SIBE2013 The Second International Conference on Sustainable Infrastructure and Built Environment – Bandung 19-20 November 2013
ISBN 978-979-98278-4-5

Variability and Uncertainty in Characterizing Emission Rates of Heavy-Duty Diesel Construction Equipment

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Abstract. Nowadays,air pollution has become a major concern. Typically construction equipment plays a major role in emitting a huge amount of pollutants. In order to address this issue, there is a need to measure the level of uncertainty for decision making of air quality modeling and emission inventories. This paper aims to propose a methodology for quantifying uncertainty of emission rates of heavy-duty diesel (HDD) construction equipment. The objective of this paper is to quantify the variability and uncertainty of emission rates of HDD construction equipment for three different pollutants (NO_x, CO, and HC). The study conducts its study based on 17 backhoes obtained from the City of Stillwater's fleet management database. Horse power (HP), cumulative hours, activity factor, and emission factors at steady-state condition are assigned as uncertain variables. Monte Carlo simulation was used to model the distributions of the uncertain variables by randomly selecting input values to produce a wide range of output using cumulative distribution functions. A sensitivity analysis was also performed in order to determine which variables that have the greatest impact on the total emission rates.

Keywords: *variability; uncertainty; Heavy-Duty Diesel (HDD) Construction Equipment; Monte Carlo Simulation; emission rates*

1 Introduction

Today, air pollution has become a major concern. Construction activities contribute a significant amount of pollutants emitted to the environment. Approximately 1.7% of total US greenhouse gas emissions are produced by the construction works.[1]In

[1]EPA (2009)

most construction activities, construction equipment is the primary sources of emissions for Oxides of Nitrogen (NO_x), Carbon Monoxide (CO), Hydro Carbon (HC), Particulate Matter (PM), and Carbon Dioxide (CO_2). A study conducted in the United States shows that construction equipment emits 30% of nitrogen oxides (NO_x) and 65% of particulate matter.[2]

Many studies have been conducted in quantifying emission estimates of construction equipment for different pollutants. Some studies quantified emissions of construction equipment based on real-world in use data.[3456]These studies heavily relied on deterministic approach using a single value or a point estimate. However, due to uncertainty in quantifying emission rates of HDD construction equipment, there is a need to measure the level of uncertainty for risk analysis with respect to human health problems. Probabilistic method is one of the techniques that can be used to quantify variability and uncertainty. Apparently, there is substantial uncertainty in quantifying emissions of HDD construction equipment. Failure to consider uncertainties in emission rates of construction equipment may lead to wrong decisions especially in quantifying emission inventory.

Several researches have also been conducted in assessing the uncertainty and variability in emission estimates. Frey et.al [7,8] assigned the uncertainty of emissions for non-road category of lawn and garden equipment. Aziz et.al [9] has presented a method for quantifying the uncertainty and variability for emission estimates with respect to hazardous air pollutants. The study focused on quantifying emissions for NO_x and HC from construction, farm, industrial engines and coal-fired power plants. The emission of construction equipment using discrete event simulation was also developed by Pan [8]. However, little research has been done in quantifying the variability and uncertainty of emissions from HDD construction equipment for different pollutants. This paper aims to propose a methodology for quantifying the uncertainty of emission rates of HDD construction equipment. The objective of this paper is to quantify the variability and uncertainty of emission rates of HDD construction equipment for each pollutant and identify key sources of uncertainty in the emission inventories. This paper fully highlights the emission rates quantification for NO_x, CO and HC.

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[2]EPA CAAAC (2006)
[3]Frey et.al (2008)
[4]Lewis (2009)
[5]Lewis et. Al (2012)
[6]Abolhasaniet. Al (2008)

2 Methodology

In this study, Monte Carlo simulation is utilized to evaluatethe variability and uncertainty of emission rates of HDD construction equipment. An emission rate equation was established based on Environmental Protection Agency's (EPA) Nonroad model. A sensitivity analysis is also conducted.

Table 1 summarizes equipment attributes of 17 backhoes examined from the City of Stillwater's fleet management database. The data consist of equipment brand (make), model, model year, displacement, engine size (horsepower), and usage hours. It is important to note that most backhoes are over 10 years old.

Table 1 Summary of Equipment Attributes

Type	Make	Model	Model Year	Displacement (L)	Horsepower (HP)	Usage (hours)
Backhoe 1	New Holland	LB90	2002	4.5	98	3583
Backhoe 2	John Deere	210C	1993	4	58	41
Backhoe 3	John Deere	310	1992	4	58	507
Backhoe 4	Ford	555	1982	4.2	28	489
Backhoe 5	Ford	575D	1995	4.5	75	2467
Backhoe 6	New Holland	LB75B	2005	4.5	95	2155
Backhoe 7	Ford	575E	1997	4.2	75	2845
Backhoe 8	John Deere	310J	2008	4.5	79	1194
Backhoe 9	New Holland	B95LR	2007	4.5	95	2193
Backhoe 10	Ford	675E	1999	5	75	5266
Backhoe 11	New Holland	575E	2000	5	75	132
Backhoe 12	New Holland	575E	2000	5	75	924
Backhoe 13	New Holland	B95LR	2007	4.5	95	3240
Backhoe 14	Ford	LB90	2001	5	98	110
Backhoe 15	Ford	555C	1991	4.5	65	1089
Backhoe 16	New Holland	LB75B	2002	4.5	95	343
Backhoe 17	Ford	575E	1997	4.2	75	-

In order to calculate the emission rates for HDD construction equipment, EPA Nonroad model was used as the basis for estimating the emission factors for NO_x, CO, and HC.Similarly, the data for emission factor at steady state condition (EF_{ss}), transient adjustment factors (TAF), activity factor (A), cumulative hour (CH), load factor (LF) and median life (ML) were obtained from EPA *Construction Fleet Inventory Guide* (EPA, 2010a, b and c).

Emission factor at steady state condition (EF_{ss}) is defined as a function of the engine's model year and engine size (horse power rating). In addition, transient adjustment factors are considered as the fraction of the transient emission factor to the steady-state emission factor.

The equation for the emission rate model is defined as follows:

$$ER = \text{EFss x TAF x HP x } [1 + \frac{\text{A(CH x LF)}}{\text{ML}}] \quad (1)$$

where:

A	= activity factor (hr/yr)
CH	= cumulative hours (hours)
EF_{ss}	= zero-hour, steady-state emission factors (gr/hp-hr)
ER	= emissions rates for NOx, HC and CO (g/hr)
HP	= engine size (hp)
LF	= load factor (unitless)
ML	= median life (hours)
TAF	= transient adjustment factor (unitless)

The pollutants that are under consideration are NOx, CO, and HC. Monte Carlo simulation was conducted by using software @Risk. Monte Carlo Simulation was used to enable modeling uncertain input variables to produce a wide range of outputs using probability distribution functions. Empirical distributions or parametric distributions for important parameters were 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 all information available for a parameter. When data for an important parameter are limited, it may be necessary to use subjective judgment in estimating the probability distribution functions of input parameters.

Based on fitted distribution function using @Risk, the probability distribution functions for each random variable are defined. **Table 2** summarizes all parametric distribution fit data for random variables that include horse power, cumulative hours, and median life. These data are applied to quantify the emission rates of NO_x, CO, and HC. The data for EF_{ss}, transient adjustment factor (TAF), and activity factor (A) are typically different depending on the types of pollutants (**Table 3**). Meanwhile, load factor is similar for specific type of equipment.

Table 2 Summary of input variables

Random variables	Probability Distribution Function	Parameters
Horse power (HP)	RiskTriangular	(88, 98, 108)
Cumulative hours	RiskTriangular	(3430, 3811, 4192)

Median life (hr)	RiskLognormal	(4667, 10%*4667)

Table 3 Summary of input variables

Variable	NOx	HC	CO
TAF	1.1	2.29	2.57
A	0.024	0.036	0.101
EFss	RiskExtValue (5.240, 1.248)	RiskWeibull (1.451, 0.627)	RiskUniform (2.201, 5.165)
LF	0.21	0.21	0.21

Statistical goodness-of-fit tests including Chi-Squares (CS), Kolmogorov-Smirnov (KS) and Anderson-Darling (AD) are used to evaluate goodness-of-fit of random variables or uncertainties. Based on the analysis, Chi-Squares (CS) appears to adequately fit the dataset.Furthermore, parameters for each random variable are varied depending on the probability distribution functions as indicated by mean and standard deviation. Based on the equation (1), models were then developed. Monte Carlo simulation was conducted to generate the data points using software @Risk with particular iterations. Similarly,statistical goodness-of-fit tests were also used to evaluate the goodness-of-fit of the outputs presented in cumulative distribution functions. Moreover, descriptive statistics of the outputs that include minimum, maximum, mean and standard deviation values were demonstrated. Sensitivity analysis was further explained. Figure 1 briefly presents the overall procedure for Monte Carlo Simulation.

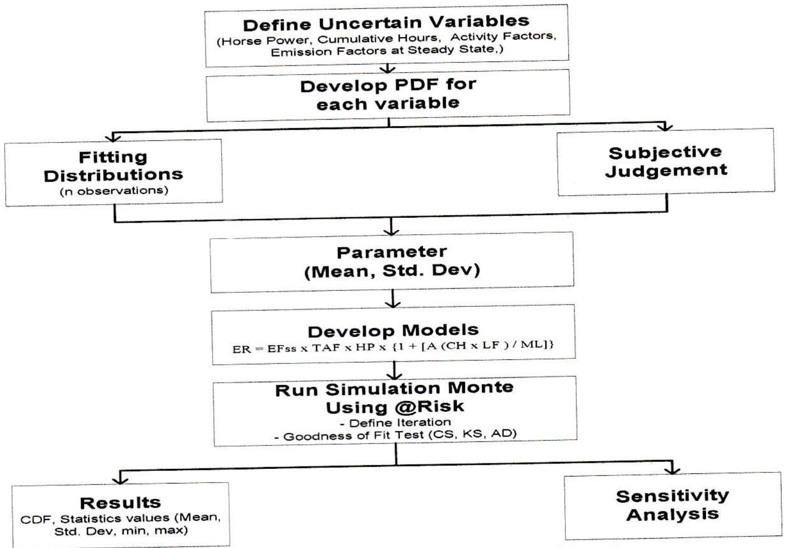

Figure 1 Procedure for Monte Carlo Simulation

3 Results and Discussion

This section demonstrates and evaluates the variability and uncertainty in quantifying emission rates of HDD construction equipment. Variability and uncertainty in the emission rates are assigned using parametric probability distributions. Using fitted distribution functions provided by software @Risk, parameters of each uncertainty is measured. Seventeen data points are generated by 10,000 iterations to best estimate the probability distribution function of outcome. Descriptive statistics such as minimum, maximum, mean and standard deviation values are provided from the simulation.

Based on the analysis, emissionrates for each pollutant vary depending on the input variables as shown in Figures 2-4. For example, emission rates for NOx, CO, and HC are within the range of 268 g/hr to1805 g/hr, 519 g/hr to1431 g/hr, and 34 g/hr to731 g/hr, respectively.

Figure 2 shows the cumulative distribution function for emission rates for NOx. It can be seen that the range of emission rates is between 268 g/hr and 1805 g/hr. Basically, this means that 95% of the emission rates of NOx are less than 973 g/hr or, 90% of confidence interval is in the range of 416 g/hr to 973 g/hr.

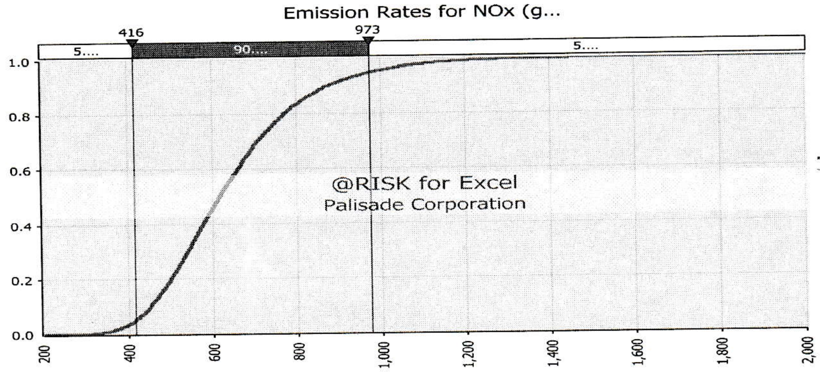

Figure 2 Cumulative distribution function for emission rates (NOx)

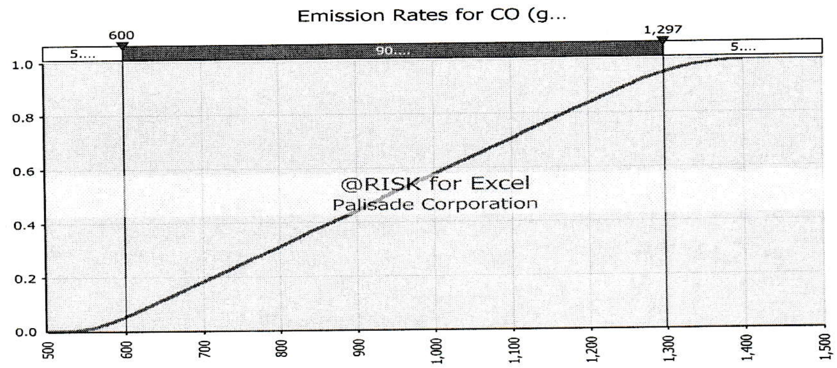

Figure 3 Cumulative distribution function for emission rates (CO)

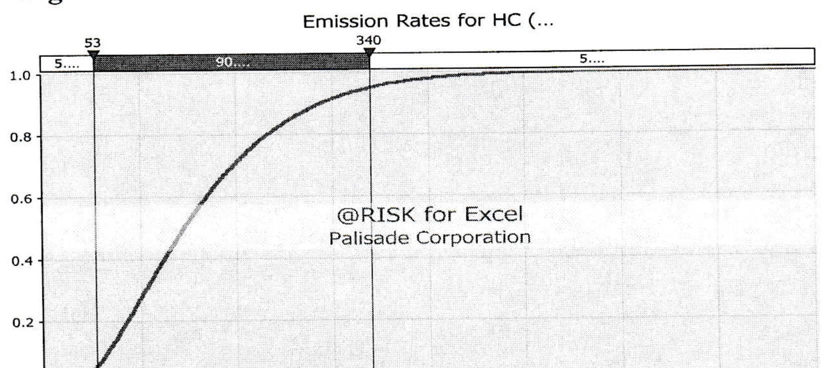

Figure 4 Cumulative distribution function for emission rates (HC)

Emission rates for CO were found to be greater than NOx and HC for each gram emissions per hour. Emission rates for HC are the lowest among other pollutants. As can be seen in **Figure 3**, 95% of the emission rates for CO are less than 1300 g/hp. However, emission rates for HC are within the ranges 53 g/hr up to 340 g/hr for 90% confidence interval. Detail summary statistics are presented in **Table 4**.

Table 4 Summary statistic of emission rates

Attributes	**NOx (g/hr)**	**CO(g/hr)**	**HC(g/hr)**
Minimum	268	519	34
Maximum	1805	1431	731
Mean	645	944	164
Std. Deviation	175	223	90.43

The key sources of uncertainty are recognized by implementing sensitivity analysis which is based on rank correlation. To illustrate how sensitive each random input variable is to the outputs, **Figure 5** briefly explains the sensitivity analysis of emission factors for NOx. Based on the analysis, emission factor at steady-state (EF-ss) is the most sensitive variable to the total emission rates. The higher the value of EF-ss is, the higher the value of emission rates for NOx. Horse power is the second most sensitive variable that affects the total emission rates. Meanwhile cumulative hours and median life are not significant given the emission rates. Similarly, the emission rates for HC and CO follow the same trends as shown in **Figures 6** and **7** respectively.

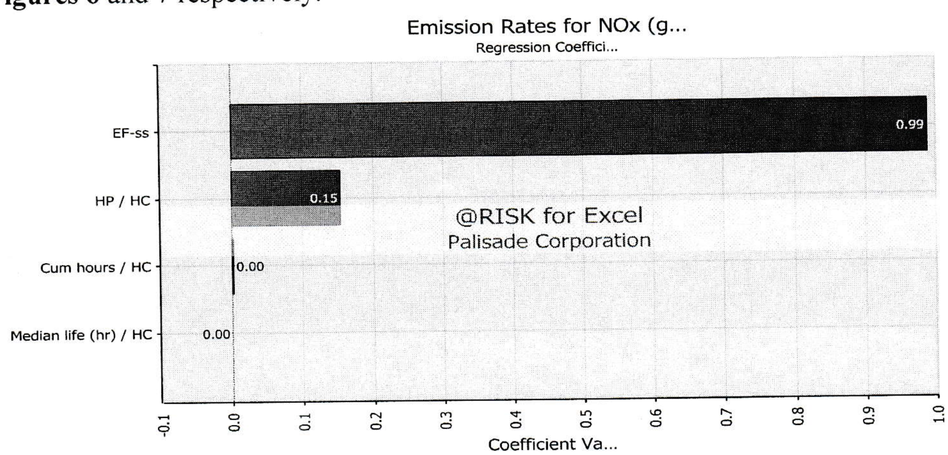

Figure 5 Sensitivity analysisof emission rates (NOx)

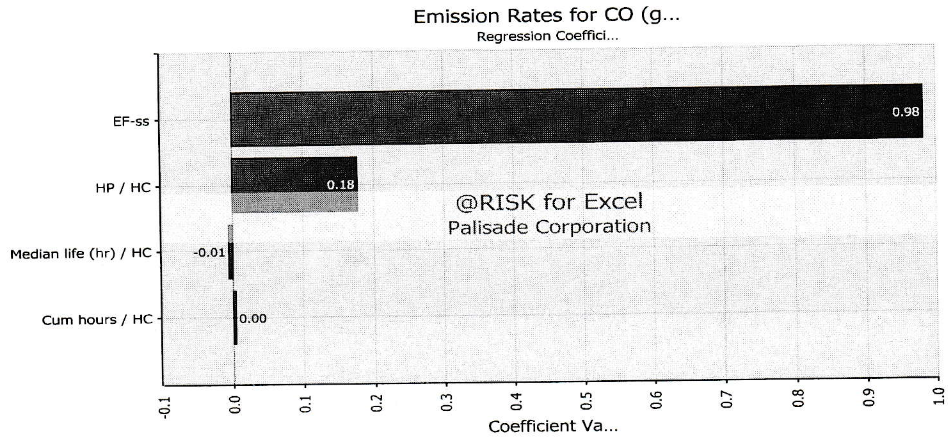

Figure 6 Sensitivity analysis of emission rates (CO)

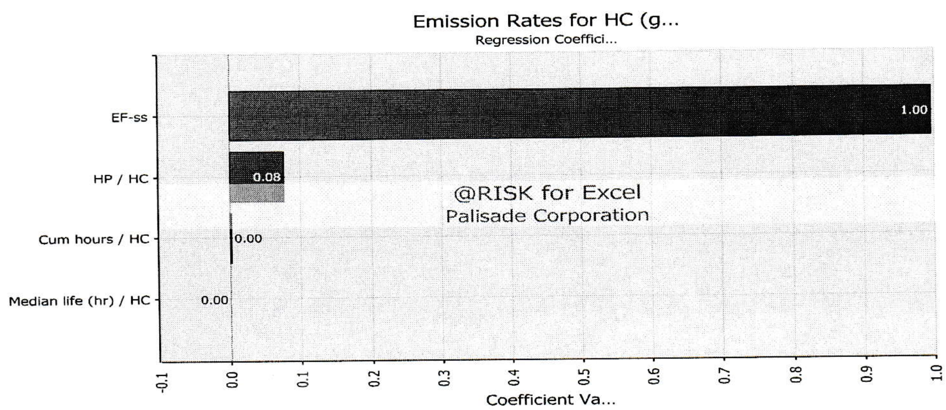

Figure 7 Sensitivity analysisof emission rates (HC)

4 Conclusions

This paper presented a procedure for quantifying the variability and uncertainty in emissions of heavy-duty diesel (HDD) construction equipment. Monte Carlo simulation is developed to enable modeling uncertain input variables to produce a wide range of output using probability distribution functions. The results show that emission rates for CO were found to be greater than NOx and HC for each gram emissions per hour. It is shown that 95% of the emission rates are less than 1300 g/hr, 973 g/hr and 340 g/hr for CO, NOx and HC, respectively.

Based on sensitivity analysis, emission factors at steady-state condition are recognized as the most sensitive variable given the total emission rates for each type of pollutant. Engine size is the second influential variable in total emission rates. Cumulative hours and median life are found be less sensitive to total emission rates for NOx, HC and CO.

A key difficulty encountered in this study was to obtain a particular probability distribution function for each input uncertain parameter. This may be due to the limited amount of data and some of the assumptions used in developing the models. However, this research may contribute to the importance of assigning variability and uncertainty of emission rates which is very critical for emission inventory decision-making.

5 Acknowledgement

The authors express gratitude to Mr. David Higgins and Mr. John Maehs with the City of Stillwater for their support and cooperation in providing the data of Stillwater Fleet Construction Equipment.

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