NOVEL DATA ANALYSIS TECHNIQUE TO EVALUATE FIELD NO_x AND CO_2 CONTINUOUS EMISSION DATA

BASED ON THE EVALUATION OF: (1) AN OFF-ROAD DIESEL COMPACTOR RUNNING ON THREE FUEL TYPES AND (2) TWO COMPACTORS RUNNING ON DIESEL FUEL

By

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Submitted to the graduate degree program in the Department of Civil, Environmental, and Architectural Engineering and the Graduate Faculty of the University of Kansas in partial fulfillment of the requirements for the degree of Doctor of Philosophy.

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Abstract

In spite of being few in number, off-road vehicles have a significant contribution to air pollutants such as NO_x and CO_2. Engine dynamometer test cycles have been developed in an effort to better characterize the emissions from off-road vehicles. However, these test cycles may not accurately represent the emission profiles under normal operating conditions. The current study seeks to: (1) collect real-world NO_x and CO_2 emission profiles from an off-road diesel vehicle; (2) analyze NO_x and CO_2 emission profiles for a diesel off-road vehicle running on no. 2 diesel, 20% biodiesel mix (B20) and ultra-low sulfur diesel (ULSD) fuels to determine potential emission reductions; (3) test the effect that temporal factors exert on NO_x and CO_2 emission profiles; (4) evaluate the emission variability between two pieces of equipment of the same model; and (5) develop a standard, systematic analysis for handling large emission data sets.

The study is based on the tailpipe emission sampling of a diesel fueled 525-horsepower Trashmaster 3-90E trash compactor operated at the N.R. Hamm Landfill facility located near the city of Perry in Jefferson County, Kansas. The sampling instrument used for the study is the Simple, Portable, On-vehicle Testing (SPOT) system manufactured by Analytical Engineering Inc. The SPOT is able to collect second-by-second data for total exhaust mass flow, relative humidity, engine speed, and NO_x and CO_2 emissions among other parameters. The fuel types used include regular no. 2 diesel, B20 and ULSD. The sampling campaign took place in two stages: (1) running the compactor with regular no. 2 diesel from August 28 to September 1 and with B20 and ULSD fuels from September 12 to September 15, 2005, and (2) running a second compactor of the same model with no. 2 diesel. The purpose of the first stage of the project was to determine the possible emission reductions from the use of B20 and ULSD. The purpose of the second stage was to test the emission variability between two compactors of the same model. This is relevant since it is commonly assumed that the emission profile from one engine is representative for all engines of the same type and family.

Initial data analysis showed a significant autocorrelation in the NO_x and CO_2 data observations. Autocorrelation is inherent in continuous data sets where sequential observations are too close together to be independent from each other and must be resolved so that a robust statistical analysis may ensue. By using a time interval data reduction technique a set of quasi-independent observations was produced. This technique allowed for a valid use of the general linear model (GLM) with e*ngine speed* as

the covariate factor to test *day*, *fuel type* and *compactor* factors. For the first stage of the project the results from the GLM showed that neither *day* nor *fuel type* factors were statistically significant on NO_x and CO_2 emissions. These results suggest that NO_x and CO_2 emissions are not dependent on the day in which they were collected or on the fuel type used. The second stage of the project involved the comparison of NO_x and CO_2 emissions from two compactors of the same model while running on no. 2 diesel fuel. The results from the temporal analysis indicated that the *day* factor was not statistically significant for either of the two pollutants. Results from the compactor analysis showed that *compactor* was not a statistically significant factor on NO_x emissions. However, the interaction of *compactor* and *engine speed* factors was found to be statistically significant on NO_x emissions. For CO_2 emissions the results indicated that *compactor* was a statistically significant factor. These results suggest that the there is a statistically significant difference between the NO_x and CO_2 emissions obtained from each of the two compactors. However, this difference is expressed differently in each of the two data sets.

In addition to the GLM analyses, a data fitting model analysis was also completed for NO_x and CO_2. The results showed that the linear and the cubic models do a good job of fitting the NO_x and CO_2 data and they both have high R^2 values. These data fitting technique may be used to estimate NO_x and CO_2 emissions based solely on engine speed after an emission profile has been collected. This information can be of great import to obtain more accurate emission estimates from off-road diesel vehicles.

This study makes three main contributions including the development of a data handling technique to deal with autocorrelation in continuous data. This study also showed that the three fuel types evaluated had no significant effect on NO_x and CO_2 emissions. Finally, the evaluation of two Trashmaster 3-90E compactors showed that NO_x and CO_2 emissions are significantly different between the compactors.

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I. INTRODUCTION

I.A. Statement of problem

The diesel engine plays a vital role in transportation, power generation, farming, construction and industrial activities. The primary advantages of this type of engine include its durability and its lower fuel consumption when compared to the gasoline spark ignition engine. The diesel engine also provides more energy per unit of fuel than a gasoline engine. At full load, a diesel engine uses approximately 70% of the fuel a comparable gasoline engine consumes for the same output (Lloyd et al., 2001). However, exhaust emissions from diesel engines are also an important source of air pollutants.

Diesel particulate matter is considered a hazardous pollutant with known health risks (U.S. EPA 2000C; CARB, 1999). Particulate matter (PM) and nitrogen oxides (NO_x) are two of the main criteria pollutants posing an important risk to public health. NO_x formation is related directly to the high temperature of the engine combustion chamber. These compounds are also an important contributor to ozone formation and irritation of the eyes, nose, throat and lungs. Particulate matter (PM) emissions result from incomplete combustion in the engine chamber. Studies have linked PM emissions with respiratory and cardiovascular conditions (U.S. EPA, 2004C). Also, growing concerns about global warming highlight the importance of CO_2 emissions from diesel engines and other combustion sources.

Research into engine emissions has historically focused on on-road vehicles. As a result, since 1985 emission standards have become more stringent for diesel on-road vehicles, whereas off-road vehicles and equipment have been subject to less stringent regulations. This situation changed in 1994, when the United States Environmental Protection Agency (EPA) adopted the first set of emission standards (Tier 1) for all new off-road diesel engines greater than 37 kilowatts (50 horsepower), except those used in locomotives and marine vessels (40 CFR 89). Further Tier 1 standards were introduced for engine sizes between 1996 and 2000 to reduce NO_x emissions by 30 percent (U.S. EPA, 2003C). Since then, the gap in emissions limits between on-road and off-road has closed rapidly. However, as of 2003, land-based off-road diesels accounted for 44 and 12 percent of the mobile source emissions of PM and NO_x, respectively (U.S. EPA, 2003A). A recently promulgated emission standard relevant to off-road vehicles calls for a reduction of sulfur in diesel fuel to 15 ppm by 2010. This reduction in sulfur is aimed at reducing PM emissions and enabling the use of advanced aftertreatment technologies such as catalytic particulate filters and NO_x adsorbers. Along with the reduction of sulfur, alternative fuels such as biodiesel may help in minimizing the harmful emissions from diesel fuel.

The emissions characterization for off-road diesel vehicles is not nearly as comprehensive as it is for on-road vehicles. This is true because of the wide variety of off-road diesel vehicles and equipment and the high cost of engine and chassis dynamometer testing. Recent research has exposed the limitations of laboratory testing in accurately characterizing emission profiles of on-road and off-road vehicles. Results from continuous sampling systems have shown that the existing test cycles for chassis and engine dynamometer cycles do not accurately characterize the actual (real-world) duty cycles of on-road and off-road vehicles. For example, Shah, et al. (2004) found that diesel emissions of elemental carbon, organic carbon and particulate matter depend strongly on the mode of operation. Yanowitz et al. (2000) also found that NO_x emissions are proportional to work done by the engine. These results emphasize the need for real-world data that characterize the relationship between duty cycles and emission profiles for diesel equipment. For this and other reasons, research has shifted towards on-board systems that are capable of collecting duty-cycle data and yield a more accurate emission profile.

Historically the air emission contributions from off-road vehicles have been overlooked since this equipment tends to be small in number and their use is generally transient and localized to a certain work site or location. In spite of being few in number, off-road vehicles make a significant contribution to air pollutants such as NO_x, PM and CO_2. It is estimated that in the US 20 million diesel engines are in operation: 13 million are on-road and 7 million are off-road vehicles (U.S. EPA, 2009A). In comparison it is estimated that 210 million cars and light duty trucks in the US (U.S. EPA, 2012A) are in operation. Furthermore, the turnover of diesel engines is slower since these engines can last between 20 and 30 years. The EPA estimated that 11 million diesel vehicles do not meet the 2005 emission standards (U.S. EPA, 2006). Thus, it is important to characterize the emissions contributions from off-road diesel equipment more accurately. The current study seeks to help in this effort by using an on-board system to collect and analyze tailpipe emissions from an off-road vehicle operating under normal conditions.

I.B. Objectives and Significance

The current study seeks to analyze NO_x and CO_2 emissions from an off-road diesel vehicle collected with a continuous emissions sampler. The first stage of the sampling involved the collection of emissions data from an off-road diesel vehicle run with three fuel types: no. 2 diesel, ultra-low sulfur diesel (ULSD, average sulfur content of 15 ppm) and 20% biodiesel mix (B20). The second stage involved the emission testing of a second off-road diesel vehicle of the same model for comparison with the one used in the first stage of the emission testing. The emissions from this compactor were sampled while it ran on no. 2 diesel fuel only. These data were then compared and analyzed with the data from the diesel portion collected from the first compactor.

The objectives of this project include

1. Collecting NO_x and CO_2 emission profiles from an off-road diesel vehicle on a second-by-second basis while under normal operation;
2. Analyzing NO_x and CO_2 emission profiles for a diesel off-road vehicle running on no. 2 diesel, 20% biodiesel mix (B20) and ultra-low sulfur diesel (ULSD) fuels to determine potential emission reductions;
3. Testing the NO_x and CO_2 emission variability between two pieces of equipment of the same model run with no. 2 diesel fuel;
4. Testing the effect that temporal factors exert on NO_x and CO_2 emission profiles;
5. Developing models to predict NO_x and CO_2 emissions from engine speed data.

The approach involves the gathering of continuous field data from an off-road diesel compactor. These type of data are valuable in investigating the relationship between diesel emissions and engine parameters. The sampling system for this study collects continuous NO_x and CO_2 exhaust emissions. By analyzing these data, we seek to assess whether the use of B20 and ULSD fuel can reduce NO_x and CO_2 emission by comparing them to baseline emissions from diesel fuel. The purpose is to find out if either of these two fuels is able to provide significant reductions in NO_x and CO_2 emissions. Additionally, by comparing the emissions profiles of two comparable compactors running on diesel fuel we can identify any differences and similarities related to testing separate equipment. This compactor analysis indicated whether the emission profiles from two compactors of the same type are similar to each other or not. This is relevant because currently it is assumed that emissions from an engine test are representative for all engines of the same type or family. This comparison is also useful in assessing the repeatability of emission profiles from two compactors and gives insight into the variability that may exist between equipment of the same type.

II. LITERATURE REVIEW

II.A. Diesel Engine

The diesel compression engine was invented by Rudolf Diesel in 1892. This type of engine produced a significant amount of power while being fuel efficient and durable. During the early 1900's diesel engines spread throughout the United States and Europe and ultimately replaced the steam-powered engines for heavy-duty applications in marine transportation and some industrial applications. Diesel engines could withstand heavy loads at relatively low speeds. Technological advances in the 1930's raised the operating speeds and decreased engine weight, allowing the use of diesel engines for on-road applications. A two-cycle diesel engine developed by General Motors was also introduced for use in railroads and was later adapted for trucks and buses (Williamson et al., 1963). From this point on, the movement of freight and passengers has depended heavily on the diesel engine.

Currently, the diesel engine is the prime mover in our society due to its power, fuel efficiency and long life span. The diesel engine is designed to reach higher peak pressures and temperatures than the spark ignited gasoline engine. This makes diesel engines heavier and more costly but also more durable and fuel efficient. At full load, the diesel engine uses only 70% of the fuel that a comparable gasoline engine consumes for the same power output (Lloyd and Cackette, 2001).

PM and NO_x are the main emissions produced from diesel fuel combustion. The process of combustion in a diesel engine occurs when the fuel blend is injected at high velocity into the cylinder where air has been compressed at a high temperature and pressure. The injected fuel does not ignite immediately but undergoes a period of ignition delay. During this ignition delay, the fuel heats up, vaporizes, mixes with the air and undergoes chemical pre-combustion reactions that produce the radicals necessary for spontaneous ignition. Ignition then occurs spontaneously at multiple nuclei in regions of stoichiometric (theoretical minimum for complete combustion) balance between fuel and air reactants. Thus, PM is formed in the areas of incomplete combustion where the air-to-fuel ratio is low. These reactions are controlled by the rate at which air is entrained and a combustible mixture is formed. Combustion in diesel engines occurs under lean-burning conditions; the excess air in the reaction results in a large amount of water vapor and oxygen in the exhaust. The nitrogen and oxygen in the excess air, along with the high temperature of the combustion chamber, create an ideal environment for NO_x production to ensue.

Diesel engines power more than 3 million highway trucks and buses and at least 6 million pieces of off-road heavy equipment (Moran, 2003). However, these diesel powered vehicles were left virtually unregulated until 1996. In 1996, the emissions from land-based non-road diesel engines, locomotive engines and marine diesel engines were estimated to be about 40 percent of the total mobile-source inventory of $PM_{2.5}$ and 25 percent of the NO_x inventory (U.S. EPA, 2004D). Also in 1996, land-based non-road diesel engines accounted for about 47 percent of the $PM_{2.5}$ emitted from all diesel engines.

II.B. Diesel Emissions

The emissions from diesel engines include a mixture of compounds in the vapor phase and very fine particles with a carbon core coated by condensed organic compounds. The gaseous constituents include carbon dioxide, carbon monoxide, nitric oxide, nitrogen dioxide, oxides of sulfur, and hydrocarbons (Dawson, et. al., 1998). The combustion process forms solid carbon cores that interact with each other and form chains and cluster aggregates. It is estimated that more than 98% of these particles are less than 1 micrometer in size (Bagley, 1996). Two of the most important emissions that are associated with diesel engines are PM and NO_x. Additionally, a growing interest in global warming highlights the attention placed on CO_2 emissions from combustion sources including diesel engines.

II.B.1 Health Effects of Diesel Exhaust. Adverse human health effects are known to be caused by exposure to diesel emissions (U.S. EPA, 2002B). The health risks identified are derived from extensive studies of human workers as well as some studies in animals, and observations of mutagenic activity in culture systems. Some of these health effects include aggravation of bronchitis and asthma, decreased lung function, decreased respiratory defense mechanisms, acute respiratory illness and increased risk for lung cancer. These effects can range from acute to chronic and in some cases they can lead to decreased life span.

Critical reviews from scientific journals (Lloyd and Cackette, 2001; Pope and Dockery, 2006) and government agencies (U.S. EPA, 2004C; CARB, 2000) have analyzed the numerous animal and human studies that relate adverse human health effects to diesel exhaust exposure. The research data obtained from these studies is extensive and confirms the chronic and acute health effects from diesel exhaust exposure. Although, some gaps still exist in the understanding of biological mechanisms that link adverse health conditions to diesel exhaust exposure, it is reasonable to conclude that exposure to diesel exhaust significantly increases human health risks.

The health effects from diesel exhaust exposure are commonly divided into two groups: 1) acute and chronic noncancer adverse respiratory health effects and 2) carcinogenic health effects. The first category is caused by fine and ultrafine particles (smaller than 0.1 micrometers) that are highly respirable and penetrate deep inside the lungs. Ultrafine particles also have a large surface area, which makes them an excellent carrier for adsorbed inorganic and organic compounds. Some of the most toxic organic compounds adsorbed onto the particles include polycyclic aromatic hydrocarbons (PAHs), nitro-PAHs, and oxidized PAH derivatives (U.S. EPA, 2000C). Diesel exhaust is also composed of hazardous particles and vapors, some of which are known or probable carcinogens.

According to the California Environmental Protection Agency (Cal/EPA, 1998), diesel exhaust can cause noncancer health effects including acute irritation (e.g. eyes, throat, and bronchial irritation), neurophysiological symptoms (e.g. lightheadedness and nausea), and respiratory symptoms (cough and phlegm). Evidence also suggests possible immunological effects and/or exacerbation of allergenic responses to known allergens. These effects aggravate respiratory illnesses such as bronchitis, emphysema and asthma. These symptoms are associated with premature deaths from cardio-pulmonary disorders. Exposure to fine particles causes changes in the lung function and inflammation of the small airways. Also PM exposure may increase susceptibility to bacterial or viral respiratory infections, and may increase the incidence of respiratory disease in vulnerable groups such as the elderly, people with chronic pulmonary diseases, and people with immune system dysfunction. In the presence of pre-existing heart or lung disease, respiratory exacerbations induced by air pollutants may lead to death.

Cancer health effects have been documented in numerous animal and human studies. In 1988 the National Institute for Occupational Safety and Health (NIOSH) recommended that diesel exhaust be regarded as a potential carcinogen. According to more than 30 epidemiological studies, people who are routinely exposed to diesel exhaust through their work on railroads, docks, trucks, or buses have a greater risk of lung cancer (CARB, 1998). On average, long-term occupational exposure to diesel exhaust is associated with an increase of about 40% in the relative risk of lung cancer (Lipsett et al., 1999; Cal. EPA, 1998). CARB (2000) estimates that diesel exhaust is responsible for 70 percent of California's cancer risk from airborne toxic pollution. This translates to 540 additional cancers per million people exposed to current outdoor levels of diesel pollution over a 70-year lifetime.

In 1989, the International Agency for Research on Cancer (IARC) concluded that diesel exhaust was a probable carcinogen to humans (WHO, 1989). In 1990, based on the IARC findings, the State of California identified diesel exhaust as a chemical known to cause cancer (Cal. EPA, 2012). Subsequently, the Health Effects Institute (1995), the World health Organization (1996), the U.S. Department of Health and Human Services (2001), the American Council of Government Industrial Hygienists (2001), and the EPA (2002) declared diesel exhaust as a likely human carcinogen.

II.C. Particulate Matter

Formation of particulate matter (PM) occurs in the center of the fuel spray where the air-to-fuel ratio is low. As the soot cools, organic compounds derived from the fuel and the lubricating oil adsorb onto the particle surface or may form organic aerosol by homogenous nucleation. Figure 1 below shows a conceptual model of such process.

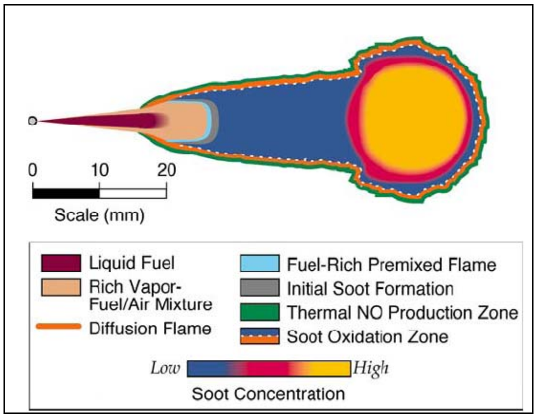


Figure 1. Conceptual model showing the main features of a reacting diesel fuel jet during quasi-steady portion of combustion (Dec, 1997).

Diesel aerosol consists of highly agglomerated solid carbonaceous material and ash, volatile organic and sulfur compounds. A schematic of this structure is shown in Figure 2 below. PM can be released directly from the exhaust stream or it may form as a secondary particle once nitrogen oxides, hydrocarbons and sulfur oxides released from the tail pipe react in the atmosphere. The diesel particles released directly from the tailpipe are composed of a carbon core with an array of toxic compounds including metals, polycyclic aromatic compounds (PAHs) and dioxins adsorbed to the particle's surface.

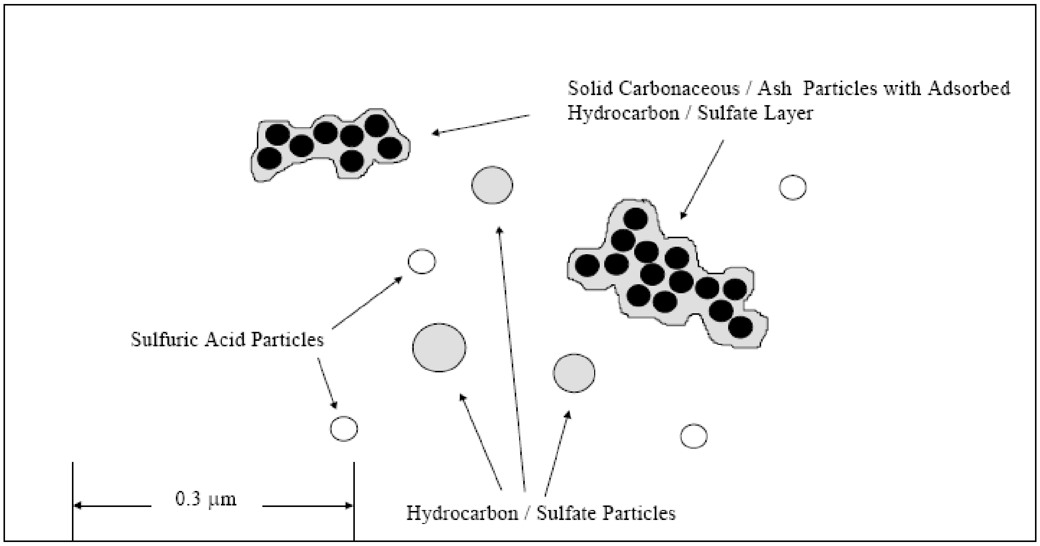


Figure 2. Typical structure of engine exhaust particles (Kittleson, 1998).

Solid carbon is formed in the combustion chamber in fuel rich regions. Much of this carbon is then oxidized as solid agglomerates. A small fraction of the fuel and atomized and evaporated lube oil escape oxidation and appear as volatile or soluble organic compounds called soluble organic fraction (SOF). The SOF contains polycyclic aromatic compounds containing oxygen, nitrogen and sulfur. Most of the sulfur in the fuel is oxidized to SO_2 and a small fraction is oxidized to SO_3, leading to sulfuric acid and sulfate aerosol. The metal compounds in the fuel and lube oil lead to a small amount of inorganic ash.

A heavy-duty diesel engine tested under the U.S. Heavy Duty Transient Test (CFR Title 40, Part 86.1333) reveals the composition of particulate matter from diesel exhaust as depicted in Figure 3. The fraction associated with unburned fuel and lube oil (SOF) varies with engine design and operating condition. It can range from 10% to 90% by mass. SOF values are highest at light engine loads when exhaust temperatures are low (Kittelson, 1999).

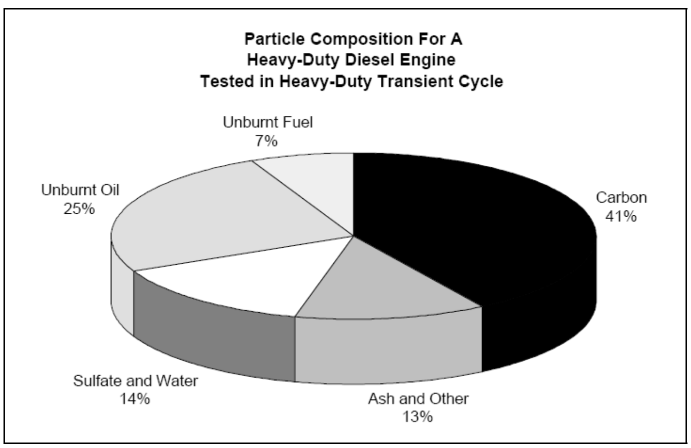


Figure 3. Particle composition for a heavy-duty diesel engine tested in a heavy-duty transient cycle (Kittelson, 1998).

<u>C.1. Aerosol Size Distribution.</u> The distribution of diesel aerosols is trimodal and lognormal in form (Kittleson, 1998). Figure 4 below shows the idealized diesel aerosol number and mass weighted size distributions. Most of the particle mass exists in the *accumulation* mode in the 0.05 to 1.0 micrometer diameter range. This is where the carbonaceous agglomerates and associated adsorbed material reside. The *nuclei* mode typically consists of particles in the 0.005 to 0.05 micrometer diameter range. This mode

usually is composed of volatile organic and sulfur compounds formed during exhaust dilution and cooling. The *nuclei* mode usually contains between 1-20% of the particle mass and more than 90% of the particle number. The *coarse* mode contains between 5-20% of the particle mass. It consists of *accumulation* mode particles that have been deposited on cylinder and exhaust system surfaces and later reentrained. By number, nearly all particles emitted by a diesel engine are nanoparticles that have a diameter of less than .05 micrometers. The same pattern is true for gasoline engine emissions.

Motor vehicles are a major source of nanoparticles in urban areas. Recent studies conducted in Southern California have shown high counts of these particles near freeways. Substantially higher numbers of particles are found near the roadway, while a sharp reduction in particle count has been shown to occur within 100- 300 meters downwind of the roadway (Zhu, 2002). These particle sizes are important because for a given mass concentration, nanoparticles have much higher numbers and surface areas compared to larger particles. These particles can act as carriers for other compounds, such as trace metals and organic compounds that can adsorb on the particles' surfaces. Thus, due to nanoparticles' larger surface area, more toxic compounds may be transported into the lungs than with larger particles. Furthermore, these particles can also be inhaled and deposited deeper into the lungs than larger particles. As much as 50% of the particles with 0.02 μm or smaller are estimated to be deposited in the alveolar region of the lung (SCAQMD, 2007).

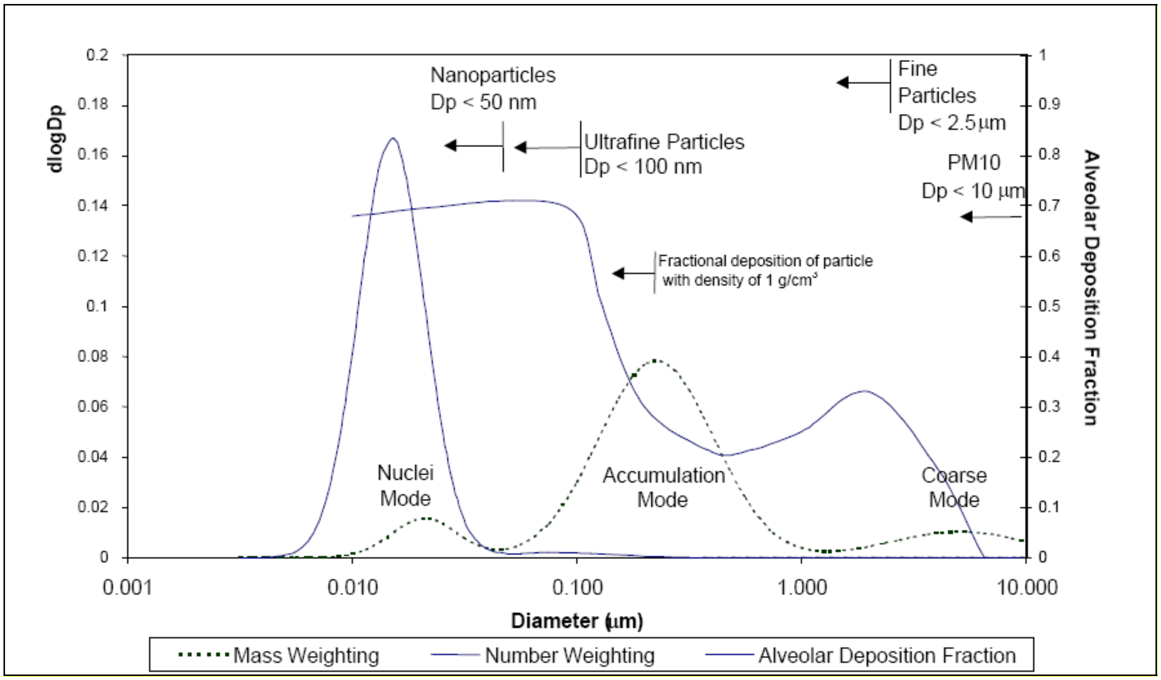


Figure 4. Typical engine exhaust size distribution. Mass and number weights are shown (Kittelson, 1998).

<u>C.2. Health Effects</u>. Diesel engines emit elemental carbon, adsorbed organic compounds, and small amount of sulfate, nitrate, metals, and other trace element particles. These diesel particulates are emitted in distinct sizes. The larger particles settle rapidly to the ground and finer particles remain suspended in the air for a longer time and may be able to travel in winds for hundreds of miles. Large particles that are inhaled get trapped by fine hairs and mucus in the nose, throat and large airways and thus pose a lower health risk than smaller size particles. Particles less than about 10 microns in diameter (PM_{10}) are more likely to make their way into the deeper portion of the lungs (U.S. EPA, 2000C). Scientific research has also found that $PM_{2.5}$ (diameter smaller than 2.5 micrometers) and ultrafine (diameter less than 0.1 micrometers) particles can travel deep into the lungs and lodge in the alveoli. There particles need to be cleared by cells of the immune system over a period of months or years. However, some of these particles are never cleared from the body and they accumulate in the lungs and the lymph nodes (Chung and Brauer, 1997). Autopsy studies of people living in urban areas have found significant blackening of the lungs due to the accumulation of fine particles (Pratt and Kilburn, 1971). Additionally, the fine particles emitted from diesel engines are coated with a mixture of PAHs, nitroaromatics, benzenem dioxins and other toxic substances

that irritate the respiratory system and can cause and exacerbate respiratory conditions and can lead to premature death. Sensitive populations include children, elderly, asthmatics, and individuals with preexisting respiratory or cardiovascular diseases.

C.3. Issues in Particulate Matter Sampling. The EPA has been regulating particulate matter smaller than 10 microns in size (PM_{10}) since 1987. However, it is estimated that 98 percent of the PM from diesel exhaust are smaller than one micron in diameter and can lodge and linger in the deepest air sacs of the lung (Bagley, 1996). PM_{10} regulations are mass-based, emphasizing the reduction of larger, heavier particles such as those occurring from earth-moving in construction and agriculture. Based on the significant risks associated with fine particles, the EPA adopted new National Ambient Air Quality Standards for particles smaller than 2.5 micrometers in size ($PM_{2.5}$) on September 16, 1997 (U.S. EPA, 1997).

Evidence suggests that fine particles may contain more reactive substances linked to health impacts than coarse particles (SCAQMD, 2007). It is estimated that between 80 and 90 percent of diesel particles fall in the ultrafine size range of 0.05 to 1.0 micron (U.S. EPA, 2000C). However, current regulations do not address growing concerns about health effects of ultrafine and nanoparticles which are difficult to measure with today's technology. These smaller particles penetrate deeper into the respiratory tract and their large surface to volume ratio could allow for more biological interaction. However, a reliable testing instrument to ensure an accurate and consistent measurement of these particles is not currently available.

Measurement of diesel aerosol is affected by three primary parameters: the environmental conditions experienced by the emissions, the sampling/measurement system used to characterize the emissions, and the chemical and physical composition of the engine emissions. An understanding of how exhaust conditions interact with exhaust constituents is critical to determine size distribution and composition. Some issues related to sampling of nanoparticles include the correct simulation of atmospheric dilution. The gas to particle conversion may happen in three ways: nucleation, condensation/adsorption, and adsorption (Kittelson, 2003). Nucleation causes a homogeneous formation of new particles. In condensation/adsorption gas molecules transfer into liquid droplets. And in adsorption, a layer of molecules is formed on solid particles. Coagulation is the other homogenous process based on particle to particle collision. Heterogeneous processes include the loss of particles (or particle precursors) to walls of sampling and dilution system and storage and release of particle precursors on walls of sampling and dilution system. It is estimated that more than 90% of the particle number may form through homogeneous nucleation of nanoparticles. From 5% to more than 50% of the particle mass may form through adsorption and nucleation (Kittelson et al., 2002). These processes are extremely sensitive to sampling and dilution conditions.

Few commercial portable emission measurement sampling instruments accurately measure particulate matter. Apparently, only three companies have such sampling devices available on the market. The SEMTECH-QCM (Quartz Crystal Microbalance) manufactured by Sensors Inc. uses electrostatic precipitation to collect aerosol particles from a known volume of air and deposit the particles on an oscillating piezoelectric crystal (Buchholz, 2004). The PM1065 PM Sampling System by Analytic Engineering Inc. (AEI) measures particulate mass, and the company claims that it exceeds the 40CFR part 1065 requirements in its testing. This system uses partial dilution and is recommended for steady and transient state applications (AEI, 2006). The Montana system by Clean Air Technologies Inc. (CATI) also measures particulate matter based on light scattering. However, the three systems were designed to measure PM mass, and they are not able to speciate by particle size.

These systems collect PM measurements from diesel exhaust. Only the Montana system by CATI is able to measure PM emissions from an off-road vehicle outside of a lab environment. However, this system uses qualitative light scattering techniques to obtain analogous PM measurements. Thus, at this point in time there is no system that is able to quantify PM emissions from off-road vehicles during real world conditions. Therefore, the current study does not address PM diesel emissions but focuses on NO_x and CO_2 emissions instead.

II.D. Nitrogen Oxides

II.D.1. Nitrogen Oxides Formation. Nitric oxide (NO) and nitrogen dioxide (NO_2) are the primary nitrogen oxides (NO_x) produced by diesel engines. NO_x is formed by four routes: the thermal route, the prompt route, the NO_2 route and the fuel-bound nitrogen route (Bowman, 1992). Out of these four routes, the fuel-bound nitrogen route is important only for coal combustion, and the NO_2 route is not a significant source of NO (Warnatz, 1999). Prompt NO results from a reaction between CH and N_2, and caused by the low activation energies of the reactions involved, is favored at lower temperatures (about 1000° K). However, thermal NO is favored at higher temperatures and is therefore the most significant source of NO_x for diesel engines.

Thermal NO is formed by the elementary reactions depicted in Figure 5. The first reaction is the rate-limiting reaction since it requires a very high activation energy due to a strong triple bond in the N_2 molecule. However, the combustion reaction inside the diesel engine is able to provide the necessary energy that makes this a viable and fast reaction.

$$O + N_2 \xrightarrow{k_1} NO + N \quad k_1 = 1.8 * 10^{14} \ \exp(-318 \text{ kJ mol-1} / (RT)) \text{ cm}^3/(\text{mol s})$$
$$N + O_2 \xrightarrow{k_2} NO + O \quad k_2 = 9.0 * 10^{9} \ \exp(-27 \text{ kJ mol-1} / (RT)) \text{ cm}^3/(\text{mol s})$$
$$N + OH \xrightarrow{k_3} NO + H \quad k_3 = 2.8 * 10^{13} \ \text{cm}^3/(\text{mol s})$$

Figure 5. Elementary reactions for thermal NO_x formation.

In the diesel combustion chamber, NO_x is created where the air to fuel ratio is near stoichiometric and high temperatures are generated. Retardation of injection timing, relative to optimum timing for fuel economy, can decrease the NO_x emissions. However, retarding the injection timing typically lowers fuel efficiency which results in higher PM emissions. Thus, a delicate balance must be kept to keep both PM and NO_x emissions controlled.

II.D.2. Health Effects. Two of the most toxicologically significant nitrogen oxides, nitric oxide and nitrogen dioxide, are produced primarily by combustion sources. NO_x's are broken down rapidly in the atmosphere. Reaction with chemicals in the air produced by sunlight leads to the formation of nitric acid, a major component of acid rain. NO_2 also reacts with sunlight, leading to the formation of ozone and smog conditions in the ambient air. Health effects from exposure to low levels of NO_x's include irritation of eyes, nose, throat, and lungs, possibly causing cough and shortness of breath, tiredness and nausea. Exposure to low NO_x levels also could be conducive to fluid build-up in the lungs 1-2 days after exposure (ATSDR, 2002). Breathing high levels of nitrogen oxides can cause rapid burning, spasms, and swelling of tissues in the throat and upper respiratory tract, reduced oxygenation of body tissues in the throat and upper respiratory tract, reduced oxygenation of body tissues, a buildup of fluid in the lungs and death.

II.E. Nitrogen Oxides and Particulate Matter Relationships

The inverse relation between NO_x and PM formation poses the primary challenge in lowering diesel engine emissions since control techniques are usually limited by a NO_x and PM tradeoff where strategies to reduce one pollutant generally result in an increase of the other. Nitric oxide formation is directly related to the temperature in the combustion chamber with increased temperatures in the combustion chamber resulting in higher NO_x emissions. However, PM is formed when there is incomplete combustion of diesel fuel. Reductions in PM emissions can be achieved by an improvement in fuel combustion that results in higher combustion temperatures and increased NO_x. Additionally, diesel engines operate with excess air, this lean burning condition creates an oxidizing environment that is favorable for NO_x formation.

II.F. Carbon Dioxide

Reports about global warming indicate that since the Industrial Revolution levels of atmospheric carbon dioxide have increased by more than 30 percent and reached concentrations higher than any observed in the last 420,000 years (Petit et al., 1999). In its Fourth Assessment Report, the Intergovernmental Panel on Climate Change (IPCC) concluded that “most of the observed increase in global average temperatures since the mid-20th century is very likely due to the observed increase in anthropogenic greenhouse gas (GHG) concentrations” (IPCC, 2007). As a result, GHG inventories of anthropogenic sources have been developed to identify the primary sources of GHGs and develop possible mitigation strategies. These inventories are relatively new and do not itemize off-road equipment specifically but include them in the transportation category. It is estimated that in 2009 about 23 percent of the CO_2 emissions in the world were produced from transportation activities (IEA, 2011).

The EPA estimates that in 2010 transportation emissions accounted for about 31% of the total CO_2 emissions. About 65 percent of these emissions were produced from gasoline consumption while the remainder was produced from other transportation activities including the combustion of diesel fuel in heavy-duty vehicles and jet fuel in aircraft (EPA, 2012B). Thus, off-road equipment is not considered a major source of CO_2 emissions. Nonetheless, obtaining a more accurate characterization of CO_2 emissions from these sources can aid in developing mitigation priorities and strategies to reduce GHGs.

II.F.1. CO_2 Formation. Diesel engines, like any other internal combustion engine, produce CO_2 emissions in the process of converting chemical energy from the fuel into mechanical power. Under ideal conditions, combustion of diesel fuel would produce only carbon dioxide (CO_2) and water vapor (H_2O) (Majewski, 2012) - the two most important greenhouse gases in the atmosphere. However, under real world conditions it is estimated that each of these emissions only accounts for 12 percent of the total diesel emissions (ibidem). For most transportation modes, other greenhouse gases such as N_2O and CH_4 comprise a relatively small proportion of overall transportation related GHG emissions (approximately 2 percent combined) (EPA, 2008). Due to the increase in fuel consumption, CO_2 emissions increase with engine torque and speed (Abdelghaffar, 2011). This means that the higher the engine load, the higher the CO_2 concentrations that will be produced. This effect can also be attributed to the improvement in turbulence at higher speeds and the higher cylinder temperature at a higher engine torque that results in better oxidation of carbon atoms to form CO_2 (ibidem).

II.F.2. Health Effects. CO_2 is a simple asphyxiant that reduces oxygen availability in the air and at concentrations above 15,000 ppm some loss of mental acuity may be noted (EPA, 2012C). According to the EPA acute effects from CO_2 exposure can occur starting at a concentration of 20,000 ppm with a recommended maximum indoor concentration of 1000 ppm for continuous exposure. The Occupational Safety and Health Administration (OSHA) permissible emission limit (PEL) for CO_2 in indoor air is set a 5,000 ppm (OSHA, 2012). The ambient CO_2 concentrations have been found to be between 300 and 400 ppm (NOAA, 2012). As a reference, CO_2 concentrations in office buildings typically range from 350 to 2,500 ppm where the primary source of CO_2 is respiration of the building occupants. (Seppänen et al., 1999). Thus, the ambient CO_2 concentrations are well below any health threshold. This means that no direct adverse health effects exist to humans from exposure to ambient levels of CO_2.

II.F.3. Greenhouse Gas Regulations in the US. The legal basis for the regulation of GHG emissions originated from the April 2, 2007 US Supreme Court ruling stating that the EPA had the authority under the Clean Air Act to regulate greenhouse gas emissions from motor vehicles (U.S. Supreme Court, 2006). The Court also stated that EPA had to determine whether GHGs endanger public health or welfare, and whether emissions from new motor vehicles contribute to this air pollution. EPA issued endangerment and contribution findings in December 2009 (EPA, 2009B). Since then, the following GHG regulations have ensued: the mandatory reporting of GHG from large GHG emissions sources finalized on October 30, 2009, the GHG Tailoring Rule finalized on May 13, 2010, and the Carbon Pollution Standard for New Power Plants proposed on March 27, 2012. These regulations affect primarily stationary sources, however, more recent GHG regulations started shifting their focus to mobile sources.

II.F.4. CO_2 regulations for Mobile Sources. On April 1, 2010, EPA and the National Highway Traffic Safety Administration (NHTSA) finalized a national program setting standards to cut greenhouse gas emissions and increase fuel economy of cars and light trucks for model years 2012-2016. These agencies also issued a Final Rulemaking with standards for model years 2017-2025 on August 28, 2012 that calls for vehicle manufacturers to meet a CO_2 standard projected to be equivalent to 54.5 miles per gallon on an average fleet-wide basis.

Regulations affecting heavy-duty vehicles have also been issued by the EPA. In August 2011, EPA and NHTSA issued the first ever greenhouse gas and fuel efficiency standards for trucks and buses. Once effective, these standards will jointly reduce fuel use and greenhouse gas emissions from medium- and heavy-duty vehicles, which range in size from the largest pickup trucks and vans to semi-trucks (EPA, 2011).

CO_2 regulations do not currently cover off-road vehicles. However, it is just a matter of time before these sources become subject to regulations similar to those applicable to on-road vehicles.

II.G. Off-road Vehicles and Equipment

The term *off-road* defines a diverse collection of outdoor power equipment, recreational vehicles, farm and construction machinery, lawn and garden equipment, marine vessels, locomotives, and other. This equipment is also referred to as *non-road* equipment making the term interchangeable with *off-road* equipment. The EPA definition for an off-road engine is based on the principle of mobility/portability and includes engines installed on (1) self propelled equipment, (2) on equipment that is propelled while performing its function, or (3) on equipment that is portable or transportable, as indicated by the presence of wheels, skids, carrying handles, dolly, trailer, or platform (U.S. EPA, 2003B). Examples include farm tractors, excavators, compactors, bulldozers, wheel loaders, road graders, diesel lawn tractors, logging equipment, portable generators, skid steer loaders, and forklifts. These vehicles are very robust and durable so their turn-over rate is rather slow. Thus, newly enacted emission standards will not have an immediate effect on the exhaust emissions of these types of vehicles. The trash compactor used in this study fits the definition of both off-road and non-road vehicles.

II.H. Trends in PM and NO_x contributions from Off-road Vehicles

Emissions from off-road equipment negatively impact air quality in the US. The National Emission Inventory (NEI) compiles information from sources such as EPA's Toxics Release Inventory (TRI), the Acid Rain Program, as well as state, local and tribal air agencies. The estimated contribution that off-road equipment have in comparison with other emission sources is shown in Figures 6-8. The NEI program develops datasets, blends data from these multiple sources, and performs quality assurance steps that further enhance and augment the compiled data. The NEI emissions data are compiled for detailed emissions processes within a facility for large "point" sources or as a county total for smaller "nonpoint" sources and spatially dispersed sources such as on-road and non-road mobile sources.

The NEI evaluates all criteria air pollutants (CAPs) associated with the National Ambient Air Quality Standards (NAAQS) along with hazardous air pollutants (HAPs) associated with EPA's Air Toxics Program. In this section, PM_{10}, $PM_{2.5}$ and NO_x pollutants are depicted for 2000 and 2011. In addition to non-road diesel vehicles, NEI's non-road category includes: non-road gasoline, aircraft, marine vessels, railroads and other gasoline equipment. However, as discussed earlier, diesel off-road equipment are the major contributors to PM and NO_x emissions when compared to gasoline equipment. Thus, the NEI non-road category is useful to gage the magnitude of pollution that diesel off-road equipment exert of ambient air concentrations in the US.

When compared with all source categories, the PM_{10} contribution from off-road vehicles was 10% and 6% in 2000 and 2011 respectively (Figure 6). However, when only mobile sources are considered the off-road contribution to PM_{10} emissions is 58% and 40% for 2000 and 2011 respectively. This reduction can be attributed to the regulations that have started to encompass off-road equipment. Nonetheless, PM_{10} emissions from off-road equipment continue to have a significant contribution comparable to that of highway vehicles.

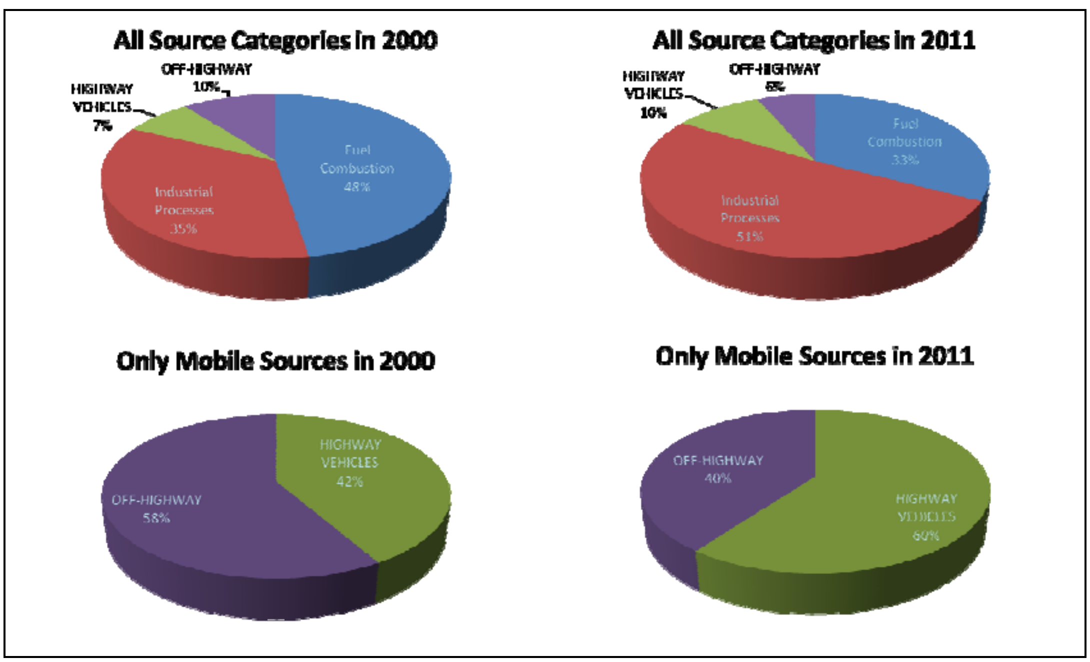


Figure 6. Comparison of PM_{10} contributions from different emission sources for years 2000 and 2011.

$PM_{2.5}$ emission trends are similar to the ones shown previously for PM_{10} (Figure 7). When compared with all source categories, the $PM_{2.5}$ contribution from off-road vehicles was 11% and 10% on 2000 and 2011 respectively. When only mobile sources are considered the off-road contribution to $PM_{2.5}$ emissions is 63% and 51% for 2000 and 2011 respectively. In 2011 off-road equipment still contributes more to $PM_{2.5}$ than highway vehicles. This shows that $PM_{2.5}$ emissions from off-road equipment have not decreased at the same rate as those from PM_{10}.

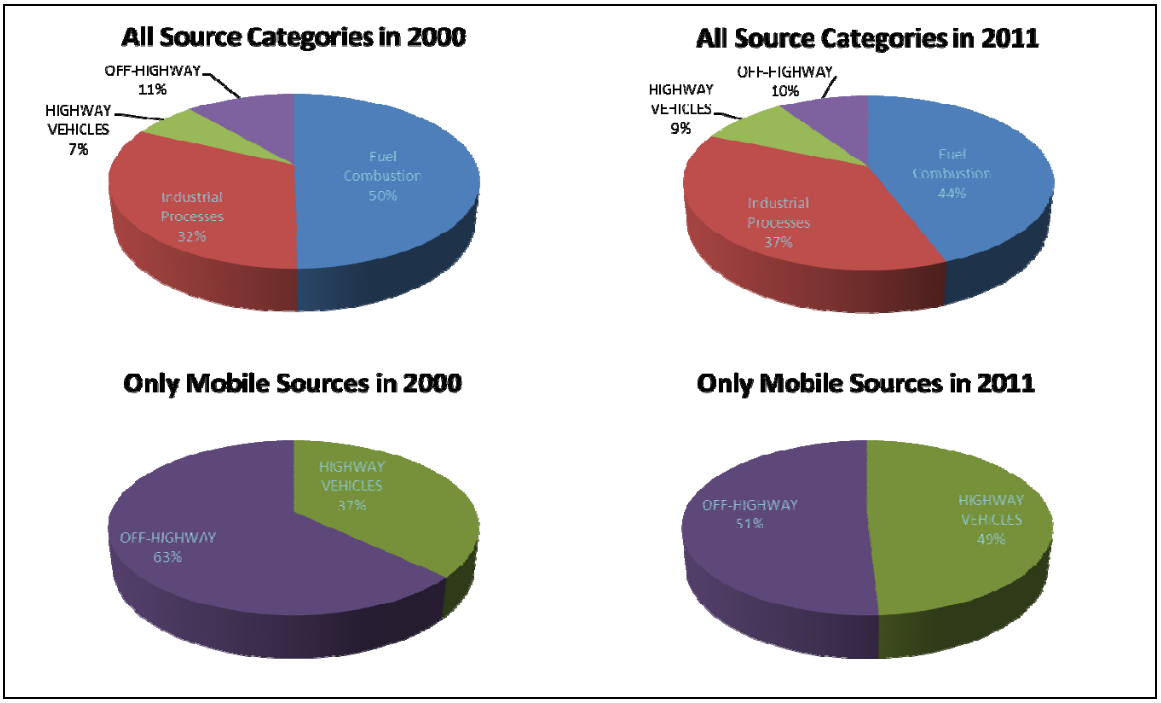


Figure 7. Comparison of $PM_{2.5}$ contributions from different emission sources for years 2000 and 2011.

The NO_x contribution from off-road emissions has increased slightly in the last decade. NO_x emission contributions have increased from 19 to 21 percent when compared to all the source categories and from 33 to 38 percent in the mobile source category (Figure 8). When compared with all source categories the NO_x contribution from off-road vehicles was 19% and 21% on 2000 and 2011 respectively. When only mobile sources are considered the off-road contribution to NO_x emissions is 33% and 38% for 2000 and 2011 respectively. This increase may be due to new regulations that have limited NO_x emissions from highway vehicles. Off-road NO_x emissions will continue to decrease as the Tier IV standards become effective for these equipment. However, since it is more challenging to control NO_x emissions from diesel engines, the contribution from these equipment most likely will continue to be significant when compared to highway vehicles that are mostly gasoline powered.

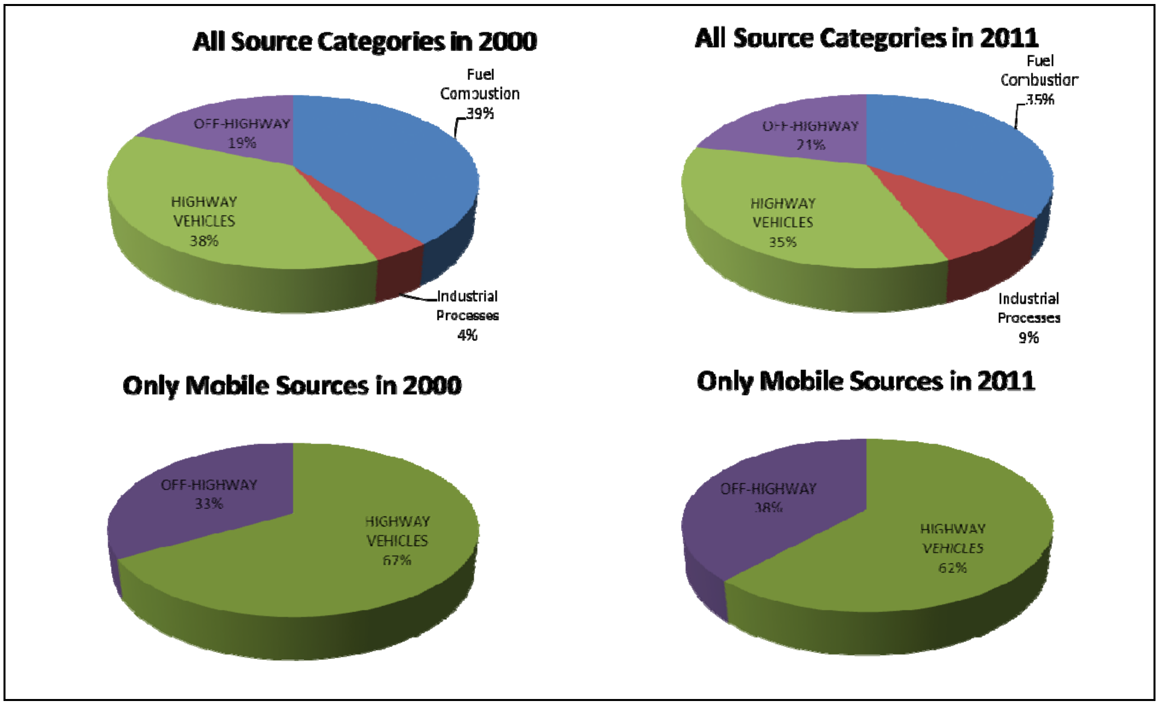


Figure 8. Comparison of NO_x contributions from different emission sources for years 2000 and 2011.

II.I. Fuels

Three fuel types are evaluated in the present study including one baseline fuel and two alternative diesel fuels. The baseline fuel considered for this study is the no. 2 diesel fuel in its conventional form. The two alternative fuels include the ultra-low sulfur diesel (ULSD) and the 20% biodiesel mix (B20). These two fuels are increasingly becoming more commonly used for on-road diesel engines. Thus, it is expected that their use will continue to increase in off-road vehicles also.

II.I.1. Petroleum Diesel. A mixture of many hydrocarbons with carbon numbers in the range of C9 to C28 and distillation range of 350 to 640 °F make up diesel fuel. Three types of diesel fuel are commonly used in the US: no. 1 diesel, no. 2 diesel, and no. 4 diesel. No. 1 and no. 2 diesel are used for highway and industrial applications. No. 4

diesel is a lower quality blend of distillates compared to no. 1 and no. 2 diesel and is used for low speed engines or non-automotive applications. (Singer and Harley, 1996).

The regular no. 2 diesel is also referred to as no. 2 low sulfur diesel, containing a maximum of 500 ppm and an average of 330 ppm of sulfur. This diesel is supplied to the Northeast Kansas area by Flint Hills Resources, LP, Corpus Christi TX and is distributed by Capitol City Oil (CCO) of Topeka. This fuel meets the ASTM D-975 diesel fuel specification.

<u>II.I.2. Ultra-low Sulfur Diesel.</u> Sulfur occurs naturally in crude oil, and is often removed in varying amounts at the refinery to create higher grades of gasoline and diesel fuel. To remove sulfur, the crude oil is heated and put under high pressure in the presence of hydrogen. The sulfur chemically combines with hydrogen and is removed as hydrogen sulfide (NYC DDC, 2004).

Sulfur significantly inhibits or impairs the function of diesel exhaust emission control devices. For example, catalysts with precious metals tend to oxidize sulfur dioxide (SO_2) to sulfur trioxide (SO_3) which inhibits the emission control performance of catalyst technology. It is expected that starting in 2011 this emission control technology will be available for road diesel engines (U.S. EPA, 2004D).

BP is one of the companies that produces and sells ULSD under the brand name of Emission Control Diesel (ECD). This fuel has maximum and average concentrations of 30 ppm and 15 ppm respectively. The no. 1 ULSD fuel was used for this study. No. 1 diesel fuel is typically used for colder climates since it is slightly lighter in density than the no. 2 diesel. Under the Clean Air Nonroad Diesel Rule announced by the U.S. Environmental Protection Agency in 2004, all off-road diesel engines are scheduled to be running on ULSD fuel since 2010. ULSD poses no compatibility or lubricity concerns to diesel engines and it is interchangeable with CARB or EPA diesel (BP America Inc., 2006). The ECD fuel meets the ASTM D-975 and the ASTM D-6078 lubricity specifications. Additionally, this fuel improves storage and thermal stability due to the hydrotreating process used to remove sulfur. The primary emission benefit from this fuel is a 18±1.5% particulate matter (PM) reduction (Durbin et al., 2003). One significant advantage of ULSD is that it allows for after-treatment technology and when used with a catalyzed particulate filter, a reduction of more than 90% in PM, hydrocarbons (HC) and carbon monoxide (CO) can be achieved.

II.I.3. Biodiesel. The first use of vegetable oil in a compression engine was demonstrated by Rudolph Diesel who used peanut oil in his diesel engine (Engler et al., 1992). However, the long term use of chemically unaltered vegetable oils leads to performance problems because of the high viscosity and low volatility of these fuels. The solution commonly used to avoid these conditions includes the transesterification of the oils with methanol or ethanol to form esters (Figure 9). In this process the glycerol esters of fatty acids (triglycerides) are exchanged for a lighter methanol or ethanol. The product is made up of fatty acid methyl esters (or ethyl esters) consisting of straight saturated and unsaturated hydrocarbon chains. The esters formed are commonly referred to as biodiesel. One of the most commonly used product is the soyate methyl ester (SME) made from the reaction of soybean and methanol (Wang et al., 2000).

$$
\begin{array}{lcccccl}
CH_2COOR_1 & & & & CH_3COOR_1 & & CH_2 - OH \\
| & & & & & & | \\
CHCOOR_2 & + & 3\ CH_3OH & \xrightarrow[(NaOCH_3)]{Catalyst} & CH_3COOR_2 & + & CH - OH \\
| & & & & & & | \\
CH_2COOR_3 & & & & CH_3COOR_3 & & CH_2 - OH \\
\text{Triglyceride} & & \text{Alcohol} & & \text{Mixture of} & & \text{Glycerin} \\
\text{(Vegetable oil)} & & & & \text{fatty esters} & &
\end{array}
$$

Figure 9. Transesterification reaction between triglycerides and alcohol.

In its pure form biodiesel is renewable, nontoxic and biodegradable. Biodiesel is also compatible with petroleum diesel fuel in compression-ignition engines and this allows for the use of a blended mix. In the US, the most common form of biodiesel used is a blended mix of 20% vol biodiesel and 80% petroleum diesel. The diesel portion of the fuel determines its toxicity and biodegradability. Exhaust emissions from biodiesel blends in general exhibits reductions in PM, HC and CO but an increase in NO_x concentrations.

Based on information from the supplier, the B20 fuel used in the study met the specifications from ASTM D6751. Table 1 below summarizes the fuel properties of the three fuels considered for this study. The three fuels have similar properties since they need to meet certain standards to be used in diesel engines. However, of particular interest is the sulfur content that is highest for diesel fuel at 500 ppm. The sulfur content in B20 is based on the assumption that the biodiesel portion has negligible amounts of sulfur and ULSD has the lowest sulfur content from the three fuels. As discussed earlier, fuel sulfur content decreases the efficiency of catalysts technologies and also contributes to particulate emissions. The current study evaluated the effect that these three fuels have on emissions of NO_x and CO_2.

Table 1. Properties of three fuel types considered.

Property	**No. 2 Diesel**	**B20**	**ULSD**
LHV (BTU/lb)	18730	18100	18452
Specific Gravity (kg/l) @ 60º F	.835-.9	0.85	.81-.82
Cetane No.	44	46	45 min
Carbon, wt%	86.4	84.5	86
Hydrogen, wt%	13.6	13.3	14
Oxygen, wt%	0	2.2	n/a
Cloud point (º F)	18	20	10 max
Flash point (º F)	150	180	100
Distillation point (T90º F)	603	640	550
Aromatics, vol%	30	24	30
Viscosity @40º C (mm^2 /s)	2.6	2.9	1.3-2.1
Sulfur content by weight (ppm)	500	400	<15

(Frey et al., 2005; BP America, Inc., 2006)

II.J. Regulatory Approach

Since the 1970's the EPA has established stringent emission standards for highway cars and trucks. On-road vehicle emissions have been dramatically reduced as a result of these regulations and periodic updates. As a result, non-road equipment have become a larger and more significant contributor, on a percentage basis, to the pollutant emissions.

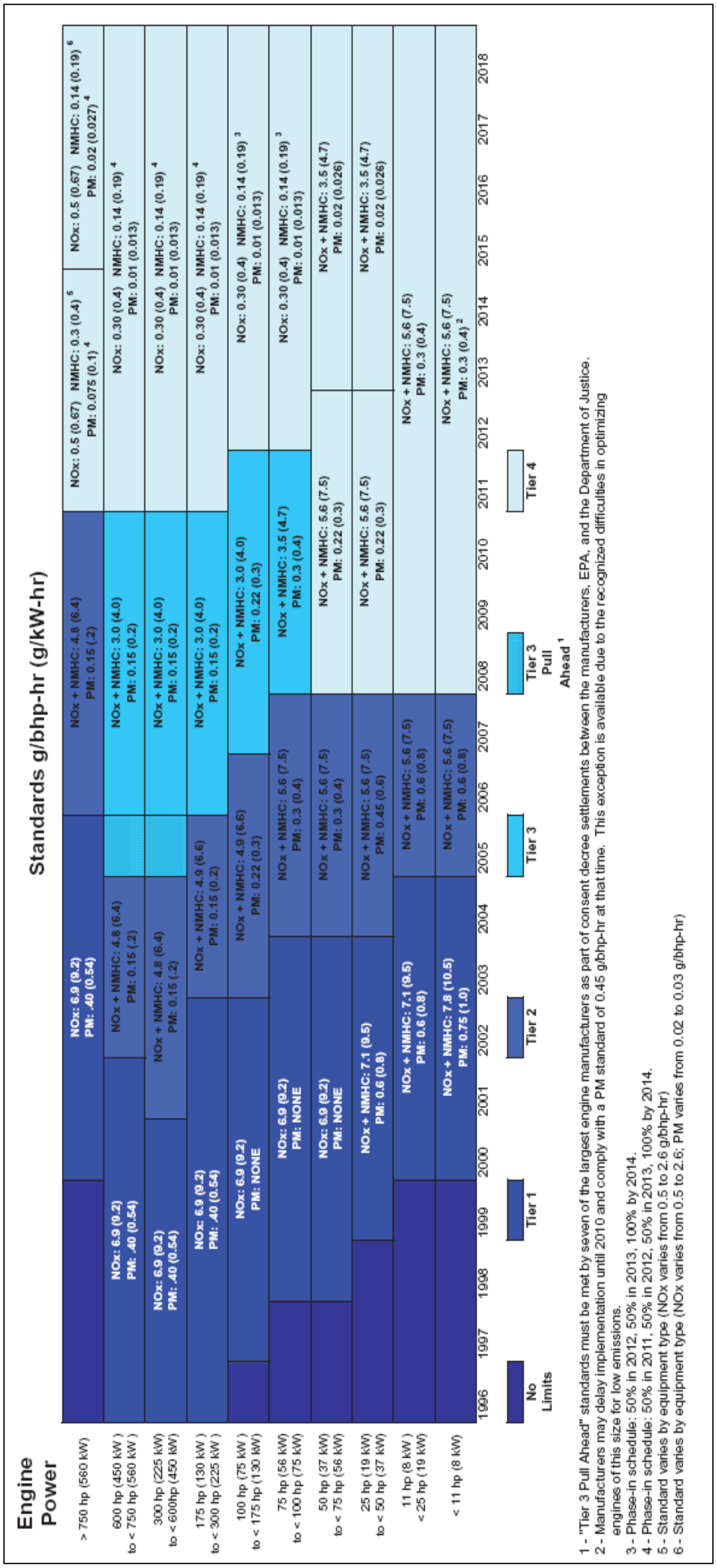
The 1990 amendments to the Clean Air Act started to call attention to off-road engines. In 1991, the EPA published a report showing that off-road equipment accounted for large amounts of nitrogen oxides, hydrocarbons, carbon monoxide and particulate matter. The report showed that, the emissions from off-road engines had total emissions almost as high as highway motor vehicles. The diesel particulate matter was found to be significantly higher than highway emissions. (U.S. EPA, 2003A).

In 1994, the EPA adopted the first set of emission standards (Tier 1) for all off-road diesel engines greater than 50 horsepower. These standards focused primarily on nitrogen oxides and smoke opacity. Larger engines were also subject to limits on carbon monoxide (CO), hydrocarbons (HC) and particulate matter (PM). These non-road regulations are being phased in over time. The emission standards are categorized in Tiers, with higher Tier numbers representing more stringent emission requirements. The Tier 1 standards were phased in for engine sizes between 1996 and 2000 reducing NO_x emissions from these engines by 30 percent (U.S. EPA, 2003A). Tier 2 and Tier 3 standards were enacted in 1998 and are scheduled to be phased-in from 2000-2008. Currently, most equipment is subject to Tier 2 and Tier 3 standards but Tier 4 standards are starting to be implemented for certain engines.

In May 2004(B), the EPA signed the final rule for stricter Tier 4 standards, scheduled to be phased in between 2008 and 2015. Additionally, on May 2004, the Bush administration issued the Clean Air Non-road Diesel Rule which is one of the most significant advancements in clean air protection since the passage of the Clean Air Act Amendments of 1990. Under this rule, stringent pollution controls on non-road diesel engines are introduced along with a significant reduction on the sulfur content of diesel fuel. This program combines cleaner engine technologies with cleaner fuel to produce significant emission reductions from non-road diesel engines (U.S. EPA, 2000B). Under it, sulfur levels are to decrease by more than 99 percent from 3000 ppm in 2004 to 15 ppm in 2010. This enables the use of advanced clean technologies (such as catalytic particulate filters and NO_x adsorbers) and a reduction of PM and SO_2 emissions in non-road diesel engines.

Table 2 below shows a summary of past, current and proposed non-road emission standards (U.S. EPA, 2004A). However, the effect from these regulations will not be immediately evident. Older equipment first needs to be replaced with newer equipment that is regulated by these emission standards. It is expected that the entire 6 million pieces of non-road equipment will be completely replaced by 2030. Also, the allowable emission levels increase as the engine rating decreases. This means that a smaller piece of equipment is regulated to emit more pollution than a larger piece of equipment performing the same activity.

Table 2. Summary of past, current and future non-road emission standards.



This EPA rule also requires a significant reduction in sulfur content for on-road fuel. These regulations were phased in between 2006 and 2010. These regulations require the use of "ultra-low sulfur diesel (ULSD)" with a maximum sulfur content of 15 ppm. Also, as of June 9, 2006, all refineries in the US have started producing some fuel with less than 15 ppm of sulfur and since 2010 all on-road diesel produced have to meet this specification. On June 2010 the ULSD standard started applying to most non-road diesel engines except locomotive and marine engines (Direct Final Rule and Notice of Proposed Rulemaking for Amendments to the Nonroad and Highway Diesel Fuel Regulations (U.S. EPA, 2006).

II.K. Exhaust Emissions Characterization for Off-road Diesel Engines

Emission standards that regulate off-road diesel vehicles are based on test cycles that evaluate the amount of pollution released under certain operating conditions. Engine manufacturers must comply with these standards by testing at least one engine of a given engine model on an engine dynamometer. Off-road engines are mostly sampled under steady-state conditions, yet a certain type of engine can be used in distinct types of equipment with unique duty cycles. One of the main criticisms of off-road emission standards is that they do not accurately account for real world emissions. Most of the regulatory decisions made for off-road diesel engines have been done without real world data. A very limited inventory of in-use emissions currently exists. Furthermore, the rugged environment under which many of these vehicles operate could translate into even higher pollutant loads.

New methods of characterizing off-road diesel emissions with conventional and non-conventional equipment include chassis dynamometer, tunnel, remote sensing and on-board emission testing. Lately, interest has shifted towards on-board systems that are able to sample during normal operating conditions that give a more accurate profile of real-world emissions.

II.K.1. Engine Dynamometer. Emission testing for off-road diesel vehicles is not well characterized mainly because the emissions standards rely on engine certification tests rather than on real-world conditions. These regulations specify the emissions levels permitted from a specific engine in units of grams/brake horsepower-hr (g/bhp-h). Steady state tests are commonly performed on off-road diesel engines. These tests involve running the engine under constant conditions, such as constant engine RPM and load. Many steady state tests involve more than one "mode" where each mode has constant conditions. This type of testing has been criticized because off-road diesels usually operate under stop-and-go or transient cycles (Moran, 2003). Ideally, engines should have to meet emission standards under transient test cycles tailored to their unique operating cycle. Transient tests vary operating conditions and thereby resemble real world conditions.

An engine dynamometer is a device that measures mechanical power of an engine. To do this the dynamometer puts a load on the engine. This device attaches directly to the engine shaft and places a specified load on the engine. To perform this type of test is difficult and costly since the engine needs to be removed from the vehicle. Additionally the engine dynamometer does not take into account the properties of the vehicle itself such as transmission or driveline losses influence the results (Canagaratna et al., 2004). Furthermore, engine manufacturers are required to test and certify their engines for deterioration for the lifetime of the engine. However, there is minimal in-use testing of engines to determine if deterioration is more significant under in-use conditions (Yanowitz, et. al., 2000). The emissions from engine dynamometers are typically reported in units of grams of pollutant emitted per brake horse power-hour of engine output (g/bhp-hr). These units are not directly related to real world activity patterns. Thus, to estimate total emissions some values need to be estimated including engine capacity (hp), load and number of hours in operation.(Frey and Kim, 2005).

II.K.2. Chassis Dynamometer. A chassis dynamometer test involves the entire vehicle. In this test, the drive wheels of the vehicle are placed upon rollers and the vehicle is tied down so that it remains stationary. The rollers along with variable weight flywheels are used to simulate inertial load. In this test, the vehicle is operated according to a predetermined speed profile shown on a computer screen that displays the current required speed. The driver operates the vehicle to closely match the speed profiles shown on the computer screen. Researchers have developed chassis dynamometer test cycles to represent highway, city and suburban conditions. For example the Central Business District cycle is an attempt to model inner-city driving conditions through repeated accelerations, decelerations and idle periods. On the other hand, the Urban Dynamometer Driving Schedule (UDDS) is characterized by high speeds representing real world highway scenarios. The advantage of this type of testing is that its transient cycles resemble more closely the real world conditions of a vehicle and account for the entire drive train and not only the engine. Additionally, the emission measurements of grams of pollutant emitted per mile of vehicle travel provide more useful information for emission inventory purposes than the one yielded from engine testing.

There is no chassis dynamometer test for regulatory purposes with heavy-duty diesel vehicles. Chassis dynamometers are commonly used for light duty vehicles (Frey and Kim, 2005). Heavy-duty diesel vehicles require larger facilities that make this type of testing exceedingly expensive.

II.K.3. Tunnel Studies. In this type of test the total emissions from vehicles that enter a tunnel during a test period are measured. Pollutant concentrations are measured in the air at the inlet to the tunnel and at the outlet. By multiplying the change in concentration by the estimated air flow through the tunnel, a rate of pollutant emissions is determined. Vehicles traveling through the tunnel are counted and divided into the total emission rate. Also taking into account the length of the tunnel makes this measurement on a per mile basis (Yanowitz et. al, 2000). The advantages of this type of study are that it can capture a cross-section of the on-road vehicle fleet and represents real world operation. On the other hand, this test is not able to assign emission profiles to individual vehicles. Furthermore, the traffic conditions of the tunnel may not be representative of conditions elsewhere. Also, far more light duty vehicles exist compared to heavy duty vehicles so the measurements collected are bound to be biased towards light duty vehicles.

II.K.4. Remote Sensing Testing. In this type of testing, emissions are measured as the vehicles pass by a measurement station. Ultraviolet (UV) and infrared (IR) light of specific wavelengths are passed through the exhaust plume of the vehicle to a detector. The light absorbed is proportional to the amount of CO, CO_2, HC and NO. Some of the applications for remote sensing devices include the monitoring of emissions to evaluate the overall effectiveness of inspection and maintenance programs, and identification of high emitting vehicles (Bishop et al., 1989). The main advantage is that it is possible to measure a large number of on-road vehicles given favorable weather conditions. The main disadvantage of such systems is that it only gives an instantaneous estimate of the emissions at a specific location. Other limitations include difficulty in dealing with multiple lanes of traffic, slow moving vehicles or closely-spaced vehicles.

II.K.5. On-board Emission Testing. This type of testing is widely recognized as a desirable approach for quantifying emissions from vehicles since data are collected under real world conditions at any location traveled by the vehicle. On-board measurements can be made with large, complex and expensive instrumentation or with smaller, less expensive and more portable systems (Frey and Kim, 2005). Until recently, the instruments capable of making these measurements were prohibitively expensive. However, in the last few years, efforts have focused on the development of less expensive on-board systems that are able to measure vehicle activity and emissions on a second-by-second basis.

Two types of on-board systems exist: the ones that involve large and complex and expensive instrumentation and smaller, less expensive and more portable systems. The former systems typically involve a permanent installation in a vehicle or trailer and take considerable room. The EPA owns one such system that is a 53 foot trailer that can be towed in a tractor-trailer configuration (Figure 10). This trailer facility is equipped with an air suspension system to minimize shock and vibration for sensitive electronic equipment. This on-board system includes a computerized Data Acquisition System (DAS) and continuous emissions monitoring systems (CEMS) analyzers that measure O_2, CO_2, CO, and total hydrocarbons (THCs) directly from the exhaust (Brown et. al., 2002).

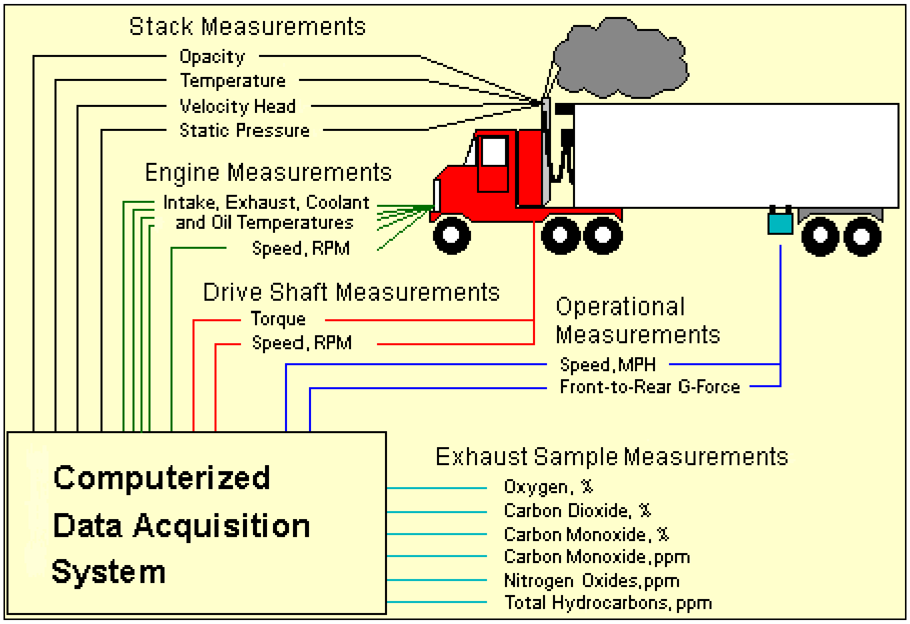


Figure 10. Schematic of on-board trailer facility (Brown et. al., 2002).

The Center for Environmental Research & Technology (CE-CERT) at the Bourns College of Engineering at the University of California, Riverside owns and operates a Mobile Emissions Laboratory (MEL). This system is able to collect emission measurements that are comparable to those collected from a dynamometer. This system is housed in a 53-foot truck trailer with a dilution tunnel, analyzers for gaseous emissions, and ports for particulate measurements (Figure 11). The MEL can be used to collect on-road NO_x, methane (CH_4), THC, CO, and CO_2 emissions at a frequency of 1 hertz while being pulled by a heavy-duty truck or it can be used as a stationary laboratory for the testing of heavy-duty vehicles, engines, or generators. A more detailed description of this system is available from Cocker, et al. (2004).

The MEL is designed and operated to meet the specifications of title 40 of the CFR Part 1065, Engine testing. The system has also been verified against CARB's heavy-duty diesel lab, the Department of Energy (DOE) lab in Denver, and a laboratory at Southwest Research (SwRI) in San Antonio. Recently, the MEL was used for the on-road verification of the Measurement Allowance program to verify portable emissions measurement system for in-use compliance testing (Johnson et al., 2009).

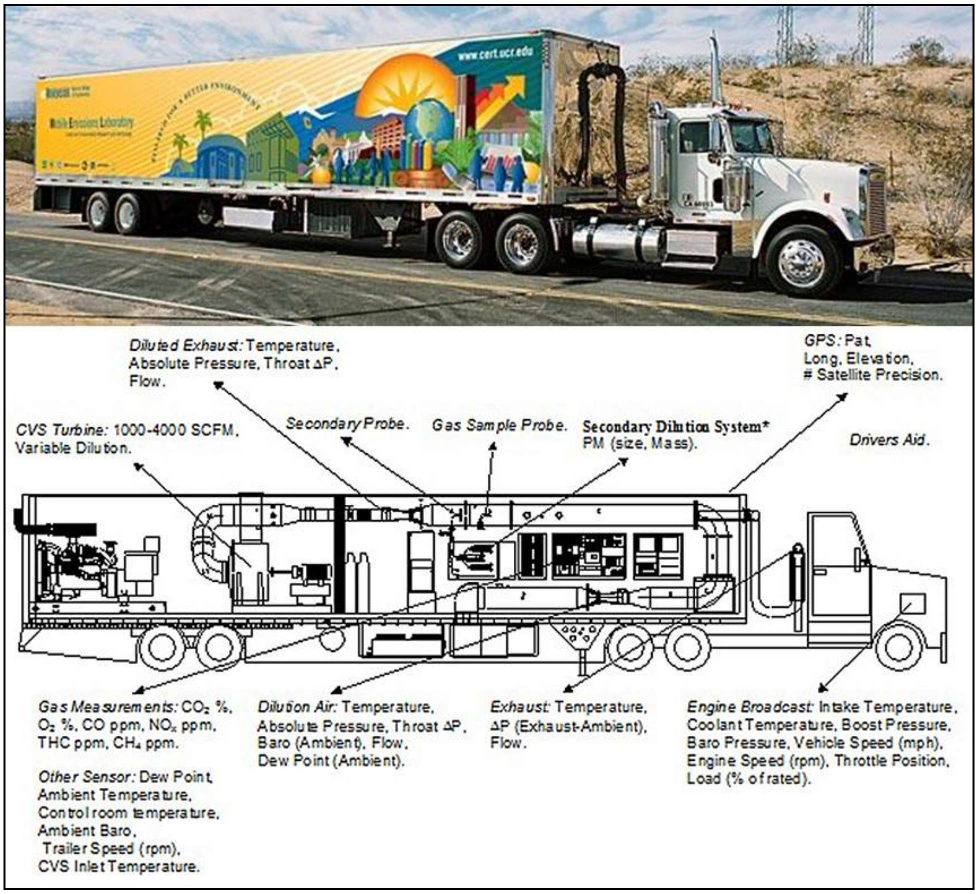


Figure 11. Image and diagram of the Mobile Emission Laboratory (MEL). (http://www.cert.ucr.edu/emissions/)

Another such system is the Aerodyne Research Inc. (ARI) Mobile laboratory system built around a 1989 Ford Econoline 350 chassis (Figure 12). The rear of the mobile lab is a box that houses all the instrumentation including the Aerodyne Aerosol Mass Spectrometer (AMS). The AMS is able to sample submicron particles into vacuum, where they are aerodynamically sized, thermally vaporized on a heated surface, and chemically analyzed via electron impact ionization quadrupole mass spectrometry. Additionally the AMS mobile lab is equipped with two ARI tunable infrared laser differential absorption spectroscopy (TILDAS) instruments utilizing lead salt diode lasers for real-time measurements of selected trace gases including NO, NO_2, CO, N_2O, CH_4, SO_2 and H_2CO. Data from each instrument is logged on a central computer that stores the data synchronously (Canagaratna, 2004). The advantage of this complex system is that it uses more advanced instrumentation that is comparable in precision and accuracy to the one from dynamometer facilities. However, these systems are more expensive and they are not suitable for off-road applications.

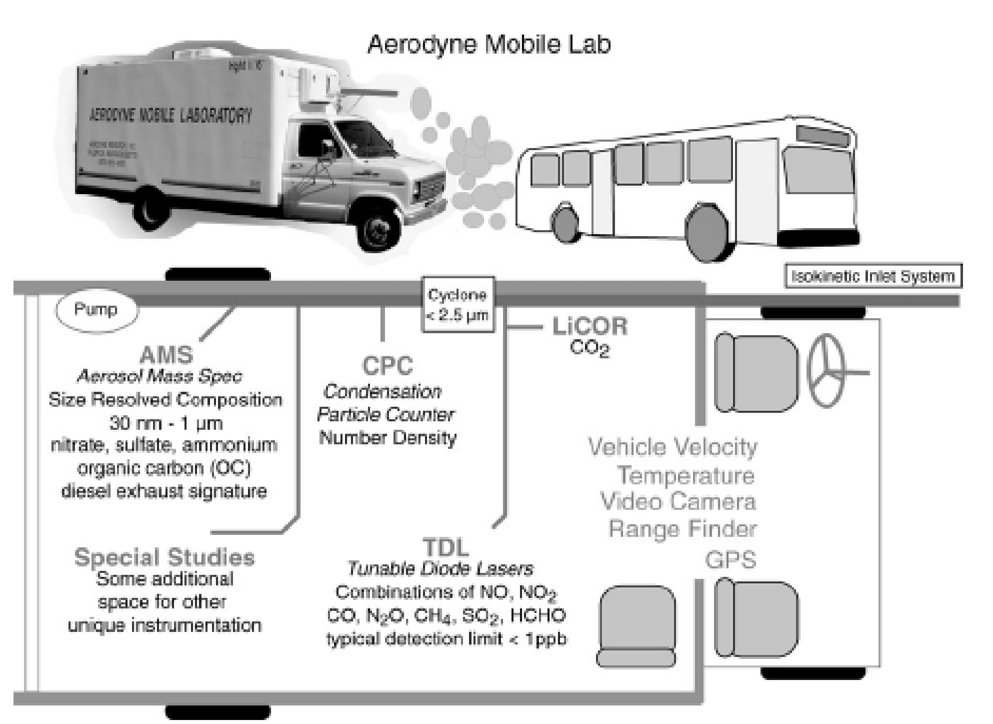


Figure 1. Schematic of the ARI mobile laboratory as instrumented for the CEPEX/PMTACS-NY experiment.

Figure 12. Schematic of the ARI mobile laboratory as instrumented for the CEPEX/PMTACS-NY experiment (Canagaratna, 2004).

Portable on-board emissions measurement systems (PEMS) are relatively simple to use and their cost is significantly lower than the complex on-board systems described above. These systems are able to collect in-use emissions during real-world on-road operation. One key advantage of these systems is that they can be easily installed in a wide variety of vehicles within an hour. Another advantage of PEMS is that their weight is usually between 30 to 100 pounds and their installation does not require major or permanent modifications on the vehicle being tested. Some of the shortcomings of these systems include the less accurate or precise methodology when compared with complex on-board systems or dynamometers. However, new technological advances are bridging this gap rapidly making PEMS measurement methods more accurate and precise.

The future of PEMS is very promising and according to the EPA (2002) on-board testing may be used at some point for on-vehicle certification. The first step envisioned is the collection of on-vehicle emissions data to create a model inventory that includes duty cycles, emissions activity and population. Then on-vehicle compliance can be achieved by establishing test protocols. After these two steps are finished, an investigation of feasibility could lead to an on-vehicle certification which would yield a more accurate emission profile for on-road and off-road vehicles.

II.K.6 Portable Emissions Measurement System (PEMS). These systems are increasingly more common in emission testing of vehicles and equipment due to their affordability, smaller size, ease of installation, and accuracy. A brief description of the main PEMS currently available is included below.

The SEMTECH PEMS from Sensors, Inc. (Sensors, 2012) is the most widely used system in emission testing research (Figure 13). This system measures CO_2 and CO concentrations by using nondispersive infrared spectroscopy (NDIR), NO and NO_2 by nondispersive ultraviolet spectroscopy (NDUV), and THC using a heated flame ionization detector (FID). This PEMS is also able to measure NO and NO_2 separately. This is a feature commonly overlooked that could provide important information about the NO_2/NO_x ratio that is becoming more important in air dispersion modeling involving the stringent 1-hour NO_2 National Ambient Air Quality Standards (NAAQS).

Figure 13. SEMTECH-DS system by Sensors, Inc. (http://www.sensors-inc.com/ds.html)

HORIBA is commonly known for its laboratory bench dynamometer systems. However, they also manufacture the OBS-2200 Series on-board emission measurement system (HORIBA, 2012). This system analyzes all gases wet without drying. CO, CO_2 and water vapor concentrations are measured by a heated NDIR analyzer (Figure 14). The water measurement compensates for water vapor interferences. THC concentrations are measured by a heated FID analyzer (190ºC), and NO_x concentrations are measured by a heated chemilumensescence detector (CLD) analyzer. This system weighs about 64 pounds plus about 140 pounds from the batteries to power it.

Figure 14. HORIBA's OBS-2200. (http://www.horiba.com)

The OEM-2100 "Montana" System, manufactured by Clean Air Technologies International, Inc. (CATI, 2012) includes a gas analyzer, an opacity measurement system, an engine scanner, a global positioning system (GPS), and an on-board computer (Figure 15). The Montana system includes a non-dispersive infrared (NDIR) sensor to collect HC, CO and CO_2 emissions. Additionally, an electrochemical cell is used to detect NO that is used to estimate total NO_x emissions. Finally, a light scattering device is used to collect opacity readings. These gas analyzers are calibrated periodically with a cylinder gas and ambient air. This unit weighs about 44 pounds and may be powered directly from a vehicle's electrical system or by AC in the case of stationary testing.

Figure 15. OEM-2100 "Montana" System, manufactured by Clean Air Technologies International, Inc.(www.cleanairt.com/)

The Simple Portable On-Vehicle Testing (SPOT) system was initially designed and developed by Analytical Engineering Inc. (AEI) under contract from the EPA, to obtain real-world data from non-road heavy equipment (AEI, 2002). The SPOT system simultaneously collects NO_x and O_2 emission concentrations with an NGK NO_x sensor. The NGK is a zirconia based electrochemical sensor located directly in the exhaust flow. This sensor has shown great accuracy and sensitivity in measuring NO_x concentrations (Figure 16). The O_2 sensor is also used to calculate CO_2 emissions in the exhaust flow.

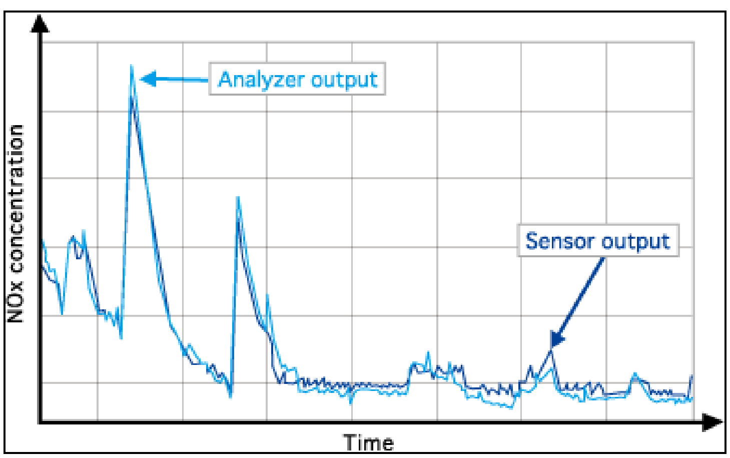


Figure 16. NGK NOx sensor accuracy and sensitivity analysis. (http://www.ngkntk.co.jp/english/product/sensors/index.html#sensor3)

The exhaust probe designed for the SPOT system contains AEI's proprietary exhaust mass flow rate device, which functions well in both diesel and gasoline exhaust.

Also, AEI worked with CARB and EPA to improve the design of the probe geometry and improve the accuracy and the signal to noise ratio (May, 2003). Furthermore, the SPOT units were utilized to collect over 6000 hours of vehicle emissions and duty cycle data on more than fifty different vehicles, which currently comprise the largest database of its kind in the world (May, et al., 2002).

Figure 17. SPOT system from AEI. (http://www.aei-tech.com/development/on-vehicle_emissions.html)

II.K.7 PEMS Validation. Accuracy evaluations of PEMS have been investigated extensively. One such study is the Kansas City PM Characterization Study (U.S. EPA, 2008B) that sampled 480 light duty gasoline vehicles (LDGV) using the SEMTECH-G. This study sought to identify how real-world on-board PEMS could be used to collect HC, CO, NO_x, CO_2 and $PM_{2.5}$ emissions data. Additionally, a dynamometer versus PEMS evaluation was performed by collecting emission data from a PEMS device while simultaneously measuring with laboratory grade instruments on a dynamometer. The evaluation analysis was mostly qualitative and concluded that there is a very favorable accuracy and a good correlation between the PEMS and the dynamometer readings.

The Bourns College of Engineering at the University of California, Riverside performed an evaluation of the Semtech G, Semtech D with a Dekati Mass Monitor for PM, and a Semtech DS (Liu, 2010). These PEMS were compared to a Burke E. Porter 48-in. single-roll electric dynamometer and a Pierburg AMA-4000 bench. The study evaluated CO, HC, NO_x, and CO_2 emissions from three diesel and three gasoline vehicles with the Federal test procedure (FTP) (40 CFR Parts 86-99), the high-speed US06 cycle, and a modal emission cycle. The results indicated an agreement between the PEMS and the Pierburg system that varied depending on the pollutant. For CO_2 and NO_x the agreement observed was 3% and 15% respectively for diesel vehicles and within 10% for CO_2 on gasoline vehicles. The PEMS showed larger deviations for HC and CO that were probably due to a decrease in agreement at very low concentrations.

Johnson et al. (2009) also performed a comparison between the Semtech DS PEMS and a mobile emissions laboratory (MEL). The MEL was validated before this study with an engine dynamometer at the SwRI in accordance to 40 CFR Part 1065. Once this validation was performed, the MEL was used as a validation tool for the PEMS. A 475 hp test truck was used in this evaluation under different road grade, vibration, altitude, electric fields, and humidity. The study found that NO_x and CO_2 emissions collected with the PEM were biased high relative to the MEL measurements. In the case of NO_x, a two-tailed t-test between the MEL and PEMS measurements was found to be statistically significant. This discrepancy could be due to the type of NO_x sensors used by each system: the PEMS uses a NDUV and the MEL uses standard chemiluminescence, However, another possible cause for the discrepancy in NO_x measurements could be due to the fact that the PEMS measures NO and NO_2 directly while the MEL uses a NO_x convertion efficiency of 96.4% per 40 CFR Part 1065.378. Very low NMHC and CO emissions were recorded with both systems. However, the analysis of these two pollutants was curtailed due to the relatively small concentrations observed compared to the not-to-exceed (NTE) thresholds.

Rubino et al. (2007) performed an accuracy verification of the Semtech-DS against a 48 inches chassis dynamometer with a Horiba MEXA-7400HTR-LE instrument to collect CO,HC, NO_x, and CO_2 measurements. Emission testing was performed on two diesel light duty vehicles with the laboratory system used in parallel to the PEMS instrument. Three testing events were performed with the New European Driving Cycle (NEDC) and three more with the Milan City cycle. This study found negligible deviations between the emissions measured from the PEMS and the reference test cell analyzer (Figure 18).

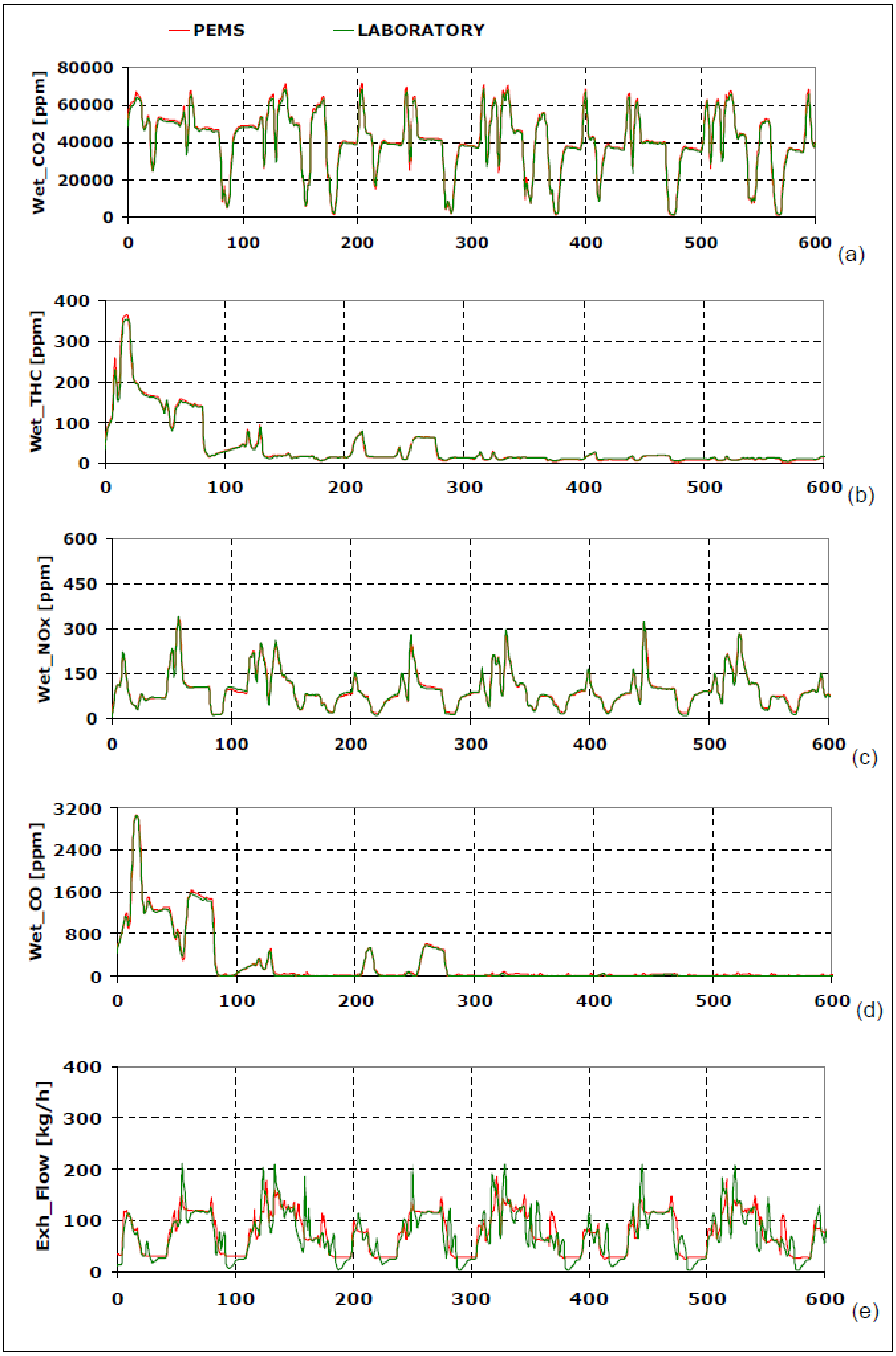


Figure 18. Comparison between reference Horiba laboratory instruments (red) and Semtech DS (green) over the NEDC cycle for (a) CO_2, (b) THC, (c) NO_x, (d) CO and (e) exhaust gas flow (Rubino, et al., 2007).

II.K.8 40 CFR 1065. In this regulation the EPA has implemented procedures of calibration and verification for PEMS use in laboratory and field emission testing. The original regulations for 40 CFR part 1065 were adopted in 2002. EPA has amended these regulations in 2004, 2005, 2006, 2008, 2009, 2010, and most recently on January 18, 2012. These amendments have expanded the scope of engines covered by this regulation and improved the procedures included therein. The long-term plan is for all types of engines to follow the procedures in 40 CFR part 1065 excluding aircraft engines and those that require vehicle testing.

EPA (2008C) performed a study to determine measurement allowances under controlled conditions in a laboratory and measurement emissions in the field using PEMS. The scope included NMHC, CO, and NO_x. The main PEMS used was the SEMTECH-DS and limited analysis was performed with the Horiba OBS-2200. A gaseous analyzer linearity audit was performed based on Table 1 from 40 CFR 1065 Subpart D – Calibrations and Verifications. Numerous SEMTECH units failed the linearity criteria specifying a tolerance on the intercept of 0.5% of the maximum value during testing. This case was especially evident for the NDUV analyzer measuring NO and NO_2. The Horiba units tested did pass the linearity checks. Another issue identified during this study was the PEMS variability. The measurement errors observed in the engines tested were not consistent. Thus, as PEMS begin to be scrutinized more rigorously, some issues have arisen. However, in their respective web sites Sensors Inc., CATI and Horiba claim that their systems are compliant with 40 CFR 1065 requirements.

II.L. Analysis of Continuous Emission Data from PEMS

The analysis of continuous emission data is paramount in finding meaning in the volumes of data collected by PEMS.

II.L.1 Autocorrelation. In 2001 the EPA started to envision the use of on-board emission data as the basis for EPA's mobile source emissions modeling program coined the *New Generation Model*. Frey et al. (2002) prepared a set of recommendations for on-board emission data analysis for these data commissioned by the Office of Transportation and Air Quality at the EPA. This document recognized the importance of identifying the nature of the data set collected. One feature identified in data collected with on-board instrumentation was the short averaging time present on the data. This means that vehicle emissions in a given second are a function of the previous second's speed and acceleration (NRC, 2000). This is referred to as autocorrelation in the time series. Brocklebank and Dickey (1986) warn that data with autocorrelation need to be treated carefully. Specifically, ordinary least squares regression should be used only if residuals are uncorrelated with each other. Thus, autocorrelation in the data needs to be investigated and addressed for a robust statistical analysis to ensue. In their recommendation report, Frey et al. identify the importance of autocorrelation in continuous emission data from PEMS and they outline a data analysis technique based on an analysis of autocorrelation and partial autocorrelation in the data. This approach is dismissed by Frey et al. because it is deemed impractical for the development of the New Generation Model.

II.L.2 Binning. Frey et al. (2002) proposed to bin vehicle emissions data based on speed and acceleration criteria to reduce the influence of autocorrelation in the data. This approach defined driving modes based upon speed criteria yielding idle, acceleration, deceleration and cruise bins. This technique segregates the original time series into shorter discontinuous time series which are supposed to reduce the influence of autocorrelation. Regression techniques were pursued once this binning technique was performed. This binning technique was also described by EPA (2002C, 2002D). However, the binning of data based on speed and acceleration will still include segments of autocorrelated data. Furthermore, no testing was performed on the binned data to determine if autocorrelation was still present in the data observations after applying the binning technique. Thus, it is not clear how the binning technique would mitigate the effect of autocorrelation.

II.L.3 Averaging. An average time approach was also evaluated by EPA (2002D). The purpose of this evaluation was to determine if 5 and 10 second averages of emissions and vehicle activity data could decrease autocorrelation. The intent was to smooth the data to remove some of the high frequency variability in the data. The results obtained showed

that 5 and 10 second averaging times offer no benefit over the 1-second averaging time in predictive ability. Thus, the 1-second averaging time approach was preferred.
This study also recognized that it may be more effective to use peak values of key variables rather than averages. The rational is that short duration of values such as acceleration will have a higher correlation to the largest share of emissions produced. Thus, an average value approach would miss these relevant peaks in assessing relationships between the independent variables in the analysis. However, a comparison analysis to test these conjectures was not provided.

A similar approach was also performed in the European Union by Weiss, et al. (2011A, 2011B) and Rubino et al. (2007). These researchers introduced the concept of averaging windows that is in line with the methodology used for the emission testing and characterization of Euro VI heavy-duty vehicles (EC, 2011) in the European Union. These individual windows represent sub-trips of a test route. This method intends to reduce fluctuation in the second-by-second emissions data to focus on the emission variability related to route averages. Thus, emissions are averaged over intervals of a predefined duration. Specifically, the duration of a window is determined by the distance traveled until the vehicle has emitted a cumulative CO_2 mass equivalent to the mass emitted during the NEDC testing. The advantage of this method is that it yields values that can be directly compared to the standard NEDC values. However, the details of the data collected are lost in the averaging windows.

II.M. Analysis of PEMS Data in Recent Publications

Kousoulidou et al. (2013) performed an evaluation of six diesel and gasoline passenger vehicles with the SEMTECH-DS. These vehicles were tested under real-world operating conditions in two routes in the region of Lombardia, Italy. Additionally, the PEMS was used to test the vehicles while under the European dynamometer cycle (NEDC). This study found that NO_x emissions for the diesel vehicles comply with the standard when operated under the NEDC. However, when operated under real-world driving conditions the NO_x emissions constantly exceed the limits. The real-world data were analyzed by dividing the trip into sub-trips based on the average speed and number of stops. These sub-trips were then classified as urban, rural, or motorway and average values were calculated. Average emission values for the complete driving cycle were also calculated for the NEDC and compared to the applicable standard. Zhihua et al. (2011) performed a similar evaluation of four diesel buses using the SEMTECH-DS analyzer in Beijing, China. This study compared real-world emissions to the European steady cycle (ESC) and the European transient cycle (ETC) limits and reported their results in average emission values. This type of averaging approach is used to determine compliance with current emission standards. However, as regulations move towards not-to-exceed standards, it will become more important to properly characterize emissions with a finer resolution.

Chao et al. (2011) performed a study to characterize heavy-duty diesel engine emissions at simulated high altitudes. The SEMTECH-DS was used to measure engine emissions at simulated 0, 100 meters, and 2000 meter altitudes at five engine loads. The comparison of HC, CO, NO_x and smoke was based on average of the five engine loads investigated. Whereas this analysis is useful, it does not look past simple averaging values.

Peltier et al. (2011) evaluated emissions from a diesel switching locomotive ran on B10, B20 and ULSD fuels with a SEMTECH-DS. The test sampled emissions from the locomotive engine for 30 minutes while at full throttle. The data were then averaged over 10-second intervals and emission benefits were reported. Cecrle et al. (2012A) performed a similar evaluation of NO_x, CO, HC and PM emissions from two engines fueled with seven types of biodiesel. The SEMTECH-DS was used to collect emission data at five engine loadings for each engine. The emission data collected were averaged over 10-second intervals to reduce background noise. In this analysis, an analysis of variance (ANOVA) was also performed to determine the variables that were most statistically significant on emissions. Jing et al. (2012) also evaluated emissions from two off-road diesel engines with the SEMTECH-DS while running on biodiesel made from waste cooking oil (WCO). In this evaluation the engines were run on idle and the significance of different variables was evaluated with an ANOVA. The results from the ANOVA indicated that biodiesel content was statistically significant for all pollutants but ambient temperature was not.

At the present time, most research is being performed by calculating an average emission value and comparing it to distinct routes, cycles, etc. Some researchers are averaging values over the period of testing and others are segregating emissions in bins based on speed and acceleration criteria. Being that the current approach to emission testing relates to set duty cycles, it is a good transition to compare these values to averaging windows that are meant to resemble these set cycles. Other researchers are performing more advanced statistics by using ANOVA and GLM tests to find significance when comparing different independent variables related to fuel, ambient and engine parameters. Thus, when comparing the effect of independent variables on emissions, an approach like the one led by the Department of Civil, Environmental, and Architectural Engineering (CEAE) at the University of Kansas (KU) is preferred.

III. METHODOLOGY AND APPROACH

III.A. Exhaust Emissions and Duty Cycle Characterization

As discussed in the previous sections, the established laboratory testing methods do not accurately characterize the emission profiles of on-road and off-road vehicles. Therefore, we used an on-board system to characterize the engine and ambient parameters from an off-road diesel vehicle. This system provided a wealth of information by allowing a second-by-second characterization of exhaust emissions.

III.A.1.On-board System. The sampling system used for this study is the Simple, Portable, On-vehicle Testing (SPOT) system. This system was manufactured by Analytical Engineering Inc. (AEI) under contract with the EPA. Under such a contract over 50 off-road vehicles underwent weeklong in-use measurements totaling over 8000 hours of accumulated vehicle information (May et al., 2002).

The SPOT system was loaned to the Department of Civil, Environmental and Architectural Engineering to carry out the present study. Per AEI's request this system was returned to them on August 29, 2007. The SPOT system is able to accurately measure NO_x and O_2 emissions, as well as exhaust mass flow, relative humidity, ambient temperature, engine speed, calculated CO_2, and a host of internal parameters on a second-by-second basis during normal operations (May et al., 2002). AEI provided technical support along with training on how to use this on-board system during June 2005 at their facilities in Columbus, Ohio.

Figure 19. SPOT system components. 1) main console, 2) alternator sensor, 3) battery connections, 4) exhaust probe.

Particulate matter is an important emission from diesel engines: however PM sampling under off-road conditions is a capability not available in the SPOT system or any other on-board system in the market. Sensors Inc. has a particulate matter sampling extension to their on-board system. However, the price of this device was outside of the budget of the present study. Furthermore, the Sensors system is not designed to be used under off-road conditions. Thus the current study focused on NO_x and CO_2 exhaust emissions.

The SPOT system is composed of four main parts including: (1) the main data logger console, (2) an alternator sensor, (3) a connector to the vehicle's battery and (4) an exhaust probe (Figure 19). The main data logger console contains a Campbell Scientific CR5000 datalogger along with sensors for ambient temperature, humidity and barometric pressure. The alternator sensor gathers the instantaneous alternator frequencies that are automatically converted to engine speed. At the beginning of each sampling run, the engine speed is directly measured at low and high idle conditions. This is done by placing reflective tape on the engine's damper and then using a laser tachometer to measure the damper's revolutions per minute (May et al., 2002). The battery connector is used to power the SPOT system when the engine is turned on. The exhaust probe has a thermocouple, a mass air flow sensor, and NO_x and O_2 sensors.

NO_x measurements are made possible by an NGK NO_x sensor. This type of sensor consists of a catalyst, a heater, a sensing element and an O_2 sensor (U.S. Patent, 1998). The catalyst is placed upstream from the flow of the gas to be measured, and it removes the CO component from it. The heater is located next to the sensor element and it maintains the sensor element and the catalyst at a constant temperature. The Zirconia multilayer ceramic sensing element responds to NO_x concentrations by a representative resistance. This measured resistance is adjusted for a given O_2 concentration to produce a representative NO_x value. The NGK NO_x sensor is an electrochemical in-situ sensor that can reside directly in the exhaust flow and measure the gas as it leaves the exhaust of an engine. This minimizes the error due to transient mixing in the extracting lines and the solubility of NO_x in water. The O_2 sensor is also used to calculate CO_2 emissions.

The SPOT system was able to provide unique information about the diesel compactor analyzed. This information is most valuable since it was collected under normal operating conditions on a piece of equipment that was used for at least 8 hours a day. This was possible due to the ease of data collection afforded by this type of system. Furthermore, this sampling equipment was rugged enough to withstand the rough conditions that trash compactors experience on a regular basis. Appendix D depicts the SPOT system and trash compactor during installation, fueling, and field sampling.

III.A.2.Partnership with a Construction Company. A construction partner was sought among numerous construction companies and organizations in the area. It was necessary to find a partner that would allow the testing of an off-road diesel vehicle and allow the use of ULSD and B20 on this piece of equipment. After contacting many companies in the KC area the KU team approached Charlie Sedlock, Operations Director for N. R. Hamm Quarry, Inc. Mr. Sedlock allowed the sampling of the trash compactors at the facility along with the fueling of these compactors with B20 and ULSD. Thus, this partnership fulfilled our criteria and in August 2005 Mr. Sedlock and the KU team agreed to partner in this study. This partnership was crucial in making the current study possible. It was important for the N.R. Hamm personnel that their two trash compactors remained in service for the duration of our study since they are critical to the operation of the facility. This condition allowed the KU team to gather real world data.

The current study also called for the sampling of three fuel types: regular no. 2 diesel fuel, ultra-low sulfur diesel and a 20% mix of biodiesel. Arrangements were made with N.R. Hamm to sample their compactor with the no. 2 diesel fuel they commonly use. Arrangements were also made with Ken Kimura, principal engineer for Fuels Product Development at BP for the donation of 500 gallons of the ultra low sulfur diesel. The biodiesel mix was then purchased from Capitol City Oil, who also provides the regular no. 2 diesel for the N.R. Hamm facility. The N.R. Hamm personnel helped in completely draining the fuel tank before refueling with a ULSD and B20 fuel types. This procedure was very important especially in the case of the ULSD which could be easily contaminated by small amounts of regular diesel fuel.

III.A.3.Selection of an Off-road Diesel Vehicle and Testing Site. N.R. Hamm personnel and a member from the KU team surveyed types of diesel engine equipment available at their facility. Among them was a backhoe, a tractor and two trash compactors. The KU team learned that the backhoe and tractor were only in use intermittently and it was hard to know when they would be in service. Additionally, the engine configurations from these two pieces of equipment were not ideal for the installation of the SPOT system. However, two trash compactors at the property were in use constantly throughout the day. This type of work regime seemed advantageous for our study given that we needed to collect as much data as possible under normal operating conditions. After the compatibility between the engine and the SPOT system was confirmed, the KU team and Charlie Sedlock agreed to the use of one of these compactors for the present study.

The off-road equipment used for the present study is a 2002 Terex CMI Trashmaster 3-90E. This landfill compactor is the largest kind offered by its manufacturer and features a Cummins Model QSK-19, 525-hp diesel engine, turbocharged and charge air cooled (TEREX, 2002). More information about this equipment is available I Appendix C. Hamm Quarry has two of these compactors at their location operating continuously from approximately 7 AM to 5:30 PM Monday through Friday while using over 200 gallons of fuel a day each. The operator of this compactor controls the front blade to move trash to its desired location as he or she steers the compactor over the trash underneath. In every pass this compactor exerts a compaction force of 767 pounds per linear inch. Figure 20 shows the compactor at N.R. Hamm's facility.

Figure 20. CMI 3-90E compactor at Hamm's landfill.

<u>III.A.4.Testing Site Description.</u> Hamm's Sanitary Landfill (Division of N.R. Hamm Quarry Inc.) served as the testing site for our study. This facility is located at the junction of U.S. Highway 24 and U.S. Highway 59 in Williamstown, Jefferson County (see Figure 21). The facility is managed by Charlie Sedlock, Operations Director for N. R. Hamm

who provided the necessary access and assistance to the KU team. The hours of operation of the landfill facility span from 7:30AM to 4:00 PM Mondays through Fridays and from7:30 AM to 1:00 PM on Saturdays. However, the two compactors in the facility continue being operated even after the facility is closed to the public. This landfill services 13 counties including cities and communities in northeast Kansas.

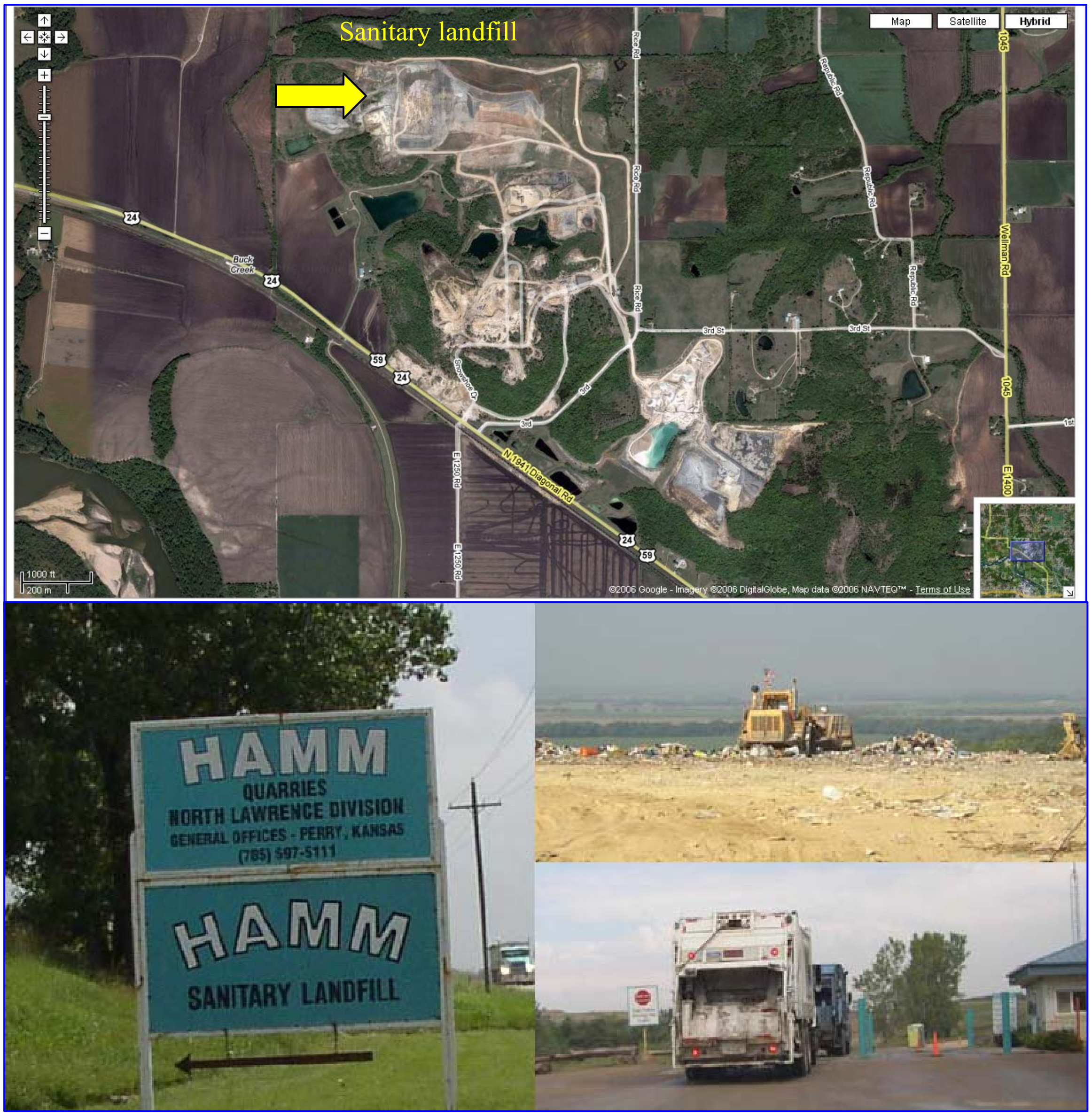


Figure 21. N.R. Hamm facility.

<u>III.A.5.Data Output and Manipulation.</u> There are very few sampling systems like the SPOT that are rugged enough to withstand the rough use that off-road equipment undergo. Consequently, emission data from off-road diesels operating under real world

conditions are quite limited. In fact, previous data were not available at the time of this literature review. Since data collected by the EPA and AEI have not been released, this research is the first to analyze this type of data for off-road diesel vehicles. Thus, the data manipulation and analysis for this output is unchartered territory.

The SPOT system collects emission, engine and ambient parameters on a second-by-second basis onto a memory card inside the main console of the system. This output includes data for NO_x, O_2, CO_2, total exhaust mass flow, relative humidity, ambient temperature, engine speed, calculated fuel consumption, and barometric pressure, among other parameters. Thus, the size of the dataset produced by the SPOT is extremely large. To analyze these data the following steps were followed:

A) Data reduction. The raw data set produced by the SPOT system included variables that were inconsequent to the scope of this study. These variables were filtered out of the dataset. Additionally, the raw data set included calibration values that were ran periodically. In other instances a communication port error produced voids in the data set. All these values were cleared from the data set before being analyzed. Once the raw data were cleaned of invalid and unneeded variables it was ready to be analyzed. This reduced data set included engine parameters and NO_x and CO_2 emissions values.

B) Preliminary analysis. The NO_x and CO_2 data were plotted in distinct ways to identify meaningful patterns and relationships between some of the variables collected. Descriptive statistics for all relevant variables needed to be also calculated.

C) The dependent variables for this study are NO_x and CO_2 concentrations. Therefore, a Pearson correlation test was necessary to identify the independent variables that exerted the greatest influence on NO_x and CO_2 emissions.

D) Subsequent to the identification of the most significant variables, a test of independence was performed to validate the assumptions necessary for statistical analyses.

E) Once independence was established, the data were tested for normality using the Ryan-Joiner test. The result from this test helped define the type of statistical analysis performed. Possible data transformations were also investigated in an effort to normalize the data. However, this approach was abandoned since no success was obtained from these data transformation techniques.

F) Based on the results from the previous steps, a statistical analysis was defined to determine the effect of the distinct fuel types on NO_x and CO_2 emissions. Pertinent statistical tests include the analysis of variance (ANOVA) or the covariate version of the General Linear Model (GLM).

G) The statistical analyses performed were used to determine whether the independent variables of fuel type and compactor were statistically significant on the emissions of NO_x and CO_2. A standard significance value of $\alpha = 0.05$ (95% confidence level) was used to define statistical significance.

III.B. Statistical Analysis

This section describes the statistical analysis that was used to determine if the factors of "fuel type" for the first part and "compactor" for the second part have a statistically significant effect on the NO_x and CO_2 concentrations. The parametric test considered was the analysis of covariance since parametric tests tend to be more powerful than nonparametric tests.

The SPOT sampler collected over 30,000 engine and emission observations during a regular day of sampling on a second-by-second basis. The advantage of this data set was the number of observations collected to characterize the diesel vehicle. However, these observations were collected so closely to each other that they had a strong dependence that violated one of the basic assumptions in parametric statistics related to independent observations. Thus, the issue of autocorrelation had to be resolved to enhance the robustness of the statistical analyses performed.

III.B.1. Analysis of Variance. The analysis of variance (anova) technique is commonly used to test whether two or more sample means could have been obtained from populations with the same parametric mean (Sokal and Rohlf, 1981). This procedure evaluates whether the mean difference between two or more treatment conditions has a significant effect on a dependent variable (Agresti & Finlay, 1997). The treatment conditions or groups are defined by the various levels of independent variables. For this study the two dependent variables being tested are NO_x and CO_2 emissions from the diesel compactor. The groups include the following: for the first part of the analysis the three fuel types used- namely no. 2 diesel, B20 and ULSD fuel; and for the second part of the analysis the compactor tested- either Compactor #1 or Compactor #2. To decide if the difference between treatment conditions is due to random variation or not, the *F*-ratio is calculated (Equation 1). This ratio compares the variance between subjects to the variance expected due to random error. The variance calculated in the numerator of the *F*-ratio describes the differences between the sample means (Equation 2) and is referred to as the *between-groups variability*. The variance in the denominator of the *F*-ratio (Equation 3) is referred to as the *error variance* or *within-groups variability* (Mertler and Vannatta, 2002). In other words, the between-groups variability actually measures the differences due to the effect of the treatment or chance and the within-groups variability measures only differences caused by chance. This calculated value is then compared to the *F*-statistic (Equation 4) which is based on levels of significance and degrees of freedom for between and within groups data (v_1 and v_2 respectively). This distribution is used to test whether two or more samples have the same variance. The null hypothesis for this statistical analysis is that two or more variances estimate the same parametric variance; the alternative hypothesis in an anova is always that the parametric variance estimated by the variance among groups is greater than that estimated by the variance within groups.

Definition of distribution statistic:

$F = MS_{\mathrm{B}} / MS_{\mathrm{W}}$: (Equation 1)

MS_{B} is the mean square difference between groups defined by the following equation:

$$\sum_{j=1}^{k} n_j \frac{(\overline{x}_j - \overline{x}_g)^2}{(k-1)} \qquad \text{(Equation 2)}$$

k = number of groups.
j = group number.
$\overline{x}_j$ = mean for j group.
$\overline{x}_g$ = mean of all groups combined.
n_j = number of observations in group j.

MS_W is the mean square difference within groups or the variance expected due to random error defined by the following equation:

$$\frac{\sum_{j=1}^{k}\sum_{i=1}^{n_j}(x_{ij}-\bar{x}_j)^2}{n_t-k} \qquad \text{(Equation 3)}$$

Where: k = number of groups.

j = group number.

x_{ij} = value i from group j.

$\bar{x}_j$ = mean of group j.

n_j = number of observations in group j.

n_t = total number of observations in all groups.

Once the F-value has been calculated, it is compared to the following F-statistic based on the level of significance. The values for this F-statistic are generally obtained from a table of values organized by levels of significance and degrees of freedom.

$$F_{(\alpha)[v_1,v_2]} = \frac{1}{F_{(1-\alpha)[v_2,v_1]}} \qquad \text{(Equation 4)}$$

Where: α = level of significance (0.05 for this study).

v_1 = degrees of freedom for between groups data.

v_2 = degrees of freedom for within groups data.

The assumptions for the analysis of variance are:

1. The observations within each sample must be independent of one another.
2. The populations from which the samples were selected must be normal.
3. The population from which the samples were selected must have equal variances (homogeneity of variance).

The first assumption was achieved by using a data reduction technique that yielded quasi-independent observations. The second assumption was not achieved, but, the one-way anova is robust to violations of the normality assumption (Harris, 1998;

Randolph, 1989). The third assumption of equal variances was tested and identified in the data sets analyzed.

III.B.2. Analysis of Covariance. This is a variation on the original analysis of variance technique. The analysis of covariance (ancova) test can be used to improve research design efficiency by adjusting the effect of variables that are related to the dependent variable. This test is particularly useful when the effect posed by one or more *concomitant* variables needs to be removed or *partialed out* from the dependent variable. In the present study, NO_x and CO_2 emissions are correlated strongly to engine speed. However, a primary interest in this study is to identify the effect of the fuel types and compactors on emissions. Thus, the ancova technique was used to *partial out* the effect of engine speed (concomitant variable) from NO_x and CO_2 emissions (dependent variables tested separately). In the analysis of variance the effect from any *concomitant* variable is ignored. Yet, in the covariance analysis this effect is removed by adjusting the scores on the dependent variable to reflect initial differences in the covariate (Mertler and Vannatta, 2002). The variable whose effects have been *partialed out* of the results is called the *covariate* in this case *Engine Speed*. Then NO_x and CO_2 emissions were used as the dependent variables that were tested separately versus the independent variables of "fuel type" and "compactor".

The primary purpose of the analysis of covariance test is to increase the sensitivity of the *F*-test to main effects and interactions by reducing the error variance. This is accomplished by removing the error term associated with the covariate(s). This predictable variance is best addressed through means of random assignment of subject groups (Stevens, 1992). However, when random assignment is not possible, the inclusion of a covariate in the analysis can be helpful in reducing the error variance. The covariate is used to assess any undesirable variance in the dependent variable by estimating scores on the covariate. If the covariate has a substantial effect on the dependent variable, a portion of the within-variability is statistically removed. This ultimately reduces the error term and produces a larger value for the *F*-statistic and a more sensitive test.

Analogous to the previously-described test (anova), in the ancova the two dependent variables that were tested separately are CO_2 and NO_x. However, in this case the covariate variable that was partialed out from the dependent variables is *Engine Speed*. This covariate variable was chosen since its effect is highly related to the emissions of CO_2 and NO_x. By removing the effect of engine speed the intent is that the *pure* effect that fuel types and compactor exert on the emissions can be identified.

In addition to the anova assumptions, the ancova also includes the following three assumptions:

1. A linear relationship exists between the dependent variable and the covariate(s).
2. The regression slopes for a covariate are homogeneous (same slope for each group).
3. The covariate is reliable and is measured without error.

The first assumption was checked by plotting the scatterplots of NO_x and CO_2 versus revolutions per minute (RPM). These plots showed a linear relationship between emissions and engine speed. The second assumption was checked by performing an F test for the interaction of emissions and engine speed. The last assumption was assumed to be true since engine speed was calibrated with a manual tachometer.

<u>III.B.4. General Linear Model.</u> This is an ANOVA procedure that can be used to analyze data collected with balanced and unbalanced designs, ANCOVA, and regression. Calculations are done using a regression approach where a "full rank" design matrix is formed from the factors and covariates and each response variable is regressed on the columns of the design matrix (Minitab, 2012). The General Linear Model assumes that, apart from residual or uncontrolled variation, the variability in the response variable(s) can be explained by a linear combination of various constant levels corresponding to different combinations of the factors and/or a linear dependence on the values of the covariate(s). In all cases, the residual variations from such a hypothetical model are assumed to be independent and normal deviates with constant variance (Minitab, 2012).

In this study, the dependent variables analyzed are NO_x and CO_2 emissions and the independent factors analyzed are fuel type and compactor. The first part of the study analyzes the effect of fuel type used on the NO_x and CO_2 emissions sampled from the first compactor. The second part of the study analyzes the effect that two compactors have on NO_x and CO_2 emissions while running on diesel fuel. Thus, fuel type and compactor are the two independent factors used in the statistical analysis. In both cases the engine speed factor was entered as a covariate term in the GLM analysis since it is an influential factor on NO_x and CO_2 emissions. By having engine speed as the covariate factor we seek to isolate the effect from fuel type and compactor in each part of the analysis.

Additionally, a temporal analysis was performed on the data. The difference from the design described earlier is that the day factor was used as the independent variable. However, NO_x and CO_2 emissions remained being the dependent variables and engine speed remained as the covariate term. This analysis was performed for the two parts of the study to identify any temporal bias in the data.

III.B.5. Hypothesis Testing. The statistical tests mentioned in this section were performed on the data collected by means of hypothesis testing. The four steps involved in hypothesis testing are:

Step 1. Formulation of null and alternate hypotheses (H_o and H_a respectively).

Step 2. Assumptions, sampling distribution and sampling statistic.

Step 3. Determine the probability value. This value determines the probability of falling in the tail bounded by the test statistic found in step 2.

Step 4. Reject or not reject the null hypothesis depending on the relation between the probability value and the level of significance or α value. This value determines the probability of committing a Type I error, where the null hypothesis is actually true, and the researcher concludes that it is false. For the current study the common significance level of $\alpha = 0.05$ was used. Therefore, the following criteria defined whether the null hypothesis is rejected or not.

If $P \leq 0.05$, then reject H_o.

If $P > 0.05$, then do not reject H_o.

The results from the hypothesis test addressed the following questions covered in the present study:

Phase 1: Fuel Analysis

1. "Are there statistically significant differences in mean NO_x concentrations from a diesel compactor running on no. 2 diesel, ULSD and B20 fuel types?"
2. "Are there statistically significant differences on NO_x concentrations due to temporal factors?"
3. "Are there statistically significant differences in CO_2 concentrations from a diesel compactor running on no. 2 diesel, ULSD and B20 fuel types?"
4. "Are there statistically significant differences in CO_2 concentrations due to temporal factors?"

Phase 2: Compactor Analysis

1. "Are there statistically significant differences in mean NO_x concentrations between Compactor #1 and Compactor #2?
2. "Are there statistically significant differences in NO_x concentrations due to temporal factors?"
3. "Are there statistically significant differences in CO_2 concentrations between Compactor #1 and Compactor #2?
4. "Are there statistically significant differences in CO_2 concentrations due to temporal factors?"

IV. RESULTS OF FUEL TYPE ANALYSIS

The first set of engine and emissions data was collected from August 28 to September 1, 2005 at the Hamm's landfill facility. This sampling campaign was originally intended to be used to identify possible problems and obtain experience with the equipment. However, given the favorable results, these data were used for the emission characterization of no. 2 diesel fuel. The sampling was continued from September 12-15, 2005 with the compactor running with B20 and ECD. The actual running times of the compactor for the days sampled are shown in Table 3. This table shows the actual number of data points available for the statistical analysis since a few readings were discarded due to calibration values and communication gaps in the SPOT system.

Table 3. Total number of hours compactor was in operation during each sampling day.

Day	Fuel type	Start time	End time	Total time	Total data points
08/29/2005	Diesel	7:07 AM	5:10 PM	10:03	36158
08/30/2005	Diesel	7:10 AM	5:57 PM	10:47	38873
08/31/2005	Diesel	7:08 AM	5:21 PM	10:13	36738
09/01/2005	Diesel	7:08 AM	4:29 PM	9:21	32383
09/12/2005	B20	7:07 AM	5:10 PM	10:03	35704
09/13/2005	B20	7:21 AM	5:11 PM	9:50	32287
09/14/2005	ECD	7:22 AM	5:02 PM	9:40	33441
09/15/2005	ECD	7:21 AM	5:00 PM	9:39	30906

The average temperature, relative humidity and sky cover conditions for each of the sampling episodes are shown in Table 4. These data were obtained from the National Climatic Data Center (NCDC) for the Lawrence municipal airport station. This station is located about 5 miles southeast of Hamm's Sanitary Landfill. In this table, scattered sky cover indicates a 1/8 to 4/8 cover and broken refers to a 5/8 to 7/8 cover.

Table 4. Average temperature, relative humidity and sky cover for sampling period.

Sampling day	Avg. temp. (°C)	Relative humidity (%)	Sky cover
08/29/2005	21.3	49.4-100	Clear
08/30/2005	21.1	51.1-96.6	mostly clear
08/31/2005	22.0	48.3-96.6	clear, scattered and broken

09/01/2005	19.8	57.5-96.6	scattered, broken and overcast
09/12/2005	23.9	58.8-84.0	clear and scattered
09/13/2005	22.9	66.3-84.6	clear, scattered and broken
09/14/2005	18.2	53.3-86.6	mostly clear
09/15/2005	15.1	77.7-93.1	overcast

IV.A. Data Screening

A profile for each fuel type used was created by collecting engine and emissions data from the compactor while running with each fuel type. This raw data included some calibration values each time the engine was started and also some missing values due to compiling gaps. These values were cleared from the final dataset prepared for the statistical analysis. Upon further analysis, the KU team also found that the ambient temperature and humidity values collected by the SPOT system were inaccurate. This was the case because of the location of the SPOT system. The only viable place for placing the SPOT was behind the operator cabin. This location, although not directly above the engine, did receive enough heat to significantly impact the ambient temperature values and consequently the relative humidity as well. Thus, weather surface data were used from the closest weather station located at the Lawrence Municipal Airport (about 5 miles southeast from the sampling location).

IV.A.1.Descriptive Statistics and Correlation Analysis. Descriptive statistics for ambient temperature, relative humidity, engine speed, mass air flow, exhaust flow, fuel flow and O_2 concentrations are shown in Tables 5 and 6. For all descriptive statistics presented, N stands for the sample size. Q1 and Q3 refer to the first and third quartiles, respectively; approximately 50% of a distribution falls between these two values.

Table 5. Descriptive statistics for ambient and engine variables for all data.

Variable	N	Mean	Median	StDev	Min.	Max.	Q1	Q3
Amb. Temp (deg. C)	122	19.8	18.9	4.2	13.9	31.1	16.1	22.8
Dew point (deg. C)	122	16.2	17.2	2.5	12.2	22.2	13.6	17.8
Relative humidity (%)	122	81.1	84.5	12.7	48.3	100.0	75.1	90.0
Engine Speed (RPM)	276486	1810.2	2106.0	545.3	781.3	2282.0	1871.0	2151.0
MAF (lbs/hr)	276486	271.4	322.3	104.8	56.2	439.4	191.6	345.4
FuelFlow (kg/hr)	276486	70.8	86.8	39.3	2.4	139.7	34.1	101.2
MAF_T (deg. C)	276486	362.2	391.4	73.6	40.2	444.5	352.3	406.7
O_2 (%)	276486	12.2	10.9	3.2	6.0	19.5	9.7	14.6

Table 6. Descriptive statistics for ambient and engine variables by fuel type.

Variable	Day	N	Mean	Median	StDev	Min.	Max.	Q1	Q3
Ambient Temperature (deg. C)	B20	29	23.3	22.8	1.8	21.1	28.9	22.2	23.9
	Diesel	50	20.9	18.9	4.1	17.2	31.1	17.8	23.1
	ECD	43	16.0	15.0	2.0	13.9	22.8	15.0	16.1
Dew point (deg. C)	B20	29	19.1	18.9	1.1	17.2	22.2	18.3	20.0
	Diesel	50	17.1	17.2	0.9	13.9	18.9	16.9	17.4
	ECD	43	13.1	12.8	0.5	12.2	13.9	12.8	13.9
Relative Humidity (%)	B20	29	77.7	78.9	8.0	58.8	87.3	74.7	82.9
	Diesel	50	81.0	85.5	16.7	48.3	100.0	66.3	96.6
	ECD	43	83.7	86.6	9.0	53.3	93.1	80.6	86.7
Engine Speed (RPM)	B20	67991	1813.5	2101.0	544.2	819.0	2282.0	1932.0	2155.0
	Diesel	144152	1810.1	2106.0	543.5	781.3	2258.0	1882.0	2146.0
	ECD	64343	1807.0	2111.0	550.5	827.0	2257.0	1687.0	2157.0
Mass Air Flow (lbs./hr)	B20	67991	260.3	309.6	97.4	61.9	426.4	196.6	328.8
	Diesel	144152	277.7	331.4	107.8	56.5	439.4	197.3	354.1
	ECD	64343	269.0	323.7	104.4	56.2	431.5	146.4	342.3
Fuel Flow (Kg/hr)	B20	67991	66.5	81.9	36.9	2.4	127.7	33.5	97.1
	Diesel	144152	73.8	90.9	40.5	2.7	139.7	36.3	105.4
	ECD	64343	68.4	84.3	38.3	2.4	130.0	22.0	100.2
Mass Air Flow Temperature (deg. C)	B20	67991	360.1	393.7	80.4	71.7	439.6	353.7	408.7
	Diesel	144152	369.0	395.0	66.2	40.2	444.5	357.5	409.1
	ECD	64343	348.9	383.0	79.7	50.6	436.1	338.1	397.7
O_2 (%)	B20	67991	12.3	10.9	3.2	7.2	19.5	9.7	14.6
	Diesel	144152	12.1	10.7	3.1	6.0	19.3	9.6	14.3
	ECD	64343	12.6	11.2	3.2	7.8	19.5	9.9	15.6

A Pearson correlation analysis was performed to assess which of the variables had the most important influence on the NO_x and CO_2 emissions. This analysis is shown in Table 7; in it we can see that ambient temperature, relative humidity and mass air flow temperature have a very small influence on these concentrations. Engine speed, mass air flow and fuel flow do have a significant influence above 0.8 on NO_x and CO_2 concentrations. However, upon closer inspection these variables are strongly dependent on each other as well. Therefore, these variables are not independent with respect to the influence they place on these two emissions. From the variables with high Pearson correlation values, engine speed is the most reliable since it is measured directly based on the alternator signal and the curve obtained from using a manual tachometer.

Table 7. Pearson correlation for main variables collected.

Factor	NO_x	CO_2	Ambient Temp.	Relative humidity	Eng. Speed	Mass air flow	Fuel Flow
CO_2	0.935						
Ambient Temp.	0.045	0.020					
Relative Humidity	-0.082	-0.011	-0.700				
Engine Speed	0.849	0.910	0.020	-0.039			
Mass Air Flow	0.910	0.970	-0.034	0.023	0.934		
Fuel Flow	0.929	0.986	-0.017	0.018	0.880	0.982	
Mass Air Flow Temp.	0.760	0.746	0.082	-0.051	0.772	0.728	0.721

The histogram of the engine speed data is shown in Figure 22. In it we can identify two separate distribution areas. The first distribution is centered near 800 RPM and is indicative of the RPM frequency when the engine is idling. The second part of the histogram shows a bimodal distribution with peaks at about 2050 and 2150 RPM that is indicative of the two gears of the compactor. Histograms with the same pattern were obtained for the data of the individual fuel types (Figure 23).

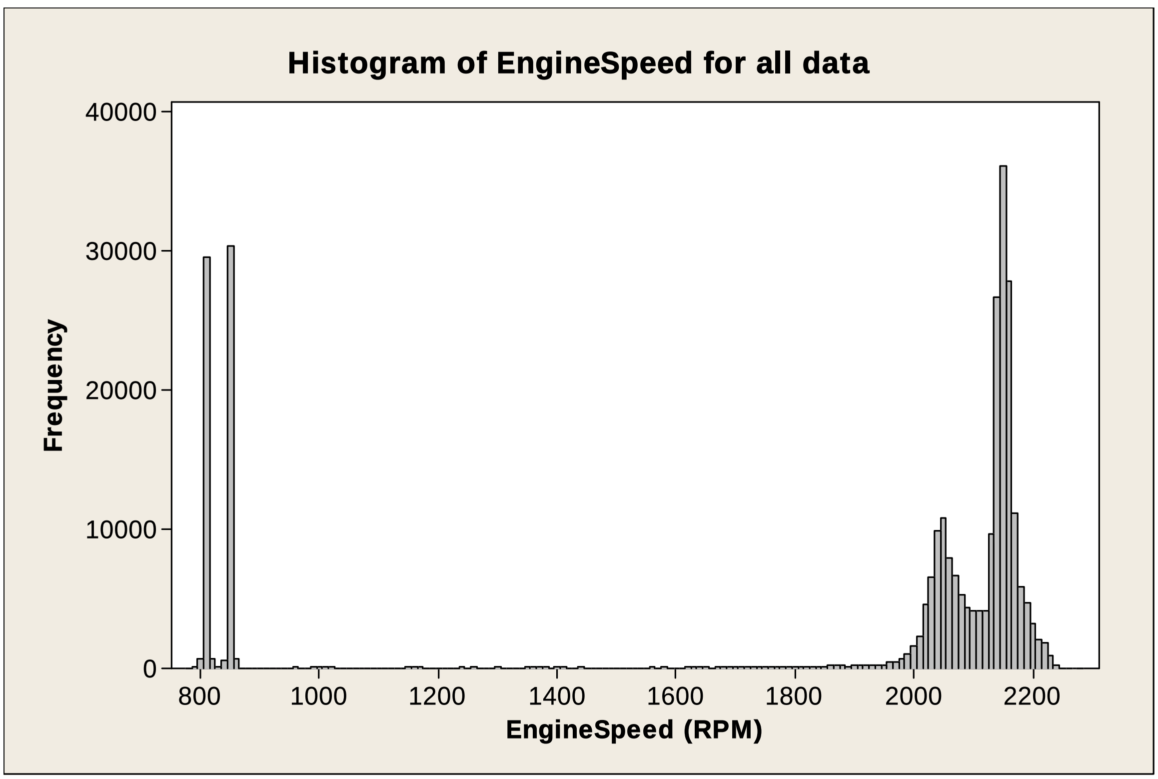


Figure 22. Histogram of engine speed for all data.

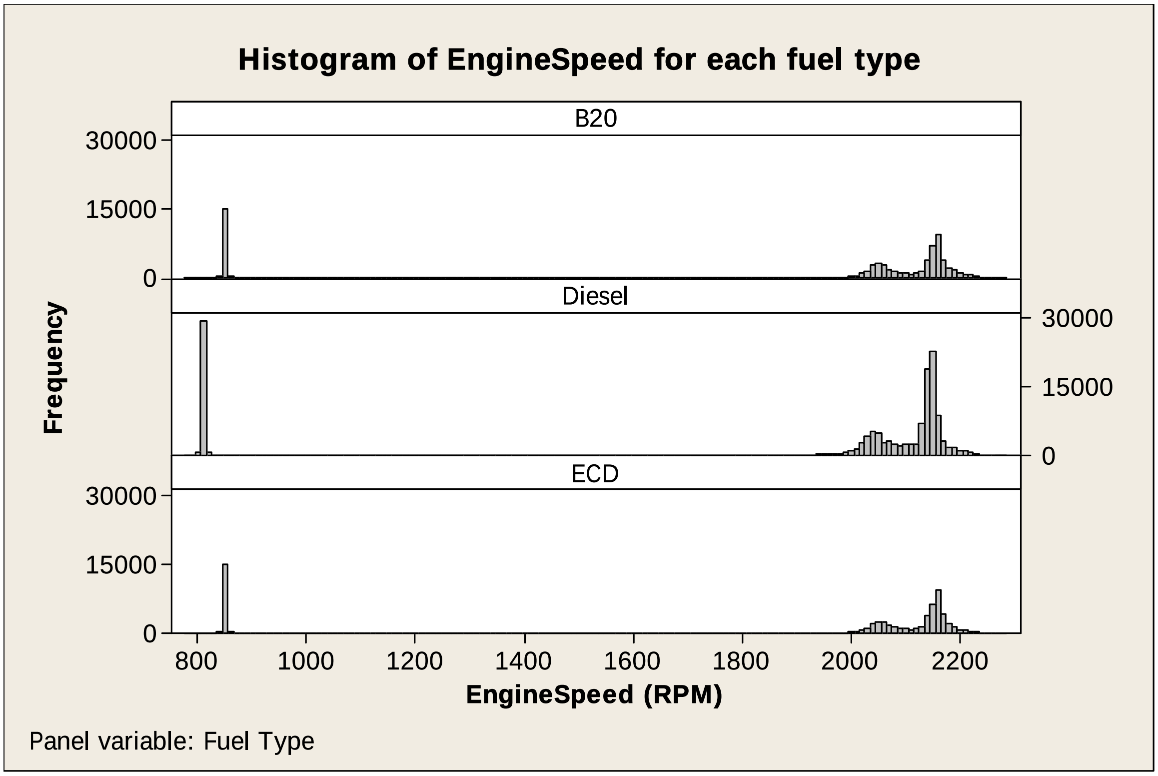


Figure 23. Histogram of engine speed for each fuel type.

<u>IV.A.2.Homogeneity of Variance.</u> The assumption of equal variances (homogeneity of variance) for the engine speed observations was evaluated with Barlett's and Levene's tests (Table 8). Levene's test is less sensitive to departures from normality and therefore more appropriate for the data analyzed than Bartlett's test. However, both tests confirmed that there was not a significant difference between the variances in engine speed observations from the three fuel types. These results were also confirmed visually in the histograms from Figures 24, 25 and 26 that show very similar distributions.

Table 8. Test of homogeneity of variance for three pairs of fuel type.

Engine Speed comparison	Factor	Test statistic	P-value	Difference Significant?
ECD, B20 and Diesel	Bartlett's-test	0.81	0.667	NO
	Levene's test	0.69	0.504	NO

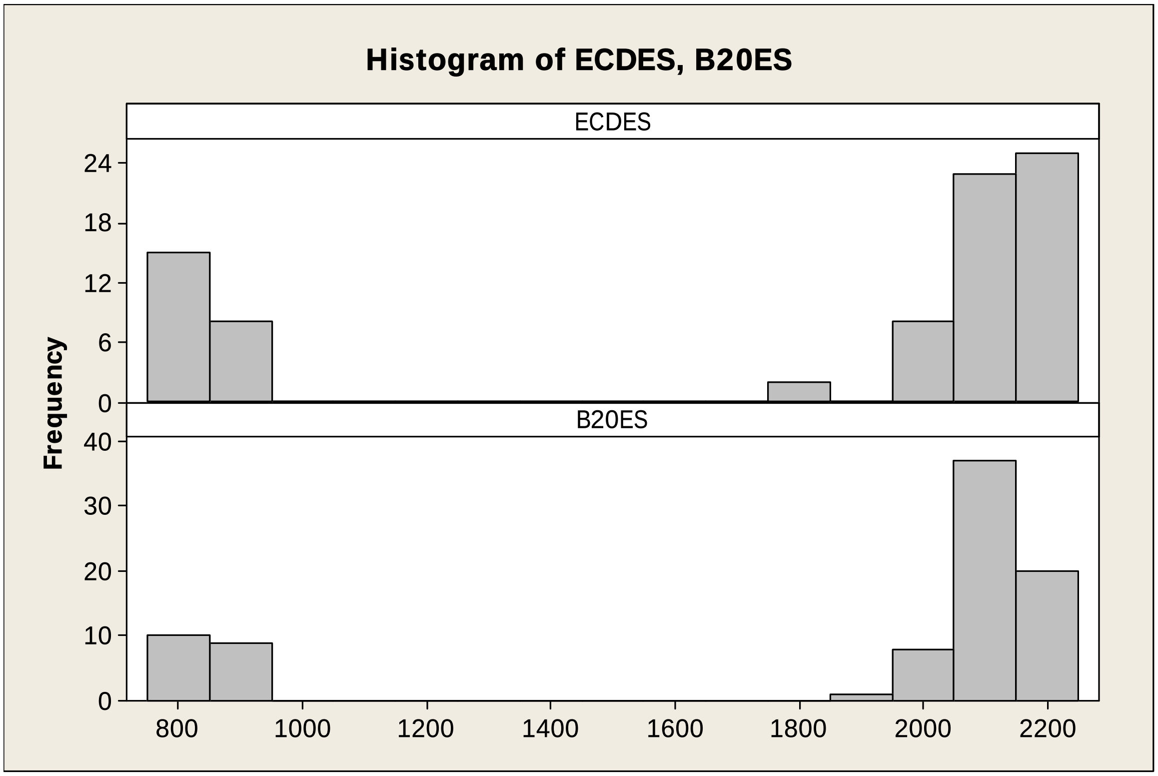


Figure 24. Histogram of engine speed for ECD and B20 fuel types.

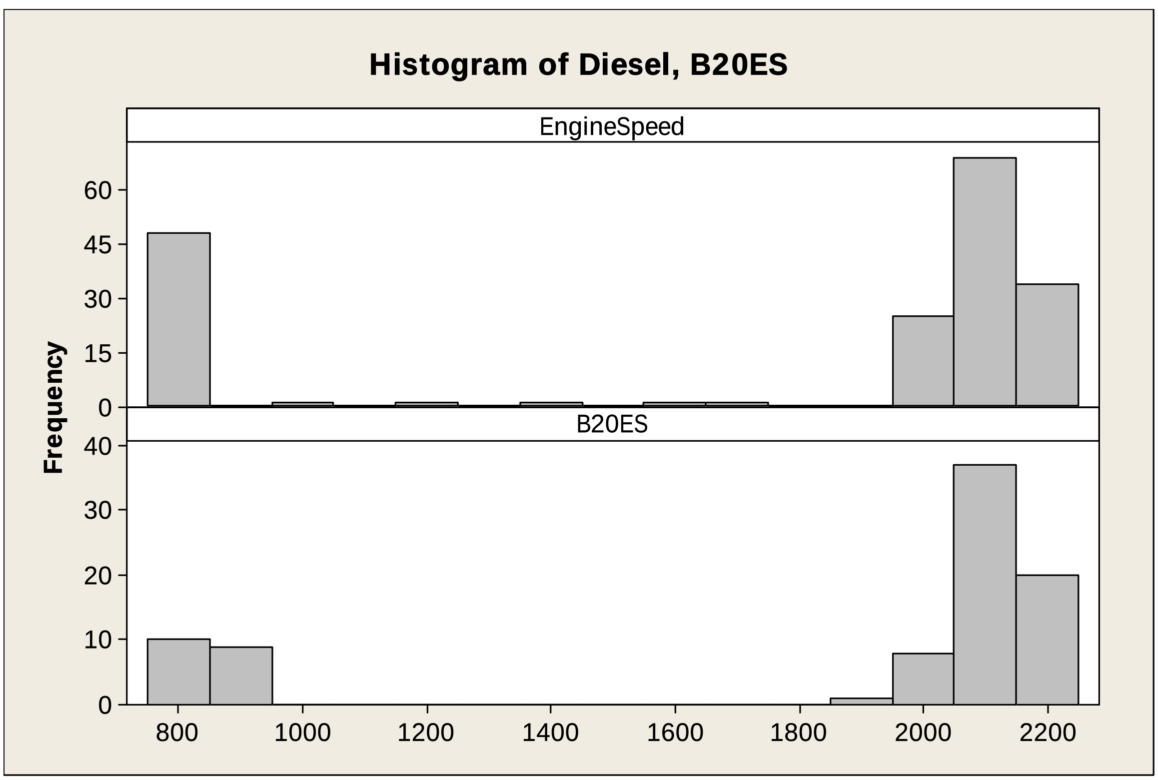


Figure 25. Histogram of engine speed for diesel and B20 fuel types.

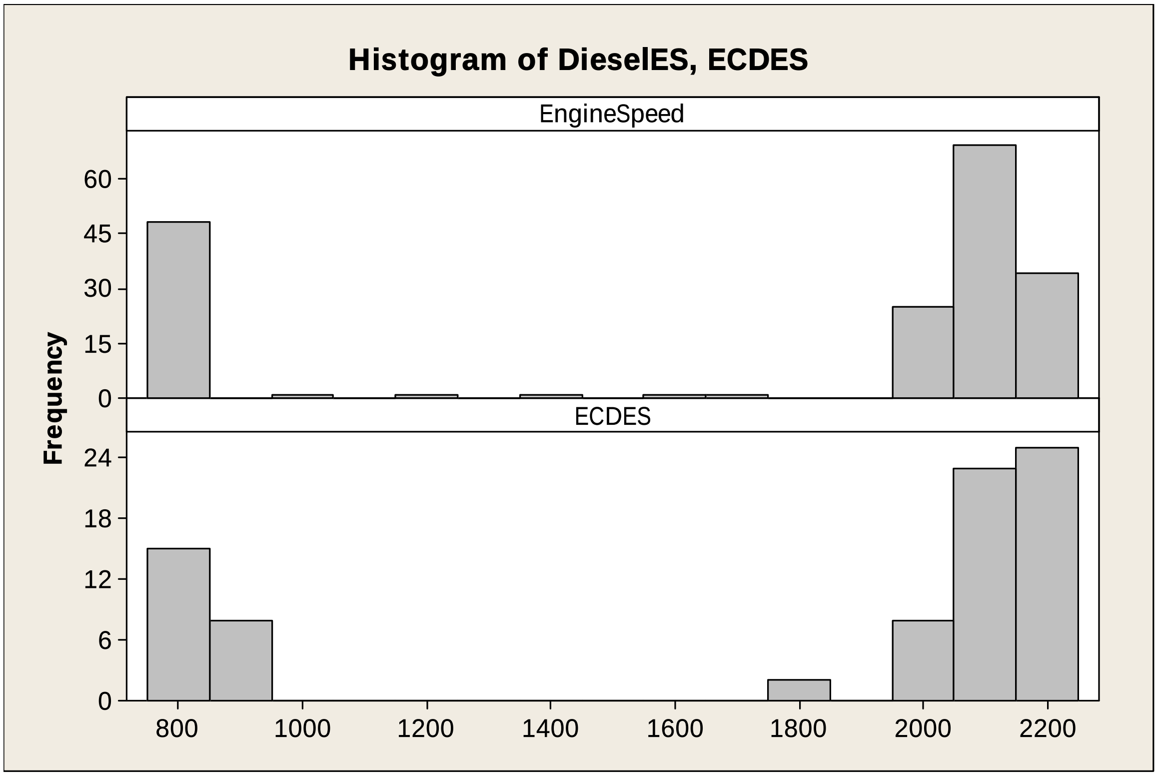


Figure 26. Histogram of engine speed for Diesel and ECD fuel types.

IV.B. NO_x Results for Fuel Analysis

IV.B.1.Scatterplots and Histograms for NO_x**.** The SPOT system used to collect data on a second-by-second basis yielded a vast and daunting dataset due to the extremely large number of data points. The following figures are a graphical representation used to identify patterns and relationships between some of the variables collected. Figure 27 shows a scatterplot for engine speed versus NO_x concentrations for the cumulative data. In it we can identify a positive relationship between NO_x concentrations and engine speed. This relationship is expected since higher emission concentrations correlate with an increase in engine loading. The scatterplot also shows an increase in NO_x variability between an engine speed of 1900 and 2200 RPM. This variability spans from approximately 200 to 700 ppm of NO_x. Figure 28 shows the same shape and pattern exhibited in Figure 27 for each fuel type tested.

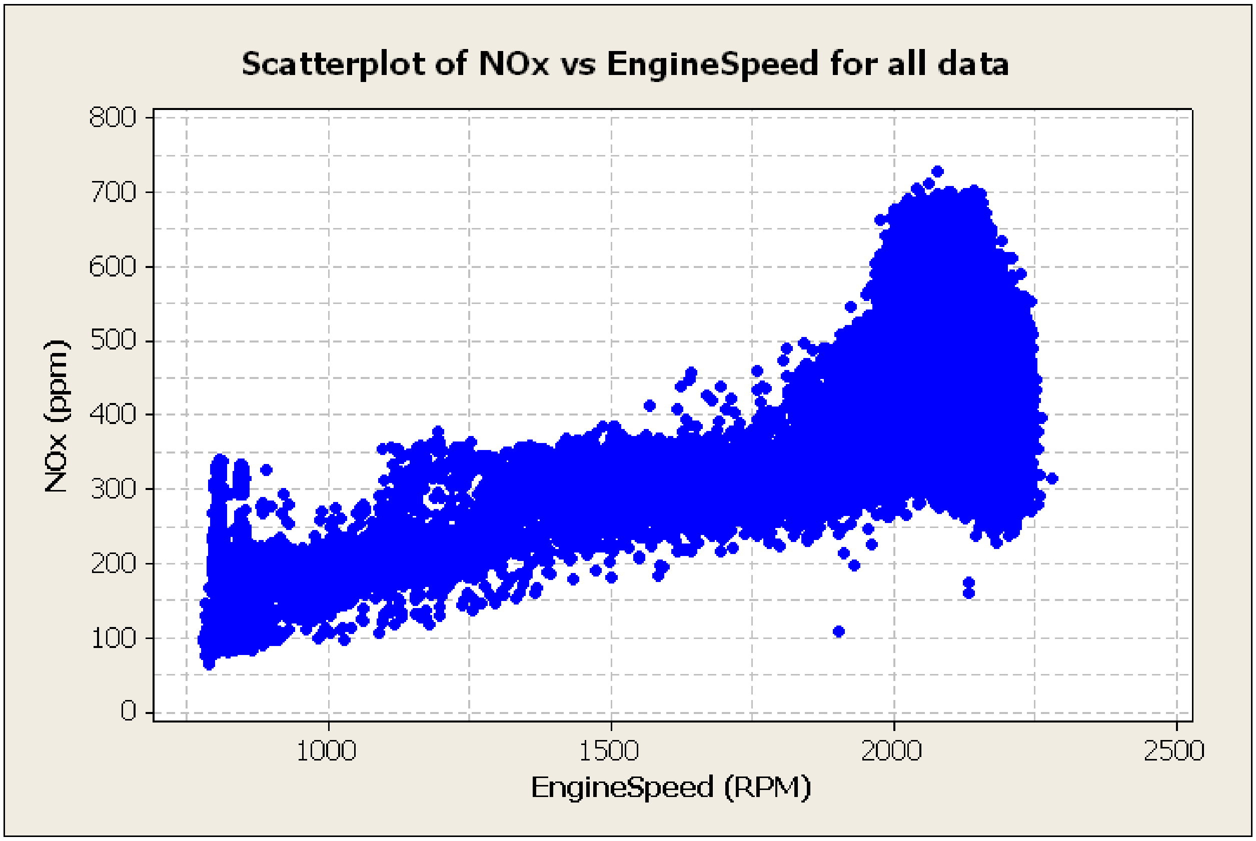


Figure 27. Scatterplot of NO_x vs. engine speed for all data.

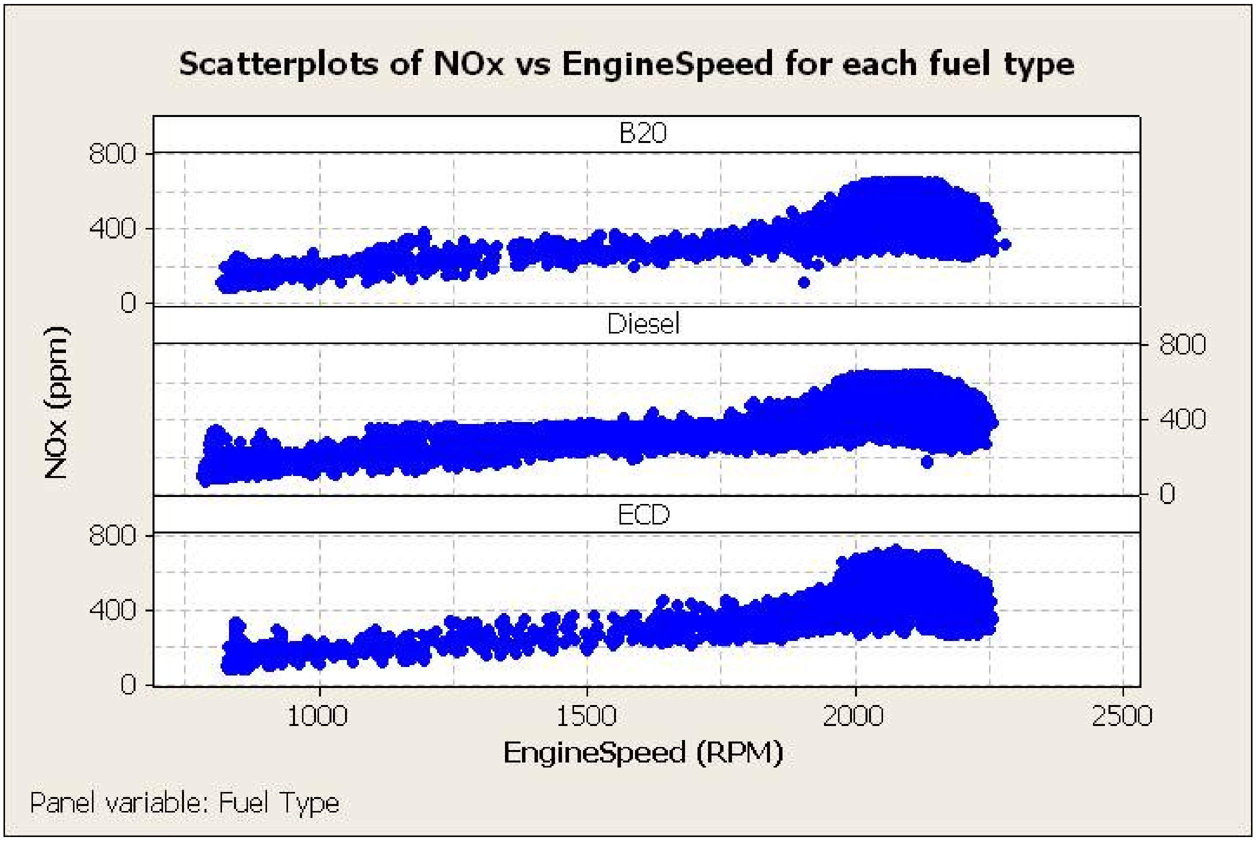


Figure 28. Scatterplot of NO_x vs. engine speed for each fuel type.

<u>IV.B.2.Preliminary Data Analysis</u>**.** The data set for the three fuel types was analyzed further. As shown in Table 9, a total of 276,486 observations were collected for the fuel analysis part of the project. These observations were subject to a General Linear Model (GLM) analysis with NO_x concentrations as the dependent variable, engine speed as the covariate independent factor and Fuel Type as an independent factor. *Engine Speed* was chosen as a covariate factor since this variable is highly related to NO_x concentrations and the intent is to segregate the effect from the "fuel type" factor. Residuals were saved for further analysis as described below.

Table 9. NO_x descriptive statistics.

Variable	Day	N	Mean	Median	StDev	Minimum	Maximum	Q1	Q3
NOx (ppm)	All	276486	415.04	445.1	141.51	63.79	728.1	320.1	532.5
Diesel	8/29/2005	36158	417.9	444.8	139.2	76.3	643.9	337.3	530.3
Diesel	8/30/2005	38873	426.6	441.2	123.8	81.2	638.7	366.6	524.7
Diesel	8/31/2005	36738	411.7	444.7	144.7	76.4	632.2	222	539.5
Diesel	9/1/2005	32383	398	420.5	135	63.8	627.7	286.6	514.9
B20	9/12/2005	35704	413.4	449.6	147.2	82.6	657.1	219.1	534.6

B20	9/13/2005	32287	414.9	453.1	139	81.2	634.5	331.4	535.2
ECD	9/14/2005	33441	417.9	456.9	162.1	87.5	728.1	213.4	543.9
ECD	9/15/2005	30906	418	450	138.1	82.1	630.4	353.2	538
All B20	9/12-9/13	67991	414.1	451.1	143.4	81.2	657.1	309.3	535
All Diesel	8/29-9/01	144152	414.2	439	136.1	63.8	643.9	326.6	527.2
All ECD	9/14-9/15	64347	418	453.8	151	82.1	728.1	294.3	539.8

The results from the GLM analysis are shown in Table 10 where a large F value and thereby a statistical significance for fuel type, engine speed and their interaction was identified. However, upon closer inspection it was realized that the P values were biased based on the very large samples. Basically, with such large sample sizes, any effect would be found to be statistically significant based on the probability value (P).

Table 10. General Linear Model for NO_x versus *Fuel Type* with *Engine Speed* as covariate.

Factor	N	DF	F	P-value
Engine Speed	276485	1	655115.01	0.000
Fuel Type		2	610.58	0.000
Fuel Type *Engine Speed		2	781.41	0.000

IV.B.3.Autocorrelation Test. An autocorrelation test was performed in the data using the residuals obtained from the previous GLM analysis. These residuals were subject to a partial autocorrelation test and the results are plotted in Figure 29. Almost imperceptible in this figure are the critical bands for an alpha value of 0.05 for the hypothesis that the correlations are equal to zero. As we can tell, the first 10 lags shown are random in their pattern but well outside the critical bands. Thus, as expected, the raw data show signs of a strong autocorrelation. This issue is inherent in any database made up of frequent successive observations. Thereby, autocorrelation needed to be addressed since it was limiting the validity and confidence of the GLM analysis (Randolf, 1989).

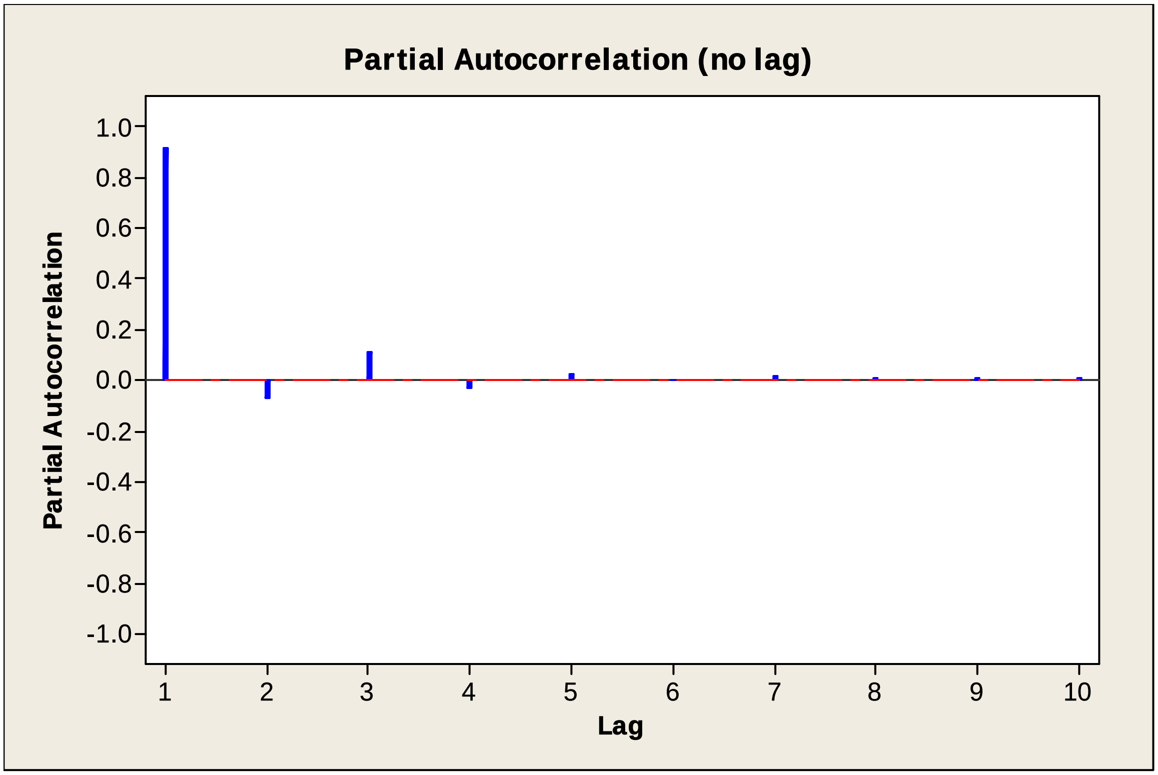


Figure 29. Plot of partial autocorrelation for all data.

IV.B.4.Time to Independence. In most data gathering campaigns a main challenge relates to collecting large enough samples. Usually, the problem is that sample sizes are too small because of financial limitations, and researchers then have to make the best out of the collected data. In the current study, the opposite is true since the SPOT system is able to collect virtually continuous samples without incurring in an added expense. For as long as the trash compactor was in operation, the SPOT system collected second-by-second data. Needless to say, this large data set poses a challenge when it comes to performing statistical analyses with using independent of observations.

Different techniques were sought to address the issue of autocorrelation. In this search, a publication by Swihart and Slade (1985) was found. Their research developed a procedure for determining the time interval at which autocorrelation becomes negligible by using location data of a radio-tagged adult female cotton rat. This study showed that if a fixed interval separates successive observations in an autocorrelated data set, the dependency can be removed by using observations separated by several intervals, thus permitting the use of statistical home range estimates. This approach was quite effective in the animal movement studies but had not been used in a data set like the one being used in the current tailpipe emissions study. This procedure was adapted and used for the current study by analyzing different time intervals to determine a time interval at which autocorrelation becomes negligible. This approach was tested with some skepticism but yielded excellent results in producing quasi-independent observations that satisfy the assumptions of the statistical analysis hereby presented. This "time to independence" can be thought of as the time necessary to produce a distribution of quasi-independent observations. Appendix A includes the results from these analyses. After several iterations an interval of 800 seconds (about 13 minutes) was identified as an adequate interval that minimized autocorrelation. Figure 30 shows that after using an interval of 800 seconds per observation, the observations are quasi-independent and virtually all are inside the 5% critical bands.

Table 11. Total number of observations used after test for independence procedure.

Fuel type	Day	Total data points
Diesel	08/29/2005-09/01/2005	181
B20	09/12/2005-09/13/2005	85
ECD	09/14/2005-09/15/2005	81

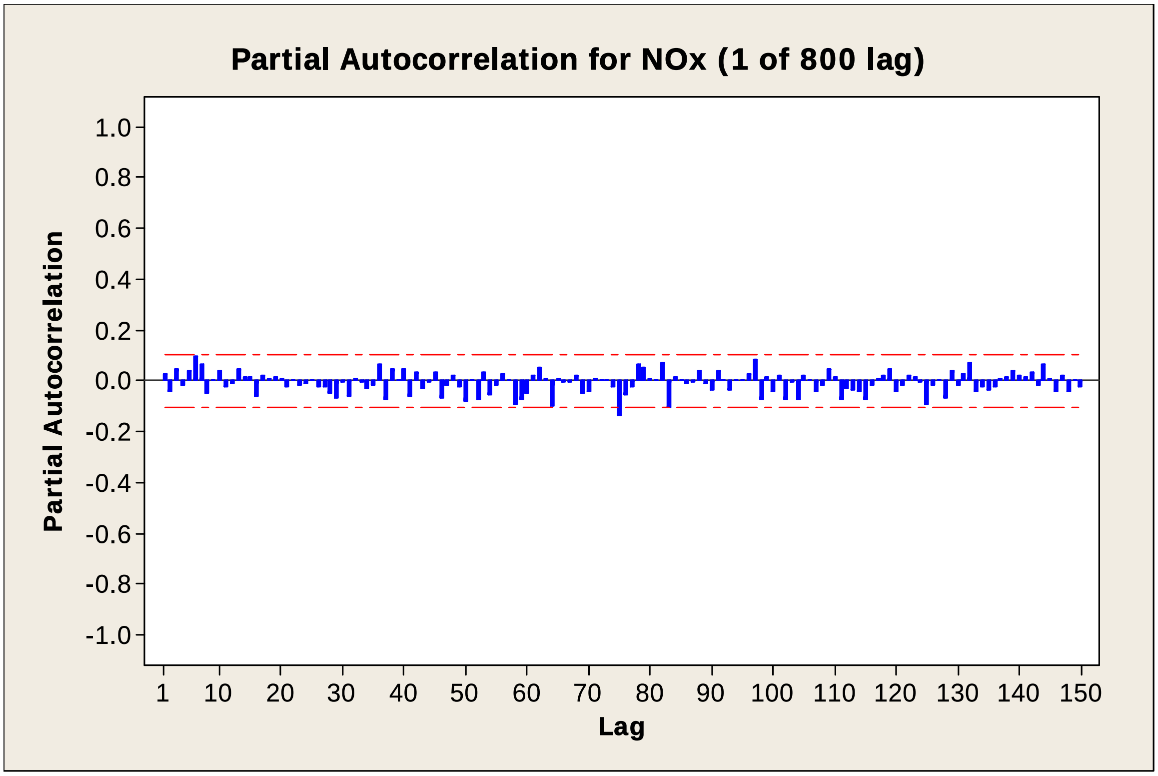


Figure 30. Plot of partial autocorrelation for NO_x data after interval of 1 of 800.

The reduced data set was also subject to a GLM analysis where *Engine Speed* was used as a covariate to *partial* out its effect. By removing the effect of *Engine Speed* the intent is that we will be able to test for the *pure* effect that fuel types have on emissions. The results in Table 12 show that at an alpha value of 0.05, engine speed is statistically significant but fuel type and the interaction of fuel type and engine speed are not. The effect of *Fuel Type* and its interaction with *Engine Speed* was opposite from what was found in the previous data set. This highlights the importance of having independent samples in performing ANOVA/GLM analyses.

The current approach was carried over to the CO_2 analysis and to the two compactor analysis.

Table 12. General Linear Model for NO_x versus *Fuel Type* with *Engine Speed* as covariate for reduced data set.

Factor	N	DF	F	P-value
Engine Speed	346	1	824.72	0.000
Fuel Type		2	0.52	0.595
Fuel Type* Engine Speed		2	0.44	0.645

IV.B.5.Temporal Analysis. A temporal analysis was also performed to identify potential daily biases. As shown in Table 13, the temporal factor and its interaction with engine speed are not statistically significant. This means that NO_x concentrations are not dependent on the day of sampling.

Table 13. General Linear Model for NO_x versus *Sampling Day* with *Engine Speed* as covariate for reduced data set.

Factor	N	DF	F	P-value
Engine Speed		1	921.77	0.000
Day	346	7	0.28	0.960
Day*Engine Speed		7	0.51	0.823

IV.B.6.Data Fitting Model Analysis. One of the goals of the current project is to develop potential models that can be used to analyze and predict diesel NO_x emissions. The nature of the data is such that most of the NO_x readings are at high engine speed values between 2000 and 2400 RPM. Then a second cluster of observations are also observed at a low engine speed between 750 and 850 RPM. A third group of observations was present at the remaining engine speeds (850-200 RPM). Needless to say, finding a valid model to represent this type of data is a cumbersome task. Nonetheless, three types of models were used to fit the NO_x data.

The first model used is the fitted line plot with logarithmic NO_x values. As shown in Figure 31, this model is quite successful in capturing most of the data observations within the 95% prediction intervals and it accounts for 81% of the variability in the data.

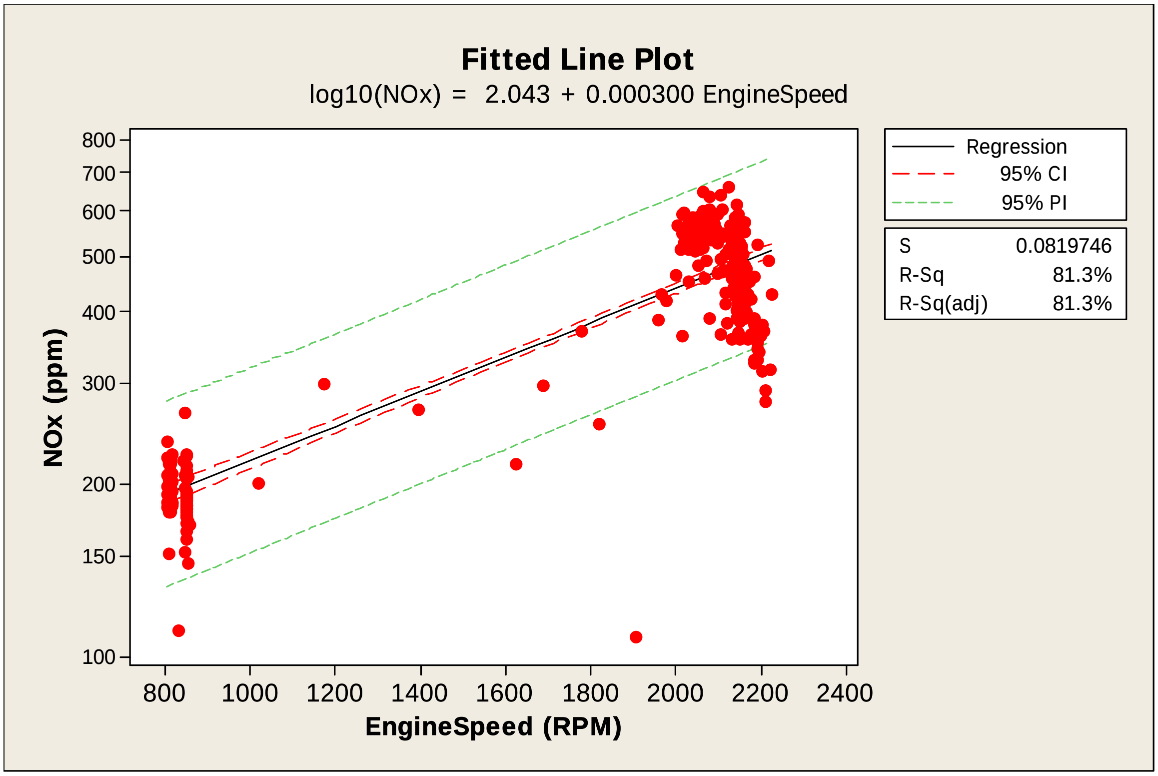


Figure 31. Fitted line plot for fuel data with a linear regression equation.

The next model used is a second order (quadratic) regression model using a log scale for NO_x observations (Figure 32). This model allowed for some curvilinear feature to fit the data but did not improve the shape fit much since it overestimates the middle values between 1200 and 2000 RPM. However, this model did achieve an improvement in the coefficient of determination, which rose to 83%.

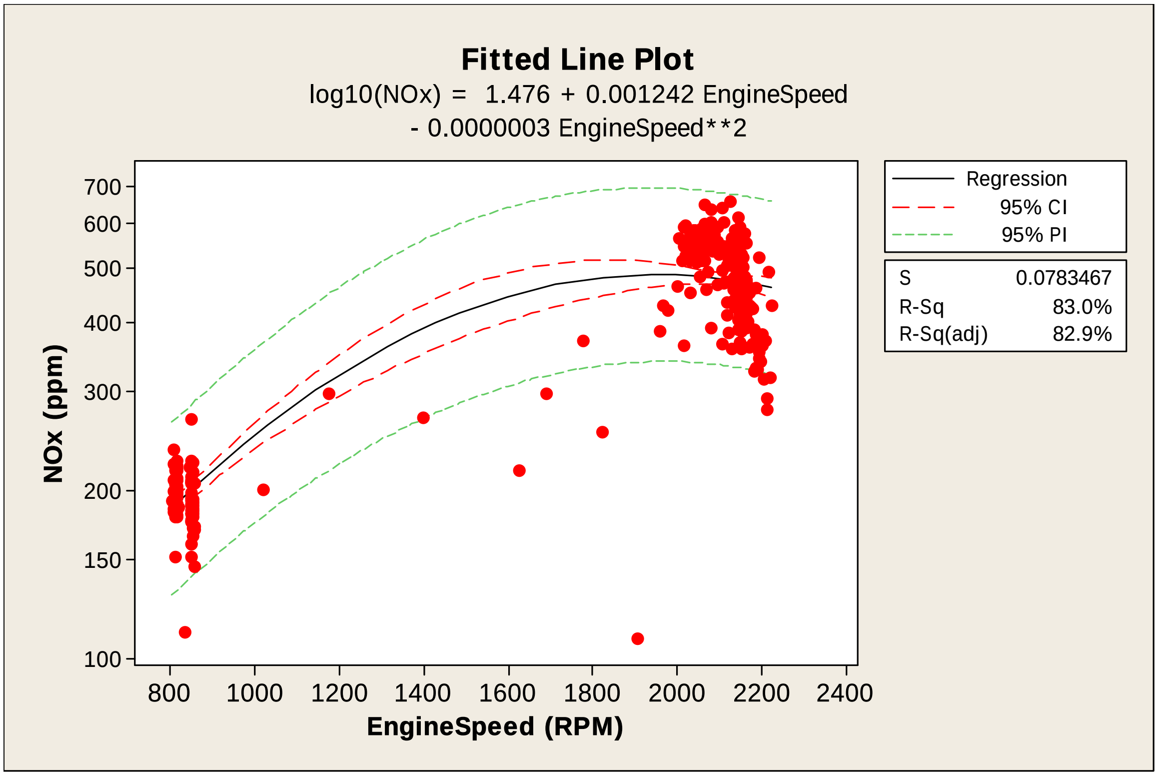


Figure 32. Fitted line plot for fuel data with a quadratic regression equation.

The third model considered was the cubic regression model also using a log scale for the NO_x observations (Figure 33). This model seemed to fit the data very closely in distinct engine speed regions, and it was able to account for the highest variability from the three models considered with 86%. Of remarkable note is the fit at the higher engine speed cluster area between 2000 and 2200 RPM where the model matched the shape almost perfectly. The fit at the low engine speed cluster was also good but perhaps not any better than the previous two models. The one weakness in predicting NO_x concentrations is evident in the 850-1300 RPM engine speed where the model seems to underpredict. However, most of the observations in that range are still within the 95% prediction interval bands.

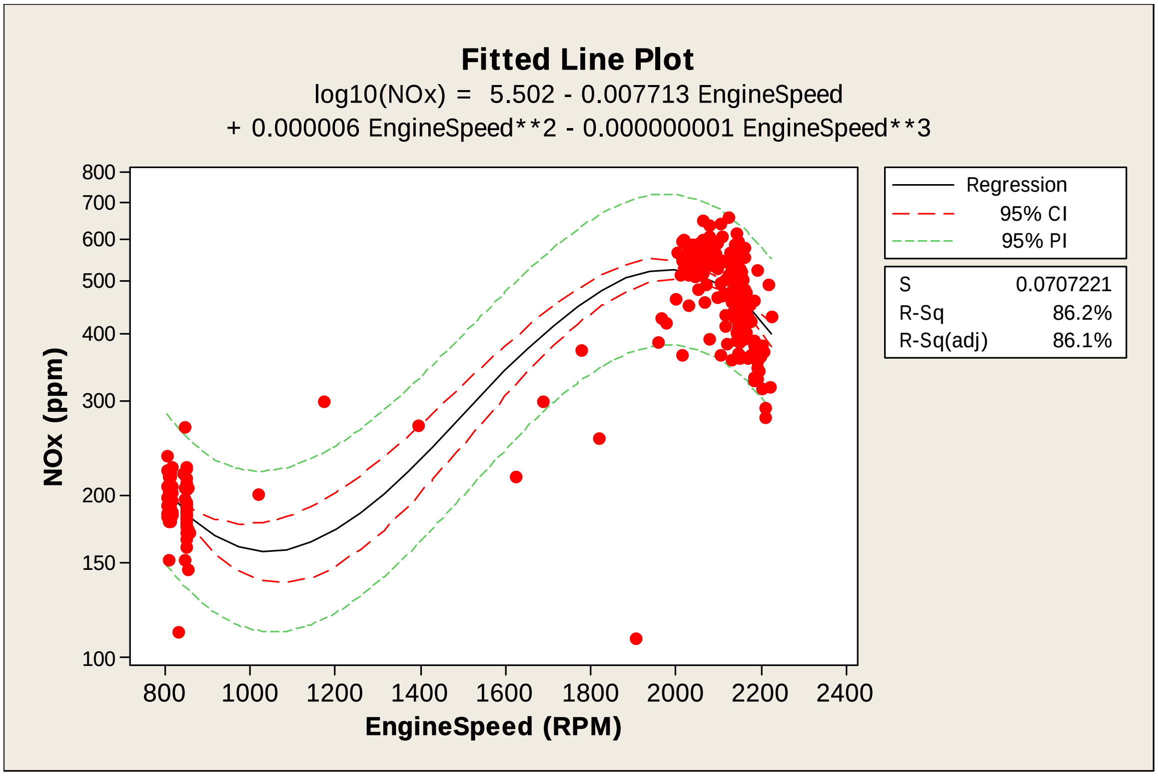


Figure 33. Fitted line plot for fuel data with a cubic regression equation.

IV.C. CO_2 Results for Fuel Analysis

The CO_2 concentrations were also plotted versus engine speed in Figure 34. In this case we identified a positive relationship between these two variables. The variability of CO_2 concentrations also increases with engine speed. This behavior creates a fanning effect where the largest variability is observed from 1600 to 2300 RPM. Figure 35 shows the same shape and pattern exhibited in Figure 34 for each fuel type tested.

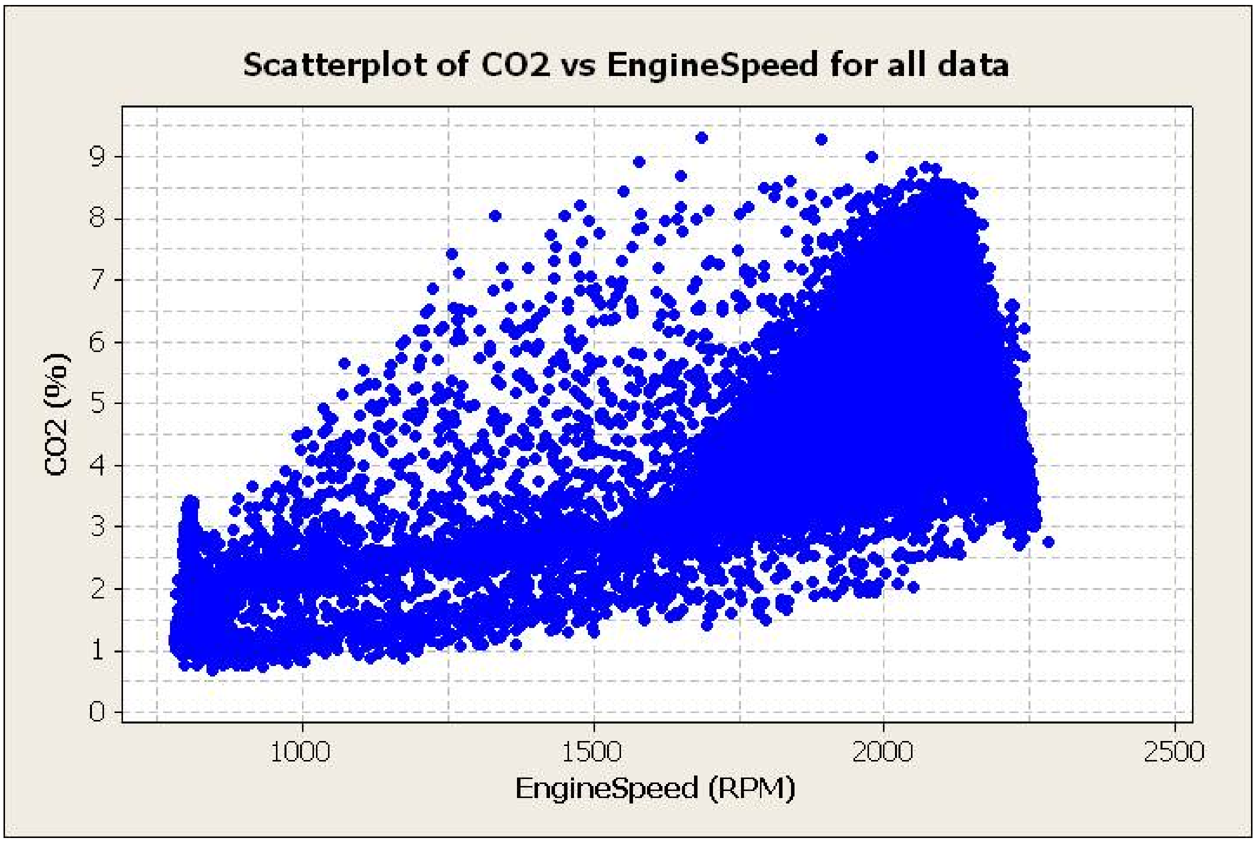


Figure 34. Scatterplot of CO_2 vs. engine speed for all data.

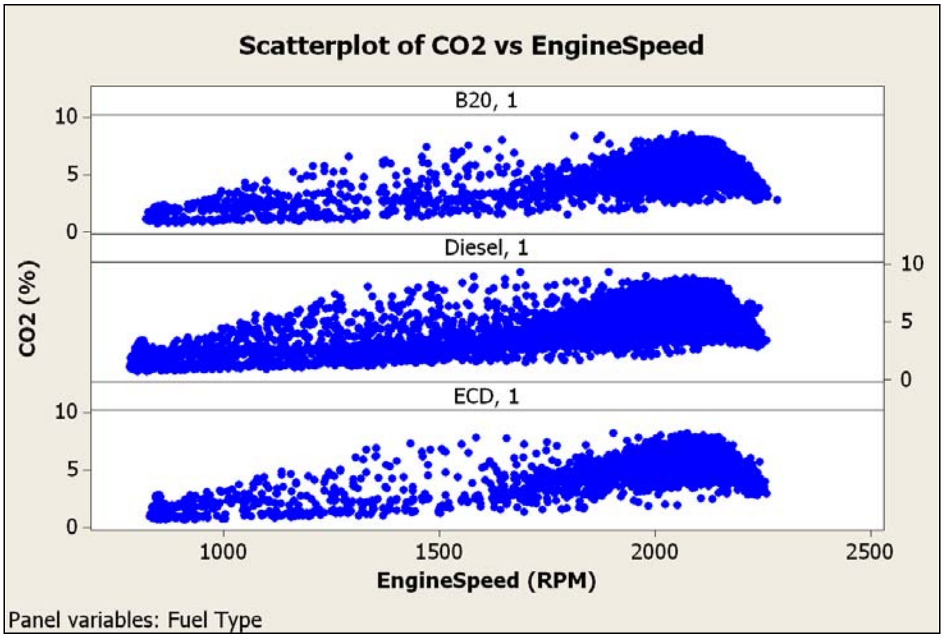


Figure 35. Scatterplot of CO_2 vs. engine speed for each fuel type.

IV.C.1.Preliminary Data Analysis. The first data set was analyzed further to determine the effect on the emissions concentrations from temporal and fuel type factors. As shown in Table 14, a total of 276,486 observations was collected for the fuel analysis part of the project. These observations were subject to a General Linear Model (GLM) analysis with CO_2 concentrations as the dependent variable, *Engine Speed* as the covariate independent factor and *Fuel Type* as an independent factor. *Engine Speed* was chosen as a covariate factor since this variable is highly related to CO_2 concentrations and the intent is to segregate the effect from the "fuel type" factor. Residuals were also saved for further analysis.

Table 14. CO_2 descriptive statistics.

Variable	Day	N	Mean	Median	StDev	Minimum	Maximum	Q1	Q3
CO2 (%)	All	276486	5.3074	6.166	2.0187	0.676	9.31	3.815	6.909
Diesel	8/29/2005	36158	5.57	6.38	1.97	1.05	9.31	4.35	7.07
Diesel	8/30/2005	38873	5.70	6.36	1.82	0.83	8.56	5.18	7.03
Diesel	8/31/2005	36738	5.22	6.24	2.16	0.75	8.82	2.13	7.08
Diesel	9/1/2005	32383	5.17	6.05	2.01	0.80	8.44	2.89	6.86
B20	9/12/2005	35704	5.09	6.03	2.07	0.68	8.55	1.98	6.75
B20	9/13/2005	32287	5.32	6.17	2.00	0.74	8.39	4.33	6.95
ECD	9/14/2005	33441	4.97	5.98	2.11	0.78	8.27	1.94	6.63
ECD	9/15/2005	30902	5.35	6.07	1.89	0.72	8.14	4.70	6.86

All B20	9/12-9/13	67991	5.20	6.09	2.04	0.68	8.55	3.74	6.91
All Diesel	8/29-9/01	144152	5.43	6.27	2.00	0.75	9.31	3.98	7.01
All ECD	9/14-9/15	64343	5.15	6.02	2.01	0.72	8.27	3.22	6.82

The results from the GLM analysis are shown in Table 15 where a large F-value and thereby a statistical significance for fuel type, engine speed and their interaction was identified. However, the same issue identified for NO_x concentrations was present for CO_2 also and the P values were biased because of the very large samples.

Table 15. General Linear Model for CO_2 versus *Fuel Type* with *Engine Speed* as covariate.

Factor	N	DF	F	P-value
Engine Speed	276485	1	1196847.29	0.000
Fuel Type		2	433.31	0.000
Fuel Type* Engine Speed		2	37.97	0.000

IV.C.2.Autocorrelation Test. An autocorrelation test was performed on the data by using the residuals obtained from the previous GLM analysis. These residuals were subject to a partial autocorrelation test and the results are plotted in Figure 36. Almost imperceptible in this figure are the critical bands for an alpha value of 0.05 for the hypothesis that the correlations are equal to zero. As we can tell, the first 10 lags shown are random in their pattern but well outside the critical bands. Thus, as expected, the raw data show signs of a strong autocorrelation. This issue is inherent in any database made up of frequent successive observations. Thereby, autocorrelation needed to be addressed since it was limiting the validity and confidence of the GLM analysis.

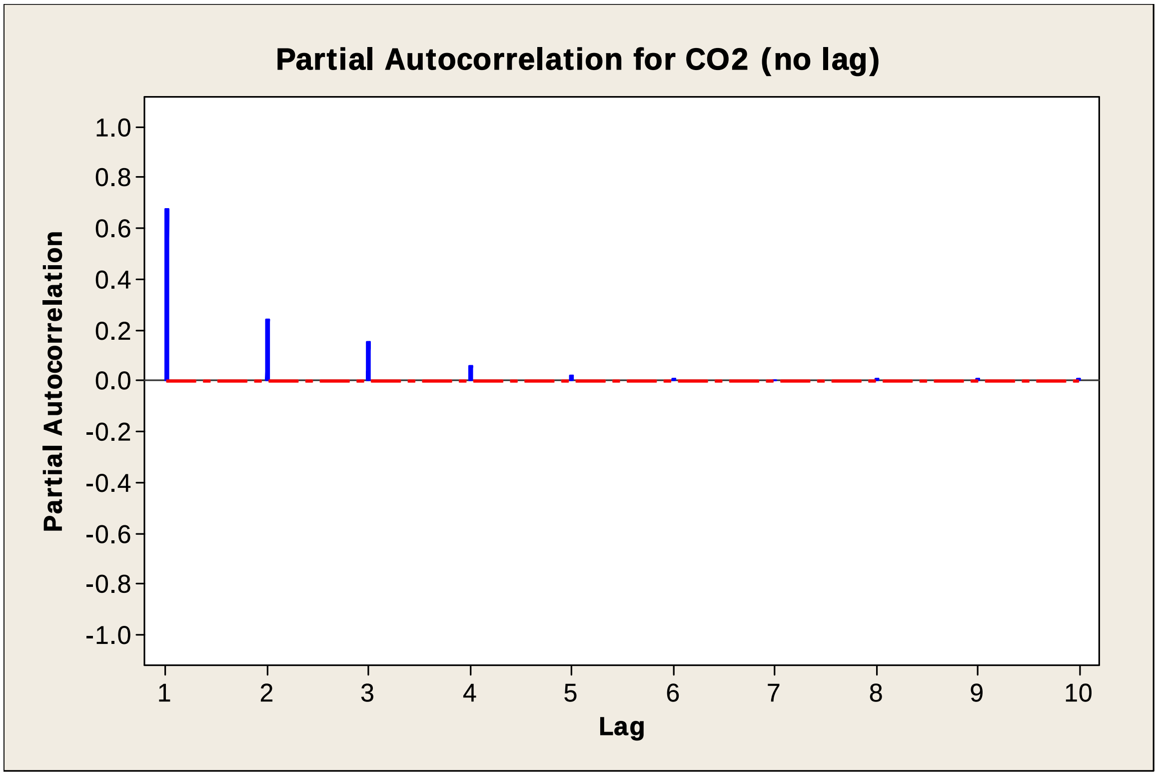


Figure 36. Plot of partial autocorrelation for all data.

<u>IV.C.3.Time to Independence.</u> The same procedure used for NO_x concentrations was used for CO_2 concentrations to develop quasi-independent observations. This data reduction technique produces a subset of observations by selecting observations from the original data set separated by a large enough interval to render autocorrelation insignificant. Appendix A includes the results from these analyses. Thus, an interval of 800 seconds (about 13 minutes) was used to minimize autocorrelation. Figure 37 shows that after using an interval of 800 seconds per observation, the observations are quasi-independent.

Table 16. Total number of observations used after test for independence procedure.

Fuel type	Day	Total data points
Diesel	08/29/2005-09/01/2005	181
B20	09/12/2005-09/13/2005	85
ECD	09/14/2005-09/15/2005	81

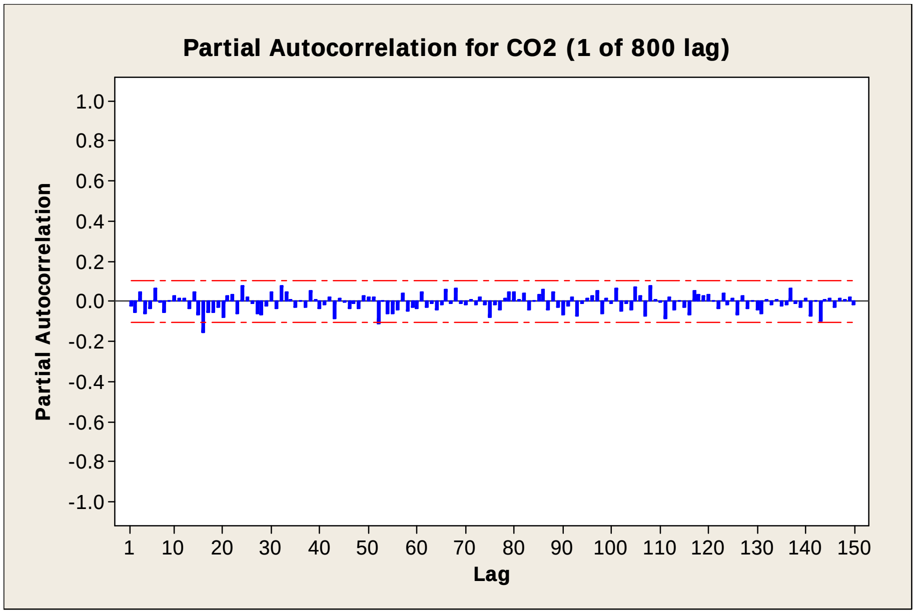


Figure 37. Plot of partial autocorrelation for CO_2 data after interval of 1 of 800.

The reduced data set was then subjected to a GLM analysis where *Engine Speed* was used as a covariate to *partial* out its effect. By removing the effect of engine speed the intent is that we will be able to test for the *pure* effect that fuel types have on emissions. The results in Table 17 show that at an alpha value of 0.05, engine speed is statistically significant, but the *Fuel Type* and the interaction of *Fuel Type* and *Engine Speed* are not. The effect of *Fuel Type* and its interaction with *Engine Speed* was the opposite of what was found in the previous data set.

Table 17. General Linear Model for CO_2 versus *Fuel Type* with *Engine Speed* as covariate for reduced data set.

Factor	N	DF	F	P-value
Engine Speed	346	1	1454.71	0.000
Fuel Type		2	0.95	0.389
Fuel Type* Engine Speed		2	0.34	0.714

<u>IV.C.4.Temporal Analysis.</u> A temporal analysis was also performed to identify potential daily biases. As shown in Table 18 below, the temporal factor and its interaction with engine speed are not statistically significant. This means that CO_2 concentrations are not dependent on the day of sampling.

Table 18. General Linear Model for CO_2 versus *Sampling Day* with *Engine Speed* as covariate for reduced data set.

Factor	N	DF	F	P-value
Engine Speed	346	1	1555.83	0.000
Day		7	0.38	0.914
Day* Engine Speed		7	0.25	0.972

<u>IV.C.5.Data Fitting Model Analysis.</u> One of the goals of the current project is to develop potential models for analyzing and predicting diesel CO_2 emissions. The nature of the data is such that most of the CO_2 readings are at high engine speed values between 2000 and 2400 RPM. Then a second cluster of observations are also observed at a low engine speed between 750 and 850 RPM. A third group of observations was present at the remaining engine speeds (850-200 RPM). Finding a valid model to represent this type of data is a cumbersome task; nonetheless, three types of models were used to fit the CO_2 data.

The first model used is the fitted line plot with logarithmic CO_2 values. As shown in Figure 38, this model is quite successful in capturing most of the data observations within the 95% prediction intervals and it accounts for 89 percent of the variability in the data. The performance of this model is better than the one exhibited for NO_x.

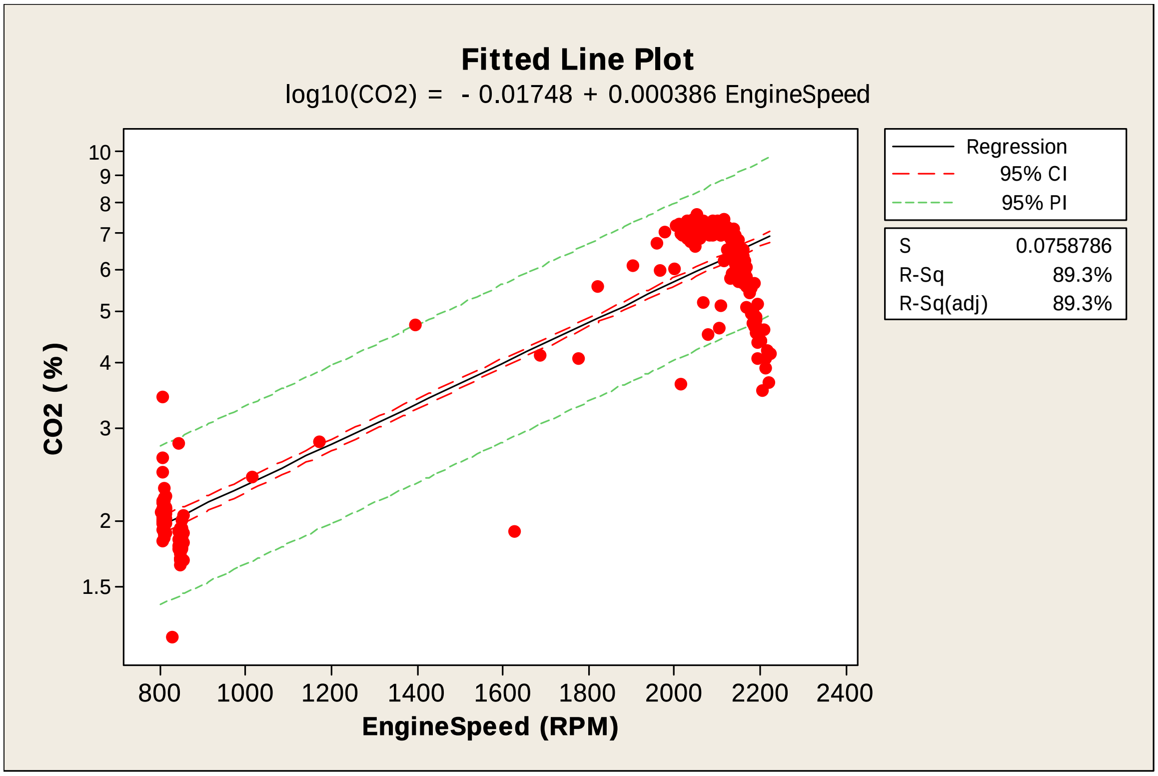


Figure 38. Fitted line plot for fuel data with a linear regression equation.

The next model used is a second order (quadratic) regression model using a log scale for CO_2 observations (Figure 39). This model allowed for some curvilinear feature to fit the data but did not improve the shape fit that much since it overestimates the middle values between 1200 and 2000 RPM. However, this model did achieve an improvement in the coefficient of determination, raising it to 92%.

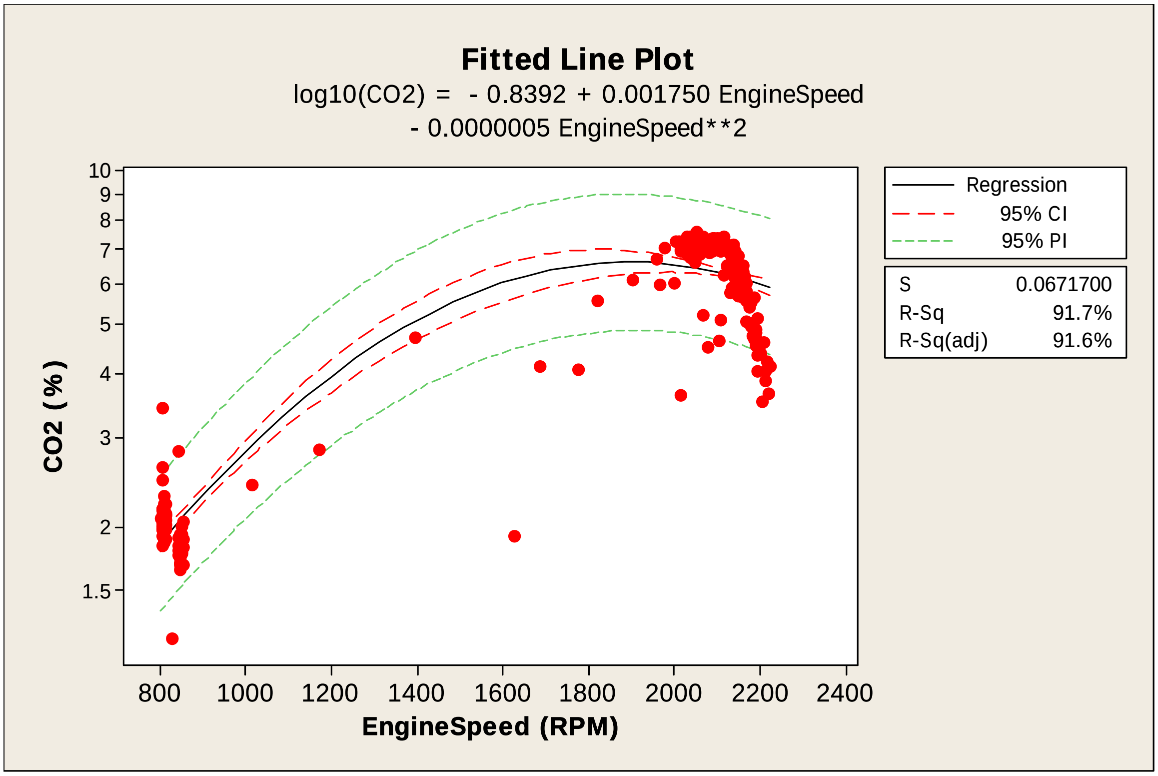


Figure 39. Fitted line plot for fuel data with a quadratic regression equation.

The last model tested is the third order (cubic) regression model also using a log scale for the CO_2 observations (Figure 40). This model seemed to fit the data very closely, in the engine speed regions it was able to account for the highest variability with 95 percent. Of note is the fit at the higher engine speed cluster area between 2000 and 2200 RPM where the model matched the shape almost perfectly. The fit at the low engine speed cluster was also good but perhaps not any better than the previous two models. The one weakness in predicting CO_2 concentrations is evident in the 850-1300 RPM engine speed were the model seems to underpredict as shown in Figure 30. However, few observations occur in that interval so this weakness is not as significant.

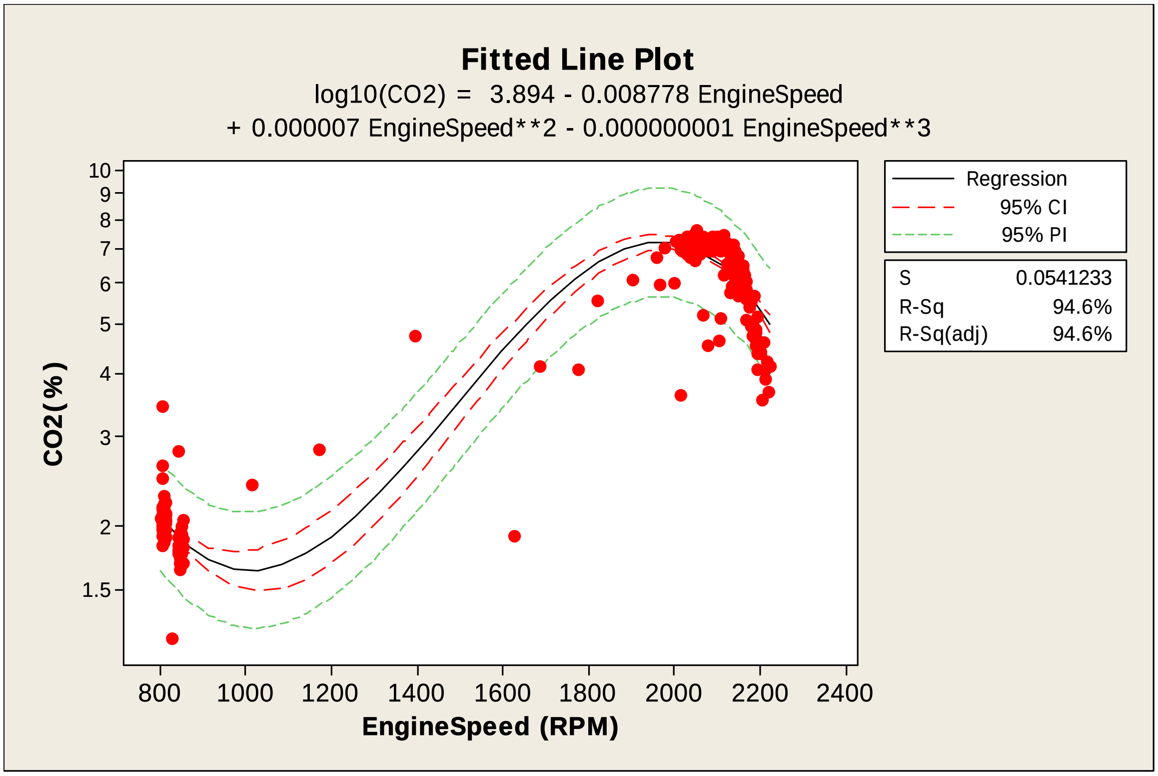


Figure 40. Fitted line plot for fuel data with a cubic regression equation.

V. RESULTS OF COMPACTOR ANALISIS

The second analysis compares two trash compactors of the same model to test the effect of individual machine on emissions and temporal factors. This analysis only entails diesel fuel. Since the fuel type analysis already collected information on one compactor running on diesel fuel, a second compactor was also tested in a second sampling campaign that occurred from June 21 to June 26, 2007 at the same location and with the same operator. The actual running time of the compactor for the days sampled are shown in Table 19. This table shows the actual number of data points available for the statistical analysis since a few readings were discarded due to calibration values and communication gaps in the SPOT system.

Table 19. Total number of hours compactor was in operation during each sampling day.

Day	Fuel type	Compactor	Start time	End time	Total time	Total data points
08/29/2005	Diesel	1	7:07 AM	5:10 PM	10:03	36158
08/30/2005	Diesel		7:10 AM	5:57 PM	10:47	38873
08/31/2005	Diesel		7:08 AM	5:21 PM	10:13	36738
09/01/2005	Diesel		7:08 AM	4:29 PM	9:21	32383
06/21/2007	Diesel	2	1:15 PM	5:05 PM	3:50	12866
06/22/2007	Diesel		7:22 AM	5:13 PM	9:51	30109
06/25/2007	Diesel		6:54 AM	5:10 PM	10:16	35741
06/26/2007	Diesel		7:29 AM	3:51 PM	8:22	23065

The average temperature, relative humidity and sky cover conditions for each of the sampling episodes are shown in Table 20. These data were obtained from the National Climatic Data Center (NCDC) for the Lawrence municipal airport station. This station is located about 5 miles southeast of Hamm's Sanitary Landfill.

Table 20. Average temperature, relative humidity and sky cover for sampling period.

Sampling day	Avg. temp. (ºC)	Relative humidity (%)	Sky cover
08/29/2005	21.3	49.4-100	Clear
08/30/2005	21.1	51.1-96.6	mostly clear
08/31/2005	22.0	48.3-96.6	clear, scattered and broken
09/01/2005	19.8	57.5-96.6	scattered, broken and overcast
06/21/2007	26.1	52-93	Few, scattered and broken
06/22/2007	25.6	48-90	Clear, few, scattered
06/25/2007	27.2	50-93	Clear, few
06/28/2007	21.1	72-93	Few, scattered, overcast

V.A. Data Screening

Profiles were created for each of the two compactors using the diesel fuel data collected for this and the previous part of the study. These raw data included some calibration values each time the engine was started and also some missing values due to compiling gaps. These values were cleared from the final dataset prepared for the statistical analysis. As mentioned earlier, the KU team also found that the ambient temperature and humidity values collected by the SPOT system were inaccurate. This was caused by the location of the SPOT system. The only viable place for placing the SPOT was behind the operator cabin. This location, although not directly above the engine, did receive enough heat to significantly impact the ambient temperature values and consequently the relative humidity ones as well. Thus, weather surface data were used from the closest weather station located at the Lawrence Municipal Airport (about 5 miles southeast from the sampling location). Descriptive statistics for engine variables are shown in Table 21.

Table 21. Descriptive statistics for engine variables by compactor

Variable	Compactor	N	Mean	Median	StDev	Min.	Max.	Q1	Q3
Engine Speed (RPM)	1	144160	1810.0	2106	543.6	781.3	2258	1882	2146
	2	102734	1767.7	2128	581.1	801.0	2290	858	2169
Mass Air Flow (lbs./hr)	1	144160	277.70	331.4	107.76	56.54	439.4	197.2	354.1
	2	102734	264.39	316.6	116.84	40.82	465.0	113.4	359.5
Fuel Flow (Kg/hr)	1	144160	73.786	90.90	40.535	2.676	139.7	36.23	105.4
	2	102734	66.037	80.95	43.159	2.710	142.2	8.57	103.2
Mass Air Flow Temperature (°C)	1	144160	369.02	395.0	66.20	40.24	444.5	357.4	409.1
	2	102734	318.30	359.8	82.25	58.72	417.2	278.9	375.2
O_2 (%)	1	144160	12.051	10.73	3.131	6.007	14.29	9.55	14.29
	2	102734	12.725	11.13	3.346	7.497	17.30	9.93	17.30

A Pearson correlation analysis assesses which of the variables had the most important influence on the NO_x and CO_2 emissions (Table 22). We can see that all variables have a significant influence on NO_x and CO_2 concentrations. A closer inspection indicates that these variables are strongly dependent on each other. Therefore, the fundamental assumption of independent observations is not met in either emission data set. From the variables with high Pearson correlation values, engine speed is the one measured directly based on the alternator signal and the curve obtained from using a manual tachometer to find the exact engine speed values. Thus, this variable is more reliable to this analysis.

Table 22. Pearson correlation for main variables collected.

Factor	NO_x	CO_2	Eng. Speed	Mass air flow	Fuel Flow
CO_2	0.911				
Engine Speed	0.787	0.914			
Mass Air Flow	0.879	0.970	0.929		
Fuel Flow	0.911	0.985	0.878	0.984	
Mass Air Flow Temp.	0.747	0.723	0.722	0.680	0.685

In the histogram of the engine speed data shown, we can identify two separate distribution areas (Figure 41). The first distribution is centered near 800 RPM and is indicative of the RPM frequency when the engine is idling. The second part of the histogram shows a bimodal distribution with peaks at about 2050 and 2150 RPM. This is the same pattern observed in the previous data analyses. Histograms with the same pattern were obtained for the data of the individual compactors (Figure 42).

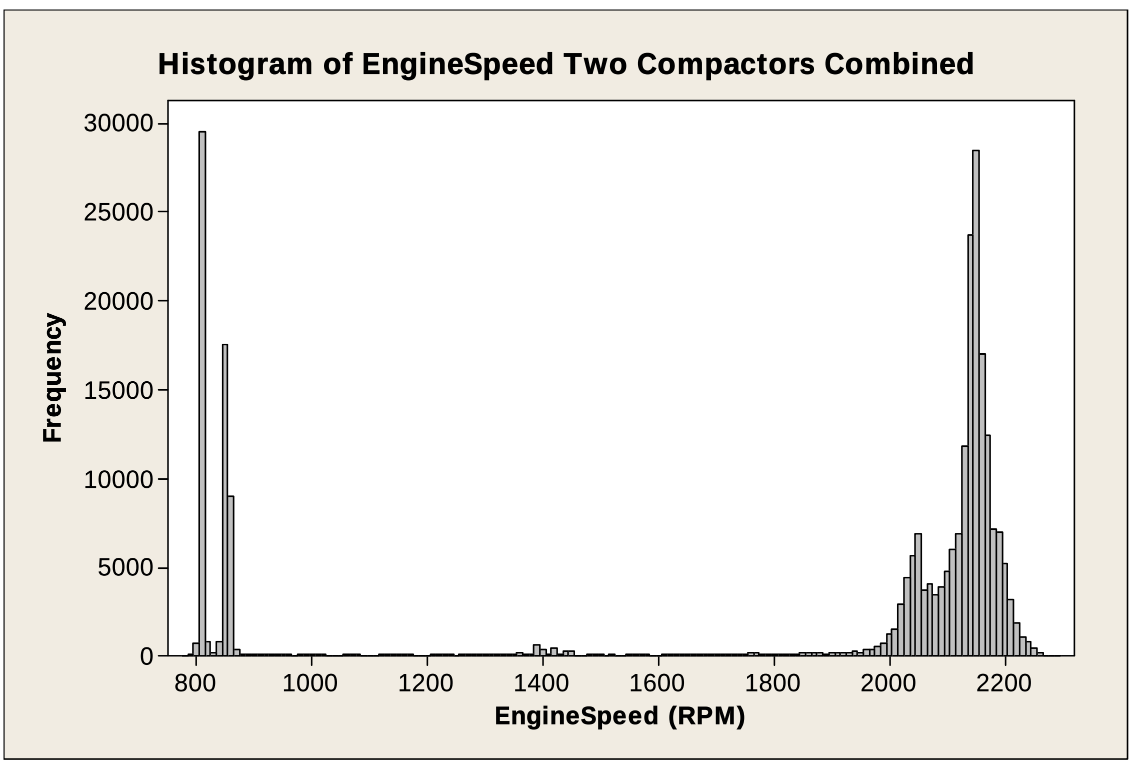


Figure 41. Histogram of engine speed for the combined data of both compactors.

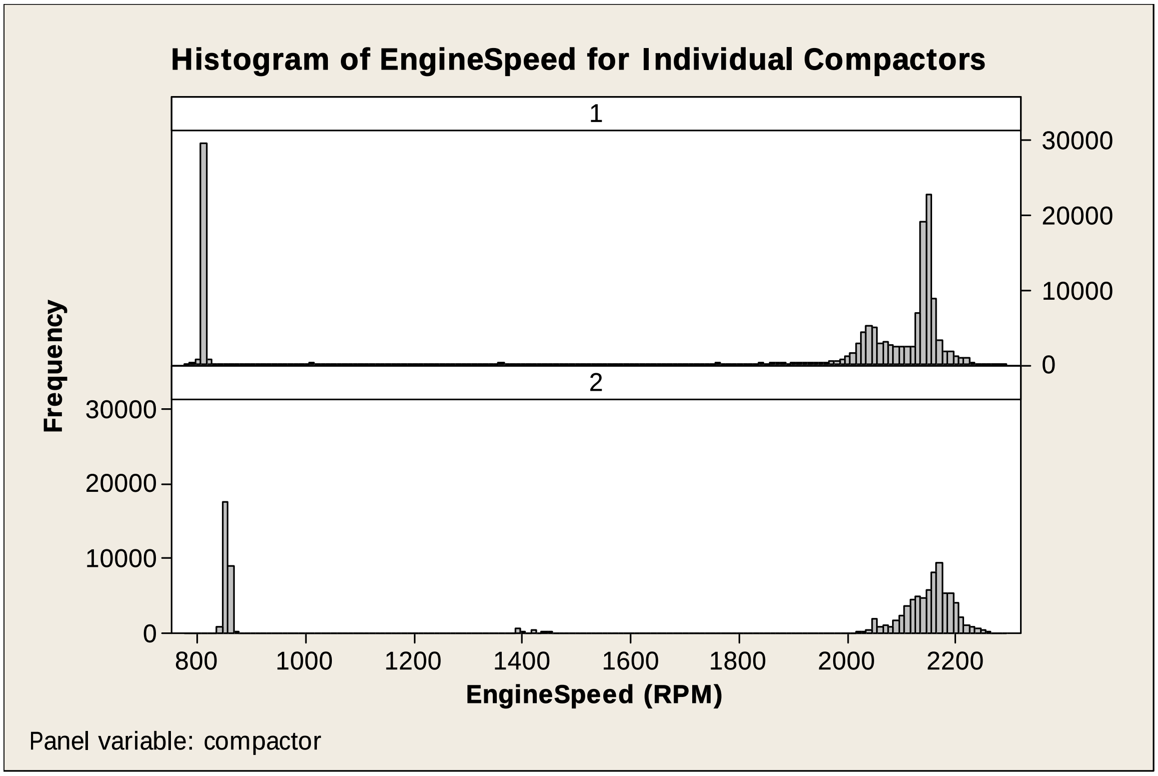


Figure 42. Histogram of engine speed for individual compactors.

V.A.1.Homogeneity of Variance. The assumption of equal variances (homogeneity of variance) for the engine speed observations was evaluated with the F-test and Levene's test (Table 23 and Figure 43). Levene's test is less sensitive to departures from normality and therefore more appropriate for the data analyzed than the F-test. However, both tests confirmed that there was not a significant difference between the variances in engine speed observations from the two compactors. These results were also confirmed visually in the histograms from Figure 42 showing very similar distributions.

Table 23. Test of homogeneity of variance for two compactors.

Engine Speed comparison	Factor	DF1	DF2	Test statistic	P-value	Difference Significant?
Compactor #1 and Compactor #2	F-test	180	127	0.94	0.699	NO
	Levene's test	1	307	0.88	0.348	NO

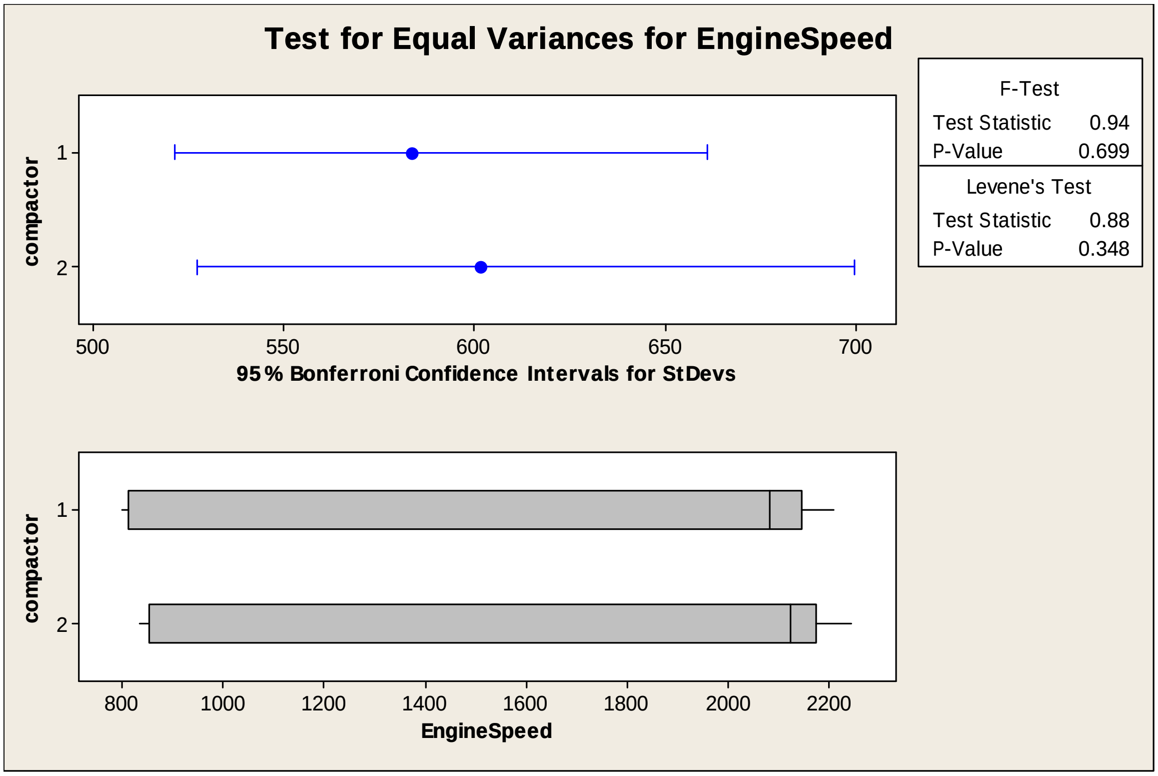


Figure 43. Test of equality of variance for engine speed.

V.B. NO_x Results for Compactor Analysis

V.B.1.Scatterplots and Histograms for NO_x. The following figures are a graphical representation used to identify patterns and relationships between the variables collected. Figure 44 shows a scatterplot for engine speed versus NO_x concentrations for the two compactors. In it we can identify a positive relationship between NO_x concentrations and engine speed. This relationship is expected since higher emission concentrations correlate with an increase in engine loading. The scatterplot also shows an increase in NO_x variability between an engine speed of 1900 and 2200 RPM. This variability spans from approximately 200 to 700 ppm of NO_x. The shapes of the scatterplots are generally similar for each compactor. The variability of the observations at a low engine speed is smaller for the second compactor. Also the observations between 1200 and 2000 RPM are more compact for the first compactor than for the second one that shows more variability. In fact at around 1600 RPM, we can identify a few observations that had NO_x concentrations similar to those observed at the highest engine speed for the second compactor.

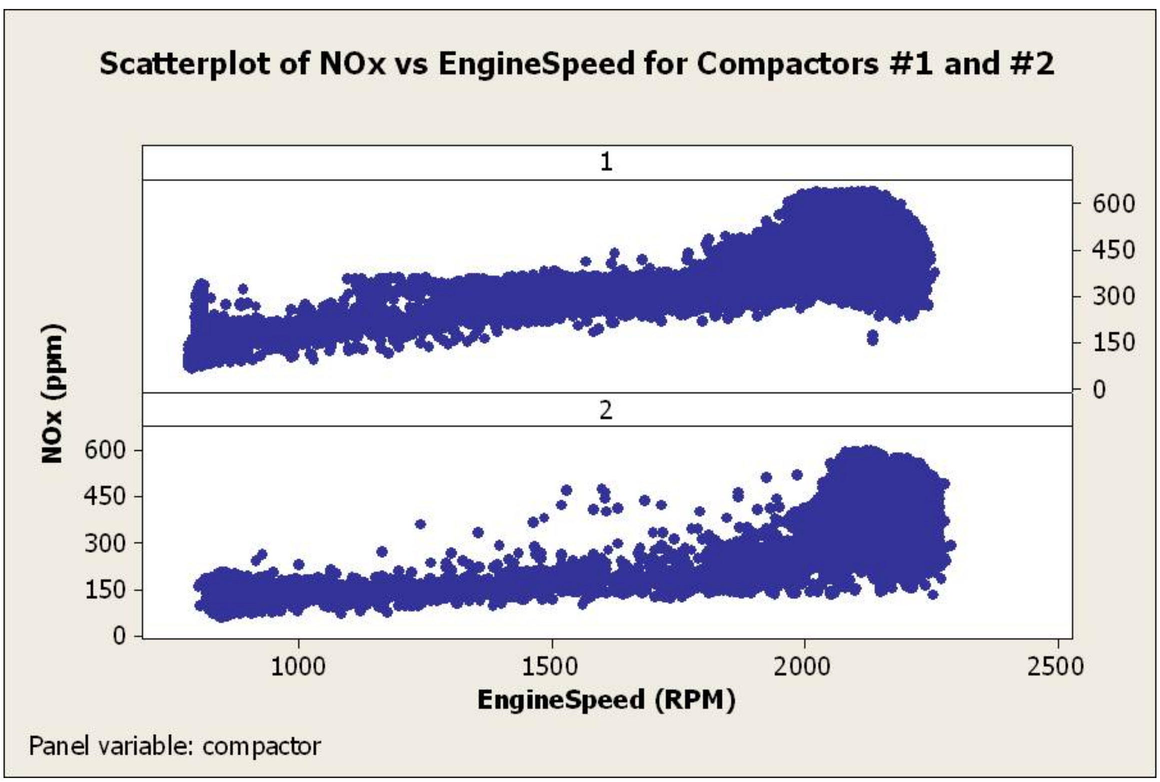


Figure 44. Scatterplot of NO_x vs. engine speed for each compactor.

V.B.2.Preliminary Data Analysis. The data set for the two compactors were analyzed further. A total of 246,893 observations were collected for this comparison analysis. These observations were subjected to a General Linear Model (GLM) analysis with NO_x concentrations as the dependent variable, *Engine Speed* as the covariate independent factor and Compactor as the independent factor. Residuals were saved for further analysis as described below.

The results from the GLM analysis are shown in Table 24 where once more we identify a large F value and a statistical significance value for *Engine Speed*, *Compactor* and their interaction. These results are the artifact of very large samples in the dataset. Basically, with such large sample sizes, any effect would be found to be statistically significant based on the probability value (P).

Table 24. General Linear Model for NO_x versus *Compactor* with *Engine Speed* as covariate.

Factor	N	DF	F statistic	P-value
Engine Speed	246893	1	482235.67	0.000
Compactor		1	1680.21	0.000
Compactor* Engine Speed		1	1314.71	0.000

V.B.3.Autocorrelation Test. An autocorrelation test was performed on the data using the residuals obtained from the previous GLM analysis in order to check the parametric assumption of independent observations. These residuals were subjected to a partial autocorrelation test and the results are plotted in Figure 45. Almost imperceptible in this figure are the critical bands for an alpha value of 0.05 for the hypothesis that the correlations are equal to zero. As we can tell, the first 10 lags shown are random in their pattern but well outside the critical bands. Thus, as expected, the raw data show signs of a strong autocorrelation. This issue is inherent in any database made up of frequent successive observations. The autocorrelation was addressed since it was limiting the validity and confidence of the GLM analysis.

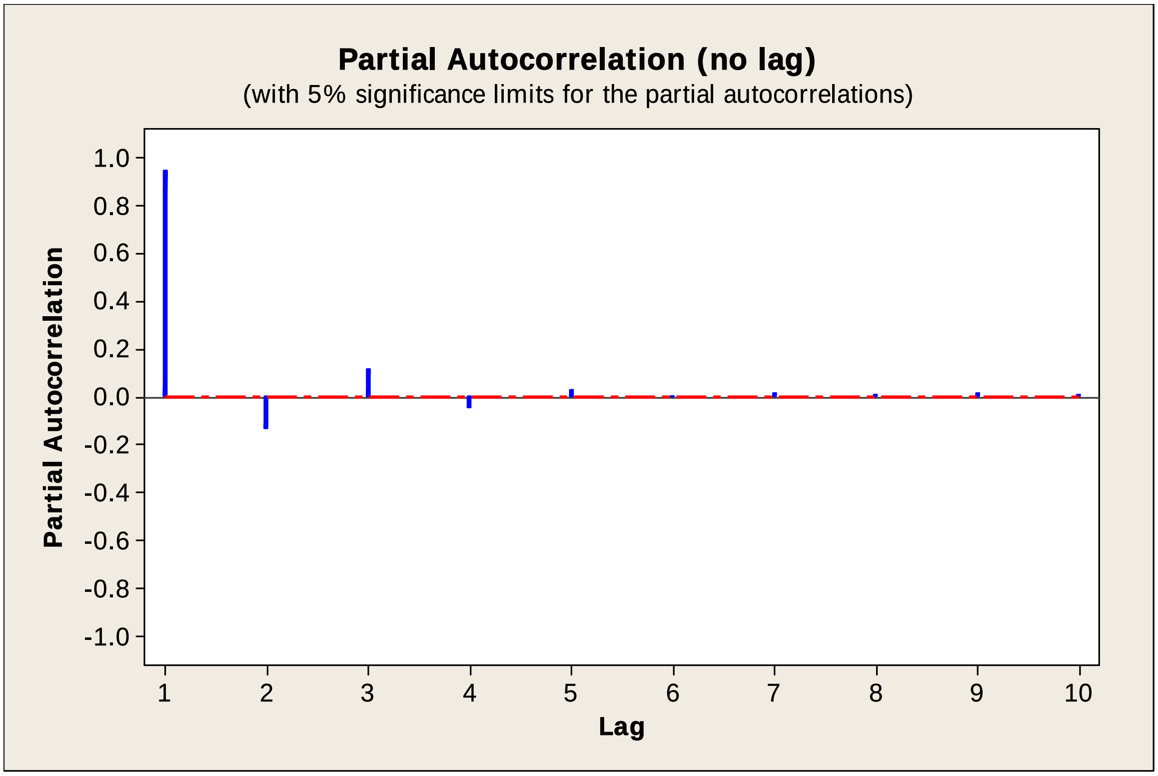


Figure 45. Plot of partial autocorrelation for all data

V.B.4.Time to Independence. The same procedure used previously in the fuel type analysis for NO_x and CO_2 concentrations was used for the two compactor analysis. This data reduction technique produces a subset of observations by selecting observations from the original data set separated by a large enough interval to render autocorrelation insignificant. Appendix B includes the results from these analyses. Thus, an interval of 800 seconds (about 13 minutes) was used to minimize autocorrelation. Figure 46 shows that after using an interval of 800 seconds per observation, the observations are quasi-independent.

Table 25. NO_x descriptive statistics.

Variable	Day	N	Mean	Median	StDev	Minimum	Maximum	Q1	Q3
NOx (ppm)	All	246894	376.57	398.1	145.43	60.81	643.9	215.8	501.9
C1	8/29/2005	36158	417.89	444.8	139.18	76.26	643.9	337.3	530.3
	8/30/2005	38873	426.57	441.2	123.81	81.2	638.7	366.55	524.7
	8/31/2005	36738	411.7	444.7	144.7	76.36	632.2	222	539.5
	9/1/2005	32391	397.98	420.5	134.99	63.79	627.7	286.4	514.9
C2	6/21/2007	12866	386.58	378.2	123.06	67.52	605.2	319.5	499.33
	6/22/2007	30109	308.58	330.9	125.67	60.81	578.2	166.7	395.8

	6/23/2007	953	269.56	306.6	89.82	74.37	433.8	155.4	341.95
	6/25/2007	35741	317.88	310.8	154.39	68.16	597.3	155.6	465.2
	6/26/2007	23065	320.07	323.7	142.63	72.82	587.2	153	444
All C1	8/29-9/01	144160	414.18	438.9	136.12	63.79	643.9	326.6	527.2
All C2	6/21-6/26	102734	323.8	330.8	141.65	60.81	605.2	165.3	437.9

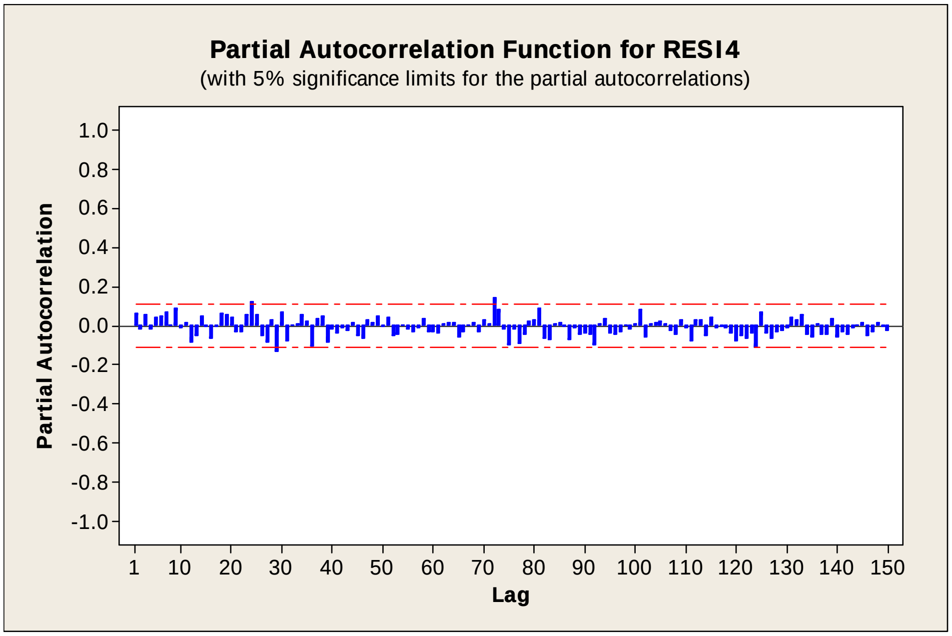


Figure 46. Plot of partial autocorrelation for NO_x data after interval of 1 of 800.

The reduced data set was then subject to a GLM analysis where *Engine Speed* was used as a covariate to *partial* out its effect. The results in Table 26 show that at an alpha value of 0.05, engine speed is statistically significant along with the interaction between compactor and engine speed. The interaction significance was an unexpected result that prompted further analysis.

Table 26. General Linear Model for NO_x versus *Fuel Type* with *Engine Speed* as covariate for reduced data set.

Factor	N	DF	F statistic	P-value
Engine Speed	308	1	715.24	0.000
Compactor		1	1.48	0.225
Compactor*Engine Speed		1	4.65	0.032

The interaction between *Engine Speed* and *Compactor* means that the difference in slopes between the regression lines for each compactor is statistically significant. This means two things: first, that the rate change in NO_x concentrations is different for each distribution and second, that at some point the two lines intersect. Thus, if a pattern is identified, it would be reversed after the two lines intersect. For example, Compactor #1 could have lower emissions than Compactor #2 at a given engine speed, however, once the lines intersect that pattern would be reversed and Compactor #2 would have lower emissions at a different engine speed. To diagnose this finding more thoroughly both regression lines were plotted in the same graph and their line equations were scrutinized. The plot of this exercise can be found in Figure 47. It is interesting to note that the two lines do not intersect at a plausible engine speed. However, the difference in slopes between the two compactors is statistically significant. This figure shows the two linear regression lines getting farther apart from each other as engine speed increases. This indicates that each compactor produces NO_x emissions at a different rate. This rate difference is shown to be statistically significant based on the GLM test performed (Table 26).

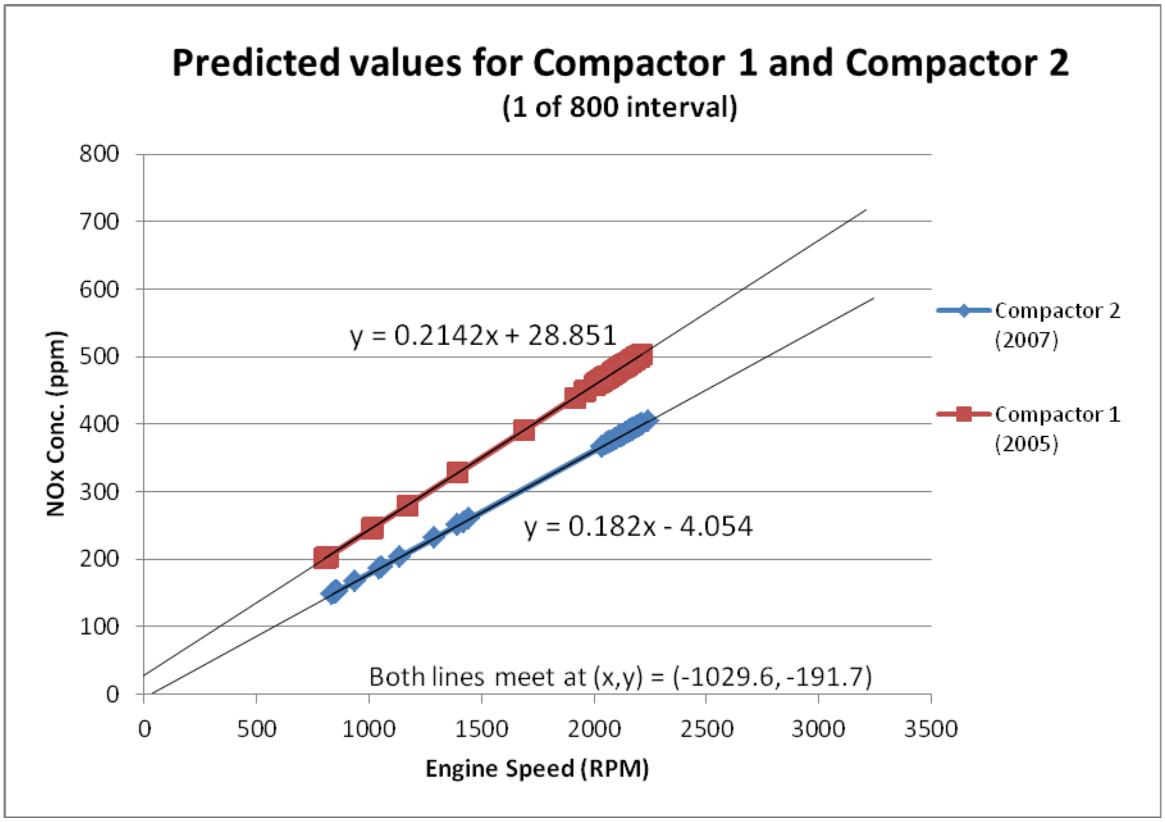


Figure 47. Plot of predicted values for two compactors with line equation and intercept value.

<u>V.B.5.Temporal Analysis.</u> A temporal analysis was also performed to identify potential daily biases. As shown in Table 27 below, the temporal factor and its interaction with

engine speed are not statistically significant. This means that NO_x concentrations are not dependent on the day of sampling.

Table 27. General Linear Model for NO_x versus *Sampling Day* with *Engine Speed* as covariate for reduced data set.

Factor	N	DF	F	P-value
Engine Speed	308	1	610.85	0.000
Day		7	0.38	0.914
Day* Engine Speed		7	1.34	0.229

V.B.6.Data Fitting Model Analysis. As discussed earlier, one of the goals of the current project is to develop potential models that can be used to analyze and predict diesel NO_x emissions. Three models tested to fit the NO_x data are presented below. The first set of analyses uses the aggregate data for both compactors. An additional comparison analysis was also performed on each data set separately since the statistical analyses suggest that the difference in the two distributions is statistically significant.

The three models use a single set of data including both compactors. The first model used is the fitted line plot with logarithmic NO_x values. As shown in Figure 48, this model is quite successful in capturing most of the data observations within the 95% confidence intervals and it accounts for 65% of the variability in the data. The performance of this model is not as good as the one exhibited in the fuel analysis where the coefficient of determination (R^2) ranged from the high 80's to mid-90's for NO_x.

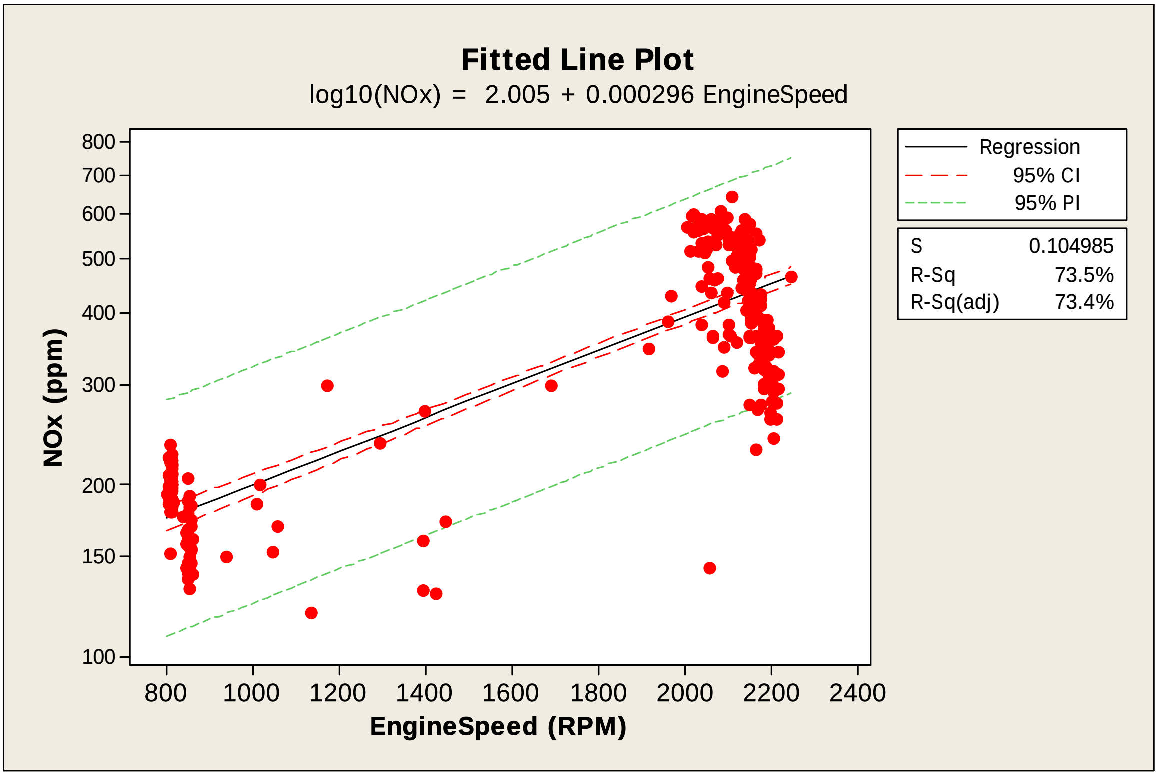


Figure 48. Fitted line plot for compactors data with a linear regression equation.

The next model used is a second order (quadratic) regression model using a log scale for NO_x observations (Figure 49). This model allowed for some curvilinear feature to fit the data but performed only marginally better than the previous linear model. Again, this model seems to have a pronounced "hump" at the middle values that is clearly overestimating NO_x concentrations. This model achieved an R^2 of 66%.

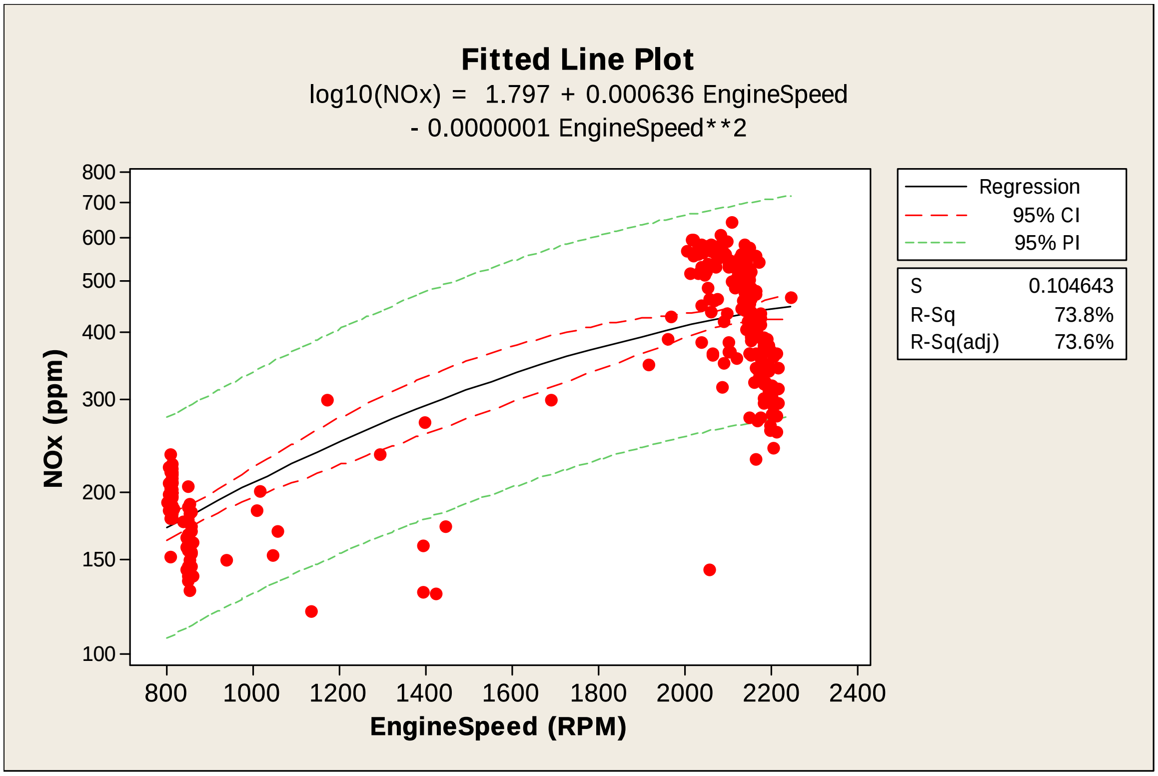


Figure 49. Fitted line plot for compactors data with a quadratic regression equation.

The third model considered was the cubic regression model also using a log scale for the NO_x observations (Figure 50). This model fit the data very closely in distinct engine speed regions, and it was able to account for the highest variability from the three models considered with 79%. Of remarkable note is the fit at the higher engine speed cluster area between 2000 and 2200 RPM where the model matched the shape almost perfectly. The fit at the low engine speed cluster was also good but perhaps not any better than the previous two models. The one weakness in predicting NO_x concentrations is evident in the 850-1300 RPM engine speed where the model seems to underpredict. However, most of the observations in that range are still within the 95% confidence interval bands.

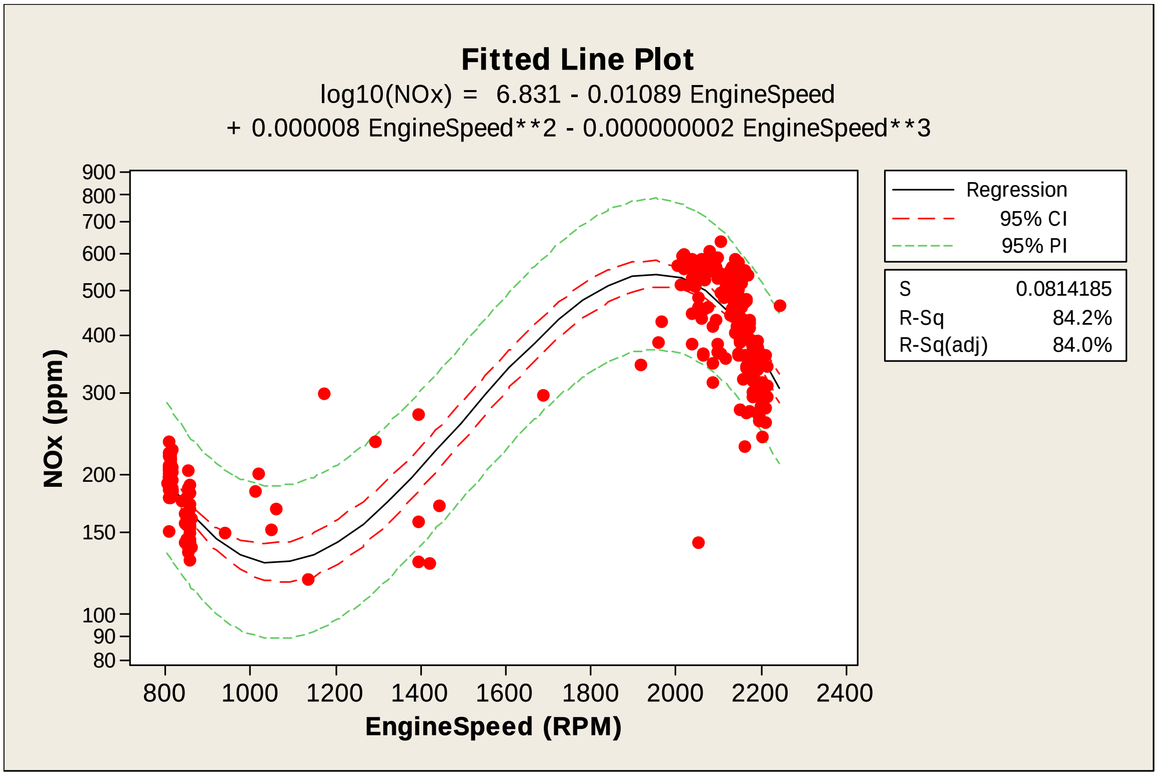


Figure 50. Fitted line plot for compactors data with a cubic regression equation.

The following models compare the performance of these three models based on an analysis of each individual compactor data set.

The first model analyzed is the fitted line plot with logarithmic NO_x values for the first and second compactor. As shown in Figures 51 and 52, this model is quite successful in capturing most of the data observations within the 95% prediction intervals and it accounts for 75% of the variability in the data for the first compactor and 64% for the second one. The performance of this model is better for the first compactor than the one exhibited when using the aggregate data for both compactors and about the same for the second compactor.

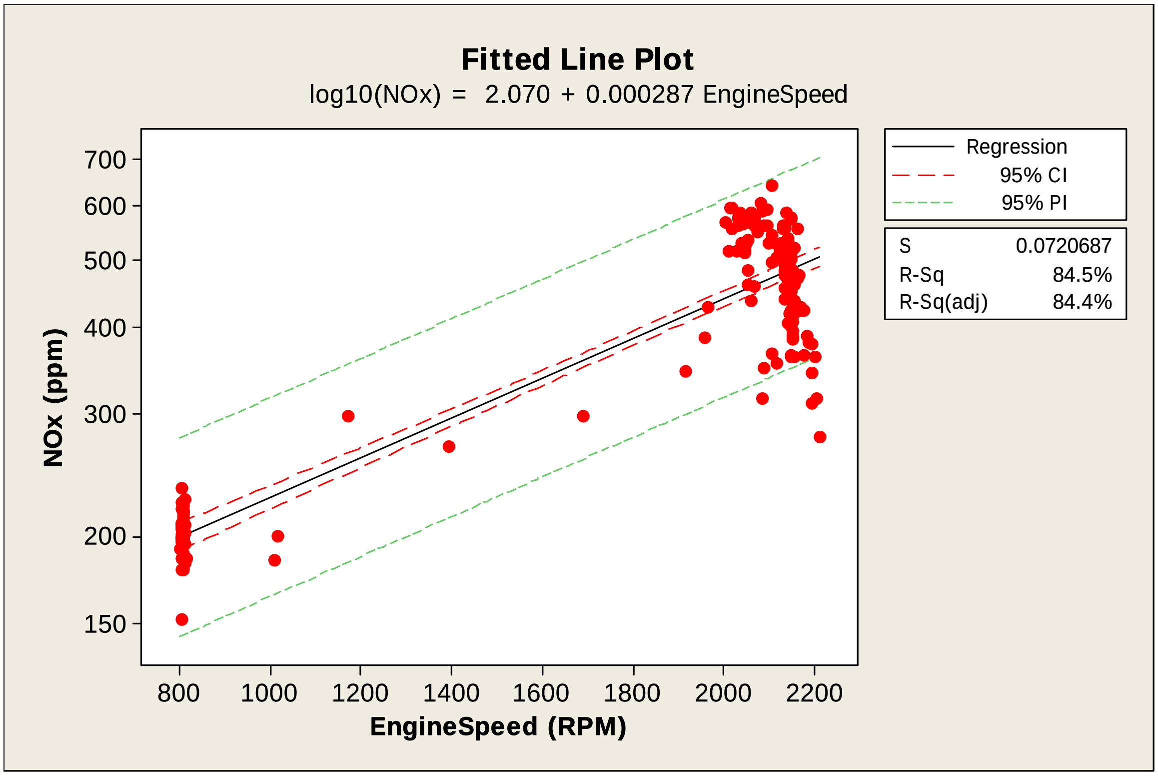


Figure 51. Fitted line plot for Compactor#1 data with a linear regression equation.

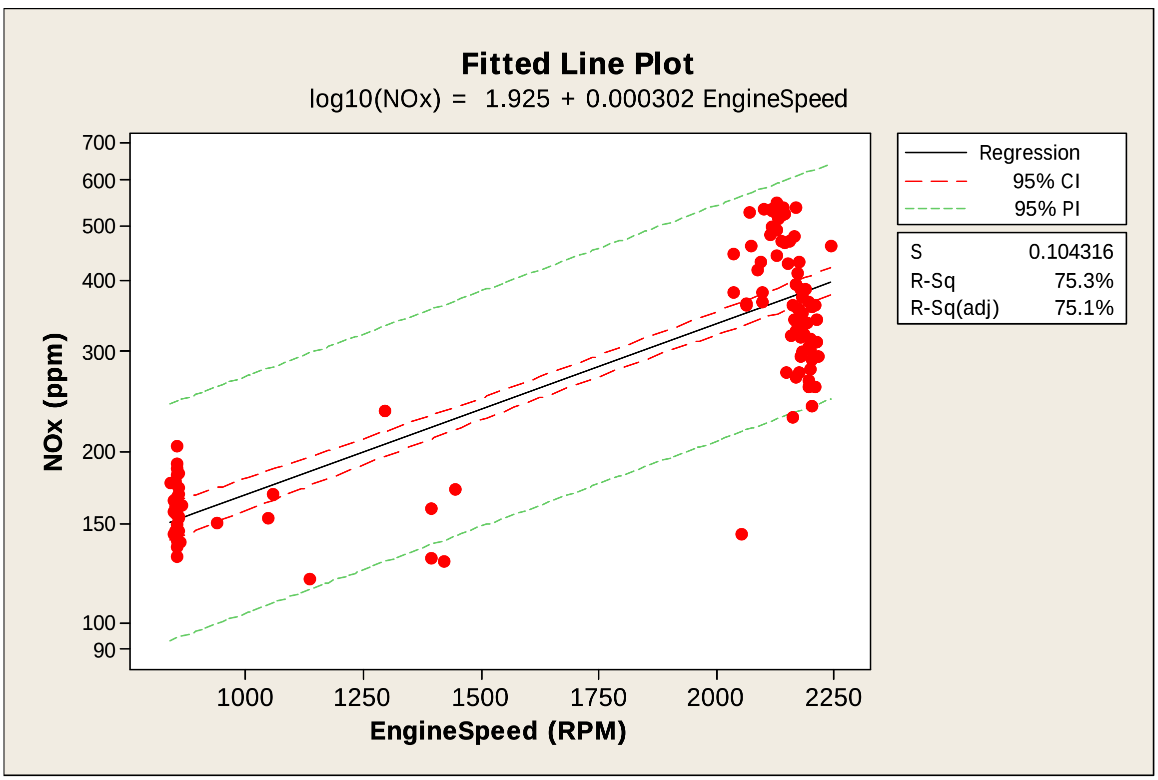


Figure 52. Fitted line plot for Compactor#2 data with a linear regression equation.

The next model analyzed is the second order (quadratic) regression model with logarithmic NO_x values for the first and second compactor. As shown in Figures 53 and 54, this model is quite successful in capturing most of the data observations within the 95% prediction intervals and it accounts for 78% of the variability in the data for the first compactor and 64% for the second one. The performance of this model is again better for the first compactor than the one exhibited when using the aggregate data for both compactors and about the same for the second compactor.

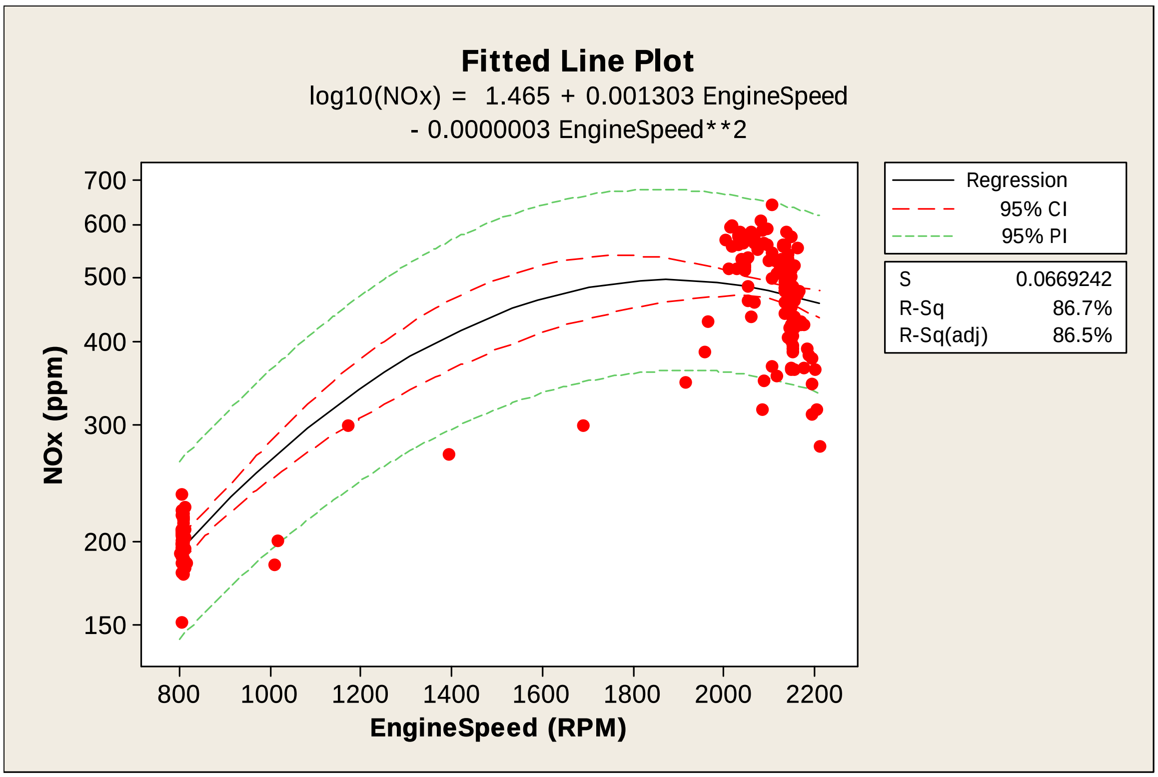


Figure 53. Fitted line plot for Compactor#1 data with a quadratic regression equation.

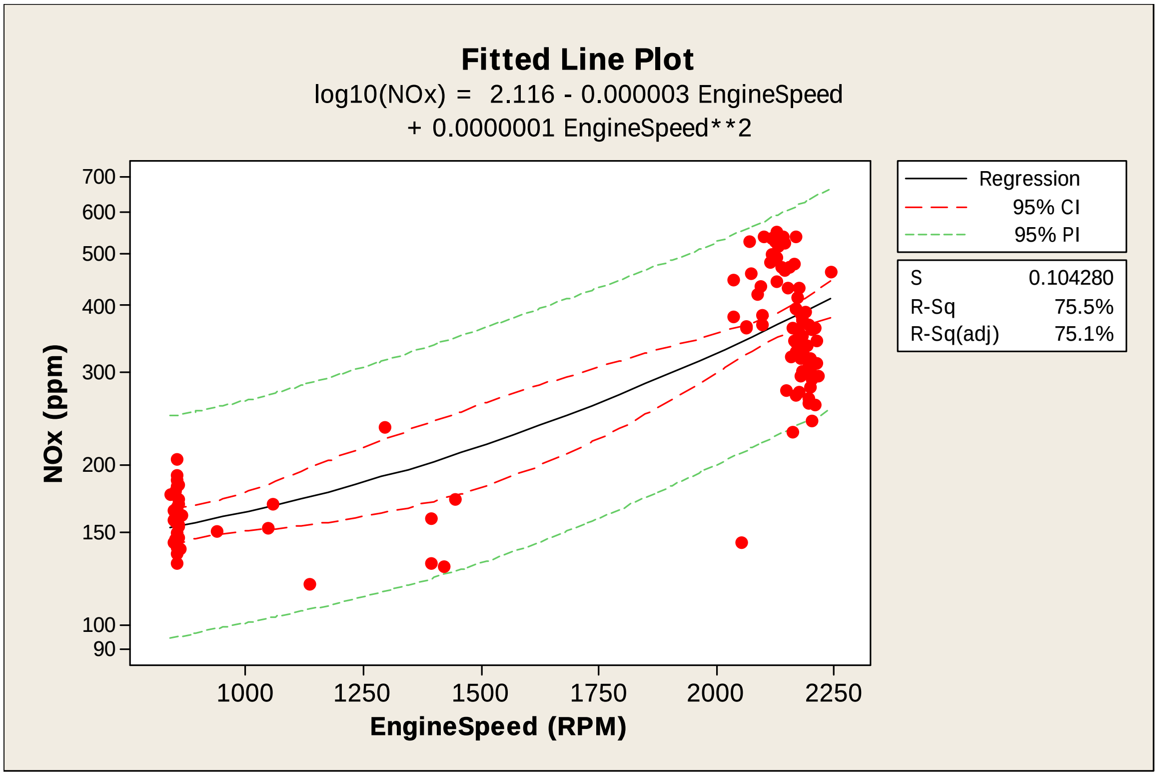


Figure 54. Fitted line plot for Compactor#2 data with a quadratic regression equation.

The cubic regression model with logarithmic NO_x values was analyzed next for the first and second compactor. As shown in Figures 55 and 56, this model is quite successful in capturing most of the data observations within the 95% prediction intervals and it accounts for 83% of the variability in the data for the first compactor and 73% for the second one. The performance of this model is again better for the first compactor than the one exhibited when using the aggregate data for both compactors. This model did show an improvement for the second compactor by yielding the highest R^2 value.

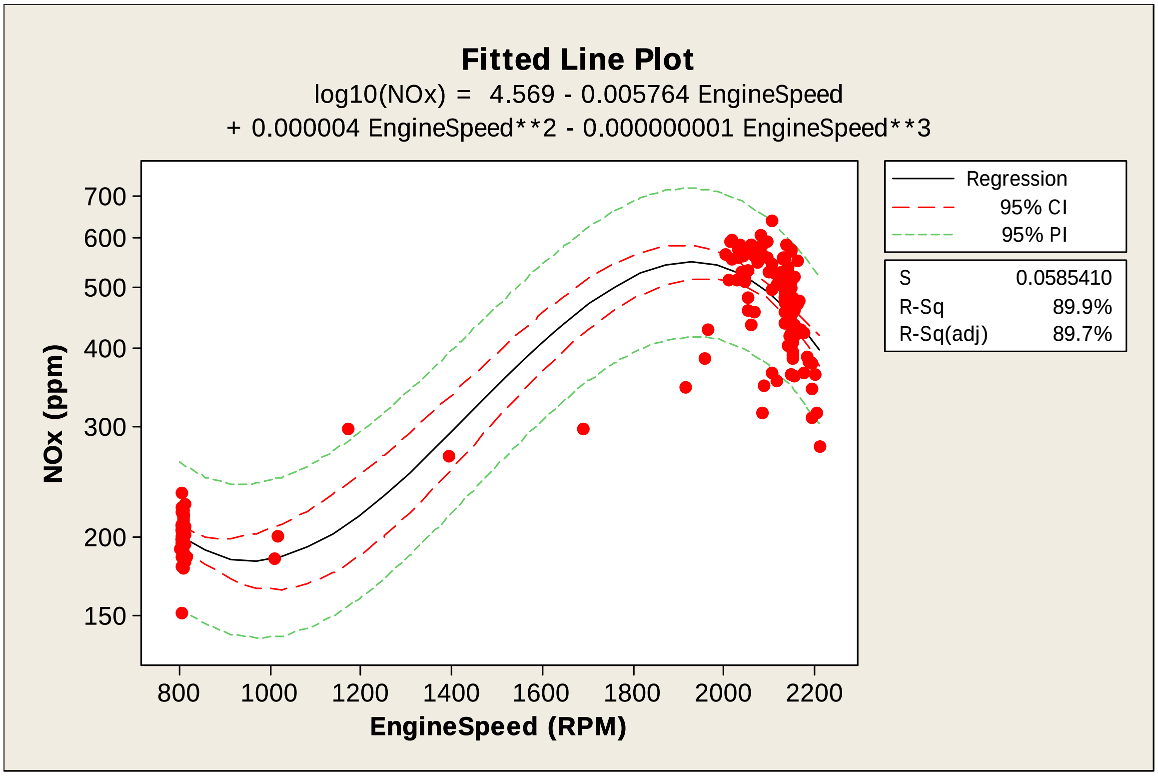


Figure 55. Fitted line plot for Compactor#1 data with a cubic regression equation.

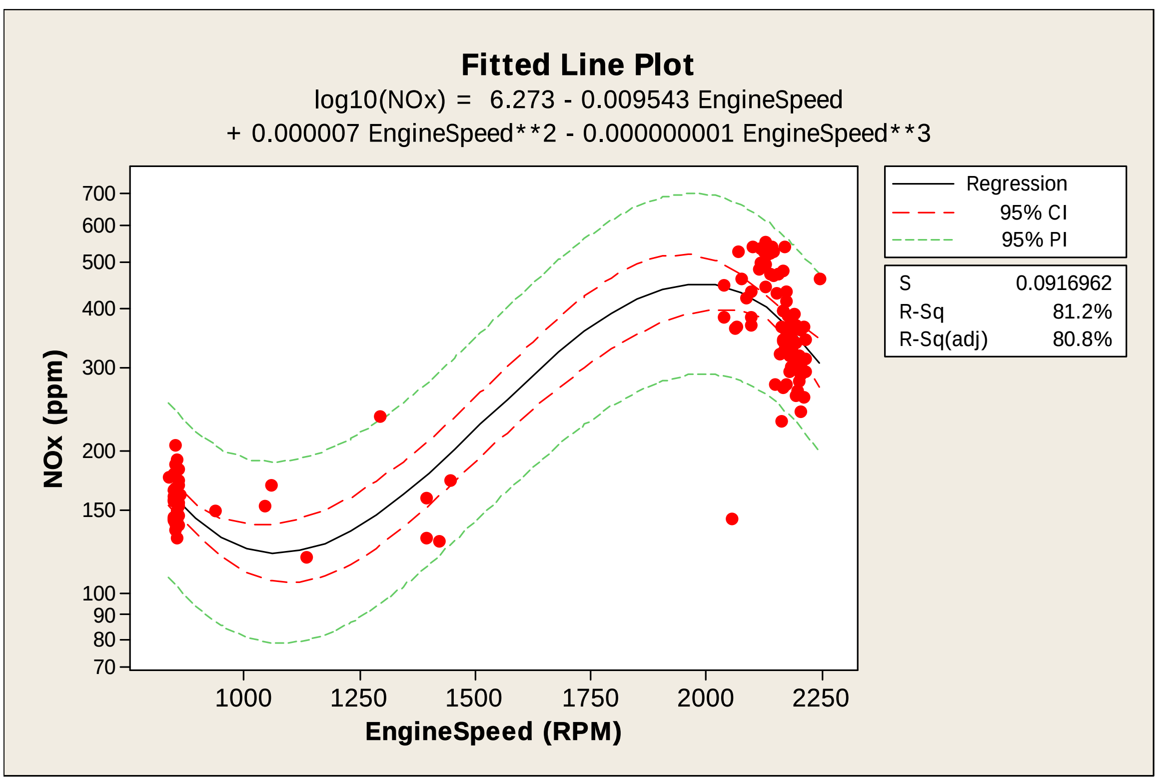


Figure 56. Fitted line plot for Compactor#2 data with a cubic regression equation.

V.C. CO_2 Results for Compactor Analysis

The CO_2 concentrations for each compactor are plotted versus engine speed in Figure 57. In this case we identified a positive relationship between these two variables. The variability of CO_2 concentrations also increases with engine speed. This behavior creates a fanning effect where the largest variability is observed from 1600 to 2300 RPM.

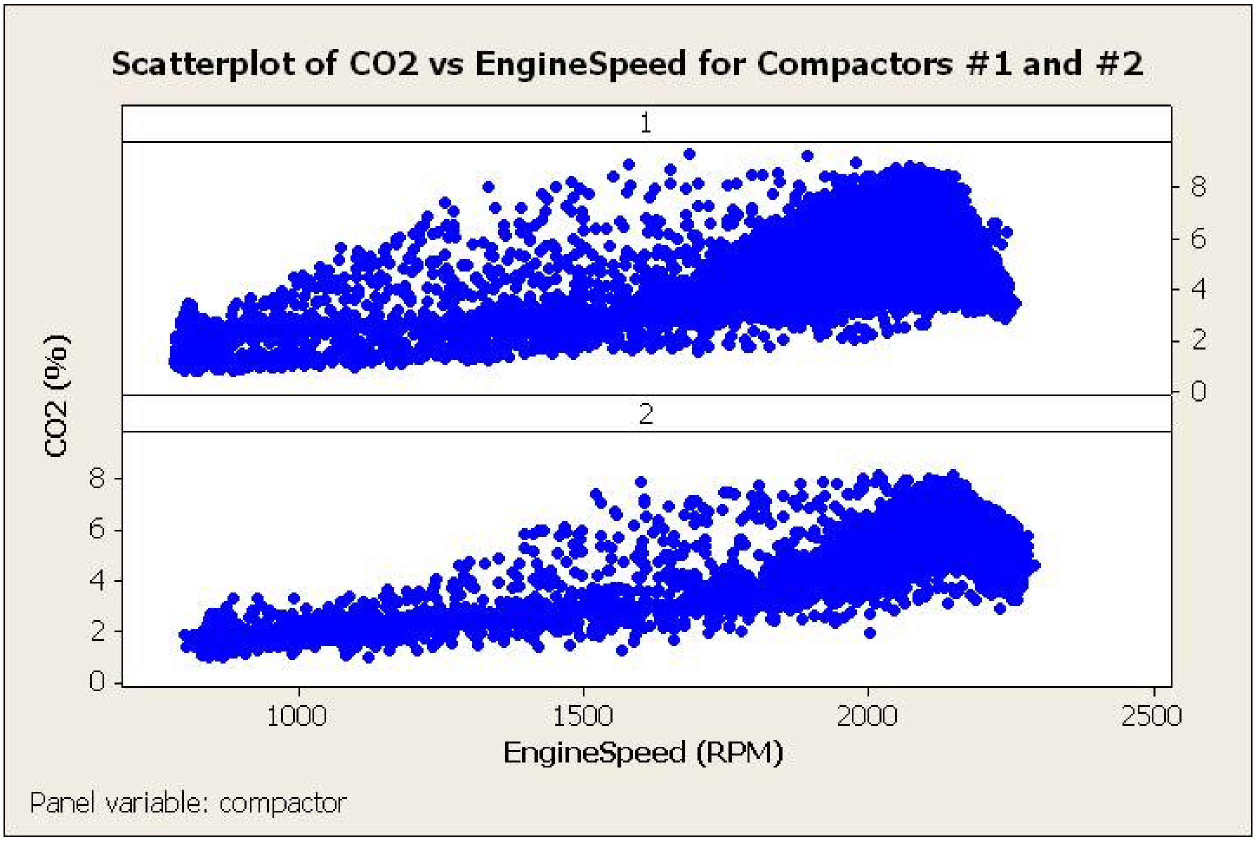


Figure 57. Scatterplot of CO_2 vs. Engine Speed for both compactors.

<u>V.C.1.Preliminary Data Analysis.</u> The data set for the two compactors was analyzed further to determine the effect on the emissions concentrations from temporal and compactor factors. A total of 246,893 observations were collected for this compactor comparison analysis part of the project (Table 28). These observations were subject to a General Linear Model (GLM) analysis with CO_2 concentrations as the dependent variable, *Engine Speed* as the covariate independent factor and Fuel Type as an independent factor. Residuals were also saved for further analysis.

Table 28. CO_2 descriptive statistics.

Variable	Day	N	Mean	Median	StDev	Minimum	Maximum	Q1	Q3
CO2 (%)	All	246894	5.1975	6.154	2.0864	0.754	9.31	2.589	6.871
C1	8/29/2005	36158	5.5675	6.382	1.9735	1.054	9.31	4.3518	7.074
	8/30/2005	38873	5.7018	6.355	1.819	0.834	8.56	5.1805	7.025
	8/31/2005	36738	5.2208	6.235	2.1569	0.754	8.82	2.131	7.078
	9/1/2005	32391	5.1724	6.05	2.0116	0.801	8.44	2.886	6.859
C2	6/21/2007	12866	5.6982	6.363	1.7336	1.135	8.06	5.3407	6.877
	6/22/2007	30109	4.8516	5.902	1.9588	1.057	7.87	2.642	6.381
	6/23/2007	953	4.8681	5.909	1.8713	1.283	7.267	2.474	6.327
	6/25/2007	35741	4.6634	5.525	2.333	1.004	8.2	1.8555	6.981
	6/26/2007	23065	4.7795	5.837	2.2355	1.008	7.935	1.702	6.736
All C1	8/29-9/01	144160	5.4266	6.271	2.0036	0.754	9.31	3.9813	7.006
All C2	6/21-6/26	102734	4.8761	5.908	2.1567	1.004	8.2	1.954	6.69

The results from the GLM analysis are shown in Table 29 where once more we identify a large F value and a statistical significance value for *Engine Speed*, *Compactor* and their interaction. These results are the artifact of very large samples in the dataset. Basically, with such large sample sizes, any effect would be found to be statistically significant based on the probability value (P).

Table 29. General Linear Model for CO_2 versus *Compactor* with *Engine Speed* as covariate.

Factor	N	DF	F statistic	P-value
Engine Speed	246893	1	1300965.75	0.000
Compactor		1	2679.29	0.000
Compactor* Engine Speed		1	257.01	0.000

<u>V.C.2.Autocorrelation Test.</u> An autocorrelation test was performed in the data by using the residuals obtained from the previous GLM analysis. These residuals were subject to a partial autocorrelation test and the results are plotted in Figure 58. Almost imperceptible in this figure are the critical bands for an alpha value of 0.05 for the hypothesis that the correlations are equal to zero. As we can tell, the first 10 lags shown are random in their

pattern but well outside the critical bands. Thus, as expected, the raw data show signs of a strong autocorrelation. This issue is inherent in any database made up of frequent successive observations. Thereby, autocorrelation needed to be addressed since it was limiting the validity and confidence of the GLM analysis.

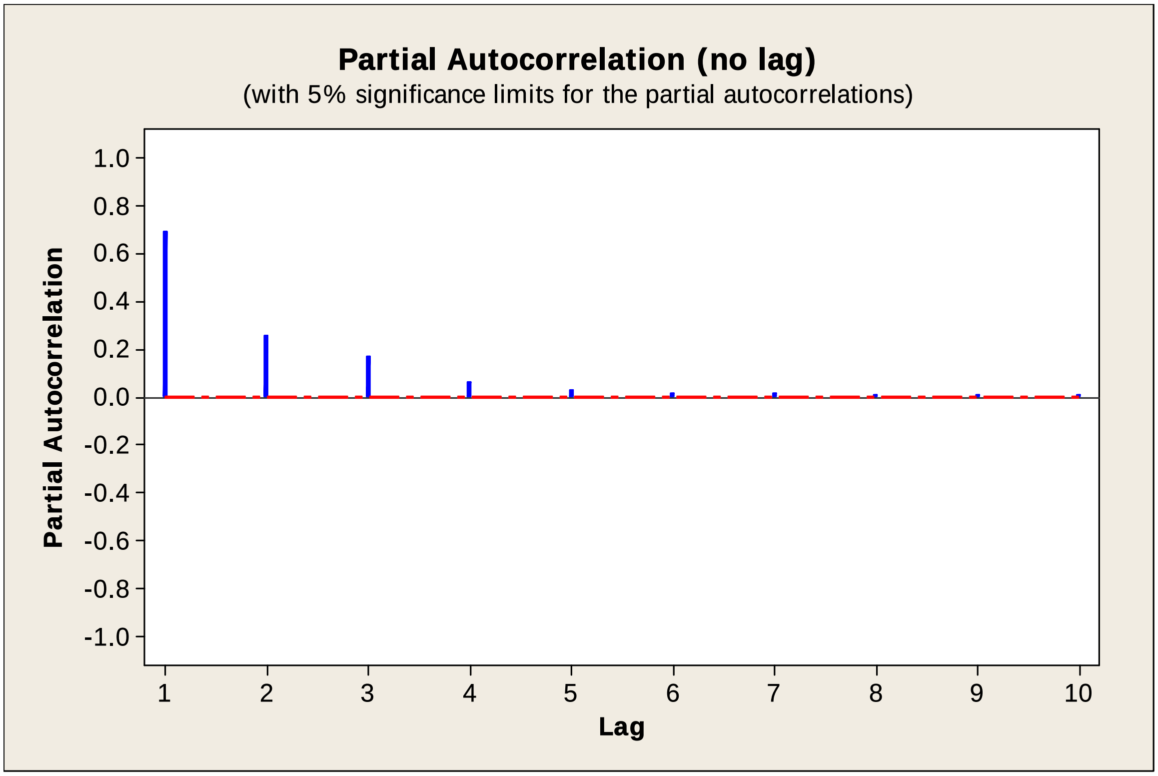


Figure 58. Plot of partial autocorrelation for all data.

<u>V.C.3.Time to Independence.</u> The same procedure used previously in the fuel type analysis for NO_x and CO_2 concentrations was used for the two compactor analysis to develop quasi-independent observations. This data reduction technique produces a subset of observations by selecting observations from the original data set separated by a large enough interval to render autocorrelation insignificant. Appendix B includes the results from these analyses. Thus, an interval of 800 seconds (about 13 minutes) was used to minimize autocorrelation. Figure 59 shows that after using an interval of 800 seconds per observation, the observations are quasi-independent.

Table 30. Total number of observations used after test for independence procedure.

Compactor	Day	Total data points
Compactor #1	08/29/2005-09/01/2005	181
Compactor #2	06/21/2007-06/26/2007	128

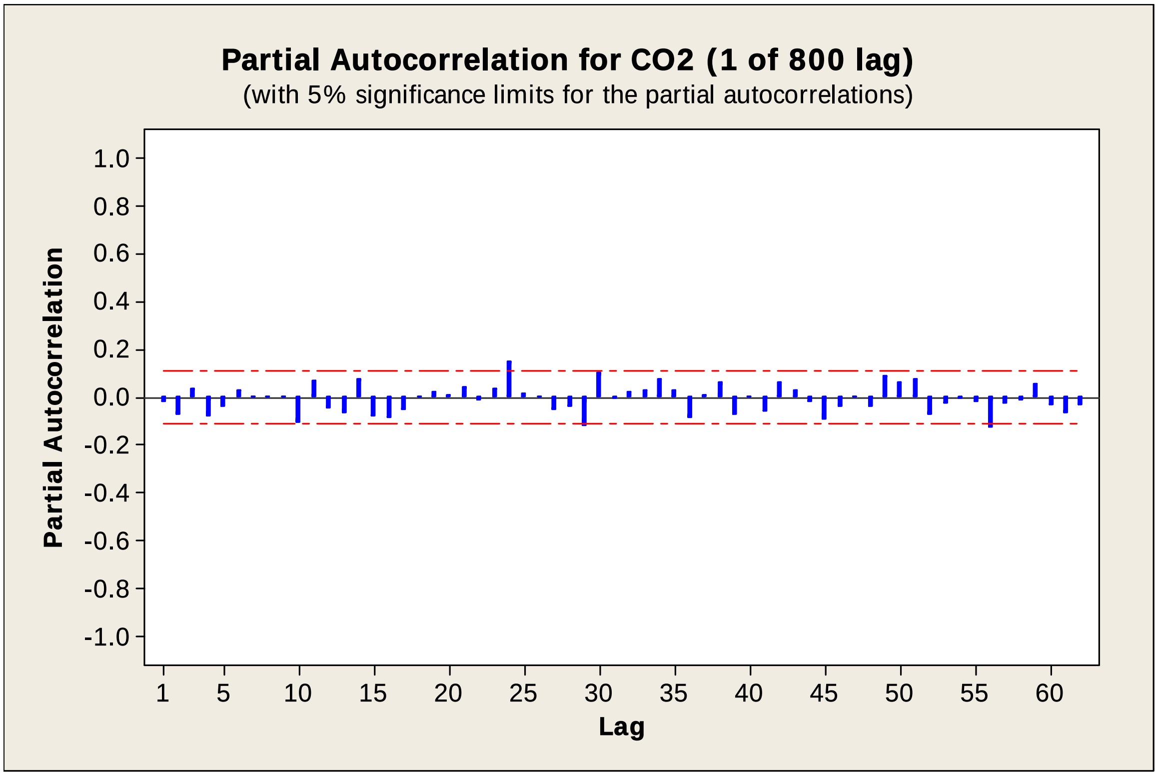


Figure 59. Plot of partial autocorrelation for CO_2 data after interval of 1 of 800.

The reduced data set was then subjected to a GLM analysis where *Engine Speed* was used as a covariate to *partial* out its effect. The results in Table 31 show that at an alpha value of 0.05, engine speed is statistically significant along with compactor. This means that the difference in the CO_2 emission distributions for the compactors is statistically significant. This was an interesting finding because the two compactors used were the exact same model and were being operated by the same person. This result along with the interaction significance identified for NO_x concentrations mean that the NO_x and CO_2 emission distributions from each compactor are in fact different from each other.

Table 31. General Linear Model for CO_2 versus *Compactor* with *Engine Speed* as covariate for reduced data set.

Factor	N	DF	F statistic	P-value
Engine Speed	308	1	1827.41	0.000
Compactor		1	5.76	0.017
Compactor* Engine Speed		1	0.24	0.623

V.C.4.Temporal Analysis. A temporal analysis was also performed to identify potential daily biases. As shown in Table 32 below, the temporal factor and its interaction with engine speed are not statistically significant. This means that CO_2 concentrations are not dependent on the day of sampling.

Table 32. General Linear Model for CO_2 versus *Sampling Day* with *Engine Speed* as covariate for reduced data set.

Factor	N	DF	F	P-value
Engine Speed	308	1	1465.63	0.000
Day		7	1.09	0.372
Day*Engine Speed		7	0.38	0.916

V.C.5.Data Fitting Model Analysis. Three types of models used to fit the CO_2 data are presented below. The first set of analyses uses the aggregate data for both compactors. An additional comparison analysis was also performed on each data set separately since the statistical analyzes suggest that the difference in the two distributions is statistically significant.

The following set of three models use one set of data that includes both compactors. The first model used is the fitted line plot with logarithmic CO_2 values. As shown in Figure 60, this model is quite successful in capturing most of the data observations within the 95% prediction intervals and it accounts for 90% of the variability in the data. The performance of this model is comparable to the one exhibited in the fuel analysis where the coefficient of determination (R^2) ranged from the high 80's to mid-90's for NO_x.

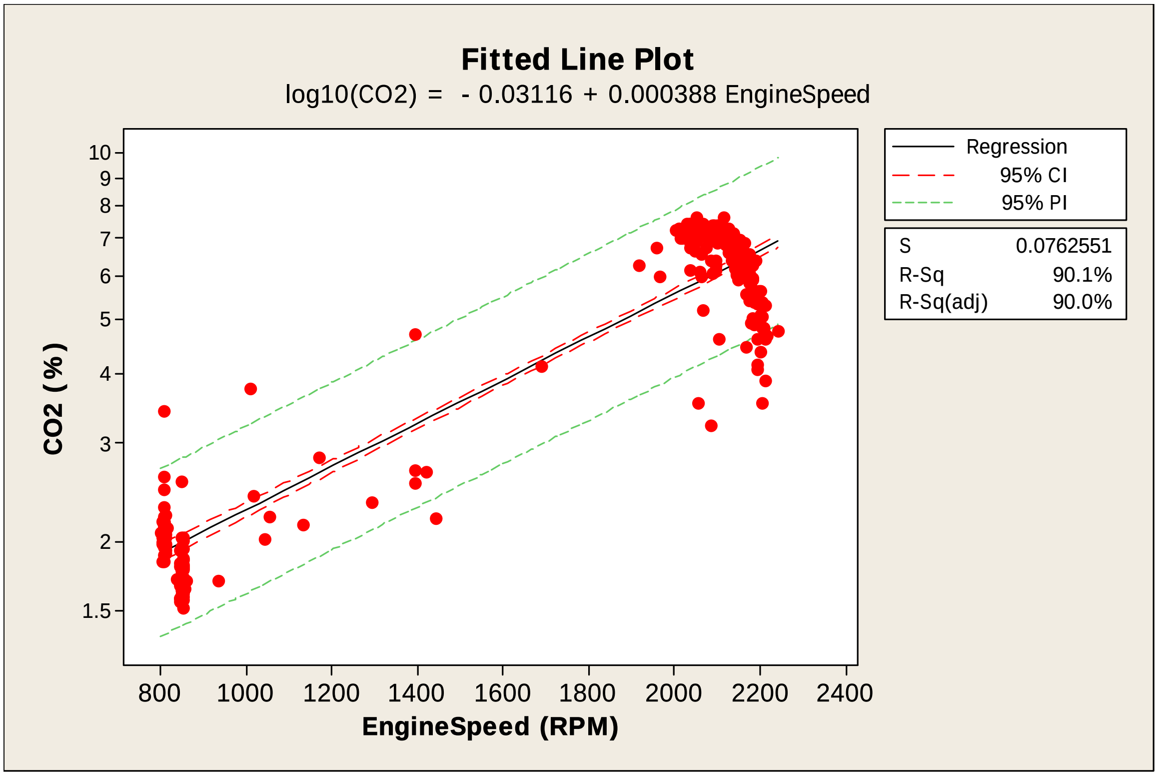


Figure 60. Fitted line plot for compactors data with a linear regression equation.

The next model used is a second order (quadratic) regression model using a log scale for CO_2 observations (Figure 61). This model allowed for some curvilinear feature to fit the data but performed only about the same as the previous linear model. Again, this model seems to have a pronounced "hump" at the middle values that is clearly overestimating NO_x concentrations. This model achieved an R^2 of 91%.

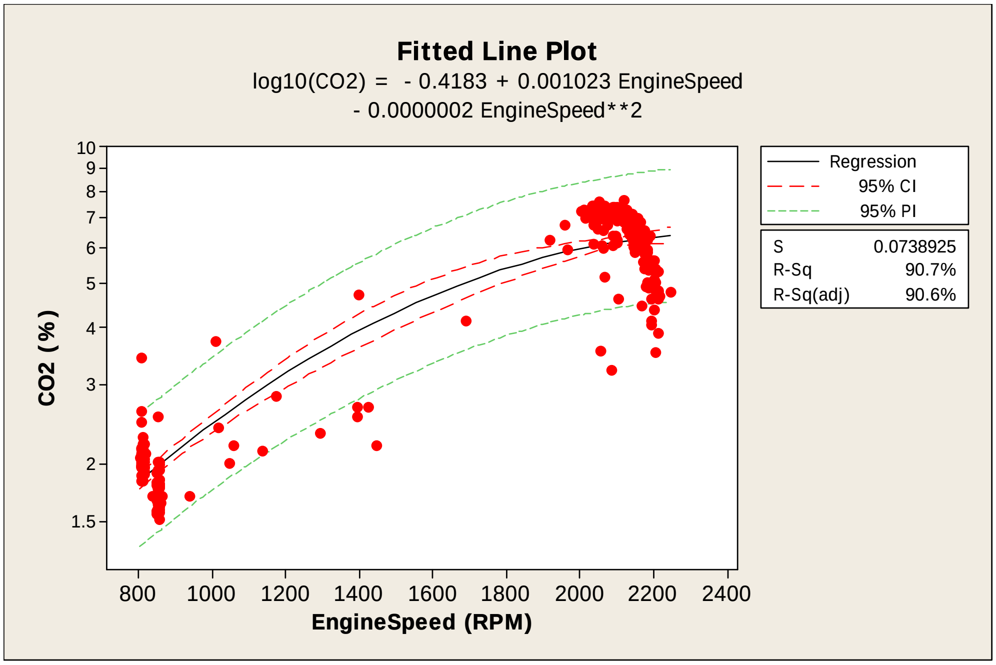


Figure 61. Fitted line plot for compactors data with a quadratic regression equation.

The third model considered was the cubic regression model also using a log scale for the CO_2 observations (Figure 62). This model seemed to fit the data very closely, in the engine speed regions it was able to account for the highest variability from the three models considered with 94 percent. Of note is the fit at the higher engine speed cluster area between 2000 and 2200 RPM where the model matched the shape almost perfectly. The fit at the low engine speed cluster was also good but perhaps not any better than the previous two models. The one weakness in predicting NO_x concentrations is evident in the 850-1300 RPM engine speed were the model seems to underpredict as shown in Figure 52. However, most of the observations in that range are still within the 95% prediction interval bands.

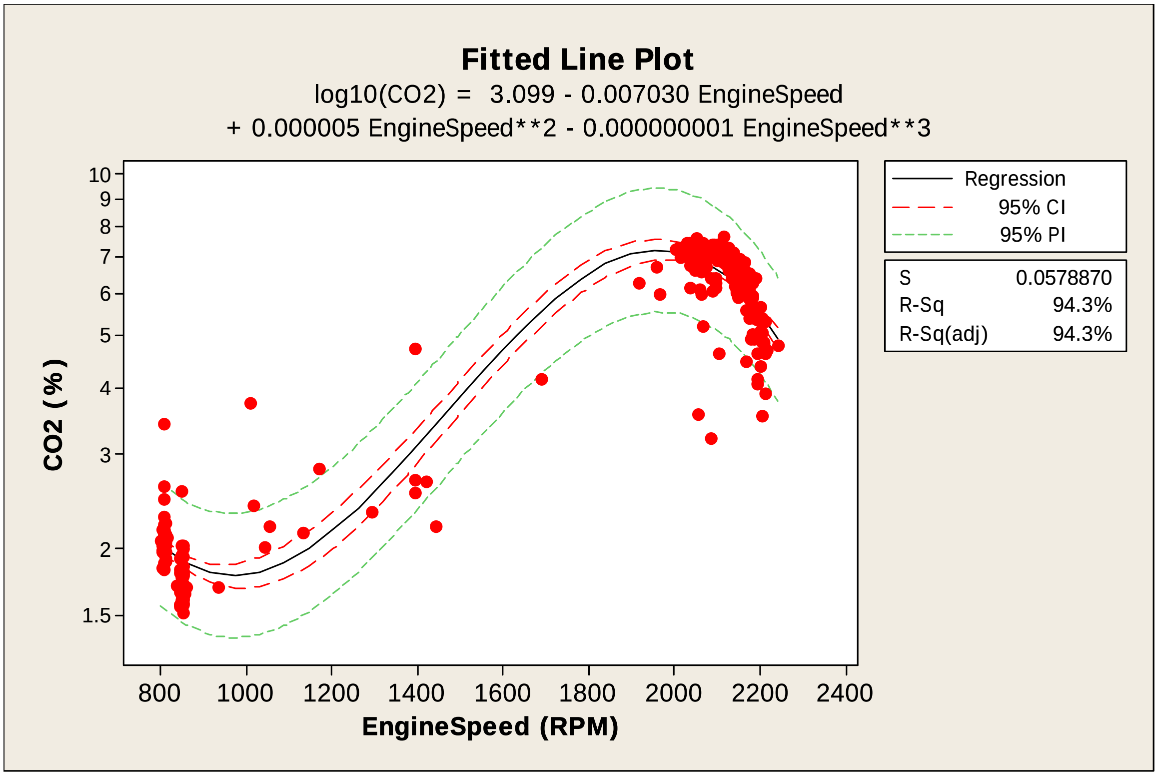


Figure 62. Fitted line plot for compactors data with a cubic regression equation.

The following models compare the performance of these three models based on an analysis of each individual compactor data set.

The first model analyzed is the fitted line plot with logarithmic CO_2 values for the first and second compactor. As shown in Figures 63 and 64, this model is quite successful in capturing most of the data observations within the 95% confidence intervals and it accounts for 90% of the variability in the data for the first compactor and 94% for the second one. The performance of this model is very good for both compactors.

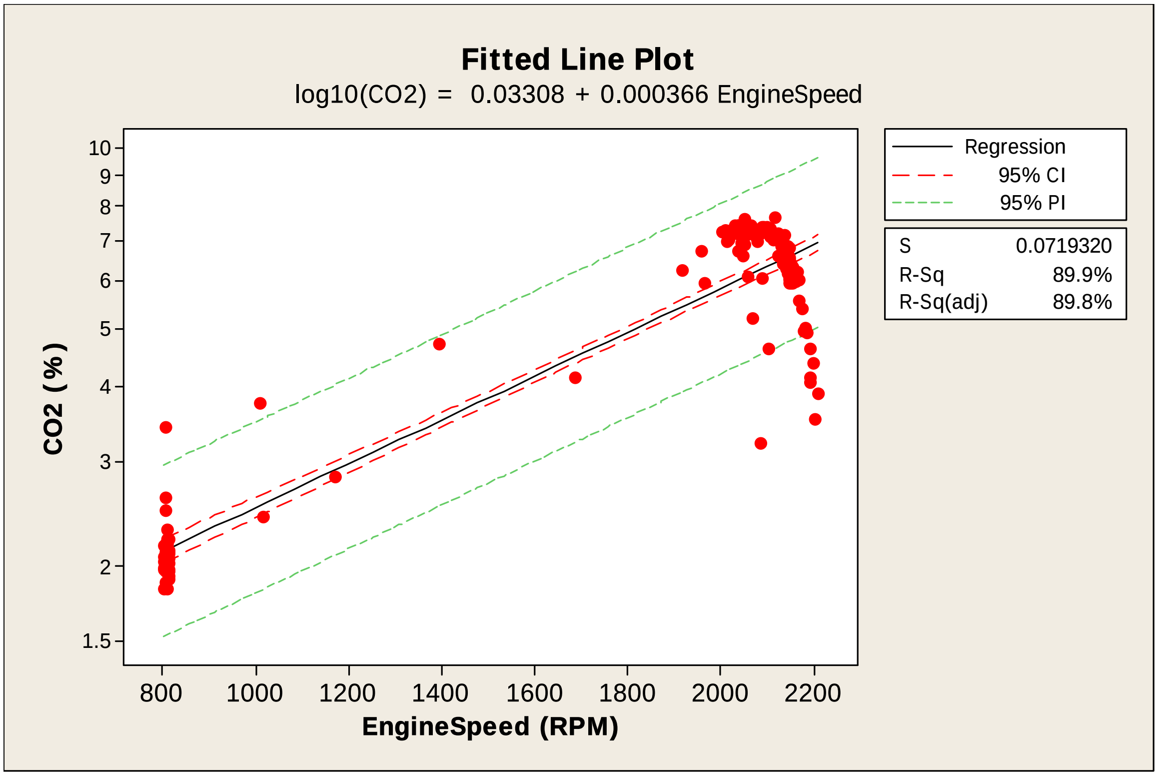


Figure 63. Fitted line plot for Compactor #1 data with a linear regression equation.

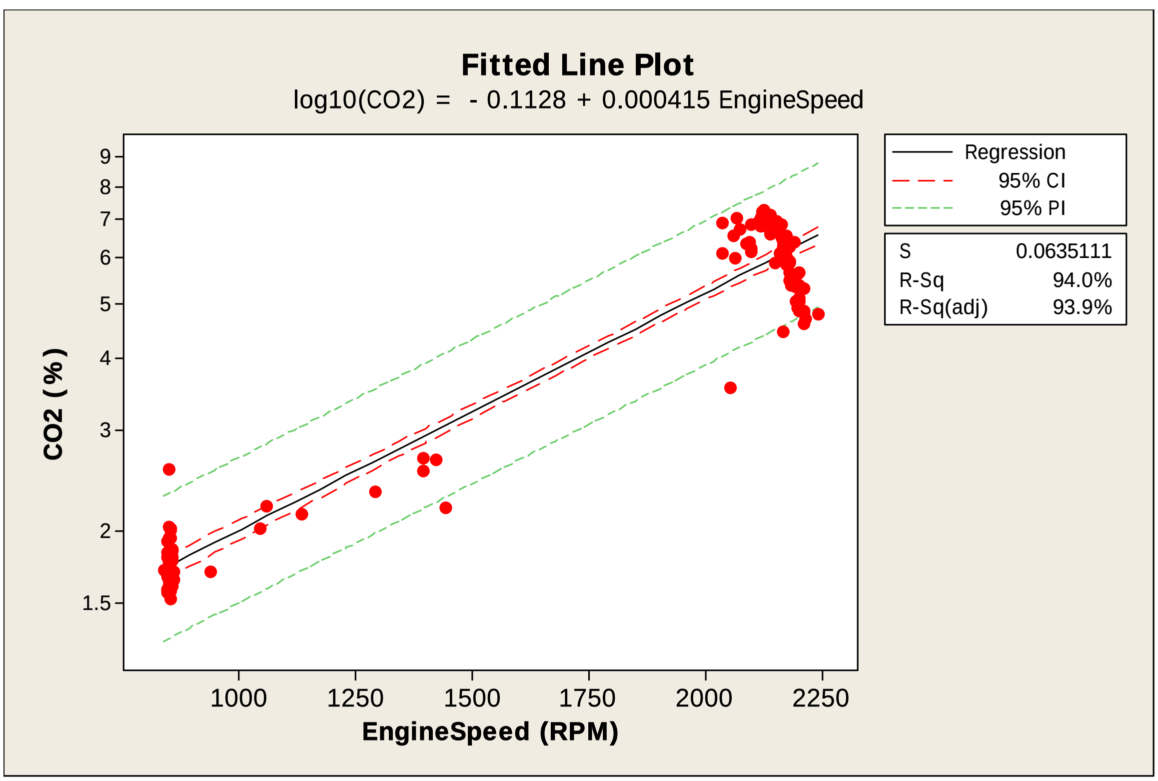


Figure 64. Fitted line plot for Compactor #2 data with a linear regression equation.

The next model analyzed is the second order (quadratic) regression model with logarithmic CO_2 values for the first and second compactor. As shown in Figures 65 and 66, this model is quite successful in capturing most of the data observations within the 95% prediction intervals and it accounts for 93% of the variability in the data for each of the two compactors. The performance of this model is about the same than the one exhibited when using the first model for both compactors.

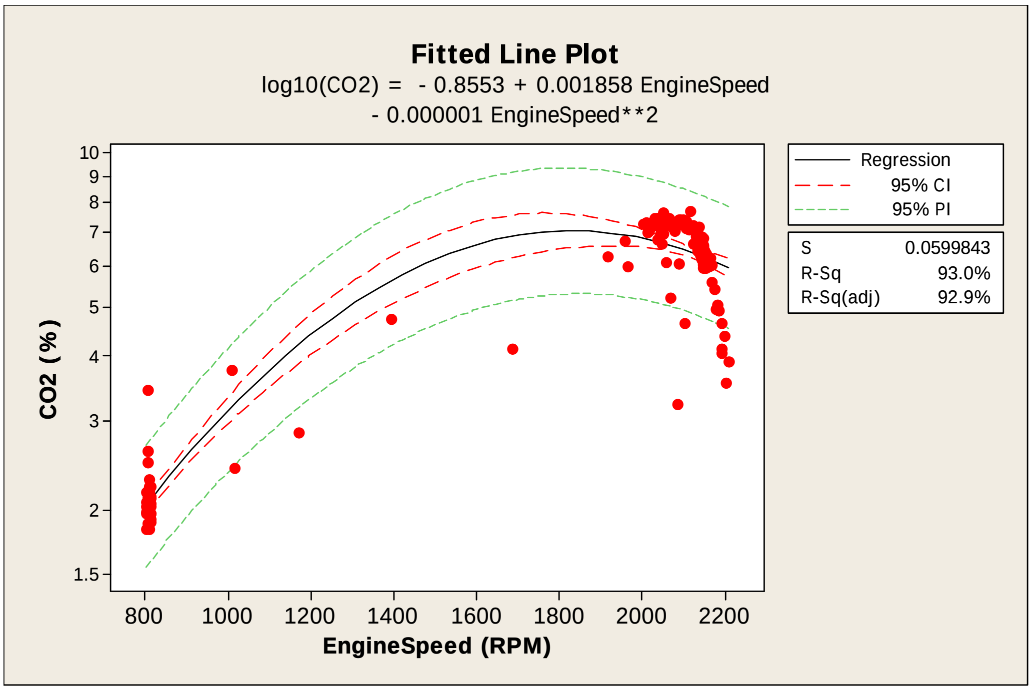


Figure 65. Fitted line plot for Compactor #1 data with a quadratic regression equation.

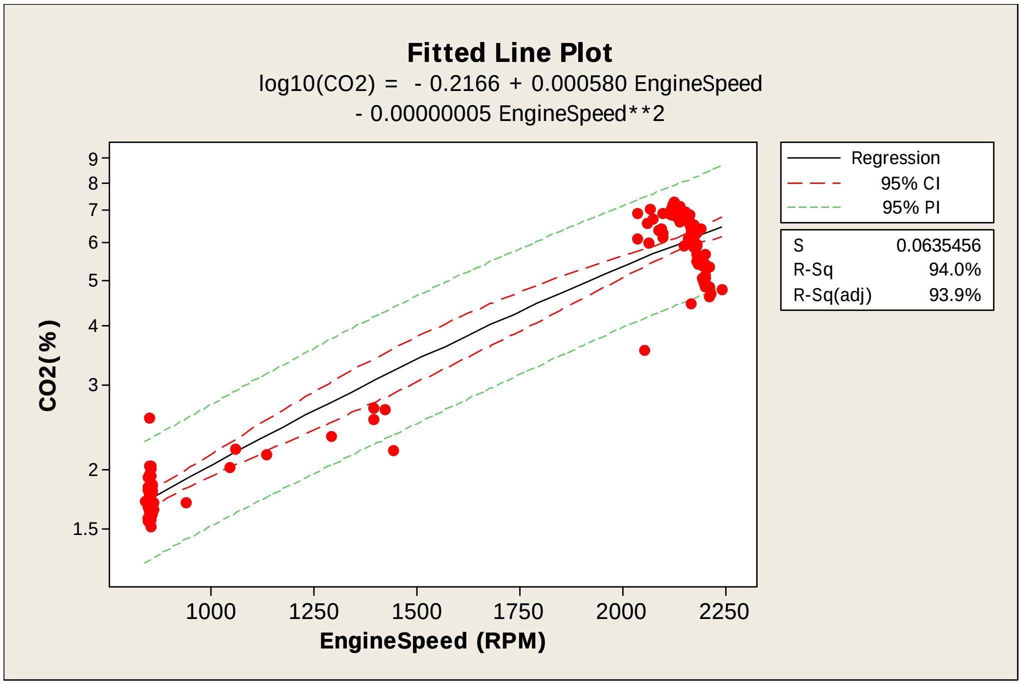


Figure 66. Fitted line plot for Compactor #2 data with a quadratic regression equation.

The cubic regression model with logarithmic CO_2 values was analyzed next for the first and second compactor. As shown in Figures 67 and 68, this model is quite successful in capturing most of the data observations within the 95% prediction intervals and it accounts for 91% of the variability in the data for the first compactor and 97% for the second one. The performance of this model is again better for the second compactor than the one exhibited when using the aggregate data for both compactors. This model did not show a significant improvement for the first compactor and in fact did more poorly than the second (quadratic) model.

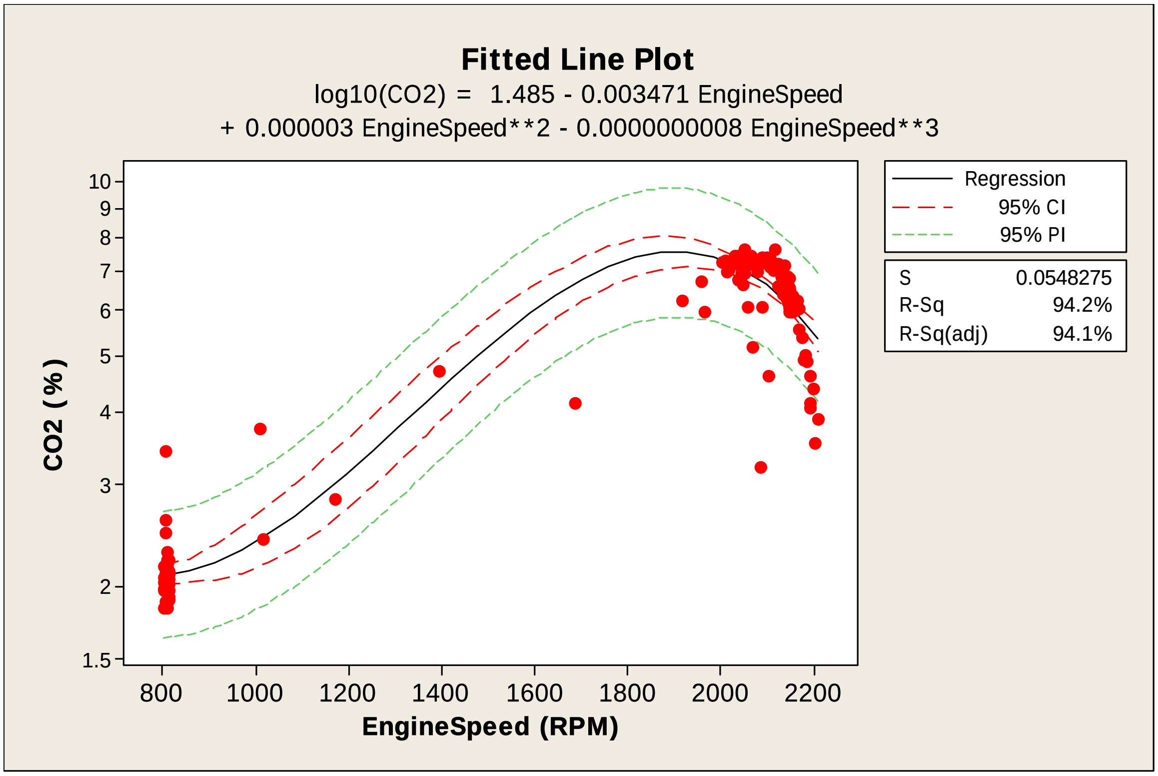


Figure 67. Fitted line plot for Compactor #1 data with a cubic regression equation.

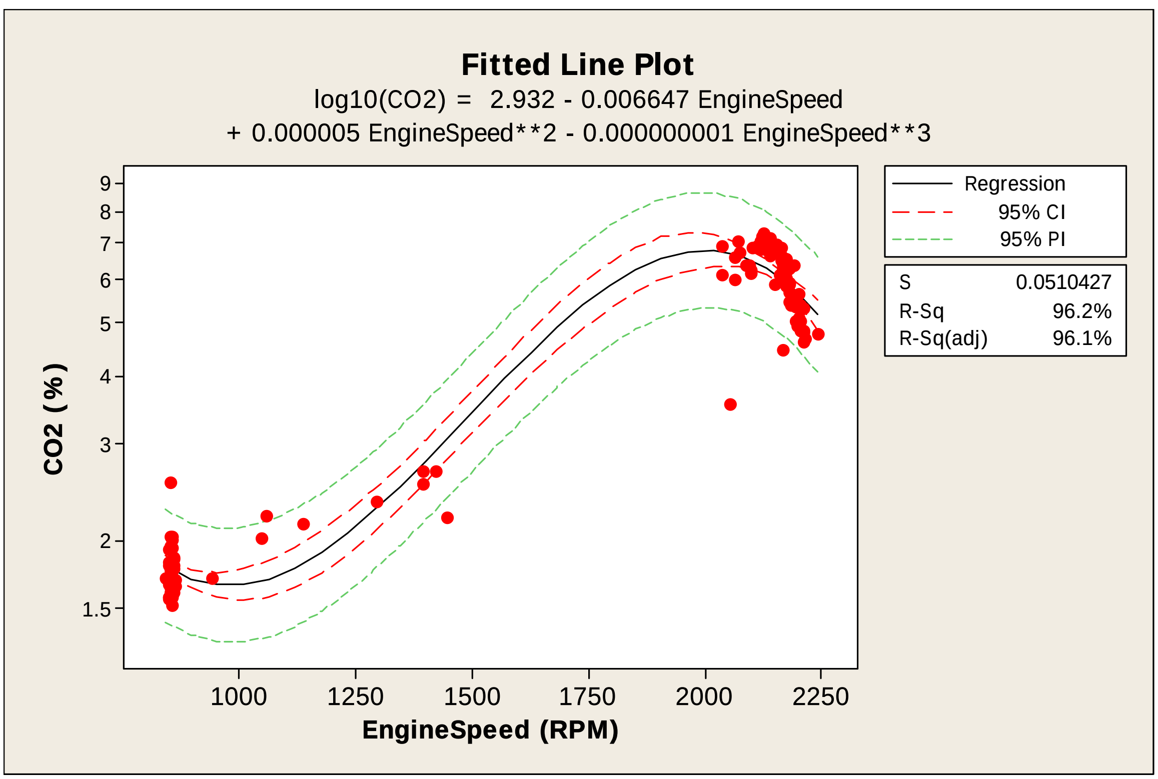


Figure 68. Fitted line plot for Compactor #2 data with a cubic regression equation.

VI. DISCUSSION AND CONCLUSIONS

This study makes three main contributions including the development of a data handling technique to deal with autocorrelation in continuous data. This study also showed that the three fuel types evaluated had no significant effect on NO_x and CO_2 emissions. Finally, the evaluation of two Trashmaster 3-90E compactors showed that NO_x and CO_2 emissions are significantly different between the compactors.

The discussion is divided in three parts: initial data analysis, comparison analysis, and model analysis. The first part covers the data screening and the data reduction technique used to address statistical biases, especially autocorrelation. The second part focuses on the comparison analysis of the three fuel types and the two compactors. The third element of this section deals with three data fitting models tested on the fuel type and compactor data subsets.

VI.A. Initial Data Analysis

Engine speed was identified as the best engine parameter for inclusion in the statistical analysis since it is measured directly and since engine speed has a strong correlation with NO_x and CO_2 emissions. This parameter is closely related to NO_x and CO_2 emissions since emissions increase as engine speed increases. Thus, the *Engine Speed* factor was partialed out as a covariate factor in the GLM test to identify the effects of fuel type and compactor on NO_x and CO_2 emissions.

The initial data analysis identified two important issues that needed to be addressed in all data collected. The first concern was related to a bias in the calculated F values due to the very large number of samples (N). The large N influenced the probability values and indicated a false statistical significance for all factors tested. This issue is due to the fact that a statistical value (e.g. t-statistic, F-statistic) can be made arbitrarily large (and the P-value associated with it arbitrarily small) by increasing the sample size (Johnson, 1999). Good (1982) suggest that P-values be standardized to a sample size of 100 to avoid this bias. Thus, researchers need to be mindful of the strong dependence of P on the sample size when devising a statistical analysis that involves large sample sizes.

Additionally, the data observations were found to be highly autocorrelated. A time interval data reduction technique was used to address these two statistical limitations to the robustness of the statistical analyses. The result in each case was a subset of quasi-independent observations sampled at an interval of 800 seconds.

The time interval data reduction technique applied in this study was used previously in animal movement studies, but this is the first time that this method is applied to a continuous emission data set. The autocorrelation and false statistical significance issues were promptly resolved using this technique. Since the issues of false statistical significance and autocorrelation are inherent in continuous data, the positive results obtained from the use of this technique can be far-reaching. This is of utmost import because continuous data collection is becoming increasingly common due to technological advances evident in devices such as smart meters, digital pedometers, and continuous emission monitoring systems. Methods like this one will allow researchers to analyze and find meaning from continuous emission data collected in many disciplines.

VI.B. Comparison Analysis: Fuel Type

It was expected that ECD and B20 fuels would provide reductions in NO_x and CO_2 emissions when compared to baseline diesel fuel, but surprisingly they did not. The first stage of the analysis used the GLM with *Engine Speed* as a covariate factor to test the effect of fuel type on NO_x and CO_2 emissions in one compactor. As shown in the results, the fuel type factor was not found to be statistically significant at an alpha value of 0.05 for either pollutant. This means that the use of diesel, ECD, or B20 fuel did not have a statistically significant effect on NO_x and CO_2 emissions. From these results we can conclude that the effect of the three fuels tested does not impact the emissions of NO_x and CO_2. Thus, no benefits should be expected from running this compactor on ECD or B20 based on NO_x and CO_2 emissions.

VI.C. Comparison Analysis: Compactor

Unexpectedly, the comparison of two Trashmaster 3-90E compactors showed that the difference in emission profiles from these was statistically significant for both NO_x and CO_2 emissions. This analysis involved the use of the GLM with *Engine Speed* as the covariate factor in testing the NO_x and CO_2 emission variability between the data collected from two compactors of the same model running on diesel fuel. As shown in the results section, the compactor factor was not found to be statistically significant at an alpha value of 0.05 for NO_x. This means that the difference in NO_x emissions from the two compactors is not statistically significant. However, the interaction of compactor and engine speed factors was statistically significant for NO_x emissions. This means that the rate (slope) at which each compactor produces NO_x emissions is significantly different from each other (α=0.05) and therefore, the rate of emissions per engine speed is significantly different for each compactor.

For CO_2, the GLM test showed that the compactor factor was statistically significant at an alpha value of 0.05. This means that the CO_2 emissions from the two compactors are significantly different. Contrary to what was found for NO_x emissions, the interaction of the compactor and engine speed factors was not statistically significant. This meant that the rate of CO_2 emissions produced as a function of engine speed from each compactor was not found to be significantly different. However, since the CO_2 emissions were found to be significantly different for each compactor, we can conclude that the two compactors have a different CO_2 emission profile.

The results of this analysis were unexpected because the two compactors sampled were of the same model, operated at the same location, and driven by the same operator. Thus, it would be expected that the difference in emissions produced from the two compactors would not be statistically significant. For CO_2 this difference was clear because the compactor factor was found to be statistically significant. However, for NO_x emissions this difference was expressed differently because the difference was not identified in the compactor factor but in the interaction of compactor and engine speed factors. These results suggest that off-road diesel equipment can produce different NO_x and CO_2 emission profiles even when the equipment are of the same model and sampled under similar conditions. These results also suggest that each off-road diesel engine can produce a unique emission profile even when the engine is of the same family and type. Further research needs to be done to investigate if this variability is pervasive among other types of diesel engines. In this study the data were collected in 2005 and 2007 so perhaps this difference influenced the emissions results. However, temporal factors were not found to be statistically significant but aging factors in engines need to be better understood to identify how emissions profiles change according to the aging engine deterioration. This unique emission "footprint" can be caused by many factors including the maintenance performed on each engine or an inherent variability of engine emissions.

VI.D. Temporal Analysis: Fuel Type and Compactor

The temporal effects evaluated for the fuel type and compactor analyses showed that these effects were not statistically significant. The fuel type and two compactor data sets were collected over ten and eight days respectively. Thus, it was important to identify if temporal factors affected the NO_x and CO_2 emissions. Emissions of NO_x and CO_2 were not found to be dependent on the day when they were collected. These results indicate that the day factor is not statistically significant for either of these data sets. This was expected since the compactor activity and the person operating the compactor were constant.

VI.E. Data Fitting Models: Fuel Analysis

The third objective of the current study relates to the development of models to predict NO_x and CO_2 emission from engine speed data. Linear, quadratic, and cubic models were evaluated for this purpose.

The fuel analysis data were fitted to each of these three models and the results were evaluated based on the coefficient of determination (R^2) and a visual analysis. For NO_x emissions R^2 values are 81%, 83%, and 86% for the linear, quadratic, and cubic models respectively. CO_2 emissions have similar R^2 values: 89%, 92%, and 95% for the linear, quadratic, and cubic models respectively (Table 33). The linear model can be an acceptable predictive tool because visually it fits the NO_x and CO_2 data nicely, and it also has a high correlation value. The quadratic model is the least acceptable model because it does not fit the data correctly. This model has a concave down shape that overestimates concentrations in the transition period between idle and high engine loading. Based on the R^2 values, the cubic model accounts for most of the data variability for both the NO_x and the CO_2 data. Based on a visual analysis, the cubic model underpredicts emissions at engine speeds between 850 and 1300 RPM for NO_x and CO_2. The best feature of the cubic model is the prediction of NO_x and CO_2 values at the higher engine speed between 2000 and 2300 RPM. At these engine speed values the cubic model is able to accurately represent the shape of the emission distribution that peaks but then tapers off. This is probably the case because engines are designed to work most efficiently at full load. Thus, NO_x and CO_2 emissions drop slightly as peak engine speeds are reached.

Table 33. Coefficient of determination (R^2) in percentage.

Emission	Linear model	Quadratic Model	Cubic Model
NO_x	81	83	86
CO_2	89	92	95

The linear and the cubic models do a good job of fitting the NO_x and CO_2 data and they both have high R^2 values. Depending on the emphasis sought, either of these two models could be used as a predictive tool. The advantage of the linear model is its simplicity while the advantage of the cubic model is the fitting of emission data at high engine speeds.

VI.E. Data Fitting Models: Compactor Analysis

Linear, quadratic, and cubic models were used to fit the diesel fuel emission data from the two compactors. This analysis evaluated the compactors separately since in the statistical analysis performed, the difference in emission profiles was found to be statistically significant. The same visual patterns found in the fuel analysis data set were observed in this data set for each compactor. For example, based on a visual analysis, the quadratic model was found to be inadequate in how it fitted the NO_x and CO_2 data. The models that best fit the NO_x and CO_2 emission data were the linear and cubic. The NO_x emission data from the second compactor showed lower correlation values with 64%, 64%, and 73% for the linear, quadratic, and cubic models respectively (Table 33). The CO_2 emission data from the second compactor showed slightly higher correlation values than the ones from the fuel type analysis with 94%, 94%, and 96% for the linear, quadratic, and cubic models respectively (Table 34). Thus, the linear and the cubic models do a good job of fitting the NO_x and CO_2 data and they both have high R^2 values. The advantage of the linear model is its simplicity while the advantage of the cubic model is the fitting of emission data at high engine speeds. Depending on the emphasis sought, either of these two models could be used as predictive tools.

Table 34. Coefficient of determination (R^2) in percentage.

Compactor	Emission	Linear model	Quadratic Model	Cubic Model
C1	NO_x	75	78	84
	CO_2	90	93	94
C2	NO_x	64	64	73
	CO_2	94	94	96

VI.F. Future Implications and Concluding Remarks

The three main contributions from this study include the development of a data handling technique to deal with autocorrelation in continuous data, the finding that NO_x and CO_2 emissions are unaffected from the use of ECD and B20 fuel, and the finding that two compactors of the same model have significantly different emission profiles.

VI.F.1. Mitigation of Autocorrelation. This is the first time that the *time to independence* data technique is used for continuous emission data. The results obtained from its use on NO_x and CO_2 emission data show that this technique is most useful and effective in mitigating autocorrelation. This technique is most relevant given the advancements in sampling devices and data collection capabilities that have afforded the collection of enormous amounts of data for a myriad of purposes. These capabilities include smart meters, digital pedometers, medical devices, and continuous emission monitoring systems in factory stacks among many more. We can currently measure every instant of virtually every activity thanks to the advances afforded by technology. That is why data handling techniques like the *time to independence* herein developed are most necessary in finding meaning out of the colossal amounts of data available at our disposal.

The *time to independence* method described is a valuable tool that can make any subsequent statistical analysis valid and robust since autocorrelation in the data would be mitigated. Thus, once data are composed of quasi-independent observations, a more meaningful statistical analysis may ensue since the correct use of an ANOVA or GLM analysis will be warranted. Under such an analysis the significance of independent variables can be determined, allowing then for the testing of the significance of fuel types, engine parameters, and ambient parameters on engine emissions. PEMS data collected at the CEAE of KU can benefit from using the approach herein presented to confirm the significance of independent variables tested previously. Furthermore, given the strong ongoing research on bio-diesel emissions at the CEAE of KU, the approach herein presented can be used to determining the benefits from distinct types and mixes of biodiesel fuel.

VI.F.2. Interval Refinements. In the current analysis an interval of 1 every 800 seconds was used to mitigate autocorrelation. This was deemed an acceptable interval since the compactor provided over 8 hours (28,800 seconds) of real-world data each day. However, this value is overly conservative and can be refined to accommodate shorter sampling campaigns. Thus, an adjustment of this lag value can yield a smaller interval within observations. Furthermore, distinct emission equipment may experience different levels of autocorrelation that may require distinct intervals. Therefore, different intervals need to be evaluated for other equipment and engine types.

VI.F.3. False Statistical Significance. Large data sets collected from PEMS can bias statistical significance by producing very small probability (P) values. This is not a common issue in most statistical analyses where researchers struggle to get enough data to analyze. However, by collecting data on a second-by-second basis, PEMS units can produce large enough data observations (N) that can bias P values and show an *artificial* significance. For example, Johnson et al. (2009) found a statistically significant difference between the NO_x emission observations collected from the MEL and PEMS units. This may be a case of a false statistical significance due to a large N since other studies (Rubino et al., 2007) showed a strong agreement between the observations collected with laboratory and on-board systems.

VI.F.4. Null Emissions Benefits from ULSD and B20. An unexpected lack of reductions in NO_x and CO_2 emissions was found from the use of ECD and B20 fuel. Both, biodiesel fuel mixes and ECD have been promoted for their emission benefits compared to regular no. 2 diesel fuel. However, these reductions were not found to be statistically significant in this study. Nonetheless, the use of biodiesel mixes and ECD fuels in diesel engines will continue to increase due to geopolitical and economic factors. Thus, emission reductions touted from the use of these fuels should be considered with reservation especially when related to NO_x and CO_2 emissions. However, these conclusions need to be confirmed by further emission testing research. Furthermore, there may be other pollutants that show reductions with ULSD and B20 fuels.

VI.F.5. Variability in Emission Profiles. Another important finding in this study was the significant difference in NO_x and CO_2 emission profiles from the two Trashmaster 3-90E compactors. This could mean that engines have a unique emission profile with significant variability, even within engines of the same model and type. The repercussions of this finding are far-reaching. If each off-road diesel equipment has a significantly different emission profile, then there is an inherent variability analogous to an individual engine emission "footprint". This would create a great challenge in characterizing emissions from mobile sources. However, additional testing is necessary to determine if this finding is in fact pervasive among other equipment and engine types.

VI.F.6. Concluding Remarks. Characterization of mobile real-world emissions has been made possible due to the latest advancements in technology that make emission measurements from on-board emission testing units as accurate and precise as laboratory-grade equipment. The EPA in the US and the EC in the European Union have started using on-board data in their New Generation Models in an effort to characterize mobile emissions more accurately. Technological advancements related to on-board emission testing systems also have allowed for the collection of continuous data. The vast amount of data that can now be collected by on-board systems also increases the complexity of data analysis, posing new challenges such as apparent statistical significance and autocorrelation. These challenges mar the validity and robustness of statistical analyses performed when determining the effect on emission from independent variables such as fuel types, altitude, and engine parameters.

Therefore, the real challenge that researchers face today when analyzing continuous data, is how to mine the mountains of data for meaning. Most research on continuous data is based on a comparison of averages that all but ignore the nature and value of the data collected. Complex data requires more advanced statistical analyses. Some other researchers have started to address this need by using ANOVA and GLM analyses to evaluate the effect of independent variables (i.e. fuel types) on specific dependent variables (i.e. emissions). The methodology outlined in this thesis is a crucial tool to make sense and find meaning from real-world, continuous data.

The Department of CEAE at KU is leading the effort in biofuels development and testing for over 10 years. In addition, the CEAE owns a SEMTECH-DS that has been thoroughly validated in accuracy and which is the most widely used instrument for on-board emission testing. Therefore, the CEAE of KU is in a prime position to use the tools herein presented for the advancement of emission testing and fuel development science and continue to be a leader in these fields.

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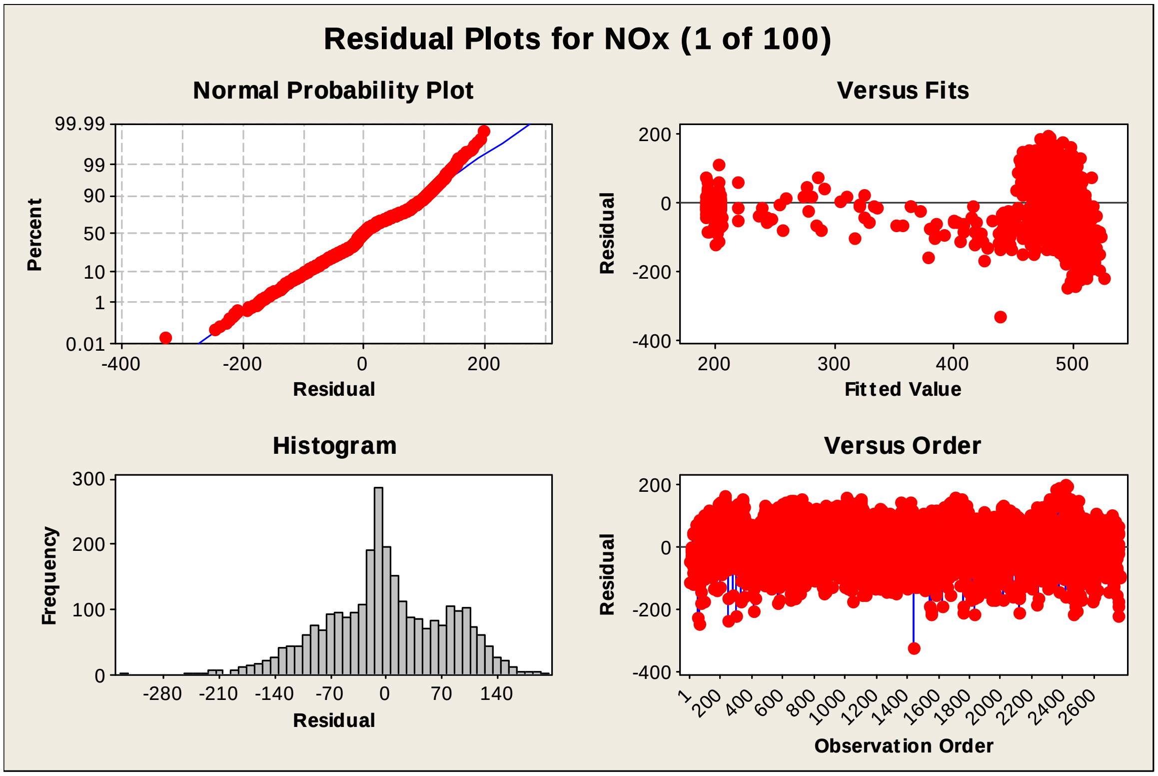
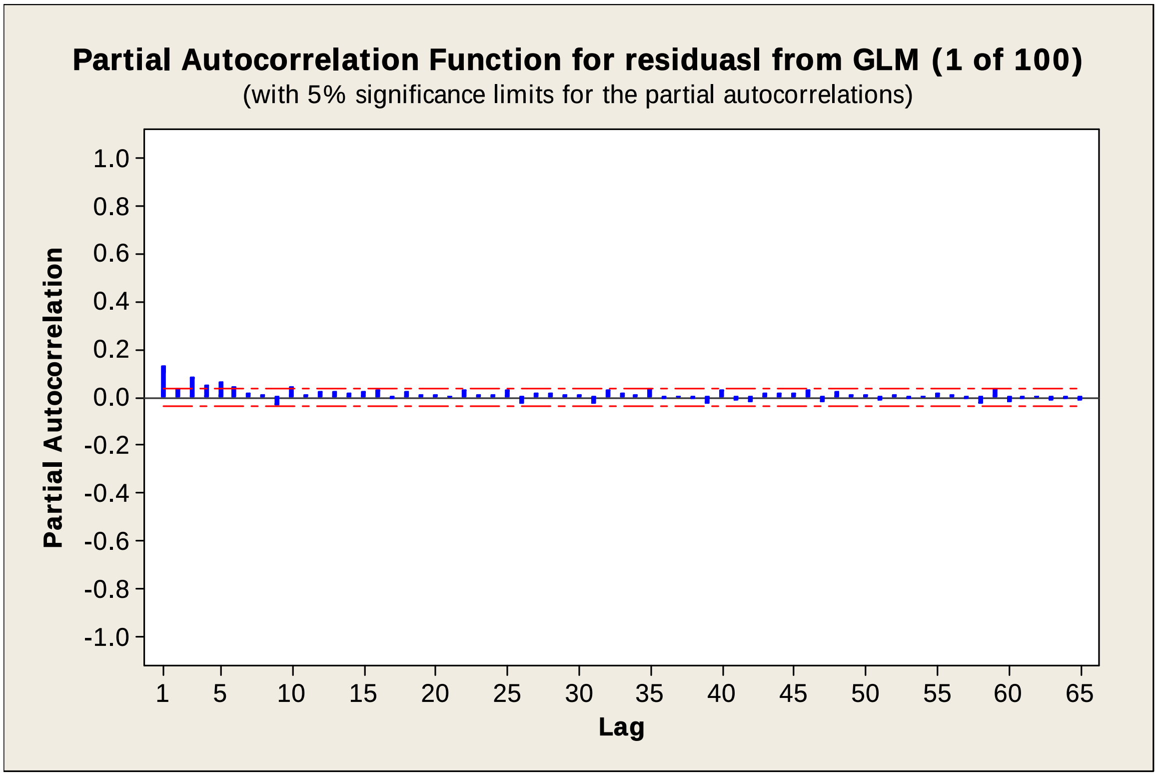
APPENDIX A: Fuel Analysis

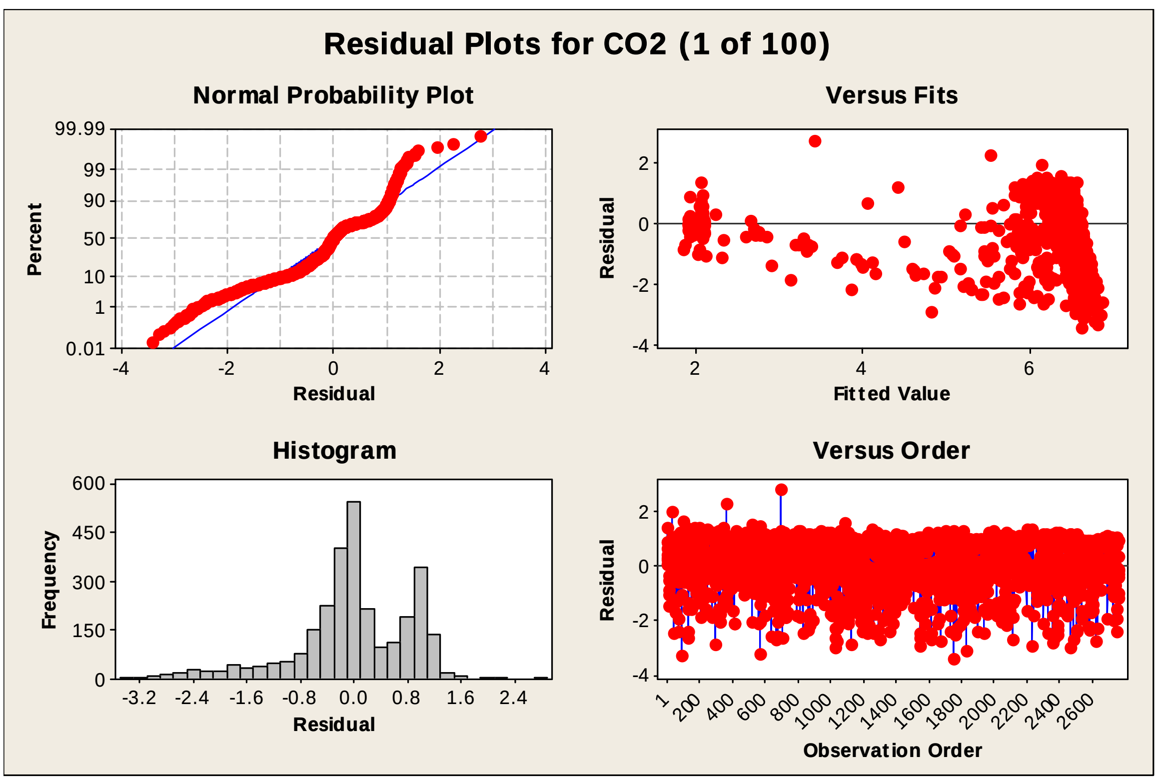


Results for: 1 of 100 lag

General Linear Model: NOx versus Fuel Type

```
Factor     Type   Levels  Values
Fuel Type  fixed       3  B20, Diesel, ECD


Analysis of Variance for NOx, using Adjusted SS for Tests

Source                 DF    Seq SS    Adj SS    Adj MS        F      P
EngineSpeed             1  41678700  37568249  37568249  6836.03  0.000
Fuel Type               2     11673     61303     30652     5.58  0.004
Fuel Type*EngineSpeed   2     81234     81234     40617     7.39  0.001
Error                2760  15167925  15167925      5496
Total                2765  56939531


S = 74.1325   R-Sq = 73.36%   R-Sq(adj) = 73.31%
```


Partial Autocorrelation Function for residuasl from GLM (1 of 100)
(with 5% significance limits for the partial autocorrelations)
Partial Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1 5 10 15 20 25 30 35 40 45 50 55 60 65
Lag


Residual Plots for CO2 (1 of 100)
Normal Probability Plot
Percent
99.99
99
90
50
10
1
0.01
-4 -2 0 2 4
Residual
Versus Fits
Residual
2
0
-2
-4
2 4 6
Fitted Value
Histogram
Frequency
600
450
300
150
0
-3.2 -2.4 -1.6 -0.8 0.0 0.8 1.6 2.4
Residual
Versus Order
Residual
2
0
-2
-4
1 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400 2600
Observation Order

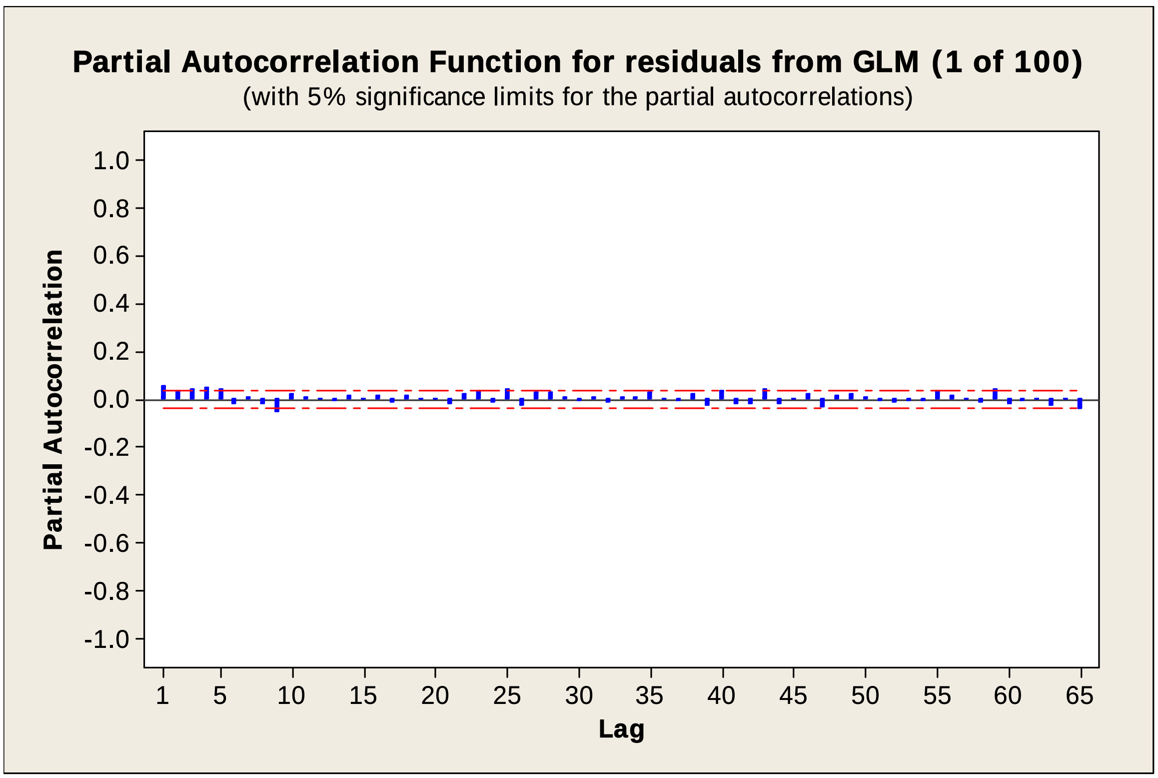
General Linear Model: CO2 versus Fuel Type

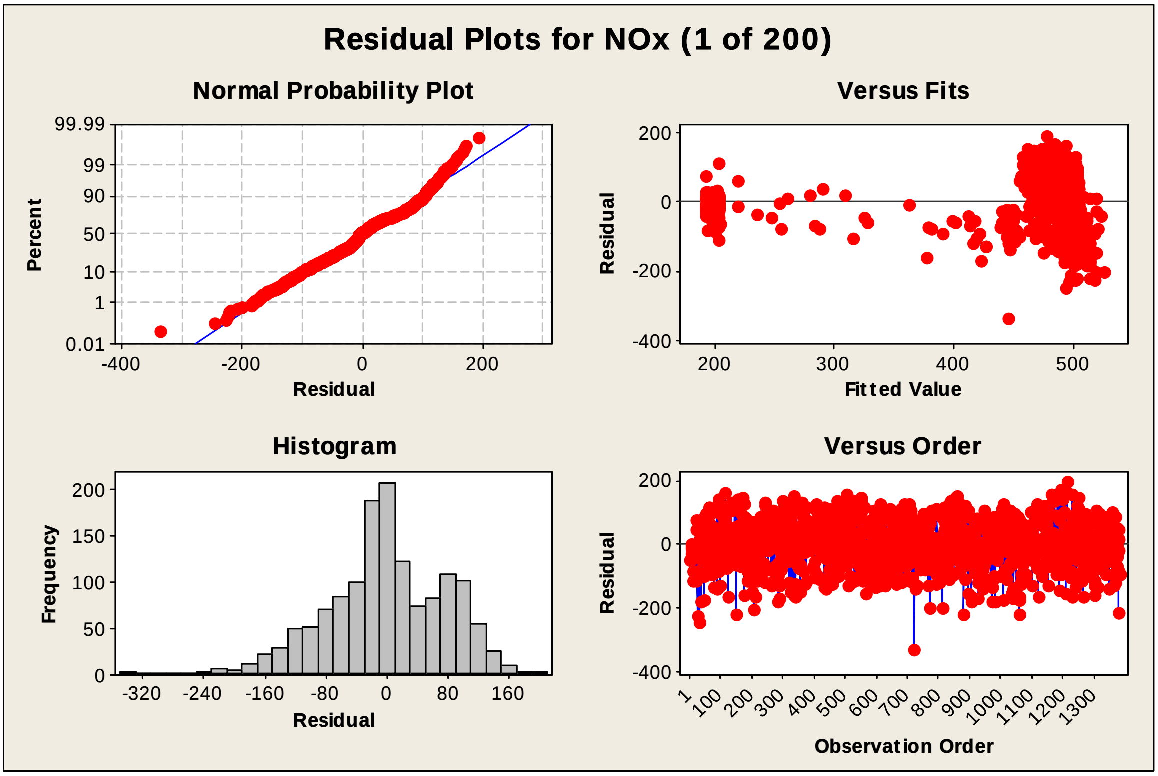
Factor	Type	Levels	Values
Fuel Type	fixed	3	B20, Diesel, ECD

Analysis of Variance for CO2, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
EngineSpeed	1	9612.6	8443.0	8443.0	12569.26	0.000
Fuel Type	2	39.3	5.8	2.9	4.32	0.013
Fuel Type*EngineSpeed	2	0.6	0.6	0.3	0.43	0.651
Error	2760	1853.9	1853.9	0.7		
Total	2765	11506.4				

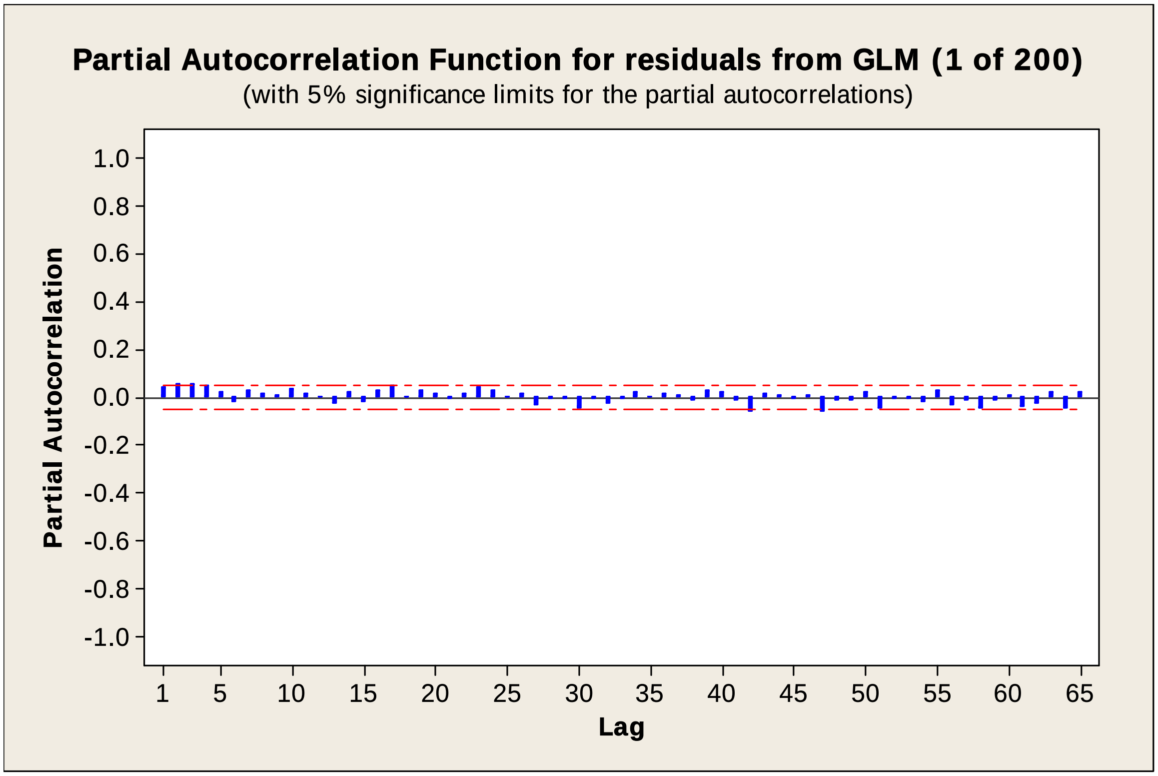
S = 0.819583   R-Sq = 83.89%   R-Sq(adj) = 83.86%

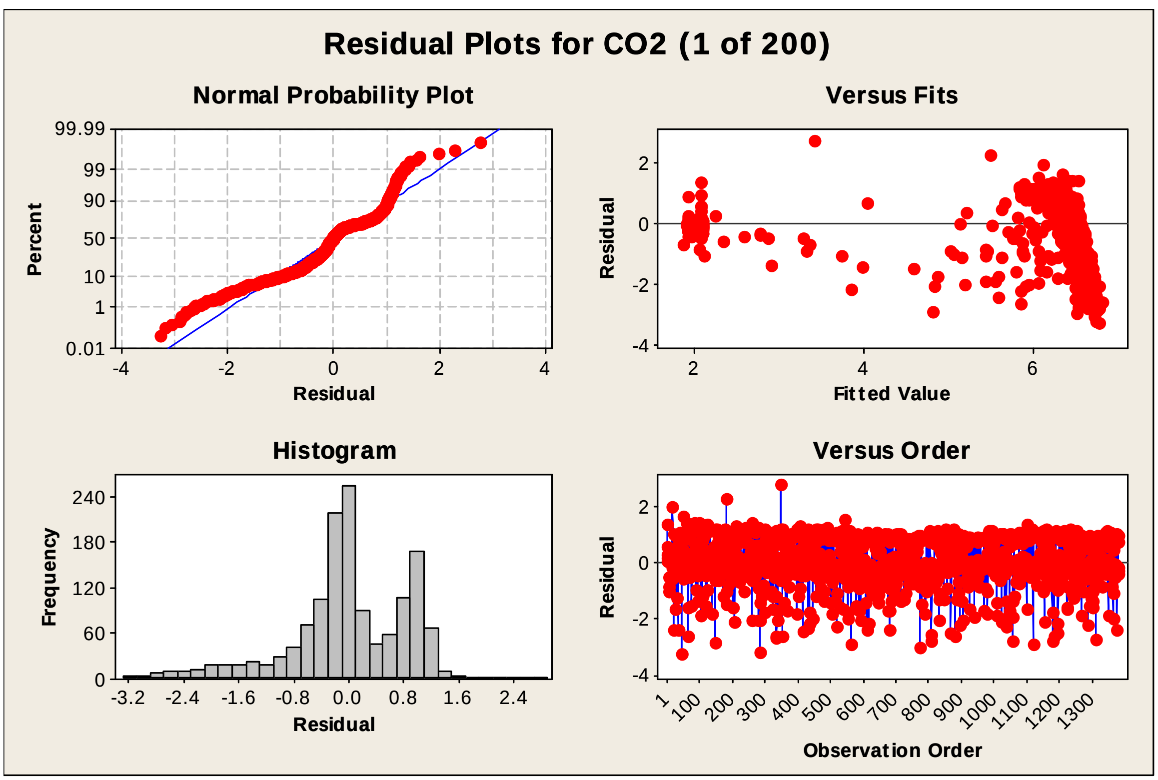




General Linear Model: NOx versus Fuel Type

```
Factor     Type   Levels  Values
Fuel Type  fixed       3  B20, Diesel, ECD


Analysis of Variance for NOx, using Adjusted SS for Tests

Source                  DF    Seq SS    Adj SS    Adj MS        F      P
EngineSpeed              1  21196529  19086141  19086141  3374.99  0.000
Fuel Type                2     11322     34465     17233     3.05  0.048
Fuel Type*EngineSpeed    2     49577     49577     24788     4.38  0.013
Error                 1377   7787164   7787164      5655
Total                 1382  29044592


S = 75.2008   R-Sq = 73.19%   R-Sq(adj) = 73.09%
```


Partial Autocorrelation Function for residuals from GLM (1 of 200)
(with 5% significance limits for the partial autocorrelations)
Partial Autocorrelation
Lag


Residual Plots for CO2 (1 of 200)
Normal Probability Plot
Percent
Residual
Versus Fits
Residual
Fitted Value
Histogram
Frequency
Residual
Versus Order
Residual
Observation Order

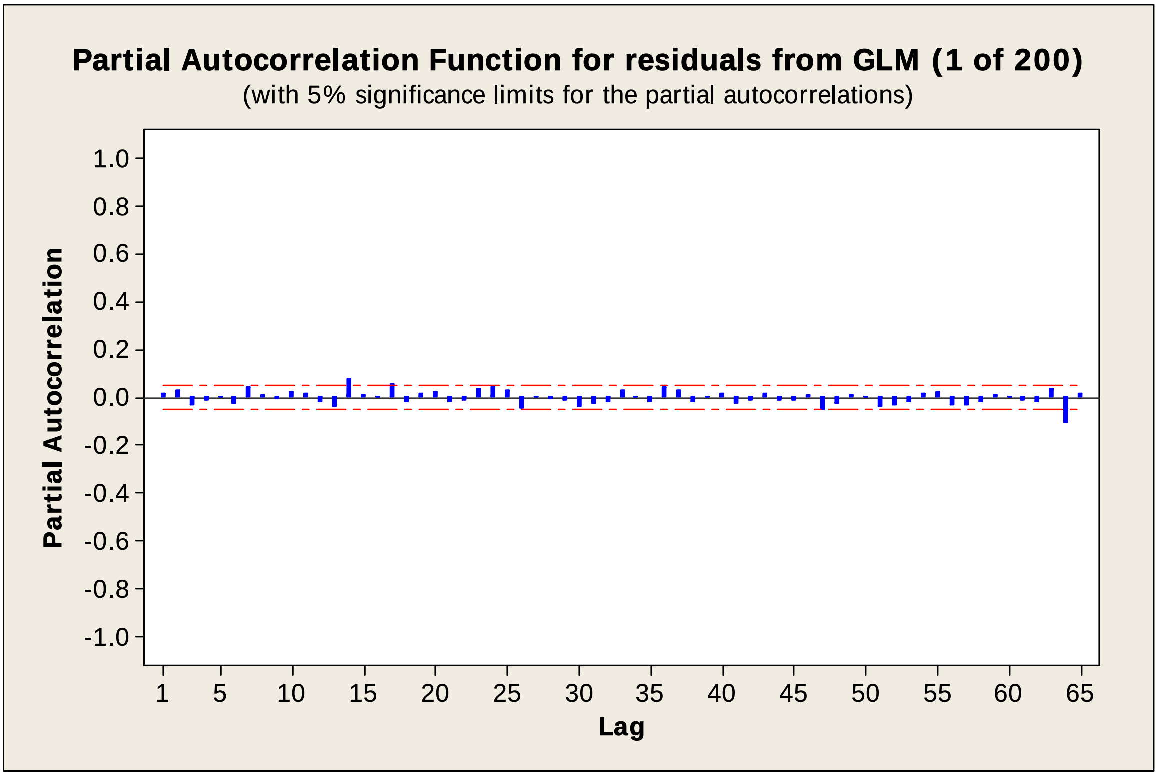
General Linear Model: CO2 versus Fuel Type

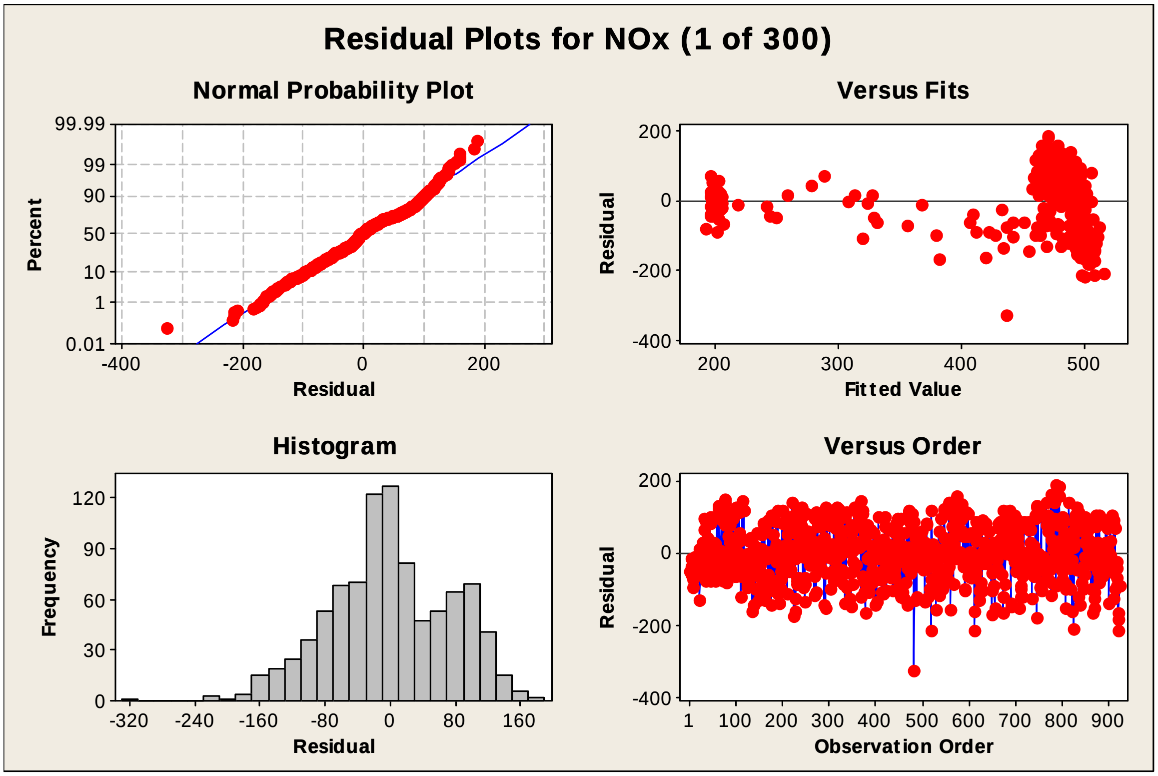
Factor	Type	Levels	Values
Fuel Type	fixed	3	B20, Diesel, ECD

Analysis of Variance for CO2, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
EngineSpeed	1	4809.86	4221.13	4221.13	5981.30	0.000
Fuel Type	2	15.10	4.05	2.03	2.87	0.057
Fuel Type*EngineSpeed	2	1.77	1.77	0.89	1.26	0.285
Error	1377	971.78	971.78	0.71		
Total	1382	5798.51				

S = 0.840073   R-Sq = 83.24%   R-Sq(adj) = 83.18%

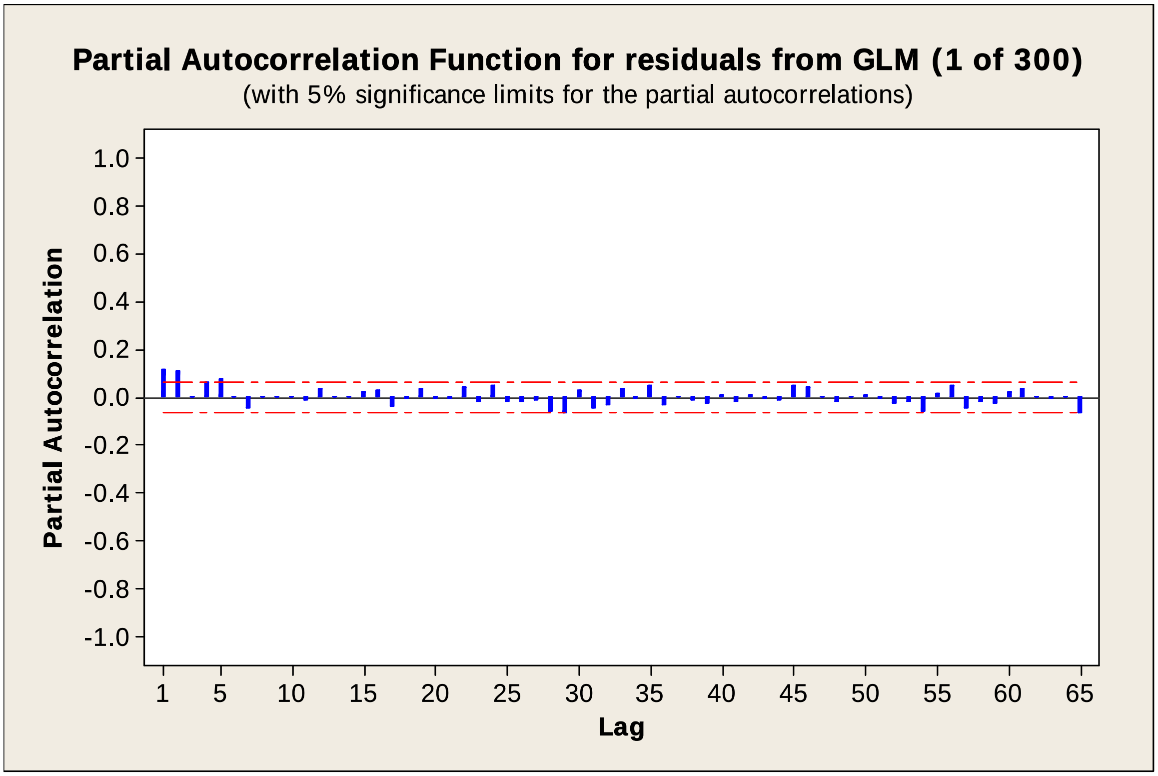


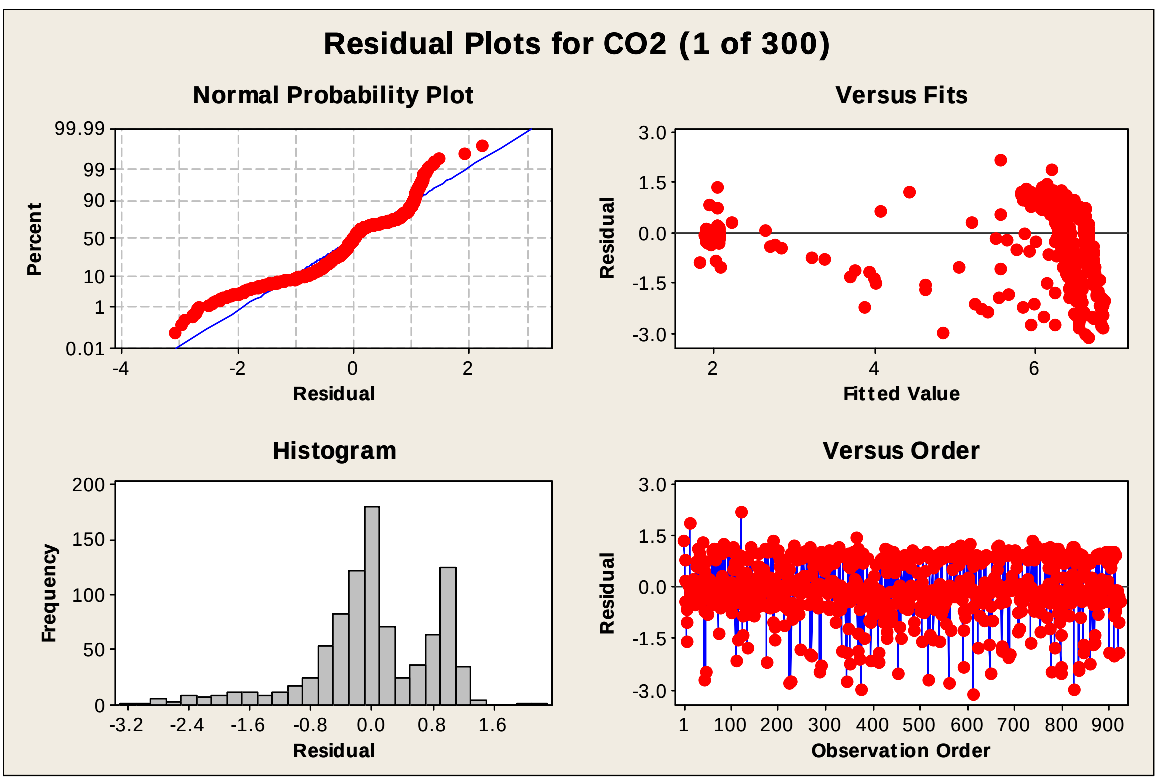


Results for: 1 of 300 lag

General Linear Model: NOx versus Fuel Type

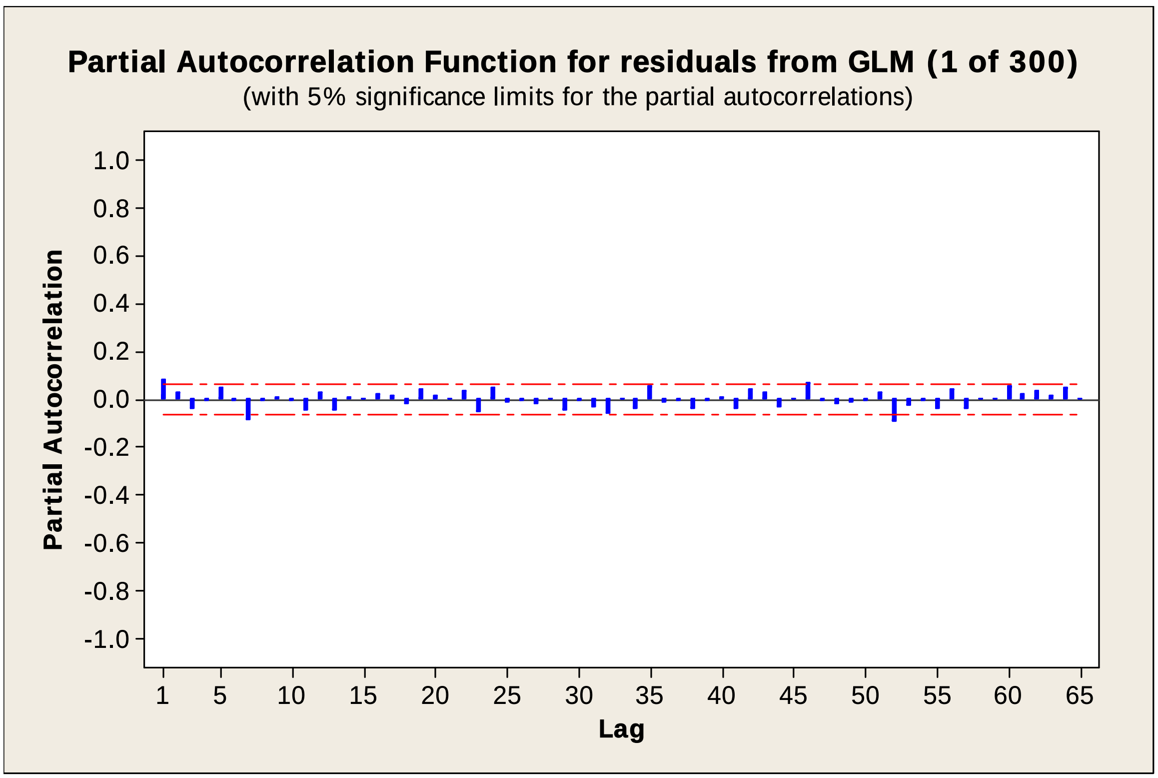
```
Factor     Type   Levels  Values
Fuel Type  fixed       3  B20, Diesel, ECD


Analysis of Variance for NOx, using Adjusted SS for Tests

Source                  DF    Seq SS    Adj SS    Adj MS        F      P
EngineSpeed              1  13824523  12038636  12038636  2156.71  0.000
Fuel Type                2     10984      9458      4729     0.85  0.429
Fuel Type*EngineSpeed    2      5085      5085      2542     0.46  0.634
Error                  917   5118640   5118640      5582
Total                  922  18959232


S = 74.7124   R-Sq = 73.00%   R-Sq(adj) = 72.85%
```

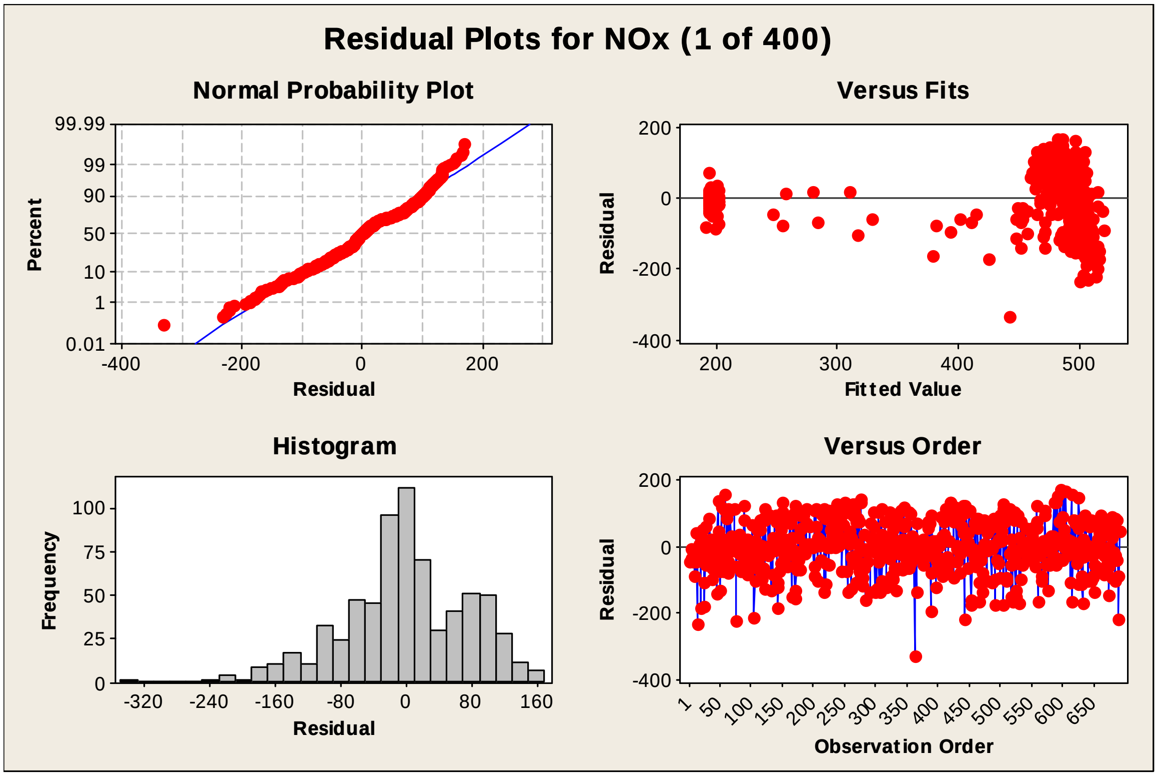

Partial Autocorrelation Function for residuals from GLM (1 of 300)
(with 5% significance limits for the partial autocorrelations)
Partial Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1 5 10 15 20 25 30 35 40 45 50 55 60 65
Lag


Residual Plots for CO2 (1 of 300)
Normal Probability Plot
Percent
99.99
99
90
50
10
1
0.01
-4 -2 0 2
Residual
Versus Fits
Residual
3.0
1.5
0.0
-1.5
-3.0
2 4 6
Fitted Value
Histogram
Frequency
200
150
100
50
0
-3.2 -2.4 -1.6 -0.8 0.0 0.8 1.6
Residual
Versus Order
Residual
3.0
1.5
0.0
-1.5
-3.0
1 100 200 300 400 500 600 700 800 900
Observation Order

General Linear Model: CO2 versus Fuel Type

```
Factor      Type   Levels  Values
Fuel Type   fixed       3  B20, Diesel, ECD


Analysis of Variance for CO2, using Adjusted SS for Tests

Source                  DF   Seq SS   Adj SS   Adj MS        F      P
EngineSpeed              1  3230.79  2763.17  2763.17  4049.45  0.000
Fuel Type                2    20.36     1.13     0.57     0.83  0.437
Fuel Type*EngineSpeed    2     0.49     0.49     0.25     0.36  0.697
Error                  917   625.72   625.72     0.68
Total                  922  3877.37


S = 0.826049   R-Sq = 83.86%   R-Sq(adj) = 83.77%
```

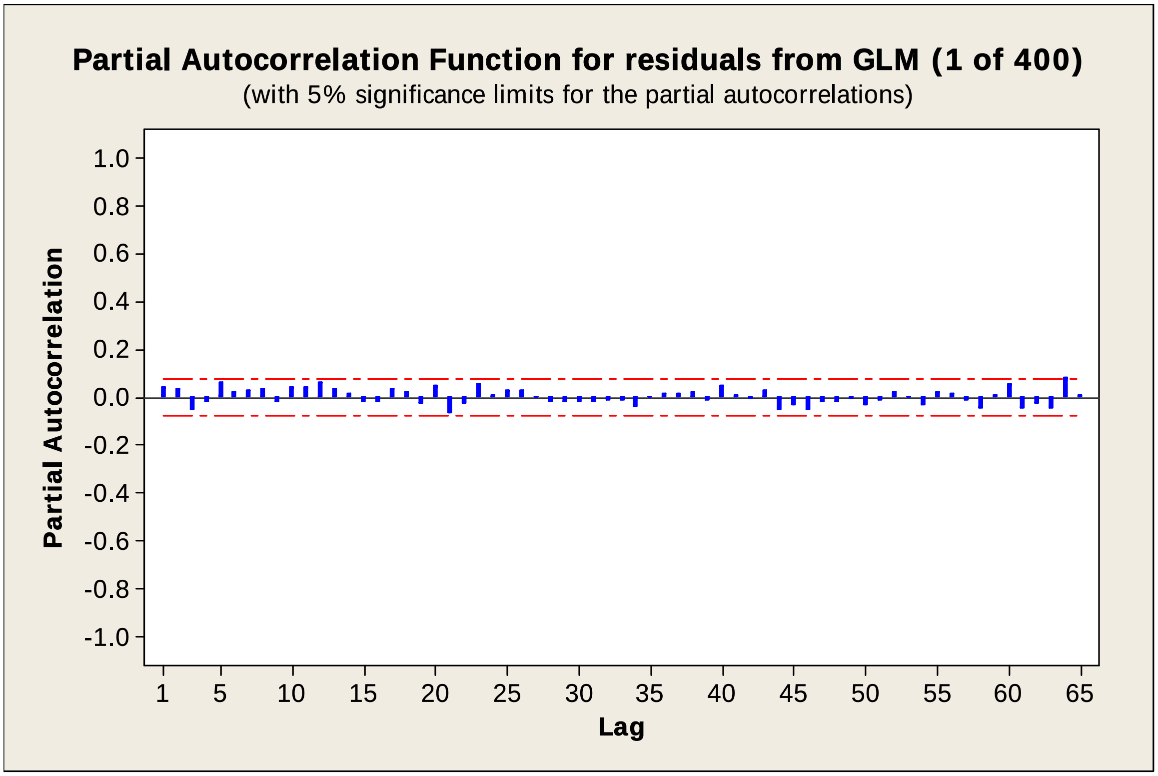




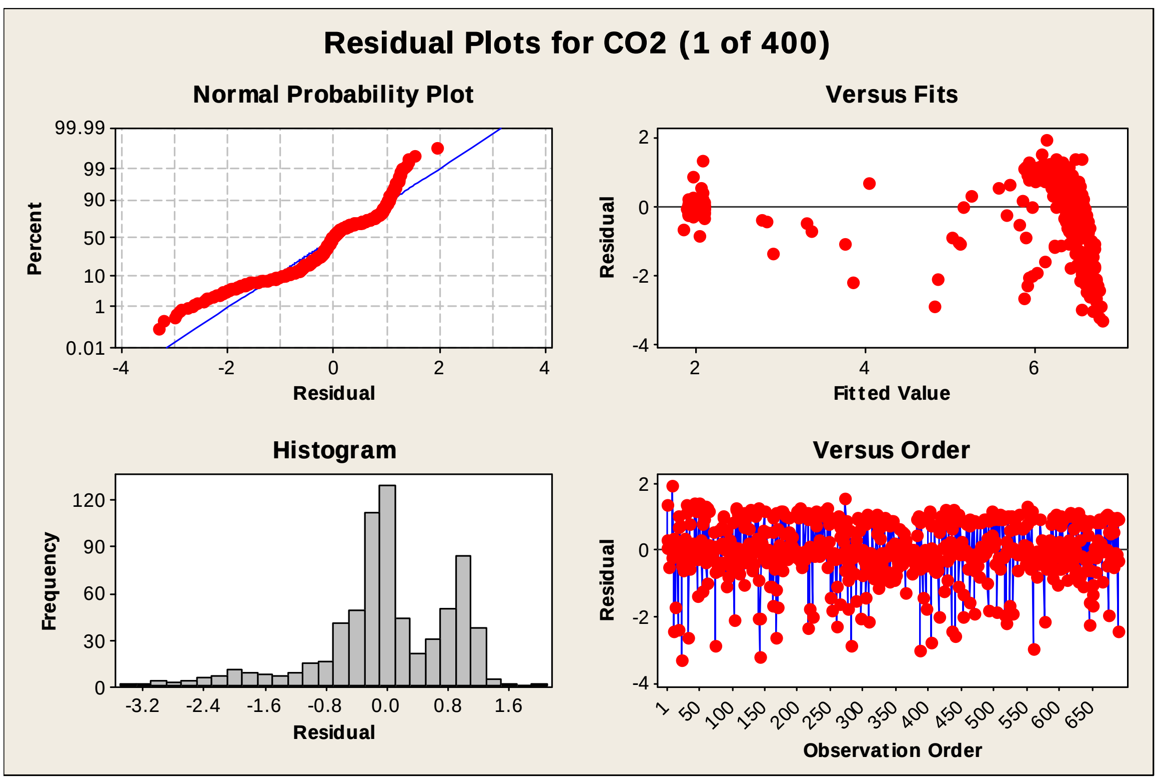
Results for: 1 of 400 lag

General Linear Model: NOx versus Fuel Type

```
Factor     Type   Levels  Values
Fuel Type  fixed       3  B20, Diesel, ECD


Analysis of Variance for NOx, using Adjusted SS for Tests

Source                  DF    Seq SS   Adj SS   Adj MS        F      P
EngineSpeed              1  11100481  9792619  9792619  1714.57  0.000
Fuel Type                2       565    12859     6430     1.13  0.325
Fuel Type*EngineSpeed    2     15203    15203     7602     1.33  0.265
Error                  686   3918029  3918029     5711
Total                  691  15034279


S = 75.5739   R-Sq = 73.94%   R-Sq(adj) = 73.75%
```



Partial Autocorrelation Function for residuals from GLM (1 of 400)
(with 5% significance limits for the partial autocorrelations)
Partial Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1 5 10 15 20 25 30 35 40 45 50 55 60 65
Lag



Residual Plots for CO2 (1 of 400)
Normal Probability Plot
Percent
99.99
99
90
50
10
1
0.01
-4 -2 0 2 4
Residual
Versus Fits
Residual
2
0
-2
-4
2 4 6
Fitted Value
Histogram
Frequency
120
90
60
30
0
-3.2 -2.4 -1.6 -0.8 0.0 0.8 1.6
Residual
Versus Order
Residual
2
0
-2
-4
1 50 100 150 200 250 300 350 400 450 500 550 600 650
Observation Order

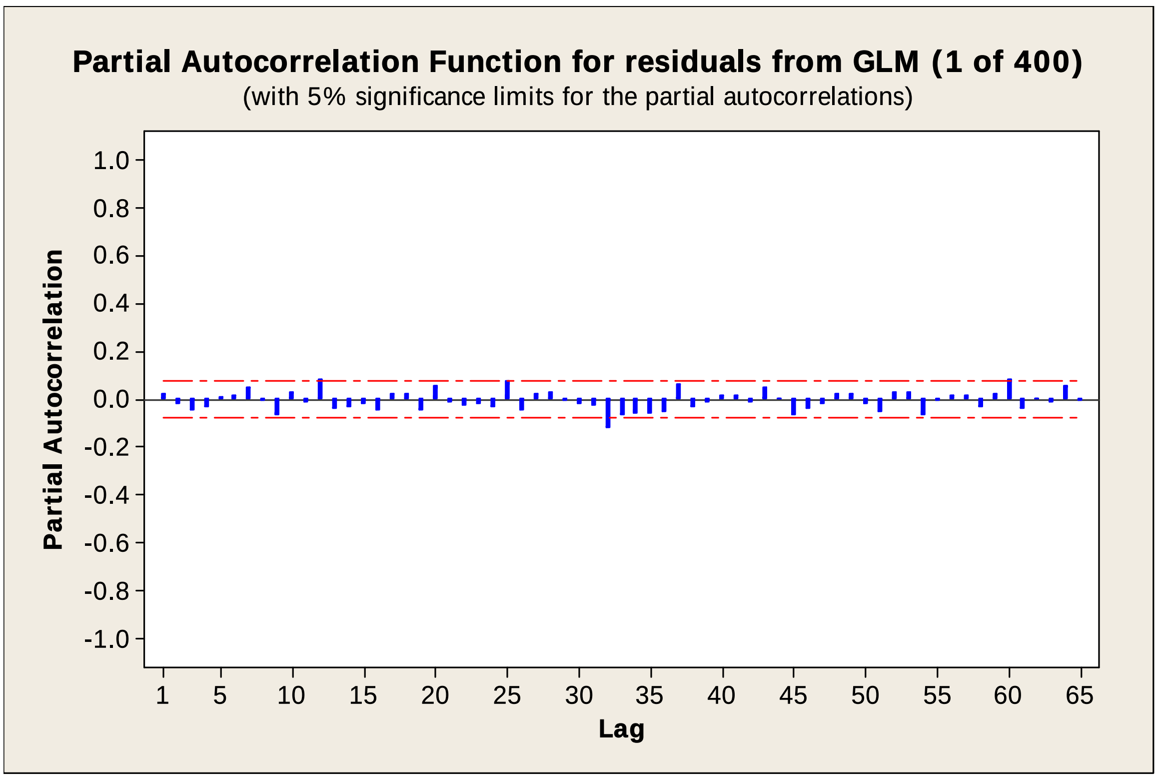
General Linear Model: CO2 versus Fuel Type

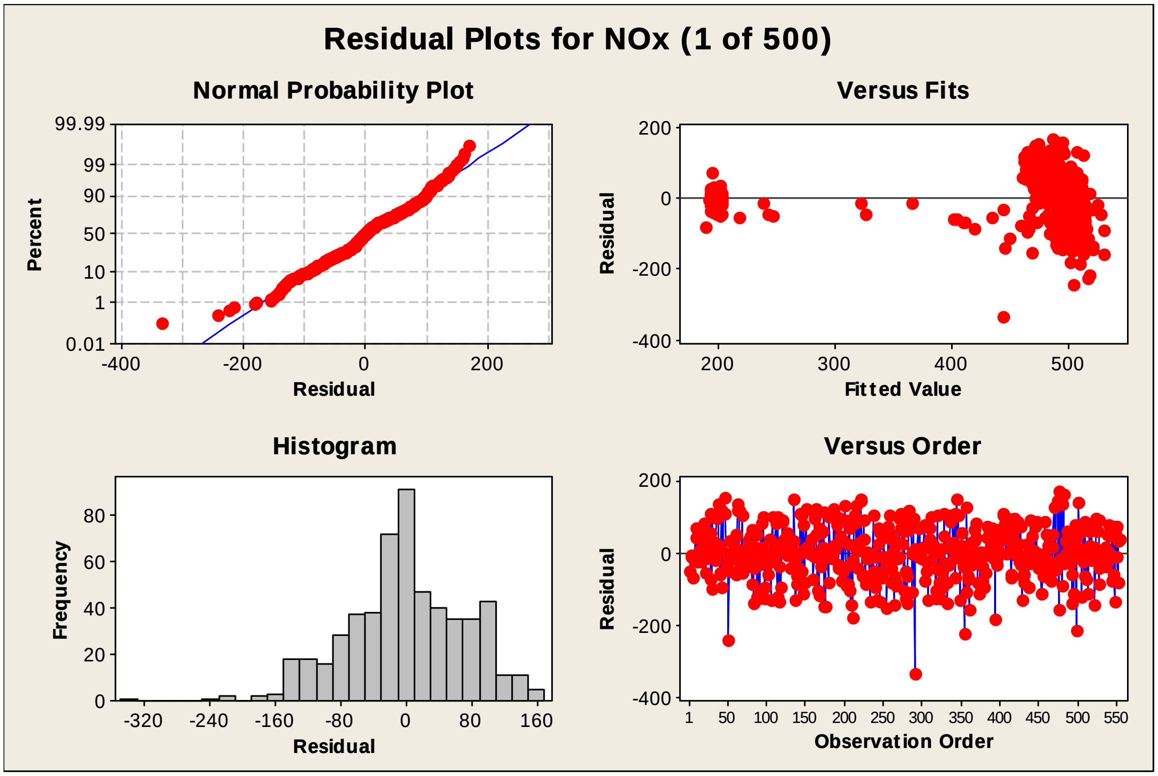
Factor	Type	Levels	Values
Fuel Type	fixed	3	B20, Diesel, ECD

Analysis of Variance for CO2, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
EngineSpeed	1	2482.98	2149.67	2149.67	2950.62	0.000
Fuel Type	2	7.54	1.87	0.93	1.28	0.279
Fuel Type*EngineSpeed	2	0.52	0.52	0.26	0.36	0.700
Error	686	499.79	499.79	0.73		
Total	691	2990.83				

S = 0.853552   R-Sq = 83.29%   R-Sq(adj) = 83.17%





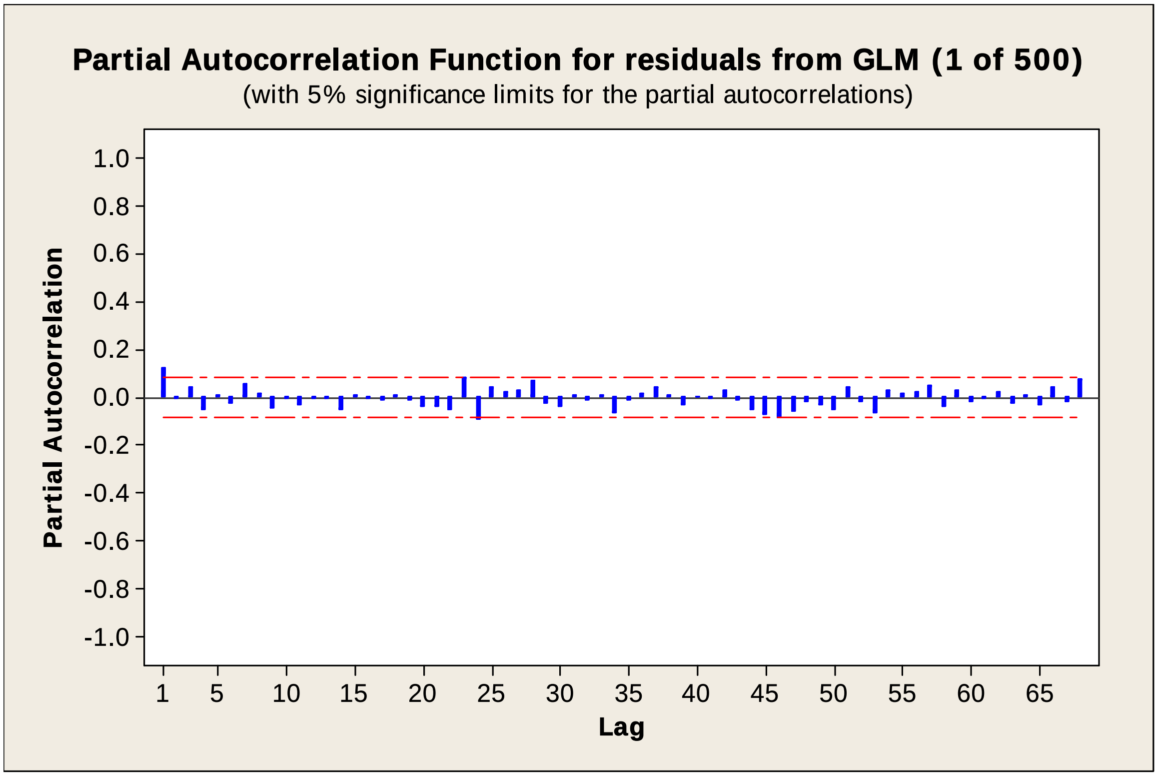
General Linear Model: NOx versus Fuel Type

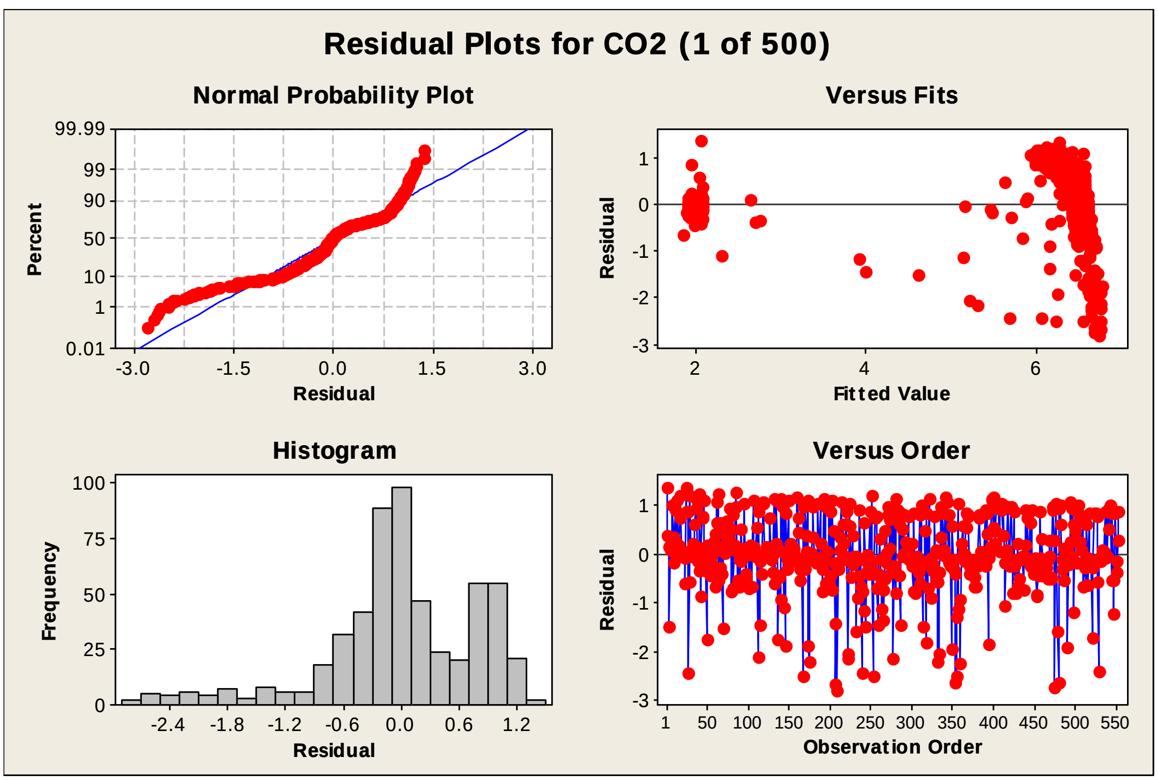
Factor	Type	Levels	Values
Fuel Type	fixed	3	B20, Diesel, ECD

Analysis of Variance for NOx, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Fuel Type	2	3693	14384	7192	1.34	0.262
EngineSpeed	1	8812595	7976444	7976444	1490.10	0.000
Fuel Type*EngineSpeed	2	21295	21295	10648	1.99	0.138
Error	548	2933421	2933421	5353		
Total	553	11771004				

S = 73.1639   R-Sq = 75.08%   R-Sq(adj) = 74.85%


Partial Autocorrelation Function for residuals from GLM (1 of 500)
(with 5% significance limits for the partial autocorrelations)
Partial Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1 5 10 15 20 25 30 35 40 45 50 55 60 65
Lag


Residual Plots for CO2 (1 of 500)
Normal Probability Plot
Percent
99.99
99
90
50
10
1
0.01
-3.0 -1.5 0.0 1.5 3.0
Residual
Versus Fits
Residual
1
0
-1
-2
-3
2 4 6
Fitted Value
Histogram
Frequency
100
75
50
25
0
-2.4 -1.8 -1.2 -0.6 0.0 0.6 1.2
Residual
Versus Order
Residual
1
0
-1
-2
-3
1 50 100 150 200 250 300 350 400 450 500 550
Observation Order

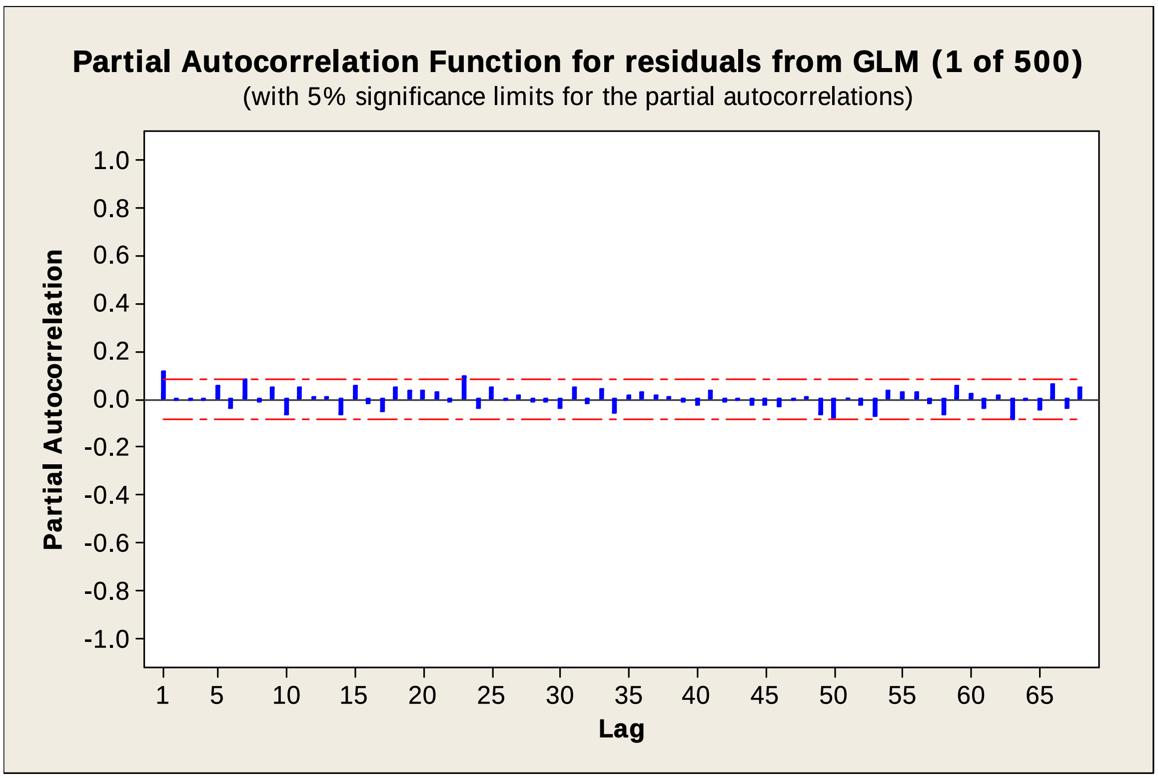
General Linear Model: CO2 versus Fuel Type

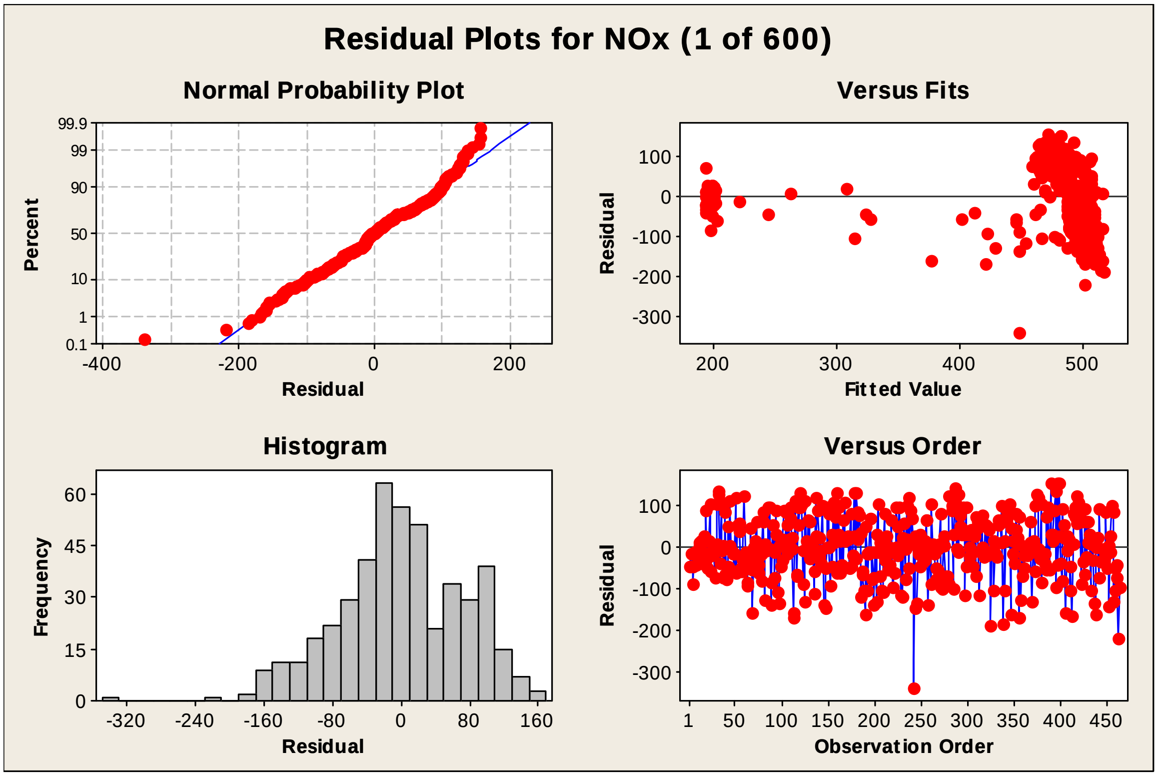
Factor	Type	Levels	Values
Fuel Type	fixed	3	B20, Diesel, ECD

Analysis of Variance for CO2, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Fuel Type	2	6.74	1.34	0.67	1.06	0.346
EngineSpeed	1	1980.68	1744.50	1744.50	2763.53	0.000
Fuel Type*EngineSpeed	2	0.42	0.42	0.21	0.33	0.719
Error	548	345.93	345.93	0.63		
Total	553	2333.77				

S = 0.794518   R-Sq = 85.18%   R-Sq(adj) = 85.04%





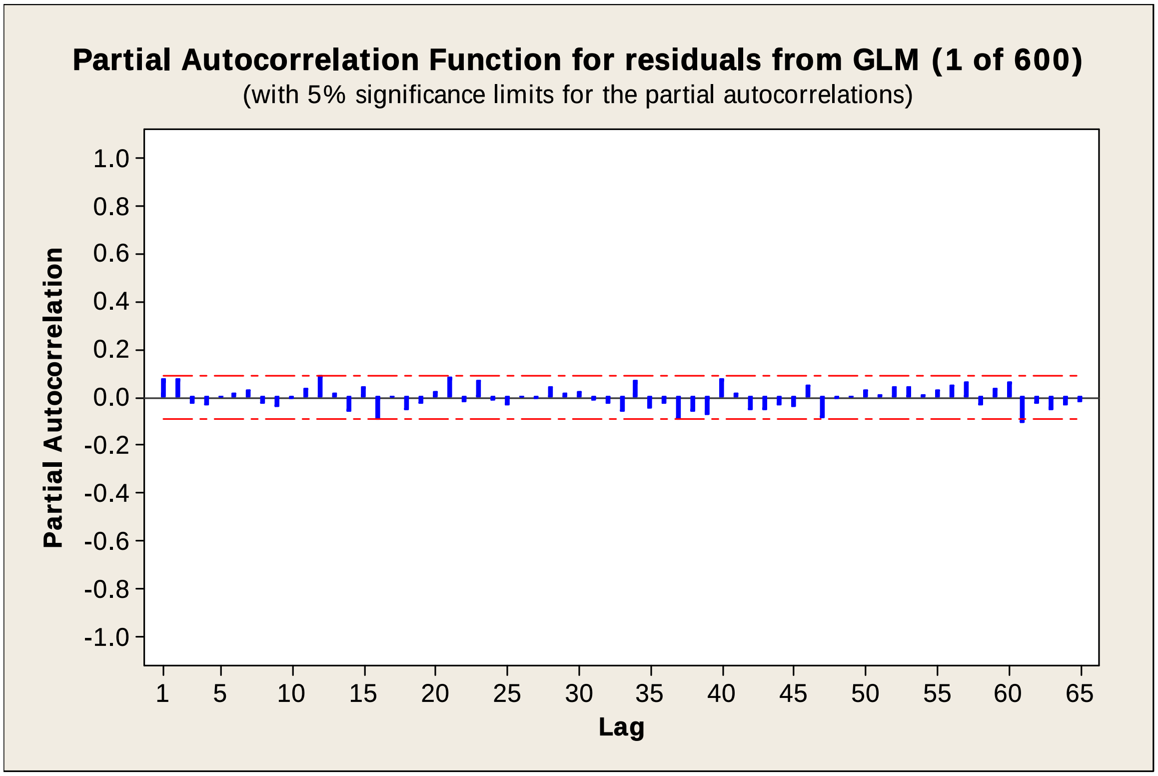
General Linear Model: NOx versus Fuel Type

Factor	Type	Levels	Values
Fuel Type	fixed	3	B20, Diesel, ECD

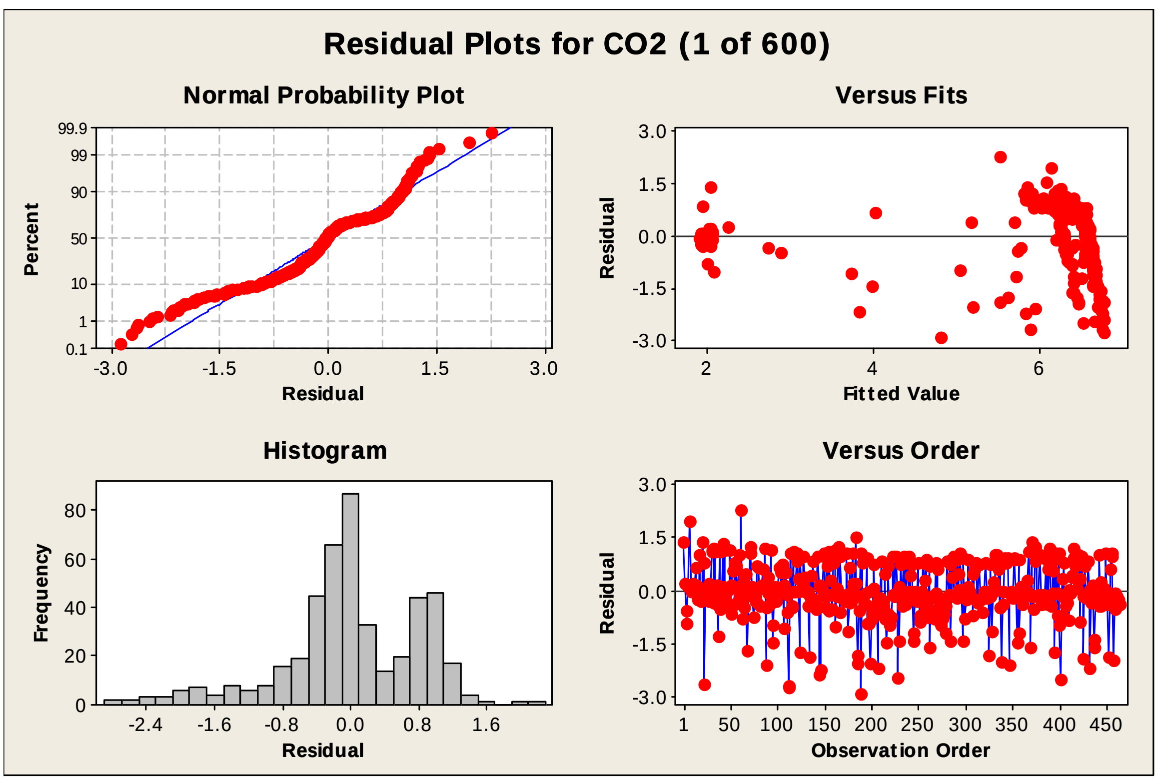
Analysis of Variance for NOx, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
EngineSpeed	1	7233331	6394569	6394569	1152.22	0.000
Fuel Type	2	5532	7068	3534	0.64	0.529
Fuel Type*EngineSpeed	2	10686	10686	5343	0.96	0.383
Error	457	2536259	2536259	5550		
Total	462	9785808				

S = 74.4970   R-Sq = 74.08%   R-Sq(adj) = 73.80%



Partial Autocorrelation Function for residuals from GLM (1 of 600)
(with 5% significance limits for the partial autocorrelations)
Partial Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1 5 10 15 20 25 30 35 40 45 50 55 60 65
Lag



Residual Plots for CO2 (1 of 600)
Normal Probability Plot
Percent
99.9
99
90
50
10
1
0.1
-3.0 -1.5 0.0 1.5 3.0
Residual
Versus Fits
Residual
3.0
1.5
0.0
-1.5
-3.0
2 4 6
Fitted Value
Histogram
Frequency
80
60
40
20
0
-2.4 -1.6 -0.8 0.0 0.8 1.6
Residual
Versus Order
Residual
3.0
1.5
0.0
-1.5
-3.0
1 50 100 150 200 250 300 350 400 450
Observation Order

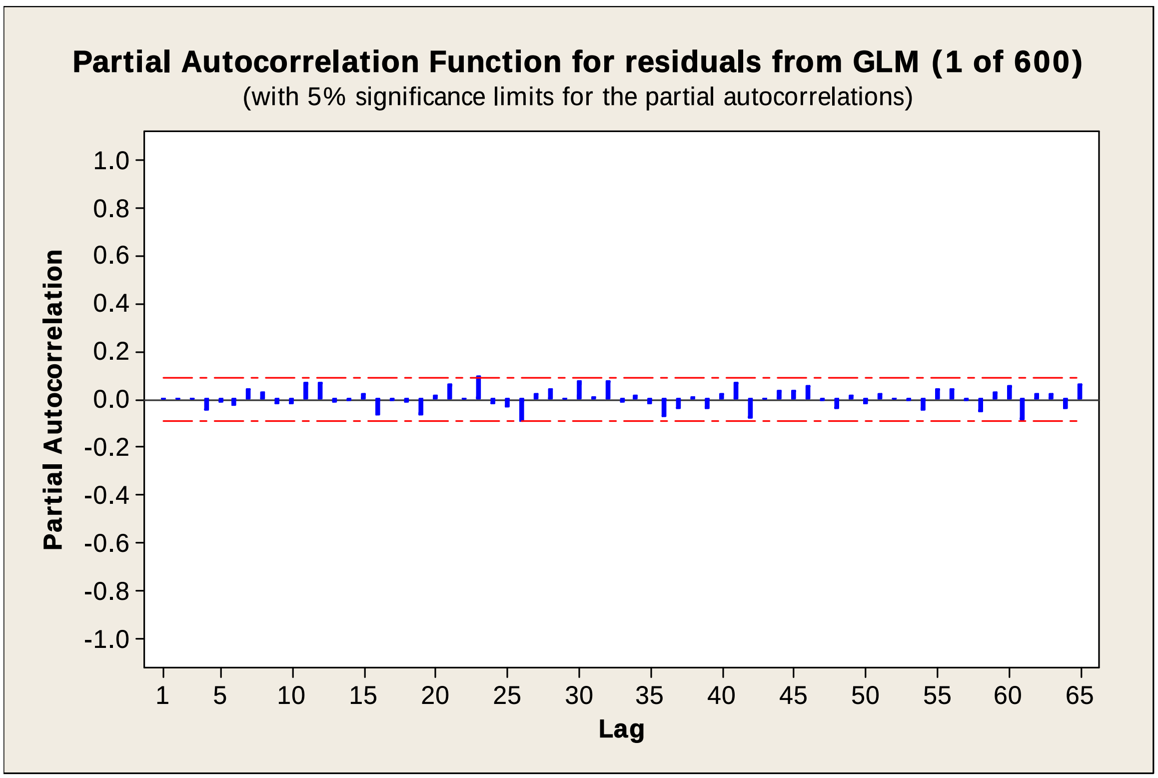
General Linear Model: CO2 versus Fuel Type

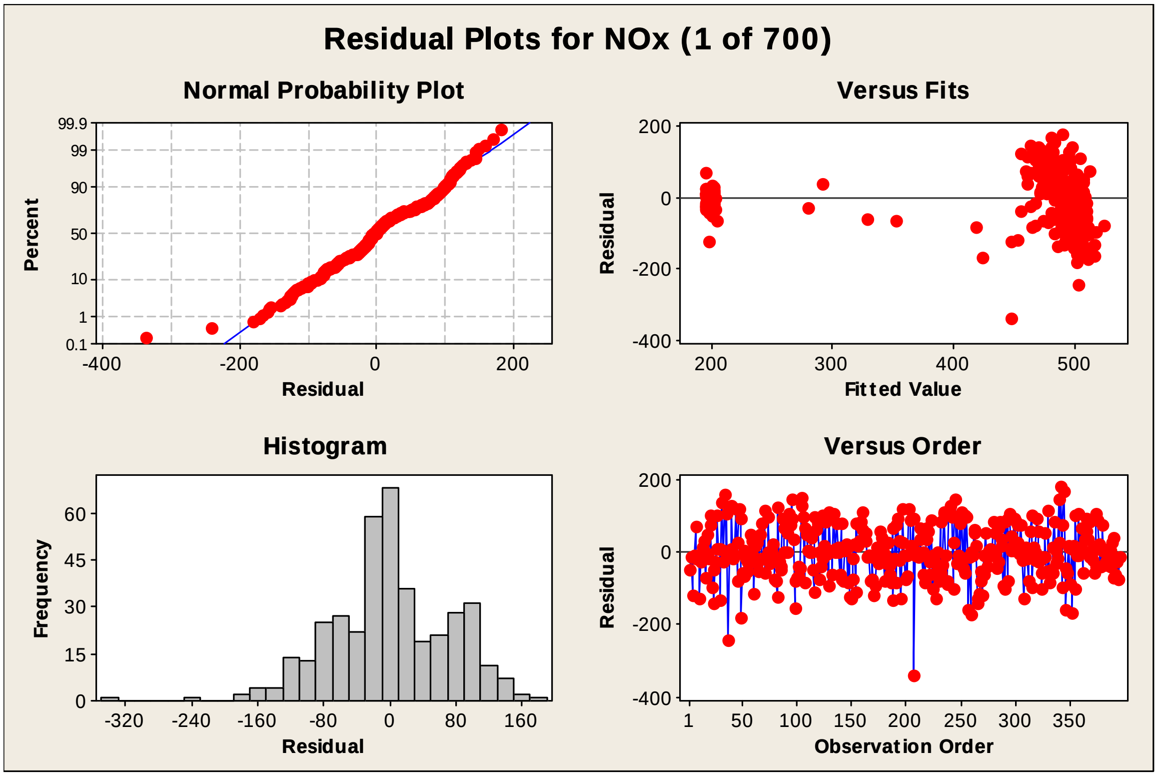
Factor	Type	Levels	Values
Fuel Type	fixed	3	B20, Diesel, ECD

Analysis of Variance for CO2, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
EngineSpeed	1	1648.66	1423.48	1423.48	2115.98	0.000
Fuel Type	2	6.39	0.91	0.46	0.68	0.509
Fuel Type*EngineSpeed	2	0.99	0.99	0.50	0.74	0.479
Error	457	307.44	307.44	0.67		
Total	462	1963.48				

S = 0.820199   R-Sq = 84.34%   R-Sq(adj) = 84.17%

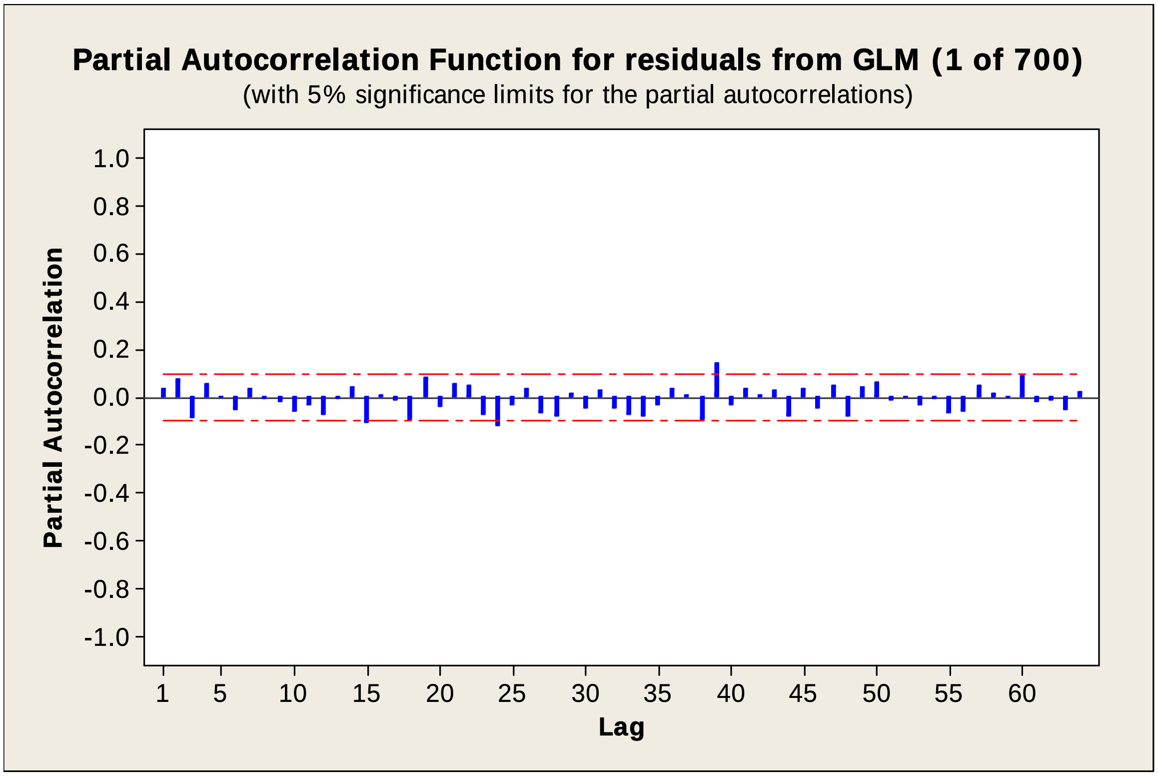


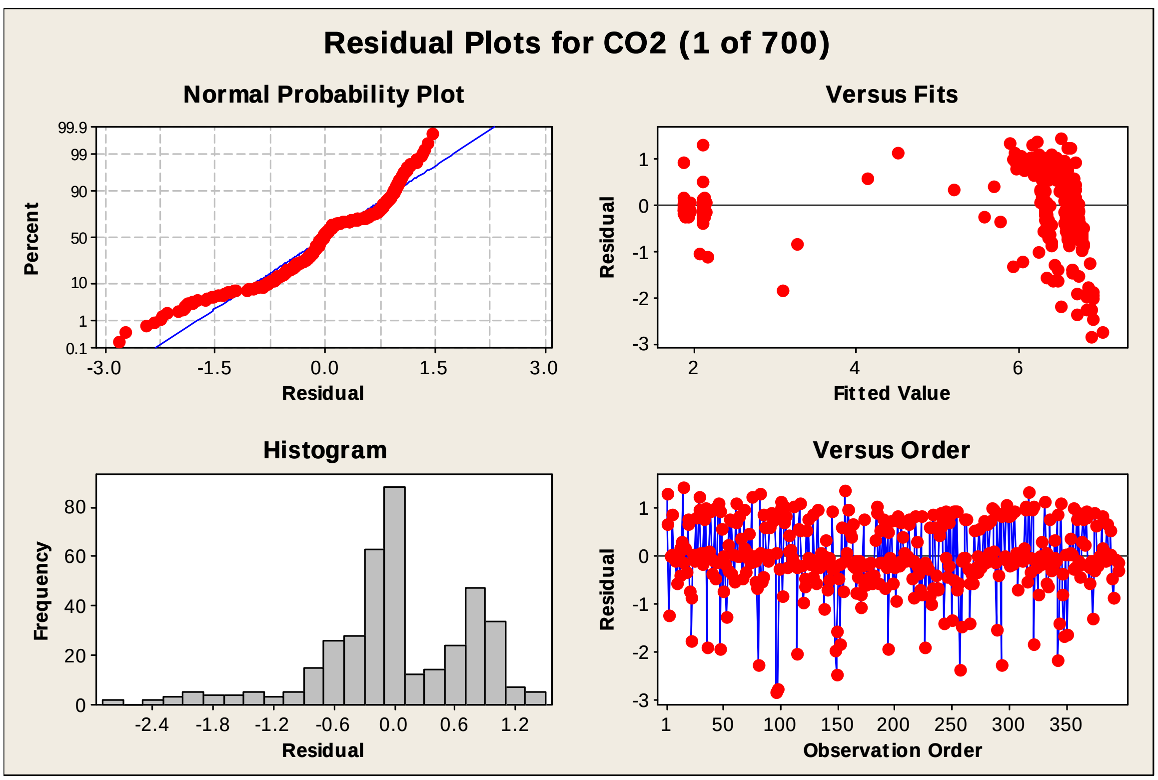


Results for: 1 of 700

General Linear Model: NOx versus Fuel Type

```
Factor      Type   Levels  Values
Fuel Type   fixed       3  B20, Diesel, ECD


Analysis of Variance for NOx, using Adjusted SS for Tests

Source                  DF   Seq SS   Adj SS   Adj MS        F      P
Fuel Type                2    32594     8510     4255     0.80  0.448
EngineSpeed              1  6752312  5896630  5896630  1115.24  0.000
Fuel Type*EngineSpeed    2    12151    12151     6075     1.15  0.318
Error                  390  2062049  2062049     5287
Total                  395  8859105


S = 72.7139   R-Sq = 76.72%   R-Sq(adj) = 76.43%
```


Partial Autocorrelation Function for residuals from GLM (1 of 700)
(with 5% significance limits for the partial autocorrelations)
Partial Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1
5
10
15
20
25
30
35
40
45
50
55
60
Lag


Residual Plots for CO2 (1 of 700)
Normal Probability Plot
Percent
99.9
99
90
50
10
1
0.1
-3.0
-1.5
0.0
1.5
3.0
Residual
Versus Fits
Residual
1
0
-1
-2
-3
2
4
6
Fitted Value
Histogram
Frequency
80
60
40
20
0
-2.4
-1.8
-1.2
-0.6
0.0
0.6
1.2
Residual
Versus Order
Residual
1
0
-1
-2
-3
1
50
100
150
200
250
300
350
Observation Order

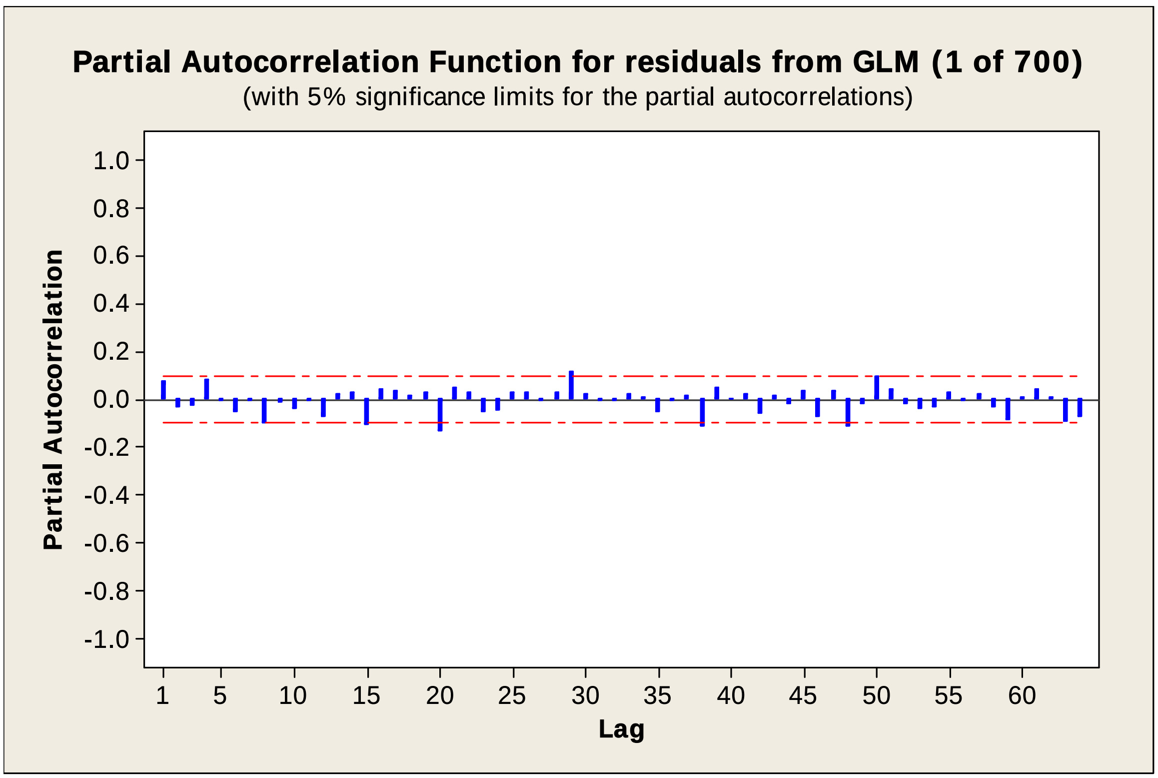
General Linear Model: CO2 versus Fuel Type

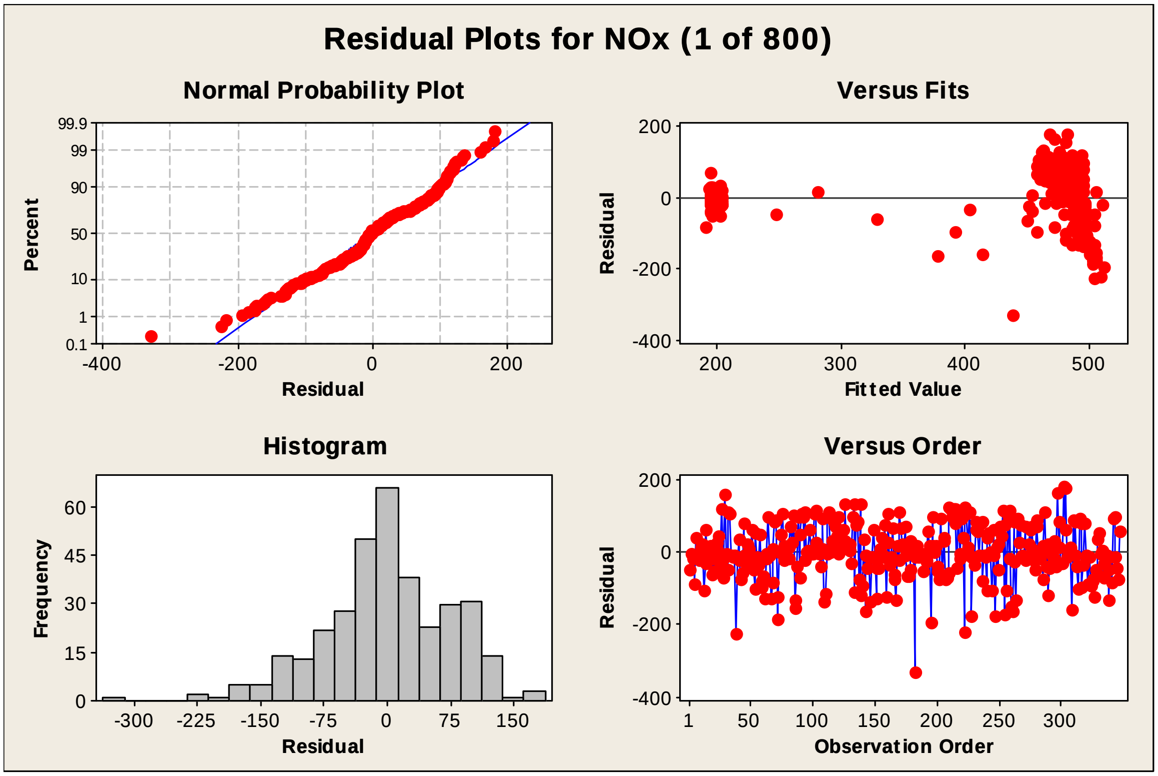
Factor	Type	Levels	Values
Fuel Type	fixed	3	B20, Diesel, ECD

Analysis of Variance for CO2, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Fuel Type	2	8.61	1.43	0.72	1.25	0.286
EngineSpeed	1	1587.95	1344.74	1344.74	2355.09	0.000
Fuel Type*EngineSpeed	2	0.37	0.37	0.19	0.33	0.723
Error	390	222.69	222.69	0.57		
Total	395	1819.61				

S = 0.755640   R-Sq = 87.76%   R-Sq(adj) = 87.60%





Results for: 1 of 800

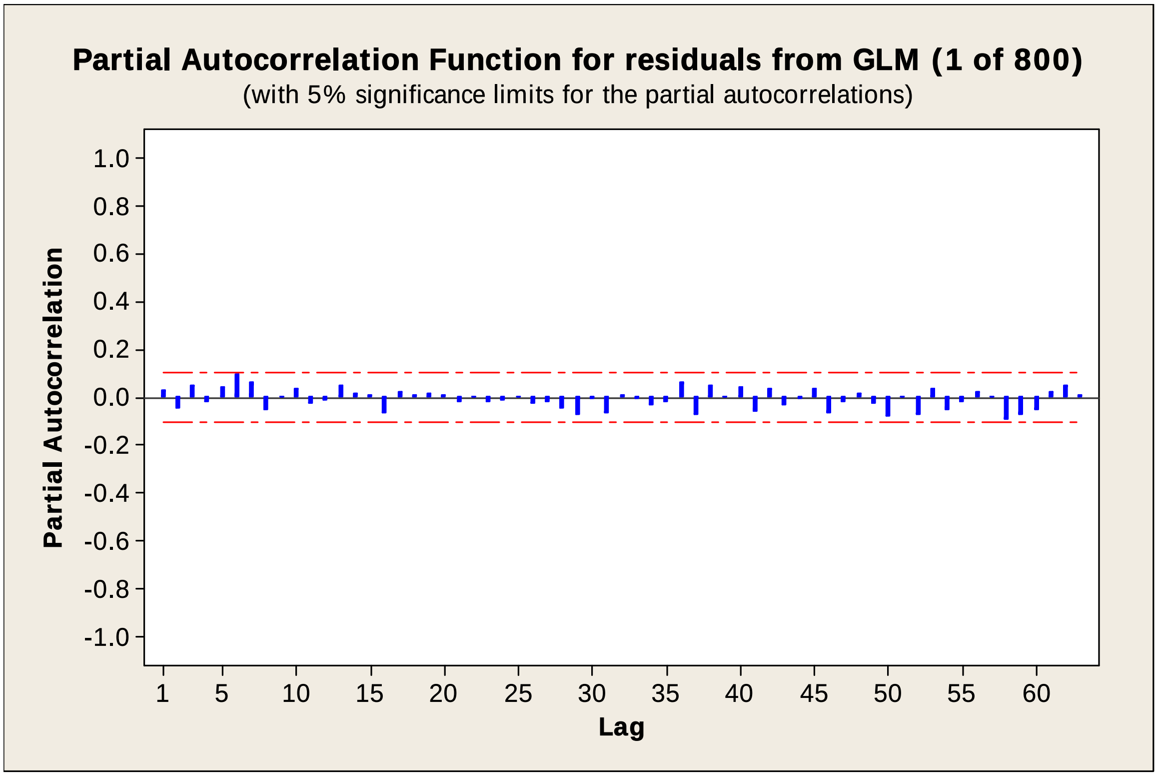
General Linear Model: NOx versus Fuel Type

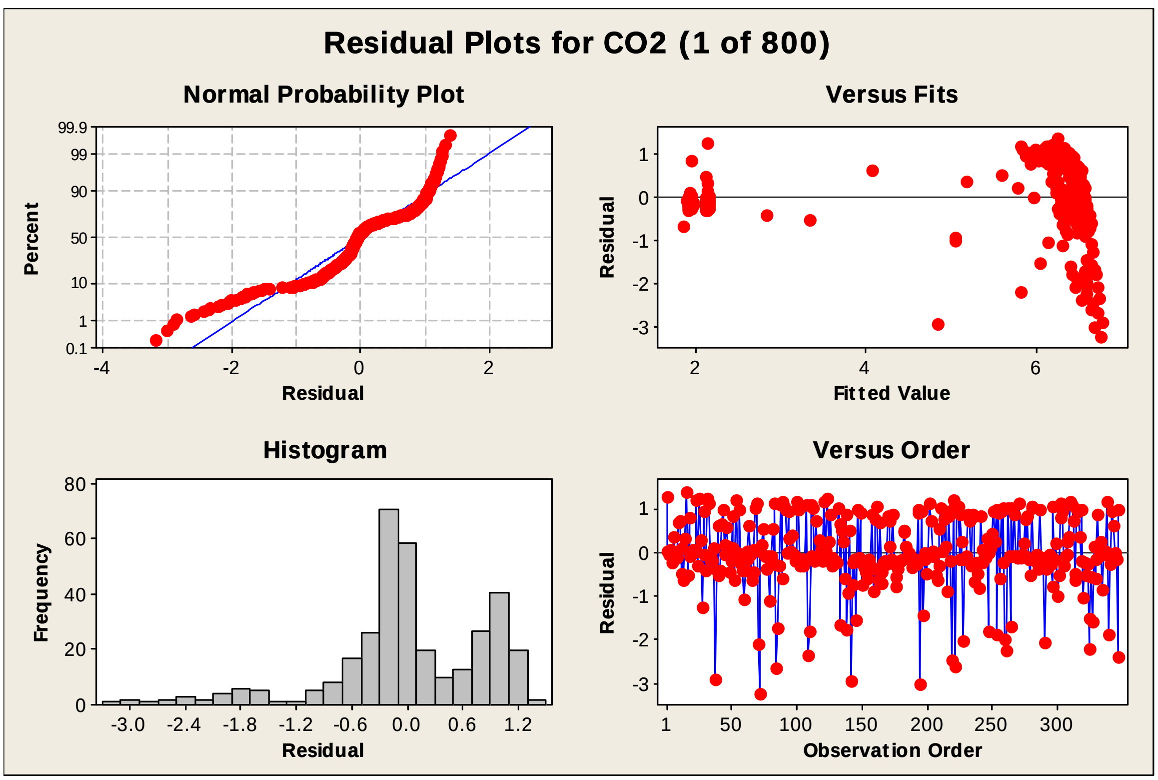
Factor	Type	Levels	Values
Fuel Type	fixed	3	B20, Diesel, ECD

Analysis of Variance for NOx, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Fuel Type	2	28293	5995	2998	0.52	0.595
EngineSpeed	1	5489489	4752988	4752988	824.72	0.000
Fuel Type*EngineSpeed	2	5063	5063	2531	0.44	0.645
Error	341	1965230	1965230	5763		
Total	346	7488075				

S = 75.9153   R-Sq = 73.76%   R-Sq(adj) = 73.37%


Partial Autocorrelation Function for residuals from GLM (1 of 800)
(with 5% significance limits for the partial autocorrelations)
Partial Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1
5
10
15
20
25
30
35
40
45
50
55
60
Lag


Residual Plots for CO2 (1 of 800)
Normal Probability Plot
Percent
99.9
99
90
50
10
1
0.1
-4
-2
0
2
Residual
Versus Fits
Residual
1
0
-1
-2
-3
2
4
6
Fitted Value
Histogram
Frequency
80
60
40
20
0
-3.0
-2.4
-1.8
-1.2
-0.6
0.0
0.6
1.2
Residual
Versus Order
Residual
1
0
-1
-2
-3
1
50
100
150
200
250
300
Observation Order

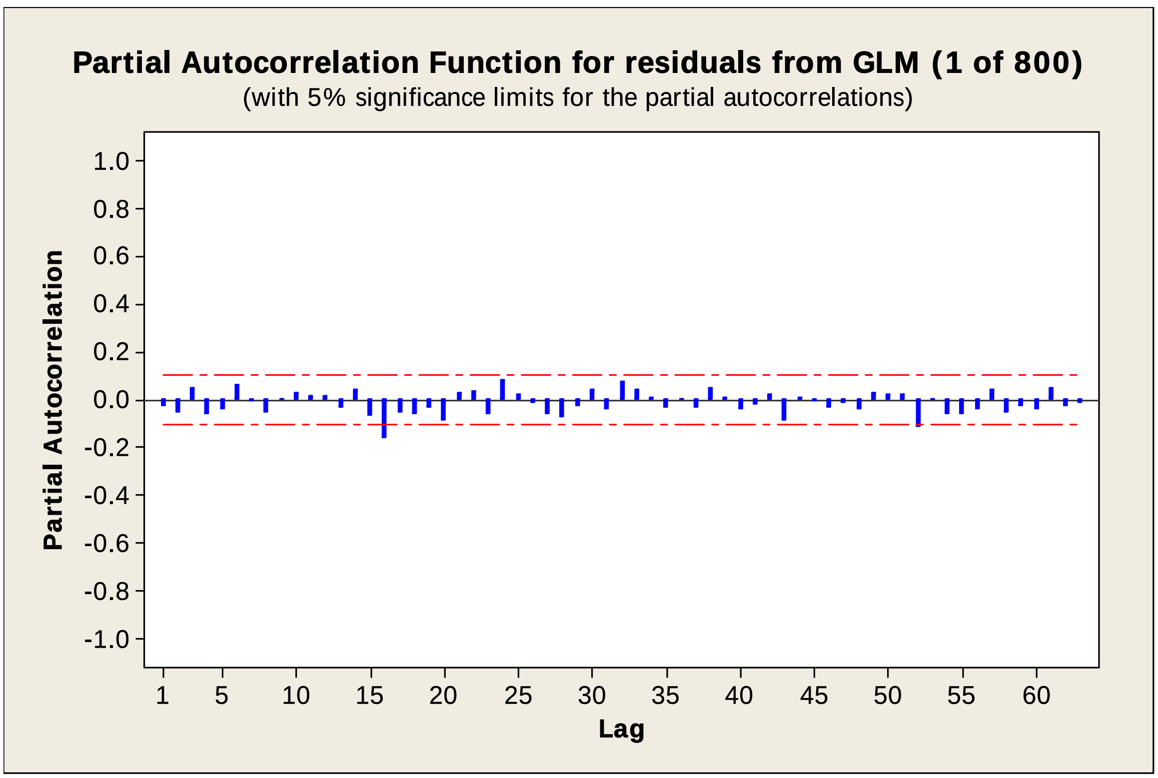
General Linear Model: CO2 versus Fuel Type

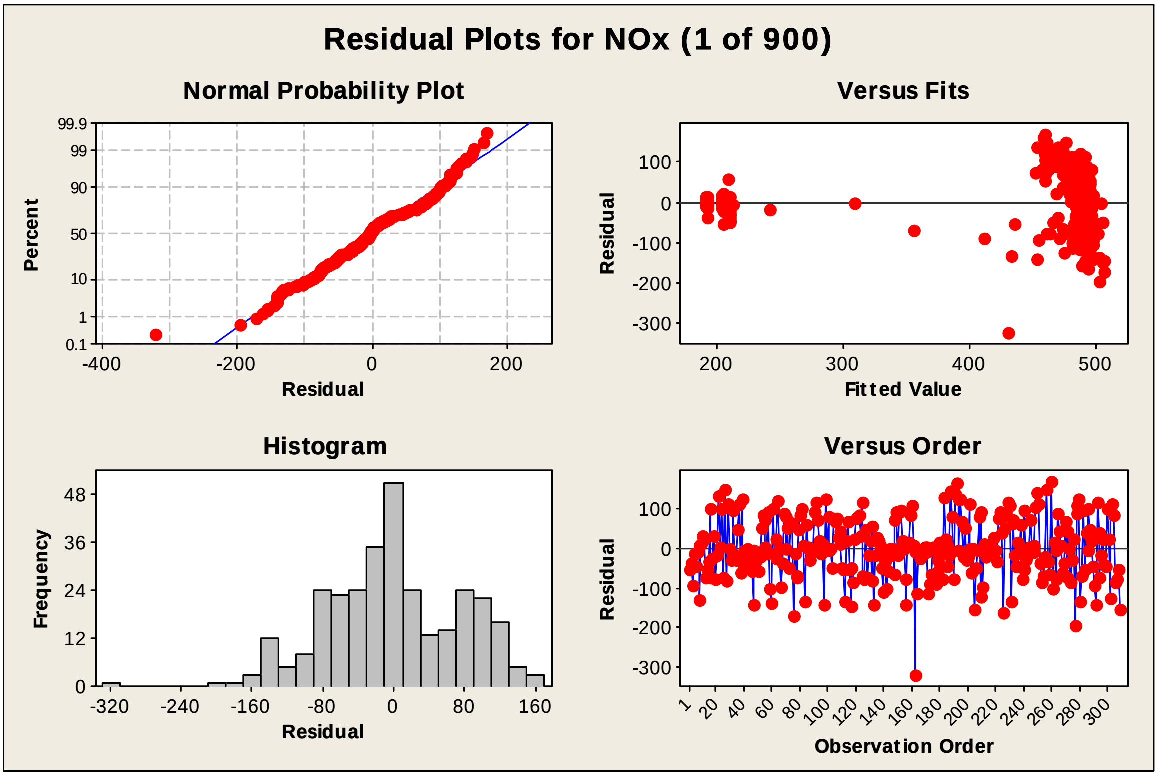
Factor	Type	Levels	Values
Fuel Type	fixed	3	B20, Diesel, ECD

Analysis of Variance for CO2, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Fuel Type	2	6.92	1.39	0.69	0.95	0.389
EngineSpeed	1	1248.25	1066.55	1066.55	1454.71	0.000
Fuel Type*EngineSpeed	2	0.49	0.49	0.25	0.34	0.714
Error	341	250.01	250.01	0.73		
Total	346	1505.68				

S = 0.856255   R-Sq = 83.40%   R-Sq(adj) = 83.15%

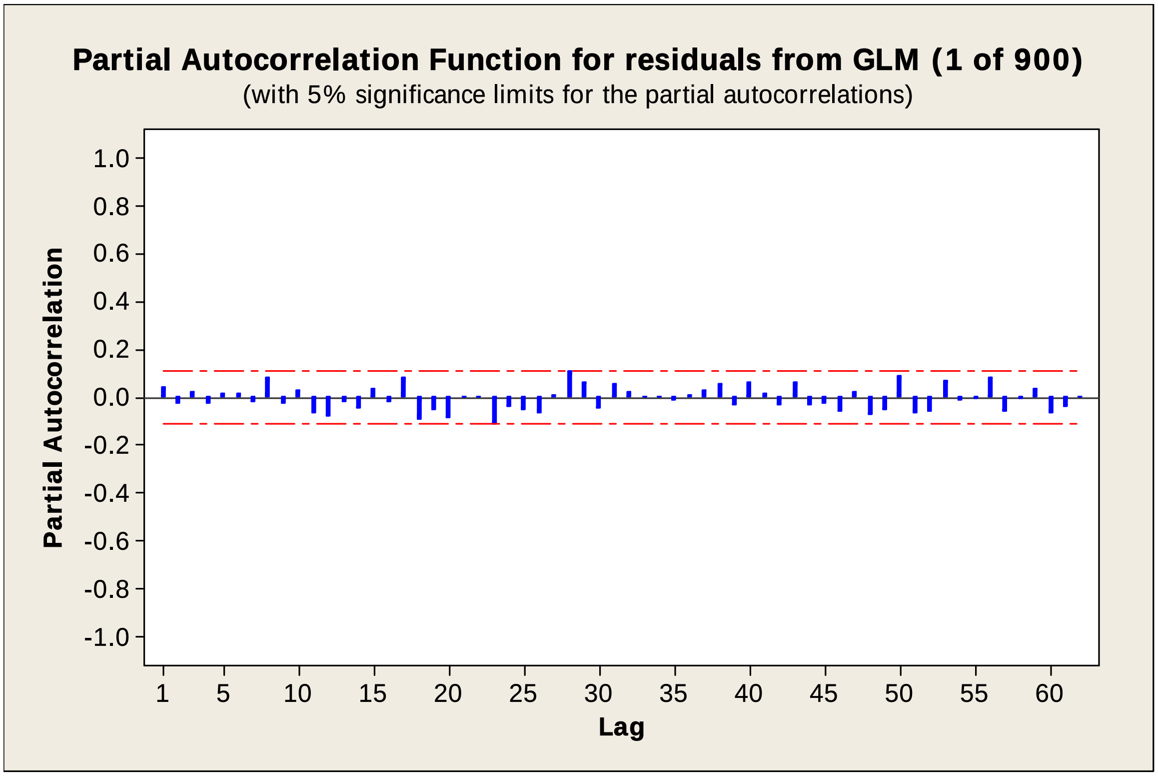




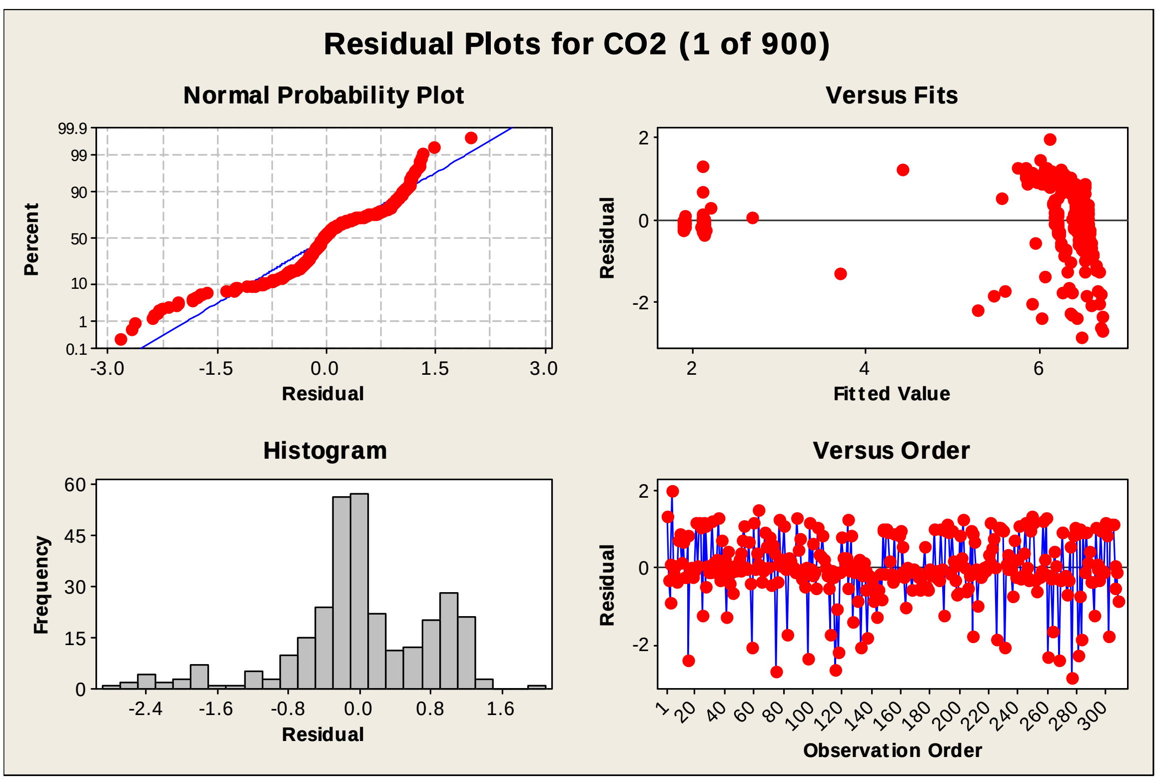
Results for: 1 of 900

General Linear Model: NOx versus Fuel Type

```
Factor     Type   Levels  Values
Fuel Type  fixed       3  B20, Diesel, ECD


Analysis of Variance for NOx, using Adjusted SS for Tests

Source                 DF   Seq SS   Adj SS   Adj MS       F      P
Fuel Type               2    19958     4054     2027    0.35  0.708
EngineSpeed             1  4104430  3384041  3384041  577.37  0.000
Fuel Type*EngineSpeed   2     2467     2467     1233    0.21  0.810
Error                 303  1775911  1775911     5861
Total                 308  5902765


S = 76.5578   R-Sq = 69.91%   R-Sq(adj) = 69.42%
```



Partial Autocorrelation Function for residuals from GLM (1 of 900)
(with 5% significance limits for the partial autocorrelations)
Partial Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1 5 10 15 20 25 30 35 40 45 50 55 60
Lag



Residual Plots for CO2 (1 of 900)
Normal Probability Plot
Percent
99.9
99
90
50
10
1
0.1
-3.0 -1.5 0.0 1.5 3.0
Residual
Versus Fits
Residual
2
0
-2
2 4 6
Fitted Value
Histogram
Frequency
60
45
30
15
0
-2.4 -1.6 -0.8 0.0 0.8 1.6
Residual
Versus Order
Residual
2
0
-2
1 20 40 60 80 100 120 140 160 180 200 220 240 260 280 300
Observation Order

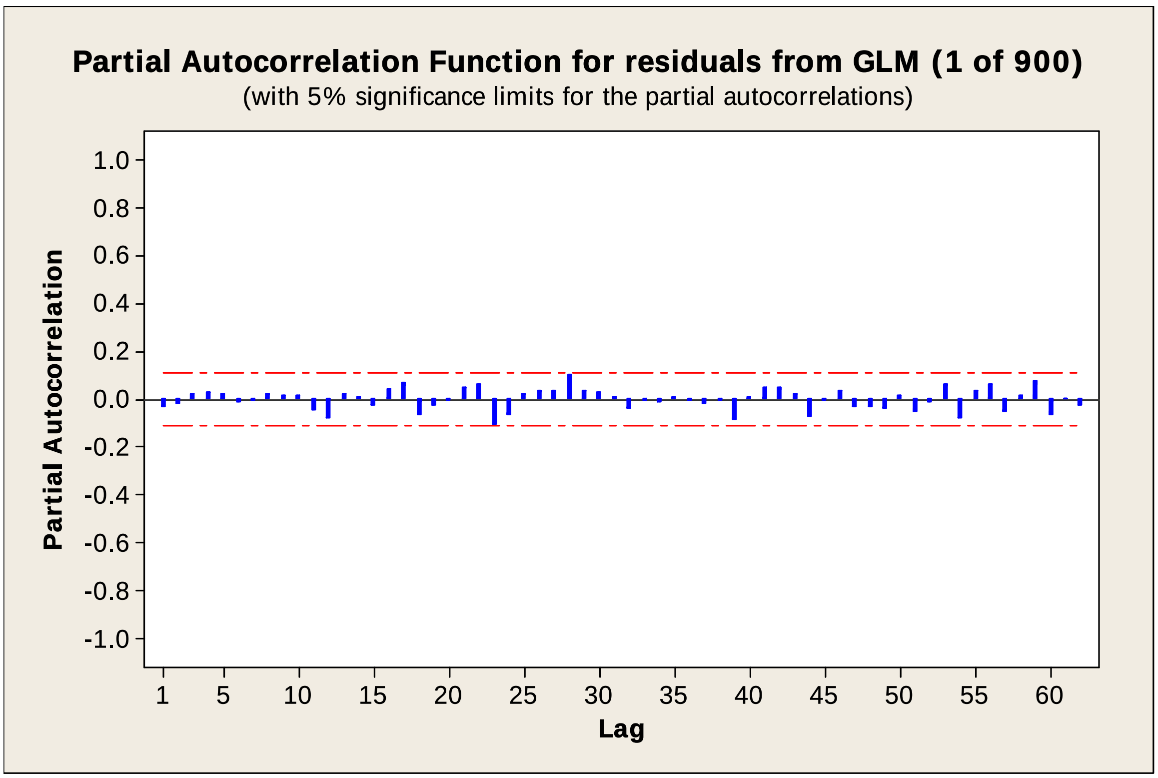
General Linear Model: CO2 versus Fuel Type

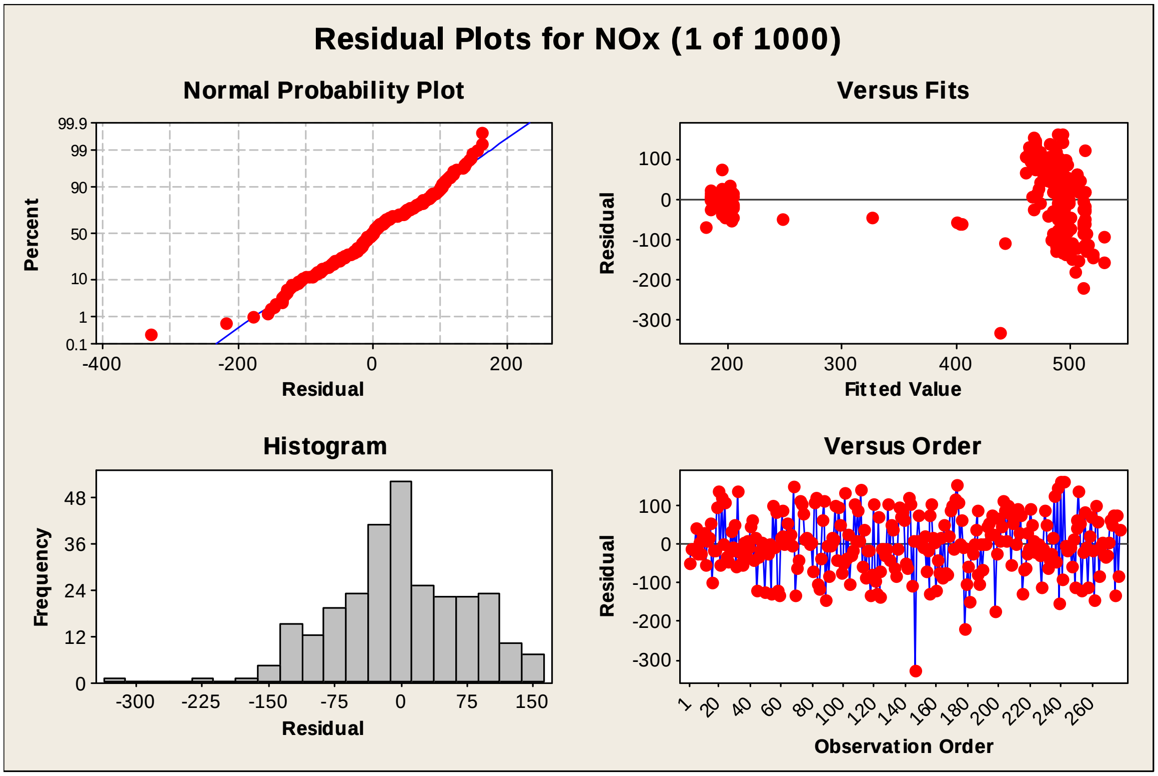
Factor	Type	Levels	Values
Fuel Type	fixed	3	B20, Diesel, ECD

Analysis of Variance for CO2, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Fuel Type	2	2.22	1.15	0.57	0.83	0.437
EngineSpeed	1	947.83	776.83	776.83	1123.31	0.000
Fuel Type*EngineSpeed	2	1.23	1.23	0.61	0.89	0.413
Error	303	209.54	209.54	0.69		
Total	308	1160.82				

S = 0.831601   R-Sq = 81.95%   R-Sq(adj) = 81.65%

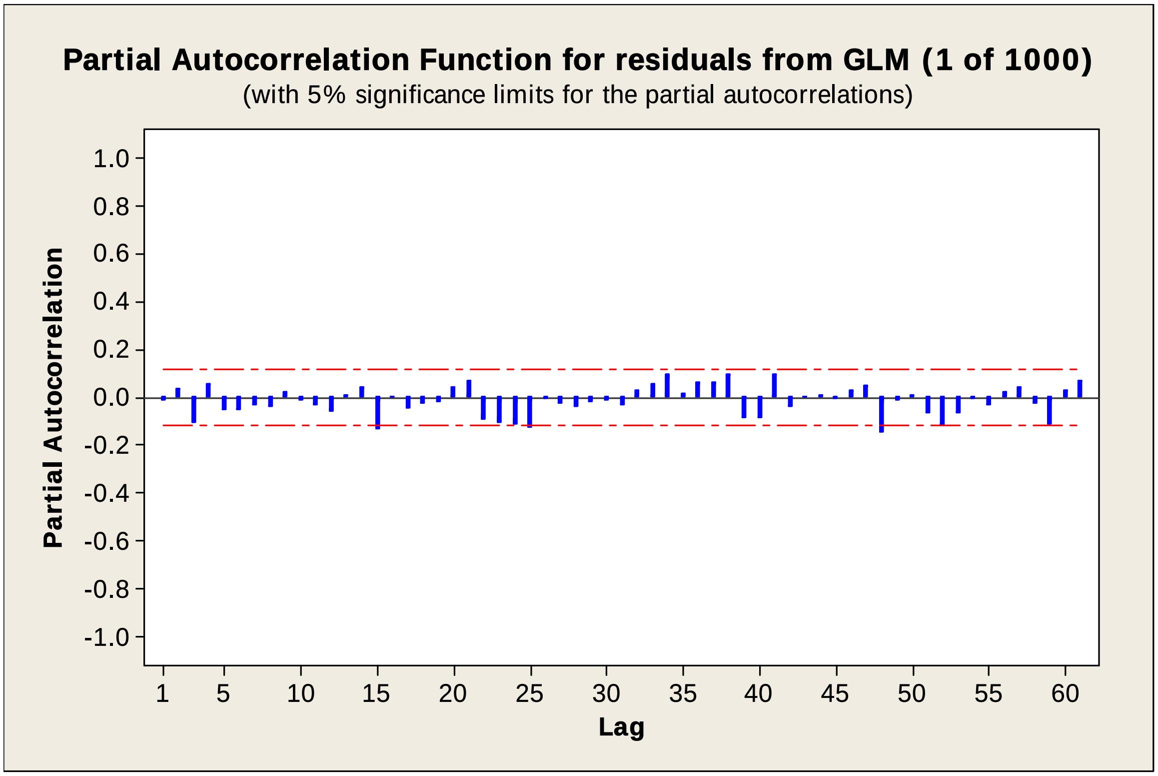


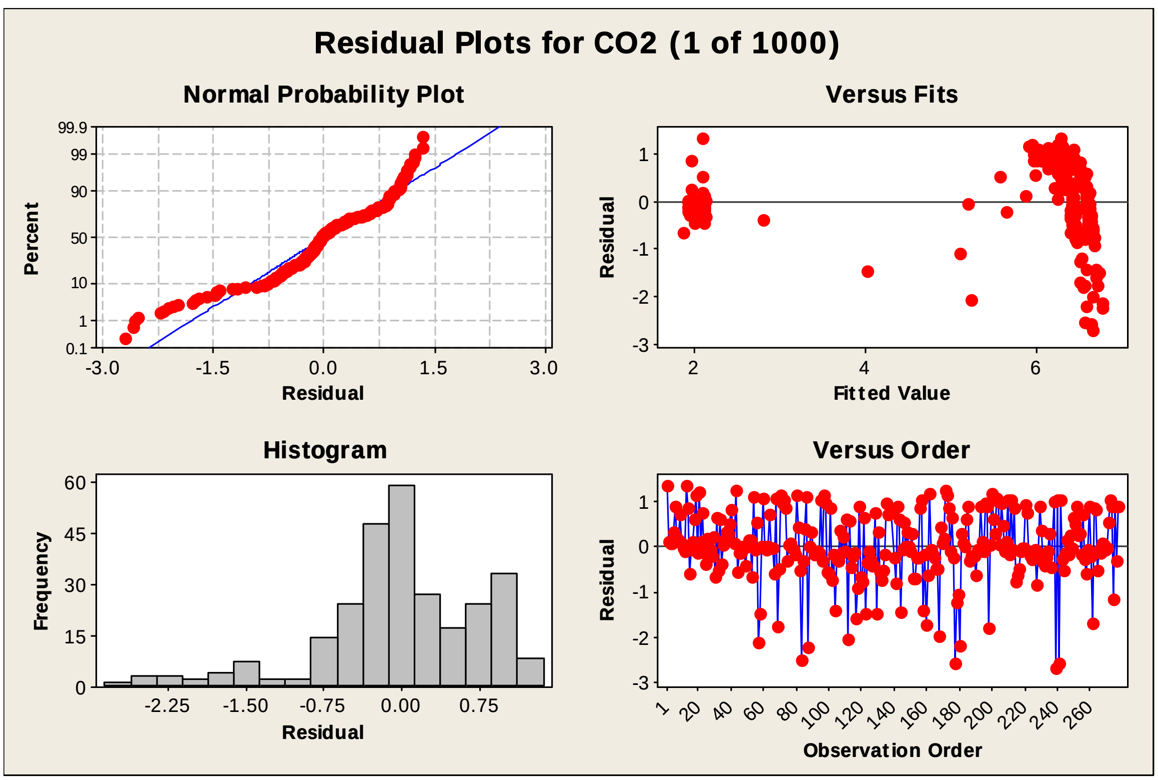


Results for: 1 of 1000

General Linear Model: NOx versus Fuel Type

```
Factor      Type   Levels  Values
Fuel Type   fixed       3  B20, Diesel, ECD


Analysis of Variance for NOx, using Adjusted SS for Tests

Source                  DF   Seq SS   Adj SS   Adj MS       F      P
Fuel Type                2    21153    11283     5641    0.97  0.380
EngineSpeed              1  4532826  3967746  3967746  682.75  0.000
Fuel Type*EngineSpeed    2    14223    14223     7111    1.22  0.296
Error                  272  1580710  1580710     5811
Total                  277  6148912


S = 76.2328   R-Sq = 74.29%   R-Sq(adj) = 73.82%
```


Partial Autocorrelation Function for residuals from GLM (1 of 1000)
(with 5% significance limits for the partial autocorrelations)
Partial Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1
5
10
15
20
25
30
35
40
45
50
55
60
Lag


Residual Plots for CO2 (1 of 1000)
Normal Probability Plot
Percent
99.9
99
90
50
10
1
0.1
-3.0
-1.5
0.0
1.5
3.0
Residual
Versus Fits
Residual
1
0
-1
-2
-3
2
4
6
Fitted Value
Histogram
Frequency
60
45
30
15
0
-2.25
-1.50
-0.75
0.00
0.75
Residual
Versus Order
Residual
1
0
-1
-2
-3
1
20
40
60
80
100
120
140
160
180
200
220
240
260
Observation Order

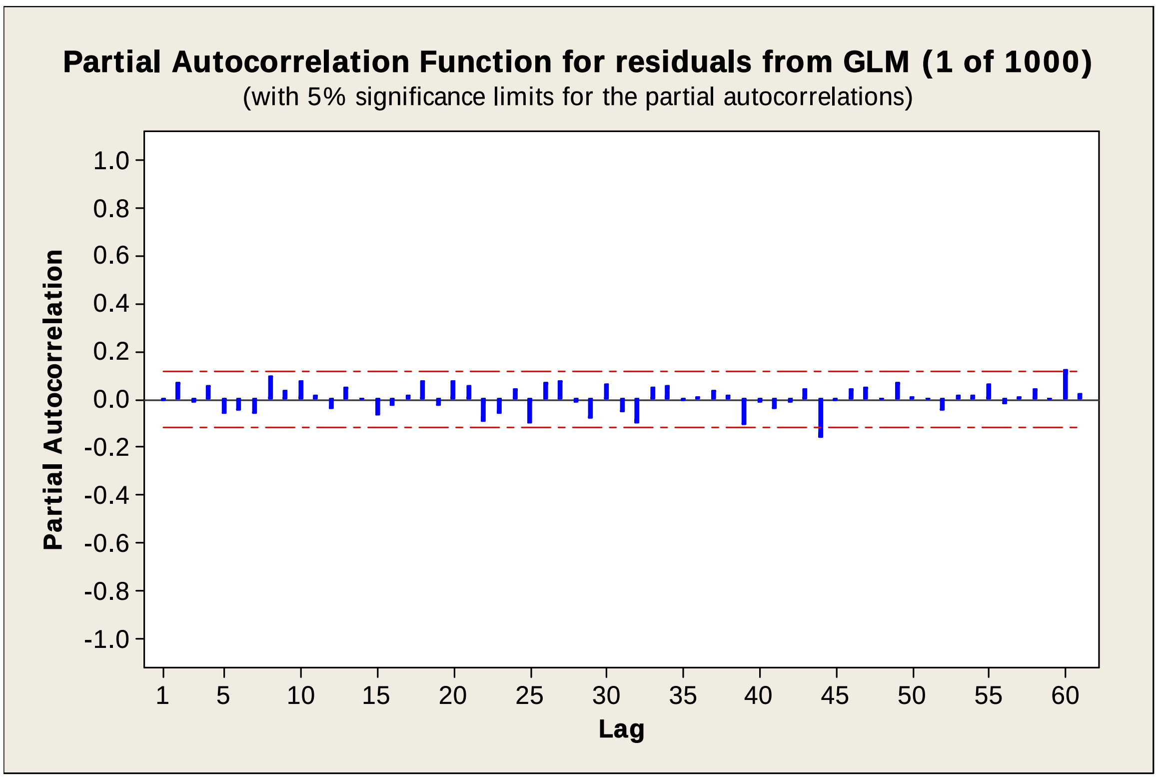
General Linear Model: CO2 versus Fuel Type

Factor	Type	Levels	Values
Fuel Type	fixed	3	B20, Diesel, ECD

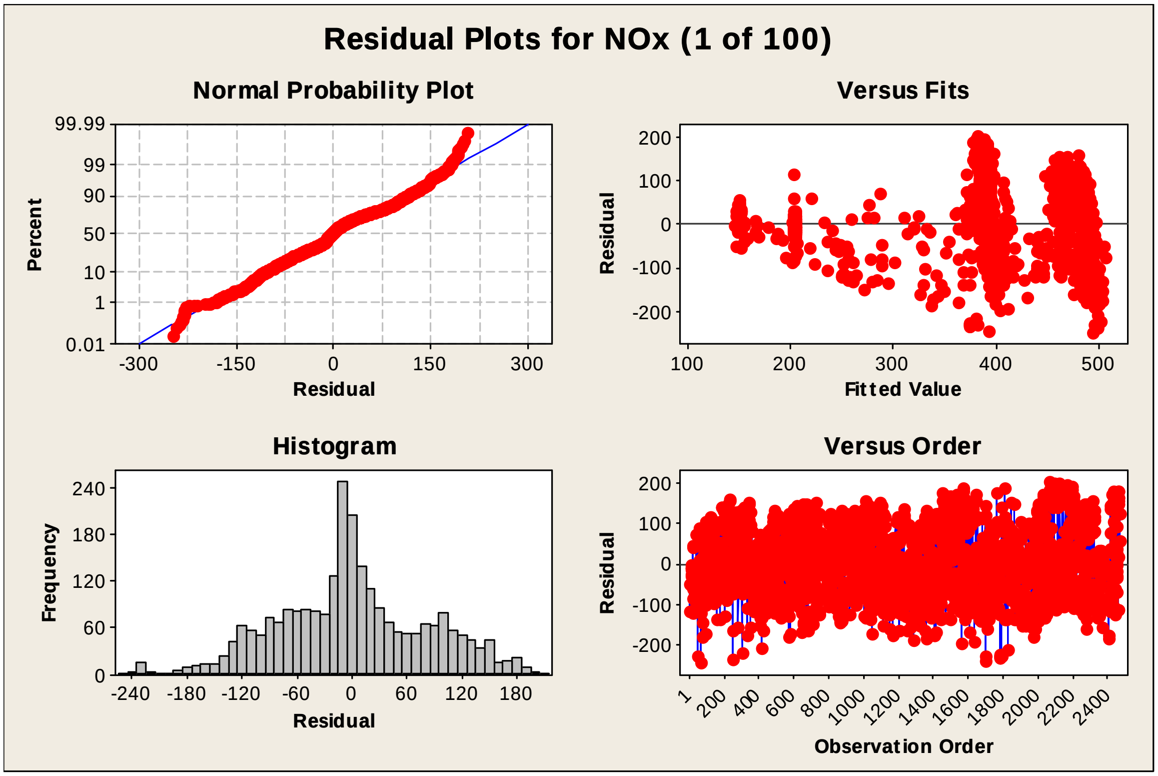
Analysis of Variance for CO2, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Fuel Type	2	12.21	0.66	0.33	0.55	0.580
EngineSpeed	1	1007.66	850.36	850.36	1398.27	0.000
Fuel Type*EngineSpeed	2	0.09	0.09	0.05	0.08	0.927
Error	272	165.42	165.42	0.61		
Total	277	1185.38				

S = 0.779838   R-Sq = 86.05%   R-Sq(adj) = 85.79%



APPENDIX B: Compactor Analysis



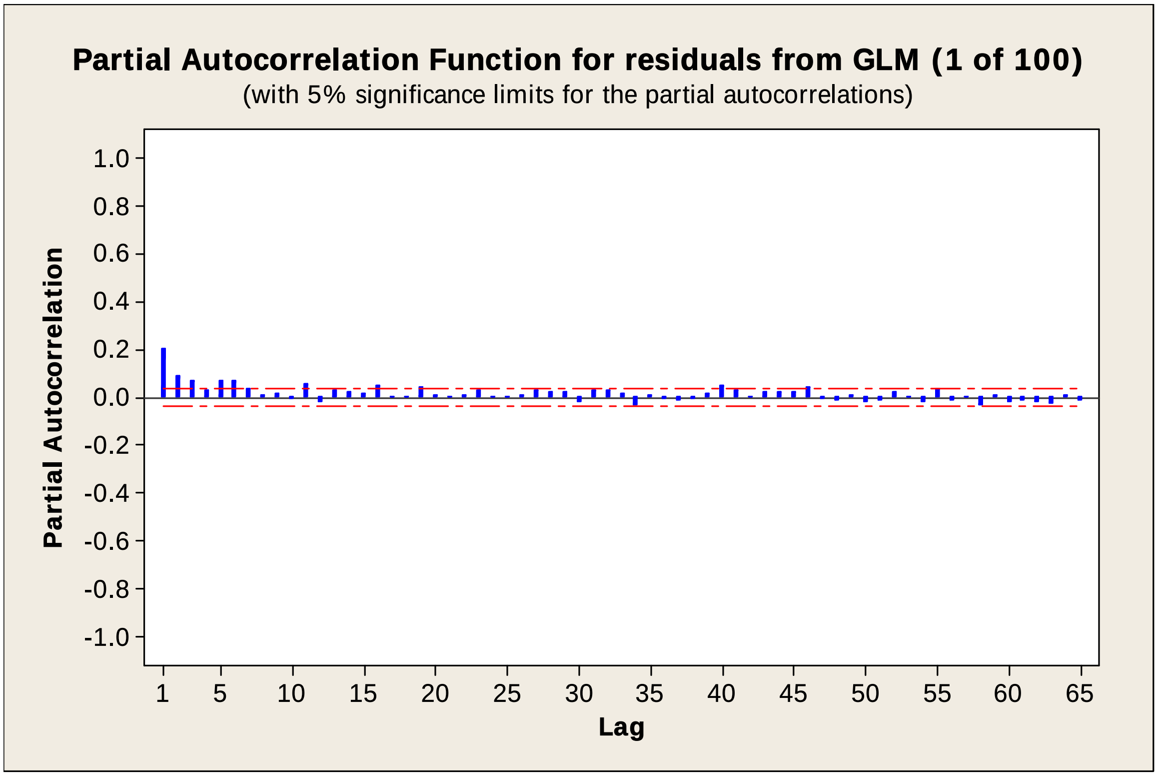
General Linear Model: NOx versus compactor

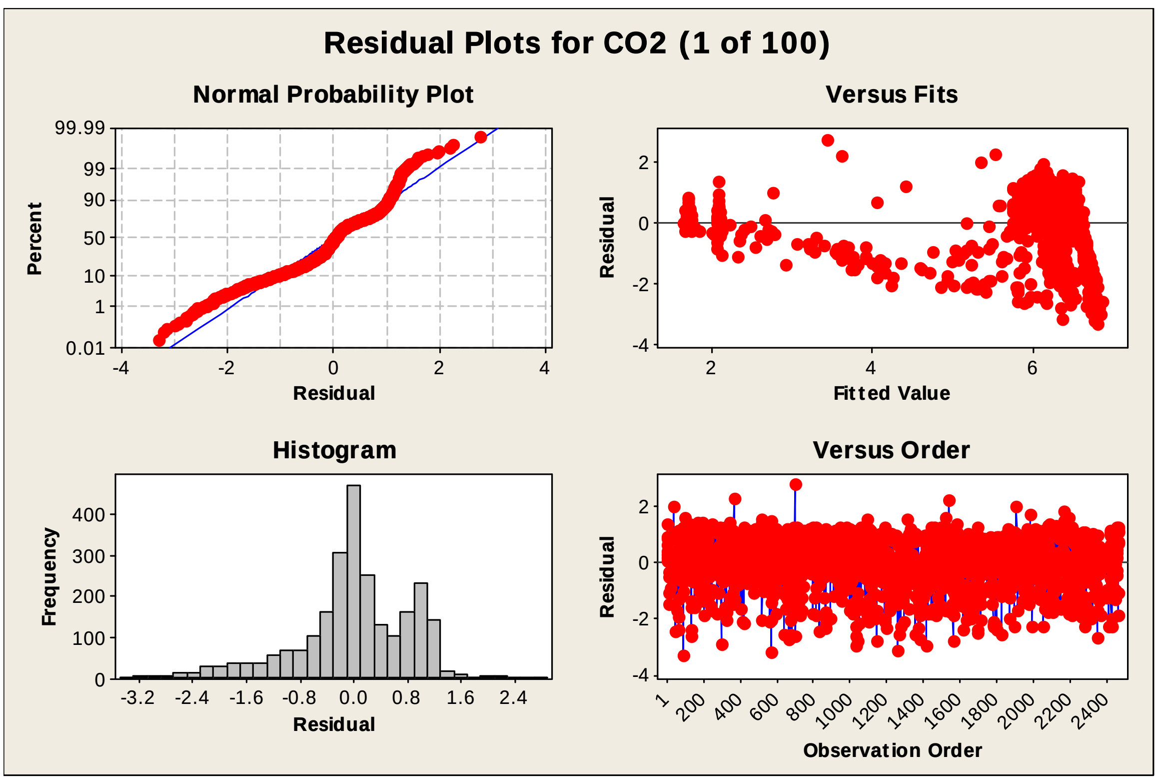
Factor	Type	Levels	Values
compactor	fixed	2	1, 2

Analysis of Variance for NOx, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
EngineSpeed	1	32475720	30913375	30913375	4723.16	0.000
compactor	1	4617459	94535	94535	14.44	0.000
compactor*EngineSpeed	1	129327	129327	129327	19.76	0.000
Error	2466	16140136	16140136	6545		
Total	2469	53362642				

S = 80.9016   R-Sq = 69.75%   R-Sq(adj) = 69.72%


Partial Autocorrelation Function for residuals from GLM (1 of 100)
(with 5% significance limits for the partial autocorrelations)
Partial Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1 5 10 15 20 25 30 35 40 45 50 55 60 65
Lag


Residual Plots for CO2 (1 of 100)
Normal Probability Plot
Percent
99.99
99
90
50
10
1
0.01
-4 -2 0 2 4
Residual
Versus Fits
Residual
2
0
-2
-4
2 4 6
Fitted Value
Histogram
Frequency
400
300
200
100
0
-3.2 -2.4 -1.6 -0.8 0.0 0.8 1.6 2.4
Residual
Versus Order
Residual
2
0
-2
-4
1 200 400 600 800 1000 1200 1400 1600 1800 2000 2200 2400
Observation Order

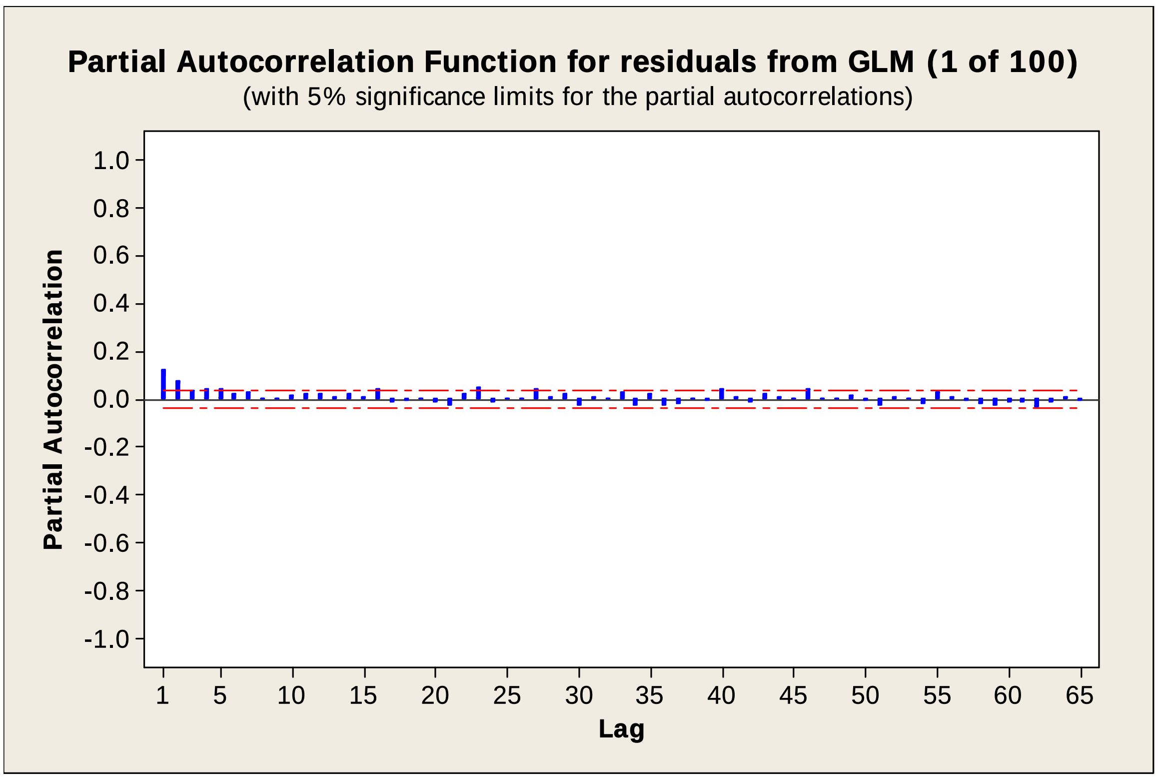
General Linear Model: CO2 versus compactor

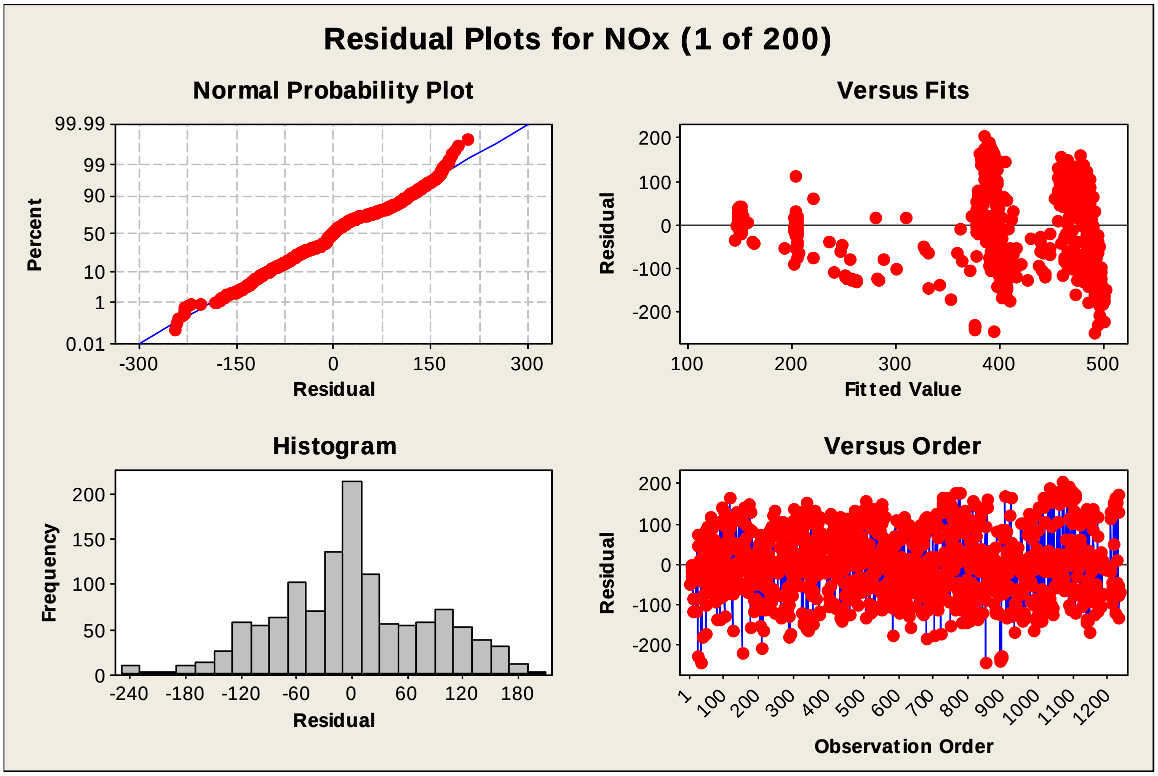
Factor	Type	Levels	Values
compactor	fixed	2	1, 2

Analysis of Variance for CO2, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
EngineSpeed	1	9009.2	8840.8	8840.8	12815.70	0.000
compactor	1	132.9	18.3	18.3	26.46	0.000
compactor*EngineSpeed	1	0.7	0.7	0.7	0.98	0.322
Error	2466	1701.2	1701.2	0.7		
Total	2469	10843.9				

S = 0.830568   R-Sq = 84.31%   R-Sq(adj) = 84.29%





Results for: 1 of 200

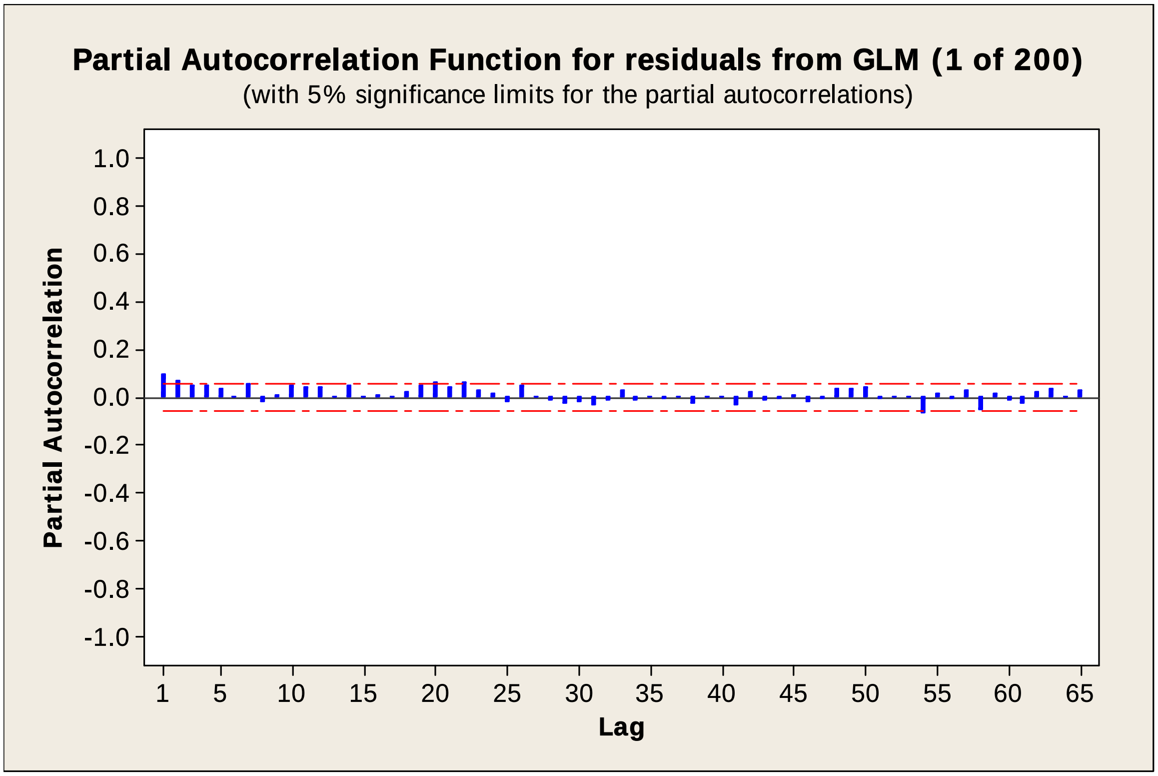
General Linear Model: NOx versus compactor

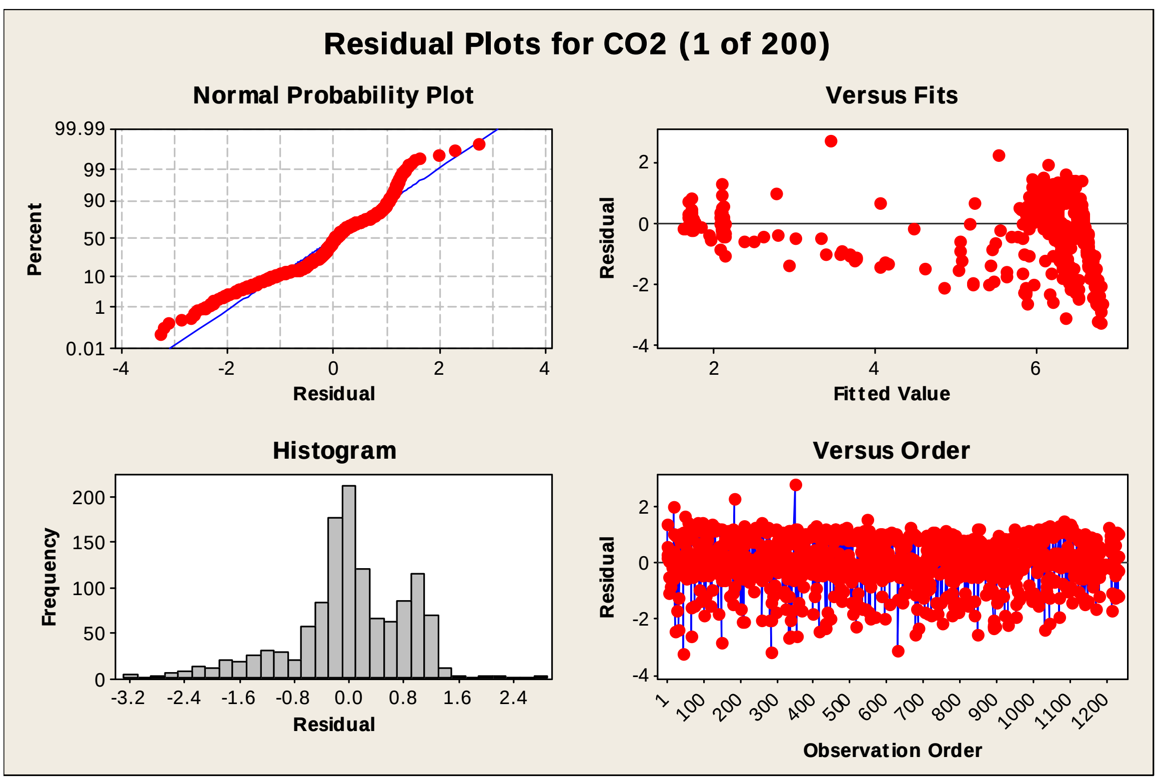
Factor	Type	Levels	Values
compactor	fixed	2	1, 2

Analysis of Variance for NOx, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
EngineSpeed	1	16158885	15497316	15497316	2358.17	0.000
compactor	1	2146991	49967	49967	7.60	0.006
compactor*EngineSpeed	1	53340	53340	53340	8.12	0.004
Error	1231	8089822	8089822	6572		
Total	1234	26449038				

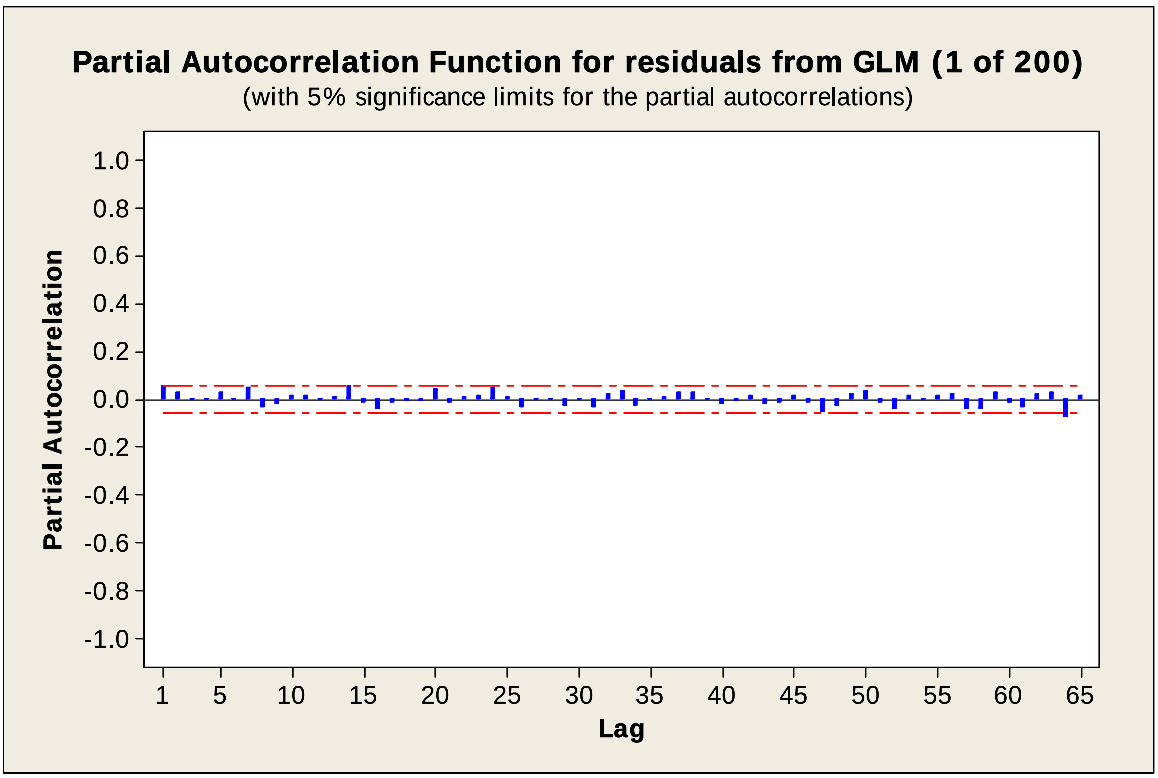
S = 81.0663   R-Sq = 69.41%   R-Sq(adj) = 69.34%

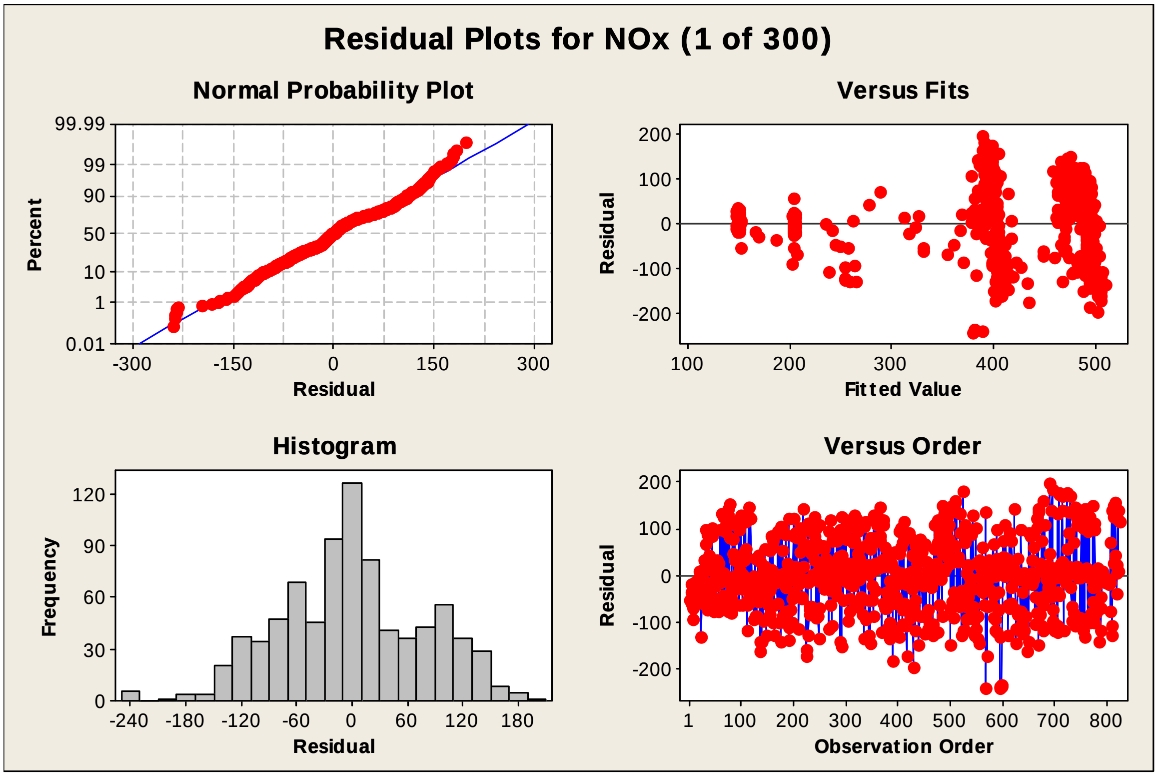

Partial Autocorrelation Function for residuals from GLM (1 of 200)
(with 5% significance limits for the partial autocorrelations)
Partial Autocorrelation
Lag
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1 5 10 15 20 25 30 35 40 45 50 55 60 65


Residual Plots for CO2 (1 of 200)
Normal Probability Plot
Percent
99.99
99
90
50
10
1
0.01
-4 -2 0 2 4
Residual
Versus Fits
Residual
2
0
-2
-4
2 4 6
Fitted Value
Histogram
Frequency
200
150
100
50
0
-3.2 -2.4 -1.6 -0.8 0.0 0.8 1.6 2.4
Residual
Versus Order
Residual
2
0
-2
-4
1 100 200 300 400 500 600 700 800 900 1000 1100 1200
Observation Order

General Linear Model: CO2 versus compactor

```
Factor     Type   Levels  Values
compactor  fixed       2  1, 2


Analysis of Variance for CO2, using Adjusted SS for Tests

Source                   DF  Seq SS  Adj SS  Adj MS        F      P
EngineSpeed               1  4492.7  4422.9  4422.9  6407.72  0.000
compactor                 1    56.8    10.7    10.7    15.47  0.000
compactor*EngineSpeed     1     1.1     1.1     1.1     1.55  0.214
Error                  1231   849.7   849.7     0.7
Total                  1234  5400.3


S = 0.830814   R-Sq = 84.27%   R-Sq(adj) = 84.23%
```

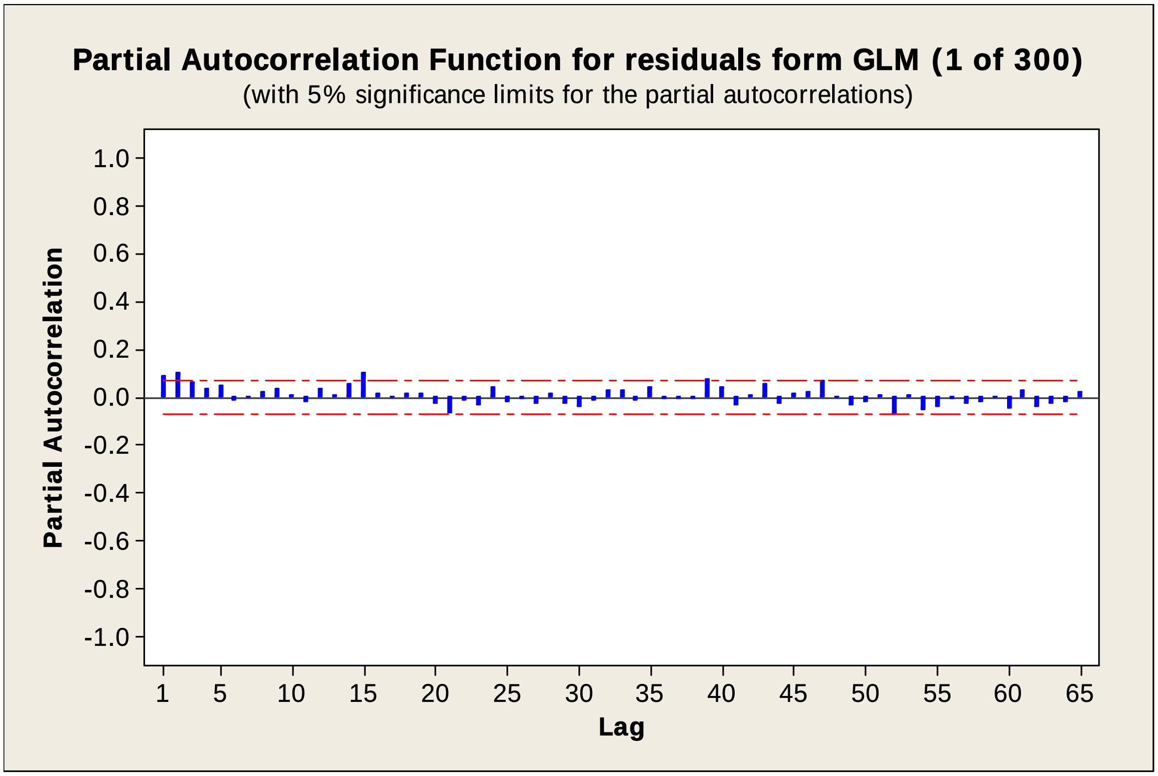




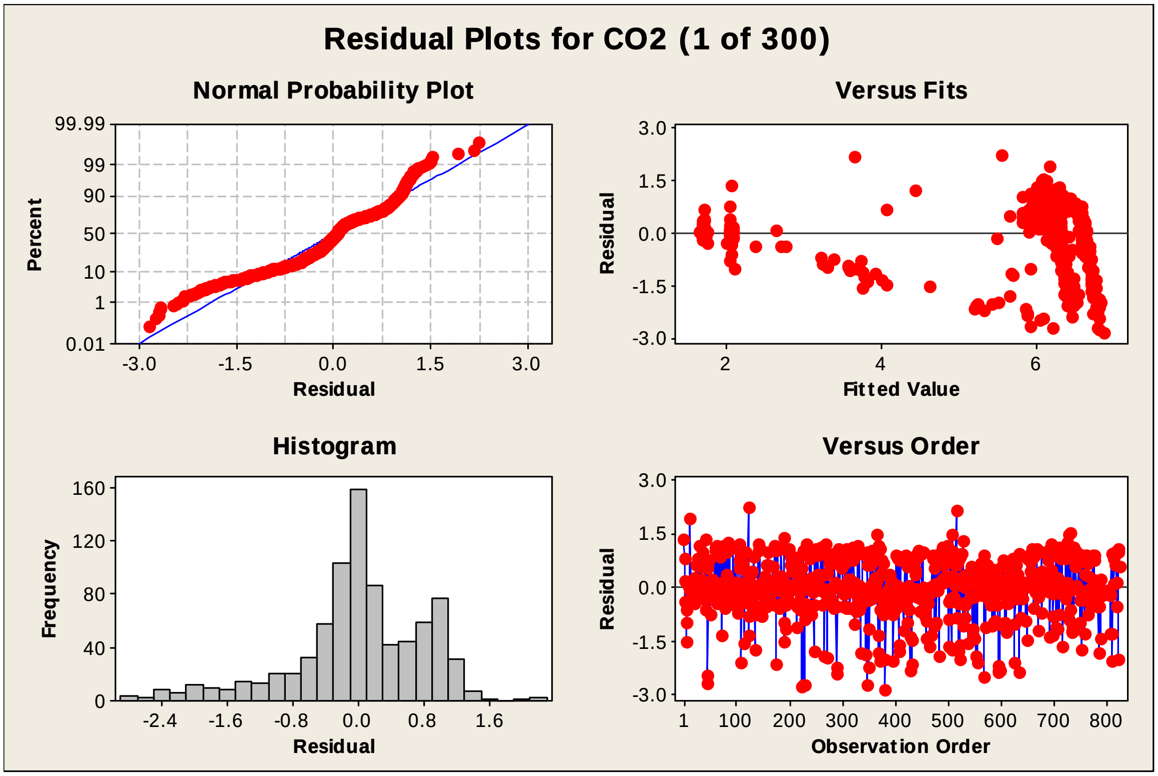
Results for: 1 of 300

General Linear Model: NOx versus compactor

```
Factor     Type   Levels  Values
compactor  fixed       2  1, 2


Analysis of Variance for NOx, using Adjusted SS for Tests

Source                  DF    Seq SS    Adj SS    Adj MS        F      P
EngineSpeed              1  11248863  10806656  10806656  1742.83  0.000
compactor                1   1513172     33442     33442     5.39  0.020
compactor*EngineSpeed    1     39398     39398     39398     6.35  0.012
Error                  820   5084533   5084533      6201
Total                  823  17885966


S = 78.7442   R-Sq = 71.57%   R-Sq(adj) = 71.47%
```



Partial Autocorrelation Function for residuals form GLM (1 of 300)
(with 5% significance limits for the partial autocorrelations)
Partial Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1 5 10 15 20 25 30 35 40 45 50 55 60 65
Lag



Residual Plots for CO2 (1 of 300)
Normal Probability Plot
Percent
99.99
99
90
50
10
1
0.01
-3.0 -1.5 0.0 1.5 3.0
Residual
Versus Fits
Residual
3.0
1.5
0.0
-1.5
-3.0
2 4 6
Fitted Value
Histogram
Frequency
160
120
80
40
0
-2.4 -1.6 -0.8 0.0 0.8 1.6
Residual
Versus Order
Residual
3.0
1.5
0.0
-1.5
-3.0
1 100 200 300 400 500 600 700 800
Observation Order

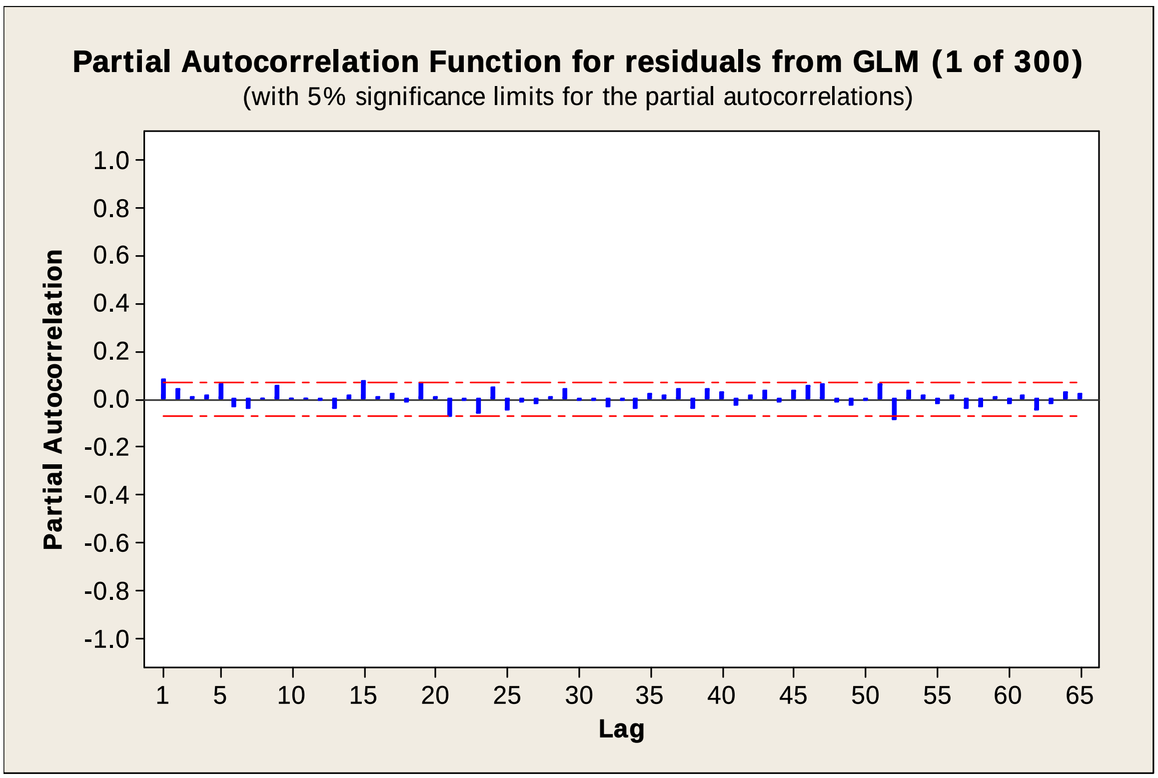
General Linear Model: CO2 versus compactor

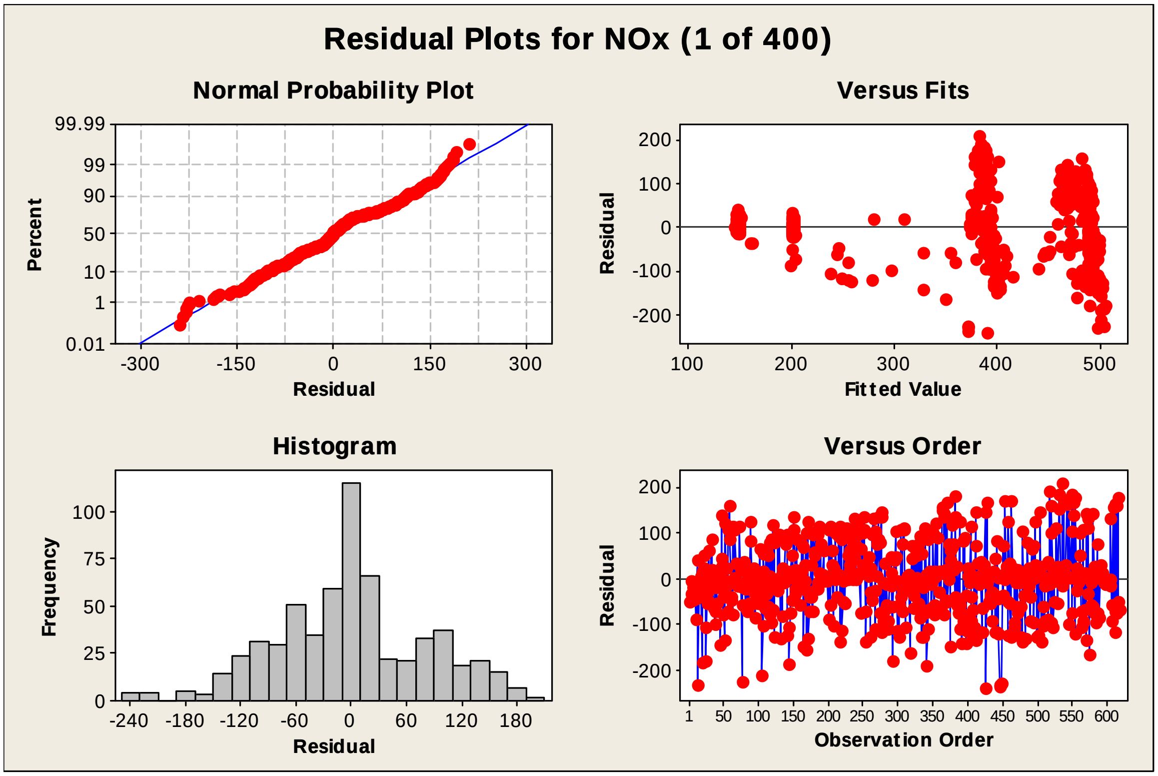
Factor	Type	Levels	Values
compactor	fixed	2	1, 2

Analysis of Variance for CO2, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
EngineSpeed	1	3088.7	3035.5	3035.5	4580.70	0.000
compactor	1	39.9	5.8	5.8	8.77	0.003
compactor*EngineSpeed	1	0.3	0.3	0.3	0.42	0.519
Error	820	543.4	543.4	0.7		
Total	823	3672.2				

S = 0.814051   R-Sq = 85.20%   R-Sq(adj) = 85.15%

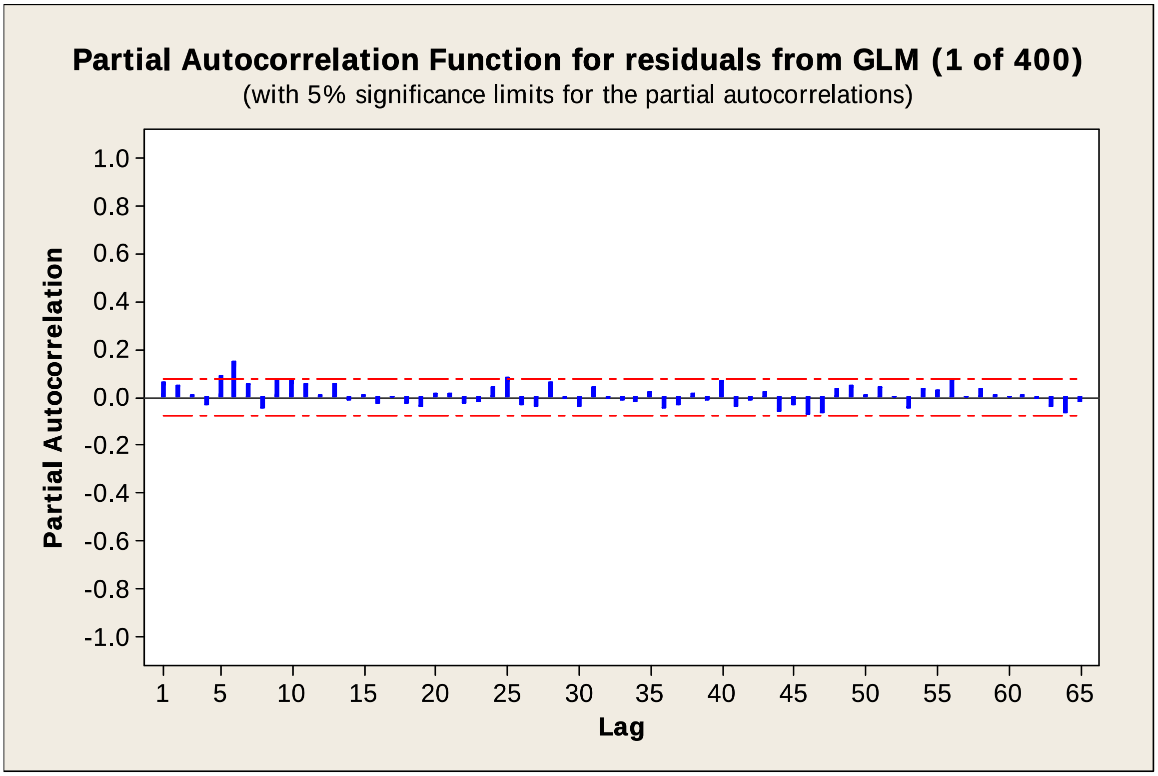


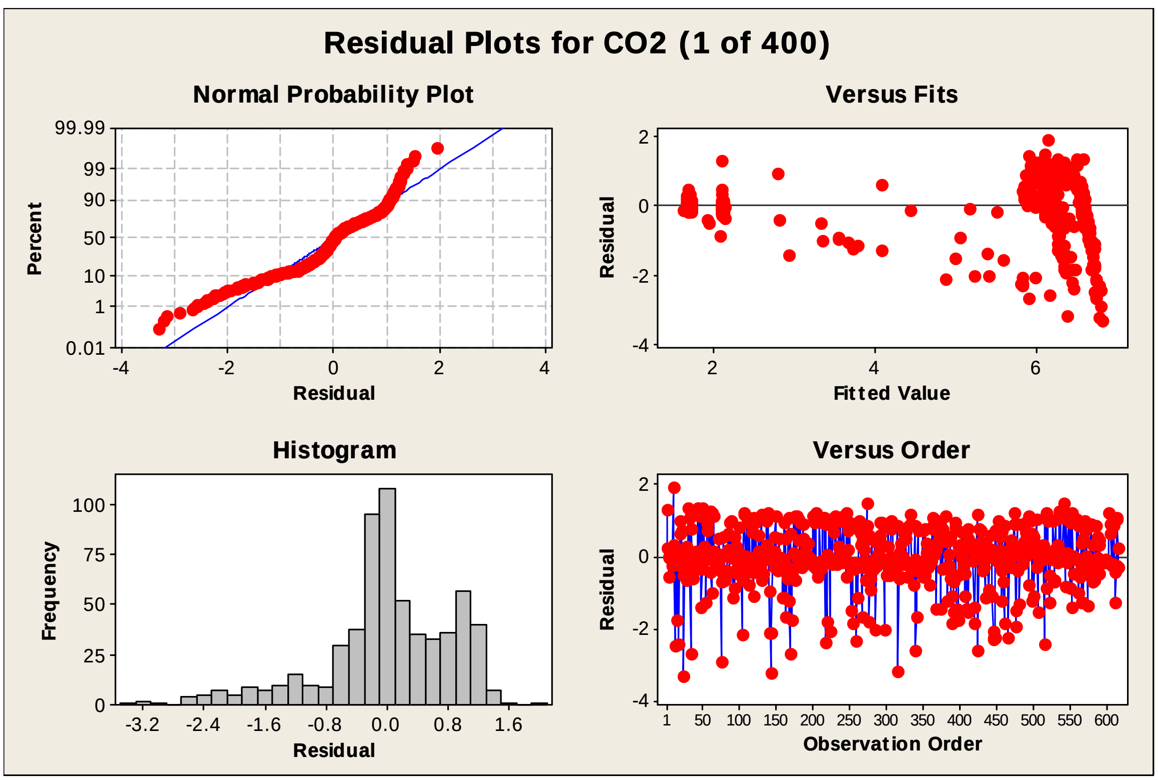


Results for: 1 of 400

General Linear Model: NOx versus compactor

```
Factor     Type   Levels  Values
compactor  fixed       2  1, 2


Analysis of Variance for NOx, using Adjusted SS for Tests

Source                  DF    Seq SS   Adj SS   Adj MS        F      P
EngineSpeed              1   8159681  7850801  7850801  1170.54  0.000
compactor                1   1225183    19764    19764     2.95  0.087
compactor*EngineSpeed    1     41880    41880    41880     6.24  0.013
Error                  614   4118077  4118077     6707
Total                  617  13544821


S = 81.8961   R-Sq = 69.60%   R-Sq(adj) = 69.45%
```


Partial Autocorrelation Function for residuals from GLM (1 of 400)
(with 5% significance limits for the partial autocorrelations)
Partial Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1 5 10 15 20 25 30 35 40 45 50 55 60 65
Lag


Residual Plots for CO2 (1 of 400)
Normal Probability Plot
Percent
99.99
99
90
50
10
1
0.01
-4 -2 0 2 4
Residual
Versus Fits
Residual
2
0
-2
-4
2 4 6
Fitted Value
Histogram
Frequency
100
75
50
25
0
-3.2 -2.4 -1.6 -0.8 0.0 0.8 1.6
Residual
Versus Order
Residual
2
0
-2
-4
1 50 100 150 200 250 300 350 400 450 500 550 600
Observation Order

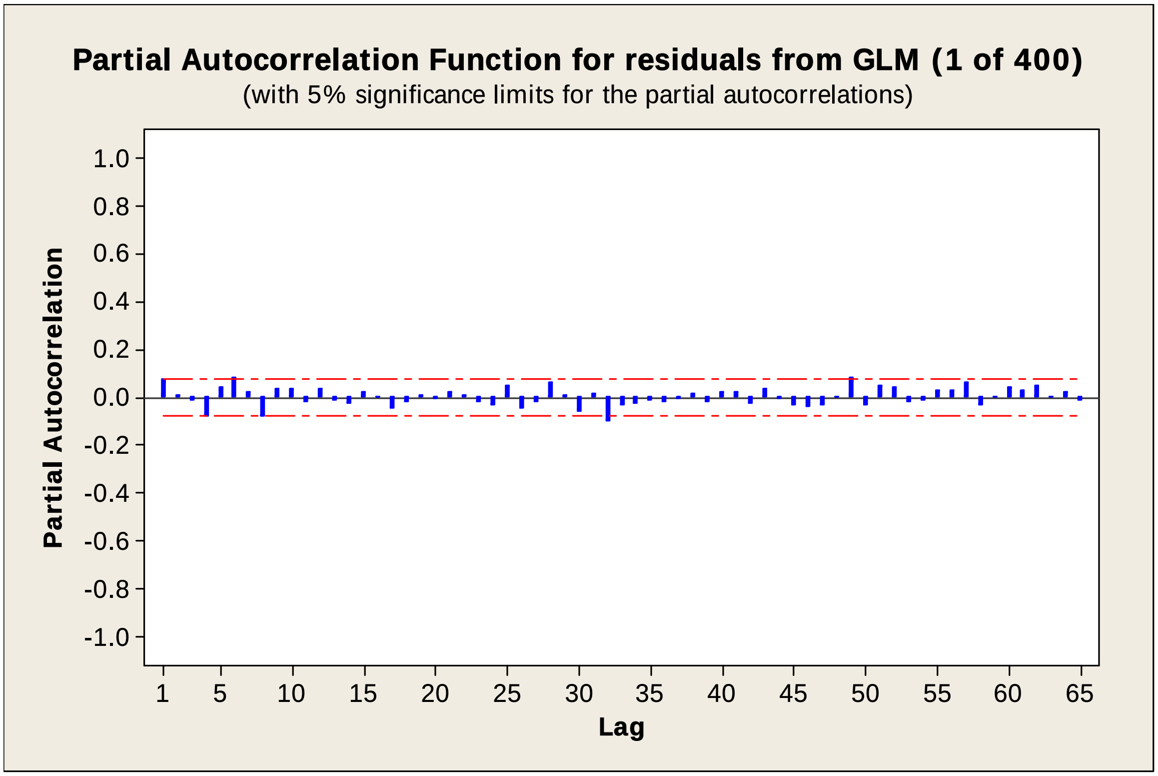
General Linear Model: CO2 versus compactor

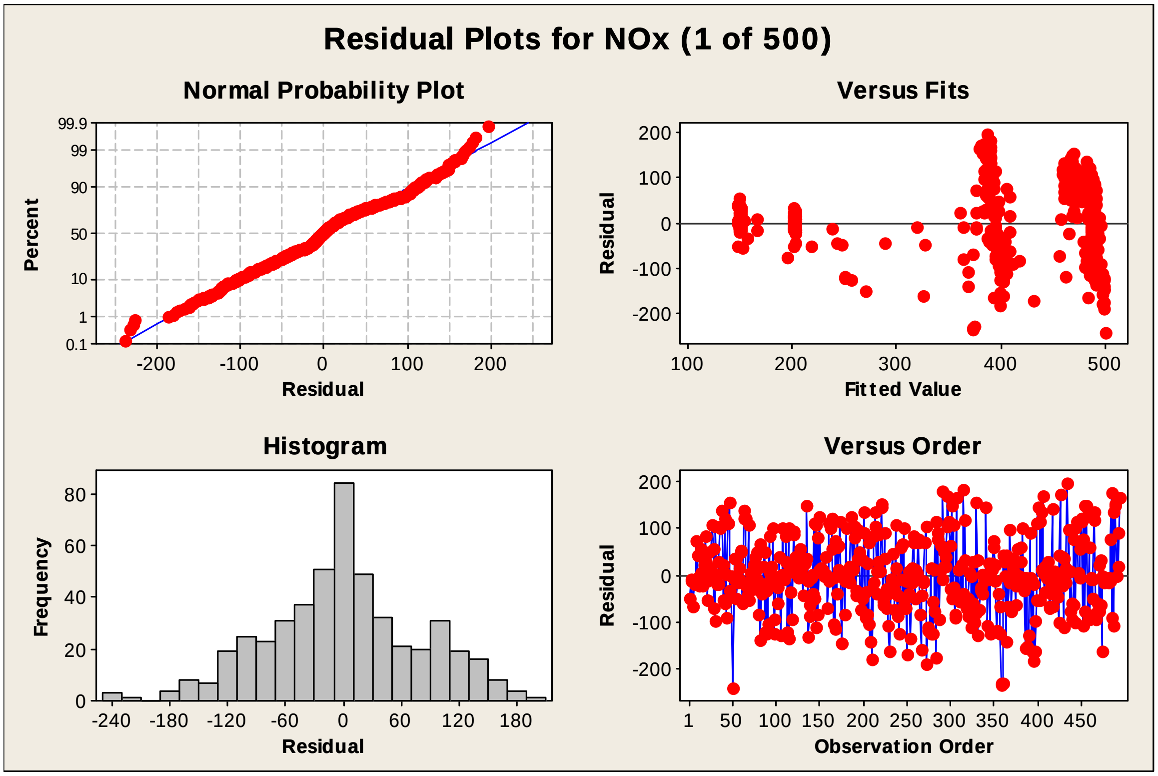
Factor	Type	Levels	Values
compactor	fixed	2	1, 2

Analysis of Variance for CO2, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
EngineSpeed	1	2258.07	2215.77	2215.77	3018.89	0.000
compactor	1	35.37	5.60	5.60	7.62	0.006
compactor*EngineSpeed	1	0.35	0.35	0.35	0.47	0.491
Error	614	450.66	450.66	0.73		
Total	617	2744.44				

S = 0.856720   R-Sq = 83.58%   R-Sq(adj) = 83.50%

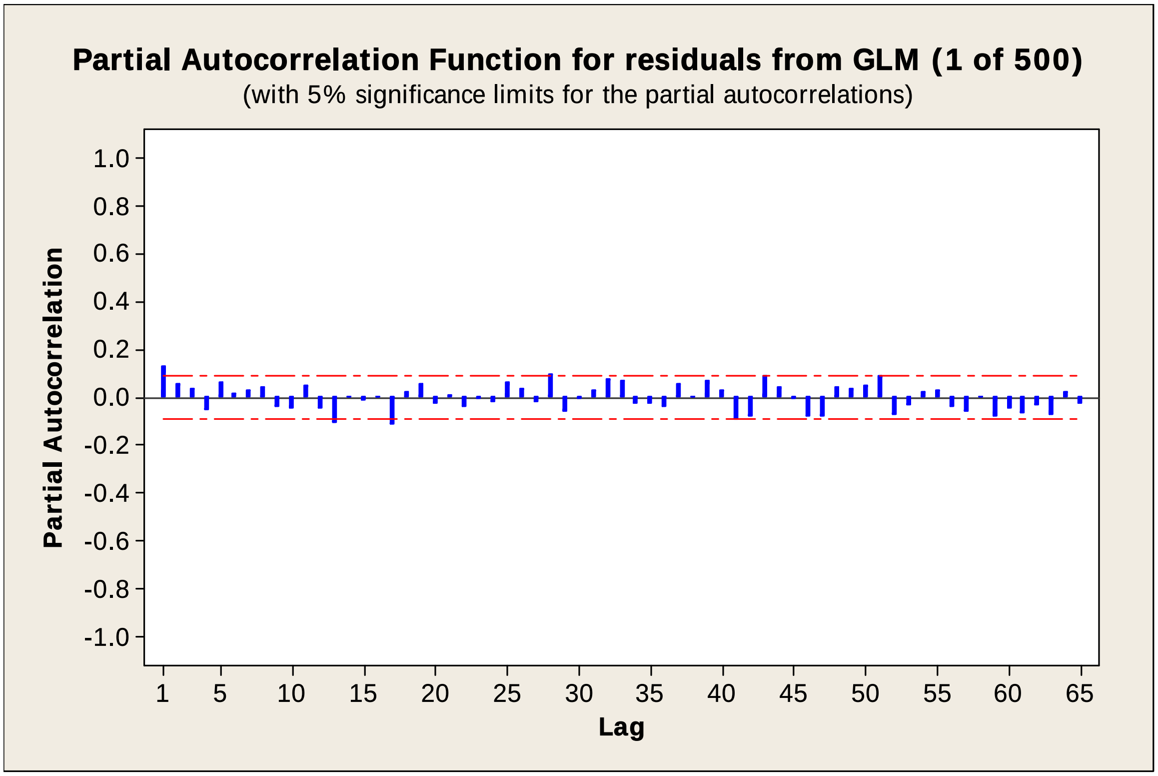


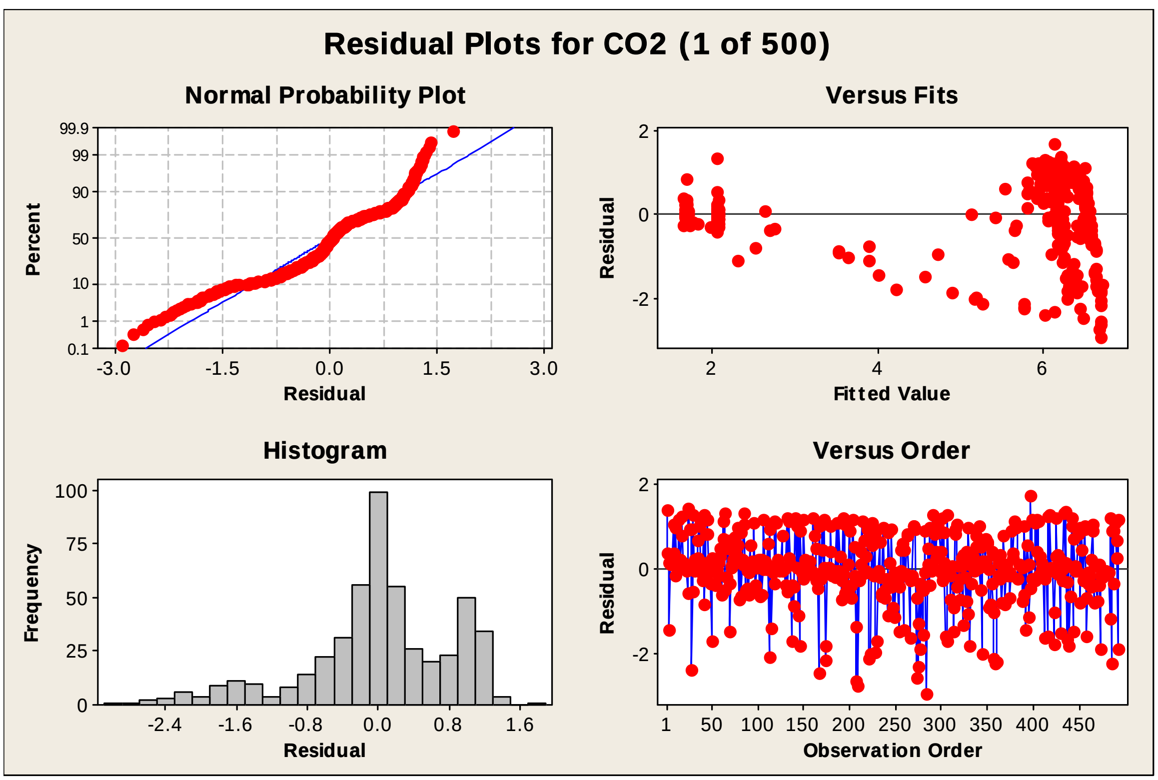


Results for: 1 of 500

General Linear Model: NOx versus compactor

```
Factor      Type    Levels  Values
compactor   fixed        2  1, 2


Analysis of Variance for NOx, using Adjusted SS for Tests

Source                  DF    Seq SS   Adj SS   Adj MS        F      P
EngineSpeed              1   6862161  6457793  6457793  1022.54  0.000
compactor                1    919757    17066    17066     2.70  0.101
compactor*EngineSpeed    1     30969    30969    30969     4.90  0.027
Error                  490   3094574  3094574     6315
Total                  493  10907461


S = 79.4698   R-Sq = 71.63%   R-Sq(adj) = 71.46%
```


Partial Autocorrelation Function for residuals from GLM (1 of 500)
(with 5% significance limits for the partial autocorrelations)
Partial Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1 5 10 15 20 25 30 35 40 45 50 55 60 65
Lag


Residual Plots for CO2 (1 of 500)
Normal Probability Plot
Percent
99.9
99
90
50
10
1
0.1
-3.0 -1.5 0.0 1.5 3.0
Residual
Versus Fits
Residual
2
0
-2
2 4 6
Fitted Value
Histogram
Frequency
100
75
50
25
0
-2.4 -1.6 -0.8 0.0 0.8 1.6
Residual
Versus Order
Residual
2
0
-2
1 50 100 150 200 250 300 350 400 450
Observation Order

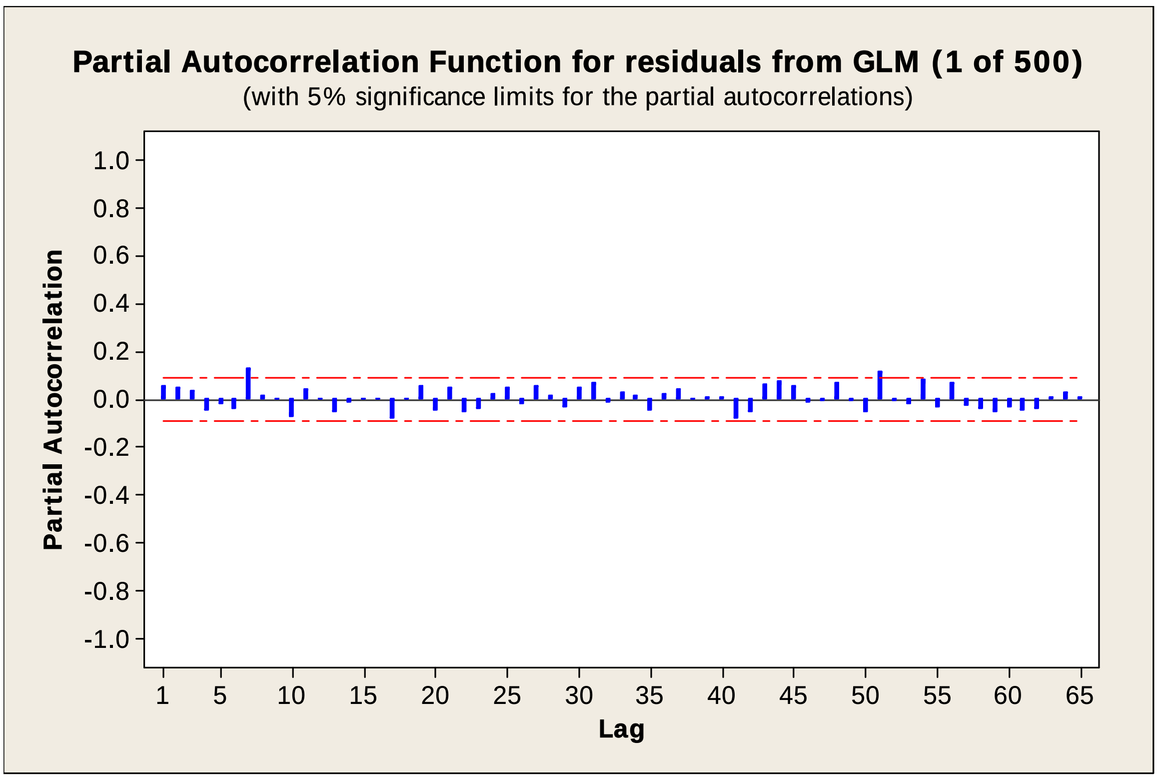
General Linear Model: CO2 versus compactor

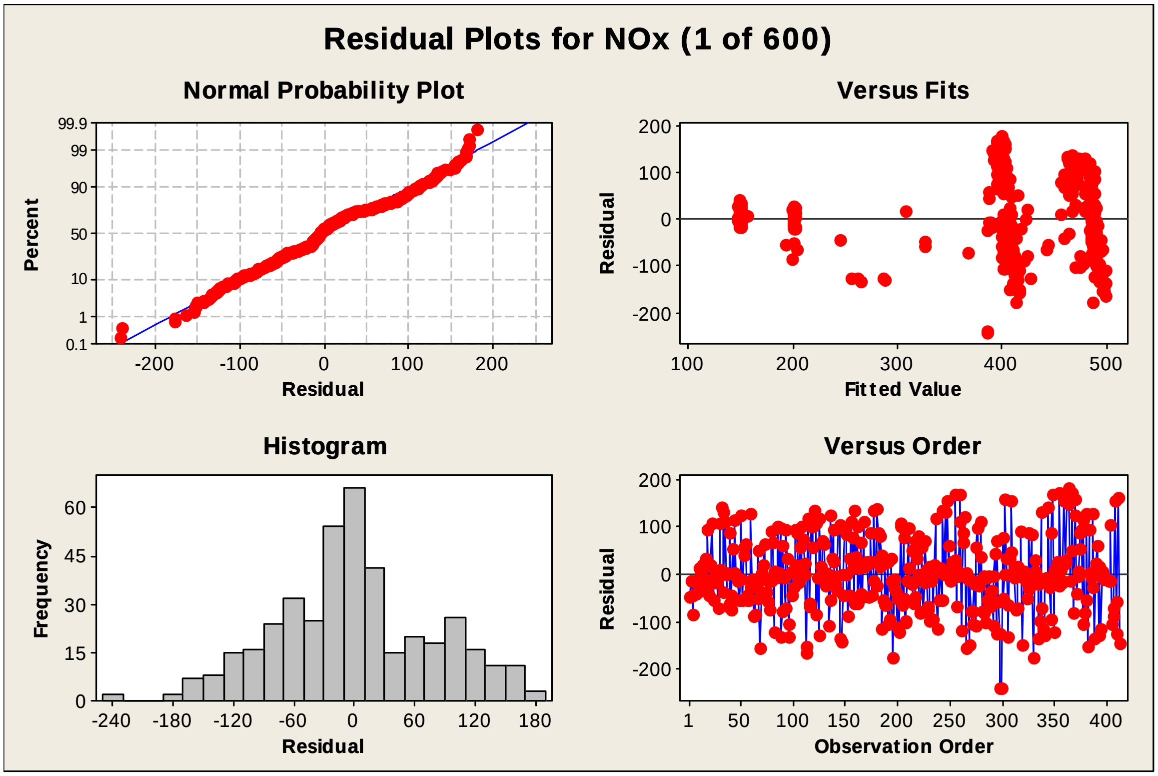
Factor	Type	Levels	Values
compactor	fixed	2	1, 2

Analysis of Variance for CO2, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
EngineSpeed	1	1851.15	1810.19	1810.19	2575.56	0.000
compactor	1	26.67	3.66	3.66	5.21	0.023
compactor*EngineSpeed	1	0.11	0.11	0.11	0.15	0.698
Error	490	344.39	344.39	0.70		
Total	493	2222.32				

S = 0.838353   R-Sq = 84.50%   R-Sq(adj) = 84.41%

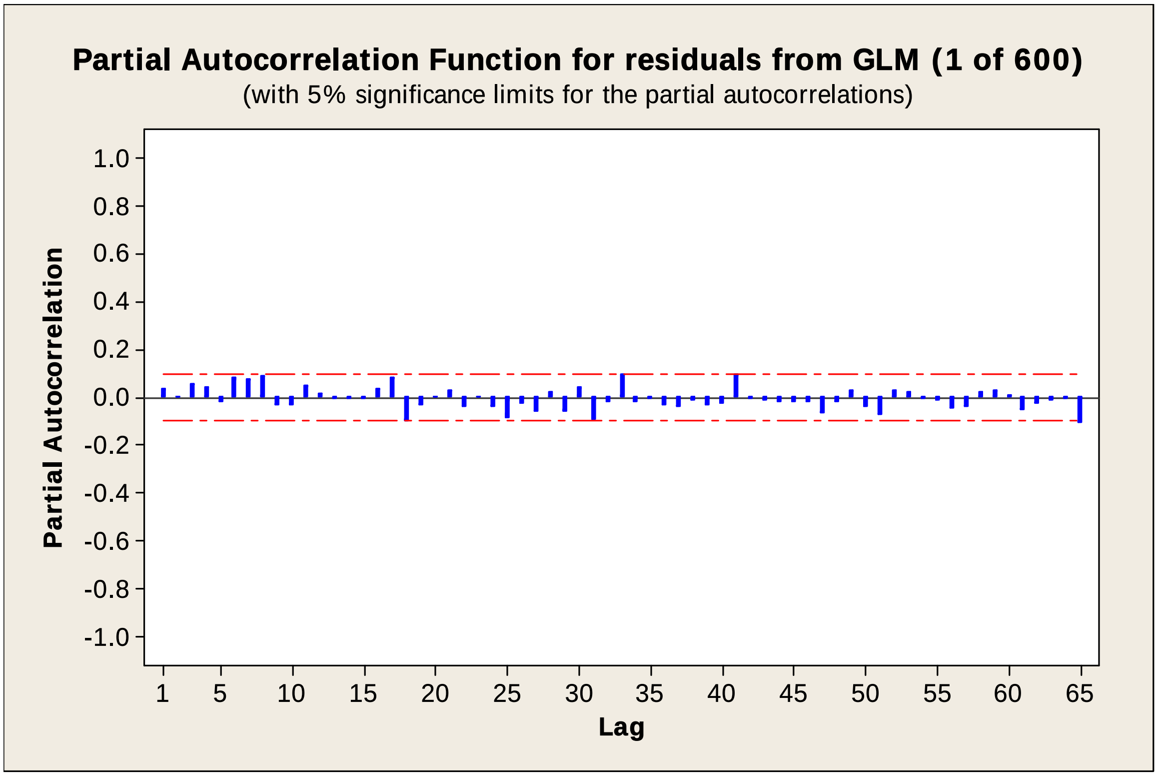


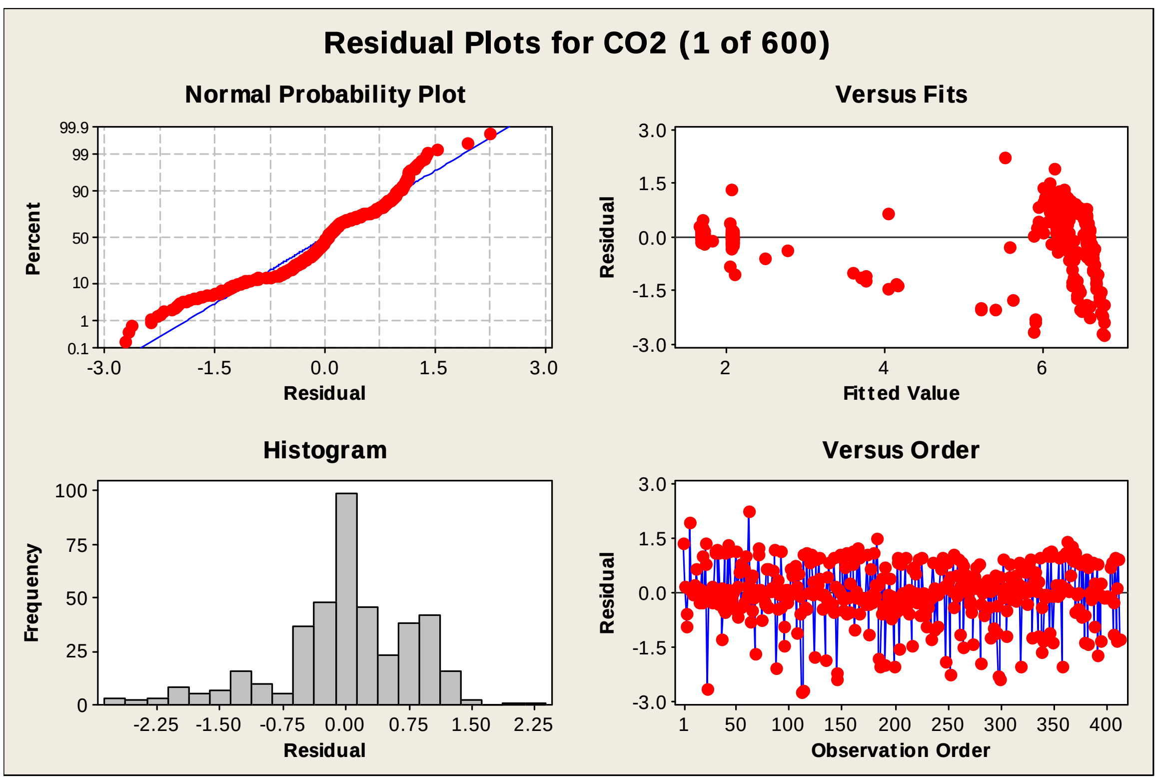


Results for: 1 of 600

General Linear Model: NOx versus compactor

```
Factor     Type   Levels  Values
compactor  fixed       2  1, 2


Analysis of Variance for NOx, using Adjusted SS for Tests

Source                 DF   Seq SS   Adj SS   Adj MS       F      P
EngineSpeed             1  5710682  5493606  5493606  894.38  0.000
compactor               1   608726    19985    19985    3.25  0.072
compactor*EngineSpeed   1    10227    10227    10227    1.66  0.198
Error                 408  2506078  2506078     6142
Total                 411  8835712


S = 78.3731   R-Sq = 71.64%   R-Sq(adj) = 71.43%
```


Partial Autocorrelation Function for residuals from GLM (1 of 600)
(with 5% significance limits for the partial autocorrelations)
Partial Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1 5 10 15 20 25 30 35 40 45 50 55 60 65
Lag


Residual Plots for CO2 (1 of 600)
Normal Probability Plot
Percent
99.9
99
90
50
10
1
0.1
-3.0 -1.5 0.0 1.5 3.0
Residual
Versus Fits
Residual
3.0
1.5
0.0
-1.5
-3.0
2 4 6
Fitted Value
Histogram
Frequency
100
75
50
25
0
-2.25 -1.50 -0.75 0.00 0.75 1.50 2.25
Residual
Versus Order
Residual
3.0
1.5
0.0
-1.5
-3.0
1 50 100 150 200 250 300 350 400
Observation Order

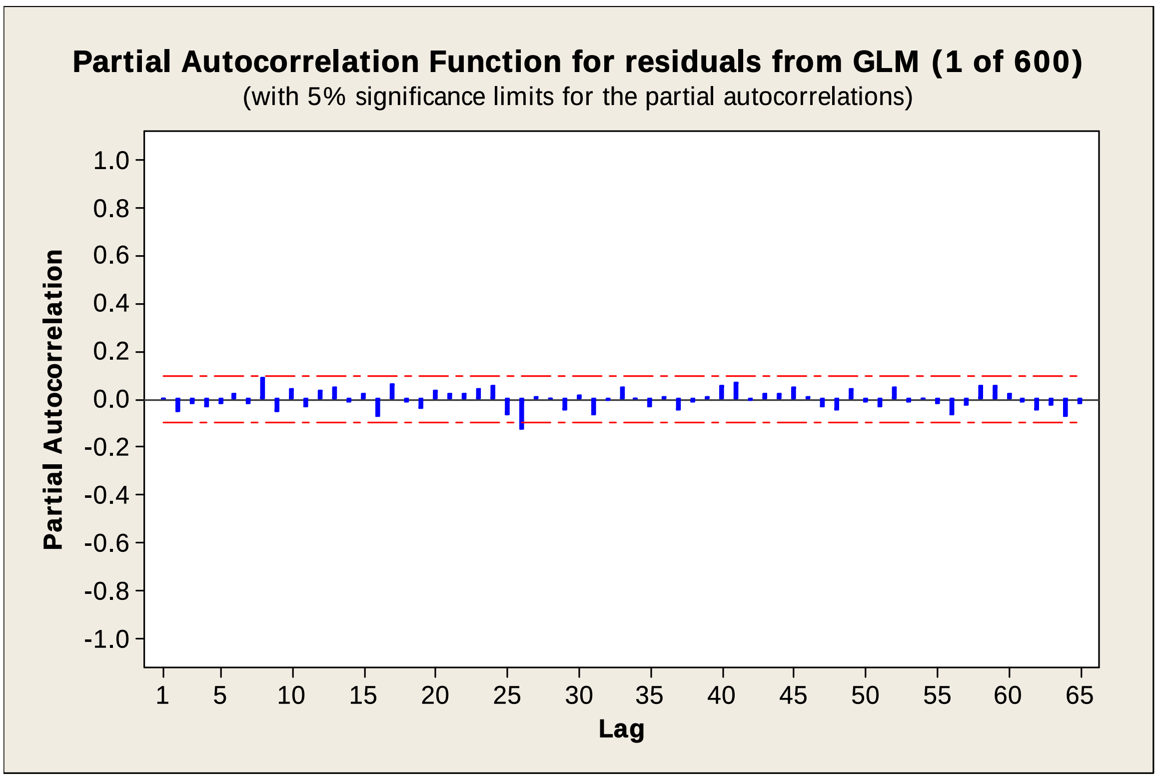
General Linear Model: CO2 versus compactor

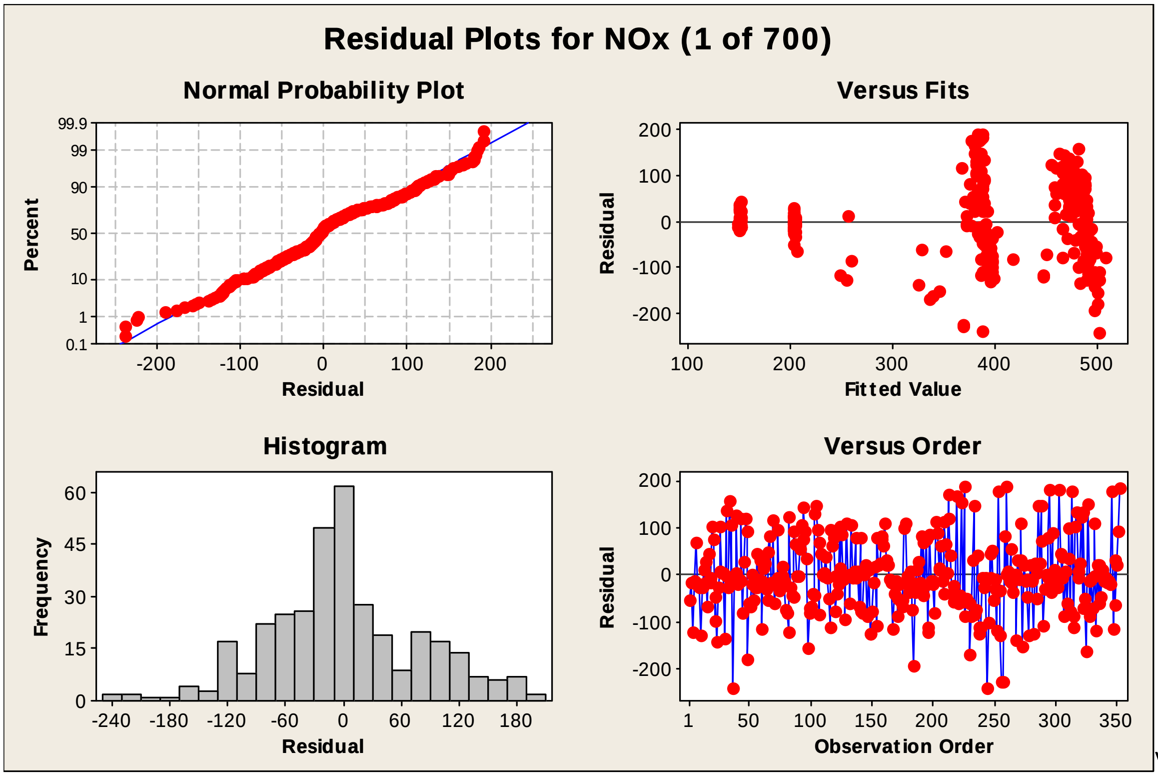
Factor	Type	Levels	Values
compactor	fixed	2	1, 2

Analysis of Variance for CO2, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
EngineSpeed	1	1559.05	1532.99	1532.99	2316.56	0.000
compactor	1	16.49	3.64	3.64	5.50	0.020
compactor*EngineSpeed	1	0.50	0.50	0.50	0.75	0.387
Error	408	270.00	270.00	0.66		
Total	411	1846.03				

S = 0.813482   R-Sq = 85.37%   R-Sq(adj) = 85.27%

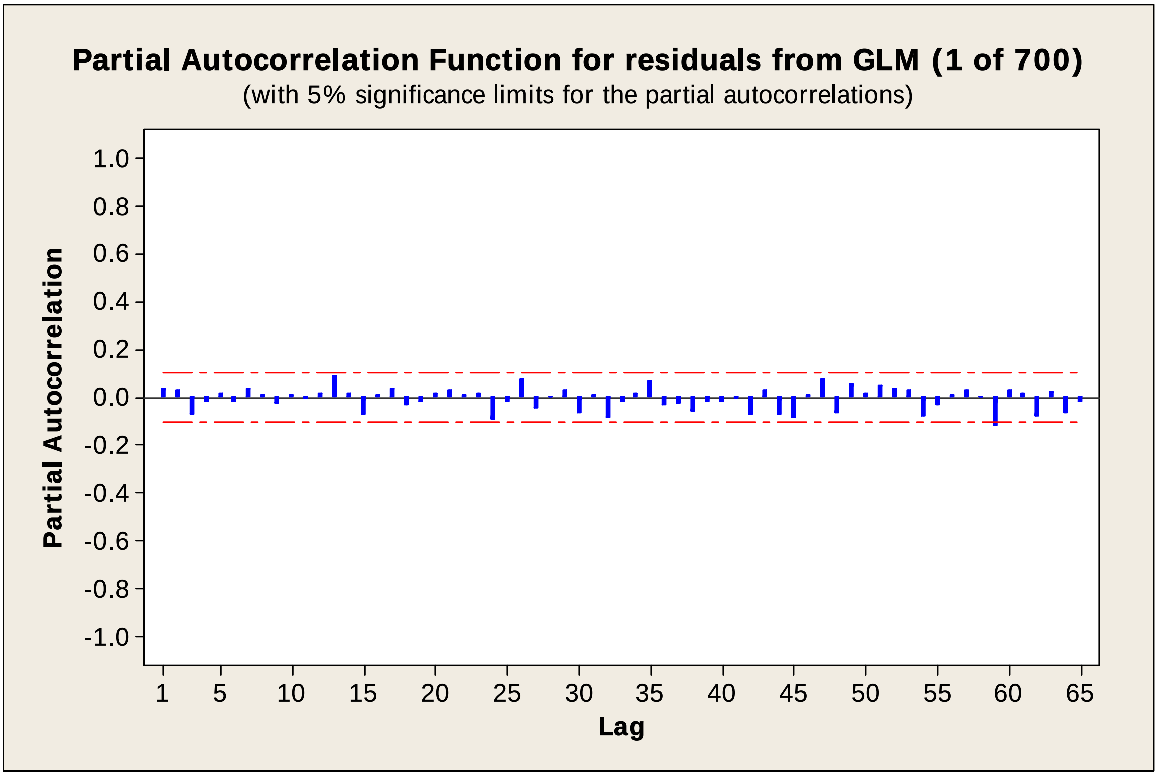


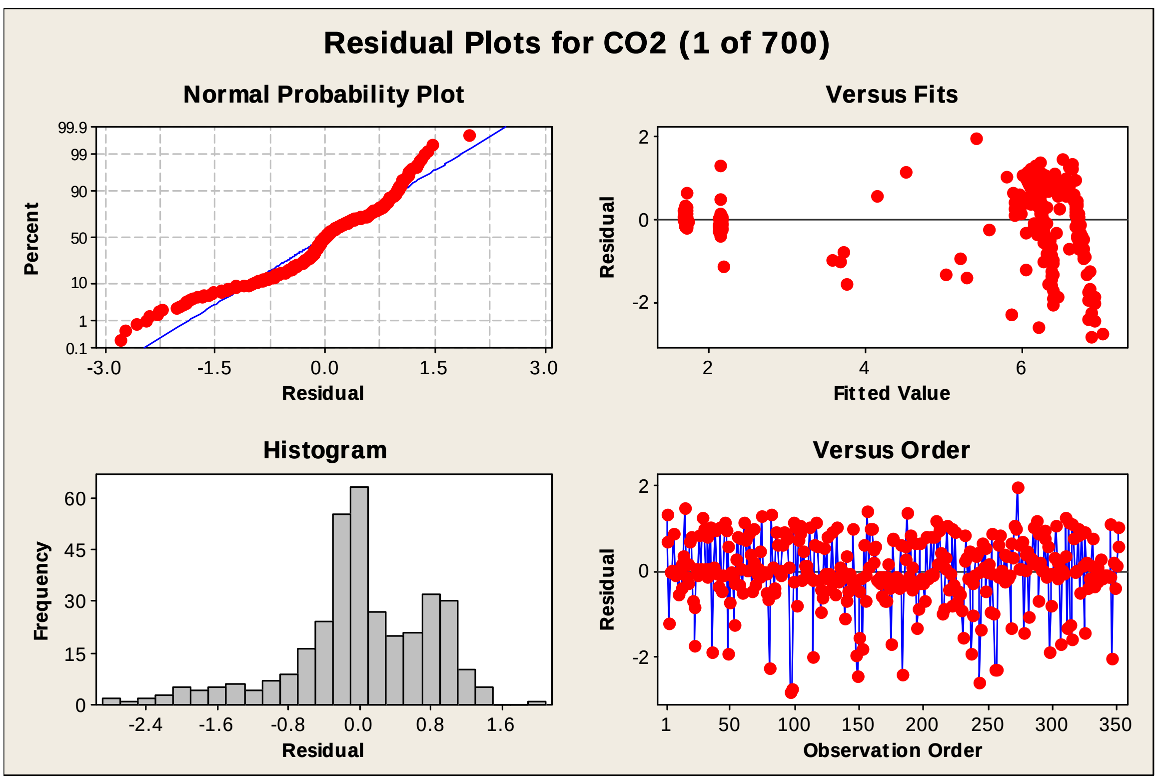


Results for: 1 of 700

General Linear Model: NOx versus compactor

```
Factor      Type   Levels  Values
compactor   fixed       2  1, 2


Analysis of Variance for NOx, using Adjusted SS for Tests

Source                  DF   Seq SS   Adj SS   Adj MS       F      P
EngineSpeed              1  4695056  4492286  4492286  706.80  0.000
compactor                1   704132    10504    10504    1.65  0.199
compactor*EngineSpeed    1    27864    27864    27864    4.38  0.037
Error                  348  2211822  2211822     6356
Total                  351  7638873


S = 79.7233   R-Sq = 71.05%   R-Sq(adj) = 70.80%
```


Partial Autocorrelation Function for residuals from GLM (1 of 700)
(with 5% significance limits for the partial autocorrelations)
Partial Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1 5 10 15 20 25 30 35 40 45 50 55 60 65
Lag


Residual Plots for CO2 (1 of 700)
Normal Probability Plot
Percent
99.9
99
90
50
10
1
0.1
-3.0 -1.5 0.0 1.5 3.0
Residual
Versus Fits
Residual
2
0
-2
2 4 6
Fitted Value
Histogram
Frequency
60
45
30
15
0
-2.4 -1.6 -0.8 0.0 0.8 1.6
Residual
Versus Order
Residual
2
0
-2
1 50 100 150 200 250 300 350
Observation Order

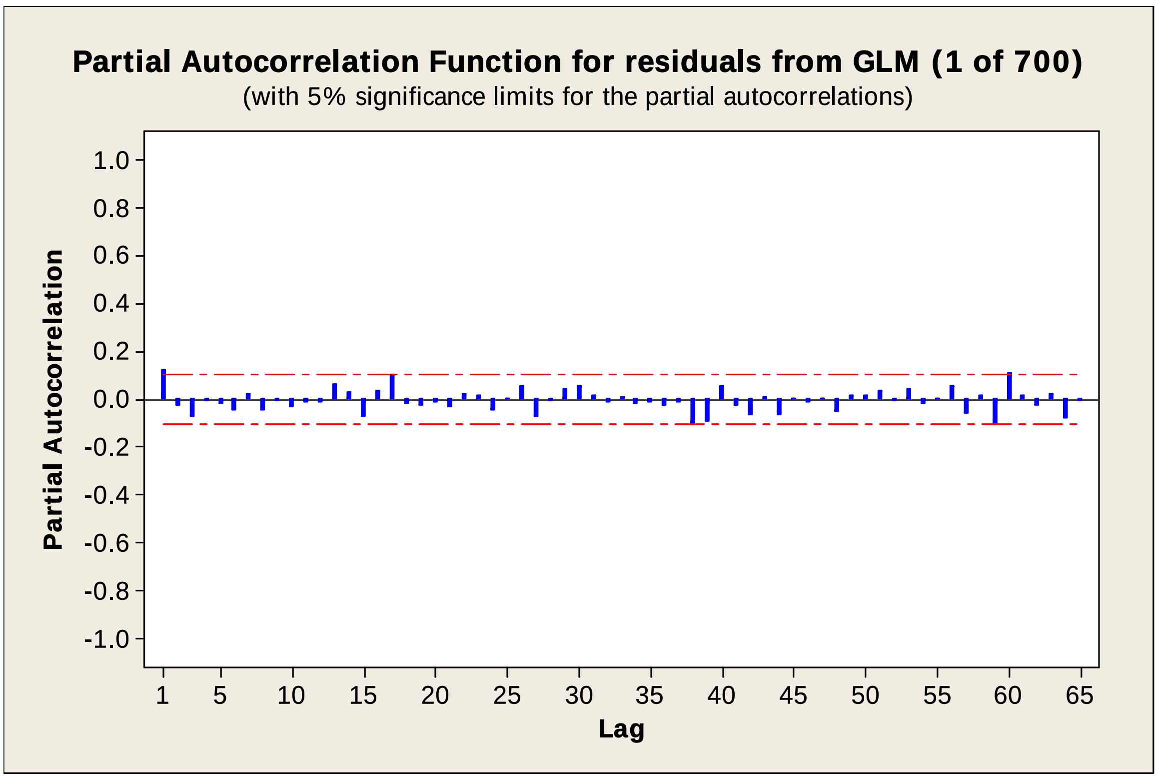
General Linear Model: CO2 versus compactor

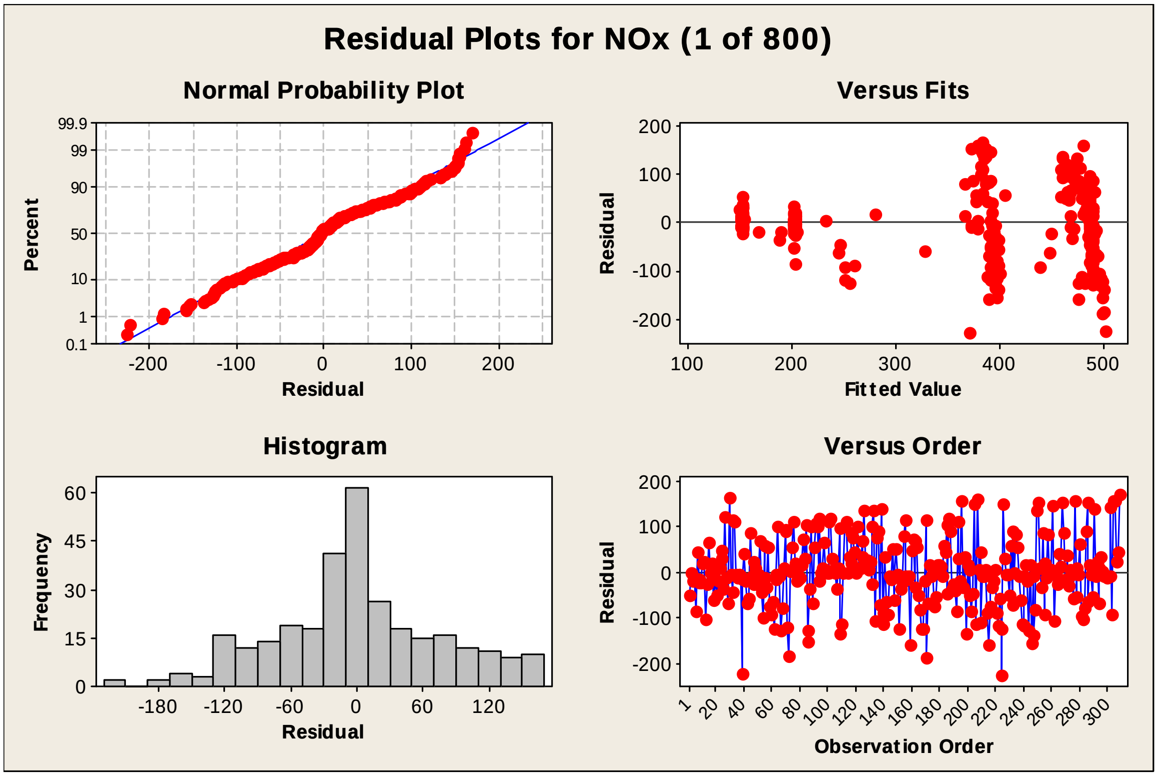
Factor	Type	Levels	Values
compactor	fixed	2	1, 2

Analysis of Variance for CO2, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
EngineSpeed	1	1388.28	1344.98	1344.98	2076.82	0.000
compactor	1	26.26	3.11	3.11	4.80	0.029
compactor*EngineSpeed	1	0.03	0.03	0.03	0.05	0.826
Error	348	225.37	225.37	0.65		
Total	351	1639.94				

S = 0.804746   R-Sq = 86.26%   R-Sq(adj) = 86.14%





Results for: 1 of 800

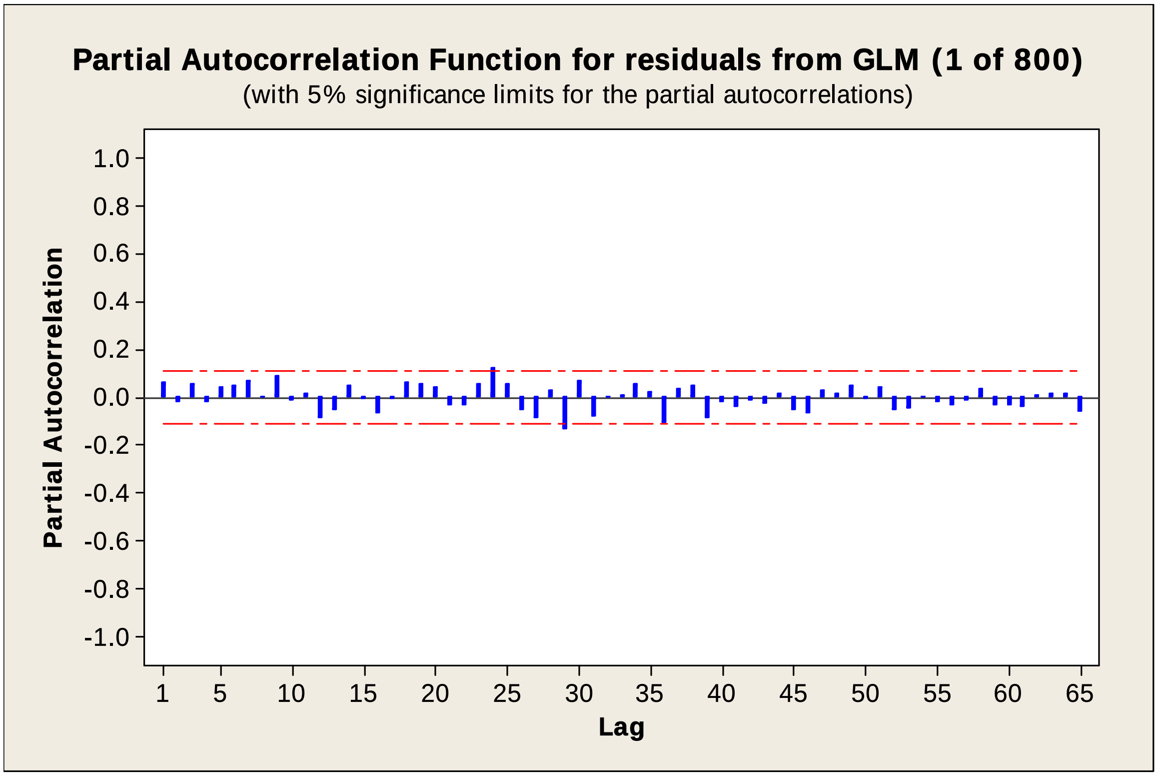
General Linear Model: NOx versus compactor

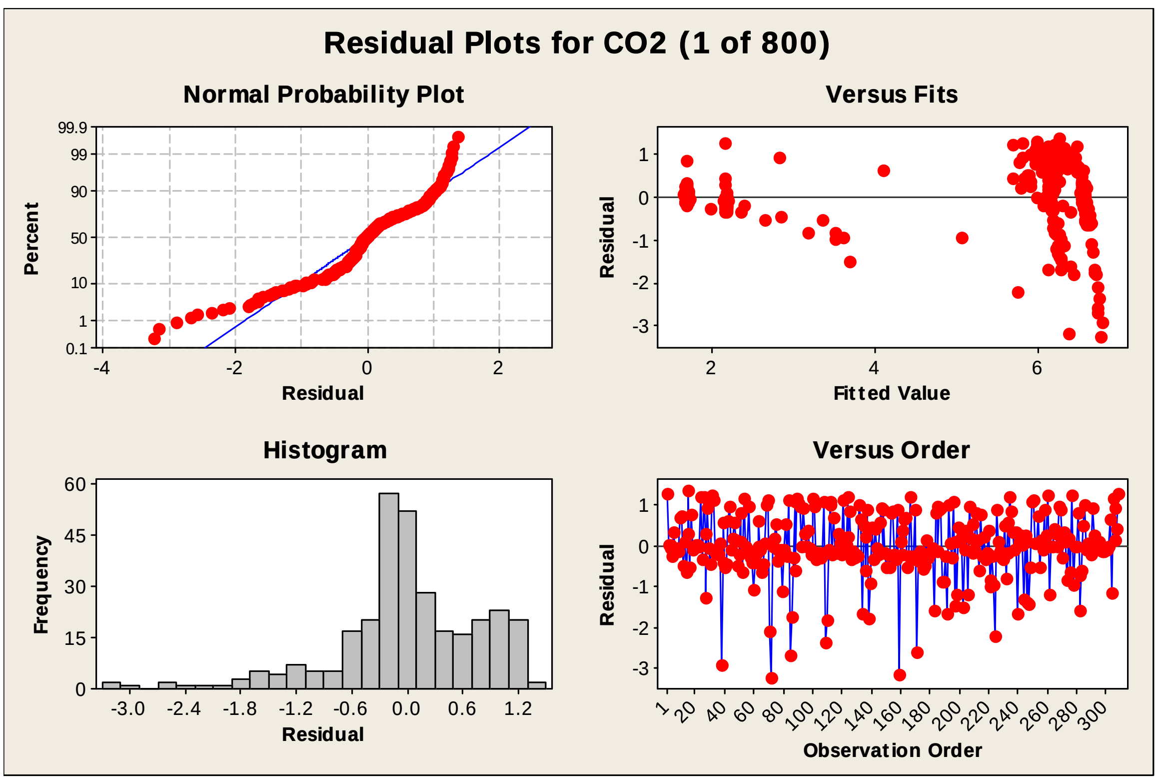
Factor	Type	Levels	Values
compactor	fixed	2	1, 2

Analysis of Variance for NOx, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
EngineSpeed	1	4396393	4130488	4130488	715.24	0.000
compactor	1	581737	8543	8543	1.48	0.225
compactor*EngineSpeed	1	26878	26878	26878	4.65	0.032
Error	305	1761365	1761365	5775		
Total	308	6766373				

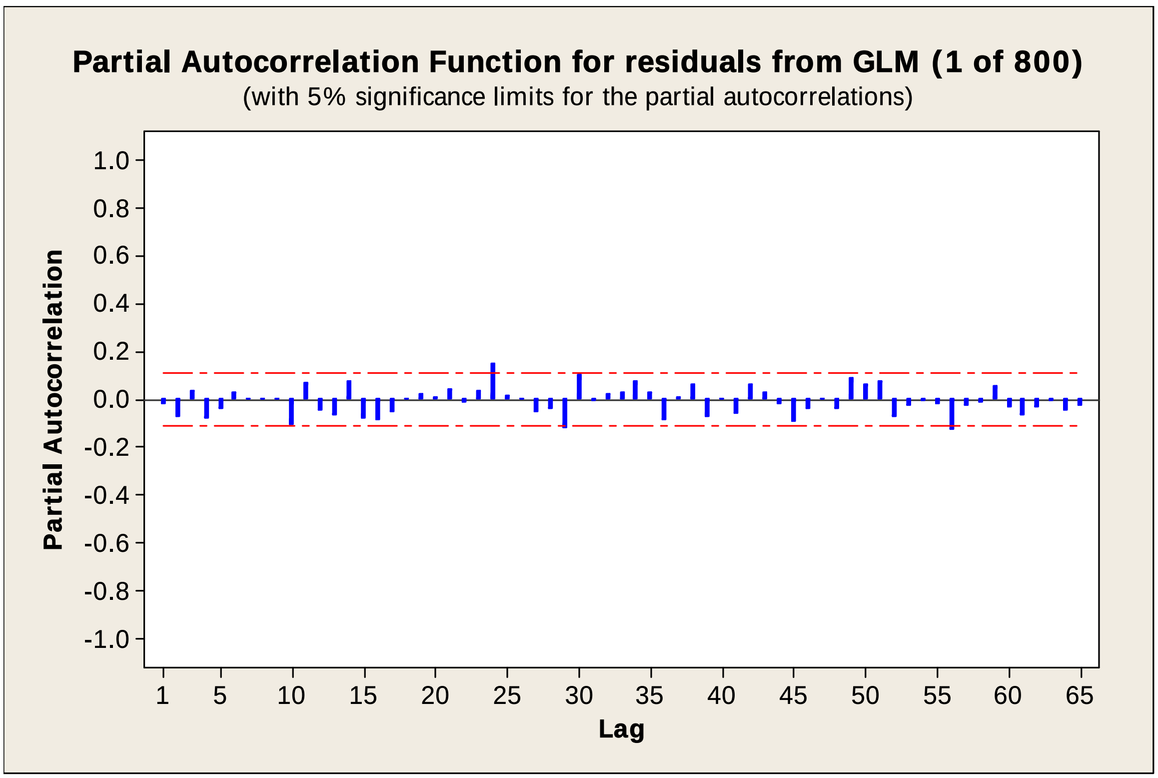
S = 75.9932   R-Sq = 73.97%   R-Sq(adj) = 73.71%

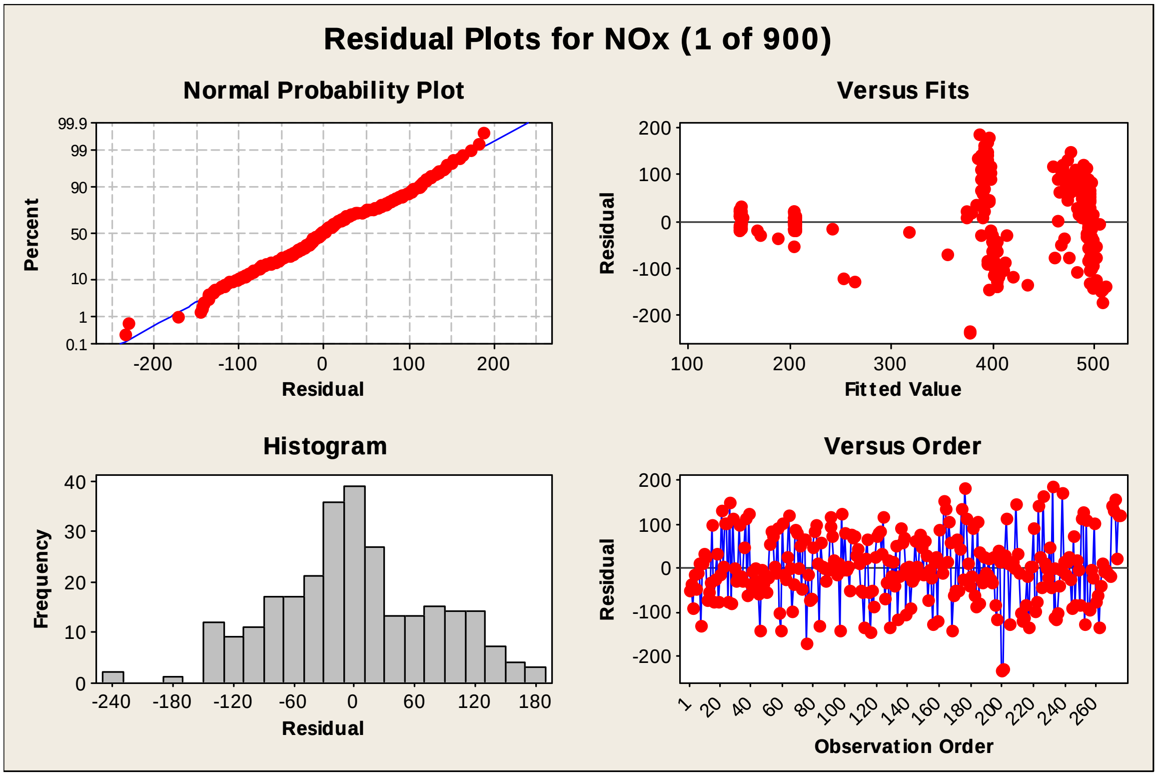

Partial Autocorrelation Function for residuals from GLM (1 of 800)
(with 5% significance limits for the partial autocorrelations)
Partial Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1 5 10 15 20 25 30 35 40 45 50 55 60 65
Lag


Residual Plots for CO2 (1 of 800)
Normal Probability Plot
Percent
99.9
99
90
50
10
1
0.1
-4 -2 0 2
Residual
Versus Fits
Residual
1
0
-1
-2
-3
2 4 6
Fitted Value
Histogram
Frequency
60
45
30
15
0
-3.0 -2.4 -1.8 -1.2 -0.6 0.0 0.6 1.2
Residual
Versus Order
Residual
1
0
-1
-2
-3
1 20 40 60 80 100 120 140 160 180 200 220 240 260 280 300
Observation Order

General Linear Model: CO2 versus compactor

```
Factor     Type   Levels  Values
compactor  fixed       2  1, 2


Analysis of Variance for CO2, using Adjusted SS for Tests

Source                  DF   Seq SS   Adj SS   Adj MS        F      P
EngineSpeed              1  1200.40  1170.98  1170.98  1827.41  0.000
compactor                1    22.78     3.69     3.69     5.76  0.017
compactor*EngineSpeed    1     0.15     0.15     0.15     0.24  0.623
Error                  305   195.44   195.44     0.64
Total                  308  1418.77


S = 0.800492   R-Sq = 86.22%   R-Sq(adj) = 86.09%
```

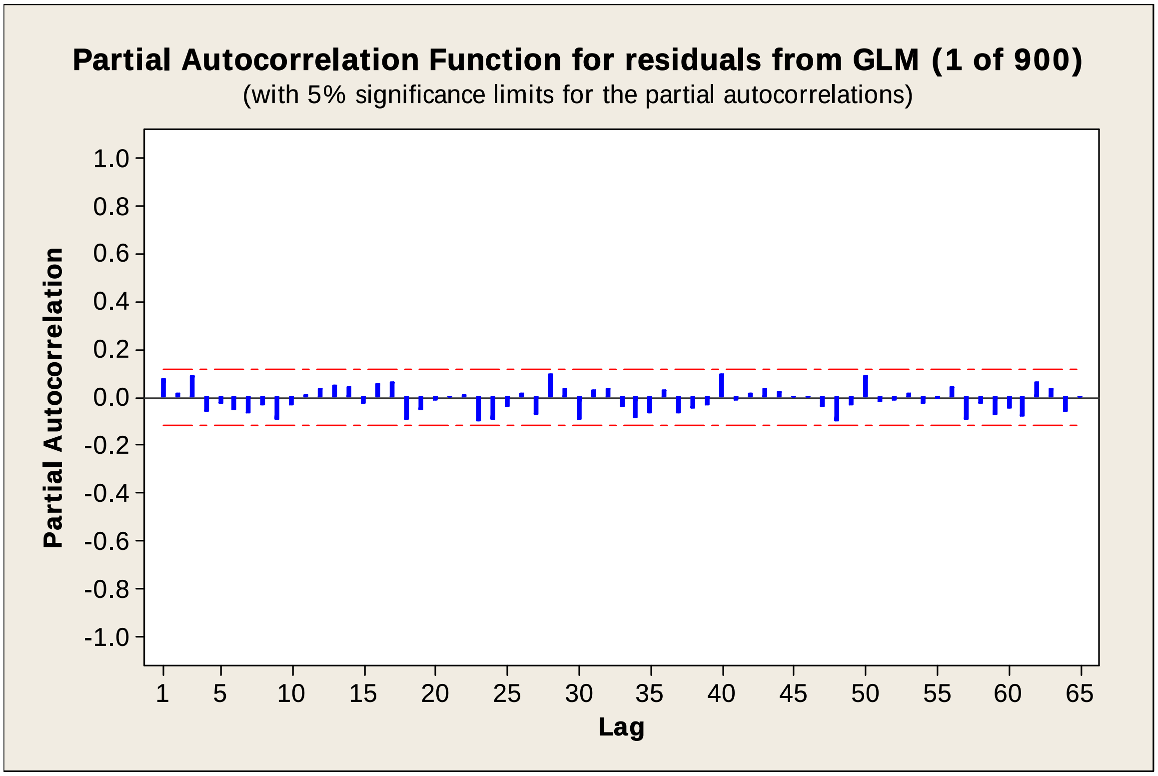


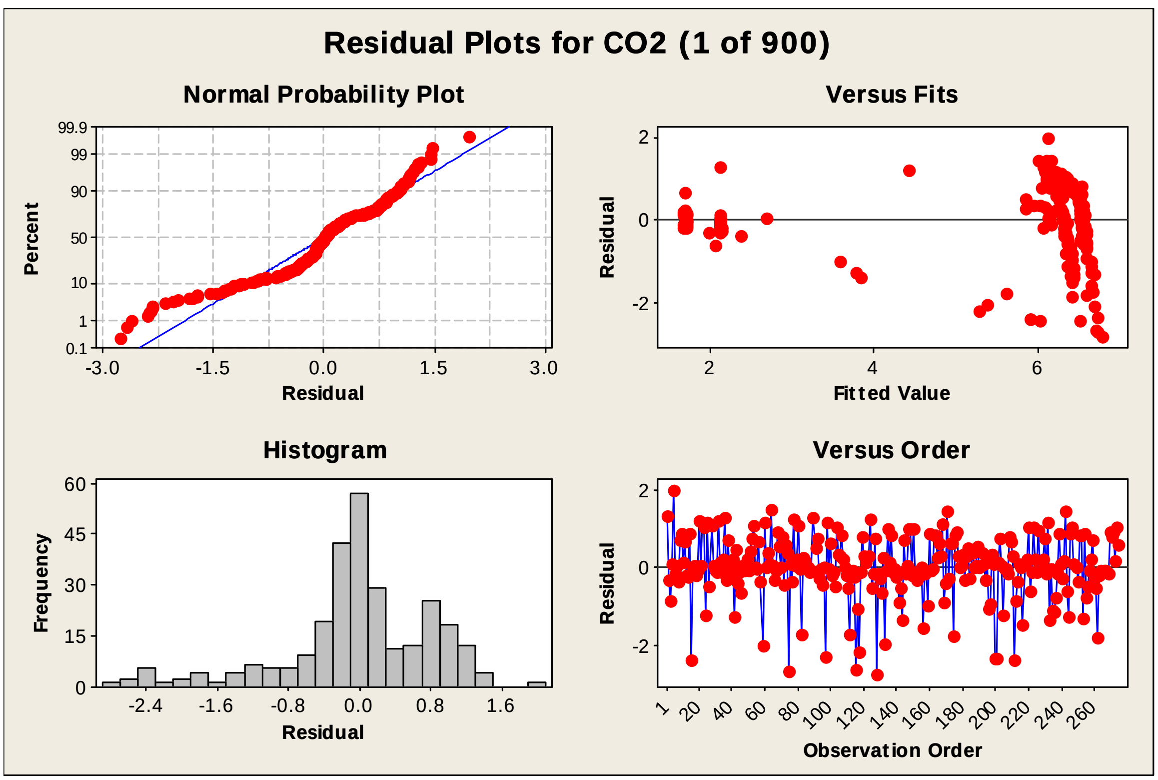


Results for: 1 of 900

General Linear Model: NOx versus compactor

```
Factor     Type   Levels  Values
compactor  fixed       2  1, 2


Analysis of Variance for NOx, using Adjusted SS for Tests

Source                  DF   Seq SS   Adj SS   Adj MS       F      P
EngineSpeed              1  3882022  3595761  3595761  589.66  0.000
compactor                1   539347     9048     9048    1.48  0.224
compactor*EngineSpeed    1    18536    18536    18536    3.04  0.082
Error                  271  1652573  1652573     6098
Total                  274  6092477


S = 78.0900   R-Sq = 72.88%   R-Sq(adj) = 72.57%
```


Partial Autocorrelation Function for residuals from GLM (1 of 900)
(with 5% significance limits for the partial autocorrelations)
Partial Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1 5 10 15 20 25 30 35 40 45 50 55 60 65
Lag


Residual Plots for CO2 (1 of 900)
Normal Probability Plot
Percent
99.9
99
90
50
10
1
0.1
-3.0 -1.5 0.0 1.5 3.0
Residual
Versus Fits
Residual
2
0
-2
2 4 6
Fitted Value
Histogram
Frequency
60
45
30
15
0
-2.4 -1.6 -0.8 0.0 0.8 1.6
Residual
Versus Order
Residual
2
0
-2
1 20 40 60 80 100 120 140 160 180 200 220 240 260
Observation Order

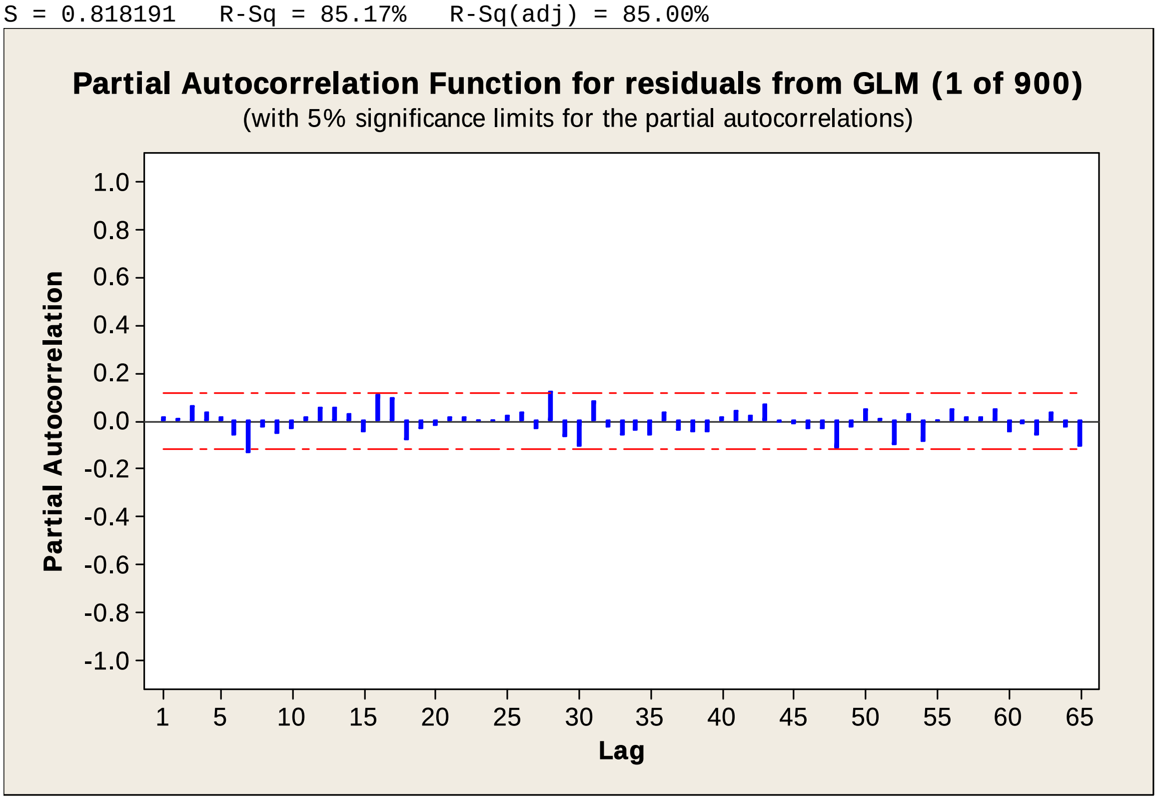
General Linear Model: CO2 versus compactor

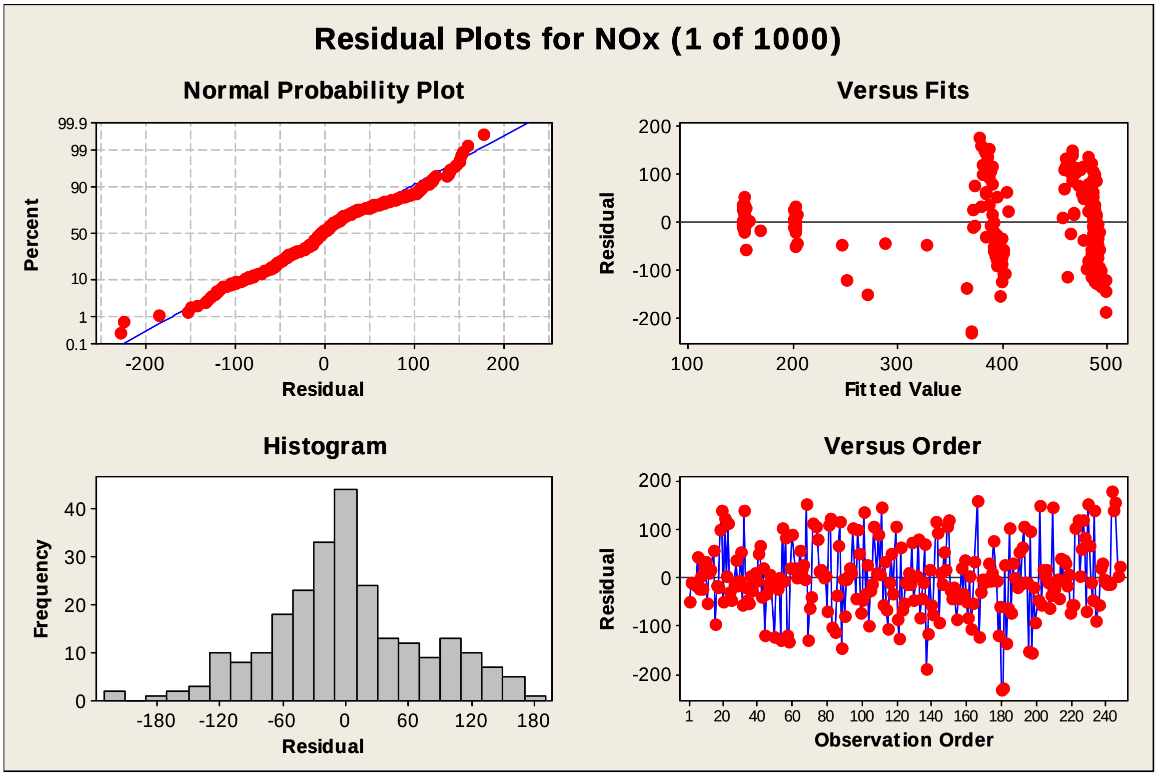
Factor	Type	Levels	Values
compactor	fixed	2	1, 2

Analysis of Variance for CO2, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
EngineSpeed	1	1030.60	1009.42	1009.42	1507.87	0.000
compactor	1	10.02	3.49	3.49	5.21	0.023
compactor*EngineSpeed	1	0.89	0.89	0.89	1.33	0.250
Error	271	181.42	181.42	0.67		
Total	274	1222.93				

S = 0.818191   R-Sq = 85.17%   R-Sq(adj) = 85.00%





Results for: 1 of 1000

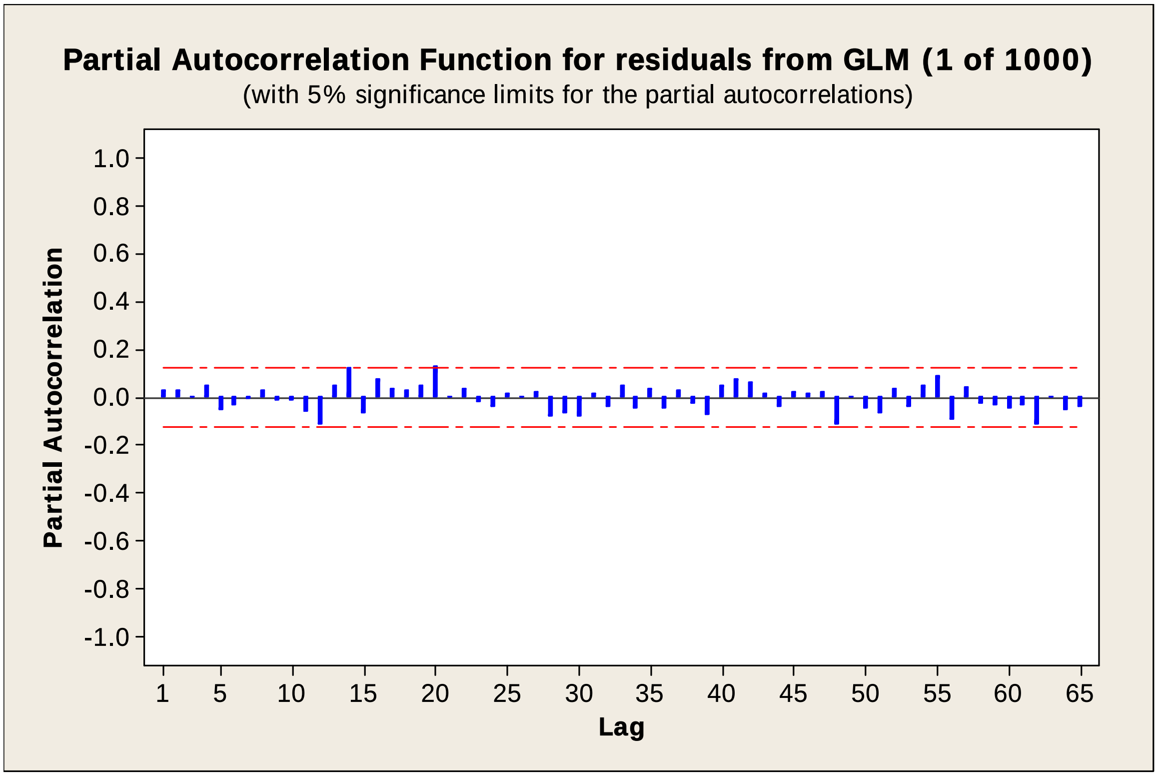
General Linear Model: NOx versus compactor

Factor	Type	Levels	Values
compactor	fixed	2	1, 2

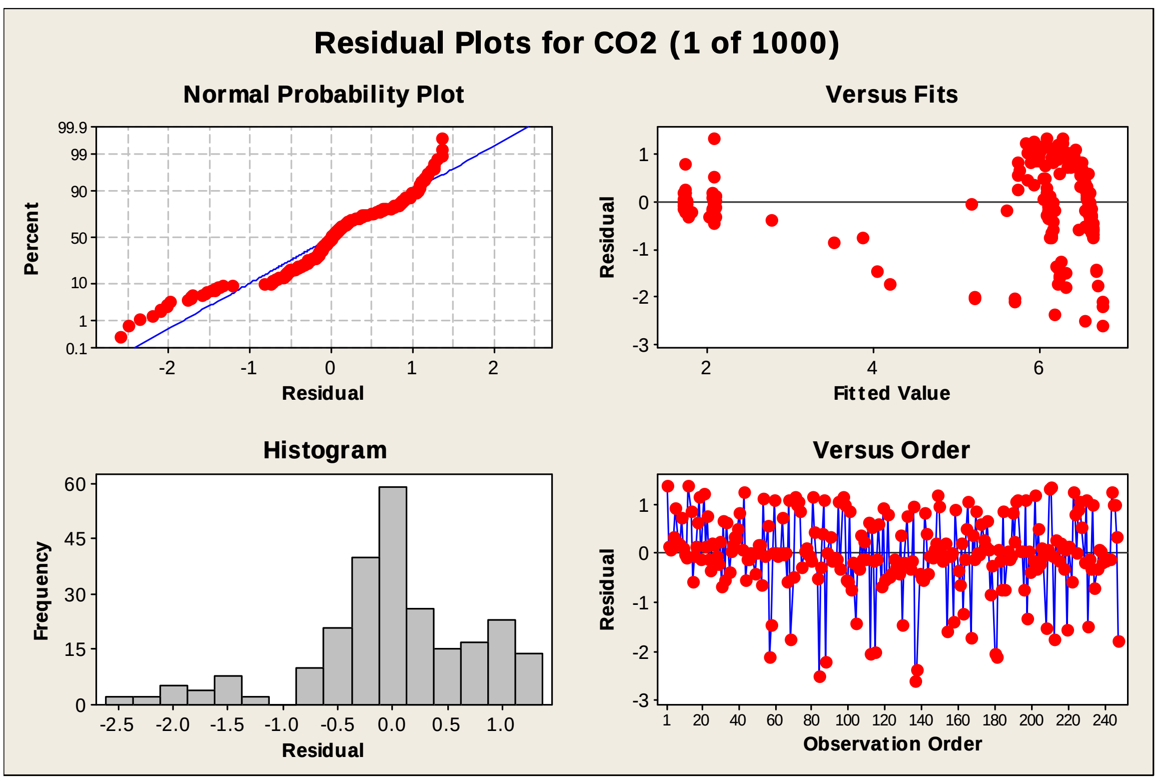
Analysis of Variance for NOx, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
EngineSpeed	1	3628836	3316541	3316541	607.30	0.000
compactor	1	456138	5635	5635	1.03	0.311
compactor*EngineSpeed	1	23460	23460	23460	4.30	0.039
Error	244	1332518	1332518	5461		
Total	247	5440952				

S = 73.8995   R-Sq = 75.51%   R-Sq(adj) = 75.21%



Partial Autocorrelation Function for residuals from GLM (1 of 1000)
(with 5% significance limits for the partial autocorrelations)
Partial Autocorrelation
1.0
0.8
0.6
0.4
0.2
0.0
-0.2
-0.4
-0.6
-0.8
-1.0
1 5 10 15 20 25 30 35 40 45 50 55 60 65
Lag



Residual Plots for CO2 (1 of 1000)
Normal Probability Plot
Percent
99.9
99
90
50
10
1
0.1
-2 -1 0 1 2
Residual
Versus Fits
Residual
1
0
-1
-2
-3
2 4 6
Fitted Value
Histogram
Frequency
60
45
30
15
0
-2.5 -2.0 -1.5 -1.0 -0.5 0.0 0.5 1.0
Residual
Versus Order
Residual
1 20 40 60 80 100 120 140 160 180 200 220 240
Observation Order

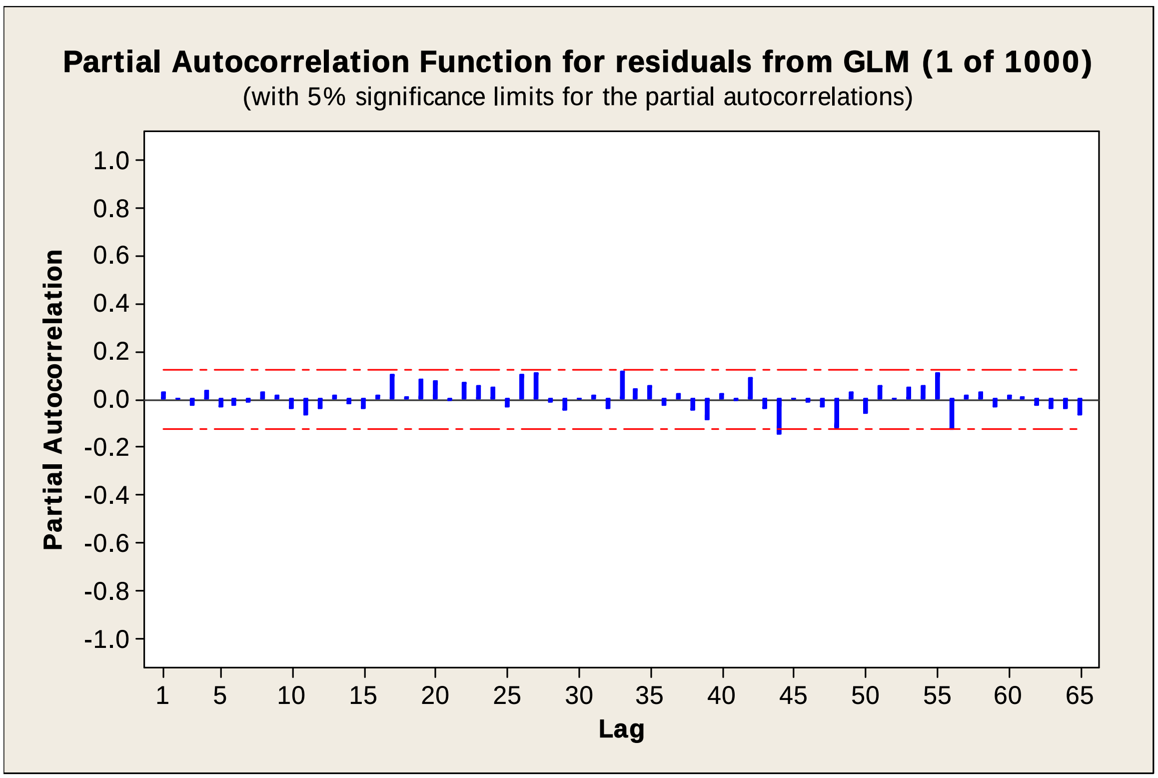
General Linear Model: CO2 versus compactor

Factor	Type	Levels	Values
compactor	fixed	2	1, 2

Analysis of Variance for CO2, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
EngineSpeed	1	978.56	940.44	940.44	1514.93	0.000
compactor	1	18.34	1.15	1.15	1.85	0.175
compactor*EngineSpeed	1	0.12	0.12	0.12	0.19	0.665
Error	244	151.47	151.47	0.62		
Total	247	1148.49				

S = 0.787899   R-Sq = 86.81%   R-Sq(adj) = 86.65%



Trashmaster 3-90E
Landfill Compactor Specifications

Horsepower:	525 hp (391 kw) @ 2,100 rpm
Application:	Extreme Service Landfill Compaction
PLI:	up to 767 lbs./linear inch (137 kg/linear cm)
Compaction Width:	13 ft. 8 in. (4166 mm)

CMI TRASHMASTER 3-90E Landfill Compactor

DIESEL ENGINE

- Cummins Model QSK-19, 525 hp (391 kW) @ 2,100 rpm.

Turbo charged and charge air-cooled.

- Fuel, lube oil and coolant filters; dry-type, replaceable air cleaner with safety element and service indicator.
- 46 in. (1168 mm) blower fan.
- The QSK-19 features robust design components, superior fuel economy, long life.

SELF-DIAGNOSTIC DRIVE SYSTEM MONITOR (DSM)

Protects power train components from failure due to:

- Low engine oil pressure.
- High engine coolant temperature.
- Loss of engine coolant.
- High hydrostatic oil temperature.
- Low hydrostatic charge pressure.
- Low battery voltage.
- High pump drive box lube oil temperature.

If the monitoring system detects a developing problem, it activates an in-cab audible and visual alarm and either automatically shuts down the engine or reduces engine speed before serious damage occurs.

DSM gauges identify the source of a problem to simplify troubleshooting and servicing.

POWER TRAIN

Engine power drives each hydrostatic system through a pump drive box which provides power to drive four variable displacement pumps, four variable displacement motors and four planetary wheel drives. A load controller in the hydrostatic system keeps engine at or near rated speed.

- Each wheel is driven independently by its own hydrostatic drive system. Each system consists of a flooded suction inlet, charge pressure filter, variable displacement pump and motor sharing a common hydrostatic reservoir with non-bypass suction filtration. Return oil is routed through an oil-to-air cooler with supplemental oil being automatically filtered and supplied from the main hydraulic reservoir.

GAUGES/INDICATORS

- Tachometer, engine oil pressure, engine coolant temperature, fuel level gauge, voltmeter, hour-meter, air filter service indicator, parking brake light and buzzer, belly pan up light, pump drive box temperature.
- Self-diagnostic DSM instrumentation with separate gauges for each hydrostatic drive system with an audible and visual alarm.

ELECTRICAL

- 24 volt system, two 8D 12 volt batteries.
- 75 amp alternator, heavy-duty starter and service shutoff.
- All wiring loom protected or run in water-tight conduit.
- Remote master disconnect switch located in cab.
- Eight, cab-mounted, 50 watt halogen lights; two front and two rear.
- Movable engine compartment service light with magnetic base.

COOLING SYSTEM

- Specially designed, large capacity, steel framed, aluminum cored, independent side-by radiator/oil cooler/CAC with widely-spaced fins and inline tubes; two side clean out doors; radiator sight glass and thermostatically controlled oil cooler by-pass valve for rapid, cold weather, hydrostatic system warmup.

WHEELS

- Four, large 85.5 in. (2172 mm) diameter wheels are designed to exert highest compaction force.
- Constructed of alloy steel 1.5 in. (38 mm) outer wrapper with .5 in. (13 mm) hard surfacing on the inner and outer wheel circumference.
- Wheel width front is 35 in. (889 mm); rear is 40 in. (1016 mm).
- Higher total ground clearance of 35 in. (889 mm).
- Inner wheels protected by labyrinth type antiwrap discs and cable traps.
- Two 19 in. (483 mm) quick opening access covers for easy visual inspection.

CLEATS

- Big Dog cleats, constructed of manganese alloy steel, provide a crisp chopping to reduce refuse size.
- The exclusive contour design of CMI cleats eliminates surface fluffing.
- CMI cleats are self-cleaning, discourage build-up and eliminate the need for power-robbing raker bars.
- Optional 2 piece Trak Lok™ and 7.25 in. (184 mm) high Terra Twist Torque® cleats available.

FENDERS

- All wheels are fender covered and available with optional integral striker bars.
- Fixed antiwrap discs fit inside the rotating wheel drum to form a labyrinth seal for superior wheel and planetary drive protection. Each planetary wheel drive also has its own multiple labyrinth seal guard.
- Cable traps provide added protection for wheel drive seals.
- Hand rails and steps provide sure cab access.

FRAME

- Front and rear frames are constructed of heavy steel plate weldments.
- Frames are connected by large, hardened steel pins riding in large, tapered roller bearings.
- Massive box section steel castings support each planetary wheel drive.

BRAKES

- Hydrodynamic service brake for each wheel.
- Oil cooled parking/emergency wet fail-safe brakes on rear wheels are spring applied with automatic hydraulic release.

HYDRAULICS / STEERING AND BLADE

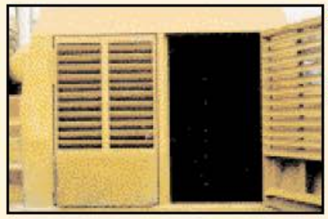
- Suction and return filters, with indicators, filter all oil entering and leaving the hydraulic reservoir.
- Tandem gear pump provides independent oil supply to the steering and blade systems.
- Steering and blade spool valves include high pressure reliefs, steering system anti-cavitation checks and cylinder port cross-over relief valves.

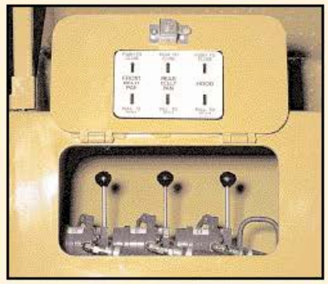
Special Access Features

These exclusive features are designed to provide fast, easy service access.

- For underneath access, two, heavy-duty reinforced belly pans swing up and down hydraulically. Separate pin lock system secures belly pans in up position.
- The reinforced steel articulation doors swing open for easy access and are secured by a positive pin lock system.
- Fenders provide stable service platforms and deflect debris.

- Hydrostatic drive system in cab gauges for wheel traction system charge pressure and oil temperature.





- Hydraulically actuated, heavy-gauge tilt hood.
- Heavy radiator grill doors swing out for easy radiator cleaning and radiator / oil cooler servicing.

- Control for tilt hood and belly pans is conveniently located in rear fender step.

- Articulated, full-power steering is actuated by two 5 x 20.5 in. (127 x 521 mm) cushioned hydraulic cylinders powered by an independent 39 gpm (148 lpm) pump for easy operation and maximum maneuverability.
- Cylinders are located high – away from debris.
- All hoses are located inside the mainframe for maximum protection.
- Total articulation is 64 degrees.

CONTROLS / STEERING & BLADE

- A joystick control is mounted on each seat arm rest.
- One joystick controls blade operation and forward/neutral/reverse propulsion.
- The other joystick controls steering and work range (2) speed selection.
- Each joystick has a horn button.
- Machine reversals can be made at maximum engine rpm without power train shocks.
- Blade and steering controls are independent of hydrostatic systems for smooth operation.
- Joystick input and output are transmitted through durable inductive coupling technology for long life operation. No solenoids. No mechanical linkages. No lubrication. Spool snifting is enclosed and operates in oil.
- Self diagnostic LED indicators simplify troubleshooting.

CAB FEATURES

- A fully enclosed, sound supressed structure with insulated walls and heavy-duty floor matting.
- High back, side facing seat with lumbar support is suspension mounted, adjusts six ways and features breathable cloth upholstery.
- Heater and defroster fans.
- Large windows all around for best 360 degree visibility in the industry.
- Independent ROPS.
- Tinted safety glass.
- Front and rear windshield wipers and washers.
- Front clean out door.
- Fenders, stairs and handrails provide sure access to the cab.

BLADE

- A 16 ft. wide x 7 ft. high (4877 x 2134 mm) semi-U shaped blade directs trash under the wheels.
- Full-width, rugged trash screen with 1 in. (25 mm) square bars.
- Blade controlled by a single 6 x 40 in. (152 x 1016 mm) hydraulic cylinder powered by an independent 50 gpm (189 lpm) pump for easy operation with up, down, hold and float positions. Cylinder and both exposed hydraulic lines are located high and guarded for maximum protection.
- Cutting edges are reversible for extended life.

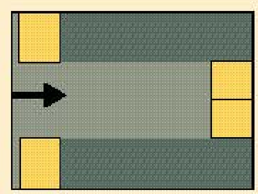
Denotes CMI standard features which may only be available at extra cost from competitors.

Powerful, yet simple to service and maintain – Each of four wheels is driven by an independent hydrostatic drive traction system consisting of a variable displacement pump, variable displacement motor, non-bypass charge pressure filter and a planetary wheel drive.

A common pump drive box, reservoir, non-bypass suction filter and oil cooler complete the hydrostatic drive traction system.

The Best Compaction In The Industry

At up to 800 PLI, the 3-90E Trashmaster exerts the greatest compaction force available in the industry. The reason is its triangular wheel configuration. Machine weight is equally distributed across three points of contact.

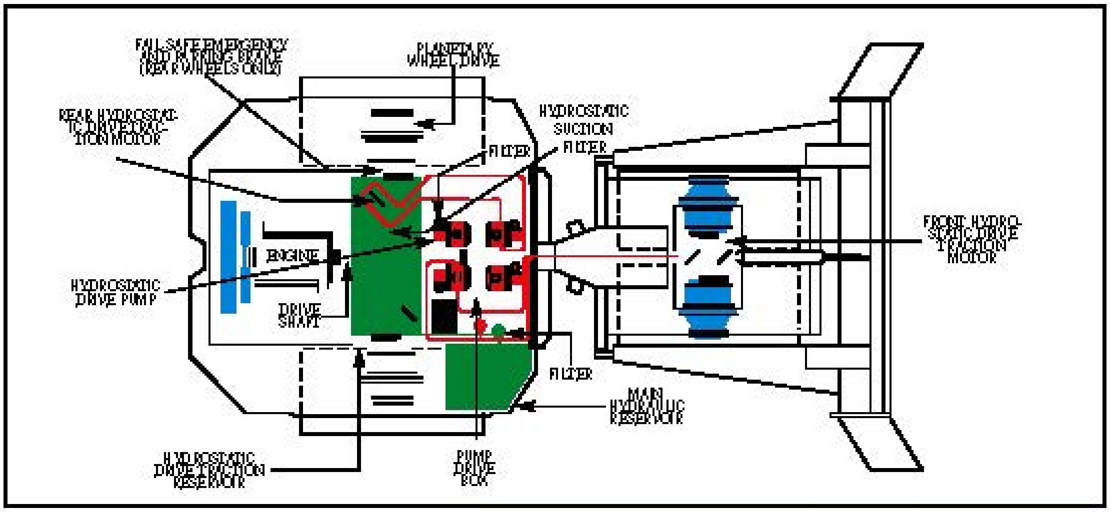


The result is:

- Much greater compaction pressure than its competitors.
- Greater landfill densities than competitors.
- Superior efficiency because of its single-pass, full-width compaction.

Consult the CMI PLI Story for more details.

Denotes CMI standard features which may only be available at extra cost from competitors.



Easy troubleshooting – Each hydrostatic drive system has its own gauges for monitoring traction system charge pressure and oil temperature, and is integrated with an automatic engine shutdown or speed reduction on fault. The source of the problem is identified. Gauges are located in the cab with individual indicator lights and audible alarm on the instrument panel.

Test ports are also located throughout the system to further facilitate trouble-shooting. For convenience, a service light with extension cord and magnetic base is located in the engine compartment.

Hydrostatic Drive

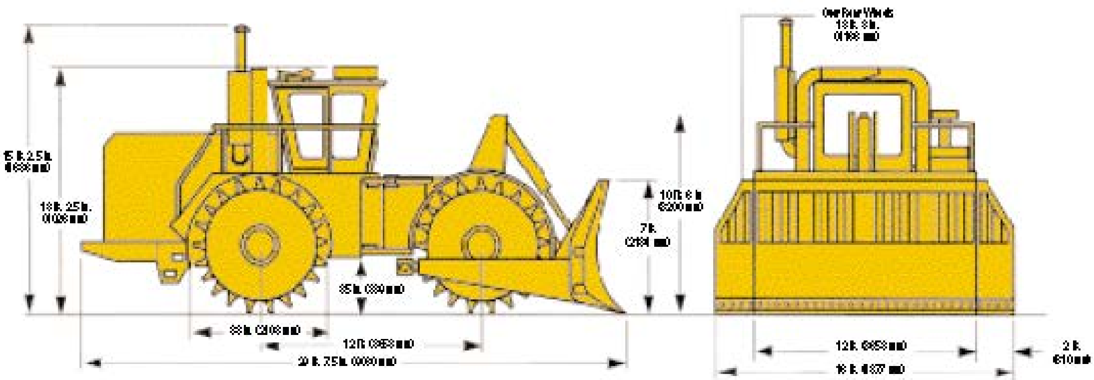
The system behind 3-90E's awesome pushing power

CMI 3-90E Trashmaster provides a superior level of pushing, climbing and compaction power no others can match — thanks to the high-performance power train system which is composed of a Cummins 525 hp QSK 19 diesel engine coupled with Trashmaster's proven hydrostatic drive system, plus extra-large diameter wheels and our ultra-efficient blade design.

On the landfill, this system has no equal. Fact is, the 3-90E power train is backed by a decade of landfill compaction experience, and field-proven results.

The new age of landfill design has begun. The large, high volume landfills are being designed to handle the world's growing waste stream. CMI's 3-90E Trashmaster offers unequalled compaction efficiency to maximize the capacity of your landfill sites, as well as the return on your investment.

CMI TRASHMASTER 3-90E Landfill Compactor



	English	Metric
Compactive Stress		
Crushing (Cleat)*	9,340 psi	660 kg/cm2
Compressing (Wheel)*	up to 767 PLI*	137 kg/cm*
Machine Dimensions		
Compaction Width	13 ft. 8 in.	4166 mm
Inside Turning Radius	12 ft. 4 in.	3759 mm
Outside Turning Radius	26 ft.	7925 mm
Blade Raise Above Grade	48 in.	1219 mm
Blade Lower Below Grade	6 in.	152 mm
Ground Clearance	35 in.	889 mm
Operating Weight*	up to 115,000 lbs.*	52163 kg
Shipping Specifications		
Shipping Weight	up to 115,000 lbs.*	52163 kg
Shipping Height	13 ft. 2.5 in.	4026 mm
Shipping Width Over Guard Rails	12 ft.	3658 mm
Shipping Length With Blade and with blade wings stored	28 ft. 8 in.	8738 mm

**Depending on options*

	English	Metric
Capacities		
Engine Coolant System	33 gals.	125 liters
Engine Crankcase	16 gals.	45 liters
Fuel	234 gals.	886 liters
Hydraulic System	110 gals.	454 liters
Hydrostatic System	60 gals.	280 liters
Wheel Ends	25 qts.	23.7 liters
Optional Equipment		
Air Conditioner With Cab Pressurizer	140 lbs.	64 kg
Back-up Alarm	4 lbs.	2 kg
Cab Fire Extinguisher	20 lbs.	9 kg
Cold Weather Starting	12 lbs.	6 kg
Fire Suppression System	115 lbs.	52 kg
Trak Lok™ Two-Piece Replaceable Cleats	1,944 lbs.	882 kg
Vandal Kit	14 lbs.	6 kg
Terra Twist Torque®	1,845 lbs.	837 kg
Wheel Rakers	1,291 lbs.	587 kg

CMI TRASHMASTER — the most efficient compactor available!

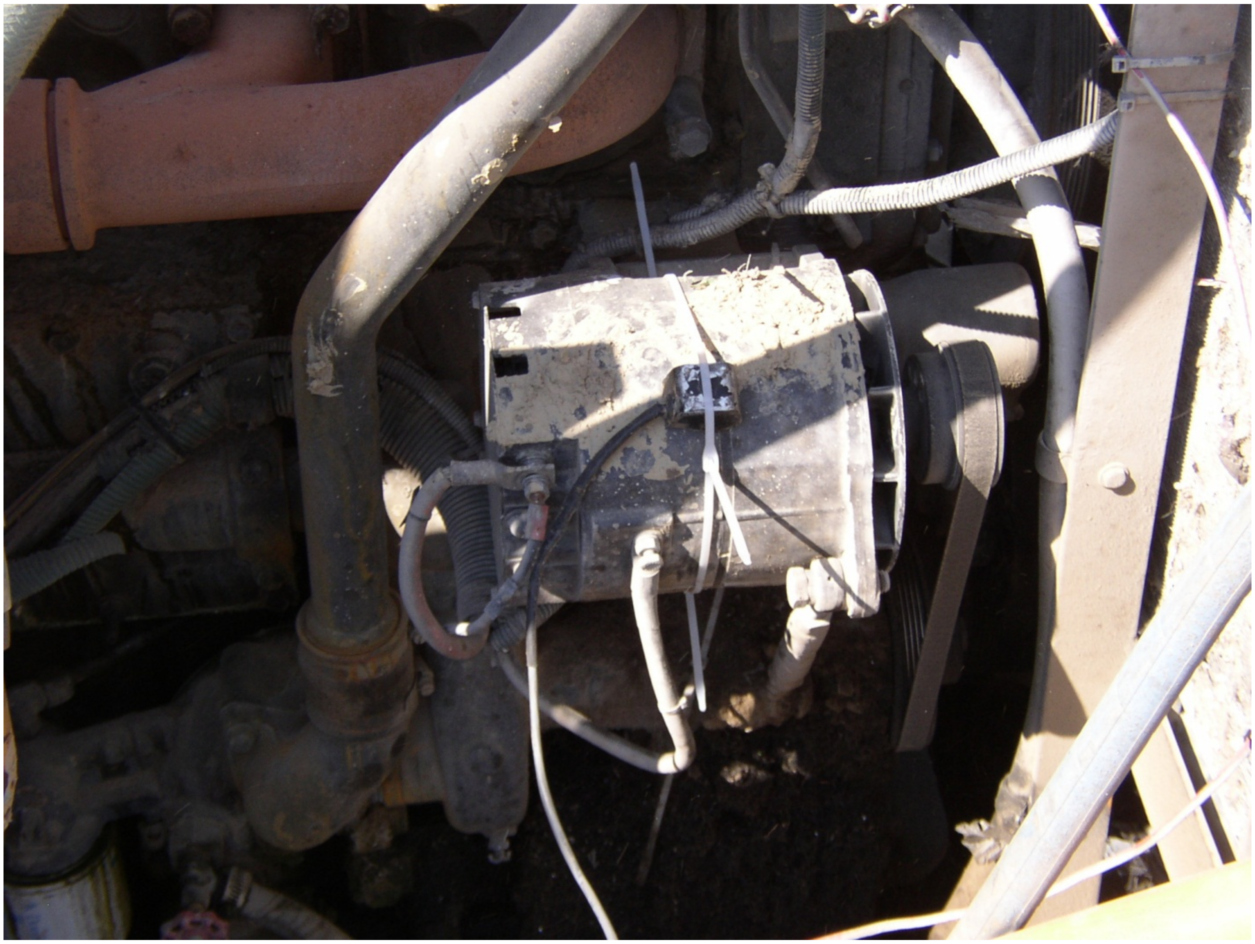
CMI TEREX Corporation
P. O. Box 1985
Oklahoma City, OK 73101-1985
Ph: 405/787-6020 Fax: 405/491-2417
Website: www.cmicorp.com

02-8383 10/02

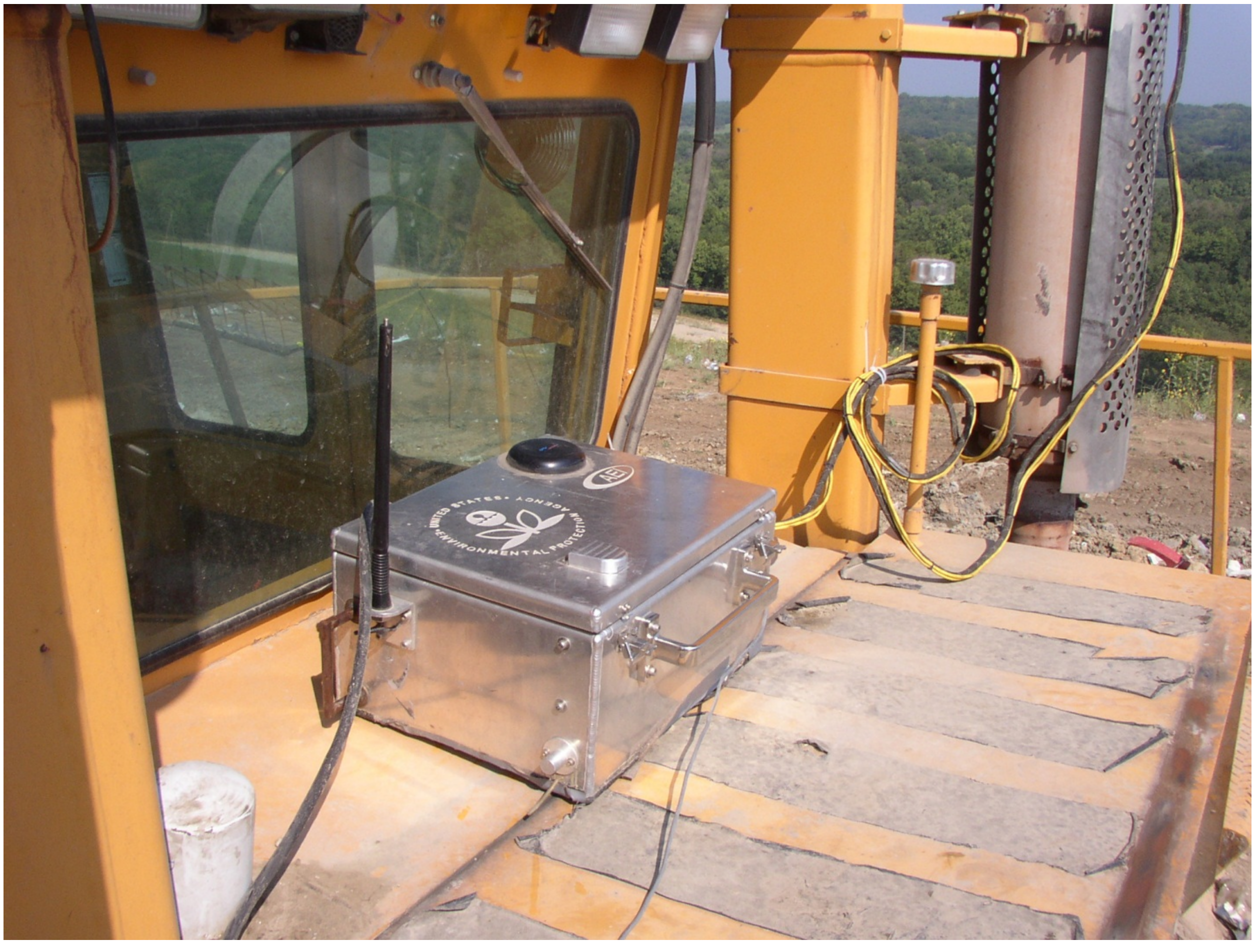
APPENDIX D: Field Sampling of Trashmaster 3-90 with SPOT Unit


NO STEP
-IMPORTANT-
DISCONNECT BATTERY CABLES
BEFORE WELDING
MAINTENANCE
FREE


NO STEP
-IMPORTANT-
DISCONNECT BATTERY CABLES
BEFORE WELDING
CAT
MAINTENANCE
FREE
153-5720

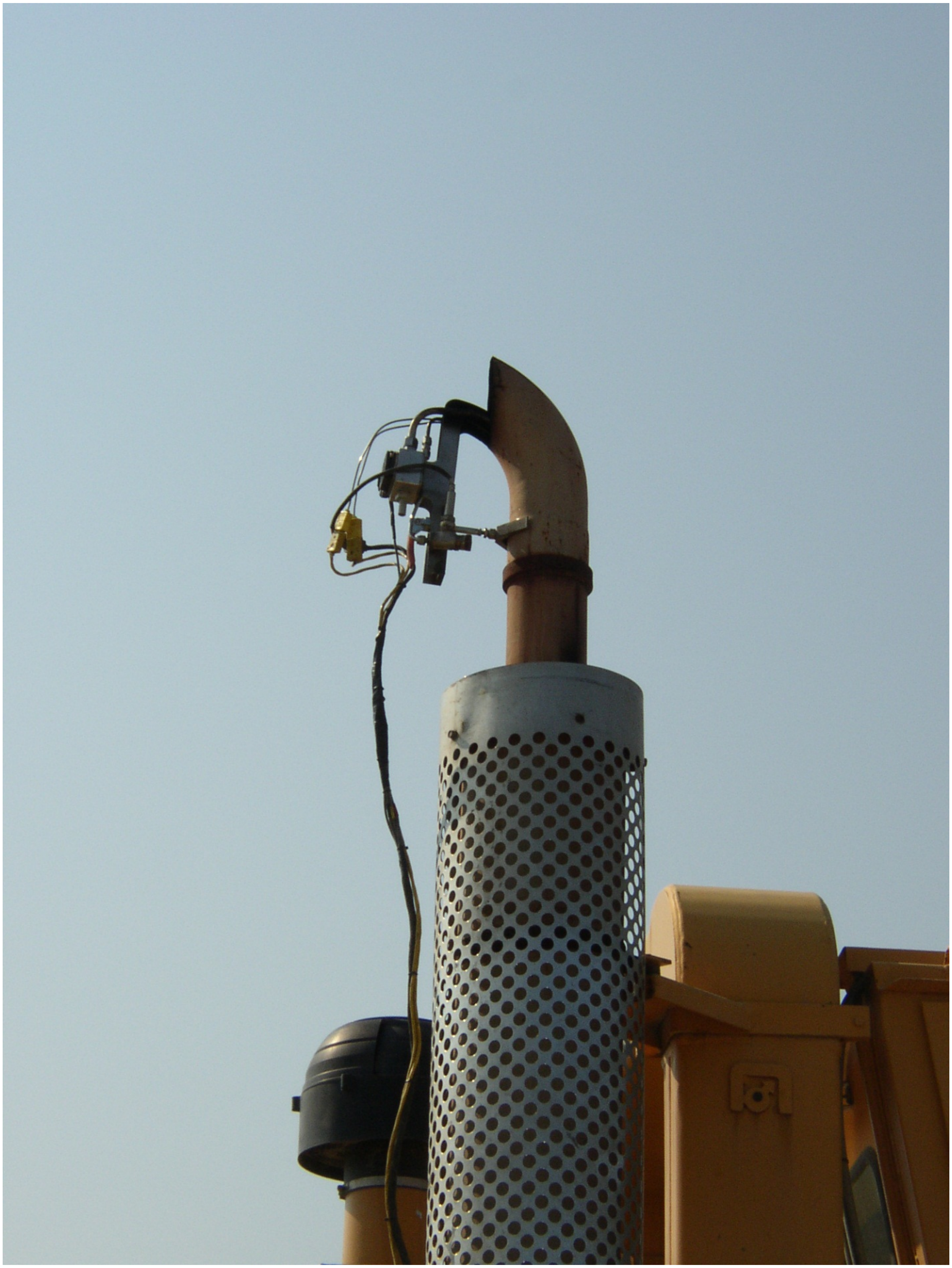



TRASHMASTER

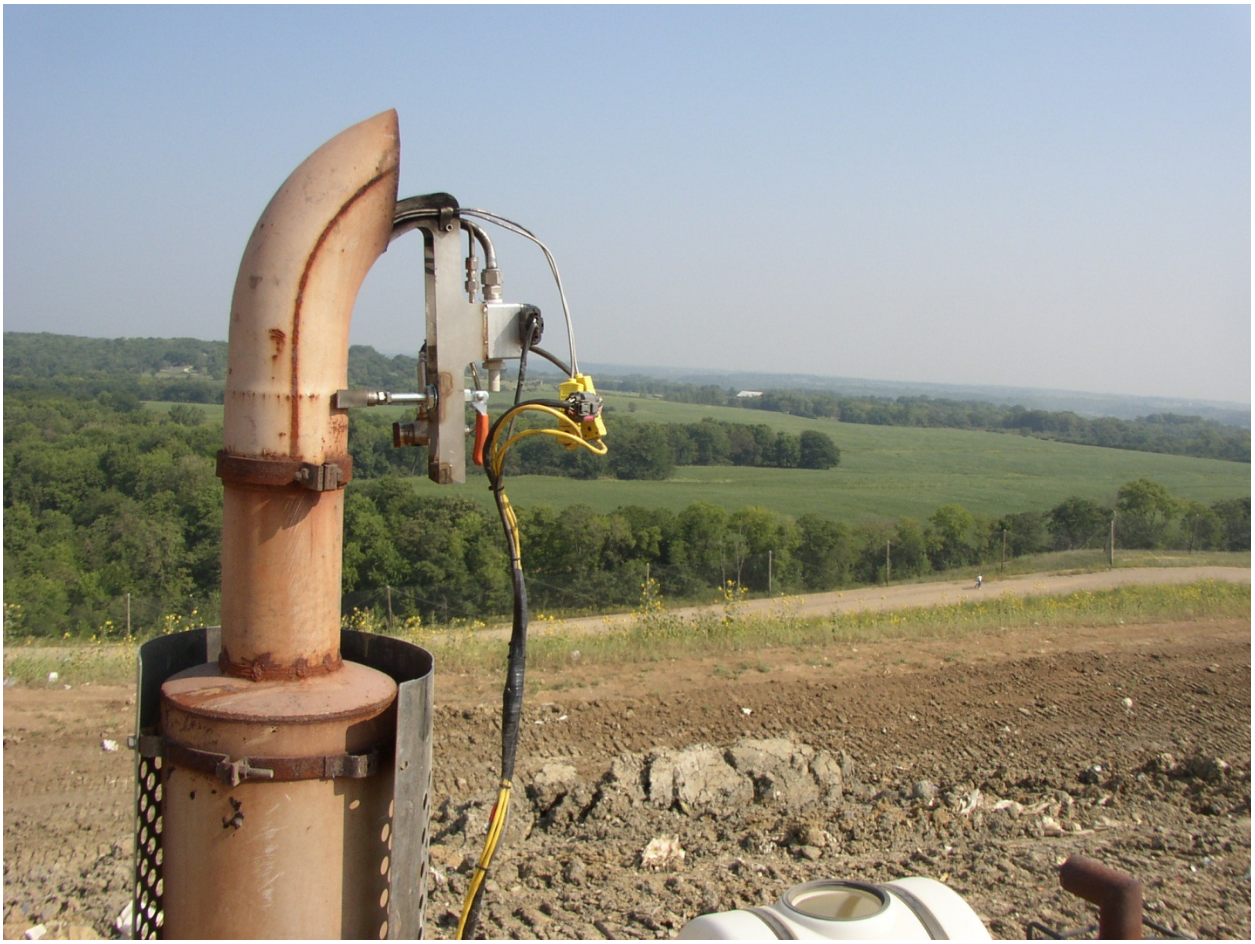



I-138 TRASHMASTER
390 E


RED DOT




ASHMASTER




FILL-RITE
Heavy Duty
12 Volt DC Pump


H38


390E


CAT
D7R


TRASHMASTER
3-90 E


TRASHMASTER


TRASHMASTER
1-138
TRASHMASTER
3·90 E