Comparison of Predictive Modeling Methodologies for Estimating Fuel Use and Emission Rates for Wheel Loaders

Heni FITRIANI[1] and Phil LEWIS, PhD, PE[2]

[1]PhD Candidate, Oklahoma State University, School of Civil and Environmental Engineering, 207 Engineering South, Stillwater, OK 74078, PH (405)-334-8641; email: heni.fitriani@okstate.edu

[2]Assistant Professor, Oklahoma State University, School of Civil and Environmental Engineering, 207 Engineering South, Stillwater, OK 74078, PH (405)-744-5207; email: phil.lewis@okstate.edu

ABSTRACT

Heavy duty diesel (HDD) construction equipment consumes significant amounts of fuel and consequently emits substantial quantities of pollutants. The purpose of this paper is to demonstrate three different predictive modeling methodologies for estimating fuel use and emission rates for HDD construction equipment based on real-world data. Engine performance data for five wheel loaders, including manifold absolute pressure (MAP), revolutions per minute (RPM), and intake air temperature (IAT) were used to develop prediction models for fuel use and emission rates of nitrogen oxides (NO_x), hydrocarbons (HC), carbon monoxide (CO), carbon dioxide (CO_2), and particulate matter (PM). For each wheel loader, predictive models were developed using simple linear regression (SLR), multiple linear regression (MLR), and artificial neural network (ANN). Results indicate that the ANN models accounted for the highest percentage of variability in the data compared to SLR and MLR based on values of the coefficient of determination (R^2) for each model. Furthermore, a variable impact analysis was conducted to determine which variables have the most significant impact on fuel use and emission rates for the wheel loaders.

INTRODUCTION

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 equipment emitted approximately 657,000 tons of nitrogen oxides (NO_x), 1,100,000 tons of carbon monoxide (CO), 63,000 tons of particulate matter (PM_{10}) and 94,000 tons of sulfur dioxide (SO_2) (EPA 2005). Of these pollutants, NO_x and PM are most prominent among HDD equipment (EPA 2006). Other pollutants found in diesel exhaust include hydrocarbons (HC) and carbon dioxide (CO_2).

In order quantify and characterize the HDD emissions problem, reliable prediction models are needed; however, most emission prediction tools are based on engine dynamometer data and not real-world data. The objective of this paper is to demonstrate three different predictive modeling methodologies for estimating fuel use and emission rates for HDD construction equipment, specifically wheel loaders, based on real-world data.

PREVIOUS WORK

Some of the most prominent real-world emissions measurements from HDD construction equipment were completed by researchers at North Carolina State University (Abolhasani *et al*. 2008; Lewis 2009; Rasdorf *et al*. 2010, Frey *et al*. 2008, Kim 2007). Abolhasani *et al*. (2008) focused on measuring fuel use and emission rates of NO_x, HC, CO, CO_2 and PM for hydraulic excavators. This study showed that nearly 90% of the field measurements were valid and approximately 50% of the NO_x emissions were produced during 30% of the time of operation. Lewis (2009) presented a methodology for measuring weighted-average fuel use and emission rates of HDD construction equipment while performing common duty cycles. Lewis *et al*. (2012) studied the influence of engine idling with respect to fuel use and emission rates for HDD construction equipment. 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.

The use of artificial neural networks (ANN) in civil engineering was initiated in 1989, primarily for structural engineering and construction engineering management applications (Adeli 2001). Moreover, its application has been wide-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 widely 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.

Tehranian (2003) used ANN to predict diesel engine emissions of NO_x, PM, HC, CO, and CO_2 using data from engine dynamometer tests based on five engine transient-test schedules. 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. 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. 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 (EGR) percentage, and nozzle diameter. This study found that EGR rates, fuel mass, and start of injection are the most reliable variables for obtaining robust models. Mudgal *et al.* (2011) used ANN to predict emissions of transit buses powered by biodiesel fuel consisting of B0 (regular diesel), B10 (10% biodiesel) and B20 (20% biodiesel).

METHODOLOGY

This paper presents three different predictive modeling methodologies for estimating fuel use and emissions rates based on the real-world dataset from the research team at North Carolina State University. Simple linear regression (SLR), multiple linear regression (MLR), and artificial neural network (ANN) models were developed and compared for five wheel loaders. Engine performance data from the wheel loaders, including manifold absolute pressure (MAP), revolutions per minute (RPM), and intake air temperature (IAT), were used to develop prediction models for fuel use and emission rates of NO_x, HC, CO, CO_2, and PM. Table 1 displays the summary of engine attribute data for each wheel loader, including engine size (HP), displacement, model year, and EPA engine tier. The rated engine horsepower (HP) ranged from 126 HP to 149 HP and the model year ranged from 2002 to 2005; thus, all five of the wheel loaders were either EPA engine tier 1 or 2.

Table 1. Summary of Engine Attribute Data

Equipment	Horsepower (HP)	Displacement (Liters)	Model Year	Engine Tier
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

Simple Linear Regression

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 that MAP is highly correlated to fuel use and emission rates (Frey *et al*. 2008; Lewis 2009), 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:

$$Y_{1\text{-}6} = mx + b \tag{1}$$

where:

$Y_{1\text{-}6}$ = Fuel use or emission rate of NO_x, HC, CO, CO_2, or PM (g/s)
m = slope of the regression line
x = MAP (kilopascal)
b = y-intercept of regression line

Multiple Linear Regression (MLR)

Multiple linear regression was used to model the relationship between three predictor variables based on engine performance data (MAP, RPM, IAT) and one response variable (either fuel use or emission rate of NO_x, HC, CO, CO_2, and PM). The MLR equations for fuel use and emission rates for each pollutant take the form of:

$$Y_{1\text{-}6} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \qquad (2)$$

where:

$Y_{1\text{-}6}$	= Fuel use or emission rate of NO_x, HC, CO, CO_2, or PM (g/s)
X_1	= MAP (kilopascal)
X_2	= Revolutions Per Minute (RPM)
X_3	= Intake Air Temperature (Celsius degrees)
β_0, β_1, β_2, β_3	= Coefficients of linear relationship

Artificial Neural Networks (ANN)

ANN is a computational model that simulates brain function. ANN models frequently perform better than other statistical techniques and usually improve predictive models. 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. In this paper, the input layers include MAP, RPM, and IAT; meanwhile, fuel use and emission rates are defined as output layers. The ANN approach used in this paper is the general regression neural network (GRNN) performed by the software @Risk. 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.

RESULTS

This section presents the results for three predictive modeling methodologies - SLR, MLR, and ANN - for wheel loaders, as well as variable correlations and model comparisons for all models. Although models were developed for all five wheel loaders, only the SLR and MLR equations for Wheel Loader 1 are presented for brevity. The validation results for the models for all five wheel loaders are presented in Table 6.

Table 2 shows the summary of the Pearson correlation coefficients for all five wheel loaders, indicating the relationship between engine data, fuel use, and emission rates. 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 variables.

Table 2. Summary of Pearson Correlations Coefficients

Equipment	Engine Data	Fuel Use	NO_x	HC	CO	CO_2	PM
WL 1	MAP	0.91	0.82	0.86	0.68	0.92	0.90
	RPM	0.87	0.77	0.87	0.67	0.87	0.75
	IAT	0.27	0.37	0.00	0.26	0.27	0.30
WL 2	MAP	0.97	0.93	0.86	0.11	0.97	0.91
	RPM	0.94	0.93	0.86	0.07	0.94	0.87
	IAT	0.16	0.22	0.27	-0.31	0.17	-0.01
WL 3	MAP	0.94	0.91	0.83	0.58	0.94	0.92
	RPM	0.89	0.86	0.84	0.61	0.89	0.89
	IAT	-0.25	-0.29	-0.01	-0.02	-0.25	-0.26
WL 4	MAP	0.92	0.88	0.37	0.56	0.92	0.87
	RPM	0.85	0.80	0.36	0.53	0.85	0.77
	IAT	-0.29	-0.34	0.24	-0.49	-0.29	-0.26
WL 5	MAP	0.97	0.94	0.65	0.70	0.97	0.92
	RPM	0.90	0.87	0.69	0.68	0.90	0.77
	IAT	-0.07	-0.08	0.04	-0.05	-0.07	-0.06

Simple Linear Regression Models

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. Table 3 presents the results of the SLR models for Wheel Loader 1. These models are based on 15,226 observations of second-by-second, real-world fuel use and emissions data. Based on the coefficient of determination (R^2), these models accounted for a high percentage of the variability in the data for fuel use, NO_x, HC, CO_2 and PM. CO had the lowest R^2 value, indicating much variability in the data, and therefore was more difficult to predict.

Table 3. Summary of SLR Models for Wheel Loader 1

Response	Model Equation	R^2
Fuel Use	$Y_1 = 5.0514\ X_1 + 0.6197$	0.84
NO_x	$Y_2 = 0.1338\ X_1 + 0.0253$	0.67
HC	$Y_3 = 0.0137\ X_1 + 0.0029$	0.74
CO	$Y_4 = 0.0582\ X_1 + 0.0096$	0.47
CO_2	$Y_5 = 15.869\ X_1 + 1.9392$	0.84
PM	$Y_6 = 1.6186\ X_1 + 0.1296$	0.81

X_1 = MAP

Multiple Linear Regression Models

Based on the correlation matrix in Table 2, MAP and RPM are highly correlated to fuel use and emissions rate for most of pollutants. Even though IAT has a lower correlation to fuel use and emissions rate, IAT was still used as an input variable for the MLR models because it may still have some predictive power.

Table 4 summarizes the models for fuel use and emissions rates for Wheel Loader 1. Overall, the MLR models yielded higher R^2 values than the SLR models for their respective response variables. 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.

Table 4. Summary of MLR Models and R^2 for Wheel Loader 1

Response	Model Equation	R^2
Fuel Use	$Y_1 = -4.07 + 0.032\ X_1 + 0.0008X_2 + 0.0254X_3$	0.86
NO_x	$Y_2 = -0.121 + 0.00084\ X_1 + 0.00002\ X_2 + 0.00151\ X_3$	0.72
HC	$Y_3 = -0.0042 + 0.00061\ X_1 + 4.13E\text{-}6\ X_2 – 0.0001X_3$	0.80
CO	$Y_4 = -0.05 + 0.000302\ X_1 + 0.00013X_2 + 0.00052X_3$	0.49
CO_2	$Y_5 = -12.8 +0.1003X_1+ 0.0024\ X_2 + 0.08X_3$	0.86
PM	$Y_6 = -1.78 + 0.0193X_1 – 0.00034\ X_2 + 0.009X_3$	0.85

X_1 = MAP, X_2 = RPM, X_3 = IAT

Artificial Neural Network Models

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. In order to validate the results, the ANN software 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 – 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. Table 5 summarizes the results of ANN for Wheel Loader 1. 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.

Table 5. Summary of Training Data for Wheel Loader 1

Pollutants	m	b	R^2
Fuel Use	0.904	0.148	0.92
NO_x	0.806	0.009	0.83
HC	0.897	0.000	0.91
CO	0.585	0.008	0.61
CO_2	0.898	0.479	0.91
PM	0.902	0.039	0.92

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

Pollutants	SLR			MLR			ANN		
	m	b	R^2	m	b	R^2	m	b	R^2
Wheel Loader 1									
Fuel Use	0.89	-0.002	0.84	0.87	0.243	0.86	0.89	0.176	0.87
NO_x	0.89	0.010	0.67	0.73	0.015	0.72	0.80	0.010	0.78
HC	0.84	0.005	0.74	0.80	0.015	0.81	0.87	0.001	0.86
CO	0.01	0.010	0.47	0.51	0.008	0.50	0.52	0.010	0.55
CO_2	0.89	-0.028	0.84	0.86	0.659	0.86	0.89	0.556	0.88
PM	0.90	0.024	0.81	0.84	0.080	0.85	0.89	0.044	0.90
Wheel Loader 2									
Fuel Use	0.94	0.078	0.94	0.95	0.046	0.96	0.96	0.050	0.96
NO_x	0.87	0.007	0.87	0.03	0.008	0.90	0.94	0.003	0.93
HC	0.74	0.002	0.74	0.79	0.021	0.78	0.85	0.001	0.84
CO	0.01	0.010	0.01	0.13	0.009	0.12	0.57	0.005	0.54
CO_2	0.94	0.245	0.94	0.95	0.069	0.96	0.96	0.154	0.96
PM	0.84	0.067	0.84	0.88	0.065	0.87	0.94	0.020	0.96
Wheel Loader 3									
Fuel Use	0.89	0.096	0.89	0.91	0.135	0.89	0.92	0.068	0.91
NO_x	0.83	0.006	0.82	0.84	0.002	0.82	0.89	0.004	0.87
HC	0.69	0.001	0.69	0.78	0.001	0.73	0.87	0.0003	0.88
CO	0.34	0.003	0.34	0.41	0.003	0.41	0.58	0.002	0.58
CO_2	0.89	0.295	0.89	0.89	0.322	0.90	0.94	0.199	0.90
PM	0.85	0.019	0.84	0.84	0.010	0.87	0.88	0.011	0.92
Wheel Loader 4									
Fuel Use	0.86	0.150	0.85	0.91	0.101	0.91	0.93	0.065	0.94
NO_x	0.78	0.009	0.78	0.84	0.007	0.84	0.91	0.004	0.91
HC	0.13	0.004	0.13	0.25	0.003	0.24	0.74	0.001	0.65
CO	0.31	0.002	0.31	0.49	0.002	0.49	0.69	0.001	0.69
CO_2	0.86	0.472	0.85	0.91	0.271	0.91	0.94	0.181	0.94
PM	0.75	0.077	0.75	0.79	0.067	0.78	0.92	0.023	0.92
Wheel Loader 5									
Fuel Use	0.95	0.036	0.95	0.97	0.047	0.95	0.96	0.023	0.96
NO_x	0.88	0.003	0.88	0.92	0.003	0.88	0.93	0.001	0.90
HC	0.42	0.001	0.43	0.49	0.001	0.50	0.65	0.001	0.64
CO	0.49	0.003	0.50	0.51	0.003	0.51	0.52	0.003	0.51
CO_2	0.95	0.113	0.95	0.96	0.080	0.95	0.98	0.033	0.96
PM	0.85	0.019	0.85	0.86	0.002	0.86	0.86	0.013	0.90

Model Comparison

Model validations for the five wheel loaders were developed 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. As shown in Table 6, 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.

Variable Impact Analysis

Using the MLR models, 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 7 presents the summary of the variable impact analysis for Wheel Loader 1. 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 7. Variable Impact Analysis for Average 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%

CONCLUSIONS AND RECOMMENDATIONS

The purpose of this paper was to demonstrate three different predictive modeling methodologies for estimating fuel use and emission rates of pollutants using real-world data. 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 least impact of the three engine performance variables on predicting fuel use and emission rates. It is recommended that other engine performance data, such as engine load or throttle position, be considered for future studies.

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. It is recommended that strong relationships between CO and other variables 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.

With regard to variable impact analysis, 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 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 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. For strictly prediction purposes, it is recommended that all three engine performance variables be used to estimate fuel use and emission rates.

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. 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.

Overall, the results of this study help to quantify and characterize the air pollution problem from HDD equipment used in construction. Although only wheel loaders were addressed in this paper, the methodologies presented may certainly be used to develop fuel use and emissions models for other types of equipment. In order to further characterize this emissions problem, it is recommended that other types of equipment, such as backhoes, bulldozers, motor graders, track loaders, excavators, and off road trucks, be targeted for future modeling efforts.

ACKNOWLEDGEMENT

The authors acknowledge the use of the real-world nonroad equipment and emission database that was developed at North Carolina State University by Dr. H. Christopher Frey and Dr. William Rasdorf.

REFERENCES

Abolhasani, S., Frey, H. C., Kim, K., Rasdorf, W., Lewis, P., & Pang, S.-H. (2008). Real-World In-Use Activity, Fuel Use, and Emissions for Nonroad Construction Vehicles: A Case Study for Excavators. *Journal of the Air & Waste Management Association, 58*(8), 1033-1046.

Adeli, H. (2001). Neural Networks in Civil Engineering: 1989 – 2000. *Journal of Computer-Aided Civil and Infrastructure Engineering*, 16(2), 126-142.

Clark, N. N., Tehranian, A., Jarret, R. P., Nine, R. D., (2002). "Translation of Distance Specific Emissions Rates between Different Heavy Duty Vehicle Chassis Test Schedules", Society of Automotive Engineers (SAE) paper 01-1754.

Desantes, J., Lopez, J., Garcia, J., Hernandez, L. (2002). "Application of Neural Networks for Prediction and Optimization of Exhaust Emissions in a HDD Engines", Society of Automotive Engineers (SAE) paper 01-1144.

Environmental Protection Agency Clean Air Act Advisory Committee (EPA CAAAC) (2006). Recommendations for reducing emissions from the Legacy Diesel Fleet. U.S. Environmental Protection Agency, Washington D.C.

EPA. (2005). "Users guide for the final NONROAD2005 model." *EPA-420-R-05-013*, Ann Arbor, MI.

EPA (2002). "Health assessment document for diesel engine exhaust." *EPA/600/8-90/057F*, U.S. Environmental Protection Agency, Washington, D.C.

Frey, H. C., Kim, K., Pang, S.-H., Rasdorf, W. J., & Lewis, P. (2008). "Characterization of Real-World Activity, Fuel Use, and Emissions for Selected Motor Graders Fueled with Petroleum Diesel and B20 Biodiesel," *Journal of the Air and Waste Management Association, 58*(10), 1274-1287.

Frey, H. C., Rasdorf, W., Kim, K., Pang, S.-H., Lewis, P., & Abolhassani, S. (2008). "Real-World Duty Cycles and Utilization for Construction Equipment in North Carolina," Dept. of Civil, Construction, and Environmental Engineering, North Carolina State University, Raleigh, NC.

Kim, K. (2007). *Operational Evaluation of In-UseEmissions and Fuel Consumption of B20 Biodiesel versus Petroleum Diesel-Fueled Onroad Heavy-Duty Diesel Dump Trucks and Nonroad Construction Vehicles.* Doctor of Philosophy, North Carolina State University, Raleigh, NC.

Lewis, P. (2009). *Estimating Fuel Use and Emission Rates of Nonroad Diesel Construction Equipment Performing Representative Duty Cycles.* Doctor of Philosophy, North Carolina State University, Raleigh, NC.

Lewis, P., Leming, M., & Rasdorf, W. (2012). "Impact of Engine Idling on Fuel Use and CO_2 Emissions of Nonroad Diesel Construction Equipment," *Journal of Management in Engineering, 28*(1), 31-38.

Mudgal, A., Gopalakhrishnan, K., & Hallmark, S. (2011). "Prediction of Emissions from Biodiesel Fueled Transit Buses using Artificial Neural Networks," *International Journal for Traffic and Transport Engineering*, 1 (2), 115-131.

Rasdorf, W., Frey, C., Lewis, P., Kim, K., Pang, S.-H., & Abolhassani, S. (2010). "Field Procedures for Real-World Measurements of Emissions from Diesel Construction Vehicles," *Journal of Infrastructure Systems, 16*(3), 216-225.

Tehranian, A. (2003). *Effects of Artificial Neural Networks Characterization on Prediction of Diesel Engine Emissions*. Master of Science, West Virginia University, Morgantown, WV.

Thompson, G. J., Atkinson, C. M., Clark, N. N., Long, T. W., Hanzevack, E., (2000). "Neural Network Modeling of the Emissions and Performance of a Heavy-Duty Diesel Engine", *Proc. Inst. Mech. Engrs*., 214, part D, 111-126.