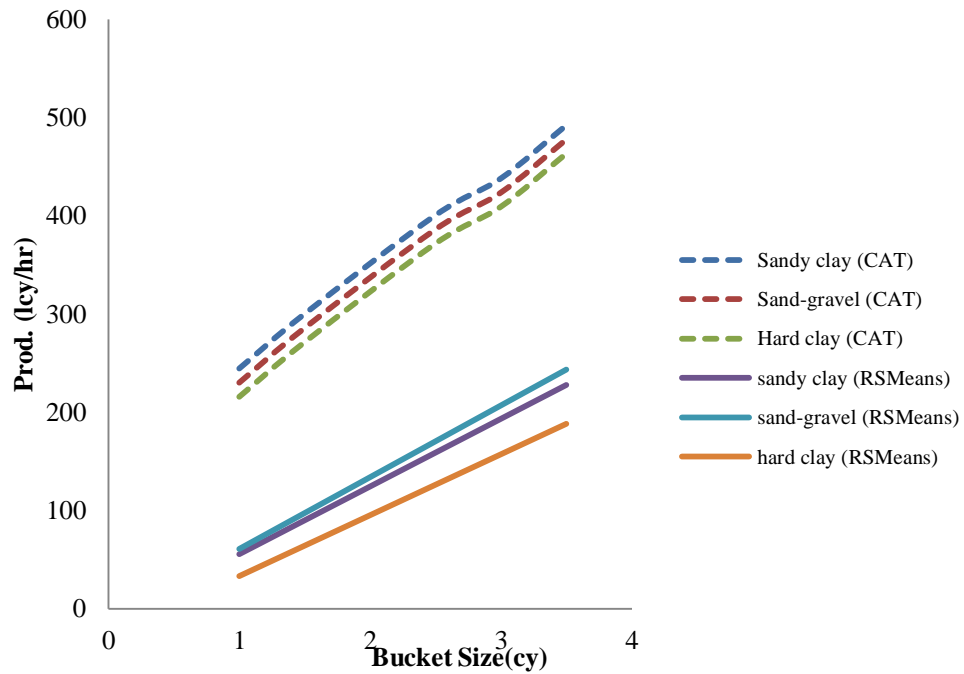


Figure 4.13. Excavator productivity comparison based on bucket size

#### 4.1.2.4 Truck

Both RSMeans model and CAT model have truck loading capacity, average hauling speed, and cycle distance in estimating productivity. The main difference of these two models is about truck's cycle time. RSMeans data have provided the productivity data with truck's cycle time, while in the CAT data the cycle time has to be estimated by breaking down the total time to its components; loading time, average hauling time (both loaded and empty), and dumping or waiting time.

To compare the RSMeans and CAT model, the relationship between the productivity rate with hauling distance and loading capacity were presented. The hauling distance used in the comparison is within range of 0.30 to 2 miles, and 22 to 60 cy for loading capacity. The comparison also applied to different total cycle time for trucks and different average hauling speed. Different cycle time represents how the supporting equipment (excavator) affects the cycle time, while different hauling speed –as specified in CAT's excavator specification- represents the model or size of truck engine.

Figure 4.14 and Figure 4.15 shows that the overall estimated productivity from two models are about the same, either as function of hauling distance or loading capacity. Figure 4.14 shows that, for both models, there is an inverse relationship between productivity and hauling distance. As hauling distance increases, the productivity rate decreases. In comparison of two models, it shows that in 15 minutes cycle time and within distance of 0.38 to 1.7 miles, RSMeans model estimated productivity higher than CAT model, and change oppositely after 1.7 miles. In 20 minutes cycle time, RSMeans model estimation is higher at 0.38 to 1.2 miles of hauling distance , while in 25 minutes cycle time, RSMeans' higher estimation occurred only at less than 0.6 miles of distance.

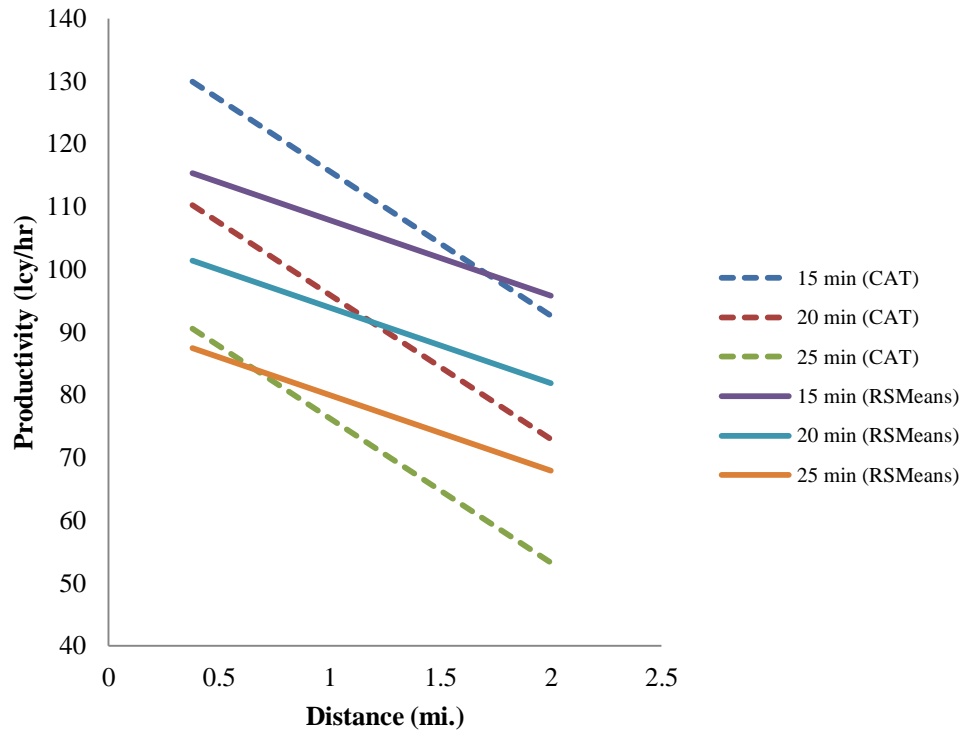


Figure 4.14. Truck productivity comparison based on distance

Figure 4.15 shows that, for both models and all average hauling speed, there is a positive relationship between productivity and loading capacity. As loading capacity increases, the productivity rate increases. The overall productivity estimation from both RSMeans and CAT models are relatively the same until the truck using 50 cy of loading capacity. When the truck uses the loading capacity of 50 cy or more, the CAT model estimate the productivity higher than those from RSMeans model.

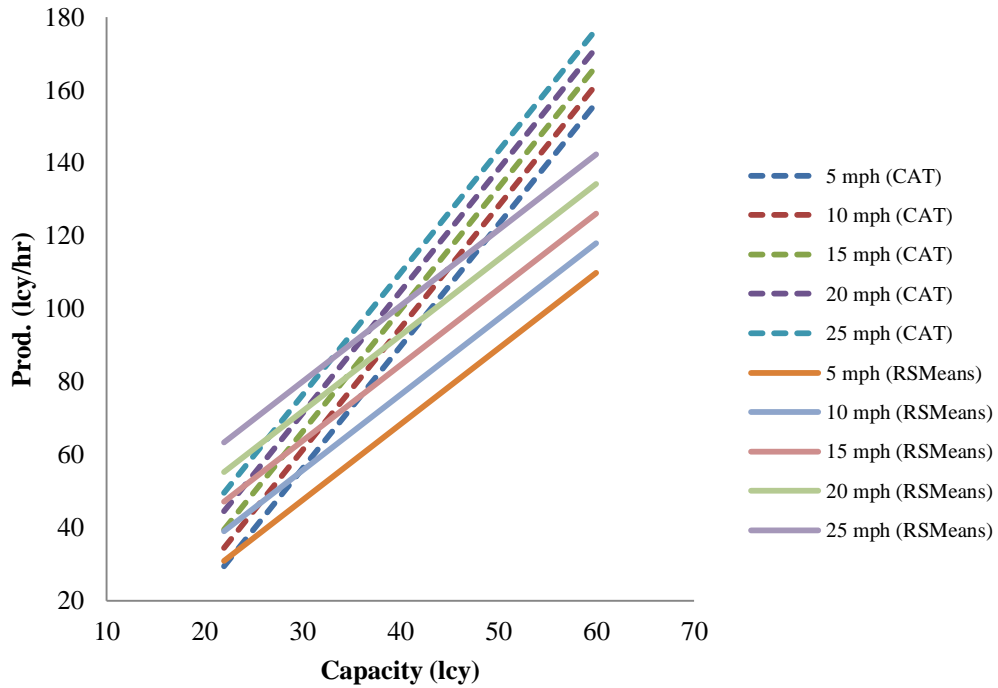


Figure 4.15. Truck productivity comparison based on loading capacity

## 4.2 Cost Models Building and Validation

The cost model is only built from RSMMeans Heavy Construction data, since CAT Performance Handbook does not provide unit cost information. As previously done for productivity models, the steps for the building of unit cost regression model involves three following phases: model building, model selection, and model validation. During the model building process, it needs to examine whether all of the potential ‘X’ variables are needed or whether a subset of them is adequate (Kutner et al, 2004). A number of useful measures have been developed to assess the adequacy of various subsets of ‘X’ variables. For the purpose of this research, one manual selection method: Mallow’s  $C_p$ ,

and an automatic model selection method: stepwise regression selection are used to develop best subset of 'X' variables

The final step in the model building process is the validation of the selected regression model. The cost models in this research are validated by using two methods: data splitting for large data set, and a plot showing comparison of predicted and actual data. In data splitting method, the original data set are split into a model-building set and a validation set (Kutner et al, 2004). The model-building set is used to develop the model. The validation set is used to evaluate the reasonableness and predictive ability of the selected model. A means of measuring the actual predictive ability is to use the model to predict each case in the validation data set and then to calculate the mean of the squared prediction errors, denoted by MSPR or *mean squared prediction error*. If the MSPR is fairly close to the MSE based on the regression fit to the model-building data set, then MSE for the selected regression model is not seriously biased and gives an appropriate indication of the predictive ability of the model.

The plot showing the predicted versus the actual result of cost model is used to identify the accuracy, precision, and bias of the model. Ideally, a plot of the predicted versus the actual results will produce a line with a slope of 1.0 (accurate),  $R^2 = 1.0$  (precise), and y-intercept = 0 (no-bias).

#### **4.2.1 Bulldozer**

The RSMeans cost model for bulldozer was based on 72 observations taken from the 'excavation bulk-dozer' activity. The response variable of unit cost was based on the sum of total labor and equipment costs plus overhead and profit, reported in units of

dollars per cubic yard (\$/cy). The predictor variables included a range of engine sizes (80-700 horsepower), dozing distance (50-300 feet), and soil types (sand-gravel, sandy clay-loam, common earth, and clay). Soil type was treated as a categorical variable with a value of 0 or 1, depending on the type of soil under consideration.

To build cost model, the data is split into two parts; model building data set and model validation data set. Since the number of data is more than 10 times of the number of predictors, the data can be equally. From the results of original regression function, it was found that the plot of residuals against the predicted values showed evidence of unequal variance. The unequal error variances and non-normality of the error terms frequently appear together.

To remedy the non-normality in the data, a Box-Cox analysis has been conducted. Based on the transformed regression equations, the value of  $R^2 = 0.9741$  showed that the cost model for bulldozer accounts approximately 97% of the variability of the RSMears data. With  $\alpha = 0.05$ , all parameters (including the intercept) in the transformed model had p-values  $< 0.0001$  and were statistically significant. The model selection result by using Mallows' Cp method shows that with C(p) value of 4.3851 and R-square of 0.9737, engine horsepower, dozing distance, and soil type can be included in the model. Meanwhile, after fourth step in stepwise selection method, dozing distance, soil type, and engine horsepower were included in the model, and gave the R-square value of 0.9737. From these two methods, the final regression model for unit cost can include bulldozer horsepower (hp), dozing distance (feet), and type of soil.

With the form of transformed regression function which can be written as:

$$\log Y = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_p x_{ip} + \varepsilon_i \text{ or,} \quad (4-73)$$

$$Y = e^{(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_p x_{ip} + \varepsilon_i)} \quad (4-74)$$

the overall cost models of bulldozer for all types of soil are shown in the Table 4.11.

Table 4.11. Cost models for bulldozer

Soil Type	Cost Model	
Sand-gravel	$Y = e^{(0.986 - 0.00398X_1 + 0.0058X_2)}$	(4-75)
Sandy clay-loam	$Y = e^{(1.021 - 0.00398X_1 + 0.0058X_2)}$	(4-76)
Common earth	$Y = e^{(1.13 - 0.00398X_1 + 0.0058X_2)}$	(4-77)
Clay	$Y = e^{(1.565 - 0.00398X_1 + 0.0058X_2)}$	(4-78)

where:

Y = unit cost (\$/cy)

X<sub>1</sub> = engine horsepower (hp)

X<sub>2</sub> = dozing distance (feet)

To validate the model, a plot in Figure 4.16 showing the predicted versus the actual results for the cost model was made. The plot from the model shows the slope of 1.0564, R<sup>2</sup> = 0.9454, and intercept = 0.091 \$/cy, thus, the model was considered to be accurate, precise, and had no bias. In cross-validation procedure, the data were split to two: 36 data for model building and 36 data for model validation. The calculation result of mean squared prediction error (MSPE), by dividing the errors sum of squares with number of data in validation data set, is 0.22355/36 = 0.0062. This result is fairly not too far compared to mean square error (MSE) in model building data set, which is 0.01431. It can be concluded that the regression model for bulldozer unit cost is not seriously biased and gives an appropriate indication of the predictive ability of the model.



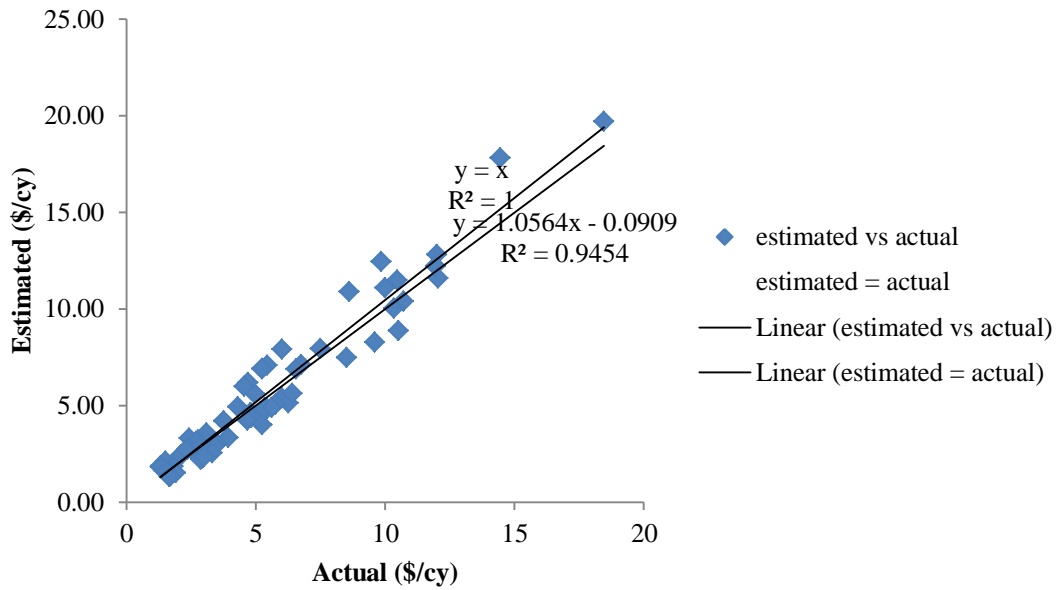


Figure 4.16. Actual and estimated cost for bulldozer

#### 4.2.2 Scraper

The RSMeans cost model for scraper was based on 60 observations taken from the ‘excavation bulk-scraper’ activity. The response variable of unit cost was based on the sum of total labor and equipment costs plus overhead and profit of each observed data, reported in units of dollars per cubic yard (\$/cy). The predictor variables included a range of bucket size (11-21 cy), distance (1500-5000 feet), type of scraper (elevated scraper, self-propelled scraper, and towed), and soil types (sand-gravel, sandy clay-loam, common earth, and clay). Soil type and type of scraper were treated as a categorical variable with a value of 0 or 1, depending on the type of soil under consideration.

From the results of original regression function, it was found that the plot of residuals against the predicted values showed evidence of unequal variance. The unequal error variances and non-normality of the error terms frequently appear together.

To remedy the non-normality in the data, a Box-Cox analysis has been conducted and the result recommended the best lambda ( $\lambda$ ) for transforming the response variables (Y) is 0. After transformation, the regression model for unit cost is formulated as:

$$\log Y = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_p x_{ip} + \varepsilon_i, \text{ or} \quad (4-79)$$

$$Y = e^{(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_p x_{ip} + \varepsilon_i)} \quad (4-80)$$

Based on the transformed regression equations, the value of  $R^2 = 0.9903$  showed that the cost model for bulldozer accounts approximately 99% of the variability of the RSMMeans data. With  $\alpha = 0.05$ , only bucket size has p-value = 0.75, and this variable is not significant for the model.

The model selection result by using Mallows' Cp method shows that with  $C(p)$  value of 5.1038 and R-square of 0.9903, type of scraper, soil type, and distance can be included in the model. Meanwhile, after sixth step in stepwise selection method, soil type, distance, and type of scraper were included in the model, and gave the R-square value of 0.9903. From these two methods, the final regression model for unit cost can include distance (feet), type scraper, and type of soil. The overall cost models for scraper are shown in Table 4.12.

To validate the model, a plot in Figure 4.17 showing the predicted versus the actual results for the cost model was made. The plot from the model shows the slope of 0.9303,  $R^2 = 0.9112$ , and intercept = 0.3883 \$/cy, thus, the model was considered to be accurate, precise, and had no bias. In cross-validation procedure, the data were split to two: 30 data for model building and 30 data for model validation. The calculation result of mean squared prediction error (MSPE), by dividing the errors sum of squares with number of data in validation data set, is  $0.01466/30 = 0.00049$ . This result is fairly not

too far compared to mean square error (MSE) in model building data set, which is 0.00018. It can be concluded that the regression model for bulldozer productivity is not seriously biased and gives an appropriate indication of the predictive ability of the model.

Table 4.12. Cost models for scraper

Type of scraper	Soil type	Cost models	
Elevated scraper	Sand-gravel	$Y = 10^{(0.505 + 0.000045X_1)}$	(4-81)
	Common earth	$Y = 10^{(0.565 + 0.000045X_1)}$	(4-82)
	Sandy-clay loam	$Y = 10^{(0.528 + 0.000045X_1)}$	(4-83)
	Clay	$Y = 10^{(0.769 + 0.000045X_1)}$	(4-84)
Self-propelled scraper	Sand-gravel	$Y = 10^{(0.475 + 0.000045X_1)}$	(4-85)
	Common earth	$Y = 10^{(0.535 + 0.000045X_1)}$	(4-86)
	Sandy-clay loam	$Y = 10^{(0.489 + 0.000045X_1)}$	(4-87)
	Clay	$Y = 10^{(0.737 + 0.000045X_1)}$	(4-88)
Towed	Sand-gravel	$Y = 10^{(0.475 + 0.000045X_1)}$	(4-89)
	Common earth	$Y = 10^{(0.535 + 0.000045X_1)}$	(4-90)
	Sandy-clay loam	$Y = 10^{(0.489 + 0.000045X_1)}$	(4-91)
	Clay	$Y = 10^{(0.737 + 0.000045X_1)}$	(4-92)

Where:

Y = unit cost (\$/cy)

X<sub>1</sub> = distance (feet)

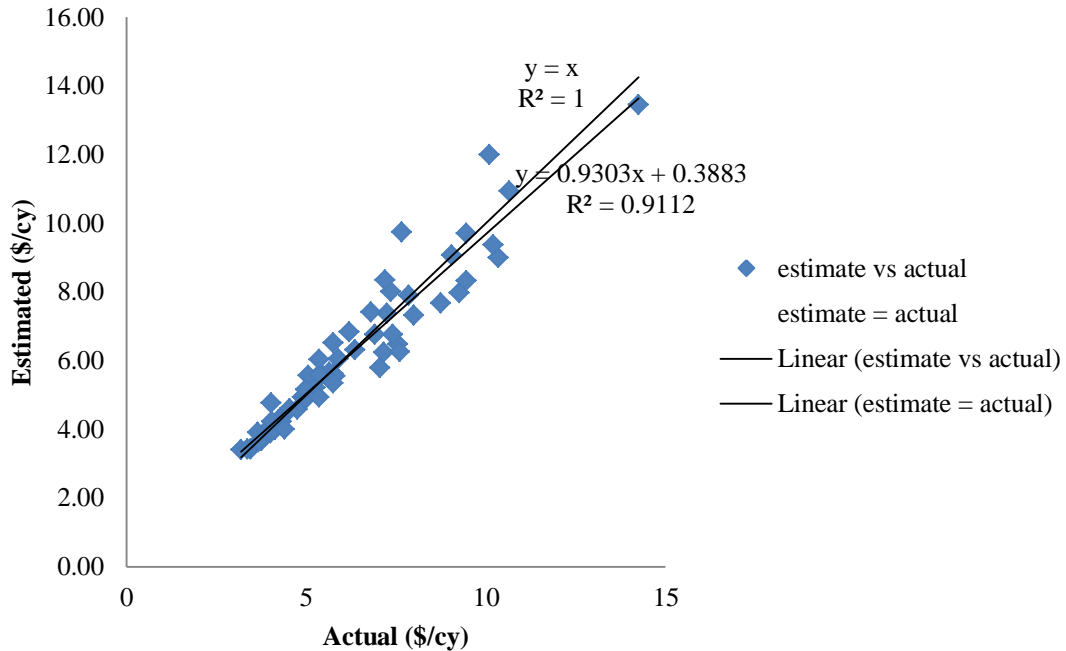


Figure 4.17. Actual and estimated cost for scraper

### 4.2.3 Excavator

The RSMeans cost model for excavator was based on 195 observations taken from the ‘excavation trench’ activity. The response variable of unit cost was based on the sum of total labor and equipment costs plus overhead and profit of each observed data, reported in units of dollars per cubic yard (\$/cy). The predictor variables included a range of trench depth (2.5-22 feet), bucket size (0.375-3.5 cy), type of excavator (excavator, excavator-truck mounted, and excavator-trench box), and soil types (common earth, loam-sandy clay, sand-gravel, and hard clay). Soil type and type of excavator were treated as a categorical variable with a value of 0 or 1.

From the results of original regression function, it was found that the plot of residuals against the predicted values showed evidence of unequal variance. The unequal

error variances and non-normality of the error terms frequently appear together. However, since the number of data is large ( $n = 195$ ), the term of normality is not important, and the transformation to remedy the non-normality is not needed.

The regression function has the value of  $R^2 = 0.6916$ , and give the ability in predicting unit cost accounts for approximately 70% of the variability in the RSMMeans data. With  $\alpha = 0.05$ , all parameters in the transformed model had p-values  $< 0.0001$  and were statistically significant. The model selection result by using Mallows' Cp method shows that with  $C(p)$  value of 5.135 and R-square of 0.6897, soil type, trench depth, bucket size, and type of excavator can be included in the model. Meanwhile, after sixth step in stepwise selection method, trench depth, soil type, type of excavator, and bucket size were included in the model, and gave the R-square value of 0.6897. From these two methods, the final regression model for unit cost can include bucket size (cy), trench depth (feet), soil type, and type of excavator.

With the form of transformed regression function which can be written as:

$$Y = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_p x_{ip} + \varepsilon_i \quad (4-93)$$

the overall RSMMeans cost models of excavator for all types of soil and types of excavator are shown in the Table 4.13.

Table 4.13. Cost models for excavator

Type of excavator	Soil type	Cost models	
Excavator	Common earth	$Y = 7.056 + 0.045X_1 - 1.658X_2$	(4-94)
	Loam-sandy clay	$Y = 6.654 + 0.045X_1 - 1.658X_2$	(4-95)
	Sand-gravel	$Y = 6.570 + 0.045X_1 - 1.658X_2$	(4-96)
	Hard clay	$Y = 7.703 + 0.045X_1 - 1.658X_2$	(4-97)
Excavator-truck mounted	Common earth	$Y = 8.044 + 0.045X_1 - 1.658X_2$	(4-98)
	Loam-sandy clay	$Y = 7.642 + 0.045X_1 - 1.658X_2$	(4-99)
	Sand-gravel	$Y = 7.558 + 0.045X_1 - 1.658X_2$	(4-100)
	Hard clay	$Y = 8.691 + 0.045X_1 - 1.658X_2$	(4-101)
Excavator-trench box	Common earth	$Y = 7.623 + 0.045X_1 - 1.658X_2$	(4-102)
	Loam-sandy clay	$Y = 7.221 + 0.045X_1 - 1.658X_2$	(4-103)
	Sand-gravel	$Y = 7.137 + 0.045X_1 - 1.658X_2$	(4-104)
	Hard clay	$Y = 8.269 + 0.045X_1 - 1.658X_2$	(4-105)

Where:

Y = unit cost (\$/cy)

X<sub>1</sub> = trench depth (feet)

X<sub>2</sub> = bucket size (cy)

To validate the model, a plot in Figure 4.18 showing the predicted versus the actual results for the cost model was made. The plot from the model shows the slope of 0.6916,  $R^2 = 0.6916$ , and intercept = 1.51 \$/cy, thus, the model was considered to be accurate, precise, and had no bias. Because the data set is large enough (n=195), the model was also validated by using cross-validation procedure or data splitting. 101 observed data were used for model building, and 94 data were used for model validation. The calculation result of mean squared prediction error (MSPE), by dividing the errors sum of squares with number of data in validation data set, is  $103.097/94 = 1.097$ . This result is fairly not too far compared to mean square error (MSE) in model building data set, which is 1.31. It can be concluded that the regression model for excavator unit cost is not seriously biased and gives an appropriate indication of the predictive ability of the model.

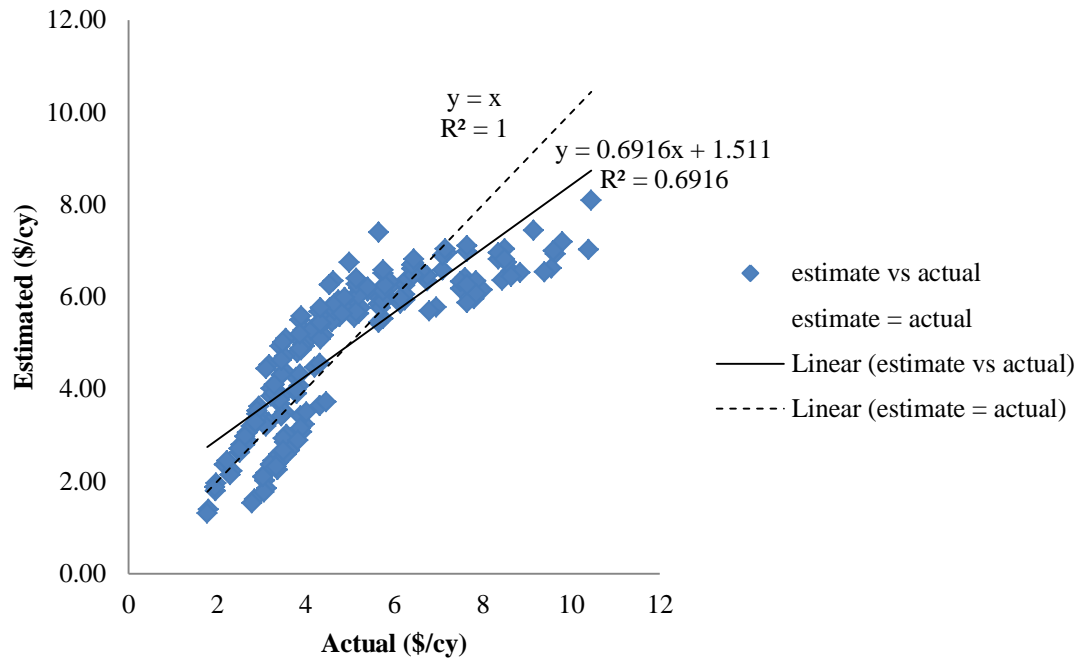


Figure 4.18. Actual and estimated cost for excavator

#### 4.2.4 Truck

The RSMeans cost model for truck was based on 240 observations taken from the ‘hauling’ activity. The response variable of unit cost was based on the sum of total labor and equipment costs plus overhead and profit of each observed data, reported in units of dollars per cubic yard (\$/cy). The predictor variables included a range of loading capacity (22-60 lcy), average hauling speed (5-25 miles per hour), cycle distance (0.38-2 miles), and cycle time (15-25 minutes).

From the results of original regression function, it was found that the plot of residuals against the predicted values showed evidence of unequal variance. The unequal error variances and non-normality of the error terms frequently appear together.

However, since the number of data is large ( $n = 240$ ), the term of normality is not important, and the transformation to remedy the non-normality is not needed.

The regression function has the value of  $R^2 = 0.8793$ , and give the ability of predicting unit cost accounts for approximately 88% of the variability in the RSMMeans data. With  $\alpha = 0.05$ , all parameters in the transformed model had p-values  $< 0.0001$  and were statistically significant is predicting productivity. The model selection result by using Mallows' Cp method shows that with  $C(p)$  value of 5.000 and R-square of 0.8793, loading capacity, average speed, cycle distance, and cycle time can be included in the model. Meanwhile, after fifth step in stepwise selection method, loading capacity, cycle distance, cycle time, and average speed were included in the model, and gave the R-square value of 0.8793. From these two methods, the final regression model for productivity can include loading capacity (lcy), average hauling speed (mph), cycle distance (miles), and cycle time (minutes).

With the form of transformed regression function which can be written as:

$$Y = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_p x_{ip} + \varepsilon_i \quad (4-106)$$

the RSMMeans cost models of truck is written as:

$$Y = 3.203 - 0.056X_1 - 0.098X_2 + 0.709X_3 + 0.143X_4 \quad (4-107)$$

where:

$Y$  = unit cost (\$/cy)

$X_1$  = loading capacity (lcy)

$X_2$  = average speed (mph)

$X_3$  = cycle distance (miles)

$X_4$  = cycle time (minutes)

To validate the model, a plot in Figure 4.19 showing the predicted versus the actual results for the cost model was made. The plot from the model shows the slope of



0.881,  $R^2 = 0.8793$ , and intercept = 0.4551 \$/cy, thus, the model was considered to be accurate, precise, and had no bias. Because the data set is large enough (n=240), the model was also validated by using cross-validation procedure or data splitting. 120 observed data were used for model building, and the remaining 120 data were used for model validation. The calculation result of mean squared prediction error (MSPR), by dividing the errors sum of squares with number of data in validation data set, is  $15.028/120 = 0.125$ . This result is fairly not too far compared to mean square error (MSE) in model building data set, which is 0.153. It can be concluded that the RSMeans regression model for truck unit cost is not seriously biased and gives an appropriate indication of the predictive ability of the model.

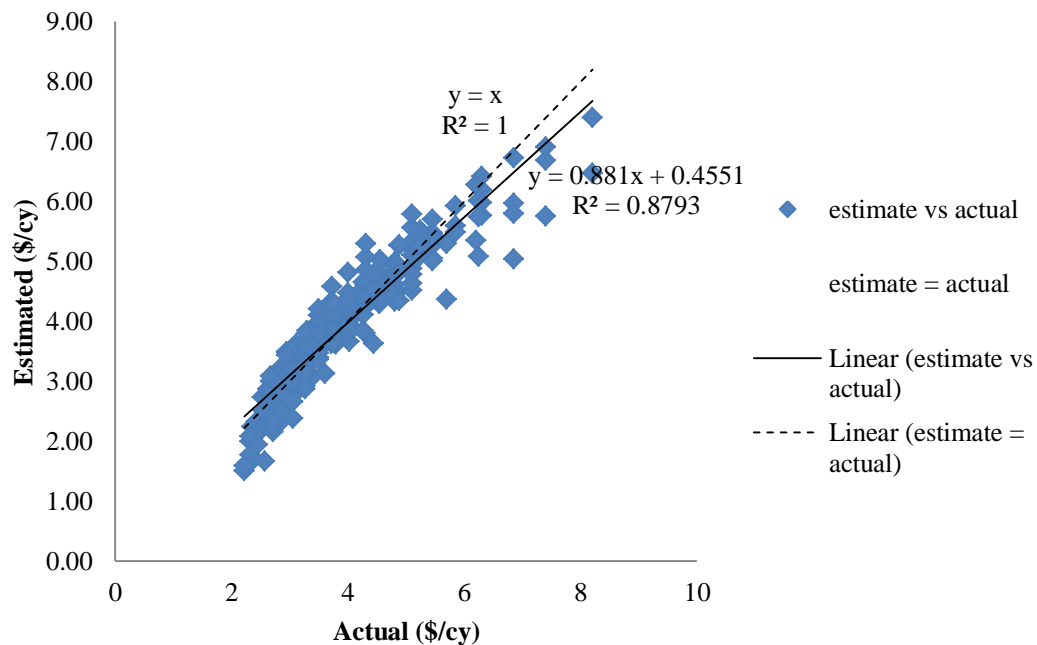


Figure 4.19. Actual and estimated cost for truck

### **4.3. Economic-Energy-Environmental (E3) Model**

The economic-energy-environmental (E3) model is developed by using productivity and cost models built from RSMMeans Heavy Construction data, combined with EPA's NONROAD model. RSMMeans data is the most powerful and nationally accepted construction tool available to construct estimates and as reference for current construction productivity and cost for any type of project. The 'economic' term is represented by cost models, and formulating the total cost required to complete a certain quantity of soil by a specific type of equipment. The 'energy' term is used to quantify the total amount of fuel needed to perform a specific type of earthwork activity. The total fuel use is obtained by using the productivity model combined with NONROAD's brake-specific-fuel-consumption (BSFC). Total estimated emissions of pollutants (NO<sub>x</sub>, PM, CO, HC), and greenhouse gas (CO<sub>2</sub>) determine the term 'environmental'. The total emissions are calculated by using productivity models to obtain activity duration, and NONROAD model to obtain emission factors.

#### **4.3.1 Total Cost Estimation Model – ECONOMIC**

The 'economic' model in E3 model is the total cost estimation model. The model is formulated by using unit cost model from RSMMeans data and multiplied by the quantity of soil dozed or hauled or excavated by a specific type of equipment. The unit cost is expressed in the unit of dollars per cubic yard (\$/cy), the quantity of soil in term of cubic yard (cy), and the total cost is in dollars (\$). The overall total cost estimating models for bulldozer, scraper, excavator, and truck are shown in Table 4.14.

Table 4.14. Total cost models for all type of HDD equipment

<b>Equipment</b>	<b>Total cost model</b>	
Bulldozer	Total cost (\$) = $(10^{1.565 - 0.00398HP + 0.0058D - fs}) \times Q$	(4-108)
	<i>fs</i> (soil type factor): sand-gravel = 0.574; sandy-clay loam = 0.539; common earth = 0.430; clay = 0	
Scraper	Total cost (\$) = $10^{(0.73663 + ft - fs + 0.000044D)} \times Q$	(4-109)
	<i>fs</i> (soil type factor): sand-gravel = 0.265; sandy-clay loam = 0.205; common earth = 0.241; clay = 0 <i>ft</i> (scraper type factor): elevated = 0.0295; self-propelled = 0; towed = 0	
Excavator	Total cost (\$) = $(8.269 - fs + 0.045d - 1.658B + ft) \times Q$	(4-110)
	<i>fs</i> (soil type factor): common earth = 0.647; sandy-clay loam = 1.049; sand-gravel = 1.133; hard clay = 0 <i>ft</i> (scraper type factor): excavator = -0.567; truck-mounted = 0.421; trench-box = 0	
Truck	Total cost (\$) = $(3.2 - 0.06C - 0.1S + 0.71D + 0.14t) \times Q$	(4-111)

where, Q = quantity of soil dozed/moved (cy)

HP = engine horsepower (hp)

D = distance (ft) – miles for truck

d = depth (ft)

B = bucket capacity (cy)

C = loading capacity (cy)

S = speed (mph)

t = cycle time (min.)

To demonstrate the total cost estimation for bulldozer, an example is presented that has inputs of a 150-hp bulldozer that has to haul 1000 cubic yard of common earth in 300 feet of distance. The result shows that the bulldozer requires \$9.02 per cubic yard or \$9,020.50 in total to complete the task. The example case for scraper is presented when an elevated type of scraper with 10 cy bucket size has to haul 1000 cubic yard of clay in

2000 feet of distance. The unit cost for this scraper is \$6.92 per cubic yard or \$6,920 in total for completing the work. As for the excavator, the example is that a regular excavator with 3 cy of bucket has to dig 12 feet deep of trench in sand-gravel type of soil. The unit cost required to complete this work is \$2.13 per cubic yard. If the length and width of the trench are 100 feet and 10 feet respectively, the total volume of the soil will be 12,000 cubic feet of equals to 444.4 cubic yard, and the total cost is \$945.72. The example estimation for truck is shown that a 30 cy truck has to haul 1000 cy of soil in 1 mile with 10 miles per hour of average hauling speed. For loading and dumping the soil, the truck needs 15 minutes. The unit cost for truck to complete the work is \$3.31 per cubic yard or \$3,314.21 in total.

#### **4.3.2 Total Fuel Use Estimation Model – ENERGY**

The ‘energy’ model in E3 is the total fuel use estimation model. The model was formulated by using the productivity model to obtain the total duration of work, and combined with the NONROAD’s brake specific fuel consumption (BSFC) to gain the fuel consumption rate in term of pounds per horsepower-hour (lbs/hp-hr). BSFC is the factor that approximates the amount of fuel consumed by a particular type of equipment during a unit of use. This factor is based on EPA’s engine dynamometer test data and adjusted accordingly to account for in-use operation that differs from the typical test conditions. The test is based on steady-state tests, and does not always accurately reflect fuel use for HDD equipment applications. Some differences are due to load or engine speed, whereas some are due to transient demands. Transient adjustment factors (TAF) are calculated as the ration of the transient fuel use factor to the corresponding steady-

state fuel use factor. TAF are applied to Tier 0, 1, 2, and 3 engines but are not applied to Tier 4 engines, because transient fuel use controls will be a part of all Tier 4 engines designs. By multiplying the BSFC with TAF, the work duration and engine horsepower (hp), the total fuel use is gained and expressed in term of pounds (lbs) or converted into gallons (gal).

#### 4.3.2.1. Total Fuel Use Estimation Model

The total fuel use estimate is calculated by multiplying the work duration (hr), engine size (hp), BSFC (gal/hp-hr), and TAF. The total work duration is obtained by dividing the total soil quantity with the productivity rate. The formula to calculate the total fuel use is as follows:

$$F \text{ (gal)} = \text{duration} * \text{engine horsepower} * \text{BSFC} * \text{TAF} \quad (4-112)$$

$$F \text{ (gal)} = \frac{\text{Soil Quantity (cy)}}{\text{Productivity Rate } \left(\frac{\text{cy}}{\text{hr}}\right)} * \text{engine horsepower (hp)} * \text{BSFC } \left(\frac{\text{gal}}{\text{hp-hr}}\right) * \text{TAF} \quad (4-113)$$

The overall total fuel use estimation models for bulldozer, scraper, excavator, and truck are shown in Table 4.15.

To demonstrate the total fuel use estimate for bulldozer, a case of 150 hp bulldozer, model year 2003 has to haul 1000 cy common earth in 300 feet is presented. The engine size, distance, and type of soil are used to generate productivity rate, while engine size and model year are used to obtain engine tier level, BSFC, and TAF. The results showed that the productivity rate is 20.02 cy/hr and it needs 49.95 hours to complete the work. This bulldozer is in Tier 2 level and has BSFC of 0.367 lbs/hp-hr and

TAF of 1.01. The total fuel consumed to complete 1000 cy common earth is 333.37 gallons.

Table 4.15. Total fuel use models for all type of HDD equipment

<b>Equipment</b>	<b>Total fuel use model</b>
Bulldozer	$\text{Fuel (gal)} = \frac{Q}{(1.876+0.0035\text{HP}-0.0024\text{D}+fs)^5} \times \text{HP} \times \text{BSFC} \times \text{TAF} \quad (4-114)$ <p><i>fs</i> (soil type factor):  sand-gravel = 0.236; sandy-clay loam = 0.217; common earth = 0.166; clay = 0</p>
Scraper	$\text{Fuel (gal)} = \frac{Q}{10(1.717+ft+0.0107\text{B}-0.00004\text{D}+fs)} \times \text{HP} \times \text{BSFC} \times \text{TAF} \quad (4-115)$ <p><i>fs</i> (soil type factor):  sand-gravel = 0.265; sandy-clay loam = 0.240; common earth = 0.204; clay = 0  <i>ft</i> (scraper type factor):  elevated = -0.087; self-propelled = 0; towed = 0</p>
Excavator	$\text{Fuel (gal)} = \frac{Q}{-3.9467+fs-2.069d+55.13\text{B}+ft} \times \text{HP} \times \text{BSFC} \times \text{TAF} \quad (4-116)$ <p><i>fs</i> (soil type factor):  common earth = 8.465; sandy-clay loam = 14.907; sand-gravel = 16.412; hard clay = 0  <i>ft</i> (scraper type factor):  excavator = 3.317; truck-mounted = 4.165; trench-box = 0</p>
Truck	$\text{Fuel (gal)} = \frac{Q}{(58.799+2.079\text{C}+1.625\text{S}-12.056\text{D}-2.789t)} \times \text{HP} \times \text{BSFC} \times \text{TAF} \quad (4-117)$

where, Q = quantity of soil dozed/moved/excavated (cy)

HP = engine horsepower (hp)

BSFC = brake specific fuel consumption (gal/hp-hr)

TAF = transient adjustment factor (unitless)

D = distance (ft) – miles for truck

d = depth (ft)

B = bucket capacity (cy)  
C = loading capacity (cy)  
S = speed (mph)  
t = cycle time (min.)

As for scraper case, an elevated type of scraper, which has 10 cy of bucket capacity, and 475 hp – model year 2003, has to haul 1000 cy clay in 2000 feet of distance is presented. The bucket size, hauling distance, type of soil, and type of scraper are analyzed to obtain the productivity rate, while engine size and its model year are utilized to define the engine tier level, BSFC, and TAF. The fuel use model results showed that the productivity rate of this scraper performing the work is 46.01 cy/hr and it needs 21.73 hours to complete the work. This scraper is categorized as Tier 2 with BSFC of 0.367 lbs/hp-hr and TAF of 1.01. The scraper needs 459.12 gallons of fuel in total.

The total fuel use estimate for excavator is presented in the following case: a regular excavator with 3 cy bucket size has to dig a 100 feet long – 10 feet wide – 12 feet deep trench in a sand-gravel type of soil. The engine has 400 hp and model year 2003. The type of soil, type of excavator, soil quantity, and bucket size is utilized to calculate the productivity rate, while the engine size and model year will determine the engine tier, BSFC, and TAF. The model showed the results that the productivity rate is 156.34 cy/hr or equals to 2.84 hours of total duration to complete the trench. The excavator is categorized in Tier 2 engine and has the BSFC of 0.367 lbs/hp-hr and TAF of 1.01. To complete digging the trench, the excavator needs 50.53 gallons of fuel.

The sample case for truck is presented as a 30 cy off-road truck has to haul 1000 cy of soil in 1 mile. The truck has 535 hp – model year 2003 with 10 miles per hour of average hauling speed. The truck needs 15 minutes on average to load and dump the soil.

The truck capacity, average speed, hauling distance, and load-dump time is utilized to determine the productivity rate, while engine size and model year will define the engine tier level, BSFC, and TAF. The fuel use model showed the results that the truck has productivity of 83.54 cy/hr or needs 11.97 hours to haul all soil quantity. Since the engine is categorized as Tier 2, the truck has BSFC of 0.367 lbs/hp-hr and TAF of 1.01. To complete the task, the truck needs 284.85 gallons of fuel in total.

#### **4.3.2.2. Results Comparison with Field Data**

The purpose of comparison between the fuel use from field data and E3 model outputs is to determine if the two sources of fuel use data were of a similar relationship. It is expected that the two data are not narrowly similar since the field data are for individual vehicles, while E3 results are based on NONROAD model, which was intended to estimate average fuel use for a fleet of HDD equipment. Results comparison is conducted by comparing the total fuel use obtained from in-use HDD equipment in the field with those estimated by using E3 model. The fuel use factors and fuel use from in-use HDD equipment from field is measured by using portable emissions measurement system (PEMS). The field data collected by using PEMS are obtained from construction equipment fleet inventory data in North Carolina Department of Transportation (NCDOT), Raleigh as the result of the research conducted by North Carolina State University (Lewis, 2009). The data, which is available for public use consists of PEMS measurement results from seven types of HDD equipment: bulldozers, backhoes, excavators, motorgraders, wheel loaders, skidsteers, and trucks (Lewis, 2009). The field HDD equipment used for this comparison are shown in Table 4.16.



The PEMS measures total fuel use of HDD equipment based on the fuel use factors at its rated engine horsepower in terms of gallons per time. Since the PEMS measurement is second-by-second data, the total duration used by the HDD equipment in seconds is converted to hours, and multiplied by the fuel use factors and engine horsepower to obtain the working total fuel use. The total fuel use from E3 model are calculated by multiplying the brake specific fuel consumption (BSFC), engine size, total duration, and equipment load factor. Table 4.17 shows the total fuel from two data sources.

Table 4.16. HDD equipment used for PEMS field measurement

<b>Equipment</b>	<b>Horsepower (HP)</b>	<b>Model Year</b>	<b>Engine Tier</b>	<b>Work Duration (hrs)</b>
Bulldozer 1	89	1988	0	0.839
Bulldozer 2	95	2002	1	5.862
Bulldozer 3	90	2003	1	2.631
Bulldozer 4	175	1998	1	2.188
Bulldozer 5	285	1995	0	2.083
Bulldozer 6	99	2005	2	1.415
Excavator 1	254	2001	1	1.027
Excavator 2	138	2003	2	4.312
Excavator 3	93	1998	1	4.994
Truck 1	306	2005	2	5.125
Truck 2	285	1998	1	1.117
Truck 3	285	1998	1	0.509

In general, the average total fuel use from E3 model is relatively similar to those from field PEMS measurement. For example in Excavator 1, 1 hour fuel use obtained from PEMS is 10.24 gallons, while from E3 model estimation is 11.60 gallons. E3 model estimates 0.5 hours fuel use from Truck 3 as 6.45 gallons, while PEMS measures fuel use as 6.66 gallons. At some points, the fuel use estimates of E3 model are higher than PEMS measurement; however at some other cases the PEMS measurement gives higher output than E3 model. As shown in Figure 4.20, the average total fuel use estimates of bulldozer

are 9% lower than those from PEMS measurement, while fuel use estimates of excavator and truck are 34% and 17% higher than the field data respectively. The overall average total fuel use estimates for these three HDD equipment is 14% higher than the field data.

Table 4.17. Fuel use comparison between E3 model and PEMS measurement results

Equipment	Fuel use			
	Fuel Use Factor (gal/hp-hr)		Total Fuel Use (gal)	
	E3	PEMS	E3	PEMS
Bulldozer 1	0.049	0.062	3.69	4.62
Bulldozer 2	0.049	0.037	27.54	20.46
Bulldozer 3	0.049	0.072	11.71	17.01
Bulldozer 4	0.044	0.056	17.03	21.29
Bulldozer 5	0.044	0.061	26.40	36.31
Bulldozer 6	0.049	0.015	6.93	2.05
Excavator 1	0.044	0.039	11.60	10.24
Excavator 2	0.044	0.017	26.47	9.86
Excavator 3	0.049	0.043	22.96	19.89
Truck 1	0.044	0.034	69.75	52.49
Truck 2	0.044	0.050	14.16	15.85
Truck 3	0.044	0.046	6.45	6.66

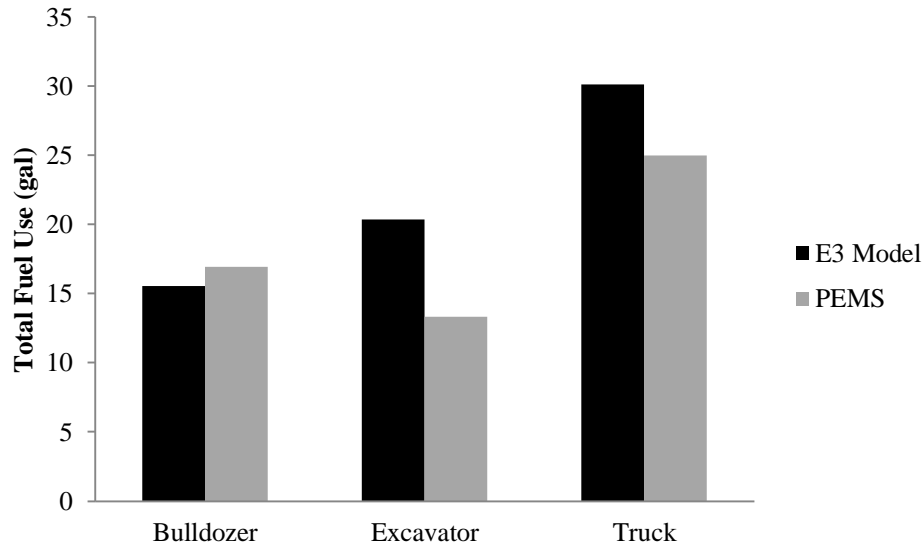


Figure 4.20. Total fuel use comparison – E3 model and PEMS result

#### **4.3.3 Total Emissions Model – ENVIRONMENTAL**

The ‘environmental’ model in E3 is the total emissions estimation models. Total emission estimates were calculated by using the emission factors (EF) from EPA’s NONROAD model and total duration of work obtained from the productivity rate. The emission factors needed are approximations of the amount of pollutants emitted by a particular type of equipment during a unit of use. The EF used here are reported in grams per horsepower-hour (g/hp-hr). The EF are based on engine dynamometer test data and adjusted accordingly to account for in-use operation that differs from the typical test conditions.

The type of equipment will define the load factor and hours activity per year. The equipment engine horsepower and model year will define the engine tier category. The engine tier will then define the median life, transient adjustment factor (TAF), deterioration factor (DF), and steady state emission factor (EFss). By using EFss, TAF, and DF, with the age of equipment, the adjusted emission factor (EFadj.) in term of grams per horsepower-hour (g/hp-hr) can be calculated.

The total emissions (in grams) released from an equipment performing work for a certain quantity of soil is calculated by using work duration (in hour) obtained from the productivity rate, engine size (in hp), and the EFadj. (in g/hp-hr). The total emissions calculations for each type of equipment are divided into three parts: first, for nitrogen oxide (NO<sub>x</sub>), hydrocarbons (HC), and carbon monoxide (CO); second, for particulate matters (PM), since it is dependent on sulfur content; and third, for carbon dioxide (CO<sub>2</sub>), since it computes in-use adjusted BSFC.

#### 4.3.3.1. Total Emissions Estimation Model

The total emissions (grams) are calculated by multiplying the work duration (hr), engine size (hp), and emission factor (g/hp-hr). The total work duration is obtained by dividing the total soil quantity with the productivity rate. The formula to calculate the total emissions is as follows:

$$E = \text{Duration} * \text{engine horsepower} * \text{Emission factor} \quad (4-118)$$

$$E \text{ (grams)} = \frac{\text{Soil Quantity (cy)}}{\text{Production Rate } \left(\frac{\text{cy}}{\text{hr}}\right)} * \text{engine horsepower (hp)} * \text{Emission factor } \left(\frac{\text{gr}}{\text{hp.hr}}\right) \quad (4-119)$$

The overall total emissions models for bulldozer are shown in Table 4.18.

Table 4.18. Total emission model for bulldozer

Pollutant(s)	Total emission model
HC, CO, NO <sub>x</sub>	$E = \frac{Q}{(1.876 + 0.0035HP - 0.0024D + fs)^5} * HP * EF_{ss} * TAF * DF \quad (4-120)$
PM	$E = \frac{Q}{(1.876 + 0.0035HP - 0.0024D + fs)^5} * HP * ((EF_{ss} * TAF * DF) - S_{PM}) \quad (4-121)$
CO <sub>2</sub>	$E = \frac{Q}{(1.876 + 0.0035HP - 0.0024D + fs)^5} * HP * ((BSFC * 453.6) - HC) * 0.87 * \left(\frac{44}{12}\right) \quad (4-122)$

where, E = total emissions (grams)

Q = quantity of soil dozed/moved/excavated (cy)

HP = engine horsepower (hp)

EF<sub>ss</sub> = steady-state emission factor (g/hp-hr)

BSFC = brake specific fuel consumption (gal/hp-hr)

TAF = transient adjustment factor (unitless)

DF = deterioration factor (unitless)

$S_{PM}$  = adjustment to PM emission factor for fuel sulfur content (g/hp-hr)

HC = in-use adjusted hydrocarbon emissions (g/hp-hr)

453.6 = conversion factor from pounds to grams

0.87 = carbon mass fraction of diesel

44/12 = ratio of CO<sub>2</sub> mass to carbon mass

D = distance (ft)

$f_s$  (soil type factor):

- Sand and gravel = 0.236
- Sandy clay and loam = 0.217
- Common earth = 0.166
- Clay = 0

To demonstrate the emission model for bulldozer, a case is presented where a 150 hp of bulldozer model year 2003 has to haul 1000 cy of common earth in distance of 300 feet. The result showed that the estimated productivity of this bulldozer is 20.02 cubic yard per hour and can approximately complete the job in 49.94 hours. Based on the engine size and model year, this bulldozer is categorized in Tier 2 engine level and has 0.59 of LF, and 936 hours of activity per year in average. This engine also has the EFss as follows: 0.3384 g/hp-hr of HC, 0.8667 g/hp-hr of CO, 4.1 g/hp-hr of NO<sub>x</sub>, 0.18 g/hp-hr of PM, and 0.367 lbs/hp-hr of BSFC. When completing the job, this bulldozer was estimated to emit 2,662 grams of HC, 9,938 grams of CO, 29,183 grams of NO<sub>x</sub>, 1,502 grams of PM, and 3.4 tons of CO<sub>2</sub>.

To demonstrate the models for estimating emissions from scraper, a case is presented where an elevated scraper with 475 horsepower of engine size and model year 2003, has to haul 1000 cy clay in 2000 feet of distance. The scraper has 10 cy of bucket capacity. The model gives the results that the scraper has the productivity of 46.01 cubic yard per hour, and needs 21.37 hours to finish the job. Based on the engine size and model year information, the engine is categorized as Tier 2 level. In this Tier level, the scraper has 0.59 of load factor and 914 hours average per year activity. This engine also

has the following EFss: 0.1669 g/hp-hr of HC, 0.8425 g/hp-hr of CO, 4.3351 g/hp-hr of NOx, 0.1316 g/hp-hr of PM, and 0.367 lbs/hp-hr of BSFC. As the job finished, the total emissions released from the scraper are: 1809 grams of HC, 13307 grams of CO, 42510 grams of NOx, 1453 grams of PM, and 4.66 tons of CO<sub>2</sub>.

The total emissions models for scraper are shown in Table 4.19.

Table 4.19. Total emission model for scraper

Pollutant(s)	Total emission model
HC, CO, NOx	$E = \frac{Q}{10^{(1.717+ft+0.0107B-0.00004D+fs)}} * HP * EF_{ss} * TAF * DF \quad (4-123)$
PM	$E = \frac{Q}{10^{(1.717+ft+0.0107B-0.00004D+fs)}} * HP * ((EF_{ss} * TAF * DF) - S_{PM}) \quad (4-124)$
CO <sub>2</sub>	$E = \frac{Q}{10^{(1.717+ft+0.0107B-0.00004D+fs)}} * HP * ((BSFC * 453.6) - HC) * 0.87 * \left(\frac{44}{12}\right) \quad (4-125)$

where, E = total emissions (grams)

Q = quantity of soil dozed/moved/excavated (cy)

HP = engine horsepower (hp)

EF<sub>ss</sub> = steady-state emission factor (g/hp-hr)

BSFC = brake specific fuel consumption (gal/hp-hr)

TAF = transient adjustment factor (unitless)

DF = deterioration factor (unitless)

S<sub>PM</sub> = adjustment to PM emission factor for fuel sulfur content (g/hp-hr)

HC = in-use adjusted hydrocarbon emissions (g/hp-hr)

453.6 = conversion factor from pounds to grams

0.87 = carbon mass fraction of diesel

44/12 = ratio of CO<sub>2</sub> mass to carbon mass

D = distance (ft)

B = bucket capacity (cy)

fs (soil type factor):

- Sand and gravel = 0.265
- Sandy clay and loam = 0.240
- Common earth = 0.204

- Clay = 0
- ft* (scraper type factor):
- Elevated = 0.06844
  - Self-propelled = 0.1123
  - Towed = 0

The total emissions models for excavator are shown in Table 4.20.

Table 4.20. Total emission model for excavator

<b>Pollutant(s)</b>	<b>Total emission model</b>	
HC, CO, NO <sub>x</sub>	$E = \frac{Q}{(-3.9467 + fs - 2.069d + 55.13B + ft)} * HP * EF_{ss} * TAF * DF$	(4-126)
PM	$E = \frac{Q}{(-3.9467 + fs - 2.069d + 55.13B + ft)} * HP * ((EF_{ss} * TAF * DF) - S_{PM})$	(4-127)
CO <sub>2</sub>	$E = \frac{Q}{(-3.9467 + fs - 2.069d + 55.13B + ft)} * HP * ((BSFC * 453.6) - HC) * 0.87 * \left(\frac{44}{12}\right)$	(4-128)

where, E = total emissions (grams)

Q = quantity of soil dozed/moved/excavated (cy)

HP = engine horsepower (hp)

EF<sub>ss</sub> = steady-state emission factor (g/hp-hr)

BSFC = brake specific fuel consumption (gal/hp-hr)

TAF = transient adjustment factor (unitless)

DF = deterioration factor (unitless)

S<sub>PM</sub> = adjustment to PM emission factor for fuel sulfur content (g/hp-hr)

HC = in-use adjusted hydrocarbon emissions (g/hp-hr)

453.6 = conversion factor from pounds to grams

0.87 = carbon mass fraction of diesel

44/12 = ratio of CO<sub>2</sub> mass to carbon mass

d = trench depth (ft)

B = bucket capacity (cy)

*fs* (soil type factor):

- Sand and gravel = 16.412
- Sandy clay and loam = 14.907
- Common earth = 8.465
- Clay = 0

*ft* (excavator type factor):

- Excavator = 3.317
- Truck-mounted = 4.165
- Trench-box = 0

To demonstrate the models for estimating total emissions from excavator, a case of a 400 hp – model year 2003 excavator is presented. The excavator has to dig a 100 feet long-10 feet wide-12 feet deep trench in sand-gravel soil with its 3 cy bucket. The results showed that the excavator has the productivity rate of 156.34 cubic yard per hour or needs 2.84 hours to complete digging the trench. Based on the horsepower and model year, the engine is categorized as Tier 2 engine and has 0.59 of load factor, 1092 hours activity per year on average, and steady state emission factors as follows: 0.1669 g/hp-hr of HC, 0.8425 g/hp-hr of CO, 4.3351 g/hp-hr of NOx, 0.1316 g/hp-hr of PM, and 0.367 lbs/hp-hr of BSFC. When finishing the trench, this excavator released 199.1 grams of HC, 1464 grams of CO, 4678.5 grams of NOx, 160 grams of PM, and 0.5 tons of CO<sub>2</sub>.

The total emissions models for truck are shown in Table 4.21.

Table 4.21. Total emission model for truck

Pollutant(s)	Total emission model	
HC, CO, NOx	$E = \frac{Q}{(58.799 + 2.079C + 1.625S - 12.056D - 2.789t)} * HP * EF_{ss} * TAF * DF$	(4-129)
PM	$E = \frac{Q}{(58.799 + 2.079C + 1.625S - 12.056D - 2.789t)} * HP * ((EF_{ss} * TAF * DF) - S_{PM})$	(4-130)
CO <sub>2</sub>	$E = \frac{Q}{(58.799 + 2.079C + 1.625S - 12.056D - 2.789t)} * HP * ((BSFC * 453.6) - HC) * 0.87 * \left(\frac{44}{12}\right)$	(4-131)

where, E = total emissions (grams)

Q = quantity of soil dozed/moved/excavated (cy)

HP = engine horsepower (hp)



EF<sub>ss</sub> = steady-state emission factor (g/hp-hr)  
BSFC = brake specific fuel consumption (gal/hp-hr)  
TAF = transient adjustment factor (unitless)  
DF = deterioration factor (unitless)  
S<sub>PM</sub> = adjustment to PM emission factor for fuel sulfur content (g/hp-hr)  
HC = in-use adjusted hydrocarbon emissions (g/hp-hr)  
453.6 = conversion factor from pounds to grams  
0.87 = carbon mass fraction of diesel  
44/12 = ratio of CO<sub>2</sub> mass to carbon mass  
C = loading capacity (cy)  
S = average hauling speed (mph)  
D = cycle distance (miles)  
t = load-dump time (minutes)

To illustrate the emissions models for truck, a simple case is presented as follows:

a 535 hp – model year 2003 truck is used to haul 1000 cy of soil in 1 mile of distance.

The truck has 30 cy of loading capacity with average hauling speed of 10 miles per hour.

For loading and dumping the soil, the truck needs 15 minutes in average. The estimated productivity rate for this truck is 83.54 cubic yard per hour, and for hauling 1000 cy of soil, the truck needs 11.97 hours. Based on the horsepower and model year, the truck is categorized as Tier 2 engine, has 0.59 of load factor with 1641 hours of activity per year in average and steady state emission factors as follows: 0.1669 g/hp-hr of HC, 0.8425 g/hp-hr of CO, 4.3351 g/hp-hr of NO<sub>x</sub>, 0.1316 g/hp-hr of PM, and 0.367 lbs/hp-hr of BSFC. When the job is completed, the truck released 1122 grams of HC, 8256 grams of CO, 26,374 grams of NO<sub>x</sub>, 902 grams of PM, and 2.9 tons of CO<sub>2</sub>.

#### **4.3.3.2. Results Comparison with Field Data**

The purpose of comparison between the field data and E3 model outputs is to determine if the two sources were of a similar relationship. It is expected that the two

data are not narrowly similar since the field data are for individual vehicles, while E3 results are based on NONROAD model, which was intended to estimate average emissions for a fleet of HDD equipment. Results comparison is conducted by comparing the total emissions obtained from in-use HDD equipment in the field with those estimated by using E3 model. The emission factors and total emissions from in-use HDD equipment from field is measured by using portable emissions measurement system (PEMS). The field HDD equipment used for this comparison are shown in Table 4.16.

The PEMS measures total emissions of HDD equipment based on the emission factors at its rated engine horsepower in terms of mass per time. Since the PEMS measurement is second-by-second data, the total duration used by the HDD equipment in seconds is converted to hours, and multiplied by the emission factors and engine horsepower to obtain the working total emissions. The total emissions from E3 model are calculated by multiplying the emission factors, engine size, total duration, and equipment load factor. Table 4.22 shows the total emissions from two data sources.

Table 4.22. Total emission comparison between E3 model and PEMS measurement

Equipment	Total Emission									
	HC (gr)		CO (gr)		NOx (gr)		PM (gr)		CO <sub>2</sub> (kg)	
	E3	PEMS	E3	PEMS	E3	PEMS	E3	PEMS	E3	PEMS
Bulldozer 1	50.2	26.0	324.2	116.7	302.9	585.9	75.9	7.7	26.1	48.9
Bulldozer 2	182.8	283.2	1243.7	249.6	1766.6	1671.2	224.5	28.4	195.3	216.3
Bulldozer 3	77.7	108.1	528.8	250.2	751.1	2398.8	95.5	48.3	83.1	180.3
Bulldozer 4	83.6	182.1	334.0	536.2	1246.4	3822.2	114.8	14.3	120.9	224.9
Bulldozer 5	267.4	92.5	1842.2	521.1	2887.0	7726.3	286.8	N/A	187.0	385.0
Bulldozer 6	32.4	43.5	312.9	39.1	370.5	167.8	27.7	9.8	49.2	21.6
Excavator 1	51.1	21.4	188.3	60.1	828.9	1186.5	60.1	14.2	82.4	108.8
Excavator 2	126.5	81.3	485.1	380.1	1372.6	798.2	85.5	7.3	187.8	104.0
Excavator 3	156.0	134.6	1102.3	204.9	1496.0	2186.4	236.2	20.6	162.9	210.8
Truck 1	164.4	404.1	1242.6	3028.1	3842.6	5447.7	159.6	59.1	495.7	552.1
Truck 2	65.4	59.7	259.9	173.3	1044.9	1365.6	111.4	14.7	100.6	167.5
Truck 3	29.8	25.9	118.3	71.9	475.7	717.4	50.7	6.1	45.8	70.6

In general, the average total emissions from E3 model are relatively similar to those from field PEMS measurement, especially for HC, CO, NO<sub>x</sub>, and CO<sub>2</sub>. For example in Bulldozer 2, 5.9 hours NO<sub>x</sub> emission obtained from PEMS is 1671 grams, while from E3 model estimation is 1767 grams. E3 model estimates 0.5 hours HC emission from truck 3 as 29.8 grams, while PEMS measures HC emission as 25.9 grams. At some points, the emissions estimates of E3 model are higher than PEMS measurement; however at some other cases the PEMS measurement gives higher output than E3 model. As shown in Figure 4.21, the average emissions estimates of HC for bulldozers and excavators have similar magnitude with those from PEMS measurement. HC emission estimates for truck are much lower than the PEMS measurement. The overall average HC emission estimates for these three HDD equipment is 22% lower than the field data.

The average emissions estimates of CO for bulldozers and excavators are higher than those from PEMS measurement; however the CO estimates for trucks are much lower than the PEMS has. The overall average CO emission estimates of these three HDD equipment is 8% higher than the average of PEMS measurement results. For NO<sub>x</sub> emissions, the E3 model estimates of all three equipment are lower than those from PEMS by 59%. The average CO<sub>2</sub> emission estimates of excavators from E3 models have similar magnitude with the PEMS measurement results, but lower for bulldozers and trucks. Overall, this CO<sub>2</sub> emission estimates are 28% lower than the field data.

The biggest differences between these two sources of data occurred at PM emissions (Figure). The E3 model estimates PM emissions much higher than PEMS measurement for all type of equipment. The estimates are about 85% higher than the field

data. According to PEMS system operation manual released by Clean Air Technologies 2003 and research conducted by Lewis et al. (2009), this is due to the fact that PM data are measured by a laser light scatter method, rather than by a filter-based method, and it makes a systematic measurement bias for PM concentration for this PEMS instrument.

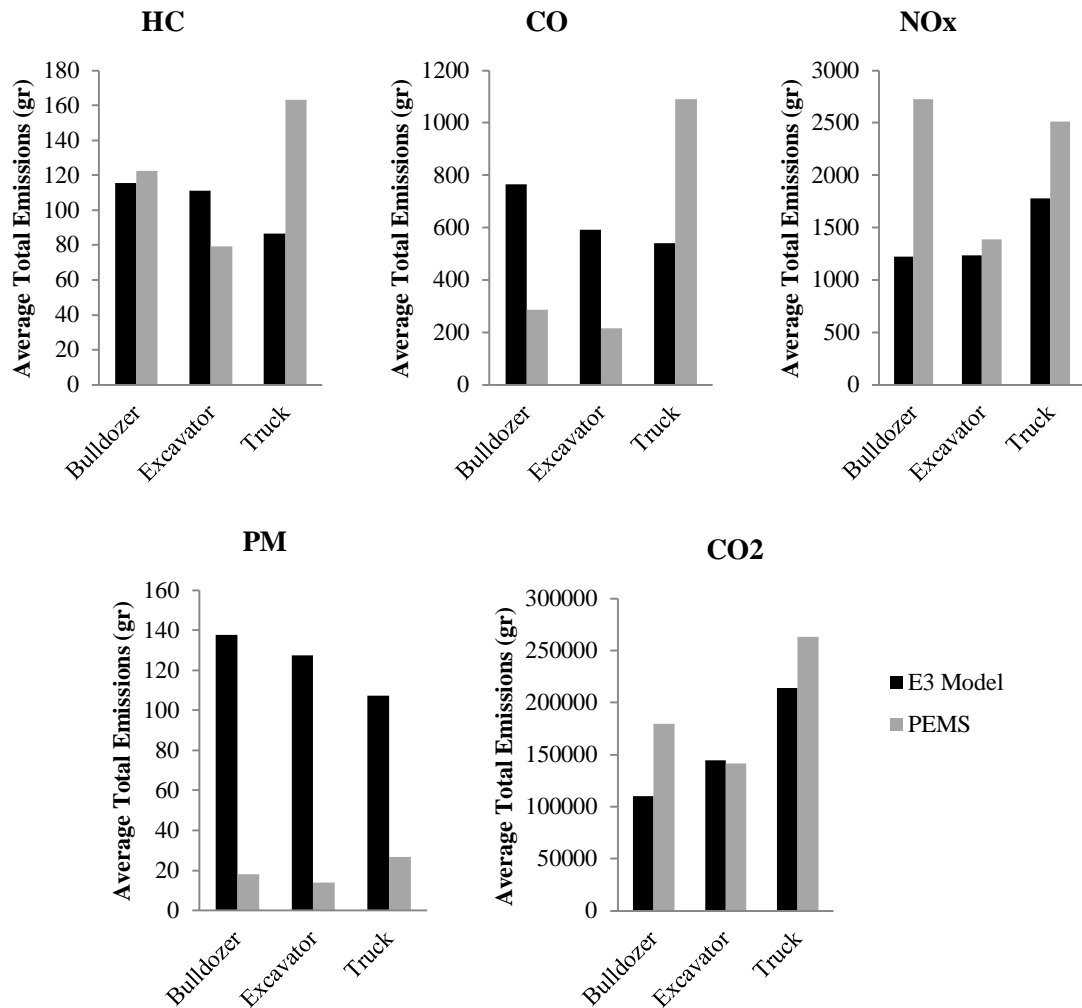


Figure 4.21. Total emission comparison – E3 model and PEMS result

#### 4.4. E3 User's Interface

A spreadsheet-based user's interface is developed to make the E3 model easy to use and run in practice. It can help construction estimator, site manager, equipment operator, or fleet manager to estimate the productivity rate, work duration, cost, fuel consumption, and pollutants emitted from the work they perform. The interface covers all type of HDD equipment usually used in earthwork construction projects. For the purpose of this research, only four types of HDD equipment is displayed; bulldozer, scraper, excavator, and off-road truck.

The interface is developed by using Visual Basic program for Microsoft Excel 2010 and structured as three main parts:

- Activity input. The part in the interface that allows users to give the input for determined variables for specific type of HDD equipment.
- Engine properties. The part in the interface showing the engine data (tier level, load factor, activity, median life, deterioration factor, steady-state emission factors, and transient adjustment factors) related to engine horsepower and model year of the HDD equipment.
- Activity output and total emissions. The part in the interface displaying the output of the model that includes: productivity rate, total duration, unit and total cost, total fuel use, and total mass emissions of all pollutants.

The overall screenshot appearances and calculation algorithm of the user's interface are shown in Figure 4.22 to Figure 4.24.

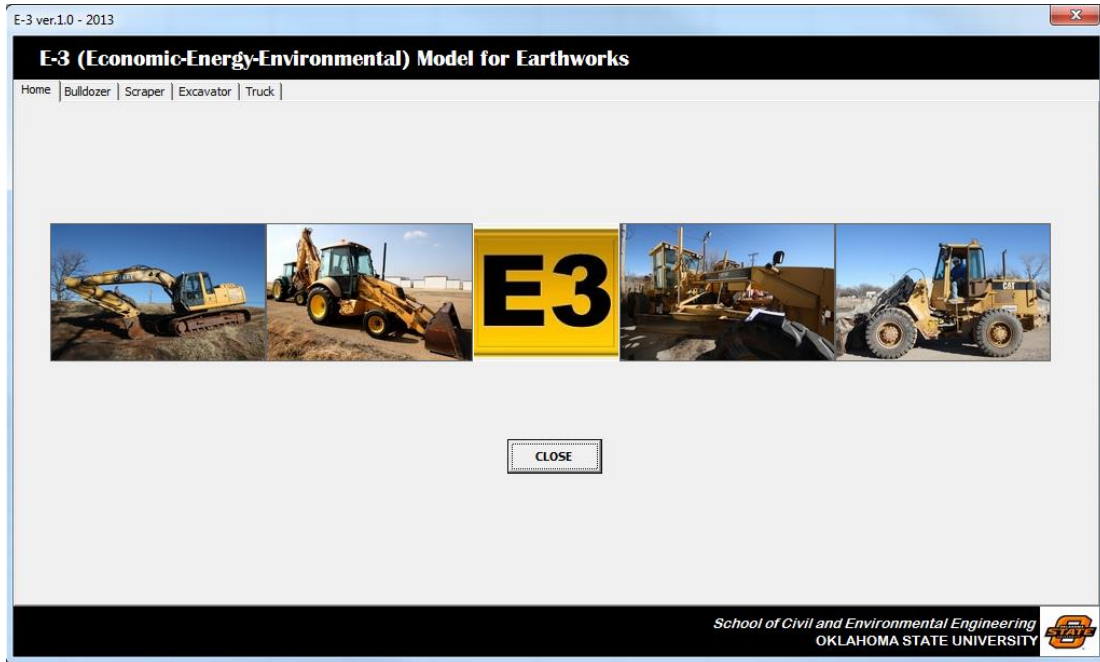


Figure 4.22. Front page screen-shot of E3 model user's interface

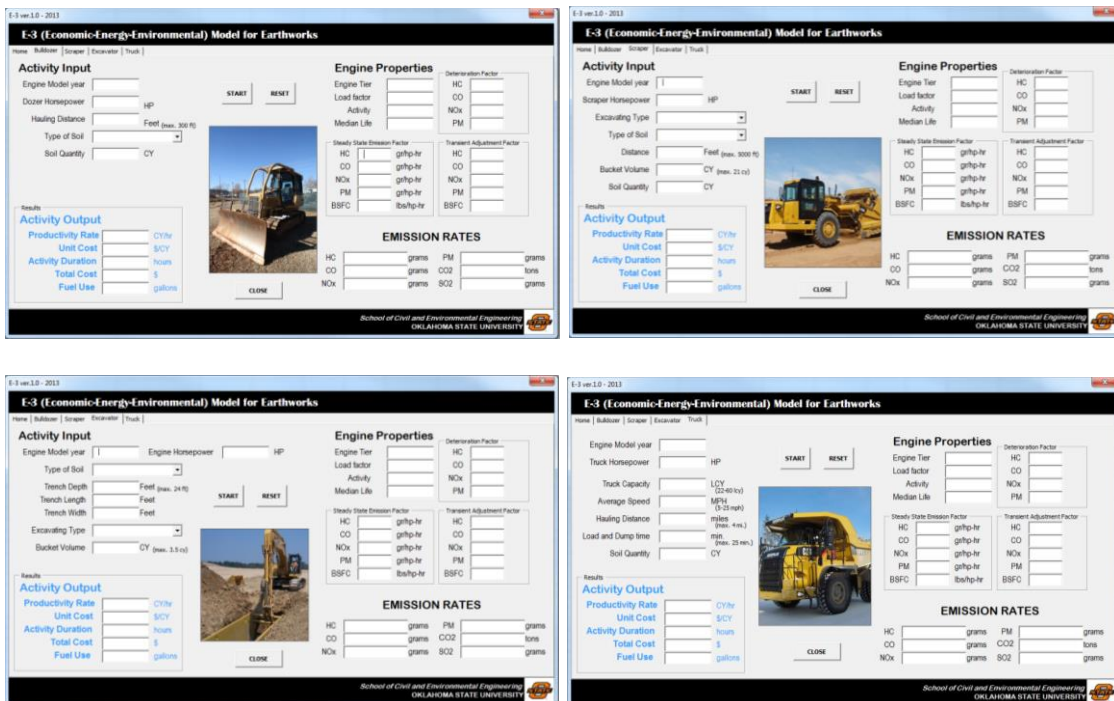


Figure 4.23. Input page screen-shot of E3 model user's interface

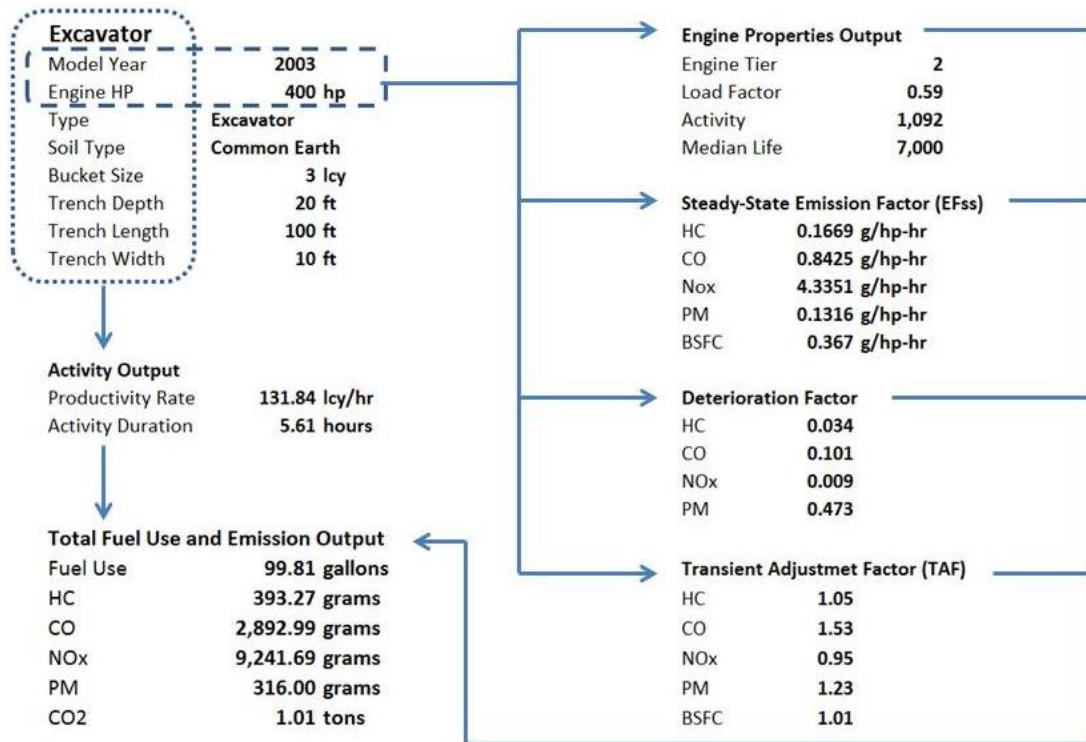


Figure 4.24. Calculation algorithm of E3 model user’s interface

As user complete filling out the activity input boxes, it can be followed by clicking the ‘start’ button to let the model generate output. As shown in Figure, once all required activity input obtained, the interface will display three groups of output: activity output, engine properties output, and total fuel use and emissions.

#### 4.5. E3 Model Application and Sensitivity Analysis

Model application and sensitivity analysis is conducted to analyze the effect of changes in explanatory variables against the output; cost, fuel use, and emissions. The analyses are useful to understand the economic, energy, and environmental impact of a certain earthwork activity performed by HDD equipment in different set of conditions.

The economic impact of the activity is determined by the total cost (including labor, equipment, overhead, and profit) to complete the activity. The energy impact of the

activity is based on the amount of diesel fuel consumed by HDD equipment in terms of total gallons. The environmental impact of the activity is based on total emissions of each pollutant (HC, CO, PM, NO<sub>x</sub>, and CO<sub>2</sub>) in terms of grams.

#### **4.5.1. Bulldozer**

The sensitivity analysis for bulldozer are constructed by two different work conditions: first, as shown in Table Table K.1, bulldozer has to haul 1000 cy of soil in 300 feet of distance, using various size of engine and all type of soil; second, as shown in Table K.2, 564 hp bulldozer – model year 2003, has to haul 1000 cy of all type of soil in various distance. Based on the information in Appendix K – Table K.1 and K.2, there is an inverse relationship between productivity rate and the other parameters including total cost, fuel use, and emissions; that is, as the productivity rate decreases, the other parameters increase. The productivity rate also decreases with the dozing resistance based on soil type; sand-gravel has the highest productivity rate whereas clay has the lowest. Likewise, activity duration, total cost, fuel use, and emissions all increase as the soil resistance increase. Furthermore, for a specific soil type, the productivity rate increases as engine size increases, and decreases as the dozing distance increases.

Figure 4.25 shows the economic impact of the activity based on engine size. For each soil type, the total cost to complete the activity decreases as the engine size increases. The estimated cost curves for each soil type has the same general shape and there is little difference in cost with respect to engine size for sand-gravel, sandy clay-loam, and common earth; there is virtually no difference in the predicted total cost for



sand-gravel and sandy clay-loam. The soil type with the highest predicted economic impact based on engine size of bulldozer is clay.

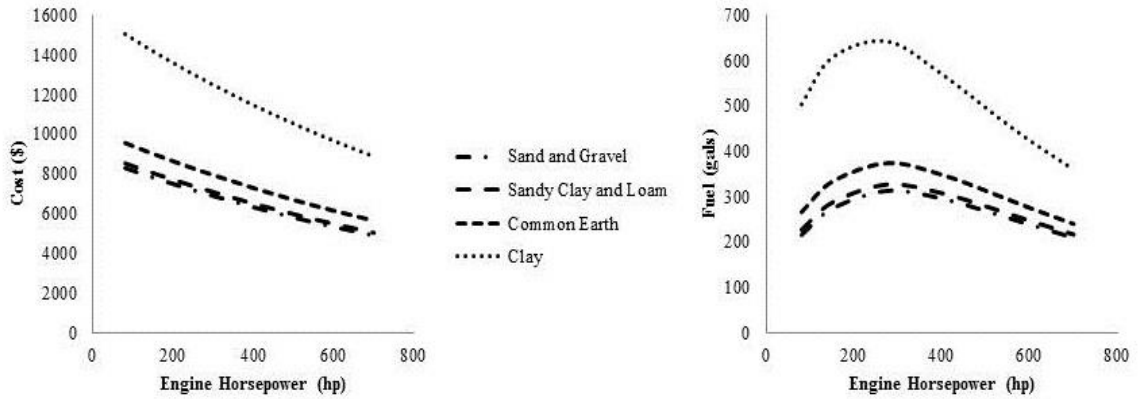


Figure 4.25. Economic and energy impact of bulldozer based on engine size

Figure 4.25 also shows the energy impact of the activity based on engine size. It presents some interesting findings of the energy impact related to the engine size of the bulldozer. Initially, fuel use increases sharply as the engine size increases and then begins to decrease, with the maximum fuel use occurring around 350 hp for each soil type. The convexity of these curves indicate that a specific quantity of fuel use for a given soil type may occur at two different engine size. For example, when hauling clay, a 100 hp and 500 hp bulldozer will both consume approximately 500 gallons of fuel to complete the activity. However, according to Figure 4.25, the total cost to complete the activity is \$15,000 for 100 hp bulldozer and \$11,000 for 500 hp bulldozer, which is nearly 30% decrease in cost. It is concluded that a substantially lower economic impact can be achieved by using a larger size of engine while having the same energy impact of the smaller bulldozer.

The environmental impact of the activity based on engine size is shown in Figure 4.26. Generally, it shows an inverse relationship between engine size and total emissions;

that is, for all types of soil, as the bulldozer uses bigger size of engine or bigger rated horsepower, the total emissions become lower. Especially for CO<sub>2</sub>, because the emission is highly correlated to fuel use, thus the shapes of the curves are the same for both fuel use and total emissions. There is little difference in total emissions for sand-gravel, sandy clay-loam, and common earth. The soil type with the highest estimated total emissions based on engine size is clay.

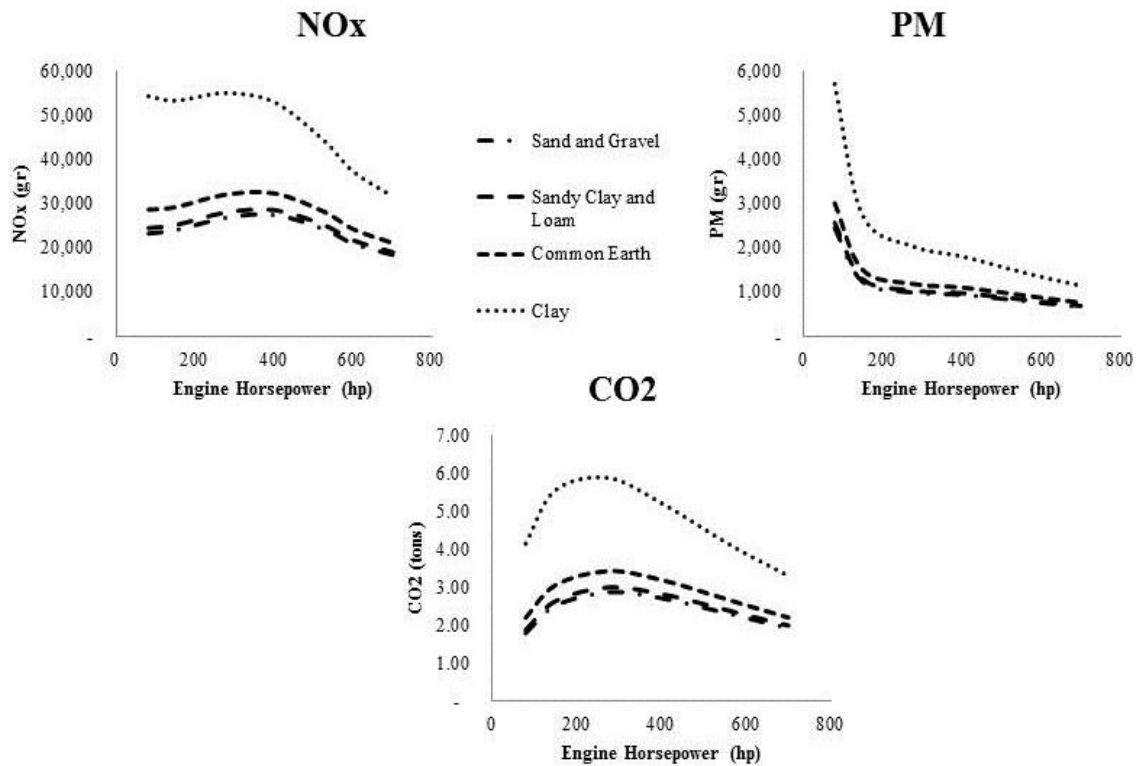


Figure 4.26. Environmental impact of bulldozer based on engine size

Figure 4.27 shows the economic and energy impact of the bulldozer activity based on the dozing distance. For each soil type, the estimated total cost and fuel use increase as the dozing distance increase. It is understood that longer distance will make the bulldozer

needs longer duration to complete the activity, and longer duration will also need higher fuel consumption. The estimated total cost and fuel use have relatively the same shape for all type of soil, with little difference of cost and fuel use for sand-gravel, sandy clay-loam, and common earth. Again, clay gives the highest estimated total cost and fuel use for the bulldozer activity based on dozing distance.

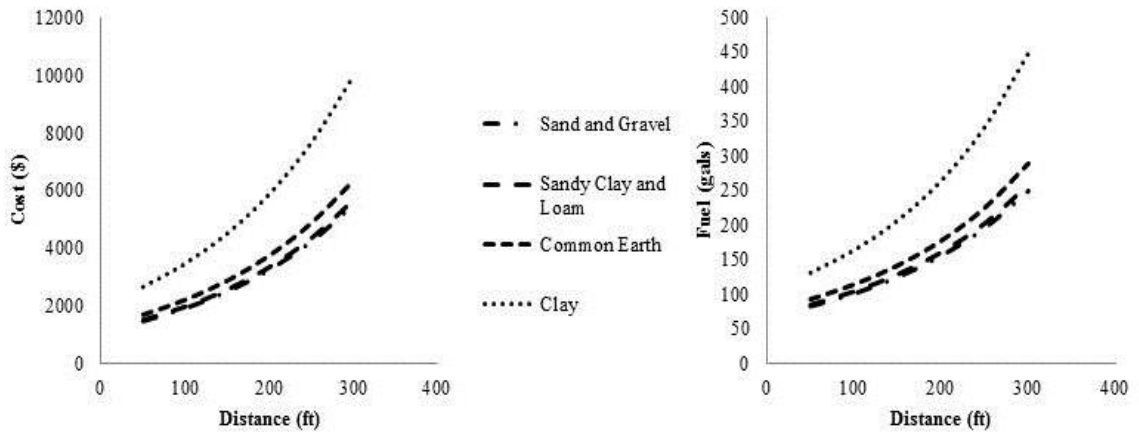


Figure 4.27. Economic and energy impact of bulldozer based on distance

Figure 4.28 shows the environmental impact of the bulldozer activity based on dozing distance. There are positive relationship between dozing distance and total emissions; that is, for all types of soil, as the bulldozer has to haul longer distance, the total emissions become higher. For all types of soil, the curve shapes are generally the same, and displays that clay gives the bulldozer the highest total emissions of all pollutants and CO<sub>2</sub> based on dozing distance.

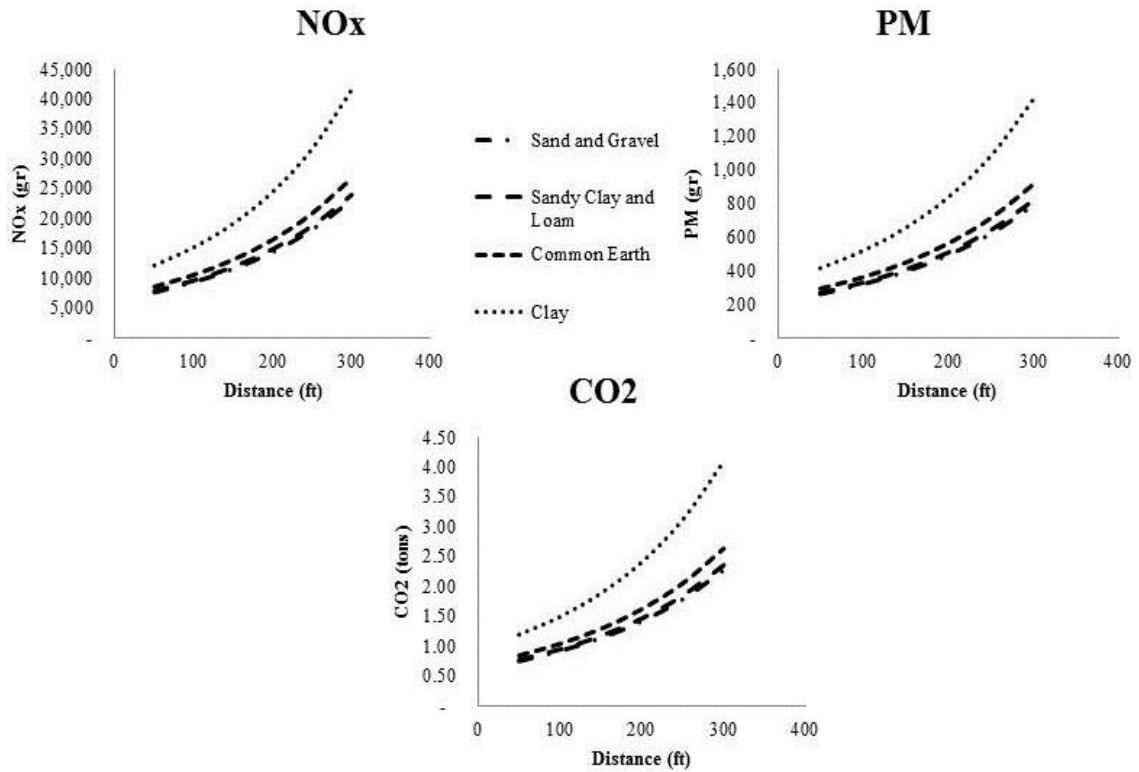


Figure 4.28. Environmental impact of bulldozer based on distance

#### 4.5.2. Scraper

The sensitivity analysis for scraper is designed in two different conditions: first, as shown in Table, a 475 hp – model year 2003 scraper has to haul 1000 cy of soil in 2000 feet of distance with various size of bucket; second, the same scraper with 15 cy of bucket size has to haul 1000 cy of soil in various distance. Based on the information in Appendix L – Table L.1 and L.2, there is an inverse relationship between productivity rate and the other parameters including total cost, fuel use, and emissions; that is, as the productivity rate decreases, the other parameters increase. The productivity rate also decreases with the hauling resistance based on soil type; sand-gravel has the highest productivity rate whereas clay has the lowest. Likewise, activity duration, total cost, fuel

use, and emissions all increase as the soil resistance increase. Furthermore, for a specific soil type, the productivity rate increases as bucket size increases, and decreases as the hauling distance increases.

Figure 4.29 shows the economic and energy impact of the activity among the types of scraper based on its bucket size. For all types of scraper, the estimated total cost and fuel use decrease as the bucket size increases. When a scraper uses bigger size of bucket, the productivity rate will increase, and then the work duration will decrease. Since the total duration decrease, the total cost and fuel use will also decrease. Among the types of scraper, towed scraper has the highest economic and energy impact, self-propelled scraper has the lowest for energy impact, and elevated scraper has the lowest for economic impact. This is an important result regarding scraper selection for hauling soil activity with respect to minimizing total cost and total fuel use.

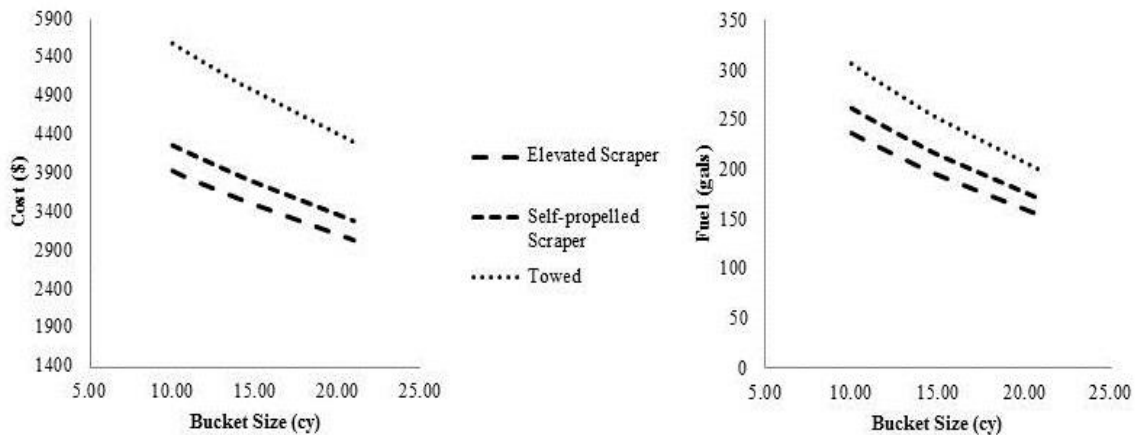


Figure 4.29. Economic and energy impact of scraper based on scraper type and bucket size

The economic and energy impact of the scraper activity based on the bucket size are shown in Figure 4.30. For all types of soil, the estimated total cost and total fuel use decrease as the scraper uses bigger bucket size. When the scraper used bigger bucket size,

the productivity increases, and the duration will decrease. The shorter duration of activity leads to less use of fuel and estimated total cost. Concerning soil type, there is little difference of total cost and total fuel use based on bucket size for sand-gravel, sandy clay-loam, and common earth, while clay gives the highest economic and energy impact of the activity.

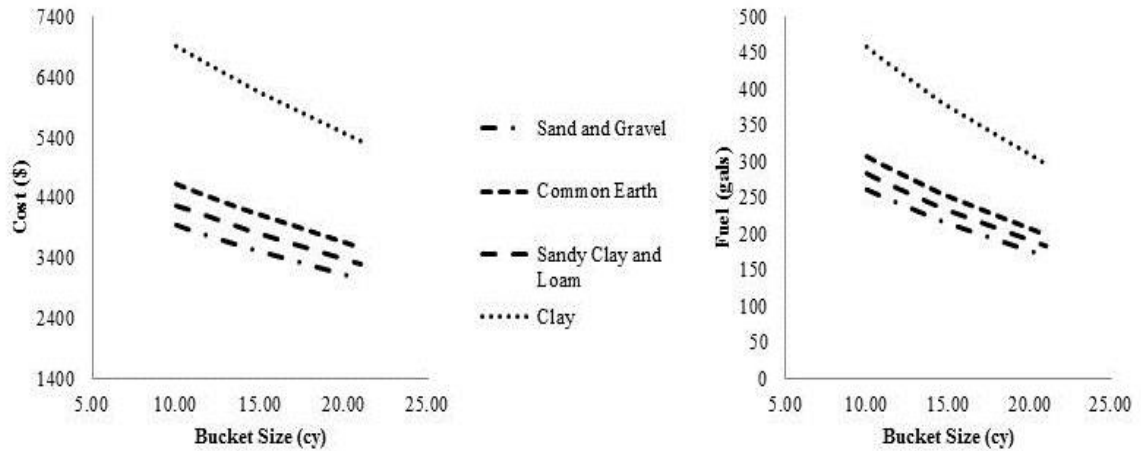


Figure 4.30. Economic and energy impact of scraper based on soil type and bucket size

Figure 4.31 shows the environmental impact of the scraper activity, which is represented by the emissions of NO<sub>x</sub>, PM, CO, and CO<sub>2</sub>, based on the bucket size. For all types of soil, as the scraper uses bigger bucket size, the estimated total emissions of each type of pollutant will decrease. Again, there is little difference of total emissions between sand-gravel, sandy clay-loam, and common earth. Based on the bucket size, clay has the highest environmental impact of the scraper activity.

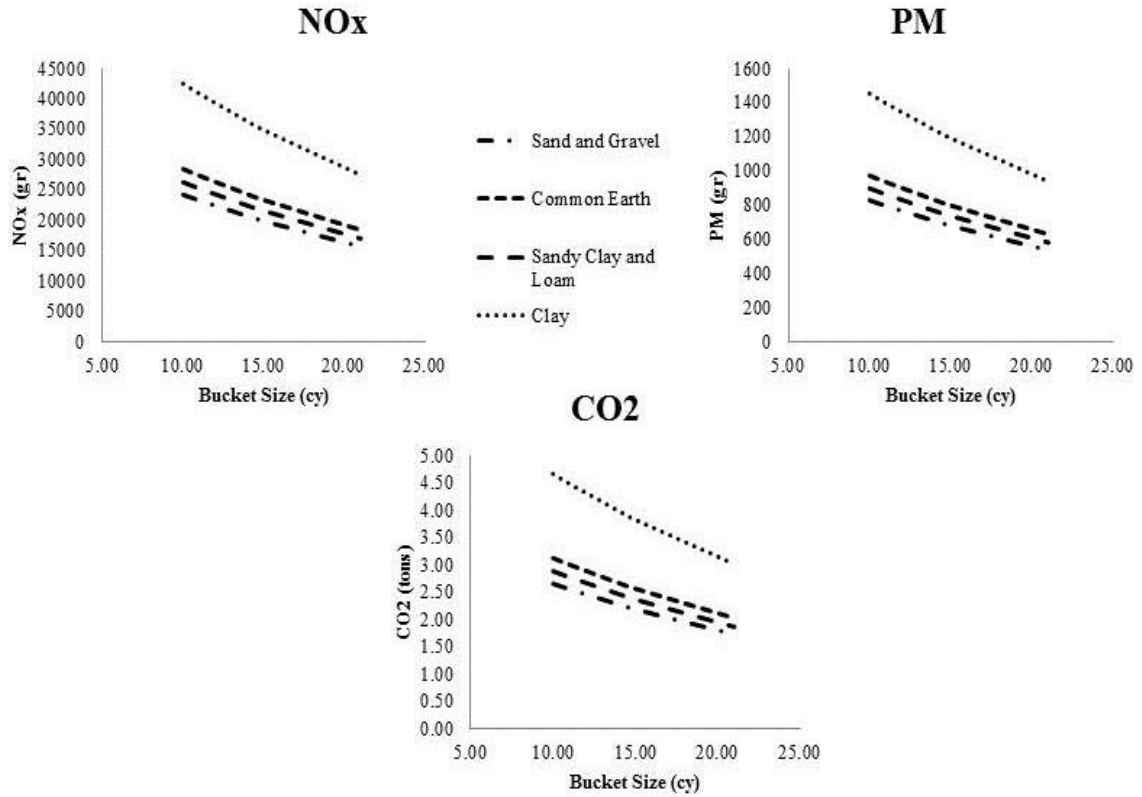


Figure 4.31. Environmental impact of scraper based on bucket size

The economic and energy impact of the scraper activity among its type and based on the hauling distance are shown in Figure 4.32. It is displayed using common earth type of soil. For all types of scraper, Figure shows the positive relationship between hauling distance and estimated total cost and total fuel use. As the scraper has to haul the soil in longer distance, the estimated total cost and total fuel use will increase. Towed scraper has the highest economic and energy impact of the activity. The lowest economic impact was given by elevated scraper, while the lowest energy impact was given by self-propelled scraper. In this case, hauling distance can also be used as a consideration of selecting type of scraper to minimize the economic and energy impact of earthwork construction activity.



Figure 4.32. Economic and energy impact of scraper based on scraper type and distance

The economic and energy impact of the scraper based on the hauling distance can also be analyzed for different types of soil. Figure 4.33 shows the relationship between the distance and estimated total cost and fuel use for all types of soil. There are positive relationships; that is as the hauling distance increase, the estimated total cost and total fuel use also increase for all types of soil. The estimated total cost and fuel use from clay are very high compared to other three types of soil; approximately two times higher than those of sand-gravel, sandy clay-loam, and common earth. Thus, for a specific soil type, clay gives the highest economic and energy impact based on the hauling distance for scraper.



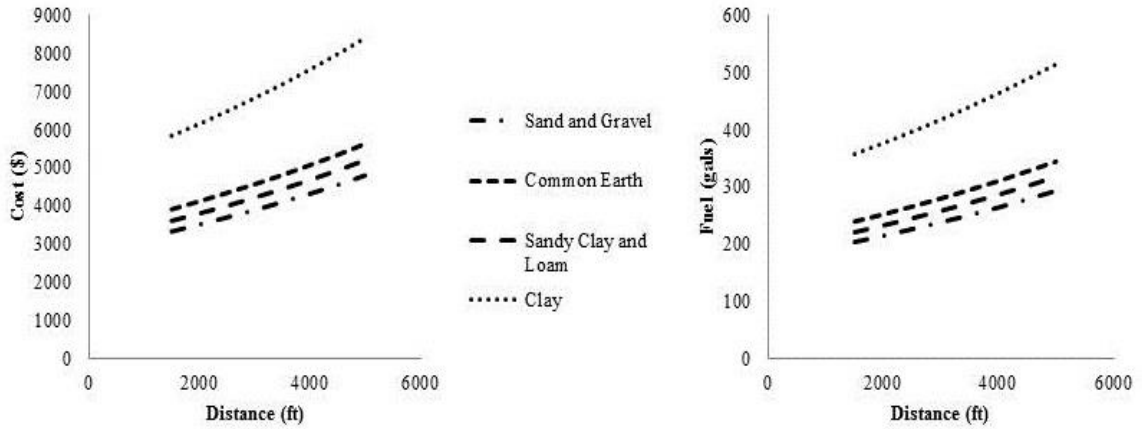


Figure 4.33. Economic and energy impact of scraper based on soil type and distance

Figure 4.34 shows the environmental impact of the scraper activity based on the hauling distance, which is represented by the total emissions of NO<sub>x</sub>, PM, CO, and CO<sub>2</sub>. It is shown that there are positive relationships between the hauling distance and estimated total emission of each pollutant based on the hauling distance. When the scraper has to haul soil in a longer distance, the total emissions will be higher. Similar with the environmental impact based on bucket size, clay also has the highest environmental impact on the scraper activity based on the hauling distance, with nearly 1.5 times than those of sand-gravel, sandy clay-loam, and common earth.

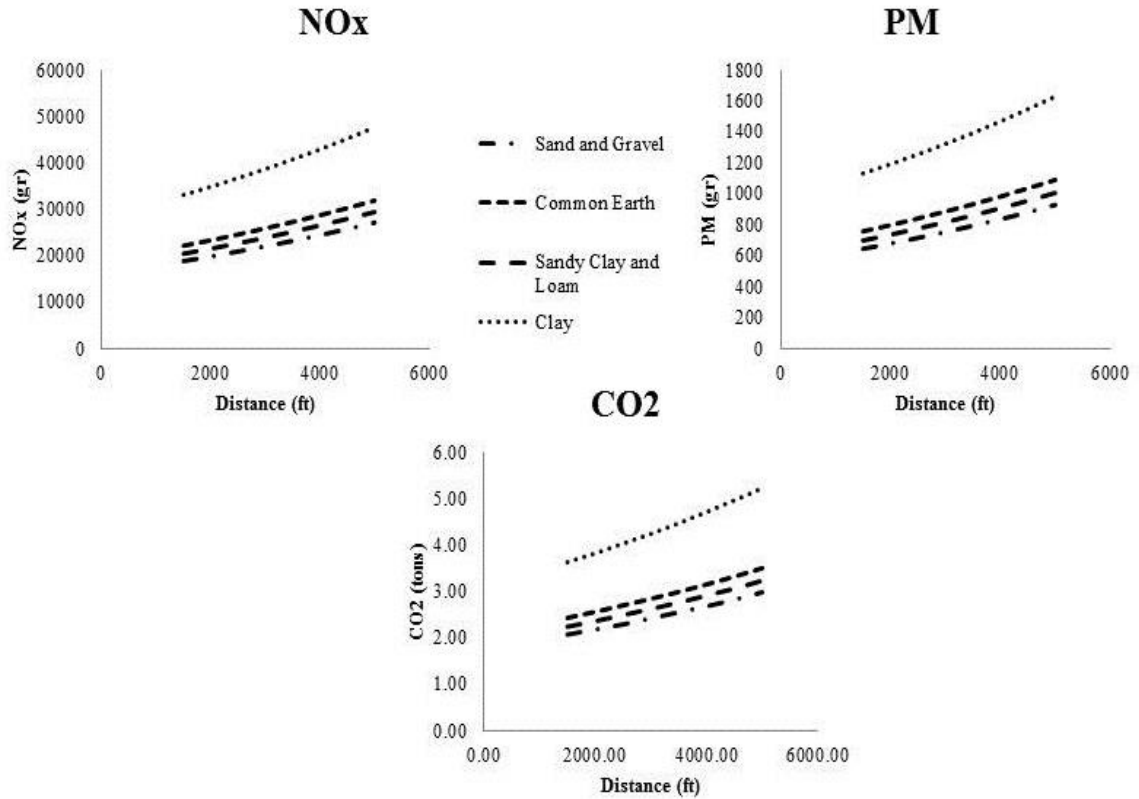


Figure 4.34. Environmental impact of scraper based on distance

### 4.5.3. Excavator

The sensitivity analysis for excavator is applied in two different work scenarios: first, a 400 hp – model year 2003 excavator has to dig 100 feet long – 10 feet wide trench in various depth, using 3 cy of bucket size on all types of soil; second, the same excavator with various size of bucket has to dig 100 feet long – 10 feet wide – 12 feet deep trench on all types of soil as well. Based on the information in Appendix M – Table M.1 and M.2, there is an inverse relationship between productivity rate and the other parameters including total cost, fuel use, and emissions; that is, as the productivity rate decreases, the other parameters increase. The productivity rate also decreases with the digging resistance based on soil type; sand-gravel has the highest productivity rate whereas clay

has the lowest. Likewise, although in very little difference productivity rate based on soil type, activity duration, total cost, fuel use, and emissions all increase as the soil resistance increase. Furthermore, for a specific soil type, the productivity rate increases as bucket size increases, and decreases as the trench depth increases.

Figure 4.35 shows the economic and energy impact of the excavator activity based on the trench depth for different types of excavator. For all types of excavator, it shows that when the excavator has to dig deeper trench, the estimated total cost and fuel use will be higher. The estimated total costs for all types of excavator are about the same for digging the trench with 5 feet or less. When the trench depth increased for more than 5 feet, the total cost of three types of excavator become more varies. Excavator with truck mounted has the highest economic impact, while regular excavator has the lowest. The estimated fuel uses of all types of excavator are considered the same for any depth of trench. It is understood that in the productivity model for excavator, the type of excavator is not significantly explain the productivity rate; that is, as the activities use different type of excavator, the productivity rates are about the same (Table). Thus, the durations needed to complete the work are also the same.

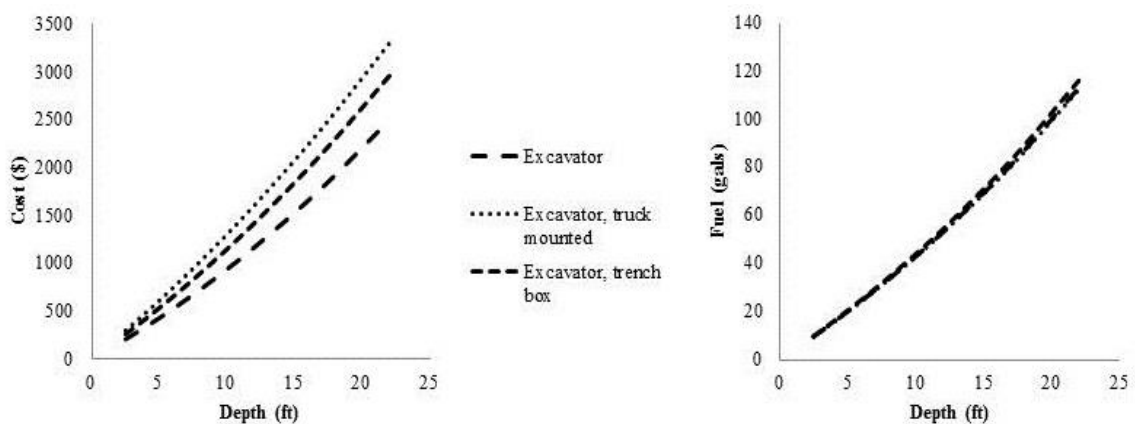


Figure 4.35. Economic and energy impact of excavator based on excavator type and trench depth

The economic and energy impact of the excavator activity based on the trench depth for all types of soil are presented in Figure 4.36. For all types of soil, the estimated total cost and fuel use increase as the trench depth increase. The total costs of the activity on different types of soil are about the same when the excavator has to dig less than 5 feet deep. As the trench depth becomes deeper than 5 feet, the total cost from all types of soil become diverges. The total cost from hard clay increases more rapidly than the other types of soil and has the highest economic impact for the activity. The lowest economic impact occurs on sand-gravel and sandy clay-loam type of soil. As the excavator digs a trench not deeper than 12 feet, the estimated fuel uses for all types of soil are about the same (Table). Although the fuel uses from all types of soil start varies when the trench went deeper than 12 feet, particularly for hard clay and common earth, the overall estimated total fuel use are considered the same. As shown in Figure 4.37, this circumstance also appears in the overall environmental impact of the activity based on the trench depth. The estimated total emissions of NO<sub>x</sub>, PM, CO, and CO<sub>2</sub> are the same for all types of soil, and increase as the depth of the trench goes deeper.

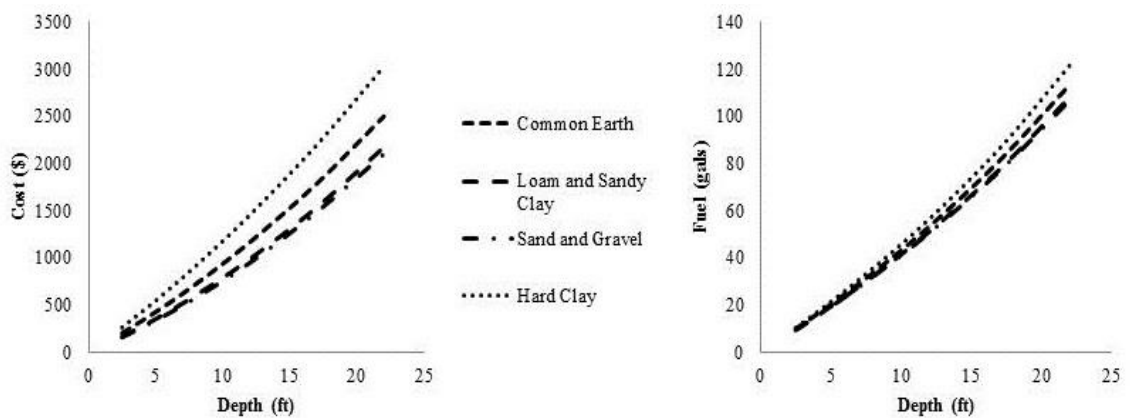


Figure 4.36. Economic and energy impact of excavator based on soil type and trench depth

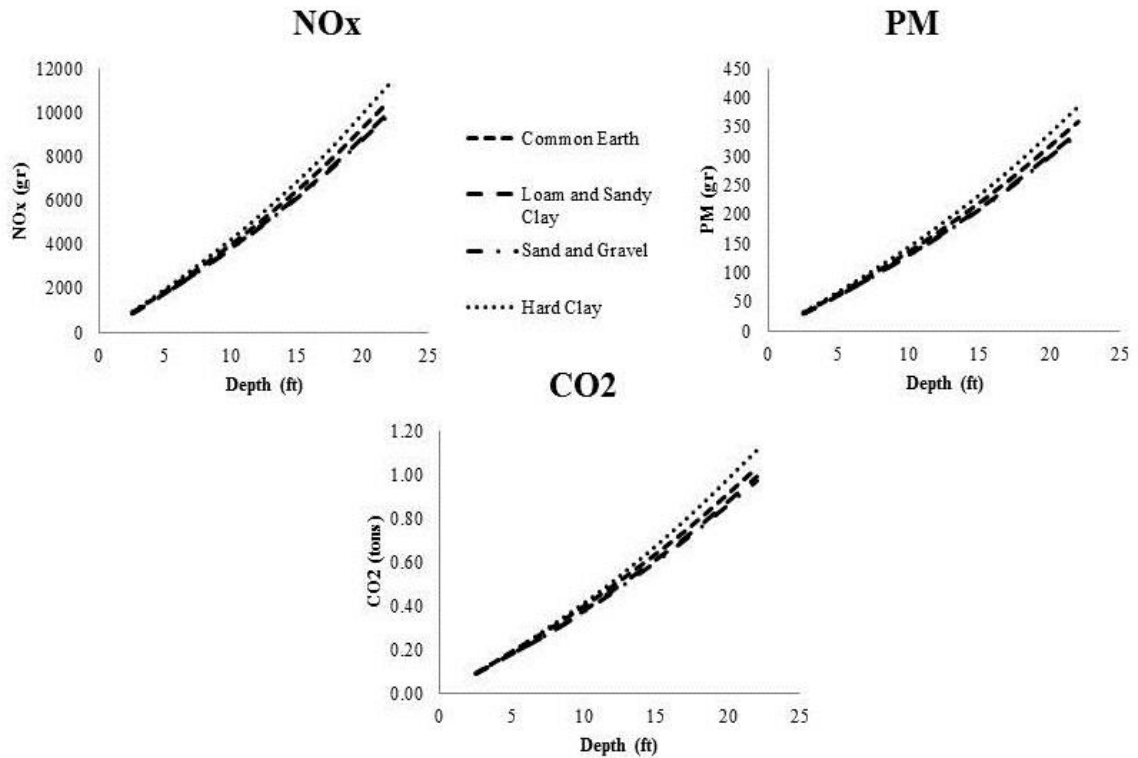


Figure 4.37. Environmental impact of excavator based on trench depth

The economic and energy impact of excavator activity based on its bucket size are presented in Figure 4.38. The estimated total cost of excavator activity has an inverse relationship with its bucket size for all types of soil; that is, as the size of bucket increases, the total cost decreases. Again, the most resistant soil type, which is hard clay, has the highest economic impact on the activity, while sand gravel and sandy clay-loam has the lowest. The Figure 4.38 also shows an interesting fact about estimated total fuel use based on the bucket size. The fuel use decreases exponentially while excavator digs the trench with bucket size less than 1.50 cy. In this range of depth, hard clay has the

highest total fuel use, while sand-gravel and sandy clay-loam has the lowest. However, when the bucket size used is bigger than 1.50 cy, the estimated total fuel use starts decreasing linearly and shows that for all types of soil, the fuel uses are the same. It indicates that the productivity rate of excavator based on the resistance of soil or soil type varies only when the excavator uses small size of bucket. For bigger bucket size, the resistance of soil does not have impact on productivity rate.

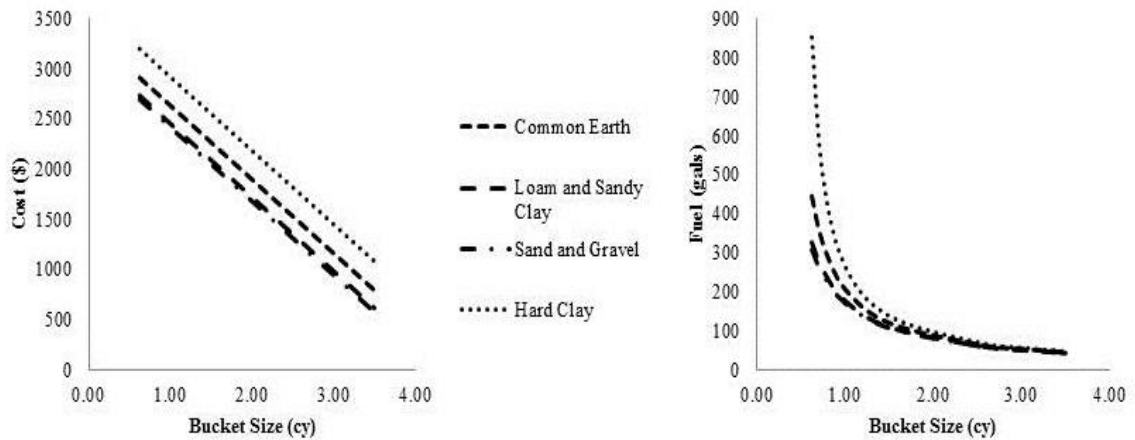


Figure 4.38. Economic and energy impact of excavator based on bucket size

Similar fact with the fuel use also occurs in the estimated total emissions.

Represented by the emissions of NO<sub>x</sub>, PM, CO, and CO<sub>2</sub>, Figure 4.39 shows how the environmental impact of the excavator activity is less varies when 1.50 cy or more bucket size is used. The shape of the line chart is the same with those in the fuel use chart, since both the emission factors and fuel use factor are multiplied with the same duration and engine size to obtain estimated total fuel use and total emissions.

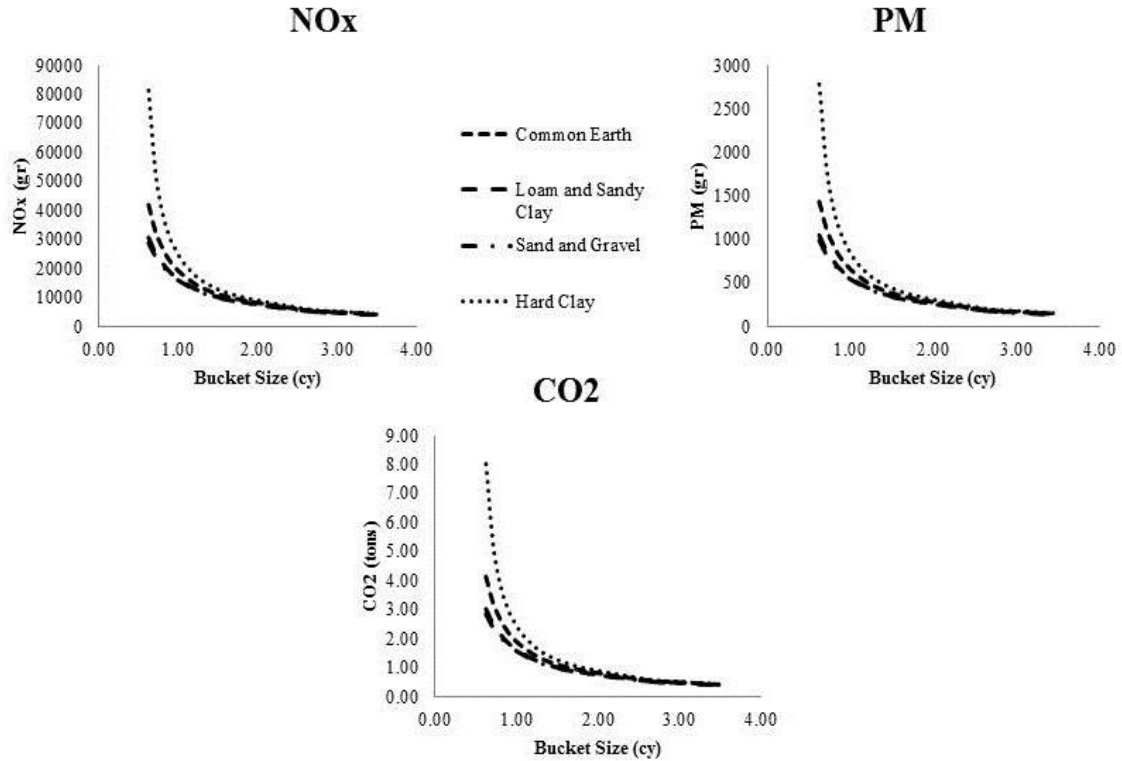


Figure 4.39. Environmental impact of excavator based on bucket size

#### 4.5.4. Truck

The sensitivity analysis for truck is applied in two different work situations: first, as shown in Table, a 535 hp – model year 2003 truck with 30 cy loading capacity has to haul 1000 cy of soil in various distance, using various hauling speed, and has to wait for dumping and loading for 15 to 25 minutes; second, the same truck with various capacity of loading has to haul 1000 cy of soil in 1 mile, using average hauling speed range of 5 to 25 miles per hour, and has to wait for loading and dumping for 15 minutes. Based on the information in Appendix N – Table N.1 and N.2, there is an inverse relationship between productivity rate and the other parameters including total cost, fuel use, and emissions; that is, as the productivity rate decreases, the other parameters increase. For any speed the

truck uses to haul the soil, the productivity rate increases as loading capacity increases, and decreases as the haul distance increases.

The economic, energy and environmental impact of truck activity based on cycle distance are shown in Figure 4.40 and Figure 4.41, analyzed using three different load-dump times: 15, 20, and 25 minutes. For all load-dump times, estimated total cost and total fuel use increase as the cycle distance increase. The longer the truck has to wait for loading and dumping, the higher total cost and total fuel use. More productive supporting equipment (such as excavator or backhoes) for loading and unloading soil to truck is needed to shorten the load-dump time and improve the truck's productivity rate. The estimated fuel use and total emissions for three load-dump time has little difference when the truck has to haul within less than 2 miles. For hauling distance more than 2 miles, the estimated fuel use and emissions vary for three different load-dump times. Truck with 25 minute load-dump time increases its fuel use, emissions of NO<sub>x</sub>, PM, CO, and CO<sub>2</sub> very rapidly compared to 15 and 20 minute load-dump time, as the hauling distance increase.

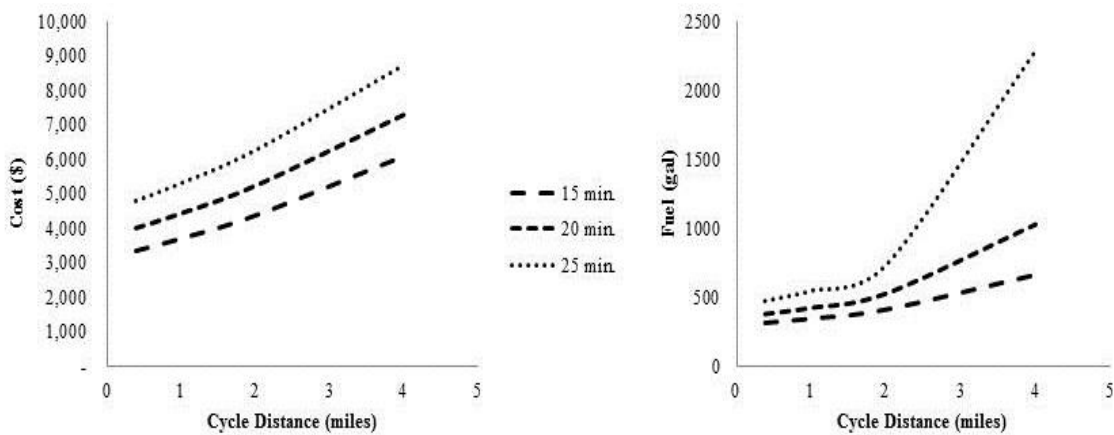


Figure 4.40. Economic and energy impact of truck based on cycle distance



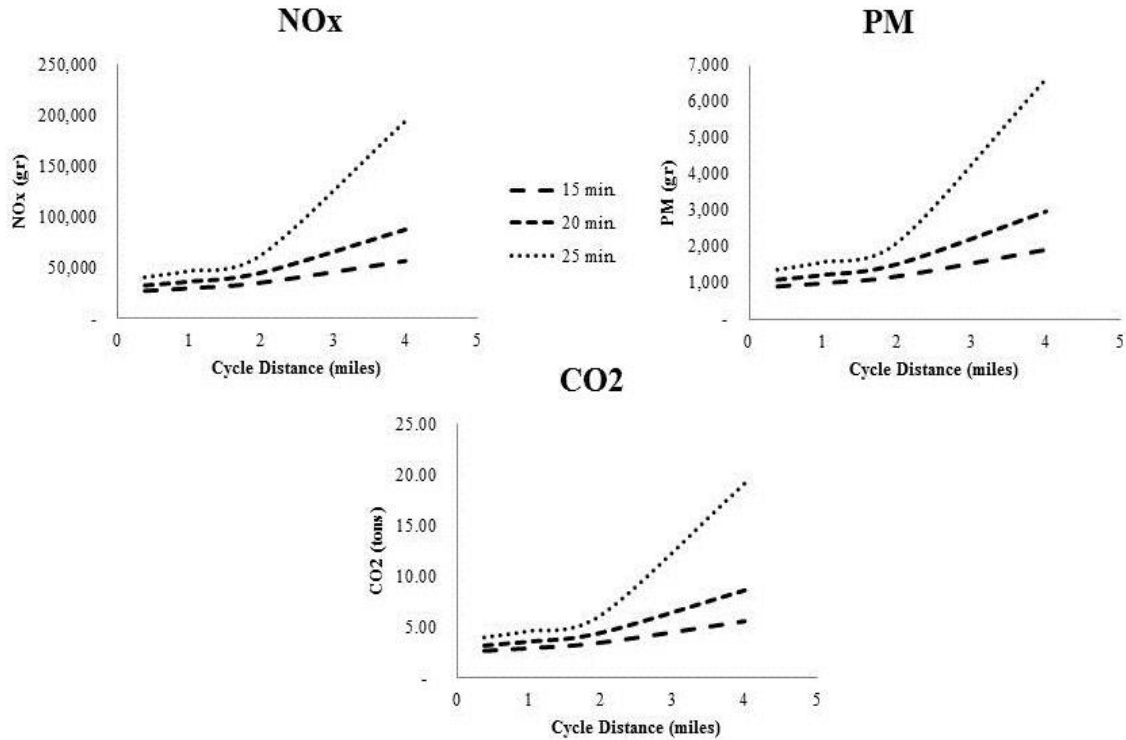


Figure 4.41. Environmental impact of truck based on cycle distance

The economic, energy, and environmental impact of truck activity based on loading capacity, and analyzed using five different hauling speeds (5,10,15,20, and 25 miles per hour), are shown in Figure 4.42 and Figure 4.43. For all hauling speeds, the estimated total cost decreases as the loading capacity increases. It is understood that the productivity rate of truck improves when using bigger loading capacity, and therefore shorten the hauling duration. Truck with highest hauling speed (25 mph) has the lowest economic impact. The estimated total fuel use and emissions for all hauling speeds decreases as the loading capacity increases. The difference of fuel use and emissions among all hauling speeds becomes smaller following the loading capacity; for instance, the difference of fuel use and emissions at 25 cy loading capacity is bigger than those at 50 cy or more loading capacity. It indicates that using various speed of hauling does not

have bigger impact on the estimated fuel use and emissions if the truck uses bigger loading capacity.

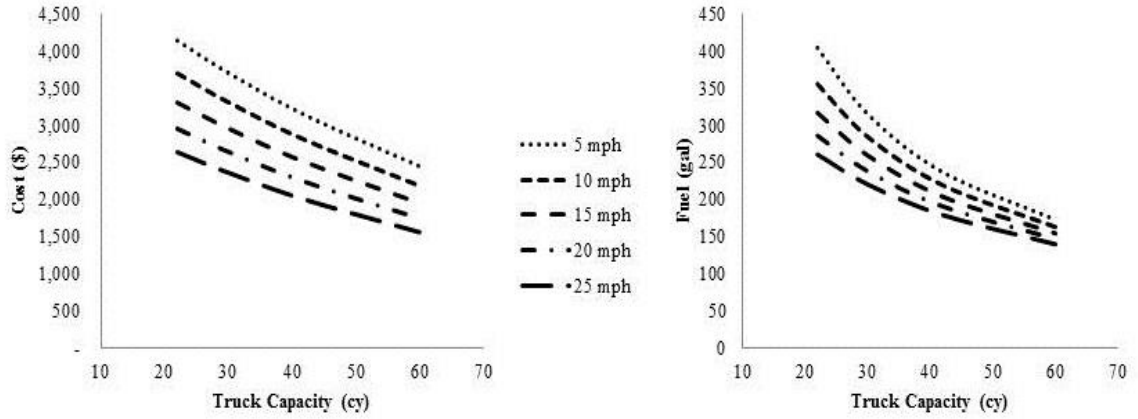


Figure 4.42. Economic and energy impact of truck based on loading capacity

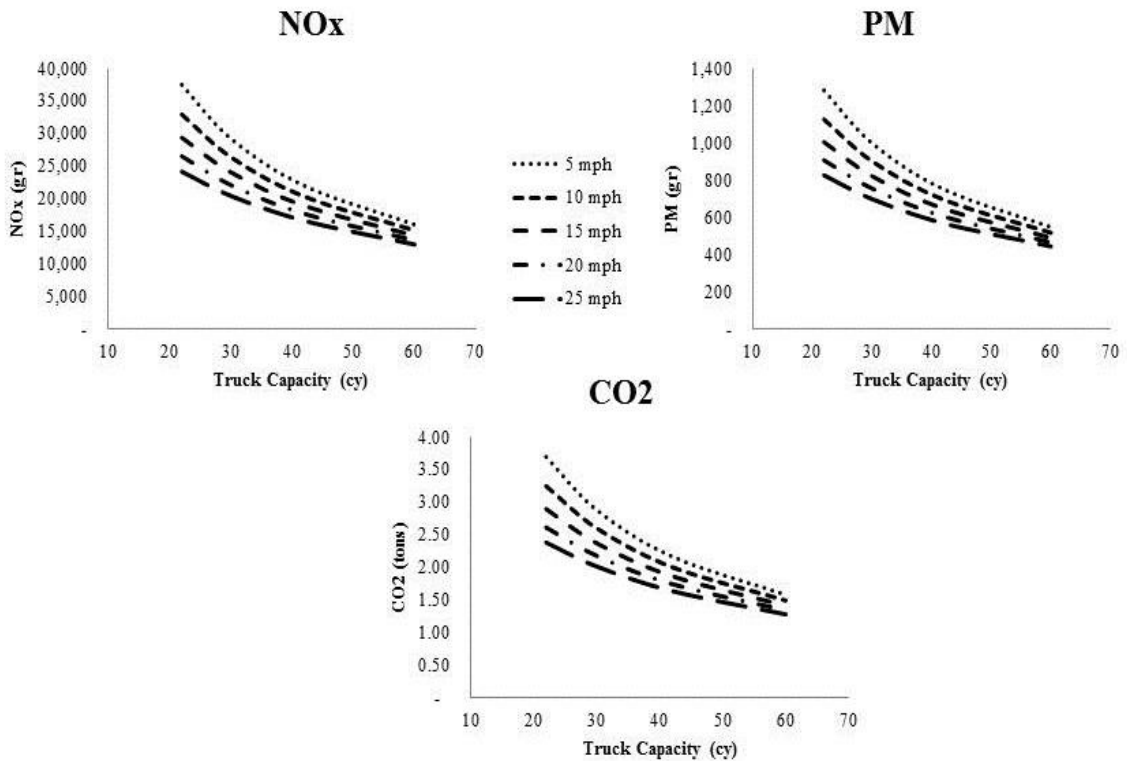


Figure 4.43. Environmental impact of truck based on loading capacity

## **CHAPTER V**

### **CONCLUSIONS AND FUTURE WORKS**

#### **5.1. Conclusions**

This research has attempted to present a methodology and tool for estimating the economic (total cost), energy (fuel use), and environmental (emissions) impact for common earthwork activities performed by HDD equipment. This tool can be used together with other common estimating approaches to gain an overall understanding of the financial, fuel, and emissions footprint for construction activities. Although there are already methods, or models, or tools for estimating productivity, costs, and emissions for construction equipment, there currently is not a means for doing all of these at once. This tool can be developed into a stand-alone model, or into a module that can be used collaboratively with other existing earthwork and emissions estimator.

Some specific conclusions from the methodology and results of the research are described as follows:

### **5.1.1. Multiple Linear Regression (MLR) for Productivity Models**

The MLR had produced two statistically accurate and precise models with low bias for productivity rate based on two independent data sources; RSMeans Data and CAT Performance Data. Each productivity prediction model accounted for a high percentage of variability in its respective data source; productivity on RSMeans Data: 95% for bulldozer, 99% for scraper, 92% for excavator, and 94% for truck, while productivity on CAT Performance Data: 64% for bulldozer, 90% for scraper, 89% for excavator, and 85% for truck. The two data sources are considered to be reliable and of good quality; well respected and frequently used in construction activity and equipment estimating. This MLR-produced methodology provides a reasonable benchmark to use for quantifying the economic, energy, and environmental impact of earthwork activities.

In the development of MLR-based productivity rate model, the two data sources are different in terms of input variables and the magnitude of productivity results. RSMeans Data mostly uses fewer variables compared to CAT Data. For example, the productivity model for bulldozer in RSMeans Data was built from engine size, distance, and soil types, whereas CAT Data has engine size, blade capacity, distance, operational efficiency, site slope, operator's skill, soil type, and dozing technique. RSMeans Data also has fewer variables for truck, which are loading capacity, speed, distance, and cycle time, while CAT Data has engine size, loading capacity, speed, distance, cycle time, operational efficiency, bucket size of excavator, and cycle time of excavator. Some additional input variables that CAT Data have indicates that the manufacturer must examine closely and comprehensively to determine its products' value in productivity rate. As one of HDD equipment manufacturer, CAT has a purpose to explain the

performances and specifications in detail to the prospective users. RSMeans Data provides with information on sizing, productivity, equipment requirements, design standards, and engineering factors for all type of major construction projects, including earthwork activities. All information are compiled and taken as averages from large number of sources including project information from many construction professional associations, construction companies, material suppliers, and manufacturers. Simpler and fewer input variables found in RSMeans Data are intended to help construction estimator to use some technical data to prepare quantity takeoffs and complete construction estimates, compare the cost of design alternatives, cost analysis, and value engineering.

Another difference is the magnitude of the productivity results. On average, CAT Performance Data produces about 130% higher productivity rates or 1.3 times higher than those from the RSMeans Data. For bulldozer, productivity rate from CAT Data is about 150%-240% higher than RSMeans Data based on engine size and dozing distance. For scraper, CAT Data produces productivity rate 100%-120% higher than RSMeans Data based on distance and bucket capacity, with an exceptional case for clay type of soil on which CAT Data and RSMeans Data give about the same productivity rate based on bucket capacity. For excavator, productivity rate based on bucket size from CAT Data is about 120%-400% higher than RSMeans for all types of soil. Productivity rates of truck from two sources of data are about the same based on distance and less-than-50 cy loading capacity. CAT Data produces 30% higher productivity rate than those from RSMeans when the trucks have more than 50 cy loading capacity. Higher productivity rates produced from CAT Data are obtained because the manufacturer calculated the productivity based on 100% efficiency in operation, by using computer analysis and

laboratory research, both on and off-site testing. 100% efficiency in operation most likely cannot be achieved continuously even under ideal conditions. RSMeans Data provides average of all data compiled from many sources; construction professional associations, construction companies, material suppliers, and manufacturers. The data in RSMeans are widely accepted and used by most construction professionals, especially for preparing quantity takeoffs and complete construction estimates. Productivity rates in RSMeans are calculated as daily output basis and represents average figures, which will vary with job conditions. Productivity rates in RSMeans Data are also provided with the estimated labor hours, unit costs, bare costs (including materials, labors, and equipment), and total cost, which includes bare cost plus profit and overhead costs. As for the purpose of practicability and the differences between these two data sources, this research has decided to use RSMeans Data for the basis of productivity and cost models building.

### **5.1.2. Multiple Linear Regression (MLR) for Cost Models**

The MLR had also produced statistically accurate and precise models with low bias for estimated unit cost based on RSMeans Data. Each cost prediction model accounted for a high percentage of variability in its respective data source: 97% for bulldozer, 99% for scraper, 70% for excavator, and 88% for truck. By using the models, construction estimators can estimate unit costs of the use of HDD equipment over a range of values of engine size, distance, bucket size, trench depth, loading capacity. Additionally, unit cost estimates can also be obtained based on some specific job conditions such as type of soil, cycle distance or average hauling speed and other supporting equipment's cycle time (for truck). For specific range of engine size, generally

it can be concluded that using bigger engine size (horsepower), which means using bigger equipment's attachments or tools (bucket, blade, or loading capacity), to perform earthwork activities will significantly decrease the total cost. Bigger engine size increases productivity significantly, reduces the duration of activities, and decreases the total costs. Concerning the job conditions, the total cost increases as the working loads of HDD equipment become higher. Higher soil density or rolling resistance, longer distances for hauling, dozing, or excavating, longer cycle times, or deeper trenches decrease the productivity rates, increase the activity duration, and increase the total cost.

Using RSMMeans Heavy Construction Data as the basis for building the cost models is reliable not only because it has been widely accepted and used by most of construction professionals, but also because it is produced with the compliance of the latest Construction Specifications Institute (CSI) MasterFormat that has a system of titles and numberings used extensively to organize construction information. All data in the RSMMeans cost data are arranged in the 50-division MasterFormat 2004 system. The overall cost data are also continuously monitored by the RSMMeans according to the developments of the construction industry in order to ensure its reliability, thoroughness, and up-to-date cost information.

### **5.1.3. Total Fuel Use Models**

Total fuel use estimates are calculated by using the total duration of the activity obtained from productivity model and fuel use factors obtained from NONROAD model. When compared with field data, the average total fuel use estimates of bulldozer are 9% lower than those from PEMS measurement, while fuel use estimates of excavator and

truck are 34% and 17% higher than the field data respectively. The overall average total fuel use estimates for these three HDD equipment is 14% higher than the field data. For fuel use, NONROAD uses constant brake specific fuel consumption (BSFC) for each engine tier within a specified engine size range, without regard for the activity being performed by the HDD equipment. The difference between E3 model results and PEMS results is due to the variation of fuel consumption rate of individual vehicles and the conditions on which the works are being performed.

The total fuel use estimates as resulted from E3 model are also useful to observe its trends and relationship with engine size and earthwork conditions performed by HDD equipment. Total fuel use estimates can help the HDD equipment operators to decide the size of engine (horsepower) to be used in the activities. Although most results from excavator, scraper, and truck showed that bigger engine size for a specific soil quantity lead to lower fuel use, however bulldozer gives a more specific result. The convex relationship between bulldozer's engine size and its fuel use is useful for selecting the appropriate engine size for an earthwork activity. Particularly when it recalls the relationships with total cost, it is possible for a HDD equipment with higher horsepower to perform an activity at a significantly lower cost than a lower horsepower HDD equipment without substantially increasing the energy (fuel use) impact. Concerning the job conditions, such as type of soil, dozing distance, cycle time, depth of trench, or equipment's attachments, usch as bucket size, blade, and loading capacity, total fuel use increases as the soil becomes more difficult to excavate, the distance becomes further, the cycle time becomes longer, the trench becomes deeper, or as the attachment size becomes smaller.



#### **5.1.4. Total Emissions Models**

Total emissions estimates are calculated by using the total duration of the activity obtained from productivity model and emissions factors obtained from NONROAD model. When compared to field data, results from E3 model give different magnitude of the average total emissions of each pollutants. 22% lower for HC, 8% higher for CO, 59% lower for NO<sub>x</sub>, 85% higher for PM, and 28% lower for CO<sub>2</sub>. Except for PM, the different results obtained from PEMS and E3 model are due to the nature of emission factors used from NONROAD model. The NONROAD model data were built to estimate average emissions for a bigger fleet of vehicles in scope of county-size fleet, state-size fleet, or sometimes for whole fleets in the US. The NONROAD model data are also obtained from the standardized engine dynamometer tests in laboratory conditions. Meanwhile, results from PEMS are gathered from individual in-use HDD equipment when it is operating on various jobsite conditions. Although the results from E3 model do not represent actual working conditions on field, it can be used as a framework and practical tool to predict the emissions from HDD equipment, its fuel use, total duration, and productivity rate at the same time, which have not currently been available by previous models and methods.

The total emissions estimates resulted from E3 model are also useful to observe its relationship with HDD equipment performance attributes, such as engine size and the attachments set up to the equipment (buckets or blades), and with various earthwork working conditions, such as type of soil, distance, depth, and cycle time. Generally, as performed in total fuel use estimates, the total emissions also decrease when the engine

size (horsepower) increase. It can be understood that by using bigger engine size, which means having bigger capacity of attachments, the productivity rate can be improved and the total duration of the work can be reduced. On the other hands, the total emissions becomes higher when the HDD equipment have to perform works on higher rolling resistance of soil, or deeper trench excavating, or further hauling and dozing distances, or longer times in completing the cycles.

The estimating tool presented in this research will be an effective means for assessing the economic, energy, and environmental impacts of construction activities and will allow HDD equipment owners or fleet managers, policy makers, and project stakeholders to evaluate more sustainable alternatives. This tool will help contractors to estimate not only fuel quantities and cost that will be required for a project, but also emissions inventories at the same time. This tool can also be used to estimate emissions for various construction sectors. By using construction plans and specifications, the methodology and tool presented in this research can be used to estimate cost, fuel use, and emissions from commercial, residential, industrial, or heavy highway. Once all types of construction can be covered by this methodology, it is possible to develop new fuel use and emissions inventories for construction industry in general.

This methodology and tool can also be used as one of basic considerations for HDD equipment selection. Since the US EPA promulgated the emissions standard for diesel equipment including all construction equipment in 1999, the environmental issues has become one of the factors in selecting equipment. Construction professionals are encouraged to select new cleaner and lower emissions HDD equipment for their fleets. By using findings in this research, a HDD fleet manager can now be able to select the right

machine for matching to the appropriate work activities, the physical properties of earth or soil, and to set the desired productivity. By using the findings in this research, the selected HDD equipment can be more economic, energy, and environmentally sound.

## **5.2. Future Works**

To address the environmental concerns associated with construction, a set of substantial data related to construction projects for developing emissions inventories is needed. The productivity-based cost, fuel use and emissions estimating tool proposed in this research can help to fill this need. To develop meaningful emissions inventories for the construction industry, some improvements and recommended works in the future are as follows:

### **5.2.1. Productivity Modeling for More Variabilities and Uncertainties**

The productivity rate models used in this research are built from RSMeans Heavy Construction Data, which is considered as reliable and widely accepted data for construction estimating. RSMeans data representing cost and productivity provide basic information that allows construction estimators to predict the productivity rates. However, the information, which is comprised of average values, provided by the RSMeans Data is not easily applied to various site conditions where numerous unexpected factors are found. Productivity models built from RSMeans Data were developed by using deterministic type of analysis, which primarily focuses on the use of a single fixed or constant value, with the assumption that any variability and uncertainty in the activities are ignored. Deterministic approach was used for simple calculation of the

productivity of HDD equipment operations based on equipment characteristics and other stated site conditions provided by the reference. Deterministic approach does not present actual productivity of HDD equipment based on real condition such as idling and loss of productivity related to random variations on site.

To overcome the limitations of deterministic models, and to match with real-world in-use emissions measurement by using PEMS, approaches in developing more accurate productivity rates estimations are needed. The use of construction simulation methods or other mathematical relations between productivity and operating conditions of HDD equipment with probabilistic approach can help these needs. The support from a large amount of input datasets covering various actual conditions is also useful to develop more reliable productivity models.

### **5.2.2. Different Types of HDD Equipment**

To create substantial data related to construction projects for developing emissions inventories of construction industry, the tool and methodology resulted from this research have to also be applied thoroughly to all available types of HDD equipment. Bulldozers, scrapers, excavators, and dump trucks are only some subtypes of bigger group of HDD equipment. There are still a lot of types of HDD equipment that can be used as sources of productivity-based cost, fuel use, and emissions estimation models, such as motorgraders, skidsteer loaders, multi-terrain loaders, track loaders, backhoe loaders, tractors, wheel loaders, integrated tool-carriers, and underground mining equipment. It can be useful since the latest EPA's NONROAD model, which is used in this research, has included more than 80 basic and 260 specific types of nonroad equipment.

### **5.2.3. Different Types of Construction Projects or Activities**

The tool presented in this research is a framework that can be used with other common estimating approaches to gain an overall understanding of the financial, fuel, and emissions footprint for a construction activity and ultimately an entire project. To draw a complete picture for an entire project, and by using construction specifications and plans, the same methodology can also be applied. Since RSMMeans has updated the organization of its database from Construction Specifications Institute's 16-Division MasterFormat 95 to the 44-Division MasterFormat 2004, a set of more detailed activities in construction projects can be used to develop comprehensive productivity models as basis for economic, energy, and environmental model. With specific-related equipment, the activities in concrete, masonry, metals, wood and plastics, thermal and moisture protections, doors and windows, finishes and equipment, plumbing, and other electrical and mechanical works can also be assessed. Particularly for earthwork activities, there are still some other works useful to develop productivity models for different types of HDD equipment, such as soil grading, dewatering, backfill, compaction, shoring, sheet piling, driven piles, drilled piles, and some earthwork specialty items.

### **5.2.4. Different Types of Fuel**

A comprehensive emissions inventory requires not only the lists of air pollutants quantities emitted, but also the insight about the distribution of emissions among different source categories, such as types of vehicles or types of fuel. Emissions inventory based on types of fuel can also help equipment fleet managers to evaluate some emissions reduction strategies. Since EPA's Clean Air Nonroad Diesel rule required that sulfur

levels in highway diesel fuel be reduced by approximately 99% from 3,000 ppm to 15 ppm in 2004, the use of alternative fuels, such as biodiesel, is encouraged to be used. Biodiesel is registered with EPA and is a legal fuel at any blend level for use in highway and nonroad vehicles. In EPA's NONROAD model itself, the model has included various fuel types, such as compressed natural gas (CNG) and liquefied petroleum gas (LPG).

#### **5.2.5. Comparison with Other Countries' Emissions Standards**

EPA's NONROAD model and Engine Tier Levels for Emissions Standard used in this research are part of EPA responsibilities under the Clean Air Act to reduce the emissions of pollutants from a range of sources in order to provide clean and healthy air in the United States. Although most of data used by the EPA are US-based data, however some construction HDD equipment included in the model and standard are also used widely in other countries in the world. Some HDD equipment manufacturers, such as Caterpillar or Komatsu, also produce their products for worldwide construction projects. To observe the magnitude of emissions reduction policies and standards in the US among all global emissions standards, a comparison showing relationships between the EPA's standard for nonroad vehicles and those from other countries is also important. For example, regulatory authorities in the European Union (EU) and Japan have been involved by the engine and equipment manufacturers to harmonize worldwide emissions standard, in order to streamline engine development and emission type certification. Similar with Engine Tiers Level 1-4 in EPA's nonroad emission standard, the European emissions standards for new nonroad diesel engines have been structured as gradually more stringent tiers known as Stage I-IV standards. By understanding and comparing other

countries' emissions standards, the estimating tool developed in this research can be modified and applied to fit with local needs and regulations.

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## APPENDICES

The appendices provides supporting results, data, calculation, or codes which are used for developing productivity, cost, fuel use, and emission models for bulldozer, scraper, excavator, and truck. The appendices are broken down as follows:

- Appendix A** Results of multiple linear regression (MLR) analysis to obtain productivity and cost models for bulldozer
- Appendix B** Results of multiple linear regression (MLR) analysis to obtain productivity and cost models for scraper
- Appendix C** Results of multiple linear regression (MLR) analysis to obtain productivity and cost models for excavator
- Appendix D** Results of multiple linear regression (MLR) analysis to obtain productivity and cost models for truck
- Appendix E** PEMS field measurement results for bulldozers
- Appendix F** PEMS field measurement results for excavators
- Appendix G** PEMS field measurement results for trucks
- Appendix H** E3 model output of emission factors for bulldozers, excavators, and trucks
- Appendix I** SAS coding for productivity and cost models
- Appendix J** Visual Basic coding for E3 model user's interface
- Appendix K** E3 model output for bulldozer
- Appendix L** E3 model output for scraper
- Appendix M** E3 model output for excavator
- Appendix N** E3 model output for truck



## Appendix A

### Results of multiple linear regression (MLR) analysis to obtain productivity and cost models for bulldozer

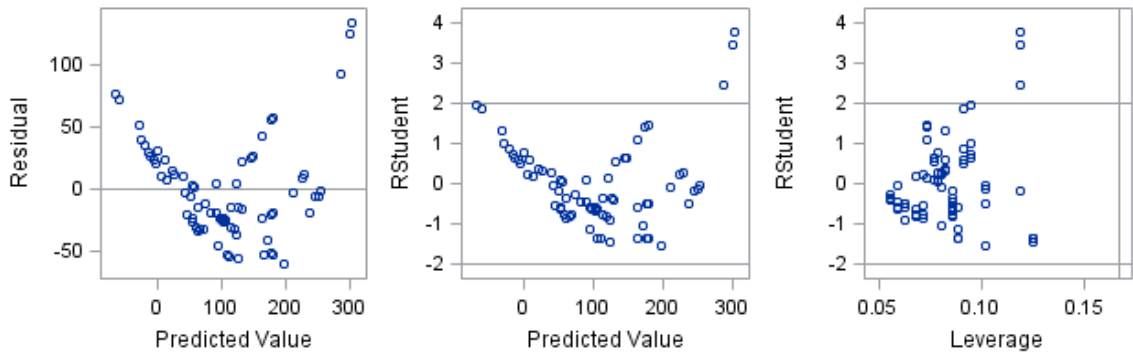


Figure A.1. Plots of predicted values versus residuals of productivity model

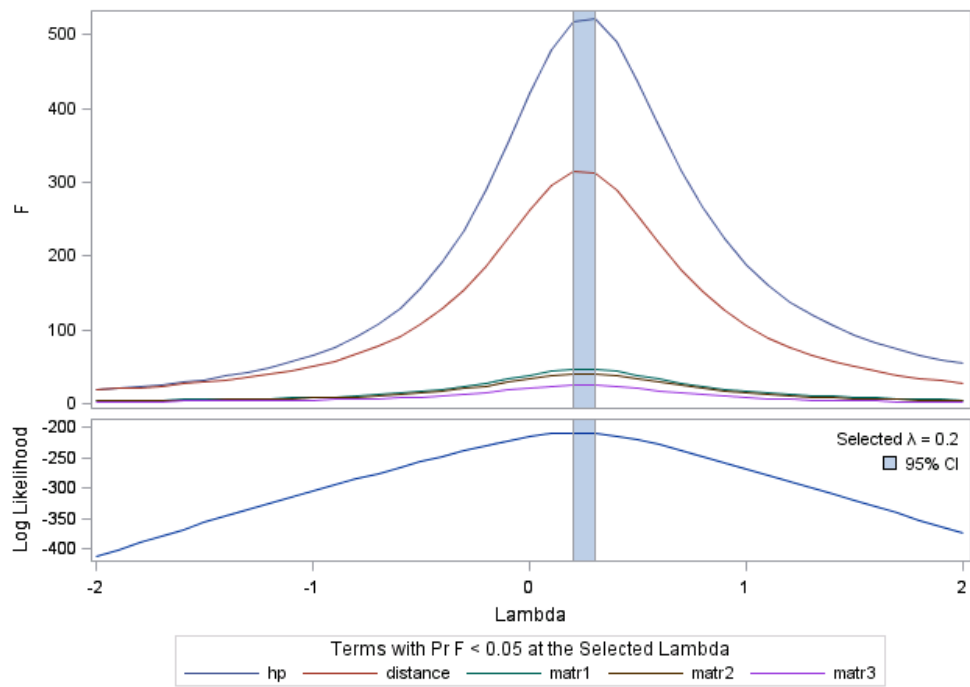


Figure A.2. The best  $\lambda$ -value of Box-Cox transformation productivity regression model

Table A.1. Regression coefficients for productivity model – RSMeans

Variable	Coefficient	Parameter estimate	t-value	p-value
Intercept	$\beta_0$	1.87859	40.56	<0.0001
Horsepower	$\beta_1$	0.00350	14.02	<0.0001
Dozing distance	$\beta_2$	-0.00240	-19.13	<0.0001
Soil type 1	$\beta_3$	0.23656	6.47	<0.0001
Soil type 2	$\beta_4$	0.21667	5.93	<0.0001
Soil type 3	$\beta_5$	0.16644	4.56	<0.0001

Table A.2. Mallows' C(p) values of variables selection for productivity model –RSMeans

C(p)	R-square	Predictors
4.2963	0.9530	Hp, distance, soil 3 soil 4
5.8891	0.9505	Hp, distance, soil 4
5.9114	0.9474	Hp, distance, soil 1, soil 4
6.0000	0.9534	Hp, distance, soil 1, soil 2, soil 3

Table A.3. Stepwise selection method result for productivity model - RSMeans

Step	Variable entered	Model R <sup>2</sup>	F-value	P-value
1	Distance	0.5667	44.65	<0.0001
2	Horsepower	0.8730	79.30	<0.0001
3	Soil 4*	0.9474	45.23	<0.0001

\*categorical variable

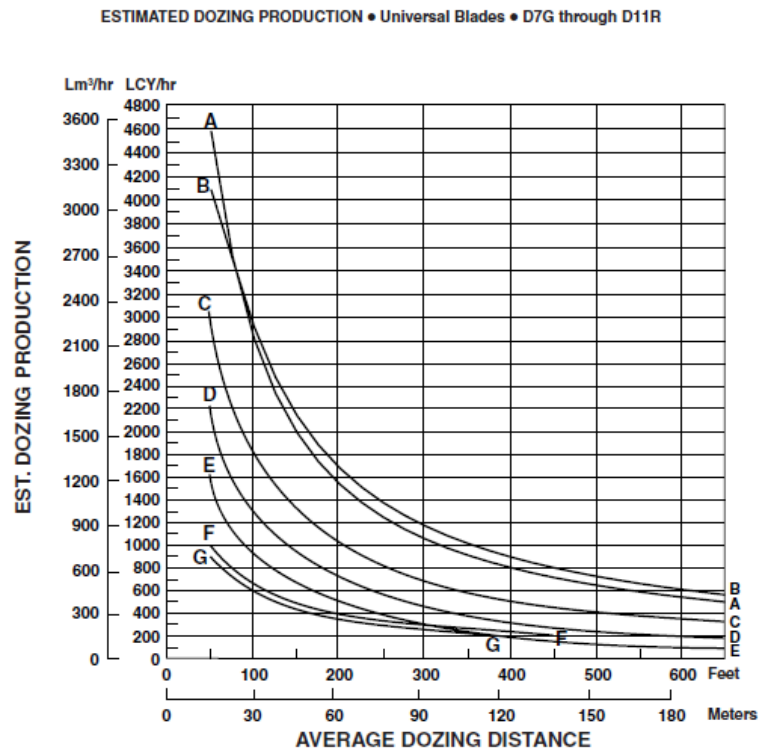


Figure A.3. Productivity estimation chart based on dozing distance for CAT bulldozer using universal blades

Table A.4. Regression coefficients for productivity – CAT

Variable	Coefficient	Parameter estimate	t-value	p-value
Intercept	$\beta_0$	-761.221	-10.28	<0.0001
Blade capacity	$\beta_1$	-7.937	-1.06	0.2896
Horsepower	$\beta_2$	1.502	3.56	0.0004
Dozing distance	$\beta_3$	-1.646	-39.06	<0.0001
Job efficiency	$\beta_4$	628.041	7.30	<0.0001
Soil grade	$\beta_5$	471.03	38.72	<0.0001
Skill 1	$\beta_6$	240.526	14.27	<0.0001
Skill 2	$\beta_7$	90.197	5.35	<0.0001
Soil type 1	$\beta_8$	342.568	17.6	<0.0001
Soil type 2	$\beta_9$	57.095	2.93	0.0034
Soil type 3	$\beta_{10}$	114.189	5.87	<0.0001
Dozing technique 1	$\beta_{11}$	20.044	1.46	0.1454

Table A.5. Mallows' C(p) values of variables selection for productivity model – CAT

C(p)	R-square	Predictors
11.122	0.642	Hp, dist., jobeff, soil grade, skill 1-2, soil type 1-3, dozing 1
11.122	0.642	Hp, dist., jobeff, soil grade, skill 1-2, soil type 1-3, dozing 2
11.122	0.642	Hp, dist., jobeff, soil grade, skill 1-2, soil type 1,3,4; dozing 1
11.122	0.642	Hp, dist., jobeff, soil grade, skill 1-2, soil type 2-4, dozing 2

Table A.6. Stepwise selection method result for productivity model - CAT

Step	Variable entered	Model R <sup>2</sup>	F-value	P-value
1	Distance	0.1904	676.82	<0.0001
2	Horsepower	0.3776	865.12	<0.0001
3	Soil grade	0.5646	1235.57	<0.0001
4	Soil type 1*	0.6049	292.91	<0.0001
5	Skill 1*	0.6272	172.39	<0.0001
6	Job efficiency	0.6339	52.19	<0.0001
7	Skill 2*	0.6375	28.30	<0.0001
8	Soil type 4*	0.6407	25.73	<0.0001
9	Soil 3*	0.6417	8.60	0.0034

\*categorical variable

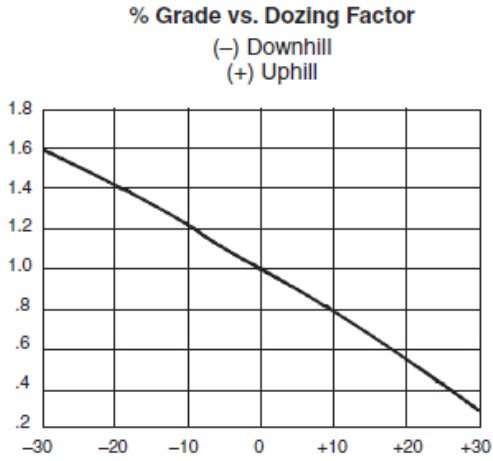


Figure A.4. Dozing factor as a function of soil grade percentage (slope)

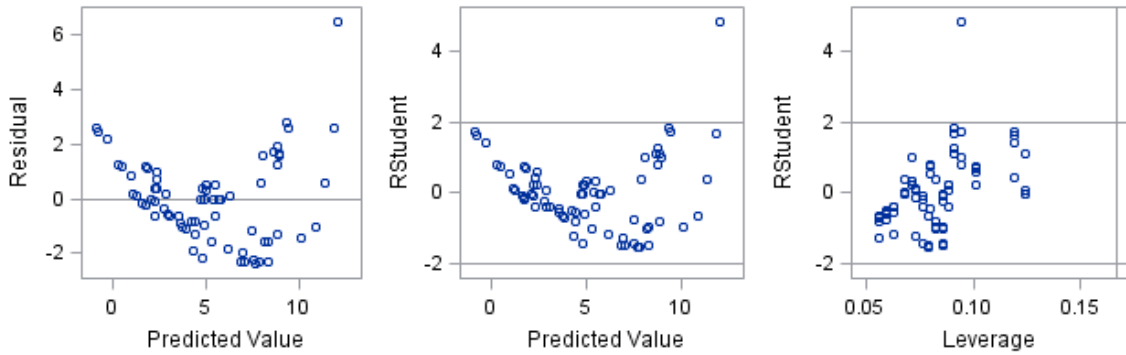


Figure A.5. Plots of predicted values versus residuals of cost model

Table A.7. Regression coefficients for cost model

Variable	Coefficient	Parameter estimate	t-value	p-value
Intercept	$\beta_0$	1.56464	21.94	<0.0001
Horsepower	$\beta_1$	-0.00398	-10.32	<0.0001
Dozing distance	$\beta_2$	0.00578	29.80	<0.0001
Soil type 1	$\beta_3$	-0.57444	-10.19	<0.0001
Soil type 2	$\beta_4$	-0.53944	-9.56	<0.0001
Soil type 3	$\beta_5$	-0.43000	-7.62	<0.0001

Table A.8. Mallows' C(p) values of variables selection for cost model

C(p)	R-square	Predictors
4.3851	0.9737	Hp, distance, soil 3 soil 4
6.0000	0.9741	Hp, distance, soil 4
6.0000	0.9741	Hp, distance, soil 2-4
6.0000	0.9741	Hp, distance, soil 1, soil 3, soil 4

Table A.9. Stepwise selection method result for cost model

Step	Variable entered	Model R <sup>2</sup>	F-value	P-value
1	Distance	0.7678	112.45	<0.0001
2	Soil type 4*	0.8758	28.69	<0.0001
3	Horsepower	0.9679	91.76	<0.0001

\*categorical variable

## Appendix B

### Results of multiple linear regression (MLR) analysis to obtain productivity and cost models for scraper

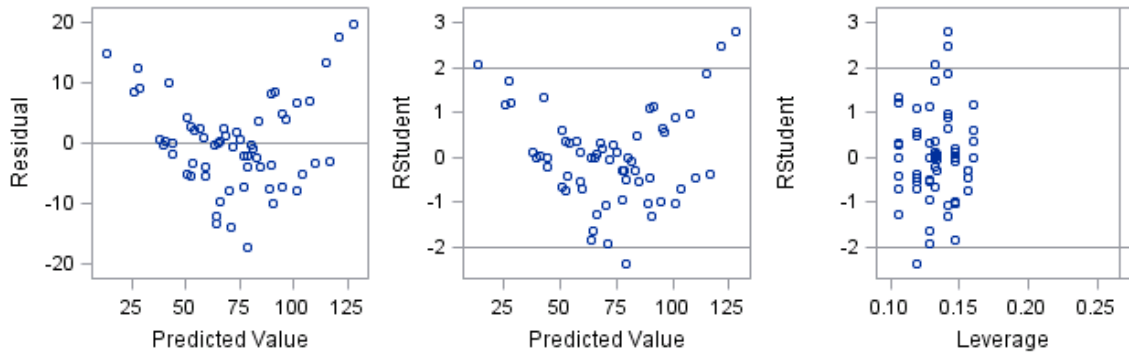


Figure B.1. Plots of predicted values versus residuals of productivity model

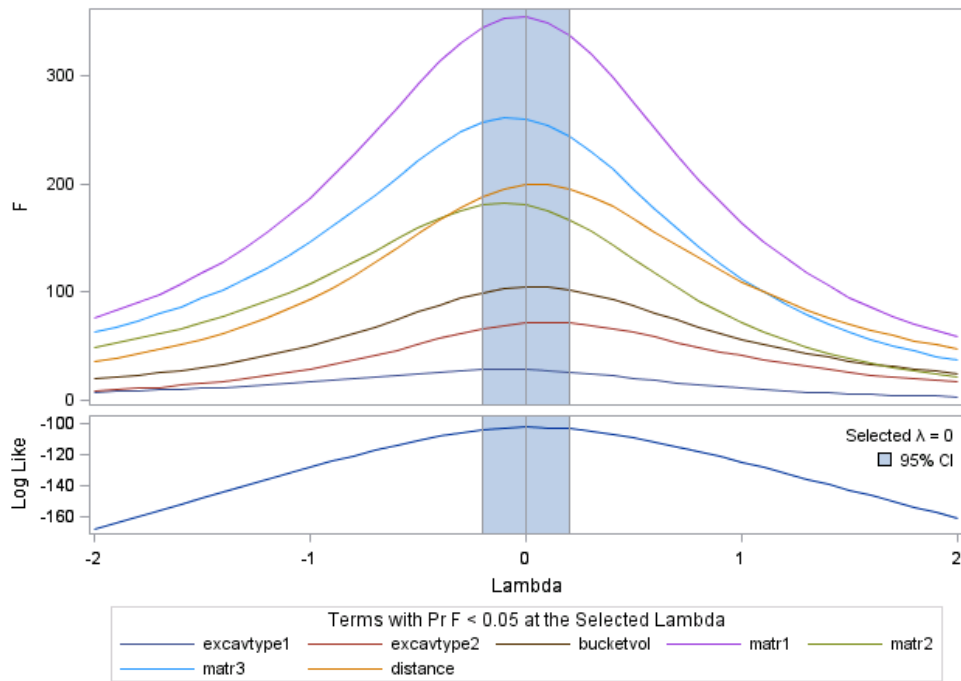


Figure B.2. The best  $\lambda$ -value of Box-Cox transformation productivity regression model

Table B.1. Regression coefficients for productivity model – RSMeans

Variable	Coefficient	Parameter estimate	t-value	p-value
Intercept	$\beta_0$	1.71676	97.23	<0.0001
Scraper type 1	$\beta_1$	-0.08669	-11.87	<0.0001
Bucket size	$\beta_3$	0.01071	10.27	<0.0001
Soil type 1	$\beta_4$	0.26481	35.42	<0.0001
Soil type 2	$\beta_5$	0.20403	27.29	<0.0001
Soil type 3	$\beta_6$	0.24017	30.76	<0.0001
Distance	$\beta_7$	0.0000448	-25.82	<0.0001

Table B.2. Mallows's C(p) values of variables selection for productivity model –RSMeans

C(p)	R-square	Predictors
7.0000	0.9936	Scraper type 1-2, bucket, soil type 1-3, distance
7.0000	0.9936	Scraper type 2-3, bucket, soil type 1-3, distance
7.0000	0.9936	Scraper type 1,3; bucket, soil type 1-3; distance
7.0000	0.9936	Scraper type 1-2, bucket, soil type 1,3,4; distance

Table B.3. Stepwise selection method result for productivity model - RSMeans

Step	Variable entered	Model R <sup>2</sup>	F-value	P-value
1	Soil type 1*	0.5319	31.82	<0.0001
2	Scraper type 2*	0.7509	23.74	<0.0001
3	Distance	0.9371	76.98	<0.0001
4	Bucket size	0.9680	24.14	<0.0001
5	Soil type 2*	0.9905	57.22	<0.0001
6	Soil type 1*	0.9936	10.86	0.0032

\*categorical variable

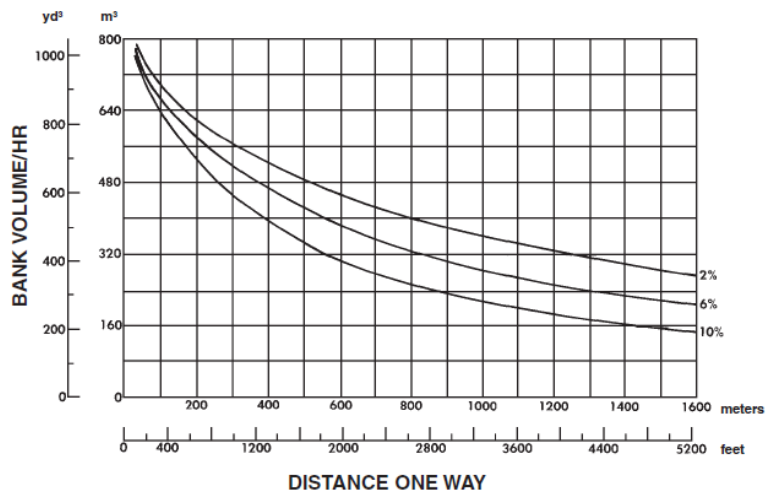


Figure B.3. Productivity estimation chart based on one way distance for CAT scraper

Table B.4. Regression coefficients for productivity – CAT

Variable	Parameter estimate	t-value	p-value
Intercept	263.973	18.53	<0.0001
Horsepower	0.337	2.22	0.0271
Bucket capacity	9.518	4.12	<0.0001
Rolling resistance distance	-1556.281	-18.45	<0.0001
	-0.092	-32.93	<0.0001

Table B.5. Mallows' C(p) values of variables selection for productivity model – CAT

C(p)	R-square	Predictors
5.000	0.9053	Hp, bucket cap., rolling resist., dist.
7.926	0.9040	Bucket cap., rolling resist., dist.
19.989	0.9008	Hp, rolling resist., dist.
343.411	0.8140	Hp, bucket cap., dist.

Table B.6. Stepwise selection method result for productivity model - CAT

Step	Variable entered	Model R <sup>2</sup>	F-value	P-value
1	Bucket capacity	0.5199	385.53	<0.0001
2	Distance	0.8127	555.06	<0.0001
3	Rolling resistance	0.9040	336.64	<0.0001
4	Horsepower	0.9053	4.93	0.0271

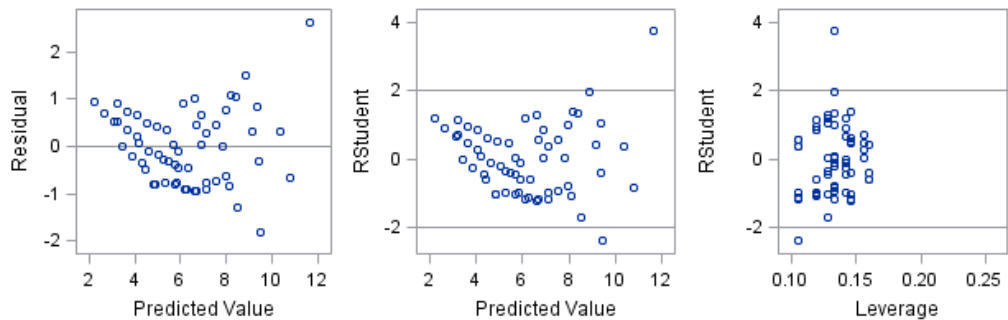


Figure B.4. Plots of predicted values versus residuals of cost model

Table B.7. Regression coefficients for cost model

Variable	Coefficient	Parameter estimate	t-value	p-value
Intercept	$\beta_0$	0.73663	42.08	<0.0001
Scraper type 1	$\beta_1$	0.02950	4.07	<0.0001
Bucket size	$\beta_2$	-0.00033	-0.32	0.750
Soil type 1	$\beta_3$	-0.26519	-35.78	<0.0001
Soil type 2	$\beta_4$	-0.20464	-27.61	<0.0001
Soil type 3	$\beta_5$	-0.24083	-31.11	<0.0001
Distance	$\beta_6$	0.0000445	26.07	<0.0001



Table B.8. Mallows' C(p) values of variables selection for cost model

C(p)	R-square	Predictors
5.1038	0.9903	Scraper type 1-2, soil type 1-3, distance
5.1038	0.9903	Scraper type 1,3; soil type 1-3, distance
5.1038	0.9903	Scraper type 2,3; soil type 1-3; distance
5.1038	0.9903	Scraper type 1-2, soil type 1,3,4; distance

Table B.9. Stepwise selection method result for cost model

Step	Variable entered	Model R <sup>2</sup>	F-value	P-value
1	Soil type 4*	0.6503	52.08	<0.0001
2	Distance	0.9358	120.15	<0.0001
3	Soil type 2*	0.9667	24.12	<0.0001
4	Scraper type 2*	0.9851	30.83	<0.0001
5	Soil type 1*	0.9903	12.84	0.0015

\*categorical variable

## Appendix C

### Results of multiple linear regression (MLR) analysis to obtain productivity and cost models for excavator

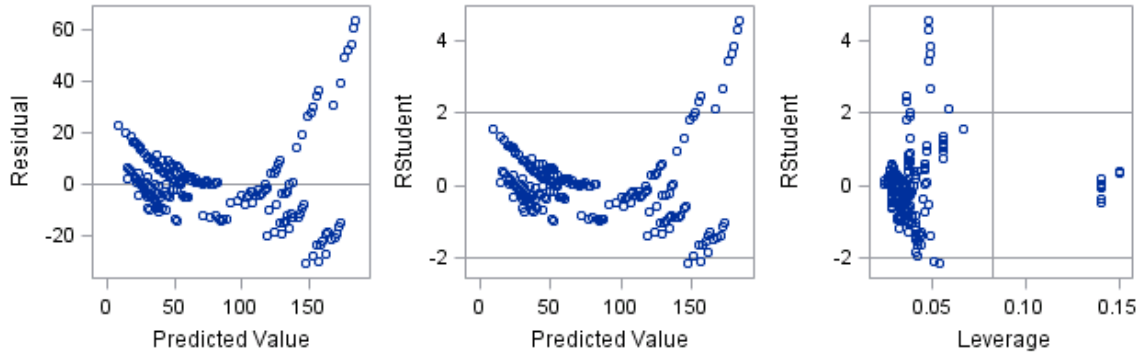


Figure C.1. Plots of predicted values versus residuals of productivity model

Table C.1. Regression coefficients for productivity model – RSMeans

Variable	Coefficient	Parameter estimate	t-value	p-value
Intercept	$\beta_0$	-3.946	-0.91	0.3656
Soil type 1	$\beta_1$	8.465	2.36	0.0193
Soil type 2	$\beta_2$	14.907	4.16	<0.0001
Soil type 3	$\beta_3$	16.412	4.58	<0.0001
Depth	$\beta_4$	-2.069	-9.92	<0.0001
Bucket Size	$\beta_5$	55.131	42.19	<0.0001
Excavator type 1	$\beta_6$	3.317	1.39	0.1676
Excavator type 2	$\beta_7$	4.166	0.72	0.4743

Table C.2. Mallows' C(p) values of variables selection for productivity model –RSMeans

C(p)	R-square	Predictors
4.297	0.9194	Soil type 1,4; depth; bucket size, excav type 3
4.309	0.9185	Soil type 1,4; depth, bucket size
4.788	0.9192	Soil type 1,4; depth, bucket size, excav type 1
6.023	0.9195	Soil type 1,3; depth, bucket size, excav type 3

Table C.3. Stepwise selection method result for productivity model - RSMeans

Step	Variable entered	Model R <sup>2</sup>	F-value	P-value
1	Bucket size	0.8654	1240.52	<0.0001
2	Depth	0.9083	89.85	<0.0001
3	Soil type 4*	0.9149	14.87	<0.0001
4	Soil type 1*	0.9185	8.38	0.0042

\*categorical variable

Cycle Time Estimating Chart

Model		307C	308D CR	308D CR SB	311D LRR	312D, 312D L	315D L	319D L, 319D LN	M312, M313C, M315C, M316C, M318C, M322C	M315, M316D	M318D	M322D	
Bucket Size	L yd <sup>3</sup>	280 0.37	220 0.30	220 0.30	450 0.59	520 0.68	520 0.68	800 1.05	610 0.80	750 0.98	900 1.18	1050 1.37	
Soil Type		Packed Earth						Sand/Gravel					
Digging Depth	m ft	1.5 5'0"	1.8 6'0"	1.8 6'0"	1.5 5'0"	1.8 6'0"	3.0 10'0"	3.0 10'0"	3.0 10'0"	3.0 10'0"	3.0 10'0"	3.0 10'0"	
Load Bucket	min	0.08	0.09	0.08	0.07	0.07	0.07	0.09	0.05	0.06	0.06	0.08	
Swing Loaded	min	0.05	0.03	0.03	0.06	0.06	0.08	0.09	0.05	0.05	0.06	0.06	
Dump Bucket	min	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.04	
Swing Empty	min	0.06	0.06	0.08	0.05	0.05	0.06	0.07	0.04	0.04	0.05	0.05	
Total Cycle Time	min	0.22	0.21	0.22	0.21	0.21	0.24	0.28	0.17	0.18	0.20	0.23	

Cycle Time Estimating Chart

Model		320D	320D RR, 321D CR, 323D	324D	328D LCR	329D	336D	345D	365C L	385C	
Bucket Size	L yd <sup>3</sup>	800 1.05	800 1.05	1000 1.31	N/A	1100 1.44	1400 1.83	2400 3.0	1900 2.5	3760 5.0	
Soil Type		Hard Clay									
Digging Depth	m ft	2.3 8	2.3 8	3.2 10	N/A	3.2 10	3.4 11	4.0 13	4.2 14	5.6 18	
Load Bucket	min	0.09	0.09	0.09	N/A	0.09	0.09	0.13	0.10	0.19	
Swing Loaded	min	0.06	0.06	0.06	N/A	0.06	0.07	0.07	0.09	0.06	
Dump Bucket	min	0.03	0.03	0.04	N/A	0.04	0.04	0.02	0.04	0.03	
Swing Empty	min	0.05	0.05	0.06	N/A	0.06	0.07	0.06	0.07	0.07	
Total Cycle Time	min	0.23	0.23	0.25	N/A	0.25	0.27	0.28	0.30	0.35	

N/A = Not Applicable

Figure C.2. Cycle time estimation chart based on soil type for CAT excavator

Cubic Yards per 60 Minute Hour\*

ESTIMATED CYCLE TIMES		ESTIMATED BUCKET PAYLOAD** — LOOSE CUBIC YARDS																		ESTIMATED CYCLE TIMES		
Cycle Time		0.25	0.50	0.75	1.00	1.25	1.50	1.75	2.00	2.25	2.50	2.75	3.00	3.25	3.50	3.75	4.00	4.50	5.00	5.25	Cycles Per Min.	Cycles Per Hr.
Seconds	Min.																					
10.0	0.17																				6.0	360
11.0	0.18																				5.5	330
12.0	0.20	75	150	225	300	375															5.0	300
13.3	0.22	67	135	202	270	337	404	472	540	607	675	742	810	877	945	1012	1080	1215	1350	1417	4.5	270
15.0	0.25	60	120	180	240	300	360	420	480	540	600	660	720	780	840	900	960	1080	1200	1260	4.0	240
17.1	0.29	52	105	157	210	262	315	367	420	472	525	577	630	682	735	787	840	945	1050	1102	3.5	210
20.0	0.33	45	90	135	180	225	270	315	360	405	450	495	540	585	630	675	720	810	900	945	3.0	180
24.0	0.40	37	75	112	150	187	225	262	300	337	375	412	450	487	525	562	600	675	750	787	2.5	150
30.0	0.50	30	60	90	120	150	180	210	240	270	300	330	360	390	420	450	480	510	600	630	2.0	120
35.0	0.58	36	51	77	102	128	154	180	205	231	256	282	308	333	360	385	410	462	513	535	1.7	102
40.0	0.67					112	135	157	180	202	225	247	270	292	315	337	360	405	450	472	1.5	90
45.0	0.75									180	200	220	240	260	280	300	320	360	400	409	1.3	78
50.0	0.83																				1.2	72

Figure C.3. Productivity estimation chart based on bucket size and cycle time for CAT excavator

Table C.4. Regression coefficients for productivity – CAT

Variable	Coefficient	Parameter estimate	t-value	p-value
Intercept	$\beta_0$	-76.986	-4.69	<0.0001
Horsepower	$\beta_1$	-0.521	-6.27	<0.0001
Bucket size	$\beta_2$	141.504	19.05	<0.0001
Soil type 1	$\beta_3$	144.037	21.40	<0.0001
Soil type 2	$\beta_4$	129.633	19.26	<0.0001
Soil type 3	$\beta_5$	115.230	17.12	<0.0001
Soil type 4	$\beta_6$	72.018	10.70	<0.0001
Cycle time	$\beta_7$	-10.228	-38.63	<0.0001
Job efficiency	$\beta_8$	290.732	16.69	<0.0001

Table C.5. Mallows' C(p) values of variables selection for productivity model – CAT

C(p)	R-square	Predictors
9.000	0.8527	Hp, bucket size, soil type 2-5, cycle time, job efficiency
9.000	0.8527	Hp, bucket size, soil type 1,3-5; cycle time, job efficiency
9.000	0.8527	Hp, bucket size, soil type 1,2,4,5; cycle time, job efficiency
9.000	0.8527	Hp, bucket size, soil type 1-3,5; cycle time, job efficiency

Table C.6. Stepwise selection method result for productivity model - CAT

Step	Variable entered	Model R <sup>2</sup>	F-value	P-value
1	Bucket size	0.5737	1693.24	<0.0001
2	Cycle time	0.7450	844.21	<0.0001
3	Soil type 5*	0.8002	347.14	<0.0001
4	Job efficiency	0.8330	246.29	<0.0001
5	Soil type 4*	0.8459	105.34	<0.0001
6	Horsepower	0.8506	38.83	<0.0001
7	Soil type 1*	0.8522	13.70	<0.0001
8	Soil type 3*	0.8527	4.58	0.0325

\*categorical variable

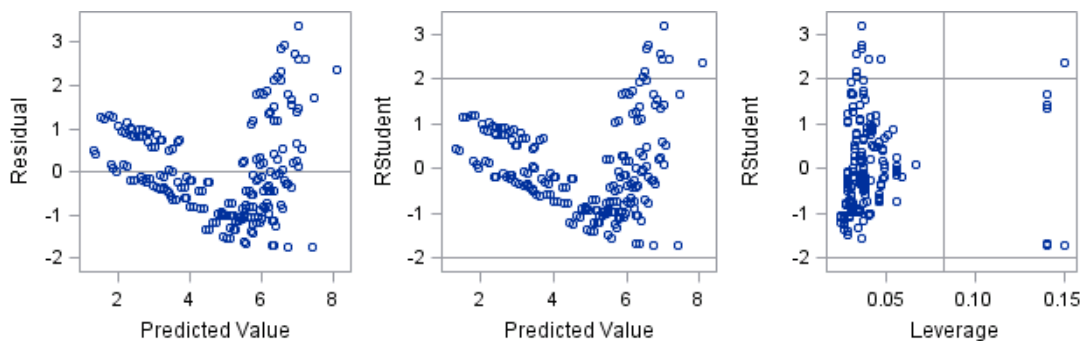


Figure C.4. Plots of predicted values versus residuals of cost model

Table C.7. Regression coefficients for cost model

Variable	Coefficient	Parameter estimate	t-value	p-value
Intercept	$\beta_0$	8.269	25.93	0.3656
Soil type 1	$\beta_1$	-0.647	-2.46	0.0147
Soil type 2	$\beta_2$	-1.049	-3.99	<0.0001
Soil type 3	$\beta_3$	-1.133	-4.31	<0.0001
Depth	$\beta_4$	0.045	2.94	0.0036
Bucket Size	$\beta_5$	-1.658	-17.31	<0.0001
Excavator type 1	$\beta_6$	-0.567	-3.23	0.0014
Excavator type 2	$\beta_7$	0.421	0.99	0.3243

Table C.8. Mallows' C(p) values of variables selection for cost model

C(p)	R-square	Predictors
5.135	0.6897	Soil type 1,4; depth; bucket size, excav type 1
6.159	0.6913	Soil type 1,4; depth, bucket size, excav type 1,3
6.159	0.6913	Soil type 1,4; depth, bucket size, excav type 1-2
6.976	0.6899	Soil type 1,2,4; depth, bucket size, excav type 1

Table C.9. Stepwise selection method result for cost model

Step	Variable entered	Model R <sup>2</sup>	F-value	P-value
1	Depth	0.6266	323.86	<0.0001
2	Soil type 4*	0.6433	8.99	0.0031
3	Excavator type 1*	0.6664	13.26	0.0003
4	Bucket size	0.6799	8.01	0.0042
5	Soil type 1*	0.6897	5.94	0.0158

\*categorical variable

## Appendix D

### Results of multiple linear regression (MLR) analysis to obtain productivity and cost models for truck

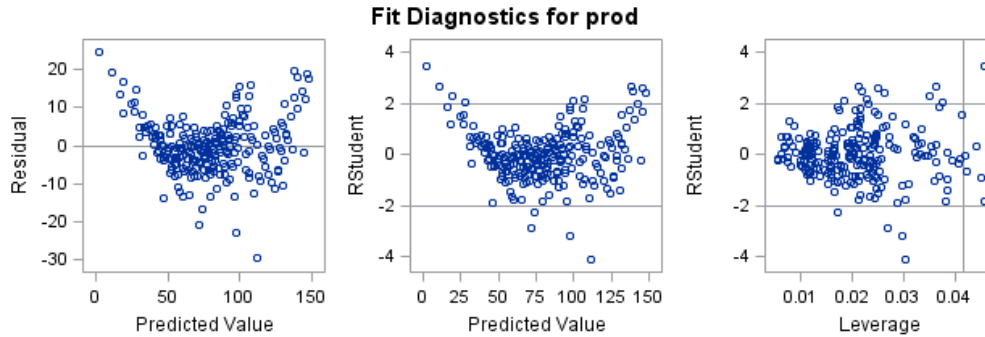


Figure D.1. Plots of predicted values versus residuals of productivity model

Table D.1. Regression coefficients for productivity model – RSMeans

Variable	Coefficient	Parameter estimate	t-value	p-value
Intercept	$\beta_0$	58.799	19.74	<0.0001
Loading capacity	$\beta_1$	2.079	55.85	<0.0001
Speed	$\beta_2$	1.625	17.52	<0.0001
Cycle distance	$\beta_3$	-12.056	-27.25	<0.0001
Cycle time	$\beta_4$	-2.789	-20.83	<0.0001

Table D.2. Mallow's C(p) values of variables selection for productivity model –RSMeans

C(p)	R-square	Predictors
5.000	0.9432	Capacity, speed, cycle distance, cycle time
309.822	0.8691	Capacity, cycle distance, cycle time
437.002	0.8384	Capacity, speed, cycle distance
734.983	0.7659	Capacity, cycle distance

Table D.3. Stepwise selection method result for productivity model - RSMeans

Step	Variable entered	Model R <sup>2</sup>	F-value	P-value
1	Loading capacity	0.6558	453.51	<0.0001
2	Cycle distance	0.7659	111.41	<0.0001
3	Cycle time	0.8691	186.06	<0.0001
4	Speed	0.9432	306.82	<0.0001

\*categorical variable

Table D.4. Regression coefficients for productivity – CAT

Variable	Coefficient	Parameter estimate	t-value	p-value
Intercept	$\beta_0$	-89.111	-4.88	<0.0001
Horsepower	$\beta_1$	0.022	0.96	0.3368
Loading capacity	$\beta_2$	3.345	13.42	<0.0001
Speed	$\beta_3$	1.007	3.82	<0.0001
Cycle distance	$\beta_4$	-23.022	-35.21	<0.0001
Excavator bucket	$\beta_5$	18.363	41.98	<0.0001
Excavator cycle time	$\beta_6$	-133.030	-33.94	<0.0001
Cycle time	$\beta_7$	-3.938	-20.44	<0.0001
Job efficiency	$\beta_8$	202.975	52.34	<0.0001

Table D.5. Mallow's C(p) values of variables selection for productivity model – CAT

C(p)	R-square	Predictors
7.474	0.8510	Capacity, speed, distance, excav-bucket, excav-cycle, truck-cycle, operation eff.
9.000	0.8511	Hp, capacity, speed, distance, excav-bucket, excav-cycle, truck-cycle, operation eff.
13.929	0.8506	Hp, capacity, distance, excav-bucket, excav-cycle, truck-cycle, operation eff.
18.477	0.8502	Capacity, distance, excav-bucket, excav-cycle, truck-cycle, operation eff.

Table D.6. Stepwise selection method result for productivity model - CAT

Step	Variable entered	Model R <sup>2</sup>	F-value	P-value
1	Truck cycle time	0.5381	2793.37	<0.0001
2	Loading capacity	0.7117	1442.88	<0.0001
3	Operation efficiency	0.8032	1114.55	<0.0001
4	Excavator bucket size	0.8163	171.31	<0.0001
5	Excavator cycle time	0.8242	106.51	<0.0001
6	Distance	0.8502	416.55	<0.0001
7	Speed	0.8510	13.01	0.0003

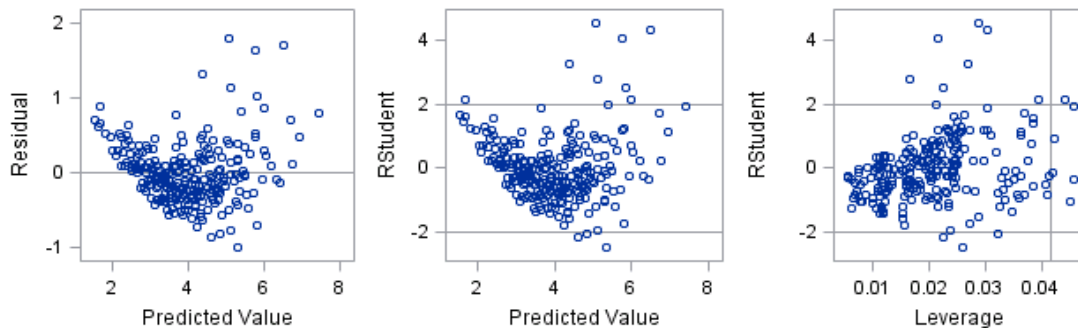


Figure D.2. Plots of predicted values versus residuals of cost model

Table D7. Regression coefficients for cost model

Variable	Coefficient	Parameter estimate	t-value	p-value
Intercept	$\beta_0$	3.203	19.27	<0.0001
Loading capacity	$\beta_1$	-0.056	-26.75	<0.0001
Speed	$\beta_2$	-0.098	-19.02	<0.0001
Cycle distance	$\beta_3$	0.709	28.71	<0.0001
Cycle time	$\beta_4$	0.143	19.20	<0.0001

Table D.8. Mallows's C(p) values of variables selection for cost model

C(p)	R-square	Predictors
5.000	0.8793	Capacity, speed, cycle distance, cycle time
364.680	0.6936	Capacity, cycle distance, cycle time
371.576	0.6900	Capacity, speed, cycle distance
718.454	0.5119	Speed, cycle distance, cycle time

Table D.9. Stepwise selection method result for cost model

Step	Variable entered	Model R <sup>2</sup>	F-value	P-value
1	Loading capacity	0.2555	81.68	<0.0001
2	Cycle distance	0.5078	121.47	<0.0001
3	Cycle time	0.6936	143.07	<0.0001
4	Speed	0.8793	361.68	<0.0001



## Appendix E

### PEMS field measurement results of emission factors and fuel use factor for bulldozers

Table E.1. Fuel use factor based on engine load

Engine Load	Fuel use factor (gal/hp-hr)					
	BD1 89 hp	BD2 95 hp	BD3 90 hp	BD4 175 hp	BD5 285 hp	BD6 99 hp
10%	0.0047	0.0039	0.0081	0.0068	0.0050	0.0074
20%	0.0130	0.0108	0.0188	0.0110	0.0145	0.011
30%	0.0188	0.0150	0.0267	0.0178	0.0220	0.0147
40%	0.0272	0.0187	0.0344	0.0245	0.0281	0.0127
50%	0.0330	0.0215	0.0416	0.0303	0.0323	0.0100
60%	0.0394	0.0244	0.0470	0.0357	0.0371	0.0105
70%	0.0447	0.0267	0.0552	0.0411	0.0434	0.0117
80%	0.0504	0.0312	0.0605	0.0470	0.0490	0.0123
90%	0.0573	0.0351	0.0668	0.0528	0.0563	0.0142
100%	0.0618	0.0367	0.0718	0.0555	0.0611	0.0146

Table E.2. HC emission factor based on engine load

Engine Load	HC emission factor (gr/hp-hr)					
	BD1 89 hp	BD2 95 hp	BD3 90 hp	BD4 175 hp	BD5 285 hp	BD6 99 hp
10%	0.1136	0.0968	0.1484	0.1410	0.0400	0.2552
20%	0.1587	0.1778	0.2354	0.2014	0.0658	0.1980
30%	0.2061	0.2232	0.2734	0.2971	0.0783	0.2885
40%	0.2340	0.2615	0.2922	0.3014	0.0921	0.1998
50%	0.2560	0.2065	0.3260	0.3124	0.1098	0.0853
60%	0.2741	0.3334	0.3459	0.3405	0.1171	0.0288
70%	0.2656	0.3765	0.3597	0.3650	0.1470	0.0812
80%	0.2737	0.4138	0.3600	0.3796	0.1397	0.1047
90%	0.3100	0.4320	0.4163	0.4243	0.1411	0.0926
100%	0.3487	0.5085	0.4567	0.4754	0.1559	0.3106

Table E.3. CO emission factor based on engine load

<b>Engine Load</b>	<b>CO emission factor (gr/hp-hr)</b>					
	<b>BD1 89 hp</b>	<b>BD2 95 hp</b>	<b>BD3 90 hp</b>	<b>BD4 175 hp</b>	<b>BD5 285 hp</b>	<b>BD6 99 hp</b>
10%	0.3498	0.2419	0.8631	0.3537	0.4348	0.3985
20%	0.7409	0.2432	0.9665	0.7437	1.6659	0.4799
30%	0.8954	0.3008	0.9602	1.0639	1.6797	0.5191
40%	0.9612	0.3605	0.9446	1.2432	1.3557	0.3266
50%	1.0034	0.3336	1.0557	1.4372	1.3382	0.1644
60%	1.0894	0.4334	1.0827	1.4200	1.1862	0.2537
70%	1.2123	0.4527	0.9790	1.6427	1.8587	0.1356
80%	1.4964	1.0352	0.9327	1.4920	1.1016	0.1442
90%	1.6405	0.4564	1.0287	1.2675	0.9203	0.2181
100%	1.5633	0.4483	1.0567	1.4001	0.8778	0.2791

Table E.4. NOx emission factor based on engine load

<b>Engine Load</b>	<b>NOx emission factor (gr/hp-hr)</b>					
	<b>BD1 89 hp</b>	<b>BD2 95 hp</b>	<b>BD3 90 hp</b>	<b>BD4 175 hp</b>	<b>BD5 285 hp</b>	<b>BD6 99 hp</b>
10%	1.1298	0.5271	1.4783	1.5548	1.2625	0.7915
20%	2.6919	1.3804	3.2683	2.3478	2.8989	1.0905
30%	3.6514	1.7455	4.5320	3.4569	3.9460	1.3864
40%	4.3427	2.0516	5.6933	4.5805	5.1201	1.1592
50%	4.9418	2.2808	6.6090	5.4093	6.0639	0.8235
60%	5.5779	2.3967	7.2307	6.3225	6.8602	0.8654
70%	5.9454	2.4612	8.7828	6.9562	7.5776	0.8330
80%	6.5944	2.8895	9.9521	7.7867	9.0207	0.8876
90%	7.4800	3.1087	10.6205	8.9848	11.2123	0.9768
100%	7.8471	3.0013	10.1311	9.9806	13.0162	1.1977

Table E.5. PM emission factor based on engine load

<b>Engine Load</b>	<b>PM emission factor (gr/hp-hr)</b>					
	<b>BD1 89 hp</b>	<b>BD2 95 hp</b>	<b>BD3 90 hp</b>	<b>BD4 175 hp</b>	<b>BD5 285 hp</b>	<b>BD6 99 hp</b>
10%	0.0055	0.0022	0.0089	0.0061	n/a	0.0049
20%	0.0170	0.0091	0.0265	0.0122	n/a	0.0076
30%	0.0319	0.0123	0.0428	0.0238	n/a	0.0138
40%	0.0427	0.0170	0.0636	0.0273	n/a	0.0162
50%	0.0496	0.0216	0.0853	0.0307	n/a	0.0152
60%	0.0583	0.0271	0.1040	0.0327	n/a	0.0171
70%	0.0687	0.0299	0.1280	0.0378	n/a	0.0188
80%	0.0874	0.0404	0.1372	0.0404	n/a	0.0226
90%	0.0959	0.0489	0.1646	0.0374	n/a	0.0383
100%	0.1031	0.0510	0.2042	0.0373	n/a	0.0702

Table E.6. CO<sub>2</sub> emission factor based on engine load

<b>Engine Load</b>	<b>CO<sub>2</sub> emission factor (gr/hp-hr)</b>					
	<b>BD1 89 hp</b>	<b>BD2 95 hp</b>	<b>BD3 90 hp</b>	<b>BD4 175 hp</b>	<b>BD5 285 hp</b>	<b>BD6 99 hp</b>
10%	49.17207	41.06598	84.45314	71.50014	53.17706	77.59042
20%	136.6877	114.961	198.8901	116.159	151.9537	118.0164
30%	198.8666	158.4868	282.4458	187.339	231.4211	154.7608
40%	287.5149	198.309	364.1341	257.8608	297.2826	133.977
50%	349.3079	228.1519	440.904	319.5726	341.4367	106.695
60%	416.5459	258.4276	498.287	376.4309	392.5481	111.3205
70%	473.0216	282.5637	585.364	433.498	458.7394	124.4445
80%	533.5579	329.5309	642.1244	497.1027	519.1926	130.6533
90%	606.1214	371.9768	709.11	558.9358	597.0806	151.4242
100%	654.5919	388.4824	761.6773	587.35	648.6315	154.0242

## Appendix F

### PEMS field measurement results of emission factors and fuel use factor for excavators

Table F.1. Fuel use factor based on engine load

<b>Engine Load</b>	<b>Fuel use factor (gal/hp-hr)</b>		
	<b>EX1 254 hp</b>	<b>EX2 138 hp</b>	<b>EX3 93 hp</b>
10%	0.0027	0.0251	0.0029
20%	0.0089	0.0227	0.0087
30%	0.0126	0.0202	0.0134
40%	0.0174	0.0186	0.0171
50%	0.0218	0.0194	0.0228
60%	0.0258	0.0173	0.0269
70%	0.0299	0.0172	0.0308
80%	0.0334	0.0168	0.0347
90%	0.0363	0.0177	0.0389
100%	0.0393	0.0166	0.0428

Table F.2. HC emission factor based on engine load

<b>Engine Load</b>	<b>HC emission factor (gr/hp-hr)</b>		
	<b>EX1 254 hp</b>	<b>EX2 138 hp</b>	<b>EX3 93 hp</b>
10%	0.0319	0.1658	0.0661
20%	0.0779	0.1549	0.0755
30%	0.0656	0.1475	0.1918
40%	0.0670	0.1389	0.2219
50%	0.0706	0.1402	0.2436
60%	0.0835	0.1326	0.2637
70%	0.0923	0.1315	0.2909
80%	0.0863	0.1317	0.3230
90%	0.0837	0.1371	0.3286
100%	0.0819	0.1367	0.2898

Table F.3. CO emission factor based on engine load

<b>Engine Load</b>	<b>CO emission factor (gr/hp-hr)</b>		
	<b>EX1 254 hp</b>	<b>EX2 138 hp</b>	<b>EX3 93 hp</b>
10%	0.0845	0.6480	0.1369
20%	0.2402	0.6080	1.0577
30%	0.2266	0.5883	0.7304
40%	0.2225	0.5787	0.4469
50%	0.2211	0.5785	0.3204
60%	0.2488	0.5674	0.2925
70%	0.2606	0.5799	0.2912
80%	0.2640	0.5581	0.3235
90%	0.2434	0.5670	0.3828
100%	0.2303	0.6387	0.4412

Table F.4. NOx emission factor based on engine load

<b>Engine Load</b>	<b>NOx emission factor (gr/hp-hr)</b>		
	<b>EX1 254 hp</b>	<b>EX2 138 hp</b>	<b>EX3 93 hp</b>
10%	0.4460	1.8696	0.5709
20%	0.8081	1.7597	1.0964
30%	1.3540	1.5870	1.2985
40%	1.9268	1.4806	1.8196
50%	2.3739	1.5148	2.6815
60%	2.7597	1.3952	3.1222
70%	3.2474	1.3780	3.5026
80%	3.7208	1.3789	3.8456
90%	4.1604	1.4297	4.2340
100%	4.5487	1.3413	4.7079

Table F.5. PM emission factor based on engine load

<b>Engine Load</b>	<b>PM emission factor (gr/hp-hr)</b>		
	<b>EX1 254 hp</b>	<b>EX2 138 hp</b>	<b>EX3 93 hp</b>
10%	0.0025	0.0201	0.0025
20%	0.0102	0.0177	0.0076
30%	0.0155	0.0153	0.0097
40%	0.0216	0.0143	0.0123
50%	0.0246	0.0148	0.0170
60%	0.0311	0.0127	0.0207
70%	0.0390	0.0124	0.0252
80%	0.0417	0.0124	0.0324
90%	0.0470	0.0126	0.0409
100%	0.0543	0.0123	0.0436

Table F.6. CO<sub>2</sub> emission factor based on engine load

<b>Engine Load</b>	<b>CO<sub>2</sub> emission factor (gr/hp-hr)</b>		
	<b>EX1 254 hp</b>	<b>EX2 138 hp</b>	<b>EX3 93 hp</b>
10%	28.1708	265.6044	30.1242
20%	94.0290	240.2125	90.19911
30%	133.0323	213.5680	141.2265
40%	184.6922	196.8202	181.0132
50%	231.6529	204.7068	241.6455
60%	274.2513	183.2738	285.1157
70%	317.2323	181.3434	326.4566
80%	354.2657	177.9367	367.8238
90%	385.7088	186.8080	412.0469
100%	416.9189	174.8290	453.9535

## Appendix G

### PEMS field measurement results of emission factors and fuel use factor for trucks

Table G.1. Fuel use factor based on engine load

<b>Engine Load</b>	<b>Fuel use factor (gal/hp-hr)</b>		
	<b>TR1 306 hp</b>	<b>TR2 285 hp</b>	<b>TR3 285 hp</b>
10%	0.0038	0.0036	0.0044
20%	0.0090	0.0133	0.0127
30%	0.0117	0.0190	0.0191
40%	0.0149	0.0239	0.0246
50%	0.0188	0.0284	0.0288
60%	0.0207	0.0323	0.0341
70%	0.0222	0.0368	0.0372
80%	0.0238	0.0397	0.0414
90%	0.0284	0.0480	0.0434
100%	0.0335	0.0498	0.0459

Table G.2. HC emission factor based on engine load

<b>Engine Load</b>	<b>HC emission factor (gr/hp-hr)</b>		
	<b>TR1 306 hp</b>	<b>TR2 285 hp</b>	<b>TR3 285 hp</b>
10%	0.042	0.0514	0.0532
20%	0.088	0.1014	0.0949
30%	0.107	0.1246	0.1121
40%	0.133	0.1342	0.1319
50%	0.158	0.1293	0.1708
60%	0.180	0.1318	0.1823
70%	0.178	0.1426	0.1718
80%	0.205	0.0976	0.2048
90%	0.223	0.0780	0.1886
100%	0.258	0.1875	0.1785

Table G.3. CO emission factor based on engine load

<b>Engine Load</b>	<b>CO emission factor (gr/hp-hr)</b>		
	<b>TR1 306 hp</b>	<b>TR2 285 hp</b>	<b>TR3 285 hp</b>
10%	0.100	0.0912	0.1762
20%	0.543	0.3938	0.3691
30%	0.771	0.4820	0.4552
40%	1.115	0.5722	0.5155
50%	1.627	0.5027	0.5547
60%	1.543	0.8443	0.5844
70%	1.528	0.7262	0.6191
80%	1.717	0.9234	0.6511
90%	1.721	1.3493	0.5508
100%	1.931	0.5442	0.4964

Table G.4. NOx emission factor based on engine load

<b>Engine Load</b>	<b>NOx emission factor (gr/hp-hr)</b>		
	<b>TR1 306 hp</b>	<b>TR2 285 hp</b>	<b>TR3 285 hp</b>
10%	0.658	0.6962	0.7951
20%	1.066	1.3203	1.3376
30%	1.335	1.9604	2.0389
40%	1.684	2.5476	2.6454
50%	2.228	2.9384	2.9845
60%	2.335	3.0139	3.2374
70%	2.461	3.3660	3.6440
80%	2.577	4.4973	4.1285
90%	3.131	4.2615	4.2935
100%	3.474	4.2888	4.9493



Table G.5. PM emission factor based on engine load

<b>Engine Load</b>	<b>PM emission factor (gr/hp-hr)</b>		
	<b>TR1 306 hp</b>	<b>TR2 285 hp</b>	<b>TR3 285 hp</b>
10%	0.003	0.0033	0.0043
20%	0.009	0.0139	0.0119
30%	0.012	0.0170	0.0158
40%	0.016	0.0203	0.0169
50%	0.021	0.0226	0.0278
60%	0.025	0.0288	0.0292
70%	0.025	0.0324	0.0290
80%	0.030	0.0554	0.0322
90%	0.036	0.0496	0.0348
100%	0.038	0.0461	0.0422

Table G.6. CO<sub>2</sub> emission factor based on engine load

<b>Engine Load</b>	<b>CO<sub>2</sub> emission factor (gr/hp-hr)</b>		
	<b>TR1 306 hp</b>	<b>TR2 285 hp</b>	<b>TR3 285 hp</b>
10%	40.4153	37.6160	46.3601
20%	95.0822	139.9120	134.3940
30%	123.1789	200.3096	202.1267
40%	156.1324	252.7273	259.9892
50%	196.6117	300.5503	304.5774
60%	217.1684	340.6927	361.3219
70%	233.1563	389.0986	393.8897
80%	249.4316	419.817	439.1392
90%	298.7024	502.8497	460.2709
100%	352.1071	526.0632	487.1354

## Appendix H

### E3 model output of emission factors for bulldozers, excavators, and trucks

Table H.1. E3 output - Emission and fuel use factor for bulldozer, excavator, and truck

HDD equipment	Engine size (hp)	Emission factor (gr/hp-hr)					Fuel Use (gal/hp- hr)
		HC	CO	NOx	PM	CO2	
BD 1	89	1.139	7.361	6.877	1.724	592.638	0.049
BD 2	95	0.556	3.785	5.377	0.683	594.498	0.049
BD 3	90	0.556	3.785	5.377	0.683	594.498	0.049
BD 4	175	0.370	1.478	5.516	0.508	535.174	0.044
BD 5	285	0.764	5.260	8.243	0.819	533.918	0.044
BD 6	99	0.392	3.785	4.483	0.335	595.024	0.049
EX 1	254	0.332	1.223	5.386	0.390	535.295	0.044
EX 2	138	0.360	1.382	3.910	0.244	535.204	0.044
EX 3	93	0.569	4.023	5.460	0.862	594.458	0.049
Truck 1	306	0.178	1.343	4.134	0.172	535.787	0.044
Truck 2	285	0.348	1.383	5.562	0.593	535.243	0.044
Truck 3	285	0.348	1.383	5.562	0.593	535.243	0.044

## Appendix I

### SAS coding for productivity and cost models

#### Bulldozer Productivity - RSMeans

```
data dozer;
input hp distance matr1 matr2 matr3 matr4 hourlyout hourlyouttrans;
datalines;
80 300 0 0 0 1 8.125 1.520
80 300 0 0 1 0 12.5 1.657
80 300 0 1 0 0 14.375 1.704
.
.
.
;
proc reg data=dozer;
model hourlyouttrans=hp distance matr1 matr2 matr3 matr4 / clb cli r p ss1 ss2;
run;
proc reg data=dozer outest=Table_Model;
model hourlyouttrans=hp distance matr1 matr2 matr3 matr4 / best=4 selection=cp;
model hourlyouttrans=hp distance matr1 matr2 matr3 matr4 / best=4 selection=aic;
run;
proc print data=Table_Model;
run;
proc reg data=dozer;
model hourlyouttrans=hp distance matr1 matr2 matr3 matr4 / selection=stepwise details
slstay=0.05 slentry=0.05;
run;
proc reg data=dozer;
model hourlyouttrans=hp distance matr1 matr2 matr3 matr4 / selection=backward details
slstay=0.05;
run;
proc reg data=dozer;
model hourlyouttrans=hp distance matr1 matr2 matr3 matr4 / selection=forward details
slentry=0.05;
run;
proc corr data=dozer plots=matrix;
var hourlyouttrans hp distance matr1 matr2 matr3 matr4;
title 'dozer RS correlation matrix';
run;
```

#### Bulldozer Productivity – CAT

```
data dozerCAT;
input blade hp distance jobeff soilgrade skill11 skill12 skill13 soil1 soil2 soil3 soil4
dozing1 dozing2 prod;
datalines;
45 850 100 0.83 1.8 1 0 0 1 0 0 0
1 0 6023.81
45 850 300 0.83 1.8 1 0 0 1 0 0 0
1 0 2366.50
45 850 500 0.83 1.8 1 0 0 1 0 0 0
1 0 1505.95
.
.
.
;
proc reg data=dozerCAT;
model prod=blade hp distance jobeff soilgrade skill11 skill12 skill13 soil1 soil2 soil3
soil4 dozing1 dozing2 / clb cli r p ss1 ss2;
run;
proc reg data=dozerCAT outest=Table_Model;
model prod=blade hp distance jobeff soilgrade skill11 skill12 skill13 soil1 soil2 soil3
soil4 dozing1 dozing2 / best=4 selection=cp;
model prod=blade hp distance jobeff soilgrade skill11 skill12 skill13 soil1 soil2 soil3
soil4 dozing1 dozing2 / best=4 selection=aic;
```

```

run;
proc print data=Table_Model;
run;
proc reg data=dozerCAT;
model prod=blade hp distance jobeff soilgrade skill1 skill2 skill3 soil1 soil2 soil3
soil4 dozing1 dozing2 / selection=stepwise details slstay=0.05 slentry=0.05;
run;
proc reg data=dozerCAT;
model prod=blade hp distance jobeff soilgrade skill1 skill2 skill3 soil1 soil2 soil3
soil4 dozing1 dozing2 / selection=backward details slstay=0.05;
run;
proc reg data=dozerCAT;
model prod=blade hp distance jobeff soilgrade skill1 skill2 skill3 soil1 soil2 soil3
soil4 dozing1 dozing2 / selection=forward details slentry=0.05;
run;
proc corr data=dozerCAT plots=matrix;
var prod blade hp distance jobeff soilgrade skill1 skill2 skill3 soil1 soil2 soil3 soil4
dozing1 dozing2;
title 'dozer CAT correlation matrix';
run;

```

### Bulldozer Cost – RSMeans

```

data dozer;
input hp distance matr1 matr2 matr3 matr4 hourlyout totalcost hourlylog lntotalcost;
datalines;
80 300 0 0 0 1 8.125 18.45 1.520 2.915
80 300 0 0 1 0 12.5 12 1.657 2.485
80 300 0 1 0 0 14.375 10.45 1.704 2.347
.
.
.
;
proc reg data=dozer;
model lntotalcost=hp distance matr1 matr2 matr3 matr4 / clb cli r p ss1 ss2;
run;
proc reg data=dozer outest=Table_Model;
model lntotalcost=hp distance matr1 matr2 matr3 matr4 / best=4 selection=cp;
model lntotalcost=hp distance matr1 matr2 matr3 matr4 / best=4 selection=aic;
run;
proc print data=Table_Model;
run;
proc reg data=dozer;
model lntotalcost=hp distance matr1 matr2 matr3 matr4 / selection=stepwise details
slstay=0.05 slentry=0.05;
run;
proc reg data=dozer;
model lntotalcost=hp distance matr1 matr2 matr3 matr4 / selection=backward details
slstay=0.05;
run;
proc reg data=dozer;
model lntotalcost=hp distance matr1 matr2 matr3 matr4 / selection=forward details
slentry=0.05;
run;

```

### Scraper Productivity and Cost - RSMeans

```

data scraper;
input excavtype1 excavtype2 excavtype3 bucketvol matr1 matr2 matr3 matr4 distance
hourlyout totalcost loghour logcost;
datalines;
1 0 0 11 1 0 0 0 1500 86.25 3.75 1.936
0.574
1 0 0 11 1 0 0 0 3000 76.25 4.24 1.882
0.627
1 0 0 11 1 0 0 0 5000 63.125 5.15 1.800
0.712
.

```

```

.
.
;
proc reg data=scrapper;
model loghour=excavtype1 excavtype2 excavtype3 bucketvol matr1 matr2 matr3 matr4 distance
/ clb cli r p ssl ss2;
run;
proc reg data=scrapper outest=Table_Model;
model loghour=excavtype1 excavtype2 excavtype3 bucketvol matr1 matr2 matr3 matr4 distance
/ best=4 selection=cp;
model loghour=excavtype1 excavtype2 excavtype3 bucketvol matr1 matr2 matr3 matr4 distance
/ best=4 selection=aic;
run;
proc print data=Table_Model;
run;
proc reg data=scrapper;
model loghour=excavtype1 excavtype2 excavtype3 bucketvol matr1 matr2 matr3 matr4 distance
/ selection=stepwise details slstay=0.05 slentry=0.05;
run;
proc reg data=scrapper;
model loghour=excavtype1 excavtype2 excavtype3 bucketvol matr1 matr2 matr3 matr4 distance
/ selection=backward details slstay=0.05;
run;
proc reg data=scrapper;
model loghour=excavtype1 excavtype2 excavtype3 bucketvol matr1 matr2 matr3 matr4 distance
/ selection=forward details slentry=0.05;
run;

```

### Scraper Productivity - CAT

```

data scrapercat;
input hp capacity rolling distance prod;
datalines;
175 8.8 0.02 400 250
175 8.8 0.02 600 225
175 8.8 0.02 800 210
.
.
.
;
proc reg data=scrapercat;
model prod=hp capacity rolling distance / clb cli r p ssl ss2;
run;
proc reg data=scrapercat outest=Table_Model;
model prod=hp capacity rolling distance / best=4 selection=cp;
model prod=hp capacity rolling distance / best=4 selection=aic;
run;
proc print data=Table_Model;
run;
proc reg data=scrapercat;
model prod=hp capacity rolling distance / selection=stepwise details slstay=0.05
slentry=0.05;
run;
proc reg data=scrapercat;
model prod=hp capacity rolling distance / selection=backward details slstay=0.05;
run;
proc reg data=scrapercat;
model prod=hp capacity rolling distance / selection=forward details slentry=0.05;
run;
proc corr data=scrapercat plots=matrix;
var prod hp capacity rolling distance;
title 'scraper CAT correlation matrix';
run;

```

### Excavator Productivity - RSMeans

```

data trench;
input soil1 soil2 soil3 soil4 depth bucket excav1 excav2 excav3 hourlyout;

```

```

datalines;
1      0      0      0      2.5    0.375  1      0      0      18.75
1      0      0      0      2.5    0.5    1      0      0      25.00
1      0      0      0      2.5    0.75   1      0      0      33.75
.
.
.
;
proc reg data=trench;
model hourlyout=soil1 soil2 soil3 soil4 depth bucket excav1 excav2 excav3 / clb cli r p
ssl ss2;
run;
proc reg data=trench outest=Table_Model;
model hourlyout=soil1 soil2 soil3 soil4 depth bucket excav1 excav2 excav3 / best=4
selection=cp;
model hourlyout=soil1 soil2 soil3 soil4 depth bucket excav1 excav2 excav3 / best=4
selection=aic;
run;
proc print data=Table_Model;
run;
proc reg data=trench;
model hourlyout=soil1 soil2 soil3 soil4 depth bucket excav1 excav2 excav3 /
selection=stepwise details slstay=0.05 slentry=0.05;
run;
proc reg data=trench;
model hourlyout=soil1 soil2 soil3 soil4 depth bucket excav1 excav2 excav3 /
selection=backward details slstay=0.05;
run;
proc reg data=trench;
model hourlyout=soil1 soil2 soil3 soil4 depth bucket excav1 excav2 excav3 /
selection=forward details slentry=0.05;
run;
proc corr data=trench plots=matrix;
var hourlyout soil1 soil2 soil3 soil4 depth bucket excav1 excav2 excav3;
title 'excavator RS correlation matrix';
run;

```

## Excavator Productivity – CAT

```

data excavcat;
input hp bucket soil1 soil2 soil3 soil4 soil5 cycle jobeff prod;
datalines;
54    0.48    1      0      0      0      0      13.3    1      135.00
54    0.48    0      1      0      0      0      13.3    1      128.25
54    0.48    0      0      1      0      0      13.3    1      121.50
.
.
.
;
proc reg data=excavcat;
model prod=hp bucket soil1 soil2 soil3 soil4 soil5 cycle jobeff / clb cli r p ssl ss2;
run;
proc reg data=excavcat outest=Table_Model;
model prod=hp bucket soil1 soil2 soil3 soil4 soil5 cycle jobeff / best=4 selection=cp;
model prod=hp bucket soil1 soil2 soil3 soil4 soil5 cycle jobeff / best=4 selection=aic;
run;
proc print data=Table_Model;
run;
proc reg data=excavcat;
model prod=hp bucket soil1 soil2 soil3 soil4 soil5 cycle jobeff / selection=stepwise
details slstay=0.05 slentry=0.05;
run;
proc reg data=excavcat;
model prod=hp bucket soil1 soil2 soil3 soil4 soil5 cycle jobeff / selection=backward
details slstay=0.05;
run;
proc reg data=excavcat;
model prod=hp bucket soil1 soil2 soil3 soil4 soil5 cycle jobeff / selection=forward
details slentry=0.05;
run;

```

```

run;
proc corr data=excavcat plots=matrix;
var prod hp bucket soil1 soil2 soil3 soil4 soil5 cycle jobeff;
title 'excavator CAT correlation matrix';
run;

```

## Excavator Cost – RSMMeans

```

data trench;
input soil1 soil2 soil3 soil4 bucket depth excav1 excav2 excav3 totalcost;
datalines;
1 0 0 0 2.5 0.375 1 0 0 8.65
1 0 0 0 2.5 0.5 1 1 0 6.75
1 0 0 0 2.5 0.75 1 0 0 6.25
.
.
.
;
proc reg data=trench;
model totalcost=soil1 soil2 soil3 soil4 depth bucket excav1 excav2 excav3 / clb cli r p
ssl ss2;
run;
proc reg data=trench outest=Table_Model;
model totalcost=soil1 soil2 soil3 soil4 depth bucket excav1 excav2 excav3 / best=4
selection=cp;
model totalcost=soil1 soil2 soil3 soil4 depth bucket excav1 excav2 excav3 / best=4
selection=aic;
run;
proc print data=Table_Model;
run;
proc reg data=trench;
model totalcost=soil1 soil2 soil3 soil4 depth bucket excav1 excav2 excav3 /
selection=stepwise details slstay=0.05 slentry=0.05;
run;
proc reg data=trench;
model totalcost=soil1 soil2 soil3 soil4 depth bucket excav1 excav2 excav3 /
selection=backward details slstay=0.05;
run;
proc reg data=trench;
model totalcost=soil1 soil2 soil3 soil4 depth bucket excav1 excav2 excav3 /
selection=forward details slentry=0.05;
run;
proc corr data=trench plots=matrix;
var totalcost soil1 soil2 soil3 soil4 depth bucket excav1 excav2 excav3;
title 'excavator RS correlation matrix';
run;

```

## Truck Productivity - RSMMeans

```

data truckRS;
input capacity speed distance cycle prod;
datalines;
22 5 0.38 15 66
22 5 0.57 15 60.5
22 5 0.76 15 55
.
.
.
;
proc reg data=truckRS;
model prod=capacity speed distance cycle / clb cli r p ssl ss2;
run;
proc reg data=truckRS outest=Table_Model;
model prod=capacity speed distance cycle / best=4 selection=cp;
model prod=capacity speed distance cycle / best=4 selection=aic;
run;
proc print data=Table_Model;

```

```

run;
proc reg data=truckRS;
model prod=capacity speed distance cycle / selection=stepwise details slstay=0.05
slentry=0.05;
run;
proc reg data=truckRS;
model prod=capacity speed distance cycle / selection=backward details slstay=0.05;
run;
proc reg data=truckRS;
model prod=capacity speed distance cycle / selection=forward details slentry=0.05;
run;
proc corr data=truckRS plots=matrix;
var prod capacity speed distance cycle;
title 'truck RS correlation matrix';
run;

```

## Truck Productivity – CAT

```

data truckCAT;
input hp capacity speed distance excavbucket excavcycle truckcycle opeff prod logprod;
datalines;
476 21.5 46.5 0.38 1.13 0.22 6.766 1 190.65
476 21.5 46.5 0.38 1.13 0.33 8.859 1 145.61
476 21.5 46.5 0.38 1.13 0.5 12.094 1 106.67
.
.
.
;
proc reg data=truckCAT;
model prod=hp capacity speed distance excavbucket excavcycle truckcycle opeff / clb cli r
p ss1 ss2;
run;
proc reg data=truckCAT outest=Table_Model;
model prod=hp capacity speed distance excavbucket excavcycle truckcycle opeff / best=4
selection=cp;
model prod=hp capacity speed distance excavbucket excavcycle truckcycle opeff / best=4
selection=aic;
run;
proc print data=Table_Model;
run;
proc reg data=truckCAT;
model prod=hp capacity speed distance excavbucket excavcycle truckcycle opeff /
selection=stepwise details slstay=0.05 slentry=0.05;
run;
proc reg data=truckCAT;
model prod=hp capacity speed distance excavbucket excavcycle truckcycle opeff /
selection=backward details slstay=0.05;
run;
proc reg data=truckCAT;
model prod=hp capacity speed distance excavbucket excavcycle truckcycle opeff /
selection=forward details slentry=0.05;
run;
proc corr data=truckCAT plots=matrix;
var prod hp capacity speed distance excavbucket excavcycle truckcycle opeff;
title 'truck CAT correlation matrix';
run;

```

## Truck Cost - RSMeans

```

data truckRS;
input capacity speed distance cycle cost;
datalines;
22 5 0.38 15 3.41
22 5 0.57 15 3.72
22 5 0.76 15 4.09
.
.
.

```



```

;
proc reg data=truckRS;
model cost=capacity speed distance cycle / clb cli r p ssl ss2;
run;
proc reg data=truckRS outest=Table_Model;
model cost=capacity speed distance cycle / best=4 selection=cp;
model cost=capacity speed distance cycle / best=4 selection=aic;
run;
proc print data=Table_Model;
run;
proc reg data=truckRS;
model cost=capacity speed distance cycle / selection=stepwise details slstay=0.05
slentry=0.05;
run;
proc reg data=truckRS;
model cost=capacity speed distance cycle / selection=backward details slstay=0.05;
run;
proc reg data=truckRS;
model cost=capacity speed distance cycle / selection=forward details slentry=0.05;
run;
proc corr data=truckRS plots=matrix;
var cost capacity speed distance cycle;
title 'truck RS correlation matrix';
run;

```

## Appendix J

### Visual Basic coding for E3 model user's interface

#### BULLDOZER

```
Private Sub cmdclose_Click()
    Unload Me
End Sub

Private Sub cmdReset_Click()
    For Each ctl In Me.Controls
        If TypeName(ctl) = "TextBox" Or TypeName(ctl) = "ComboBox" Then
            ctl.Value = ""
        End If
    Next ctl
End Sub

Private Sub cmdstart_Click()
    Dim RowCount As Long
    Dim ctl As Control
    If Me.Dozmodelyear.Value = "" Then
        MsgBox "Please enter Dozer Model Year.", vbExclamation, "Missing Input"
        Me.Dozmodelyear.SetFocus
        Exit Sub
    End If
    If Not IsNumeric(Me.Dozmodelyear.Value) Then
        MsgBox "must be in number only.", vbExclamation, "Wrong Input"
        Me.Dozmodelyear.SetFocus
        Exit Sub
    End If
    If Me.horsepower.Value = "" Then
        MsgBox "Please enter Dozer Horsepower.", vbExclamation, "Missing Input"
        Me.horsepower.SetFocus
        Exit Sub
    End If
    If Not IsNumeric(Me.horsepower.Value) Then
        MsgBox "must be in number only.", vbExclamation, "Wrong Input"
        Me.horsepower.SetFocus
        Exit Sub
    End If

    If Me.Dozmodelyear.Value > 0 Then
        Me.dozlf.Value = 0.59
        Me.dozact.Value = 936
    End If

    If Me.horsepower.Value > 300 Then
        Me.dozmed.Value = 7000
    End If
    If Me.horsepower.Value <= 300 Then
        Me.dozmed.Value = 4667
    End If

    To the rest of Tier Level determination
    .
    .
    .
    End If

    If Me.doztier.Value = "0" Then
        Me.dozAhc.Value = 0.047
        Me.dozAco.Value = 0.185
        Me.dozAnox.Value = 0.024
        Me.dozApm.Value = 0.473
        Me.dozThc.Value = 1.05
        Me.dozTco.Value = 1.53
        Me.dozTnox.Value = 0.95
    End If
End Sub
```

```

        Me.dozTpm.Value = 1.23
        Me.dozTbsfc.Value = 1.01
    End If

    To the rest of deterioration factor, transient adjustment factor, and steady-state
    emission factor for each pollutant
    .
    .
    .
    End If

    If Me.distance.Value = "" Then
        MsgBox "Please enter Hauling Distance.", vbExclamation, "Missing Input"
        Me.distance.SetFocus
        Exit Sub
    End If
    If Not IsNumeric(Me.distance.Value) Then
        MsgBox "must be in number only.", vbExclamation, "Wrong Input"
        Me.distance.SetFocus
        Exit Sub
    End If
    If Me.distance.Value > 300 Then
        MsgBox "inappropriate distance!", vbExclamation, "Out of Range"
        Me.distance.SetFocus
        Exit Sub
    End If
    If Me.soiltype.Value = "" Then
        MsgBox "Please select Soil Type.", vbExclamation, "Missing Input"
        Me.soiltype.SetFocus
        Exit Sub
    End If
    If Me.soilquantity.Value = "" Then
        MsgBox "Please enter Soil Quantity.", vbExclamation, "Missing Input"
        Me.soilquantity.SetFocus
        Exit Sub
    End If
    If Not IsNumeric(Me.soilquantity.Value) Then
        MsgBox "must be in number only.", vbExclamation, "Wrong Input"
        Me.soilquantity.SetFocus
        Exit Sub
    End If
    If Me.soiltype.Value = "Sand and Gravel" Then
        Me.productivity.Value = Round((2.14 + (0.0015 * CDb1(Me.horsepower.Value)) -
(0.0025 * CDb1(Me.distance.Value)) + (0.279 * 1)) ^ 5, 2)
        Me.unitcost.Value = Round(Exp(1.19 - (0.00085 * CDb1(Me.horsepower.Value)) +
(0.0053 * CDb1(Me.distance.Value)) - (0.595 * 1)), 2)
    End If
    If Me.soiltype.Value = "Sandy Clay and Loam" Then
        Me.productivity.Value = Round((2.14 + (0.0015 * CDb1(Me.horsepower.Value)) -
(0.0025 * CDb1(Me.distance.Value)) + (0.261 * 1)) ^ 5, 2)
        Me.unitcost.Value = Round(Exp(1.19 - (0.00085 * CDb1(Me.horsepower.Value)) +
(0.0053 * CDb1(Me.distance.Value)) - (0.567 * 1)), 2)
    End If
    If Me.soiltype.Value = "Common Earth" Then
        Me.productivity.Value = Round((2.14 + (0.0015 * CDb1(Me.horsepower.Value)) -
(0.0025 * CDb1(Me.distance.Value)) + (0.206 * 1)) ^ 5, 2)
        Me.unitcost.Value = Round(Exp(1.19 - (0.00085 * CDb1(Me.horsepower.Value)) +
(0.0053 * CDb1(Me.distance.Value)) - (0.453 * 1)), 2)
    End If
    If Me.soiltype.Value = "Clay" Then
        Me.productivity.Value = Round((2.14 + (0.0015 * CDb1(Me.horsepower.Value)) -
(0.0025 * CDb1(Me.distance.Value)) + (0 * 1)) ^ 5, 2)
        Me.unitcost.Value = Round(Exp(1.19 - (0.00085 * CDb1(Me.horsepower.Value)) +
(0.0053 * CDb1(Me.distance.Value)) - (0 * 1)), 2)
    End If
    Me.duration.Value = Round(CDb1(Me.soilquantity.Value) / CDb1(Me.productivity.Value),
2)
    Me.totalcost.Value = Round(CDb1(Me.soilquantity.Value) * CDb1(Me.unitcost.Value), 2)
    Me.fuel.Value = Round(CDb1(Me.dozEbsfc.Value) * CDb1(Me.dozTbsfc.Value) * 0.12 *
CDb1(Me.horsepower.Value) * CDb1(Me.duration.Value), 2)
    Me.emission.Value = Round((10.15 * CDb1(Me.fuel.Value)) / 1000, 2)

```

```

    Me.dozHC.Value = Round((1 + (Cdbl(Me.dozAhc.Value) * (2012 -
Cdbl(Me.Dozmodelyear.Value) + 1) / Cdbl(Me.dozmed.Value))) * Cdbl(Me.dozEhc.Value) *
Cdbl(Me.dozThc.Value) * Cdbl(Me.horsepower.Value) * Cdbl(Me.duration.Value), 2)
    Me.dozCO.Value = Round((1 + (Cdbl(Me.dozAco.Value) * (2012 -
Cdbl(Me.Dozmodelyear.Value) + 1) / Cdbl(Me.dozmed.Value))) * Cdbl(Me.dozEco.Value) *
Cdbl(Me.dozTco.Value) * Cdbl(Me.horsepower.Value) * Cdbl(Me.duration.Value), 2)
    Me.dozNOX.Value = Round((1 + (Cdbl(Me.dozAnox.Value) * (2012 -
Cdbl(Me.Dozmodelyear.Value) + 1) / Cdbl(Me.dozmed.Value))) * Cdbl(Me.dozEnox.Value) *
Cdbl(Me.dozTnox.Value) * Cdbl(Me.horsepower.Value) * Cdbl(Me.duration.Value), 2)
    Me.dozPM.Value = Round(((1 + (Cdbl(Me.dozApm.Value) * (2012 -
Cdbl(Me.Dozmodelyear.Value) + 1) / Cdbl(Me.dozmed.Value))) * Cdbl(Me.dozEpm.Value) *
Cdbl(Me.dozTpm.Value)) - ((Cdbl(Me.dozEbsfc.Value) * Cdbl(Me.dozTbsfc.Value)) * 453.6 * 7
* 0.02247 * 0.01 * 0.08)) * Cdbl(Me.horsepower.Value) * Cdbl(Me.duration.Value), 2)
    Me.dozSO2.Value = Round(((Cdbl(Me.dozEbsfc.Value) * Cdbl(Me.dozTbsfc.Value)) * 453 *
(1 - 0.02247)) - Cdbl(Me.dozEhc.Value) * 0.01 * 0.25 * 2 * Cdbl(Me.horsepower.Value) *
Cdbl(Me.duration.Value), 2)
    RowCount = Worksheets("Bulldozer").range("A1").CurrentRegion.Rows.Count
    With Worksheets("Bulldozer").range("A1")
        .Offset(RowCount, 0).Value = Me.horsepower.Value
        .Offset(RowCount, 1).Value = Me.Dozmodelyear.Value
        .Offset(RowCount, 2).Value = Me.doztier.Value
        .Offset(RowCount, 3).Value = Me.distance.Value
        .Offset(RowCount, 4).Value = Me.soiltype.Value
        .Offset(RowCount, 5).Value = Me.soilquantity.Value
        .Offset(RowCount, 6).Value = Me.productivity.Value
        .Offset(RowCount, 7).Value = Me.unitcost.Value
        .Offset(RowCount, 8).Value = Me.duration.Value
        .Offset(RowCount, 9).Value = Me.totalcost.Value
        .Offset(RowCount, 10).Value = Me.fuel.Value
        .Offset(RowCount, 11).Value = Me.dozHC.Value
        .Offset(RowCount, 12).Value = Me.dozCO.Value
        .Offset(RowCount, 13).Value = Me.dozNOX.Value
        .Offset(RowCount, 14).Value = Me.dozPM.Value
        .Offset(RowCount, 15).Value = Me.emission.Value
        .Offset(RowCount, 16).Value = Me.dozSO2.Value
    End With
End Sub

Private Sub CloseButton_Click()
    Unload Me
End Sub

```

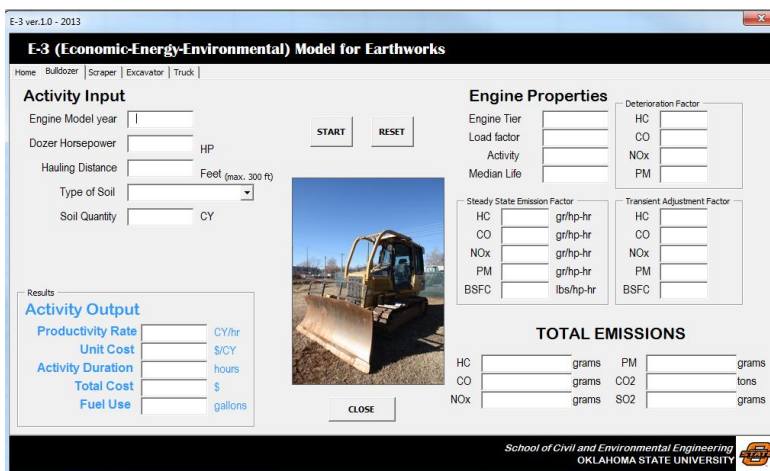


Figure J.1. E3 user's interface for bulldozer

## SCRAPER

```

Private Sub ResetButton_Click()
    For Each ctl In Me.Controls
        If TypeName(ctl) = "TextBox" Or TypeName(ctl) = "ComboBox" Then
            ctl.Value = ""
        End If
    Next

```

```

        End If
    Next ctl
End Sub

Private Sub StartButton_Click()
Dim RowCount As Long
Dim ctl As Control
    If Me.Scramodelyear.Value = "" Then
        MsgBox "Please enter Scraper Model Year.", vbExclamation, "Missing Input"
        Me.Scramodelyear.SetFocus
        Exit Sub
    End If
    If Not IsNumeric(Me.Scramodelyear.Value) Then
        MsgBox "must be in number only.", vbExclamation, "Wrong Input"
        Me.Scramodelyear.SetFocus
        Exit Sub
    End If
    If Me.boxhp.Value = "" Then
        MsgBox "Please enter Scraper Horsepower.", vbExclamation, "Missing Input"
        Me.boxhp.SetFocus
        Exit Sub
    End If
    If Not IsNumeric(Me.boxhp.Value) Then
        MsgBox "must be in number only.", vbExclamation, "Wrong Input"
        Me.boxhp.SetFocus
        Exit Sub
    End If

    If Me.Scramodelyear.Value > 0 Then
        Me.scralf.Value = 0.59
        Me.scract.Value = 914
    End If

    If Me.boxhp.Value > 300 Then
        Me.scramed.Value = 7000
    End If
    If Me.boxhp.Value <= 300 Then
        Me.scramed.Value = 4667
    End If

    If Me.boxhp.Value < 50 Then
        If Me.Scramodelyear.Value < 1999 Then
            Me.scratier.Value = "0"
        End If
    End If
    If Me.boxhp.Value < 50 Then
        If Me.Scramodelyear.Value >= 1999 Then
            If Me.Scramodelyear.Value < 2004 Then
                Me.scratier.Value = "1"
            End If
        End If
    End If
    End If

To the rest of Tier Level determination
.
.
.

    If Me.scratier.Value = "0" Then
        Me.scrAhc.Value = 0.047
        Me.scrAco.Value = 0.185
        Me.scrAnox.Value = 0.024
        Me.scrApm.Value = 0.473
        Me.scrAthc.Value = 1.05
        Me.scrATco.Value = 1.53
        Me.scrATnox.Value = 0.95
        Me.scrATpm.Value = 1.23
        Me.scrATbsfc.Value = 1.01
    End If
    If Me.scratier.Value = "1" Then
        Me.scrAhc.Value = 0.036

```

```

    Me.scraAco.Value = 0.101
    Me.scraAnox.Value = 0.024
    Me.scraApm.Value = 0.473
    Me.scraThc.Value = 1.05
    Me.scraTco.Value = 1.53
    Me.scraTnox.Value = 0.95
    Me.scraTpm.Value = 1.23
    Me.scraTbsfc.Value = 1.01
End If

```

To the rest of deterioration factor, transient adjustment factor, and steady-state emission factor for each pollutant

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End If

If Me.boxexcav.Value = "" Then
    MsgBox "Please select Excavation Type.", vbExclamation, "Missing Input"
    Me.boxexcav.SetFocus
Exit Sub
End If
If Me.boxsoil.Value = "" Then
    MsgBox "Please select Soil Type.", vbExclamation, "Missing Input"
    Me.boxsoil.SetFocus
Exit Sub
End If
If Me.boxdist.Value = "" Then
    MsgBox "Please enter Distance.", vbExclamation, "Missing Input"
    Me.boxdist.SetFocus
Exit Sub
End If
If Not IsNumeric(Me.boxdist.Value) Then
    MsgBox "must be in number only.", vbExclamation, "Wrong Input"
    Me.boxdist.SetFocus
Exit Sub
End If
If Me.boxdist.Value > 5000 Then
    MsgBox "inappropriate distance!", vbExclamation, "Out of Range"
    Me.boxdist.SetFocus
Exit Sub
End If
If Me.boxbucket.Value = "" Then
    MsgBox "Please enter Bucket Volume.", vbExclamation, "Missing Input"
    Me.boxbucket.SetFocus
Exit Sub
End If
If Not IsNumeric(Me.boxbucket.Value) Then
    MsgBox "must be in number only.", vbExclamation, "Wrong Input"
    Me.boxbucket.SetFocus
Exit Sub
End If
If Me.boxbucket.Value > 21 Then
    MsgBox "inappropriate bucket volume!", vbExclamation, "Out of Range"
    Me.boxbucket.SetFocus
Exit Sub
End If
If Me.boxsoilqua.Value = "" Then
    MsgBox "Please enter Soil Quantity.", vbExclamation, "Missing Input"
    Me.boxsoilqua.SetFocus
Exit Sub
End If
If Not IsNumeric(Me.boxsoilqua.Value) Then
    MsgBox "must be in number only.", vbExclamation, "Wrong Input"
    Me.boxsoilqua.SetFocus
Exit Sub
End If
If Me.boxexcav.Value = "Elevated Scrapper" Then
    If Me.boxsoil.Value = "Sand and Gravel" Then

```

```

        Me.boxprod.Value = Round(10 ^ (1.5124 + (0.06844 * 1) + (0.01724 *
Cdbl(Me.boxbucket.Value)) + (0.24427 * 1) - (0.00004519 * Cdbl(Me.boxdist.Value))), 2)
        Me.boxunitcost.Value = Round(10 ^ (1.00358 - (0.15182 * 1) - (0.01021 *
Cdbl(Me.boxbucket.Value)) - (0.24407 * 1) + (0.00004525 * Cdbl(Me.boxdist.Value))), 2)
    End If
End If
If Me.boxexcav.Value = "Elevated Scrapper" Then
    If Me.boxsoil.Value = "Common Earth" Then
        Me.boxprod.Value = Round(10 ^ (1.5124 + (0.06844 * 1) + (0.01724 *
Cdbl(Me.boxbucket.Value)) + (0.17427 * 1) - (0.00004519 * Cdbl(Me.boxdist.Value))), 2)
        Me.boxunitcost.Value = Round(10 ^ (1.00358 - (0.15182 * 1) - (0.01021 *
Cdbl(Me.boxbucket.Value)) - (0.1746 * 1) + (0.00004525 * Cdbl(Me.boxdist.Value))), 2)
    End If
End If
If Me.boxexcav.Value = "Elevated Scrapper" Then
    If Me.boxsoil.Value = "Sandy Clay and Loam" Then
        Me.boxprod.Value = Round(10 ^ (1.5124 + (0.06844 * 1) + (0.01724 *
Cdbl(Me.boxbucket.Value)) + (0.2092 * 1) - (0.00004519 * Cdbl(Me.boxdist.Value))), 2)
        Me.boxunitcost.Value = Round(10 ^ (1.00358 - (0.15182 * 1) - (0.01021 *
Cdbl(Me.boxbucket.Value)) - (0.20927 * 1) + (0.00004525 * Cdbl(Me.boxdist.Value))), 2)
    End If
End If
If Me.boxexcav.Value = "Elevated Scrapper" Then
    If Me.boxsoil.Value = "Clay" Then
        Me.boxprod.Value = Round(10 ^ (1.5124 + (0.06844 * 1) + (0.01724 *
Cdbl(Me.boxbucket.Value)) + (0 * 1) - (0.00004519 * Cdbl(Me.boxdist.Value))), 2)
        Me.boxunitcost.Value = Round(10 ^ (1.00358 - (0.15182 * 1) - (0.01021 *
Cdbl(Me.boxbucket.Value)) - (0 * 1) + (0.00004525 * Cdbl(Me.boxdist.Value))), 2)
    End If
End If
If Me.boxexcav.Value = "Self-propelled Scrapper" Then
    If Me.boxsoil.Value = "Sand and Gravel" Then
        Me.boxprod.Value = Round(10 ^ (1.5124 + (0.1123 * 1) + (0.01724 *
Cdbl(Me.boxbucket.Value)) + (0.24427 * 1) - (0.00004519 * Cdbl(Me.boxdist.Value))), 2)
        Me.boxunitcost.Value = Round(10 ^ (1.00358 - (0.11694 * 1) - (0.01021 *
Cdbl(Me.boxbucket.Value)) - (0.24407 * 1) + (0.00004525 * Cdbl(Me.boxdist.Value))), 2)
    End If
End If
If Me.boxexcav.Value = "Self-propelled Scrapper" Then
    If Me.boxsoil.Value = "Common Earth" Then
        Me.boxprod.Value = Round(10 ^ (1.5124 + (0.1123 * 1) + (0.01724 *
Cdbl(Me.boxbucket.Value)) + (0.17427 * 1) - (0.00004519 * Cdbl(Me.boxdist.Value))), 2)
        Me.boxunitcost.Value = Round(10 ^ (1.00358 - (0.11694 * 1) - (0.01021 *
Cdbl(Me.boxbucket.Value)) - (0.1746 * 1) + (0.00004525 * Cdbl(Me.boxdist.Value))), 2)
    End If
End If
If Me.boxexcav.Value = "Self-propelled Scrapper" Then
    If Me.boxsoil.Value = "Sandy Clay and Loam" Then
        Me.boxprod.Value = Round(10 ^ (1.5124 + (0.1123 * 1) + (0.01724 *
Cdbl(Me.boxbucket.Value)) + (0.2092 * 1) - (0.00004519 * Cdbl(Me.boxdist.Value))), 2)
        Me.boxunitcost.Value = Round(10 ^ (1.00358 - (0.11694 * 1) - (0.01021 *
Cdbl(Me.boxbucket.Value)) - (0.20927 * 1) + (0.00004525 * Cdbl(Me.boxdist.Value))), 2)
    End If
End If
If Me.boxexcav.Value = "Self-propelled Scrapper" Then
    If Me.boxsoil.Value = "Clay" Then
        Me.boxprod.Value = Round(10 ^ (1.5124 + (0.1123 * 1) + (0.01724 *
Cdbl(Me.boxbucket.Value)) + (0 * 1) - (0.00004519 * Cdbl(Me.boxdist.Value))), 2)
        Me.boxunitcost.Value = Round(10 ^ (1.00358 - (0.11694 * 1) - (0.01021 *
Cdbl(Me.boxbucket.Value)) - (0 * 1) + (0.00004525 * Cdbl(Me.boxdist.Value))), 2)
    End If
End If
If Me.boxexcav.Value = "Towed" Then
    If Me.boxsoil.Value = "Sand and Gravel" Then
        Me.boxprod.Value = Round(10 ^ (1.5124 + (0 * 1) + (0.01724 *
Cdbl(Me.boxbucket.Value)) + (0.24427 * 1) - (0.00004519 * Cdbl(Me.boxdist.Value))), 2)
        Me.boxunitcost.Value = Round(10 ^ (1.00358 - (0 * 1) - (0.01021 *
Cdbl(Me.boxbucket.Value)) - (0.24407 * 1) + (0.00004525 * Cdbl(Me.boxdist.Value))), 2)
    End If
End If
If Me.boxexcav.Value = "Towed" Then

```

```

    If Me.boxsoil.Value = "Common Earth" Then
        Me.boxprod.Value = Round(10 ^ (1.5124 + (0 * 1) + (0.01724 *
Cdbl(Me.boxbucket.Value)) + (0.17427 * 1) - (0.00004519 * Cdbl(Me.boxdist.Value))), 2)
        Me.boxunitcost.Value = Round(10 ^ (1.00358 - (0 * 1) - (0.01021 *
Cdbl(Me.boxbucket.Value)) - (0.1746 * 1) + (0.00004525 * Cdbl(Me.boxdist.Value))), 2)
    End If
End If
If Me.boxexcav.Value = "Towed" Then
    If Me.boxsoil.Value = "Sandy Clay and Loam" Then
        Me.boxprod.Value = Round(10 ^ (1.5124 + (0 * 1) + (0.01724 *
Cdbl(Me.boxbucket.Value)) + (0.2092 * 1) - (0.00004519 * Cdbl(Me.boxdist.Value))), 2)
        Me.boxunitcost.Value = Round(10 ^ (1.00358 - (0 * 1) - (0.01021 *
Cdbl(Me.boxbucket.Value)) - (0.20927 * 1) + (0.00004525 * Cdbl(Me.boxdist.Value))), 2)
    End If
End If
If Me.boxexcav.Value = "Towed" Then
    If Me.boxsoil.Value = "Clay" Then
        Me.boxprod.Value = Round(10 ^ (1.5124 + (0 * 1) + (0.01724 *
Cdbl(Me.boxbucket.Value)) + (0 * 1) - (0.00004519 * Cdbl(Me.boxdist.Value))), 2)
        Me.boxunitcost.Value = Round(10 ^ (1.00358 - (0 * 1) - (0.01021 *
Cdbl(Me.boxbucket.Value)) - (0 * 1) + (0.00004525 * Cdbl(Me.boxdist.Value))), 2)
    End If
End If
Me.boxduration.Value = Round(Cdbl(Me.boxsoilqua.Value) / Cdbl(Me.boxprod.Value), 2)
Me.boxtotalcost.Value = Round(Cdbl(Me.boxsoilqua.Value) * Cdbl(Me.boxunitcost.Value),
2)
Me.boxfuel.Value = Round(Cdbl(Me.scraEbsfc.Value) * Cdbl(Me.scraTbsfc.Value) * 0.12 *
Cdbl(Me.boxhp.Value) * Cdbl(Me.boxduration.Value), 2)
Me.boxco2.Value = Round((10.15 * Cdbl(Me.boxfuel.Value)) / 1000, 2)
Me.scraHC.Value = Round((1 + (Cdbl(Me.scraAhc.Value) * (2012 -
Cdbl(Me.Scramodelyear.Value) + 1) / Cdbl(Me.scramed.Value))) * Cdbl(Me.scraEhc.Value) *
Cdbl(Me.scraThc.Value) * Cdbl(Me.boxhp.Value) * Cdbl(Me.boxduration.Value), 2)
Me.scraCO.Value = Round((1 + (Cdbl(Me.scraAco.Value) * (2012 -
Cdbl(Me.Scramodelyear.Value) + 1) / Cdbl(Me.scramed.Value))) * Cdbl(Me.scraEco.Value) *
Cdbl(Me.scraTco.Value) * Cdbl(Me.boxhp.Value) * Cdbl(Me.boxduration.Value), 2)
Me.scraNOX.Value = Round((1 + (Cdbl(Me.scraAnox.Value) * (2012 -
Cdbl(Me.Scramodelyear.Value) + 1) / Cdbl(Me.scramed.Value))) * Cdbl(Me.scraEnox.Value) *
Cdbl(Me.scraTnox.Value) * Cdbl(Me.boxhp.Value) * Cdbl(Me.boxduration.Value), 2)
Me.scraPM.Value = Round((((1 + (Cdbl(Me.scraApm.Value) * (2012 -
Cdbl(Me.Scramodelyear.Value) + 1) / Cdbl(Me.scramed.Value))) * Cdbl(Me.scraEpm.Value) *
Cdbl(Me.scraTpm.Value)) - ((Cdbl(Me.scraEbsfc.Value) * Cdbl(Me.scraTbsfc.Value)) * 453.6
* 7 * 0.02247 * 0.01 * 0.08)) * Cdbl(Me.boxhp.Value) * Cdbl(Me.boxduration.Value), 2)
Me.scraSO2.Value = Round((((Cdbl(Me.scraEbsfc.Value) * Cdbl(Me.scraTbsfc.Value)) *
453 * (1 - 0.02247)) - Cdbl(Me.scraEhc.Value)) * 0.01 * 0.25 * 2 * Cdbl(Me.boxhp.Value) *
Cdbl(Me.boxduration.Value), 2)
RowCount = Worksheets("Scraper").range("A1").CurrentRegion.Rows.Count
With Worksheets("Scraper").range("A1")
    .Offset(RowCount, 0).Value = Me.boxhp.Value
    .Offset(RowCount, 1).Value = Me.Scramodelyear.Value
    .Offset(RowCount, 2).Value = Me.scratier.Value
    .Offset(RowCount, 3).Value = Me.boxexcav.Value
    .Offset(RowCount, 4).Value = Me.boxsoil.Value
    .Offset(RowCount, 5).Value = Me.boxdist.Value
    .Offset(RowCount, 6).Value = Me.boxbucket.Value
    .Offset(RowCount, 7).Value = Me.boxsoilqua.Value
    .Offset(RowCount, 8).Value = Me.boxprod.Value
    .Offset(RowCount, 9).Value = Me.boxunitcost.Value
    .Offset(RowCount, 10).Value = Me.boxduration.Value
    .Offset(RowCount, 11).Value = Me.boxtotalcost.Value
    .Offset(RowCount, 12).Value = Me.boxfuel.Value
    .Offset(RowCount, 13).Value = Me.scraHC.Value
    .Offset(RowCount, 14).Value = Me.scraCO.Value
    .Offset(RowCount, 15).Value = Me.scraNOX.Value
    .Offset(RowCount, 16).Value = Me.scraPM.Value
    .Offset(RowCount, 17).Value = Me.boxco2.Value
    .Offset(RowCount, 18).Value = Me.scraSO2.Value
End With
End Sub
Private Sub tclose_Click()
    Unload Me
End Sub

```



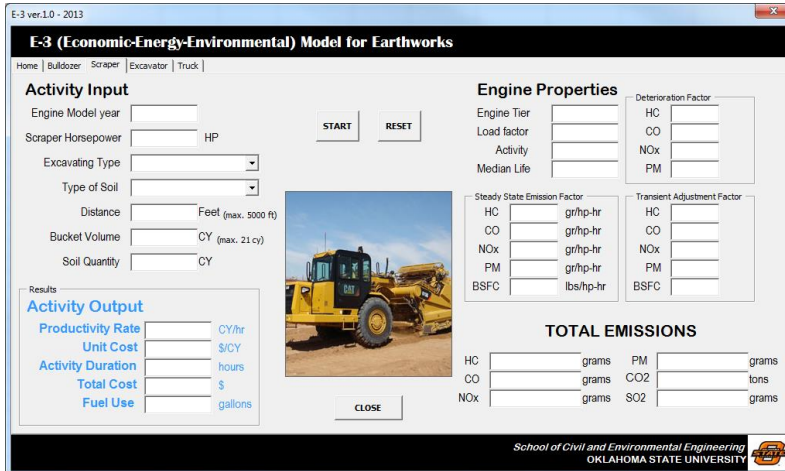


Figure J.2. E3 user's interface for scraper

## EXCAVATOR

```

Private Sub treset_Click()
    For Each ctl In Me.Controls
        If TypeName(ctl) = "TextBox" Or TypeName(ctl) = "ComboBox" Then
            ctl.Value = ""
        End If
    Next ctl
End Sub

Private Sub tstart_Click()
    Dim RowCount As Long
    Dim ctl As Control
    If Me.Tremodelyear.Value = "" Then
        MsgBox "Please enter excavator Model Year.", vbExclamation, "Missing Input"
        Me.Tremodelyear.SetFocus
        Exit Sub
    End If
    If Not IsNumeric(Me.Tremodelyear.Value) Then
        MsgBox "must be in number only.", vbExclamation, "Wrong Input"
        Me.Tremodelyear.SetFocus
        Exit Sub
    End If
    If Me.thp.Value = "" Then
        MsgBox "Please enter excavator Horsepower.", vbExclamation, "Missing Input"
        Me.thp.SetFocus
        Exit Sub
    End If
    If Not IsNumeric(Me.thp.Value) Then
        MsgBox "must be in number only.", vbExclamation, "Wrong Input"
        Me.thp.SetFocus
        Exit Sub
    End If

    If Me.Tremodelyear.Value > 0 Then
        Me.trelf.Value = 0.59
        Me.treact.Value = 1092
    End If

    If Me.thp.Value > 300 Then
        Me.tremed.Value = 7000
    End If
    If Me.thp.Value <= 300 Then
        Me.tremed.Value = 4667
    End If

```

To the rest of Tier Level determination

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End If

```
If Me.tretier.Value = "0" Then
    Me.treAhc.Value = 0.047
    Me.treAco.Value = 0.185
    Me.treAnox.Value = 0.024
    Me.treApm.Value = 0.473
    Me.treThc.Value = 1.05
    Me.treTco.Value = 1.53
    Me.treTnox.Value = 0.95
    Me.treTpm.Value = 1.23
    Me.treTbsfc.Value = 1.01
End If
```

To the rest of deterioration factor, transient adjustment factor, and steady-state emission factor for each pollutant

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End If

```
If Me.tsoil.Value = "" Then
    MsgBox "Please select Soil Type.", vbExclamation, "Missing Input"
    Me.tsoil.SetFocus
    Exit Sub
End If
If Me.tdepth.Value = "" Then
    MsgBox "Please enter Trench Depth.", vbExclamation, "Missing Input"
    Me.tdepth.SetFocus
    Exit Sub
End If
If Not IsNumeric(Me.tdepth.Value) Then
    MsgBox "must be in number only.", vbExclamation, "Wrong Input"
    Me.tdepth.SetFocus
    Exit Sub
End If
If Me.tdepth.Value > 24 Then
    MsgBox "inappropriate depth!", vbExclamation, "Out of Range"
    Me.tdepth.SetFocus
    Exit Sub
End If
If Me.tlength.Value = "" Then
    MsgBox "Please enter Trench Length.", vbExclamation, "Missing Input"
    Me.tlength.SetFocus
    Exit Sub
End If
If Not IsNumeric(Me.tlength.Value) Then
    MsgBox "must be in number only.", vbExclamation, "Wrong Input"
    Me.tlength.SetFocus
    Exit Sub
End If
If Me.twidth.Value = "" Then
    MsgBox "Please enter Trench Width.", vbExclamation, "Missing Input"
    Me.twidth.SetFocus
    Exit Sub
End If
If Not IsNumeric(Me.twidth.Value) Then
    MsgBox "must be in number only.", vbExclamation, "Wrong Input"
    Me.twidth.SetFocus
    Exit Sub
End If
If Me.texcav.Value = "" Then
    MsgBox "Please select Excavation Type.", vbExclamation, "Missing Input"
    Me.texcav.SetFocus
```

```

Exit Sub
End If
If Me.tbucket.Value = "" Then
    MsgBox "Please enter Bucket Volume.", vbExclamation, "Missing Input"
    Me.tbucket.SetFocus
Exit Sub
End If
If Not IsNumeric(Me.tbucket.Value) Then
    MsgBox "must be in number only.", vbExclamation, "Wrong Input"
    Me.tbucket.SetFocus
Exit Sub
End If
If Me.tbucket.Value > 3.5 Then
    MsgBox "inappropriate bucket volume!", vbExclamation, "Out of Range"
    Me.tbucket.SetFocus
Exit Sub
End If
If Me.thp.Value = "" Then
    MsgBox "Please enter Engine Horsepower.", vbExclamation, "Missing Input"
    Me.thp.SetFocus
Exit Sub
End If
If Not IsNumeric(Me.thp.Value) Then
    MsgBox "must be in number only.", vbExclamation, "Wrong Input"
    Me.thp.SetFocus
Exit Sub
End If
If Me.texcav.Value = "Excavator" Then
    If Me.tsoil.Value = "Common Earth" Then
        Me.tprod.Value = Round(-3.9467 + 8.46539 - (2.06932 * CDb1(Me.tdepth.Value))
+ (55.13072 * CDb1(Me.tbucket.Value)) + 3.31699, 2)
        Me.tunitcost.Value = Round(8.2689 - 0.64735 + (0.04504 *
CDb1(Me.tdepth.Value)) - (1.65841 * CDb1(Me.tbucket.Value)) - 0.56754, 2)
    End If
End If
If Me.texcav.Value = "Excavator" Then
    If Me.tsoil.Value = "Loam and Sandy Clay" Then
        Me.tprod.Value = Round(-3.9467 + 14.90685 - (2.06932 * CDb1(Me.tdepth.Value))
+ (55.13072 * CDb1(Me.tbucket.Value)) + 3.31699, 2)
        Me.tunitcost.Value = Round(8.2689 - 1.04899 + (0.04504 *
CDb1(Me.tdepth.Value)) - (1.65841 * CDb1(Me.tbucket.Value)) - 0.56754, 2)
    End If
End If
If Me.texcav.Value = "Excavator" Then
    If Me.tsoil.Value = "Sand and Gravel" Then
        Me.tprod.Value = Round(-3.9467 + 16.41176 - (2.06932 * CDb1(Me.tdepth.Value))
+ (55.13072 * CDb1(Me.tbucket.Value)) + 3.31699, 2)
        Me.tunitcost.Value = Round(8.2689 - 1.13299 + (0.04504 *
CDb1(Me.tdepth.Value)) - (1.65841 * CDb1(Me.tbucket.Value)) - 0.56754, 2)
    End If
End If
If Me.texcav.Value = "Excavator" Then
    If Me.tsoil.Value = "Dense Hard Clay" Then
        Me.tprod.Value = Round(-3.9467 - (2.06932 * CDb1(Me.tdepth.Value)) +
(55.13072 * CDb1(Me.tbucket.Value)) + 3.31699, 2)
        Me.tunitcost.Value = Round(8.2689 + (0.04504 * CDb1(Me.tdepth.Value)) -
(1.65841 * CDb1(Me.tbucket.Value)) - 0.56754, 2)
    End If
End If
If Me.texcav.Value = "Excavator, truck mounted" Then
    If Me.tsoil.Value = "Common Earth" Then
        Me.tprod.Value = Round(-3.9467 + 8.46539 - (2.06932 * CDb1(Me.tdepth.Value))
+ (55.13072 * CDb1(Me.tbucket.Value)) + 4.16554, 2)
        Me.tunitcost.Value = Round(8.2689 - 0.64735 + (0.04504 *
CDb1(Me.tdepth.Value)) - (1.65841 * CDb1(Me.tbucket.Value)) + 0.42075, 2)
    End If
End If
If Me.texcav.Value = "Excavator, truck mounted" Then
    If Me.tsoil.Value = "Loam and Sandy Clay" Then
        Me.tprod.Value = Round(-3.9467 + 14.90685 - (2.06932 * CDb1(Me.tdepth.Value))
+ (55.13072 * CDb1(Me.tbucket.Value)) + 4.16554, 2)

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        Me.tunitcost.Value = Round(8.2689 - 1.04899 + (0.04504 *
Cdbl(Me.tdepth.Value)) - (1.65841 * Cdbl(Me.tbucket.Value)) + 0.42075, 2)
    End If
End If
If Me.texcav.Value = "Excavator, truck mounted" Then
    If Me.tsoil.Value = "Sand and Gravel" Then
        Me.tprod.Value = Round(-3.9467 + 16.41176 - (2.06932 * Cdbl(Me.tdepth.Value))
+ (55.13072 * Cdbl(Me.tbucket.Value)) + 4.16554, 2)
        Me.tunitcost.Value = Round(8.2689 - 1.13299 + (0.04504 *
Cdbl(Me.tdepth.Value)) - (1.65841 * Cdbl(Me.tbucket.Value)) + 0.42075, 2)
    End If
End If
If Me.texcav.Value = "Excavator, truck mounted" Then
    If Me.tsoil.Value = "Dense Hard Clay" Then
        Me.tprod.Value = Round(-3.9467 - (2.06932 * Cdbl(Me.tdepth.Value)) +
(55.13072 * Cdbl(Me.tbucket.Value)) + 4.16554, 2)
        Me.tunitcost.Value = Round(8.2689 + (0.04504 * Cdbl(Me.tdepth.Value)) -
(1.65841 * Cdbl(Me.tbucket.Value)) + 0.42075, 2)
    End If
End If
If Me.texcav.Value = "Excavator, with trench box" Then
    If Me.tsoil.Value = "Common Earth" Then
        Me.tprod.Value = Round(-3.9467 + 8.46539 - (2.06932 * Cdbl(Me.tdepth.Value))
+ (55.13072 * Cdbl(Me.tbucket.Value)), 2)
        Me.tunitcost.Value = Round(8.2689 - 0.64735 + (0.04504 *
Cdbl(Me.tdepth.Value)) - (1.65841 * Cdbl(Me.tbucket.Value)), 2)
    End If
End If
If Me.texcav.Value = "Excavator, with trench box" Then
    If Me.tsoil.Value = "Loam and Sandy Clay" Then
        Me.tprod.Value = Round(-3.9467 + 14.90685 - (2.06932 * Cdbl(Me.tdepth.Value))
+ (55.13072 * Cdbl(Me.tbucket.Value)), 2)
        Me.tunitcost.Value = Round(8.2689 - 1.04899 + (0.04504 *
Cdbl(Me.tdepth.Value)) - (1.65841 * Cdbl(Me.tbucket.Value)), 2)
    End If
End If
If Me.texcav.Value = "Excavator, with trench box" Then
    If Me.tsoil.Value = "Sand and Gravel" Then
        Me.tprod.Value = Round(-3.9467 + 16.41176 - (2.06932 * Cdbl(Me.tdepth.Value))
+ (55.13072 * Cdbl(Me.tbucket.Value)), 2)
        Me.tunitcost.Value = Round(8.2689 - 1.13299 + (0.04504 *
Cdbl(Me.tdepth.Value)) - (1.65841 * Cdbl(Me.tbucket.Value)), 2)
    End If
End If
If Me.texcav.Value = "Excavator, with trench box" Then
    If Me.tsoil.Value = "Dense Hard Clay" Then
        Me.tprod.Value = Round(-3.9467 - (2.06932 * Cdbl(Me.tdepth.Value)) +
(55.13072 * Cdbl(Me.tbucket.Value)), 2)
        Me.tunitcost.Value = Round(8.2689 + (0.04504 * Cdbl(Me.tdepth.Value)) -
(1.65841 * Cdbl(Me.tbucket.Value)), 2)
    End If
End If
    Me.tduration.Value = Round((0.037 * Cdbl(Me.tlength.Value * Me.twidth.Value *
Me.tdepth.Value)) / Cdbl(Me.tprod.Value), 2)
    Me.ttotalcost.Value = Round((0.037 * Cdbl(Me.tlength.Value * Me.twidth.Value *
Me.tdepth.Value)) * Cdbl(Me.tunitcost.Value), 2)
    Me.tfuel.Value = Round(Cdbl(Me.treEbsfc.Value) * Cdbl(Me.treTbsfc.Value) * 0.12 *
Cdbl(Me.thp.Value) * Cdbl(Me.tduration.Value), 2)
    Me.tco2.Value = Round((10.15 * Cdbl(Me.tfuel.Value)) / 1000, 2)
    Me.treHC.Value = Round((1 + (Cdbl(Me.treAhc.Value) * (2012 -
Cdbl(Me.Tremodelyear.Value) + 1) / Cdbl(Me.tremed.Value))) * Cdbl(Me.treEhc.Value) *
Cdbl(Me.treThc.Value) * Cdbl(Me.thp.Value) * Cdbl(Me.tduration.Value), 2)
    Me.treCO.Value = Round((1 + (Cdbl(Me.treAco.Value) * (2012 -
Cdbl(Me.Tremodelyear.Value) + 1) / Cdbl(Me.tremed.Value))) * Cdbl(Me.treEco.Value) *
Cdbl(Me.treTco.Value) * Cdbl(Me.thp.Value) * Cdbl(Me.tduration.Value), 2)
    Me.treNOx.Value = Round((1 + (Cdbl(Me.treAnox.Value) * (2012 -
Cdbl(Me.Tremodelyear.Value) + 1) / Cdbl(Me.tremed.Value))) * Cdbl(Me.treEnox.Value) *
Cdbl(Me.treTnox.Value) * Cdbl(Me.thp.Value) * Cdbl(Me.tduration.Value), 2)
    Me.trePM.Value = Round(((1 + (Cdbl(Me.treApm.Value) * (2012 -
Cdbl(Me.Tremodelyear.Value) + 1) / Cdbl(Me.tremed.Value))) * Cdbl(Me.treEpm.Value) *

```

```

Cdbl(Me.treTpm.Value)) - ((Cdbl(Me.treEbsfc.Value) * Cdbl(Me.treTbsfc.Value)) * 453.6 * 7
* 0.02247 * 0.01 * 0.08)) * Cdbl(Me.thp.Value) * Cdbl(Me.tduration.Value), 2)
Me.treSO2.Value = Round(((Cdbl(Me.treEbsfc.Value) * Cdbl(Me.treTbsfc.Value)) * 453 *
(1 - 0.02247)) - Cdbl(Me.treEhc.Value)) * 0.01 * 0.25 * 2 * Cdbl(Me.thp.Value) *
Cdbl(Me.tduration.Value), 2)
RowCount = Worksheets("Excavator").range("A1").CurrentRegion.Rows.Count
With Worksheets("Excavator").range("A1")
.Offset(RowCount, 0).Value = Me.thp.Value
.Offset(RowCount, 1).Value = Me.Tremodelyear.Value
.Offset(RowCount, 2).Value = Me.tretier.Value
.Offset(RowCount, 3).Value = Me.tsoil.Value
.Offset(RowCount, 4).Value = Me.tdepth.Value
.Offset(RowCount, 5).Value = Me.tlength.Value
.Offset(RowCount, 6).Value = Me.twidth.Value
.Offset(RowCount, 7).Value = Me.texcav.Value
.Offset(RowCount, 8).Value = Me.tbucket.Value
.Offset(RowCount, 9).Value = Me.tprod.Value
.Offset(RowCount, 10).Value = Me.tunitcost.Value
.Offset(RowCount, 11).Value = Me.tduration.Value
.Offset(RowCount, 12).Value = Me.tttotalcost.Value
.Offset(RowCount, 13).Value = Me.tfuel.Value
.Offset(RowCount, 14).Value = Me.treHC.Value
.Offset(RowCount, 15).Value = Me.treCO.Value
.Offset(RowCount, 16).Value = Me.treNOx.Value
.Offset(RowCount, 17).Value = Me.trePM.Value
.Offset(RowCount, 18).Value = Me.tco2.Value
.Offset(RowCount, 19).Value = Me.treSO2.Value
End With
End Sub

```

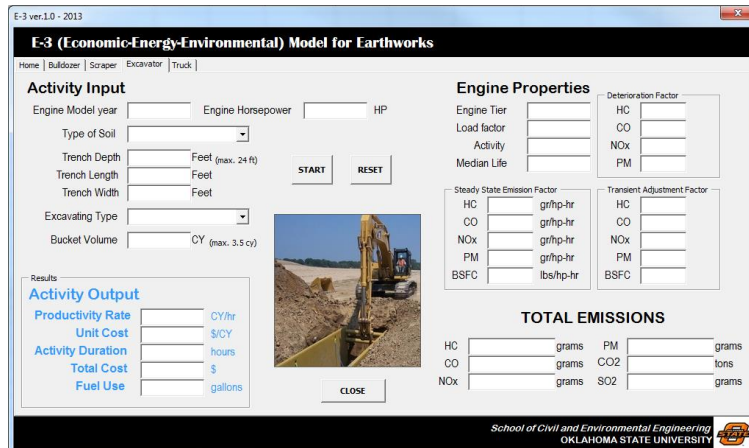


Figure J.3. E3 user's interface for excavator

## TRUCK

```

Private Sub truReset_Click()
    For Each ctl In Me.Controls
        If TypeName(ctl) = "TextBox" Or TypeName(ctl) = "ComboBox" Then
            ctl.Value = ""
        End If
    Next ctl
End Sub

Private Sub trustart_Click()
    Dim RowCount As Long
    Dim ctl As Control
    If Me.truhp.Value = "" Then
        MsgBox "Please enter truck Horsepower.", vbExclamation, "Missing Input"
        Me.truhp.SetFocus
    Exit Sub

```

```

End If
If Not IsNumeric(Me.truhp.Value) Then
    MsgBox "must be in number only.", vbExclamation, "Wrong Input"
    Me.truhp.SetFocus
    Exit Sub
End If
If Me.trumodelyear.Value = "" Then
    MsgBox "Please enter truck Model Year.", vbExclamation, "Missing Input"
    Me.trumodelyear.SetFocus
    Exit Sub
End If
If Not IsNumeric(Me.trumodelyear.Value) Then
    MsgBox "must be in number only.", vbExclamation, "Wrong Input"
    Me.trumodelyear.SetFocus
    Exit Sub
End If

If Me.trumodelyear.Value > 0 Then
    Me.trulf.Value = 0.59
    Me.truact.Value = 1641
End If

If Me.truhp.Value > 300 Then
    Me.trumed.Value = 7000
End If
If Me.truhp.Value <= 300 Then
    Me.trumed.Value = 4667
End If

To the rest of Tier Level determination
.
.
.

End If

If Me.trutier.Value = "0" Then
    Me.truAhc.Value = 0.047
    Me.truAco.Value = 0.185
    Me.truAnox.Value = 0.024
    Me.truApm.Value = 0.473
    Me.truThc.Value = 1.05
    Me.truTco.Value = 1.53
    Me.truTnox.Value = 0.95
    Me.truTpm.Value = 1.23
    Me.truTbsfc.Value = 1.01
End If

To the rest of deterioration factor, transient adjustment factor, and steady-state
emission factor for each pollutant

.
.
.

End If

If Me.trucap.Value = "" Then
    MsgBox "Please enter truck capacity.", vbExclamation, "Missing Input"
    Me.trucap.SetFocus
    Exit Sub
End If
If Not IsNumeric(Me.trucap.Value) Then
    MsgBox "must be in number only.", vbExclamation, "Wrong Input"
    Me.trucap.SetFocus
    Exit Sub
End If
If Me.trucap.Value < 20 Then
    MsgBox "inappropriate capacity!", vbExclamation, "Out of Range"

```

```

        Me.trucap.SetFocus
    Exit Sub
End If
If Me.trucap.Value > 60 Then
    MsgBox "inappropriate capacity!", vbExclamation, "Out of Range"
    Me.trucap.SetFocus
    Exit Sub
End If
If Me.truspeed.Value = "" Then
    MsgBox "Please enter truck speed.", vbExclamation, "Missing Input"
    Me.truspeed.SetFocus
    Exit Sub
End If
If Not IsNumeric(Me.truspeed.Value) Then
    MsgBox "must be in number only.", vbExclamation, "Wrong Input"
    Me.truspeed.SetFocus
    Exit Sub
End If
If Me.truspeed.Value < 5 Then
    MsgBox "inappropriate speed!", vbExclamation, "Out of Range"
    Me.truspeed.SetFocus
    Exit Sub
End If
If Me.truspeed.Value > 25 Then
    MsgBox "inappropriate speed!", vbExclamation, "Out of Range"
    Me.truspeed.SetFocus
    Exit Sub
End If
If Me.trudist.Value = "" Then
    MsgBox "Please enter hauling distance", vbExclamation, "Missing Input"
    Me.trudist.SetFocus
    Exit Sub
End If
If Not IsNumeric(Me.trudist.Value) Then
    MsgBox "must be in number only.", vbExclamation, "Wrong Input"
    Me.trudist.SetFocus
    Exit Sub
End If
If Me.trudist.Value < 0 Then
    MsgBox "inappropriate distance!", vbExclamation, "Out of Range"
    Me.trudist.SetFocus
    Exit Sub
End If
If Me.trudist.Value > 4 Then
    MsgBox "inappropriate distance!", vbExclamation, "Out of Range"
    Me.trudist.SetFocus
    Exit Sub
End If
If Me.trutime.Value = "" Then
    MsgBox "Please enter wait-dump time.", vbExclamation, "Missing Input"
    Me.trutime.SetFocus
    Exit Sub
End If
If Not IsNumeric(Me.trutime.Value) Then
    MsgBox "must be in number only.", vbExclamation, "Wrong Input"
    Me.trutime.SetFocus
    Exit Sub
End If
If Me.trutime.Value < 0 Then
    MsgBox "inappropriate time!", vbExclamation, "Out of Range"
    Me.trutime.SetFocus
    Exit Sub
End If
If Me.trutime.Value > 25 Then
    MsgBox "inappropriate time!", vbExclamation, "Out of Range"
    Me.trutime.SetFocus
    Exit Sub
End If
If Me.trusoil.Value = "" Then
    MsgBox "Please enter Soil Quantity.", vbExclamation, "Missing Input"
    Me.trusoil.SetFocus

```

```

Exit Sub
End If
If Not IsNumeric(Me.trusoil.Value) Then
    MsgBox "must be in number only.", vbExclamation, "Wrong Input"
    Me.trusoil.SetFocus
Exit Sub
End If

Me.truprod.Value = Round((58.799 + (2.07931 * CDb1(Me.trucap.Value)) + (1.62496 *
CDbl(Me.truspeed.Value)) - (12.05623 * CDb1(Me.trudist.Value)) - (2.78874 *
CDbl(Me.trutime.Value))), 2)
Me.trucost.Value = Round((3.203 - (0.055 * CDb1(Me.trucap.Value)) - (0.098 *
CDbl(Me.truspeed.Value)) + (0.709 * CDb1(Me.trudist.Value)) + (0.143 *
CDbl(Me.trutime.Value))), 2)
Me.trudur.Value = Round(CDb1(Me.trusoil.Value) / CDb1(Me.truprod.Value), 2)
Me.trutotcost.Value = Round(CDb1(Me.trusoil.Value) * CDb1(Me.trucost.Value), 2)
Me.trufuel.Value = Round(CDb1(Me.truEbsfc.Value) * CDb1(Me.truTbsfc.Value) * 0.12 *
CDbl(Me.truHP.Value) * CDb1(Me.trudur.Value), 2)
Me.truCO2.Value = Round((10.15 * CDb1(Me.trufuel.Value)) / 1000, 2)
Me.truHC.Value = Round((1 + (CDbl(Me.truAHC.Value) * (2012 - CDb1(Me.trumodelyear.Value)
+ 1) / CDb1(Me.trumed.Value))) * CDb1(Me.truEHC.Value) * CDb1(Me.truTHC.Value) *
CDbl(Me.truHP.Value) * CDb1(Me.trudur.Value), 2)
Me.truCO.Value = Round((1 + (CDbl(Me.truACO.Value) * (2012 - CDb1(Me.trumodelyear.Value)
+ 1) / CDb1(Me.trumed.Value))) * CDb1(Me.truECO.Value) * CDb1(Me.truTCO.Value) *
CDbl(Me.truHP.Value) * CDb1(Me.trudur.Value), 2)
Me.truNOx.Value = Round((1 + (CDbl(Me.truANOx.Value) * (2012 -
CDbl(Me.trumodelyear.Value) + 1) / CDb1(Me.trumed.Value))) * CDb1(Me.truENOx.Value) *
CDbl(Me.truTNOx.Value) * CDb1(Me.truHP.Value) * CDb1(Me.trudur.Value), 2)
Me.truPM.Value = Round((((1 + (CDbl(Me.truAPM.Value) * (2012 -
CDbl(Me.trumodelyear.Value) + 1) / CDb1(Me.trumed.Value))) * CDb1(Me.truEPM.Value) *
CDbl(Me.truTPM.Value)) - ((CDbl(Me.truEbsfc.Value) * CDb1(Me.truTbsfc.Value)) * 453.6 * 7
* 0.02247 * 0.01 * 0.08)) * CDb1(Me.truHP.Value) * CDb1(Me.trudur.Value), 2)
Me.truSO2.Value = Round((((CDbl(Me.truEbsfc.Value) * CDb1(Me.truTbsfc.Value)) * 453 * (1
- 0.02247)) - CDb1(Me.truEHC.Value)) * 0.01 * 0.25 * 2 * CDb1(Me.truHP.Value) *
CDbl(Me.trudur.Value), 2)
RowCount = Worksheets("Truck").range("A1").CurrentRegion.Rows.Count
With Worksheets("Truck").range("A1")
    .Offset(RowCount, 0).Value = Me.truHP.Value
    .Offset(RowCount, 1).Value = Me.trumodelyear.Value
    .Offset(RowCount, 2).Value = Me.trutier.Value
    .Offset(RowCount, 3).Value = Me.trucap.Value
    .Offset(RowCount, 4).Value = Me.truspeed.Value
    .Offset(RowCount, 5).Value = Me.trudist.Value
    .Offset(RowCount, 6).Value = Me.trutime.Value
    .Offset(RowCount, 7).Value = Me.trusoil.Value
    .Offset(RowCount, 8).Value = Me.truprod.Value
    .Offset(RowCount, 9).Value = Me.trucost.Value
    .Offset(RowCount, 10).Value = Me.trudur.Value
    .Offset(RowCount, 11).Value = Me.trutotcost.Value
    .Offset(RowCount, 12).Value = Me.trufuel.Value
    .Offset(RowCount, 13).Value = Me.truHC.Value
    .Offset(RowCount, 14).Value = Me.truCO.Value
    .Offset(RowCount, 15).Value = Me.truNOx.Value
    .Offset(RowCount, 16).Value = Me.truPM.Value
    .Offset(RowCount, 17).Value = Me.truCO2.Value
    .Offset(RowCount, 18).Value = Me.truSO2.Value
End With
End Sub

```



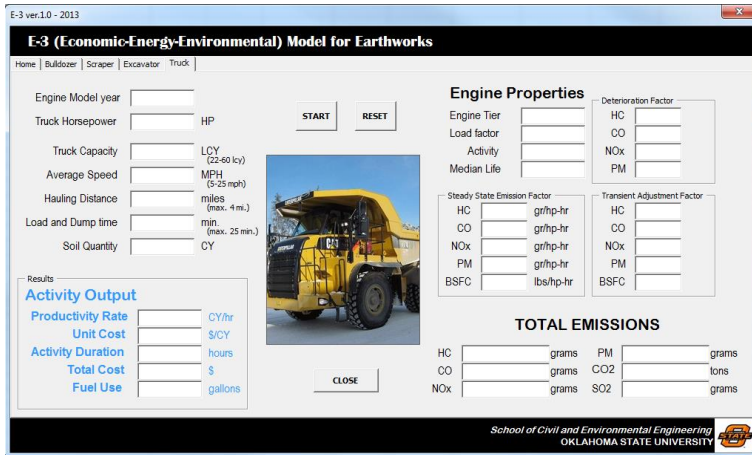


Figure J.4. E3 user's interface for truck

VITA

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