DEVELOPMENT OF PREDICTIVE MODELING TOOLS FOR ESTIMATING FUEL USE AND EMISSION RATES FOR HEAVY-DUTY DIESEL CONSTRUCTION EQUIPMENT

By

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DEVELOPMENT OF PREDICTIVE MODELING

TOOLS FOR ESTIMATING FUEL USE AND

EMISSION RATES FOR HEAVY-DUTY DIESEL

CONSTRUCTION EQUIPMENT

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ABSTRACT:

Heavy-duty diesel (HDD) construction equipment consumes a substantial amount of fuels and consequently emits a substantial amount of pollutants into the environment. This dissertation presents methodologies for estimating fuel use and emission rates for HDD construction equipment based on real-world in-use data. Second-by-second data for fuel use and emission rates of nitrogen oxides (NO_x), hydrocarbons (HC), carbon monoxide (CO), carbon dioxide (CO_2), and particulate matter (PM) along with engine data were collected from 32 items of equipment using Portable Emission Measurement Systems (PEMS). The HDD construction equipment consists of six backhoes, six bulldozers, three excavators, six motor graders, three off-road trucks, three track loaders, and five wheel loaders. Engine performance data that include manifold absolute pressure (MAP), revolutions per minute (RPM), and intake air temperature (IAT) were used to measure the fuel use and emission rates of NO_x, HC, CO, CO_2, and PM. Predictive fuel use and emission rates models were developed using the weighted average approach, simple linear regression (SLR), multiple linear regression (MLR), and artificial neural network (ANN). Variable correlations and variable impact analysis were also developed for each item of equipment. Based on the summary of Pearson correlation coefficients, MAP had a high positive correlation to fuel use and emission rates of NO_x, CO_2, and PM, but had a moderate positive relationship with HC and CO. Although not as highly correlated, RPM had a strong positive relationship with fuel use and emissions. IAT was shown to have the lowest correlation of the three engine performance variables on predicting fuel use and emission rates. The weighted average approach is a practical tool to estimate the fuel consumption and emission rates for HDD construction equipment. The method is reliable for real-world use. For SLR, MLR and ANN modeling approaches, CO proved to be the most difficult pollutant emission rate to predict, as evidenced by its low R^2 values. Based on the model comparisons, ANN models generally performed the best with respect to precision, accuracy, and bias. In most cases, the ANN approach produced highly precise models for NO_x, CO_2, and PM; while the models for HC and CO were moderately precise. A potential drawback to the ANN approach is that the equations for each response variable are not actually provided, thus the user must have access to the artificial neural network. Although, the SLR and MLR approaches yielded models that were slightly less accurate and precise than the ANN approach, these models are still useful.

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CHAPTER I

INTRODUCTION

1.1 Background

Construction activities consume a substantial amount of fuel and consequently emit a substantial amount of pollutants into the environment. According to the United States Environmental Protection Agency (EPA, 2005), there are approximately two million items of construction and mining equipment in the United States that consume about six billions gallons of diesel fuel annually. Furthermore, in most construction activities, heavy-duty diesel (HDD) construction equipment is the primary source of emissions. EPA also estimates that in 2005, HDD construction vehicles produced U.S. national annual totals of 657,000 tons of NO_x, 1,100,000 tons of CO, 63,000 tons of PM_{10} and 94,000 tons of SO_2 (EPA, 2005). Of these pollutants, NO_x and PM are the most prominent among HDD equipment (EPA, 2006). Other pollutants found in diesel exhaust (DE) include hydrocarbons (HC) and carbon dioxide (CO_2).

As stated by EPA (2002), diesel exhaust (DE) exposure may cause both long term and short term effects. Long term or chronic exposure to DE is potentially a trigger to lung cancer and lung damage risk to humans. Meanwhile, short term or acute exposure to DE may pose irritation of the eyes and throat, neurophysiological symptoms (lightheadedness, nausea) and respiratory symptoms (cough, phlegm). Moreover, studies by EPA in 2002 concluded that DE may be a potential human carcinogen.

Table 1.1 presents the summary of several studies on the effects of DE to humans conducted by The National Institute for Occupational Safety and Health (NIOSH), The International Agency for Research on Cancer (IARC), The International Programme on Chemical Safety (IPCS), The California EPA, and The National Toxicology Program (NTP). Although limited studies have been directed in human areas, animal studies mainly are the indicators to demonstrate a causal relationship on the exposure of DE and cancer risk. The studies ultimately declared that DE is a potential carcinogen to humans.

Table 1.1 Evaluation of DE as to human carcinogenic potential (EPA, 2002)

Organization	**Human data**	**Animal Data**	**Overall evaluation**
NIOSH (1988)	Limited	Confirmatory	Potential occupational carcinogen
IARC (1989)	Limited	Sufficient	Probably carcinogenic to humans
IPCS (1996)	N/A	N/A	Probably carcinogenic to humans
California EPA (1998)	Consistent evidence for a causal association	Demonstrated carcinogenicity	Diesel Particulate Matter (DPM) as a “toxic air contaminant”
NTP (2000)	Elevated lung cancer in exposed groups	Supporting animal and mechanistic data	Diesel Particulate Matter (DPM)- anticipated to be a carcinogen

N/A = Not applicable

Studies on quantification and characterization of emission pollutants from HDD equipment have been increasing due to the requirements of stringent emissions standards compliance by EPA. Of these studies, some addressed the use of engine dynamometer tests based on steady-state conditions (Tehranian, 2003; Atkinson *et al*., 2000; Thompson *et al*., 2000; Clark *et al*., 2002; Hashemi, 2007); meanwhile, others focused on real-world emissions measurements. Some of the prominent real-world emissions measurements from HDD construction equipment were accomplished by researchers at North Carolina State University (Abolhasani *et al*., 2008; Lewis, 2009; Rasdorf *et al*., 2010; Frey *et al*., 2008; Kim, 2007).

The California Air Resource Board in 2013 also conducted a study on in-use emissions from diesel off-road equipment. This study measured 27 items of construction equipment using portable emissions measurement systems (PEMS) and then developed relationships between emission rates and fuel use as well as engine brake horsepowers. In order to quantify and characterize HDD emissions problems, a thorough and reliable study on emissions quantification is needed. This dissertation presents some methodologies to estimate fuel use and emission rates based on real-world in-use data for different types of HDD equipment.

1.2 Problem Statement

Developing accurate fuel use and emission prediction tools is important for estimating energy use and emissions footprints. Prediction modeling tools are needed to quantify and characterize the air pollution problems from HDD equipment used in construction. These can help some users such as fleet managers, contractors, and owners to estimate fuel use and emissions footprints of their equipment. Prediction emissions measurement tools developed by using engine dynamometer data may be less accurate compared to PEMS. This is due to the fact that dynamometer tests are measured at steady-state conditions; meanwhile, PEMS are based on real-world, in-use emissions measurements while HDD equipment is performing its duty cycle.

Although much work has also been done by using PEMS data, there is lack of prediction fuel use and emissions modeling tools to accurately predict the fuel use and emission rates. Therefore, predictive modeling tools for estimating fuel use and emission rates for HDD construction equipment using real-world data are required.

1.3 Research Objective

The main goal of this research is to develop predictive modeling tools for estimating fuel use and emissions rates for HDD construction equipment based on real-world data. Second-by-second data for fuel use and emissions of nitrogen oxides (NO_x), hydrocarbons (HC), carbon monoxide (CO), carbon dioxide (CO_2), and particulate matter (PM) along with engine data were collected and analyzed from 32 items of equipment using PEMS. The HDD construction equipment consists of six backhoes, six bulldozers, three excavators, six motor graders, three off - road trucks, three track loaders, and five wheel loaders. Engine performance data that include manifold absolute pressure (MAP), revolutions per minute (RPM), and intake air temperature (IAT) were also used to measure fuel use and emission rates of NO_x, HC, CO, CO_2, and PM. The following research objectives are defined as follows:

1. Develop prediction models for fuel use and emission rates based on equipment type and engine load.
2. Develop prediction models of fuel use and emission rates based on engine performance data.
3. Assess inter-vehicle variability of fuel use and emission rates.
4. Develop a taxonomy of average fuel use and emission rates for different types of equipment and engine technology.

1.4 Scope of the Research

This research focuses on developing predictive modeling tools for estimating fuel use and emission rates of NO_x, HC, CO, CO_2, and PM using a real-world dataset from a research team at North Carolina State University. This dataset includes 32 items of equipment consisting of seven different types of HDD equipment. Real-world data collected based on a second-by-second basis along with engine performance data such as manifold absolute pressure (MAP), revolutions per minute (RPM), and intake air temperature (IAT) from HDD equipment are used to produce precise models for fuel use and emission rates estimations. Prediction modeling methods cover weighted average approaches, simple linear regression (SLR), multiple linear regression (MLR), and artificial neural network (ANN).

1.5 Outcomes

The primary outcome of this research is a set of reliable predictive models for estimating fuel use and emission rates for specific HDD construction equipment based on real-world data. For the specific objectives of the study, the outcomes are:

1. A reliable methodology for estimating fuel use and emission rates based on equipment type and engine load.
2. A reliable methodology for estimating fuel use and emission rates based on engine performance data.
3. A better understanding of the influence of equipment and engine activity on fuel use and emission estimation.
4. A taxonomy of real-world emission factors for HDD equipment.

CHAPTER II

REVIEW OF LITERATURE

As the need of conforming emission standards has been largely increasing, numerous studies have been extensively piloted to quantify and characterize emissions and energy consumption of HDD construction equipment. Many studies have been completed using experimental designs such as dynamometer tests and real-world in-use measurements. Dynamometer tests are commonly used in quantifying emissions at steady-state conditions in the laboratory. Other studies conducted emission quantification by engaging Portable Emission Measurement Systems (PEMS), models, and simulations. The Environmental Protection Agency (EPA) and other government agency also develop other models such as the Nonroad model, the Offroad model, and the Urbemis model. This chapter provides and overviews aforementioned studies related to emissions measurement.

2.1 Methods of Emissions Measurement using Experimental Data

Research using experimental equipment in measuring emission is commonly employed by using chassis dynamometer test and PEMS for any types of vehicle along with different types of fuels. The following section concisely overviews two common experimental methods of quantifying emissions of engines.

2.1.1 Dynamometer

Dynamometer test is typically used in quantifying emissions at steady-state conditions in the laboratory using relatively constant load and engine speed on an uninstalled stationary. Much of the work related to emissions measurements were conducted using dynamometer laboratory test for both light- and heavy-duty vehicles (Frey *et al*., 2003; Tehranian, 2003; Atkinson *et al*., 2000; Thompson *et al*., 2000; Clark *et al*., 2002; Hashemi, 2007; Pelkmans and Debal, 2006; Kyto and Murtonen, 2012).

Figure 2.1. Engine Dynamometer (Mudgal, 2009)

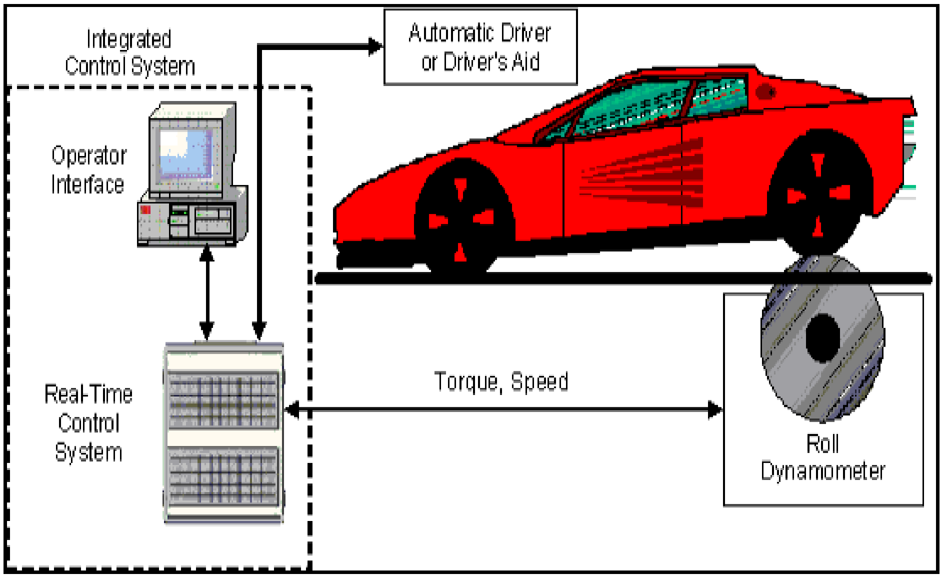

Figure 2.2. Chassis Dynamometer Testing (Mudgal, 2009)

In order to measure emissions of the engines, several approaches that are typically employed based upon dynamometer test may be conducted either for the entire chassis or engine only. Figure 2.1 and 2.2 present the tests carried out on engine dynamometer and chassis dynamometer respectively. Dynamometer test is run into specified engine modes representing engine load. According to Abolhasani *et al*. (2008), the most common operating modes consist of 8-, 13- and 21-mode tests. The EPA has largely used the 8-mode test and defined this test as the basis for developing the EPA Nonroad model. Engine is tracked at specified revolutions per minute (RPM) at different levels of torque. To obtain representative emission rates for a specific type of equipment, adjustment factors are applied to the test cycle data. Since involving a constant load and engine speed, dynamometer tests are considered not fully representative of the real-world data (Abolhasani *et al*., 2008).

Abolhasani *et al*. (2008) mentioned that The Clean Air Technologies International (CATI), Inc. conducted a study to compare a dynamometer test with the PEMS measurements at the New York Departmental Conservation (NYDEC) and The EPA's National Fuel and Emission Laboratory. The result of this study indicated that the PEMS produced much higher coefficient of determination (R^2) and slopes within the range of 0.9 - 0.99 compared to the dynamometer test for specified emissions. These indicated good precision and accuracy of the PEMS.

2.1.2 Portable Emissions Measurement System (PEMS)

PEMS is generally used to gather fuel use and emissions field data of vehicles based upon real-world measurement. In-use emissions quantification enables data collection by capturing the actual duty cycle on a second-by-second basis measurement. Commercial PEMS are obtainable for any kinds of applications as well as for different types of fuel use. The overall procedures of PEMS are briefly explained in Chapter 3.

An example of a specific item of HDD equipment while performing its duty cycle was presented in Figure 2.3. Lewis (2009) described the relationship of tasks, fuel consumptions, and emissions conducted by a rubber tire loader. It was obvious that while executing the activities such as scooping dirt, traveling loaded, dumping dirt, and returning empty, the rubber tire loader consumed a substantial amount of diesel fuel and emitted pollutant emissions into the environment.

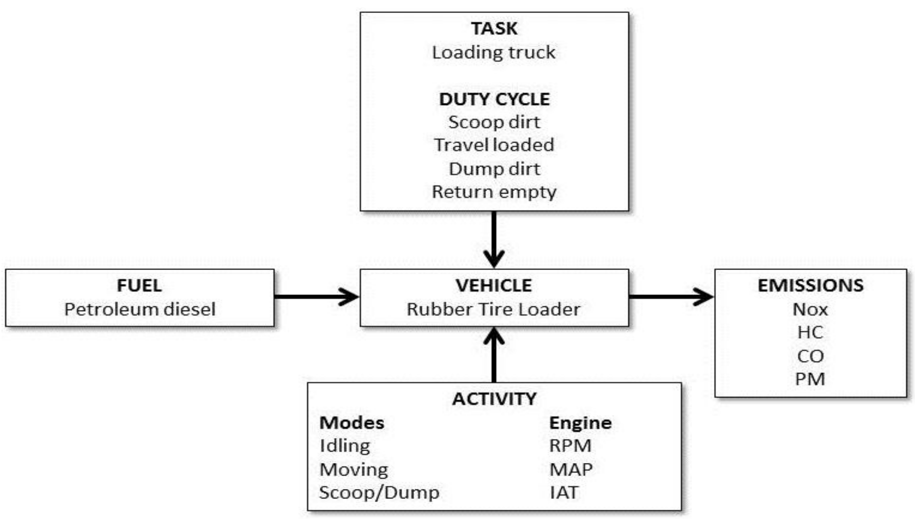

Figure 2.3. Real world-based emission inventory from construction vehicles (Lewis *et al*., 2009; Rasdorf *et. al*., 2010)

Some of the most prominent real-world emissions measurements from HDD construction equipment were completed by the researchers at North Carolina State University (Abolhasani *et al*., 2008; Lewis, 2009; Rasdorf *et al*., 2010; Frey *et al*., 2008; Kim, 2007). Other researchers from West Virginia University and the University of California – Riverside also directed their studies on the use of on-board emission measurement for particular construction equipment. For example, Barth *et al*. (2005) developed modal emissions and fuel consumption model for HDD especially for transit buses and heavy trucks.

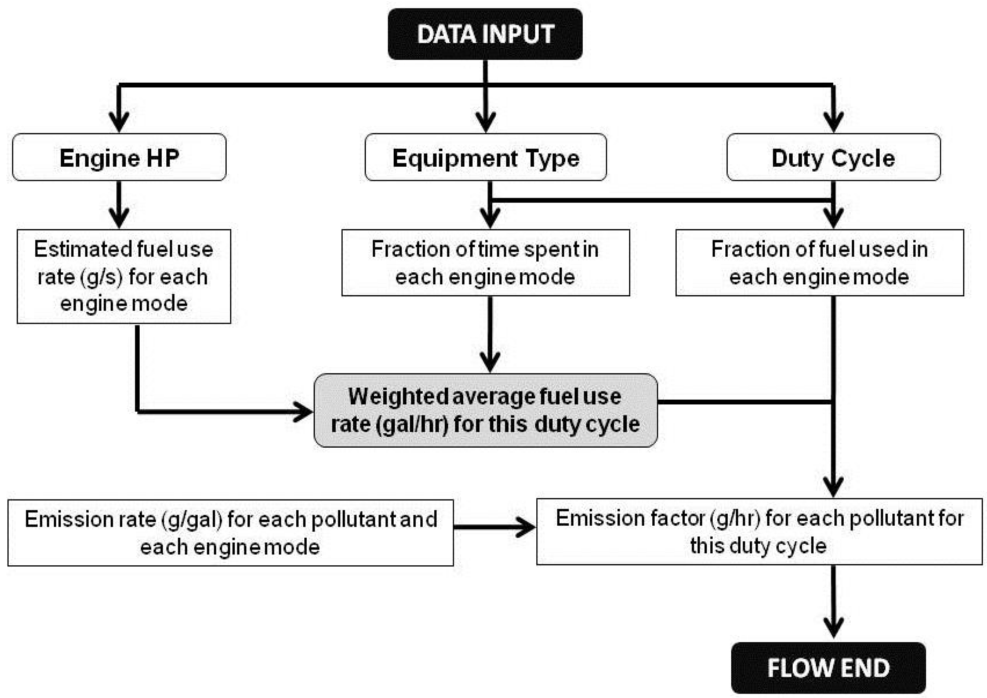

Figure 2.4. Equipment data to measure the emission rate (Lewis, 2009)

Lewis (2009) presented a methodology for measuring the weighted-average fuel use and emission rates of HDD construction equipment while performing common duty cycles. Data were collected from 34 items of equipment using PEMS. Engine modal analysis was used to define the variability of fuel use and emission rates regarding 10 individual engine modes. Fraction of time in each engine mode was determined to estimate the weighted average fuel use and emission rates of NO_x, HC, CO, CO_2, and PM. Multiple linear regression models were developed for engine mode 2-10 based upon horsepower and engine tier. However, results showed that R^2 values were low and ineffective. Thus, average modal emission rates of each pollutant were developed to obtain more reliable models. With respect to the results indicating comparison of the actual and estimated fuel use and emission rates, the response plots demonstrated that the methodology was reliable enough in estimating fuel use and emission rates.

Lewis *et al*. (2012) studied the influence of engine idling with respect to fuel use and emission rates of CO_2 for HDD construction equipment. Similar to the prior study, this study also investigated 34 items of construction equipment which comprised of 8 backhoes, 6 bulldozers, 3 excavators, 6 motor graders, 3 off-road trucks, 3 truck loaders, and 5 wheel loaders. Moreover, this study determined the operational efficiency of each item of equipment indicated by the ratio of nonidle time to total equipment use time. The results showed that nonidle fuel use and emission rates were significantly higher than those in idle condition. In addition, results also showed that as idle time increased, the fuel use and emissions rates of CO_2 increased significantly.

Abolhasani *et al*. (2008) mainly focused on measuring fuel use and emission rates of NO_x, CO, HC, CO_2 and PM for hydraulic excavators using real-world measurement. This study showed that nearly 90% of measurement was valid and approximately 50% of nitric oxides emissions were produced during 30% of the time of operation. Moreover, mass per time emission rates for nonidle activity modes were significantly higher; seven times compared to those of idle modes. Frey *et al*. (2008a) compared petroleum diesel and B20 emissions from backhoes, motor graders, and wheel loaders while performing typical duty-cycles. Furthermore, Frey *et al*. (2008b) highlighted the field activity, fuel use, and emissions of motor graders in terms of using petroleum diesel and B20 biodiesel.

Frey *et al*. (2003) highlighted study on emission measurement using on-board system under real-world conditions for light-duty vehicles powered by gasoline. This study showed that emission rates for each modal activitity such as idle, acceleration, cruise and deceleration were statistically different. It was also found that the average emission rates of HC and CO_2 on a mass per time basis for acceleration were five times higher compared to those on idle rates. For NO_x and CO, it was approximately ten times greater in acceleration than in idle time. Sensitivity analysis for different emissions factor estimation methods such as distance-based, time-based and fuel-based were developed based on activity modes. This study found that time- and distance-based emission factors and fuel consumption were more sensitive to activity modes.

2.2 Methods of Emissions Estimating using Model and Simulation

Model and simulation are becoming popular among many other applications in emission measurement. Typically, these approaches are developed based on data collected from experimental tests such as either dynamometer tests or real-world in-use measurements. Numerous methods are available for modeling purposes consisting of conventional and intelligent-based approaches. The types of modeling categorized as conventional approaches include simple linear regression and multiple linear regression. Even though, these methods are relatively simple involving the use of ordinary differential equations; they have been widely used in many applications due to its simplicity and practicality. However, intelligence based approaches such as artificial neural network (ANN), genetic algorithm (GA), fuzzy and expert systems as well as simulation have been emerging due to their contributions to produce more robust models for decision making.

In this study, predictive modelings that are discussed include regressions, ANN, and probabilistic approaches. According to Dickey (2012) predictive modeling is aimed to find a mathematical relationship between a response variable and two or more predictor variables in order to predict future values.

2.2.1 Regression Analysis

Regression analysis is the most common and simple approach to describe the relationship between variables. This technique has been extensively used in various applications such as engineering, economics, and any other fields. Regression analysis is a technique to model the relationship between two or more variables. Two common types of regression are comprised of simple linear regression (SLR) and multiple linear regression (MLR) that are described as follows.

2.2.1.1 Simple Linear Regression (SLR)

Simple linear regression consists of only a single response variable (Y) and a single predictor variable (x). SLR is performed to estimate the relationship between x and Y from a given set of data (Dickey, 2012). The model can be obtained by plotting the dataset of x and y so that a correlation coefficient between variables can be defined. The model is of the form Y = mx + b where m and b are the slope and intercept of the line relating Y to x respectively. The lower the value of intercept (b) that is closer to 0, the better the model is. Additionally, if the slope (m) is closer to 1, this indicates the model is closer to perfect.

The model can also be extended to Y = mx + b + *e*, in which *e* is defined as an error term indicating uncertainty in the model. Typically, the *e* is assumed to have a mean value of 0. The least squares criterion is used to estimate the equations by minimizing the sum of errors between the actual and predicted values for each observation. The differences between the actual and predicted values are called residuals, which are typically normally distributed.

In order to assess the model, correlation coefficient (r) is used to indicate that the model perform well. The range of r is between -1 and +1. If the value of r is 0, this means the variables are not correlated to each other; meanwhile, if the value of r is 1, this indicates the variables are positively highly correlated, and -1 for negatively highly correlated.

The r for SLR is calculated as follows:

$$r = \frac{Cov\ (X,Y)}{\sqrt{Var\ (X)Var\ (Y)}} \tag{2-1}$$

where:

$$\text{Var (X)} = \frac{\sum_{i=1}^{n}(xi-\bar{x})^2}{n-1} \tag{2-2}$$

$$\text{Var (Y)} = \frac{\sum_{i=1}^{n}(yi-\bar{y})^2}{n-1} \tag{2-3}$$

Var (X) and Var (Y) denote the variance of X and variance of Y, and covariance of X and Y is shown by:

$$\text{Cov (X, Y)} = \frac{\sum_{i=1}^{n}(xi-\bar{x})(yi-\bar{y})}{n-1} \tag{2-4}$$

$$m = \frac{Cov\ (X,Y)}{Var\ (X)} \quad \text{and} \quad \text{b} = \text{y} - \text{m}\bar{x} \tag{2-5}$$

2.2.1.2 Multiple Linear Regression (MLR)

Similar to SLR, multiple linear regression (MLR) is carried out to predict the values of response variable (Y), given two or more predictor variables (x_1, x_2… x_p). The following equation is used to describe the MLR:

$$Y \ = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \tag{2-6}$$

where:

Y = Response variable

X_1, X_2, and X_3 = Predictor variables

β_0 = Constant term

β_1, β_2, β_3 = Coefficients of linear relationship

The equation above can be extended to using error term as described below:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + e \tag{2-7}$$

The error term (e) is typically unknown; however, if the model has been built the error term can be defined as:

$$e = yi - \widehat{yi} \tag{2-8}$$

Where:

yi = Observed value of response variable for i

$\widehat{yi}$ = Predicted value of response variable for i

The residuals or the error term is used to measure the difference between the predicted and the observed value of response variable. In other words, the residuals are indicators for measuring variances. Typically, the residuals have a mean of zero.

According to Ostrom (1990), the MLR has several assumptions that can be defined as follows:

1. Linearity, there is a linear relationship between the response and the predictor variables. If the relationship is likely to be nonlinear, transformation should be applied. Typically, scatterplot is used to measure the linearity of the response and predictor variables.
2. Nonstochastic X: $E[e_i X_{i,k}] = 0$, typically the errors are not associated with the individual predictor variables.
3. Zero mean: $E[e_i] = 0$, the mean value of the residuals is zero. The least-squares method used to predict the regression equation indicates that the mean value of the residuals is zero.
4. Constant variance: $E[e_i^2] = \sigma^2$, the variance of the residuals is constant.
5. Nonautoregression: $E[e_i X_{i-m}] = 0$, $m \neq 0$, the residuals are random.
6. Normality, the error term is normally distributed.

Some statistics indicators in the MLR are:

$$\text{SSE} = \sum_{i=0}^{n} \hat{e_i}^2 \tag{2-9}$$

$$\text{SST} = \sum_{i=0}^{n} (y_i - \hat{y})^2 \tag{2-10}$$

$$\text{SSR} = \sum_{i=0}^{n} (\hat{y_i} - \hat{y})^2 \tag{2-11}$$

where:

SSE = Sum of squares error

SST = Sum of squares total (the sum of SSE and SSR)

SSR = Sum of squares regression

n = Sample size

Coeeficient of determination (R^2) used to show the proportion of variance described by regression is defined in the equation below. If R^2 is 1, the regression is perfect and the residuals are zero; conversely, if R^2 is 0, there is no variance explained by the regression. The sum of squares terms is summarized in Analysis of variance (ANOVA) Table 2.1.

$$R^2 = \frac{\text{SSR}}{\text{SST}} = 1 - \frac{\text{SSE}}{\text{SST}} \tag{2-12}$$

Table 2.1. Summary of ANOVA table

Source	**df**	**SS**	**MS**
Total	n-1	SST	MST = SST/(n-1)
Regression	K	SSR	MSR = SSR/K
Residual	n-K-1	SSE	MSE = SST/(n-K-1)

where:

SS = Sum of squares term

df = Degrees of freedom for SS term

MS = Mean squared term

K = Number of predictors

Another indicator is F ratio, indicating the comparison of mean squares of regression over mean squares error. F ratio considers the degrees of freedom, containing the sample size and the number of predictor variables. The number of sample sizes is very significant to indicate the statistics significance of the model. The model may have higher value of R^2, but still not be statistically significant.

$$F = \frac{\text{MSR}}{\text{MSE}} \tag{2-13}$$

Multicollinearity is defined as the intercorrelation among predictor variables. If the intercorrelation is high, it can affect the regression model by reducing the precision of the estimates of the individual regression coefficients. Moreover, the standard error can inflate significantly. Multicollinearity also indicates the redundance of information used to predict the model due to high correlation between predictor variables.

Variation Inflation Factor (VIF) is used to identify the colinearity among predictor variables. VIF can be a problem if the value of VIF becomes large. If VIF is larger than 10, there is a high collinearity in the model; thus one of the predictor variables should be removed from the model. If there is no predicted variables associated with one another, VIF will be 1. The formula of VIF is shown as follows:

$$VIF = \frac{1}{1-R^2} \tag{2-14}$$

where:

VIF	= Variation Inflation Factor
R^2	= Coefficient of Determination

In order to select which predictor variables included in the model, there are three types of model selection methods: backward selection, forward selection, and stepwise selection. In backward selection approach, the model will include all predictor variables. Then, during the selection, the model will remove the variables that are least significant. Thus, this selection can refit the model. This process is repeated several times until meeting the stopping criterion. The significant predictor variables will be included in the models. Conversely, in forward selection approach, the model starts with no variables in the model. The forward selection calculates based on the significant contribution of F statistics, indicating the largest F values. If p-value shows lower than 5% of significance level, the predictor variables will be included in the model. The forward selection approach adds one by one of the predictor variables. The forward selection stops if there is no more predictor variable that has high value of F tests.

Stepwise selection is typically the combination of forward and backward selection. This approach begins with no predictor variables in the model. The model is developed gradually, using step by step approach. The predictor variables that are highly correlated to the response variable are initially included in the model, following the second highly correlated to the response variable. This process is repeated until no more predictor variables are significant. If the variables that have been included in the beginning are no longer significant, those variables can be eliminated in the model.

2.2.2 Artificial Neural Network (ANN)

The use of artificial neural network (ANN) in civil engineering was initiated in 1889, primarily for structural engineering and construction engineering management applications (Adeli, 2001). Moreover, its application has been widely spread in many fields such as water resources and environmental engineering. Much work has also been conducted in characterizing emissions from diesel engines using ANN. ANN has been commonly employed and it is generally considered to be a reliable method to achieve high quality models due to its capabilities in overcoming nonlinearity, processing large quantities of data, and overall accuracy.

ANN is a computational model that simulates brain function and uses biological system. The ANN attempts to mimic the process of human brain and nervous system using the computer (Palisade, 2010). ANN models frequently perform better than other statistical techniques and usually improve predictive models. According to Pao (2008), it is not necessary to specify the relationship among variables prior to building the ANN models due to its learning process. Moreover, ANN models do not need to assume the distributions of the population.

The concept of ANN can be defined as a black-box system (Schalkoff, 1997). ANN models are trained through an iterative process by learning the complexities between input and output. ANN is comprised of input, hidden and output layers. The input layer as well as the output layer consists of one or more processing elements (PE) as commonly known as neurons. Each layer comprises of multiple neurons that are connected to other neurons following a specific network patterns. Additionally, the hidden layer connects the input and output layers which typically consists of one or more hidden layers. In order to increase the complexity of the model, more hidden layers and more neurons per layer are required.

The main component in the ANN is the weight (w) of each input connected to the hidden layer and output layer. This connection illustrates how patterns of information are learned through the neurons or processing elements in the network. During the training period, the network learns the data patterns as well as modifies the weights throughout the process to minimize the error. Back propagation is adopted through each layer of the network.

As shown in Figure 2.5, the ANN model consists of an input layer with three input nodes (x_1, x_2, and x_3), one hidden layer with two nodes (H_1 and H_2), and an output layer with a single output node (y). The general equation can be written in the following form:

$$y = w_0 + w_1 H_1 + w_2 H_2 \tag{2-15}$$

where:

$$H_1 = g_1 (w_{01} + w_{11} x_1 + w_{21} x_2 + w_{31} x_3) \tag{2-16}$$

$$H_2 = g_2 (w_{02} + w_{12} x_1 + w_{22} x_2 + w_{32} x_3) \tag{2-17}$$

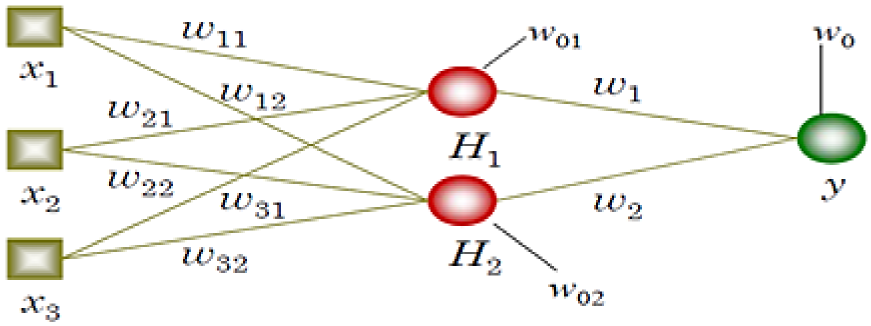

Figure 2.5. The Architecture of ANN (Berry & Linoff, 2004)

In order to clearly illustrate the difference between the structures established by ANN and MLR, Figure 2.6 presents the general equation for MLR with three input variables and a single output.

The general equation of MLR takes the form of:

$$y = w_0 + w_1 x_1 + w_2 x_2 + w_3 x_3 \tag{2-18}$$

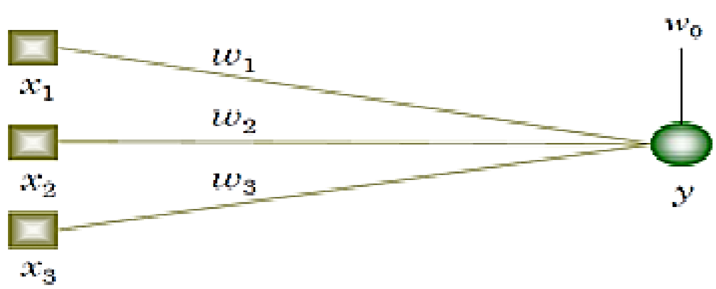

Figure 2.6. The Architecture of MLR (Berry & Linoff, 2004)

According to Palisade (2010), there are three different configurations available in the ANN, namely Probabilistic Neural Networks (PNN), Generalized Regresion Neural Networks (GRNN), and Multi-layer Feedforward Networks (MLF). The PNN and GRNN are typically closely related to each other. PNN is mostly used for categorical prediction; meanwhile the GRNN is used for numeric prediction. In these two approaches, it is not necessary to define the structure of a net, even for the number of nodes in each hidden layer. In other words, the network will be automatically trained using the default options.

The MLF architecture consists of the input layer, one or two hidden layers, and one or more output layers. The number of layer in the hidden layer can be specified either one or more than two layers. In order to construct the net, a number of nodes in the hidden layers should be specified.

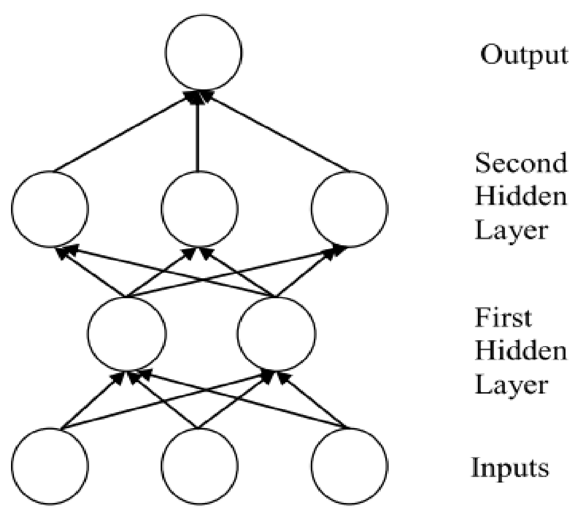

Figure 2.7. The MLF Architecture (Palisade, 2010)

Palisade (2010) mentioned the MLF net is typically influenced by:

1. Topology, comprising of the number of hidden layers and the number of nodes in the layers.

2. The weights of connections and bias terms, indicating the parameter allotted in each connection and the parameter allotted in each neuron, respectively.
3. Activation/transfer function, transforming the inputs of each node/neuron into its output. The activation function in the hidden layer neurons uses a sigmoid (s-shaped) function and generates the output of the neuron. In the training net of MLF, a set of connection weights and bias terms are determined. A prediction is performed for each training case; thus there will be a difference between the predicted and the actual value of response variable, indicating the measure of error.

Much work has been completed in using ANN to predict the emisssions from different engine sources. Some of the works are described as follows. Tehranian (2003) used ANN to predict diesel engine emissions of NO_x, PM, HC, CO, and CO_2 using data from engine dynamometer test based on five engine transient-test schedules. This study emphasized the relationship between engine parameters and emissions for each different pollutant. This study showed that the ANN was accurate in predicting emissions with approximately 0.009% error from the total output value.

Atkinson *et al*. (2000) developed ANN to quantify prompt torque, power output, and exhaust emissions by deploying engine performance and fuel efficiency. Similarly, Thompson *et al*. (2000) predicted the emissions of NO_x, PM, HC, CO, and CO_2 by using a three-layer ANN based on dynamometer test data. The variable inputs consisted of engine speed, intake air temperature, exhaust temperature, engine oil temperature, engine coolant temperature, intake air pressure, injection pressure, injection pulse width, start of injection and acceleration position.

Clark *et al*. (2002) found that ANN offered the best model compared to other models in predicting NO_x emissions for 16 dissimilar chassis test schedules. Axle torque and axle speed were used as the input variables resulting only 5% error for the prediction models. In other research, Clark *et al*. (2001) also employed ANN which was incorporated with a software package namely ADVISOR (Advanced Vehicle SimulatOR) to predict NO_x and CO_2 emissions. In this study, comparisons between prediction models from software and actual emissions from vehicles tested in the laboratory were conducted. The results demonstrated that there was a good correlation between prediction models and actual measurements.

In order to predict emissions and fuel consumption, Desantes *et al*. (2002) developed mathematical models using ANN with several inputs, such as engine speed, fuel mass, air mass, fuel injection pressure, start of injection, exhaust gas recirculation (ERG) percentage, and nozzle diameter. This study found that EGR rates, fuel mass and start of injection were the most reliable variables for obtaining robust models.

Hashemi (2007) presented ANN model to estimate emissions of NO_x, CO_2, HC and CO for heavy-duty vehicle based on dynamometer test data and identified the influence of vehicle parameters to the emissions. The input variables comprised of axle speed and torque. This study showed that prediction models using ANN produced good accuracy and mimicked the real life emissions of vehicles.

Mudgal *et al*. (2011) used ANN method to predict emissions of transit buses powered by biodiesel fuel consisting of B0 (regular diesel), B10 (10% biodiesel) and B20 (20% biodiesel) based on PEMS. This study concluded that linear models were considered to have failed in explaining the spikes in the data. Therefore, data were then analyzed using ANN resulting robust models with higher R^2 for emissions of NO_x, HC, CO, CO_2 and PM. Sensitivity analysis was also run on the input parameters, hidden layers, learning rates, and learning algorithms.

Krishnamurthy (2006) used ANN to predict NO_x emissions of heavy diesel engine by inputting several engine parameters such as engine speed, engine torque, injection timing, fuel rate, manifold air temperature, manifold air pressure, coolant temperature and oil temperature. The results indicated that predictive models produced better models with approximately 20% variability from the actual values.

Table 2.2 summarizes the study conducted in emissions quantification using different test methods. Most research employed the data from dynamometer test in order to develop prediction models using ANN. Other studies deployed portable emissions measurement system for collecting data. Those studies used different model assessment methods when evaluating the performances of the models.

Table 2.2. Summary of Test Methods and Model Assessment used in the ANN Study

Research	**Year**	**Test Methods**	**Model Assessment**
Tehranian	2003	Dynamometer	-
Atkinson et al	2000	Dynamometer	-
Thompson et al	2000	Dynamometer	Absolute measurement error (%)
Clark et al	2002	Dynamometer	-
Steyskal et al	2001	PEMS (Parametric Emissions Monitoring System)	-
Desantes et al	2002	Dynamometer	Measurement error
Hashemi	2007	Dynamometer	-
Krishnamurthy	2006	Mobile Emissions Measurement System (MEMS)	-
Mudgal et al	2011	PEMS	-
Ogus et al.	2010	Dynamometer	MSE
Cay et al.	2011		RMSE, R^2, and ME
Alonso et al.	2006	Dynamometer	ME

Table 2.3 displays the summary of aforementioned studies using different vehicles when predicting the emissions of pollutants along with the input and output variables used when developing the ANN models.

Table 2.3. Summary of studies using ANN

Research	Year	Vehicles	Input variables	Output variables
Tehranian	2003	Diesel engine		Emissions (NO_x, PM, HC, CO, and CO_2)
Atkinson et al.	2000	Diesel engine	Engine parameter, fuel efficiency	Torque, power, exhaust emissions
Thompson et al.	2000	Heavy-duty diesel engine	Engine speed, intake air temperature, exhaust temperature, engine oil temperature, engine coolant temperature, intake air pressure, injection pressure, injection pulse width, start of injection and acceleration position	Emissions (NO_x, PM, HC, CO, and CO_2)
Clark et al.	2002		Axle torque and speed	Emissions (NO_x)
Steyskal et al.	2001	Large bore natural gas engine	Engine parameter	Emissions (NO_x)
Desantes et al.	2002	Diesel engine	Engine speed, fuel mass, air mass, fuel injection pressure, start of injection, exhaust gas recirculation (ERG) rate, nozzle diameter	Emissions (NO_x and PM) and Brake Specific Fuel Consumption (BSFC)
Hashemi	2007	Heavy-duty diesel engine	Axle speed, torque	Emissions (NO_x, CO_2, HC, CO)
Krishnamurthy	2006	Heavy-duty diesel engine	Engine speed, engine torque, injection timing, fuel rate, manifold air temperature, manifold air pressure, coolant temperature and oil temperature	Emissions (NO_x)
Mudgal et al.	2011	Transit bus	% Biodiesel, speed, acceleration, VSP, passenger count, RPM, IAT, MAP	Emissions (NO_x, PM, HC, CO, and CO_2)
Ogus et al.	2010	Diesel engine	Engine speed and biofuel blends (fuel type)	Engine performance (torque, power, fuel consumption, specific fuel consumption)
Cay et al.	2011	Combustion engine	Engine speed, torque, fuel flow, intake manifold mean temperature, cooling water entrance temperature	Emission CO, CO_2, NO_x),Brake specific fuel consumption, power, pressure, gas temperature
Alonso et al.	2006	Diesel Engine	Engine speed, fuel mass injected, air mass, exhaust gas circulation, injection pressure, start of pilot injection, start of main injection, intake temperature, water temperature	Emissions (NO_x, PM, HC, CO) and brake specific fuel consumption (BSFC)

2.2.3 Probabilistic Approach

Probabilistic approach provides a range and likelihood estimate rather than a single point estimate. It is a tool that can provide additional information to improve decision making. Due to uncertainty in quantifying emissions rates of HDD construction equipment, there is a need to measure the level of uncertainty for decision making. Probabilistic methods quantify variability and uncertainty. Apparently, there is substantial uncertainty in quantifying emissions of HDD construction equipment. Failure to consider uncertainties in emission rates and fuel use of construction equipment may lead to wrong decisions.

Several researches have also been conducted in assessing the uncertainty and variability in emission estimates. Frey and Bammi (2002 and 2003) assigned uncertainty of emissions for non-road category of lawn and garden equipment. Aziz and Frey (2003) presented method for quantifying uncertainty and variability for emission estimate with respect to hazardous air pollutant and focused on emissions quantification for NO_x and HC from construction, farm, and industrial engine and coal-fired power plants. Pan (2011) addressed the emission of construction equipment using discrete event simulation.

Frey and Bammi (2003) presented a probabilistic approach to quantify emission factors of nonroad mobile equipment. This study emphasized the characterization of variability and uncertainty of nitrogen oxides (NO_x) and hydrocarbon emissions by comparing different older and newer diesel engines in construction, farm and industrial engines. This study also grouped data based on fuel, engine age, technology (two-stroke and four-stroke engines), engine type, and engine size. The results showed that emissions among both older and newer engines were not statistically significant. Conversely, among diesel versus gasoline engines, the test statistics showed there was a huge statistic difference. Several probability distribution functions including Weibull, gamma, and lognormal distributions were applied for determining inter-engine variability. According to Frey and Bammi (2009), some limitations faced by using probabilistic approach were the restrictive assumptions of the shape of probability distribution functions, failure in determining variability and uncertainty, and small sample sizes. Frey and Bammi (2009) compared different number of engine modes at steady-state test conditions. A mode is considered as an operation at a particular engine speed or load for a specified length of time. Frey and Zheng (2011) used a methodology for quantification of variability and uncertainty of emission pollutant of coal-fired power plants.

Monte Carlo analysis is a viable tool for analyzing variability and uncertainty using probabilistic analysis. The EPA has also developed guidelines for probabilistic analysis using Monte Carlo Simulation. According to the EPA (1997), the fundamental goal of a Monte Carlo analysis is to quantitatively characterize the uncertainty and variability in estimating exposure or risk as well as to identify key sources of variability and uncertainty.

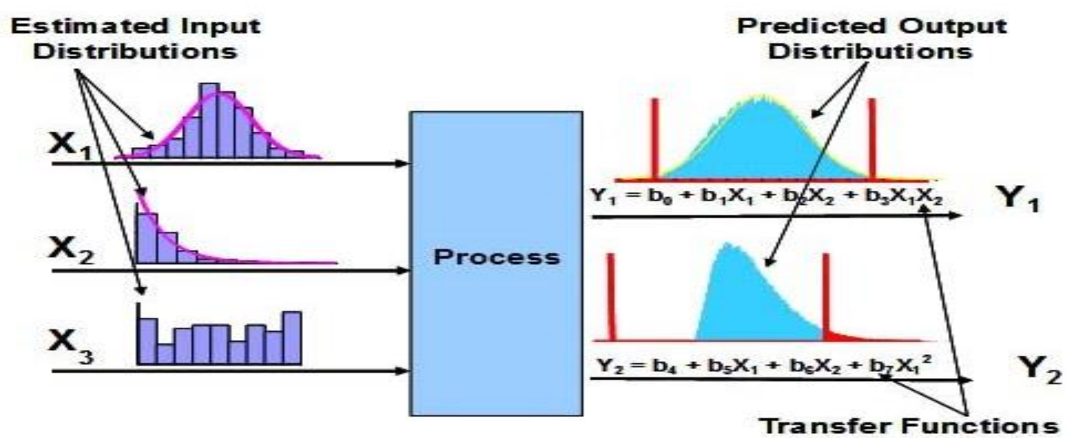

Figure 2.8. Monte Carlo Simulation

Selection of distributions for the input of Monte Carlo Simulation is considerably significant. Empirical distributions or parametric distributions for important parameters can be employed. Therefore, specifying distributions for all or most variables in a Monte Carlo analysis is useful for exploring and characterizing the full range of variability and uncertainty. The choice of input distribution should always be based on information available for a parameter. When data for an important parameter are limited, it may be necessary to use expert judgment in estimating the probability distribution functions of input parameters. Figure 2.8 presents the overall procedure for Monte Carlo simulation.

Table 2.4. Summary of Aforementioned Studies using Probabilistic Approach

Studies	**Year**	**Pollutant**	**Method used**
Tong *et al*	2012	Greenhouse gas inventories	Bootstrap confidence interval Distribution used are normal, lognormal and uniform
Frey	2007	Air pollutant emission inventories	Monte Carlo Simulation
Zhao & Frey	2006	Combustion based sources	-
Mokhtari & Frey	2005	-	Sensitivity analysis methods
Zheng & Frey	2005	Emission factors in construction, farm, and industrial engines	Measurement error to the estimated inter unit variability
Monni *et al*	2004	Greenhouse gas emissions inventory (CO2)	Estimating uncertainties based on available measurement data, and international literature, and expert judgment
Zhao & Frey	2004	On road motor vehicle	-
Frey & Bammi	2003	NO_x and HC pollutants in construction, farm, and industrial engines	Bootstrap simulation and parametric distribution (Weibull, Gamma, and Lognormal dist)
Frey & Li	2003	Emissions in natural gas-fired internal combustion engines	-
Frey & Zheng	2002	Emissions of NOx of coal-fired power plants	-
Frey et al	2002	-	Quantifying uncertainty of EPA vehicle emission model
Frey & Zheng	2002	NOx emissions of coal power plants	Sensitivity analysis
Winiwarter & Rypdal	2001	Greenhouse gas emission (CO2, CH4, N2O)	Estimating uncertainty using expert interview
NRC	2000	-	Uncertainty analysis for mobile sources
Cullen & Frey	1999	-	Probabilistic analysis method
Frey & Rhodes	1998	-	Evaluating the implications of choices of parametric distribution
Beck & Wilson	1997	-	Using Data Attribute Rating Systems (DARS) to combine emission factors and activity data
Frey & Rhodes	1996	Hazardous air pollutants of coal-fired power plant	-
Efron & Tibshirani	1993	-	Using bootstrap simulation to estimate sampling distribution and confidence interval

2.3 Current Emissions Estimating Models

The United States Environmental Protection Agency (USEPA) has developed a model for estimating emissions for HDD construction equipment called as the EPA nonroad model. This model is typically based on dynamometer tests conducted in the laboratory to quantify CO_2, CO, NO_x, PM, HC, and SO_x emissions. The primary use of this model is to estimate air pollution inventories. Other state such as California has also proposed its own model titled the California Offroad model. Similarly, Sacramento also developed a model called the Urbemis model. More detail information regarding those models will be briefly explained.

2.3.1 NONROAD Model

The EPA nonroad model was established in 2005 and designed to estimate CO_2, CO, NO_x, PM, HC, and SO_x emissions from non-road equipment. Typically, this model includes 80 basic and 260 specific items of equipment (Pan, 2011). The inputs for this model consist of equipment population, average load factors, average power in horsepower, activity in hours of use per year, and emission factors. Emission factors are commonly reported in grams per hour (g/h), grams per mile (g/mile), grams per brake horse power hour (g/hp-h), grams per kilowatt hour (g/kW-h) or grams per gallon (g/gal). Figure 2.9 demonstrates the algorithm for calculating emission factor of nonroad diesel vehicles.

Emission factors for HC, CO, and NO_x are counted separately from those for PM, CO_2 and SO_2 as briefly explained below.

$$EFadj\ (HC, CO, NO_x) = EFss \times TAF \times DF \tag{2-19}$$

$$EFadj(PM) = (EFss \times TAF \times DF) - SPMadj \tag{2-20}$$

$$EFadj(BSFC) = EFss \times TAF \tag{2-21}$$

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)

BSFC = Brake-specific fuel consumption

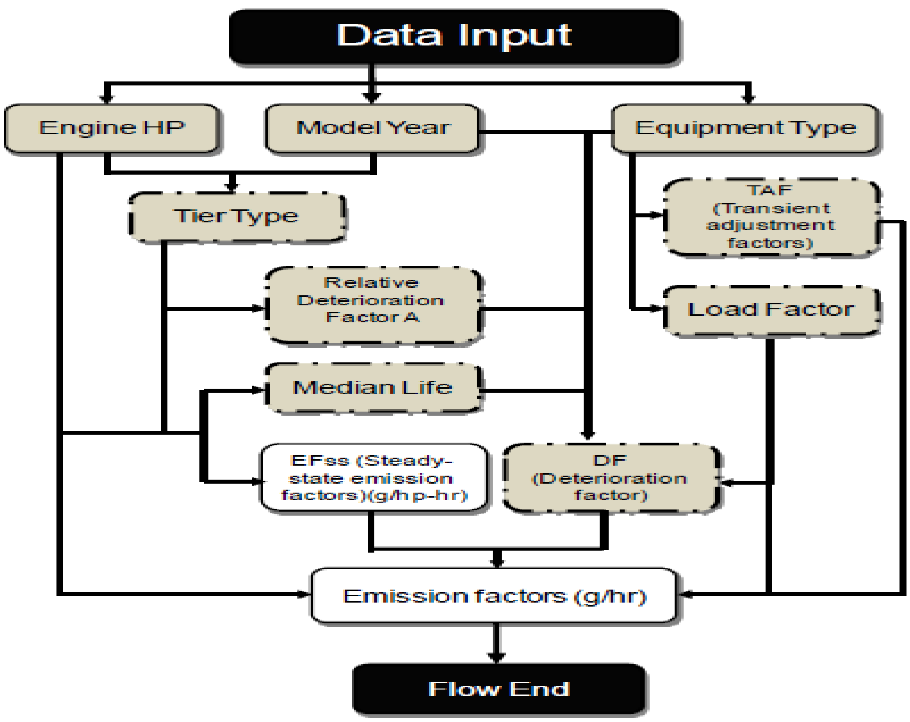

Figure 2.9. The Procedure of the NONROAD Model (Pan, 2011)

In order to comply with the emission standards for all nonroad diesel engines, EPA categorized nonroad equipment based on engine tier. Engine tiers consisting of Tier 1, Tier 2, Tier 3, and Tier 4 are classified based on engine size and engine age. Engine size and engine age are represented as horsepower rating and model year of the equipment, respectively. Table 2.5 demonstrates the general guide for tier level of nonroad diesel engine established by EPA.

Table 2.5. General Guide to EPA Tier Level for Off-Road Diesel Engines (EPA, 2010)

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

The higher the level of engine tiers, the more stringent the standards of the emissions are. For instance, Tier 2 is more stringent than Tier 1 and so forth. Tier 1, 2 and 3 are introduced from 1996 to 2000, 2001 to 2006, and 2006 to 2008, respectively. Tier 4 emission standards are implemented over the period 2008-2015. Tier 4 leads emission reduction of PM and NO_x to 50% and 90%, respectively (Abolhasani *et al*., 2008). This also basically means engine manufacturers should comply with the EPA standards and require development of emission control technologies to meet the standards as an effort to decrease emissions. With the aim of responding the National Research Council (NRC) in developing a modeling tool of accurate emission prediction, EPA established motor vehicle emission simulator (MOVES) for both on-road and nonroad mobile sources. This tool includes numerous pollutants, for example HC, CO, NO_x, PM and CO_2.

2.3.2 OFFROAD Model

As a way to estimate emission of nonroad equipment, The California Air Resource Board (CARB) developed Offroad Model as well. This model may consider the effects of regulations, technology types, and periodic conditions on emissions. The main inputs for this model are equipment population, equipment activity (hr/yr) and emission factors (g/bhp-hr). For equipment population, this model takes into account the growth and scrappage factors specifically the increasing of new equipment and the decreasing of older equipment. Moreover, information about annual average use hours, engine load factors, brake-specific fuel consumption, engine fuel type, engine type and horsepower group are provided in the equipment activity. Emission factors are typically based on fuel type, horsepower group, and model year. Finally, emission factors are adjusted based on some factors including duty-cycle and deterioration rate of the engines.

2.3.3 URBEMIS Model

The Sacramento Metropolitan Air Quality Management District (SMAQMD) developed URBEMIS Model as a software to quantify pollutant emissions (NO_x, CO, PM, CO_2 and SO_x) and greenhouse gases for land use development purposes. Emissions are reported in unit of pounds per day (lb/day) or tons per year (ton/yr). Seven project phases covered in this model included demolition, fine site grading, mass site grading, trenching, building construction, architectural coating, and paving. Although Urbemis seems to be quite difficult and complex; this model may help projects to better understand the impact of emissions.

CHAPTER III

RESEARCH METHODOLOGY

This chapter presents the overall techniques and steps conducted in this research that include field data collection, exploratory data analysis, and predictive models for estimating fuel use and emission rates for HDD construction equipment. First, field data collection will be briefly explained in terms of procedures for collecting field data that cover study design, vehicle selection, preinstallation and installation of instrumentation. These procedures will refer to the aforementioned studies presented by Lewis (2009) and Rasdorf *et al*. (2010). Second, exploratory data analysis with regards to summary statistics, distribution fittings, and correlation variables, are further presented. Finally, the overall methods for analyzing data in terms of model development, model validation, and model comparison for each predictive model as well as variable impact analysis will be fully addressed. The methods used for estimating the fuel use and emission rates include weighted average approach, simple linear regression (SLR), multiple linear regression (MLR), and artificial neural network (ANN). Figure 3.1 summarizes the overall steps conducted in this research, starting from defining research questions, objectives, and summarizing literature reviews. The methodology as well as model development is also presented. The entire process is ultimately briefly described in a flow chart as shown in figure below.

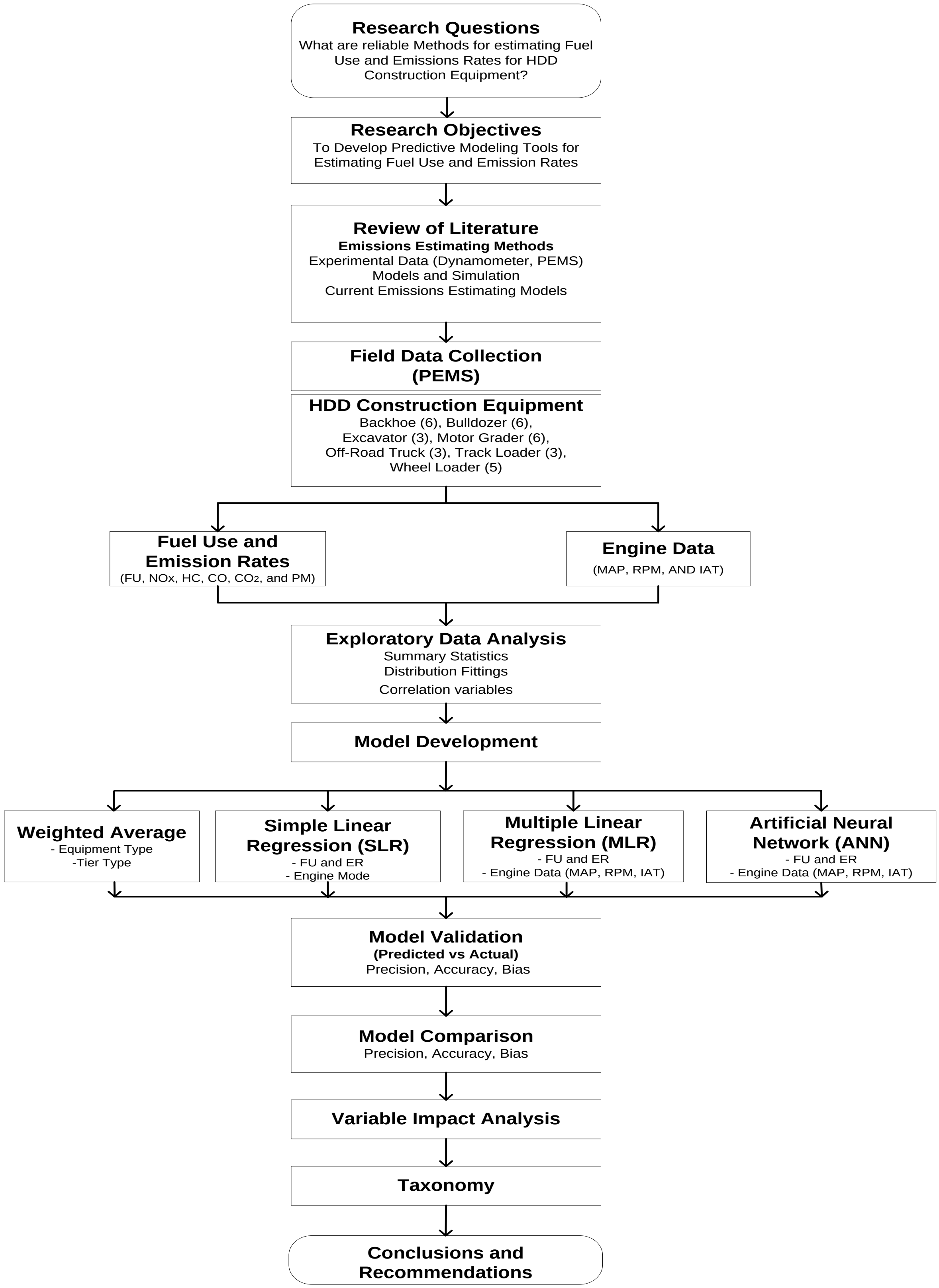

Figure 3.1. Flow Chart of Research Steps

3.1 Field Data Collection

This section includes a discussion on the research study design conducted by a group of researchers from North Carolina State University (NCSU). This study aimed to quantify the air pollutants emissions from HDD construction equipment using portable emissions measurement system (PEMS). Second-by-second fuel use and emissions data of NO_x, HC, CO, CO_2, and PM as well as engine performance data were collected for each item of equipment while performing their duty-cycle.

3.1.1 Study Design

The main component of the study design was to collect fuel use and emissions data that included vehicle selection, vehicle activity, vehicle location, and scheduling for vehicle data collection (Lewis, 2009 and Rasdorf *et al*., 2010). The selected types of HDD equipment on this study were based upon the vehicles listed on EPA NONROAD with respect to their significant contributions of emitting pollutants into the environment. It was estimated that approximately 70% of all pollutants for NO_x, CO_2, and PM inherently came from the selected equipment that include backhoes, bulldozers, excavators, motor graders, off-road trucks, track loaders, and wheel loaders (Lewis, 2009). Even though there were other types of equipment selected by NCSU team study such as skid-steer loaders and generators, these data are not taken into consideration in this dissertation due to their incomplete data.

The types of equipment activity can also influence the amount of air pollutants emitted. For instance, when a backhoe performs its duty cyles such as idling, scooping, moving, or dumping its bucket, the pollutants emitted from each activity will be different, depending on the working load. The bigger the engine load, the more pollutants emitted. However, in the analysis of this dissertation, types of activity modes such as idling, moving and scooping, will not be included in the analysis. Thus, the analysis will be based only on the equipment type and engine type in order to quantify fuel use and emission rates when using the weighted average method. In terms of location where field data collection conducted, it was taken progressively in 2006 near the campus of North Carolina State University (NCSU). During that time, there were several construction projects that used HDD construction equipment.

Scheduling for vehicle data collection was also the primary concern of obtaining good data. Several restrictions were taken into consideration since involving many participants such as vehicle owners, project supervisors, and vehicle operators. It was noted that data collection would not disturb the productivity of the overall construction activities in the projects. Moreover, since the whole process of collecting data consumed a great amount of time, it was reported that some owners were willing to participate as well as providing responsive answers; others were not responsive at all (Rasdorf *et al*., 2010). For the latter case, more efforts in looking for other owners were certainly required. However, it was noticeable that NCSU team had been successfully collecting emissions data from seven different owners.

3.1.2 Real-World Data Collection Procedures

The overall procedures for data collection include preinstallation and installation of instrumentation, data collection for emissions, visual data, and vehicle activity, decommissioning of instrumentation, and data quality assurance (Rasdorf *et al*., 2010). These procedures will be briefly presented in this section.

Preinstallation was typically conducted a day prior to collecting data from the HDD equipment. Some works of the preinstallation process included the following:

- Installation of the safety cage to help sheltered the PEMS on the HDD equipment from damage and movement
- Installation of the sensor array on the HDD equipment to gather engine data such as MAP, RPM, and IAT
- Installation of the external battery to afford extra power to the HDD equipment

- Installation of the global positioning system (GPS) to keep track of the location during data collection

Once preinstallation had been accomplished, the next step was to set up the PEMS into the safety cage which was typically deployed on the day of data collection. Sample hoses were also connected from the tailpipe of HDD equipment to the PEMS. In order complete the whole procedures during the installation stage, the cables from sensor array, external battery, and the GPS should be connected to the PEMS. Figure 3.2 and 3.3 present the diagram for installation of PEMS for HDD equipment.

Figure 3.2. Installation of PEMS on HDD Equipment (Frey *et al*., 2008)

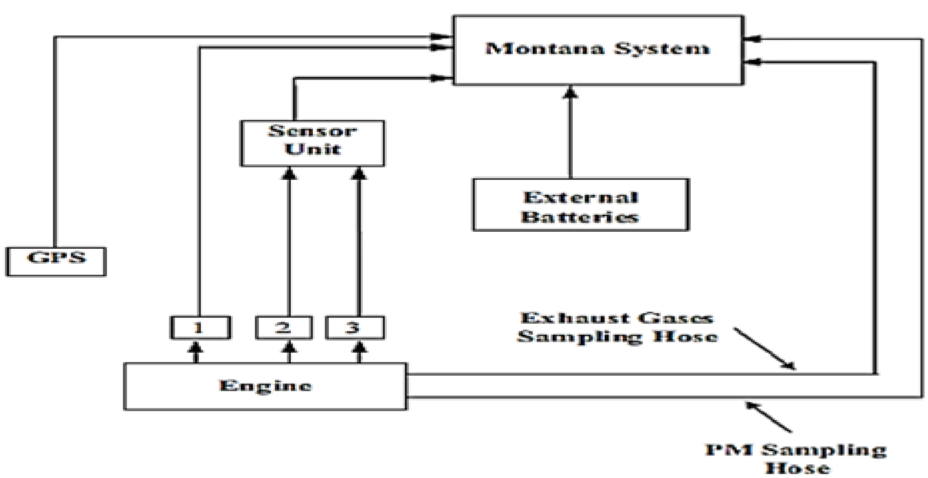

Figure 3.3. Diagram for Installation of PEMS for HDD Equipment (Abolhasani *et al*., 2008)

Emissions data were measured by inserting a sample probe into the tailpipe. Second-by-second emissions data for NO_x, HC, CO, CO_2, and PM were collected along with engine data for HDD construction equipment using the PEMS. To quantify CO, CO_2 and HC, the PEMS uses non-dispersive infrared (NDIR) detection; meanwhile NO_x and O_2 are measured by electrochemical cells. Additionally, PM is measured by using a light scattering laser photometer detection method. With respect to collecting engine performance data, the PEMS uses either an electronic control unit (ECU) or a sensor array to measure manifold absolute pressure (MAP), revolutions per minute (RPM), and intake air temperature (IAT). However, the NCSU research team collected engine performance data by using sensor array connected to the engine of the equipment.

Some other instruments in the PEMS include a laptop computer, a global positional system (GPS), and a video camera. A laptop computer is employed to record data regarding the equipment activity. GPS is used to determine the position of the equipment on the construction site and a video camera is used to record the visual data in terms of duty-cycles performed by HDD equipment. When the process of gathering data was completed, decommissioning process was begun. All of the instrumentations installed on the HDD equipment were ready to remove. This process typically took approximately 30 minutes to complete. Then, the data were saved and ready to analyze.

3.1.3 Data Quality Assurance

In order to determine any errors or problems found in the data that had been collected, data screening and quality assurance were piloted for each item of equipment. As part of this process, it is essential to detect the synchronization of the data within the PEMS that typically involved the unusual or negative values of emissions and engine data. If errors were found, it was required to correct the data in order to produce the valid data for further analysis; otherwise, the data should be omitted from the dataset. A complete procedure for data quality assurance is shown in Figure 3.4.

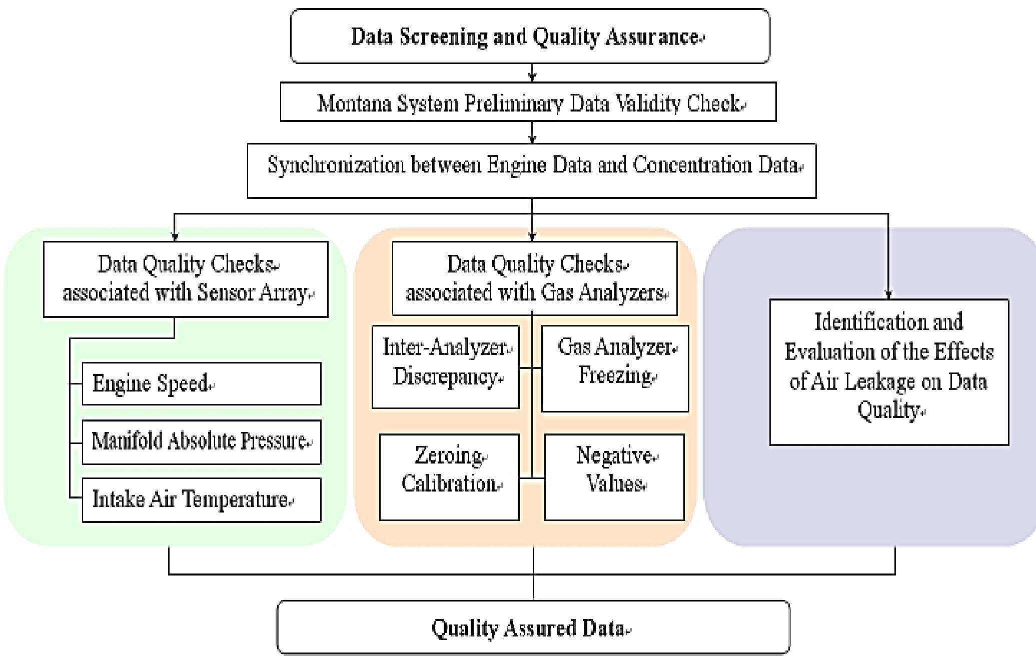

Figure 3.4. Data Quality Assurance Procedures (Lewis, 2009)

3.2 Exploratory Data Analysis (EDA)

This section discusses the exploratory data analysis (EDA) of the dataset for each item of equipment. EDA is a procedure to analyze the data in order to determine the patterns in the data. Even though a number of tools are available for EDA purposes, this study will only highlight on summary statistics, distribution fittings, and correlations among variables for further analysis.

3.2.1 Summary Statistics

Summary statistics were used to recapitulate a set of observations in the dataset in order to easily recognize the main properties of the data. Summary statistics included the following:

- A measure of central tendency including mean, median, minimum or maximum values
- The measure of data dispersion using standard deviation
- The number of observations or cases
- Distribution fittings

Summary statistics were investigated to summarize the minimum, maximum, mean, standard deviation values of fuel use and emission rates for each item of equipment. Those values were defined for each case using the @Risk software.

3.2.2 Distribution Fittings

In practice, the use of distribution fitting is applied in many miscellaneous fields especially when dealing with risk and uncertainty, such as in market research, risk analysis, and engineering. Distribution fitting is a tool for decision making. This study will explore the distribution fittings of fuel use and emission rates for each pollutant for all items of HDD equipment.

Distribution fitting is a procedure of defining a particular statistical distribution from a set of observations that best fits the dataset driven by a random process (Palisade, 2010). The distribution fitting can visualize how well distributions match the data. The shape of the distribution may depend on the nature of the data. The parameters or properties of the fitted distributions such as mean, standard deviation, range, and skewness should also be considered when choosing the best fit distributions. There are many types of probability distributions available for use. The most common statistical distribution is the normal distribution that has a symmetric and constant shape. Some of the probability distributions that are also common include exponential distribution, weibull distribution, pareto distribution, and pearson distribution.

3.2.3 Correlations

Correlation is determined to measure how two variables are associated. Correlation coefficient (r), also known as pearson's correlation coefficient, denotes the strength of the linear relationship between two variables either in positive or negative direction. The values of correlation coefficient are always between the range -1 and +1. The correlation coefficient of +1 indicates the perfect positive linear relationship between two variables; meanwhile, the correlation coefficient of -1 shows the perfect negative linear relationship. Additionally, a correlation coefficient of 0 indicates that a linear relationship does not exist between two variables.

3.3 Predictive Modeling

According to Dickey (2012), predictive modeling is a process of determining the mathematical relationships between a response variable and numerous predictor variables to predict the future values of the response variable. This section presents four different types of predictive modeling methodologies for estimating fuel use and emission rates of specified pollutants based on real-world PEMS data. The methods include weighted average approach, simple linear regression (SLR), multiple linear regression (MLR), and artificial neural network

(ANN). Furthermore, this section also highlights model validations, model comparisons, and variable impact analysis.

3.3.1 Weighted Average Approach

This section discusses the methodology of the weighted average approach for estimating fuel use and emission rates of NO_x, HC, CO, CO_2, and PM using real-world in-use data. As mentioned, data on a second-by-second basis were gathered from 32 items of equipment using the PEMS. In order to develop this method, a number of tasks were conducted as follows:

1. *Identify and classify the dataset of 32 items of HDD equipment based on equipment attributes in terms of equipment types and engine tier types.*

   In this study, data were classified into seven types of HDD equipment consisting of six backhoes, six bulldozers, three excavators, six motor graders, three off-road trucks, three track loaders, and five wheel loaders. For each item of equipment, the datasets were comprised of a second-by-second basis of fuel use and emission rates of NO_x, HC, CO, CO_2, and PM along with the engine performance data (MAP, RPM, and IAT). Based upon the engine attributes, the equipment was further categorized into engine tier types containing of engine tier 0, tier 1, tier 2, and tier 3. The engine tier types were determined based on the model year and the engine size of the specified HDD equipment.

2. *Perform the engine modal analysis for each item of equipment by stratifying the engine load into 10 individual engine modes.*

   In this research, engine load was determined by measuring the MAP, which was used as a surrogate for engine load. Since most of the equipment had various ranges of MAP values, normalization of the MAP was conducted as explained by the following equation.

$$MAP\ nor = \frac{\mathrm{MAP} - \mathrm{MAP\ min}}{\mathrm{MAP\ max} - MAP\ min} \tag{3-1}$$

where:

MAP_{nor} = Normalized MAP for a measured MAP for a specific item of equipment

MAP_{max} = Maximum MAP for a specific item of equipment

MAP_{min} = Minimum MAP for a specific item of equipment

MAP = Measured MAP for a specific item of equipment

The normalized MAP falls within the range of 0 and +1. The values of MAP from minimum to maximum were further categorized into 10 individual bins, ranging from 0.0 to 0.1, 0.1 to 0.2… 0.9 to 1.0. These bins represent the increasing engine modes. For instance, the bins of 0.0 to 0.1 and 0.1 to 0.2 indicate the engine mode 1 and engine mode 2, respectively. Engine mode 1 typically shows the idling activity mode; meanwhile, engine modes 2-10 present the working (non-idling) modes (Lewis, 2009).

Emission rates are reported in several ways. If emissions and time are identified, emissions are reported in g/s. Similarly, if the fuel flow rate is measured, emissions can also be reported in mass per time basis (g/s) or mass per fuel basis (g/gal). Additionally, if equipment activity and its duty cycle are documented, then emission can be associated with activity modes, engine activity and single equipment tasks. However, in this research, when using the weighted average approach for quantifying fuel use and emission rates, emissions will be reported in g/hp-hr.

The datasets of fuel use and emission rates of NO_x, HC, CO, and CO_2, for each item of equipment collected from the PEMS were reported in unit of grams per second (g/s), and PM in mg/s. Thus, for the weighted average approach purpose, the units were converted into grams per horse power hours (g/hp-hr). The conversion factors were defined as 3,600 seconds per hour, 454 grams per pound, and 7.4 pounds of diesel fuel per gallon. For example, if the fuel use rate of wheel loader is 0.05226 g/s given the engine size of 89 horsepower, then the conversion of fuel use rate can be calculated as follows:

Fuel use rate = (0.543 g/s *3600) / (454*7.4*89) = 0.00638 g/hp-hr

In the engine modal analysis, the fuel use and emission rates were quantified for 10 different individual engine modes. Once the engine modal analysis for each engine mode was conducted, the average of fuel use and emission rates for each engine mode could be determined. In other words, the fraction of fuel use and emission rates in each engine mode for each item of equipment could be quantified.

3. *Quantify the amount of time (Ti) spent in each engine mode for each item of equipment.* The amount of time in each engine mode for each item of equipment was quantified. Furthermore, the total fractions of time were calculated based on the equipment type. In order to calculate the total average of time spent in each engine mode for specified type of equipment, the fraction of time from each item of equipment was averaged. Then, the average percentage of time (Ti) for specified type of equipment was determined. The average percentage of time was calculated for seven types of equipment. In order to simply demonstrate the relationships between the time spent in each engine mode and the amount of fuel use and emission rates spent in each engine mode, histograms were developed. The graphs illustrate the engine mode versus the average percentage of time and the engine mode versus the fuel use and emission rates.

4. *Quantify the average of fuel use (FFi) and emission rates (EFi) in each engine mode.* After classifying the equipment based on equipment type and engine tier type, the average of fuel use and emission rates spent in each engine mode could be determined. The average of fuel use and emission rates of NO_x, HC, CO, CO_2, and PM were grouped based on the engine tier type. Additionally, the fuel use was also grouped by the equipment type. This is

due to the fact that fuel use is mostly not affected by the engine tier, but more on the equipment types. However, calculations on the fuel use were conducted for both classifications.

5. *Determine the weighted average of fuel use and emissions rates.*

The overall modal weighted average fuel use and emission rates of NO_x, HC, CO, CO_2, and PM were calculated by multiplying the percentage of time spent in each engine mode for each type of equipment and the average of fuel use and emission rates in that particular engine mode. The modal weighted average of fuel use and emission rates can further be determined based on the engine tier types. In order to quantify the total amount of fuel use and emission rates in each engine tier for each type of equipment, the summations of fuel use and emission rates with *n* engine modes were conducted. The equations take the form of:

$$\text{FFi wt. av} = \sum_{i=0}^{n} T_i \; x \; FF_i \tag{3-2}$$

$$\text{EFi wt. av} = \sum_{i=0}^{n} T_i \; x \; EF_i \tag{3-3}$$

Figure 3.5 presents a conceptual flowchart of the overall procedure for estimating fuel use and emission rates using the weighted average approach.

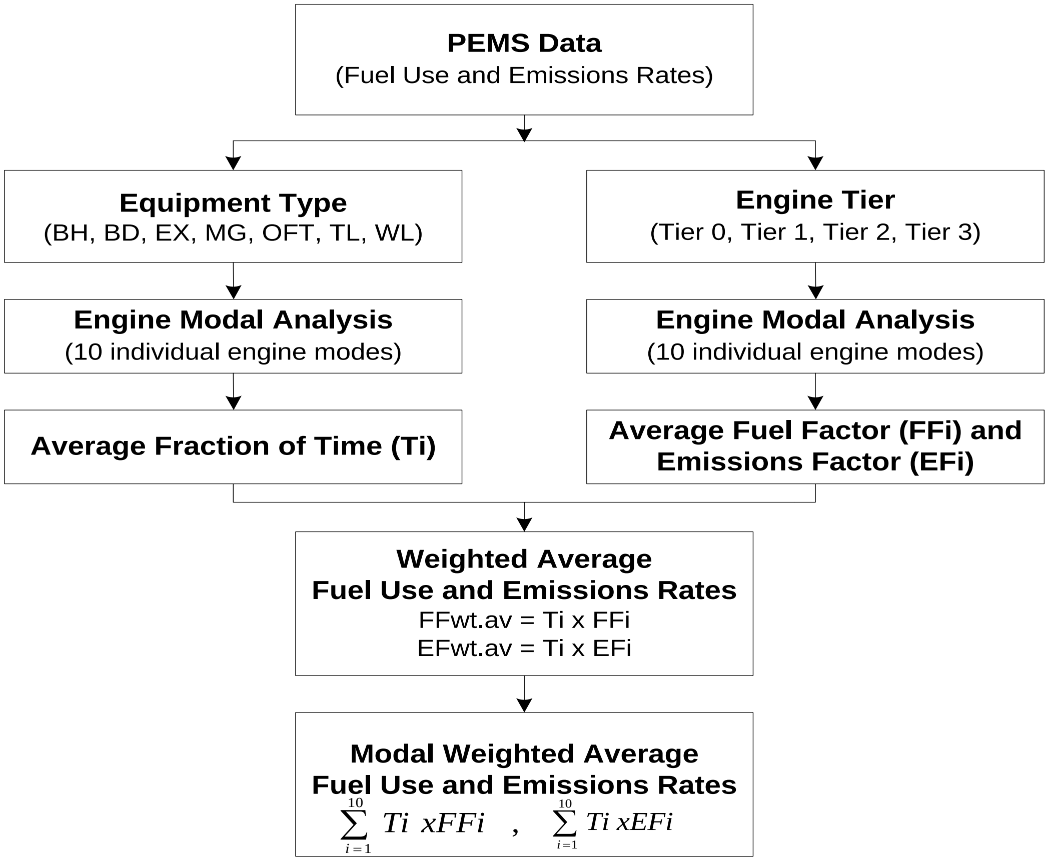

Figure 3.5. The Weighted Average Approach for Estimating Fuel Use and Emission Rates

3.3.2 Simple Linear Regression (SLR)

Simple linear regression models were developed to determine the relationship between a single response variable and a single predictor variable. Since it has been shown by others and the correlation analysis in this research that MAP is highly correlated to fuel use and emission rates (Frey *et al.*, 2008; Lewis, 2009; Fitriani, 2013), simple linear regression models were formulated based on the relationship between MAP as a predictor variable and fuel use as a response variable, as well as MAP and mass per time (grams per second) emission rates of NO_x, HC, CO, CO_2, and PM. These SLR models take the form of:

$$Y_i = m_i x_i + b_i \tag{3-4}$$

where:

i = 1,2,..,6

Y = Fuel use, or emission rates of NO_x, HC, CO, CO_2, or PM (grams per second)

m = slope of the regression line

x = MAP (kilopascal)

b = y-intercept of regression line

3.3.3 Multiple Linear Regression (MLR)

Multiple linear regression was used to model the relationship between two or more predictor variables and a response variable. In this study, three predictor variables representing as engine performance data (MAP, RPM, and IAT) and one response variable (either fuel use or emission rate of NO_x, HC, CO, CO_2, or PM) were used in MLR models.

The MLR equations for fuel use and emission rates for each pollutant take the form of:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \tag{3-5}$$

where:

Y = Fuel use or emission rates (Either NO_x, HC, CO, CO_2, or PM in grams per second)

X_1 = Manifold Absolute Pressure (MAP in Kilo Pascal)

X_2 = Revolutions Per Minute (RPM)

X_3 = Intake Air Temperature (IAT in Celsius degrees)

β_0, β_1, β_2, β_3 = Coefficients of linear relationship

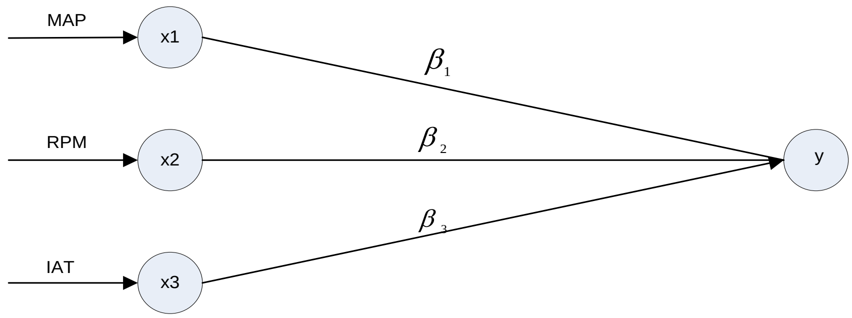

Figure 3.6. The Architecture of MLR

In order to evaluate the significance of variables in MLR, the stepwise model selection method was performed. The criteria to include the variables in the model were based on the coefficient of p-values. If p-value of the variable is less than 0.05, the variable is included in the model. Conversely, if p-value is greater than 0.05, the variable is excluded from the model. The analysis of variance and analysis of maximum likelihood for each response variable were also conducted.

The conditions of the MLR models were investigated using the Minitab software to demonstrate the residual plots, comprising of normal probability plot of the residuals, residual versus the fitted values, histogram of the residual, and residuals versus the order of data. The tests for residuals were conducted whether the residuals or error terms are normally distributed as used in the assumptions.

In order to exhibit the relation among predictor variables, multicollinearity was also conducted. Multicollinearity was used to show that two or more predictor variables are highly correlated to one another. Multicollinearity increases the standard error of the coefficient, leading to unexpected model. The multicollinearity was explained by the value of Variance Inflation Factor (VIF), which is used to measure the variance of the estimated regression coefficients. The general form of VIF can be seen in equation 2-14.

3.3.4 Artificial Neural Network (ANN)

In this study, the ANN was also used to develop the relationships between the response variable and some predictor variables. This approach is mostly used in a complex and nonlinear function, indicating an emerging alternative to more traditional statistical approaches. The ANN models are trained through an iterative process by learning the complexities between input and output. The structure of ANN is comprised of input, hidden and output layers. Each layer may consist of one or more processing elements or nodes or neurons. In this study, the input layers are comprised of MAP, RPM, and IAT; meanwhile, the fuel use and emission rates of NO_x, HC, CO, CO_2, and PM are defined as the output layers. The architecture of ANN is presented in Figure 3.7.

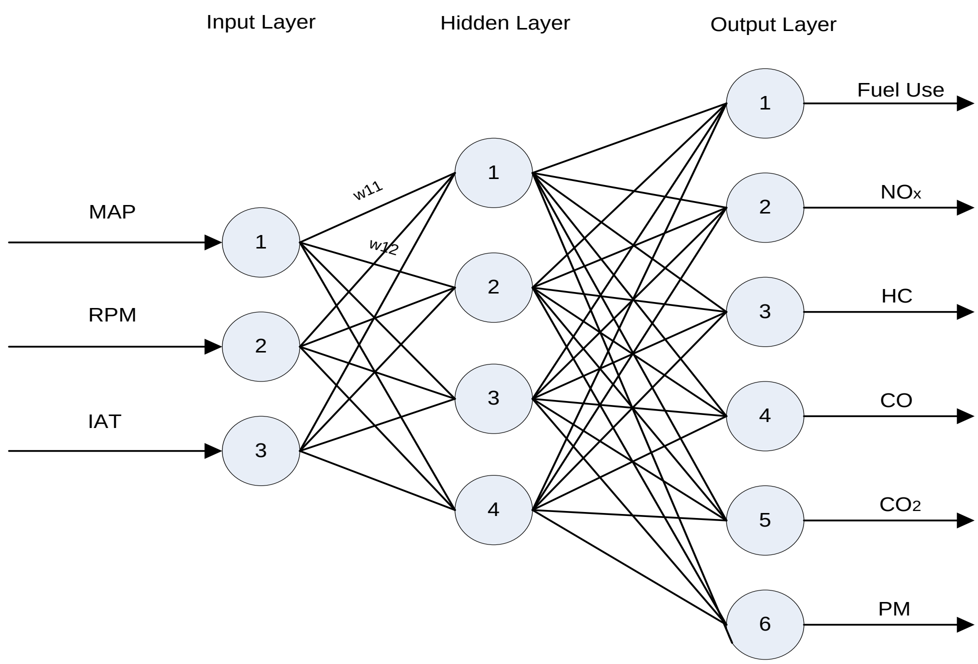

Figure 3.7. The Architecture of ANN

The datasets of each variable contain a set of observations. Three important process generated in the ANN are the training, test, and prediction process. In the training process, the ANN generates a set of observations using the known output values (fuel use and emissions rates datasets) gathered using PEMS. Meanwhile, in the test process, the ANN tests the trained network to evaluate the performance of trained models to predict the known output values. The data used in the testing are typically a subset of the input data. In order to generate the models, 60% of the data were used to train the models and 40% of the data were used to validate the models. The trained neural network can also be used to predict the unknown output values or commonly known as prediction process (Palisade, 2010). The percentage of known correctly answers predicted are given as well.

In this study, the ANN prediction models were carried out by using the @Risk software. @Risk supports the users to define the data whether training, testing or prediction datasets by utilizing the Neuraltools. Different neural network configurations are available for predicting the best possible outputs, comprising of Probabilistic Neural Networks (PNN), Generalized Regresion Neural Networks (GRNN), and Multi-layer Feedforward Networks (MLF). The numeric predictions can be carried out by using MLF and GRNN. The latter are essentially similar to PNN networks. Since this study uses the numeric output, thus the MLF was applied using the default setting.

After defining the configuration used, the MLF will select the best net when training and testing the datasets. When reaching the stopping conditions or global optimum, the training process will stop and report the results. If the stopping conditions are not determined, the training will stop ultimately. The stopping time will be longer for MLF nets compared to PNN/GRNN nets. Although there are six different nodes in the output layer comprising of the fuel use and emission rates of each pollutant, the models were essentially trained for each specified output. For instance, the training net was built based on three input nodes (MAP, RPM, and IAT), one or two hidden layers with a number of nodes, and one output node (either fuel use or specified emission rate).

3.1.5 Model Validations

Once the models have been developed, it is essential to validate the models. Model validations are used to determine whether the results from the predicted models fit the actual data. Model validations were only conducted for three predictive modelings that include SLR, MLR, and ANN by plotting the predicted versus the actual results. Three components to assess or validate the models comprise of coefficient determination (R^2), slope (m), and y-intercept (b). The R^2 is used as a model assessment to indicate the linear relationship between the predicted and the actual data. The value of R^2 indicates the precision of the models. If R^2 is close to 1, it means the predicted values from the model are highly correlated to the actual data. Conversely, if R^2 is close to 0, it means the predicted values from the model are not correlated to the actual data. Additionally, slope (m) is used to indicate the accuracy of the models. Similarly to R^2, values close to 1 indicate high accuracy. The y-intercept (b) is an indicator of bias in the model, with values close to zero being desirable.

3.1.6 Model Comparisons

Model comparisons were used to compare the performance of SLR, MLR, and ANN methodologies. Likewise the model validations, model comparisons exhibit each model from three different basic indicators that include coefficient determination (R^2), slope (m), and y-intercept (b). The values for each indicator reflect the same values as already mentioned in section 3.1.5. Model comparisons were conducted for analyzing the fuel use and emission rates for each item of equipment.

3.1.7 Variable Impact Analysis (VIA)

Variable impact analysis (VIA) was used to measure the sensitivity of the outputs given the changes of the predictor variables (Palisade, 2010). VIA was only performed on the training data. The lower the percent value of the predictor variable, the less that variable influence the response variable. VIA can also help in the selection of predictor variables (Palisade, 2010). In other words, if the predictor variable has a small impact to the response variable, that variable can be excluded in the model.

In this study, the variable impact analysis was used to determine the percentage of contribution of the input variables (MAP, RPM, and IAT) to the prediction of fuel use and emission rates of each pollutant. The VIA was employed to each item of HDD in terms of fuel use and emission rates of each pollutant.

CHAPTER IV

RESEARCH RESULTS

This chapter describes results with respect to estimating fuel use and emission rates from 32 items of HDD construction equipment, which consist of six backhoes, six bulldozers, three excavators, six motor graders, three off-road trucks, three track loaders, and five wheel loaders. All equipment were analyzed using different methodologies that include weighted average approach, simple linear regression (SLR), multiple linear regression (MLR), and artificial neural network (ANN). In order to fully understand the relationships among variables, exploratory data analysis in terms of summary statistics, distribution fittings, and correlation variables will be further explained.

4.1 Field Data Collection

The data used in this research are based on the real-world datasets from the research team at North Carolina State University. Since there are still many areas not fully covered by previous research, this study highlights other methodologies or approaches on developing prediction models for estimating fuel use and emission rates using PEMS data.

Table 4.1. Summary of Engine Attributes

Equipment	Horsepower (HP)	Displacement (Liters)	Model Year	Engine Tier
Backhoe 1	88	4.0	2004	2
Backhoe 2	88	4.2	1999	1
Backhoe 3	88	4.2	2000	1
Backhoe 4	97	3.9	2004	2
Backhoe 5	99	4.5	1999	1
Backhoe 6	97	4.5	2004	2
Bulldozer 1	89	5.0	1988	0
Bulldozer 2	95	3.9	2002	1
Bulldozer 3	90	5.0	2003	1
Bulldozer 4	175	10.5	1998	1
Bulldozer 5	285	14.2	1995	0
Bulldozer 6	99	4.2	2005	2
Excavator 1	254	8.3	2001	1
Excavator 2	138	6.4	2003	2
Excavator 3	93	3.9	1998	1
Motor Grader 1	195	8.3	2001	1
Motor Grader 2	195	7.1	2004	2
Motor Grader 3	195	8.3	2001	1
Motor Grader 4	167	8.3	1990	0
Motor Grader 5	160	8.3	1993	0
Motor Grader 6	198	7.2	2007	3
Off-Road Truck 1	306	9.6	2005	2
Off-Road Truck 2	285	10.3	1998	1
Off-Road Truck 3	285	10.3	1998	1
Track Loader 1	121	7.2	1998	1
Track Loader 2	70	4.5	1997	0
Track Loader 3	127	7.2	2006	2
Wheel Loader 1	149	5.9	2004	2
Wheel Loader 2	130	5.9	2002	1
Wheel Loader 3	130	5.9	2002	1
Wheel Loader 4	126	5.9	2002	1
Wheel Loader 5	133	6.0	2005	2

Data from 32 items of equipment, consisting of six backhoes, six bulldozers, three excavators, six motor graders, three off-road trucks, three track loaders, and five wheel loaders were gathered by deploying the PEMS manufactured by The Clean Air Technologies International (CATI), Inc. The PEMS provided data based on second-per-second measurement for fuel use and emission rates of specified pollutants (NO_x, HC, CO, CO_2, and PM) as well as engine performance data (MAP, RPM, and IAT).

Table 4.1 displays the data of engine attributes for each of the 32 items of equipment, in terms of engine size (HP), displacement, model year, and EPA engine tier. The rated engine horsepower (HP) ranged from 88 HP to 306 HP. The off-road trucks have the highest values for engine power among other types of equipment, ranging from 285 to 306. The engine powers for six bulldozers range from 89 to 285. All six backhoes have the engine power lower than 100 HP. It is more likely that the higher the engine power, the more fuel consumed and the more pollutants emitted. It is shown that engine displacements are also diverse, ranging from 3.9 to 14.2 liters. The engine displacements for all wheel loaders are relatively similar, indicating almost the same amount of fuel needed to power the engine.

Table 4.2. Summary of Engine Tier Classification by Equipment Type

Equipment Type	# Tested	Engine Tier Classification			
		Tier 0	Tier 1	Tier 2	Tier 3
Backhoe	6	0	3	3	0
Bulldozer	6	2	3	1	0
Excavator	3	0	2	1	0
Motor Grader	6	2	2	1	1
Off-Road Truck	3	0	2	1	0
Track Loader	3	1	1	1	0
Wheel Loader	5	0	3	2	0
Total	**32**	**5**	**16**	**10**	**1**

With respect to the engine model years, the ranges varied from 1988 to 2007. One of the bulldozers has the oldest model of all equipment. It was found that most of the vehicles are ancient, indicating more than 10 years old. It may be concluded that the older the equipment, the more fuel consumed and the more pollutants emitted.

Engine tiers were classified based upon the EPA standards as shown in Table 2.4, considering the engine power and the engine model year. The engine tiers varied, range from tier 0 to tier 3, in which half of the total equipment is classified into tier 1. Since there is only 1 item of equipment in engine tier 3, this data was excluded when using the weighted average approach. A more detailed classification based on the number of engine tier types can be seen in Table 4.2.

4.2 Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) was performed for each item of equipment. However, for brevity, the detailed results put in this section only focus on specified items of equipment and the rest of the equipment are provided in the Appendix. The EDA includes summary statistics, distribution fittings, and correlation variables.

4.2.1 Summary Statistics

In order to fully understand the nature of data for 32 items of equipment, gathered by the PEMS, the statistical analyses for each item of equipment were implemented. However, in order to be concise, this section only provides the summary of statistical analysis of one type of equipment, namely the wheel loaders. The statistical summary is comprised of the average fuel use and emission rates of NO_x, HC, CO, CO_2, and PM as well as engine performance data (MAP, RPM, and IAT). The summary is associated with the four order statistics such as minimum, maximum, mean, and standard deviation. The detail descriptions of statistical summary for each specified response variables for each individual wheel loader are presented in Table 4.3.

Table 4.3. Summary Statistics of Fuel Use and Emission Rates for Wheel Loaders

Equipment	Min	Max	Mean	Std.Dev	# of Case	Fitting Distribution
			Fuel Use Rates (g/s)			
WL 1	0.122	7.22	1.540	1.220	15226	RiskInvGauss
WL 2	0.200	5.64	1.380	1.080	19064	RiskInvGauss
WL 3	0.010	4.65	0.835	0.955	3404	RiskInvGauss
WL 4	0.100	4.20	1.030	0.806	6718	Risk Lognorm
WL 5	0.260	6.32	0.691	0.729	11827	RiskPareto
			NO_x (g/s)			
WL 1	0.00043	0.267	0.0467	0.0361	15226	RiskPearson
WL 2	0.00347	0.188	0.0540	0.0372	19064	RiskPearson
WL 3	0.00191	0.171	0.0365	0.0328	3404	RiskPearson
WL 4	0.00595	0.175	0.0433	0.0290	6718	RiskInvGauss
WL 5	0.00509	0.186	0.2180	0.0193	11827	RiskPearson
			HC (g/s)			
WL 1	0.00000	0.0283	0.00538	0.00353	15226	RiskPearson
WL 2	0.00168	0.0375	0.00915	0.00358	19064	RiskPearson
WL 3	0.00000	0.0108	0.00214	0.00168	3404	RiskLogLogistic
WL 4	0.00033	0.0202	0.00422	0.00235	6718	RiskLogLogistic
WL 5	0.00000	0.0126	0.00216	0.00102	11827	RiskLogLogistic
			CO (g/s)			
WL 1	0.00037	0.3000	0.0202	0.01880	15226	Risk Lognorm
WL 2	0.00059	0.1070	0.0105	0.00299	19064	RiskNormal
WL 3	0.00016	0.0309	0.0499	0.00284	3404	RiskLogLogistic
WL 4	0.00021	0.0302	0.0033	0.00242	6718	RiskLogLogistic
WL 5	0.00037	0.0803	0.0063	0.00359	11827	RiskLogLogistic
			CO_2 (g/s)			
WL 1	0.364	23.99	4.830	3.820	15226	RiskInvGauss
WL 2	0.624	17.79	4.320	3.390	19064	RiskPearson
WL 3	0.018	14.36	2.570	2.950	3404	RiskPearson
WL 4	0.309	13.26	3.250	2.550	6718	RiskInvGauss
WL 5	0.821	19.96	2.170	2.300	11827	RiskLogLogistic
			PM (mg/s)			
WL 1	0.050	3.29	0.425	0.397	15226	RiskExpon
WL 2	0.030	4.62	0.410	0.396	19064	RiskExtValue
WL 3	0.010	0.93	0.119	0.161	3404	RiskTriang
WL 4	0.010	2.10	0.305	0.284	6718	RiskGamma
WL 5	0.050	1.75	0.128	0.162	11827	RiskPareto

Table 4.4. Summary Statistics of Average Fuel Use and Emission Rates for Wheel Loaders

Respond	Min (g/s)	Max (g/s)	Mean (g/s)	Std.Dev (g/s)	Distribution Fitting
Fuel Use	0.1380	5.606	1.095	0.958	Risk InvGauss
NO_x	0.0030	0.197	0.080	0.031	Risk Pearson
HC	0.0004	0.022	0.005	0.002	Risk Logistic
CO	0.0003	0.110	0.018	0.006	Risk Logistic
CO_2	0.4270	17.87	3.430	3.002	Risk Pearson
PM	0.0300	2.538	0.277	0.251	Risk Expon

Table 4.3 summarizes the statistical analysis of fuel use and emission rates for five wheel loaders along with the number of observations and distribution fittings. In order to easily determine the amount of fuel use and emission rates for all wheel loaders, the four order statistics were averaged.

Table 4.4 clearly shows the summary statistics of the average fuel consumption and emission rates for wheel loaders in unit grams per seconds (g/s). The mean values showing the central location for fuel use and emission rates of CO_2 account for about 1.1 g/s and 3.43 g/s respectively. The emission rates of CO_2 have the highest mean values compared to other pollutants such as NO_x, HC, CO, and PM. It can also be said that there are approximately 1.1 g/s of diesel fuel utilized for wheel loaders, resulting more than 3 grams per second emissions of CO_2. It is likely that the standard deviations for all response variables are relatively low, ranging from 0.002 to 0.251 g/s for each pollutant excluding CO_2.

With respect to defining the distributions of the data, based upon a set of observations, the summaries of distribution fittings are also shown in Table 4.3 and 4.4. However, further description regarding the distribution fittings are provided in section 4.2.2. It was found that risk inverse gauss is the best fitted distribution for fuel use, risk pearson for NO_x and CO_2, and risk logistic for HC and CO.

The summary statistics for average engine performance data that include MAP, RPM, and IAT are displayed in Table 4.5. The minimum and maximum values range from 99 to 206 kPa for MAP, 650 to 2323 for RPM, and 17 to 31 degree celsius for IAT. The detailed summary statistics for engine data for all wheel loaders based on PEMS data are presented in Table 4.6.

Table 4.5. Summary Statistics of Average Engine Data for Wheel Loaders

Engine Data	Min	Max	Mean	Std Dev	Distribution Fitting
MAP (kPa)	99	206	118	22	Risk Triang
RPM	650	2323	1249	340	Risk Pareto
IAT (C)	17	31	24	3.22	Risk BetaGeneral

Table 4.6. Summary Statistics of Engine data for Wheel Loaders

Equipment	Min	Max	Mean	Std.Dev	# of Case	Fitting Distribution
			MAP (kPa)			
WL 1	102	214	122	24.71	15226	RiskTriang
WL 2	101	193	118	18.02	19064	Risk Uniform
WL 3	98	219	119	26.85	3404	RiskTriang
WL 4	97	210	126	26.80	6718	RiskTriang
WL 5	97	192	105	13.72	11827	RiskTriang
			RPM			
WL 1	810	2420	1217	424	15226	RiskPareto
WL 2	694	2140	1373	280	19064	RiskLogLogistic
WL 3	324	2375	1192	481	3404	RiskPearson
WL 4	493	2344	1392	312	6718	RiskInvGauss
WL 5	928	23359	1072	203	11827	RiskLogNormal
			IAT (C)			
WL 1	19	40	30	5.14	15226	RiskExpon
WL 2	10	28	21	4.37	19064	RiskBetaGeneral
WL 3	14	24	19	3.34	3404	RiskBetaGeneral
WL 4	14	23	18	1.74	6718	RiskTriang
WL 5	28	39	33	1.51	11827	RiskUniform

In summary, the statistical analyses were performed for each item of equipment using the real-world data. The data analysis can indicate the characteristics of the data. It was found that the quantity of fuel use and emissions rates vary, depending on the type of the equipment. Even, within the same type of equipment, the amount of fuel used and pollutants emitted are also different. However, by performing the statistical analysis, it will easily help recognize the nature of data.

4.2.2 Distribution Fittings

In order to define the distributions of data for each item of equipment, distribution fittings were carried out by matching the distributions to fit data well. The @Risk software was used to specify the distribution types for each variable using fitting distribution toolbar. To determine the best distributions based on the data given, @Risk estimates the distribution parameters using the Maximum Likelihood Estimators (MLEs) and the Method of Least Squares (MLS). The MLEs are used to maximize the probability of achieving the given datasets for sample data; meanwhile, the MLS method is used to minimize the root-mean square error between the curve points and the theoretical function (Palisade, 2010).

Based on the goodness of fit statistics that include Chi Squared statistic (χ_2), Kolmogorov-Smirnoff statistic (K-S), and Anderson Darling statistic (A-D), @Risk ranks all the fitted distributions. However, in this research, the fitted distributions were determined based on the Chi-Squared statistic. The CS statistic indicates the deviation of the fitted distributions from the input data.

Figures 4.1 - 4.7 illustrate how input data and the fitted probability distribution functions (PDF) are achieved by generating a random process from a set of observations. The fitted distributions of fuel use for each wheel loader are displayed as comparisons, resulting in different kinds of distributions. As shown in Figure 4.1, given a certain range of input data, ranging from 0.122 g/s to 7.72 g/s of fuel use in wheel loader 1, the best fit distribution function results in the risk inverse gauss. The results are based upon the Chi Square goodness of fit test. The PDF describes a range of possible values of fuel use and their likelihood of occurrence, indicating the variability of fuel use rates. The figure clearly shows that most of data are concentrated on the left side, clearly indicating longer right tail (positive skewed). It appears that for the input data, 90% of confidence interval falls in the range of 0.42 – 4.12 g/s of fuel use; whereas, 87% confidence interval for fitted distribution.

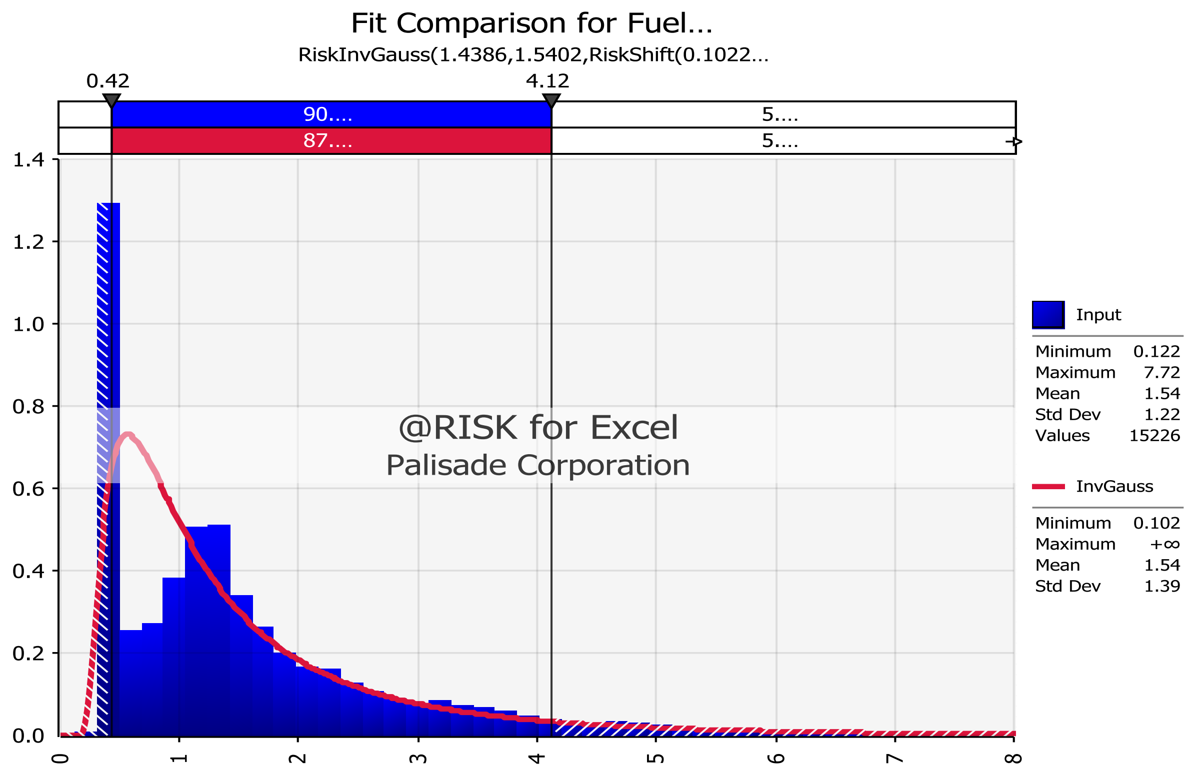

Figure 4.1. Fitting Distribution of Fuel Use for Wheel Loader 1

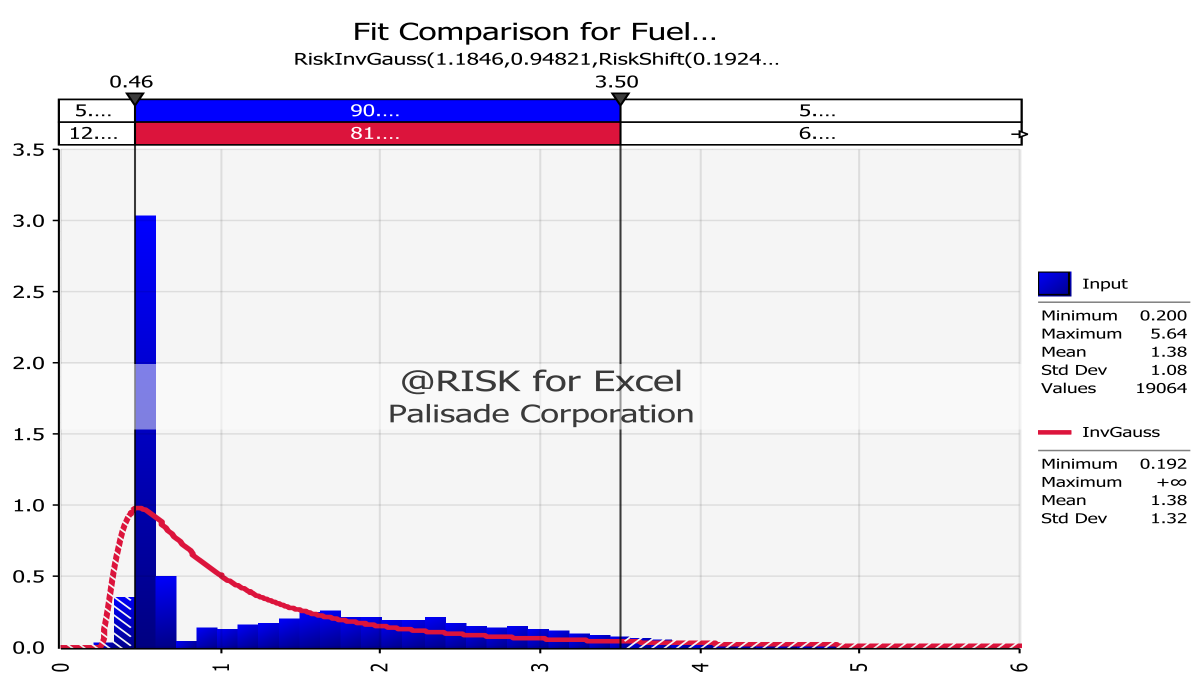

Figure 4.2. Fitting Distribution of Fuel Use for Wheel Loader 2

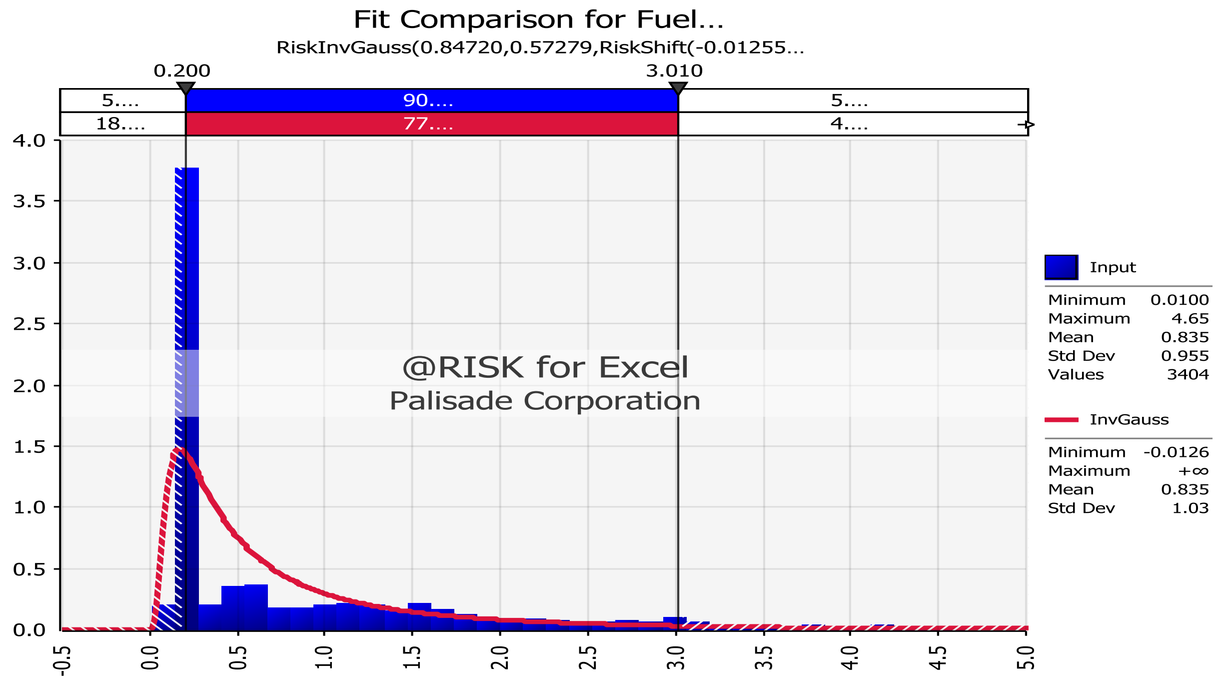

Figure 4.3. Fitting Distribution of Fuel Use for Wheel Loader 3

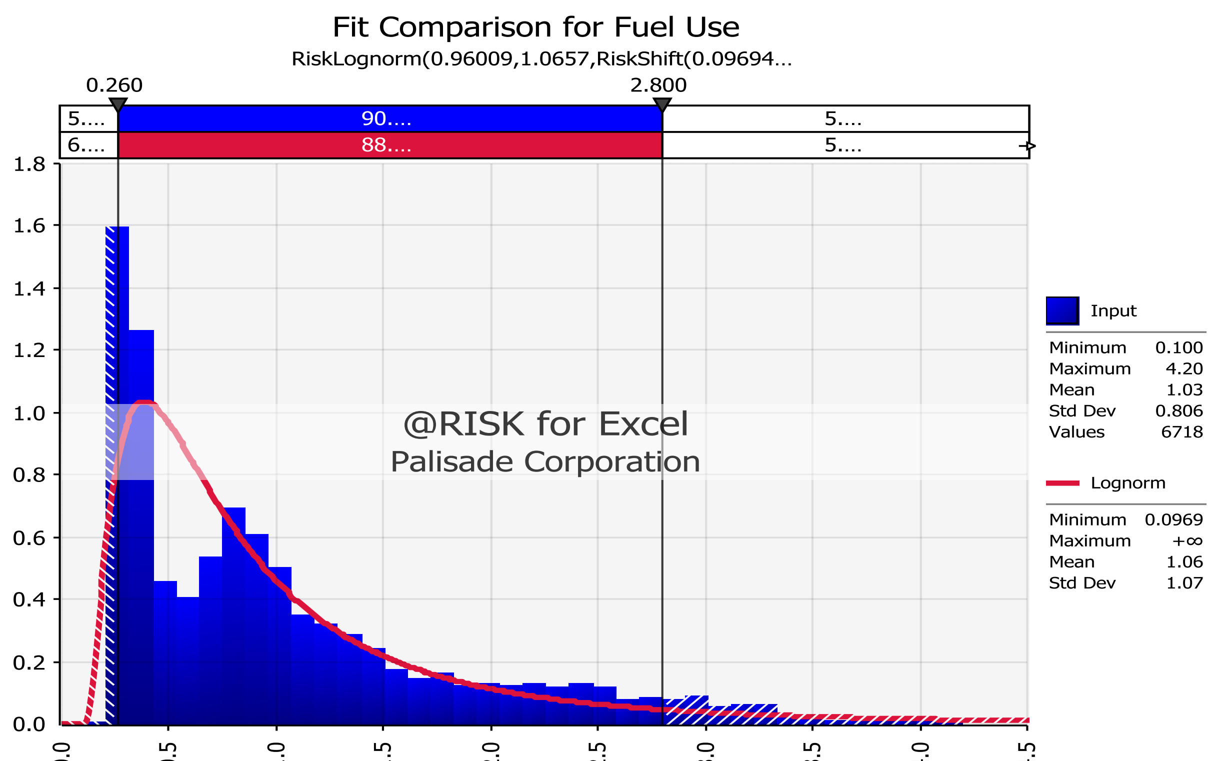

Figure 4.4. Fitting Distribution of Fuel Use for Wheel Loader 4

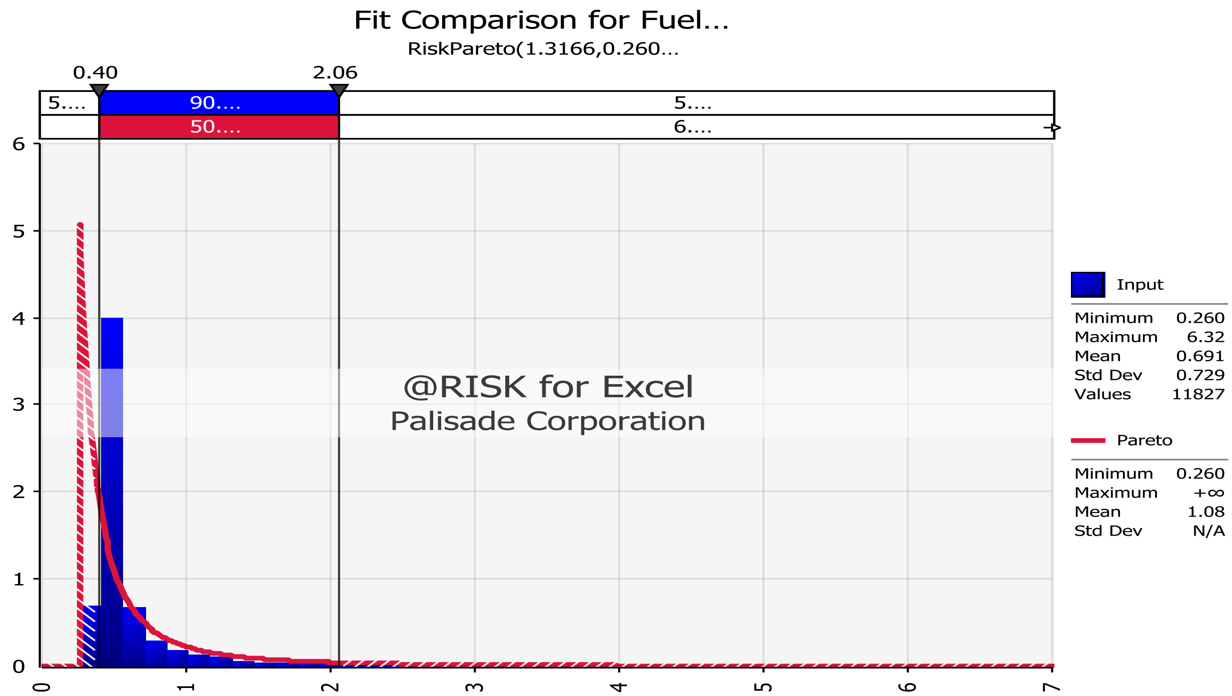

Figure 4.5. Fitting Distribution of Fuel Use for Wheel Loader 5

From the figures above, there is variability in the fitted distributions of fuel use for each wheel loader. It can be concluded that all fitted distributions of five wheel loaders have longer left tail (positively skewed), resulting in different distribution types as well. However, the results typically show similar trends of fuel use distributions.

The distribution fittings were fully performed for all fuel use and emissions rates of NO_x, HC, CO, CO_2, and PM as well as engine data (MAP, RPM, and IAT) for each 32 items of equipment. However, in this section only one or two specified variables are presented, the rest are provided in the Appendix.

Figure 4.6 and 4.7 illustrate the distribution fittings for RPM and IAT for wheel loader 1. As seen in figures, the generating distributions result in risk pareto and risk exponential for RPM and IAT, respectively. Similarly, they are positively skewed, ranging from 830 to 2092 for RPM, and 21 to 38 degree Celsius for 90% of confidence interval for input data.

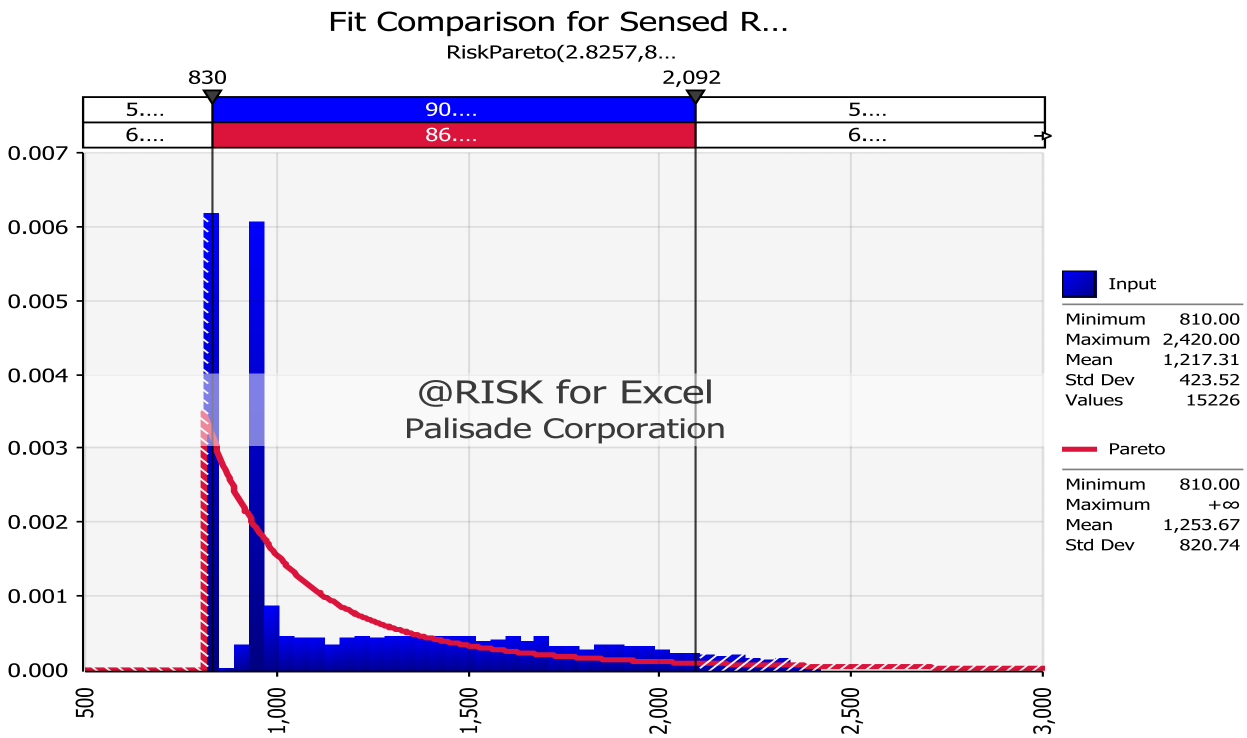

Figure 4.6. Fitting Distribution of RPM for Wheel Loader 1

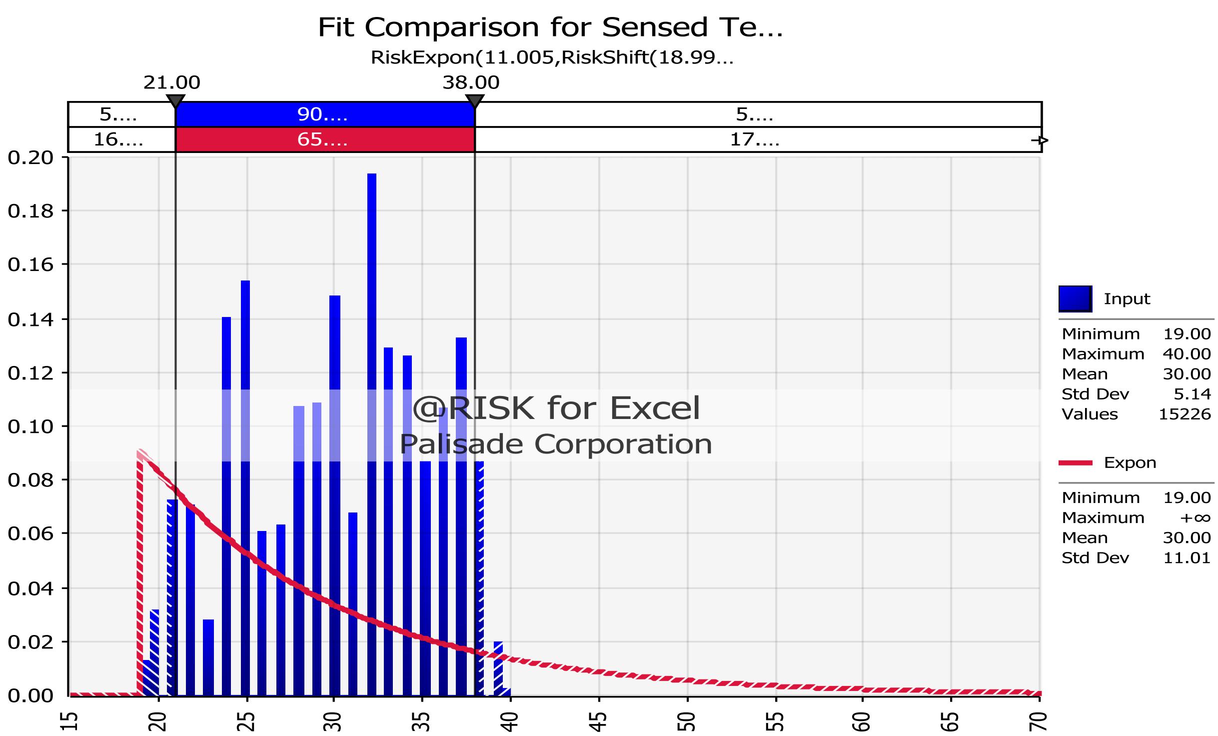

Figure 4.7. Fitting Distribution of IAT for Wheel Loader 1

The overall summary of distribution fittings for fuel use and emission rates of each pollutant for each type of equipment is presented in Table 4.7. The Pearson distribution is the most likely to happen for fuel use and emission rates for most types of equipment. The second and third most likely distributions are inverse gaussian and betageneral respectively. Table 4.8 presents the summary of distribution fittings for engine performance data – MAP, RPM, and IAT. It was found that the triangular distribution is the most likely to occur for engine performance data for most types of equipment. The distribution fittings ultimately can be used to benchmark the types of distributions for fuel use, emission rates, and engine data for further purposes such as for performing Monte Carlo Simulation.

Table 4.7. Summary of Distribution Fittings for Fuel Use and Emission Rates

Respond	**BH**	**BD**	**EX**	**MG**	**OFT**	**TL**	**WL**
Fuel Use	InvGauss	InvGauss	Pearson	Betageneral	Pearson	Triang	InvGauss
NO_x	Pearson	Pearson	Pearson	Pearson	Pearson	Betageneral	Pearson
HC	Pearson	InvGauss	InvGauss	InvGauss	Pearson	Lognorm	Logistic
CO	InvGauss	Pearson	Pearson	Loglogistic	Pearson	Pearson	Logistic
CO_2	Pearson	InvGauss	Pearson	Betageneral	Pearson	Betageneral	Pearson
PM	Normal	Betageneral	Expon	Expon	Lognorm	Expon	Expon

Table 4.8. Summary of Distribution Fittings for Engine Performance Data

Engine Data	**BH**	**BD**	**EX**	**MG**	**OFT**	**TL**	**WL**
MAP (kPa)	Triang	Triang	Betageneral	Triang	Triang	Triang	Triang
RPM	InvGauss	Triang	Triang	Betageneral	Loglogistic	Triang	Pareto
IAT (C)	Uniform	Expon	Uniform	Uniform	Uniform	Uniform	BetaGeneral

4.2.3 Correlations

The tests of correlations were also conducted for each item of equipment. However, for brevity, this section provides only the correlations of wheel loaders and excavators as illustrations. Table 4.9 shows the summary of the Pearson correlation coefficients for all five wheel loaders, indicating the relationship between engine data, fuel use, and emission rates. It appears that MAP has a strong positive relationship with fuel use and emission rates of NO_x, CO_2, and PM, but a moderate positive relationship with HC and CO. RPM has the second strongest relationship with fuel use and emission rates. Meanwhile, IAT has the weakest relationship with fuel use and emission rates as indicated by the lower (and sometimes negative) values of correlation to the specified response variable.

Table 4.9. Summary of Pearson Correlations Coefficients for Wheel Loaders

Equipment	**Engine Data**	**Fuel Use**	**NO_x**	**HC**	**CO**	**CO_2**	**PM**
WL 1	MAP	0.9171	0.8182	0.8585	0.6847	0.9169	0.8990
	RPM	0.8735	0.7684	0.8726	0.6683	0.8731	0.7455
	IAT	0.2743	0.3654	0.0040	0.2560	0.2746	0.3037
WL 2	MAP	0.9714	0.9346	0.8597	0.1117	0.9712	0.9151
	RPM	0.9440	0.9259	0.8641	0.0757	0.9438	0.8669
	IAT	0.1686	0.2219	0.2705	-0.3121	0.1686	-0.0062
WL 3	MAP	0.9408	0.9081	0.8283	0.5824	0.9408	0.9190
	RPM	0.8948	0.8614	0.8362	0.6164	0.8946	0.8990
	IAT	-0.2489	-0.2962	-0.0100	-0.0191	-0.2494	-0.2595
WL 4	MAP	0.9246	0.8854	0.3662	0.5556	0.9244	0.8652
	RPM	0.8518	0.8043	0.3563	0.5289	0.8516	0.7762
	IAT	-0.2974	-0.3410	0.2361	-0.4971	-0.2979	-0.2643
WL 5	MAP	0.9736	0.9357	0.6535	0.7047	0.9735	0.9232
	RPM	0.9001	0.8677	0.6976	0.6759	0.8998	0.7661
	IAT	-0.0683	-0.0835	0.0367	-0.0482	-0.0684	-0.0597

Similarly, in the case of excavators, MAP also has a strong positive relationship with fuel use and emissions rates of NO_x, CO_2, and PM. RPM tends to be the second variable that has linear relationship with fuel use and emissions rates. In the meantime, IAT has the weakest correlation with fuel use and emission rates, given the small values of correlation coefficients as shown in Table 4.10.

Based on the correlation coefficients from each item of equipment, as also provided in the Appendix, it appears that each item of equipment seems likely to follow the same trends of linear relationship among variables. MAP is the most highly correlated to fuel use and emissions rates, RPM is moderately correlated, and IAT is the least correlated to fuel use and emissions rates.

Table 4.10. Summary of Pearson Correlations Coefficients for Excavators

Equipment	**Engine Data**	**Fuel Use**	**NO_x**	**HC**	**CO**	**CO_2**	**PM**
EX 1	MAP	0.9909	0.9737	0.5920	0.7367	0.9909	0.9386
	RPM	0.7975	0.7352	0.6324	0.8547	0.7971	0.7391
	IAT	0.5647	0.5893	0.0704	0.3720	0.5650	0.5137
EX 2	MAP	0.9814	0.9219	0.6245	0.4684	0.9815	0.9421
	RPM	0.8519	0.8511	0.6210	0.5682	0.8512	0.6894
	IAT	0.5458	0.5649	0.3294	0.2967	0.5457	0.4359
EX 3	MAP	0.9645	0.9357	0.4400	0.1353	0.9640	0.5767
	RPM	0.8407	0.7917	0.4182	0.2254	0.8397	0.4689
	IAT	0.3222	0.3998	0.3578	-0.1177	0.3218	0.4366

4.3 Predictive Modeling

Predictive models were developed using four different approaches, comprising of weighted average approach, simple linear regression (SLR), multiple linear regression (MLR), and artificial neural network (ANN). Each method is briefly explained.

4.3.1 Weighted Average Approach

As clearly mentioned in the methodology, initially PEMS data were categorized based on equipment type and engine tier type. 32 items of equipment were categorized based on seven types of equipment and four types of engine tier. Fuel use and emission rates were quantified based on these classifications. The average of fuel use and emission rates of NO_x, HC, CO, CO_2, and PM were grouped based on engine tier type. Additionally, the fuel use was also grouped by equipment type. It was found by the previous research (Lewis, 2009) that CO_2 is highly correlated to fuel use. Thus, the emission rates of CO_2 can actually be estimated from the fuel use model.

MAP as a surrogate for engine load was further categorized into 10 engine modes. Additionally, fraction of time in each engine mode was quantified to obtain the average percentage of time in each engine mode. The tabulations of percentage of time were performed for each type of equipment. Table 4.11 and Figure 4.8 present the distributions of amount of time in each engine mode along with the average percentage of time in each engine mode from five wheel loaders; whereas, the other equipment is presented in the Appendix. As seen in the table, it was found that the higher the engine load (shown by the minimum to maximum orders of engine modes), the lower the percentage of time spent in each engine mode. As indicated from the Table 4.11, approximately 40% of time was spent in engine mode 1, 20% in engine mode 2, and 13% in engine mode 3, and less than 2% of time in engine mode 10.

Table 4.11. Percentage of Time in each Engine Mode for Wheel Loaders

Modes	WL1	WL2	WL3	WL4	WL5	Average
1	46.99%	20.73%	48.44%	28.99%	54.71%	39.97%
2	18.98%	18.07%	17.22%	23.09%	22.49%	19.97%
3	9.83%	19.52%	8.74%	17.99%	5.84%	12.38%
4	6.78%	15.49%	6.96%	7.51%	4.61%	8.27%
5	4.85%	11.83%	4.65%	3.54%	2.80%	5.53%
6	3.89%	6.53%	3.94%	3.69%	2.26%	4.06%
7	2.37%	4.04%	3.27%	4.82%	1.55%	3.21%
8	2.36%	2.10%	2.83%	6.21%	1.72%	3.04%
9	2.33%	0.94%	2.31%	3.74%	2.09%	2.28%
10	1.63%	0.75%	1.64%	0.42%	1.93%	1.27%
			Total			**100.00%**

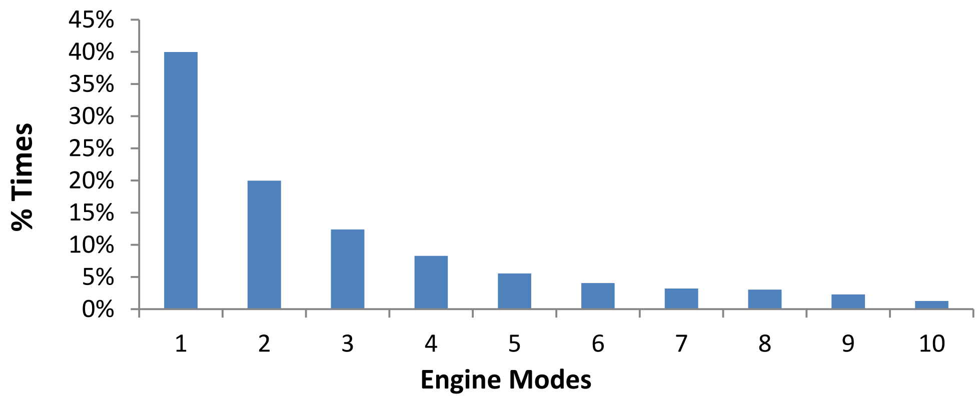

Figure 4.8. Average Percentage of Time in Each Engine Mode for Wheel Loaders

Table 4.12. Summary of Average Percentage of Time for All Types of HDD Equipment

Modes	BH	BD	EX	MG	OT	TL	WL
1	29.10%	24.92%	31.40%	24.19%	71.82%	26.98%	39.97%
2	25.90%	15.46%	5.21%	6.65%	10.07%	4.97%	19.97%
3	23.58%	15.63%	7.93%	9.93%	4.82%	3.91%	12.38%
4	9.91%	9.15%	8.38%	11.23%	2.90%	3.95%	8.27%
5	3.41%	6.68%	9.81%	9.57%	2.48%	7.68%	5.53%
6	2.09%	6.50%	10.52%	12.11%	2.21%	13.03%	4.06%
7	1.47%	5.05%	9.64%	12.30%	1.60%	8.59%	3.21%
8	1.86%	4.02%	8.57%	5.93%	1.69%	7.88%	3.04%
9	1.59%	6.74%	6.48%	4.53%	1.36%	9.39%	2.28%
10	1.09%	5.83%	2.07%	3.55%	1.04%	13.62%	1.27%

Table 4.12 illustrates the summary of the average fraction of time spent in each engine mode for each type of equipment. Similarly, for most type of equipment, the time spent in each engine mode lessens as the engine modes increase. In contrast, the track loader is likely to have a different pattern of time distributions. However, overall it appears that the fractions of time decrease when engine modes increase.

It was also found that off-road truck has the highest amount of time spent in engine mode 1 compared to the other equipment, accounting for more than 70% of time. This is then followed by the wheel loader and the excavator as the second and third vehicles that spend more time in engine mode 1. Figure 4.9 clearly displays the graphical illustration of the average of time spent in each engine mode for all given types of equipment. If a trendline is conducted on the graph, a logarithmic function is obtained with R^2 less than 0.6, indicating moderate relationship between times and engine modes.

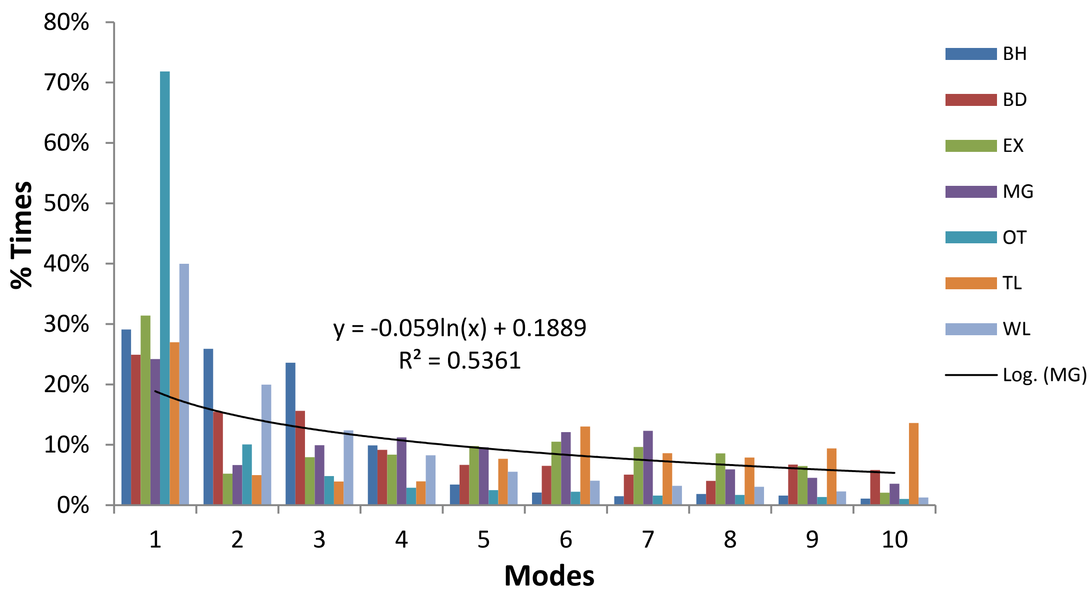

Figure 4.9. Average Percentage of Time in Each Engine Mode for All Type of HDD Equipment

Figure 4.10 also illustrates the distribution of percentage of time and fuel use rates in each engine mode for wheel loader 1. As seen in the graph, the percentage of time decreases as engine mode increases. In contrast, the fuel use rates increase as engine mode increases. For example, there is approximately 40% of time spent in engine mode 1, resulting less than 0.005 grams per horsepower hour (g/hp-hr) of fuel consumption. Meanwhile, the time spent in engine mode 10 is less than 5%, consuming approximately 0.04 g/hp-hr of fuel use. The average percentages of time for each type of equipment are used to calculate the weighted average fuel use and emission rates.

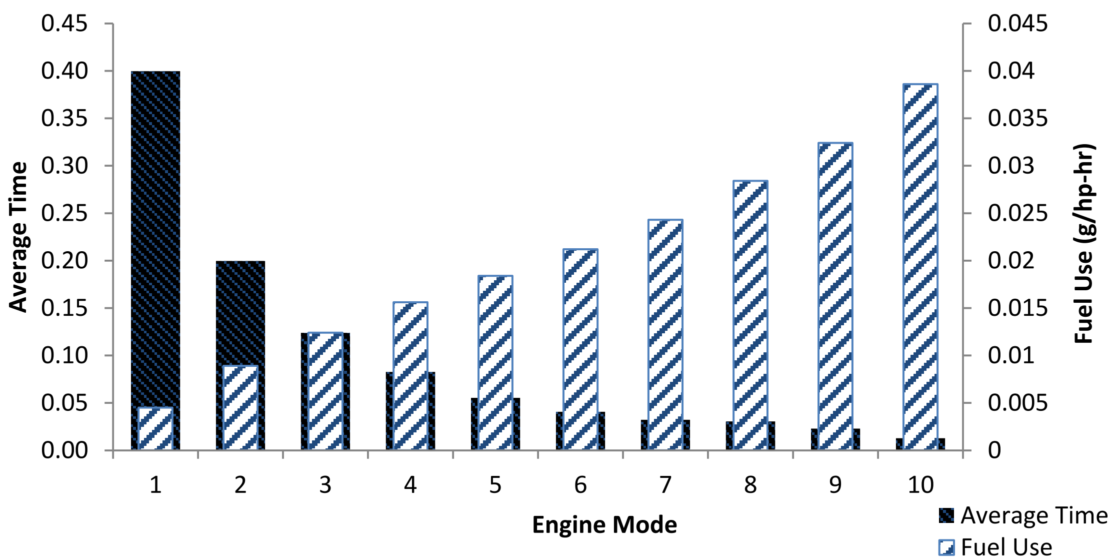

Figure 4.10. Average Percentage of Time and Fuel Use Rates in Each Engine Mode for All Types of HDD Equipment

Figure 4.11 presents the emission rates of each pollutant in each engine mode for wheel loader 1. As seen from the graphs, the emissions rates of NO_x, HC, CO, CO_2, and PM increase as engine modes increase. It was found that emission rates (g/hp-hr) increase significantly when engine modes reach to maximum values. This simply means that there are linear relationships between the emission rates and engine modes.

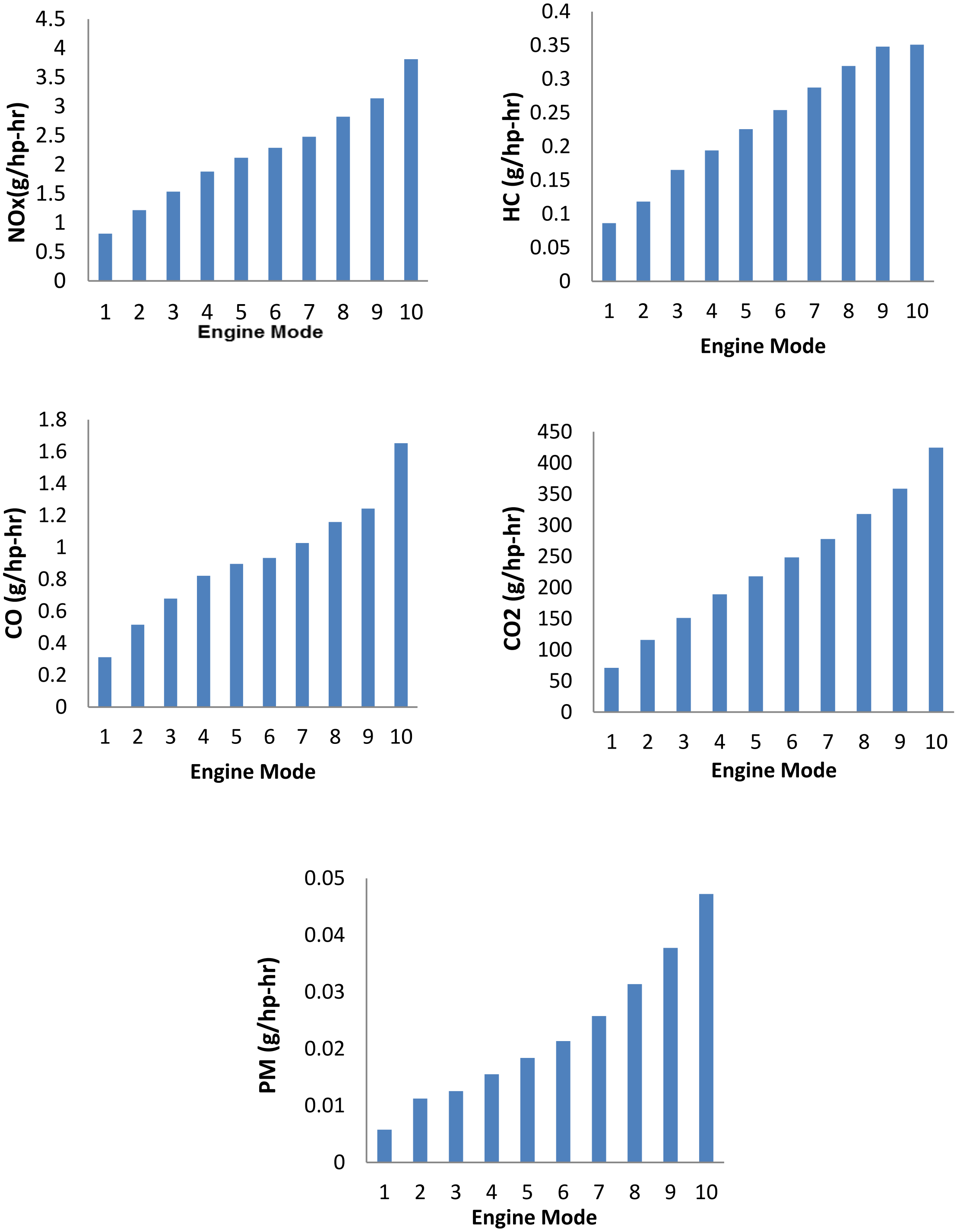

Figure 4.11. Average Emissions Rates in Each Engine Mode for Wheel Loader 1

In order to calculate the weighted average of fuel use and emissions rates of NO_x, HC, CO, CO_2, and PM, 32 items of equipment were classified by engine tier types. There are seven types of equipment and three engine tier types (tier 0, 1, and 2). Tier 0 consists of 5 vehicles (bulldozer 1 and 5, motor grader 4 and 5, and truck loader 2), tier 1(16 vehicles), tier 2 (10 vehicles) and tier 3 (1 vehicle). Since tier 3 only has 1 item of equipment, tier 3 is not considered in this calculation.

The estimations of average fuel use rates were conducted based on the equipment type and engine tier type. However, in this section, only the calculation of fuel use based on the equipment type is presented; meanwhile, the results of fuel use for a tier type basis are displayed in the Appendix. The averages of emission rates for fuel use, as grouped by the equipment types, are shown in Table 4.13. Furthermore, the overall tabulations for all seven types of equipment are summarized in Table 4.14.

Additionally, the estimations of average NO_x (g/hp-hr) in each engine mode for tier 0 are also given as shown in Table 4.15; whereas, the summaries of average emission rates for other pollutants in each tier are incorporated in the Appendix. The average fuel use and emission rates are used to calculate the weighted average fuel use and emission rates.

Table 4.13. Average Fuel Use Rates (g/hp-hr) for Wheel Loaders based on Equipment Type

Modes	**Average Fuel Use Rates FFi (g/hp-hr) based on Equipment Type**					
	WL 1	**WL 2**	**WL 3**	**WL 4**	**WL 5**	**Average**
1	0.0067	0.0056	0.0023	0.0028	0.0049	**0.0045**
2	0.0110	0.0121	0.0067	0.0068	0.0080	**0.0089**
3	0.0144	0.0158	0.0109	0.0091	0.0121	**0.0124**
4	0.0180	0.0194	0.0129	0.0117	0.0161	**0.0156**
5	0.0207	0.0232	0.0156	0.0137	0.0190	**0.0184**
6	0.0236	0.0267	0.0179	0.0162	0.0215	**0.0212**
7	0.0263	0.0305	0.0218	0.0178	0.0254	**0.0243**
8	0.0301	0.0346	0.0250	0.0213	0.0311	**0.0284**
9	0.0340	0.0385	0.0293	0.0254	0.0346	**0.0324**
10	0.0402	0.0423	0.0339	0.0329	0.0435	**0.0386**

Table 4.14. Summary of Average Fuel Use Rates (g/hp-hr) based on Equipment Type

Modes	Average Fuel Use Rates FFi (g/hp-hr) based on Equipment Type						
	BH	**BD**	**EX**	**MG**	**OFT**	**TL**	**WL**
1	0.0041	0.0060	0.0102	0.0034	0.0039	0.0102	0.0045
2	0.0076	0.0133	0.0134	0.0089	0.0117	0.0125	0.0089
3	0.0111	0.0192	0.0154	0.0132	0.0166	0.0173	0.0124
4	0.0135	0.0243	0.0177	0.0164	0.0211	0.0277	0.0156
5	0.0162	0.0282	0.0213	0.0199	0.0253	0.0323	0.0184
6	0.0187	0.0324	0.0234	0.0239	0.0290	0.0352	0.0212
7	0.0213	0.0372	0.0260	0.0275	0.0321	0.0397	0.0243
8	0.0243	0.0418	0.0283	0.0316	0.0350	0.0478	0.0284
9	0.0271	0.0471	0.0310	0.0366	0.0399	0.0558	0.0324
10	0.0302	0.0503	0.0329	0.0424	0.0431	0.0625	0.0386

The average emission rates of NO_x, in tier 0 in each engine mode were calculated from the total emission rates of NO_x from all equipment classified in engine tier 0. This comprised of 2 bulldozers, 2 motor graders, and 1 track loader (Table 4.15). The calculations were performed for each tier for all pollutants as presented in the Appendix.

Table 4.15. Average Emission Rates of NO_x (g/hp-hr) for Tier 0 based on Tier Type

Modes	Average Emission Rates of NO_x (g/hp-hr) for Tier 0					
	BD 1	**BD 5**	**MG 4**	**MG 5**	**TL 2**	**Average**
1	1.1298	1.2625	0.3637	1.1837	1.3695	**1.0618**
2	2.6919	2.8989	0.8152	2.5540	3.0581	**2.4036**
3	3.6514	3.9460	1.1493	3.5436	4.3217	**3.3224**
4	4.3427	5.1201	1.3455	4.3983	6.7458	**4.3905**
5	4.9418	6.0639	1.3392	4.8543	7.3315	**4.9061**
6	5.5779	6.8602	1.5778	5.7840	6.6888	**5.2977**
7	5.9454	7.5776	1.8595	7.0653	7.0560	**5.9008**
8	6.5944	9.0207	2.4554	8.3775	11.5483	**7.5992**
9	7.4800	11.2123	2.9158	9.7611	15.2835	**9.3305**
10	7.8471	13.0162	3.9970	10.2801	19.5845	**10.945**

As seen from the Tables 4.13-4.15, the average emission rates for fuel use and NO_x (g/hp-hr) typically follow the similar trends. As engine modes increased, the average fuel use and emission rates of NO_x also significantly increased. These behaviours also apply to other types of pollutants for each different tier. The calculations of emission rates of NO_x for tier 1 and 2 are displayed in the Appendix; however, the summaries are presented in Table 4.16.

In order to easily calculate the modal weighted average of NO_x emission for wheel loader, Table 4.16 presents the average fraction of time and average emission rates in one table. Thus, by multiplying the time and emission rates, the weighted average emission rates can be calculated. As shown in Table 4.14, tier 0 has the highest average emission rates compared to tier 1 and tier 2. What this basically means is that the higher the engine tier, the lower the emission rates.

Table 4.16. Summary of Average Time and Emission Rates of NO_x (g/hp-hr) based on Tier Type for Wheel Loader

Modes	**Average Time (Ti) of Wheel Loader**	**Average Emission Rates (EF_i) of NO_x (g/hp-hr)**		
		Tier 0	**Tier 1**	**Tier 2**
1	39.97%	1.0618	0.7395	0.8053
2	19.97%	2.4036	1.3587	1.1281
3	12.38%	3.3224	1.9171	1.3745
4	8.27%	4.3905	2.3604	1.5131
5	5.53%	4.9061	2.7199	1.6763
6	4.06%	5.2977	3.0150	1.8524
7	3.21%	5.9008	3.4367	1.9539
8	3.04%	7.5992	3.9325	2.2193
9	2.28%	9.3305	4.3663	2.4310
10	1.27%	10.9450	4.8511	2.7752

The modal weighted average fuel use and emission rates were calculated by multiplying the percentage of time and average fuel use rates and emission rates.These results were then totaled for all engine mode in order to obtain the total fuel use and emission rates, as shown in the formulas below.

$$FF\ wt.av = \sum_{i=1}^{10} Ti\ x\ FFi$$

$$EF\ wt.av = \sum_{i=1}^{10} Ti\ x\ EFi$$

The distributions of weighted average fuel use and emission rates of NO_x (g/hp-hr) in each engine mode for each equipment type and engine tier type are summarized in Table 4.17 and 4.18. Based on Table 4.17, there is variability in the weighted average fuel use rates for each type of equipment in each engine mode. In summary, the track loaders comsumed more fuel use than other types of equipment, accounting for 0.0332 grams per horsepower-hours, followed by bulldozer as the second consumptive in fuel use (0.0224 g/hp-hr).

Table 4.17. Summary of Modal Weighted Average Fuel Use Rates (g/hp-hr) based on Equipment Type

Modes	**Weighted Average Fuel Use Rates (Ti x FFi) (g/hp-hr)**						
	BH	**BD**	**EX**	**MG**	**OFT**	**TL**	**WL**
1	0.0012	0.0015	0.0032	0.0008	0.0028	0.0028	0.0018
2	0.0020	0.0021	0.0007	0.0006	0.0012	0.0006	0.0018
3	0.0026	0.0030	0.0012	0.0013	0.0008	0.0007	0.0015
4	0.0013	0.0022	0.0015	0.0018	0.0006	0.0011	0.0013
5	0.0006	0.0019	0.0021	0.0019	0.0006	0.0025	0.0010
6	0.0004	0.0021	0.0025	0.0029	0.0006	0.0046	0.0009
7	0.0003	0.0019	0.0025	0.0034	0.0005	0.0034	0.0008
8	0.0005	0.0017	0.0024	0.0019	0.0006	0.0038	0.0009
9	0.0004	0.0032	0.0020	0.0017	0.0005	0.0052	0.0007
10	0.0003	0.0029	0.0007	0.0015	0.0004	0.0085	0.0005
Total	**0.0096**	**0.0224**	**0.0188**	**0.0178**	**0.0088**	**0.0332**	**0.0112**

Based on Table 4.18, it can be seen that tier 0 emits the highest amount of emission rates of NO_x compared to tier 1 and 2, accounting for 2.9372 g/hp-hr in total. Tier 1 is the second largest contributor of NO_x, followed by tier 2. The former comprises of 1.6632, while the latter consists of 1.2312 g/hp-hr.

Table 4.18. Summary of Modal Weighted Average Emission Rates of NO_x (g/hp-hr) for each tier

Modes	Modal Wgt. Average NO_x (g/hp-hr) for Wheel Loader		
	Tier 0	**Tier 1**	**Tier 2**
1	0.4244	0.2956	0.3219
2	0.4800	0.2713	0.2253
3	0.4113	0.2373	0.1702
4	0.3631	0.1952	0.1251
5	0.2713	0.1504	0.0927
6	0.2151	0.1224	0.0752
7	0.1894	0.1103	0.0627
8	0.2310	0.1195	0.0675
9	0.2127	0.0996	0.0554
10	0.1390	0.0616	0.0352
Total	**2.9373**	**1.6632**	**1.2312**

To conclude, the calculation for modal weighted average emission rates were conducted for emission rates of NO_x, HC, CO, CO_2, and PM. This section only highlights the weighted average emission rates of NO_x based on engine tier types; however, the summary of all types of equipment is illustrated in Table 4.19. Table 4.19 and Figure 4.12 show that the track loaders emit the highest amount of NO_x for engine tier 0 compared to other types of equipment, as well as the emissions in tier 1 and 2. In contrast, the off-road trucks emit the lowest amount of NO_x emissions for each tier. The summary of modal weighted average emission rates of HC, CO, CO_2, and PM are presented in the Appendix.

Table 4.19. Summary of Modal Weighted Average Emission Rates of NO_x (g/hp-hr) for each tier

Equipment	Total Wgt. Average NO_x (Ti x EFi) in g/hp-hr		
	Tier 0	**Tier 1**	**Tier 2**
BH	2.9238	1.6548	1.2353
BD	4.0997	2.1964	1.4743
EX	4.1799	2.2885	1.5003
MG	4.3384	2.3760	1.5415
OT	1.9944	1.1942	1.0153
TL	5.2489	2.7128	1.7059
WL	2.9374	1.6633	1.2312
Total	**3.6746**	**2.0123**	**1.3863**

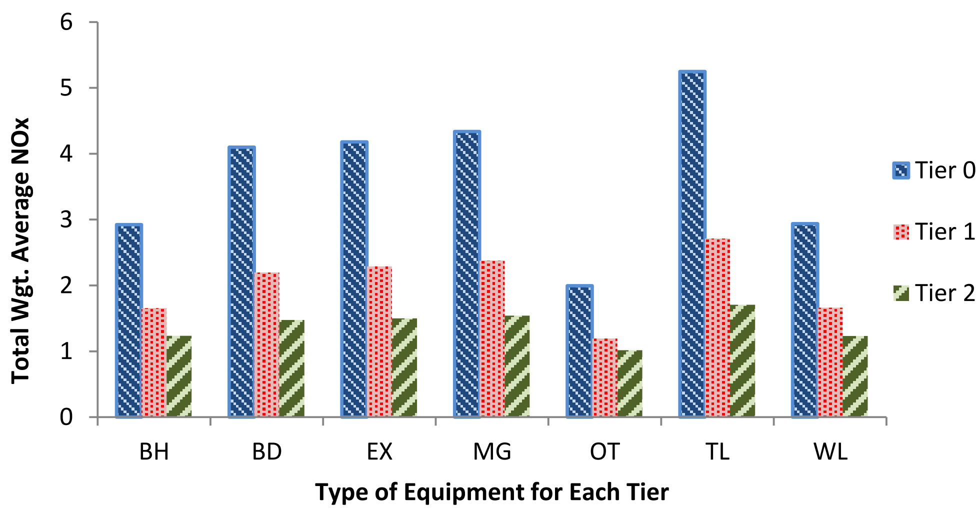

Figure 4.12. Total Weighted Average of NO_x based on Equipment Type and Tier Type

4.3.2 Simple Linear Regression (SLR)

As mentioned in the methodology, SLR was performed for each item of equipment. Although SLR models were performed for each item of equipment, this section fully highlights the SLR models for wheel loaders and excavators for brevity, and the other equipment is presented in the Appendix. Based on their high correlation values, SLR models were developed using MAP as a predictor variable to predict fuel use and emission rates of each pollutant. Figure 4.13 illustrates the relationship between fuel use and emission rates of each pollutant to MAP. The overall models are summarized in Table 4.20.

Table 4.20. Summary of SLR Models for Wheel Loaders

Equipment	Response	Equation	R^2
Wheel Loader 1	Fuel Use	$Y_1 = 5.0514\ X_1 + 0.6197$	0.8411
	NO_x	$Y_2 = 0.1338\ X_1 + 0.0253$	0.6694
	HC	$Y_3 = 0.0137\ X_1 + 0.0029$	0.7371
	CO	$Y_4 = 0.0582\ X_1 + 0.0096$	0.4689
	CO_2	$Y_5 = 15.869\ X_1 + 1.9392$	0.8408
	PM	$Y_6 = 1.6186\ X_1 + 0.1296$	0.8082
Wheel Loader 2	Fuel Use	$Y_1 = 5.3330\ X_1 + 0.3938$	0.9435
	NO_x	$Y_2 = 0.1776\ X_1 + 0.0213$	0.8735
	HC	$Y_3 = 0.0157\ X_1 + 0.0063$	0.7390
	CO	$Y_4 = 0.0017X_1 + 0.0102$	0.0125
	CO_2	$Y_5 = 16.83\ X_1 + 1.2122$	0.9433
	PM	$Y_6 = 1.8032X_1 + 0.0774$	0.8373
Wheel Loader 3	Fuel Use	$Y_1 = 4.0493\ X_1 + 0.1357$	0.8851
	NO_x	$Y_2 = 0.1344\ X_1 + 0.0133$	0.8246
	HC	$Y_3 = 0.0063X_1 + 0.0011$	0.6861
	CO	$Y_4 = 0.0074X_1 + 0.0037$	0.3392
	CO_2	$Y_5 = 12.505\ X_1 + 0.4110$	0.8851
	PM	$Y_6 = 0.6665\ X_1 + 0.004$	0.8446
Wheel Loader 4	Fuel Use	$Y_1 = 3.1426\ X_1 + 0.2368$	0.8548
	NO_x	$Y_2 = 0.1083\ X_1 + 0.0159$	0.7840
	HC	$Y_3 = 0.0036X_1 + 0.0033$	0.1341
	CO	$Y_4 = 0.0057X_1 + 0.0018$	0.3086
	CO_2	$Y_5 = 9.9274\ X_1 + 0.7368$	0.8546
	PM	$Y_6 = 1.0348X_1 + 0.0438$	0.7486
Wheel Loader 5	Fuel Use	$Y_1 = 4.911\ X_1 + 0.2673$	0.9479
	NO_x	$Y_2 = 0.125\ X_1 + 0.0110$	0.8756
	HC	$Y_3 = 0.0046X_1 + 0.0018$	0.4271
	CO	$Y_4 = 0.0175X_1 + 0.0048$	0.4966
	CO_2	$Y_5 = 15.503X_1 + 0.8337$	0.9478
	PM	$Y_6 = 1.0348X_1 + 0.0392$	0.8524

X_1 = MAP

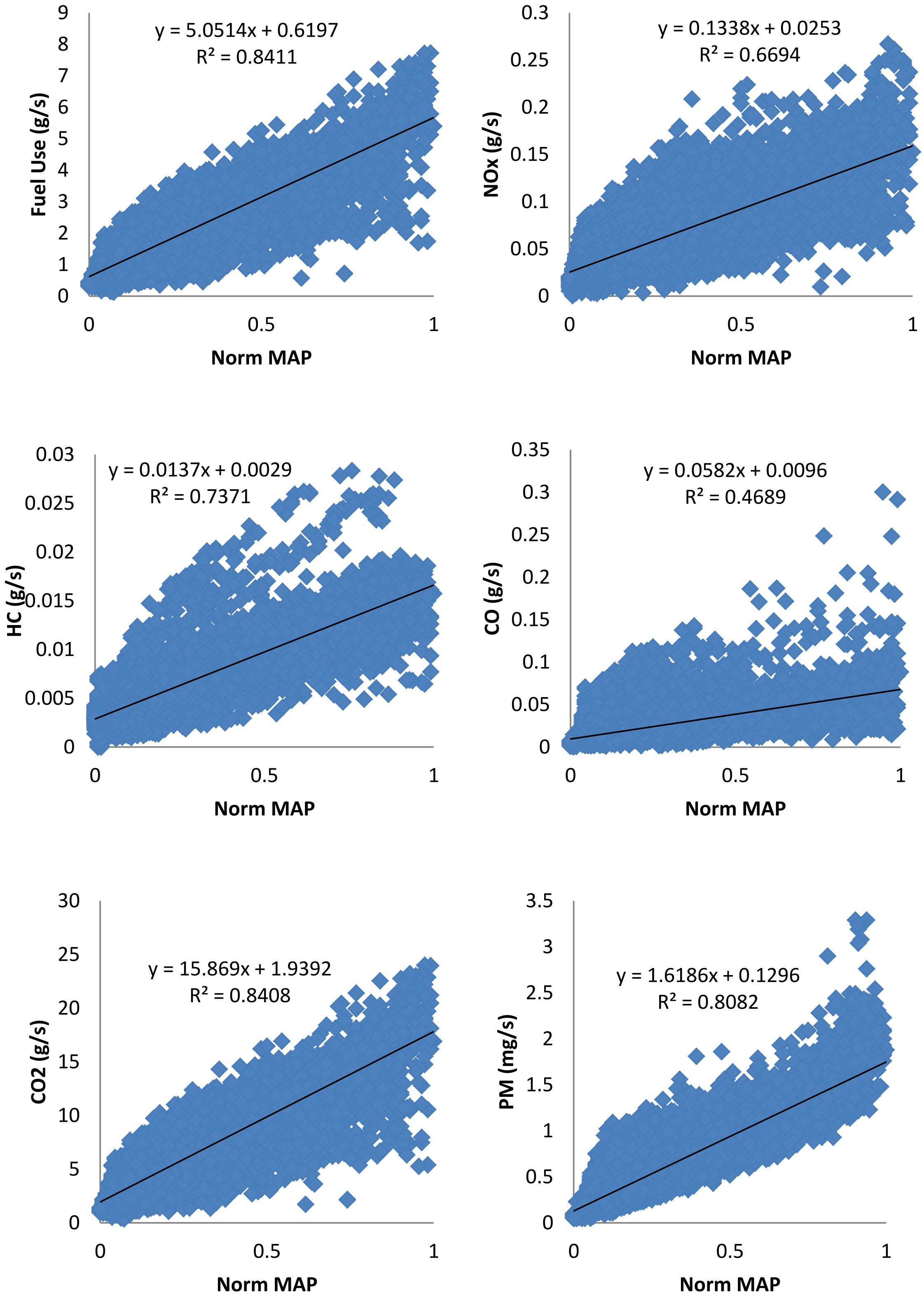

Figure 4.13. The SLR Model for Wheel Loader 1

Table 4.20 and 4.21 present the results of the SLR models for five wheel loaders and three excavators. These models are based on a set of observations of second-by-second, real-world fuel use and emissions data. In this study, the SLR models were developed based on more than 11,000 observations on a second-by-second basis for three wheel loaders, and the other two wheel loaders had less than 7,000 observations. This implies that the data are relatively reliable to develop the models. Based on the coefficient of determination (R^2), these models mostly accounted for a high percentage of the variability in the data for fuel use, NO_x, CO_2, and PM. In other words, MAP accounted for approximately more than 80% for the variation in the fuel use and emission rates of NO_x, CO_2, and PM for all wheel loaders. CO had the lowest R^2 values, indicating high variability in the data, and therefore was more difficult to predict.

Similarly, for three excavators, the fuel use and emission rates of NO_x, CO_2, and PM primarily had higher values of R^2 compared to emission rates of HC and CO. This indicates that the fuel use and emission rates of NO_x, CO_2, and PM had a higher percentage of variability, and thus are relatively easier to predict. Meanwhile, MAP only accounts for less than 50% for the variation in the emission rates of HC and CO. This indicates that approximately 50% of the variation is explained by other factors. Overall, other equipment such as backhoes, bulldozers, off-road trucks, track loaders, and motor graders as summarized in the Appendix, show the same trends. The SLR models for HC and CO had lower R^2 values, and therefore were much more difficult to predict.

Table 4.21. Summary of SLR Models for Excavators

Equipment	Response	Equations	R^2
Excavator 1	Fuel Use	$Y_1 = 9.9429\ X_1 + 0.4704$	0.9819
	NO_x	$Y_2 = 0.3545\ X_1 + 0.0242$	0.9481
	HC	$Y_3 = 0.0054\ X_1 + 0.0024$	0.3505
	CO	$Y_4 = 0.0175\ X_1 + 0.0066$	0.5427
	CO_2	$Y_5 = 31.431\ X_1 + 1.4720$	0.9819
	PM	$Y_6 = 3.8619\ X_1 + 0.1076$	0.8810
Excavator 2	Fuel Use	$Y_1 = 6.4485X_1 + 0.5302$	0.9632
	NO_x	$Y_2 = 0.1202\ X_1 + 0.0209$	0.8499
	HC	$Y_3 = 0.0083\ X_1 + 0.0031$	0.3901
	CO	$Y_4 = 0.0239X_1 + 0.0142$	0.2194
	CO_2	$Y_5 = 20.358X_1 + 1.6475$	0.9633
	PM	$Y_6 = 1.8463X_1 + 0.0354$	0.8876
Excavator 3	Fuel Use	$Y_1 = 3.9492\ X_1 + 0.1231$	0.9302
	NO_x	$Y_2 = 0.1231\ X_1 + 0.0098$	0.8755
	HC	$Y_3 = 0.0084X_1 + 0.0021$	0.1936
	CO	$Y_4 = 0.0051X_1 + 0.0055$	0.0183
	CO_2	$Y_5 = 12.468\ X_1 + 0.3748$	0.9294
	PM	$Y_6 = 1.0842\ X_1 - 0.0099$	0.3326

X_1 = MAP

4.3.3 Multiple Linear Regression (MLR)

Predictive fuel use and emission rates models of each pollutant for each item of equipment were developed using three input engine parameters, namely MAP, RPM and IAT. For brevity, this section only describes the results of MLR models for wheel loaders and excavators; meanwhile, the other equipment is provided in the Appendix. Based on the correlation variables in Tables 4.9 and 4.10, MAP and RPM are highly correlated to fuel use and emission rates for most of pollutants. Even though IAT has a lower correlation to fuel use and emission rates, IAT was still used as an input variable for the MLR models because it may still have some predictive power.

Although correlation variables have shown that three predictor variables have a significant impact to the response variable, the tests of significance of variables were still conducted. In order to evaluate the significance of variables in MLR, the stepwise selection method was conducted for fuel use rates in wheel loader 1 as an example. The results for MLR models as well as the statistical tests results were obtained by using the Minitab software.

As shown in Table 4.23, all variables are statistically significant due to their lower p-values which are less than 5% of their level of significance. If the variables have p-values greater than 0.05, they will be excluded in the model. Based on p-values, it was found that three predictor variables are statistically significant; thus they are significant for predicting the response variable.

The p-values show the level of significance of hypothesis tests. Moreover, the values of sum of squares and mean squares are used to show the variation of models. Table 4.22 and 4.23 present the analysis of variance and analysis of maximum likelihood estimates. T-test was performed in order to reject the null hypothesis. The higher the value of T-tests, it is more likely to reject the null hypothesis. The MLR models including the R^2 are summarized in Table 4.24 and 4.25.

Table 4.22. Analysis of Variance for Fuel Use Rates for wheel loader 1

Source	**DF**	**SS**	**Mean Square**	**P-value**
Model	3	19371	4169.11	< .0001
Error	15221	3113.7	0.046	
Corrected Total	15224	22485.2		

Table 4.23. Analysis of Maximum Likelihood Estimates for Fuel Use Rates

Source	**DF**	**Estimate**	**St.Error**	**t-value**	**P-value**	**VIF**
Intercept	1	-4.952	0.028690	-143.02	0.000	-
MAP	1	0.0392	0.000361	89.78	0.000	6.233
RPM	1	0.00131	0.000021	35.85	0.000	6.103
IAT	1	-0.0045	0.000733	34.87	0.000	1.053

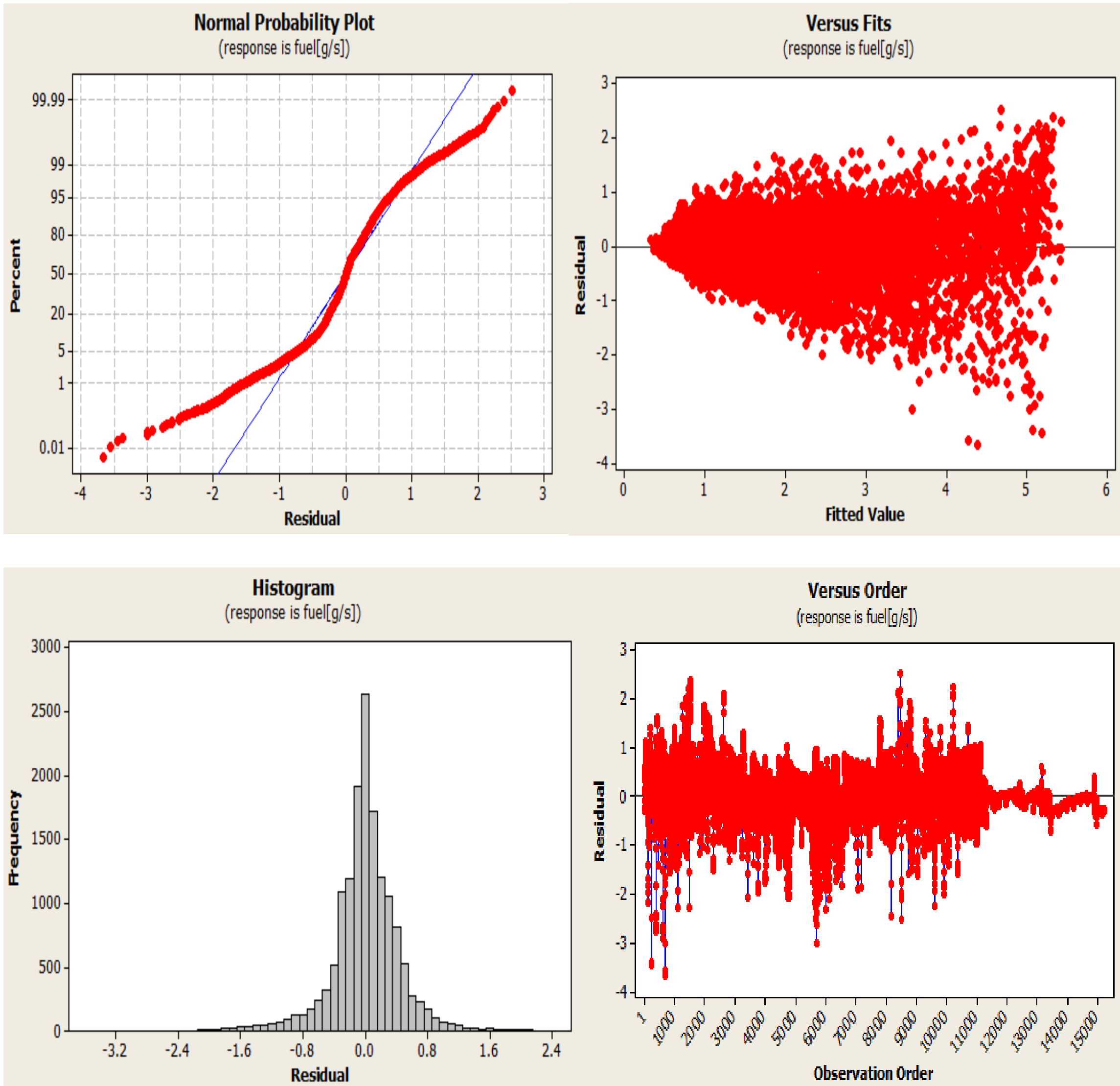

Figure 4.14. The Residual plots to Test the MLR Model before Transformation

Figure 4.14 illustrates the residual plots of the fuel use model in wheel loader 1 given as example. The residual plots are comprised of normal probability plot of the residuals, residual versus the fitted values, histogram of the residual, and residuals versus the order of data. The normal probability plot indicates that the residuals are not normally distributed. Based on the residuals versus fitted values graph, it shows that the residuals do not have constant variance. The residuals versus the order of data present the interdependence among the residuals. Overall, the results show that the assumptions used in the MLR were not normally distributed.

In order to remedy the model, the Box-Cox transformation was applied using the Minitab software. This transformation aims to produce the normally distributed data. Using the similar sets of observations, the normality plots were conducted. The results show that there is a better improvement on the model indicated by the normal probability plot that is relatively close to normal. However, the plot does not fully present the linear relationship on the normality graph. Due to the large sample sizes (=15225 observations), the Box-Cox transformation can be ignored. In this research the MLR were developed for the purpose of estimation model only, not for finding the confidence interval or developing the hypothetical tests on the models. Thus, the MLR predictive models are presented without using the transformation.

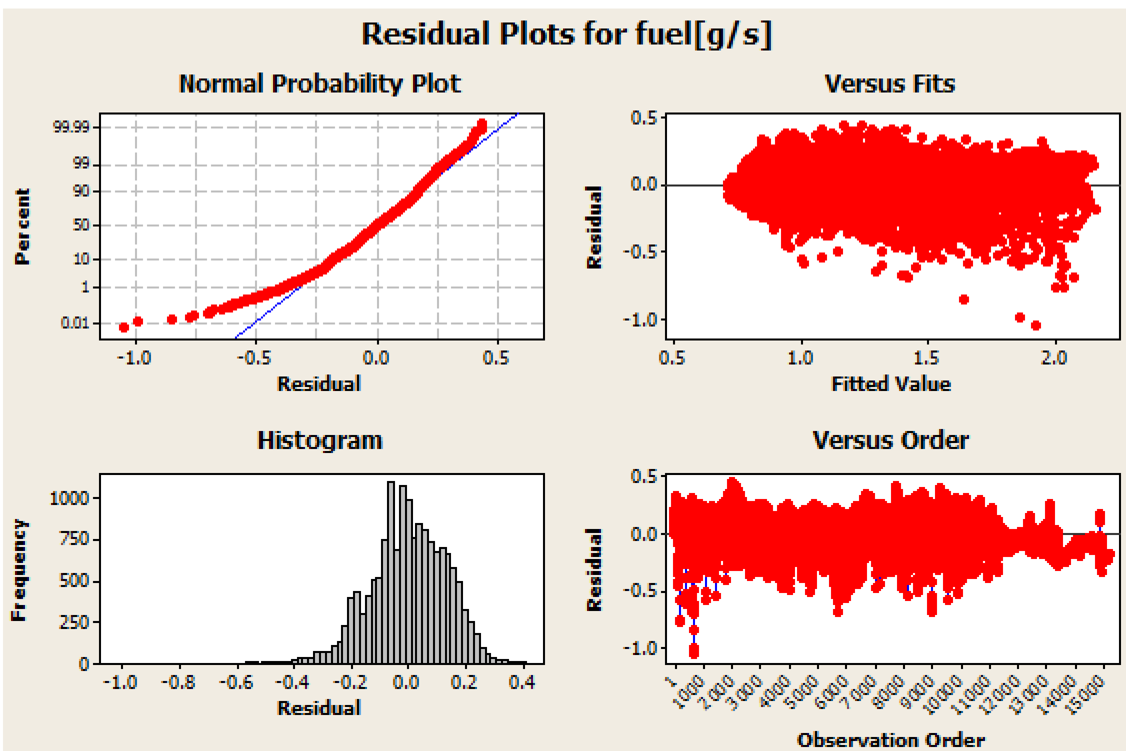

Figure 4.15. The Residual plots to test the MLR model after Transformation

Multicollinearity among predictor variables was also investigated by the software Minitab as shown by the value of variation inflation factor (VIF) in Table 4.23. It was found that VIF values for each predictor variable of fuel use model in wheel loader 1 are less than 10, indicating that there is moderate collinearity in the model. Thus, the three predictor variables can be used in the model.

Table 4.24. Summary of MLR Models for Wheel Loaders

Equipment	Response	Equations	R^2
Wheel Loader 1	Fuel Use	$Y_1 = -4.07 + 0.032\ X_1 + 0.0008X_2 + 0.0254X_3$	0.860
	NO_x	$Y_2 = -0.121 + 0.00084\ X_1 + 0.00002\ X_2 + 0.00151\ X_3$	0.719
	HC	$Y_3 = -0.0042 + 0.000061\ X_1 + 4.13E\text{-}6\ X_2 – 0.0001X_3$	0.802
	CO	$Y_4 = -0.05 + 0.000302\ X_1 + 0.000013X_2 + 0.00052X_3$	0.491
	CO_2	$Y_5 = -12.8 +0.1003X_1+ 0.0024\ X_2 + 0.08X_3$	0.859
	PM	$Y_6 = -1.78 + 0.0193X_1 – 0.00034\ X_2 + 0.009X_3$	0.849
Wheel Loader 2	Fuel Use	$Y_1 = -4.952 + 0.0392\ X_1 + 0.0013\ X_2\text{-}\ 0.0045\ X_3$	0.960
	NO_x	$Y_2 = -\ 0.16 + 0.00011\ X_1 +0.0006\ X_2 +0.0008X_3$	0.902
	HC	$Y_3 = -0.0105+ 0.000086X_1 +5.68E\text{-}6X_2 + 0.00008X_3$	0.780
	CO	$Y_4 = 0.0123 + 0.000028\ X_1 -\ 0.00024\ X_3$	0.134
	CO_2	$Y_5 = -15.66+ 0.124X_1 + 0.004\ X_2 – 0.014\ X_3$	0.959
	PM	$Y_6 = -1.52 + 0.0152X_1+ 0.00036X_2 – 0.016X_3$	0.868
Wheel Loader 3	Fuel Use	$Y_1 = -\ 2.63 + 0.026X_1 + 0.00048X_2 – 0.0073X_3$	0.898
	NO_x	$Y_2 = -0.07 + 0.00087X_1 + 0.000013X_2 -\ 0.00085X_3$	0.841
	HC	$Y_3 = -0.005 +0.000023X_1 +2.0E\text{-}6X_2 + 0.00011X_3$	0.776
	CO	$Y_4 = -0.0027+0.000013X_1 +3.26E\text{-}6X_2 + 0.00012X_3$	0.392
	CO_2	$Y_5 = -7.76 +0.076X_1 + 0.0016X_2\text{-}\ 0.030X_3$	0.886
	PM	$Y_6 = -0.38 +0.0031X_1 +0.000132X_2 -0.00192X_3$	0.871
Wheel Loader 4	Fuel Use	$Y_1 = -1.5+0.0197X_1+0.00082X_2– 0.0594X_3$	0.908
	NO_x	$Y_2 = -0.024 +0.0007X_1 +0.000024X_2 – 0.003X_3$	0.843
	HC	$Y_3 = -0.009+0.000023X_1 +1.61E\text{-}6X_2 +0.00045X_3$	0.253
	CO	$Y_4 = 0.0075+0.00003X_1+1.59E\text{-}6X_2\text{-}0.00056X_3$	0.477
	CO_2	$Y_5 = -4.74+0.062X_1 +0.0026X_2 -0.19X_3$	0.908
	PM	$Y_6 = -0.583 + 0.0071X_1 + 0.00021X_2 -0.0163X_3$	0.793
Wheel Loader 5	Fuel Use	$Y_1 = -4.202+0.044X_1+0.00064X_2\text{-}0.012X_3$	0.957
	NO_x	$Y_2 = -0.094 + 0.0011X_1 + 0.00002X_2 -0.0006X_3$	0.893
	HC	$Y_3 = -0.0038 +0.00002X_1 +2.31E\text{-}6X_2+0.000045X_3$	0.507
	CO	$Y_4 = -0.012 +0.000124X_1 +4.6E\text{-}6X_2$	0.520
	CO_2	$Y_5 = -13.27 +0.138X_1 + 0.002X_2 -0.037X_3$	0.957
	PM	$Y_6 = -0.99 +0.0134X_1 – 0.0002X_2– 0.0028X_3$	0.867

X_1 = MAP, X_2 = RPM, X_3 = IAT

Table 4.25. Summary of MLR Models for Excavators

Equipment	Response	Equations	R^2
Exc 1	Fuel Use	Y_1 = -5.748 + 0.0728 X_1 + 0.000301X_2 - 0.0296X_3	0.9848
	NO_x	Y_2 = -0.2093 + 0.00247X_1 - 0.00002 X_2 + 0.000176X_3	0.9537
	HC	Y_3 = 0.0056 + 0.000034 X_1 + 2.64E-6 X_2 - 0.00021X_3	0.5821
	CO	Y_4 = -0.00003 + 0.000041 X_1 + 0.000011X_2 - 0.00018X_3	0.8007
	CO_2	Y_5 = -18.21 +0.230X_1+ 0.00093 X_2 - 0.093X_3	0.9847
	PM	Y_6 = -2.21 + 0.0293X_1 - 0.0136X_3	0.8799
Exc 2	Fuel Use	Y_1 = -5.07 + 0.0524 X_1 + 0.00069 X_2- 0.0085 X_3	0.9716
	NO_x	Y_2 = - 0.089 + 0.00082 X_1 +0.000024 X_2 +0.000134X_3	0.8838
	HC	Y_3 = -0.0024+ 0.000048X_1 +3.14E-6X_2 - 0.00008X_3	0.4021
	CO	Y_4 = -0.0004 + 0.000013 X_1 + 0.000019 X_2- 0.00024 X_3	0.3395
	CO_2	Y_5 = -16.05+ 0.166X_1 + 0.00213 X_2 – 0.0262 X_3	0.9715
	PM	Y_6 = -1.53 + 0.021X_1 - 0.00026X_2 – 0.0064X_3	0.9125
Exc 3	Fuel Use	Y_1 = -2.343 + 0.0295X_1 + 0.00006X_2 - 0.007X_3	0.9346
	NO_x	Y_2 = -0.079 + 0.00096X_1 – 5.33E-6X_2 + 0.000096X_3	0.8798
	HC	Y_3 = -0.0071 +0.000034X_1 +1.57E-6X_2 + 0.000094X_3	0.2459
	CO	Y_4 = 0.0094 - 0.00005X_1 +9.92E-6X_2 - 0.00018X_3	0.0964
	CO_2	Y_5 = -7.409 +0.0932X_1 + 0.00017X_2 - 0.022X_3	0.9338
	PM	Y_6 = -1.142 +0.0081X_1 - 0.00013X_2 +0.0104X_3	0.3903

X_1 = MAP, X_2 = RPM, X_3 = IAT

Table 4.24 and 4.25 summarize the models for fuel use and emission rates for all wheel loaders and excavators. Generally, the MLR models for wheel loaders yielded higher R^2 values for their respective response variables. The MLR R^2 values for fuel use and emission rates for NO_x, CO_2, and PM had higher R^2 values, indicating that the models perform well. The model for HC and CO, however, accounted for less than 50% of the variability in the data; thus, the MLR models for wheel loaders also indicate that the emission rates of HC and CO are more difficult to predict compared to fuel use and the other pollutants.

Like wheel loaders, the MLR models of fuel use and emission rates for three excavators typically show similar results. Based on the coefficient of determination (R^2), the fuel use and emission rates of NO_x, CO_2 and PM also had a high percentage of variability in the data as shown by high values of R^2, but having lower R^2 values for HC and CO. To conclude, most HDD equipment examined in this research show that the MLR models for fuel use and emission rates of NO_x, CO_2, and PM had high values of R^2, indicating that the models perform well, and therefore are relatively easier to predict compared with the emission rates of HC and CO.

4.3.4 Artificial Neural Networks (ANN)

As mentioned in the previous section, the ANN models were trained through an iterative process by learning the complexities between inputs and outputs. The inputs consist of three engine performance data (MAP, RPM, and IAT); meanwhile, the outputs were the individuals of fuel use and emission rates of NO_x, HC, CO, CO_2, and PM. The models were performed by using the multilayer feed forward network (MLF). For wheel loader 1 given as an example, the numbers of observations consist of 15226 data points, 60% of points for training data and 40% for testing data. The results indicate that approximately 15% of the training data and 17% of the testing data produce bad predictions. Bad predictions indicate the the number of observations that are not matching between the predicted values from the model versus the actual values.

Unlike the SLR and MLR approaches, ANN does not produce equations for each response variables because they are developed in the network's hidden layer. Based on these results, ANN produced networks that were highly accurate and precise and unbiased for fuel use, NO_x, HC, CO_2, and PM. As with the SLR and MLR models, CO was the most difficult of the pollutants to predict. However, compared to the SLR and MLR approaches, the ANN methodologies show the most highly precise and accurate with the lowest bias.

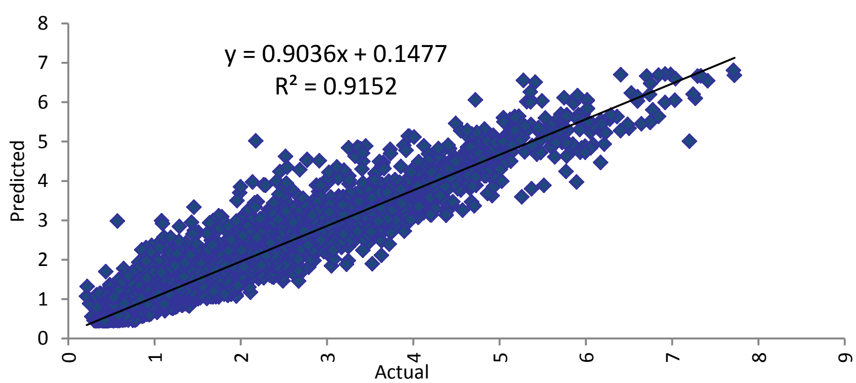

Figure 4.16. The Model for Training Data for Fuel Use in Wheel Loader 1

Figure 4.16 illustrates the scatter plot for the predicted values versus the actual data in the training data. It can be seen that there is a strong positive linear relationship between the predicted and actual values as indicated by the high value of coefficient determination (R^2) accounting for more than 90% of variability. The model also indicates higher accuracy (m= 0.9036) with lower bias (b= 0.148). This indicates that the model in the training data performs well. The summary of the overall results for five wheel loaders are shown in Table 4.26.

Table 4.26. Summary of Training Data for Wheel Loaders

Equipment	**Response**	**m**	**b**	**R^2**
Wheel Loader 1	Fuel Use	0.9036	0.1477	0.9152
	NO_x	0.8058	0.0095	0.8320
	HC	0.8972	0.0005	0.9129
	CO	0.5854	0.0083	0.6132
	CO_2	0.8982	0.4792	0.9112
	PM	0.9017	0.0387	0.9210
Wheel Loader 2	Fuel Use	0. 9672	0.0389	0 .9718
	NO_x	0.9459	0.0028	0.9446
	HC	0.8613	0.0013	0.8800
	CO	0.6816	0.0034	0.7353
	CO_2	0.9673	0.1283	0.9716
	PM	0.9589	0.0137	0.9668
Wheel Loader 3	Fuel Use	0.9390	0.0475	0.9514
	NO_x	0.9157	0.0030	0.9287
	HC	0.8921	0.0002	0.9077
	CO	0.7245	0.0014	0.7564
	CO_2	0.9611	0.0899	0.9715
	PM	0.9570	0.0041	0.9681
Wheel Loader 4	Fuel Use	0.9564	0.0406	0.9617
	NO_x	0.9301	0.0030	0.9406
	HC	0.7858	0.0009	0.7997
	CO	0.7351	0.0008	0.7604
	CO_2	0.9539	0.1384	0.9595
	PM	0.9615	0.0103	0.9652
Wheel Loader 5	Fuel Use	0.9758	0.0101	0.9797
	NO_x	0.9435	0.0008	0.9490
	HC	0.6476	0.0008	0.6641
	CO	0.6445	0.0023	0.6931
	CO_2	0.9808	0.0072	0.9834
	PM	0.9117	0.0080	0.9293

In order to check the residuals of the models in the training data, the normality plots that include the histogram of residuals and the residual versus the predicted values were also conducted using the @Risk software. The histogram of the residuals is likely to be symmetric; meanwhile, the residual vs predicted graph tends to have a constant variance.

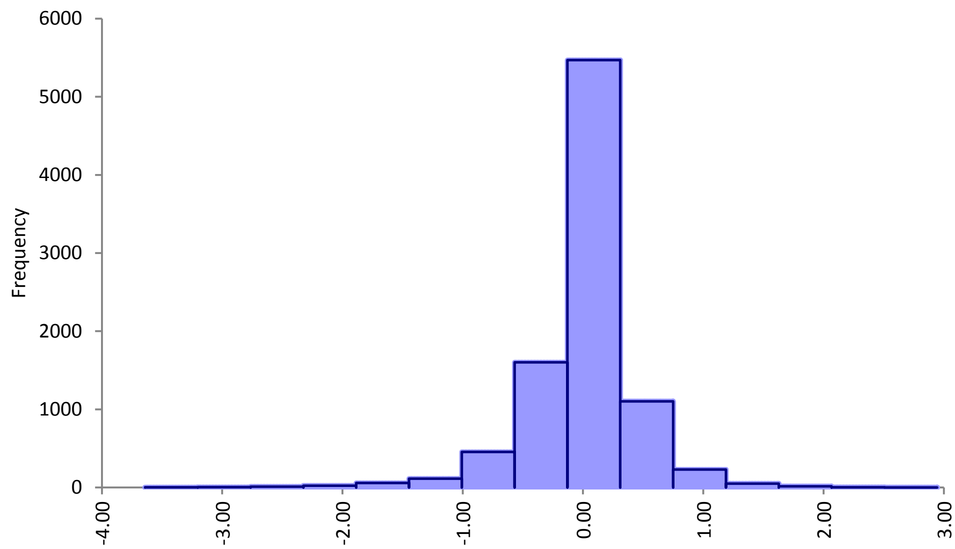

Figure 4.17. Histogram of Residuals for Fuel Use in Wheel Loader 1 (Training Data)

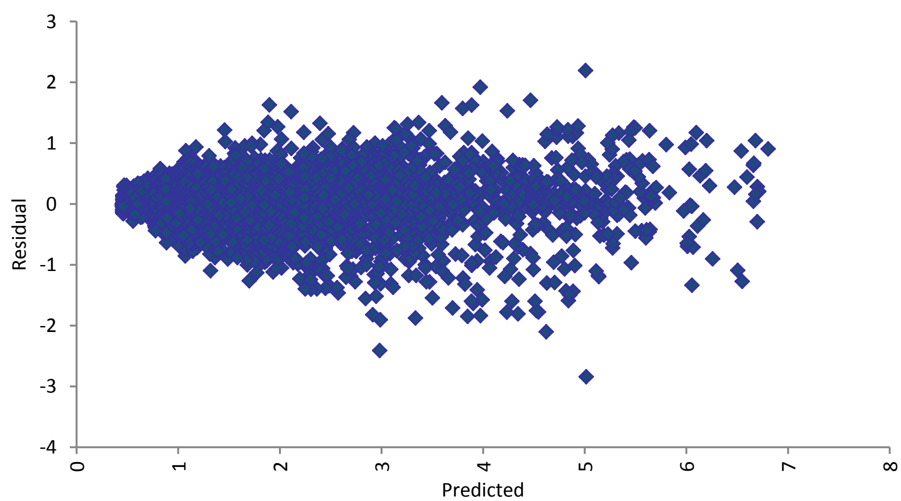

Figure 4.18. Residuals vs Predicted for Fuel Use in Wheel Loader 1 (Training Data)

4.3.5 Model Validation

Model validations were developed for all items of equipment in order to compare and evaluate the performance of SLR, MLR, and ANN methodologies. The models were validated by plotting the predicted values of the models versus the actual data for each model and fitting a trend line to the data. For each trend line, the values of accuracy (m), bias (b), and precision (R^2) were determined.

4.3.5.1 Model Validation for SLR

As mentioned, the model validations for 32 items of equipment were developed by plotting the predicted values of the models versus the actual data in each model and then fitting the trend line to the data. For brevity, the model validation for fuel use and emission rates for each pollutant in wheel loader 1 was illustrated by the example as seen in Figure 4.18. Based on the results, the model validation yielded higher accuracy and precision for fuel use and emission rates of NO_x, HC, CO_2, and PM, but lower accuracy and precision for CO. In terms of bias, each model resulted in lower bias, indicating that the models performed well. The summary of model validations for each wheel loader for fuel use and emission rates in terms of accuracy, precision, and bias was shown in Table 4.27.

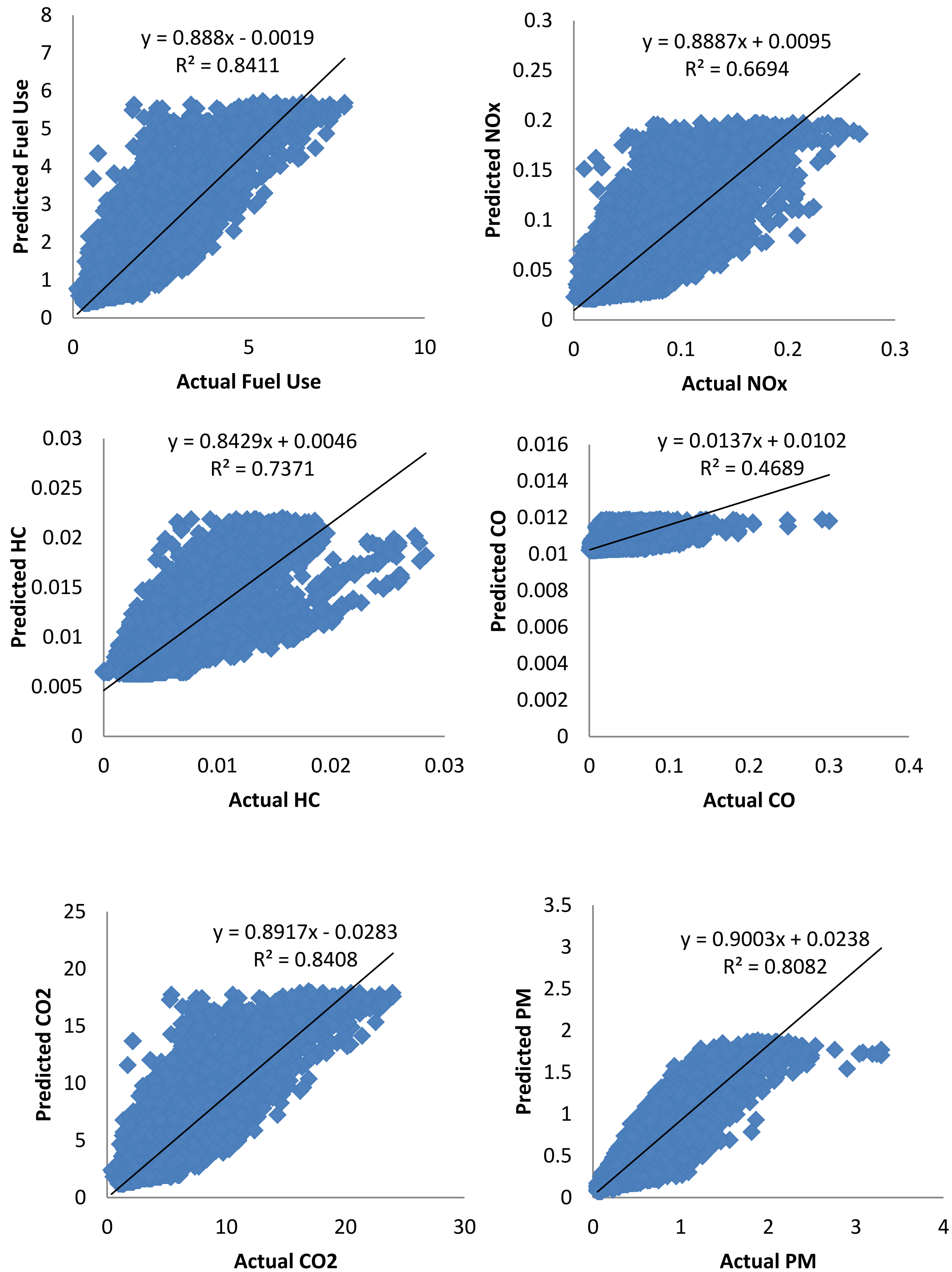

Figure 4.19. Model Validation using SLR for Fuel Use and Emission Rates in Wheel Loader 1

Table 4.27. Summary of Model Validation using SLR for Wheel Loaders

Equipment	**Response**	**SLR**		
		m	**b**	**R^2**
Wheel Loader 1	Fuel Use	0.888	-0.002	0.84
	NO_x	0.889	0.010	0.67
	HC	0.843	0.005	0.74
	CO	0.014	0.010	0.47
	CO_2	0.892	-0.028	0.84
	PM	0.900	0.024	0.81
Wheel Loader 2	Fuel Use	0.944	0.078	0.94
	NO_x	0.874	0.007	0.87
	HC	0.738	0.002	0.74
	CO	0.012	0.010	0.01
	CO_2	0.943	0.245	0.94
	PM	0.837	0.067	0.84
Wheel Loader 3	Fuel Use	0.885	0.096	0.89
	NO_x	0.825	0.006	0.82
	HC	0.688	0.001	0.69
	CO	0.337	0.003	0.34
	CO_2	0.885	0.295	0.89
	PM	0.845	0.019	0.84
Wheel Loader 4	Fuel Use	0.8851	0.096	0.85
	NO_x	0.8247	0.006	0.78
	HC	0.6883	0.001	0.13
	CO	0.3371	0.003	0.31
	CO_2	0.8851	0.295	0.85
	PM	0.8446	0.019	0.75
Wheel Loader 5	Fuel Use	0.948	0.036	0.95
	NO_x	0.875	0.003	0.88
	HC	0.424	0.001	0.43
	CO	0.496	0.003	0.50
	CO_2	0.948	0.113	0.95
	PM	0.853	0.019	0.85

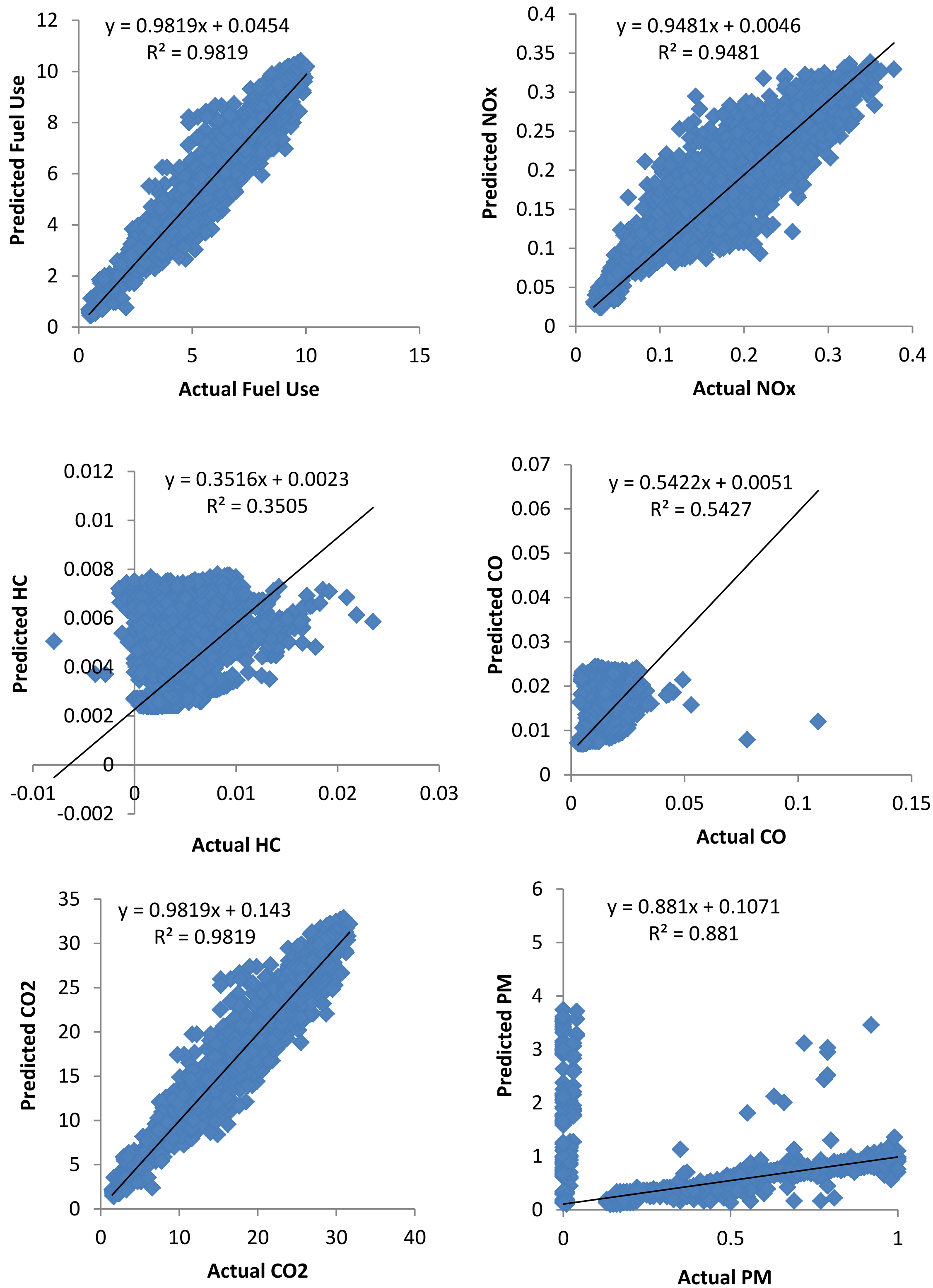

Figure 4.20. Model Validation using SLR for Fuel Use and Emission Rates in Excavator 1

Similarly, Figure 4.20 illustrates the plotting lines between the predicted and actual values for excavators related to the fuel use and emission rates of each pollutant. It was found that the models produced higher accuracy and precision for fuel use, CO, CO_2, and PM, but lower for HC and CO. The values of bias for each model are likely to be low, primarily close to zero. This corroborates that these models were close to the true models.

Table 4.28. Summary of Model Validation using SLR for Excavators

Equipment	**Response**	**SLR**		
		m	**b**	**R^2**
Excavator 1	Fuel Use	0.982	0.045	0.9819
	NO_x	0.948	0.005	0.9481
	HC	0.352	0.002	0.3505
	CO	0.542	0.005	0.5427
	CO_2	0.982	0.143	0.9819
	PM	0.881	0.107	0.8810
Excavator 2	Fuel Use	0.963	0.074	0.9632
	NO_x	0.850	0.007	0.8499
	HC	0.392	0.003	0.3901
	CO	0.220	0.015	0.2194
	CO_2	0.963	0.234	0.9633
	PM	0.889	0.052	0.8876
Excavator 3	Fuel Use	0.930	0.120	0.9302
	NO_x	0.875	0.007	0.8755
	HC	0.193	0.004	0.1936
	CO	0.018	0.008	0.0183
	CO_2	0.930	0.381	0.9294
	PM	0.333	0.284	0.3326

4.3.5.2 Model Validation for MLR

Like SLR, model validations for wheel loaders and excavators are presented. The models mostly yielded the higher accuracy and precision for fuel use and emission rates of NO_x, CO_2, and PM excluding the HC and CO.

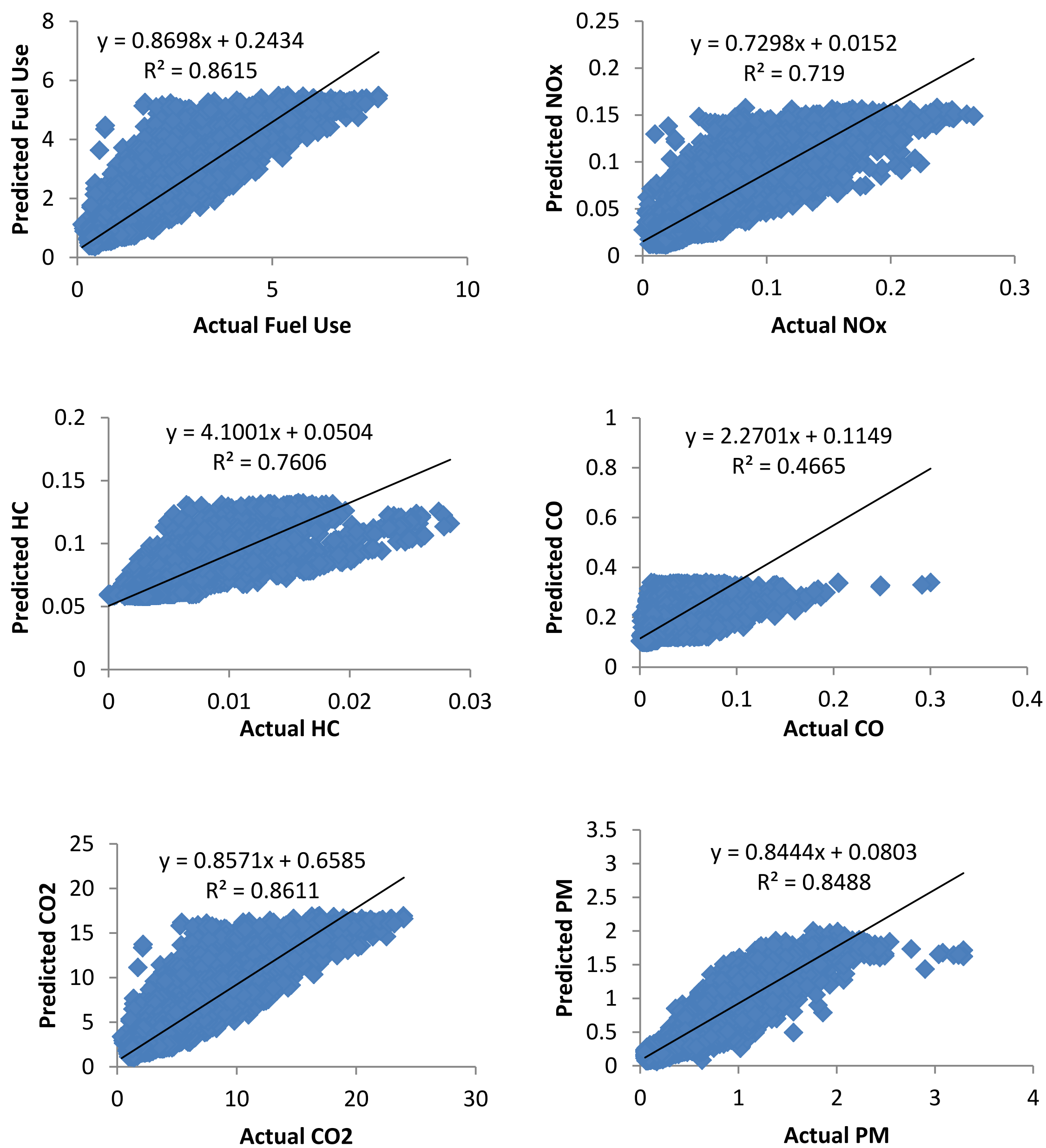

Figure 4.21. Model Validation for MLR of Fuel Use and Emission Rates in Wheel Loader 1

Table 4.29. Summary of Model Validation using MLR for Wheel Loaders

Equipment	**Response**	**MLR**		
		m	**b**	**R^2**
Wheel Loader 1	Fuel Use	0.870	0.243	0.86
	NO_x	0.730	0.015	0.72
	HC	0.799	0.015	0.76
	CO	0.505	0.008	0.47
	CO_2	0.857	0.659	0.86
	PM	0.844	0.080	0.85
Wheel Loader 2	Fuel Use	0.954	0.046	0.96
	NO_x	0.034	0.008	0.90
	HC	0.794	0.021	0.52
	CO	0.128	0.009	0.12
	CO_2	0.948	0.069	0.96
	PM	0.877	0.065	0.87
Wheel Loader 3	Fuel Use	0.910	0.135	0.89
	NO_x	0.836	0.002	0.82
	HC	0.780	0.001	0.73
	CO	0.410	0.003	0.41
	CO_2	0.893	0.322	0.90
	PM	0.840	0.010	0.87
Wheel Loader 4	Fuel Use	0.914	0.101	0.91
	NO_x	0.842	0.007	0.84
	HC	0.251	0.003	0.24
	CO	0.495	0.002	0.49
	CO_2	0.913	0.271	0.91
	PM	0.786	0.067	0.78
Wheel Loader 5	Fuel Use	0.969	0.047	0.95
	NO_x	0.918	0.003	0.82
	HC	0.497	0.001	0.50
	CO	0.510	0.003	0.51
	CO_2	0.962	0.080	0.95
	PM	0.858	0.002	0.86

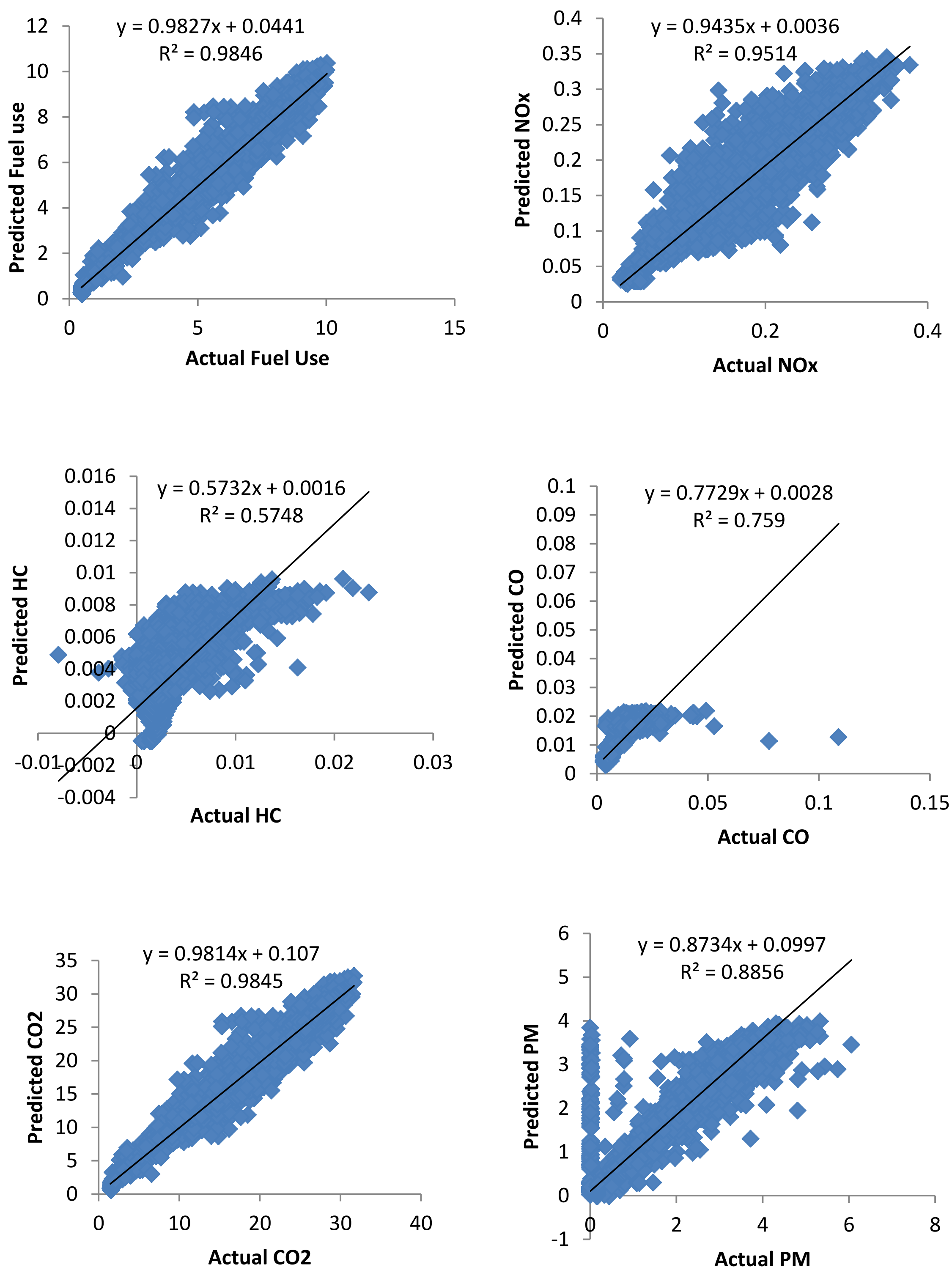

Figure 4.22. Model Validation for MLR of Fuel Use and Emission Rates in Excavator 1

Table 4.30. Summary of Model Validation using MLR for Excavators

Equipment	Response	MLR		
		m	b	R^2
Excavator 1	Fuel Use	0.983	0.044	0.985
	NO_x	0.944	0.004	0.951
	HC	0.573	0.002	0.575
	CO	0.773	0.003	0.759
	CO_2	0.981	0.107	0.985
	PM	0.873	0.099	0.886
Excavator 2	Fuel Use	0.974	0.063	0.971
	NO_x	0.887	0.006	0.879
	HC	0.441	0.003	0.434
	CO	0.322	0.013	0.327
	CO_2	0.974	0.206	0.971
	PM	0.917	0.053	0.909
Excavator 3	Fuel Use	0.936	0.113	0.935
	NO_x	0.878	0.007	0.878
	HC	0.243	0.004	0.239
	CO	0.105	0.007	0.100
	CO_2	0.933	0.354	0.934
	PM	0.384	0.252	0.387

4.3.5.3 Model Validation for ANN

In order to validate the results, the @Risk software for the ANN plots the predicted versus actual results based on the validation data and provides the results of the fitted line parameters including slope (m), y-intercept (b), and R^2. Slope (m) indicates the accuracy of the model and R^2 indicates precision. However, values close to 1.0 for each parameter indicate high accuracy and high precision, respectively. The y-intercept (b) is an indicator of bias in the model, with values close to zero being desirable. Figure 4.22 presents the scatter plot of predicted values of the model and actual data in the ANN model validation. The overall results are summarized in Table 4.31 and 4.32.

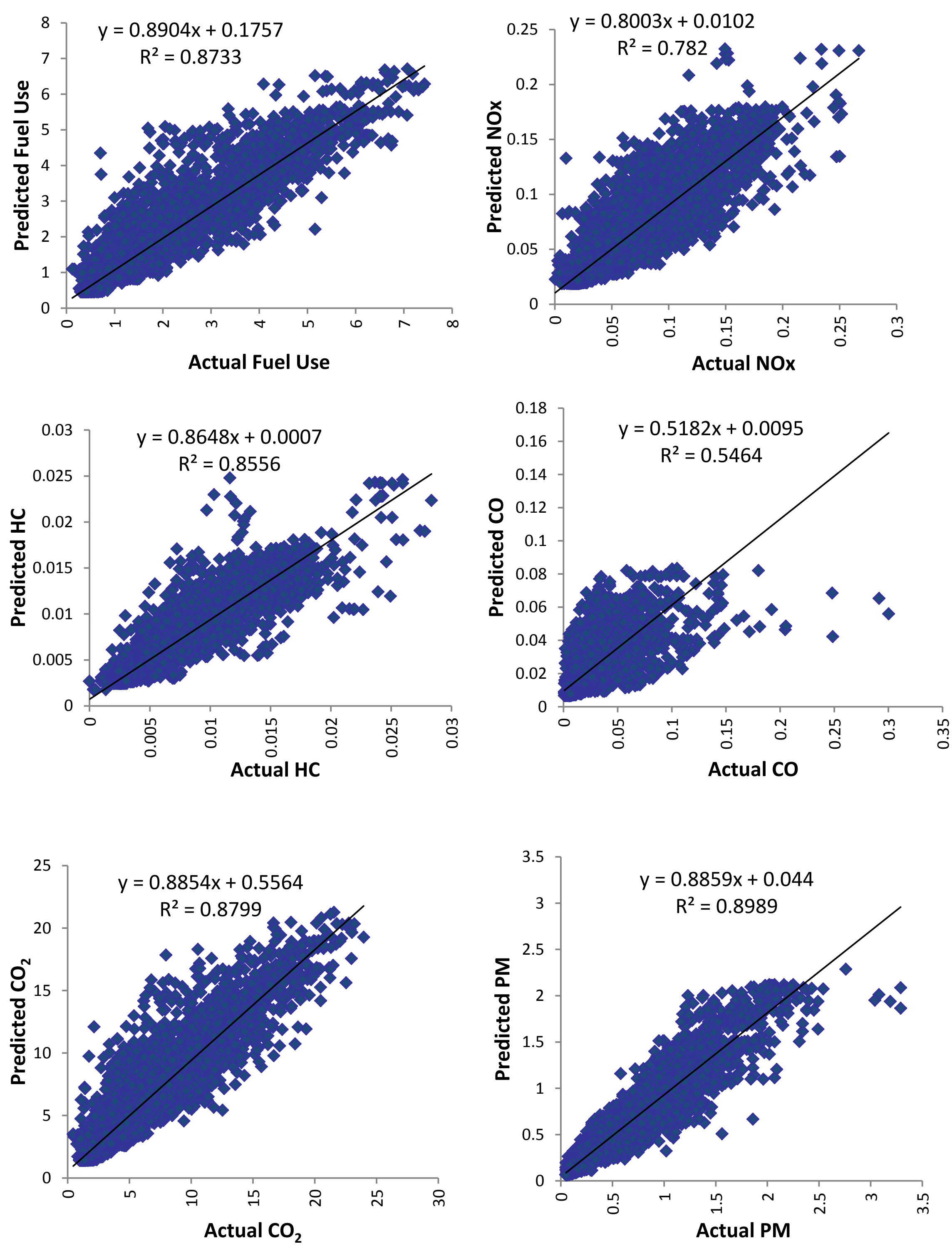

Figure 4.23. Model Validation for ANN (Testing) of Fuel Use and Emission Rates in Wheel Loader 1

Table 4.31. Summary of Model Validation using ANN for Wheel Loaders

Equipment	**Response**	**ANN**		
		m	**b**	**R^2**
Wheel Loader 1	Fuel Use	0.890	0.176	0.87
	NO_x	0.800	0.010	0.78
	HC	0.865	0.001	0.86
	CO	0.518	0.010	0.55
	CO_2	0.885	0.556	0.88
	PM	0.886	0.044	0.90
Wheel Loader 2	Fuel Use	0.956	0.050	0.96
	NO_x	0.942	0.003	0.93
	HC	0.845	0.001	0.84
	CO	0.570	0.005	0.54
	CO_2	0.963	0.154	0.96
	PM	0.941	0.020	0.96
Wheel Loader 3	Fuel Use	0.921	0.068	0.91
	NO_x	0.889	0.004	0.87
	HC	0.874	0.0003	0.88
	CO	0.577	0.002	0.58
	CO_2	0.939	0.199	0.90
	PM	0.878	0.011	0.92
Wheel Loader 4	Fuel Use	0.932	0.065	0.94
	NO_x	0.913	0.004	0.91
	HC	0.744	0.001	0.65
	CO	0.695	0.001	0.69
	CO_2	0.944	0.181	0.94
	PM	0.917	0.023	0.92
Wheel Loader 5	Fuel Use	0.957	0.023	0.96
	NO_x	0.925	0.001	0.90
	HC	0.645	0.001	0.64
	CO	0.518	0.003	0.51
	CO_2	0.975	0.033	0.96
	PM	0.857	0.013	0.90

Table 4.32. Summary of Model Validation using ANN for Excavators

Equipment	Response	ANN		
		m	**b**	**R^2**
Excavator 1	Fuel Use	0.9836	0.0386	0.9856
	NO_x	0.9749	0.0030	0.9624
	HC	0.7685	0.0008	0.7402
	CO	0.9121	0.0010	0.8836
	CO_2	0.9913	0.1119	0.9852
	PM	0.8887	0.1080	0.8786
Excavator 2	Fuel Use	0.9701	0.0579	0.9746
	NO_x	0.9012	0.0049	0.8990
	HC	0.4589	0.0027	0.4595
	CO	0.5504	0.0086	0.5699
	CO_2	0.9689	0.1665	0.9747
	PM	0.9400	0.0204	0.9530
Excavator 3	Fuel Use	0.9545	0.0763	0.9584
	NO_x	0.9128	0.0052	0.9144
	HC	0.6549	0.0019	0.6535
	CO	0.2707	0.0054	0.2683
	CO_2	0.9547	0.2370	0.9593
	PM	0.7695	0.0896	0.7911

4.3.6 Model Comparison

In order to evaluate and compare the performance of three models in terms of SLR, MLR, and ANN methodologies, model validations for the five wheel loaders were developed. The models were validated by plotting the predicted values versus actual results for each model and fitting a trend line to the data. For each trend line, the values of accuracy (m), bias (b), and precision (R^2) were determined. As shown in Table 4.33, ANN produces higher R^2 values compared to SLR and MLR for fuel use and all emissions rates. SLR has the lowest R^2 value for fuel use and emissions rates. Overall, ANN outperformed SLR and MLR with respect to precision, accuracy, and bias. In most cases, the ANN approach produced highly precise models for NO_x, CO_2, and PM; while the models for HC and CO were likely to be moderately precise with R^2 values ranging from 0.50 – 0.87.

Table 4.33. Comparison of Validation Results for SLR, MLR and ANN

Response	SLR			MLR			ANN		
	m	**b**	**R^2**	**m**	**b**	**R^2**	**m**	**b**	**R^2**
Wheel Loader 1									
Fuel Use	0.888	-0.002	0.84	0.870	0.243	0.86	0.890	0.176	0.87
NO_x	0.889	0.010	0.67	0.730	0.015	0.72	0.800	0.010	0.78
HC	0.843	0.005	0.74	0.799	0.015	0.81	0.865	0.001	0.86
CO	0.014	0.010	0.47	0.505	0.008	0.50	0.518	0.010	0.55
CO_2	0.892	-0.028	0.84	0.857	0.659	0.86	0.885	0.556	0.88
PM	0.900	0.024	0.81	0.844	0.080	0.85	0.886	0.044	0.90
Wheel Loader 2									
Fuel Use	0.944	0.078	0.94	0.954	0.046	0.96	0.956	0.050	0.96
NO_x	0.874	0.007	0.87	0.034	0.008	0.90	0.942	0.003	0.93
HC	0.738	0.002	0.74	0.794	0.021	0.78	0.845	0.001	0.84
CO	0.012	0.010	0.01	0.128	0.009	0.12	0.570	0.005	0.54
CO_2	0.943	0.245	0.94	0.948	0.069	0.96	0.963	0.154	0.96
PM	0.837	0.067	0.84	0.877	0.065	0.87	0.941	0.020	0.96
Wheel Loader 3									
Fuel Use	0.885	0.096	0.89	0.910	0.135	0.89	0.921	0.068	0.91
NO_x	0.825	0.006	0.82	0.836	0.002	0.82	0.889	0.004	0.87
HC	0.688	0.001	0.69	0.780	0.001	0.73	0.874	0.0003	0.88
CO	0.337	0.003	0.34	0.410	0.003	0.41	0.577	0.002	0.58
CO_2	0.885	0.295	0.89	0.893	0.322	0.90	0.939	0.199	0.90
PM	0.845	0.019	0.84	0.840	0.010	0.87	0.878	0.011	0.92
Wheel Loader 4									
Fuel Use	0.855	0.150	0.85	0.914	0.101	0.91	0.932	0.065	0.94
NO_x	0.784	0.009	0.78	0.842	0.007	0.84	0.913	0.004	0.91
HC	0.133	0.004	0.13	0.251	0.003	0.24	0.744	0.001	0.65
CO	0.311	0.002	0.31	0.495	0.002	0.49	0.695	0.001	0.69
CO_2	0.855	0.472	0.85	0.913	0.271	0.91	0.944	0.181	0.94
PM	0.749	0.077	0.75	0.786	0.067	0.78	0.917	0.023	0.92
Wheel Loader 5									
Fuel Use	0.948	0.036	0.95	0.969	0.047	0.95	0.957	0.023	0.96
NO_x	0.875	0.003	0.88	0.918	0.003	0.88	0.925	0.001	0.90
HC	0.424	0.001	0.43	0.497	0.001	0.50	0.645	0.001	0.64
CO	0.496	0.003	0.50	0.510	0.003	0.51	0.518	0.003	0.51
CO_2	0.948	0.113	0.95	0.962	0.080	0.95	0.975	0.033	0.96
PM	0.853	0.019	0.85	0.858	0.002	0.86	0.857	0.013	0.90

4.3.7 Variable Impact Analysis

Variable impact analyses were also performed for each item of equipment. However, for the sake of brevity, this section only fully addresses one item of equipment, namely wheel loaders. The summary of variable impact analysis for the other equipment is presented in the Appendix.

Using the ANN models perfomed by the @Risk software, a variable impact analysis was conducted to determine the percentage of contribution of the input variables (MAP, RPM, and IAT) to the prediction of fuel use and emission rates of each pollutant. Table 4.34 presents the overall variable impact analysis for each wheel loader with respect to the percentage contribution of engine data to the estimation of fuel use and emission rates of NO_x, HC, CO, CO_2, and PM. It was found that there is variability in the percentage of contribution of MAP, RPM, and IAT to the prediction of fuel use and emission rates for each pollutant. However, it can be concluded that the MAP is the most significant variable that contributes the highest impact to the total prediction of fuel use, NO_x, CO_2, and PM. Meanwhile, RPM has the highest contribution for the HC and CO. IAT has the lowest impact to the prediction of fuel use and emission rates.

In addition, Table 4.35 presents the summary of the average variable impact analysis for all wheel loaders. Similarly, it was found that MAP is the most significant variable for fuel use, NO_x, CO_2, and PM which are 44.25%, 38.83%, 46.67% and 79.39%, respectively. RPM, however, has the most contribution for HC and CO. IAT did not have the highest impact for any of the response variables.

Table 4.34. Variable Impact Analysis for All Wheel Loaders

Engine Data	Fuel Use	NOx	HC	CO	CO2	PM
			Wheel Loader 1			
MAP	44.25%	38.83%	27.77%	36.25%	46.67%	79.39%
RPM	38.85%	38.42%	54.75%	40.88%	37.97%	11.63%
IAT	16.91%	22.76%	17.49%	22.87%	15.36%	8.97%
			Wheel Loader 2			
MAP	66.11%	66.75%	22.02%	40.25%	72.63%	51.97%
RPM	29.57%	26.82%	59.06%	33.17%	25.04%	25.68%
IAT	4.33%	6.43%	18.92%	26.58%	2.33%	22.34%
			Wheel Loader 3			
MAP	42.38%	55.02%	16.39%	42.57%	48.20%	38.06%
RPM	51.65%	39.02%	52.26%	33.09%	46.37%	49.92%
IAT	5.97%	5.96%	31.35%	24.35%	5.43%	12.03%
			Wheel Loader 4			
MAP	37.31%	38.77%	24.06%	19.31%	41.06%	38.97%
RPM	49.02%	39.93%	50.09%	39.48%	47.49%	39.34%
IAT	13.67%	21.30%	25.85%	41.21%	11.45%	21.69%
			Wheel Loader 5			
MAP	72.51%	69.05%	23.93%	77.11%	61.78%	80.66%
RPM	23.63%	21.66%	68.78%	9.25%	34.97%	13.85%
IAT	3.86%	9.29%	7.29%	13.64%	3.26%	5.49%

Table 4.35. Average Variable Impact Analysis for Wheel Loaders

Engine Data	Fuel Use	NO_x	HC	CO	CO_2	PM
MAP	54.66%	54.35%	28.66%	26.30%	54.65%	59.42%
RPM	36.71%	34.89%	53.89%	36.80%	36.76%	25.47%
IAT	8.63%	10.76%	17.45%	36.90%	8.59%	15.11%

4.3.8 Taxonomy

A taxonomy of the average fuel use and emission rates of all pollutants in unit grams per horse-power (g/hp-hr) for different types of equipment and engine technology was developed. The taxonomy indicates a brief outlook for comparing fuel use and emission rates in terms of equipment types and engine tier types. As seen in Table 4.36, it was obvious that the fuel use and emission rates of NO_x, HC, CO, CO_2, and PM for all types of equipment in engine tier 0 are the highest among other engine tier types (tier 1 and 2). The fuel use and emission rates of all pollutants in engine tier 2 are the second highest, and those in engine tier 2 are the lowest of all. Furthermore, among other types of equipment, the track loaders had the highest fuel consumptions and emission rates of each pollutant; meanwhile, the off-road trucks had the lowest of all. The emission rates of CO_2 are the highest among other emission rates, accounting for approximately 325 g/hp-hr in the track loaders, 280 g/hp-hr in motor graders, and only 116 g/hp-hr in the off-road trucks. The detailed summary can be seen in Table 4.36.

The other taxonomies of fuel use and emission rates using simple linear regression (SLR) and multiple linear regression (MLR) were also developed. These taxonomies were classified based on engine tier technology. There are five vehicles in engine tier 0, 16 in tier 1, and 10 in tier 2. All the response variables (fuel use and emission rates of each pollutant) were averaged based on engine tiers. For SLR, the average values of slope (m) and intercept (b) were given. Meanwhile, for MLR, the averages of coefficients of linear relationships for each parameter were presented as shown in Table 4.37 and 4.38.

Table 4.36. Taxonomy of Modal Weighted Average Fuel Use and Emission Rates (g/hp-hr) for each tier for All Types of Equipment

Response	Engine Tier	BH	BD	EX	MG	OFT	TL	WL	Average
Fuel Use (g/hp-hr)	Tier 0	0.017	0.024	0.025	0.026	0.011	0.031	0.017	0.019
	Tier 1	0.013	0.018	0.019	0.02	0.009	0.023	0.013	0.016
	Tier 2	0.012	0.015	0.016	0.016	0.001	0.018	0.012	0.013
NO_x (g/hp-hr)	Tier 0	2.9	4.1	4.2	4.3	1.9	5.2	2.9	3.6
	Tier 1	1.7	2.2	2.3	2.4	1.2	2.7	1.7	2.0
	Tier 2	1.2	1.5	1.5	1.5	1.0	1.7	1.2	1.4
HC (g/hp-hr)	Tier 0	0.25	0.30	0.31	0.32	0.18	0.34	0.25	0.28
	Tier 1	0.17	0.20	0.21	0.22	0.13	0.23	0.17	0.19
	Tier 2	0.15	0.16	0.16	0.17	0.12	0.17	0.14	0.15
CO (g/hp-hr)	Tier 0	0.68	0.71	0.69	0.73	0.49	0.72	0.64	0.67
	Tier 1	0.43	0.59	0.61	0.61	0.33	0.75	0.44	0.54
	Tier 2	0.39	0.44	0.44	0.46	0.29	0.49	0.38	0.41
CO_2 (g/hp-hr)	Tier 0	175	251	264	275	116	325	178	226
	Tier 1	136	192	203	212	95	247	139	175
	Tier 2	127	162	167	172	99	195	128	150
PM (g/hp-hr)	Tier 0	0.017	0.024	0.026	0.027	0.011	0.031	0.017	0.022
	Tier 1	0.014	0.020	0.021	0.022	0.010	0.027	0.014	0.018
	Tier 2	0.009	0.012	0.012	0.013	0.007	0.015	0.009	0.011

Table 4.37. Taxonomy of Fuel Use and Emission Rates (g/s) for each tier for All Types of Equipment using SLR based on MAP

Response	Tier 0		Tier 1		Tier 2	
	m	**b**	**m**	**b**	**m**	**b**
Fuel Use (g/s)	8.980	0.456	6.078	0.438	4.954	0.440
Nox (g/s)	0.494	0.028	0.194	0.023	0.123	0.081
HC (g/s)	0.014	0.007	0.014	0.004	0.010	0.004
CO (g/s)	0.030	0.025	0.043	0.007	0.042	0.007
CO2 (g/s)	20.19	0.753	19.06	1.356	15.59	1.370
PM (mg/s)	1.704	0.041	2.024	0.109	1.270	0.075

m = slope , b = y-intercept

Table 4.38. Taxonomy of Fuel Use and Emission Rates (g/s) for each tier for All Types of Equipment using MLR

Response	Tier 0				Tier 1				Tier 2			
	c	**X_1**	**X_2**	**X_3**	**c**	**X_1**	**X_2**	**X_3**	**c**	**X_1**	**X_2**	**X_3**
Fuel Use (g/s)	-9.863	0.1025	0.0005	-0.0034	-4.7976	0.0493	0.0006	-0.0012	-2.7458	0.0311	0.0009	-0.0015
Nox (g/s)	-0.484	0.0049	0.0000	0.0008	-0.1904	0.0017	0.0000	0.0005	-0.0771	0.0007	0.0000	0.0003
HC (g/s)	-0.0014	0.0001	0.0000	-0.0002	0.0054	0.0001	0.0000	-0.0003	-0.0041	0.0000	0.0000	-0.0001
CO (g/s)	-0.029	0.0005	0.0000	-0.0016	0.0212	0.0006	0.0000	0.0000	-0.0200	0.0001	0.0000	0.0000
CO2 (g/s)	-31.22	0.3258	0.0012	0.0078	-16.69	0.1690	0.0020	-0.0131	-10.45	0.0976	0.0027	-0.0028
PM (mg/s)	-2.313	0.0252	0.0001	-0.0052	-1.5360	0.0225	0.0001	-0.0059	-0.8997	0.0101	0.0001	-0.0005

X_1 = MAP, X_2 = RPM, X_3 = IAT, c = constant

CHAPTER V

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

This chapter presents the findings and conclusions conducted in this study. This research has attempted to develop predictive modeling tools for estimating fuel use and emission rates for HDD construction equipment based on real-world data. Using four different approaches in predictive modeling that include weighted average approach, simple linear regression (SLR), multiple linear regression (MLR), and artificial neural network (ANN), the results of this study can be used as a tool in predicting the fuel use and emission rates specifically for HDD construction equipment. The models developed can be used for many stakeholders, such as engine manufacturers, construction equipment owners, contractors, consultants, fleet management, regulators, and environmentalists. The detailed conclusions are briefly described as follows:

5.1.1 Field Data Collection

Data from 32 items of equipment consisting of six backhoes, six bulldozers, three excavators, six motor graders, three off-road trucks, three track loaders, and five wheel loaders were gathered by deploying the PEMS manufactured by The Clean Air Technologies International (CATI), Inc. The datasets were obtained from a research team from North Carolina State University. The PEMS provided data based on second-per-second measurement for fuel use and emission rates of specified pollutants (NO_x, HC, CO, CO_2, and PM) as well as engine performance data (MAP, RPM, and IAT). The real-world data are needed to accurately develop predictive models for estimating fuel consumption and emission rates for HDD construction equipment. These models will help establish the actual baseline for emission footprints.

5.1.2 Exploratory Data Analysis

The conclusions for exploratory data analysis are divided into three sections that include summary statistics, distribution fittings, and correlation variables. Each subsection will be presented as follows.

5.1.2.1 Summary Statistics

Summary statistics were conducted to fully understand the nature of data. The statistical analysis was carried out for each item of equipment using the real-world in-use data, containing the average fuel use and emission rates of NO_x, HC, CO, CO_2, and PM as well as engine performance data (MAP, RPM, and IAT). The summary statistics are associated with the four order statistics including minimum, maximum, mean, and standard deviation. It is concluded that the average quantities of diesel fuel consumed and pollutants emitted vary among each item of equipment. The emission rates of CO_2 in mass per time (g/s) for all items of equipment have the highest mean values compared to other pollutants such as NO_x, HC, CO, and PM. For example, there are approximately 1.1 g/s of diesel fuel utilized for wheel loaders, resulting more than 3 g/s emissions of CO_2 and less than 1.0 g/s for NO_x, HC, CO, and PM pollutants emitted from wheel loaders.

5.1.2.2 Distribution Fittings

Distribution fittings were performed for each of the response and predictor variables. The software @Risk was used to specify the distribution types for both response and predictor variables by generating a random process from a set of observations. The fitted probability distribution functions (PDF) were determined based on the Chi Squares statistics. The PDF describes a range of possible values of fuel use and their likelihood of occurrence, indicating the variability of fuel use rates. The fitted distributions were conducted for each item of equipment, but the general forms of distributions for each type of variable based on the most frequent ones were determined.

Based on the results, most of the data are not normally distributed. They are concentrated on the left side, clearly indicating longer right tail (positive skewed). Overall, the results typically show similar trends of the distributions. For instance, the fitted distributions for wheel loaders in terms of fuel use and emission rates of NO_x, HC, CO, CO_2, and PM are risk inverse gaussian, risk pearson, risk logistic, risk logistic, risk pearson, and risk exponential respectively. Meanwhile, risk triangular, risk pareto, and risk beta general are determined for MAP, RPM, and IAT, respectively. For other equipment, the fitted distributions vary and follow the same trend as positively skewed.

5.1.2.3 Correlations

Based on the summary of Pearson correlation coefficients, MAP had a high positive correlation to fuel use and emission rates of NO_x, CO_2, and PM, but had a moderate positive relationship with HC and CO. Although not as highly correlated, RPM had a strong positive relationship with fuel use and emissions. IAT was shown to have the lowest correlation of the three engine performance variables on predicting fuel use and emission rates. Based on the correlation coefficients from each item of equipment, it appears that each item of equipment seems likely to follow the same trends of linear relationship among variables. MAP indicates to be the most highly correlated to fuel use and emission rates, RPM as moderately correlated, and IAT as the least correlated to fuel use and emissions rates.

5.1.3 Predictive Modeling

5.1.3.1 Weighted Average Approach

The weighted average approach is a practical tool to estimate the fuel consumption and emission rates for HDD construction equipment. The method is reliable for real-world use. In order to calculate the weighted average fuel use and emission rates, the average percentages of time for each type of equipment are utilized. Thus, by multiplying the time and emission rates, the weighted average emission rates can be calculated.

For most type of equipment, typically the time spent in each engine mode decreases as the engine modes increase. For example, for wheel loaders, it was approximately 40% of time spent in engine mode 1, 20% in engine mode 2, 13% in engine mode 3, and reaching less than 2% of time in engine mode 10. It was also found that the off-road truck has the highest amount of time spent in engine mode 1 compared to the other equipment, accounting for more than 70% of time. This is then followed by the wheel loader and the excavator as the second and third vehicles that spend more time in engine mode 1. In contrast, the track loader is likely to have a different pattern of time distributions. However, overall it appears that the fractions of time decrease when engine modes increase.

It was found that there is variability in the weighted average fuel use rates for each type of equipment in each engine mode. To summarize, the track loaders comsumed more fuel use than other types of equipment, accounting for 0.0332 grams per horsepower-hours (g/hp-hr), followed by bulldozer as the second consumptive in fuel use (0.0224 g/hp-hr). Moreover, for emission rates of NO_x, tier 0 emits the highest amount of emission rates of NO_x compared to tier 1 and 2, accounting for 2.9372 g/hp-hr in total. Tier 1 is the second larger contributor of NO_x and followed by tier 2, comprising of 1.6632 and 1.2312 g/hp-hr, respectively.

In addition, track loaders emit a substantial amount of NO_x for engine tier 0 compared to other types of equipment, as well as the emissions in tier 1 and 2. Meanwhile, the off-road trucks emit the lowest amount of NO_x emissions for each tier. In summary, the total weighted average emission rates of NO_x for all equipment can be calculated as the sums for weighted average emission rates from each type of equipment. In general, it can be seen that the total weighted average emission rates of NO_x accounts for approximately 3.7 g/hp-hr for engine tier 0, 2.01 g/hp-hr for tier 1, and1.4 g/hp-hr for tier 2.

5.1.3.2 Simple Linear Regression (SLR)

Simple linear regression is a very powerful and practical tool in estimating the total amount of fuel use and emission rates for HDD construction equipment by only using one predictor variable. Based on their high correlation values, SLR models were developed using MAP as a predictor variable to predict fuel use and emission rates of each pollutant. The models are based on a set of observations of second-by-second, real-world fuel use and emissions data. For instance, in terms of the coefficient of determination (R^2), the SLR models of wheel loaders mostly accounted for a high percentage of the variability in the data for fuel use, NO_x, CO_2, and PM. In other words, MAP accounted for approximately more than 80% for the variation in the fuel use and emission rates of NO_x, CO_2, and PM for all wheel loaders. CO had the lowest R^2 values, indicating much variability in the data, and therefore was more difficult to predict. Overall, other equipment such as backhoes, bulldozers, off-road trucks, track loaders and motor graders show the same trends. The SLR models for HC and CO had lower R^2 values, and therefore much more difficult to calculate.

5.1.3.3 Multiple Linear Regression (MLR)

The MRL models are mostly applicable for engine manufactures due to using the main variables of engine performance data. Overall, the MLR models yielded higher R^2 values than the SLR models for their respective response variables. For wheel loaders, The MLR R^2 values for fuel use and emission rates for NO_x, HC, CO_2 and PM indicate that the models perform well. The model for CO, however, accounted for less than 50% of the variability in the data; thus, the MLR models also indicate that emission rates of CO are more difficult to predict compared to fuel use and the other pollutants.

To conclude, most HDD equipment examined in this research show that the MLR models for fuel use and emission rates of NO_x, CO_2 and PM had high values of R^2, indicating that the models perform well, and therefore are relatively easier to predict compared to the emission rates of HC and CO.

5.1.3.4 Artificial Neural Network (ANN)

The ANN approach has been successful to accurately estimate the fuel use and emission rates of each pollutant for HDD construction equipment. This method has offered an alternative way to come up with higher precision and accuracy, but lower bias. Unlike the SLR and MLR approaches, ANN does not produce equations for each response variables because they are developed in the network’s hidden layer. Based on the results, ANN produced networks that were highly accurate and precise and unbiased for fuel use, NO_x, HC, CO_2, and PM for most items of equipment. As with the SLR and MLR models, CO was the most difficult of the pollutants to predict, given the lower values of coefficient of determination (R^2).

5.1.3.5 Model Validation

Model validations were developed for all items of equipment in order to compare and evaluate the performance of SLR, MLR, and ANN methodologies. The models were validated by plotting the predicted versus actual results for each model and fitting a trend line to the data. For each trend line, the values of accuracy (m), bias (b), and precision (R^2) were determined.

Based on the results, model validation for all three models (SLR, MLR, and ANN) yielded higher accuracy and precision for fuel use and emission rates of NO_x, HC, CO_2, and PM, but lower accuracy and precision for CO. Overall, it was found that each model resulted in lower bias, indicating that the models performed well.

5.1.3.6 Model Comparison

For all three modeling approaches, CO proved to be the most difficult pollutant emission rate to predict, as evidenced by its low R^2 values. Typically, there is high variability in CO data which confounds the prediction effort, as well as the fact that CO did not have a strong correlation with any of the engine data predictor variables.

Based on the model comparisons, ANN models generally performed the best with respect to precision, accuracy, and bias. In most cases, the ANN approach produced highly precise models for NO_x, CO_2, and PM; while the models for HC and CO were moderately precise. A potential drawback to the ANN approach is that the equations for each response variable are not actually provided, thus the user must have access to the artificial neural network. Although, the SLR and MLR approaches yielded models that were slightly less accurate and precise than the ANN approach, these models are still useful.

Overall, based on the results regarding the models developed, PEMS had been able to accurately measure the fuel use and emission rates of NO_x, CO_2, and PM. In other words, there is less variability for fuel use and emission models of NO_x, CO_2, and PM. This condition indicates that the models perform well. In contrast, HC and CO can have either more moderate or lower accuracy or precision for most equipment, indicating that there is a high variability in the models. Thus, HC and CO are more difficult to predict.

Overall, the results of this study help quantify and characterize the air pollution problems from HDD equipment used in construction. The methodologies presented may certainly be used to develop fuel use and emissions models for other types of equipment.

5.1.3.7 Variable Impact Analysis (VIA)

Variable impact analysis was used determine the percentage of contribution of the input variables (MAP, RPM, and IAT) to the total prediction of fuel use and emission rates of each pollutant. The VIA was employed to each item of HDD in terms of fuel use and emission rates of each pollutant. In the case of wheel loaders, it can be concluded that MAP has the highest percentage of contribution in the prediction of fuel use and emission rates, accounting for approximately 60% of the total impact, although for HC and CO it had the second highest impact. For these two pollutants, RPM had the highest impact but it was the second for fuel use, NO_x, CO_2, and PM. Although IAT had the lowest ranking impact among the three engine performance variables, it still may have some predictive power, especially for CO.

5.2 Recommendations

Some recommendations can be described as follows:

1. The weighted average approach is mostly used by policy makers, municipalities, and regulators.
2. The simplicity of the one variable SLR models may be appealing to some users, such as fleet managers, that want to estimate the fuel use and emissions footprints of their equipment. Other users, such as engine manufacturers, may like the MLR approach because they would be able to reasonably estimate each of the engine performance variables. The ANN models are mostly used for academia purposes due to their higher accuracy and precision.
3. It is recommended that other engine performance data, such as engine load or throttle position, be considered for future studies.
4. The strong relationships between CO and other variables should also be considered. For example, it there exists a strong relationship between CO and fuel use (which is accurately and precisely predicted by each of the three modeling approaches), then fuel use may be used as a predictor variable for CO.
5. Other types of equipment such as cranes and scrapers with different types of fuels (biodiesel) should be targeted for future modeling efforts.
6. It is also recommended to develop other predictive modeling tools using more advanced methodologies or using other nonlinear models to exhibit the differences of each method to find the most robust models for estimating fuel use and emission rates for HDD construction equipment.

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APPENDICES

The appendices provide supporting results, data, or calculation used as part of the overall results. The appendices are divided into several appendixes as follows:

Appendix A	Summary statistics for each item of equipment
Appendix B	Summary of Pearson correlation coefficients for each item of equipment
Appendix C	Distributions fittings for each item of equipment
Appendix D	Summary of SLR models for each item of equipment
Appendix E	Summary of MLR models for each item of equipment
Appendix F	Model validations for SLR
Appendix G	Model validations for MLR
Appendix H	Weighted average fuel use and emissions rates
Appendix I	Average engine mode distributions
Appendix J	Summary of training and validation data using ANN
Appendix K	Comparison of validation results for SLR, MLR, and ANN for all types of equipment
Appendix L	Variable impact analysis

Appendix A

Summary statistics for each item of equipment

Table A.1. Summary statistics of fuel use and emission rates for backhoes

Equipment	Min	Max	Mean	Std.Dev	# of Case	Fitting Distribution
			Fuel Use Rates(g/s)			
BH 1	0.070	3.96	0.427	0.344	8780	RiskLogLogistic
BH 2	0.135	4.21	0.932	0.688	13407	RiskExpon
BH 3	0.070	3.29	0.739	0.595	9853	RiskInvGauss
BH 4	0.030	1.81	0.407	0.309	6406	RiskBetaGeneral
BH 5	0.020	3.75	0.714	0.556	9782	RiskInvGauss
BH 6	0.050	3.72	0.421	0.322	5379	RiskExpon
			NO_x (g/s)			
BH 1	0.00247	0.1610	0.0167	0.0124	8780	RiskPearson
BH 2	0.00307	0.1440	0.0311	0.0257	13407	RiskInvGauss
BH 3	0.00241	0.1430	0.0202	0.0174	9853	RiskPearson
BH 4	0.00127	0.0752	0.0178	000993	6406	RiskWeibull
BH 5	0.00123	111.84	0.0425	1.1300	9782	RiskLognorm
BH 6	0.00145	0.1510	0.0192	0.0120	5379	RiskPearson
			HC (g/s)			
BH 1	0.00	0	0	0	8780	RiskLogLogistic
BH 2	-0.00015	0.0296	0.00256	0.00305	13407	RiskPearson
BH 3	0.0000	0.00615	0.00184	0.00101	9853	RiskPearson
BH 4	0.0000	0.00893	0.00161	0.00116	6406	RiskBetaGeneral
BH 5	0.00016	6.90000	0.00262	0.06980	9782	RiskPearson
BH 6	0.0000	0.00686	0.00171	0.00100	5379	RiskPearson
			CO (g/s)			
BH 1	0	0	0	0	8780	RiskInvGauss
BH 2	0.0000	0.2330	0.00972	0.01160	13407	RiskPearson
BH 3	-0.00491	0.1050	0.00416	0.00400	9853	RiskLogLogistic
BH 4	0.0000	0.0118	0.00131	0.00123	6406	RiskInvGauss
BH 5	0.00048	52.260	0.01990	0.53000	9782	RiskLognorm
BH 6	0.0000	0.0227	0.00283	0.00188	5379	RiskPearson
			CO_2 (g/s)			
BH 1	0.1890	12.47	1.33	1.090	8780	RiskLogLogistic
BH 2	0.4280	13.29	2.93	2.170	13407	RiskInvGauss
BH 3	0.2110	10.38	2.32	1.870	9853	RiskPearson
BH 4	0.0978	5.710	1.28	0.973	6406	RiskInvGauss
BH 5	0.0715	8035	3.05	81.24	9782	RiskLognorm
BH 6	0.1480	11.71	1.32	1.020	5379	RiskPearson
			PM (mg/s)			
BH 1	0.002	1.290	0.0222	0.0380	8780	RiskNormal
BH 2	0.020	4.970	0.2970	0.5550	13407	RiskExpon
BH 3	0.080	3.470	0.3510	0.220	9853	RiskNormal
BH 4	0.010	0.880	0.0966	0.0799	6406	RiskTriang
BH 5	0.000	2.880	0.2020	0.2620	9782	RiskNormal
BH 6	0.000	0.920	0.1130	0.0967	5379	RiskTriang

Table A.2. Summary statistics of engine performance data for backhoes

Equipment	Min	Max	Mean	Std.Dev	# of Case	Fitting Distribution
			MAP (kPa)			
BH 1	99	181	104	8.54	8780	RiskTriang
BH 2	93	143	101	7.06	13407	RiskUniform
BH 3	97	135	104	7.42	9853	RiskUniform
BH 4	95	178	112	15.30	6406	RiskTriang
BH 5	93	133	101	5.4	9782	RiskTriang
BH 6	95	181	111	16	5379	RiskTriang
			RPM			
BH 1	508	2314	905	175	8780	RiskLogLogistic
BH 2	790	2331	1256	385	13407	RiskInvGauss
BH 3	779	2291	1225	480	9853	RiskInvGauss
BH 4	92	2286	1119	318	6406	RiskWeibull
BH 5	161	2096	1231	447	9782	RiskWeibull
BH 6	138	5000	1095	290	5379	RiskInvGauss
			IAT (C)			
BH 1	14	35	20	5.29	8780	RiskBetaGeneral
BH 2	12	38	26	4.81	13407	RiskUniform
BH 3	32	75	56	11	9853	RiskUniform
BH 4	35	127	51	6	6406	RiskPareto
BH 5	19	61	45	10.22	9782	RiskUniform
BH 6	27	127	47	5.03	5379	RiskTriang

Table A.3. Summary statistics of fuel use and emission rates for bulldozers

Equipment	Min	Max	Mean	Std.Dev	# of Case	Fitting Distribution
			Fuel Use Rates (g/s)			
BD 1	0.06	5.24	1.47	1.32	5019	RiskInvGauss
BD 2	-7.39	6.28	0.757	0.733	39919	RiskLogLogistic
BD 3	0.343	6.73	2.27	0.984	3231	RiskLogLogistic
BD 4	0.07	9.68	3.04	2.90	12697	RiskInvGauss
BD 5	0.02	18.52	8.87	6.46	10550	RiskBetaGeneral
BD 6	0.15	1.90	0.992	0.379	5156	RiskTriang
			NO_x (g/s)			
BD 1	0.00576	0.247	0.0701	0.0541	5019	RiskPearson
BD 2	-0.00652	0.153	0.0255	0.0216	39919	RiskPearson
BD 3	0.0214	0.424	0.113	0.0537	3231	RiskLogLogistic
BD 4	0.00621	0.571	0.170	0.147	12697	RiskPearson
BD 5	0.00426	1.290	0.531	0.402	10550	RiskLognorm
BD 6	0.00559	0.0554	0.0288	0.0103	5156	RiskTriang
			HC (g/s)			
BD 1	-0.00377	0.0145	0.00447	0.0021	5019	RiskExtValue
BD 2	-0.00374	0.00032	0	0	39919	RiskNormal
BD 3	0.00204	0.0185	0.00637	0.002	3231	RiskGamma
BD 4	0	0.0389	0.0109	0.00683	12697	RiskInvGauss
BD 5	0.00	0.0586	0.00905	0.00478	10550	RiskPearson
BD 6	-0.00192	0.0233	0.00665	0.0049	5156	RiskInvGauss
			CO (g/s)			
BD 1	0.00205	0.175	0.0175	0.0158	5019	RiskPearson
BD 2	-0.00329	0.00812	0	0	39919	RiskInvGauss
BD 3	0.00522	0.0667	0.0235	0.0063	3231	RiskGamma
BD 4	0.00059	1.39	0.0364	0.0553	12697	RiskPearson
BD 5	0.00632	1.57	0.0666	0.0615	10550	RiskLogLogistic
BD 6	0.00	0.14	0.0122	0.0057	5156	RiskLogistic
			CO_2 (g/s)			
BD 1	0.187	16.51	4.63	4.17	5019	RiskInvGauss
BD 2	-6.75	14.04	2.37	2.31	39919	RiskExtValue
BD 3	1.07	21.24	7.12	3.11	3231	RiskLogLogistic
BD 4	0.164	30.64	9.53	9.12	12697	RiskInvGauss
BD 5	0.00804	58.39	27.96	20.43	10550	RiskBetaGeneral
BD 6	0.43	5.95	3.10	1.19	5156	RiskTriang
			PM (mg/s)			
BD 1	0.0	5.51	0.641	0.711	5019	RiskLogNorm
BD 2	0.02	2.77	0.19	0.29	39919	RiskBetaGeneral
BD 3	0.08	8.24	1.25	1.18	3231	RiskPearson
BD 4	0.09	5.67	0.813	0.746	12697	RiskBetaGeneral
BD 5	0	0	0	0	10550	-
BD 6	0.02	2.7	0.255	0.196	5156	RiskGamma

Table A.4. Summary statistics of engine performance data for bulldozers

Equipment	Min	Max	Mean	Std.Dev	# of Case	Fitting Distribution
			MAP (kPa)			
BD 1	93	141	104	11	5019	RiskUniform
BD 2	99	244	119	28.84	39919	RiskTriang
BD 3	100	159	114	9.36	3231	RiskTriang
BD 4	98	179	120	24.4	12697	RiskUniform
BD 5	98	199	147	40	10550	RiskBetaGeneral
BD 6	98	182	113	9.54	5156	RiskTriang
			RPM			
BD 1	658	2236	1386	507	5019	RiskTriang
BD 2	502	2491	1341	332	39919	RiskLogNorm
BD 3	520	2976	2182	214	3231	RiskLogistic
BD 4	419	2155	1335	448	12697	RiskBetaGeneral
BD 5	716	2480	1624	634	10550	RiskExtValue
BD 6	502	3444	1856	417	5156	RiskNormal
			IAT (C)			
BD 1	30	64	34	1.15	5019	RiskExpon
BD 2	22	35	30	2.62	39919	RiskUniform
BD 3	6	70	8	1.49	3231	RiskExtValue
BD 4	21	32	25	2.35	12697	RiskInvGauss
BD 5	8	19	13	2.77	10550	RiskExpon
BD 6	16	25	21	1.67	5156	RiskTriang

Table A.5. Summary statistics of fuel use and emission rates for excavators

Equipment	Min	Max	Mean	Std.Dev	# of Case	Fitting Distribution
			Fuel Use Rates (g/s)			
EX 1	0.464	10.03	2.51	2.83	6420	RiskLogNorm
EX 2	0.114	7.21	2.02	1.88	23593	RiskPearson
EX 3	0.08	4.74	1.71	1.16	19063	RiskBetaGeneral
			NO_x (g/s)			
EX 1	0.0215	0.378	0.0887	0.0910	6420	RiskPearson
EX 2	5.87E-005	0.384	0.0487	0.0373	23593	RiskPearson
EX 3	0.00419	0.153	0.0705	0.037	19063	RiskExpon
			HC (g/s)			
EX 1	-0.00792	0.0235	0.00353	0.00256	6420	RiskExtValue
EX 2	0.00	0.108	0.00501	0.00375	23593	RiskInvGauss
EX 3	-0.00017	0.0539	0.00547	0.00541	19063	RiskInvGauss
			CO (g/s)			
EX 1	0.00308	0.109	0.0101	0.0067	6420	RiskInvGauss
EX 2	0.000587	0.232	0.0197	0.0146	23593	RiskPearson
EX 3	0.00	0.339	0.00759	0.0106	19063	RiskLogLogistic
			CO_2 (g/s)			
EX 1	1.46	31.69	7.92	8.94	6420	RiskInvGauss
EX 2	0.359	22.71	6.36	5.93	23593	RiskPearson
EX 3	0.26	15.0	5.39	3.65	19063	RiskBetaGeneral
			PM (mg/s)			
EX 1	0.00	6.06	0.9	1.16	6420	RiskInvGauss
EX 2	0.00	4.53	0.463	0.561	23593	RiskExpon
EX 3	0.01	5.81	0.426	0.531	19063	RiskBetaGeneral

Table A.6. Summary statistics of engine performance data for excavators

Equipment	Min	Max	Mean	Std.Dev	# of Case	Fitting Distribution
			MAP (kPa)			
EX 1	99	235	127	38	6420	RiskBetaGeneral
EX 2	98	206	123	31	23593	RiskTriang
EX 3	93	228	147	38	19063	RiskBetaGeneral
			RPM			
EX 1	788	1936	1247	470	6420	RiskBetaGeneral
EX 2	501	1994	1373	455	23593	RiskNormal
EX 3	258	2083	1568	496	19063	RiskTriang
			IAT (C)			
EX 1	38	64	46	6	6420	RiskUniform
EX 2	23	45	34	6	23593	RiskPareto
EX 3	25	75	55	12	19063	RiskUniform

Table A.7. Summary statistics of fuel use and emission rates for motor graders

Equipment	Min	Max	Mean	Std.Dev	# of Case	Fitting Distribution
			Fuel Use Rates (g/s)			
MG 1	0.25	19.48	4.81	2.93	16293	RiskBetaGeneral
MG 2	0.125	9.48	1.51	1.81	10767	RiskPearson
MG 3	0.02	7.35	2.24	1.49	5590	RiskExpon
MG 4	0.12	9.50	2.58	1.52	10040	RiskBetaGeneral
MG 5	0.14	9.55	2.31	2.33	9788	RiskInvGauss
MG 6	0.220	8.05	2.19	1.47	7757	RiskBetaGeneral
			NO_x (g/s)			
MG 1	0.000148	0.78	0.179	0.110	16293	RiskBetaGeneral
MG 2	0.00449	0.342	0.0533	0.00478	10767	RiskPearson
MG 3	0.00112	0.314	0.0765	0.0501	5590	RiskExpon
MG 4	0.0112	0.803	0.166	0.0995	10040	RiskGamma
MG 5	0.0118	0.668	0.117	0.112	9788	RiskPearson
MG 6	0.00521	0.359	0.0453	0.0276	7757	RiskExtValue
			HC (g/s)			
MG 1	0.00	0.0802	0.0148	0.00993	16293	RiskGamma
MG 2	-0.0129	0.180	0.0138	0.0141	10767	RiskLogLogistic
MG 3	0.00171	0.150	0.0421	0.0295	5590	RiskBetaGeneral
MG 4	0.00091	0.123	0.0264	0.0143	10040	RiskInvGauss
MG 5	0	0.0413	0.00727	0.0059	9788	RiskPearson
MG 6	-0.00145	0.0633	0.0059	0.0062	7757	RiskInvGauss
			CO (g/s)			
MG 1	0.00075	0.354	0.0185	0.0139	16293	RiskInvGauss
MG 2	-0.0456	0.520	0.0133	0.0294	10767	RiskLogLogistic
MG 3	-0.0746	0.087	-0.0075	0.0207	5590	RiskWeibull
MG 4	0.00454	0.238	0.0393	0.0259	10040	RiskLogLogistic
MG 5	0.00602	133.54	0.0507	1.35	9788	RiskLogLogistic
MG 6	-0.0336	0.399	0.0048	0.0132	7757	RiskLogLogistic
			CO_2 (g/s)			
MG 1	0.777	61.46	15.17	9.26	16293	RiskBetaGeneral
MG 2	0.320	29.92	4.71	5.69	10767	RiskPearson
MG 3	-0.0375	23.04	6.97	4.66	5590	RiskWeibull

MG 4	0.305	29.91	8.01	4.77	10040	RiskBetaGeneral
MG 5	0.39	26013	9.88	263	9788	RiskInvGauss
MG 6	0.693	24893	10.12	283	7757	RiskLogNorm
			PM (mg/s)			
MG 1	0.05	5.26	1.37	0.768	16293	RiskWeibull
MG 2	0.05	3.67	0.272	0.405	10767	RiskInvGauss
MG 3	0.05	3.36	0.785	0.525	5590	RiskNormal
MG 4	0.02	3.96	0.635	0.551	10040	RiskExpon
MG 5	0.00	3.26	0.528	0.572	9788	RiskExpon
MG 6	0.04	2.71	0.508	0.304	7757	RiskLogLogistic

Table A.8. Summary statistics of engine performance data for motor graders

Equipment	**Min**	**Max**	**Mean**	**Std.Dev**	**# of Case**	**Fitting Distribution**
			MAP (kPa)			
MG 1	100	239	174	43	16293	RiskBetaGeneral
MG 2	100	246	115	26.72	10767	RiskTriang
MG 3	96	223	149	35.21	5590	RiskTriang
MG 4	96	160	113	10.98	10040	RiskUniform
MG 5	100	201	120	23.61	9788	RiskTriang
MG 6	97	290	169	47.21	7757	RiskTriang
			RPM			
MG 1	511	3877	1789	508	16293	RiskLogistic
MG 2	711	2394	1167	622	10767	RiskPearson
MG 3	745	2347	1746	587	5590	RiskBetaGeneral
MG 4	505	2711	1827	532	10040	RiskTriang
MG 5	597	2464	1405	625	9788	RiskInvGauss
MG 6	508	2286	1839	528	7757	RiskBetaGeneral
			IAT (C)			
MG 1	18	35	30	2.73	16293	RiskUniform
MG 2	34	57	45	4.39	10767	RiskUniform
MG 3	36	47	41	2.18	5590	RiskUniform
MG 4	0	0	0	0	10040	-
MG 5	10	15	12	0.99	9788	RiskPareto
MG 6	51	65	60	2.44	7757	RiskExpon

Table A.9. Summary statistics of fuel use and emission rates for off-road trucks

Equipment	Min	Max	Mean	Std.Dev	# of Case	Fitting Distribution
			Fuel Use Rates (g/s)			
ORT 1	0.260	14.79	2.09	2.31	21746	RiskPearson
ORT 2	-1.40	13.35	1.49	1.54	5565	RiskPearson
ORT 3	0.0202	13.59	1.69	2.21	4541	RiskLogLogistic
			NO_x (g/s)			
ORT 1	0.0081	298	0.0965	2.02	21746	RiskPearson
ORT 2	-0.0341	246	0.112	3.29	5565	RiskPearson
ORT 3	0.0021	0.441	0.0744	0.0597	4541	RiskLogLogistic
			HC (g/s)			
ORT 1	0.00	0.0448	0.0062	0.0056	21746	RiskPearson
ORT 2	-0.00491	15.02	0.00687	0.201	5565	RiskPearson
ORT 3	0.00	0.0343	0.00477	0.00314	4541	RiskLogLogistic
			CO (g/s)			
ORT 1	0.00	1.99	0.0335	0.0897	21746	RiskPearson
ORT 2	-0.0102	40.83	0.0187	0.547	5565	RiskLognorm
ORT 3	0.000461	0.186	0.0164	0.0111	4541	RiskPearson
			CO_2 (g/s)			
ORT 1	0.81	46.47	6.54	7.20	21746	RiskPearson
ORT 2	-4.20	16904	7.73	227	5565	RiskLognorm
ORT 3	-0.0248	42.91	5.30	6.97	4541	RiskLogLogistic
			PM (mg/s)			
ORT 1	0.11	6.31	0.618	0.848	21746	RiskLognorm
ORT 2	-0.201	1467	0.671	19.67	5565	RiskLognorm
ORT 3	0.00	8.24	0.437	0.646	4541	RiskExtValue

Table A.10. Summary statistics of engine performance data for off-road trucks

Equipment	Min	Max	Mean	Std.Dev	# of Case	Fitting Distribution
			MAP (kPa)			
ORT 1	100	270	124	38.67	21746	RiskTriang
ORT 2	99	239	104	13.10	5565	RiskBetaGeneral
ORT 3	97	242	106	22.68	4541	RiskInvGauss
			RPM			
ORT 1	622	2189	934	399	21746	RiskInvGauss
ORT 2	381	1919	885	306	5565	RiskLogLogistic
ORT 3	415	2020	968	322	4541	RiskLogLogistic
			IAT (C)			
ORT 1	13	27	19	2.34	21746	RiskUniform
ORT 2	19	127	34	8.48	5565	RiskBetaGeneral
ORT 3	32	78	38	8.41	4541	RiskTriang

Table A.11. Summary statistics of fuel use and emission rates for track loaders

Equipment	Min	Max	Mean	Std.Dev	# of Case	Fitting Distribution
			Fuel Use Rates (g/s)			
TL 1	0.18	6.25	2.59	1.33	5515	RiskNormal
TL 2	0.191	6.86	2.53	1.95	5250	RiskTriang
TL 3	0.354	7.06	3.28	2.46	3306	RiskBetaGeneral
			NO_x (g/s)			
TL 1	0.00333	0.143	0.0471	0.0235	5515	RiskWeibull
TL 2	0.00514	0.554	0.143	0.134	5250	RiskBetaGeneral
TL 3	0.0023	0.145	0.060	0.0437	3306	RiskExpon
			HC (g/s)			
TL 1	0.00	29.48	0.0135	0.397	5515	RiskLognorm
TL 2	-0.000340	21.82	0.0102	0.301	5250	RiskLognorm
TL 3	-0.00187	0.011	0.0020	0.00197	3306	RiskPearson
			CO (g/s)			
TL 1	0.00089	67.01	0.0308	0.902	5515	RiskLognorm
TL 2	0.00	0.0283	0.0105	0.00607	5250	RiskTriang
TL 3	0.00081	57.51	0.0334	1.00	3306	RiskPearson
			CO_2 (g/s)			
TL 1	0.52	29297	13.45	394	5515	RiskLognorm
TL 2	0.604	21.66	7.98	6.15	5250	RiskTriang
TL 3	1.11	22.32	10.34	7.76	3306	RiskBetaGeneral
			PM (mg/s)			
TL 1	0.05	4.60	0.64	0.458	5515	RiskInvGauss
TL 2	0.06	2.55	0.586	0.343	5250	RiskBetaGeneral
TL 3	0.10	2.92	0.617	0.443	3306	RiskExpon

Table A.12. Summary statistics of engine performance data for track loaders

Equipment	Min	Max	Mean	Std.Dev	# of Case	Fitting Distribution
			MAP (kPa)			
TL 1	95	179	120	22.76	5515	RiskTriang
TL 2	98	152	122	17.95	5250	RiskUniform
TL 3	100	192	142	36.14	3306	RiskBetaGeneral
			RPM			
TL 1	626	2192	1700	456	5515	RiskLogistic
TL 2	500	2864	1692	560	5250	RiskTriang
TL 3	835	2422	1590	599	3306	RiskUniform
			IAT (C)			
TL 1	29	44	32	2.79	5515	RiskUniform
TL 2	10	19	13	1.74	5250	RiskPareto
TL 3	13	54	30	7.73	3306	RiskUniform

Appendix B

Summary of Pearson correlation coefficients for each item of equipment

Table B.1. Summary of Pearson Correlation Coefficients for Backhoes

Equipment	Engine Data	Fuel Use	NO_x	HC	CO	CO_2	PM
BH 1	MAP	0.9291	0.7901	0.4139	0.1083	0.9293	0.2563
	RPM	0.8477	0.7479	0.5232	0.2534	0.8463	0.2970
	IAT	0.4361	0.6146	-0.1834	-0.6499	0.4415	0.0289
BH 2	MAP	0.9112	0.7865	0.2163	0.3723	0.9111	0.5295
	RPM	0.8838	0.9023	0.3823	0.3103	0.8834	0.3734
	IAT	-0.0175	0.1741	0.0834	-0.1692	-0.0166	-0.1736
BH 3	MAP	0.9802	0.8808	0.8162	0.4958	0.9803	0.6071
	RPM	0.8895	0.9044	0.8027	0.4151	0.8888	0.4564
	IAT	0.5359	0.6740	0.3822	0.1724	0.5350	0.0390
BH 4	MAP	0.9428	0.8879	0.8129	0.7881	0.9427	0.9420
	RPM	0.8406	0.8264	0.7913	0.6830	0.8403	0.7657
	IAT	0.4271	0.5251	0.5579	0.4084	0.4263	0.3939
BH 5	MAP	0.9227	0.0731	0.0656	0.0961	0.0801	0.6502
	RPM	0.8263	0.0311	0.0262	0.0342	0.0373	0.4116
	IAT	0.6633	0.0270	0.0179	0.0263	0.0302	0.3730
BH 6	MAP	0.8793	0.8679	0.6345	0.7041	0.8790	0.9202
	RPM	0.8946	0.8573	0.7282	0.7305	0.8941	0.7593
	IAT	0.3280	0.3937	0.1157	0.1015	0.3281	0.1815

Table B.2. Summary of Pearson Correlation Coefficients for Bulldozers

Equipment	Engine Data	Fuel Use	NO_x	HC	CO	CO_2	PM
BD 1	MAP	0.9726	0.9128	0.7241	0.5140	0.9723	0.8888
	RPM	0.8956	0.9189	0.7720	0.3669	0.8957	0.7796
	IAT	-0.0584	-0.0509	-0.0154	-0.0226	-0.0584	-0.0669
BD 2	MAP	0.9677	0.9085	0.1180	0.0488	0.9692	0.8896
	RPM	0.8779	0.8340	0.1176	0.0447	0.8791	0.7359
	IAT	-0.0440	-0.0474	0.0286	-0.0191	-0.0448	-0.0877
BD 3	MAP	0.9585	0.8609	0.4288	-0.0926	0.9587	0.6360
	RPM	0.5800	0.4354	0.5406	0.2474	0.5786	0.3275
	IAT	-0.1094	-0.0912	-0.0896	-0.0109	-0.1092	-0.1319
BD 4	MAP	0.9910	0.9547	0.8344	0.4031	0.9906	0.8584
	RPM	0.8079	0.7809	0.8434	0.2408	0.8080	0.7836
	IAT	0.0701	0.1023	0.1787	0.0381	0.0693	-0.0014
BD 5	MAP	0.9926	0.9614	0.5424	0.2327	0.9926	N/A
	RPM	0.9225	0.9114	0.5681	0.2312	0.9223	N/A
	IAT	-0.4935	-0.4733	-0.2503	-0.2692	-0.4928	N/A
BD 6	MAP	0.5711	0.4377	-0.0770	-0.0186	0.5755	0.6137
	RPM	0.8157	0.7679	0.1300	0.4166	0.8157	0.5179
	IAT	0.1205	0.1106	-0.2040	0.0500	0.1234	0.0095

Table B.3. Summary of Pearson Correlation Coefficients for Excavators

Equipment	Engine Data	Fuel Use	NO_x	HC	CO	CO_2	PM
EX 1	MAP	0.9909	0.9737	0.5920	0.7367	0.9909	0.9386
	RPM	0.7975	0.7352	0.6324	0.8547	0.7971	0.7391
	IAT	0.5647	0.5893	0.0704	0.3720	0.5650	0.5137
EX 2	MAP	0.9814	0.9219	0.6245	0.4684	0.9815	0.9421
	RPM	0.8519	0.8511	0.6210	0.5682	0.8512	0.6894
	IAT	0.5458	0.5649	0.3294	0.2967	0.5457	0.4359
EX 3	MAP	0.9645	0.9357	0.4400	0.1353	0.9640	0.5767
	RPM	0.8407	0.7917	0.4182	0.2254	0.8397	0.4689
	IAT	0.3222	0.3998	0.3578	-0.1177	0.3218	0.4366

Table B.4. Summary of Pearson Correlation Coefficients for Motor Graders

Equipment	Engine Data	Fuel Use	NO_x	HC	CO	CO_2	PM
MG 1	MAP	0.8743	0.7765	0.4356	0.5094	0.8741	0.8961
	RPM	0.7326	0.6300	0.3883	0.4147	0.7324	0.7508
	IAT	0.3605	0.3767	-0.2044	0.3077	0.3616	0.2468
MG 2	MAP	0.9770	0.8886	0.4880	0.3435	0.9776	0.8206
	RPM	0.8784	0.8632	0.6096	0.3135	0.8777	0.7925
	IAT	0.0623	0.0699	-0.1233	0.0199	0.0634	0.0594
MG 3	MAP	0.9579	0.8687	0.7171	0.0055	0.9568	0.9565
	RPM	0.8027	0.6548	0.6861	0.0205	0.8003	0.7900
	IAT	-0.4814	-0.4163	-0.5927	-0.0785	-0.4783	-0.5242
MG 4	MAP	0.9360	0.8596	0.4257	0.3190	0.9356	0.8310
	RPM	0.7667	0.5995	0.4764	0.1106	0.7666	0.5057
	IAT	N/A	N/A	N/A	N/A	N/A	N/A
MG 5	MAP	0.9880	0.9442	0.6981	0.2753	0.9879	0.9039
	RPM	0.9343	0.8842	0.7384	0.3249	0.9337	0.8849
	IAT	-0.4230	-0.3981	-0.5097	-0.2704	-0.4218	-0.4333
MG 6	MAP	0.9579	0.6665	0.2645	0.2523	0.9577	0.9215
	RPM	0.6227	0.4419	0.4325	0.0498	0.6221	0.7497
	IAT	0.3810	0.2538	-0.5444	0.1982	0.3831	0.1865

Table B.5. Summary of Pearson Correlation Coefficients for Off-Road Trucks

Equipment	Engine Data	Fuel Use	NO_x	HC	CO	CO_2	PM
OT 1	MAP	0.9115	0.8603	0.8246	0.5189	0.9119	0.9127
	RPM	0.8593	0.8239	0.8066	0.5548	0.8583	0.8640
	IAT	0.0737	0.0999	0.0832	0.0607	0.0733	0.0631
OT 2	MAP	0.9705	0.8790	0.6268	0.6489	0.9703	0.8967
	RPM	0.8121	0.6741	0.6603	0.5549	0.8117	0.8235
	IAT	0.0594	0.0335	0.2938	0.0601	0.0580	0.0907
OT 3	MAP	0.9844	0.9559	0.8244	0.7651	0.9845	0.8179
	RPM	0.8101	0.7105	0.8246	0.8363	0.8094	0.7510
	IAT	0.3756	0.3626	0.3133	0.3283	0.3756	0.2444

Table B.6. Summary of Pearson Correlation Coefficients for Track Loaders

Equipment	**Engine Data**	**Fuel Use**	**NO_x**	**HC**	**CO**	**CO_2**	**PM**
TL 1	MAP	0.7416	0.5927	0.6567	0.3989	0.7397	0.5608
	RPM	0.8245	0.7269	0.3360	0.4640	0.8242	0.6407
	IAT	0.0771	0.1218	-0.0233	-0.0458	0.0776	0.3413
TL 2	MAP	0.8304	0.8002	0.3386	0.6052	0.8307	0.8625
	RPM	0.7414	0.6613	0.3958	0.6592	0.7412	0.8137
	IAT	0.2302	0.1920	-0.1533	0.2315	0.2308	0.2668
TL 3	MAP	0.9824	0.9332	0.2664	0.7827	0.9825	0.8396
	RPM	0.8354	0.7430	0.3275	0.8310	0.8352	0.8334
	IAT	0.3940	0.4071	-0.1004	0.2803	0.3943	0.2493

Appendix C

Distributions Fittings for Each Item of Equipment

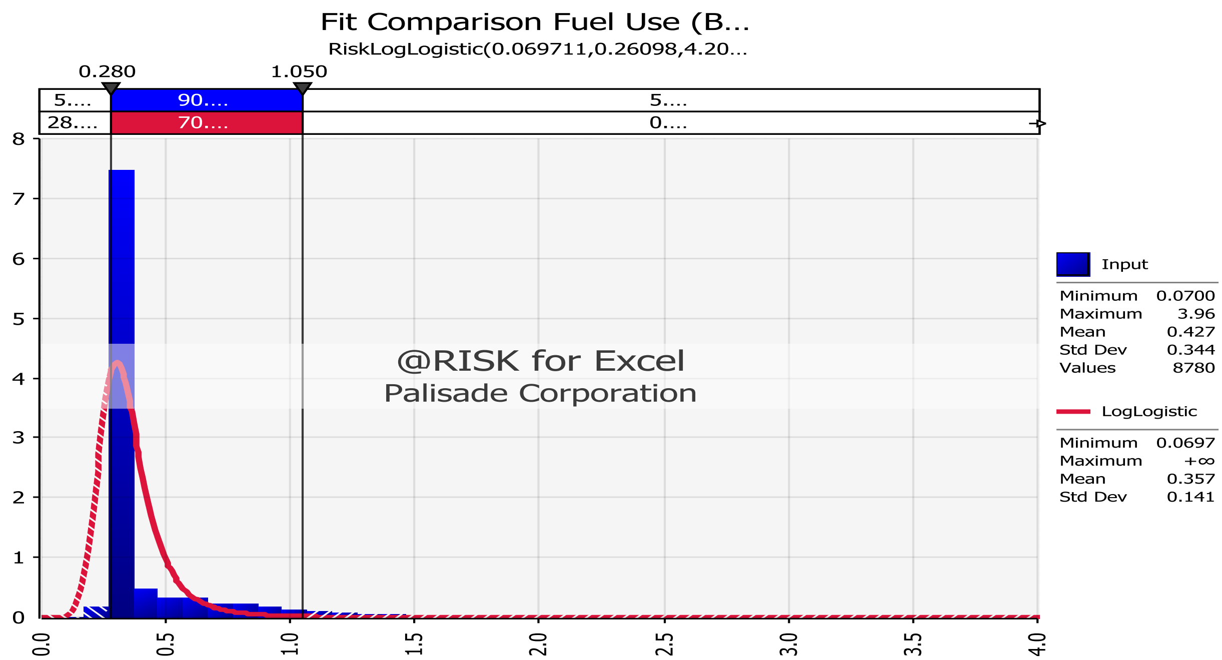

Figure C.1. Distribution fittings of fuel use for backhoe 1

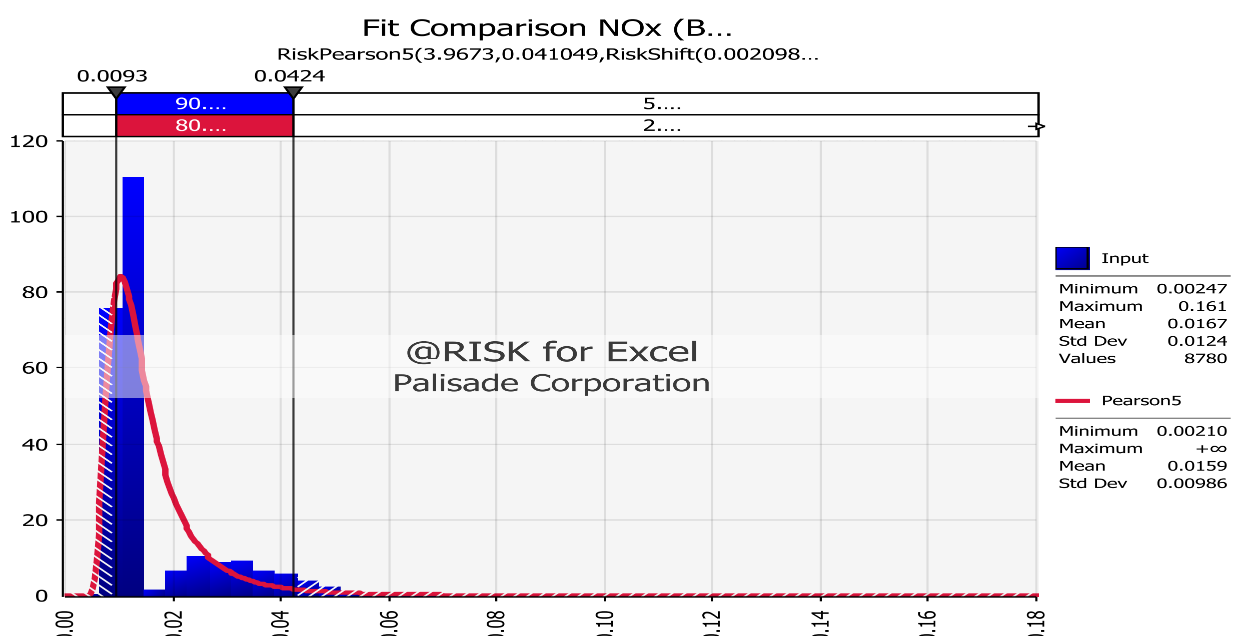

Figure C.2. Distribution fittings of NO_x for backhoe 1

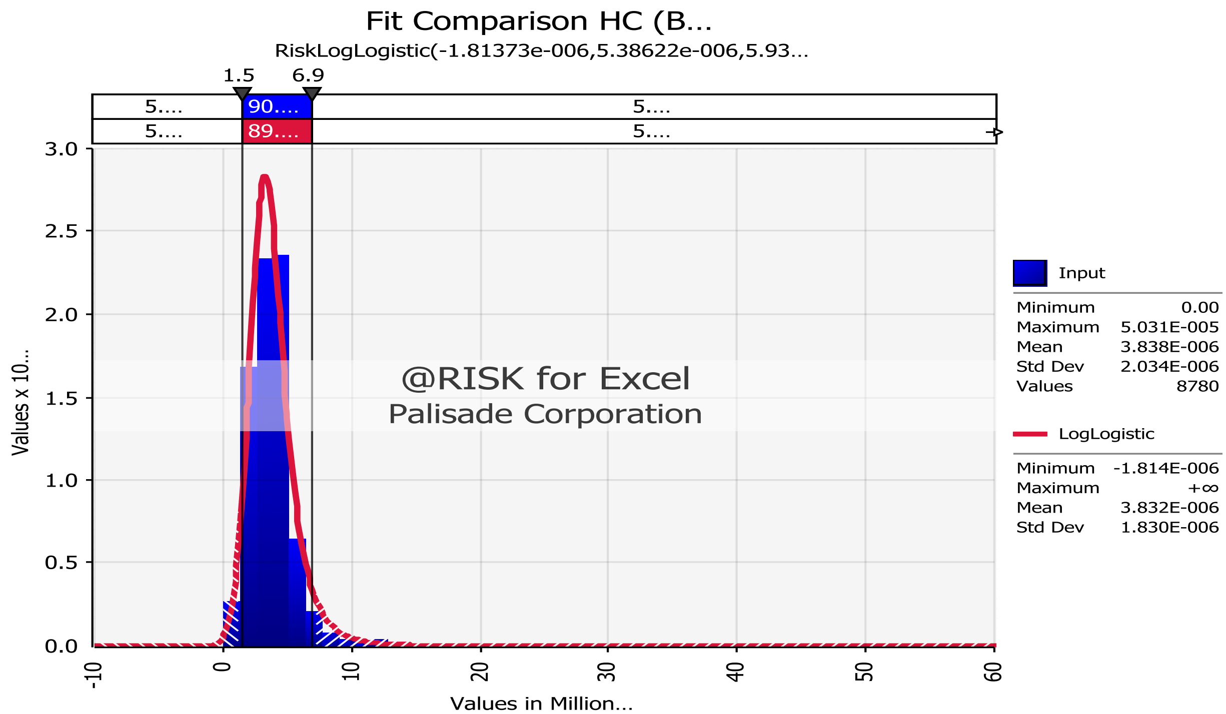

Figure C.3. Distribution fittings of HC for backhoe 1

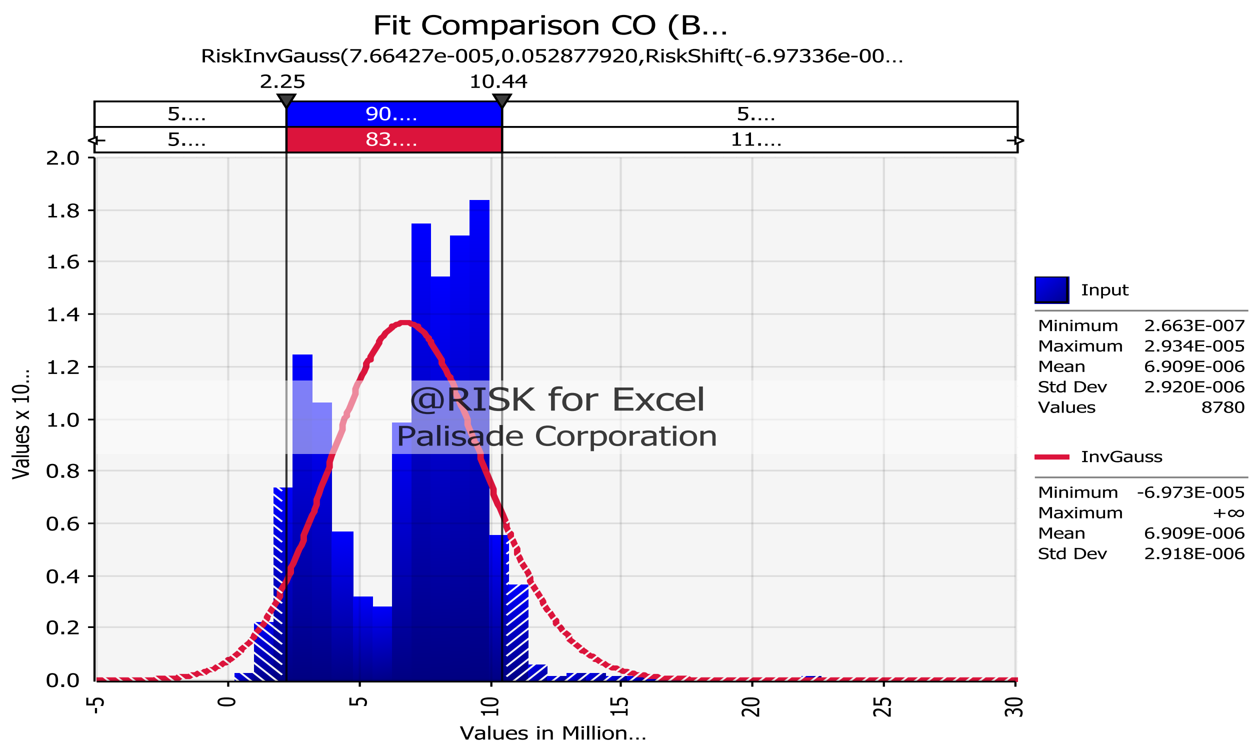

Figure C.4. Distribution fittings of CO for backhoe 1

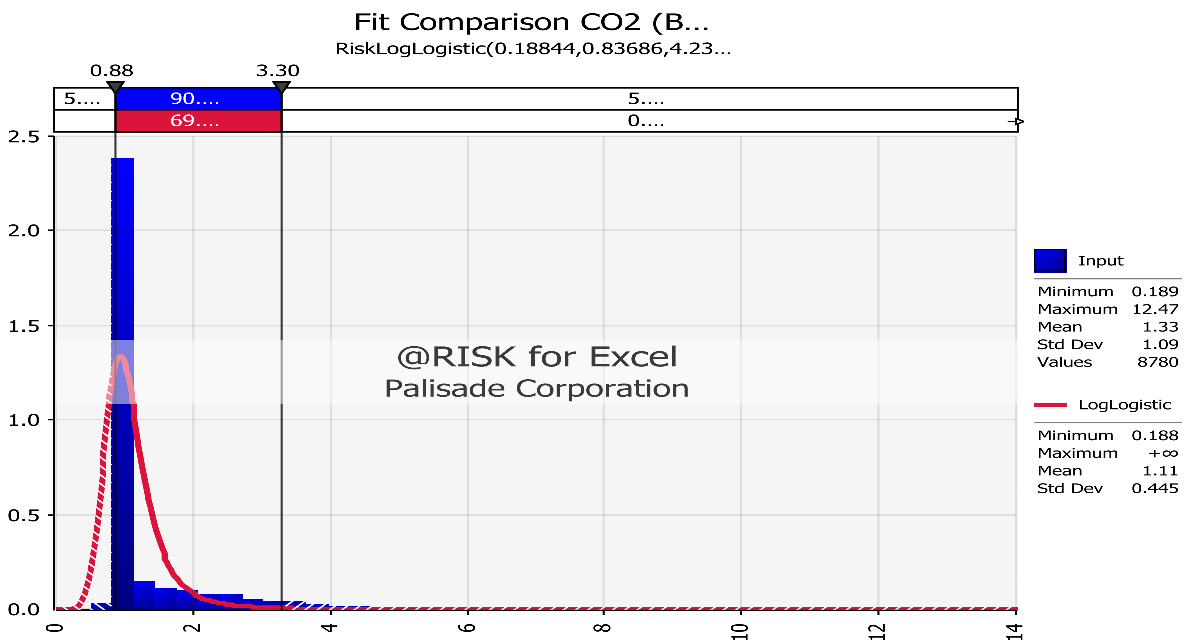

Figure C.5. Distribution fittings of CO_2 for backhoe 1

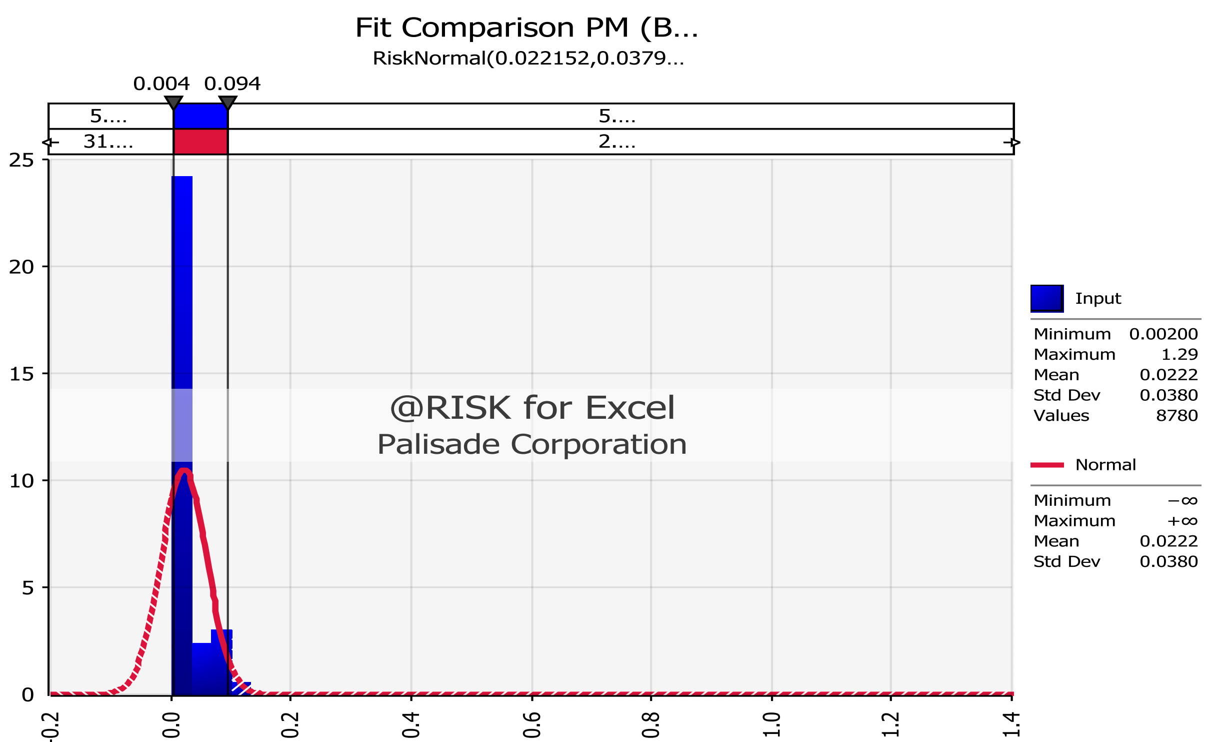

Figure C.6. Distribution fittings of PM for backhoe 1

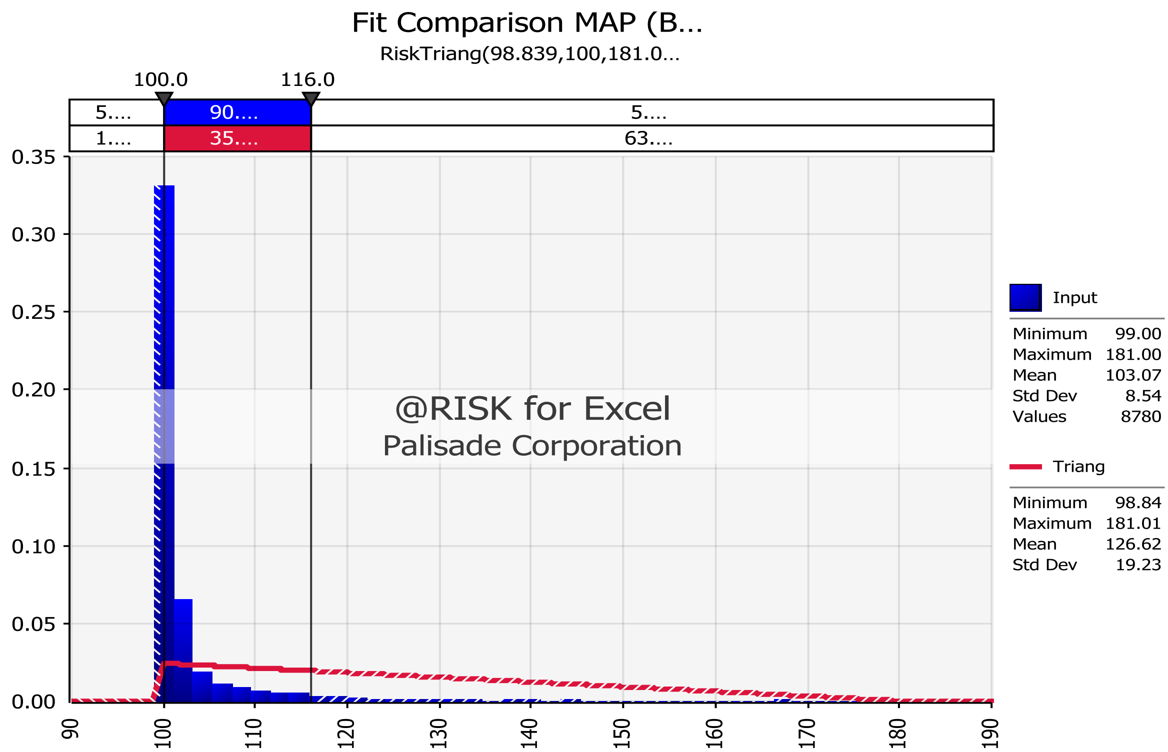

Figure C.7. Distribution fittings of MAP for backhoe 1

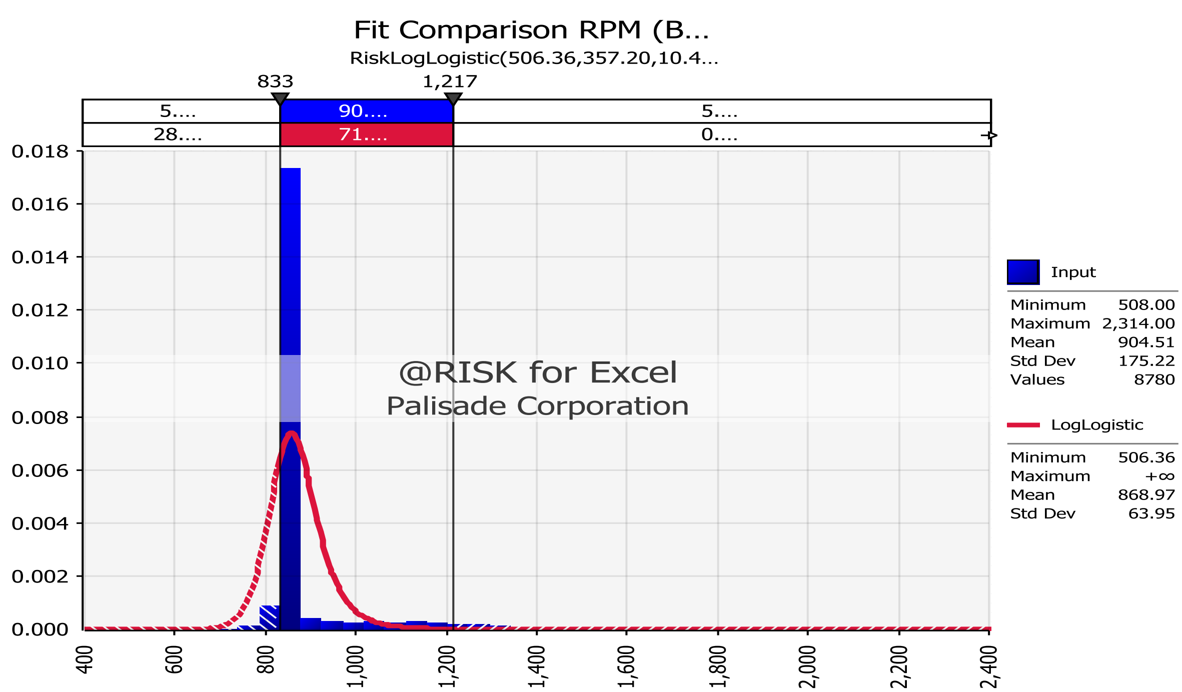

Figure C.8. Distribution fittings of RPM for backhoe 1

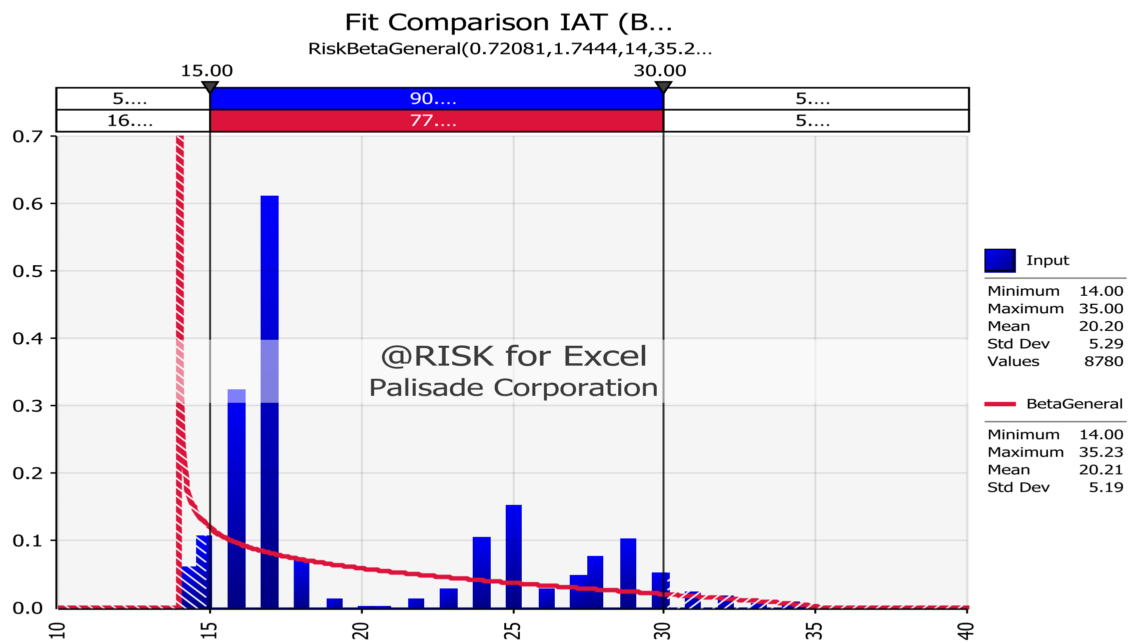

Figure C.9. Distribution fittings of IAT for backhoe 1

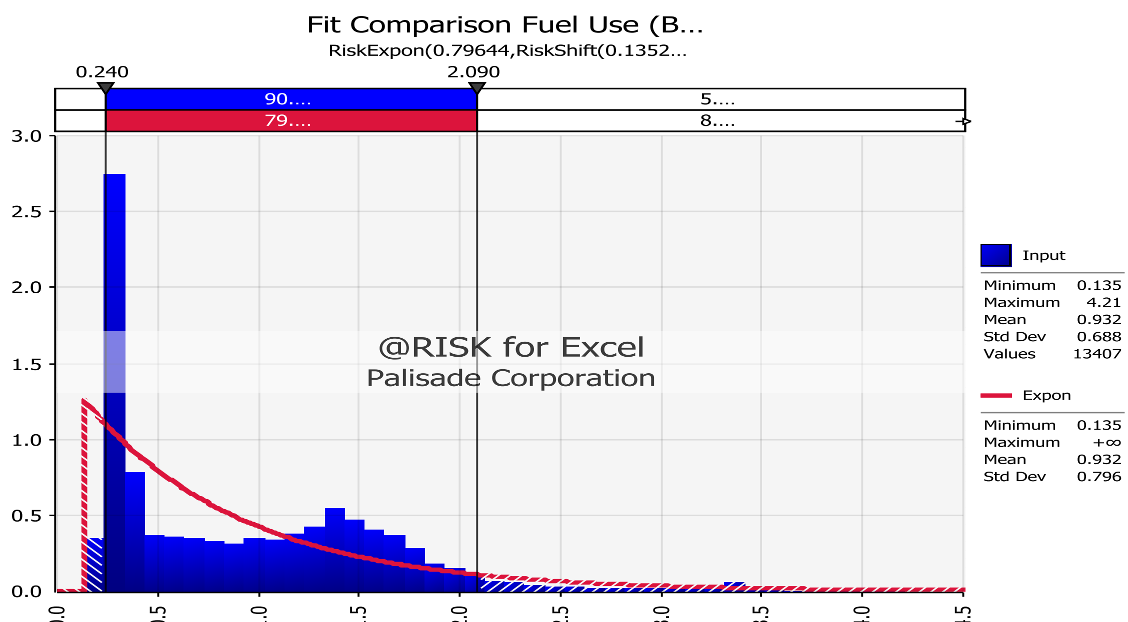

Figure C.10. Distribution fittings of Fuel use for backhoe 2

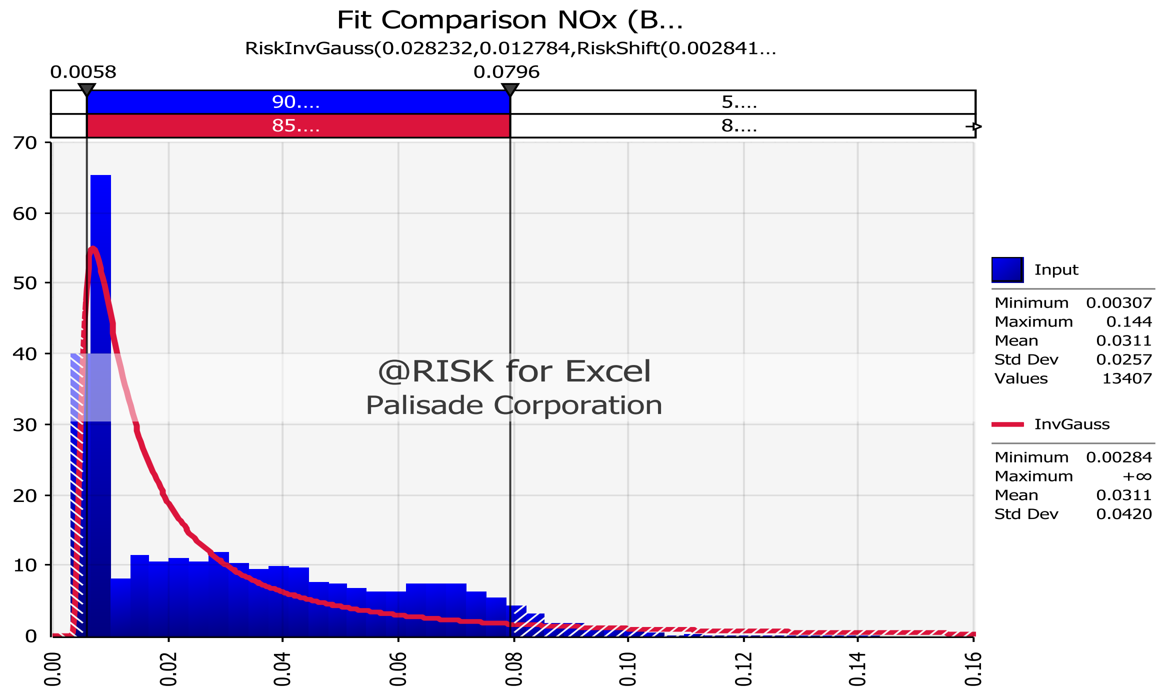

Figure C.11. Distribution fittings of NO_x for backhoe 2

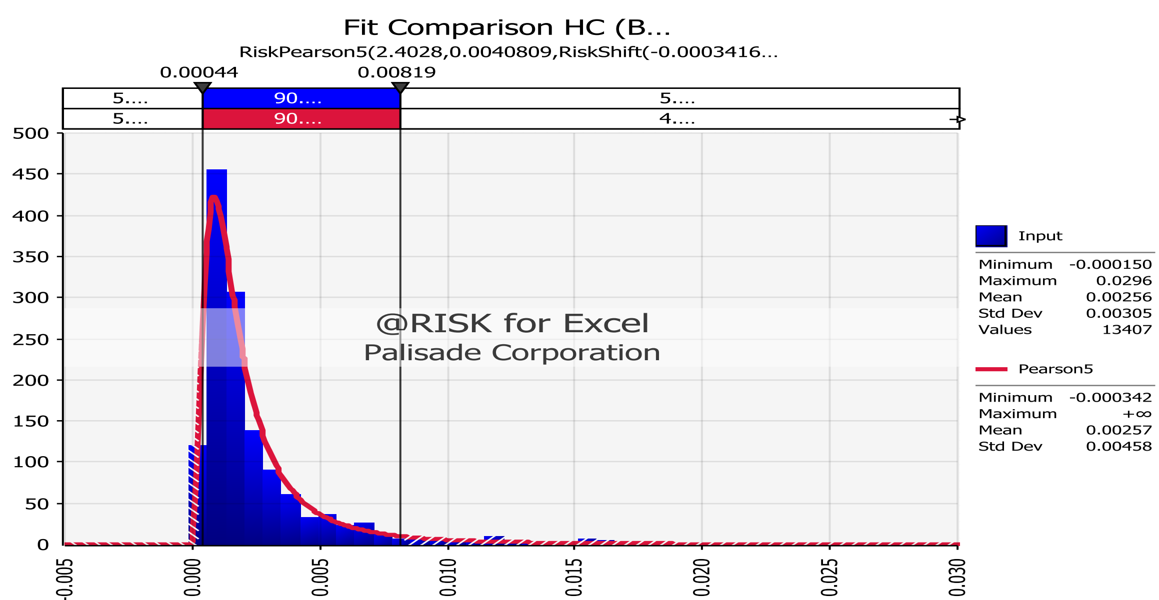

Figure C.12. Distribution fittings of HC for backhoe 2

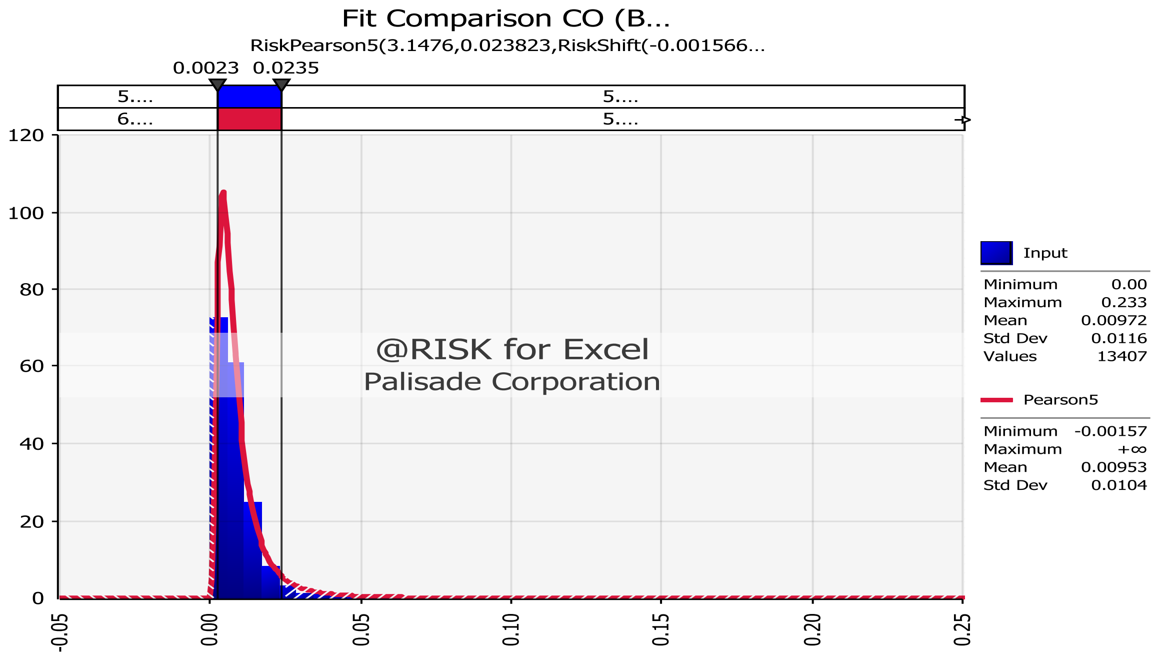

Figure C.13. Distribution fittings of CO for backhoe 2

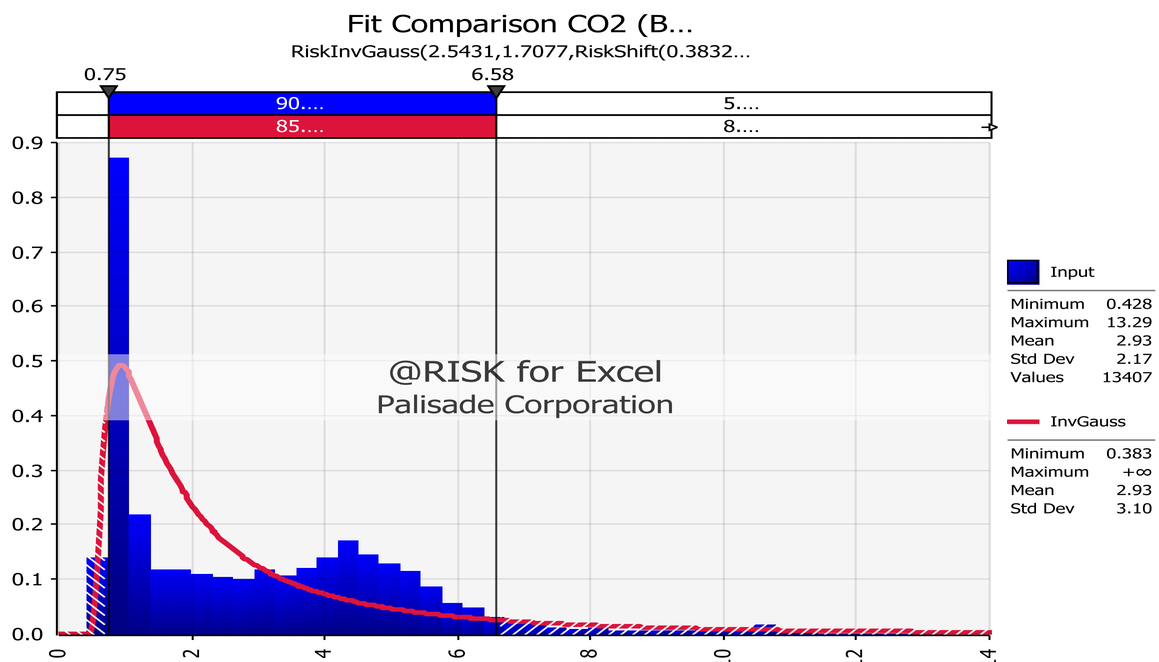

Figure C.14. Distribution fittings of CO_2 for backhoe 2

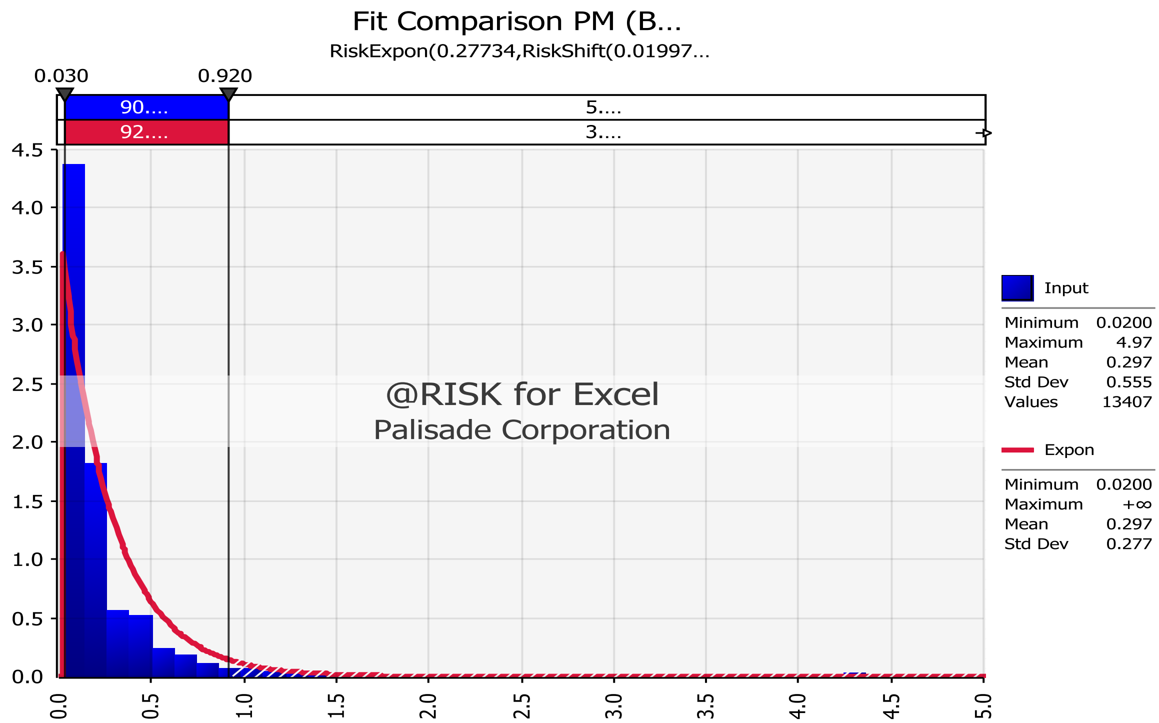

Figure C.15. Distribution fittings of PM for backhoe 2

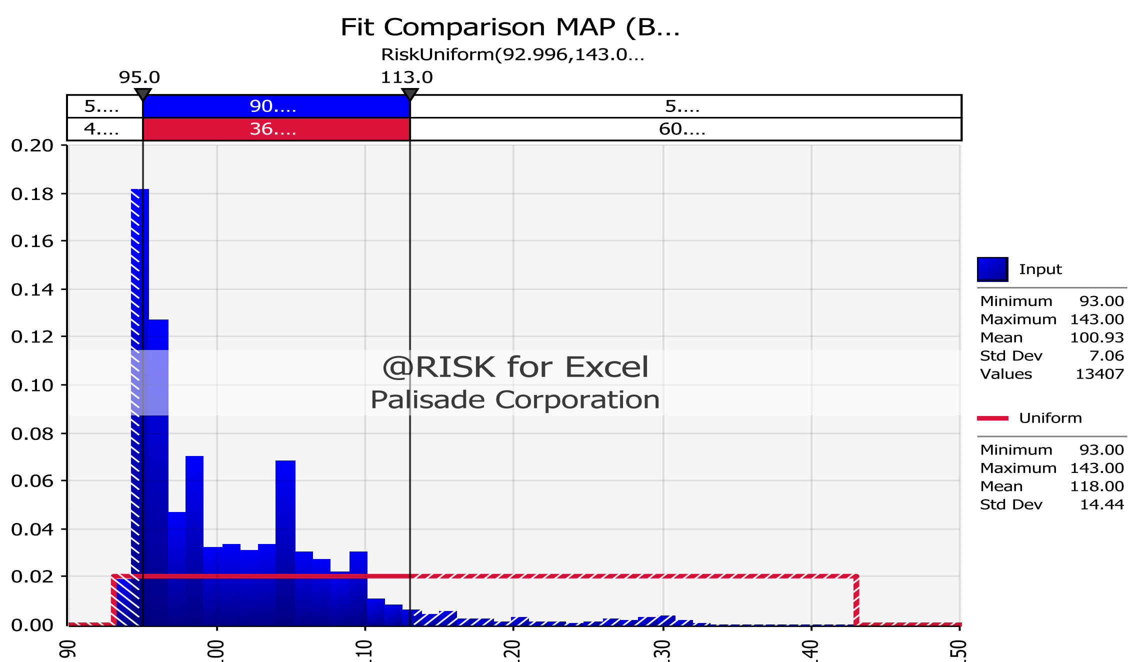

Figure C.16. Distribution fittings of MAP for backhoe 2

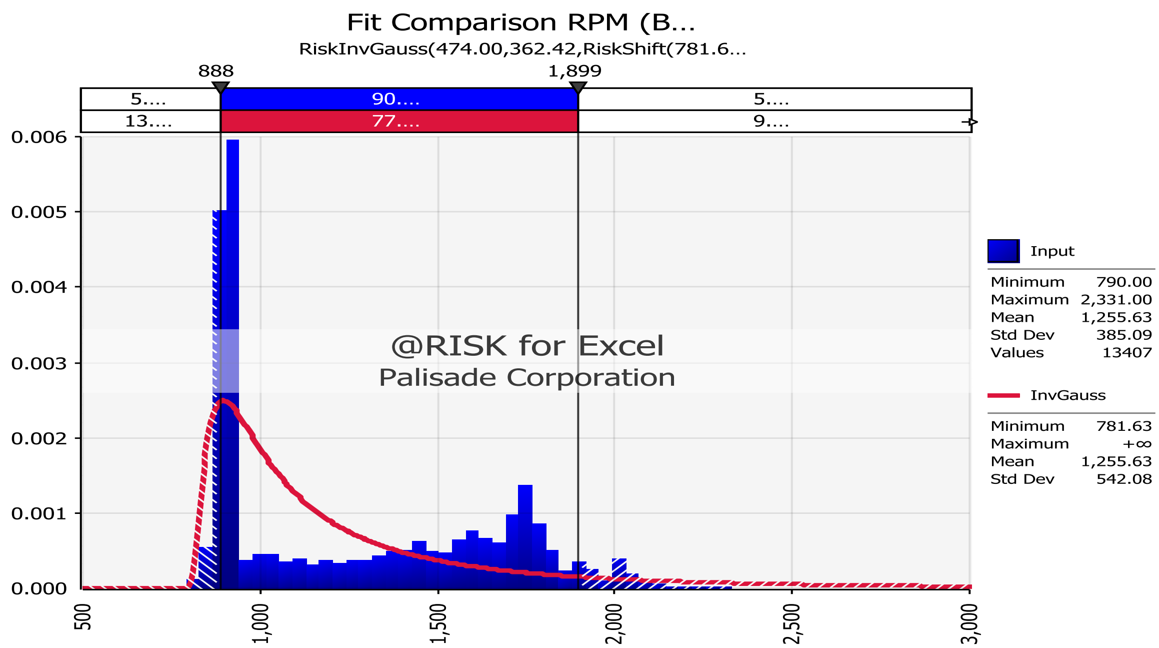

Figure C.17. Distribution fittings of RPM for backhoe 2

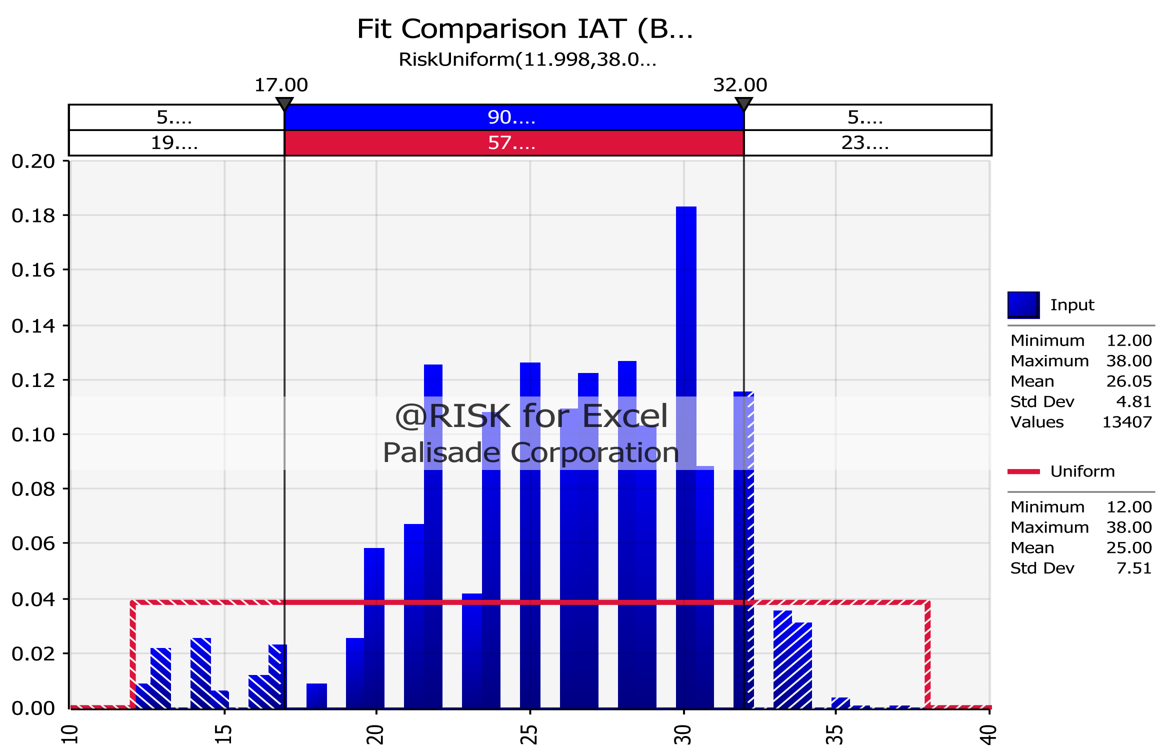

Figure C.18. Distribution fittings of IAT for backhoe 2

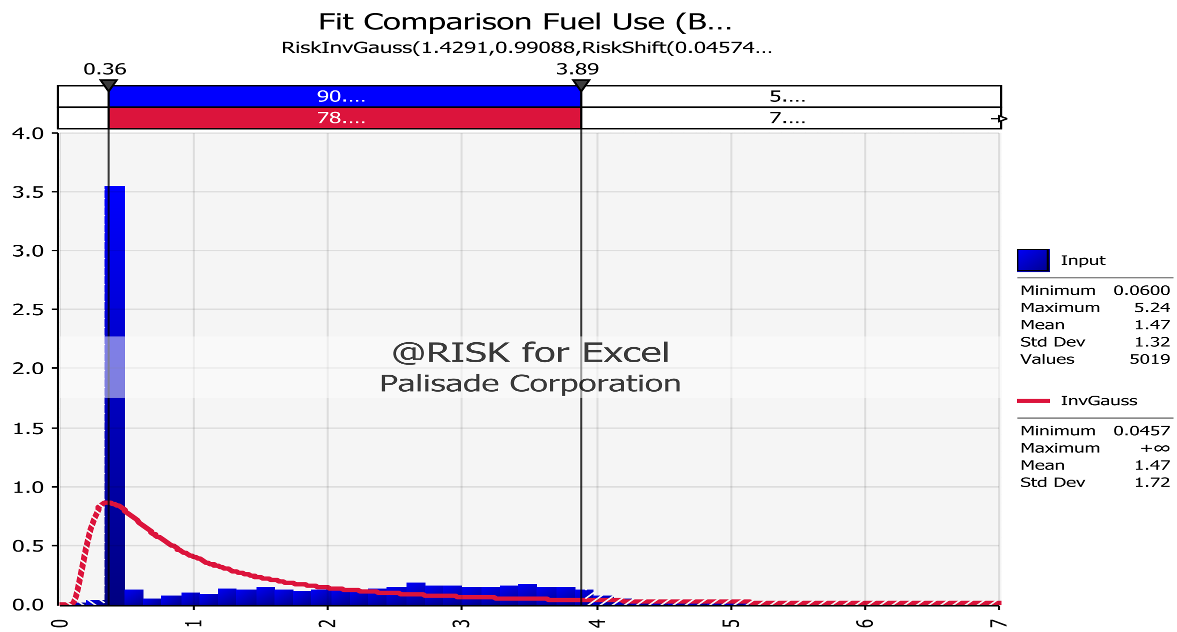

Figure C.19. Distribution fittings of fuel use for buldozer1

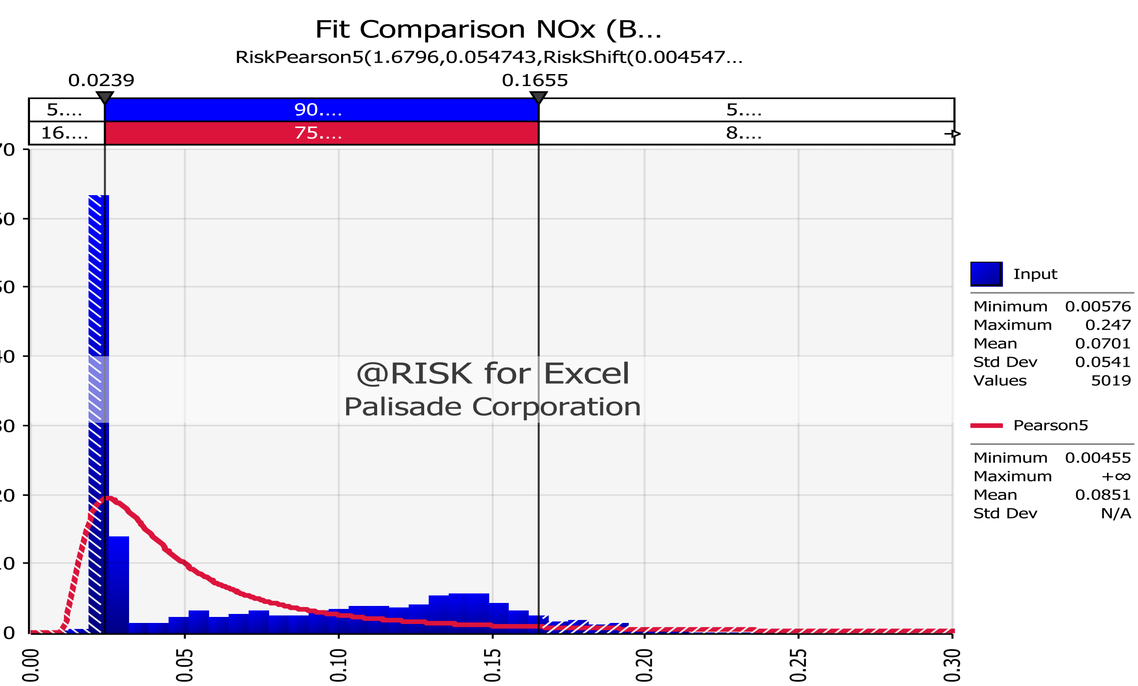

Figure C.20. Distribution fittings of NO_x for bulldozer 1

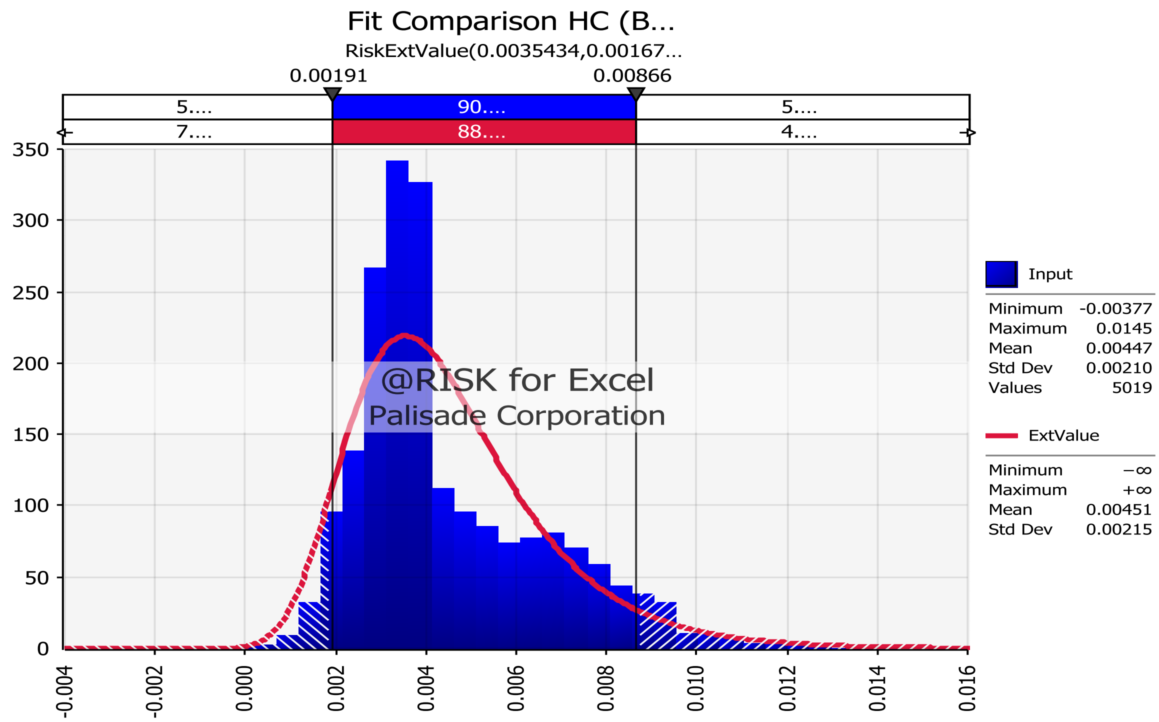

Figure C.21. Distribution fittings of HC for bulldozer 1

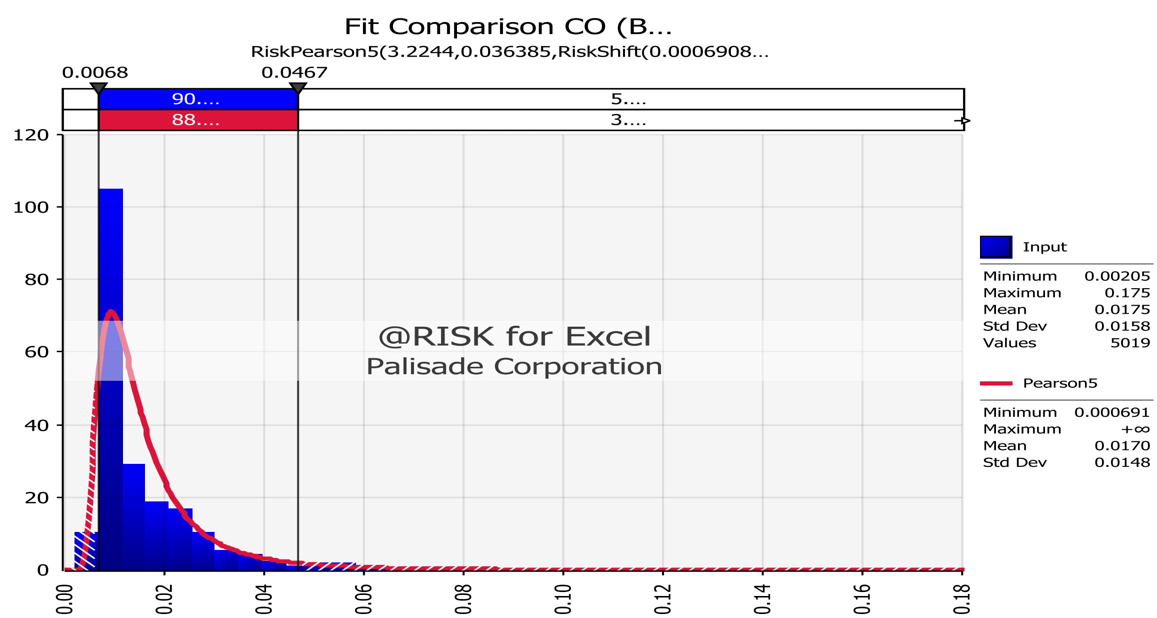

Figure C.22. Distribution fittings of CO for bulldozer 1

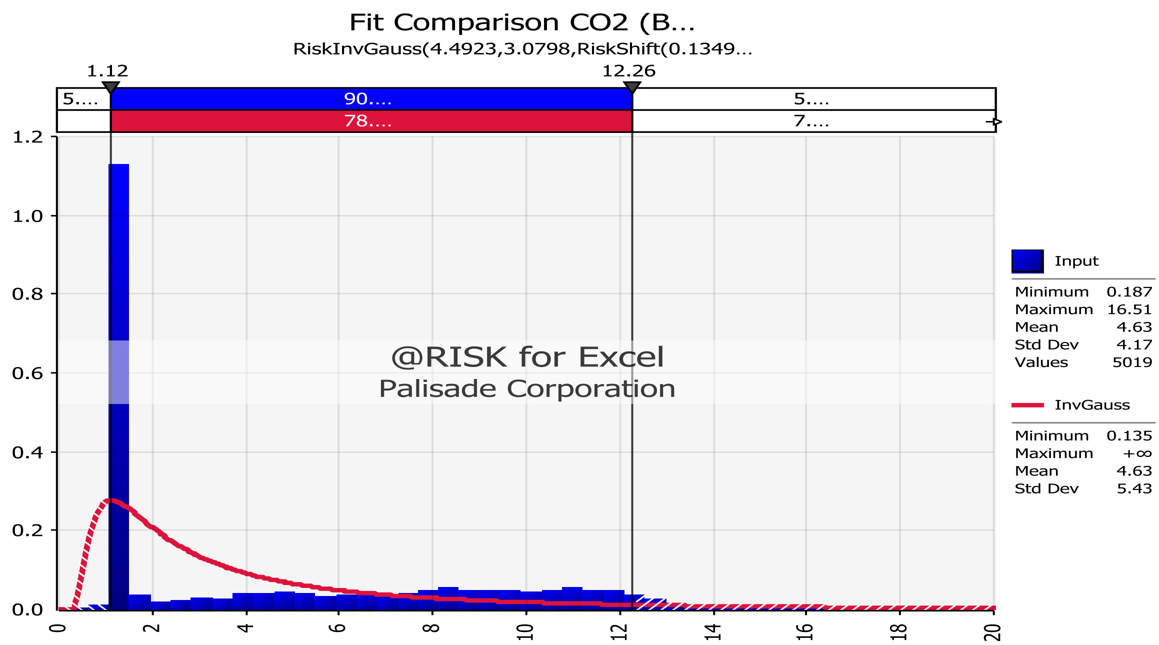

Figure C.23. Distribution fittings of CO_2 for bulldozer 1

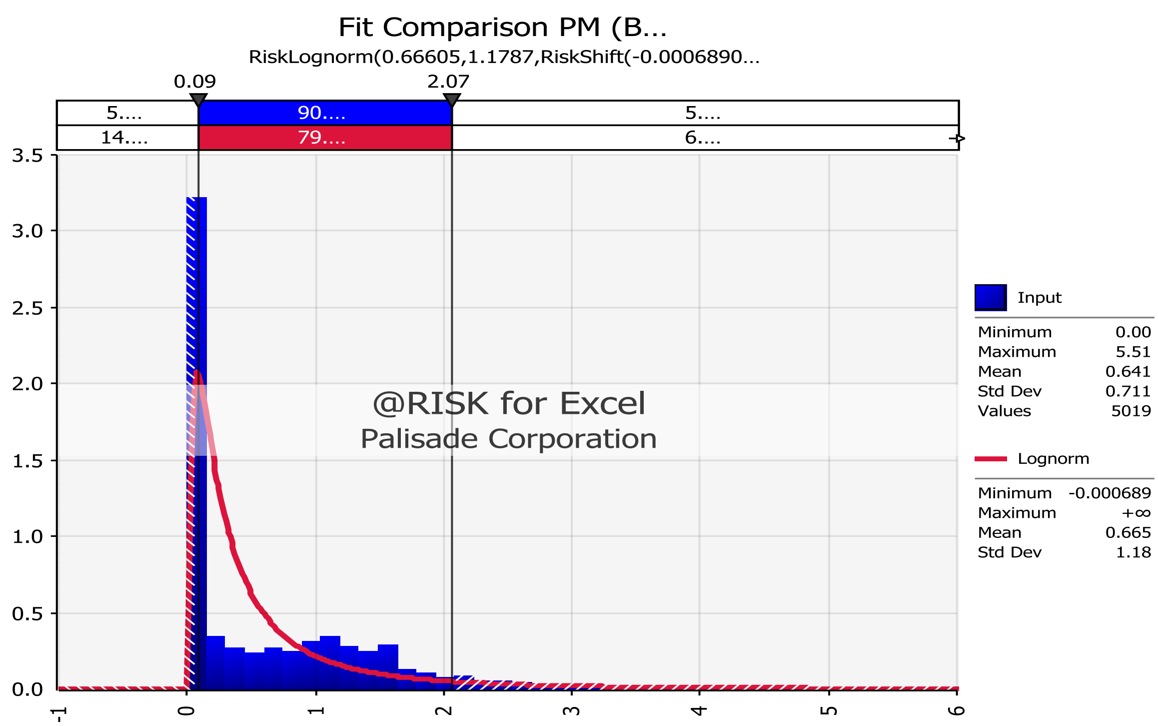

Figure C.24. Distribution fittings of PM for bulldozer 1

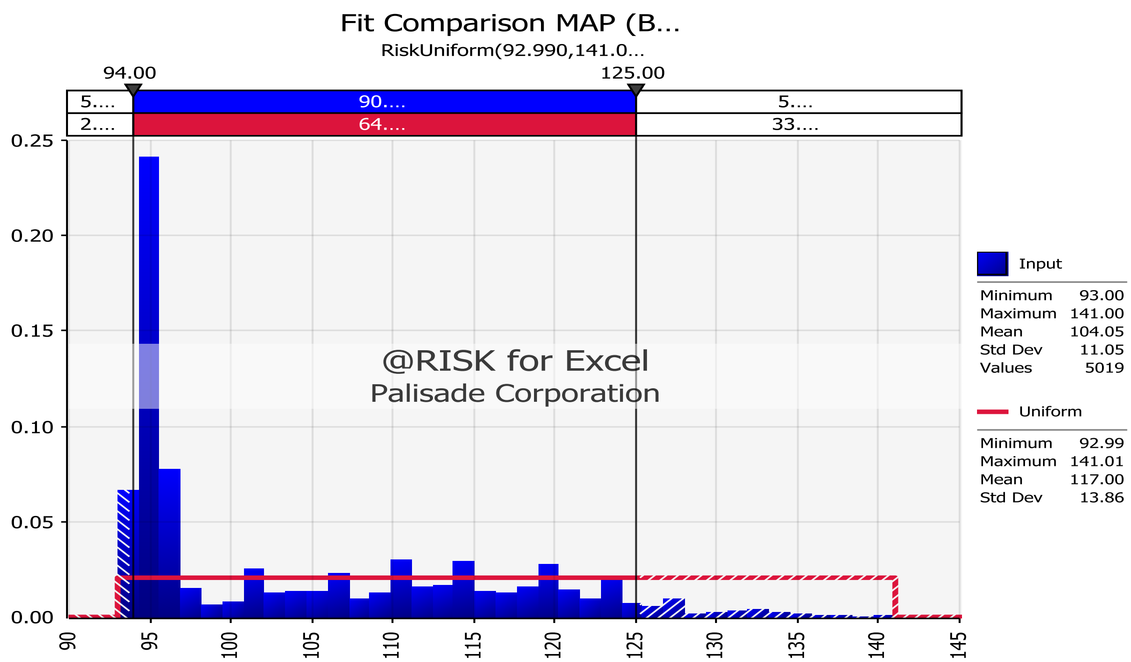

Figure C.25. Distribution fittings of MAP for bulldozer 1

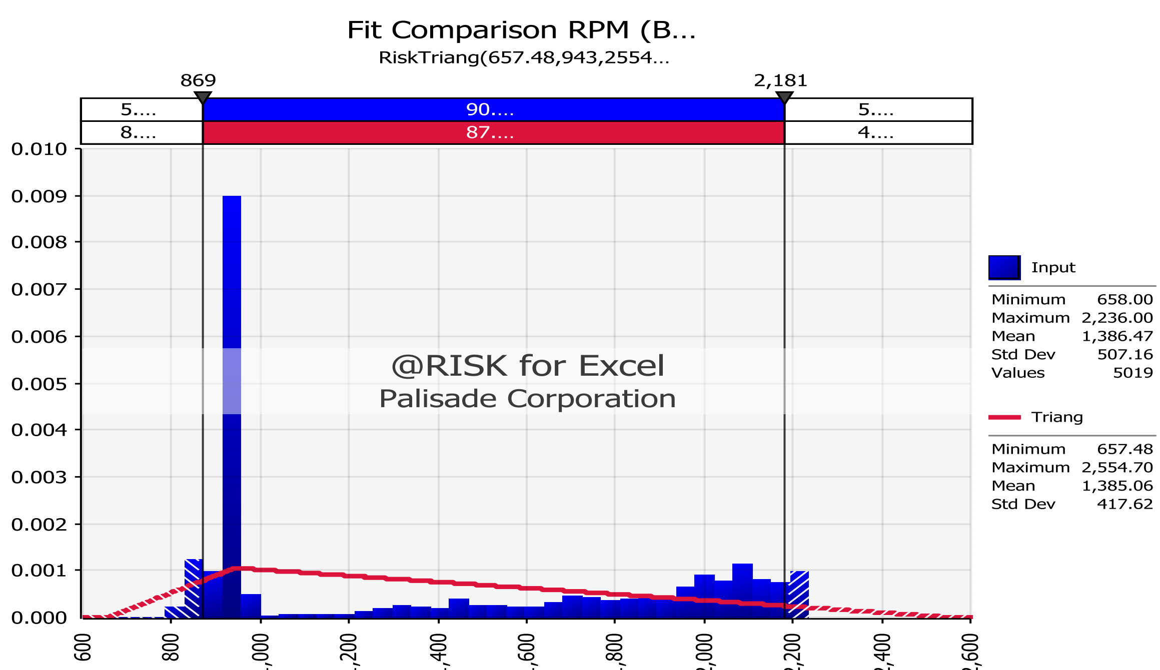

Figure C.26. Distribution fittings of RPM for bulldozer 1

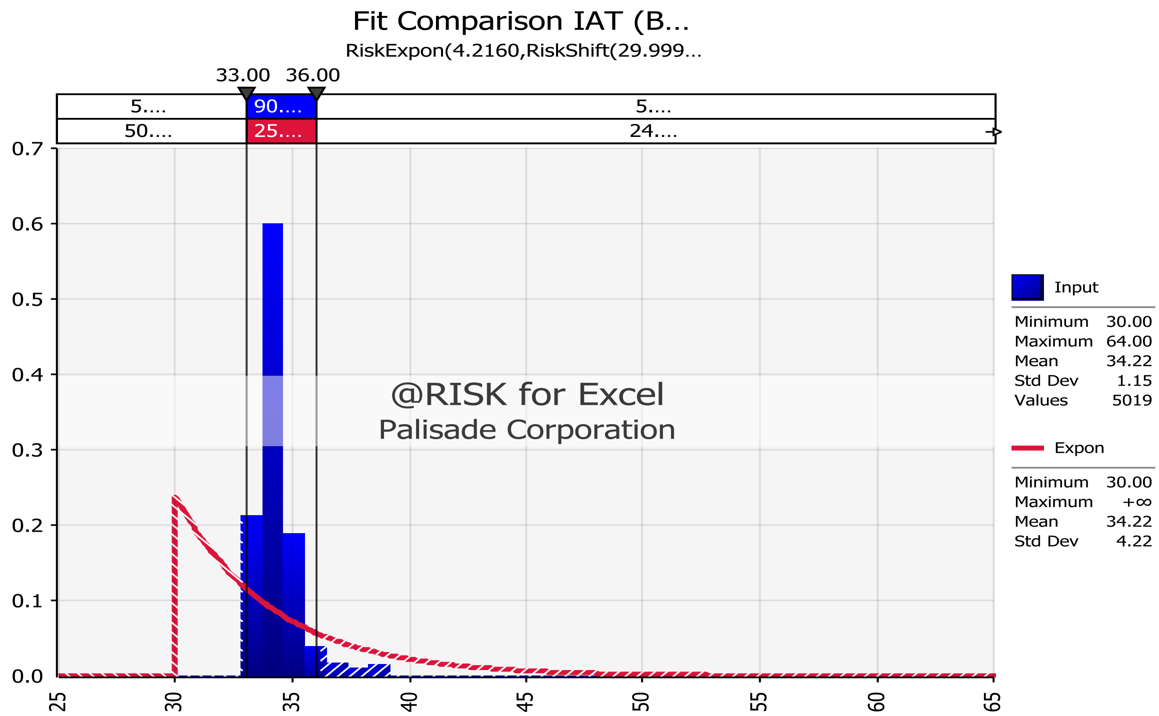

Figure C.27. Distribution fittings of IAT for bulldozer 1

Appendix D

Summary of SLR Models for Each Item of Equipment

Table D.1. Summary of SLR models for backhoes

Equipment	Response	Equations	R^2
Backhoe 1	Fuel Use	$Y_1 = 3.0676\ X_1 + 0.2750$	0.8633
	NO_x	$Y_2 = 0.0938\ X_1 + 0.6244$	0.6244
	HC	$Y_3 = 0.0081\ X_1 + 0.0034$	0.1714
	CO	$Y_4 = 0.0300\ X_1 + 0.0068$	0.0117
	CO_2	$Y_5 = 9.6812\ X_1 + 0.8500$	0.8636
	PM	$Y_6 = 0.0934\ X_1 + 0.0175$	0.0657
Backhoe 2	Fuel Use	$Y_1 = 4.4375\ X_1 + 0.2283$	0.8302
	NO_x	$Y_2 = 0.1429\ X_1 + 0.0084$	0.6186
	HC	$Y_3 = 0.0047\ X_1 + 0.0018$	0.0468
	CO	$Y_4 = 0.0306X_1 + 0.0049$	0.1386
	CO_2	$Y_5 =13.985\ X_1 + 0.7096$	0.8302
	PM	$Y_6 = 2.0801X_1 - 0.0324$	0.2803
Backhoe 3	Fuel Use	$Y_1 = 2.9861X_1 + 0.1638$	0.9608
	NO_x	$Y_2 = 0.0786\ X_1 + 0.005$	0.7759
	HC	$Y_3 = 0.0042X_1 + 0.001$	0.6662
	CO	$Y_4 = 0.0102X_1 + 0.0022$	0.2458
	CO_2	$Y_5 = 9.4212\ X_1 + 0.5084$	0.9610
	PM	$Y_6 = 0.6847X_1 + 0.2194$	0.3686
Backhoe 4	Fuel Use	$Y_1 = 1.5798\ X_1 + 0.09$	0.8889
	NO_x	$Y_2 = 0.0478\ X_1 + 0.0083$	0.7884
	HC	$Y_3 = 0.0051X_1 + 0.0006$	0.6607
	CO	$Y_4 = 0.0052X_1 + 0.0003$	0.6212
	CO_2	$Y_5 = 4.9756\ X_1 + 0.283$	0.8887
	PM	$Y_6 = 0.4081X_1 + 0.0148$	0.8874
Backhoe 5	Fuel Use	$Y_1 = 3.8167\ X_1 + 0.022$	0.8543
	NO_x	$Y_2 = 0.1059\ X_1 + 0.0106$	0.7500
	HC	$Y_3 = 0.0027X_1 + 0.0014$	0.2975
	CO	$Y_4 = 0.1409X_1 - 0.0127$	0.2205
	CO_2	$Y_5 = 10.851X_1 - 0.0546$	0.8527
	PM	$Y_6 = 1.2633X_1 - 0.0414$	0.4229
Backhoe 6	Fuel Use	$Y_1 = 1.5255\ X_1 + 0.1365$	0.7724
	NO_x	$Y_2 = 0.0563\ X_1 + 0.0087$	0.7530
	HC	$Y_3 = 0.0034X_1 + 0.0011$	0.4010
	CO	$Y_4 = 0.0071X_1 + 0.0015$	0.4950
	CO_2	$Y_5 = 4.8026X_1 + 0.4282$	0.7719
	PM	$Y_6 = 0.4790X_1 + 0.0239$	0.8464

X_1 = MAP

Table D.2. Summary of SLR models for bulldozers

Equipment	Response	Equations	R^2
Bulldozer 1	Fuel Use	$Y_1 = 5.5917\ X_1 + 0.1873$	0.9460
	NO_x	$Y_2 = 0.2143\ X_1 + 0.0208$	0.8333
	HC	$Y_3 = 0.0066\ X_1 + 0.0029$	0.5243
	CO	$Y_4 = 0.0353\ X_1 + 0.0094$	0.2642
	CO_2	$Y_5 = 17.625\ X_1 + 0.5692$	0.9454
	PM	$Y_6 = 2.7449\ X_1 + 0.0088$	0.7899
Bulldozer 2	Fuel Use	$Y_1 = 3.4176X_1 + 0.3432$	0.9102
	NO_x	$Y_2 = 0.0898\ X_1 + 0.0163$	0.7516
	HC	$Y_3 = 0.0111\ X_1 + 0.0025$	0.0095
	CO	$Y_4 = 0.0126X_1 + 0.0054$	0.0022
	CO_2	$Y_5 =10.767X_1 + 1.0709$	0.9147
	PM	$Y_6 = 1.2813X_1 + 0.0221$	0.7246
Bulldozer 3	Fuel Use	$Y_1 = 6.6024X_1 + 0.5076$	0.9269
	NO_x	$Y_2 = 0.3006\ X_1 + 0.0318$	0.7581
	HC	$Y_3 = 0.0090X_1 + 0.0041$	0.3910
	CO	$Y_4 = 0.0060X_1 + 0.0224$	0.0129
	CO_2	$Y_5 = 20.879\ X_1 + 1.5601$	0.9272
	PM	$Y_6 = 4.9067X_1 + 0.0956$	0.4894
Bulldozer 4	Fuel Use	$Y_1 = 9.5352\ X_1 + 0.5115$	0.9820
	NO_x	$Y_2 = 0.4646\ X_1 + 0.0469$	0.9115
	HC	$Y_3 = 0.0189X_1 + 0.0059$	0.6963
	CO	$Y_4 = 0.0740X_1 + 0.0167$	0.1625
	CO_2	$Y_5 = 30.002\ X_1 + 1.5675$	0.9813
	PM	$Y_6 = 2.1253X_1 + 0.2477$	0.7369
Bulldozer 5	Fuel Use	$Y_1 = 16.331\ X_1 + 1.007$	0.9853
	NO_x	$Y_2 = 0.9846\ X_1 + 0.0572$	0.9243
	HC	$Y_3 = 0.0066X_1 + 0.0059$	0.2942
	CO	$Y_4 = 0.0365X_1 + 0.0490$	0.0542
	CO_2	$Y_5 = 10.851X_1 - 0.0546$	0.9853
	PM	$Y_6 = 0$	0
Bulldozer 6	Fuel Use	$Y_1 = 1.9053\ X_1 + 0.6512$	0.3261
	NO_x	$Y_2 = 0.0396\ X_1 + 0.0217$	0.1915
	HC	$Y_3 = -0.0033X_1 + 0.0072$	0.0059
	CO	$Y_4 = -0.0009X_1 + 0.0123$	0.0003
	CO_2	$Y_5 = 6.0455X_1 + 2.0201$	0.3312
	PM	$Y_6 = 1.0571X_1 + 0.0655$	0.3766

X_1 = MAP

Table D.3. Summary of SLR models for excavators

Equipment	Response	Equations	R^2
Excavator 1	Fuel Use	$Y_1 = 9.9429\ X_1 + 0.4704$	0.9819
	NO_x	$Y_2 = 0.3545\ X_1 + 0.0242$	0.9481
	HC	$Y_3 = 0.0054\ X_1 + 0.0024$	0.3505
	CO	$Y_4 = 0.0175\ X_1 + 0.0066$	0.5427
	CO_2	$Y_5 = 31.431\ X_1 + 1.4720$	0.9819
	PM	$Y_6 = 3.8619\ X_1 + 0.1076$	0.8810
Excavator 2	Fuel Use	$Y_1 = 6.4485X_1 + 0.5302$	0.9632
	NO_x	$Y_2 = 0.1202\ X_1 + 0.0209$	0.8499
	HC	$Y_3 = 0.0083\ X_1 + 0.0031$	0.3901
	CO	$Y_4 = 0.0239X_1 + 0.0142$	0.2194
	CO_2	$Y_5 = 20.358X_1 + 1.6475$	0.9633
	PM	$Y_6 = 1.8463X_1 + 0.0354$	0.8876
Excavator 3	Fuel Use	$Y_1 = 3.9492\ X_1 + 0.1231$	0.9302
	NO_x	$Y_2 = 0.1231\ X_1 + 0.0098$	0.8755
	HC	$Y_3 = 0.0084X_1 + 0.0021$	0.1936
	CO	$Y_4 = 0.0051X_1 + 0.0055$	0.0183
	CO_2	$Y_5 = 12.468\ X_1 + 0.3748$	0.9294
	PM	$Y_6 = 1.0842\ X_1 - 0.0099$	0.3326

X_1 = MAP

Table D.4. Summary of SLR models for off-road trucks

Equipment	Response	Equations	R^2
Off-Road Truck 1	Fuel Use	$Y_1 = 9.2441\ X_1 + 0.7993$	0.8309
	NO_x	$Y_2 = 0.2724\ X_1 + 0.0448$	0.7401
	HC	$Y_3 = 0.0202\ X_1 + 0.0034$	0.6799
	CO	$Y_4 = 0.2047\ X_1 + 0.0049$	0.2692
	CO_2	$Y_5 = 28.878\ X_1 + 2.5125$	0.8316
	PM	$Y_6 = 3.4028\ X_1 + 0.1439$	0.8330
Off-Road Truck 2	Fuel Use	$Y_1 = 16.01\ X_1 + 0.8791$	0.9419
	NO_x	$Y_2 = 0.3916X_1 + 0.0532$	0.7726
	HC	$Y_3 = 0.022\ X_1 + 0.0033$	0.3929
	CO	$Y_4 = 0.1162X_1 + 0.0069$	0.4210
	CO_2	$Y_5 = 50.364X_1 + 2.7599$	0.9415
	PM	$Y_6 = 4.3965X_1 + 0.2386$	0.8040
Off-Road Truck 3	Fuel Use	$Y_1 = 13.952\ X_1 + 0.8604$	0.9690
	NO_x	$Y_2 = 0.3664\ X_1 + 0.0526$	0.9138
	HC	$Y_3 = 0.0166X_1 + 0.0038$	0.6797
	CO	$Y_4 = 0.0546X_1 + 0.0132$	0.5854
	CO_2	$Y_5 = 44.031\ X_1 + 2.6901$	0.9692
	PM	$Y_6 = 3.3891\ X_1 +0.2359$	0.6689

X_1 = MAP

Table D.5. Summary of SLR models for track loaders

Equipment	Response	Equations	R^2
Track Loader 1	Fuel Use	$Y_1 = 3.6538\ X_1 + 1.5090$	0.5500
	NO_x	$Y_2 = 0.0514\ X_1 + 0.0319$	0.3513
	HC	$Y_3 = 0.0142\ X_1 + 0.0040$	0.4313
	CO	$Y_4 = 0.0188\ X_1 + 0.0131$	0.1591
	CO_2	$Y_5 = 11.492X_1 + 4.7453$	0.5472
	PM	$Y_6 = 0.9486\ X_1 + 0.3602$	0.3144
Track Loader 2	Fuel Use	$Y_1 = 4.8661\ X_1 + 0.3972$	0.6896
	NO_x	$Y_2 = 0.3219X_1 + 0.0016$	0.6403
	HC	$Y_3 = 0.0047\ X_1 + 0.0040$	0.1146
	CO	$Y_4 = 0.0111X_1 + 0.0057$	0.3662
	CO_2	$Y_5 = 15.382X_1 + 1.2363$	0.6900
	PM	$Y_6 = 0.8884X_1 + 0.1963$	0.7439
Track Loader 3	Fuel Use	$Y_1 = 6.1424\ X_1 + 0.4803$	0.9650
	NO_x	$Y_2 = 0.1037\ X_1 + 0.0128$	0.8708
	HC	$Y_3 = 0.0013X_1 + 0.0014$	0.0710
	CO	$Y_4 = 0.0173X_1 + 0.0081$	0.6126
	CO_2	$Y_5 = 19.419\ X_1 + 1.5042$	0.9653
	PM	$Y_6 = 0.9452\ X_1 +0.1864$	0.7050

X_1 = MAP

Table D.6. Summary of SLR models for motor graders

Equipment	**Response**	**Equations**	**R^2**
Motor Grader 1	Fuel Use	$Y_1 = 8.3269 X_1 + 0.3940$	0.7644
	NO_x	$Y_2 = 0.2279 X_1 + 0.0310$	0.6030
	HC	$Y_3 = 0.014 X_1 + 0.0073$	0.1898
	CO	$Y_4 = 0.023 X_1 + 0.0063$	0.2595
	CO_2	$Y_5 = 26.289 X_1 + 1.2149$	0.7641
	PM	$Y_6 = 2.2335 X_1 + 0.1851$	0.8029
Motor Grader 2	Fuel Use	$Y_1 = 9.6592 X_1 + 0.5452$	0.9546
	NO_x	$Y_2 = 0.2319 X_1 + 0.0302$	0.7896
	HC	$Y_3 = 0.0376 X_1 + 0.0101$	0.2382
	CO	$Y_4 = 0.0552 X_1 + 0.0078$	0.1180
	CO_2	$Y_5 = 30.38 X_1 + 1.6838$	0.9557
	PM	$Y_6 = 1.8136X_1 + 0.0915$	0.6733
Motor Grader 3	Fuel Use	$Y_1 = 5.1464 X_1 + 0.0872$	0.9176
	NO_x	$Y_2 = 0.157 X_1 + 0.0108$	0.7546
	HC	$Y_3 = 0.0764X_1 + 0.0102$	0.5143
	CO	$Y_4 = 0.0148X_1 + 0.0024$	0.1677
	CO_2	$Y_5 = 16.082 X_1 + 0.2454$	0.9155
	PM	$Y_6 = 1.8094X_1 + 0.0288$	0.9149
Motor Grader 4	Fuel Use	$Y_1 = 8.2799 X_1 + 0.3621$	0.8761
	NO_x	$Y_2 = 0.4989 X_1 + 0.0321$	0.7390
	HC	$Y_3 = 0.0354X_1 + 0.0169$	0.1813
	CO	$Y_4 = 0.0481X_1 + 0.0264$	0.1018
	CO_2	$Y_5 = 26.027 X_1 + 1.0529$	0.8754
	PM	$Y_6 = 2.6718X_1 - 0.0799$	0.6906
Motor Grader 5	Fuel Use	$Y_1 = 9.8301X_1 + 0.3243$	0.9762
	NO_x	$Y_2 = 0.4527 X_1 + 0.0261$	0.8915
	HC	$Y_3 = 0.0177X_1 + 0.0037$	0.4874
	CO	$Y_4 = 0.0214X_1 + 0.0328$	0.0758
	CO_2	$Y_5 = 31.038X_1 + 0.9633$	0.9760
	PM	$Y_6 = 2.2131X_1 + 0.0811$	0.8170
Motor Grader 6	Fuel Use	$Y_1 = 5.7478 X_1 + 0.0348$	0.9176
	NO_x	$Y_2 = 0.0752 X_1 + 0.0171$	0.4442
	HC	$Y_3 = 0.0067X_1 + 0.0034$	0.0699
	CO	$Y_4 = 0.0136X_1 - 0.0003$	0.0636
	CO_2	$Y_5 = 18.151X_1 + 0.1004$	0.9172
	PM	$Y_6 = 1.146X_1 + 0.0776$	0.8492

X_1 = MAP

Appendix E

Summary of MLR Models for Each Item of Equipment

Table E.1. Summary of MLR models for backhoes

Equipment	Response	Equations	R^2
Backhoe 1	Fuel Use	$Y_1 = -2.914 + 0.0263\ X_1 + 0.00062X_2 + 0.0033X_3$	0.9027
	NO_x	$Y_2 = -0.077 + 0.00055X_1 + 0.000023\ X_2 + 0.00079X_3$	0.7581
	HC	$Y_3 = -0.0029 + 0.000046\ X_1 + 5.99E\text{-}6\ X_2 - 0.00017X_3$	0.4238
	CO	$Y_4 = 0.0051 + 0.000047\ X_1 + 7.07E\text{-}6\ X_2 - 0.00047X_3$	0.6692
	CO_2	$Y_5 = -9.22 + 0.083X_1 + 0.0019\ X_2 + 0.012X_3$	0.9027
	PM	$Y_6 = -0.065 + 0.00056X_1 + 0.00005\ X_2 - 0.0008X_3$	0.1116
Backhoe 2	Fuel Use	$Y_1 = -\ 5.32 + 0.0547X_1 + 0.00082X_2 - 0.0114X_3$	0.9181
	NO_x	$Y_2 = -0.13 + 0.00083X_1 + 0.000048X_2 + 0.0006X_3$	0.8462
	HC	$Y_3 = 0.0045 - 0.00008X_1 + 3.9E\text{-}6X_2 + 0.000033X_3$	0.1533
	CO	$Y_4 = -0.039 + 0.00057X_1 + 1.7E\text{-}6X_2 - 0.00044X_3$	0.1802
	CO_2	$Y_5 = -16.79 + 0.173X_1 + 0.0026X_2 - 0.036X_3$	0.9173
	PM	$Y_6 = -3.66 + 0.046X_1 - 0.0001X_2 - 0.023X_3$	0.3207
Backhoe 3	Fuel Use	$Y_1 = -7.06 + 0.0734X_1 + 0.00008\ X_2 + 0.0009\ X_3$	0.9632
	NO_x	$Y_2 = -0.12 + 0.00096\ X_1 + 0.000015X_2 + 0.000302\ X_3$	0.8722
	HC	$Y_3 = -0.0044 + 0.000056X_1 + 1.18E\text{-}6X_2 - 0.00002X_3$	0.7125
	CO	$Y_4 = 0.025 + 0.0003\ X_1 - 0.00004\ X_3$	0.2393
	CO_2	$Y_5 = -22.33 + 0.232X_1 + 0.00024\ X_2 + 0.003\ X_3$	0.9633
	PM	$Y_6 = -1.82 + 0.025X_1 - 0.00004X_2 – 0.0068X_3$	0.5009
Backhoe 4	Fuel Use	$Y_1 = -1.56 + 0.0143X_1 + 0.00031X_2 + 0.00052X_3$	0.9362
	NO_x	$Y_2 = -0.049 + 0.00038X_1 + 0.00001X_2 + 0.00026X_3$	0.8708
	HC	$Y_3 = -0.006 + 0.000035X_1 + 1.2E\text{-}6X_2 + 0.000046X_3$	0.7802
	CO	$Y_4 = -0.0058 + 0.00005X_1 + 7.7E\text{-}7X_2 + 0.00002X_3$	0.6553
	CO_2	$Y_5 = -4.84 + 0.045X_1 + 0.00098X_2$	0.9358
	PM	$Y_6 = -0.43 + 0.0043X_1 + 0.000042X_2$	0.8946
Backhoe 5	Fuel Use	$Y_1 = -7.212 + 0.0752X_1 + 0.00032X_2 - 0.0009X_3$	0.8712
	NO_x	$Y_2 = -0.170 + 0.00173X_1 + 5.06E\text{-}7X_2 + 0.00041X_3$	0.8103
	HC	$Y_3 = -0.000172 + 0.000017X_1 + 1.63E\text{-}6X_2 - 0.00004X_3$	0.7013
	CO	$Y_4 = 0.616 + 0.0071X_1 - 0.00004X_2 - 0.0008X_3$	0.3371
	CO_2	$Y_5 = -21.84 + 0.226X_1 + 0.0011X_2$	0.8738
	PM	$Y_6 = -3.90 + 0.043X_1 - 0.00018X_2$	0.4499
Backhoe 6	Fuel Use	$Y_1 = -1.407 + 0.01X_1 + 0.00059X_2 + 0.0018X_3$	0.9134
	NO_x	$Y_2 = -0.0561 + 0.000383X_1 + 0.00002X_2 + 0.00025X_3$	0.8759
	HC	$Y_3 = -\ 0.001 + 0.000014X_1 + 2.14E\text{-}6X_2 - 0.00003X_3$	0.5717
	CO	$Y_4 = -0.0031 + 0.000045X_1 + 3.23E\text{-}6X_2 - 0.00006X_3$	0.6189
	CO_2	$Y_5 = -4.43 + 0.0311X_1 + 0.002X_2 - 0.006X_3$	0.9126
	PM	$Y_6 = -0.407 + 0.0047X_1 + 0.000075X_2 - 0.002X_3$	0.8751

X_1 = MAP, X_2 = RPM, X_3 = IAT

Table E.2. Summary of MLR models for bulldozers

Equipment	Response	Equations	R^2
Bulldozer 1	Fuel Use	$Y_1 = -8.925 + 0.0974\ X_1 + 0.000467X_2 - 0.0111X_3$	0.9542
	NO_x	$Y_2 = -0.2412 + 0.00227\ X_1 + 0.000054\ X_2$	0.8918
	HC	$Y_3 = -0.0045 + 0.000026\ X_1 + 2.68E\text{-}6\ X_2 + 0.000075X_3$	0.5963
	CO	$Y_4 = -0.0896 + 0.00118\ X_1 - 0.00001X_2$	0.2868
	CO_2	$Y_5 = -28.08 +0.3063X_1+ 0.0015\ X_2 - 0.036X_3$	0.9537
	PM	$Y_6 = -5.279 + 0.0569X_1$	0.7954
Bulldozer 2	Fuel Use	$Y_1 = -\ 1.59 + 0.022X_1 + 0.00023X_2 - 0.021X_3$	0.9440
	NO_x	$Y_2 = -0.381 + 0.00059X_1 + 0.000009X_2 - 0.00063X_3$	0.8350
	HC	$Y_3 = -0.011 +0.000044X_1 +3.4E\text{-}6X_2 +0.00017X_3$	0.0150
	CO	$Y_4 = 0.0089 + 0.000063X_1 +1.36E\text{-}6X_2 - 0.00035X_3$	0.0349
	CO_2	$Y_5 = -5.006+ 0.0702X_1 + 0.00073X_2 -0.0661X_3$	0.9470
	PM	$Y_6 = -0.498 +0.011X_1 - 0.00023X_2 - 0.012X_3$	0.8150
Bulldozer 3	Fuel Use	$Y_1 = -1.58 + 0.0224X_1 + 0.00022\ X_2- 0.0213\ X_3$	0.9473
	NO_x	$Y_2 = -0.434 + 0.0044\ X_1 +0.000002X_2$	0.8753
	HC	$Y_3 = -0.0034+ 0.000064X_1 +2.16E\text{-}6X_2 - 0.00023X_3$	0.6390
	CO	$Y_4 = 0.0408 - 0.00023\ X_1+3.4E\text{-}6X_2 + 0.0004\ X_3$	0.0349
	CO_2	$Y_5 = -30.61+ 0.3033X_1 + 0.0012\ X_2 +0.074\ X_3$	0.9679
	PM	$Y_6 = -7.34 + 0.0793X_1 - 0.00013X_2 – 0.026X_3$	0.5913
Bulldozer 4	Fuel Use	$Y_1 = -10.18+0.1125X_1+0.000382X_2– 0.0297X_3$	0.9838
	NO_x	$Y_2 = -0.5263 +0.00546X_1 +0.000019X_2 + 0.00075X_3$	0.9161
	HC	$Y_3 = -0.0203+0.000123X_1 +7.44E\text{-}6X_2 +0.000264X_3$	0.7915
	CO	$Y_4 = -0.082+0.00122X_1- 0.00002X_2$	0.2083
	CO_2	$Y_5 = -31.98+0.354X_1 +0.00121X_2 -0.097X_3$	0.9833
	PM	$Y_6 = -1.419 + 0.0194X_1 + 0.00049X_2 -0.0295X_3$	0.7731
Bulldozer 5	Fuel Use	$Y_1 = -15.02+0.152X_1+0.00072X_2 +0.0298X_3$	0.9862
	NO_x	$Y_2 = -0.9175 + 0.00825X_1 + 0.000112X_2 +0.00421X_3$	0.9315
	HC	$Y_3 = -0.00064 +0.000018X_1 +3.43E\text{-}6X_2+0.00011X_3$	0.3275
	CO	$Y_4 = 0.0995 +0.0002X_1 - 0.0047X_3$	0.0816
	CO_2	$Y_5 = -47.7+0.4813X_1 + 0.00227X_2+0.101X_3$	0.9862
	PM	$Y_6 = 0$	0
Bulldozer 6	Fuel Use	$Y_1 = -0.843+0.011X_1+0.00065X_2-0.0284X_3$	0.7337
	NO_x	$Y_2 = -0.00624 + 0.000136X_1 + 0.000018X_2 -0.00067X_3$	0.6204
	HC	$Y_3 = 0.0225 - 0.00007X_1 +2.67E\text{-}6X_2- 0.00066X_3$	0.0865
	CO	$Y_4 = 0.0162 - 0.00016X_1 +7.49E\text{-}6X_2$	0.2853
	CO_2	$Y_5 = -2.764 +0.0345X_1 + 0.00203X_2 -0.088X_3$	0.7353
	PM	$Y_6 = -0.682 +0.0101X_1 + 0.00016X_2– 0.025X_3$	0.5217

X_1 = MAP, X_2 = RPM, X_3 = IAT

Table E.3. Summary of MLR models for excavators

Equipment	Response	Equations	R^2
Excavator 1	Fuel Use	Y_1 = -5.748 + 0.0728 X_1 + 0.000301X_2 - 0.0296X_3	0.9848
	NO_x	Y_2 = -0.2093 + 0.00247X_1 - 0.00002 X_2 + 0.000176X_3	0.9537
	HC	Y_3 = 0.0056 + 0.000034 X_1 + 2.64E-6 X_2 - 0.00021X_3	0.5821
	CO	Y_4 = -0.00003 + 0.000041 X_1 + 0.000011X_2 - 0.00018X_3	0.8007
	CO_2	Y_5 = -18.21 +0.230X_1+ 0.00093 X_2 - 0.093X_3	0.9847
	PM	Y_6 = -2.21 + 0.0293X_1 - 0.0136X_3	0.8799
Excavator 2	Fuel Use	Y_1 = -5.07 + 0.0524 X_1 + 0.00069 X_2- 0.0085 X_3	0.9716
	NO_x	Y_2 = - 0.089 + 0.00082 X_1 +0.000024 X_2 +0.000134X_3	0.8838
	HC	Y_3 = -0.0024+ 0.000048X_1 +3.14E-6X_2 - 0.00008X_3	0.4021
	CO	Y_4 = -0.0004 + 0.000013 X_1 + 0.000019 X_2- 0.00024 X_3	0.3395
	CO_2	Y_5 = -16.05+ 0.166X_1 + 0.00213 X_2 – 0.0262 X_3	0.9715
	PM	Y_6 = -1.53 + 0.021X_1 - 0.00026X_2 – 0.0064X_3	0.9125
Excavator 3	Fuel Use	Y_1 = -2.343 + 0.0295X_1 + 0.00006X_2 - 0.007X_3	0.9346
	NO_x	Y_2 = -0.079 + 0.00096X_1 – 5.33E-6X_2 + 0.000096X_3	0.8798
	HC	Y_3 = -0.0071 +0.000034X_1 +1.57E-6X_2 + 0.000094X_3	0.2459
	CO	Y_4 = 0.0094 - 0.00005X_1 +9.92E-6X_2 - 0.00018X_3	0.0964
	CO_2	Y_5 = -7.409 +0.0932X_1 + 0.00017X_2 - 0.022X_3	0.9338
	PM	Y_6 = -1.142 +0.0081X_1 - 0.00013X_2 +0.0104X_3	0.3903

X_1 = MAP, X_2 = RPM, X_3 = IAT

Table E.4. Summary of MLR models for track loaders

Equipment	Response	Equations	R^2
Track Loader 1	Fuel Use	Y_1 = -3.49 + 0.0284 X_1 + 0.00184X_2 - 0.0145X_3	0.8760
	NO_x	Y_2 = -0.0575 + 0.00037X_1 + 0.00003X_2 + 0.0003X_3	0.6360
	HC	Y_3 = -0.00841 + 0.000161 X_1 + 0.000001X_2 - 0.000145 X_3	0.2985
	CO	Y_4 = - 0.00121+ 0.000142 X_1 + 0.00001X_2 - 0.00047X_3	0.2790
	CO_2	Y_5 = -11.49 +0.09X_1+ 0.0058X_2 - 0.032X_3	0.7306
	PM	Y_6 = -2.424 + 0.0072X_1 + 0.00047X_2 + 0.044X_3	0.8016
Track Loader 2	Fuel Use	Y_1 = -5.841 + 0.0637 X_1 + 0.00033 X_2 - 0.0146 X_3	0.9685
	NO_x	Y_2 = - 0.105 + 0.00126 X_1 – 8.21E-6X_2	0.8818
	HC	Y_3 = 0.0019 + 1.51E-6X_2 - 0.00008X_3	0.1807
	CO	Y_4 = -0.0049 + 0.000084 X_1 + 8.51E-6X_2 - 0.00015 X_3	0.7280
	CO_2	Y_5 = -18.49+ 0.2015X_1 + 0.000094 X_2 – 0.046 X_3	0.9686
	PM	Y_6 = -0.505 + 0.0063X_1 + 0.00036X_2 – 0.0116X_3	0.8181
Track Loader 3	Fuel Use	Y_1 = -3.501 + 0.029X_1 + 0.00184X_2 - 0.0147X_3	0.8821
	NO_x	Y_2 = -0.056 + 0.000373X_1 + 0.00003X_2 + 0.00025X_3	0.6422
	HC	Y_3 = -0.00825 +0.00016X_1 +1.18E-6X_2 - 0.00014X_3	0.4261
	CO	Y_4 = -0.00381 + 0.000145X_1 + 0.00001X_2 - 0.0004X_3	0.2869
	CO_2	Y_5 = -11.05 +0.0898X_1 + 0.0058X_2 - 0.0456X_3	0.8799
	PM	Y_6 = -0.52 +0.0063X_1 + 0.00037X_2 - 0.0113X_3	0.7960

X_1 = MAP, X_2 = RPM, X_3 = IAT

Table E.5. Summary of MLR models for off-road trucks

Equipment	Response	Equations	R^2
Off-Road Truck 1	Fuel Use	$Y_1 = -4.738 + 0.0375X_1 + 0.00198X_2 + 0.0185X_3$	0.8684
	NOx	$Y_2 = -0.1343 + 0.00104X_1 + 0.000064X_2 + 0.00151X_3$	0.7830
	HC	$Y_3 = -0.0092 + 0.000072\ X_1 + 5.55E\text{-}6\ X_2 + 0.00007X_3$	0.7308
	CO	$Y_4 = -0.121 + 0.00047X_1 + 0.000084\ X_2 + 0.00095X_3$	0.3180
	CO2	$Y_5 = -14.78 + 0.118X_1 + 0.00612X_2 + 0.057X_3$	0.8680
	PM	$Y_6 = -1.776 + 0.0137X_1 + 0.000757X_2$	0.8757
Off-Road Truck 2	Fuel Use	$Y_1 = -5.841 + 0.0637\ X_1 + 0.00033\ X_2 - 0.0146\ X_3$	0.9685
	NOx	$Y_2 = -\ 0.105 + 0.00126\ X_1 - 8.21E\text{-}6X_2$	0.8818
	HC	$Y_3 = 0.0019 + 1.51E\text{-}6X_2 - 0.00008X_3$	0.1867
	CO	$Y_4 = -0.0049 + 0.000084\ X_1 + 8.51E\text{-}6X_2 - 0.00015\ X_3$	0.7280
	CO2	$Y_5 = -18.49 + 0.2015X_1 + 0.000094\ X_2 - 0.046\ X_3$	0.9686
	PM	$Y_6 = -0.505 + 0.0063X_1 + 0.00036X_2 - 0.0116X_3$	0.8181
Off-Road Truck 3	Fuel Use	$Y_1 = -8.298 + 0.086X_1 + 0.000924X_2$	0.9783
	NOx	$Y_2 = -0.2025 + 0.00263X_1 - 0.00002X_2 + 0.00037X_3$	0.9229
	HC	$Y_3 = -0.0054 + 0.000065X_1 + 5.11E\text{-}6X_2 - 0.00004X_3$	0.7798
	CO	$Y_4 = -0.015 + 0.000137X_1 + 0.000023X_2 - 0.00015X_3$	0.7932
	CO2	$Y_5 = -26.22 + 0.272X_1 + 0.0029X_2$	0.9783
	PM	$Y_6 = -1.668 + 0.0176X_1 + 0.00075X_2 - 0.0126X_3$	0.7302

X_1 = MAP, X_2 = RPM, X_3 = IAT

Table E.6. Summary of MLR models for motor graders

Equipment	Response	Equations	R^2
Motor Grader 1	Fuel Use	$Y_1 = -6.432 + 0.053X_1 + 0.00072X_2 + 0.0264X_3$	0.7755
	NO_x	$Y_2 = -0.2682 + 0.00182X_1 + 0.00001X_2 + 0.00374X_3$	0.6183
	HC	$Y_3 = 0.0388 + 0.000103 X_1 + 3.85E\text{-}6 X_2 - 0.00163X_3$	0.3557
	CO	$Y_4 = -0.025 + 0.000136X_1 + 1.22E\text{-}6 X_2 +0.0006X_3$	0.3126
	CO_2	$Y_5 = -20.46 + 0.167X_1 + 0.00226X_2 + 0.0882X_3$	0.7753
	PM	$Y_6 = -0.622 + 0.0146X_1 + 0.000244X_2 - 0.0326X_3$	0.8267
Motor Grader 2	Fuel Use	$Y_1 = -4.9814 + 0.054 X_1 + 0.000635 X_2 - 0.00131 X_3$	0.9688
	NO_x	$Y_2 = -0.088 + 0.000995 X_1 +0.000031 X_2 - 0.00019X_3$	0.8375
	HC	$Y_3 = -0.0258 - 0.00004X_1 +0.000016X_2 - 0.00056X_3$	0.4103
	CO	$Y_4 = -0.0253 + 0.000295 X_1 +4.45E\text{-}6 X_2$	0.1209
	CO_2	$Y_5 = -15.28 + 0.1703X_1 + 0.002 X_2 – 0.0397 X_3$	0.9693
	PM	$Y_6 = -0.817 + 0.00795X_1 + 0.000232X_2 – 0.00021X_3$	0.7207
Motor Grader 3	Fuel Use	$Y_1 = - 4.57 + 0.0436X_1 - 0.00017X_2 + 0.0152X_3$	0.9200
	NO_x	$Y_2 = -0.1196 + 0.0017X_1 - 0.00003X_2$	0.7862
	HC	$Y_3 = 0.1246 +0.000384X_1 +6.83E\text{-}6X_2 - 0.00374X_3$	0.5838
	CO	$Y_4 = -0.032 + 0.00014X_1 + 0.0005X_3$	0.1780
	CO_2	$Y_5 = -14.608 +0.137X_1 - 0.00058X_2 +0.0537X_3$	0.9183
	PM	$Y_6 = -0.674 +0.0156X_1 - 0.00013X_2 - 0.0157X_3$	0.9190
Motor Grader 4	Fuel Use	$Y_1 = -10.88+0.1095X_1+0.00059X_2$	0.8995
	NO_x	$Y_2 = -0.7341 +0.00804X_1 – 5.04E\text{-}6X_2$	0.7483
	HC	$Y_3 = -0.0185+0.00025X_1 + 9.104E\text{-}6X_2$	0.2519
	CO	$Y_4 = -0.071+0.00117X_1 - 0.00001X_2$	0.1322
	CO_2	$Y_5 = -34.28+0.355X_1 +0.00185X_2$	0.8989
	PM	$Y_6 = -4.502 + 0.0485X_1 - 0.00019X_2$	0.7079
Motor Grader 5	Fuel Use	$Y_1 = -8.65+0.09X_1+0.00027X_2 - 0.0213X_3$	0.9768
	NO_x	$Y_2 = -0.421 + 0.00447X_1$	0.8909
	HC	$Y_3 = 0.0146 + 5.99E\text{-}6X_2 - 0.00128X_3$	0.5814
	CO	$Y_4 = -0.0787 - 0.00017X_1 +0.000013X_2 - 0.0032X_3$	0.1258
	CO_2	$Y_5 = -27.56+0.285X_1 + 0.00029X_2 - 0.026X_3$	0.9765
	PM	$Y_6 = -1.28+0.0143X_1 + 0.000286X_2 - 0.026X_3$	0.8296
Motor Grader 6	Fuel Use	$Y_1 = -4.107+0.031X_1 - 0.00022X_2 + 0.0241X_3$	0.9248
	NO_x	$Y_2 = -0.02 + 0.000413X_1 - 2.61E\text{-}6X_2$	0.4537
	HC	$Y_3 = 0.099 + 0.000033X_1 +4.19E\text{-}6X_2 - 0.00176X_3$	0.5959
	CO	$Y_4 = -0.036 + 0.00012X_1 -6.73E\text{-}6X_2 + 0.00055X_3$	0.1160
	CO_2	$Y_5 = -13.25 +0.098X_1 - 0.0007X_2 + 0.081X_3$	0.9247
	PM	$Y_6 = 0.433 + 0.00543X_1 + 0.000103X_2 – 0.0172X_3$	0.8960

X_1 = MAP, X_2 = RPM, X_3 = IAT

Appendix F

Model validations for SLR

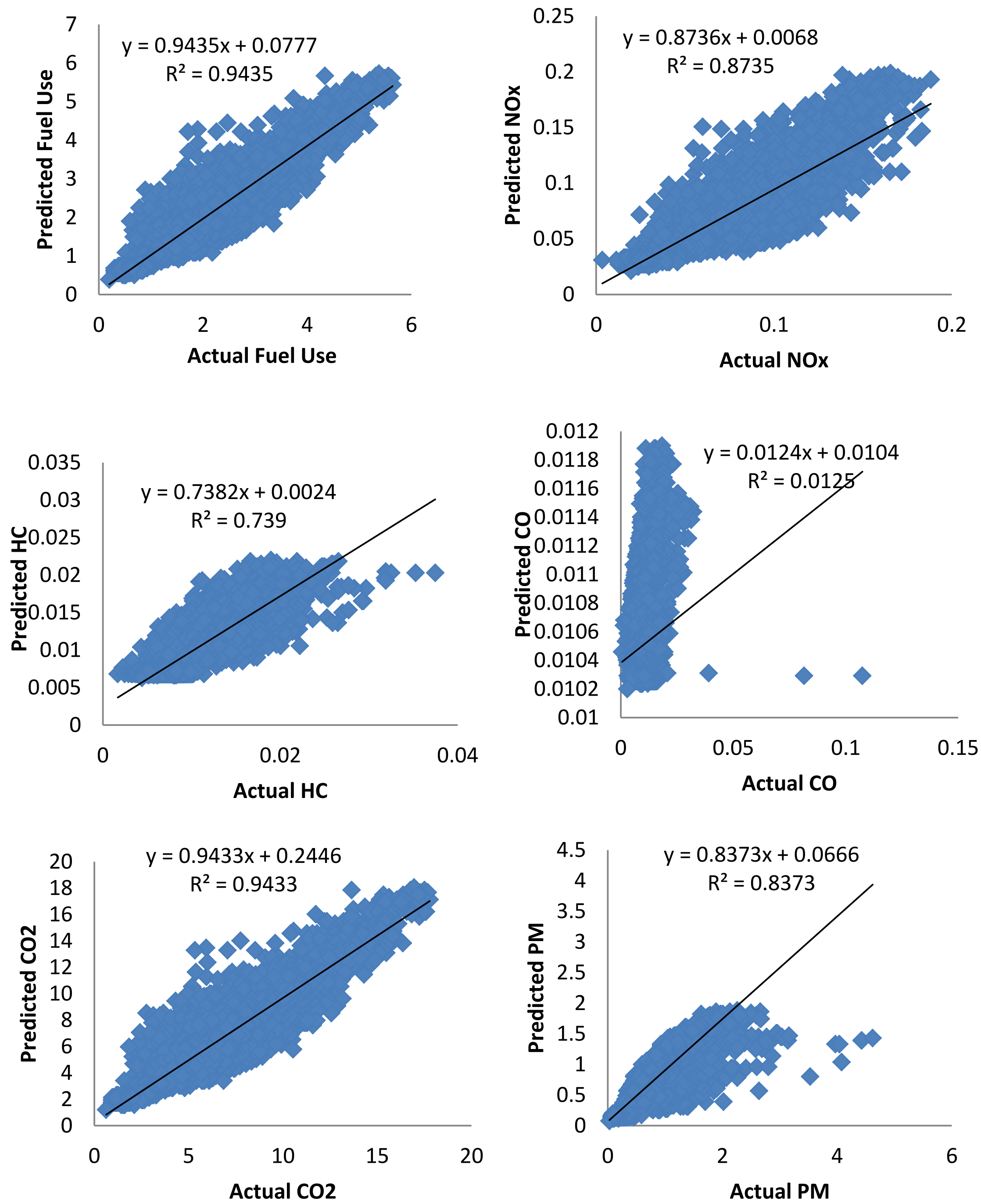

Figure F.1. Model Validation for SLR for Wheel Loader 2

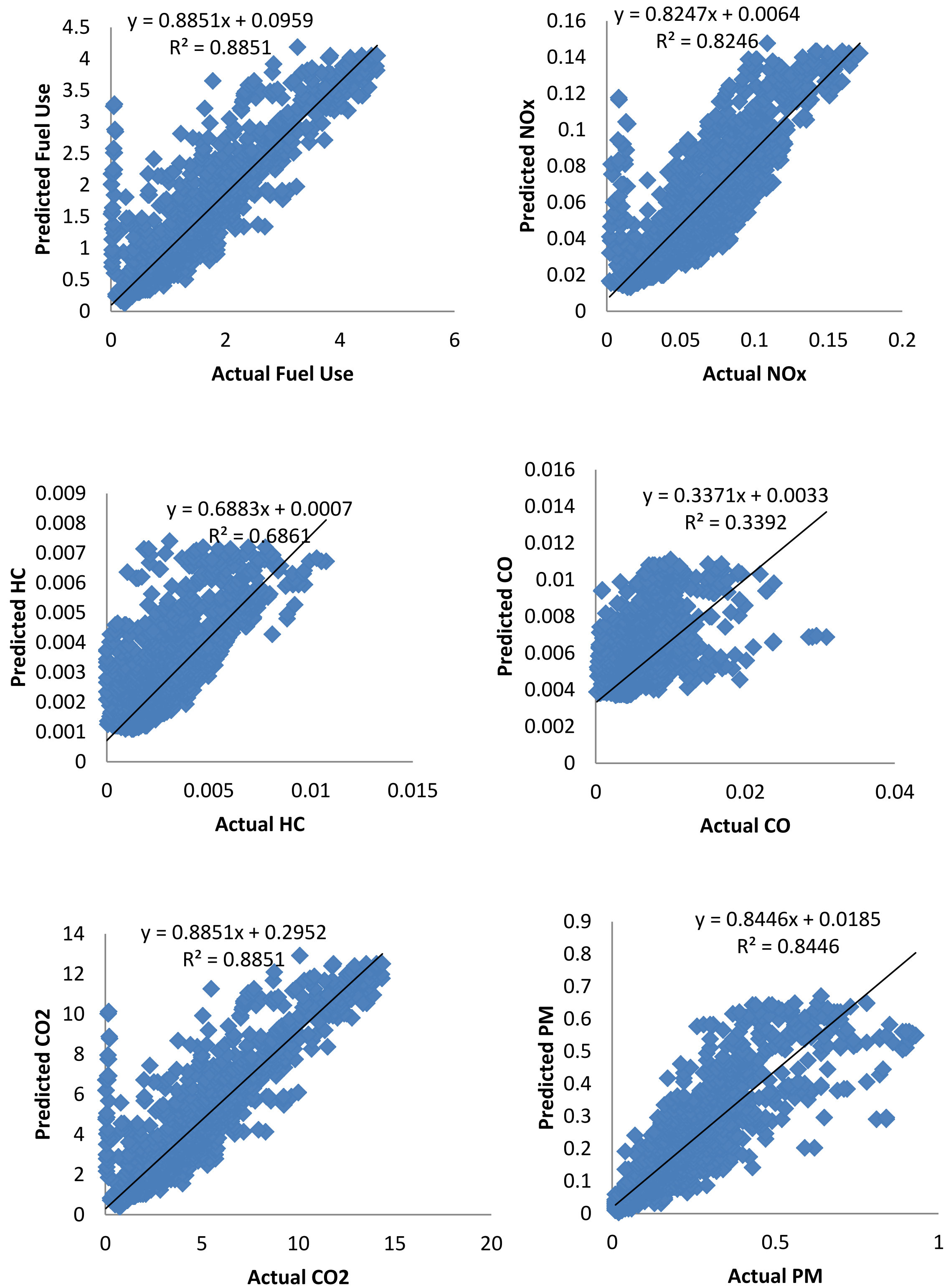

Figure F.2. Model Validation for SLR for Wheel Loader 3

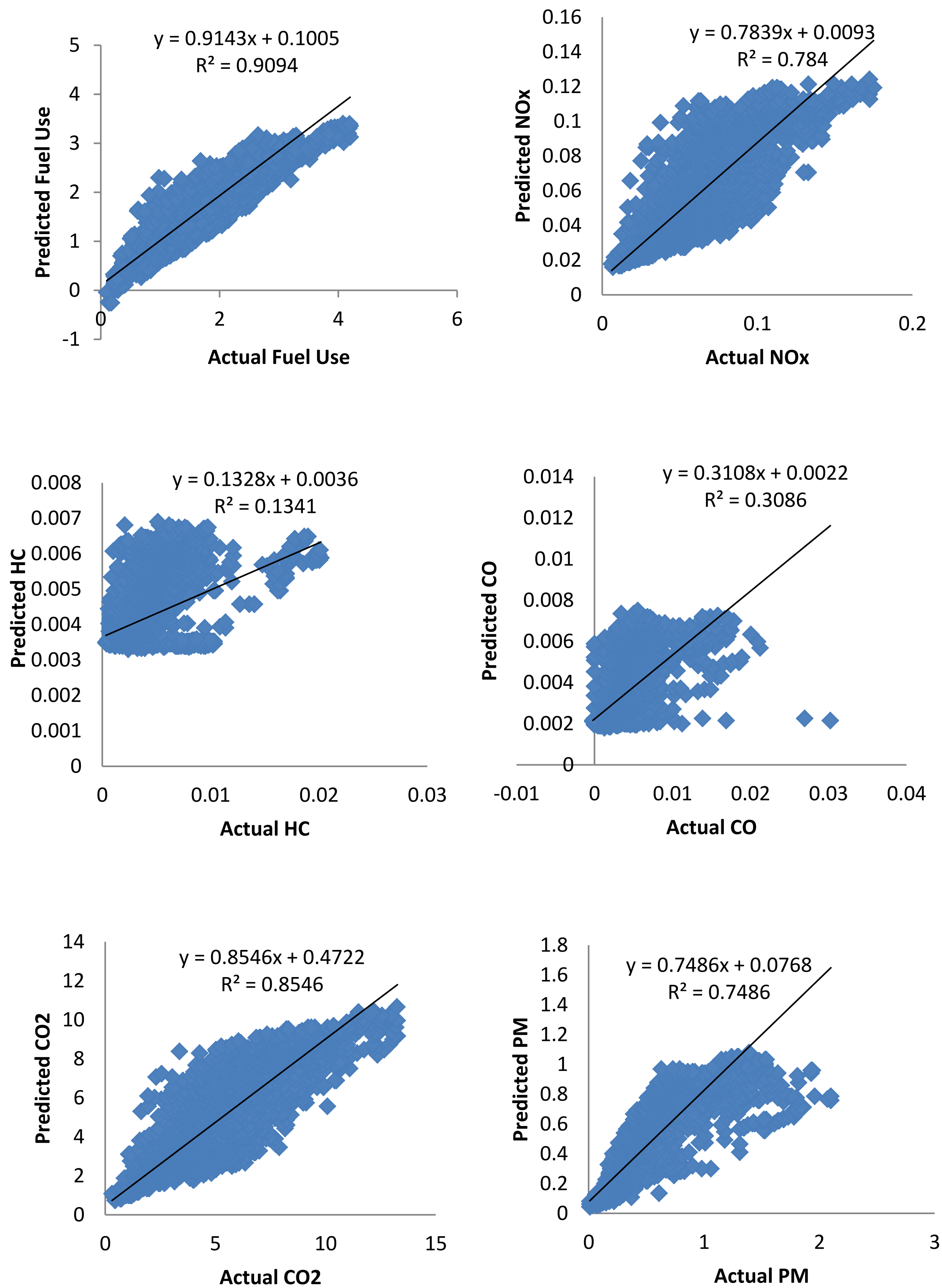

Figure F.3. Model Validation for SLR for Wheel Loader 4

Appendix G

Model validations for MLR

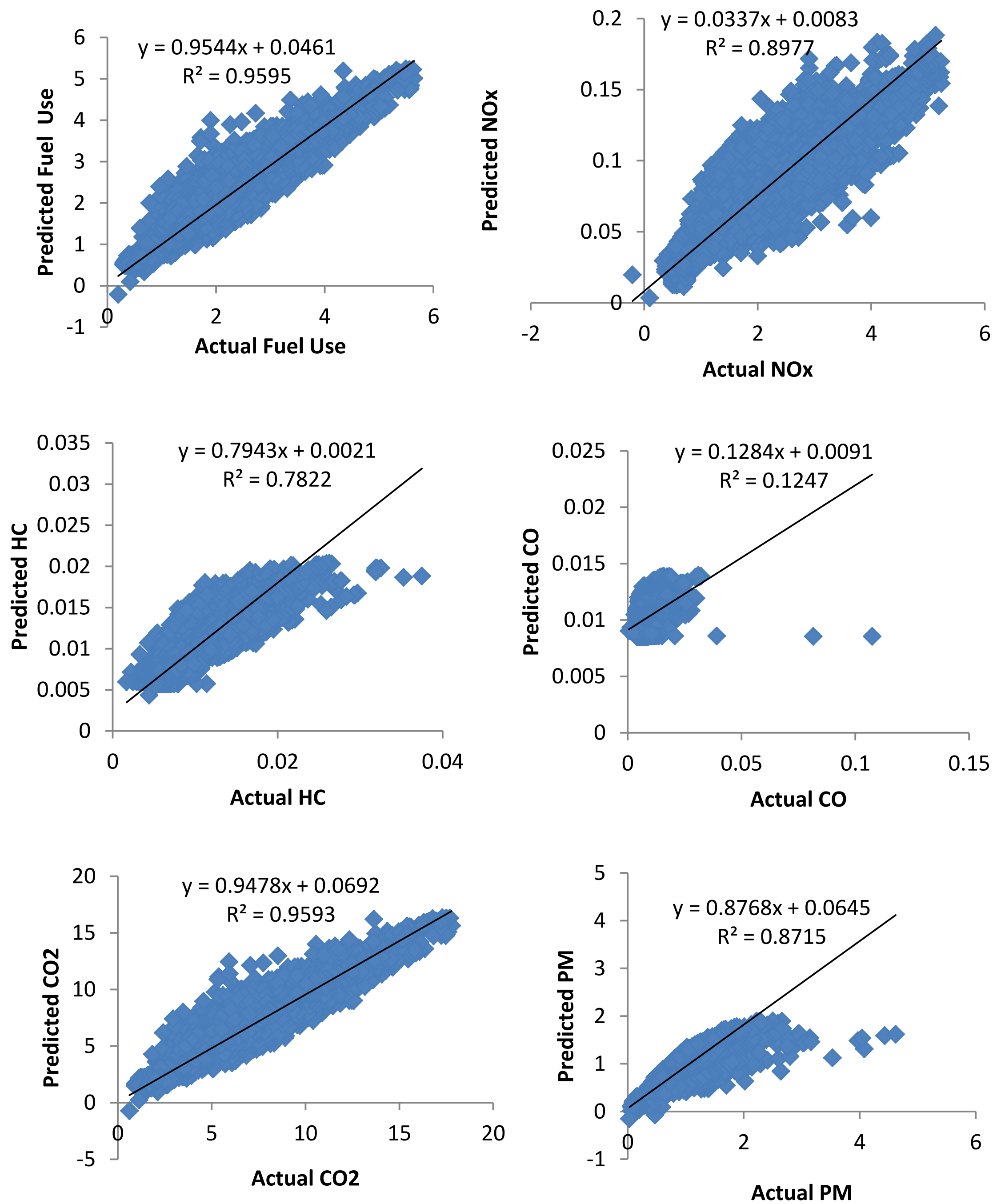

Figure G.1. Model Validation for MLR for Wheel Loader 2

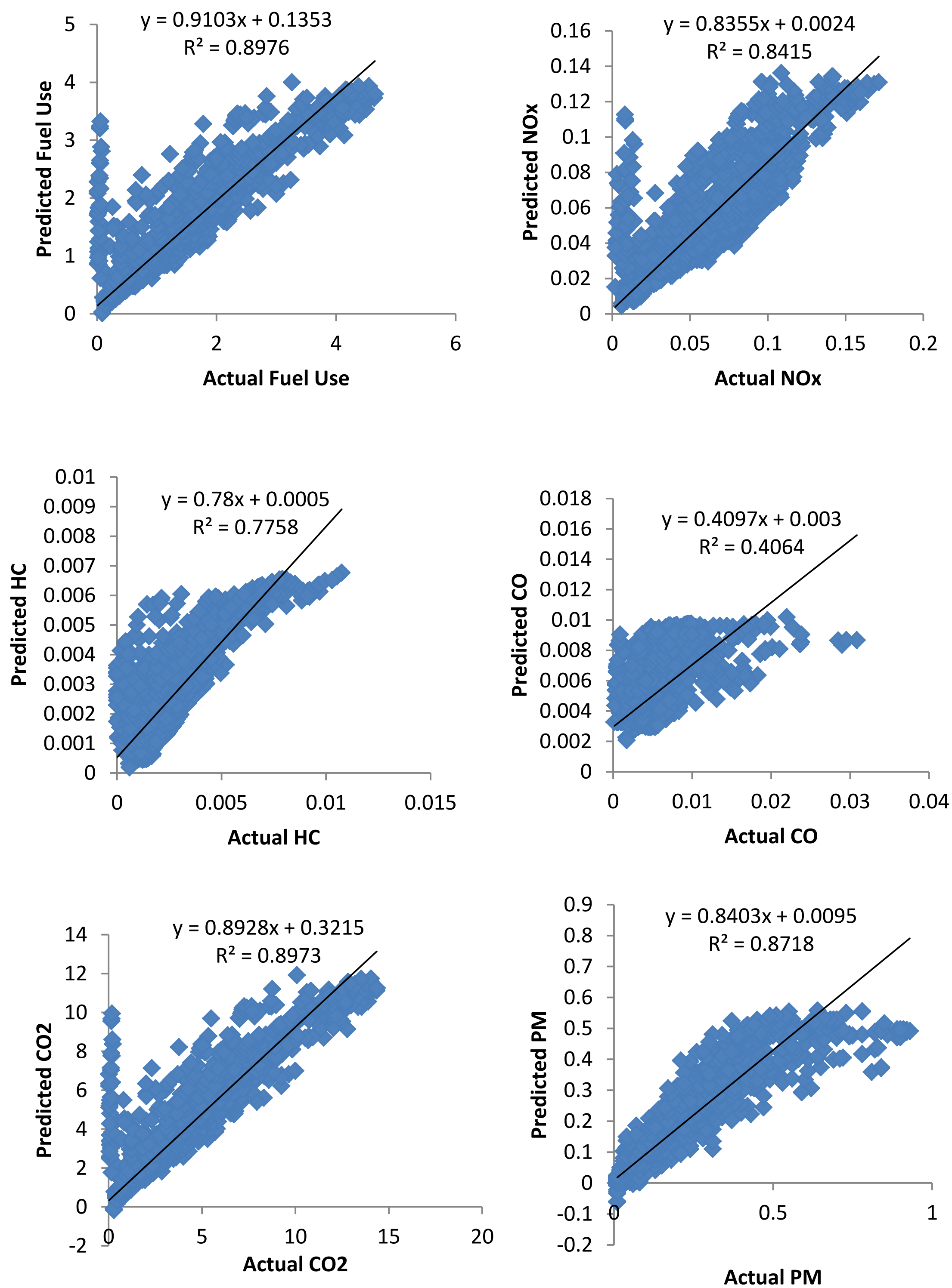

Figure G.2. Model Validation for MLR for Wheel Loader 3

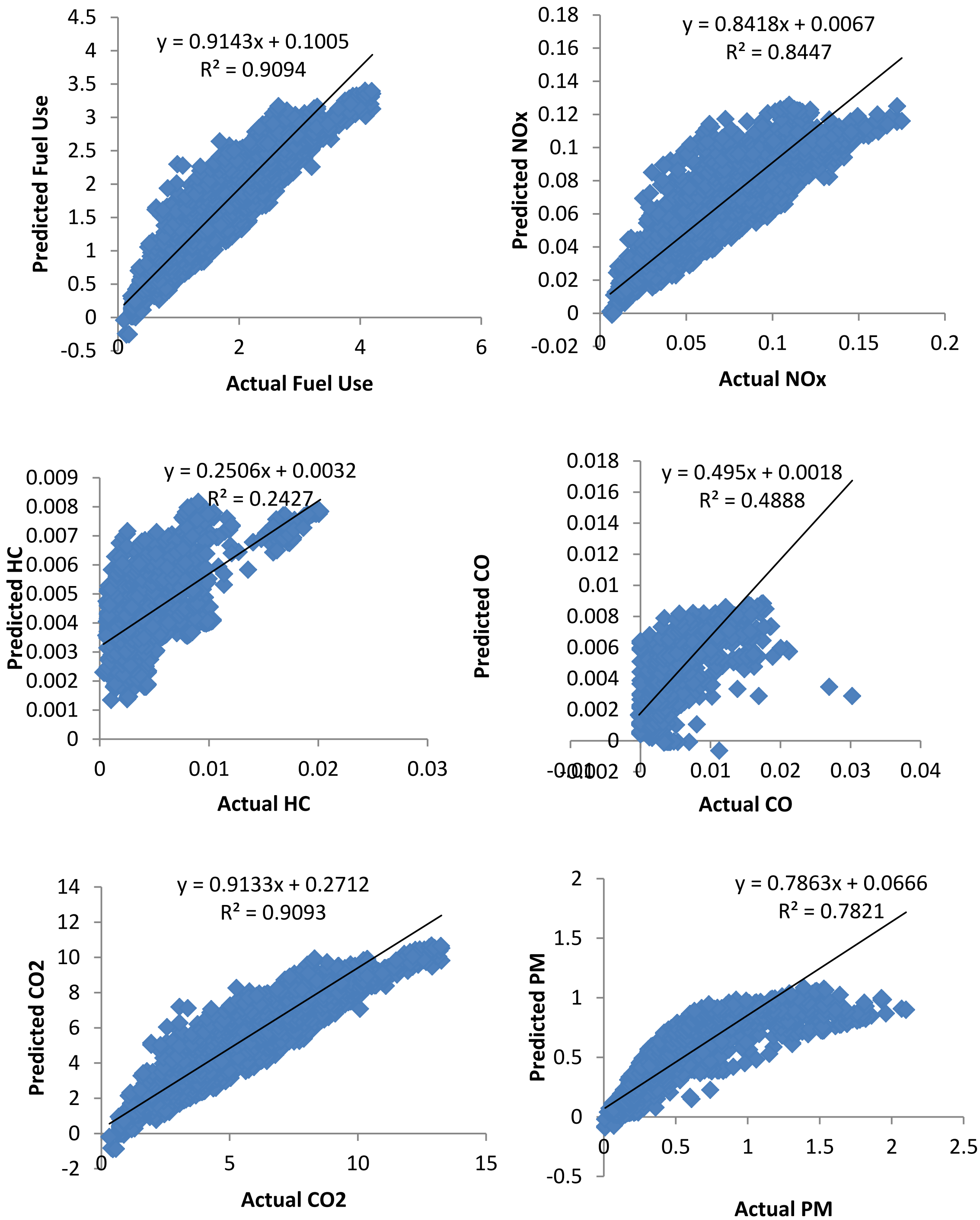

Figure G.3. Model Validation for MLR for Wheel Loader 4

Appendix H

Weighted average fuel use and emissions rates

Table H.1. Percentage of time in each engine mode for backhoes

Modes	BH1	BH2	BH3	BH4	BH5	BH6	Average
1	63.25%	52.90%	14.04%	7.61%	22.65%	14.15%	29.10%
2	18.73%	19.19%	15.81%	29.99%	37.02%	34.66%	25.90%
3	6.84%	16.19%	36.70%	37.91%	17.23%	26.65%	23.58%
4	3.64%	7.30%	8.11%	14.62%	14.06%	11.73%	9.91%
5	2.22%	2.36%	6.23%	1.76%	5.78%	2.10%	3.41%
6	1.24%	0.87%	5.22%	1.24%	2.03%	1.91%	2.09%
7	0.89%	0.46%	3.94%	0.80%	0.83%	1.91%	1.47%
8	0.98%	0.51%	6.12%	0.82%	0.18%	2.54%	1.86%
9	1.64%	0.15%	3.49%	1.66%	0.10%	2.48%	1.59%
10	0.58%	0.06%	0.34%	3.58%	0.11%	1.88%	1.09%
			Total				**100.00%**

Table H.2. Percentage of time in each engine mode for bulldozers

Modes	BD1	BD2	BD3	BD4	BD5	BD6	Average
1	18.47%	39.53%	19.88%	22.43%	9.16%	40.06%	24.92%
2	10.10%	12.35%	32.76%	12.66%	2.75%	22.16%	15.46%
3	13.45%	13.80%	24.25%	10.62%	3.30%	28.38%	15.63%
4	14.81%	10.18%	9.78%	9.18%	4.49%	6.49%	9.15%
5	12.95%	7.68%	5.47%	7.76%	4.81%	1.44%	6.68%
6	15.14%	7.02%	3.56%	7.45%	5.33%	0.51%	6.50%
7	9.30%	5.31%	2.26%	6.05%	6.94%	0.43%	5.05%
8	3.59%	2.62%	1.15%	5.52%	10.86%	0.39%	4.02%
9	1.79%	1.00%	0.64%	10.99%	25.89%	0.10%	6.74%
10	0.40%	0.50%	0.23%	7.35%	26.48%	0.04%	5.83%
			Total				**100.00%**

Table H.3. Percentage of time in each engine mode for excavators

Modes	EXC1	EXC2	EXC3	Average
1	29.75%	37.28%	27.17%	31.40%
2	12.58%	2.29%	0.76%	5.21%
3	10.06%	10.22%	3.51%	7.93%
4	7.32%	9.78%	8.04%	8.38%
5	7.92%	9.51%	12.00%	9.81%
6	7.00%	8.62%	15.95%	10.52%
7	5.88%	7.25%	15.77%	9.64%
8	9.46%	6.14%	10.10%	8.57%
9	7.35%	6.05%	6.04%	6.48%
10	2.68%	2.85%	0.66%	2.07%
		Total		**100.00%**

Table H.4. Percentage of time in each engine mode for motor graders

Modes	MG1	MG2	MG3	MG4	MG5	MG6	Average
1	15.06%	49.97%	23.79%	24.74%	17.96%	13.63%	24.19%
2	4.15%	7.03%	3.82%	3.97%	16.96%	3.96%	6.65%
3	3.82%	15.61%	9.46%	5.85%	13.52%	11.33%	9.93%
4	4.76%	12.25%	7.38%	7.67%	9.43%	25.91%	11.23%
5	7.10%	6.21%	9.13%	9.50%	9.74%	15.76%	9.57%
6	11.06%	4.18%	17.66%	18.37%	9.41%	11.97%	12.11%
7	16.53%	0.96%	16.46%	17.12%	17.46%	5.30%	12.30%
8	14.30%	0.64%	5.76%	5.99%	4.36%	4.50%	5.93%
9	13.92%	1.44%	3.16%	3.29%	0.91%	4.44%	4.53%
10	9.29%	1.71%	3.37%	3.51%	0.25%	3.20%	3.55%
				Total			**100.00%**

Table H.5. Percentage of time in each engine mode for off-road trucks

Modes	OFT1	OFT2	OFT3	Average
1	67.02%	80.06%	68.39%	71.82%
2	7.83%	9.87%	12.51%	10.07%
3	5.20%	5.16%	4.12%	4.82%
4	3.90%	2.77%	2.03%	2.90%
5	4.18%	1.45%	1.81%	2.48%
6	3.42%	0.47%	2.74%	2.21%
7	2.23%	0.10%	2.47%	1.60%
8	1.84%	0.05%	3.18%	1.69%
9	1.81%	0.02%	2.25%	1.36%
10	2.57%	0.05%	0.49%	1.04%
		Total		**100.00%**

Table H.6. Percentage of time in each engine mode for track loaders

Modes	TL1	TL2	TL3	Average
1	45.99%	19.05%	15.89%	26.98%
2	1.56%	13.18%	0.17%	4.97%
3	2.09%	5.67%	3.97%	3.91%
4	1.76%	4.89%	5.22%	3.95%
5	9.42%	5.13%	8.49%	7.68%
6	23.02%	9.15%	6.91%	13.03%
7	10.01%	9.73%	6.04%	8.59%
8	4.49%	12.91%	6.25%	7.88%
9	0.99%	11.57%	15.60%	9.39%
10	0.68%	8.72%	31.46%	13.62%
		Total		**100.00%**

Table H.7. Average Emission Rates of Fuel Use (g/hp-hr) for Tier 0 based on Tier Type

Modes	BD 1	BD 5	MG 4	MG 5	TL 2	Average
1	0.0047	0.0051	0.0017	0.0056	0.0091	**0.0052**
2	0.0130	0.0146	0.0054	0.0131	0.0200	**0.0132**
3	0.0189	0.0220	0.0084	0.0193	0.0259	**0.0189**
4	0.0272	0.0282	0.0107	0.0256	0.0381	**0.0260**
5	0.0331	0.0323	0.0127	0.0315	0.0411	**0.0301**
6	0.0394	0.0371	0.0154	0.0387	0.0400	**0.0341**
7	0.0447	0.0435	0.0179	0.0447	0.0450	**0.0392**
8	0.0505	0.0490	0.0219	0.0494	0.0600	**0.0461**
9	0.0573	0.0563	0.0246	0.0557	0.0724	**0.0533**
10	0.0619	0.0612	0.0320	0.0596	0.0846	**0.0598**

Table H.8. Average Emission Rates of NO_x (g/hp-hr) for Tier 0 based on Tier Type

Modes	BD 1	BD 5	MG 4	MG 5	TL 2	Average
1	1.1298	1.2625	0.3637	1.1837	1.3695	**1.0618**
2	2.6919	2.8989	0.8152	2.5540	3.0581	**2.4036**
3	3.6514	3.9460	1.1493	3.5436	4.3217	**3.3224**
4	4.3427	5.1201	1.3455	4.3983	6.7458	**4.3905**
5	4.9418	6.0639	1.3392	4.8543	7.3315	**4.9061**
6	5.5779	6.8602	1.5778	5.7840	6.6888	**5.2977**
7	5.9454	7.5776	1.8595	7.0653	7.0560	**5.9008**
8	6.5944	9.0207	2.4554	8.3775	11.5483	**7.5992**
9	7.4800	11.2123	2.9158	9.7611	15.2835	**9.3305**
10	7.8471	13.0162	3.9970	10.2801	19.5845	**10.9450**

Table H.9. Average Emission Rates of HC (g/hp-hr) for Tier 0 based on Tier Type

Modes	BD 1	BD 5	MG 4	MG 5	TL 2	Average
1	0.1136	0.0400	0.1981	0.1057	0.1507	0.1216
2	0.1587	0.0658	0.4468	0.1745	0.3494	0.2391
3	0.2061	0.0783	0.6357	0.2140	0.3538	0.2976
4	0.2340	0.0921	0.7276	0.2545	0.4691	0.3555
5	0.2560	0.1098	0.8138	0.2908	0.3418	0.3624
6	0.2741	0.1171	0.9395	0.3377	0.3510	0.4039
7	0.2656	0.1470	1.1299	0.3116	0.3173	0.4343
8	0.2737	0.1397	1.4263	0.3337	0.3494	0.5046
9	0.3100	0.1411	1.5287	0.2997	0.4126	0.5384
10	0.3487	0.1559	1.1038	0.2861	0.4258	0.4640

Table H.10. Average Emission Rates of CO (g/hp-hr) for Tier 0 based on Tier Type

Modes	BD 1	BD 5	MG 4	MG 5	TL 2	Average
1	0.3498	0.4348	0.0340	0.7236	0.2751	0.3634
2	0.7409	1.6659	0.0490	0.9389	0.5088	0.7807
3	0.8954	1.6797	0.0611	0.9647	0.5390	0.8280
4	0.9612	1.3557	0.0496	1.0403	0.6347	0.8083
5	1.0034	1.3382	0.0462	1.0756	0.6208	0.8168
6	1.0894	1.1862	0.0851	1.1604	0.5193	0.8081
7	1.2123	1.8587	0.1027	0.8993	0.5940	0.9334
8	1.4964	1.1016	0.0811	0.9637	0.6888	0.8663
9	1.6405	0.9203	0.0887	0.9584	0.7828	0.8781
10	1.5633	0.8778	0.2005	0.8116	0.8575	0.8622

Table H.11. Average Emission Rates of CO_2 (g/hp-hr) for Tier 0 based on Tier Type

Modes	BD 1	BD 5	MG 4	MG 5	TL 2	Average
1	49.1721	53.1771	17.7460	58.0116	96.2118	54.8637
2	136.6877	151.9537	55.9283	136.9682	210.8496	138.4775
3	198.8666	231.4211	88.0256	202.6647	273.6407	198.9237
4	287.5149	297.2826	112.0666	269.9017	402.7584	273.9048
5	349.3079	341.4367	132.5044	332.5563	435.0316	318.1674
6	416.5459	392.5481	161.4220	408.8536	423.3363	360.5412
7	473.0216	458.7394	186.9827	472.9580	477.2701	413.7944
8	533.5579	519.1926	228.8917	522.9305	635.8830	488.0911
9	606.1214	597.0806	257.8863	590.1020	767.4256	563.7232
10	654.5919	648.6315	337.3661	631.6890	897.1549	633.8867

Table H.12. Average Emission Rates of PM (g/hp-hr) for Tier 0 based on Tier Type

Modes	BD 1	BD 5	MG 4	MG 5	TL 2	Average
1	0.0055	0.0000	0.0019	0.0045	0.0105	0.0056
2	0.0170	0.0000	0.0076	0.0107	0.0148	0.0125
3	0.0319	0.0000	0.0098	0.0152	0.0199	0.0192
4	0.0427	0.0000	0.0120	0.0202	0.0291	0.0260
5	0.0496	0.0000	0.0150	0.0272	0.0317	0.0309
6	0.0583	0.0000	0.0187	0.0295	0.0352	0.0354
7	0.0687	0.0000	0.0210	0.0331	0.0394	0.0406
8	0.0874	0.0000	0.0246	0.0353	0.0424	0.0474
9	0.0959	0.0000	0.0295	0.0400	0.0520	0.0544
10	0.1031	0.0000	0.0378	0.0395	0.0524	0.0582

Table H.13. Average Emission Rates of Fuel Use (g/hp-hr) for Tier 2 based on Tier Type

Modes	BH 1	BH 4	BH 8	BD 6	EX 2	MG 2	ORT 1	TL 3	WL 1	WL 5	Average
1	0.0066	0.0026	0.0035	0.0074	0.0251	0.0035	0.0038	0.0041	0.0067	0.0049	0.0068
2	0.0110	0.0046	0.0058	0.0112	0.0227	0.0120	0.0090	0.0095	0.0110	0.0080	0.0105
3	0.0139	0.0060	0.0066	0.0147	0.0202	0.0184	0.0117	0.0162	0.0144	0.0121	0.0134
4	0.0163	0.0072	0.0077	0.0127	0.0186	0.0228	0.0149	0.0245	0.0180	0.0161	0.0159
5	0.0184	0.0085	0.0093	0.0101	0.0194	0.0275	0.0188	0.0300	0.0207	0.0190	0.0182
6	0.0201	0.0101	0.0112	0.0105	0.0173	0.0321	0.0207	0.0354	0.0236	0.0215	0.0203
7	0.0259	0.0105	0.0113	0.0117	0.0172	0.0345	0.0222	0.0386	0.0263	0.0254	0.0224
8	0.0287	0.0131	0.0127	0.0123	0.0168	0.0379	0.0238	0.0432	0.0301	0.0311	0.0250
9	0.0341	0.0144	0.0147	0.0143	0.0177	0.0436	0.0284	0.0485	0.0340	0.0346	0.0284
10	0.0372	0.0161	0.0158	0.0146	0.0166	0.0480	0.0335	0.0513	0.0402	0.0435	0.0317

Table H.14. Average Emission Rates of NO_x (g/hp-hr) for Tier 2 based on Tier Type

Modes	BH 1	BH 4	BH 8	BD 6	EX 2	MG 2	ORT 1	TL 3	WL 1	WL 5	Average
1	1.1144	0.5634	0.6129	0.7915	1.8696	0.5730	0.6576	0.4386	0.8124	0.6198	0.8053
2	1.6006	0.7489	0.8589	1.0905	1.7597	1.4504	1.0656	0.5260	1.2159	0.9641	1.1281
3	1.6492	0.8129	0.9149	1.3864	1.5870	2.0642	1.3352	1.2072	1.5335	1.2546	1.3745
4	1.7631	0.8860	1.0127	1.1592	1.4806	2.2963	1.6843	1.3954	1.8795	1.5740	1.5131
5	1.9223	1.0321	1.3271	0.8235	1.5148	2.3867	2.2279	1.6835	2.1175	1.7273	1.6763
6	2.0183	1.2342	1.6646	0.8654	1.3952	2.7924	2.3345	1.9461	2.2878	1.9850	1.8524
7	2.2854	1.2650	1.6498	0.8330	1.3780	2.7608	2.4614	2.1080	2.4778	2.3196	1.9539
8	2.9418	1.5596	1.8088	0.8876	1.3789	3.2086	2.5771	2.2568	2.8229	2.7508	2.2193
9	2.9770	1.5924	1.9729	0.9768	1.4297	3.3574	3.1314	2.8089	3.1386	2.9250	2.4310
10	3.2384	1.8666	2.1080	1.1977	1.3413	4.0015	3.4739	3.2039	3.8105	3.5100	2.7752

Table H.15. Average Emission Rates of HC (g/hp-hr) for Tier 2 based on Tier Type

Modes	BH 1	BH 4	BH 8	BD 6	EX 2	MG 2	ORT 1	TL 3	WL 1	WL 5	Average
1	0.1266	0.0561	0.0351	0.2552	0.1658	0.1730	0.0423	0.0126	0.0863	0.0456	0.0999
2	0.1848	0.0717	0.0644	0.1980	0.1549	0.4235	0.0884	0.0155	0.1183	0.0580	0.1378
3	0.2455	0.0746	0.0866	0.2885	0.1475	0.5351	0.1068	0.0506	0.1654	0.0752	0.1776
4	0.3514	0.0808	0.1104	0.1998	0.1389	0.5727	0.1330	0.0491	0.1942	0.0887	0.1919
5	0.3752	0.1143	0.0866	0.0853	0.1402	0.5247	0.1582	0.0667	0.2257	0.1084	0.1885
6	0.2532	0.1421	0.1027	0.0288	0.1326	0.4428	0.1802	0.0815	0.2539	0.1300	0.1748
7	0.3624	0.1381	0.0929	0.0812	0.1315	0.5013	0.1782	0.0984	0.2874	0.1253	0.1997
8	0.3690	0.1459	0.1051	0.1047	0.1317	0.4538	0.2045	0.1058	0.3193	0.1361	0.2076
9	0.3729	0.1600	0.1291	0.0926	0.1371	0.4537	0.2229	0.0880	0.3481	0.1376	0.2142
10	0.5212	0.1824	0.1502	0.3106	0.1367	0.4489	0.2577	0.0542	0.3510	0.1933	0.2606

Table H.16. Average Emission Rates of CO (g/hp-hr) for Tier 2 based on Tier Type

Modes	BH 1	BH 4	BH 8	BD 6	EX 2	MG 2	ORT 1	TL 3	WL 1	WL 5	Average
1	0.1473	0.0325	0.0654	0.3985	0.6480	0.1333	0.0995	0.1610	0.3120	0.1338	0.2131
2	0.2221	0.0539	0.1030	0.4799	0.6080	0.8961	0.5429	0.6132	0.5162	0.1652	0.4201
3	0.2703	0.0611	0.1306	0.5191	0.5883	0.6461	0.7711	0.4763	0.6797	0.2509	0.4393
4	0.3550	0.0700	0.1739	0.3266	0.5787	0.7063	1.1151	0.5427	0.8227	0.3056	0.4997
5	0.3818	0.0966	0.1555	0.1644	0.5785	0.6771	1.6271	0.6206	0.8971	0.3356	0.5534
6	0.3696	0.1144	0.1899	0.2537	0.5674	0.4959	1.5428	0.6596	0.9345	0.4249	0.5553
7	0.5327	0.1096	0.1989	0.1356	0.5799	0.6249	1.5278	0.6485	1.0272	0.4061	0.5791
8	0.5697	0.1361	0.2314	0.1442	0.5581	0.5515	1.7172	0.6893	1.1597	0.4928	0.6250
9	0.5681	0.1510	0.3043	0.2181	0.5670	0.3893	1.7215	0.6316	1.2432	0.5980	0.6392
10	0.6204	0.2029	0.2895	0.2791	0.6387	0.3380	1.9310	0.6098	1.6530	0.5621	0.7125

Table H.17. Average Emission Rates of CO_2 (g/hp-hr) for Tier 2 based on Tier Type

Modes	BH 1	BH 4	BH 8	BD 6	EX 2	MG 2	ORT 1	TL 3	WL 1	WL 5	Average
1	69.2761	27.2396	36.9089	77.5904	265.6044	36.5919	40.4153	43.2188	71.0010	51.7995	71.9646
2	115.9918	48.5618	61.1485	118.0164	240.2126	124.8879	95.0822	99.6206	116.0014	84.5978	110.4121
3	146.2958	63.3521	69.9466	154.7608	213.5680	193.4620	123.1789	171.0642	151.2667	128.1508	141.5046
4	172.2482	76.0774	80.8806	133.9770	196.8202	239.4675	156.1324	259.7457	189.1865	170.7970	167.5333
5	194.3656	90.2493	98.8317	106.6950	204.7068	289.4408	196.6117	318.1022	217.9453	201.6018	191.8550
6	212.6233	106.2269	118.9704	111.3205	183.2739	339.7344	217.1684	375.3068	248.4232	227.4828	214.0530
7	273.3026	111.5485	119.7249	124.4445	181.3435	364.7677	233.1563	409.3168	277.8221	268.8945	236.4321
8	302.7389	138.7378	134.7379	130.6533	177.9368	400.5872	249.4316	457.7529	317.9905	329.0658	263.9633
9	360.2063	152.7578	155.9868	151.4242	186.8080	462.0439	298.7024	515.0813	358.5896	366.7121	300.8312
10	393.0936	170.5054	166.7066	154.0242	174.8291	508.5997	352.1071	544.1284	424.5247	460.9100	334.9429

Table H.18. Average Emission Rates of PM (g/hp-hr) for Tier 2 based on Tier Type

Modes	BH 1	BH 4	BH 8	BD 6	EX 2	MG 2	ORT 1	TL 3	WL 1	WL 5	Average
1	0.0009	0.0021	0.0026	0.0049	0.0201	0.0019	0.0027	0.0036	0.0058	0.0031	0.0048
2	0.0016	0.0035	0.0044	0.0076	0.0177	0.0081	0.0091	0.0101	0.0112	0.0044	0.0078
3	0.0019	0.0047	0.0056	0.0138	0.0153	0.0129	0.0123	0.0199	0.0126	0.0061	0.0105
4	0.0021	0.0061	0.0067	0.0162	0.0143	0.0158	0.0163	0.0205	0.0155	0.0090	0.0123
5	0.0024	0.0068	0.0088	0.0152	0.0148	0.0161	0.0209	0.0229	0.0184	0.0116	0.0138
6	0.0023	0.0079	0.0118	0.0171	0.0127	0.0179	0.0248	0.0247	0.0214	0.0149	0.0156
7	0.0032	0.0081	0.0125	0.0188	0.0124	0.0234	0.0255	0.0267	0.0258	0.0162	0.0173
8	0.0035	0.0106	0.0139	0.0226	0.0124	0.0229	0.0297	0.0292	0.0314	0.0200	0.0196
9	0.0037	0.0126	0.0169	0.0383	0.0126	0.0237	0.0359	0.0282	0.0378	0.0268	0.0236
10	0.0037	0.0144	0.0178	0.0702	0.0123	0.0290	0.0377	0.0271	0.0472	0.0343	0.0294

Table H.19. Summary of Average Time and Emission Rates of Fuel Use (g/hp-hr) based on Tier Type for Backhoe

Modes	Average Time (Ti) of Backhoe	Wgt. Average Fuel Use (Ti x EFi)		
		Tier 0	Tier 1	Tier 2
1	29.10%	0.0052	0.0050	0.0068
2	25.90%	0.0132	0.0099	0.0105
3	23.58%	0.0189	0.0146	0.0134
4	9.91%	0.0260	0.0190	0.0159
5	3.41%	0.0301	0.0231	0.0182
6	2.09%	0.0341	0.0268	0.0203
7	1.47%	0.0392	0.0307	0.0224
8	1.86%	0.0461	0.0348	0.0250
9	1.59%	0.0533	0.0392	0.0284
10	1.09%	0.0598	0.0436	0.0317

Table H.20. Summary of Average Time and Emission Rates of NO_x (g/hp-hr) based on Tier Type for Backhoe

Modes	Average Time (Ti) of Backhoe	Wgt. Average NOx (Ti x Efi)		
		Tier 0	Tier 1	Tier 2
1	29.10%	1.0618	0.7395	0.8053
2	25.90%	2.4036	1.3587	1.1281
3	23.58%	3.3224	1.9171	1.3745
4	9.91%	4.3905	2.3604	1.5131
5	3.41%	4.9061	2.7199	1.6763
6	2.09%	5.2977	3.0150	1.8524
7	1.47%	5.9008	3.4367	1.9539
8	1.86%	7.5992	3.9325	2.2193
9	1.59%	9.3305	4.3663	2.4310
10	1.09%	10.9450	4.8511	2.7752

Table H.21. Summary of Average Time and Emission Rates of HC (g/hp-hr) based on Tier Type for Backhoe

Modes	Average Time (Ti) of Backhoe	Wgt. Average HC (Ti x Efi)		
		Tier 0	Tier 1	Tier 2
1	29.10%	0.1216	0.0967	0.0999
2	25.90%	0.2391	0.1449	0.1378
3	23.58%	0.2976	0.1914	0.1776
4	9.91%	0.3555	0.2231	0.1919
5	3.41%	0.3624	0.2375	0.1885
6	2.09%	0.4039	0.2707	0.1748
7	1.47%	0.4343	0.2904	0.1997
8	1.86%	0.5046	0.3335	0.2076
9	1.59%	0.5384	0.3502	0.2142
10	1.09%	0.4640	0.3472	0.2606

Table H.22. Summary of Average Time and Emission Rates of CO (g/hp-hr) based on Tier Type for Backhoe

Modes	Average Time (Ti) of Backhoe	Wgt. Average CO (Ti x Efi)		
		Tier 0	Tier 1	Tier 2
1	29.10%	0.3634	0.2146	0.2131
2	25.90%	0.7807	0.4116	0.4201
3	23.58%	0.8280	0.4728	0.4393
4	9.91%	0.8083	0.4721	0.4997
5	3.41%	0.8168	0.5047	0.5534
6	2.09%	0.8081	0.7078	0.5553
7	1.47%	0.9334	0.9045	0.5791
8	1.86%	0.8663	1.1592	0.6250
9	1.59%	0.8781	1.5543	0.6392
10	1.09%	0.8622	1.3570	0.7125

Table H.23. Summary of Average Time and Emission Rates of CO_2 (g/hp-hr) based on Tier Type for Backhoe

Modes	Average Time (Ti) of Backhoe	Wgt. Average CO_2 (Ti x Efi)		
		Tier 0	Tier 1	Tier 2
1	29.10%	54.8637	52.1271	71.9646
2	25.90%	138.4775	104.4610	110.4121
3	23.58%	198.9237	153.7432	141.5046
4	9.91%	273.9048	200.3489	167.5333
5	3.41%	318.1674	243.7317	191.8550
6	2.09%	360.5412	283.1555	214.0530
7	1.47%	413.7944	324.1951	236.4321
8	1.86%	488.0911	367.0358	263.9633
9	1.59%	563.7232	412.8435	300.8312
10	1.09%	633.8867	459.4457	334.9429

Table H.24. Summary of Average Time and Emission Rates of PM (g/hp-hr) based on Tier Type for Backhoe

Modes	Average Time (Ti) of Backhoe	Wgt. Average PM (Ti x Efi)		
		Tier 0	Tier 1	Tier 2
1	29.10%	0.0056	0.0048	0.005
2	25.90%	0.0125	0.0106	0.008
3	23.58%	0.0192	0.0152	0.011
4	9.91%	0.0260	0.0192	0.012
5	3.41%	0.0309	0.0245	0.014
6	2.09%	0.0354	0.0296	0.016
7	1.47%	0.0406	0.0344	0.017
8	1.86%	0.0474	0.0421	0.020
9	1.59%	0.0544	0.0458	0.024
10	1.09%	0.0582	0.0522	0.029

Table H.25. Summary of Modal Weighted Average Fuel Use (g/hp-hr) for each tier for Backhoe

Modes	Wgt. Average Fuel Use (Ti x FFi) for Backhoe		
	Tier 0	Tier 1	Tier 2
1	0.0015	0.0014	0.0020
2	0.0034	0.0026	0.0027
3	0.0045	0.0034	0.0032
4	0.0026	0.0019	0.0016
5	0.0010	0.0008	0.0006
6	0.0007	0.0006	0.0004
7	0.0006	0.0005	0.0003
8	0.0009	0.0006	0.0005
9	0.0008	0.0006	0.0005
10	0.0007	0.0005	0.0003
Total	**0.0167**	**0.0129**	**0.0121**

Table H.26. Summary of Modal Weighted Average Fuel Use (g/hp-hr) for each tier for Bulldozer

Modes	Wgt. Average Fuel Use (Ti x FFi) for Bulldozer		
	Tier 0	**Tier 1**	**Tier 2**
1	0.0013	0.0012	0.0017
2	0.0020	0.0015	0.0016
3	0.0030	0.0023	0.0021
4	0.0024	0.0017	0.0015
5	0.0020	0.0015	0.0012
6	0.0022	0.0017	0.0013
7	0.0020	0.0016	0.0011
8	0.0019	0.0014	0.0010
9	0.0036	0.0026	0.0019
10	0.0035	0.0025	0.0018
Total	**0.0238**	**0.0182**	**0.0153**

Table H.27. Summary of Modal Weighted Average Fuel Use (g/hp-hr) for each tier for Excavators

Modes	Wgt. Average Fuel Use (Ti x FFi) for Excavators		
	Tier 0	**Tier 1**	**Tier 2**
1	0.0016	0.0016	0.0021
2	0.0007	0.0005	0.0005
3	0.0015	0.0012	0.0011
4	0.0022	0.0016	0.0013
5	0.0030	0.0023	0.0018
6	0.0036	0.0028	0.0021
7	0.0038	0.0030	0.0022
8	0.0040	0.0030	0.0021
9	0.0035	0.0025	0.0018
10	0.0012	0.0009	0.0007
Total	**0.0250**	**0.0193**	**0.0158**

Table H.28. Summary of Modal Weighted Average Fuel Use (g/hp-hr) for each tier for Motor Graders

Modes	Wgt. Average Fuel Use (Ti x FFi) for Motor Graders		
	Tier 0	**Tier 1**	**Tier 2**
1	0.0013	0.0012	0.0017
2	0.0009	0.0007	0.0007
3	0.0019	0.0014	0.0013
4	0.0029	0.0021	0.0018
5	0.0029	0.0022	0.0017
6	0.0041	0.0032	0.0025
7	0.0048	0.0038	0.0028
8	0.0027	0.0021	0.0015
9	0.0024	0.0018	0.0013
10	0.0021	0.0015	0.0011
Total	**0.0260**	**0.0201**	**0.0163**

Table H.29. Summary of Modal Weighted Average Fuel Use (g/hp-hr) for each tier for Off-Road Trucks

Modes	Wgt. Average Fuel Use (Ti x FFi) for Off-Road Truck		
	Tier 0	**Tier 1**	**Tier 2**
1	0.0038	0.0036	0.0049
2	0.0013	0.0010	0.0011
3	0.0009	0.0007	0.0006
4	0.0008	0.0006	0.0005
5	0.0007	0.0006	0.0005
6	0.0008	0.0006	0.0004
7	0.0006	0.0005	0.0004
8	0.0008	0.0006	0.0004
9	0.0007	0.0005	0.0004
10	0.0006	0.0005	0.0003
Total	**0.0110**	**0.0091**	**0.0095**

Table H.30. Summary of Modal Weighted Average Fuel Use (g/hp-hr) for each tier for Track Loaders

Modes	Wgt. Average Fuel Use (Ti x FFi) for Track Loaders		
	Tier 0	**Tier 1**	**Tier 2**
1	0.0014	0.0013	0.0018
2	0.0007	0.0005	0.0005
3	0.0007	0.0006	0.0005
4	0.0010	0.0008	0.0006
5	0.0023	0.0018	0.0014
6	0.0044	0.0035	0.0026
7	0.0034	0.0026	0.0019
8	0.0036	0.0027	0.0020
9	0.0050	0.0037	0.0027
10	0.0082	0.0059	0.0043
Total	**0.0307**	**0.0234**	**0.0184**

Table H.31. Summary of Modal Weighted Average Fuel Use (g/hp-hr) for each tier for Wheel Loaders

Modes	Wgt. Average Fuel Use (Ti x FFi) for Wheel Loaders		
	Tier 0	**Tier 1**	**Tier 2**
1	0.0021	0.0020	0.0027
2	0.0026	0.0020	0.0021
3	0.0023	0.0018	0.0017
4	0.0021	0.0016	0.0013
5	0.0017	0.0013	0.0010
6	0.0014	0.0011	0.0008
7	0.0013	0.0010	0.0007
8	0.0014	0.0011	0.0008
9	0.0012	0.0009	0.0006
10	0.0008	0.0006	0.0004
Total	**0.0169**	**0.0132**	**0.0122**

Table H.32. Summary of Modal Weighted Average Emission Rates of NO_x (g/hp-hr) for each tier for Backhoes

Modes	**Wgt. Average NOx (Ti x EFi) for Backhoes**		
	Tier 0	**Tier 1**	**Tier 2**
1	0.3090	0.2152	0.2343
2	0.6225	0.3519	0.2922
3	0.7834	0.4521	0.3241
4	0.4351	0.2339	0.1499
5	0.1673	0.0927	0.0572
6	0.1107	0.0630	0.0387
7	0.0867	0.0505	0.0287
8	0.1413	0.0731	0.0413
9	0.1484	0.0694	0.0387
10	0.1193	0.0529	0.0302
Total	**2.9238**	**1.6548**	**1.2353**

Table H.33. Summary of Modal Weighted Average Emission Rates of NO_x (g/hp-hr) for each tier for Bulldozers

Modes	**Wgt. Average NOx (Ti x EFi) for Bulldozers**		
	Tier 0	**Tier 1**	**Tier 2**
1	0.2646	0.1843	0.2007
2	0.3716	0.2101	0.1744
3	0.5193	0.2996	0.2148
4	0.4017	0.2160	0.1384
5	0.3277	0.1817	0.1120
6	0.3444	0.1960	0.1204
7	0.2980	0.1736	0.0987
8	0.3055	0.1581	0.0892
9	0.6289	0.2943	0.1638
10	0.6381	0.2828	0.1618
Total	**4.0997**	**2.1964**	**1.4743**

Table H.34. Summary of Modal Weighted Average Emission Rates of NO_x (g/hp-hr) for each tier for Excavators

Modes	Wgt. Average NOx (Ti x EFi) for Excavators		
	Tier 0	Tier 1	Tier 2
1	0.3334	0.2322	0.2529
2	0.1252	0.0708	0.0588
3	0.2635	0.1520	0.1090
4	0.3679	0.1978	0.1268
5	0.4813	0.2668	0.1644
6	0.5573	0.3172	0.1949
7	0.5688	0.3313	0.1884
8	0.6513	0.3370	0.1902
9	0.6046	0.2829	0.1575
10	0.2266	0.1004	0.0574
Total	**4.1799**	**2.2885**	**1.5003**

Table H.35. Summary of Modal Weighted Average Emission Rates of NO_x (g/hp-hr) for each tier for Motor Graders

Modes	Wgt. Average NOx (Ti x EFi) for Motor Graders		
	Tier 0	Tier 1	Tier 2
1	0.2568	0.1789	0.1948
2	0.1598	0.0904	0.0750
3	0.3299	0.1904	0.1365
4	0.4931	0.2651	0.1699
5	0.4695	0.2603	0.1604
6	0.6416	0.3651	0.2243
7	0.7258	0.4227	0.2403
8	0.4506	0.2332	0.1316
9	0.4227	0.1978	0.1101
10	0.3885	0.1722	0.0985
Total	**4.3384**	**2.3760**	**1.5415**

Table H.36. Summary of Modal Weighted Average Emission Rates of NO_x (g/hp-hr) for each tier for Off-Road Trucks

Modes	**Wgt. Average NOx (Ti x EFi) for Off-Road Trucks**		
	Tier 0	**Tier 1**	**Tier 2**
1	0.7626	0.5311	0.5784
2	0.2420	0.1368	0.1136
3	0.1601	0.0924	0.0663
4	0.1273	0.0685	0.0439
5	0.1217	0.0675	0.0416
6	0.1171	0.0666	0.0409
7	0.0944	0.0550	0.0313
8	0.1284	0.0665	0.0375
9	0.1269	0.0594	0.0331
10	0.1138	0.0505	0.0289
Total	**1.9944**	**1.1942**	**1.0153**

Table H.37. Summary of Modal Weighted Average Emission Rates of NO_x (g/hp-hr) for each tier for Track Loaders

Modes	**Wgt. Average NOx (Ti x EFi) for Track Loaders**		
	Tier 0	**Tier 1**	**Tier 2**
1	0.2865	0.1995	0.2173
2	0.1195	0.0675	0.0561
3	0.1299	0.0750	0.0537
4	0.1734	0.0932	0.0598
5	0.3768	0.2089	0.1287
6	0.6903	0.3929	0.2414
7	0.5069	0.2952	0.1678
8	0.5988	0.3099	0.1749
9	0.8761	0.4100	0.2283
10	1.4907	0.6607	0.3780
Total	**5.2489**	**2.7128**	**1.7059**

Table H.38. Summary of Modal Weighted Average Emission Rates of NO_x (g/hp-hr) for each tier for Wheel Loaders

Modes	Wgt. Average NOx (Ti x EFi) for Wheel Loaders		
	Tier 0	**Tier 1**	**Tier 2**
1	0.4244	0.2956	0.3732
2	0.4800	0.2713	0.2424
3	0.4113	0.2373	0.2292
4	0.3631	0.1952	0.2042
5	0.2713	0.1504	0.1647
6	0.2151	0.1224	0.1398
7	0.1894	0.1103	0.1275
8	0.2310	0.1195	0.1436
9	0.2127	0.0996	0.1246
10	0.1390	0.0616	0.0787
Total	**2.9374**	**1.6633**	**1.8280**

Table H.39. Summary of Modal Weighted Average Emission Rates of HC (g/hp-hr) for each tier for Backhoes

Modes	Wgt. Average HC (Ti x EFi) for Backhoes		
	Tier 0	**Tier 1**	**Tier 2**
1	0.0354	0.0281	0.0291
2	0.0619	0.0375	0.0357
3	0.0702	0.0451	0.0419
4	0.0352	0.0221	0.0190
5	0.0124	0.0081	0.0064
6	0.0084	0.0057	0.0037
7	0.0064	0.0043	0.0029
8	0.0094	0.0062	0.0039
9	0.0086	0.0056	0.0034
10	0.0051	0.0038	0.0028
Total	**0.2529**	**0.1665**	**0.1488**

Table H.40. Summary of Modal Weighted Average Emission Rates of HC (g/hp-hr) for each tier for Bulldozers

Modes	Wgt. Average HC (Ti x EFi) for Bulldozers		
	Tier 0	**Tier 1**	**Tier 2**
1	0.0303	0.0241	0.0249
2	0.0370	0.0224	0.0213
3	0.0465	0.0299	0.0278
4	0.0325	0.0204	0.0176
5	0.0242	0.0159	0.0126
6	0.0263	0.0176	0.0114
7	0.0219	0.0147	0.0101
8	0.0203	0.0134	0.0083
9	0.0363	0.0236	0.0144
10	0.0271	0.0202	0.0152
Total	**0.3023**	**0.2022**	**0.1635**

Table H.41. Summary of Modal Weighted Average Emission Rates of HC (g/hp-hr) for each tier for Excavators

Modes	Wgt. Average HC (Ti x EFi) for Excavators		
	Tier 0	**Tier 1**	**Tier 2**
1	0.0382	0.0304	0.0314
2	0.0125	0.0076	0.0072
3	0.0236	0.0152	0.0141
4	0.0298	0.0187	0.0161
5	0.0356	0.0233	0.0185
6	0.0425	0.0285	0.0184
7	0.0419	0.0280	0.0192
8	0.0432	0.0286	0.0178
9	0.0349	0.0227	0.0139
10	0.0096	0.0072	0.0054
Total	**0.3117**	**0.2100**	**0.1619**

Table H.42. Summary of Modal Weighted Average Emission Rates of HC (g/hp-hr) for each tier for Motor Graders

Modes	Wgt. Average HC (Ti x EFi) for Motor Graders		
	Tier 0	**Tier 1**	**Tier 2**
1	0.0294	0.0234	0.0242
2	0.0159	0.0096	0.0092
3	0.0296	0.0190	0.0176
4	0.0399	0.0251	0.0216
5	0.0347	0.0227	0.0180
6	0.0489	0.0328	0.0212
7	0.0534	0.0357	0.0246
8	0.0299	0.0198	0.0123
9	0.0244	0.0159	0.0097
10	0.0165	0.0123	0.0093
Total	**0.3226**	**0.2163**	**0.1675**

Table H.43. Summary of Modal Weighted Average Emission Rates of HC (g/hp-hr) for each tier for Off-Road Trucks

Modes	Wgt. Average HC (Ti x EFi) for Off-Road Trucks		
	Tier 0	**Tier 1**	**Tier 2**
1	0.0874	0.0694	0.0717
2	0.0241	0.0146	0.0139
3	0.0143	0.0092	0.0086
4	0.0103	0.0065	0.0056
5	0.0090	0.0059	0.0047
6	0.0089	0.0060	0.0039
7	0.0069	0.0046	0.0032
8	0.0085	0.0056	0.0035
9	0.0073	0.0048	0.0029
10	0.0048	0.0036	0.0027
Total	**0.1816**	**0.1303**	**0.1206**

Table H.44. Summary of Modal Weighted Average Emission Rates of HC (g/hp-hr) for each tier for Track Loaders

Modes (TL)	Wgt. Average HC (Ti x EFi) for Track Loaders		
	Tier 0	**Tier 1**	**Tier 2**
1	0.0328	0.0261	0.0269
2	0.0119	0.0072	0.0068
3	0.0116	0.0075	0.0069
4	0.0140	0.0088	0.0076
5	0.0278	0.0182	0.0145
6	0.0526	0.0353	0.0228
7	0.0373	0.0249	0.0172
8	0.0398	0.0263	0.0164
9	0.0506	0.0329	0.0201
10	0.0632	0.0473	0.0355
Total	**0.3417**	**0.2345**	**0.1747**

Table H.45. Summary of Modal Weighted Average Emission Rates of HC (g/hp-hr) for each tier for Wheel Loaders

Modes (WL)	Wgt. Average HC (Ti x EFi) for Wheel Loaders		
	Tier 0	**Tier 1**	**Tier 2**
1	0.0486	0.0386	0.0399
2	0.0477	0.0289	0.0275
3	0.0368	0.0237	0.0220
4	0.0294	0.0184	0.0159
5	0.0200	0.0131	0.0104
6	0.0164	0.0110	0.0071
7	0.0139	0.0093	0.0064
8	0.0153	0.0101	0.0063
9	0.0123	0.0080	0.0049
10	0.0059	0.0044	0.0033
Total	**0.2465**	**0.1657**	**0.1437**

Table H.46. Summary of Modal Weighted Average Emission Rates of CO (g/hp-hr) for each tier for Backhoes

Modes (BH)	**Wgt. Average CO (Ti x EFi) for Backhoes**		
	Tier 0	**Tier 1**	**Tier 2**
1	0.1058	0.0624	0.0620
2	0.2022	0.1066	0.1088
3	0.1952	0.1115	0.1036
4	0.0801	0.0468	0.0495
5	0.0279	0.0172	0.0189
6	0.0169	0.0148	0.0116
7	0.0137	0.0133	0.0085
8	0.0161	0.0216	0.0116
9	0.0140	0.0247	0.0102
10	0.0094	0.0148	0.0078
Total	**0.6812**	**0.4337**	**0.3925**

Table H.47. Summary of Modal Weighted Average Emission Rates of CO (g/hp-hr) for each tier for Bulldozers

Modes (BD)	**Wgt. Average CO (Ti x EFi) for Bulldozers**		
	Tier 0	**Tier 1**	**Tier 2**
1	0.0906	0.0535	0.0531
2	0.1207	0.0636	0.0649
3	0.1294	0.0739	0.0687
4	0.0740	0.0432	0.0457
5	0.0546	0.0337	0.0370
6	0.0525	0.0460	0.0361
7	0.0471	0.0457	0.0292
8	0.0348	0.0466	0.0251
9	0.0592	0.1048	0.0431
10	0.0503	0.0791	0.0415
Total	**0.7131**	**0.5901**	**0.4445**

Table H.48. Summary of Modal Weighted Average Emission Rates of CO (g/hp-hr) for each tier for Excavators

Modes (EX)	**Wgt. Average CO (Ti x EFi) for Excavators**		
	Tier 0	**Tier 1**	**Tier 2**
1	0.1141	0.0674	0.0669
2	0.0407	0.0214	0.0219
3	0.0657	0.0375	0.0348
4	0.0677	0.0396	0.0419
5	0.0801	0.0495	0.0543
6	0.0850	0.0745	0.0584
7	0.0900	0.0872	0.0558
8	0.0742	0.0993	0.0536
9	0.0569	0.1007	0.0414
10	0.0178	0.0281	0.0147
Total	**0.6923**	**0.6052**	**0.4438**

Table H.49. Summary of Modal Weighted Average Emission Rates of CO (g/hp-hr) for each tier for Motor Graders

Modes (MG)	**Wgt. Average CO (Ti x EFi) for Motor Graders**		
	Tier 0	**Tier 1**	**Tier 2**
1	0.0879	0.0519	0.0516
2	0.0519	0.0274	0.0279
3	0.0822	0.0470	0.0436
4	0.0908	0.0530	0.0561
5	0.0782	0.0483	0.0530
6	0.0979	0.0857	0.0672
7	0.1148	0.1112	0.0712
8	0.0514	0.0687	0.0371
9	0.0398	0.0704	0.0290
10	0.0306	0.0482	0.0253
Total	**0.7254**	**0.6118**	**0.4620**

Table H.50. Summary of Modal Weighted Average Emission Rates of CO (g/hp-hr) for each tier for Off-Road Trucks

Modes (ORT)	**Wgt. Average CO (Ti x EFi) for Off-Road Truck**		
	Tier 0	**Tier 1**	**Tier 2**
1	0.2610	0.1541	0.1531
2	0.0786	0.0415	0.0423
3	0.0399	0.0228	0.0212
4	0.0234	0.0137	0.0145
5	0.0203	0.0125	0.0137
6	0.0179	0.0156	0.0123
7	0.0149	0.0145	0.0093
8	0.0146	0.0196	0.0106
9	0.0119	0.0211	0.0087
10	0.0090	0.0141	0.0074
Total	**0.4916**	**0.3295**	**0.2930**

Table H.51. Summary of Modal Weighted Average Emission Rates of CO (g/hp-hr) for each tier for Track Loaders

Modes (TL)	**Wgt. Average CO (Ti x EFi) for Track Loaders**		
	Tier 0	**Tier 1**	**Tier 2**
1	0.0981	0.0579	0.0575
2	0.0388	0.0205	0.0209
3	0.0324	0.0185	0.0172
4	0.0319	0.0186	0.0197
5	0.0627	0.0388	0.0425
6	0.1053	0.0922	0.0724
7	0.0802	0.0777	0.0497
8	0.0683	0.0913	0.0492
9	0.0825	0.1459	0.0600
10	0.1174	0.1848	0.0970
Total	**0.7175**	**0.7463**	**0.4862**

Table H.52. Summary of Modal Weighted Average Emission Rates of CO (g/hp-hr) for each tier for Wheel Loaders

Modes (WL)	Wgt. Average CO (Ti x EFi) for Wheel Loaders		
	Tier 0	**Tier 1**	**Tier 2**
1	0.1453	0.0858	0.0852
2	0.1559	0.0822	0.0839
3	0.1025	0.0585	0.0544
4	0.0668	0.0390	0.0413
5	0.0452	0.0279	0.0306
6	0.0328	0.0287	0.0225
7	0.0300	0.0290	0.0186
8	0.0263	0.0352	0.0190
9	0.0200	0.0354	0.0146
10	0.0109	0.0172	0.0090
Total	**0.6358**	**0.4391**	**0.3791**

Table H.53. Summary of Modal Weighted Average Emission Rates of CO_2 (g/hp-hr) for each tier for Backhoes

Modes (BH)	Wgt. Average CO2 (Ti x EFi) for Backhoes		
	Tier 0	**Tier 1**	**Tier 2**
1	15.9653	15.1690	20.9417
2	35.8657	27.0554	28.5967
3	46.9062	36.2526	33.3668
4	27.1440	19.8546	16.6025
5	10.8495	8.3113	6.5423
6	7.5353	5.9179	4.4737
7	6.0828	4.7657	3.4756
8	9.0785	6.8269	4.9097
9	8.9632	6.5642	4.7832
10	6.9094	5.0080	3.6509
Total	**175.2998**	**135.7255**	**127.3431**

Table H.54. Summary of Modal Weighted Average Emission Rates of CO_2 (g/hp-hr) for each tier for Bulldozers

Modes (BD)	Wgt. Average CO2 (Ti x EFi) for Bulldozers		
	Tier 0	**Tier 1**	**Tier 2**
1	13.6720	12.9901	17.9336
2	21.4086	16.1497	17.0697
3	31.0918	24.0301	22.1172
4	25.0623	18.3319	15.3293
5	21.2536	16.2813	12.8159
6	23.4352	18.4051	13.9134
7	20.8966	16.3719	11.9398
8	19.6213	14.7548	10.6113
9	37.9949	27.8257	20.2760
10	36.9556	26.7857	19.5272
Total	**251.3919**	**191.9262**	**161.5335**

Table H.55. Summary of Modal Weighted Average Emission Rates of CO_2 (g/hp-hr) for each tier for Excavators

Modes (EX)	Wgt. Average CO2 (Ti x EFi) for Excavators		
	Tier 0	**Tier 1**	**Tier 2**
1	17.2272	16.3679	22.5969
2	7.2147	5.4424	5.7525
3	15.7747	12.1918	11.2213
4	22.9532	16.7892	14.0393
5	31.2122	23.9101	18.8210
6	37.9289	29.7880	22.5184
7	39.8898	31.2524	22.7921
8	41.8294	31.4550	22.6217
9	36.5293	26.7523	19.4939
10	13.1215	9.5105	6.9333
Total	**263.6808**	**203.4596**	**166.7902**

Table H.56. Summary of Modal Weighted Average Emission Rates of CO_2 (g/hp-hr) for each tier for Motor Graders

Modes (MG)	**Wgt. Average CO2 (Ti x EFi)** for Motor Graders		
	Tier 0	**Tier 1**	**Tier 2**
1	13.2715	12.6096	17.4082
2	9.2088	6.9467	7.3424
3	19.7531	15.2667	14.0514
4	30.7595	22.4992	18.8140
5	30.4486	23.3251	18.3605
6	43.6615	34.2901	25.9218
7	50.8967	39.8760	29.0812
8	28.9438	21.7652	15.6530
9	25.5367	18.7018	13.6277
10	22.5030	16.3103	11.8905
Total	**274.9832**	**211.5907**	**172.1507**

Table H.57. Summary of Modal Weighted Average Emission Rates of CO_2 (g/hp-hr) for each tier for Off-Road Trucks

Modes (ORT)	**Wgt. Average CO2 (Ti x EFi) for Off-Road Trucks**		
	Tier 0	**Tier 1**	**Tier 2**
1	39.4031	37.4377	51.6850
2	13.9447	10.5192	11.1185
3	9.5881	7.4104	6.8205
4	7.9432	5.8101	4.8585
5	7.8906	6.0445	4.7580
6	7.9680	6.2577	4.7306
7	6.6207	5.1871	3.7829
8	8.2487	6.2029	4.4610
9	7.6666	5.6147	4.0913
10	6.5924	4.7782	3.4834
Total	**115.8662**	**95.2627**	**99.7896**

Table H.58. Summary of Modal Weighted Average Emission Rates of CO_2 (g/hp-hr) for each tier for Track Loaders

Modes (TL)	Wgt. Average CO2 (Ti x EFi) for Track Loaders		
	Tier 0	**Tier 1**	**Tier 2**
1	14.8022	14.0639	19.4160
2	6.8823	5.1917	5.4875
3	7.7779	6.0114	5.5328
4	10.8192	7.9138	6.6176
5	24.4353	18.7186	14.7345
6	46.9785	36.8952	27.8911
7	35.5449	27.8484	20.3095
8	38.4616	28.9224	20.8003
9	52.9336	38.7660	28.2481
10	86.3354	62.5765	45.6192
Total	**324.9710**	**246.9078**	**194.6566**

Table H.59. Summary of Modal Weighted Average Emission Rates of CO_2 (g/hp-hr) for each tier for Wheel Loaders

Modes (WL)	Wgt. Average CO2 (Ti x EFi) for Wheel Loaders		
	Tier 0	**Tier 1**	**Tier 2**
1	21.9290	20.8352	28.7642
2	27.6540	20.8609	22.0493
3	24.6268	19.0334	17.5183
4	22.6519	16.5689	13.8550
5	17.5947	13.4784	10.6096
6	14.6380	11.4961	8.6906
7	13.2828	10.4067	7.5895
8	14.8380	11.1579	8.0245
9	12.8529	9.4128	6.8590
10	8.0504	5.8350	4.2538
Total	**178.1183**	**139.0852**	**128.2136**

Table H.60. Summary of Modal Weighted Average Emission Rates of PM (g/hp-hr) for each tier for Backhoes

Modes (BH)	Wgt. Average PM (Ti x EFi) for Backhoes		
	Tier 0	**Tier 1**	**Tier 2**
1	0.0016	0.0014	0.0014
2	0.0032	0.0028	0.0020
3	0.0045	0.0036	0.0025
4	0.0026	0.0019	0.0012
5	0.0011	0.0008	0.0005
6	0.0007	0.0006	0.0003
7	0.0006	0.0005	0.0003
8	0.0009	0.0008	0.0004
9	0.0009	0.0007	0.0004
10	0.0006	0.0006	0.0003
Total	**0.0167**	**0.0137**	**0.0092**

Table H.61. Summary of Modal Weighted Average Emission Rates of PM (g/hp-hr) for each tier for Bulldozers

Modes (BD)	Wgt. Average PM (Ti x EFi) for Bulldozers		
	Tier 0	**Tier 1**	**Tier 2**
1	0.0014	0.0012	0.0012
2	0.0019	0.0016	0.0012
3	0.0030	0.0024	0.0016
4	0.0024	0.0018	0.0011
5	0.0021	0.0016	0.0009
6	0.0023	0.0019	0.0010
7	0.0020	0.0017	0.0009
8	0.0019	0.0017	0.0008
9	0.0037	0.0031	0.0016
10	0.0034	0.0030	0.0017
Total	**0.0241**	**0.0201**	**0.0120**

Table H.62. Summary of Modal Weighted Average Emission Rates of PM (g/hp-hr) for each tier for Excavators

Modes (EX)	**Wgt. Average PM (Ti x EFi) for Excavators**		
	Tier 0	**Tier 1**	**Tier 2**
1	0.0018	0.0015	0.0015
2	0.0007	0.0006	0.0004
3	0.0015	0.0012	0.0008
4	0.0022	0.0016	0.0010
5	0.0030	0.0024	0.0014
6	0.0037	0.0031	0.0016
7	0.0039	0.0033	0.0017
8	0.0041	0.0036	0.0017
9	0.0035	0.0030	0.0015
10	0.0012	0.0011	0.0006
Total	**0.0256**	**0.0214**	**0.0122**

Table H.63. Summary of Modal Weighted Average Emission Rates of PM (g/hp-hr) for each tier for Motor Graders

Modes (MG)	**Wgt. Average PM (Ti x EFi) for Motor Graders**		
	Tier 0	**Tier 1**	**Tier 2**
1	0.0013	0.0012	0.0012
2	0.0008	0.0007	0.0005
3	0.0019	0.0015	0.0010
4	0.0029	0.0022	0.0014
5	0.0030	0.0023	0.0013
6	0.0043	0.0036	0.0019
7	0.0050	0.0042	0.0021
8	0.0028	0.0025	0.0012
9	0.0025	0.0021	0.0011
10	0.0021	0.0019	0.0010
Total	**0.0266**	**0.0221**	**0.0127**

Table H.64. Summary of Modal Weighted Average Emission Rates of PM (g/hp-hr) for each tier for Off-Road Trucks

Modes (ORT)	Wgt. Average PM (Ti x EFi) for Off-Road Trucks		
	Tier 0	**Tier 1**	**Tier 2**
1	0.0040	0.0035	0.0034
2	0.0013	0.0011	0.0008
3	0.0009	0.0007	0.0005
4	0.0008	0.0006	0.0004
5	0.0008	0.0006	0.0003
6	0.0008	0.0007	0.0003
7	0.0006	0.0006	0.0003
8	0.0008	0.0007	0.0003
9	0.0007	0.0006	0.0003
10	0.0006	0.0005	0.0003
Total	**0.0113**	**0.0095**	**0.0070**

Table H.65. Summary of Modal Weighted Average Emission Rates of PM (g/hp-hr) for each tier for Track Loaders

Modes **(TL)**	Wgt. Average PM (Ti x EFi) for Track Loaders		
	Tier 0	**Tier 1**	**Tier 2**
1	0.0015	0.0013	0.0013
2	0.0006	0.0005	0.0004
3	0.0008	0.0006	0.0004
4	0.0010	0.0008	0.0005
5	0.0024	0.0019	0.0011
6	0.0046	0.0039	0.0020
7	0.0035	0.0030	0.0015
8	0.0037	0.0033	0.0015
9	0.0051	0.0043	0.0022
10	0.0079	0.0071	0.0040
Total	**0.0311**	**0.0266**	**0.0149**

Table H.66. Summary of Modal Weighted Average Emission Rates of PM (g/hp-hr) for each tier for Wheel Loaders

Modes (WL)	Wgt. Average PM (Ti x EFi) for Wheel Loaders		
	Tier 0	**Tier 1**	**Tier 2**
1	0.0022	0.0019	0.0019
2	0.0025	0.0021	0.0016
3	0.0024	0.0019	0.0013
4	0.0022	0.0016	0.0010
5	0.0017	0.0014	0.0008
6	0.0014	0.0012	0.0006
7	0.0013	0.0011	0.0006
8	0.0014	0.0013	0.0006
9	0.0012	0.0010	0.0005
10	0.0007	0.0007	0.0004
Total	**0.0171**	**0.0142**	**0.0092**

Table H.67. Summary of Modal Weighted Average Fuel Use Rates (g/hp-hr) for each tier for All Type of Equipment

Equipment	**Total Wgt. Average Fuel Use (Ti x EFi)**		
	Tier 0	**Tier 1**	**Tier 2**
BH	0.0167	0.0129	0.0121
BD	0.0238	0.0182	0.0153
EX	0.0250	0.0193	0.0158
MG	0.0260	0.0201	0.0163
OT	0.0110	0.0091	0.0095
TL	0.0307	0.0234	0.0184
WL	0.0169	0.0132	0.0122

Table H.68. Summary of Modal Weighted Average Emission Rates of NO_x (g/hp-hr) for each tier for All Type of Equipment

Equipment	Total Wgt. Average NOx (Ti x EFi)		
	Tier 0	**Tier 1**	**Tier 2**
BH	2.9238	1.6548	1.2353
BD	4.0997	2.1964	1.4743
EX	4.1799	2.2885	1.5003
MG	4.3384	2.3760	1.5415
OT	1.9944	1.1942	1.0153
TL	5.2489	2.7128	1.7059
WL	2.9374	1.6633	1.2312

Table H.69. Summary of Modal Weighted Average Emission Rates of HC (g/hp-hr) for each tier for All Type of Equipment

Equipment	Total Wgt. Average HC (Ti x EFi)		
	Tier 0	**Tier 1**	**Tier 2**
BH	0.2529	0.1665	0.1488
BD	0.3023	0.2022	0.1635
EX	0.3117	0.2100	0.1619
MG	0.3226	0.2163	0.1675
OT	0.1816	0.1303	0.1206
TL	0.3417	0.2345	0.1747
WL	0.2465	0.1657	0.1437

Table H.70. Summary of Modal Weighted Average Emission Rates of CO (g/hp-hr) for each tier for All Type of Equipment

Equipment	Total Wgt. Average CO (Ti x EFi)		
	Tier 0	Tier 1	Tier 2
BH	0.6812	0.4337	0.3925
BD	0.7131	0.5901	0.4445
EX	0.6923	0.6052	0.4438
MG	0.7254	0.6118	0.4620
OT	0.4916	0.3295	0.2930
TL	0.7175	0.7463	0.4862
WL	0.6358	0.4391	0.3791

Table H.71. Summary of Modal Weighted Average Emission Rates of CO_2 (g/hp-hr) for each tier for All Type of Equipment

Equipment	Total Wgt. Average CO2(Ti x EFi)		
	Tier 0	Tier 1	Tier 2
BH	175.2998	135.7255	127.3431
BD	251.3919	191.9262	161.5335
EX	263.6808	203.4596	166.7902
MG	274.9832	211.5907	172.1507
OT	115.8662	95.2627	99.7896
TL	324.9710	246.9078	194.6566
WL	178.1183	139.0852	128.2136

Table H.72. Summary of Modal Weighted Average Emission Rates of PM (g/hp-hr) for each tier for All Type of Equipment

Equipment	**Total Wgt. Average PM (Ti x EFi)**		
	Tier 0	**Tier 1**	**Tier 2**
BH	0.0167	0.0137	0.0092
BD	0.0241	0.0201	0.0120
EX	0.0256	0.0214	0.0122
MG	0.0266	0.0221	0.0127
OT	0.0113	0.0095	0.0070
TL	0.0311	0.0266	0.0149
WL	0.0171	0.0142	0.0092

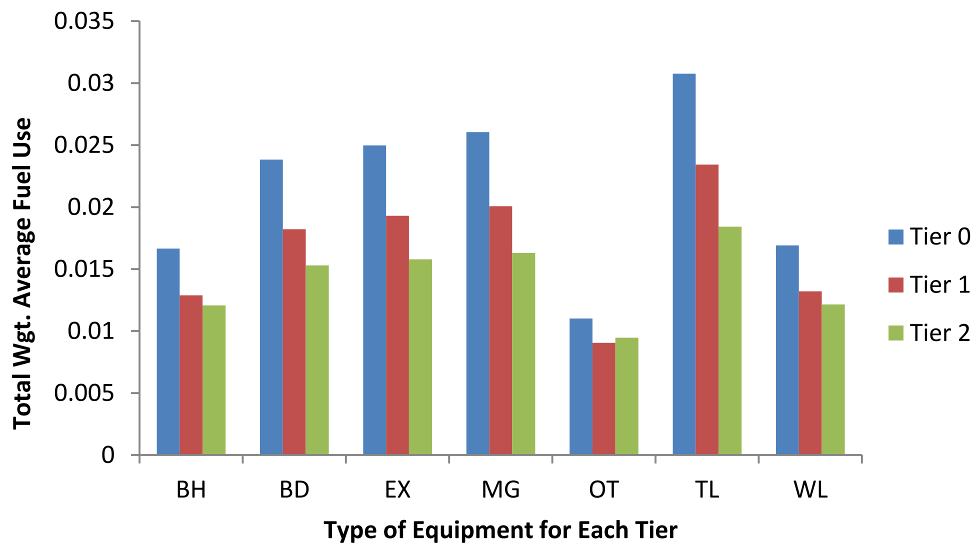

Figure H.1. Total Weighted Average of Fuel Use Rates based on Equipment Type and Tier Type

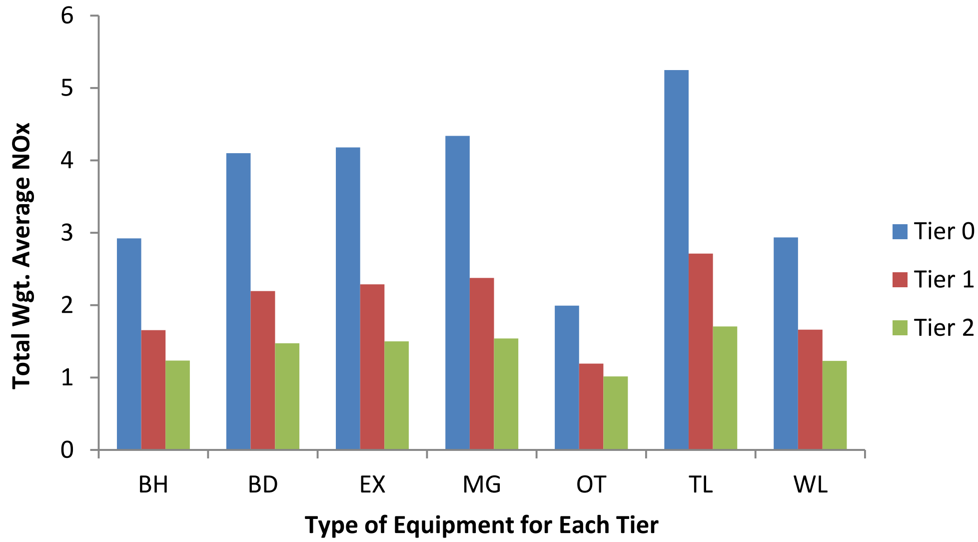

Figure H.2. Total Weighted Average of Emission Rates of NO_x based on Equipment Type and Tier Type

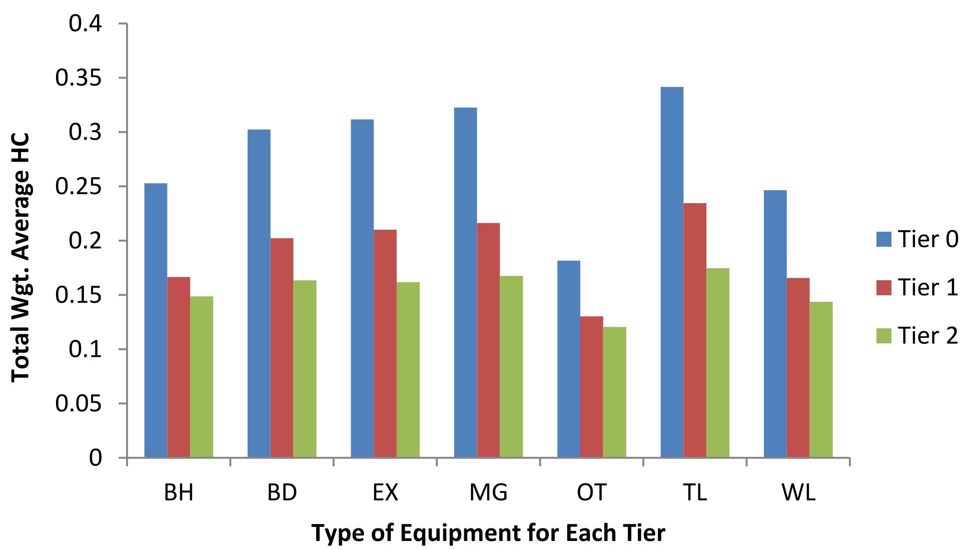

Figure H.3. Total Weighted Average of Emission Rates of HC based on Equipment Type and Tier Type

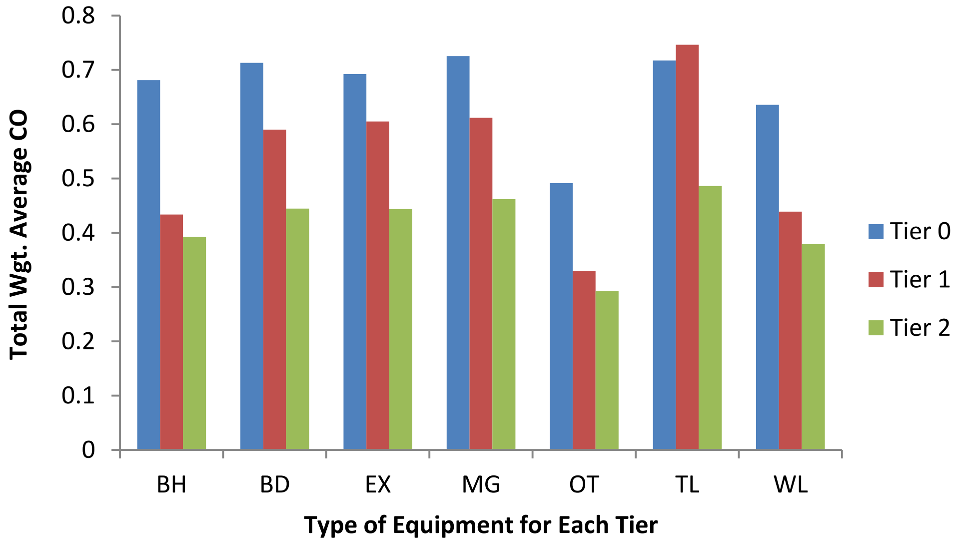

Figure H.4. Total Weighted Average of Emission Rates of CO based on Equipment Type and Tier Type

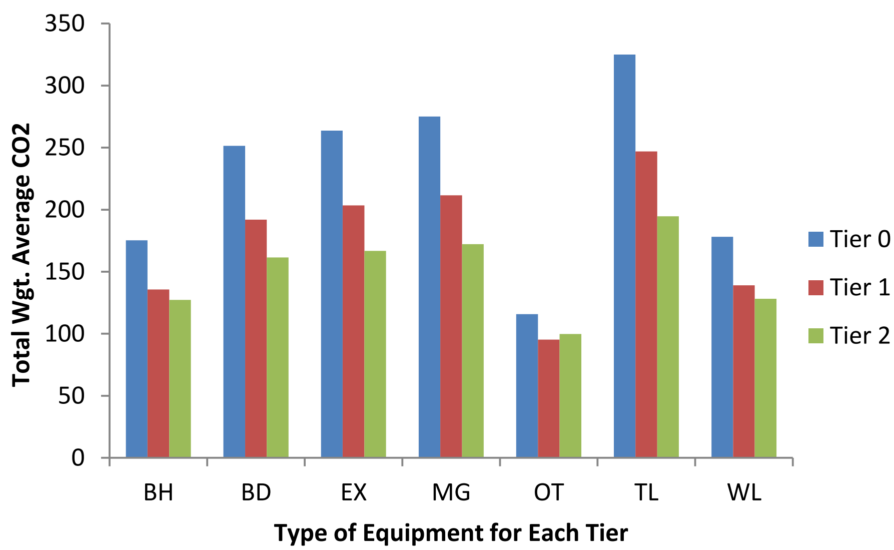

Figure H.5. Total Weighted Average of Emission Rates of CO_2 based on Equipment Type and Tier Type

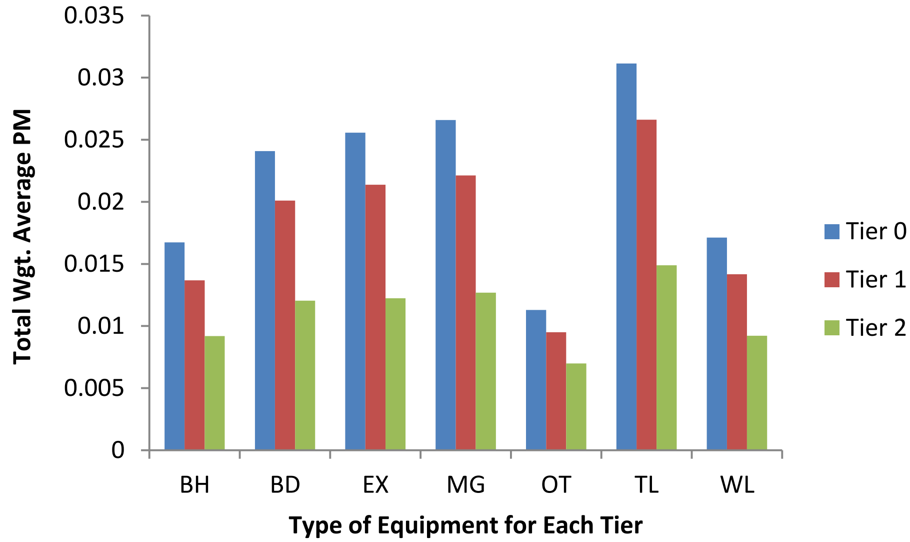

Figure H.6. Total Weighted Average of Emission Rates of PM based on Equipment Type and Tier Type

Appendix I

Average Engine Mode Distributions

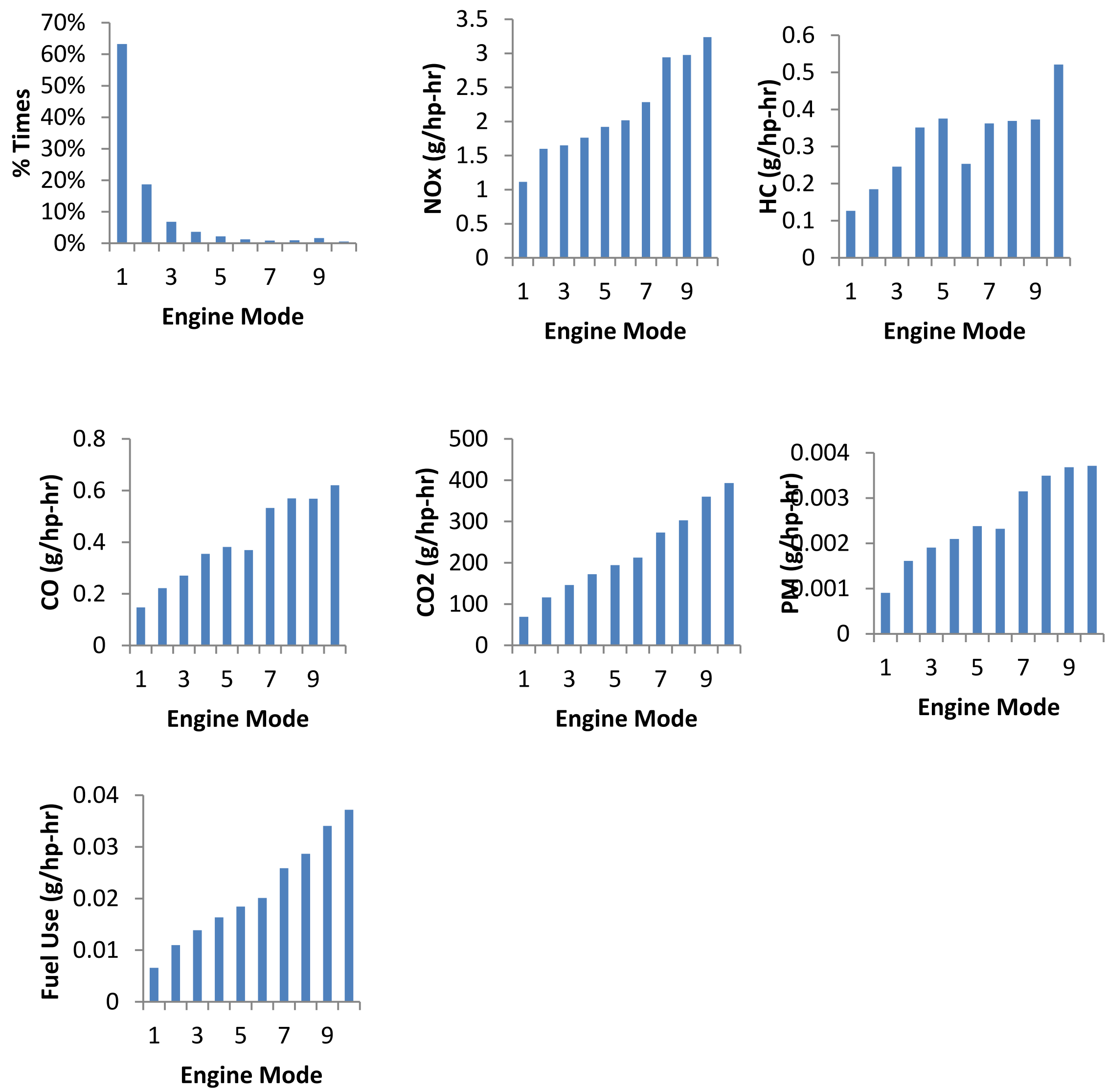

Figure I.1. Average Engine Mode Distribution of Fuel Use and Emission Rates for Backhoe 1

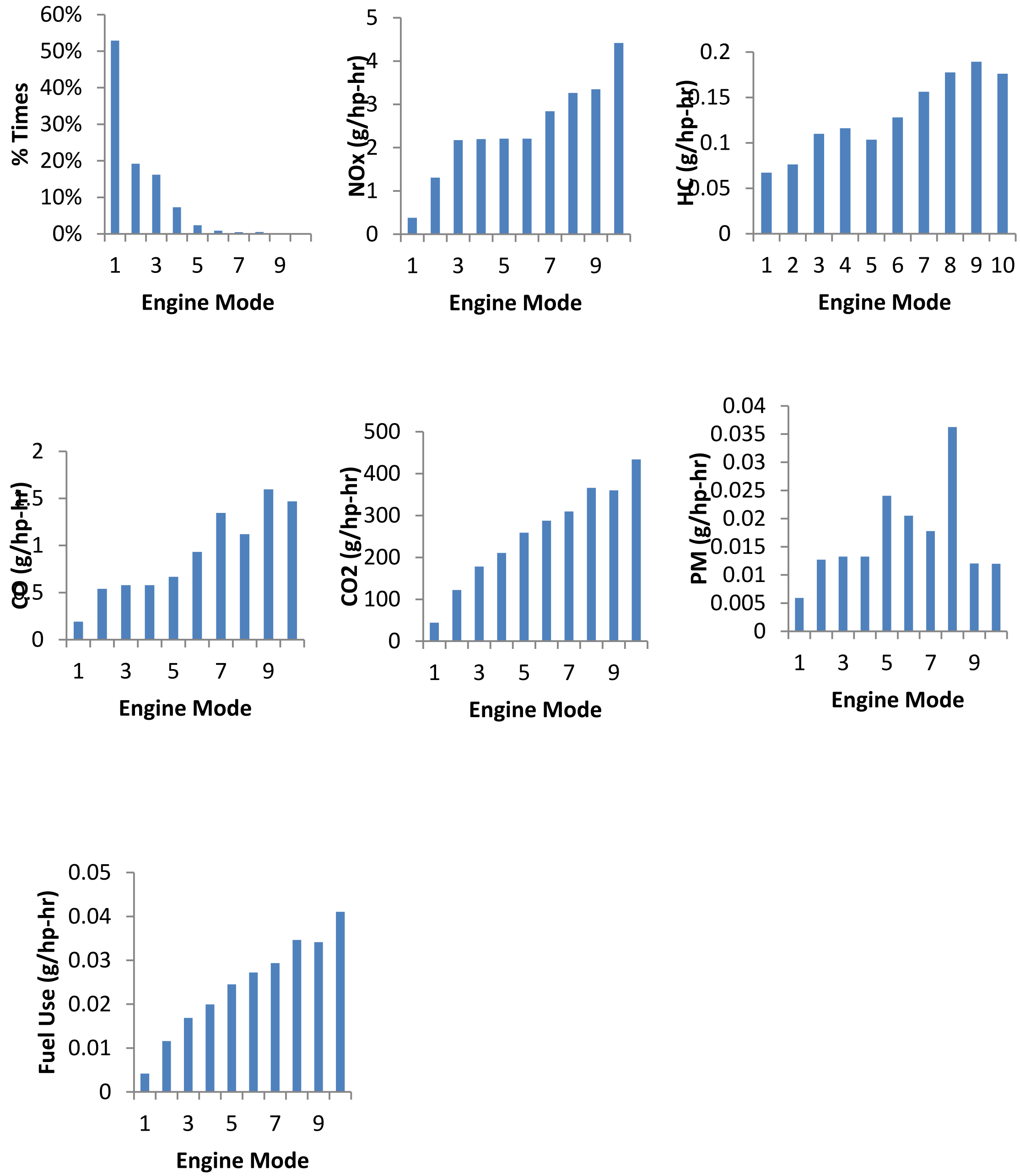

Figure I.2. Average Engine Mode Distribution of Fuel Use and Emission Rates for Backhoe 2

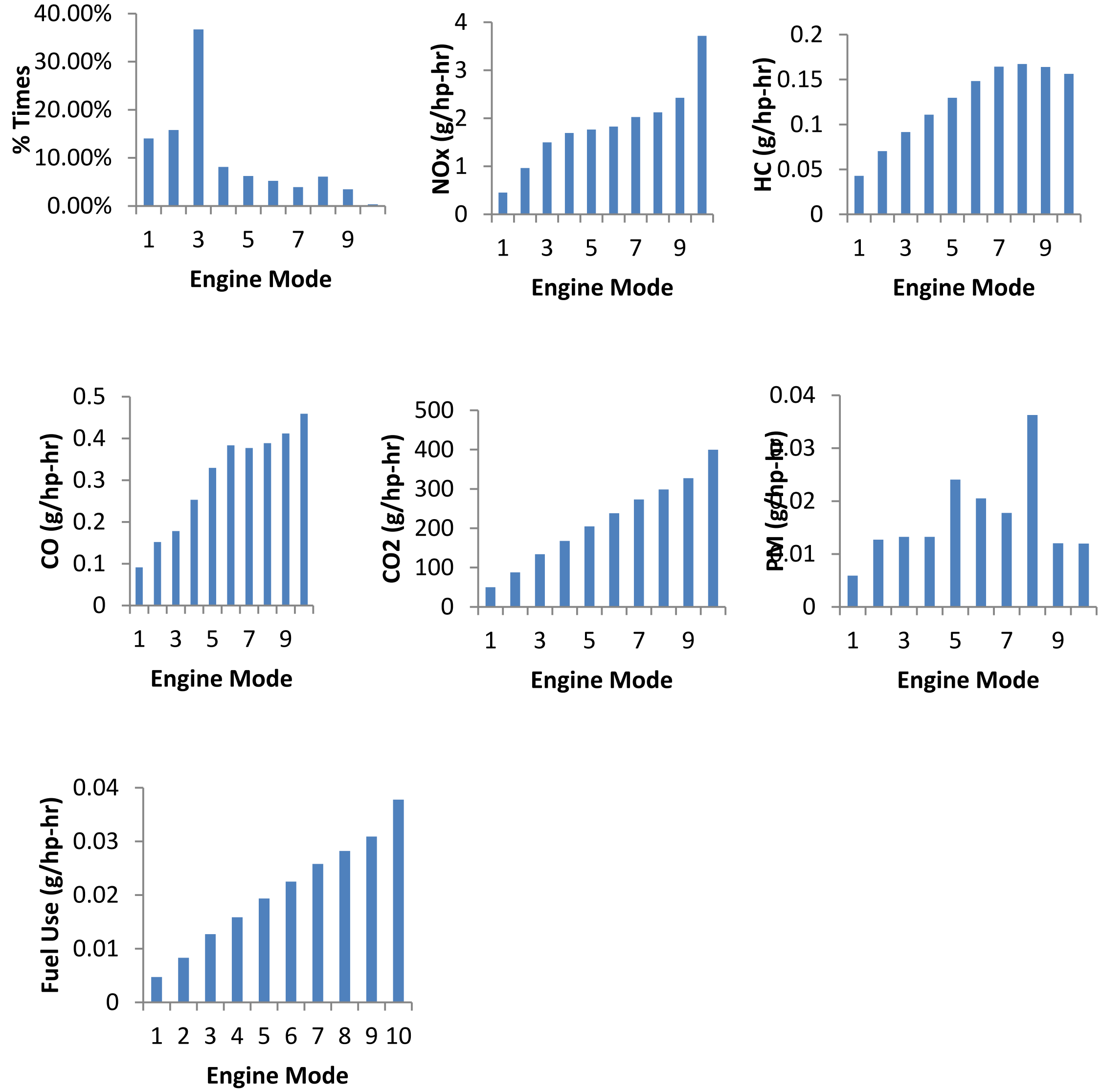

Figure I.3. Average Engine Mode Distribution of Fuel Use and Emission Rates for Backhoe 3

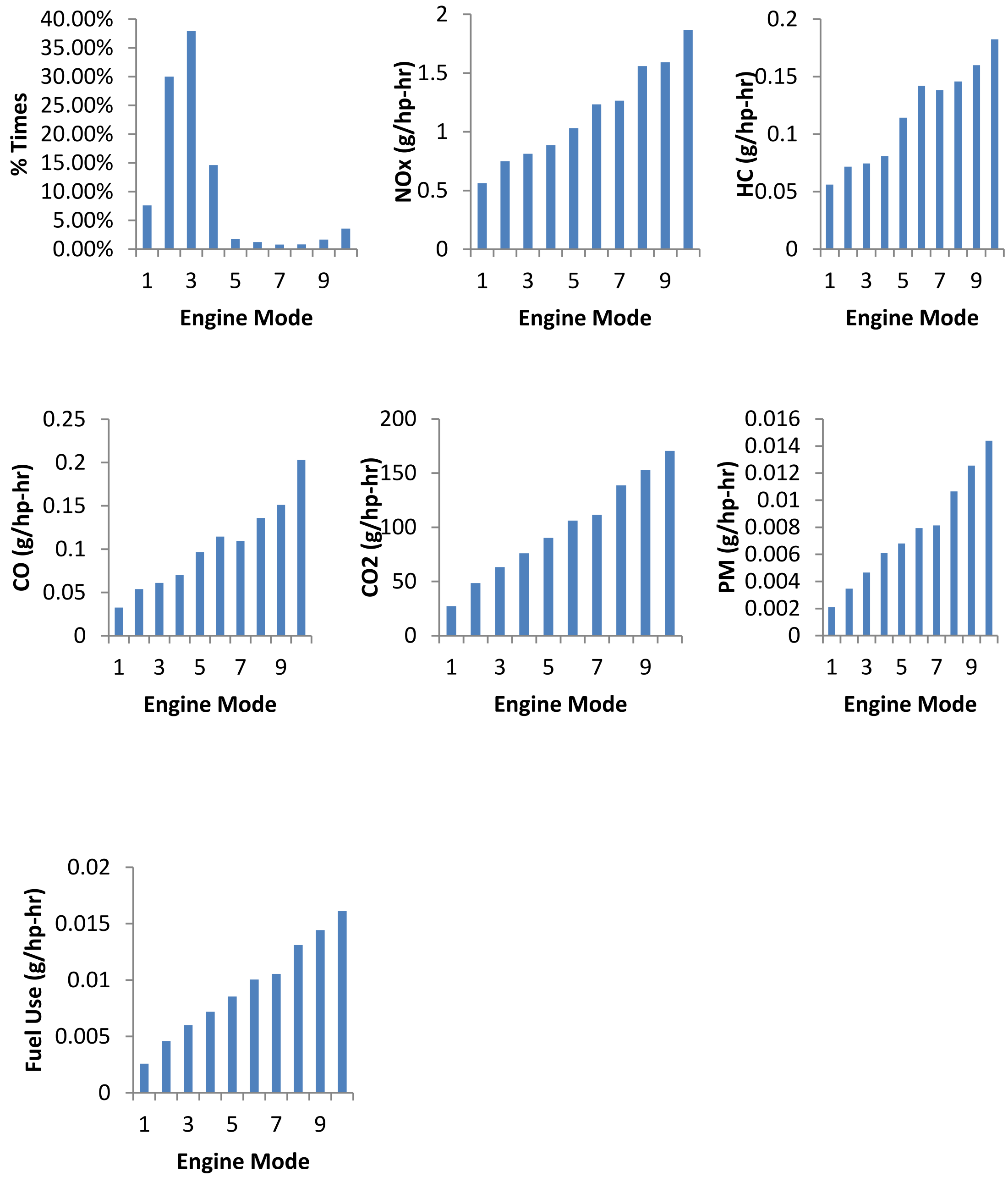

Figure I.4. Average Engine Mode Distribution of Fuel Use and Emission Rates for Backhoe 4

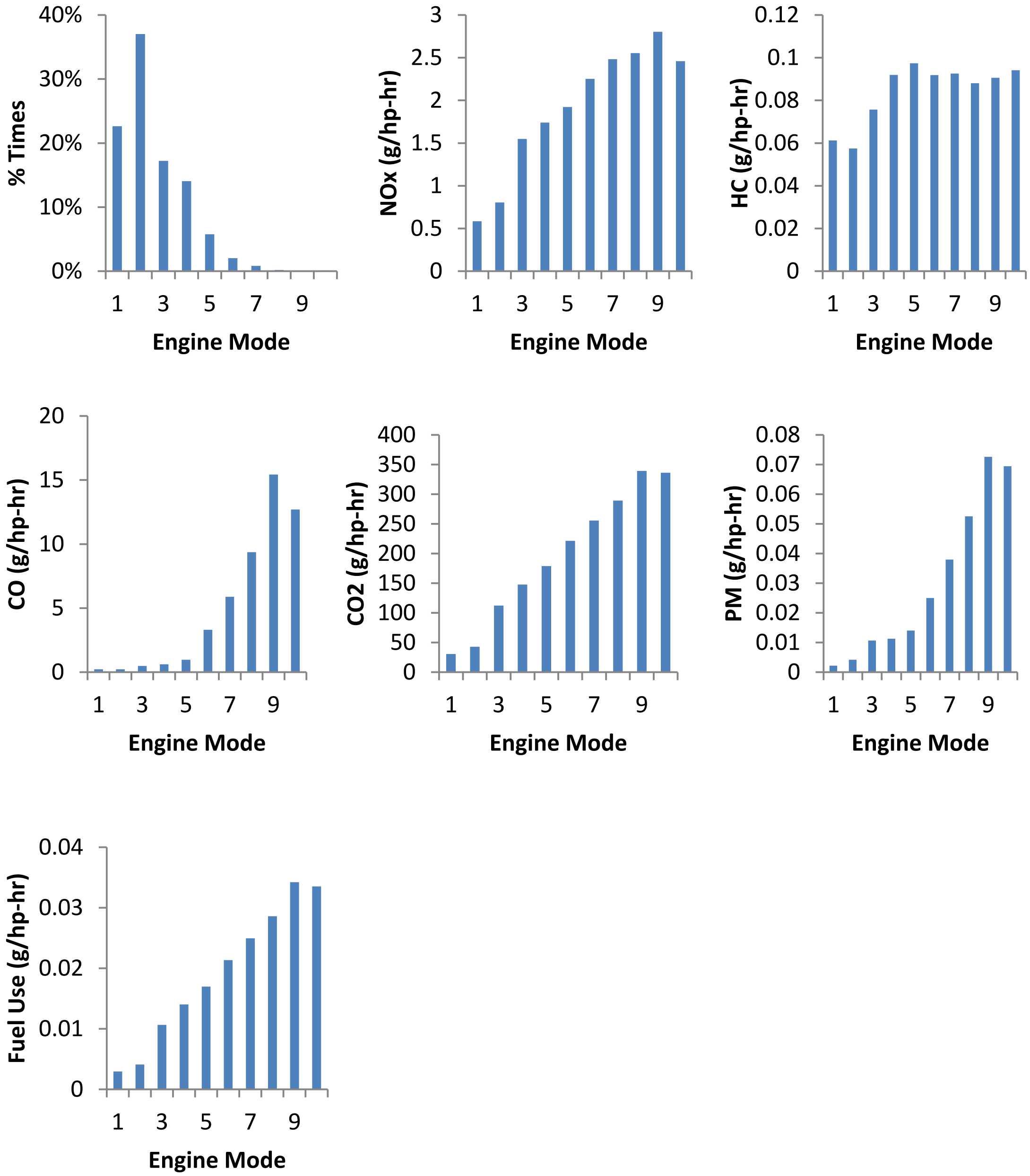

Figure I.5. Average Engine Mode Distribution of Fuel Use and Emission Rates for Backhoe 5

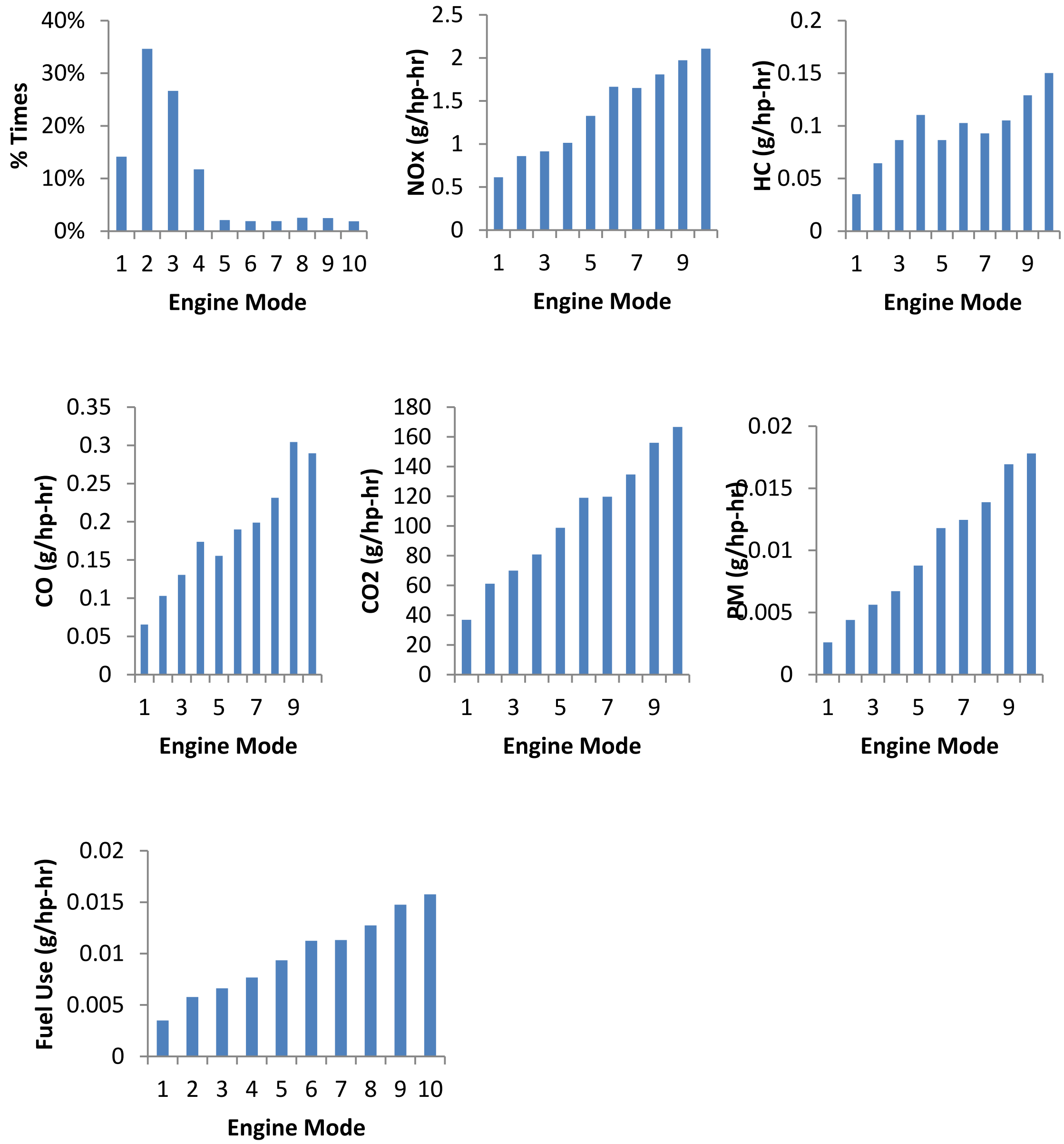

Figure I.6. Average Engine Mode Distribution of Fuel Use and Emission Rates for Backhoe 6

Appendix J

Summary of Training and Validation Data using ANN

Table J.1. Summary of Training Data using ANN for Backhoes

Equipment	Response	m	b	R^2
Backhoe 1	Fuel Use	0.9803	0.0056	0.9853
	NOx	0.984	0.0002	0.9866
	HC	0.7451	0.001	0.7687
	CO	0.9021	0.0007	0.9014
	CO2	0.9681	0.0309	0.9754
	PM	0.4215	0.00126	0.4277
Backhoe 2	Fuel Use	0.9561	0.0326	0.9582
	NOx	0.9379	0.0018	0.9349
	HC	0.6910	0.0008	0.7402
	CO	0.4207	0.0053	0.4857
	CO2	0.9564	0.1051	0.958
	PM	0.9197	0.0212	0.9323
Backhoe 3	Fuel Use	0.9833	0.0119	0.9873
	NOx	0.9585	0.0007	0.9715
	HC	0.8916	0.0002	0.9029
	CO	0.6963	0.0012	0.7356
	CO2	0.9869	0.0294	0.9897
	PM	0.9770	0.0077	0.9777
Backhoe 4	Fuel Use	0.9613	0.0153	0.9654
	NOx	0.9151	0.0014	0.9265
	HC	0.8949	0.0002	0.9071
	CO	0.8086	0.0002	0.8363
	CO2	0.9589	0.0476	0.9677
	PM	0.9537	0.004	0.9669
Backhoe 5	Fuel Use	0.9468	0.0357	0.9605
	NOx	0.0071	0.0330	0.3249
	HC	1.0000	0.0000	1.0000
	CO	0.3315	0.0098	0.3315
	CO2	0.8557	0.279	0.8757
	PM	0.7268	0.0529	0.7765
Backhoe 6	Fuel Use	0.9714	0.0117	0.9743
	NOx	0.9567	0.0007	0.9667
	HC	0.891	0.0002	0.8969
	CO	0.8476	0.0004	0.868
	CO2	0.9619	0.0487	0.9654
	PM	0.9528	0.0043	0.9685

Table J.2. Summary of Validation Data using ANN for Backhoes

Equipment	**Response**	**m**	**b**	**R^2**
Backhoe 1	Fuel Use	0.9478	0.0207	0.927
	NO_x	0.8884	0.0017	0.8433
	HC	0.6359	0.0014	0.6472
	CO	0.8562	0.001	0.8485
	CO_2	0.9508	0.0486	0.9200
	PM	0.2387	0.0163	0.2365
Backhoe 2	Fuel Use	0.9448	0.0388	0.9317
	NO_x	0.9174	0.0024	0.8986
	HC	0.6087	0.001	0.5932
	CO	0.2820	0.0066	0.2457
	CO_2	0.9497	0.1377	0.9331
	PM	0.9263	0.0455	0.773
Backhoe 3	Fuel Use	0.9719	0.0196	0.9809
	NO_x	0.9403	0.0011	0.9444
	HC	0.8626	0.0002	0.8222
	CO	0.4243	0.0023	0.4221
	CO_2	0.9845	0.0328	0.9804
	PM	0.9591	0.0126	0.9233
Backhoe 4	Fuel Use	0.9477	0.019	0.9556
	NO_x	0.9071	0.0015	0.9043
	HC	0.8604	0.0002	0.8727
	CO	0.7258	0.0004	0.6659
	CO_2	0.9401	0.0669	0.9563
	PM	0.9309	0.0065	0.9394
Backhoe 5	Fuel Use	0.9322	0.0461	0.9312
	NO_x	0.6517	0.0127	0.3066
	HC	0.8434	0.0003	0.8207
	CO	0.0048	0.0144	0.0177
	CO_2	0.0012	2.1934	0.0068
	PM	0.6913	0.0619	0.6552
Backhoe 6	Fuel Use	0.9407	0.0242	0.9236
	NO_x	0.9351	0.0012	0.9238
	HC	0.8512	0.0003	0.8251
	CO	0.8108	0.0006	0.7690
	CO_2	0.9522	0.0617	0.9147
	PM	0.9128	0.0083	0.9143

Table J.3. Summary of Training Data using ANN for Bulldozers

Equipment	Response	m	b	R^2
Bulldozer 1	Fuel Use	0.9624	0.0543	0.9705
	NO_x	0.9353	0.0044	0.943
	HC	0.7132	0.0013	0.756
	CO	0.6376	0.0061	0.7153
	CO_2	0.9627	0.1778	0.9692
	PM	0.8598	0.0834	0.8818
Bulldozer 2	Fuel Use	0.9729	0.0202	0.9763
	NO_x	0.8406	0.0041	0.8406
	HC	0	0	0.4772
	CO	0.0026	0.0074	0.0026
	CO_2	1.0000	-0.0038	1.0000
	PM	0.887	0.00188	0.9048
Bulldozer 3	Fuel Use	0.9756	0.0281	0.9827
	NO_x	0.9113	0.005	0.9220
	HC	0.693	0.0015	0.7129
	CO	0.6037	0.0102	0.6356
	CO_2	0.9769	0.0842	0.9836
	PM	0.6883	0.1897	0.733
Bulldozer 4	Fuel Use	0.9903	0.0311	0.9906
	NO_x	0.9578	0.0074	0.9588
	HC	0.8654	0.0015	0.8739
	CO	0.6879	0.0104	0.745
	CO_2	0.9918	0.0871	0.9917
	PM	0.8643	0.1058	0.8798
Bulldozer 5	Fuel Use	0.922	0.0803	0.9908
	NO_x	0.97	0.0183	0.9692
	HC	0.5287	0.0043	0.5436
	CO	0.4594	0.0356	0.5246
	CO_2	0.9916	0.2984	0.9901
	PM	0	0	0
Bulldozer 6	Fuel Use	0.9875	0.0129	0.9895
	NO_x	0.969	0.0009	0.9736
	HC	0.7699	0.0015	0.7894
	CO	0.9469	0.0006	0.95
	CO_2	0.9817	0.0575	0.9855
	PM	0.7823	0.0563	0.8109

Table J.4. Summary of Validation Data using ANN for Bulldozers

Equipment	Response	m	b	R^2
Bulldozer 1	Fuel Use	0.9531	0.0704	0.9574
	NO_x	0.9327	0.0051	0.923
	HC	0.6450	0.0015	0.6755
	CO	0.4643	0.0090	0.4185
	CO_2	0.9548	0.2334	0.9541
	PM	0.8115	0.116	0.8075
Bulldozer 2	Fuel Use	0.9628	0.0293	0.9594
	NO_x	0.002	0.0254	0.0036
	HC	0.0013	0.004	0.0026
	CO	0.0002	0.0074	0.0011
	CO_2	0.9645	0.0753	0.9666
	PM	0.8729	0.0224	0.8734
Bulldozer 3	Fuel Use	0.9663	0.0368	0.9773
	NO_x	0.9118	0.0057	0.9019
	HC	0.6769	0.0016	0.6809
	CO	0.4629	0.0139	0.3715
	CO_2	0.9763	0.1010	0.9766
	PM	0.6510	0.2099	0.6341
Bulldozer 4	Fuel Use	0.9915	0.0326	0.9895
	NO_x	0.9552	0.0077	0.9466
	HC	0.8632	0.0016	0.8533
	CO	0.5504	0.0156	0.5550
	CO_2	0.9904	0.106	0.9889
	PM	0.8647	0.1116	0.8554
Bulldozer 5	Fuel Use	0.9915	0.1087	0.9886
	NO_x	0.9700	0.0203	0.9617
	HC	0.4821	0.0047	0.4889
	CO	0.3441	0.0427	0.3573
	CO_2	0.9921	0.3038	0.9889
	PM	0	0	0
Bulldozer 6	Fuel Use	0.9652	0.0352	0.9576
	NO_x	0.9305	0.0021	0.9145
	HC	0.6592	0.0023	0.5735
	CO	0.6332	0.0045	0.5611
	CO_2	0.9675	0.1035	0.9585
	PM	0.6191	0.0959	0.5691

Table J.5. Summary of Training Data using ANN for Motor Graders

Equipment	Response	m	b	R^2
Motor Grader 1	Fuel Use	0.8640	0.6566	0.8749
	NO_x	0.7766	0.0402	0.8013
	HC	0.7808	0.0032	0.8096
	CO	0.3663	0.0116	0.4075
	CO_2	0.8661	2.0565	0.8739
	PM	0.9243	0.1026	0.9298
Motor Grader 2	Fuel Use	0.9801	0.0284	0.9797
	NO_x	0.8776	0.0064	0.8900
	HC	0.5921	0.0057	0.6297
	CO	0.5816	0.0049	0.6462
	CO_2	0.9832	0.0713	0.983
	PM	0.8104	0.0487	0.8294
Motor Grader 3	Fuel Use	0.9579	0.0938	0.9645
	NO_x	0.9305	0.0051	0.9432
	HC	0.8152	0.0077	0.8326
	CO	0.0502	-0.0073	0.0785
	CO_2	0.9438	0.3766	0.9559
	PM	0.9624	0.0269	0.9694
Motor Grader 4	Fuel Use	0.9331	0.1743	0.9366
	NO_x	0.8736	0.0212	0.8816
	HC	0.5477	0.0119	0.5926
	CO	0.4739	0.0202	0.5178
	CO_2	0.9242	0.6080	0.9278
	PM	0.7696	0.1408	0.7889
Motor Grader 5	Fuel Use	0.9848	0.0332	0.9857
	NO_x	0.9404	0.0068	0.9469
	HC	0.7162	0.0021	0.7350
	CO	0.2729	0.0267	0.3377
	CO_2	0.9846	0.1075	0.9851
	PM	0.8821	0.0576	0.8909
Motor Grader 6	Fuel Use	0.9531	0.0967	0.9582
	NO_x	0.6336	0.0162	0.67
	HC	0.848	0.0009	0.8567
	CO	0.3324	0.0029	0.4691
	CO_2	0.9510	0.3052	0.9599
	PM	0.9572	0.0211	0.9617

Table J.6. Summary of Validation Data using ANN for Motor Graders

Equipment	Response	m	b	R^2
Motor Grader 1	Fuel Use	0.8382	0.7655	0.8412
	NO_x	0.7312	0.0487	0.7112
	HC	0.7244	0.0041	0.6949
	CO	0.3542	0.012	0.3609
	CO_2	0.8408	2.4194	0.834
	PM	0.9024	0.1269	0.8962
Motor Grader 2	Fuel Use	0.9839	0.0307	0.9737
	NO_x	0.8531	0.0073	0.8516
	HC	0.5664	0.0061	0.5167
	CO	0.4247	0.0065	0.449
	CO_2	0.9675	0.1142	0.9731
	PM	0.7059	0.0718	0.7343
Motor Grader 3	Fuel Use	0.9393	0.1306	0.9428
	NO_x	0.8517	0.0102	0.8491
	HC	0.7973	0.0086	0.8007
	CO	0.0296	-0.0075	0.0275
	CO_2	0.9474	0.3752	0.9459
	PM	0.9409	0.0448	0.9436
Motor Grader 4	Fuel Use	0.9316	0.1898	0.9174
	NO_x	0.8608	0.0237	0.824
	HC	0.4468	0.0145	0.4086
	CO	0.3884	0.0233	0.3856
	CO_2	0.9121	0.6981	0.9225
	PM	0.7562	0.1482	0.7663
Motor Grader 5	Fuel Use	0.9773	0.0545	0.9793
	NO_x	0.9177	0.0095	0.9177
	HC	0.7005	0.0022	0.6809
	CO	0.2507	0.0276	0.2834
	CO_2	0.9893	0.0966	0.9794
	PM	0.835	0.0793	0.8387
Motor Grader 6	Fuel Use	0.9503	0.1079	0.9444
	NO_x	0.5415	0.0202	0.5359
	HC	0.8155	0.0012	0.7573
	CO	0.2280	0.0034	0.2311
	CO_2	0.9341	0.4383	0.9461
	Fuel Use	0.9543	0.0250	0.9406

Table J.7. Summary of Training Data using ANN for Excavators

Equipment	**Response**	**m**	**b**	**R^2**
Excavator 1	Fuel Use	0.9878	0.0313	0.9896
	NO_x	0.9760	0.0021	0.9819
	HC	0.8321	0.0006	0.8624
	CO	0.9133	0.0009	0.9278
	CO_2	0.9874	0.0953	0.9894
	PM	0.9020	0.0833	0.914
Excavator 2	Fuel Use	0.9744	0.0526	0.9774
	NO_x	0.8793	0.006	0.8825
	HC	0.5262	0.0024	0.5311
	CO	0.5894	0.0079	0.6215
	CO_2	0.9735	0.1641	0.9764
	PM	0.9567	0.0172	0.9658
Excavator 3	Fuel Use	0.9623	0.0622	0.969
	NO_x	0.9244	0.0044	0.9335
	HC	0.7198	0.0016	0.7581
	CO	0.4952	0.0037	0.5768
	CO_2	0.9608	0.2057	0.9676
	PM	0.8325	0.0686	0.8666

Table J.8. Summary of Validation Data using ANN for Excavators

Equipment	**Response**	**m**	**b**	**R^2**
Excavator 1	Fuel Use	0.9836	0.0386	0.9856
	NO_x	0.9749	0.0030	0.9624
	HC	0.7685	0.0008	0.7402
	CO	0.9121	0.0010	0.8836
	CO_2	0.9913	0.1119	0.9852
	PM	0.8887	0.1080	0.8786
Excavator 2	Fuel Use	0.9701	0.0579	0.9746
	NO_x	0.9012	0.0049	0.899
	HC	0.4589	0.0027	0.4595
	CO	0.5504	0.0086	0.5699
	CO_2	0.9689	0.1665	0.9747
	PM	0.9400	0.0204	0.953
Excavator 3	Fuel Use	0.9545	0.0763	0.9584
	NO_x	0.9128	0.0052	0.9144
	HC	0.6549	0.0019	0.6535
	CO	0.2707	0.0054	0.2683
	CO_2	0.9547	0.237	0.9593
	PM	0.7695	0.0896	0.7911

Table J.9. Summary of TrainingData using ANN for Track Loaders

Equipment	Response	m	b	R^2
Track Loader 1	Fuel Use	0.9714	0.0751	0.9746
	NO_x	0.8762	0.0057	0.8982
	HC	0.6332	0.0028	0.6674
	CO	0.8928	0.0020	0.9032
	CO_2	0.9696	0.2465	0.9737
	PM	0.9637	0.0224	0.9685
Track Loader 2	Fuel Use	0.8518	0.3822	0.8599
	NO_x	0.8674	0.0189	0.8760
	HC	0.6903	0.0019	0.7090
	CO	0.6971	0.0032	0.7087
	CO_2	0.8663	1.1046	0.8743
	PM	0.9584	0.0241	0.9683
Track Loader 3	Fuel Use	0.9787	0.0663	0.9807
	NO_x	0.9379	0.0039	0.9417
	HC	0.6397	0.0007	0.6626
	CO	0.9204	0.0013	0.9325
	CO_2	0.9770	0.2449	0.9792
	PM	0.9602	0.0229	0.9694

Table J.10. Summary of Validation Data using ANN for Track Loaders

Equipment	Response	m	b	R^2
Track Loader 1	Fuel Use	0.9612	0.0950	0.9624
	NO_x	0.8498	0.0067	0.8602
	HC	0.5825	0.0033	0.5757
	CO	0.8392	0.0028	0.8361
	CO_2	0.9658	0.2705	0.9670
	PM	0.8881	0.0636	0.8863
Track Loader 2	Fuel Use	0.8100	0.4845	0.8063
	NO_x	0.8187	0.0242	0.8233
	HC	0.5875	0.0024	0.5881
	CO	0.6498	0.0037	0.6016
	CO_2	0.8473	1.3388	0.8096
	PM	0.9383	0.0334	0.9074
Track Loader 3	Fuel Use	0.967	0.0809	0.9716
	NO_x	0.9410	0.0044	0.9177
	HC	0.6152	0.0008	0.6022
	CO	0.8339	0.0027	0.7875
	CO_2	0.9749	0.3069	0.9734
	PM	0.9255	0.0408	0.9292

Table J.11. Summary of TrainingData using ANN for Off-Road Trucks

Equipment	Response	m	b	R^2
Off-Road Truck 1	Fuel Use	0.9004	0.1975	0.9195
	NO_x	0.8568	0.0121	0.8822
	HC	0.7768	0.0013	0.7952
	CO	0.3944	0.0197	0.4239
	CO_2	0.8939	0.6867	0.9064
	PM	0.9071	0.0535	0.9208
Off-Road Truck 2	Fuel Use	0.9756	0.0346	0.9819
	NO_x	0.8807	0.0082	0.9059
	HC	0.6674	0.0014	0.7070
	CO	0.7564	0.0024	0.8292
	CO_2	0.9389	0.1204	0.9788
	PM	0.8805	0.0399	0.9066
Off-Road Truck 3	Fuel Use	0.9916	0.0075	0.9930
	NO_x	0.9651	0.0022	0.9712
	HC	0.9316	0.0003	0.9418
	CO	0.8915	0.0018	0.9220
	CO_2	0.9912	0.0275	0.9928
	PM	0.9749	0.0085	0.9839

Table J.12. Summary of Validation Data using ANN for Off-Road Trucks

Equipment	Response	m	b	R^2
Off-Road Truck 1	Fuel Use	0.8883	0.2418	0.8894
	NO_x	0.8347	0.0143	0.8310
	HC	0.7618	0.0014	0.7714
	CO	0.3469	0.0207	0.3511
	CO_2	0.8714	0.7926	0.8915
	PM	0.9029	0.0598	0.8862
Off-Road Truck 2	Fuel Use	0.9545	0.0627	0.9584
	NO_x	0.8439	0.0107	0.8404
	HC	0.6175	0.0015	0.6331
	CO	0.5361	0.0046	0.5602
	CO_2	0.9471	0.2153	0.9571
	PM	0.8435	0.0538	0.8448
Off-Road Truck 3	Fuel Use	0.9824	0.0227	0.9860
	NO_x	0.9519	0.0030	0.9317
	HC	0.9214	0.0004	0.8621
	CO	0.7977	0.0033	0.7992
	CO_2	0.9933	0.0236	0.9866
	PM	0.9555	0.0153	0.9190

Table J.13. Summary of Training Data using ANN for Wheel Loaders

Equipment	Response	m	b	R^2
Wheel Loader 1	Fuel Use	0.9036	0.1477	0.9152
	NO_x	0.8058	0.0095	0.8320
	HC	0.8972	0.0005	0.9129
	CO	0.5854	0.0083	0.6132
	CO_2	0.8982	0.4792	0.9112
	PM	0.9017	0.0387	0.9210
Wheel Loader 2	Fuel Use	0. 9672	0.0389	0 .9718
	NO_x	0.9459	0.0028	0.9446
	HC	0.8613	0.0013	0.8800
	CO	0.6816	0.0034	0.7353
	CO_2	0.9673	0.1283	0.9716
	PM	0.9589	0.0137	0.9668
Wheel Loader 3	Fuel Use	0.9390	0.0475	0.9514
	NO_x	0.9157	0.0030	0.9287
	HC	0.8921	0.0002	0.9077
	CO	0.7245	0.0014	0.7564
	CO_2	0.9611	0.0899	0.9715
	PM	0.957	0.0041	0.9681
Wheel Loader 4	Fuel Use	0.9564	0.0406	0.9617
	NO_x	0.9301	0.0030	0.9406
	HC	0.7858	0.0009	0.7997
	CO	0.7351	0.0008	0.7604
	CO_2	0.9539	0.1384	0.9595
	PM	0.9615	0.0103	0.9652
Wheel Loader 5	Fuel Use	0.9758	0.0101	0.9797
	NO_x	0.9435	0.0008	0.9490
	HC	0.6476	0.0008	0.6641
	CO	0.6445	0.0023	0.6931
	CO_2	0.9808	0.0072	0.9834
	PM	0.9117	0.0080	0.9293

Table J.14. Summary of Validation Data using ANN for Wheel Loaders

Equipment	Response	m	b	R^2
Wheel Loader 1	Fuel Use	0.8904	0.1757	0.8733
	NO_x	0.8003	0.0102	0.7820
	HC	0.8648	0.0007	0.8556
	CO	0.5182	0.0095	0.5464
	CO_2	0.8854	0.5564	0.8799
	PM	0.8859	0.0440	0.8989
Wheel Loader 2	Fuel Use	0.9557	0.0495	0.9602
	NO_x	0.942	0.0032	0.9320
	HC	0.8453	0.0014	0.8426
	CO	0.5703	0.0046	0.5419
	CO_2	0.9632	0.1536	0.9616
	PM	0.9414	0.0198	0.9556
Wheel Loader 3	Fuel Use	0.9207	0.0677	0.9051
	NO_x	0.8887	0.0043	0.8692
	HC	0.8736	0.0003	0.8780
	CO	0.5773	0.0020	0.5828
	CO_2	0.9390	0.1987	0.8967
	PM	0.8783	0.0108	0.9163
Wheel Loader 4	Fuel Use	0.9318	0.0650	0.9361
	NO_x	0.9131	0.0038	0.9117
	HC	0.7438	0.0011	0.6463
	CO	0.6950	0.0010	0.6945
	CO_2	0.9442	0.1807	0.9396
	PM	0.9168	0.0231	0.9229
Wheel Loader 5	Fuel Use	0.9566	0.0226	0.9642
	NO_x	0.9248	0.0012	0.9034
	HC	0.6453	0.0008	0.6376
	CO	0.5180	0.0030	0.5055
	CO_2	0.9749	0.0330	0.9629
	PM	0.8574	0.0129	0.8950

Appendix K
Comparison of Validation Results for SLR, MLR, and ANN for All Type of Equipment

Table K.1. Comparison of Validation Results for SLR, MLR and ANN for Wheel Loaders

Response	SLR			MLR			ANN		
	m	**b**	**R^2**	**m**	**b**	**R^2**	**m**	**b**	**R^2**
Wheel Loader 1									
Fuel Use	0.888	-0.002	0.84	0.870	0.243	0.86	0.890	0.176	0.87
NO_x	0.889	0.010	0.67	0.730	0.015	0.72	0.800	0.010	0.78
HC	0.843	0.005	0.74	0.799	0.015	0.81	0.865	0.001	0.86
CO	0.014	0.010	0.47	0.505	0.008	0.50	0.518	0.010	0.55
CO_2	0.892	-0.028	0.84	0.857	0.659	0.86	0.885	0.556	0.88
PM	0.900	0.024	0.81	0.844	0.080	0.85	0.886	0.044	0.90
Wheel Loader 2									
Fuel Use	0.944	0.078	0.94	0.954	0.046	0.96	0.956	0.050	0.96
NO_x	0.874	0.007	0.87	0.034	0.008	0.90	0.942	0.003	0.93
HC	0.738	0.002	0.74	0.794	0.021	0.78	0.845	0.001	0.84
CO	0.012	0.010	0.01	0.128	0.009	0.12	0.570	0.005	0.54
CO_2	0.943	0.245	0.94	0.948	0.069	0.96	0.963	0.154	0.96
PM	0.837	0.067	0.84	0.877	0.065	0.87	0.941	0.020	0.96
Wheel Loader 3									
Fuel Use	0.8851	0.0959	0.89	0.910	0.135	0.89	0.921	0.068	0.91
NO_x	0.8247	0.0064	0.82	0.836	0.002	0.84	0.889	0.004	0.87
HC	0.6883	0.0007	0.69	0.780	0.001	0.78	0.874	0.0003	0.88
CO	0.3371	0.0033	0.34	0.410	0.003	0.41	0.577	0.002	0.58
CO_2	0.8851	0.2952	0.89	0.893	0.322	0.90	0.939	0.199	0.90
PM	0.8446	0.0185	0.84	0.840	0.010	0.87	0.878	0.011	0.92
Wheel Loader 4									
Fuel Use	0.8548	0.1498	0.85	0.914	0.101	0.91	0.932	0.065	0.94
NO_x	0.7839	0.0093	0.78	0.842	0.007	0.84	0.913	0.004	0.91
HC	0.1328	0.0036	0.13	0.251	0.003	0.24	0.744	0.001	0.65
CO	0.3108	0.0022	0.31	0.495	0.002	0.49	0.695	0.001	0.69
CO_2	0.8546	0.4722	0.85	0.913	0.271	0.91	0.944	0.181	0.94
PM	0.7486	0.0768	0.75	0.786	0.067	0.78	0.917	0.023	0.92
Wheel Loader 5									
Fuel Use	0.9479	0.0360	0.95	0.969	0.047	0.95	0.957	0.023	0.96
NO_x	0.8754	0.0027	0.88	0.918	0.003	0.88	0.925	0.001	0.90
HC	0.4243	0.0013	0.43	0.497	0.001	0.50	0.645	0.001	0.64
CO	0.4964	0.0032	0.50	0.510	0.003	0.51	0.518	0.003	0.51
CO_2	0.9478	0.1134	0.95	0.962	0.080	0.95	0.975	0.033	0.96
PM	0.8525	0.019	0.85	0.858	0.002	0.86	0.857	0.013	0.90

Table K.2. Comparison of Validation Results for SLR, MLR and ANN for Backhoes

Equipment	Response	SLR			MLR			ANN		
		m	b	R^2	m	b	R^2	m	b	R^2
Backhoe 1	Fuel Use	0.863	0.058	0.8633	0.897	0.041	0.907	0.9478	0.0207	0.9270
	NO_x	0.625	0.006	0.6244	0.752	0.004	0.767	0.8884	0.0017	0.8433
	HC	0.172	0.003	0.1714	0.432	0.002	0.431	0.6359	0.0014	0.6472
	CO	0.012	0.007	0.0117	0.677	0.002	0.674	0.8562	0.001	0.8485
	CO_2	0.864	0.182	0.8636	0.893	0.108	0.907	0.9508	0.0486	0.9200
	PM	0.066	0.021	0.0657	0.097	0.020	0.097	0.2387	0.0163	0.2365
Backhoe 2	Fuel Use	0.830	0.158	0.8302	0.919	0.077	0.920	0.9448	0.0388	0.9317
	NO_x	0.619	0.012	0.6186	0.849	0.003	0.849	0.9174	0.0024	0.8986
	HC	0.047	0.002	0.0468	0.153	0.002	0.163	0.6087	0.001	0.5932
	CO	0.139	0.008	0.1386	0.178	0.008	0.176	0.282	0.0066	0.2457
	CO_2	0.830	0.497	0.8302	0.923	0.296	0.920	0.9497	0.1377	0.9331
	PM	0.280	0.214	0.2803	0.319	0.163	0.323	0.9263	0.0455	0.7730
Backhoe 3	Fuel Use	0.961	0.029	0.9608	0.964	0.034	0.962	0.9719	0.0196	0.9809
	NO_x	0.776	0.005	0.7759	0.862	-0.002	0.866	0.9403	0.0011	0.9444
	HC	0.663	0.001	0.6662	0.711	0.001	0.715	0.8626	0.0002	0.8222
	CO	0.247	0.003	0.2458	0.257	0.053	0.256	0.4243	0.0023	0.4221
	CO_2	0.961	0.091	0.9610	0.964	0.097	0.962	0.9845	0.0328	0.9804
	PM	0.369	0.222	0.3686	0.459	0.196	0.476	0.9591	0.0126	0.9233
Backhoe 4	Fuel Use	0.889	0.045	0.8889	0.940	0.028	0.934	0.9477	0.019	0.9556
	NO_x	0.788	0.004	0.7884	0.866	0.002	0.870	0.9071	0.0015	0.9043
	HC	0.660	0.000	0.6607	0.769	0.000	0.778	0.8604	0.0002	0.8727
	CO	0.616	0.001	0.6212	0.668	0.001	0.649	0.7258	0.0004	0.6659
	CO_2	0.889	0.143	0.8887	0.936	0.082	0.934	0.9401	0.0669	0.9563
	PM	0.887	0.011	0.8874	0.904	0.010	0.898	0.9309	0.0065	0.9394
Backhoe 5	Fuel Use	0.854	0.104	0.8543	0.875	0.091	0.875	0.9322	0.0461	0.9312
	NO_x	0.751	0.008	0.7500	0.693	0.002	0.805	0.6517	0.0127	0.3066
	HC	0.303	0.001	0.2975	0.714	0.000	0.701	0.8434	0.0003	0.8207
	CO	0.221	0.011	0.2205	0.332	1.241	0.329	0.0048	0.0144	0.0177
	CO_2	0.853	0.329	0.8527	0.888	0.295	0.878	0.0012	2.1934	0.0068
	PM	0.423	0.117	0.4229	0.449	0.118	0.456	0.6913	0.0619	0.6552
Backhoe 6	Fuel Use	0.773	0.096	0.7724	0.919	0.046	0.915	0.9407	0.0242	0.9236
	NO_x	0.753	0.005	0.7530	0.895	0.003	0.876	0.9351	0.0012	0.9238
	HC	0.399	0.001	0.4010	0.576	0.001	0.572	0.8512	0.0003	0.8251
	CO	0.493	0.001	0.4950	0.617	0.001	0.623	0.8108	0.0006	0.7690
	CO_2	0.772	0.302	0.7719	0.931	-0.298	0.911	0.9522	0.0617	0.9147
	PM	0.846	0.017	0.8464	0.867	0.006	0.875	0.9128	0.0083	0.9143

Table K.3. Comparison of Validation Results for SLR, MLR and ANN for Bulldozers

Equipment	Response	SLR			MLR			ANN		
		m	**b**	**R^2**	**m**	**b**	**R^2**	**m**	**b**	**R^2**
Bulldozer 1	Fuel Use	0.946	0.080	0.9460	0.952	0.074	0.952	0.9531	0.0704	0.9574
	NO_x	0.833	0.012	0.8333	0.889	0.008	0.891	0.9327	0.0051	0.9230
	HC	0.523	0.002	0.5243	0.597	0.002	0.604	0.645	0.0015	0.6755
	CO	0.264	0.013	0.2642	0.306	0.014	0.297	0.4643	0.009	0.4185
	CO_2	0.945	0.253	0.9454	0.951	0.237	0.949	0.9548	0.2334	0.9541
	PM	0.790	0.135	0.7899	0.786	0.138	0.790	0.8115	0.1160	0.8075
Bulldozer 2	Fuel Use	0.910	0.104	0.9102	0.933	0.009	0.944	0.9628	0.0293	0.9594
	NO_x	0.752	0.009	0.7516	0.848	-0.338	0.835	0.002	0.0254	0.0036
	HC	0.009	0.005	0.0095	0.015	0.004	0.015	0.0013	0.004	0.0026
	CO	0.002	0.008	0.0022	-0.001	-0.007	0.001	0.0002	0.0074	0.0011
	CO_2	0.915	0.309	0.9147	0.947	0.124	0.947	0.9645	0.0753	0.9666
	PM	0.725	0.090	0.7246	0.789	-0.003	0.815	0.8729	0.0224	0.8734
Bulldozer 3	Fuel Use	0.927	0.148	0.9269	0.284	0.612	0.952	0.9663	0.0368	0.9773
	NO_x	0.758	0.024	0.7581	0.717	-0.011	0.865	0.9118	0.0057	0.9019
	HC	0.392	0.004	0.3910	0.651	0.002	0.635	0.6769	0.0016	0.6809
	CO	0.013	0.024	0.0129	0.035	0.024	0.032	0.4629	0.0139	0.3715
	CO_2	0.927	0.464	0.9272	0.970	0.158	0.968	0.9763	0.101	0.9766
	PM	0.490	0.528	0.4894	0.585	0.237	0.582	0.651	0.2099	0.6341
Bulldozer 4	Fuel Use	0.982	0.055	0.9820	0.985	0.039	0.984	0.9915	0.0326	0.9895
	NO_x	0.912	0.015	0.9115	0.914	0.015	0.913	0.9552	0.0077	0.9466
	HC	0.699	0.003	0.6963	0.792	0.002	0.793	0.8632	0.0016	0.8533
	CO	0.162	0.030	0.1625	0.178	0.031	0.178	0.5504	0.0156	0.5550
	CO_2	0.981	0.181	0.9813	0.984	0.143	0.983	0.9904	0.106	0.9889
	PM	0.737	0.215	0.7369	0.776	0.189	0.773	0.8647	0.1116	0.8554
Bulldozer 5	Fuel Use	0.985	0.130	0.9853	0.985	0.096	0.986	0.9915	0.1087	0.9886
	NO_x	0.925	0.040	0.9243	0.930	0.037	0.930	0.9700	0.0203	0.9617
	HC	0.312	0.007	0.2942	0.322	0.006	0.329	0.4821	0.0047	0.4889
	CO	0.054	0.064	0.0542	0.087	0.060	0.085	0.3441	0.0427	0.3573
	CO_2	0.985	0.411	0.9853	0.986	0.347	0.986	0.9921	0.3038	0.9889
	PM	0	0	0	0	0	0	0	0	0
Bulldozer 6	Fuel Use	0.322	0.669	0.3261	0.727	0.300	0.727	0.9652	0.0352	0.9576
	NO_x	0.194	0.023	0.1915	0.604	0.011	0.606	0.9305	0.0021	0.9145
	HC	0.006	0.007	0.0059	0.086	0.005	0.087	0.6592	0.0023	0.5735
	CO	0.0003	0.012	0.0003	0.234	0.009	0.229	0.6332	0.0045	0.5611
	CO_2	0.332	2.074	0.3312	0.723	0.847	0.728	0.9675	0.1035	0.9585
	PM	0.378	0.160	0.3766	0.477	0.120	0.483	0.6191	0.0959	0.5691

Table K.4. Comparison of Validation Results for SLR, MLR and ANN for Motor Graders

Equipment	Response	SLR			MLR			ANN		
		m	b	R^2	m	b	R^2	m	b	R^2
Motor Grader 1	Fuel Use	0.764	1.134	0.7644	0.777	1.119	0.772	0.8382	0.7655	0.8412
	NO_x	0.495	0.0637	0.6030	0.613	0.069	0.612	0.7312	0.0487	0.7112
	HC	0.189	0.012	0.1898	0.362	0.009	0.364	0.7244	0.0041	0.6949
	CO	0.260	0.014	0.2595	0.268	0.014	0.275	0.3542	0.012	0.3609
	CO_2	0.764	3.579	0.7641	0.775	3.492	0.772	0.8408	2.4194	0.8340
	PM	0.803	0.270	0.8029	0.822	0.247	0.822	0.9024	0.1269	0.8962
Motor Grader 2	Fuel Use	0.955	0.068	0.9546	0.971	0.422	0.967	0.9839	0.0307	0.9737
	NO_x	0.790	0.011	0.7896	0.842	0.009	0.838	0.8531	0.0073	0.8516
	HC	0.238	0.011	0.2382	0.415	-0.043	0.406	0.5664	0.0061	0.5167
	CO	0.118	0.012	0.1180	0.122	0.012	0.120	0.4247	0.0065	0.4490
	CO_2	0.956	0.209	0.9557	0.972	0.184	0.969	0.9675	0.1142	0.9731
	PM	0.673	0.089	0.6733	0.713	0.161	0.711	0.7059	0.0718	0.7343
Motor Grader 3	Fuel Use	0.918	0.185	0.9176	0.923	0.184	0.919	0.9393	0.1306	0.9428
	NO_x	0.755	0.019	0.7546	0.808	0.020	0.787	0.8517	0.0102	0.8491
	HC	0.514	0.021	0.5143	0.588	0.017	0.584	0.7973	0.0086	0.8007
	CO	0.167	0.007	0.1677	-0.003	0.009	0.0002	0.0296	-0.0075	0.0275
	CO_2	0.915	0.593	0.9155	0.920	0.570	0.918	0.9474	0.3752	0.9459
	PM	0.915	0.067	0.9149	0.921	0.065	0.921	0.9409	0.0448	0.9436
Motor Grader 4	Fuel Use	0.8761	0.3193	0.8761	0.900	0.265	0.896	0.9316	0.1898	0.9174
	NO_x	0.7406	0.0432	0.7390	0.746	0.043	0.739	0.8608	0.0237	0.824
	HC	0.1814	0.0217	0.1813	0.244	0.020	0.242	0.4468	0.0145	0.4086
	CO	0.1018	0.0353	0.1018	0.140	0.041	0.128	0.3884	0.0233	0.3856
	CO_2	0.8755	0.9986	0.8754	0.922	1.865	0.896	0.9121	0.6981	0.9225
	PM	0.6902	0.1960	0.6906	0.710	0.187	0.706	0.7562	0.1482	0.7663
Motor Grader 5	Fuel Use	0.976	0.055	0.9762	0.947	0.053	0.977	0.9773	0.0545	0.9793
	NO_x	0.892	0.013	0.8915	0.889	0.013	0.892	0.9177	0.0095	0.9177
	HC	0.497	0.004	0.4874	0.577	0.003	0.585	0.7005	0.0022	0.6809
	CO	0.085	0.034	0.0758	0.132	-0.125	0.131	0.2507	0.0276	0.2834
	CO_2	0.976	0.173	0.9760	0.930	0.118	0.976	0.9893	0.0966	0.9794
	PM	0.817	0.097	0.8170	0.829	0.086	0.831	0.835	0.0793	0.8387
Motor Grader 6	Fuel Use	0.918	0.181	0.9176	0.921	0.178	0.923	0.9503	0.1079	0.9444
	NO_x	0.444	0.025	0.4442	0.445	0.025	0.445	0.5415	0.0202	0.5359
	HC	0.070	0.006	0.0699	0.601	0.003	0.599	0.8155	0.0012	0.7573
	CO	0.064	0.005	0.0636	0.115	0.005	0.103	0.228	0.0034	0.2311
	CO_2	0.917	0.572	0.9172	0.923	0.583	0.923	0.9341	0.4383	0.9461
	PM	0.852	0.077	0.8492	0.885	0.054	0.889	0.9543	0.0250	0.9406

Table K.5. Comparison of Validation Results for SLR, MLR and ANN for Excavators

Equipment	Response	SLR			MLR			ANN		
		m	**b**	**R^2**	**m**	**b**	**R^2**	**m**	**b**	**R^2**
Excavator 1	Fuel Use	0.982	0.045	0.9819	0.983	0.044	0.985	0.9836	0.0386	0.9856
	NO_x	0.948	0.005	0.9481	0.944	0.004	0.951	0.9749	0.003	0.9624
	HC	0.352	0.002	0.3505	0.573	0.002	0.575	0.7685	0.0008	0.7402
	CO	0.542	0.005	0.5427	0.773	0.003	0.759	0.9121	0.001	0.8836
	CO_2	0.982	0.143	0.9819	0.981	0.107	0.985	0.9913	0.1119	0.9852
	PM	0.881	0.107	0.8810	0.873	0.099	0.886	0.8887	0.1080	0.8786
Excavator 2	Fuel Use	0.963	0.074	0.9632	0.974	0.063	0.971	0.9701	0.0579	0.9746
	NO_x	0.850	0.007	0.8499	0.887	0.006	0.879	0.9012	0.0049	0.8990
	HC	0.392	0.003	0.3901	0.441	0.003	0.434	0.4589	0.0027	0.4595
	CO	0.220	0.015	0.2194	0.322	0.013	0.327	0.5504	0.0086	0.5699
	CO_2	0.963	0.234	0.9633	0.974	0.206	0.971	0.9689	0.1665	0.9747
	PM	0.889	0.052	0.8876	0.917	0.053	0.909	0.94	0.0204	0.9530
Excavator 3	Fuel Use	0.930	0.120	0.9302	0.936	0.113	0.935	0.9545	0.0763	0.9584
	NO_x	0.875	0.007	0.8755	0.878	0.007	0.878	0.9128	0.0052	0.9144
	HC	0.193	0.004	0.1936	0.243	0.004	0.239	0.6549	0.0019	0.6535
	CO	0.018	0.008	0.0183	0.105	0.007	0.100	0.2707	0.0054	0.2683
	CO_2	0.930	0.381	0.9294	0.933	0.354	0.934	0.9547	0.2370	0.9593
	PM	0.333	0.284	0.3326	0.384	0.252	0.387	0.7695	0.0896	0.7911

Table K.6. Comparison of Validation Results for SLR, MLR and ANN for Track Loaders

Equipment	Response	SLR			MLR			ANN		
		m	b	R^2	m	b	R^2	m	b	R^2
Track Loader 1	Fuel Use	0.549	1.166	0.5500	0.875	0.314	0.879	0.9612	0.095	0.9624
	NO_x	0.351	0.031	0.3513	0.657	0.020	0.636	0.8498	0.0067	0.8602
	HC	0.431	0.005	0.4313	0.439	0.004	0.442	0.5825	0.0033	0.5757
	CO	0.161	0.016	0.1591	0.272	0.013	0.279	0.8392	0.0028	0.8361
	CO_2	0.547	3.685	0.5472	0.876	1.003	0.877	0.9658	0.2705	0.9670
	PM	0.315	0.439	0.3144	0.591	0.262	0.590	0.8881	0.0636	0.8863
Track Loader 2	Fuel Use	0.690	0.786	0.6896	0.555	0.875	0.700	0.8100	0.4845	0.8063
	NO_x	0.641	0.051	0.6403	0.158	0.040	0.631	0.8187	0.0242	0.8233
	HC	0.115	0.005	0.1146	0.078	0.003	0.200	0.5875	0.0024	0.5881
	CO	0.364	0.007	0.3662	0.658	0.011	0.446	0.6498	0.0037	0.6016
	CO_2	0.690	2.478	0.6900	0.492	1.670	0.697	0.8473	1.3388	0.8096
	PM	0.745	0.150	0.7439	0.748	0.282	0.757	0.9383	0.0334	0.9074
Track Loader 3	Fuel Use	0.965	0.114	0.9650	0.776	0.553	0.902	0.967	0.0809	0.9716
	NO_x	0.873	0.008	0.8708	0.612	0.015	0.741	0.941	0.0044	0.9177
	HC	0.069	0.002	0.0710	0.957	0.010	0.099	0.6152	0.0008	0.6022
	CO	0.613	0.006	0.6126	0.946	0.006	0.716	0.8339	0.0027	0.7875
	CO_2	0.965	0.359	0.9653	0.767	1.607	0.901	0.9749	0.3069	0.9734
	PM	0.705	0.182	0.7050	0.801	0.127	0.796	0.9255	0.0408	0.9292

Table K.7. Comparison of Validation Results for SLR, MLR and ANN for Off-Road Trucks

Equipment	Response	SLR			MLR			ANN		
		m	b	R^2	m	b	R^2	m	b	R^2
Off-Road Truck 1	Fuel Use	0.831	0.354	0.8309	0.869	0.279	0.870	0.8883	0.2418	0.8894
	NO_x	0.739	0.022	0.7401	0.778	0.018	0.786	0.8347	0.0143	0.831
	HC	0.681	0.002	0.6799	0.733	0.002	0.734	0.7618	0.0014	0.7714
	CO	0.270	0.025	0.2692	0.314	0.023	0.321	0.3469	0.0207	0.3511
	CO_2	0.832	1.099	0.8316	0.870	0.899	0.870	0.8714	0.7926	0.8915
	PM	0.833	0.103	0.8330	0.879	0.085	0.875	0.9029	0.0598	0.8862
Off-Road Truck 2	Fuel Use	0.942	0.088	0.9419	0.573	0.260	0.929	0.9545	0.0627	0.9584
	NO_x	0.773	0.016	0.7726	0.307	-0.002	0.781	0.8439	0.0107	0.8404
	HC	0.393	0.003	0.3929	-0.057	-0.001	0.076	0.6175	0.0015	0.6331
	CO	0.421	0.007	0.4210	0.124	0.005	0.308	0.5361	0.0046	0.5602
	CO_2	0.941	0.275	0.9415	0.528	-1.437	0.930	0.9471	0.2153	0.9571
	PM	0.803	0.082	0.8040	0.340	-0.067	0.575	0.8435	0.0538	0.8448
Off-Road Truck 3	Fuel Use	0.969	0.052	0.9690	0.975	0.032	0.977	0.9824	0.0227	0.9860
	NO_x	0.913	0.007	0.9138	0.893	0.004	0.916	0.9519	0.003	0.9317
	HC	0.696	0.002	0.6797	0.785	0.001	0.780	0.9214	0.0004	0.8621
	CO	0.590	0.007	0.5854	0.733	0.004	0.746	0.7977	0.0033	0.7992
	CO_2	0.969	0.173	0.9692	0.977	0.133	0.977	0.9933	0.0236	0.9866
	PM	0.669	0.145	0.6689	0.745	0.108	0.724	0.9555	0.0153	0.9190

Appendix L

Variable Impact Analysis

Table L.1. Variable Impact Analysis for Wheel Loaders

Equipment	**Fuel Use**	**NOx**	**HC**	**CO**	**CO2**	**PM**
			Wheel Loader 1			
MAP	44.25%	38.83%	27.77%	36.25%	46.67%	79.39%
RPM	38.85%	38.42%	54.75%	40.88%	37.97%	11.63%
IAT	16.91%	22.76%	17.49%	22.87%	15.36%	8.97%
			Wheel Loader 2			
MAP	66.11%	66.75%	22.02%	40.25%	72.63%	51.97%
RPM	29.57%	26.82%	59.06%	33.17%	25.04%	25.68%
IAT	4.33%	6.43%	18.92%	26.58%	2.33%	22.34%
			Wheel Loader 3			
MAP	42.38%	55.02%	16.39%	42.57%	48.20%	38.06%
RPM	51.65%	39.02%	52.26%	33.09%	46.37%	49.92%
IAT	5.97%	5.96%	31.35%	24.35%	5.43%	12.03%
			Wheel Loader 4			
MAP	37.31%	38.77%	24.06%	19.31%	41.06%	38.97%
RPM	49.02%	39.93%	50.09%	39.48%	47.49%	39.34%
IAT	13.67%	21.30%	25.85%	41.21%	11.45%	21.69%
			Wheel Loader 5			
MAP	72.51%	69.05%	23.93%	77.11%	61.78%	80.66%
RPM	23.63%	21.66%	68.78%	9.25%	34.97%	13.85%
IAT	3.86%	9.29%	7.29%	13.64%	3.26%	5.49%

Table L.2. Variable Impact Analysis for Backhoes

Equipment	**Fuel Use**	**NOx**	**HC**	**CO**	**CO2**	**PM**
			Backhoe 1			
MAP	61.63%	31.54%	42.60%	5.22%	72.21%	33.50%
RPM	30.65%	60.64%	34.55%	49.76%	24.62%	41.64%
IAT	7.72%	7.82%	22.86%	45.02%	3.17%	24.87%
			Backhoe 2			
MAP	51.28%	33.00%	31.31%	62.39%	43.65%	19.77%
RPM	38.49%	53.89%	50.58%	25.91%	49.18%	42.26%
IAT	10.23%	13.11%	18.11%	11.70%	7.17%	37.97%
			Backhoe 3			
MAP	77.38%	46.16%	13.79%	37.44%	80.18%	35.08%
RPM	12.99%	37.98%	55.87%	30.54%	11.62%	31.49%
IAT	9.63%	15.86%	13.79%	32.03%	8.20%	33.43%
			Backhoe 4			
MAP	46.91%	42.29%	16.87%	9.85%	27.09%	58.68%
RPM	32.56%	34.85%	58.06%	63.17%	50.68%	23.26%
IAT	20.53%	22.86%	25.07%	26.98%	22.23%	18.06%
			Backhoe 5			
MAP	30.94%	93.86%	25.23%	NA	NA	54.13%
RPM	50.34%	3.33%	12.57%	NA	NA	32.09%
IAT	18.72%	2.80%	62.20%	NA	NA	13.77%
			Backhoe 6			
MAP	23.11%	16.00%	16.16%	16.84%	16.85%	23.58%
RPM	58.54%	75.99%	66.68%	67.04%	73.11%	66.63%
IAT	18.36%	8.01%	17.16%	16.12%	10.03%	9.79%

Table L.3. Variable Impact Analysis for Bulldozers

Equipment	Fuel Use	NOx	HC	CO	CO2	PM
			Buldozer 1			
MAP	55.29%	30.18%	21.88%	66.81%	67.94%	51.05%
RPM	16.06%	53.84%	59.19%	24.66%	21.76%	26.82%
IAT	28.65%	15.98%	18.93%	8.53%	10.30%	22.13%
			Buldozer 2			
MAP	73.65%	NA	NA	NA	86.30%	61.37%
RPM	17.47%	NA	NA	NA	4.26%	20.89%
IAT	8.88%	NA	NA	NA	9.44%	17.47%
			Buldozer 3			
MAP	64.34%	76.75%	11.56%	31.54%	55.48%	47.02%
RPM	30.22%	20.73%	69.64%	42.43%	23.57%	33.00%
IAT	5.43%	2.52%	18.79%	26.02%	20.95%	19.99%
			Buldozer 4			
MAP	76.52%	53.85%	24.31%	59.28%	68.96%	57.10%
RPM	20.69%	37.76%	57.71%	38.74%	28.02%	31.95%
IAT	2.79%	8.39%	17.98%	1.96%	3.02%	10.95%
			Buldozer 5			
MAP	76.42%	47.70%	17.50%	39.10%	78.09%	NA
RPM	20.12%	46.43%	43.55%	53.97%	17.86%	NA
IAT	3.45%	5.87%	38.95%	6.93%	4.05%	NA
			Buldozer 6			
MAP	42.24%	34.63%	33.79%	22.65%	45.21%	72.45%
RPM	41.77%	46.80%	37.08%	38.64%	36.94%	8.80%
IAT	15.99%	18.57%	29.13%	38.72%	17.85%	18.76%

Table L.4. Variable Impact Analysis for Motor Graders

Equipment	Fuel Use	NOx	HC	CO	CO2	PM
			Motor Grader 1			
MAP	39.52%	38.84%	25.05%	28.60%	45.11%	33.17%
RPM	50.68%	46.89%	30.59%	40.34%	44.51%	51.54%
IAT	9.81%	14.27%	44.36%	31.06%	10.38%	15.29%
			Motor Grader 2			
MAP	88.44%	71.76%	42.51%	71.46%	81.62%	60.63%
RPM	9.19%	23.66%	36.23%	24.96%	15.22%	27.27%
IAT	3.37%	4.58%	21.26%	3.58%	3.16%	12.11%
			Motor Grader 3			
MAP	70.66%	59.46%	39.15%	41.18%	62.75%	68.25%
RPM	17.94%	22.28%	31.22%	2.11%	21.05%	13.77%
IAT	11.40%	18.26%	29.62%	56.71%	16.21%	18.00%
			Motor Grader 4			
MAP	69.27%	72.46%	29.79%	55.41%	71.56%	73.92%
RPM	30.73%	27.54%	70.21%	44.60%	28.44%	26.08%
IAT	0.00	0.00	0.00	0.00	0.00	0.00
			Motor Grader 5			
MAP	76.47%	44.44%	41.96%	66.59%	78.91%	63.93%
RPM	17.15%	41.37%	31.87%	25.26%	13.26%	21.75%
IAT	6.38%	14.19%	26.16%	8.15%	7.83%	14.32%
			Motor Grader 6			
MAP	70.81%	46.17%	25.00%	54.85%	62.83%	74.76%
RPM	21.50%	13.80%	22.96%	32.78%	24.44%	9.62%
IAT	7.69%	40.04%	52.04%	12.37%	12.74%	15.62%

Table L.5. Variable Impact Analysis for Excavators

Equipment	Fuel Use	NOx	HC	CO	CO2	PM
			Excavator 1			
MAP	84.79%	46.16%	30.84%	62.65%	91.40%	89.15%
RPM	12.05%	37.61%	33.05%	22.70%	4.95%	4.66%
IAT	3.16%	13.23%	36.11%	14.65%	3.66%	6.19%
			Excavator 2			
MAP	66.57%	40.82%	22.46%	62.12%	78.79%	61.66%
RPM	28.34%	47.30%	43.15%	32.19%	19.48%	19.44%
IAT	5.09%	11.88%	34.38%	5.69%	1.72%	18.90%
			Excavator 3			
MAP	40.52%	33.31%	19.88%	36.40%	41.26%	27.69%
RPM	41.23%	44.70%	33.85%	50.18%	41.29%	34.90%
IAT	18.25%	21.99%	46.28%	13.42%	17.44%	37.41%

Table L.6. Variable Impact Analysis for Track Loaders

Equipment	Fuel Use	NOx	HC	CO	CO2	PM
			Track Loader 1			
MAP	49.11%	34.74%	25.16%	46.53%	54.33%	40.69%
RPM	35.42%	46.47%	44.57%	35.13%	39.39%	34.98%
IAT	15.47%	18.80%	30.27%	18.33%	6.28%	24.32%
			Track Loader 2			
MAP	40.67%	41.60%	23.12%	24.75%	36.39%	26.82%
RPM	27.55%	26.33%	41.62%	42.06%	32.91%	44.40%
IAT	31.78%	32.07%	35.26%	33.20%	30.70%	28.78%
			Track Loader 3			
MAP	64.72%	32.96%	12.71%	56.32%	61.36%	7.96%
RPM	16.70%	53.59%	23.28%	30.98%	18.09%	51.12%
IAT	18.58%	13.45%	64.01%	12.69%	20.55%	40.91%

Table L.7. Variable Impact Analysis for Off-Road Trucks

Equipment	Fuel Use	NOx	HC	CO	CO2	PM
Off-Road Truck 1						
MAP	65.17%	62.62%	41.81%	31.84%	68.19%	46.53%
RPM	30.63%	24.63%	41.93%	51.85%	30.57%	46.18%
IAT	4.20%	12.76%	16.25%	16.31%	1.24%	7.29%
Off-Road Truck 2						
MAP	65.32%	74.71%	27.69%	73.19%	74.40%	81.72%
RPM	34.68%	21.09%	39.81%	22.71%	21.26%	7.45%
IAT	0.00	4.20%	32.50%	4.10%	4.34%	10.83%
Off-Road Truck 3						
MAP	84.08%	75.67%	27.75%	53.90%	85.16%	74.76%
RPM	14.17%	18.45%	37.58%	37.83%	7.42%	4.58%
IAT	1.75%	5.88%	34.67%	8.27%	7.42%	20.65%

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