ON-ROAD MEASUREMENT OF NO_X AND CO_2 EMISSIONS FROM BIODIESEL PRODUCED FROM DIFFERENT FEEDSTOCKS

by

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ABSTRACT

ON-ROAD MEASUREMENT OF NO_X AND CO_2 EMISSIONS FROM BIODIESEL PRODUCED FROM DIFFERENT FEEDSTOCKS

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Biodiesel has generated increased interest in the US and elsewhere recently as an alternative to petroleum-derived diesel. Because it can be produced from domestic feedstocks such as soybeans, canola oil, and even recycled cooking oil, biodiesel can help reduce dependence on foreign petroleum. Due to its high oxygen content, biodiesel typically burns more completely than petroleum diesel, and thus has lower emissions of hydrocarbons (HC), carbon monoxide (CO), and particulate matter (PM). However, biodiesel may increase or decrease nitrogen oxide (NO_x) and carbon dioxide (CO_2) emissions, depending on engine type, test cycle, and biodiesel feedstock. Therefore, the purpose of this study was to compare emissions from biodiesel blend 20% (B20) made from various feedstocks, in an on-road setting using a portable emissions measurement system (PEMS) and a chassis dynamometer setting for a test vehicle (1994 Chevy Silverado). The study tested 4 biodiesel feedstocks (soybean oil, canola oil, waste cooking oil, and animal fat) compared with ultra low sulfur diesel (ULSD) using on-road testing under real-world driving conditions with a Horiba On-Board Measurement System OBS-1300 on a highway route and arterial route, and chassis dynamometer with Urban

Dynamometer Drive Schedule. Emissions of NO_x and CO_2 were measured second-by-second and compared for each feedstock with ULSD. For the dynamometer only, HC, CO, and PM were also measured. Biodiesel fuel specifications from each feedstock were tested and compared. The dynamometer test results showed statistically significant lower emissions of HC, CO, and PM from all B20 blends compared to ULSD. For CO_2, on-road testing (arterial, highway, and idling) and dynamometer testing showed no statistically significant difference in emissions among the B20 blends and ULSD. For NO_x, dynamometer testing showed only B20 from soybean oil to have statistically significant higher emissions. This is generally consistent with the on-road testing (arterial, highway, and idling), which showed no statistically significant difference in NO_x emissions between ULSD and the B20 blends. The results above are specific to the 1994 Chevy Silverado tested, and cannot be generalized to other vehicles.

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CHAPTER 1

INTRODUCTION

As global population increases and developing countries industrialize, energy demand around the world is increasing markedly. World energy consumption is expected to increase by 50% to 180,000 GWh/year by 2020 [1]. According to the Energy Information Administration's (EIA's) International Energy Outlook, world demand for crude oil is expected to grow from 84 million barrels/day in 2005 to over 114 million barrels/day in 2030 [2].

Biodiesel has generated increased interest in the US and elsewhere recently as an alternative to petroleum-derived diesel. Because it can be produced from domestic natural sources such as soybeans, rapeseed, and even recycled cooking oil, biodiesel can help reduce dependence on petroleum fuel from foreign sources, and thus foster energy independence [3]. The Energy Independence and Security Act, signed into law in December 2007, increased nationwide Renewable Fuels Standard (RFS) volume mandates: the total volume of renewable fuels, such as ethanol and biodiesel, blended into the US fuel supply must be 9 billion gallons in 2008 and 11.1 billion gallons in 2009 [4].

Biodiesel offers a number of advantages in addition to its potential for domestic production. Since it is made from animal and vegetable fats and oils, it is a renewable resource. It is more biodegradable than petroleum-derived diesel: over 90% of biodiesel will be degraded in 4 weeks in case of an accidental spill [5]. Blends of standard diesel fuel with up to 20% biodiesel (B20) can be used in existing engines without modification [6]. It burns more smoothly and quietly than petroleum-derived diesel, due to its higher cetane number [7]. Its lower vapor pressure and higher flash point than petroleum-derived diesel make it safer to handle and store

[8]. Moreover, biodiesel has better lubricant properties than diesel fuel. In terms of emissions, biodiesel has lower sulfur content, leading to lower emissions of sulfur dioxide. Its oxygen content improves the combustion process, which is more complete, leading to decreased tailpipe emissions. Its aromatic content is also lower, which is important because many aromatics are hazardous air pollutants, and are active in forming ground-level ozone.

However, biodiesel has some disadvantages compared with diesel fuel, including the fact that biodiesel fuel produces slightly lower power and torque and thus consumes more fuel than petrodiesel. It has higher viscosity, higher cloud point and pour point, and injector coking. Other disadvantages include fuel freezing in cold weather, reduced energy density, and degradation of fuel under storage for prolonged periods.

Biodiesel consists of alkyl monoesters of fatty acids. It is obtained from triglycerides through the tranesterification process, which involves reaction with an alcohol such as methanol or ethanol. Global biodiesel production capacity is growing rapidly, with average annual growth from 2002-2006 of over 40% [9]. Sales of biodiesel in the US were estimated to be 250 million gallons in 2006, which was 0.5% of the total market [10]. US biodiesel production potential, based on soybean feedstock alone and current levels of soybean production, is 1.5-3 billion gallons [11]. As oil prices continue to rise, energy independence is emphasized, and U.S. and international markets for biodiesel are likely to grow.

Previous studies agree that biodiesel reduces emissions of hydrocarbons, carbon monoxide, particulate matter, and sulfur dioxide compared to regular diesel. Previous studies of nitrogen oxide (NO_x) and carbon dioxide (CO_2) emissions, however, are inconclusive, with some reporting higher emissions and some reporting lower emissions of biodiesel compared to regular petroleum diesel; these studies will be discussed in detail in Chapter 2. The purpose of this study is thus to compare NO_x and CO_2 emissions from biodiesel made from various feedstocks, in an on-road setting using a portable emissions measurement system (PEMS) and a chassis dynamometer setting.

The 3 factors that determine the amount of pollutant reduction for biodiesel, compared to regular diesel, are biodiesel feedstock, test cycle, and engine type. This study examines the impact of 4 biodiesel feedstocks (soybean oil, canola oil, waste cooking oil, and animal fat) and 4 test cycles (arterial on-road, highway on-road, idling, and dynamometer UDDS driving cycle) on NOx and CO_2 emissions from one vehicle. This study is more comprehensive than previous biodiesel feedstock comparison studies, in terms of number of test cycles examined (4): previous studies tested at most two test cycles or used steady-state testing. In addition, no previous study to our knowledge has compared biodiesel NO_x and CO_2 emissions from a variety of feedstocks using on-road testing. Only one on-road biodiesel emissions study has been conducted, and it looked at biodiesel from only one feedstock (rapeseed). A study by Frey and Kim (2006) [50] of dump trucks indicates that biodiesel emissions in real-world settings may differ considerably from studies conducted using a chassis dynamometer or engine test stand.

Impact of biodiesel emissions on NO_X is of particular concern to Texas, with ozone non-attainment regions of Dallas-Fort Worth, Houston-Galveston-Brazoria, and Beaumont-Port Arthur, with NO_X serving as a significant precursor. Quantifying CO_2 emissions from biodiesel is important given EPA's authority to regulate CO_2 and the mandatory greenhouse gas reporting rule.

CHAPTER 2

LITERATURE REVIEW

Recently, fossil fuel has been the main energy supply for the world. Fossil fuel energy sources include petroleum, coal, natural gas, bitumens, oil shales, and tar sands. Fossil fuels are not renewable over human life spans and are the primary sources globally of traditional air pollutants (nitrogen oxides, sulfur oxides, carbon monoxide, and particulates), as well as carbon dioxide. Therefore, clean energy sources which are renewable and environmentally cleaner are needed to replace fossil fuel. Biodiesel fuel is one alternative fuel to consider because it is renewable, available to use, low in sulfur and aromatic content, biodegradable, non-toxic, and lowers some pollutants compared to fossil fuel. Base on life cycle analysis of biodiesel and petroleum diesel, biodiesel from pure vegetable oil reduces carbon dioxide emissions when used to replace petroleum diesel [12]. One study found that compared to petroleum diesel, biodiesel reduces net emissions of CO_2 by 78%. [13] Another life cycle analysis of used vegetable oil biodiesel compared to petro-diesel found that CO_2 emissions of B100 were 92% lower and emissions of B20 were 18% lower than those from petroleum diesel [14].

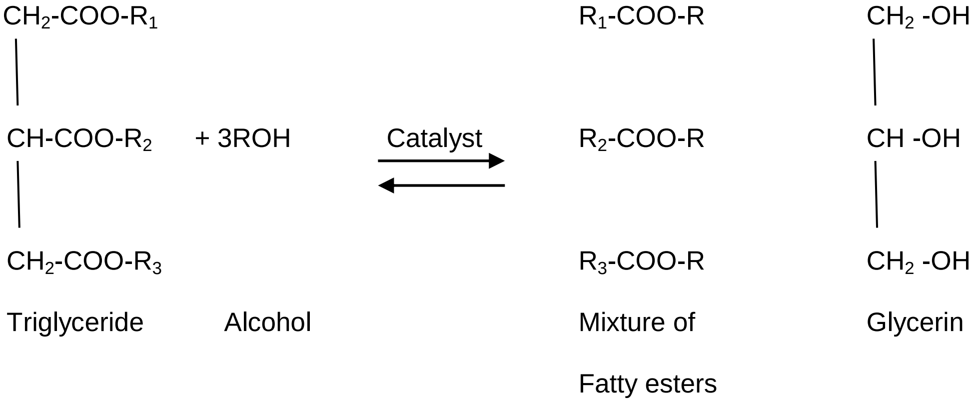
Biodiesel can be produced from various feedstocks, including pure vegetable oil such as rapeseed and soybean, which are most commonly used in Europe and the United States, respectively, along with other crops such as mustard, palm oil, cottonseed, sunflower, hemp, and algae. In addition, waste vegetable oil; animal fats including tallow, lard, and yellow grease; and non-edible oils such as jatropha, neem oil, castor oil, and tall oil, are also used to produce biodiesel. Biodiesel made from non-food crops is called “second generation” biodiesel, and is increasingly emphasized so that it does not compete with food as an end-use of crops. In the

United States, soybean oil is the primary feedstock because the United States is the largest producer of soybean oil. In Malaysia and Indonesia, palm oil is used as main feedstock for biodiesel production. In India and southeast Asia, jatropha, a non-food plant, is used as a common base source [12]. The biodiesel cost varies depending on different feedstocks, geographic area, crop production by season, crude petroleum price, and other factors.

Biodiesel can be used both pure (also called neat or 100%), or blended with regular diesel fuel in different ratios. Biodiesel blends are referred to as BXX. The XX indicates the amount of biodiesel in the blend; for example, a B20 is 20% biodiesel and 80% petrodiesel.

Biodiesel is a typically produced through the reaction process between a vegetable oil or animal fat with an alcohol (methanol or ethanol) in the presence of a catalyst such as sodium or potassium hydroxide to yield methyl or ethyl esters (biodiesel) and glycerin [15]. The process to produce biodiesel is called transesterification. Generally, methanol is preferred in the transesterification process because it is less expensive than ethanol [16].

The transesterification process product is known as biodiesel. Tranesterification is the reaction between fat or oil triglyceride and an alcohol to form esters and glycerol as byproduct. Figure 2.2 shows transesterification reaction. In the process, a catalyst is used to activate the reaction rate and yield. The reaction is reversible; excess alcohol is used to shift the equilibrium to the byproduct [12].



$$\begin{array}{lcccc} CH_2\text{-}COO\text{-}R_1 & & & R_1\text{-}COO\text{-}R & CH_2\text{-}OH \\ | & & & & | \\ CH\text{-}COO\text{-}R_2 & +\ 3ROH & \underset{}{\overset{\text{Catalyst}}{\rightleftarrows}} & R_2\text{-}COO\text{-}R & CH\text{-}OH \\ | & & & & | \\ CH_2\text{-}COO\text{-}R_3 & & & R_3\text{-}COO\text{-}R & CH_2\text{-}OH \\ \text{Triglyceride} & \text{Alcohol} & & \text{Mixture of Fatty esters} & \text{Glycerin} \end{array}$$

Figure 2.1 Transesterification reaction between triglyceride and alcohol.

2.1 General Biodiesel Emission Trends

Around 10% of biodiesel by weight is oxygen; this oxygen leads to more complete combustion, which lowers emissions of hydrocarbons (HC)/volatile organic compounds (VOCs), carbon monoxide (CO), and particulate matter (PM) compared with petroleum diesel [3,7,17]. All 3 of these pollutants result from incomplete combustion of fuel: hydrocarbons from fuel fragments that are not oxidized, CO from incomplete oxidation of fuel (CO_2 is not formed), and PM from unburned hydrocarbons in solid form. The 3 factors that determine the amount of reduction of these pollutants for biodiesel are engine type, test cycle, and biodiesel feedstock. The U.S. Environmental Protection Agency [18] summarized biodiesel emission data published through 2001 for heavy duty engines, and reported the % changes compared to standard diesel as summarized for a 20% biodiesel/80% standard diesel blend (B20) in Table 2.1. McCormick et al. (2006) summarized data published since the EPA review; McCormick's findings are also summarized in Table 2.1. Since biodiesel is essentially free of sulfur, SO_2 emissions are 99% lower than for petroleum diesel. It is also essentially free of aromatics, some of which are carcinogens [3, 19].

Table 2.1 Summary of Biodiesel Emissions Compared with Standard Diesel (EPA, 2002 & McCormick, 2006)

Pollutant	B20 Emission Percent Change Compared to Standard Diesel			
	EPA Range	EPA Avg.	McCormick Range	McCormick Avg.
NO_X	-7 to +7	-2.0	-10.3 to +6.0	-0.6 to 2.0 (95% CI)
PM	-5 to -60	-10.1	-31 to 0	-14.1
CO	-5 to -35	-11.0	-38 to 0	-16.6
HC	---	-21.1	-30 to 0	-11.4

As shown in Table 2.1, biodiesel's impact on nitrogen oxide (NO_X) emissions varies. When 100% biodiesel (B100) is burned in a diesel engine without modification, NO_X increases in most cases [17]. When B20 is burned, NO_X emissions may increase or decrease, depending on engine type, test cycle, and biodiesel feedstock [17, 20]. Potential NO_X increases pose a concern since NO_2 itself is a criteria pollutant, and NO_X contributes to formation of ozone, fine particles, and acid precipitation.

Similarly, biodiesel's impact on carbon dioxide (CO_2) emissions varies. Previous studies have reported CO_2 emission changes ranging from a 19% increase to a 24% decrease, for biodiesel use compared with standard diesel [21]. As is the case with NO_X, these variations likely depend on engine type, test cycle, and biodiesel feedstock. However, noone to our knowledge has thus far systematically investigated the influence of biodiesel feedstock on CO_2 emissions. For a given engine type and drive cycle, CO_2 produced should correlate with the carbon content of the fuel, which would vary according to feedstock. For a given feedstock and driving cycle, emissions would vary according to the engine efficiency, with less efficient engines requiring more fuel to be burned per mile and thus producing more CO_2 per mile.

The Supreme Court ruled in 2007 that the Environmental Protection Agency has the authority to regulate carbon dioxide as a pollutant under the Clean Air Act. Additionally, in 2008 Congress directed EPA to publish a mandatory greenhouse gas reporting rule, using the Agency's existing authority under the Clean Air Act. The rule requires mandatory reporting of greenhouse gases "above appropriate thresholds in all sectors of the economy." Thus, gaining a better understanding of potential CO_2 emissions from biodiesel is important.

2.2 Impact of Biodiesel Feedstock on NO_X Emissions

Biodiesel is derived from vegetable oils or animal fats via transesterification, in which a triglyceride (a glycerine ester of 3 fatty acids) reacts with an alcohol (methanol or ethanol) via a catalyst (KOH or NaOH). The triglyceride splits into a mixture of methyl or ethyl esters of their free fatty acids, which is called biodiesel, and the byproduct glycerol. Since vegetable oils are triglycerides of a variety of fatty acids, when different oils are transesterified to methyl esters, the resulting different compositions of methyl esters lead to different combustion characteristics for the biodiesel [3].

NO_X production in particular would be anticipated to vary for biodiesel from different feedstocks. A number of studies have compared NO_X emissions from standard diesel with emissions from biodiesel [11, 19-48, 55-56]. Most of these, however, do not report the biodiesel feedstock, or only tested one feedstock. Comparing emissions among studies is difficult due to different engines and testing protocols.

Table 2.2 summarizes the handful of studies that have compared NO_X emissions from biodiesel from various feedstocks. NO_X emissions may increase or decrease for a given feedstock, due to differences in engine type and test cycle.

Table 2.2 Comparison of NO_X Emissions from Biodiesel from Various Feedstocks

Study	Vehicle/ Engine Tested	Test Method	Feedstocks	Blend	NO_X Emissions Change due to Biodiesel	Change Statistically Significant?
Peterson et al. (2000)	1994 Dodge 2500 pickup truck	Chassis dyno, EPA driving schedule for heavy-duty vehicles	Coconut ethyl ester, hydrogenated soy methyl ester, rapeseed ethyl ester, mustard ethyl ester, safflower ethyl ester, soy oil methyl ester	B20	-5 to -13%, NO_X emissions correlated with blend iodine number	No statistical analysis
				B100	0 to -23%	No statistical analysis
Tat (2003)	John Deere 4045T engine	Engine dyno, steady-state, 1400 rpm	Soy	B100	+14%	Yes (95%)
			Yellow grease (waste oil from restaurants)		+1%	No (95%)
Rakopoulos et al. (2006)	Ricardo/ Cussons “Hydra” Diesel engine	Engine dyno, 2000 rpm, 38% and 75% of full load	Methyl esters from 5 feedstocks (cottonseed, soybean, sunflower, rapeseed, and palm oils) 5 vegetable oils (olive cottonseed, soybean, sunflower, corn)	B10, 20	0 to -5%	Yes, slightly (confidence level not reported)

Table 2.2 – *Continued*

Frey, Kim (2006)	Dump trucks (single rear Tier 1, 2, tandems Tier 1, 2	On-road	Soy	B20	-10% of NO	No
Ropkins et al. (2007)	EURO I Ford Mondeo	On-road	Rapeseed methyl ester	B5	+8 to +13%	Yes (95%)
Frey et al. (2008)	Nonroad vehicles	On-road	Soy	B20	-2% of NO	No
Muncrief et al. (2008)	Refuse hauler	Chassis dyno, West Virginia University (WVU) refuse truck duty cycle	Soy	B100	0	No
			Cottonseed	B20, 50, 100	0.9 to -13%	No
Frey, Kim (2009)	Cement mixer trucks	On-road	Soy	B20	-2% of NO	No
Karavalakis, Stournas, and Bakeas (2009)	1998 Toyota Corolla 2.0 TD	Chassis dyno, Athens Driving Cycle (ADC) and New European Driving Cycle (NEDC)	Soy	B5, 10, 20	0 to +12%	Yes (95%)
Karavalakis, Stournas, and Bakeas (2009)	1998 Toyota Corolla 2.0 TD	Chassis dyno, ADC and NEDC	Rapeseed and Palm oil	B5, 10, 20	+2.3% RME20 -10.9% PME5 -12.1% PME10 +2% PME20	No (95%)
Fontaras et al. (2009)	VW Golf 1.9 TDi	Chassis dyno, NEDC	Soy	B50, 100	-2 to -3% for B50, +6 to +9% for B100	No statistical analysis
Wu, Wang, Chen, and Shuai (2009)	Cummins ISBe 6	Engine dyno	Palm oil, Soybean, Rapeseed, Cottonseed, and Waste cooking oil	B100	+10 to +23%	No statistical analysis
Aydin, and Ilkilic (2010)	Rainbow 186	Engine dyno	Sunflower oil	B20, BE20	Slightly increase	No statistical analysis

Table 2.2 – *Continued*

Buyukkaya (2010)	Man TDi	Engine dyno	Rapeseed	B5, 20, 70, 100	+6% B20, +9% B70, +12% B100	No statistical analysis
Fontaras et al. (2010)	Renault Laguna 1.9 DCi	Chassis dyno (NEDC)	Rapeseed, Soybean, Sunflower, Palm, and Waste fried oil	B10	+8% PME +11% SUME -6% UFOME -7% SME 0% RME	Yes (95%)
Gumus, and Kasifoglu (2010)	Lombardini 6 LD 400	Engine dyno	Apricot seed kernel oil methyl ester (ASKOME)	B5, 20, 50	Slightly higher than diesel fuel	No statistical analysis
Kousoulidou et al. (2010)	PSA DW12A TED 2.2 L	Engine dyno	Palm oil, Rapeseed	B10	-6 to +4%	No
Ryu (2010)	HD D4BB	Engine dyno	Soybean plus antioxidant	B100	Slightly higher than diesel fuel	No statistical analysis

Seven studies in Table 2.2 did statistical analysis, with the following results:

- Two studies – Tat (2003) and Karavalakis, Stournas, and Bakeas (2009) – found that only soy biodiesel increased NO_x emissions by an amount that was statistically significant; biodiesel from yellow grease, rapeseed, and palm oil did not.
- Three studies - Muncrief (2008), Ropkins et al. (2007), and Kousoulidou et al. (2010) - found that neither soy, cottonseed, rapeseed, nor palm biodiesel changed NO_x emissions significantly.
- Rakopoulos et al. (2006) reported statistically significant decreases in NO_x from biodiesel from a variety of feedstocks, including soybean.
- Fontaras et al. (2010) found statistically significant increases and decreases, depending on feedstock. NO_x emissions from soy biodiesel were 7% lower than those from regular diesel.

Currently, 90% of US biodiesel is produced from soybeans, so emissions from soy-derived biodiesel are of particular interest. The studies above that included statistical analysis found that NO_x emissions from soy-derived biodiesel in 2 cases increased, in one case were the same, and in two cases decreased. This is likely due to variability in results among vehicles: previous studies indicate that biodiesel emission results for one vehicle cannot be generalized. Frey et al. [55, 56] found that the use of B20 instead of petroleum diesel led to an insignificant 2% decrease in the NO emissions.

Only one study in Table 2.2 involved on-road testing. Frey and Kim [50] indicate that biodiesel emissions in real-world on-road settings may differ considerably from studies conducted using a chassis dynamometer or engine test stand. Testing four categories of dump trucks in a real-world setting, Frey and Kim found biodiesel NO_X emissions to be 20% lower than standard diesel emissions. Dynamometer testing, particularly using a standard driving cycle, may not adequately capture real-world acceleration/deceleration patterns, which significantly impact emissions. Although Frey and Kim only measured NO emissions (not NO_2), 90% of emissions from fossil fuel combustion typically are NO.

California Air Resources Board is currently conducting a biodiesel emissions study, but it involves a limited feedstock comparison of soy-derived biodiesel vs. animal-derived biodiesel [51].

Feedstocks that produce greater numbers of unsaturated hydrocarbon molecules in the biodiesel would be anticipated to increase biodiesel NO_x emissions, due to three factors:

- Unsaturated hydrocarbons have higher adiabatic flame temperatures, due to greater energy contained in their double bonds. They would thus be anticipated to burn at higher temperatures and produce more NO_x according to the Zeldovich mechanism (NO_x emissions are a strong function of flame temperature) [3].
- Unsaturated molecules burn slower, increasing ignition delay. The longer the ignition delay, the longer time the reactants (fuel and oxygen) have to preheat, which increases flame temperature and increases NO_x emissions according to the Zeldovich mechanism [3]. (Cetane number is used as a measure of a fuel's ignition delay. Unsaturated molecules have lower cetane numbers and greater ignition delay.)

- Unsaturated molecules have a higher bulk modulus of compressibility, or resistance to uniform compression. Pump-line-nozzle (PLN) injection systems generally start fuel injection when the fuel reaches a certain pressure. When compressed, fuels with higher resistance to compressibility achieve higher pressures sooner. Fuel injection thus starts earlier, increasing the residence time of the burning mixture in the cylinder and allowing NO_x formation to proceed [3], [7].

Not only variation in the number of unsaturated molecules but also in the length of hydrocarbon molecules can cause NO_x emissions from biodiesel of different feedstocks to vary. Cetane number increases as molecule length increases, with a corresponding decrease in NO_x emissions [3].

2.3 CO_2 Emissions from Biodiesel

Most biodiesel studies do not include CO_2, focusing instead on PM, NO_X, HC, and/or CO [22-24, 28-30, 32, 34-38, 40-42, 44, 46, 48, 52-54, 56]. Table 2.3 summarizes the few studies that have measured biodiesel impacts on CO_2.

Table 2.3 CO_2 Emissions from Biodiesel Compared with Standard Diesel

Study	Vehicle/ Engine Tested	Test Method	Feedstock	Blend	CO_2 Emissions Change due to Biodiesel	Change Statistically Significant?
Kocak, Ileri, Utlu (2007)	Land Rover TDI 110	Engine dyno, full load, various rpms	Waste cooking oil, hazelnut oil, canola oil	B100	-12 to -14%	No statistical analysis
Lin, Wu, and Chang (2007)	Yueloong Diesel SD22	Rpms from 1000 to 2000	Waste oil	B20, 50, 80, 100	-19 to +24%	No statistical analysis
Ropkins et al. (2007)	EURO I Ford Mondeo	On-road	Rapeseed methyl ester	B5	No significant change	No (95%)

Table 2.3 – *Continued*

Muncrief et al. (2008)	Refuse hauler	Chassis dyno, West Virginia University (WVU) refuse truck duty cycle	Soy	B100	0	No
			Cottonseed	B20, 50, 100	- 0.9 to -3.4%	No
Utlu and Kocak (2008)	Land Rover TDI 110	Engine dyno, full load, various rpms	Waste frying oil	B100	-8%	No statistical analysis
Frey, Kim (2009)	Cement mixer trucks	On-road	Soy	B20	+0.5%	NO
Karavalakis, Stournas, and Bakeas (2009)	1998 Toyota Corolla 2.0 TD	Chassis dyno, Athens Driving Cycle and New European Driving Cycle	Soy	B5, 10, 20	-5.1 to +0.8%	No (95%)
Karavalakis, Stournas, and Bakeas (2009)	1998 Toyota Corolla 2.0 TD	Chassis dyno, Athens Driving Cycle and New European Driving Cycle	Rapeseed, and Palm oil	B5, 10, 20	-3 to -14% for RME5, RME10, PME5, PME10 -4.8 to +1.2% for PME20	No (95%)
Fontara et al. (2009)	VW Golf 1.9 TDi	Chassis dyno, NEDC	Soy	B50, 100	B50 had no impact on CO_2 with Artemis driving cycles, +2 to +4% for B100	No statistical analysis
Aydin, and Ilkilic (2010)	Rainbow 186	Engine dyno	Sunflower oil	B20, BE20	-67% for B20 compare with diesel fuel	No statistical analysis
Fontaras et al. (2010)	Renault Laguna 1.9 DCi	Chassis dyno (NEDC)	Rapeseed, Soybean, Sunflower, Palm, and Waste fried oil	B10	+4% SUME -2% UFOME	Yes (95%)
Gumus, and Kasifoglu (2010)	Lombardini 6 LD 400	Engine dyno	Apricot seed kernel oil methyl ester (ASKOME)	B5, 20, 50	Lower for B5 and B20, Increasing with increasing blend	No statistical analysis

The studies in Table 2.3 observed CO_2 emission changes associated with biodiesel use ranging from a 24% increase to a 19% decrease. Of the six studies that conducted statistical analysis, only one found a statistically significant difference in CO_2 emissions from biodiesel (an increase from one feedstock and a decrease from another). Only one study in Table 2.3 involved on-road testing.

CO_2 emissions needed for a greenhouse gas inventory, in g/mi (multiplied then by vehicle miles traveled to obtain g), cannot be obtained simply from a mass balance on the feedstock carbon. For a given feedstock, the amount of fuel used, and thus the emissions in g/mi, will vary according to the engine efficiency, with less efficient engines requiring more fuel to be burned per mile and thus producing more CO_2; and according to driving cycle, with driving cycles with more accelerations requiring more power, and thus more fuel, and thus producing more CO_2 per mile. Therefore, dynamometer and/or on-road studies will be necessary to quantify CO_2 emissions for regional inventories. Although biodiesel fuel sales could be used to quantify regional emissions, such data is likely proprietary and therefore not obtainable. According to previous experience with the Dallas/Fort Worth regional emission inventory, statewide gasoline sales are available, but sales by county are not.

MOVES (MOtor Vehicle Emissions Simulator), the EPA model for estimating emissions from on-road mobile sources, currently do not include biodiesel as a fuel. When enough dynamometer and on-road studies measuring CO_2 from biodiesel are completed, a biodiesel fuel option will be able to be incorporated into MOVES. The data from this study would contribute toward that end.

CHAPTER 3

METHODOLOGY

This chapter provides an overview of testing including test vehicle characteristics, biodiesel fuel preparation and properties, on-road testing equipment and procedure, meteorological data collection, and dynamometer test procedure.

3.1 Test Vehicle

The test vehicle was a 1994 diesel Chevy C/K 2500 ¾ ton pickup truck, with an extended cab and long bed, shown in Figure 3.1. Information about the vehicle is given in Table 3.1.

Figure 3.1 1994 Chevy C/K 2500

Table 3.1 Test Vehicle Specifications

Parameter	Value
Overall length, in.	236.6
Overall height, in.	73.8
Overall width, in.	76.8
Engine	155 hp, 6.5 L Detroit Diesel V-8
Fuel Tank capacity	34 gallons
Curb Weight, lbs	4387
Transmission	4-speed automatic

3.2 Biodiesel Fuel Properties

Biodiesel from the following feedstocks were tested including soybean oil, canola oil, waste cooking oil, and animal fat. Soybean and canola oil were selected to represent biodiesel made from vegetable oil. As mentioned previously in the United States, soybean oil is the primary feedstock because the United States is the largest producer of soybean oil. Waste cooking oil and animal fat biodiesel included as waste product sources which would not compete with food crops. B20 was tested, because it is more likely to be used in commercial. In addition, blends of standard diesel fuel with up to 20% can be used in existing engines without modification [6]. Ultra low sulfur diesel was tested as a baseline fuel.

Chemical and physical properties of the biodiesels from 4 feedstocks and ULSD were determined by an independent testing laboratory. Properties measured included acid number, viscosity, flash point, cloud point, sulfur content, distillation, cetane number, ash content, water and sediment, copper corrosion, oxidation stability, biodiesel content, carbon weight percent, hydrogen weight percent, nitrogen weight percent, and oxygen weight percent, all according to ASTM methods.

3.3 Biodiesel Fuel Preparation

Vegetable oil (soybean and canola) and waste cooking oil biodiesel fuel were produced at the Mechanical and Aerospace Engineering Laboratory, University of Texas at Arlington

(UTA). The process of preparing biodiesel from soybean, canola and waste cooking oil is shown in Figure 3.2 and Figure 3.3. Animal fat biodiesel was provided by Houston Biodiesel.

Figure 3.2 Biodiesel fuel preparation from soybean, canola and waste cooking oil

The transesterification method that was used for producing biodiesel from vegetable oil and waste cooking oil was as follows:

1. Soybean and canola oil were obtained from the J.M. Smucker Company (Crisco) and Wal-Mart Great Value, respectively. Waste cooking oil was collected from the cafeteria at UTA and then filtered using a filter cloth and a strainer.

2. The vegetable oil or waste cooking oil was mixed with methanol in a molar ratio of 7.55:1 methanol to oil and 0.9 M concentration of KOH to achieve 1.77 wt%.

3. The vegetable oil or waste cooking oil/methanol/KOH mixture was heated to about 60°C and then stirred for 1 hour.

4. Stirring was stopped and the mixture was allowed to settle. Phase separation was observed within 10 minutes and was complete within 2 hours. Complete settling could take as long up to 20 hours. The glycerol layer, which settled down, was drained from the bottom of the container, as shown in the right-most picture of Figure 3.2.

5. The methyl ester, which formed the upper layer in the container, then needed to be washed. The washing process was carried out to remove some unreacted remaining methanol and catalyst by using water and blowing air by bubbling it approximately 3 to 4 hours. After that, the soapy water was drained from the container and replaced with fresh water, and air was blown again. The same process was repeated until the methyl ester layer was clear and the water was also clear. This process required replacing the water 4-5 times.

6. After washing methyl ester, then the byproduct of process was pure biodiesel (B100). B20 was prepared by mixing B100-20% with diesel fuel-80%. Mixing was conducted in a fuel tank and stirred by hand.

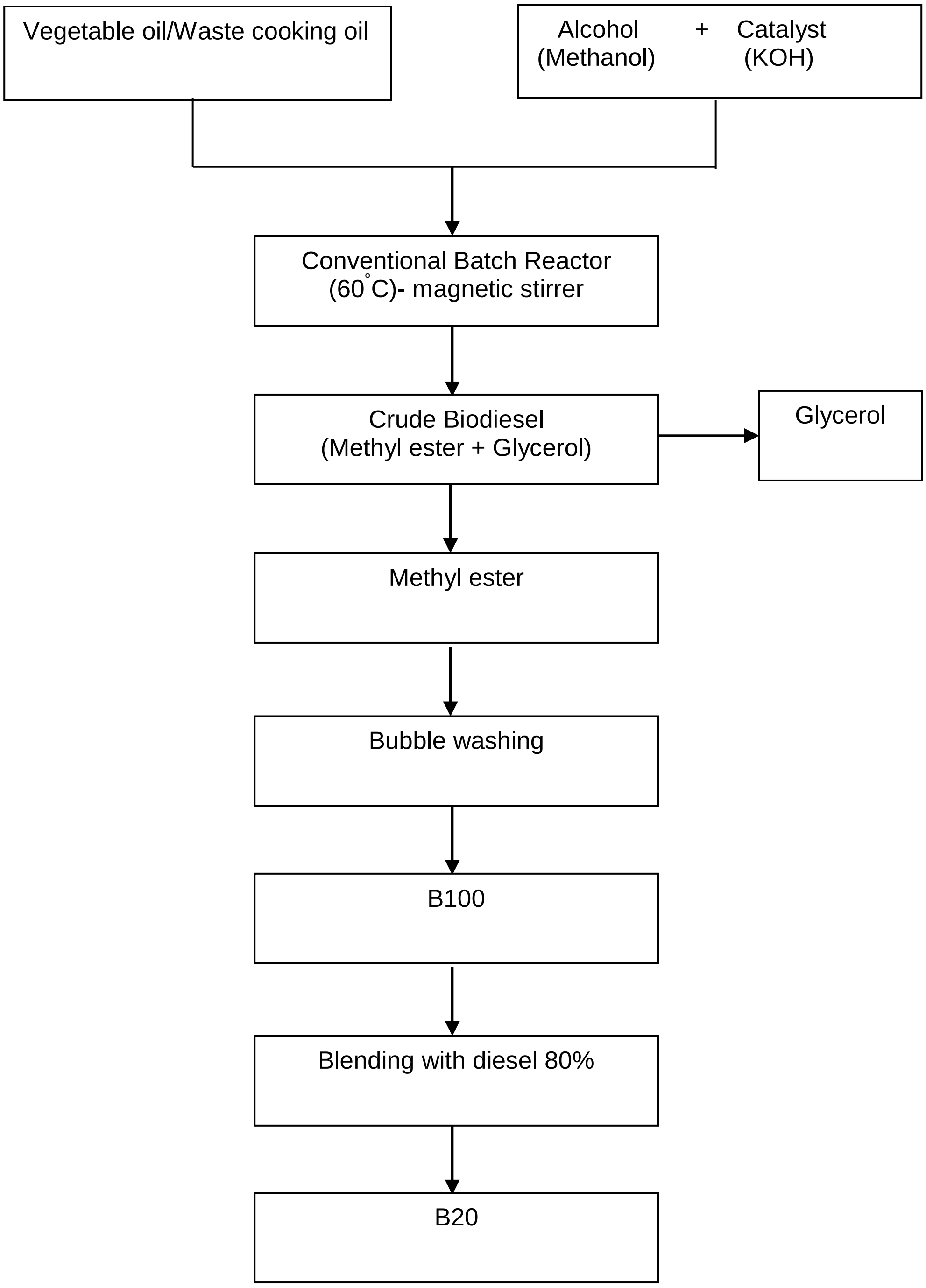


Figure 3.3 Transesterification of vegetable oil and waste cooking oil

3.4 Meteorological Data Measurements

A weather station (Davis Instruments Wireless Vantage Pro2 Plus with Weatherlink, shown in Figure 3.4) was used to continuously automatically record temperature, humidity, pressure, wind direction and speed, UV and solar radiation, and rainfall.

Figure 3.4 Davis Instruments Wireless Vantage Pro2 Plus with Weatherlink

3.5 On-Road Testing Equipment

Emissions were measured as the vehicle traveled on-road using a portable emission measurement system (PEMS), or On-Board emission measurement System OBS-1300, manufactured by Horiba, Inc., shown in Figures 3.5 and 3.6. OBS-1300 measures NO_X, HC, CO, and CO_2 second-by-second, along with vehicle velocity and exhaust temperature/pressure. The OBS-1300 system consists of a MEXA-1170 HNDIR analyzer, a MEXA-720 NO_X analyzer, a Power Supply Unit, a data logger PC and other accessories.

Figure 3.5 OBS-1300 setup

Figure 3.6 NO_X sensor attached to tailpipe

3.6 On-Road Test Procedure

The OBS-1300 system was installed on the test vehicle described above (1994 diesel Chevy C/K 2500). For each kind of biodiesel, 1.5 hours of highway testing and 1.5 hours of arterial testing was conducted during off-peak weekday hours (9 a.m.–4 p.m.). However, the driving time on both highway and arterial routes were depending on the power supply. The order of testing with each feedstock and each route was randomly determined using SAS program to reduce systematic error and bias conditions. The testing order is shown in Table 3.2.

Table 3.2 On-Road Testing Order

Test #	Fuel	Route Type
1	ULSD	Arterial
2	Soybean	Highway
3	WCO	Highway
4	WCO	Arterial
5	Soybean	Arterial
6	Canola	Highway
7	Canola	Arterial
8	Animal Fat	Highway
9	ULSD	Highway
10	Animal Fat	Arterial

The on-road testing started with ultra low sulfur diesel being driven for 1.5 hours on arterial route during off-peak weekday hours (9 a.m.–4 p.m.). 15 minutes of data was then collected while the vehicle idled. Following the first run with ULSD, the fuel tank was drained and soybean biodiesel was added, as shown in Figure 3.7. After that, the vehicle was driven on Highway for 1.5 hours and measured idling for 15 minutes. Testing continued following the order shown in Table 3.2.

Figure 3.7 The fuel tank being drained and replaced with another fuel

Highway and arterial test routes are shown in Figures 3.8 and 3.9. The arterial test route was about 6.5 miles which centered on UTA, and the highway test route was about 50 miles which centered on Arlington. The driver was the same for all testing, to eliminate variability associated with different driving habits. The truck was be warmed up prior to data collection to avoid cold-start conditions. Calibration of the analyzers and sensors was performed regularly.

For the highway route, start driving at Cooper St., then travel west on I-30 to 820, from south on I-820 to I-20, east on I-20 to Spur-408, north on Spur-408 to Loop-12, north on Loop-12 to I-30, and west on I-30 to Cooper St. and repeat.

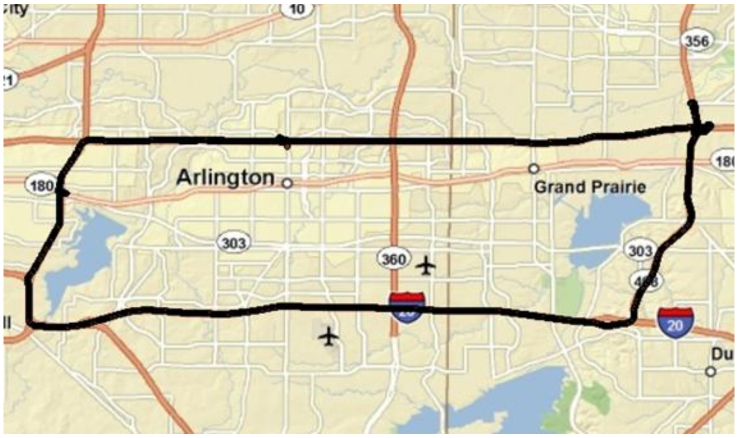


Figure 3.8 Highway test track

For the arterial route, start from UTA Blvd., then travel North on Cooper to Division, east on Division to Collins, south on Collins to Pioneer, west on Pioneer to Cooper, and north on Cooper to UTA Blvd., then repeat.

Figure 3.9 Arterial test track

3.7 Dynamometer System Test Procedure

Chassis dynamometer testing was done at the University of Houston’s Texas Diesel Testing and Research Center. Testing was done on a 500HP AC chassis dynamometer (Burke Porter, model 6356-6419). Vehicles are driven on the dynamometer which simulates real-world driving conditions. This is done by simulating forces not present while the vehicle is driven on the dynamometer, but that would be present on the road. Emissions were analyzed by a five gas analytical bench (Horiba, MEXA 7100). The MEXA 7100 was used to measure NO_X, HC, CO, CO_2 and O_2. The MEXA system is designed specifically for raw gas analysis and is equipped with sample pre-filtering and conditioning. The MEXA has a Chemiluminescent Detector (CLD) for measuring total NO_X (or NO only), a Flame Ionization Detector (FID) for measuring total hydrocarbons (HC), a magneto-pneumatic detector (MPD) for measuring O_2, and three Non-Dispersive Infrared (NDIR) analyzers for measuring CO (high), CO (low) and CO_2.

The Urban Dynamometer Drive Schedule (UDDS) was used for testing. It simulates a combination of low speed and idling as well as high speed and high acceleration driving. The driving pattern is shown in Figure 3.10.

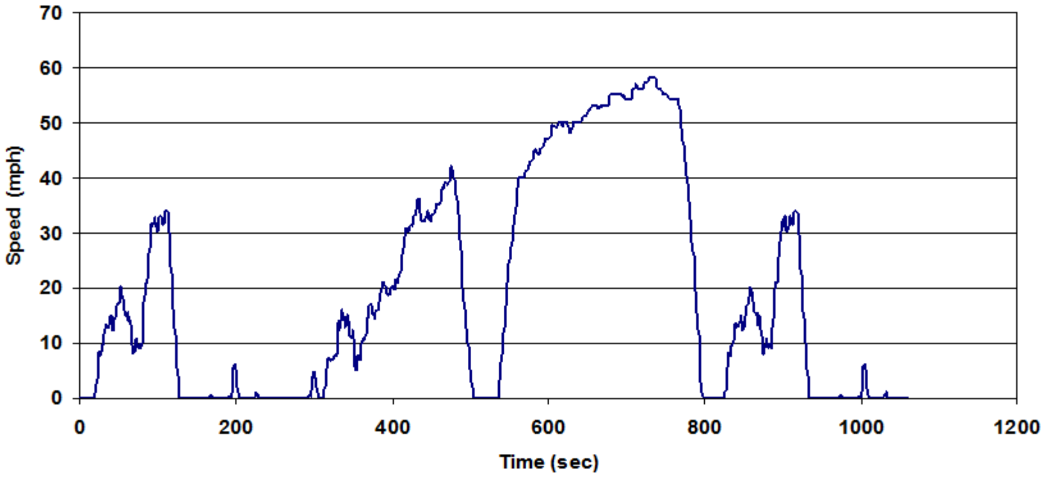


Figure 3.10 Urban Dynamometer Drive Schedule (UDDS)

Prior to dynamometer testing, the vehicle was tied down to the dynamometer as shown in Figure 3.11. Each of the five fuels was tested on the dynamometer, in the order shown in Table 3.3. The order of testing was random to reduce bias and system errors by using SAS program. ULSD was tested first, followed by biodiesel from canola, animal fat, waste cooking oil, and soybean oil, respectively. Test conditions such as ambient temperature, vehicle load, and driver were kept the same. The ambient temperature was controlled about 23-25 ^{o}C.

Each drive cycle test consists of:

1. Vehicle fuel system purge with the fuel to be tested
2. Vehicle warm-up
3. Set of three repeated runs, with a 20 minute soaking period between runs.

Emissions data for each drive cycle were given in terms of average g/mile for the entire drive cycle.

Figure 3.11 Dynamometer testing

Table 3.3 Dynamometer Testing Order

Test #	Fuel
1	Ultra Low Sulfur Diesel
2	Canola B20
3	Animal Fat B20
4	Waste Cooking Oil B20
5	Soybean B20

CHAPTER 4

RESULTS AND DISCUSSION

This chapter presents the results and discussion of the study. This study compared emissions from regular diesel with emissions from biodiesel made from 4 different feedstocks, including soybean, canola, waste cooking oil (WCO), and animal fat (AF), which were blended with regular diesel at 20%. The information in this chapter is separated into 3 sections: fuel properties, on-road test results, and chassis dynamometer results.

4.1 Fuel Properties

Biodiesel fuel was prepared in the laboratory from 3 different feedstocks, including vegetable oil (soybean and canola) and waste cooking oil. B100 of vegetable oil and waste cooking oil were tested using gas chromatography (GC), according to the ASTM 6584 test procedure for quantifying free and bound glycerin. A gas chromatograph (GC) equipped with flame ionization detector (SRI 8610C) was used. The accuracy of the testing procedure was verified by testing a commercial B-100 biodiesel sample. The test results for vegetable oil and waste cooking oil B100 were compared with B100 standard, as shown in Table 4.1 and Figure 4.1. The graph results of vegetable oil and waste cooking oil B100 show similar composition to the B100 standard. GC results confirmed that vegetable oil and WCO were converted to biodiesel completely.

Table 4.1 Comparison of Gas Chromatograph Results between B100 Standard, Vegetable Oil B100, and Waste Cooking Oil B100

Fuel Type	Total Monoglycerides	Tricaprin (Internal Standard)	Total Triglycerides
B100 Standard	13.883	18.883	22.350
B100 Soybean	14.066	18.900	22.350
B100 Canola	13.866	18.916	22.283
B100 WCO	13.966	18.866	22.333

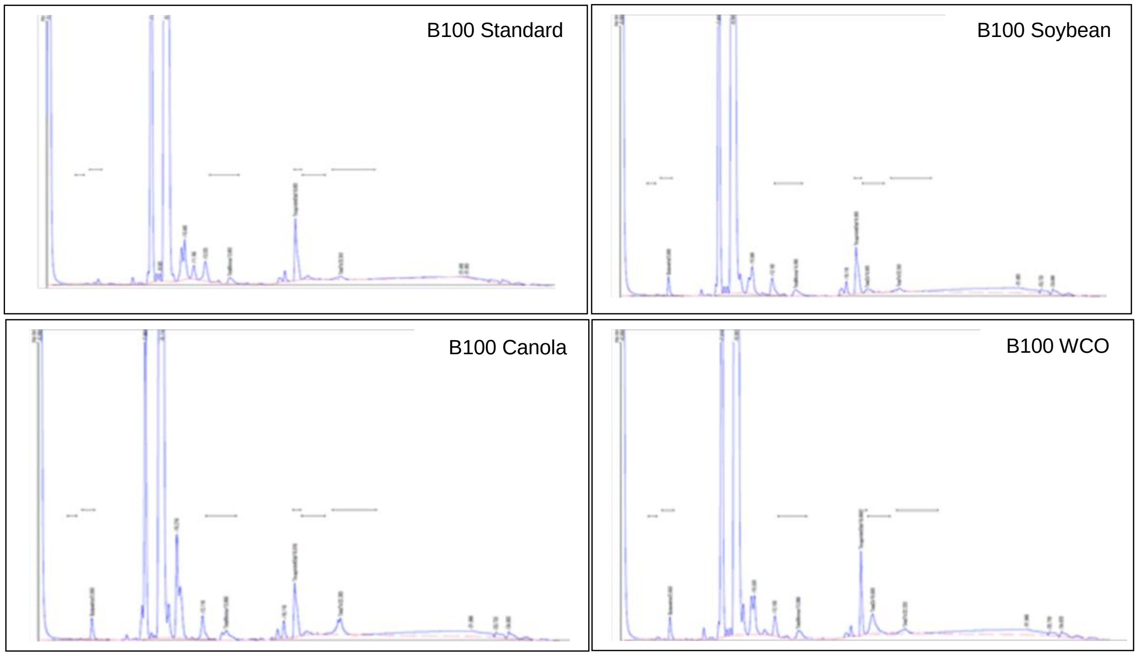


Figure 4.1 Gas chromatograph test results of vegetable oil and waste cooking oil B100

Ultra Low Sulfur Diesel (ULSD) was selected a baseline fuel for comparison. ULSD contains ≤15 ppm sulfur. The properties of USLD and biodiesel fuels were measured by Iowa Central Fuel Testing Laboratory following ASTM standards (ASTM D 975 and D 7467 for petroleum diesel and biodiesel, respectively), C, H, O, N content was measured by Intertek QTI. The properties of biodiesel fuel blends (B20) are compared to ULSD in Table 4.2.

Table 4.2 Fuel Properties of ULSD and Biodiesel from 4 Feedstocks.

Properties	Unit	ASTM limit	ULSD	Soybean B20	Canola B20	WCO B20	AF B20
Acid number	mg KOH/g	0.3 max	N/A	0.12	0.16	0.18	0.06
Viscosity	mm^2/sec	1.9-4.1	2.150[a]	2.458	2.456	3.107	3.072
Flash Point	^oC	52, min	63	68	67	65	69
Cloud Point	^oC		-21	-15	-17	-8	-7
Sulfur Content	ppm (μg/g)	15, max	2.75	2.28	2.85	6.05	6.65
Distillation Temp	^oC	343, max	297.8[b]	330.0	328.9	337.6	337.3
Ash Content	% mass	0.01, max	0.0000	0.00085	0.00055	0.00046	0.00031
Water&Sediment	% volume	0.05, max	<0.005	<0.005	<0.005	<0.005	<0.005
Copper Corrosion	n/a	No. 3, max	1a	1a	1a	1a	1a
Oxidation Stability	hours	6, min	N/A	3.04	2.37	2.14	13.35
Cetane Number	n/a	47, min	51.6[c]	55.7	55.7	49.3	48.3
Blend Content	% (V/V)		0.03	22.8	20.33	20.96	21.07
C	%		85.97	83.75	83.64	83.85	84.76
H	%		14.01	13.23	13.44	13.35	12.94
O	%		<0.10	1.32	1.99	1.91	1.37
N	%		0.08	0.05	0.10	<0.05	<0.05

[a] ASTM limit for diesel is 1.9-6.0.
[b] ASTM limit for diesel is 338, max.
[c] ASTM limit for diesel is 40, min.

Viscosity is the most important property of biodiesel due to the potential of high viscosity to adversely affect fuel injection. Viscosity affects the atomization of the fuel on injection into the combustion chamber. The higher the viscosity, the greater the potential of the fuel to cause engine problems. High viscosity leads to poor atomization of fuel spray and fuel injection operation [53]. Kinematic viscosity has been included in biodiesel standards (1.9–4.1 mm^2/s in ASTM D7467). From Table 4.2, ULSD as expected has the lowest viscosity compared to B20 from the 4 different feedstocks. The viscosity of soybean B20 is comparable to canola B20, while waste cooking oil B20 and animal fat B20 have higher viscosity. However, B20 blends of all 4 feedstocks do not exceed the ASTM D7467 limit.

Flash point is the lowest temperature at which a substance vaporizes to form an ignitable mixture in air. Higher flash points are advantageous from a safety perspective. Biodiesel typically has a higher flash point than regular diesel. Table 4.2 shows that ULSD has the lowest flash point (63 ^oC), while B20 blends of animal fat, soybean oil, canola oil, and waste cooking oil have higher flash points (69, 68, 67, and 65 ^oC, respectively).

Testing for cloud point is required by ASTM protocol for biodiesel fuel properties, but there is not a specific limit. Cloud point is the temperature below which wax in diesel forms a cloudy appearance. The solidified wax can clog fuel filters and injectors in engines. Thus, a lower cloud point is preferable. Generally, biodiesel blends have higher cloud points than petroleum diesel fuel. From Table 4.2, animal fat B20 has the highest cloud point, which is close to that of waste cooking oil, while biodiesel from vegetable feedstocks (soybean and canola) have similar intermediate values of cloud points, with ULSD having the lowest. Cloud points from all B20 blends were significantly higher than those from petroleum diesel fuel, to a 95% level of confidence.

Sulfur content is important because fuels with high sulfur content produce higher sulfur dioxide emissions. To meet requirements for ultra-low sulfur diesel, a fuel's sulfur content must be ≤ 15 ppm. The sulfur content for all 4 B20 blends was less than 15 ppm, qualifying them as ultra-low sulfur diesel fuels. The sulfur content of B20 from soybean feedstock was lower than that of ULSD, and the sulfur content of biodiesel from canola was comparable to that of ULSD; however, the sulfur contents of biodiesel from WCO and animal fat were over twice that of ULSD, although still substantially below 15 ppm. This is surprising, since one of the advantages often associated with biodiesel is lower sulfur content compared to petroleum diesel.

The cetane number is one of the most important properties of diesel fuel quality. It can affect engine starting ability, noise level, and exhaust emissions. A higher cetane number means a shorter ignition delay time, more complete combustion, and lower NO_x emissions. According to Table 4.2, vegetable oil biodiesel B20 has highest cetane number (55.7 for both soybean and canola B20). WCO B20 and animal fat B20 have cetane numbers (49.3 and 48.3, respectively) lower than ULSD (51.6). This is surprising, since biodiesels typically have higher cetane numbers than petroleum diesel.

The oxygen content of biodiesel fuel is typically higher than that for regular petroleum diesel, leading to more complete combustion and lower emissions of CO, HC, and PM. Table

4.2 shows that B20 from canola has highest oxygen content (1.99%), other B20 blends of waste cooking oil, animal fat, and soybean oil have higher oxygen content (1.91, 1.37, and 1.32%, respectively).

Considering carbon and hydrogen contents, ULSD has the maximum level. Higher carbon content may mean that ULSD emits greater CO_2 emissions. However, ULSD has lower nitrogen content than the B20 blends. Higher nitrogen content can lead to higher fuel NO_x emissions, although thermal NO_x also plays a role in total NO_x emissions.

Other properties of the biodiesel fuel blends such as acid number, distillation temperature, ash content, water and sediment, and copper corrosion do not exceed the ASTM standards. Ash content refers to the amount of metals contained in the fuel. The PM emission index is affected by the fuel ash content. The only biodiesel property which did not meet ASTM standards was oxidation stability, for 3 of the 4 B20 blends. Only animal fat B20 met the ASTM standard because it was made by a commercial company, which has more complicated process to produce biodiesel than making it in the laboratory. Heating value did not measure in this research.

Table 4.3 summarizes the major biodiesel fuel properties for the 4 B20 blends. Canola B20 had the best properties affecting emissions (sulfur content, cetane number, and oxygen content); its properties were better than those of ULSD. B20 from waste cooking oil and animal fat had the worst properties affecting emissions; their properties were worse than those of ULSD. The results for soybean B20 were mixed: it had lower sulfur content and a higher cetane number and oxygen content compared to ULSD.

Table 4.3 Summary of Major Biodiesel Fuel Properties

Property	B20 Summary
Viscosity	Viscosity of B20 from all 4 feedstocks met standards
Flash point	Flash point for B20 from all 4 feedstocks was higher than that of ULSD, which is advantageous from a safety perspective
Sulfur content	Sulfur content of B20 from all 4 feedstocks met the definition of ultra-low sulfur diesel (≤15 ppm). Sulfur content of soybean B20 was lower than that of ULSD, sulfur content of canola B20 was comparable, but sulfur content of B20 from WCO and animal fat was higher.
Cetane number	Cetane numbers for soybean and canola B20 were higher (better) than those for ULSD, but those for WCO and animal fat B20 were lower.
Oxygen content	Oxygen content of B20 from all 4 feedstocks was higher than that of ULSD.

4.2 On-Road Testing

Emissions of interest were oxides of nitrogen and carbon dioxide. CO_2 and NO_x emissions were reported as second-by-second data, in volume percent and ppm, respectively, and then converted to grams/mile. The mass of CO_2 emissions were determined by the following equation:

$$CO_{2mass} = \frac{1000 \times [CO_{2c}] \times 1000 \times 44 \times 0.001}{\dfrac{\left[\dfrac{0.08206 \times \left(Exh_{temp} + 273K\right)}{\dfrac{Exh_{press}}{101.3}}\right] Exh_{fr}}{60} \times \dfrac{10^{-6}}{GPS_{vel}}}$$

Equation 1

where

CO_{2mass} = Carbon dioxide concentration, in g/mile

CO_{2c} = Carbon dioxide concentration of the exhaust sample, in Vol%

Exh $_{temp}$ = Exhaust temperature, in ^{o}C

Exh $_{press}$ = Exhaust pressure, in kPa

Exh $_{fr}$ = Exhaust flow rate, in L/min

GPS$_{vel}$ = GPS velocity, in mile/sec

The mass of NO$_x$ emissions were determined by the following equation:

$$NO_{xmass} = \frac{1000 \times [NO_{xc}] \times 31.6 \times 0.001}{\dfrac{\left[\dfrac{0.08206 \times \left(Exh_{temp} + 273K\right)}{\dfrac{Exh_{press}}{101.3}}\right] Exh_{fr}}{60} \times \dfrac{10^{-6}}{GPS_{vel}}}$$

Equation 2

where

NO$_{xmass}$ = Nitrogen oxide concentration, in g/mile

NO$_{xc}$ = Nitrogen oxide concentration of the exhaust sample, in ppm

E$_{xh\ temp}$ = Exhaust temperature, in ^{o}C

E$_{xh\ press}$ = Exhaust pressure, in kPa

E$_{xh\ flow\ rate}$ = Exhaust flow rate, in L/min

GPS$_{vel}$ = GPS velocity, in mile/sec

Two replications were conducted for each fuel/roadway type combination. Average CO$_2$ and NO$_x$ emissions for the two replicates for the arterial and highway routes are shown in Table 4.4. Emissions from the arterial route were higher than those from the highway route; this may be due to the engine operating more efficiently at highway speeds.

As shown in Table 4.4 and Figure 4.2, for the arterial route, animal fat B20 produced more CO$_2$ than ULSD, but biodiesel from the other 3 feedstocks produced lower CO$_2$ compared to ULSD, by amounts ranging from 2-21%. For the highway route, however, soybean B20 and WCO B20 produced higher CO$_2$ emissions compared to ULSD, while animal fat B20 and canola

B20 produced lower CO_2 emissions. The only biodiesel feedstock that produced lower CO_2 emissions for both the arterial and highway routes compared to ULSD was canola. Whether the differences in emissions among B20 blends were statistically significant will be evaluated in the next section.

Table 4.4 Data from On-Road Testing

Fuel Type	Average Emissions Results (g/mile)			
	Arterial Route		Highway	
	CO_2	NO_X	CO_2	NO_X
ULSD	46.61	0.240	35.74	0.159
Soybean B20	45.76	0.248	38.81	0.138
Canola B20	36.95	0.233	32.57	0.153
Waste Cooking Oil B20	41.90	0.239	36.39	0.172
Animal Fat B20	48.78	0.227	32.71	0.161
% Diff Soybean B20	-1.82	3.33	8.59	-13.21
% Diff Canola B20	-20.73	-2.92	-8.87	-3.77
% Diff WCO B20	-10.11	-0.42	1.82	8.18
% Diff Animal Fat B20	4.66	-5.42	-8.48	1.26

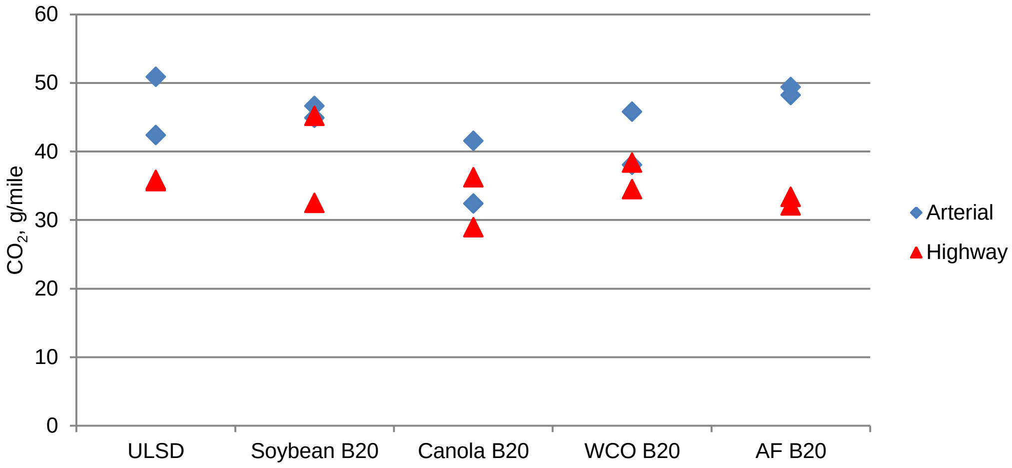


Figure 4.2 CO_2 from on-road testing with different routes

Figure 4.3 shows an example of second by second CO_2 results for on-road testing of soybean B20 with different routes versus time.

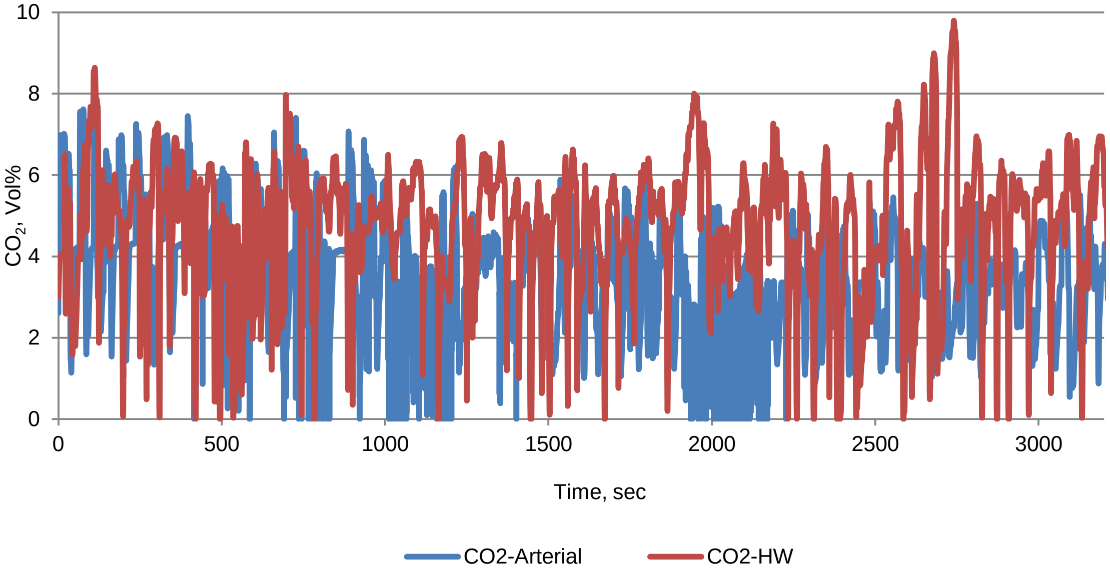


Figure 4.3 CO_2 from on-road testing of soybean B20 for different routes

As shown in Table 4.4 and Figure 4.4, for the arterial route, soybean B20 produced slightly more NO_x than ULSD, but biodiesel from the other 3 feedstocks produced lower NO_x compared to ULSD, by amounts ranging from 0.4 to 5.4%. This is somewhat surprising, given that soybean and canola B20 had identical cetane numbers, which were higher than the cetane number for ULSD. For the highway route, however, WCO B20 and animal fat B20 produced higher NO_x than ULSD, but biodiesel from soybean and canola produced lower NO_x compared to ULSD. The only biodiesel feedstock that produced lower NO_x emissions for both the arterial and highway routes compared to ULSD was canola. Whether the differences in emissions among B20 blends were statistically significant will be evaluated in a later section.

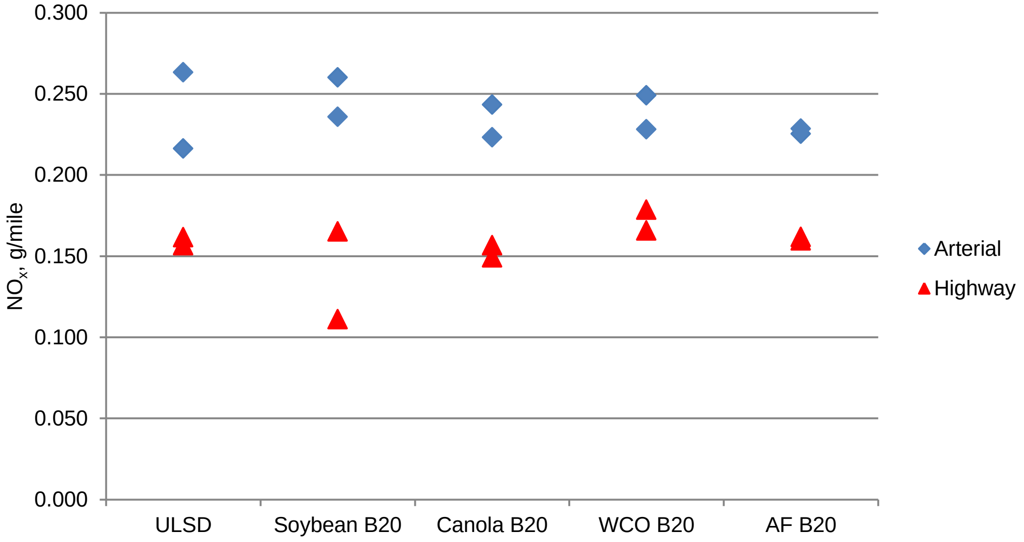


Figure 4.4 NO_x from on-road testing with different routes

Figure 4.5 shows an example of second by second NO_x results for on-road testing of soybean B20 with different routes versus time.

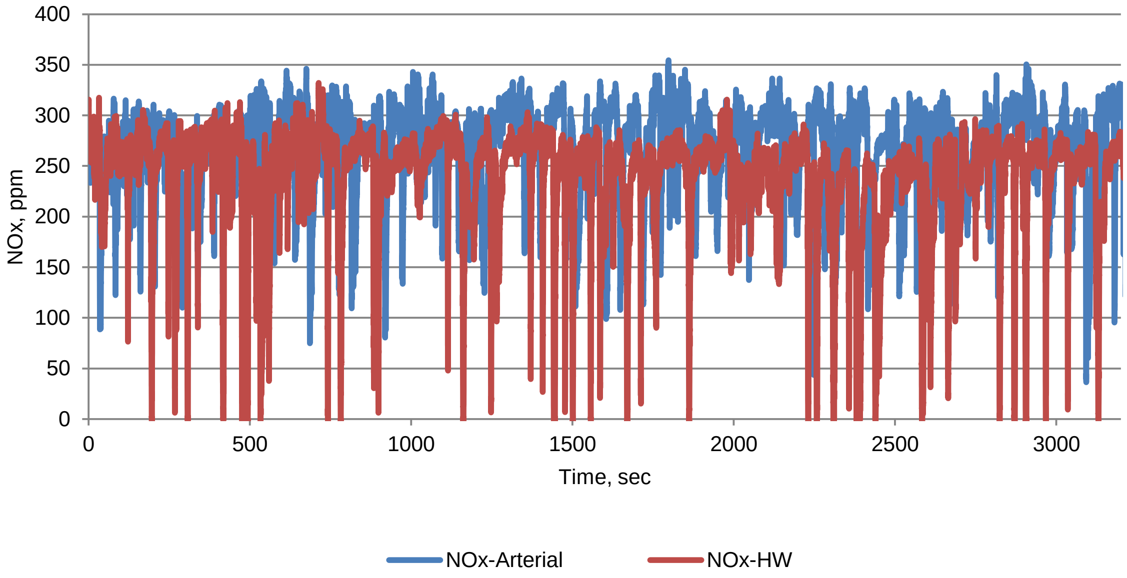


Figure 4.5 NO_x from on-road testing of soybean B20 for different routes

Table 4.5 Idling Test Results

Fuel Type	Average Idle CO_2		Average Idle NO_X	
ULSD	(g/sec)	STDEV	(g/sec)	STDEV
Soybean B20	0.125	0.036	0.0008	0.00001
Canola B20	0.086	0.097	0.0004	0.00040
Waste Cooking Oil B20	0.153	0.017	0.0012	0.00001
Animal Fat B20	0.094	0.048	0.0006	0.00040
% Diff Soybean B20	-31.2		-50.0	
% Diff Canola B20	22.4		50.0	
% Diff WCO B20	-24.8		-25.0	
% Diff Animal Fat B20	-32.0		12.5	

Table 4.5 and Figure 4.6 show CO_2 results from idle testing. Canola B20 produced the highest CO_2 emissions, which were higher than ULSD by about 22%. Biodiesel from the other 3 feedstocks produced lower CO_2 compared to ULSD, by amounts ranging from 24.8 to 32%. Due to the large standard deviations, however, the differences in CO_2 emissions from the idle test between ULSD and the B20 blends were not statistically significant using two-sample t-tests, to a 95% level of confidence. Among the B20 blends in terms of CO_2 emissions, there were not statistically significant differences, either. Figure 4.7 shows an example of second by second CO_2 from WCO B20 versus time for idle testing.

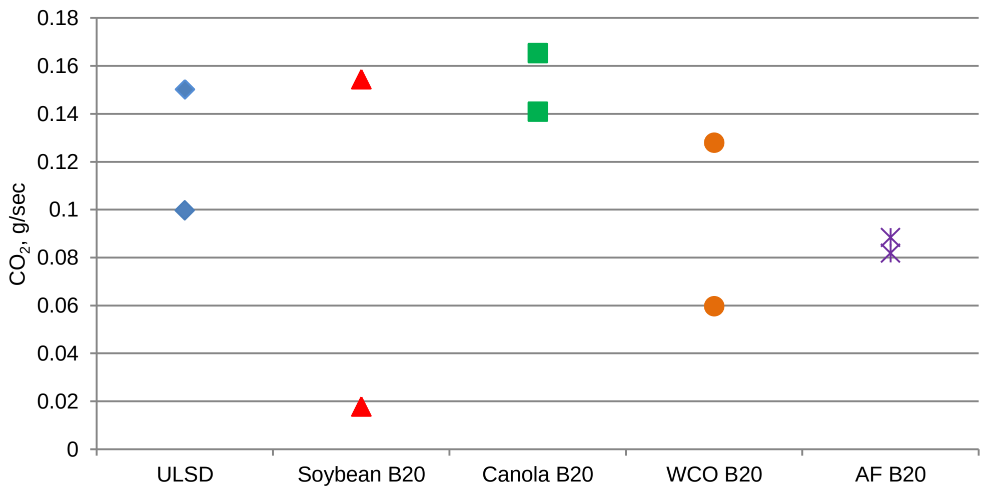


Figure 4.6 Average CO_2 from idling testing with different feedstocks

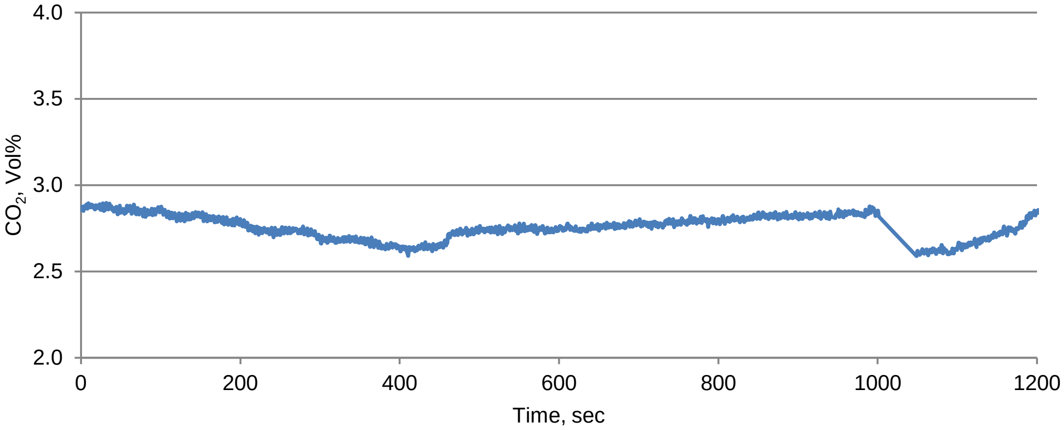


Figure 4.7 CO_2 from idling testing of WCO B20

Table 4.5 and Figure 4.8 show NO_x emissions from idle testing. Canola B20 produced the highest NO_x, which was higher than that for ULSD by about 50%. NO_x from animal fat B20 and ULSD were comparable. Biodiesel from the other 2 feedstocks, soybean B20 and waste cooking oil B20, produced lower NO_x compared to ULSD, by amounts of 50 and 25%, respectively. However, the differences in NO_x emissions from idle test between ULSD and the B20 blends were not statistically significant using two-sample t-tests, to a 95% level of confidence.

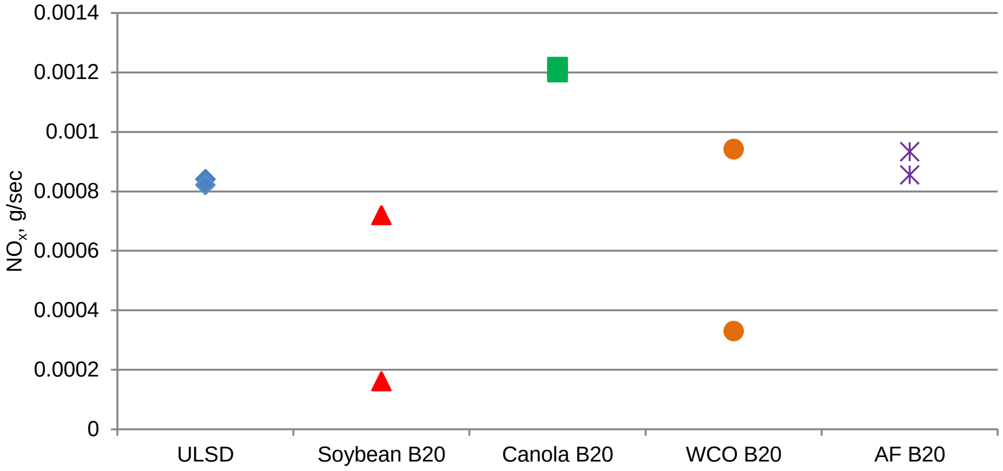


Figure 4.8 Average NO_x from idling testing with different feedstocks

Figure 4.9 shows an example of second-by-second NO_x from WCO B20 versus time for idle testing of WCO B20.

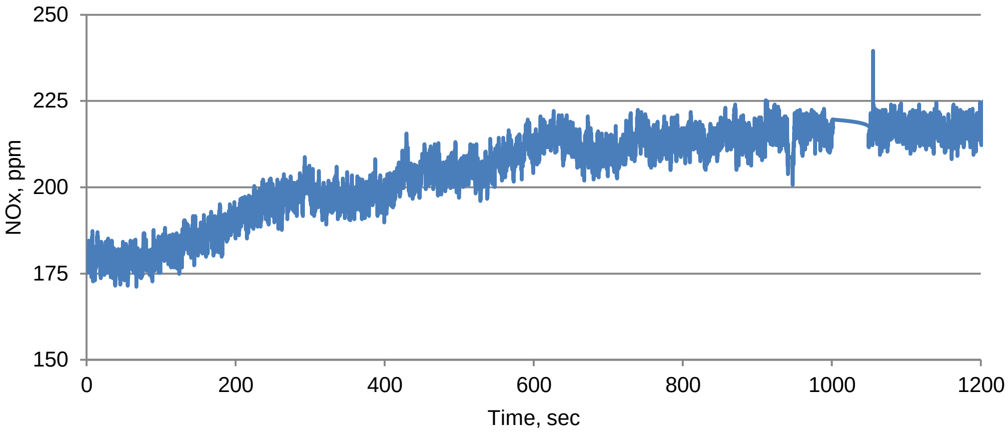


Figure 4.9 NO_x from idling testing of WCO B20

As shown in Table 4.6, the weather conditions were measured for each test. The ambient temperature from each day was slightly different, with the daily average temperature ranging between 83.1-91.1°F. This small range in temperatures most likely did not impact vehicle emissions substantially; differences in engine load due to differences in air conditioning usage were likely small. Humidity ranged between 48.3-64.4%. Greater humidity can potentially reduce NO_x emissions, by reducing engine temperature due to evaporation of water. Observed wind speeds ranged between 1.5-5.5 mph. Driving against a stronger wind could place greater load on the engine, which could increase emissions; conversely, driving with a stronger tail wind would place less load on the engine, which would presumably decrease emissions. For the driving patterns used in this study, the vehicle would experience a tail wind for part of the trip and a head wind for an equal part of the trip, meaning that the impacts would likely offset each other. Given the fact that CO_2 and NO_x emissions from ULSD and the different B20 blends were not significantly different from each other, as discussed above, one can conclude that differences in weather among test runs most likely did not impact vehicle emissions significantly.

Table 4.6 Weather Conditions for On-Road Testing

Test condition	Avg. Temp (°F)	High Temp (°F)	Low Temp (°F)	Humidity (%)	Dew Point (°F)	Wind Speed (mph)	Wind Direction
ULSD-Arterial	83.9	83.9	83.9	64.4	70.6	3.4	SW
ULSD-HW	85.4	85.4	85.3	62.1	70.9	5.3	W
Soybean-Arterial	84.1	84.1	84.0	63.5	70.3	3.2	SE
Soybean-HW	84.6	84.6	84.5	52.3	65.2	2.4	W
Canola-Arterial	85.8	85.8	85.8	63.7	72.1	1.5	SW
Canola-HW	87.1	87.1	87.0	51.9	67.2	4.5	W
WCO-Arterial	83.1	83.1	83.0	61.6	68.5	3.3	W
WCO-HW	85.5	85.5	85.5	51.6	65.6	2.4	NW
AF-Arterial	83.9	83.9	83.9	64.0	70.4	5.5	W
AF-HW	91.1	91.1	91.0	48.3	68.8	4.6	W

Data collection for on-road testing

A single factor experimental design was employed, so as to enable an analysis of variance for fuel type with different routes (arterial and highway). Five fuel types were studied:

1. Ultra Low Sulfur Diesel (ULSD)
2. Soybean biodiesel B20
3. Canola biodiesel B20
4. Waste cooking oil biodiesel B20
5. Animal fat biodiesel B20

Two routes were studied:

1. Arterial route
2. Highway route

This yields a total of 10 treatment combinations. Ten vehicle runs as experimental units enabled 2 replications per treatment. The response variables in this study are the emissions of CO_2 and NO_x from on-road testing using biodiesel fuel B20 with different feedstocks. The emissions were measured in grams per mile.

The types of treatments are shown below in Table 4.7.

Table 4.7 Ten Factor-Level Combinations

Factor-Level Combination	Fuel Type (Factor A)	Route Type (Factor B)	Replications
1	ULSD	Arterial	2
2	ULSD	Highway	2
3	Soybean B20	Arterial	2
4	Soybean B20	Highway	2
5	Canola B20	Arterial	2
6	Canola B20	Highway	2
7	Waste cooking oil B20	Arterial	2
8	Waste cooking oil B20	Highway	2
9	Animal fat B20	Arterial	2
10	Animal fat B20	Highway	2

The experiment was conducted in a randomized order to minimize serial correlation, and to overcome any experimental bias. The order in which the experiments were conducted is shown in Table 3.2.

4.2.1 Data Analysis of Carbon Dioxide (CO_2)

4.2.1.1 Carbon Dioxide (CO_2) for Arterial Route

Figure 4.10 shows the mean CO_2 emissions for each run for each type of fuel on the arterial route. The actual data are shown in Table 4.8. The number of loops per each test was considered as the traffic condition that might affect CO_2 emissions. The maximum time per loop(s) and the average speed for each test show the traffic condition, where lower speed means more congestion, such that emissions do not burn completely, and more emissions are generated. From the plot, it can be noticed that the difference between mean CO_2 emissions for the replicate runs is especially large for ULSD (fuel type 1), canola B20 (fuel type 3), and waste cooking oil B20 (fuel type 4).

Table 4.8 Actual results for on-road testing on arterial route

Test #	Fuel Type	Route Type	# Loops	Actual time (s)	Min. Time/Loop (s)	Max. Time/Loop (s)	Avg. Speed (mile/sec)	CO_2 (g/mile)	NO_x (g/mile)
1	ULSD	Arterial 1	8	6645	762	889	0.0074	42.349	0.216
2	ULSD	Arterial 2	7	6280	777	1020	0.0068	50.867	0.263
3	Soybean B20	Arterial 1	8	5940	792	940	0.0075	44.902	0.260
4	Soybean B20	Arterial 2	7	6120	789	966	0.0070	46.618	0.236
5	Canola B20	Arterial 1	6	4980	785	905	0.0074	32.371	0.243
6	Canola B20	Arterial 2	7	5320	788	922	0.0073	41.518	0.223
7	WCO B20	Arterial 1	7	6017	752	949	0.0072	45.758	0.249
8	WCO B20	Arterial 2	6	5110	783	906	0.0074	38.035	0.228
9	AF B20	Arterial 1	5	4318	784	1029	0.0074	48.195	0.225
10	AF B20	Arterial 2	6	5230	757	934	0.0070	49.357	0.229

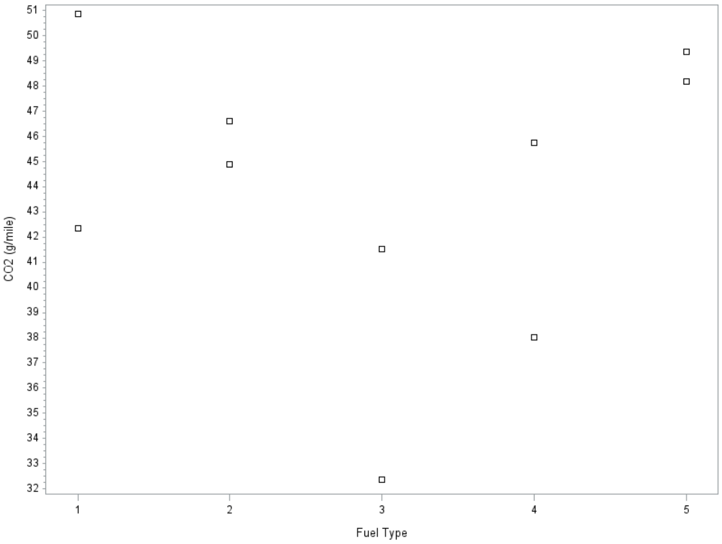


Figure 4.10 Mean CO_2 emissions from replicate runs for various fuel types on the arterial route

There is one factor (fuel type) with two covariates (maxloop, average speed) possibly affecting the concentration of emissions. Five types of fuel were tested. Therefore, there are 5 treatment combinations, and 2 replications were conducted for each treatment. The individual effects of the fuel types with two covariates are included in the analysis of covariance model, which is as follows:

$$Y_{it} = \mu_i + \gamma_1 x_{it1} + \gamma_2 x_{it2} + \varepsilon_{it}$$

where $i = 1,2,3,4,5;\ t = 1,2$

Each term could be defined as:

μ_i = The mean CO_2 emissions for treatment effect

X_1 = Maxloop with coefficient γ_1

X_2 = Average speed with coefficient γ_2

ε_{it} = Random error iid N$(0,\sigma^2)$

A residual plot can clearly show if there is any deviation from the above assumptions. We are looking to detect problems such as a funnel shape as shown in Figure 4.11, which indicates that the constant variance assumption is not satisfied.

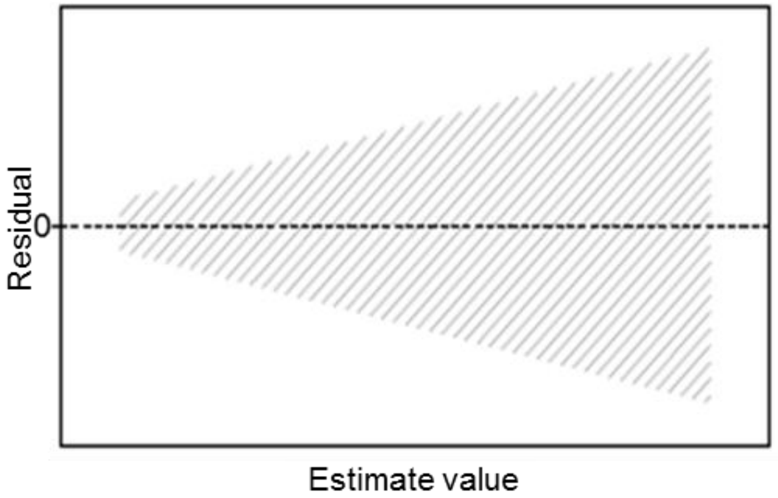


Figure 4.11 Residual plot with funnel shape

To verify the constant variance assumption, the plot of the residuals versus the estimate mean of CO_2 on the arterial route in Figure 4.12 is checked for a funnel shape. A funnel shape is observed in this plot; there seems to be a non-constant variance.

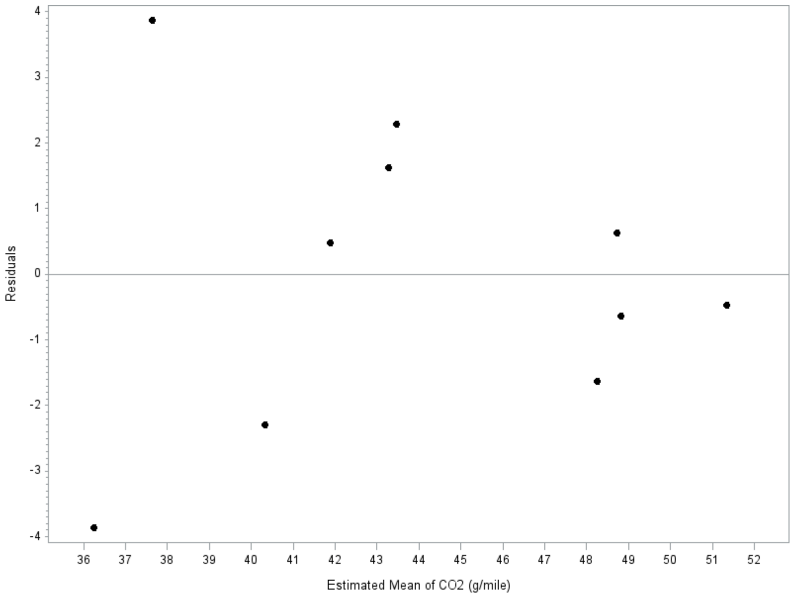


Figure 4.12 Residuals versus estimate mean of CO_2 on the arterial route

To test for constant variance, a Modified-Levene test is conducted for the following two hypotheses:

H_0 : Errors variance is constant

H_1 : Errors variance is non-constant

The decision rule rejects H_0 if the p-value (seen in the SAS output in Table 4.9 as 0.4703) is less than the significance level of α, where α represents the probability of incorrectly rejecting H_0. For an α of 0.05, we fail to reject H_0; therefore, the Modified-Levene test says that the variance is constant. However, the plot shows a funnel shape, indicating non-constant variance. The assessment using the plot carries more weight than the Modified-Levene test; therefore, we conclude that variance is non-constant.

Table 4.9 SAS output of constant variance testing

```
                          The ANOVA Procedure
                         Dependent Variable: d
Source           DF  Sum of Squares  Mean Square  F Value  Pr > F

Model            4   59.0069182      14.7517295   1.04     0.4703

Error            5   70.9676454      14.1935291

Corrected Total  9   129.9745636

              R-Square  Coeff Var  Root MSE  d Mean

              0.453988  90.93000   3.767430  4.143220

          Source  DF  Anova SS     Mean Square  F Value  Pr > F

          FUEL    4   59.00691816 14.75172954  1.04     0.4703
```

In the normal probability plot of the residuals in Figure 4.13, a linear pattern is observed. Consequently, the normality assumption for error distribution appears to be reasonable.

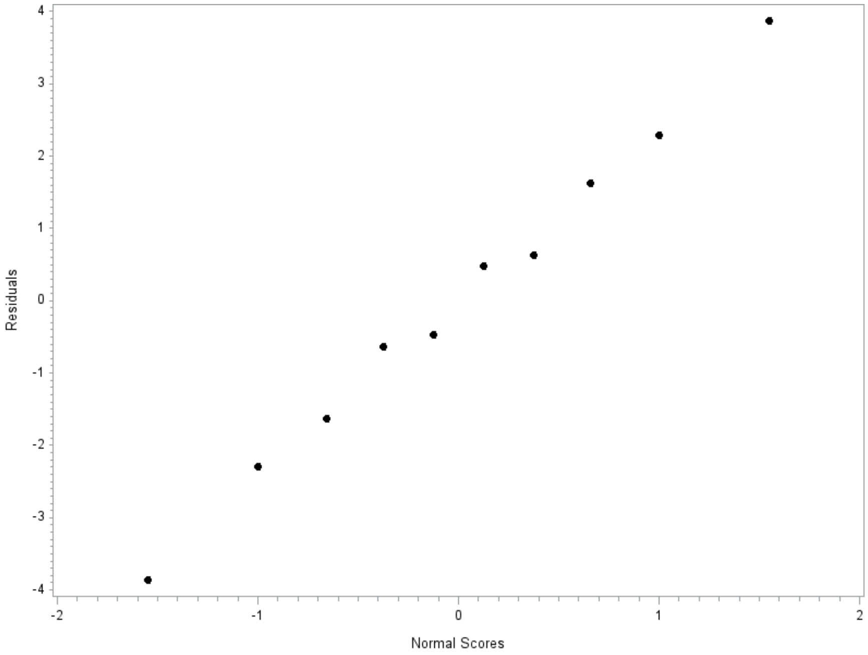


Figure 4.13 Normal probability plot of residuals

Test for Normality

To test for normality, the following two hypotheses are tested:

H_0 : Normality is satisfied.

H_1 : Normality is violated.

Table 4.10 SAS output of normality test analysis

```
Pearson   Correlation   Coefficients,   N   =   10
Prob > |r| under H0: Rho=0

                        e            enrm

e               1.00000                    0.99695
Residuals                                  <.0001

enrm            0.99695    1.00000
Normal Scores   <.0001
```

For an $\alpha = 0.05$, we have the critical value $c(\alpha,n) = c(0.05, 10) = 0.918$. The decision rule fails to reject H_0 if the correlation value (seen in the SAS output Table 4.10 as 0.99695) is greater than $c(\alpha,n)$. Since $\rho = 0.99695 > c = 0.918$, we fail to reject H_0; therefore, the normality assessed in Figure 4.13 is verified.

The plot of residuals versus estimate mean of CO_2 shows a funnel shape, despite the results of the Modified Levene test, and normality is satisfied. Therefore, the Weighted Least Squares (WLS) approach for ANOVA should be conducted.

An analysis of variance (ANOVA) was obtained using WLS. The SAS output ANOVA is shown in Table 4.11.

To test for the fuel type effect, an F-test is conducted for the following two hypotheses:

H_0 : $\mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$ (No difference in treatment means)

H_1 : Not all μ_i are equal (At least two treatment means are different)

Table 4.11 SAS output of Weighted Least Squares for CO_2 emissions and fuel type for the arterial route

```
                          The GLM Procedure
                  Dependent Variable: y CO2 (g/mile)
                           Weight: w Weight

Source            DF  Sum of Squares  Mean Square  F Value  Pr > F
Model              6     19.26223055   3.21037176     4.61  0.1187
Error              3      2.08841030   0.69613677
Corrected Total    9     21.35064084

            R-Square  Coeff Var  Root MSE    y Mean
            0.902185   1.752531  0.834348  47.60819

     Source       DF     Type I SS  Mean Square  F Value   Pr > F
     FUEL          4   16.35080409   4.08770102     5.87   0.0888
     MAXLOOP       1    0.26686501   0.26686501     0.38   0.5797
     AVGSPEED      1    2.64456144   2.64456144     3.80   0.1464

      Source      DF  Type III SS  Mean Square  F Value   Pr > F
      FUEL         4   9.65973680   2.41493420     3.47   0.1674
      MAXLOOP      1   0.27254775   0.27254775     0.39   0.5759
      AVGSPEED     1   2.64456144   2.64456144     3.80   0.1464
```

The decision rule rejects H_0 if the Type III SS p-value (seen in the SAS output in Table 4.11 as 0.1674) is less than the significance level of α, where α represents the probability of incorrectly rejecting H_0. For an α of 0.05, we fail to reject H_0 and do not detect differences in the mean CO_2 emissions for the different fuel types. However, for an α of 0.10, we reject H_0 and detect differences in the mean CO_2 emissions for the different fuel types. We can interpret these differences to be marginally significant, and there is potential that a stronger conclusion would be possible with more data. The two covariates are seen to be insignificant.

4.2.1.1 Carbon Dioxide (CO_2) for Highway Route

Figure 4.14 shows the mean CO_2 emissions for each replicate run for each type of fuel for the highway route. The actual data is shown in Table 4.12. The maximum time per loop (s) and the average speed for each test show the traffic condition, in which lower speed means more congestion, such that emissions do not burn completely, and more emissions are generated. From the plot, it can be noticed that the difference between mean CO_2 emissions for the replicate runs is especially large for soybean B20 (fuel type 2) and canola B20 (fuel type 3).

Table 4.12 Actual results for on-road testing on highway route

Test #	Fuel Type	Route Type	#Loops	Actual time (s)	Min. Time/Loop (S)	Max. Time/Loop (S)	Avg. Speed (mile/sec)	CO_2 (g/mile)	NO_x (g/mile)
1	ULSD	HW 1	1	3694	3440	3440	0.0131	35.841	0.162
2	ULSD	HW 2	1	3340	3054	3054	0.0159	35.642	0.157
3	Soybean B20	HW 1	1	3965	3435	3435	0.0152	45.140	0.165
4	Soybean B20	HW 2	1	3840	3297	3297	0.0154	32.476	0.111
5	Canola B20	HW 1	1	3393	3355	3355	0.0163	28.911	0.157
6	Canola B20	HW 2	1	3350	3290	3290	0.0146	36.220	0.149
7	WCO B20	HW 1	1	3538	3337	3337	0.0157	34.461	0.166
8	WCO B20	HW 2	1	3890	3378	3378	0.0114	38.327	0.179
9	AF B20	HW 1	1	4698	3285	3285	0.0165	32.096	0.162
10	AF B20	HW 2	1	3968	3387	3387	0.0161	33.332	0.160

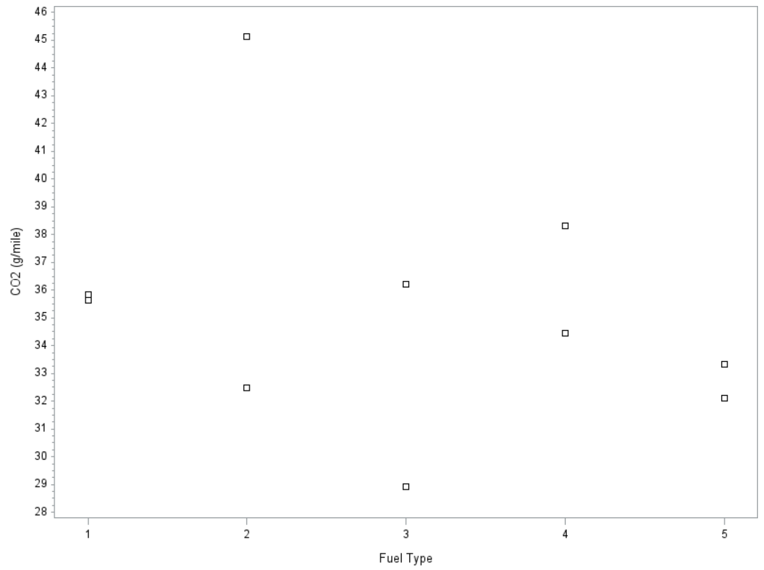


Figure 4.14 Mean CO_2 emissions from replicate runs for various fuel types on the highway route

To verify the constant variance assumption, the plot of the residuals versus the estimate mean of CO_2 on the highway route in Figure 4.15 is checked for a funnel shape. No funnel shape is observed; therefore, the constant variance may be reasonable.

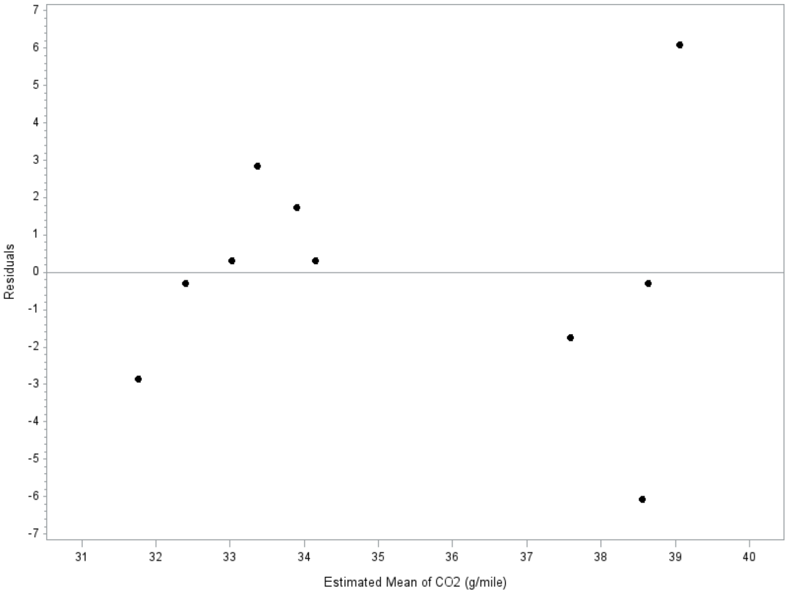


Figure 4.15 Residuals versus estimate mean of CO_2 on the highway route

To test for constant variance, a Modified-Levene test is conducted for the following two hypotheses:

H_0 : Errors variance is constant

H_1 : Errors variance is non-constant

The decision rule rejects H_0 if the p-value (seen in the SAS output in Table 4.13 as 0.3436) is less than the significance level of α, where α represents the probability of incorrectly rejecting H_0. For an α of 0.05, we fail to reject H_0; therefore, the variance is constant.

Table 4.13 SAS output of constant variance testing

```
                         The ANOVA Procedure
                        Dependent Variable: d
Source           DF  Sum of Squares  Mean Square  F Value  Pr > F

Model            4   49.91333250     12.47833313  1.44     0.3436

Error            5   43.26385450     8.65277090

Corrected Total  9   93.17718700


                R-Square  Coeff Var  Root MSE  d Mean

                0.535682  113.8476   2.941559  2.583770


          Source  DF  Anova SS     Mean Square  F Value  Pr > F

          FUEL    4   49.91333250  12.47833313  1.44     0.3436
```

In the normal probability plot of the residuals in Figure 4.16, a linear pattern is observed. Consequently, the normality assumption for error distribution appears to be reasonable.

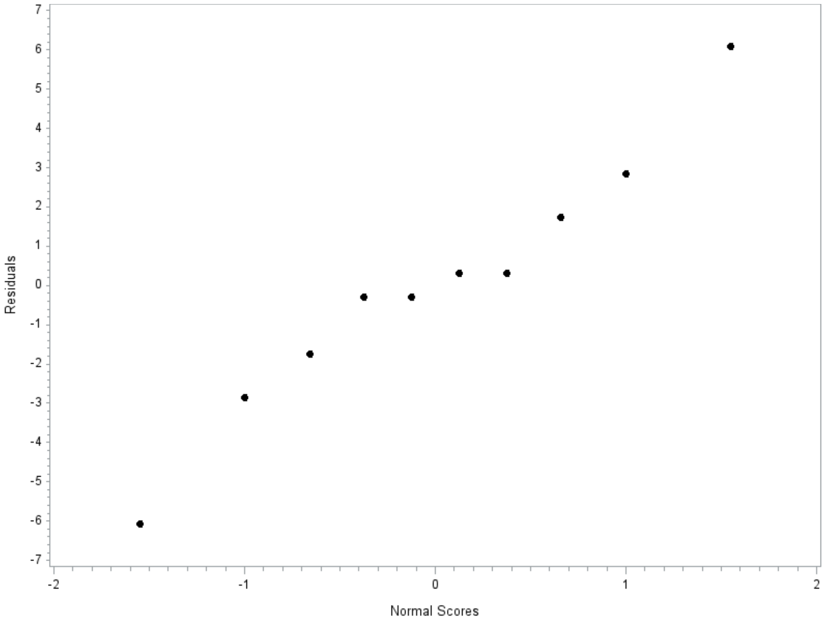


Figure 4.16 Normal probability plot of residuals

Test for Normality

To test for normality, the following two hypotheses have to be tested:

H_0 : Normality is satisfied.

H_1 : Normality is violated.

Table 4.14 SAS output of normality test analysis

```
         Pearson Correlation Coefficients, N = 10
                Prob > |r| under H0: Rho=0

                               e        enrm

e                        1.00000     0.97734
Residuals                             <.0001

enrm                     0.97734     1.00000
Normal Scores             <.0001
```

For an $\alpha = 0.05$, we have the critical value $c(\alpha,n) = c(0.05, 10) = 0.918$. The decision rule fails to reject H_0 if the correlation value (seen in the SAS output Table 4.14 as 0.97734) is greater than $c(\alpha,n)$. Since $\rho = 0.97734 > c = 0.918$, we fail to reject H_0; therefore, the normality assessed in Figure 4.16 is satisfied.

An analysis of variance (ANOVA) was obtained using SAS. The SAS output ANOVA is shown in Table 4.15.

To test for the fuel type effect, an F-test is conducted for the following two hypotheses:

H_0 : $\mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$ (No difference in treatment means)

H_1 : Not all μ_i are equal (At least two treatment means are different)

The decision rule rejects H_0 if the Type III SS p-value (seen in the SAS output Table 4.15 as 0.8503) is less than the significance level of α, where α represents the probability of incorrectly rejecting H_0. For an α of 0.05, we fail to reject H_0 and do not detect differences in the mean CO_2 emissions for the different fuel types.

Table 4.15 SAS output of ANOVA of CO_2 emissions and fuel type for highway route

```
                          The GLM Procedure

                    Dependent Variable: CO2 (g/mile)

Source            DF  Sum of Squares  Mean Square  F Value  Pr > F
Model              6      74.1042616   12.3507103     0.38  0.8537
Error              3      96.7499470   32.2499823
Corrected Total    9     170.8542085

           R-Square  Coeff Var  Root MSE    Y Mean
           0.433728   16.11280  5.678907  35.24470

      Source    DF     Type I SS  Mean Square  F Value  Pr > F
      FUEL       4  55.69810932   13.92452733     0.43  0.7827
      maxloop    1   7.24159993    7.24159993     0.22  0.6679
      avgspeed   1  11.16455231   11.16455231     0.35  0.5976

      Source    DF   Type III SS  Mean Square  F Value  Pr > F
      FUEL       4  41.23253810   10.30813453     0.32  0.8503
      maxloop    1   0.30529702    0.30529702     0.01  0.9286
      avgspeed   1  11.16455231   11.16455231     0.35  0.5976
```

4.2.1.3 Comparison between Arterial and Highway Route

There is one factor (route type), involving in the concentration of emissions. Two types of route were tested as arterial and highway. Therefore, there are 10 treatment combinations, and 2 replications were conducted for each treatment. The individual effects of the fuel types are included in the model, which is as follows:

$$Y_{it} = \mu_i + \varepsilon_{it}$$

where $i = 1, \ldots, 10;\ t = 1,2$

Each term could be defined as:

Y_{it} = CO_2 emissions (g/mile)

μ_i = True mean CO_2 emissions for treatment effect (i)

ε_{ijt} = Random error iid N$(0,\sigma^2)$

To verify the constant variance assumption, the plot of the residuals versus the estimate mean of CO_2 on on-road testing in Figure 4.17 is checked for a funnel shape. No funnel shape is observed in this plot; there seems to be a constant variance.

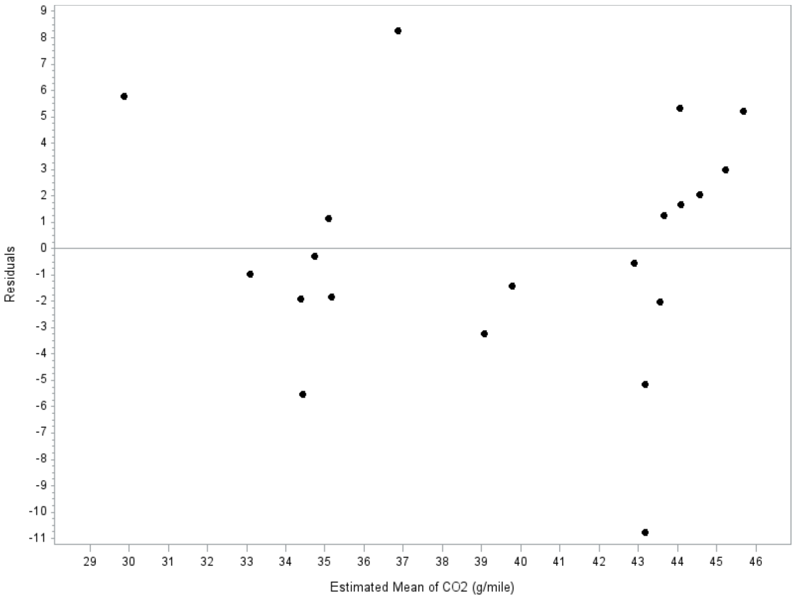


Figure 4.17 Residuals versus estimate mean of CO_2 with different routes

To test for constant variance, a Modified Levene test is conducted for the following two hypotheses:

H_0 : Errors variance is constant

H_1 : Errors variance is non-constant

The decision rule rejects H_0 if the p-value (seen in the SAS output in Table 4.16 as 0.4530) is less than the significance level of α, where α represents the probability of incorrectly rejecting H_0. For an α of 0.05, we fail to reject H_0; therefore, the variance is constant.

Table 4.16 SAS output of constant variance testing

```
                         The ANOVA Procedure
                        Dependent Variable: d
Source           DF  Sum of Squares  Mean Square  F Value   Pr > F

Model             1       6.8757746    6.8757746     0.59   0.4530

Error            18     210.3102466   11.6839026

Corrected Total  19     217.1860212

              R-Square  Coeff Var  Root MSE    d Mean

              0.031658   95.59249  3.418172  3.575775

        Source  DF    Anova SS  Mean Square  F Value   Pr > F

        ROUTE    1  6.87577464   6.87577464     0.59   0.4530
```

In the normal probability plot of the residuals in Figure 4.18, a linear pattern is observed. Consequently, the normality assumption for error distribution appears to be reasonable.

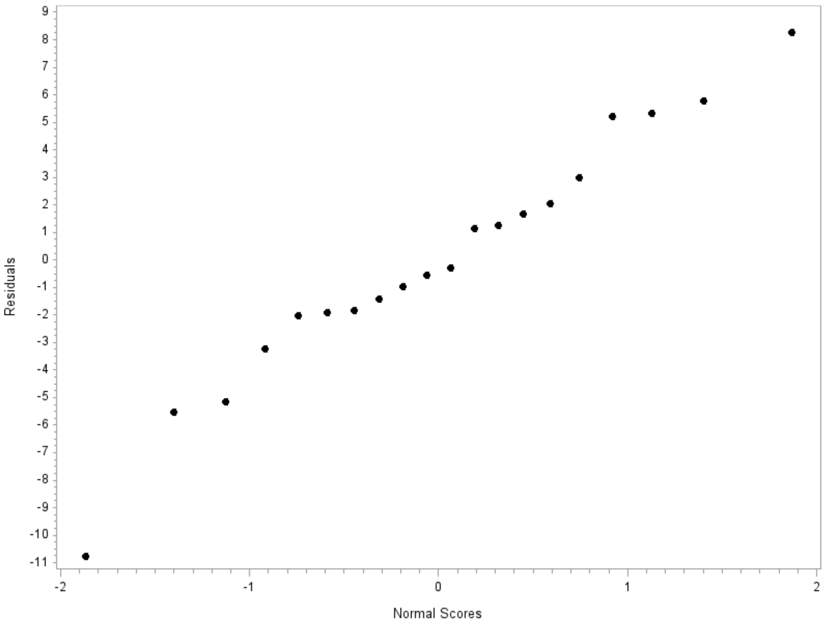


Figure 4.18 Normal probability plot of residuals

Test for Normality

To test for normality, the following two hypotheses have to be tested:

H_0 : Normality is satisfied.

H_1 : Normality is violated.

Table 4.17 SAS output of normality test analysis

```
             Pearson Correlation Coefficients, N = 20
                   Prob > |r| under H0: Rho=0

                                    e         enrm

        e                     1.00000      0.98374
        Residuals                           <.0001

        enrm                  0.98374      1.00000
        Normal Scores          <.0001
```

For an $\alpha = 0.05$, we have the critical value $c(\alpha,n) = c(0.05, 20) = 0.951$. The decision rule fails to reject H_0 if the correlation value (seen in the SAS output Table 4.17 as 0.98374) is greater than $c(\alpha,n)$. Since $\rho = 0.98374 > c = 0.951$, we fail to reject H_0; therefore, the normality assessed in Figure 4.18 is satisfied.

An analysis of variance (ANOVA) was obtained using SAS. The SAS output ANOVA is shown in Table 4.18.

To test for the fuel type effect, an F-test is conducted for the following two hypotheses:

$H_0 : \mu_1 = \mu_2$ (No difference in treatment means)

$H_1 :$ μ_1 and μ_2 are not equal (The treatment means are different)

The decision rule rejects H_0 if the Type III SS p-value (seen in the SAS output Table 4.18 as 0.0011) is less than the significance level of α, where α represents the probability of incorrectly rejecting H_0. For an α of 0.05, we reject H_0 and detect differences in the mean CO_2 emissions for the different route types.

Table 4.18 SAS output of ANOVA of CO_2 emissions and fuel type for the different routes

```
                             The GLM Procedure
                      Dependent Variable: CO2 (g/mile)
Source           DF  Sum of Squares  Mean Square  F Value   Pr > F

Model             1     383.0246618  383.0246618    15.16   0.0011

Error            18     454.7708477   25.2650471

Corrected Total  19     837.7955095

               R-Square  Coeff Var  Root MSE    Y Mean

               0.457182   12.68633  5.026435  39.62089

      Source  DF      Type I SS  Mean Square  F Value   Pr > F

      Route    1  383.0246618    383.0246618    15.16   0.0011

      Source  DF    Type III SS  Mean Square  F Value   Pr > F

      Route    1  383.0246618    383.0246618    15.16   0.0011
```

4.2.2 Data Analysis of Nitrogen Oxides (NO_x)

4.2.2.1 Nitrogen Oxides (NO_x) for Arterial Route

Figure 4.19 shows mean NO_x emissions for each replicate run for each type of fuel for the arterial route. The actual data is shown in Table 4.8. From the plot, it can be noticed that the mean NO_x emissions for the replicate runs are different for each type of fuel, with the exception of animal fat B20 (fuel type 5).

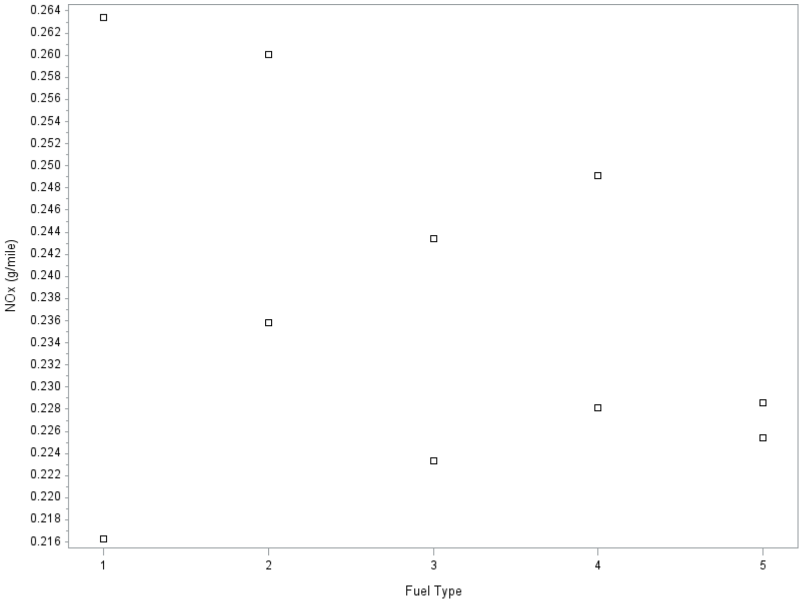


Figure 4.19 Mean NO_x emissions from replicate runs for various fuel types on the arterial route

There is one factor (fuel type) with two covariates (maxloop, average speed) possibly affecting the concentration of emissions. Five types of fuel were tested. Therefore, there are 5 treatment combinations, and 2 replications were conducted for each treatment. The individual effects of the fuel types with two covariates are included in the analysis of covariance model, which is as follows:

$$Y_{it} = \mu_i + \gamma_1 x_{it1} + \gamma_2 x_{it2} + \varepsilon_{it}$$

where $i = 1,2,3,4,5;\ t = 1,2$

Each term could be defined as:

μ_i = The mean NO_x emissions for treatment effect

X_1 = Maxloop with coefficient γ_1

X_2 = Average speed with coefficient γ_2

ε_{it} = Random error iid N$(0,\sigma^2)$

To verify the constant variance assumption, the plot of the residuals versus the estimate mean of NO_x on the arterial route in Figure 4.20 is checked for a funnel shape. No funnel shape is observed. Constant variance is reasonable.

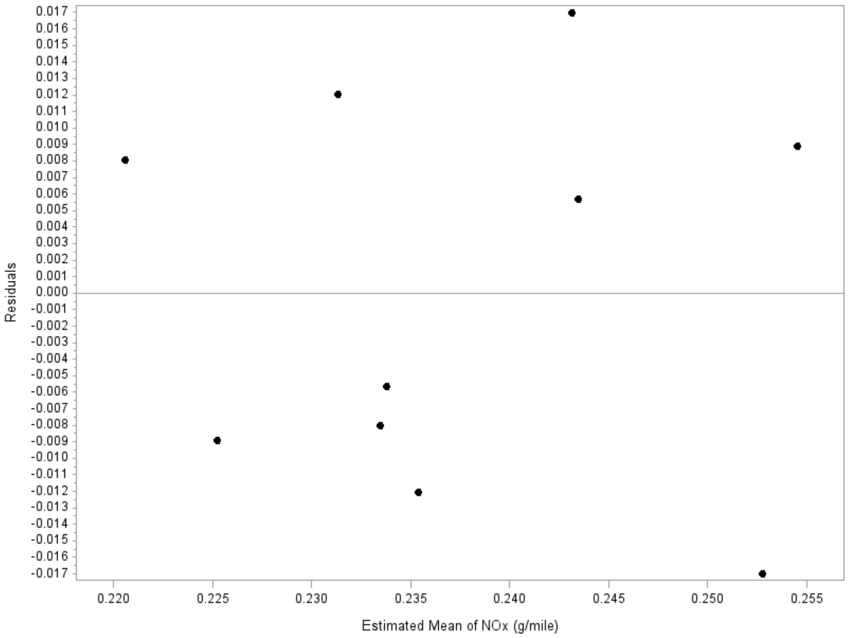


Figure 4.20 Residuals versus estimate mean of NO_x on the arterial route

To test for constant variance, a Modified-Levene test is conducted for the following two hypotheses:

H_0 : Errors variance is constant

H_1 : Errors variance is non-constant

The decision rule rejects H_0 if the p-value (seen in the SAS output in Table 4.19 as 0.3162) is less than the significance level of α, where α represents the probability of incorrectly rejecting H_0. For an α of 0.05, we fail to reject H_0; therefore, the variance is constant.

Table 4.19 SAS output of constant variance testing

```
                       The ANOVA Procedure
                      Dependent Variable: d
Source            DF  Sum of Squares  Mean Square  F Value   Pr > F
Model              4      0.00049343   0.00012336     1.56   0.3162
Error              5      0.00039657   0.00007931
Corrected Total    9      0.00088999

            R-Square  Coeff Var  Root MSE    d Mean
            0.554417   76.97310  0.008906  0.011570

       Source  DF    Anova SS  Mean Square  F Value   Pr > F
       FUEL     4  0.00049343   0.00012336     1.56   0.3162
```

In the normal probability plot of the residuals in Figure 4.21, an S-shaped pattern is observed. Consequently, the distribution of the errors follows a distribution that has longer tails than the normal distribution, and normality is violated.

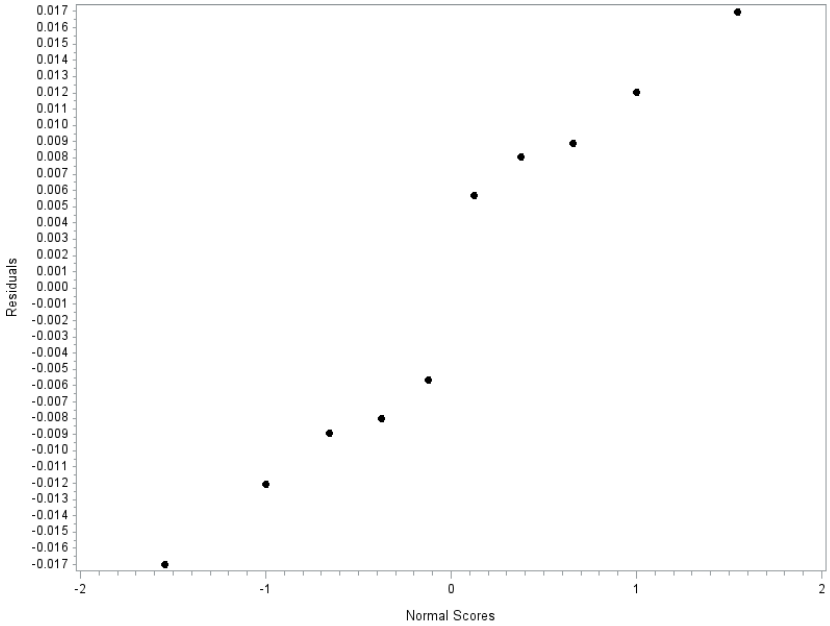


Figure 4.21 Normal probability plot of residuals

Test for Normality

To test for normality, the following two hypotheses have to be tested:

H_0 : Normality is satisfied.

H_1 : Normality is violated.

For an $\alpha = 0.05$, we have a critical value $c(\alpha,n) = c(0.05, 10) = 0.918$. The decision rule fails to rejects H_0 if the correlation value (seen in the SAS output Table 4.20 as 0.97190) is greater than $c(\alpha,n)$. Since $\rho = 0.97190 > c = 0.918$, we fail to reject H_0; therefore, the test is unable to detect the non-normality that is apparent in Figure 4.21. Normality is not required for valid ANOVA.

Table 4.20 SAS output of normality test analysis

```
Pearson Correlation Coefficients, N = 10
Prob > |r| under H0: Rho=0

                        e          enrm

 e                1.00000       0.97190
 Residuals                       <.0001

 enrm             0.97190       1.00000
 Normal Scores     <.0001
```

An analysis of variance (ANOVA) was obtained using SAS. The SAS output ANOVA is shown in Table 4.21.

To test for the fuel type effect, an F-test is conducted for the following two hypotheses:

H_0 : $\mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$ (No difference in treatment means)

H_1 : Not all μ_i are equal (At least two treatment means are different)

The decision rule rejects H_0 if the Type III SS p-value (seen in the SAS output Table 4.21 as 0.7748) is less than the significance level of α, where α represents the probability of incorrectly rejecting H_0. For an α of 0.05, we fail to reject H_0 and do not detect differences in the mean NO_x emissions for the different fuel types.

Table 4.21 SAS output of ANOVA of NO_x emissions and fuel type for arterial route

```
                          The GLM Procedure

                   Dependent Variable: NOx (g/mile)
Source            DF  Sum of Squares  Mean Square  F Value  Pr > F
Model              6      0.00109985   0.00018331     0.45  0.8131
Error              3      0.00121882   0.00040627
Corrected Total    9      0.00231867

              R-Square  Coeff Var  Root MSE    Y Mean
              0.474345   8.492185  0.020156  0.237350
```

Table 4.21 – *Continued*

Source	DF	Type I SS	Mean Square	F Value	Pr > F
FUEL	4	0.00048659	0.00012165	0.30	0.8628
Maxloop	1	0.00057912	0.00057912	1.43	0.3183
Avgspeed	1	0.00003414	0.00003414	0.08	0.7908
Source	**DF**	**Type III SS**	**Mean Square**	**F Value**	**Pr > F**
FUEL	4	0.00072346	0.00018086	0.45	0.7748
Maxloop	1	0.00037949	0.00037949	0.93	0.4051
Avgspeed	1	0.00003414	0.00003414	0.08	0.7908

4.2.2.2 Nitrogen Oxides (NO_x) for Highway Route

Figure 4.22 shows mean NO_x emissions for each replicate run for each type of fuel for the highway route. The actual data is shown in Table 4.12. From the plot, it can be noticed that the mean NO_x emissions for the replicate runs are different for soybean B20 (fuel type 2) and to a lesser extent for waste cooking oil B20 (fuel type 4).

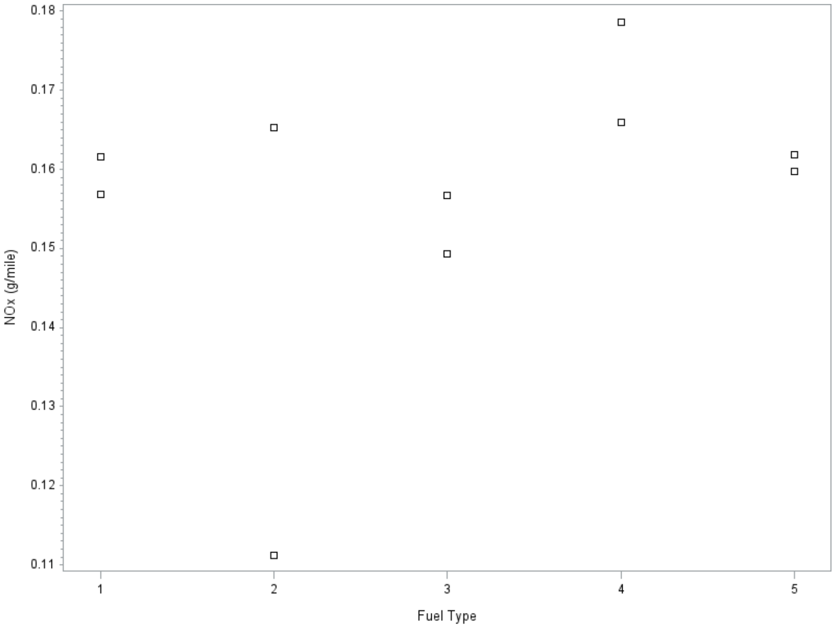


Figure 4.22 Mean NO_x emissions from replicate runs for various fuel types on the highway route

To verify the constant variance assumption, the plot of the residuals versus the estimate mean of NO_x on the highway route in Figure 4.23 is checked for a funnel shape. A funnel shape is not clear to observed; therefore, the errors variance may be reasonable.

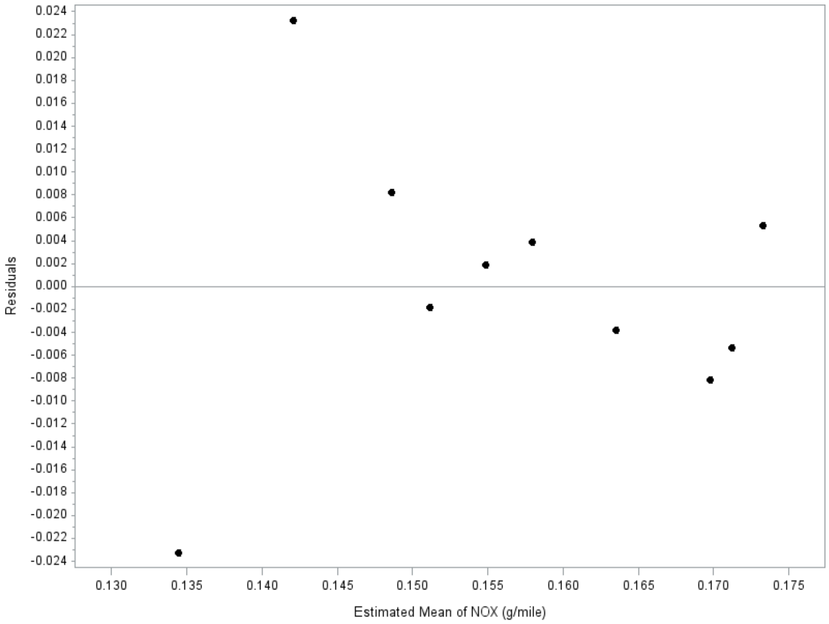


Figure 4.23 Residuals versus estimate mean of NO_x on the highway route

To test for constant variance, a Modified-Levene test is conducted for the following two hypotheses:

H_0 : Errors variance is constant

H_1 : Errors variance is non-constant

The decision rule rejects H_0 if the p-value (seen in the SAS output in Table 4.22 as 0.4759) is less than the significance level of α, where α represents the probability of incorrectly rejecting H_0. For an α of 0.05, we fail to reject H_0; thus, the variance is constant according to this test.

Table 4.22 SAS output of constant variance testing

```
                    The ANOVA Procedure
                   Dependent Variable: d
Source           DF  Sum of Squares  Mean Square  F Value   Pr > F
Model             4      0.00066100   0.00016525     1.02   0.4759
Error             5      0.00080625   0.00016125
Corrected Total   9      0.00146725
           R-Square  Coeff Var  Root MSE    d Mean
           0.450504   113.6223  0.012698  0.011176
              Source  DF    Anova SS  Mean Square  F Value   Pr > F
              FUEL     4  0.00066100   0.00016525     1.02   0.4759
```

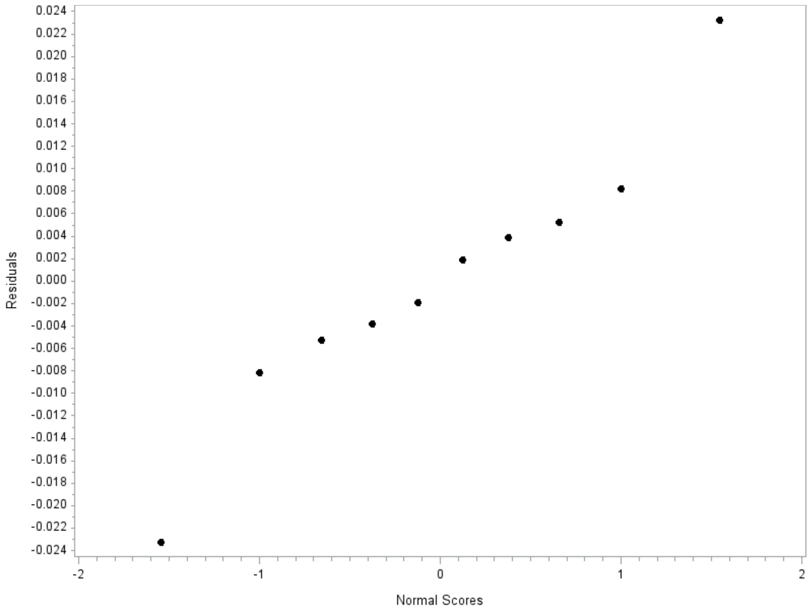


Figure 4.24 Normal probability plot of residuals

In the normal probability plot of the residuals in Figure 4.24, a type of S-shaped pattern with longer tail is observed. Consequently, the distribution of the errors may be close to a normal distribution but not perfect. However, normality is not required for a valid ANOVA.

Test for Normality

To test for normality, the following two hypotheses have to be tested:

H_0 : Normality is satisfied.

H_1 : Normality is violated.

Table 4.23 SAS output of normality test analysis

```
              Pearson Correlation Coefficients, N = 10
                    Prob > |r| under H0: Rho=0

                                      e        enrm

          e                    1.00000      0.96654
          Residuals                          <.0001

          enrm                 0.96654      1.00000
          Normal Scores         <.0001
```

For an $\alpha = 0.05$, we have the critical value $c(\alpha,n) = c(0.05, 10) = 0.918$. The decision rule fails to reject H_0 if the correlation value (seen in the SAS output Table 4.23 as 0.96654) is greater than $c(\alpha,n)$. Since $\rho = 0.96654 > c = 0.918$, we fail to reject H_0; therefore, the normality assessed in Figure 4.24 is satisfied.

An analysis of variance (ANOVA) was obtained using SAS. The SAS output ANOVA is shown in Table 4.24.

To test for the fuel type effect, an F-test is conducted for the following two hypotheses:

$H_0 : \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$ (No difference in treatment means)

H_1 : Not all μ_i are equal (At least two treatment means are different)

The decision rule rejects H_0 if the Type III SS p-value (seen in the SAS output Table 4.24 as 0.6578) is less than the significance level of α, where α represents the probability of incorrectly rejecting H_0. For an α of 0.05, we fail to reject H_0 and do not detect differences in the mean NO_x emissions for the different fuel types.

Table 4.24 SAS output of ANOVA of NO_x emissions and fuel type for the highway route

```
                              The GLM Procedure

                       Dependent Variable: NOx (g/mile)
      Source            DF  Sum of Squares  Mean Square  F Value   Pr > F
      Model              6      0.00151413   0.00025236     0.58   0.7398
      Error              3      0.00130811   0.00043604
      Corrected Total    9      0.00282225

                   R-Square  Coeff Var  Root MSE    Y Mean
                   0.536499   13.32665  0.020882  0.156690

          Source      DF   Type I SS  Mean Square  F Value   Pr > F
          FUEL         4  0.00123709   0.00030927     0.71   0.6371
          maxloop      1  0.00027701   0.00027701     0.64   0.4837
          avgspeed     1  0.00000003   0.00000003     0.00   0.9938

          Source      DF  Type III SS  Mean Square  F Value   Pr > F
          FUEL         4  0.00116030   0.00029007     0.67   0.6578
          maxloop      1  0.00020424   0.00020424     0.47   0.5429
          avgspeed     1  0.00000003   0.00000003     0.00   0.9938
```

4.2.2.3 Comparison between Arterial and Highway Route

There is one factor (route type), involving in the concentration of emissions. Two types of route were tested. Therefore, there are 10 treatment combinations, and 2 replications were conducted for each treatment. The individual effects of the fuel types are included in the model which is as follows:

$$Y_{it} = \mu_i + \varepsilon_{it}$$

where $i = 1, \dots, 10;\ t = 1,2$

Each term can be defined as:

Y_{it} = NO_x emissions (g/mile)

μ_i = True mean NO_x emissions for treatment effect (i)

ε_{ijt} = Random error iid N$(0,\sigma^2)$

To verify the constant variance assumption, the plot of the residuals versus the estimate mean of NO_x with different routes in Figure 4.25 is checked for a funnel shape. No funnel shape is observed in this plot; there seems to be a constant variance.

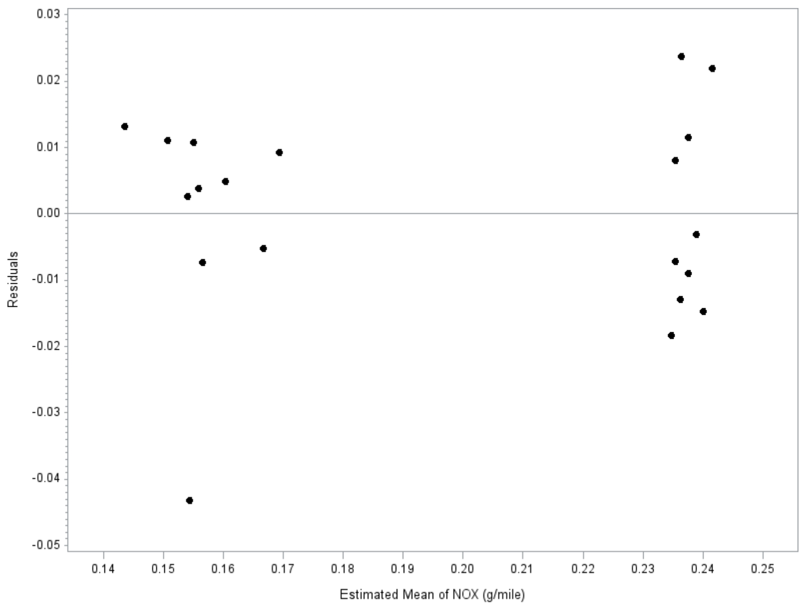


Figure 4.25 Residuals versus estimate mean of NO_x with different routes

To test for constant variance, a Modified-Levene test is conducted for the following two hypotheses:

H_0 : Errors variance is constant

H_1 : Errors variance is non-constant

The decision rule rejects H_0 if the p-value (seen in the SAS output in Table 4.25 as 0.5952) is less than the significance level of α, where α represents the probability of incorrectly rejecting H_0. For an α of 0.05, we fail to reject H_0; therefore, the variance is constant.

Table 4.25 SAS output of constant variance testing

```
                        The ANOVA Procedure
                       Dependent Variable: d
Source           DF  Sum of Squares  Mean Square  F Value   Pr > F

Model             1      0.00004682   0.00004682     0.29   0.5952

Error            18      0.00288033   0.00016002

Corrected Total  19      0.00292715

             R-Square  Coeff Var  Root MSE    d Mean

             0.015994   110.1902  0.012650  0.011480

       Source  DF     Anova SS  Mean Square  F Value   Pr > F

       ROUTE    1  0.00004682   0.00004682      0.29   0.5952
```

In the normal probability plot of the residuals in Figure 4.26, a linear pattern is observed. Consequently, the normality assumption for error distribution appears to be reasonable.

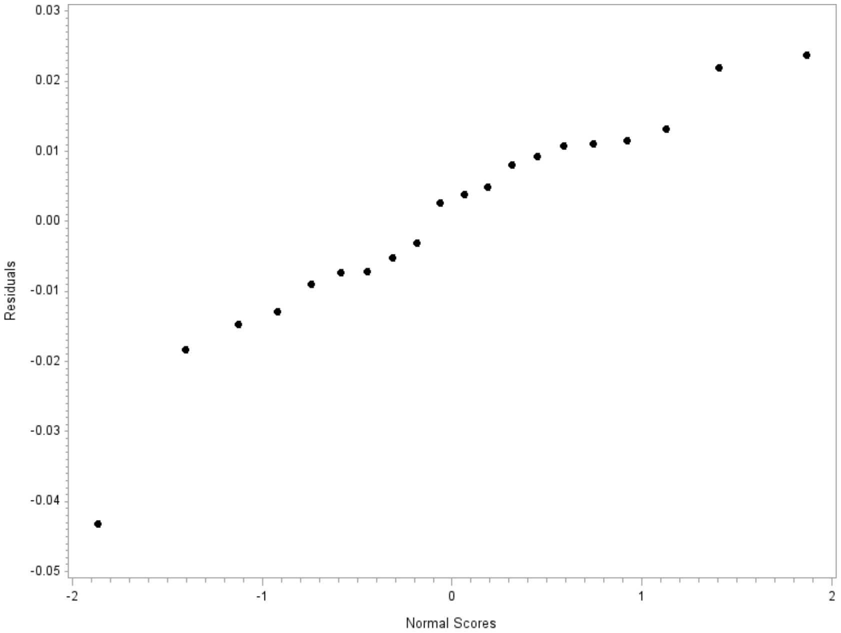


Figure 4.26 Normal probability plot of residuals

Test for Normality

To test for normality, the following two hypotheses have to be tested:

H_0 : Normality is satisfied.

H_1 : Normality is violated.

Table 4.26 SAS output of normality test analysis

```
            Pearson Correlation Coefficients, N = 20
                  Prob > |r| under H0: Rho=0

                                    e         enrm

            e                 1.00000      0.96311
            Residuals                       <.0001

            enrm              0.96311      1.00000
            Normal Scores      <.0001
```

For an $\alpha = 0.05$, we have the critical value $c(\alpha,n) = c(0.05, 20) = 0.951$. The decision rule fails to reject H_0 if the correlation value (seen in the SAS output Table 4.26 as 0. 0.96311) is greater than $c(\alpha,n)$. Since $\rho = 0.96311 > c = 0.951$, we fail to reject H_0; therefore, the normality assessed in Figure 4.26 is verified.

An analysis of variance (ANOVA) was obtained using SAS. The SAS output ANOVA is shown in Table 4.27.

To test for the fuel type effect, an F-test is conducted for the following two hypotheses:

$H_0 : \mu_1 = \mu_2$ (No difference in treatment means)

$H_1 :$ μ_1 and μ_2 are not equal (The treatment means are different)

The decision rule rejects H_0 if the Type III SS p-value (seen in the SAS output Table 4.27 as < 0.0001) is less than the significance level of α, where α represents the probability of incorrectly rejecting H_0. For an α of 0.05, we reject H_0 and detect differences in the mean NO_x emissions for the different route types.

Table 4.27 SAS output of ANOVA of NO$_x$ emissions and fuel type for the different routes

```
                         The GLM Procedure
                   Dependent Variable: NOX (g/mile)
Source           DF  Sum of Squares  Mean Square  F Value   Pr > F
Model             1      0.03253018   0.03253018   113.90  <.0001
Error            18      0.00514091   0.00028561
Corrected Total  19      0.03767109

          R-Square  Coeff Var  Root MSE    Y Mean
          0.863532   8.577754  0.016900  0.197020

      Source  DF    Type I SS  Mean Square  F Value   Pr > F
      ROUTE    1  0.03253018    0.03253018   113.90  <.0001

      Source  DF  Type III SS  Mean Square  F Value   Pr > F
      ROUTE    1  0.03253018    0.03253018   113.90  <.0001
```

4.3 Dynamometer Testing

The vehicle was driven on the chassis dynamometer which simulates real-world driving conditions. This case study used the Urban Dynamometer Drive Schedule (UDDS) driving pattern, which simulates a combination of low speed and idling as well as high speed and high acceleration driving. Oxides of nitrogen, total hydrocarbons, carbon monoxide, carbon dioxide, and total particulate matter were measured. Fuel consumption data were collected from direct gravimetric measurement, and emission carbon balance inference.

4.3.1 Overall Emission Test Results

The average of emissions test results from chassis dynamometer using the UDDS driving pattern with 3 replications of each fuel are shown in Table 4.28.

Table 4.28 Data from Chassis Dynamometer Tests with Urban Dynamometer Drive Schedule

Fuel Type	Average Emissions Results (g/mile)					Fuel Economy (mile/gal)	
	CO_2	CO	HC	NO_X	PM	Direct gravimetric	Carbon balance
ULSD	697.6	0.845	0.135	4.44	0.116	14.00	14.27
Soybean B20	702.2	0.792	0.115	4.51	0.111	13.62	14.18
Canola B20	696.0	0.736	0.107	4.49	0.106	13.73	14.30
Waste Cooking Oil B20	700.0	0.715	0.102	4.49	0.111	13.69	14.22
Animal Fat B20	697.0	0.770	0.112	4.45	0.110	13.86	14.29
% Diff Soybean B20	0.66	-6.27	-14.81	1.58	-4.31	-2.71	-0.63
% Diff Canola B20	-0.23	-12.90	-20.74	1.13	-8.62	-1.93	0.21
% Diff WCO B20	0.34	-15.38	-24.44	1.13	-4.31	-2.21	-0.35
% Diff Animal Fat B20	-0.09	-8.88	-17.04	0.23	-5.17	-1.00	0.14

4.3.1.1 Carbon Dioxide (CO_2)

As shown in Figure 4.27, CO_2 emissions from B20 blends were slightly lower or higher compared to ULSD, depending on feedstock.

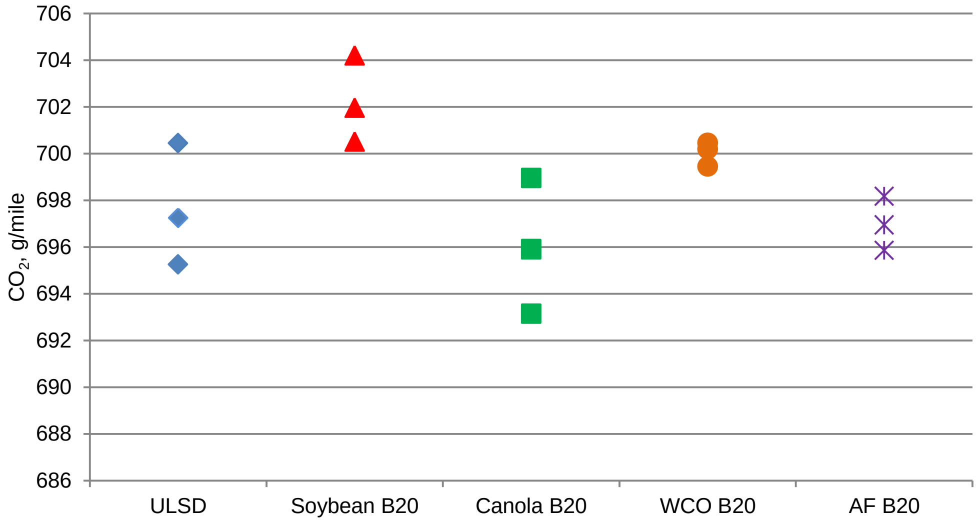


Figure 4.27 Comparison of average CO_2 (g/mile) emissions from UDDS driving cycle for B20 from different feedstocks and ULSD

Figure 4.28 shows an example of CO_2 (Vol%) emissions from UDDS driving cycle for B20 canola. It can be seen that CO_2 emissions are generally higher when speeds are higher, presumably due to more fuel being burned in the engine.

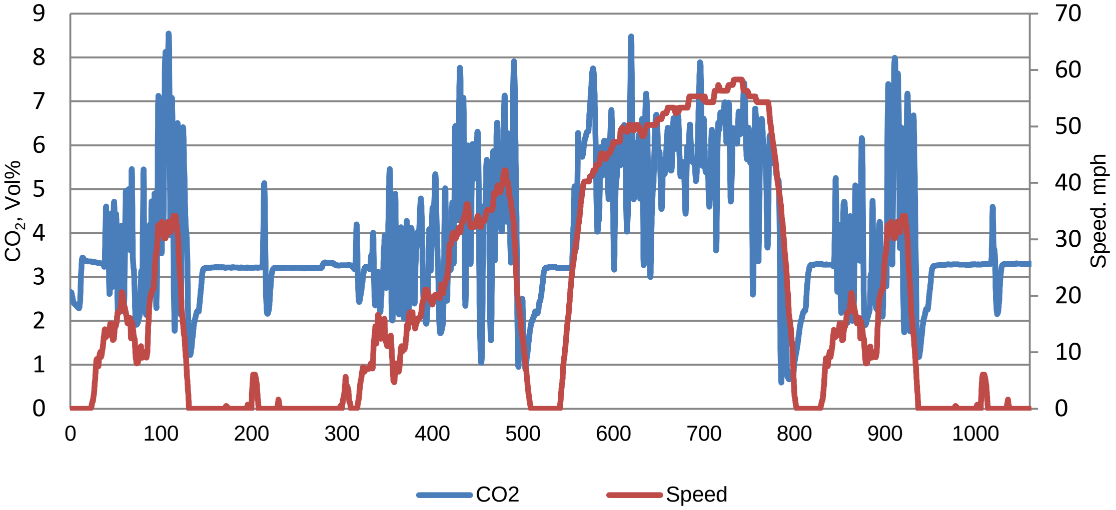


Figure 4.28 CO_2 (Vol%) emissions from UDDS driving cycle for B20 canola

It should be noted that the magnitude of CO_2 emissions from dynamometer testing is much greater than those from on-road testing. The test results are not directly comparable, because the vehicle load was different. For dynamometer testing, load was added to the vehicle to achieve 6000 lbs, to meet the minimum requirement of the laboratory equipment.

4.3.1.2 Carbon Monoxide (CO)

As shown in Figure 4.29, CO emissions from all B20 blends were lower than those from petroleum diesel fuel. Since CO results from incomplete combustion, higher oxygen content typically lowers CO emissions by producing more complete combustion. Figure 4.30 shows an example of CO_{low} (ppm) emissions from UDDS driving cycle for B20 canola.

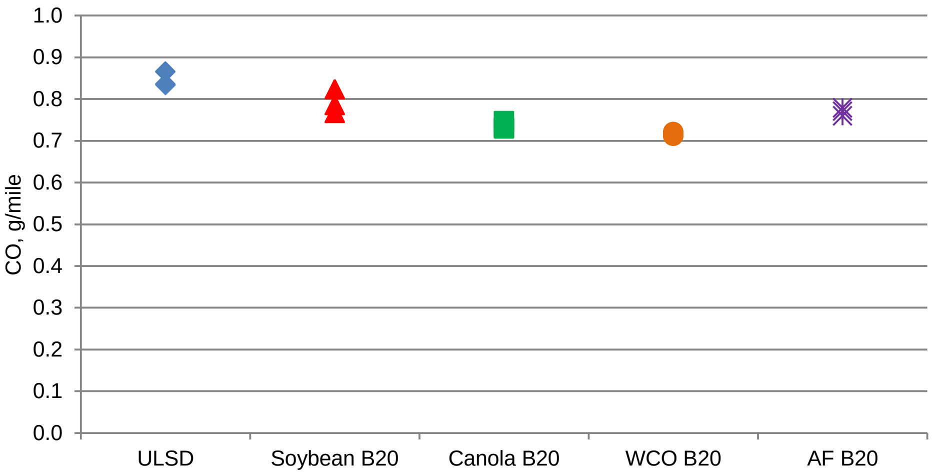


Figure 4.29 Comparison of average CO (g/mile) emissions from UDDS driving cycle for B20 from different feedstocks and ULSD

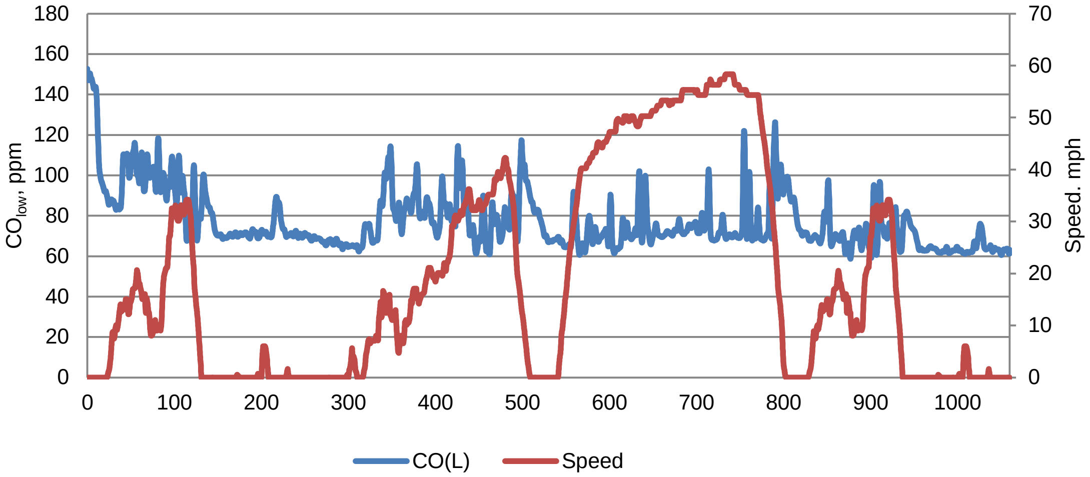


Figure 4.30 CO_{low} (ppm) emissions from UDDS driving cycle for B20 canola

4.3.1.3 Hydrocarbons (HC)

As shown in Figure 4.31, HC emissions from all B20 blends were lower than those from petroleum diesel fuel. Since HC results from incomplete combustion, higher oxygen content typically lowers HC emissions by producing more complete combustion.

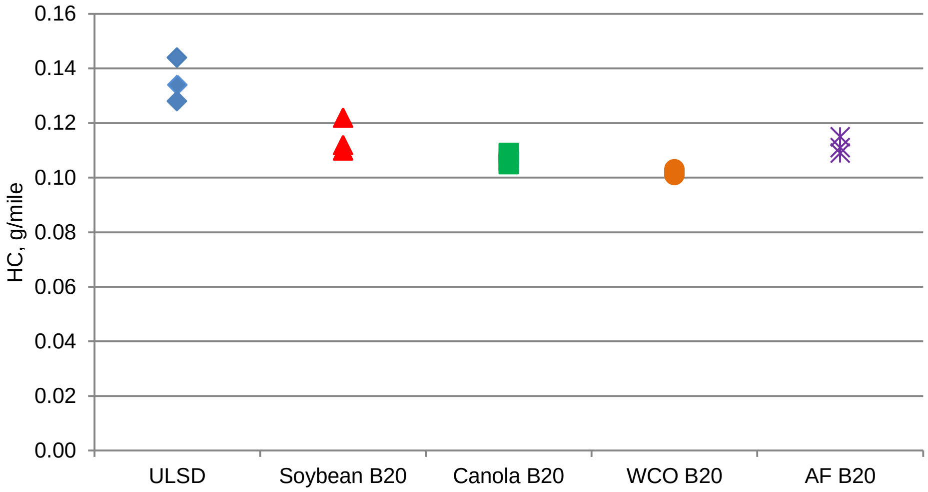


Figure 4.31 Comparison of average HC (g/mile) emissions from UDDS driving cycle for B20 from different feedstocks and ULSD

Figure 4.32 shows an example of HC (ppm) emissions from UDDS driving cycle for B20 canola. It can be seen that hydrocarbon emissions are generally higher when speeds are higher, presumably due to more fuel being burned in the engine.

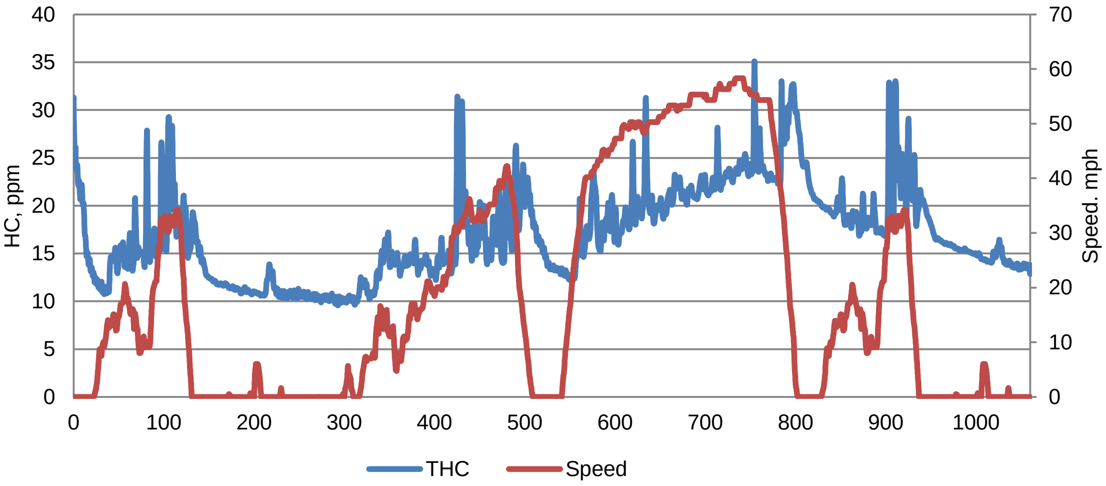


Figure 4.32 HC (ppm) emissions from UDDS driving cycle for B20 canola

4.3.1.4 Nitrogen Oxides (NO_x)

As shown in Figure 4.33, NO_x emissions from all B20 blends were slightly higher than those from petroleum diesel fuel. Figure 4.34 shows an example of NO_x (ppm) emissions from UDDS driving cycle for B20 canola. It can be seen that NO_x emissions are generally higher when speeds are higher, presumably because engine temperatures are hotter due to more fuel being burned in the engine.

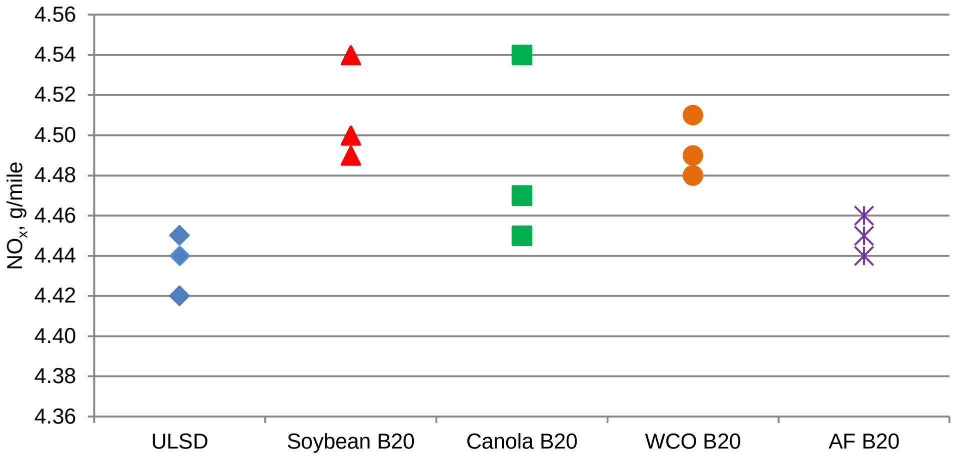


Figure 4.33 Comparison of average NO_x (g/mile) emissions from UDDS driving cycle for B20 from different feedstocks and ULSD

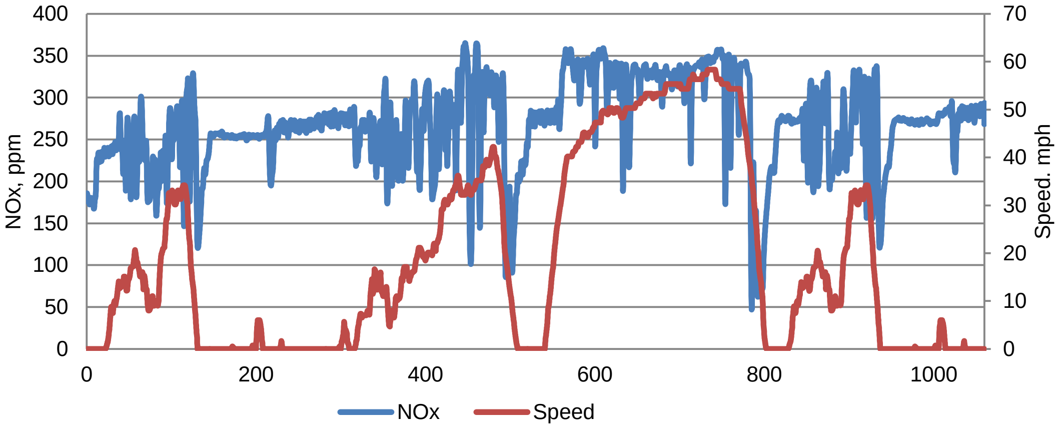


Figure 4.34 NO_x (ppm) emissions from UDDS driving cycle for B20 canola

It should be noted that the magnitude of NO_x emissions from dynamometer testing is much greater than those from on-road testing. The test results are not directly comparable, because the vehicle load was different, as explained above.

4.3.1.5 Particulate Matter (PM)

As shown in Figure 4.35, PM emissions from all B20 blends were lower than those from petroleum diesel fuel. Since PM results from incomplete combustion, higher oxygen content typically lowers PM emissions by producing more complete combustion. PM emissions were measured by weighing; therefore, no second by second data is available.

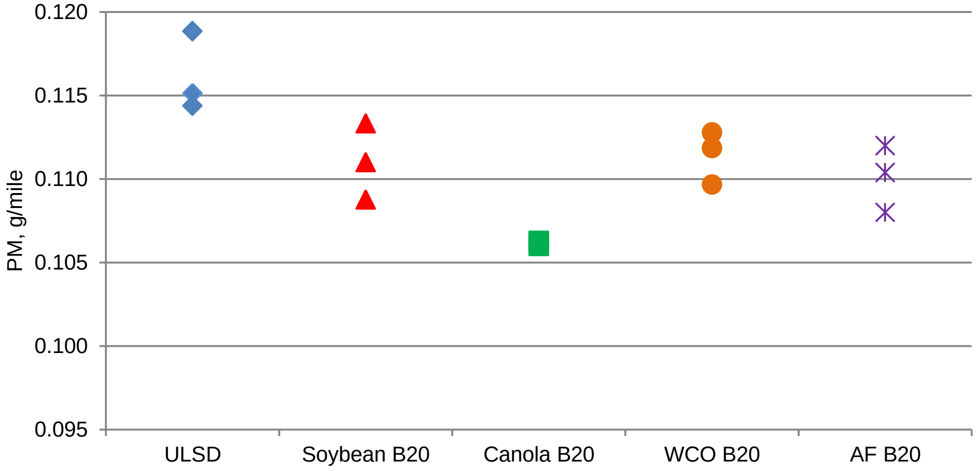


Figure 4.35 Comparison of average PM (g/mile) emissions from UDDS driving cycle for B20 from different feedstocks and ULSD

4.3.1.6 Fuel Economy (FE)

As shown in Figure 4.36, driving with B20 consumed more fuel than ULSD. This is consistent with the results from other studies, which show that fuel economy from biodiesel is typically a few percent lower than that from regular diesel, by amounts ranging from 1 to 2.7%.

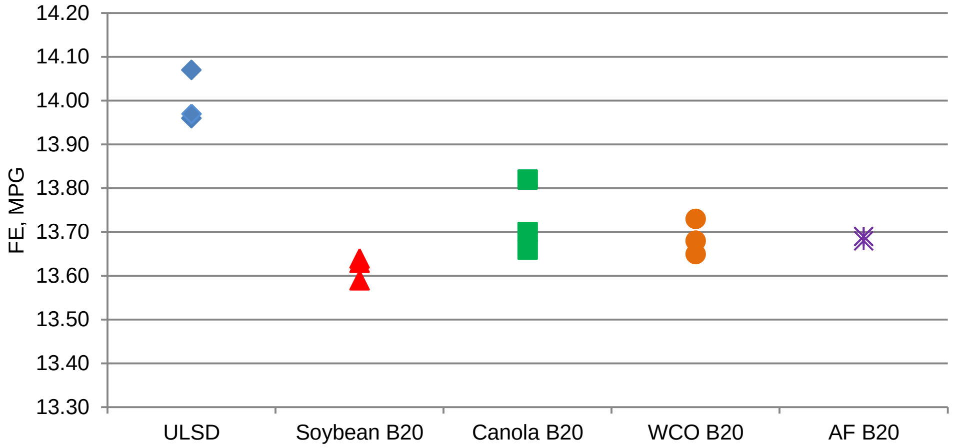


Figure 4.36 Comparison of average fuel economy (mile/gal) from UDDS driving cycle for B20 from different feedstocks and ULSD

4.3.2 Data Collection of Dynamometer Testing

A single factor experimental design was employed to study the five fuel types. Fifteen vehicle runs as experimental units enabled 3 replications per fuel type treatment.

The response variables in this study are the emissions of CO_2, CO, HC, NO_x, PM and fuel economy from dynamometer testing with urban dynamometer drive schedule (UDDS) using biodiesel fuel B20 from different feedstocks. The emissions were measured in gram per mile.

The types of treatments involved are shown below in Table 4.29.

Table 4.29 Factors with Replications

Test #	Fuel Type (Factor)	Replications
1	ULSD	3
2	Soybean B20	3
3	Canola B20	3
4	Waste cooking oil B20	3
5	Animal fat B20	3

The experiment was conducted in a randomized order to minimize serial correlation, and to overcome any experimental bias. The order of the experiments is shown in Table 3.3.

4.3.2.1 Data Analysis of Carbon Dioxide (CO_2)

Figure 4.37 shows the mean CO_2 emissions for each run for each type of fuel on the dynamometer testing. From the plot, it can be noticed that the difference between mean CO_2 emissions for the 3 replicate runs is slightly different.

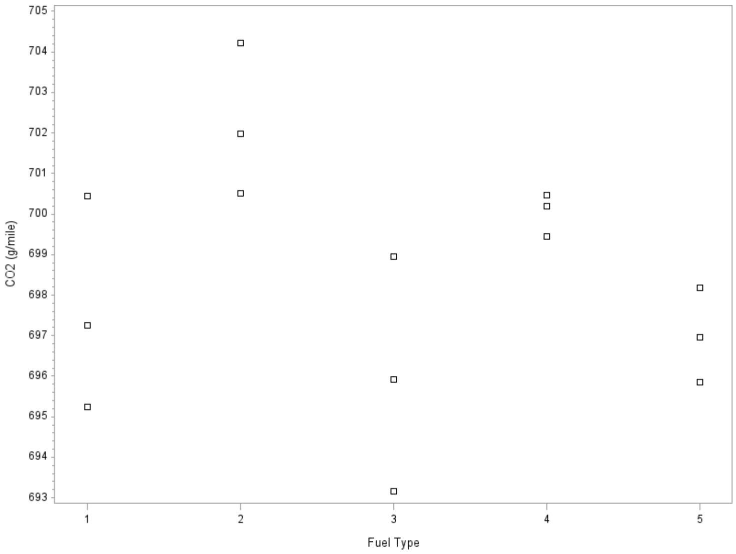


Figure 4.37 Mean CO_2 emissions from replicate runs for various fuel types on the dynamometer testing

There is one factor (fuel type), involving in the concentration of emissions. Five types of fuel were tested. Therefore, there are 5 treatment combinations, and 3 replications were conducted for each treatment. The individual effects of the fuel types are included in the model which is as follows:

$$Y_{it} = \mu_i + \varepsilon_{it}$$

where $i = 1,2,3,4,5;\ t = 1,2,3$

Each term can be defined as:

Y_{it} = CO_2 emissions (g/mile)

μ_i = True mean CO_2 emissions for treatment effect (i)

ε_{ijt} = Random error iid N$(0,\sigma^2)$

To verify the constant variance assumption, the plot of the residuals versus the estimate mean of CO_2 on dynamometer testing in Figure 4.38 is checked for a funnel shape. No funnel shape is observed in this plot; the error variance appears to be mostly constant, although two of the treatments may have smaller variance.

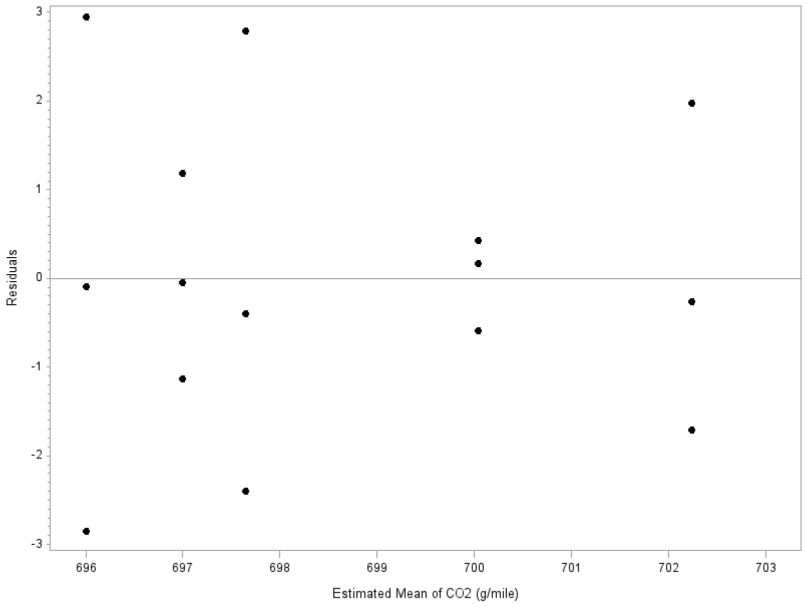


Figure 4.38 Residuals versus estimate mean of CO_2 on dynamometer testing

To test for constant variance, a Modified Levene test is conducted for the following two hypotheses:

H_0 : Errors variance is constant

H_1 : Errors variance is non-constant

The decision rule rejects H_0 if the p-value (seen in the SAS output in Table 4.30 as 0.5008) is less than the significance level of α, where α represents the probability of incorrectly rejecting H_0. For an α of 0.05, we fail to reject H_0; therefore, the variance is constant. Since the Modified

Levene test does not detect non-constant variance; therefore, we will conclude overall that the variance is relatively constant.

Table 4.30 SAS output of constant variance testing

```
                          The ANOVA Procedure
                         Dependent Variable: d
Source            DF  Sum of Squares  Mean Square  F Value   Pr > F

Model              4      5.25557333   1.31389333     0.90   0.5008

Error             10     14.64380000   1.46438000

Corrected Total   14     19.89937333

              R-Square  Coeff Var  Root MSE    d Mean

              0.264107   100.7311  1.210116  1.201333

        Source  DF    Anova SS  Mean Square  F Value   Pr > F

        FUEL     4  5.25557333   1.31389333     0.90   0.5008
```

In the normal probability plot of the residuals in Figure 4.39, a type of S-shaped pattern is observed. Consequently, the distribution of the errors follows a distribution that has longer tails than the normal distribution, and normality is violated.

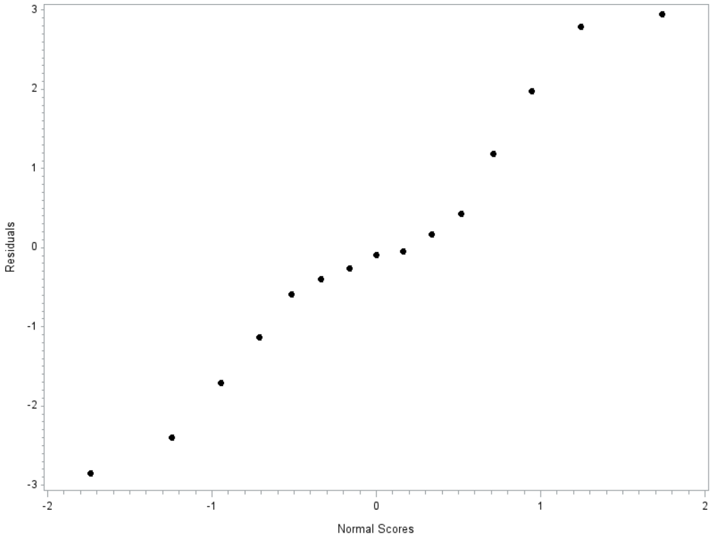


Figure 4.39 Normal probability plot of residuals

Test for Normality

Table 4.31 SAS output of normality test analysis

```
                 Pearson Correlation Coefficients, N = 15
                      Prob > |r| under H0: Rho=0

                                           e          enrm

                e                    1.00000       0.98447
                Residuals                           <.0001

                enrm                 0.98447       1.00000
                Normal Scores         <.0001
```

To test for normality, the following two hypotheses have to be tested:

H_0 : Normality is satisfied.

H_1 : Normality is violated.

For an $\alpha = 0.05$, we have the critical value $c(\alpha,n) = c(0.05, 15) = 0.938$. The decision rule fails to reject H_0 if the correlation value (seen in the SAS output Table 4.31 as 0.98447) is greater than $c(\alpha,n)$. Since $\rho = 0.98447 > c = 0.938$, we fail to reject H_0; therefore, the test is unable to detect the non-normality. However, normality is not required for a valid ANOVA.

An analysis of variance (ANOVA) was obtained using SAS. The SAS output ANOVA is shown in Table 4.32.

To test for the fuel type effect, an F-test is conducted for the following two hypotheses:

$H_0 : \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$ (No difference in treatment means)

H_1 : Not all μ_i are equal (At least two treatment means are different)

The decision rule rejects H_0 if the Type III SS p-value (seen in the SAS output Table 4.32 as 0.0217) is less than the significance level of α, where α represents the probability of incorrectly rejecting H_0. For an α of 0.05, we reject H_0 and detect differences in the mean CO_2 emissions for the different fuel types.

Table 4.32 SAS output of ANOVA of CO_2 emissions and fuel type

```
                              The GLM Procedure

                       Dependent Variable: CO2 (g/mile)

       Source           DF  Sum of Squares  Mean Square  F Value   Pr > F
       Model             4      76.4062267   19.1015567     4.69   0.0217
       Error            10      40.7527333    4.0752733
       Corrected Total  14     117.1589600

                   R-Square  Coeff Var  Root MSE    Y Mean
                   0.652159   0.288975  2.018731  698.5840

            Source  DF     Type I SS  Mean Square  F Value   Pr > F
            Fuel     4  76.40622667  19.10155667     4.69   0.0217

            Source  DF   Type III SS  Mean Square  F Value   Pr > F
            Fuel     4  76.40622667  19.10155667     4.69   0.0217
```

Pairwise comparisons was appropriate, since ULSD was used as a baseline to compare with varieties feedstock of biodiesel (B20); therefore, the most appropriate statistical methods to use for this study were Dunnett’s T test and Tukey’s studentized range. Dunnett’s test was used to compare group means. This method designed for situations where all groups are to be compared against a reference group. Tukey’s studentized range was applied for all pairwise comparisons. The Tukey’s test conducts a family of multiple comparisons to find which means are significantly different from one another.

The pairwise comparisons, comparing different feedstocks of biodiesel B20 with ULSD baseline, were done for fuel type using Dunnett’s method. The following hypotheses were tested for the differences listed below:

H_0: Differences D1, D2, …. =0 : treatments are statistically same.

H_1: Differences D1, D2,…. ≠0 : treatments are statistically different.

Decision rule: Reject H_0 if the confidence intervals do not contain zero (0).

The confidence intervals for pairwise comparisons are shown in Table 4.33, where factor level (1) ULSD, (2) soybean B20, (3) canola B20, (4) waste cooking oil B20, and (5) animal fat B20. The differences which are statistically significant indicated by ***.

As shown in Table 4.33, it can be observed that zero is contained in the confidence intervals for the Dunnett pairwise comparisons. Therefore, we fail to reject H_0, which means we can conclude that at 95% confidence, the differences between CO_2 emissions for different fuel types are not statistically significant for dynamometer testing on UDDS driving cycle.

Table 4.33 SAS output of Dunnett's t Test of CO_2 emissions

```
                         Dunnett's t Tests for Y
 Note: This test controls the Type I experimentwise error for comparisons of all
       treatments against a control.

                 Alpha                              0.05
                 Error Degrees of Freedom             10
                 Error Mean Square              4.075273
                 Critical Value of Dunnett's t   2.89050
                 Minimum Significant Difference   4.7644

                 Comparisons significant at the 0.05 level
                          are indicated by ***.

            Fuel      Difference  Simultaneous 95% Confidence
         Comparison    Between              Limits
                        Means
            2 - 1        4.587          -0.178        9.351
            4 - 1        2.390          -2.374        7.154
            5 - 1       -0.650          -5.414        4.114
            3 - 1       -1.640          -6.404        3.124
```

For comparison among feedstocks of biodiesel B20, Tukey's method was used with a 95% confidence level when pairwise comparisons were required. The following hypotheses were tested for the differences:

H_0: Differences D1, D2, …. = 0 : treatments are statistically same.

H_1: Differences D1, D2,…. ≠ 0 : treatments are statistically different.

Decision rule: Reject H_0 if the confidence intervals do not contain zero (0).

Pairwise comparisons for fuel type and the confidence intervals for pairwise comparisons between the different fuel types are shown in Table 4.34.

Table 4.34 SAS output of Tukey pairwise comparison for fuel type effect on CO_2 emissions for dynamometer testing

Tukey's Studentized Range (HSD) Test for Y

Note: This test controls the Type I experimentwise error rate.

Alpha	0.05
Error Degrees of Freedom	10
Error Mean Square	4.075273
Critical Value of Studentized Range	4.65425
Minimum Significant Difference	5.4246

Comparisons significant at the 0.05 level are indicated by *.**

Fuel Comparison	**Difference Between Means**	**Simultaneous 95% Confidence Limits**		
2 - 4	2.197	-3.228	7.621	
2 - 1	4.587	-0.838	10.011	
2 - 5	5.237	-0.188	10.661	
2 - 3	6.227	0.802	11.651	***
4 - 2	-2.197	-7.621	3.228	
4 - 1	2.390	-3.035	7.815	
4 - 5	3.040	-2.385	8.465	
4 - 3	4.030	-1.395	9.455	
1 - 2	-4.587	-10.011	0.838	
1 - 4	-2.390	-7.815	3.035	
1 - 5	0.650	-4.775	6.075	
1 - 3	1.640	-3.785	7.065	

Table 4.34 – *Continued*

Comparisons significant at the 0.05 level are indicated by *.**

Fuel Comparison	**Difference Between Means**	**Simultaneous 95% Confidence Limits**		
5 - 2	-5.237	-10.661	0.188	
5 - 4	-3.040	-8.465	2.385	
5 - 1	-0.650	-6.075	4.775	
5 - 3	0.990	-4.435	6.415	
3 - 2	-6.227	-11.651	-0.802	***
3 - 4	-4.030	-9.455	1.395	
3 - 1	-1.640	-7.065	3.785	
3 - 5	-0.990	-6.415	4.435	

As shown in Table 4.34, it can be observed that among all types of B20, only soybean B20 and canola B20 do not contain zero in the confidence interval for the Tukey pairwise comparison. Therefore, we reject H_0, and conclude that at 95% confidence level, the differences of CO_2 emissions among soybean B20 and canola B20 for dynamometer testing are statistically significant.

4.3.2.2 Data Analysis of Carbon Monoxide (CO)

Figure 4.40 shows the mean CO emissions for each run for each type of fuel on the dynamometer testing. From the plot, it can be noticed that the difference between mean CO emissions for the 3 replicate runs is slightly different.

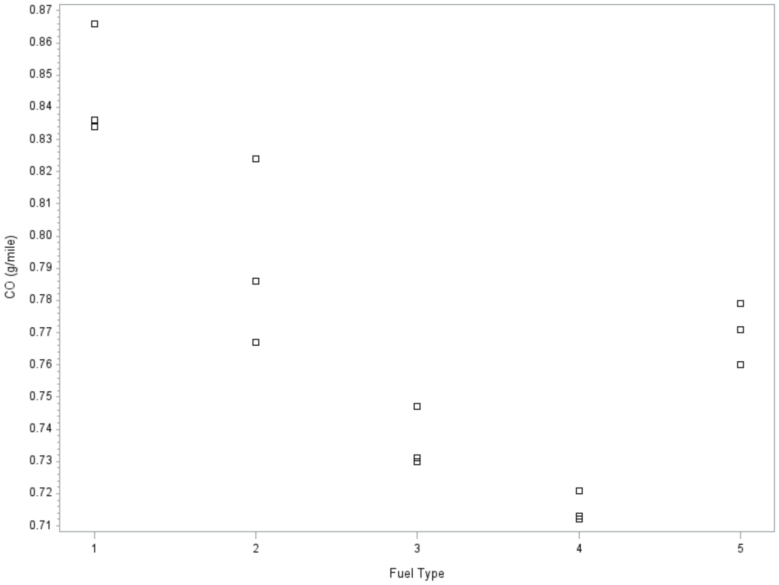


Figure 4.40 Mean CO emissions from replicate runs for various fuel types on the dynamometer testing

There is one factor, (fuel type) which may impact the level of emissions. Five types of fuel were tested. Therefore, there are 5 treatment combinations, and 3 replications were conducted for each treatment. The individual effects of the fuel types are included in the model, which is as follows:

$Y_{it} = \mu_i + \varepsilon_{it}$

where $i = 1,2,3,4,5;\ t = 1,2,3$

Each term can be defined as:

Y_{it} = CO emissions (g/mile)

μ_i = True mean CO emissions for treatment effect (i)

ε_{ijt} = Random error iid N$(0,\sigma^2)$

To verify the constant variance assumption, the plot of the residuals versus the estimate mean of CO on dynamometer testing in Figure 4.41 is checked for a funnel shape. No funnel shape is observed in this plot; there seems to be a constant variance.

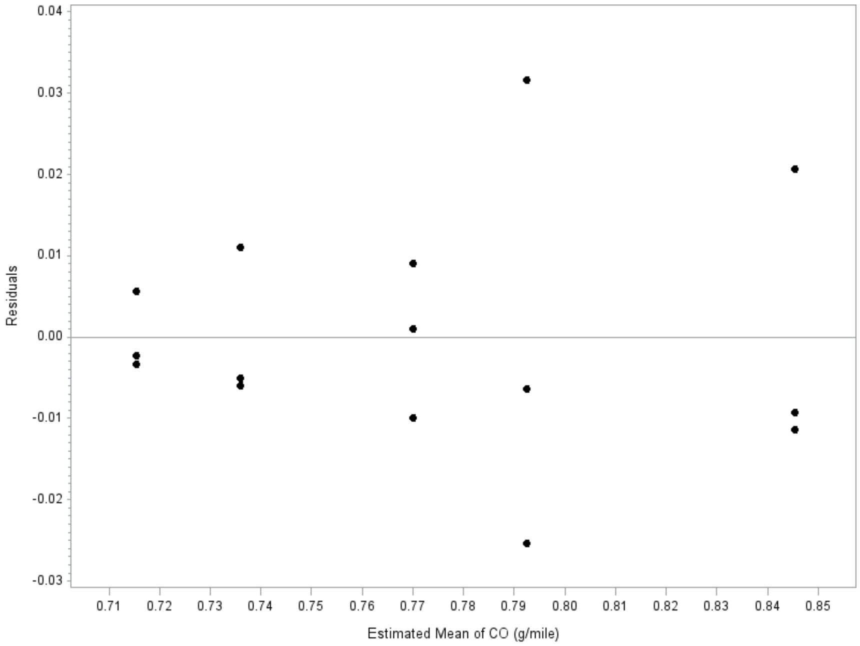


Figure 4.41 Residuals versus estimate mean of CO on dynamometer testing

To test for constant variance, a Modified Levene test is conducted for the following two hypotheses:

H_0 : Errors variance is constant

H_1 : Errors variance is non-constant

The decision rule rejects H_0 if the p-value (seen in the SAS output in Table 4.35 as 0.5741) is less than the significance level of α, where α represents the probability of incorrectly rejecting H_0. For an α of 0.05, we fail to reject H_0; therefore, the variance is constant.

Table 4.35 SAS output of constant variance testing

```
                          The ANOVA Procedure
                          Dependent Variable: d
Source            DF  Sum of Squares  Mean Square  F Value   Pr > F
Model              4      0.00047093   0.00011773     0.76   0.5741
Error             10      0.00154800   0.00015480
Corrected Total   14      0.00201893

             R-Square  Coeff Var  Root MSE    d Mean
             0.233258   139.2746  0.012442  0.008933

         Source  DF    Anova SS  Mean Square  F Value   Pr > F
         FUEL     4  0.00047093   0.00011773     0.76   0.5741
```

In Figure 4.42, the normal probability plot of the residuals seems to be not straight but close to linear pattern which is not perfect. Accordingly, the assumption of normality for the distribution of residuals may be violated.

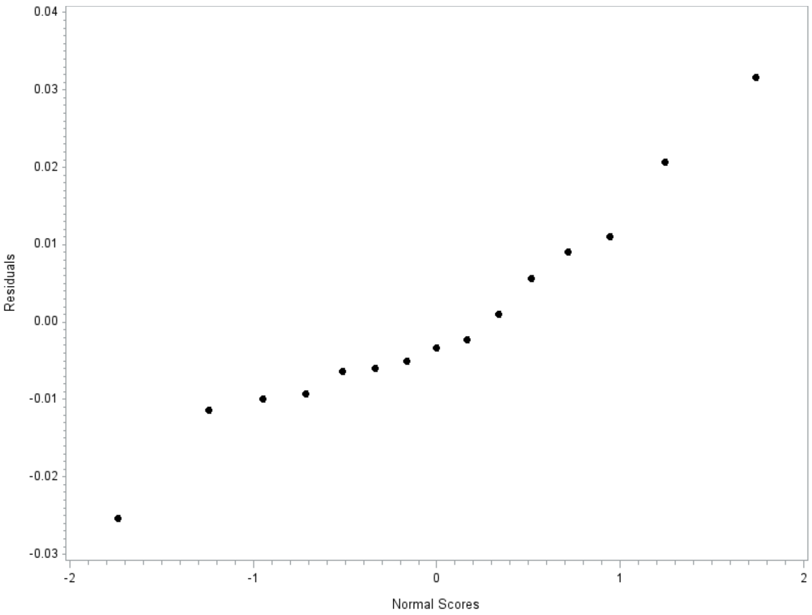


Figure 4.42 Normal probability plot of residuals

Test for Normality

Table 4.36 SAS output of normality test analysis

```
             Pearson Correlation Coefficients, N = 15
                   Prob > |r| under H0: Rho=0

                                    e          enrm

            e                 1.00000       0.96714
            Residuals                        <.0001

            enrm              0.96714       1.00000
            Normal Scores      <.0001
```

To test for normality, the following two hypotheses have to be tested:

H_0 : Normality is satisfied.

H_1 : Normality is violated.

For an $\alpha = 0.05$, we have the critical value $c(\alpha,n) = c(0.05, 15) = 0.938$. The decision rule fail to rejects H_0 if the correlation value (seen in the SAS output Table 4.36 as 0.96714) is greater than $c(\alpha,n)$. Since $\rho = 0.96714 > c = 0.938$, we fail to reject H_0; therefore, the test is unable to detect the non-normality.

Since the error variance appears to be mostly constant, although one of the treatments may have larger variance. The Modified Levene test does not detect non-constant variance, so we will conclude overall that the variance is relatively constant. However, in this case, one could argue there is funnel shape. Since normality is not perfect, a transformation should be conducted.

A transformation is conducted since a funnel shape was observed in the plots of residuals versus CO emissions on dynamometer testing. It is necessary to perform some kind of transformation to satisfy model form requirement. Therefore, a square root transformation was performed on CO emissions (Y). It should be noted that this transformation will affect all five fuels.

To verify the constant variance assumption, the plot of the residuals versus the estimate value of square root CO is checked for a funnel shape. No funnel shape is observed in Figure 4.43. Therefore, the error variance appears to be mostly constant.

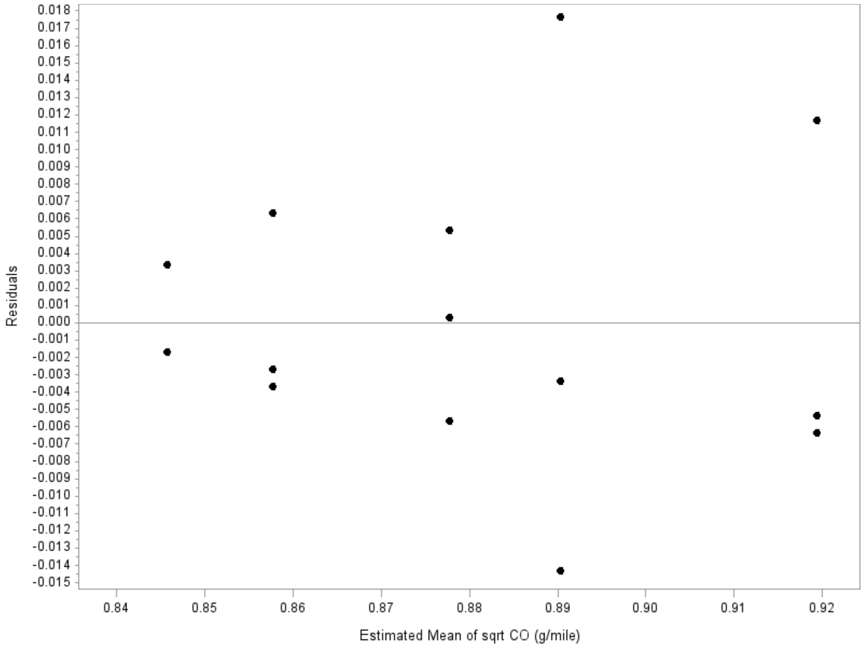


Figure 4.43 Residuals versus estimate mean of transformation of CO

In the normal probability plot of the residuals in Figure 4.44, a linear pattern is observed. It can be seen that the normality improved after performing the square root transformation. The normal probability plot is straighter, and it is reasonable to conclude that the residuals are close to following a normal distribution.

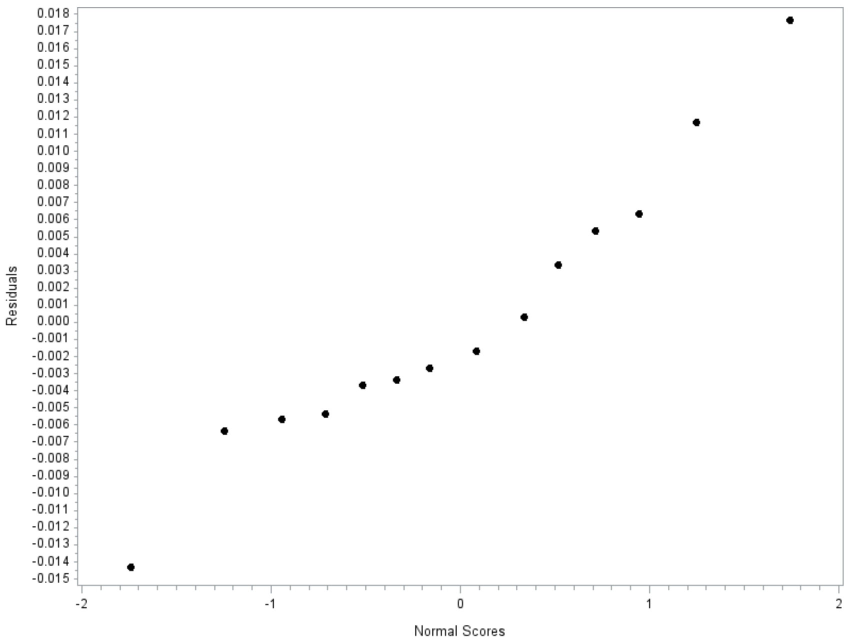


Figure 4.44 Normal probability plot of transformation of CO

An analysis of variance (ANOVA) was obtained after transformation using SAS. The SAS output ANOVA is shown in Table 4.37.

To test for the fuel type effect, an F-test is conducted for the following two hypotheses:

H_0 : $\mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$ (No difference in treatment means)

H_1 : Not all μ_i are equal (At least two treatment means are different)

The decision rule rejects H_0 if the Type III SS p-value (seen in the SAS output Table 4.37 as < 0.0001) is less than the significance level of α, where α represents the probability of incorrectly rejecting H_0. For an α of 0.05, we reject H_0 and detect differences in the mean CO emissions for the different fuel types.

Table 4.37 SAS output of ANOVA of CO emissions after transformation and fuel type

```
                          The GLM Procedure
                   Dependent Variable: sqrt CO (g/mile)
Source            DF  Sum of Squares  Mean Square  F Value   Pr > F

Model              4      0.00995840   0.00248960    28.57  <.0001

Error             10      0.00087133   0.00008713

Corrected Total   14      0.01082973

            R-Square  Coeff Var  Root MSE    Y Mean

            0.919542   1.062996  0.009335  0.878133

       Source  DF     Type I SS  Mean Square  F Value   Pr > F

       FUEL     4  0.00995840     0.00248960    28.57  <.0001

       Source  DF   Type III SS  Mean Square  F Value   Pr > F

       FUEL     4  0.00995840     0.00248960    28.57  <.0001
```

Pairwise comparisons are appropriate since ULSD was used as a baseline to compare with varieties feedstock of biodiesel (B20); therefore, pairwise comparisons were done for fuel type using Dunnett's method. The following hypotheses were tested for the differences listed below:

H_0: Differences D1, D2, …. =0 : treatments are statistically same.

H_1: Differences D1, D2,…. ≠0 : treatments are statistically different.

Decision rule: Reject H_0 if the confidence intervals do not contain zero (0).

As shown in Table 4.38, it can be observed that the confidence interval does not contain zero for Dunnett pairwise comparison. Therefore, we can reject $H_{0,}$ which means we can conclude that at 95% confidence, the differences of CO emission between ULSD and biodiesel B20 (for all feedstocks) are statistically significant for dynamometer testing on UDDS driving cycle.

Table 4.38 SAS output of Dunnett’s t Test of CO after transformation

```
                      Dunnett's t Tests for sqrt CO (g/mile)
Note: This test controls the Type I experimentwise error for comparisons of all
      treatments against a control.

                   Alpha                                  0.05
                   Error Degrees of Freedom                 10
                   Error Mean Square                  0.000087
                   Critical Value of Dunnett's t       2.89050
                   Minimum Significant Difference        0.022

                Comparisons significant at the 0.05 level are
                              indicated by ***.

              Fuel      Difference  Simultaneous 95% Confidence
           Comparison     Between              Limits
                           Means

              2 - 1     -0.029000      -0.051030      -0.006970  ***
              5 - 1     -0.041667      -0.063697      -0.019636  ***
              3 - 1     -0.061667      -0.083697      -0.039636  ***
              4 - 1     -0.073667      -0.095697      -0.051636  ***
```

For comparison among feedstocks of biodiesel B20, Tukey’s method was used with a 95% confidence level. The following hypotheses were tested for the differences listed below:

H_0: Differences D1, D2, …. = 0 : treatments are statistically same.

H_1: Differences D1, D2,…. ≠ 0 : treatments are statistically different.

Decision rule: Reject H_0 if the confidence intervals do not contain zero (0).

Pairwise comparison for fuel type and confidence intervals are shown in Table 4.39.

Table 4.39 SAS output of Tukey pairwise comparison for different fuel type of CO emissions after transformation for dynamometer testing

```
           Tukey's Studentized Range (HSD) Test for sqrt CO (g/mile)
     Note: This test controls the Type I experimentwise error rate.

          Alpha                                        0.05
          Error Degrees of Freedom                       10
          Error Mean Square                        0.000087
          Critical Value of Studentized Range       4.65425
          Minimum Significant Difference             0.0251

          Comparisons significant at the 0.05 level are
                       indicated by ***.

      Fuel     Difference  Simultaneous 95% Confidence
 Comparison       Between              Limits
                    Means

      1 - 2      0.029000      0.003917      0.054083  ***
      1 - 5      0.041667      0.016584      0.066750  ***
      1 - 3      0.061667      0.036584      0.086750  ***
      1 - 4      0.073667      0.048584      0.098750  ***
      2 - 1     -0.029000     -0.054083     -0.003917  ***
      2 - 5      0.012667     -0.012416      0.037750
      2 - 3      0.032667      0.007584      0.057750  ***
      2 - 4      0.044667      0.019584      0.069750  ***
      5 - 1     -0.041667     -0.066750     -0.016584  ***
      5 - 2     -0.012667     -0.037750      0.012416
      5 - 3      0.020000     -0.005083      0.045083
      5 - 4      0.032000      0.006917      0.057083  ***
      3 - 1     -0.061667     -0.086750     -0.036584  ***
      3 - 2     -0.032667     -0.057750     -0.007584  ***
      3 - 5     -0.020000     -0.045083      0.005083
      3 - 4      0.012000     -0.013083      0.037083
      4 - 1     -0.073667     -0.098750     -0.048584  ***
      4 - 2     -0.044667     -0.069750     -0.019584  ***
      4 - 5     -0.032000     -0.057083     -0.006917  ***
      4 - 3     -0.012000     -0.037083      0.013083
```

As shown in Table 4.39, it can be observed that at 95% confidence, CO emissions from ULSD were statistically different from all types of B20. CO emissions from soybean B20 were significantly higher than canola and WCO B20, and CO emissions from animal fat B20 were significantly higher than WCO B20, to a 95% level of confidence.

4.3.2.3 Data Analysis of Hydrocarbons (HC)

Figure 4.45 shows the mean HC emissions for each run for each type of fuel on the dynamometer testing. From the plot, it can be noticed that the difference between mean HC emissions for the 3 replicate runs is slightly different, especially for ULSD and soybean B20.

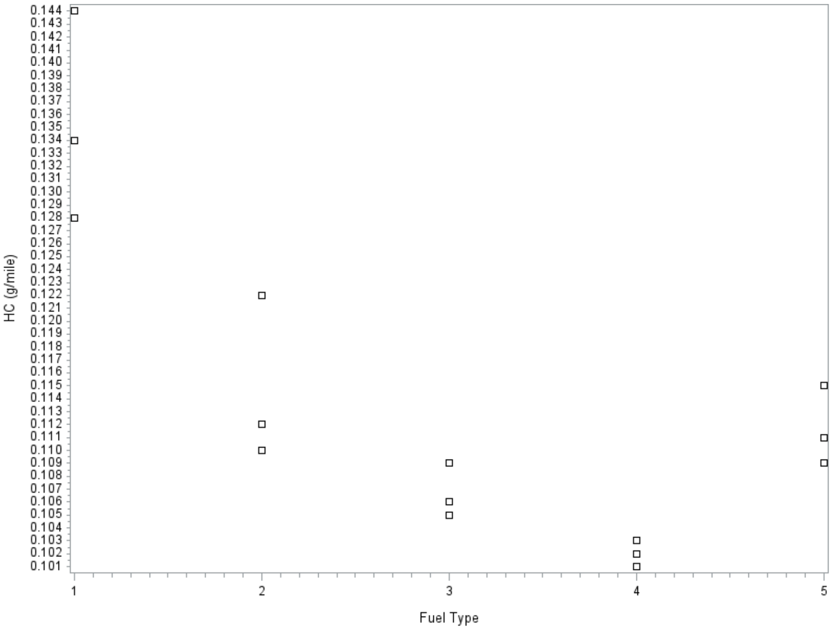


Figure 4.45 Mean HC emissions from replicate runs for various fuel types on the dynamometer testing

There is one factor (fuel type) that impacts the level of emissions. Five types of fuel were tested. Therefore, there are 5 treatment combinations, and 3 replications were conducted for each treatment. The individual effects of the fuel types are included in the model, which is as follows:

$Y_{it} = \mu_i + \varepsilon_{it}$

where $i = 1,2,3,4,5;\ t = 1,2,3$

Each term can be defined as:

Y_{it} = HC emissions (g/mile)

μ_i = True mean HC emissions for treatment effect (i)

ε_{ijt} = Random error iid N$(0,\sigma^2)$

To verify the constant variance assumption, the plot of the residuals versus the estimate mean of HC on dynamometer testing in Figure 4.46 is checked for a funnel shape. A funnel shape is observed in this plot; therefore, the error variance is not constant.

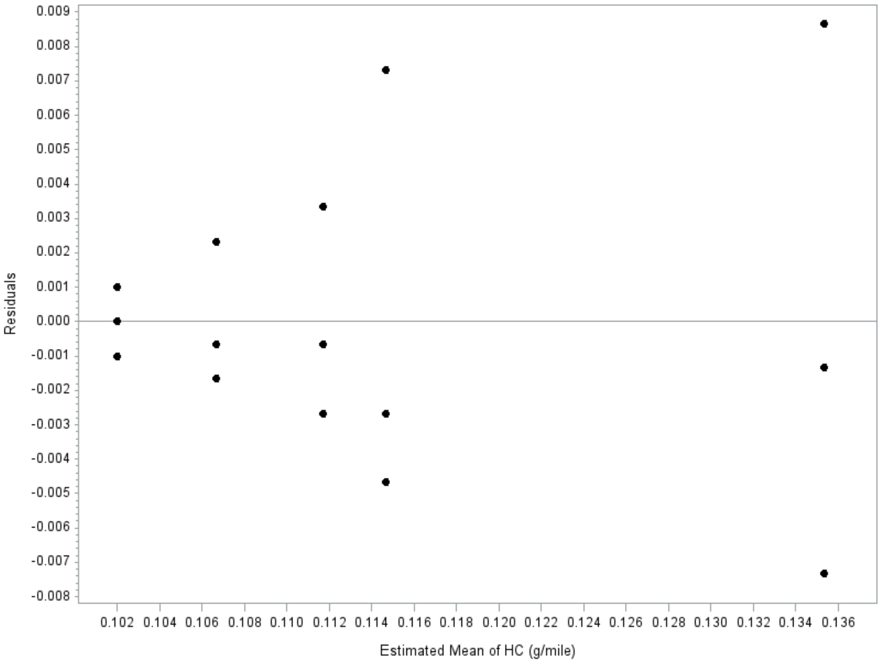


Figure 4.46 Residuals versus estimate mean of HC on dynamometer testing

To test for constant variance, a Modified Levene test is conducted for the following two hypotheses:

H_0 : Errors variance is constant

H_1 : Errors variance is non-constant

The decision rule rejects H_0 if the p-value (seen in the SAS output in Table 4.40 as 0.0448) is less than the significance level of α, where α represents the probability of incorrectly rejecting H_0. For an α of 0.05, we reject H_0; therefore, the Modified Levene test detects nonconstant variance. Hence, we have concluded that the constant variance assumption is violated.

Table 4.40 SAS output of constant variance testing

```
                      The ANOVA Procedure
                     Dependent Variable: d
Source            DF  Sum of Squares  Mean Square  F Value   Pr > F
Model              4      0.00024373   0.00006093     3.63   0.0448
Error             10      0.00016800   0.00001680
Corrected Total   14      0.00041173

            R-Square  Coeff Var  Root MSE    d Mean
            0.591969   54.89438  0.004099  0.007467

       Source  DF    Anova SS  Mean Square  F Value   Pr > F
       Fuel     4  0.00024373   0.00006093     3.63   0.0448
```

In the normal probability plot of the residuals in Figure 4.47, a slight S-shaped pattern is observed. Consequently, the distribution of the errors follows a distribution that has shorter tails than the normal distribution, and normality may be violated.

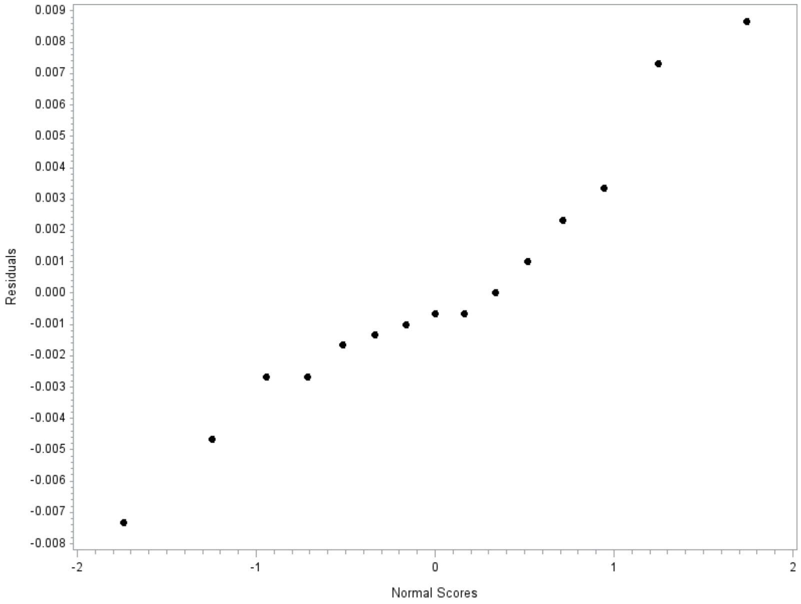


Figure 4.47 Normal probability plot of residuals

Test for Normality

Table 4.41 SAS output of normality test analysis

```
          Pearson Correlation Coefficients, N = 15
                  Prob > |r| under H0: Rho=0

                                e         enrm

 e                        1.00000      0.96812
 Residuals                              <.0001

 enrm                     0.96812      1.00000
 Normal Scores             <.0001
```

To test for normality, the following two hypotheses have to be tested:

H_0 : Normality is satisfied.

H_1 : Normality is violated.

For an $\alpha = 0.05$, we have the critical value c(α,n) = c(0.05, 15) = 0.938. The decision rule fail to rejects H_0 if the correlation value (seen in the SAS output Table 4.41 as 0.96812) is greater than c(α,n). Since $\rho = 0.96812 > c = 0.938$, we fail to reject H_0; therefore, the test is unable to detect the non-normality. However, we conclude that normality is violated.

Since the error variance appears to be nonconstant, and normality is violated, a variance stabilizing transformation should be conducted. In this particular case, the values of HC emissions (Y) from each fuel type are close together. Therefore, initial attempts at transformation did not produce any effect. By creating more separation between the HC values, the transformation will be better able to compress the higher values (corresponding to the wide end of the funnel in Figure 4.46). To do this, we standardized the Y values by subtracting the sample mean and dividing by the standard deviation. Then a small constant was added (in this case, we added 3) to shift all the values above 1.0, and refer to these modified values as Yprime (see in Table 4.42). The variance stabilizing transformation known as the inverse transformation was then applied (1/Yprime). It should be noted that this transformation will affect all five fuels.

Table 4.42 HC emissions transformation data

Test #	Fuel Type	HC (g/mile)	STD Y	Yprime (g/mile)	1/Yprime (g/mile)
1	ULSD	0.144	2.378	5.378	0.186
2	ULSD	0.134	1.583	4.583	0.218
3	ULSD	0.128	1.107	4.107	0.244
4	Soybean B20	0.122	0.630	3.630	0.275
5	Soybean B20	0.112	-0.164	2.836	0.353
6	Soybean B20	0.110	-0.323	2.677	0.374
7	Canola B20	0.109	-0.402	2.598	0.385
8	Canola B20	0.106	-0.641	2.359	0.424
9	Canola B20	0.105	-0.720	2.280	0.439
10	WCO B20	0.101	-1.038	1.962	0.510
11	WCO B20	0.102	-0.958	2.042	0.490
12	WCO B20	0.103	-0.879	2.121	0.471
13	AF B20	0.115	0.074	3.074	0.325
14	AF B20	0.111	-0.244	2.756	0.363
15	AF B20	0.109	-0.402	2.598	0.385

To verify the constant variance assumption after transformation, the plot of the residuals versus the estimate value of 1/Yprime is checked for a funnel shape. No funnel shape appears in Figure 4.48. Therefore, the error variance appears to be reasonably constant after transformation.

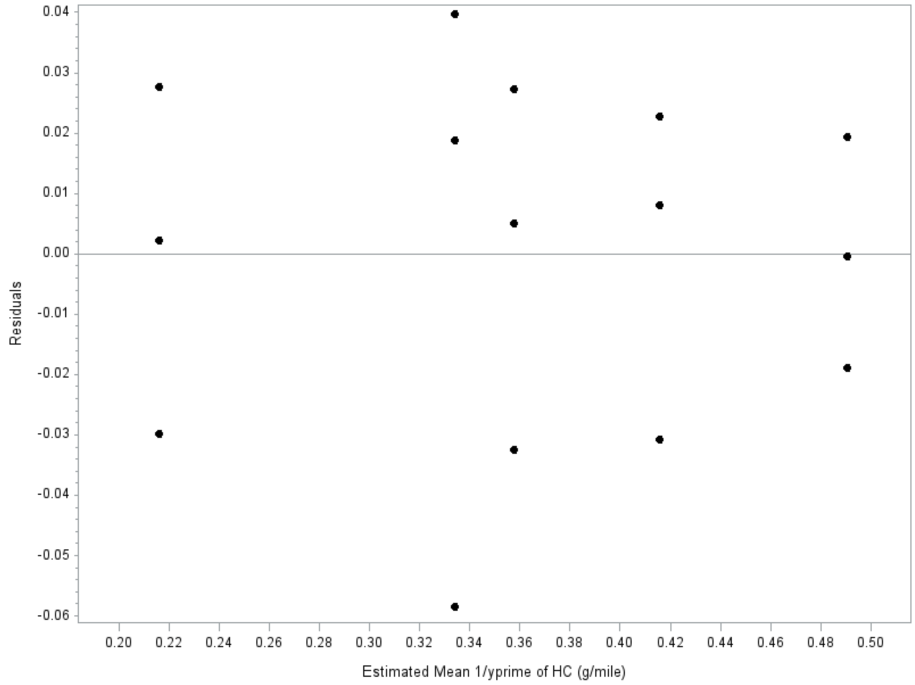


Figure 4.48 Residuals versus estimate mean of transformation of HC

In the normal probability plot of the residuals in Figure 4.49, after the transformation a more linear pattern is observed, indicating a distribution closer to normality

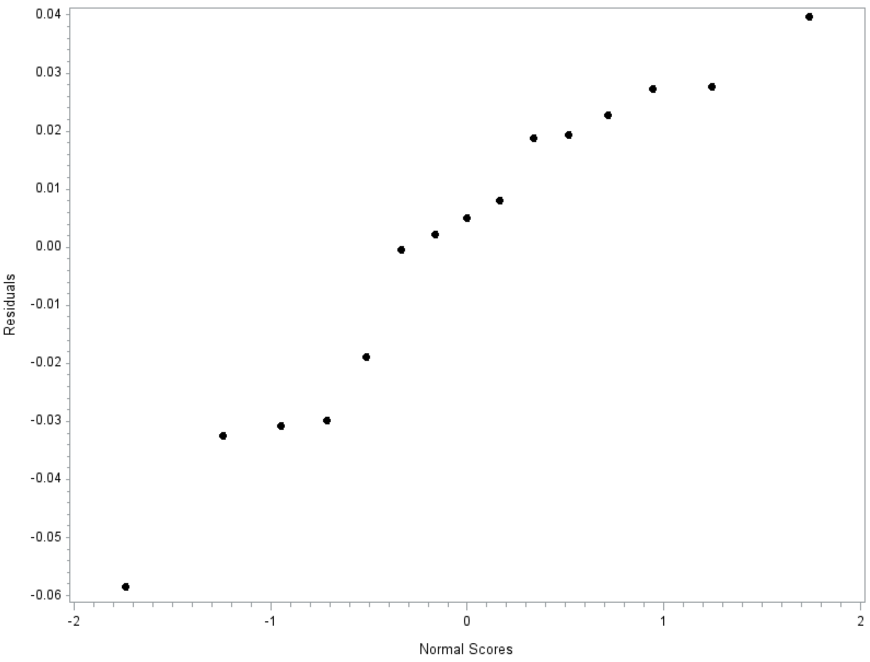


Figure 4.49 Normal probability plot of transformation of HC

An analysis of variance (ANOVA) was obtained after transformation by using SAS. The SAS output ANOVA is shown in Table 4.43.

To test for the fuel type effect, an F-test is conducted for the following two hypotheses:

H_0 : $\mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$ (No difference in treatment means)

H_1 : Not all μ_i are equal (At least two treatment means are different)

The decision rule rejects H_0 if the Type III SS p-value (seen in the SAS output Table 4.43 as < 0.0001) is less than the significance level of α, where α represents the probability of incorrectly rejecting H_0. For an α of 0.05, we reject H_0 and detect differences in the mean HC emissions for the different fuel types.

Table 4.43 SAS output of ANOVA of HC after transformation and fuel type

```
                              The GLM Procedure

                     Dependent Variable: 1/Yprime HC (g/mile)
        Source          DF  Sum of Squares  Mean Square  F Value   Pr > F
        Model            4      0.12456377   0.03114094    28.09  <.0001
        Error           10      0.01108693   0.00110869
        Corrected Total 14      0.13565070
               R-Square  Coeff Var  Root MSE  onebyprime Mean
               0.918269   9.179821  0.033297         0.362720
             Source  DF    Type I SS  Mean Square  F Value   Pr > F
             Fuel     4  0.12456377    0.03114094    28.09  <.0001
             Source  DF  Type III SS  Mean Square  F Value   Pr > F
             Fuel     4  0.12456377    0.03114094    28.09  <.0001
```

Pairwise comparison was used to compare different feedstocks of biodiesel B20 with ULSD baseline using Dunnett's method. The following hypotheses were tested for the differences listed below:

H_0: Differences D1, D2, …. =0 : treatments are statistically same.

H_1: Differences D1, D2,…. ≠0 : treatments are statistically different.

Decision rule: Reject H_0 if the confidence intervals do not contain zero (0).

As shown in Table 4.44, it can be observed that the confidence interval does not contain zero for Dunnett pairwise comparison. Therefore, we can reject $H_{0,}$ which means we can conclude that at 95% confidence, the differences of mean HC emissions between ULSD and biodiesel B20 (for all feedstocks) are statistically significant for dynamometer testing on UDDS driving cycle.

Table 4.44 SAS output of Dunnett's t Test of HC after transformation

```
                         Dunnett's t Tests for 1/Yprime
  Note:  This test controls the Type I experimentwise error for comparisons of all
         treatments against a control.
                    Alpha                                   0.05
                    Error Degrees of Freedom                  10
                    Error Mean Square                   0.001109
                    Critical Value of Dunnett's t        2.89050
                    Minimum Significant Difference        0.0786

                    Comparisons significant at the 0.05 level
                              are indicated by ***.
           Fuel      Difference  Simultaneous 95% Confidence
        Comparison     Between             Limits
                        Means

           4 - 1      0.27444        0.19586        0.35303  ***
           3 - 1      0.19994        0.12136        0.27853  ***
           5 - 1      0.14181        0.06322        0.22039  ***
           2 - 1      0.11801        0.03942        0.19659  ***
```

To compare among feedstocks of biodiesel B20, Tukey's method was used with a 95% confidence level. The following hypotheses were tested for the differences listed below:

H_0: Differences D1, D2, …. =0 : treatments are statistically same.

H_1: Differences D1, D2,…. ≠0 : treatments are statistically different.

Decision rule: Reject H_0 if the confidence intervals do not contain zero (0).

Pairwise comparisons for fuel type and the confidence intervals are shown in Table 4.45.

Table 4.45 SAS output of Tukey pairwise comparison for different fuel type of HC emissions after transformation for dynamometer testing

```
                 Tukey's Studentized Range (HSD) Test for 1/Yprime
     Note: This test controls the Type I experimentwise error rate.

          Alpha                                        0.05
          Error Degrees of Freedom                       10
          Error Mean Square                        0.001109
          Critical Value of Studentized Range       4.65425
          Minimum Significant Difference             0.0895

                Comparisons significant at the 0.05 level
                          are indicated by ***.

        Fuel       Difference  Simultaneous 95% Confidence
     Comparison      Between              Limits
                       Means

        4 - 3        0.07450      -0.01497       0.16397
        4 - 5        0.13264       0.04316       0.22211  ***
        4 - 2        0.15644       0.06696       0.24591  ***
        4 - 1        0.27444       0.18497       0.36392  ***
        3 - 4       -0.07450      -0.16397       0.01497
        3 - 5        0.05814      -0.03134       0.14761
        3 - 2        0.08194      -0.00754       0.17141
        3 - 1        0.19994       0.11047       0.28942  ***
        5 - 4       -0.13264      -0.22211      -0.04316  ***
        5 - 3       -0.05814      -0.14761       0.03134
        5 - 2        0.02380      -0.06567       0.11327
        5 - 1        0.14181       0.05233       0.23128  ***
        2 - 4       -0.15644      -0.24591      -0.06696  ***
        2 - 3       -0.08194      -0.17141       0.00754
        2 - 5       -0.02380      -0.11327       0.06567
        2 - 1        0.11801       0.02853       0.20748  ***
        1 - 4       -0.27444      -0.36392      -0.18497  ***
        1 - 3       -0.19994      -0.28942      -0.11047  ***
        1 - 5       -0.14181      -0.23128      -0.05233  ***
        1 - 2       -0.11801      -0.20748      -0.02853  ***
```

As shown in Table 4.45, it can be observed that at 95% confidence, HC emissions from ULSD were statistically higher than all types of B20. The HC emissions from soybean and AF B20 were statistically higher than WCO B20.

4.3.2.4 Data Analysis of Nitrogen Oxides (NO_x)

Figure 4.50 shows the mean NO_x emissions for each run for each type of fuel on the dynamometer testing. From the plot, it can be noticed that the difference between mean NO_x emissions for the 3 replicate runs is slightly different, especially for soybean B20 and canola B20.

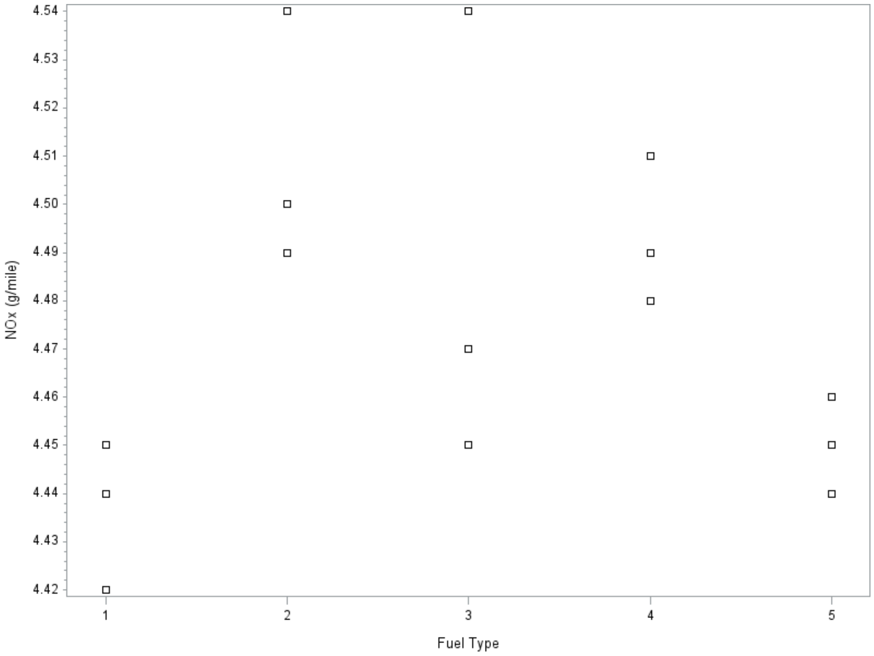


Figure 4.50 Mean NO_x emissions from replicate runs for various fuel types on the dynamometer testing

There is one factor (fuel type) which impacts the level of emissions. Five types of fuel were tested. Therefore, there are 5 treatment combinations, and 3 replications were conducted for each treatment. The individual effects of the fuel types are included in the model, which is as follows:

$Y_{it} = \mu_i + \varepsilon_{it}$

where $i = 1,2,3,4,5;\ t = 1,2,3$

Each term can be defined as:

Y_{it} = NO_x emissions (g/mile)

μ_i = True mean NO_x emissions for treatment effect (i)

ε_{ijt} = Random error iid N$(0,\sigma^2)$

To verify the constant variance assumption, the plot of the residuals versus the estimate mean of NO_x on dynamometer testing in Figure 4.51 is checked for a funnel shape. No funnel shape is observed in this plot; the error variance appears to be mostly constant, although one of the treatments may have larger variance.

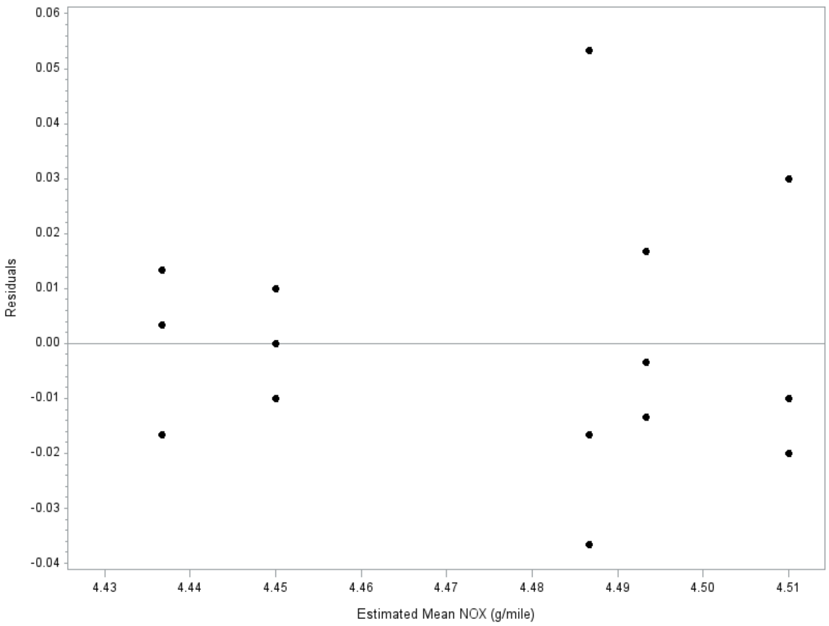


Figure 4.51 Residuals versus estimate mean of NO_x on dynamometer testing

To test for constant variance, a Modified Levene test is conducted for the following two hypotheses:

H_0 : Errors variance is constant

H_1 : Errors variance is nonconstant

The decision rule rejects H_0 if the p-value (seen in the SAS output in Table 4.46 as 0.6330) is less than the significance level of α, where α represents the probability of incorrectly rejecting H_0. For an α of 0.05, we fail to reject H_0. The Modified Levene test does not detect nonconstant variance; therefore, we will conclude overall that the variance is relatively constant.

Table 4.46 SAS output of constant variance testing

```
                        The ANOVA Procedure
                       Dependent Variable: d
Source            DF  Sum of Squares  Mean Square  F Value   Pr > F
Model              4      0.00104000   0.00026000     0.66   0.6330
Error             10      0.00393333   0.00039333
Corrected Total   14      0.00497333

              R-Square  Coeff Var  Root MSE    d Mean
              0.209115   135.2225  0.019833  0.014667

         Source  DF    Anova SS  Mean Square  F Value   Pr > F
         FUEL     4  0.00104000   0.00026000     0.66   0.6330
```

In the normal probability plot of the residuals in Figure 4.52, a linear pattern is observed. Consequently, the normality assumption for error distribution appears to be reasonable.

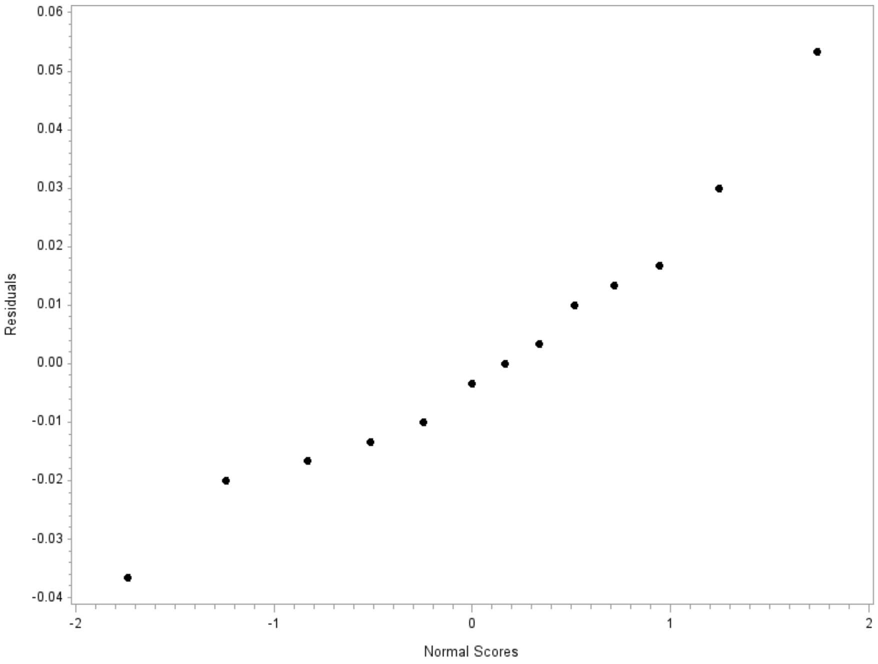


Figure 4.52 Normal probability plot of residuals

Test for Normality

Table 4.47 SAS output of normality test analysis

```
                 Pearson Correlation Coefficients, N = 15
                        Prob > |r| under H0: Rho=0

                                              e         enrm

                 e                      1.00000      0.97116
                 Residuals                            <.0001

                 enrm                   0.97116      1.00000
                 Normal Scores           <.0001
```

To test for normality, the following two hypotheses have to be tested:

H_0 : Normality is satisfied.

H_1 : Normality is violated.

For an $\alpha = 0.05$, we have the critical value $c(\alpha,n) = c(0.05, 15) = 0.938$. The decision rule fail to rejects H_0 if the correlation value (seen in the SAS output Table 4.47 as 0.97116) is greater than $c(\alpha,n)$. Since $\rho = 0.97116 > c = 0.938$, we fail to reject H_0; therefore, the test is unable to detect the non-normality. However, normality is not required for a valid ANOVA.

An analysis of variance (ANOVA) was obtained using SAS. The SAS output ANOVA is shown in Table 4.48.

To test for the fuel type effect, an F-test is conducted for the following two hypotheses:

$H_0 : \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$ (No difference in treatment means)

H_1 : Not all μ_i are equal (At least two treatment means are different)

The decision rule rejects H_0 if the Type III SS p-value (seen in the SAS output Table 4.48 as 0.0329) is less than the significance level of α, where α represents the probability of incorrectly rejecting H_0. For an α of 0.05, we reject H_0 and detect differences in the mean NO_x emissions for the different fuel types.

Table 4.48 SAS output of ANOVA of NO_x emissions and fuel type

```
                              The GLM Procedure

                      Dependent Variable: NOx (g/mile)
     Source           DF  Sum of Squares  Mean Square  F Value   Pr > F
     Model             4      0.01137333   0.00284333     4.06   0.0329
     Error            10      0.00700000   0.00070000
     Corrected Total  14      0.01837333

                 R-Square  Coeff Var  Root MSE    Y Mean
                 0.619013   0.591185  0.026458  4.475333

           Source  DF     Type I SS  Mean Square  F Value   Pr > F
           Fuel     4  0.01137333     0.00284333     4.06   0.0329

           Source  DF   Type III SS  Mean Square  F Value   Pr > F
           Fuel     4  0.01137333     0.00284333     4.06   0.0329
```

Pairwise comparisons between different feedstocks of biodiesel B20 with baseline were done using Dunnett's method. The following hypotheses were tested for the differences listed below:

H_0: Differences D1, D2, …. =0 : treatments are statistically same.

H_1: Differences D1, D2,…. ≠0 : treatments are statistically different.

Decision rule: Reject H_0 if the confidence intervals do not contain zero (0).

As shown in Table 4.49, it can be observed that only ULSD and soybean B20 does not contain zero in the confidence interval for Dunnett pairwise comparison. Therefore, we can reject $H_{0,}$ which means we can conclude that at 95% confidence, the difference of NO_x emissions between ULSD and soybean B20 is statistically significant for dynamometer testing on UDDS driving cycle.

Table 4.49 SAS output of Dunnett's t Test of NO_x emissions

```
                         Dunnett's t Tests for Y
Note:   This test controls the Type I experimentwise error for comparisons of all
        treatments against a control.
                      Alpha                                 0.05
                      Error Degrees of Freedom                10
                      Error Mean Square                   0.0007
                      Critical Value of Dunnett's t      2.89050
                      Minimum Significant Difference      0.0624

                      Comparisons significant at the 0.05 level
                                are indicated by ***.
              Fuel      Difference  Simultaneous 95% Confidence
           Comparison     Between              Limits
                           Means
              2 - 1       0.07333        0.01089        0.13578  ***
              4 - 1       0.05667       -0.00578        0.11911
              3 - 1       0.05000       -0.01244        0.11244
              5 - 1       0.01333       -0.04911        0.07578
```

For comparison among feedstocks of biodiesel B20, Tukey's method was used with a 95% confidence level. The following hypotheses were tested for the differences listed below:

H_0: Differences D1, D2, …. =0 : treatments are statistically same.

H_1: Differences D1, D2,…. ≠0 : treatments are statistically different.

Decision rule: Reject H_0 if the confidence intervals do not contain zero (0).

Pairwise comparison for fuel type and confidence intervals are shown in Table 4.50.

Table 4.50 SAS output of Tukey pairwise comparison for different fuel type of NO_x emissions for dynamometer testing

```
              Tukey's Studentized Range (HSD) Test for Y
     Note: This test controls the Type I experimentwise error rate.
            Alpha                                        0.05
            Error Degrees of Freedom                       10
            Error Mean Square                          0.0007
            Critical Value of Studentized Range       4.65425
            Minimum Significant Difference             0.0711

               Comparisons significant at the 0.05 level
                        are indicated by ***.

        Fuel     Difference  Simultaneous 95% Confidence
     Comparison    Between             Limits
                    Means

        2 - 4      0.01667        -0.05443      0.08776
        2 - 3      0.02333        -0.04776      0.09443
        2 - 5      0.06000        -0.01109      0.13109
        2 - 1      0.07333         0.00224      0.14443  ***
        4 - 2     -0.01667        -0.08776      0.05443
        4 - 3      0.00667        -0.06443      0.07776
        4 - 5      0.04333        -0.02776      0.11443
        4 - 1      0.05667        -0.01443      0.12776
        3 - 2     -0.02333        -0.09443      0.04776
        3 - 4     -0.00667        -0.07776      0.06443
        3 - 5      0.03667        -0.03443      0.10776
```

Table 4.50 – *Continued*

Comparisons significant at the 0.05 level are indicated by *.**

Fuel Comparison	Difference Between Means	Simultaneous 95% Confidence Limits		
3 - 1	0.05000	-0.02109	0.12109	
5 - 2	-0.06000	-0.13109	0.01109	
5 - 4	-0.04333	-0.11443	0.02776	
5 - 3	-0.03667	-0.10776	0.03443	
5 - 1	0.01333	-0.05776	0.08443	
1 - 2	-0.07333	-0.14443	-0.00224	***
1 - 4	-0.05667	-0.12776	0.01443	
1 - 3	-0.05000	-0.12109	0.02109	
1 - 5	-0.01333	-0.08443	0.05776	

As shown in Table 4.50, it can be observed that at 95% confidence, the only difference that was significant was that for soybean B20. These results are consistent with the fact that the ULSD had the lowest N content, but are surprising in light of the fact that soybean B20 had a higher cetane number than ULSD, and would have thus been expected to produce lower NO_x emissions. With the exception of the higher emissions for soybean B20, these results are consistent with the on-road testing results, which showed no statistically significant difference between NO_x emissions from ULSD and the B20 blends. These results are consistent with two studies discussed in the literature review – Tat (2003) and Karavalakis, Stournas, and Bakeas (2009) – which found that only soy biodiesel increased NO_x emissions by an amount that was statistically significant; biodiesel from yellow grease, rapeseed, and palm oil did not.

4.3.2.5 Data Analysis of Particulate Matter (PM)

Figure 4.53 shows the mean PM emissions for each run for each type of fuel on the dynamometer testing. From the plot, it can be noticed that the difference between mean PM emissions for the 3 replicate runs is slightly different, especially for ULSD and soybean B20.

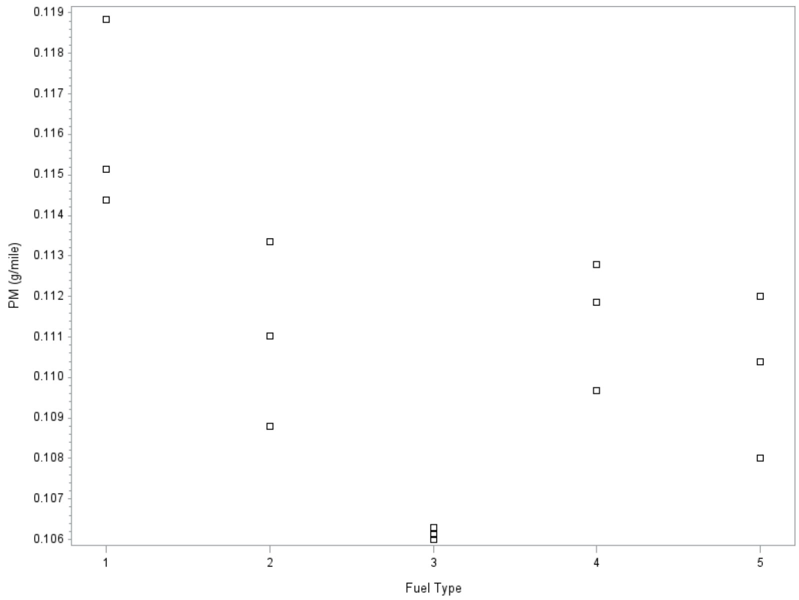


Figure 4.53 Mean PM emissions from replicate runs for various fuel types on the dynamometer testing

There is one factor (fuel type) which impacts the level of emissions. Five types of fuel were tested. Therefore, there are 5 treatment combinations, and 3 replications were conducted for each treatment. The individual effects of the fuel types are included in the model, which is as follows:

$Y_{it} = \mu_i + \varepsilon_{it}$

where $i = 1,2,3,4,5;\ t = 1,2,3$

Each term can be defined as:

Y_{it} = PM emissions (g/mile)

μ_i = True mean PM emissions for treatment effect (i)

ε_{ijt} = Random error iid N$(0,\sigma^2)$

To verify the constant variance assumption, the plot of the residuals versus the estimate mean of PM on dynamometer testing in Figure 4.53 is checked for a funnel shape. A funnel shape is observed in this plot; there seems to be a nonconstant error variance.

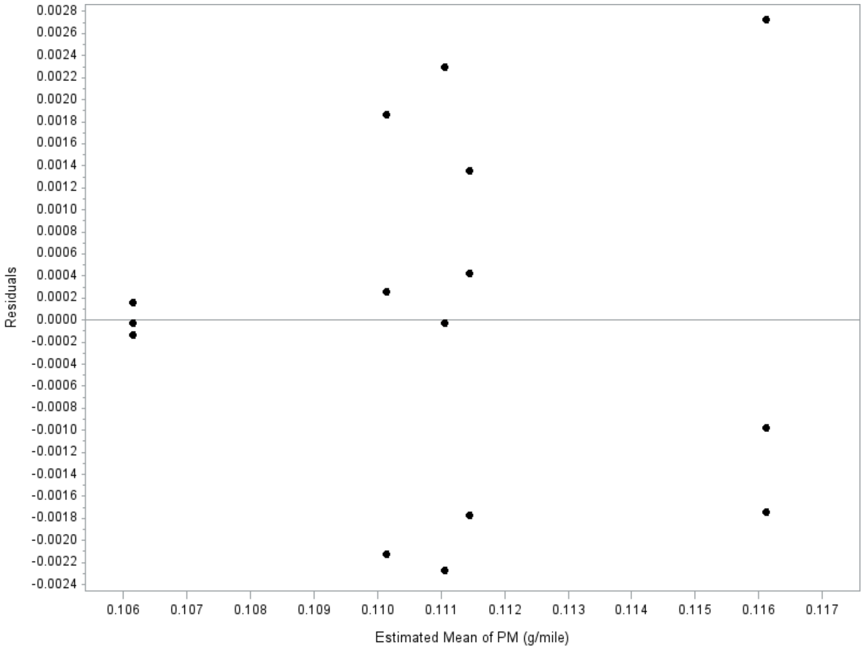


Figure 4.54 Residuals versus estimate mean of PM on dynamometer testing

To test for constant variance, a Modified-Levene test is conducted for the following two hypotheses:

H_0 : Errors variance is constant

H_1 : Errors variance is non-constant

The decision rule rejects H_0 if the p-value (seen in the SAS output in Table 4.51 as 0.2623) is less than the significance level of α, where α represents the probability of incorrectly rejecting H_0. For an α of 0.05, we fail to reject H_0; therefore, the Modified Levene test is not able to detect the funnel shape and indicates constant variance.

Table 4.51 SAS output of constant variance testing

```
                         The ANOVA Procedure
                        Dependent Variable: d
Source           DF  Sum of Squares  Mean Square  F Value   Pr > F

Model             4      0.00001883   0.00000471     1.55   0.2623

Error            10      0.00003047   0.00000305

Corrected Total  14      0.00004930

             R-Square  Coeff Var  Root MSE    d Mean

             0.382025   70.25820  0.001745  0.002484


        Source  DF     Anova SS  Mean Square  F Value   Pr > F

        Fuel     4   0.00001883   0.00000471     1.55   0.2623
```

In the normal probability plot of the residuals in Figure 4.55, a shorter tail pattern is observed. Consequently, the normality assumption for error distribution appears to be violated.

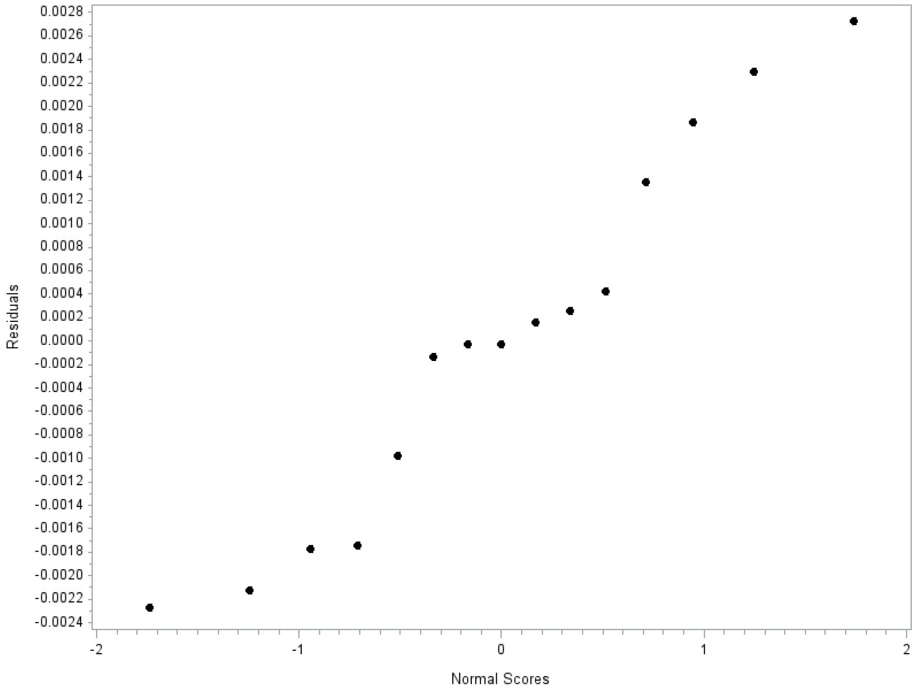


Figure 4.55 Normal probability plot of residuals

Test for Normality

To test for normality, the following two hypotheses have to be tested:

H_0 : Normality is satisfied.

H_1 : Normality is violated.

Table 4.52 SAS output of normality test analysis

```
            Pearson Correlation Coefficients, N = 15
                  Prob > |r| under H0: Rho=0

                                     e          enrm

             e                 1.00000       0.97894
             Residuals                        <.0001

             enrm              0.97894       1.00000
             Normal Scores      <.0001
```

For an $\alpha = 0.05$, we have the critical value $c(\alpha,n) = c(0.05, 15) = 0.938$. The decision rule fail to rejects H_0 if the correlation value (seen in the SAS output Table 4.52 as 0.97894) is greater than $c(\alpha,n)$. Since $\rho = 0.97894 > c = 0.938$, we fail to reject H_0; therefore, the test is unable to detect the non-normality.

Since the error variance appears to be nonconstant, and normality is violated, a variance stabilizing transformation should be conducted. In this particular case, the values of PM emissions (Y) from each fuel type are close together. Therefore, initial attempts at transformation did not produce any effect. By creating more separation between the PM values, the transformation will be better able to compress the higher values (corresponding to the wide end of the funnel in Figure 4.54). To do this, we standardized the Y values by subtracting the sample mean and dividing by the standard deviation. Then a small constant was added (in this case, we added 3) to shift all the values above 1.0, and refer to these modified values as Yprime (see in Table 4.53). The variance stabilizing transformation known as the inverse transformation was then applied (1/Yprime). It should be noted that this transformation will affect all five fuels.

Table 4.53 PM emissions transformation data

Test #	Fuel Type	PM (g/mile)	STD Y	Yprime	1/Yprime
1	ULSD	0.119	2.196	5.196	0.192
2	ULSD	0.115	1.107	4.107	0.243
3	ULSD	0.114	0.835	3.835	0.261
4	Soybean B20	0.113	0.563	3.563	0.281
5	Soybean B20	0.111	0.018	3.018	0.331
6	Soybean B20	0.109	-0.526	2.474	0.404
7	Canola B20	0.106	-1.343	1.657	0.603
8	Canola B20	0.106	-1.343	1.657	0.603
9	Canola B20	0.106	-1.343	1.657	0.603
10	WCO B20	0.112	0.290	3.290	0.304
11	WCO B20	0.110	-0.254	2.746	0.364
12	WCO B20	0.113	0.563	3.563	0.281
13	AF B20	0.110	-0.254	2.746	0.364
14	AF B20	0.112	0.290	3.290	0.304
15	AF B20	0.108	-0.798	2.202	0.454

To verify the constant variance assumption, the plot of the residuals versus the estimate value of 1/Yprime is checked for a funnel shape. No funnel shape appears in Figure 4.56. Therefore, the error variance appears to be reasonable after transform.

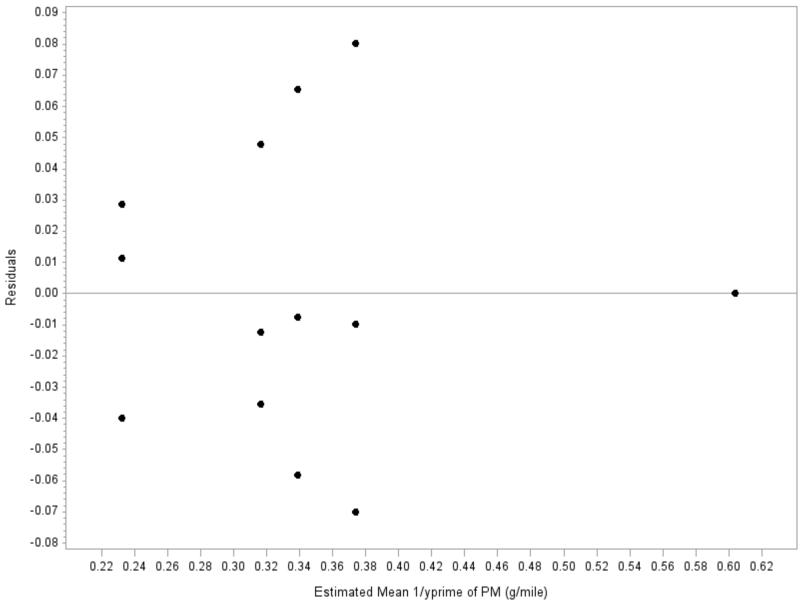


Figure 4.56 Residuals versus estimate mean of transformation of PM

In the normal probability plot of the residuals in Figure 4.57, a linear pattern is observed after transform. Consequently, the normality assumption for error distribution appears to be reasonable.

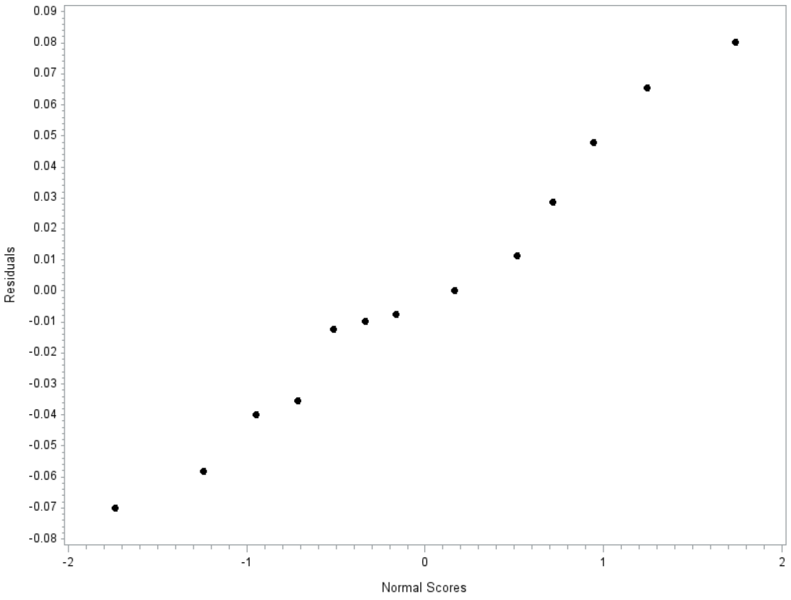


Figure 4.57 Normal probability plot of transformation of PM

An analysis of variance (ANOVA) was obtained using SAS after transformation. The SAS output ANOVA is shown in Table 4.54.

To test for the fuel type effect, an F-test is conducted for the following two hypotheses:

$H_0 : \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$ (No difference in treatment means)

$H_1 :$ Not all μ_i are equal (At least two treatment means are different)

Table 4.54 SAS output of ANOVA of PM emissions after transformation and fuel type

```
                         The GLM Procedure

                 Dependent Variable: 1/Yprime PM
Source           DF  Sum of Squares  Mean Square  F Value  Pr > F
Model             4      0.23196954   0.05799238    22.83  <.0001
Error            10      0.02539679   0.00253968
Corrected Total  14      0.25736632

            R-Square  Coeff Var  Root MSE  onebyprime Mean
            0.901320   13.51194  0.050395         0.372968

          Source  DF    Type I SS  Mean Square  F Value  Pr > F
          Fuel     4  0.23196954    0.05799238    22.83  <.0001

          Source  DF  Type III SS  Mean Square  F Value  Pr > F
          Fuel     4  0.23196954    0.05799238    22.83  <.0001
```

The decision rule rejects H_0 if the Type III SS p-value (seen in the SAS output Table 4.54 as < 0.0001) is less than the significance level of α, where α represents the probability of incorrectly rejecting H_0. For an α of 0.05, we reject H_0 and detect differences in the mean PM emissions for the different fuel types.

Pairwise comparisons between different feedstocks of biodiesel B20 and ULSD baseline were done using Dunnett's method. The following hypotheses were tested for the differences:

H_0: Differences D1, D2, …. =0 : treatments are statistically same.

H_1: Differences D1, D2,…. ≠0 : treatments are statistically different.

Decision rule: Reject H_0 if the confidence intervals do not contain zero (0).

As shown in Table 4.55, it can be observed that the confidence interval does not contain zero for Dunnett pairwise comparison. Therefore, we can reject $H_{0,}$ which means we can conclude that at 95% confidence, the PM emissions of ULSD are higher than biodiesel B20 (for all feedstocks) for dynamometer testing on UDDS driving cycle.

Table 4.55 SAS output of Dunnett's t Test of PM emissions after transformation

Dunnett's t Tests for 1/Yprime PM

Note: This test controls the Type I experimentwise error for comparisons of all treatments against a control.

Alpha	0.05
Error Degrees of Freedom	10
Error Mean Square	0.00254
Critical Value of Dunnett's t	2.89050
Minimum Significant Difference	0.1189

Comparisons significant at the 0.05 level are indicated by *.**

Fuel Comparison	**Difference Between Means**	**Simultaneous 95% Confidence Limits**		
3 - 1	0.37123	0.25229	0.49017	***
5 - 1	0.14187	0.02293	0.26081	***
2 - 1	0.10652	0.01242	0.22546	***
4 - 1	0.08402	0.03491	0.20296	***

To compare between different feedstock of biodiesel B20, Tukey's method was used with a 95% confidence level. The following hypotheses were tested for the differences:

H_0: Differences D1, D2, …. =0 : treatments are statistically same.

H_1: Differences D1, D2,…. ≠0 : treatments are statistically different.

Decision rule: Reject H_0 if the confidence intervals do not contain zero (0). Pairwise comparison for fuel type and confidence intervals are shown in Table 4.56.

As shown in Table 4.56, it can be observed that at 95% confidence, PM emissions from ULSD were higher than for all types of B20. However, among all types of B20, only PM emissions from canola B20 were significantly lower than from soybean B20, WCO B20, and AF B20.

Table 4.56 SAS output of Tukey pairwise comparison for different fuel type of PM emissions after transformation for dynamometer testing

```
              Tukey's Studentized Range (HSD) Test for 1/Yprime
        Note: This test controls the Type I experimentwise error rate.

                 Alpha                                    0.05
                 Error Degrees of Freedom                   10
                 Error Mean Square                     0.00254
                 Critical Value of Studentized Range   4.65425
                 Minimum Significant Difference         0.1354

                   Comparisons significant at the 0.05 level
                            are indicated by ***.

          Fuel      Difference  Simultaneous 95% Confidence
       Comparison     Between             Limits
                       Means

          3 - 5       0.22936       0.09394      0.36478  ***
          3 - 2       0.26471       0.12929      0.40013  ***
          3 - 4       0.28721       0.15179      0.42263  ***
          3 - 1       0.37123       0.23581      0.50665  ***
          5 - 3      -0.22936      -0.36478     -0.09394  ***
          5 - 2       0.03535      -0.10007      0.17077
          5 - 4       0.05785      -0.07757      0.19326
          5 - 1       0.14187       0.00645      0.27729  ***
          2 - 3      -0.26471      -0.40013     -0.12929  ***
          2 - 5      -0.03535      -0.17077      0.10007
          2 - 4       0.02250      -0.11292      0.15791
```

Table 4.56 – *Continued*

Comparisons significant at the 0.05 level are indicated by *.**

Fuel Comparison	**Difference Between Means**	**Simultaneous 95% Confidence Limits**		
2 - 1	0.10652	0.02890	0.24194	***
4 - 3	-0.28721	-0.42263	-0.15179	***
4 - 5	-0.05785	-0.19326	0.07757	
4 - 2	-0.02250	-0.15791	0.11292	
4 - 1	0.08402	0.05140	0.21944	***
1 - 3	-0.37123	-0.50665	-0.23581	***
1 - 5	-0.14187	-0.27729	-0.00645	***
1 - 2	-0.10652	0.24194	0.02890	***
1 - 4	-0.08402	0.21944	0.05140	***

4.3.2.6 Data Analysis of Fuel Economy (FE)

Figure 4.58 shows the mean fuel economy for each run for each type of fuel on the dynamometer testing. From the plot, it can be noticed that the difference between mean fuel economy for the 3 replicate runs is slightly different.

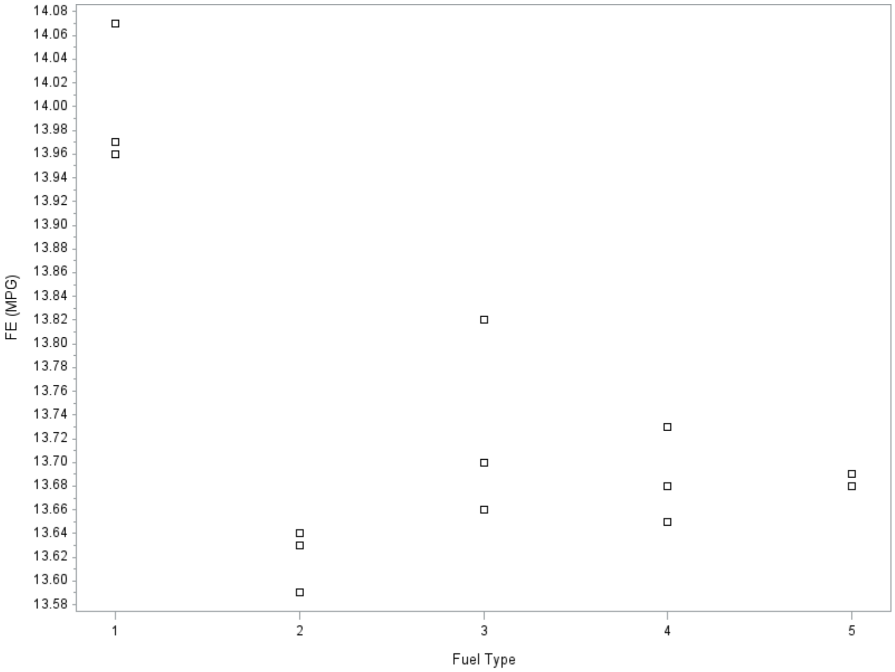


Figure 4.58 Mean fuel economy from replicate runs for various fuel types on the dynamometer testing

There is one factor (fuel type) which impacts the fuel economy. Five types of fuel were tested. Therefore, there are 5 treatment combinations, and 3 replications were conducted for each treatment. The individual effects of the fuel types are included in the model, which is as follows:

$Y_{it} = \mu_i + \varepsilon_{it}$

where $i = 1,2,3,4,5;\ t = 1,2,3$

Each term could be defined as:

Y_{it} = Fuel economy (miles/gallon)

μ_i = True mean fuel economy (miles/gallon) for treatment effect (i)

ε_{ijt} = Random error iid N$(0,\sigma^2)$

To verify the constant variance assumption, the plot of the residuals versus the estimate mean of fuel economy on dynamometer testing in Figure 4.59 is checked for a funnel shape. No funnel shape is observed in this plot; the error of variance appears to be mostly constant.

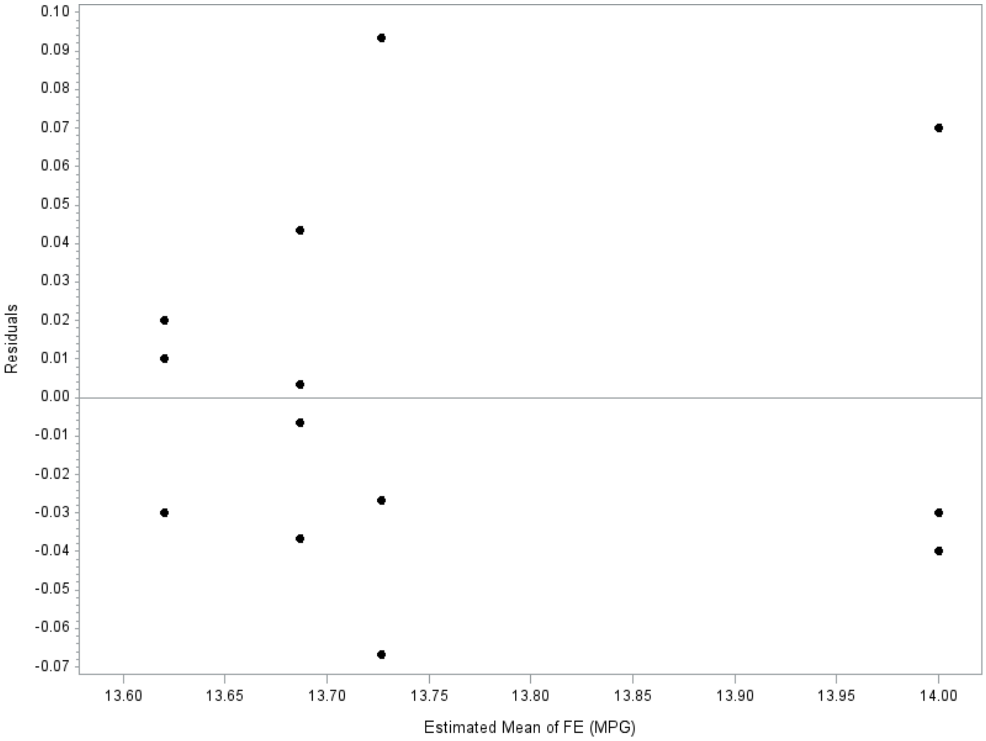


Figure 4.59 Residuals versus estimate mean of fuel economy on dynamometer testing

To test for constant variance, a Modified Levene test is conducted for the following two hypotheses:

H_0 : Errors variance is constant

H_1 : Errors variance is non-constant

The decision rule rejects H_0 if the p-value (seen in the SAS output in Table 4.57 as 0.6137) is less than the significance level of α, where α represents the probability of incorrectly rejecting H_0. For an α of 0.05, we fail to reject H_0; therefore, the variance is constant.

Table 4.57 SAS output of constant variance testing

```
                          The ANOVA Procedure
                         Dependent Variable: d
Source             DF  Sum of Squares  Mean Square  F Value   Pr > F

Model               4      0.00436000   0.00109000     0.69   0.6137

Error              10      0.01573333   0.00157333

Corrected Total    14      0.02009333

              R-Square  Coeff Var  Root MSE     d Mean

              0.216987   145.1168  0.039665   0.027333


       Source  DF     Anova SS  Mean Square  F Value   Pr > F

       FUEL     4   0.00436000   0.00109000     0.69   0.6137
```

In the normal probability plot of the residuals in Figure 4.59, a linear pattern is observed. Consequently, the normality assumption for error distribution appears to be reasonable.

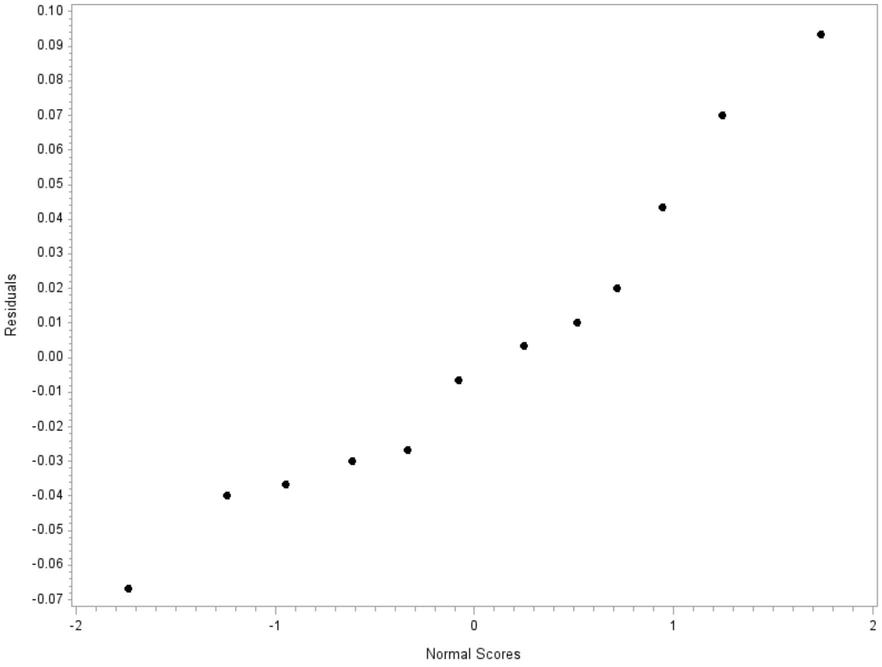


Figure 4.60 Normal probability plot of residuals

Test for Normality

Table 4.58 SAS output of normality test analysis

```
          Pearson Correlation Coefficients, N = 15
                 Prob > |r| under H0: Rho=0

                                    e        enrm

        e                     1.00000     0.97185
        Residuals                          <.0001

        enrm                  0.97185     1.00000
        Normal Scores          <.0001
```

To test for normality, the following two hypotheses have to be tested:

H_0 : Normality is satisfied.

H_1 : Normality is violated.

For an $\alpha = 0.05$, we have the critical value $c(\alpha,n) = c(0.05, 15) = 0.938$. The decision rule fail to rejects H_0 if the correlation value (seen in the SAS output Table 4.58 as 0.97185) is greater than $c(\alpha,n)$. Since $\rho = 0.97185 > c = 0.938$, we fail to reject H_0; therefore, the test is unable to detect the non-normality. However, normality is not required for a valid ANOVA.

An analysis of variance (ANOVA) was obtained using SAS. The SAS output ANOVA is shown in Table 4.59.

To test for the fuel type effect, an F-test is conducted for the following two hypotheses:

$H_0 : \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5$ (No difference in treatment means)

H_1 : Not all μ_i are equal (At least two treatment means are different)

The decision rule rejects H_0 if the Type III SS p-value (seen in the SAS output Table 4.59 as <0.0001) is less than the significance level of α, where α represents the probability of incorrectly rejecting H_0. For an α of 0.05, we reject H_0 and detect differences in the mean fuel economy for the different fuel types.

Table 4.59 SAS output of ANOVA of fuel economy and fuel type

```
                 Dependent Variable: Fuel Economy (MPG)
Source           DF  Sum of Squares  Mean Square  F Value   Pr > F
Model             4      0.26336000   0.06584000    25.32  <.0001
Error            10      0.02600000   0.00260000
Corrected Total  14      0.28936000

             R-Square  Coeff Var  Root MSE    Y Mean
             0.910147   0.371000  0.050990  13.74400

       Source  DF     Type I SS  Mean Square  F Value   Pr > F
       Fuel     4  0.26336000     0.06584000    25.32  <.0001

       Source  DF   Type III SS  Mean Square  F Value   Pr > F
       Fuel     4  0.26336000     0.06584000    25.32  <.0001
```

Pairwise comparisons, between different feedstocks of biodiesel B20 with ULSD baseline were done using Dunnett’s method. The following hypotheses were tested for the differences listed below:

H_0: Differences D1, D2, …. =0 : treatments are statistically same.

H_1: Differences D1, D2,…. ≠0 : treatments are statistically different.

Decision rule: Reject H_0 if the confidence intervals do not contain zero (0).

As shown in Table 4.60, it can be observed that zero is not contained in the confidence interval for Dunnett pairwise comparison. Therefore, we can reject $H_{0,}$ which means we can conclude that at 95% confidence, the differences of fuel economy between ULSD and biodiesel B20 (all feedstocks) are statistically significant for dynamometer testing on UDDS driving cycle.

Table 4.60 SAS output of Dunnett’s t Test of fuel economy

```
                              Dunnett's t Tests for Y
 Note:   This test controls the Type I experimentwise error for comparisons of all
         treatments against a control.
                          Alpha                                  0.05
                          Error Degrees of Freedom                 10
                          Error Mean Square                    0.0026
                          Critical Value of Dunnett's t       2.89050
                          Minimum Significant Difference       0.1203

                          Comparisons significant at the 0.05 level
                                    are indicated by ***.

                    Fuel       Difference  Simultaneous 95% Confidence
                 Comparison      Between              Limits
                                  Means

                    3 - 1       -0.27333      -0.39367      -0.15299  ***
                    4 - 1       -0.31333      -0.43367      -0.19299  ***
                    5 - 1       -0.31333      -0.43367      -0.19299  ***
                    2 - 1       -0.38000      -0.50034      -0.25966  ***
```

For comparing among different feedstocks of biodiesel B20, Tukey’s method was used with a 95% confidence level. The following hypotheses were tested for the differences listed below:

H_0: Differences D1, D2, …. =0 : treatments are statistically same.

H_1: Differences D1, D2,…. ≠0 : treatments are statistically different.

Decision rule: Reject H_0 if the confidence intervals do not contain zero (0).

Pairwise comparison for fuel type and confidence intervals are shown in Table 4.61.

Table 4.61 SAS output of Tukey pairwise comparison for different fuel type of fuel economy for dynamometer testing

```
                 Tukey's Studentized Range (HSD) Test for Y
          Note: This test controls the Type I experimentwise error rate.

               Alpha                                      0.05
               Error Degrees of Freedom                     10
               Error Mean Square                        0.0026
               Critical Value of Studentized Range     4.65425
               Minimum Significant Difference            0.137

                   Comparisons significant at the 0.05 level
                            are indicated by ***.

             Fuel     Difference   Simultaneous 95% Confidence
          Comparison     Between             Limits
                           Means

              1 - 3      0.27333      0.13632      0.41035  ***
              1 - 4      0.31333      0.17632      0.45035  ***
              1 - 5      0.31333      0.17632      0.45035  ***
              1 - 2      0.38000      0.24298      0.51702  ***
              3 - 1     -0.27333     -0.41035     -0.13632  ***
              3 - 4      0.04000     -0.09702      0.17702
              3 - 5      0.04000     -0.09702      0.17702
              3 - 2      0.10667     -0.03035      0.24368
              4 - 1     -0.31333     -0.45035     -0.17632  ***
              4 - 3     -0.04000     -0.17702      0.09702
              4 - 5      0.00000     -0.13702      0.13702
              4 - 2      0.06667     -0.07035      0.20368
              5 - 1     -0.31333     -0.45035     -0.17632  ***
              5 - 3     -0.04000     -0.17702      0.09702
              5 - 4     -0.00000     -0.13702      0.13702
              5 - 2      0.06667     -0.07035      0.20368
              2 - 1     -0.38000     -0.51702     -0.24298  ***
              2 - 3     -0.10667     -0.24368      0.03035
              2 - 4     -0.06667     -0.20368      0.07035
              2 - 5     -0.06667     -0.20368      0.07035
```

As shown in Table 4.61, it can be observed that fuel economies from all B20 blends were significantly lower than those from petroleum diesel fuel, to a 95% level of confidence. Among the B20 blends in terms of fuel economy, there were no statistically significant differences.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

The 3 factors that determine the amount of pollutant reduction for biodiesel, compared to regular diesel, are engine type, test cycle, and biodiesel feedstock. This study examined the impact of 4 biodiesel feedstocks (soybean oil, canola oil, waste cooking oil, and animal fat) and 4 test cycles (arterial on-road, highway on-road, idling, and dynamometer UDDS driving cycle) on NO_x and CO_2 emissions from one vehicle. Previous studies had been inconclusive concerning whether NO_x and CO_2 emissions from biodiesel were lower or higher than those for regular diesel. Major conclusions include the following:

- Emissions from the on-road arterial route were higher than those from the highway route at a 95% level of confidence for both CO_2 and NO_x for all types of B20 and ULSD.
- For CO_2, on-road testing (arterial, highway, and idling) and dynamometer testing showed no statistically significant difference in emissions among the B20 blends and ULSD, with the exception of the difference between soybean B20 and canola B20 for dynamometer testing.
- For NO_x, dynamometer testing showed only B20 from soybean oil to have statistically significant higher emissions. This was generally consistent with the on-road testing (arterial, highway, and idling), which showed no statistically significant difference in NO_x emissions between ULSD and the B20 blends. These results were not what would have been anticipated based on cetane number of the B20 blends and ULSD.
- The dynamometer test results showed statistically significant lower emissions of HC, CO, and PM from all B20 blends compared to ULSD, to a 95% level of confidence. These

results were not what would have been anticipated based on oxygen content of the B20 blends and ULSD.

- CO emissions from soybean B20 were significantly higher than canola and WCO B20, and CO emissions from animal fat B20 were significantly higher than WCO B20, to a 95% level of confidence, according to dynamometer test results.
- HC emissions from ULSD were statistically higher than all types of B20. The HC emissions from soybean and animal fat B20 were statistically higher than WCO B20.
- PM emissions from canola B20 were significantly lower than for the other B20 blends, according to dynamometer test results.
- Fuel economies from all B20 blends were significantly lower than those from petroleum diesel fuel, to a 95% level of confidence, according to dynamometer test results. Among the B20 blends in terms of fuel economy, there were not statistically significant differences.

The results above are specific to the 1994 Chevy Silverado tested, and cannot be generalized to other vehicles.

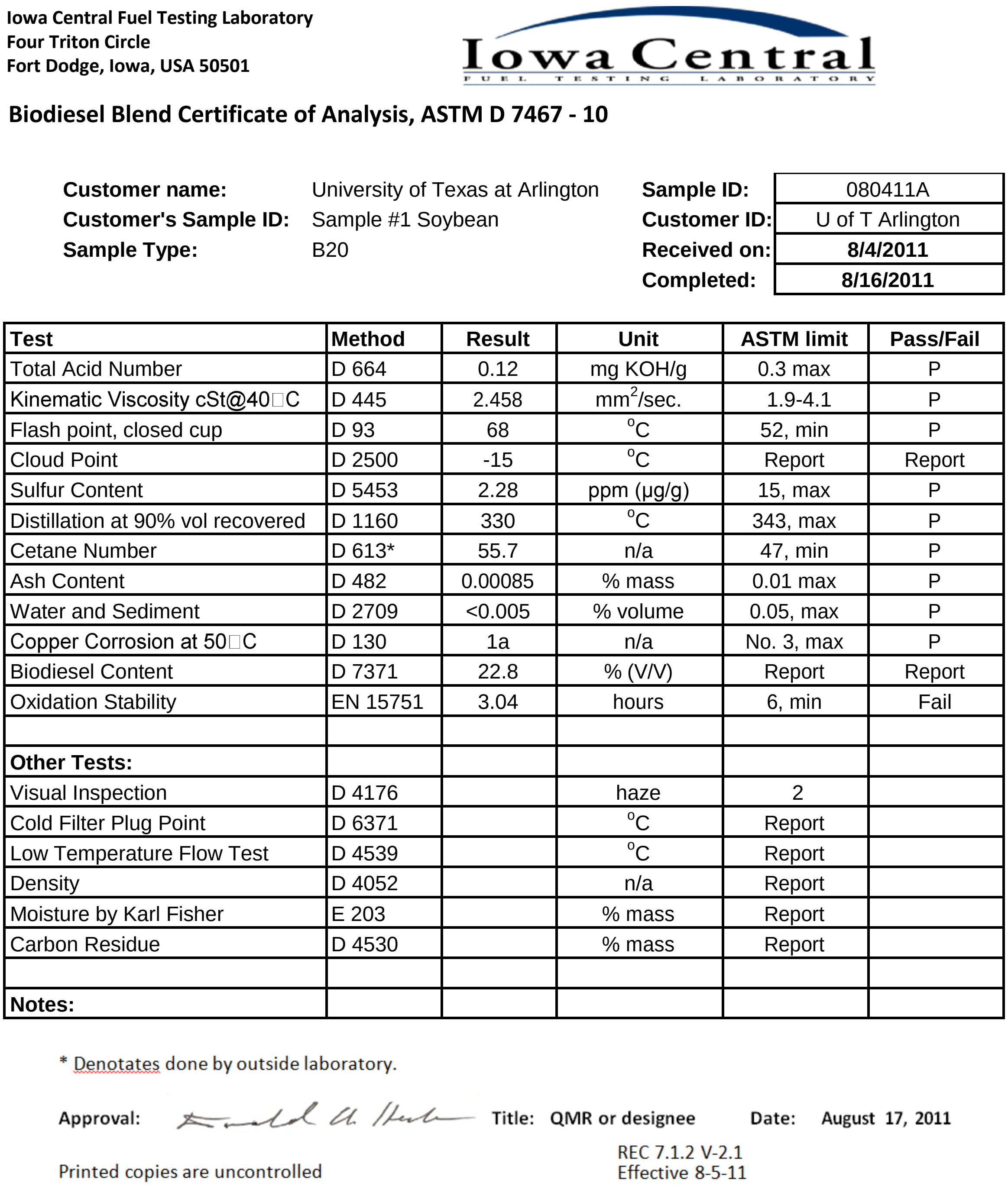
5.2 Recommendations for Future Work

- This study indicated high percent reductions in PM emissions for biodiesel; in future work, the PM size distribution should be examined. The changing composition of different feedstocks of biodiesel fuel might affect the particle size.
- In the future, since testing from the 3 on-road cycles and the dynamometer cycle provided the same results (no statistically significant difference in emissions, with the exception of NO_x emissions from soy biodiesel), one testing cycle would likely be sufficient. This should be confirmed by testing multiple cycles on additional vehicles.
- Trends in biodiesel NO_x and CO_2 emissions with vehicle/engine type should be identified.

APPENDIX A

PHYSICAL AND CHEMICAL PROPERTIES OF THE FUEL SAMPLES USED

Table A.1 Physical and Chemical Properties of Soybean B20



Iowa Central Fuel Testing Laboratory
Four Triton Circle
Fort Dodge, Iowa, USA 50501

Iowa Central
FUEL TESTING LABORATORY

Biodiesel Blend Certificate of Analysis, ASTM D 7467 - 10

Customer name: University of Texas at Arlington
Customer's Sample ID: Sample #1 Soybean
Sample Type: B20

Sample ID: 080411A
Customer ID: U of T Arlington
Received on: **8/4/2011**
Completed: **8/16/2011**

Test	**Method**	**Result**	**Unit**	**ASTM limit**	**Pass/Fail**
Total Acid Number	D 664	0.12	mg KOH/g	0.3 max	P
Kinematic Viscosity cSt@40□C	D 445	2.458	mm^2/sec.	1.9-4.1	P
Flash point, closed cup	D 93	68	°C	52, min	P
Cloud Point	D 2500	-15	°C	Report	Report
Sulfur Content	D 5453	2.28	ppm (µg/g)	15, max	P
Distillation at 90% vol recovered	D 1160	330	°C	343, max	P
Cetane Number	D 613*	55.7	n/a	47, min	P
Ash Content	D 482	0.00085	% mass	0.01 max	P
Water and Sediment	D 2709	<0.005	% volume	0.05, max	P
Copper Corrosion at 50□C	D 130	1a	n/a	No. 3, max	P
Biodiesel Content	D 7371	22.8	% (V/V)	Report	Report
Oxidation Stability	EN 15751	3.04	hours	6, min	Fail
Other Tests:					
Visual Inspection	D 4176		haze	2	
Cold Filter Plug Point	D 6371		°C	Report	
Low Temperature Flow Test	D 4539		°C	Report	
Density	D 4052		n/a	Report	
Moisture by Karl Fisher	E 203		% mass	Report	
Carbon Residue	D 4530		% mass	Report	
Notes:					

* Denotates done by outside laboratory.

Approval: **Title:** QMR or designee **Date:** August 17, 2011

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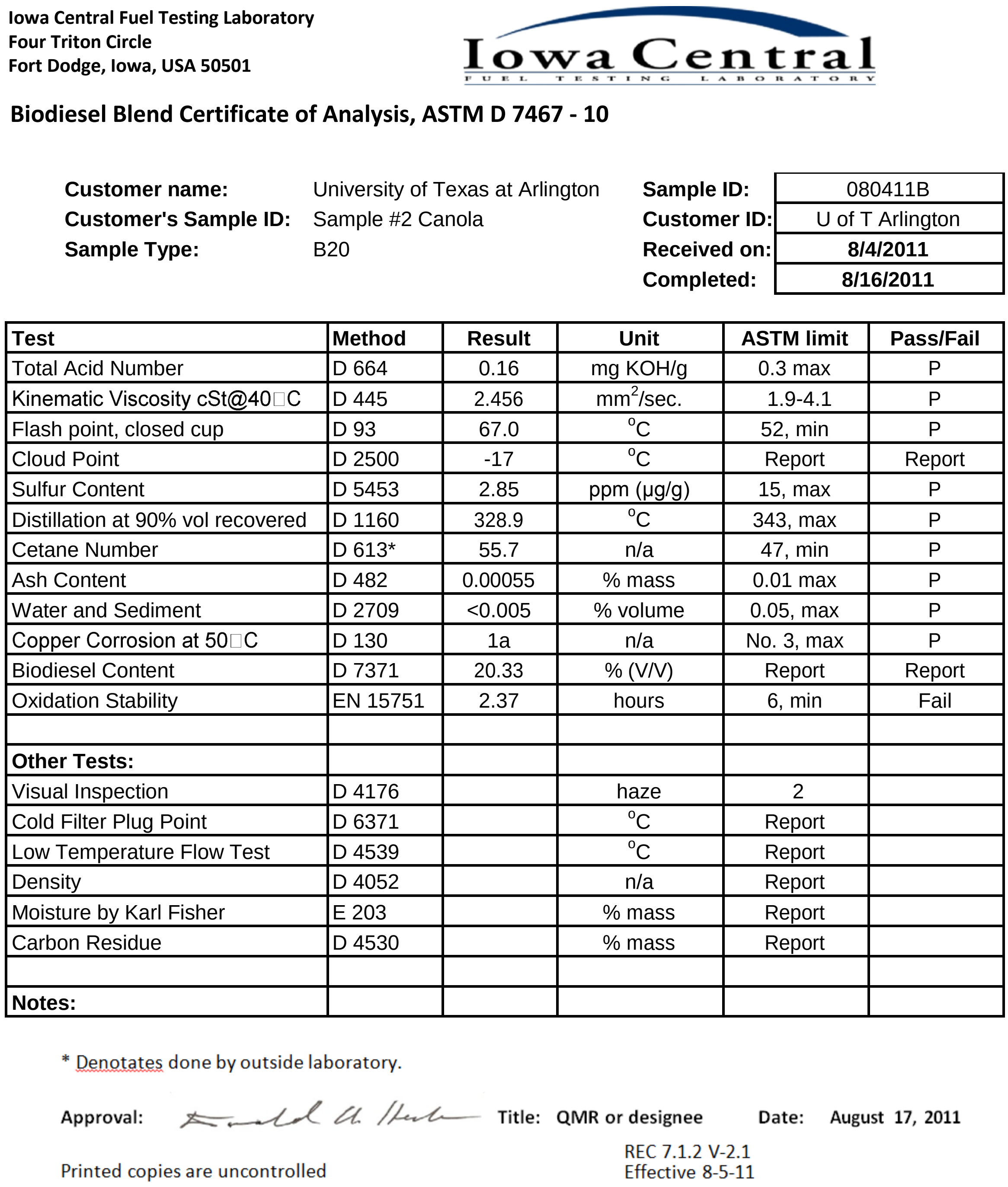
Table A.2 Physical and Chemical Properties of Canola B20



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Four Triton Circle
Fort Dodge, Iowa, USA 50501

Biodiesel Blend Certificate of Analysis, ASTM D 7467 - 10

Customer name:	University of Texas at Arlington	**Sample ID:**	080411B
Customer's Sample ID:	Sample #2 Canola	**Customer ID:**	U of T Arlington
Sample Type:	B20	**Received on:**	**8/4/2011**
		Completed:	**8/16/2011**

Test	**Method**	**Result**	**Unit**	**ASTM limit**	**Pass/Fail**
Total Acid Number	D 664	0.16	mg KOH/g	0.3 max	P
Kinematic Viscosity cSt@40□C	D 445	2.456	mm^2/sec.	1.9-4.1	P
Flash point, closed cup	D 93	67.0	^{o}C	52, min	P
Cloud Point	D 2500	-17	^{o}C	Report	Report
Sulfur Content	D 5453	2.85	ppm (µg/g)	15, max	P
Distillation at 90% vol recovered	D 1160	328.9	^{o}C	343, max	P
Cetane Number	D 613*	55.7	n/a	47, min	P
Ash Content	D 482	0.00055	% mass	0.01 max	P
Water and Sediment	D 2709	<0.005	% volume	0.05, max	P
Copper Corrosion at 50□C	D 130	1a	n/a	No. 3, max	P
Biodiesel Content	D 7371	20.33	% (V/V)	Report	Report
Oxidation Stability	EN 15751	2.37	hours	6, min	Fail
Other Tests:					
Visual Inspection	D 4176		haze	2	
Cold Filter Plug Point	D 6371		^{o}C	Report	
Low Temperature Flow Test	D 4539		^{o}C	Report	
Density	D 4052		n/a	Report	
Moisture by Karl Fisher	E 203		% mass	Report	
Carbon Residue	D 4530		% mass	Report	
Notes:					

* Denotates done by outside laboratory.

Approval: Title: QMR or designee Date: August 17, 2011

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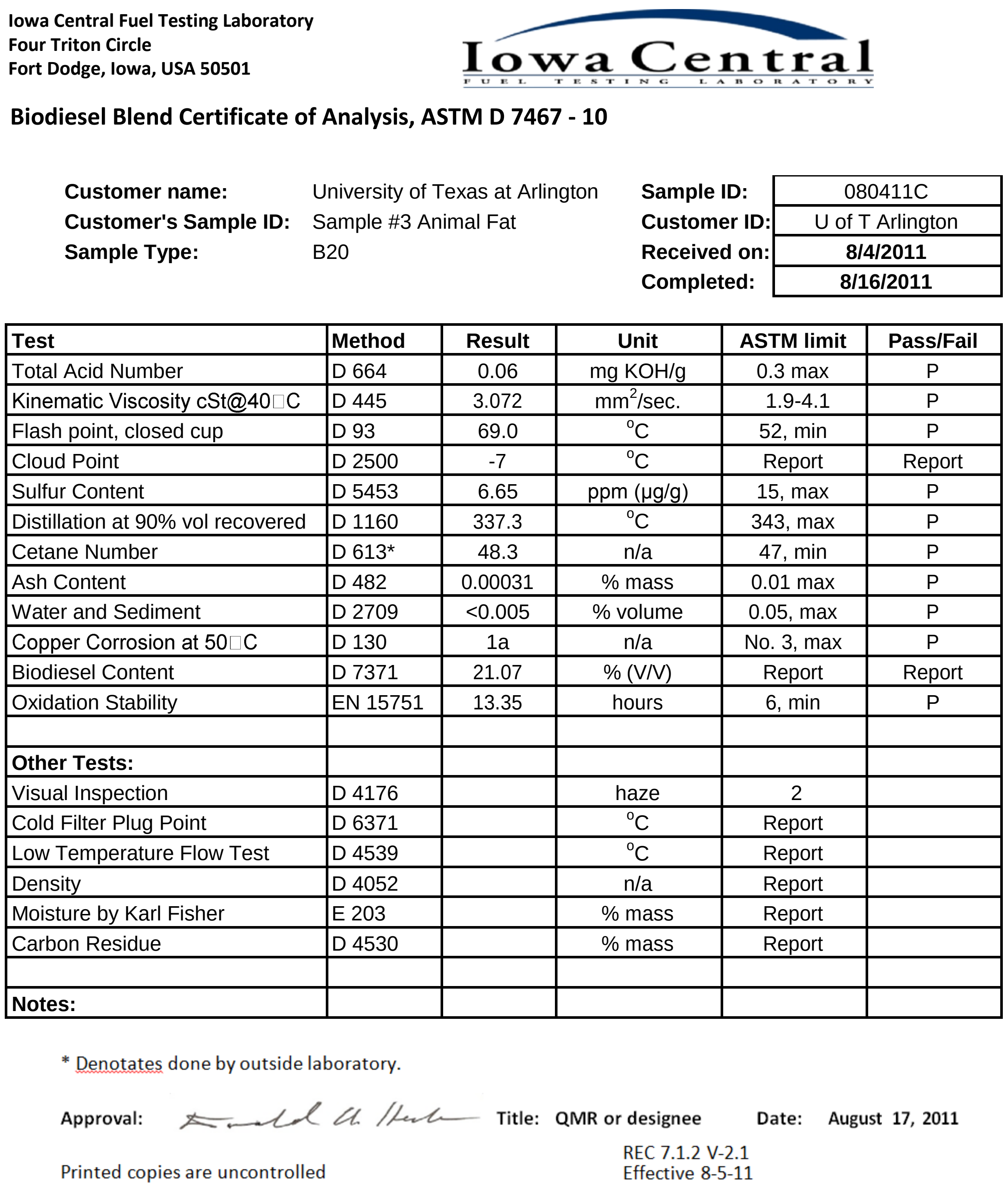
Table A.3 Physical and Chemical Properties of Animal Fat B20



Iowa Central Fuel Testing Laboratory
Four Triton Circle
Fort Dodge, Iowa, USA 50501

Iowa Central
FUEL TESTING LABORATORY

Biodiesel Blend Certificate of Analysis, ASTM D 7467 - 10

Customer name:	University of Texas at Arlington	**Sample ID:**	080411C
Customer's Sample ID:	Sample #3 Animal Fat	**Customer ID:**	U of T Arlington
Sample Type:	B20	**Received on:**	**8/4/2011**
		Completed:	**8/16/2011**

Test	**Method**	**Result**	**Unit**	**ASTM limit**	**Pass/Fail**
Total Acid Number	D 664	0.06	mg KOH/g	0.3 max	P
Kinematic Viscosity cSt@40□C	D 445	3.072	mm^2/sec.	1.9-4.1	P
Flash point, closed cup	D 93	69.0	^oC	52, min	P
Cloud Point	D 2500	-7	^oC	Report	Report
Sulfur Content	D 5453	6.65	ppm (µg/g)	15, max	P
Distillation at 90% vol recovered	D 1160	337.3	^oC	343, max	P
Cetane Number	D 613*	48.3	n/a	47, min	P
Ash Content	D 482	0.00031	% mass	0.01 max	P
Water and Sediment	D 2709	<0.005	% volume	0.05, max	P
Copper Corrosion at 50□C	D 130	1a	n/a	No. 3, max	P
Biodiesel Content	D 7371	21.07	% (V/V)	Report	Report
Oxidation Stability	EN 15751	13.35	hours	6, min	P
Other Tests:					
Visual Inspection	D 4176		haze	2	
Cold Filter Plug Point	D 6371		^oC	Report	
Low Temperature Flow Test	D 4539		^oC	Report	
Density	D 4052		n/a	Report	
Moisture by Karl Fisher	E 203		% mass	Report	
Carbon Residue	D 4530		% mass	Report	
Notes:					

* Denotates done by outside laboratory.

Approval: Title: QMR or designee Date: August 17, 2011

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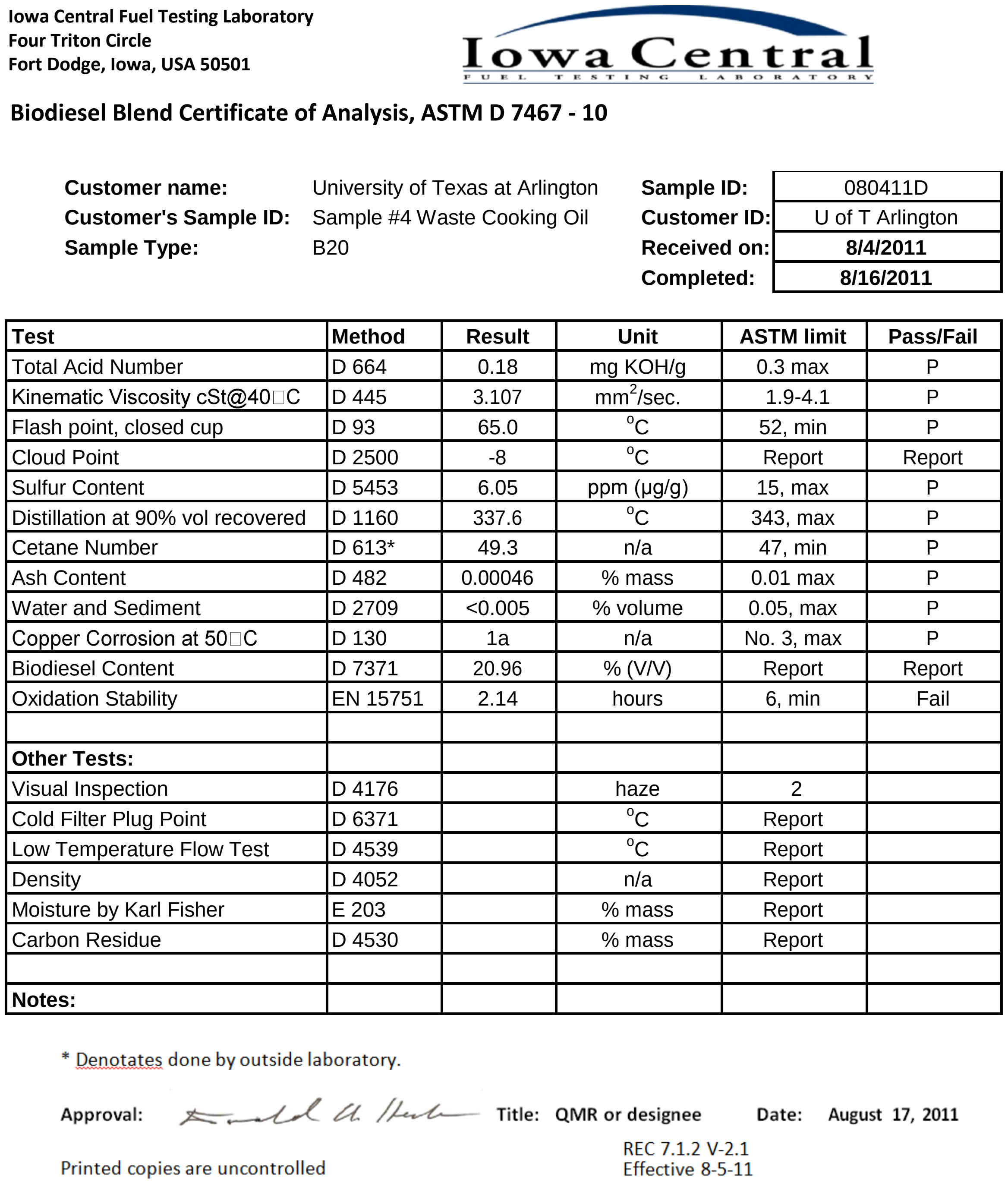
Table A.4 Physical and Chemical Properties of Waste Cooking Oil B20



Iowa Central Fuel Testing Laboratory
Four Triton Circle
Fort Dodge, Iowa, USA 50501

Biodiesel Blend Certificate of Analysis, ASTM D 7467 - 10

Customer name:	University of Texas at Arlington	**Sample ID:**	080411D
Customer's Sample ID:	Sample #4 Waste Cooking Oil	**Customer ID:**	U of T Arlington
Sample Type:	B20	**Received on:**	**8/4/2011**
		Completed:	**8/16/2011**

Test	**Method**	**Result**	**Unit**	**ASTM limit**	**Pass/Fail**
Total Acid Number	D 664	0.18	mg KOH/g	0.3 max	P
Kinematic Viscosity cSt@40□C	D 445	3.107	mm^2/sec.	1.9-4.1	P
Flash point, closed cup	D 93	65.0	^{o}C	52, min	P
Cloud Point	D 2500	-8	^{o}C	Report	Report
Sulfur Content	D 5453	6.05	ppm (µg/g)	15, max	P
Distillation at 90% vol recovered	D 1160	337.6	^{o}C	343, max	P
Cetane Number	D 613*	49.3	n/a	47, min	P
Ash Content	D 482	0.00046	% mass	0.01 max	P
Water and Sediment	D 2709	<0.005	% volume	0.05, max	P
Copper Corrosion at 50□C	D 130	1a	n/a	No. 3, max	P
Biodiesel Content	D 7371	20.96	% (V/V)	Report	Report
Oxidation Stability	EN 15751	2.14	hours	6, min	Fail
Other Tests:					
Visual Inspection	D 4176		haze	2	
Cold Filter Plug Point	D 6371		^{o}C	Report	
Low Temperature Flow Test	D 4539		^{o}C	Report	
Density	D 4052		n/a	Report	
Moisture by Karl Fisher	E 203		% mass	Report	
Carbon Residue	D 4530		% mass	Report	
Notes:					

* Denotates done by outside laboratory.

Approval: Title: QMR or designee Date: August 17, 2011

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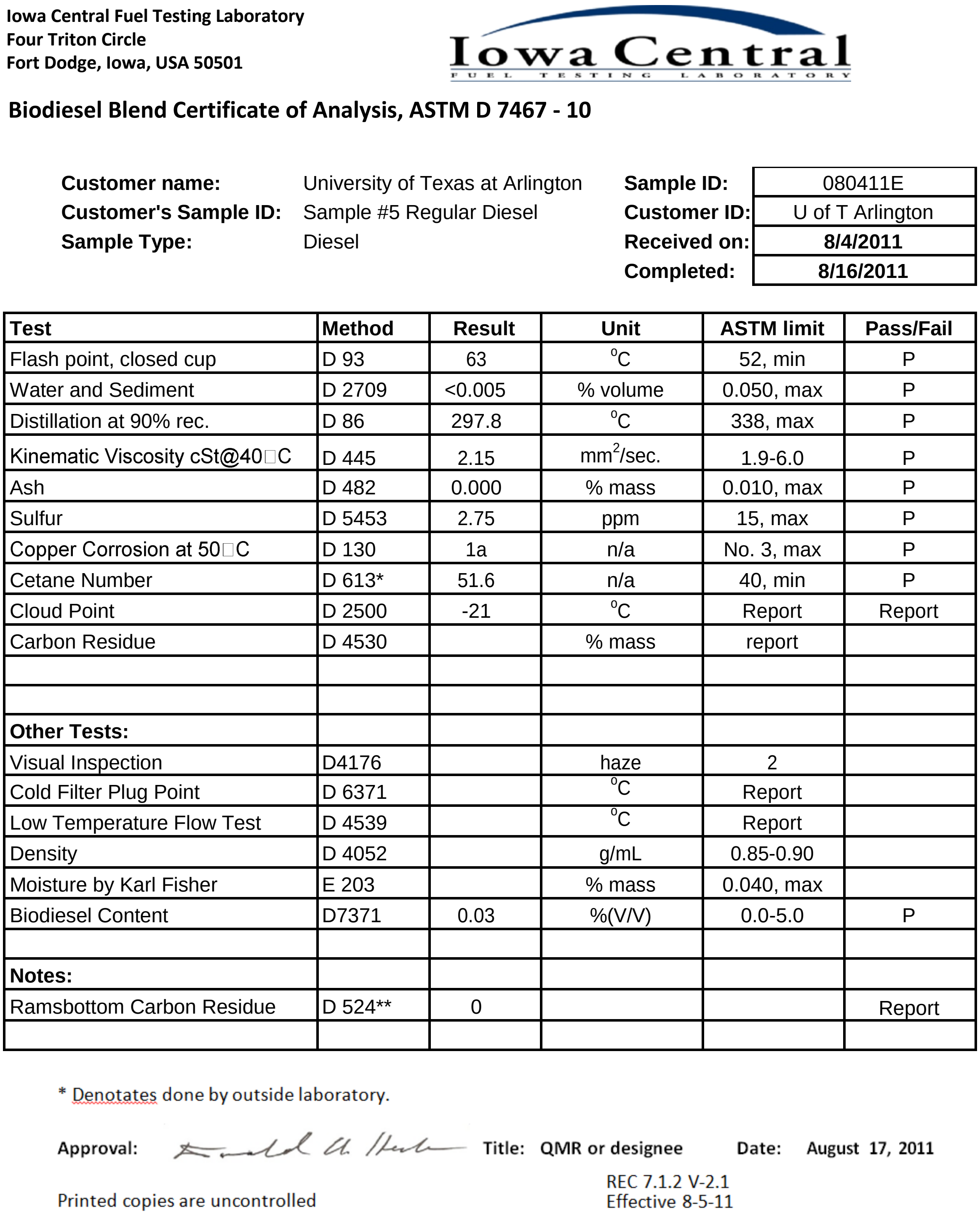
Table A.5 Physical and Chemical Properties of ULSD Diesel



Iowa Central Fuel Testing Laboratory
Four Triton Circle
Fort Dodge, Iowa, USA 50501

Iowa Central
FUEL TESTING LABORATORY

Biodiesel Blend Certificate of Analysis, ASTM D 7467 - 10

Customer name:	University of Texas at Arlington	**Sample ID:**	080411E
Customer's Sample ID:	Sample #5 Regular Diesel	**Customer ID:**	U of T Arlington
Sample Type:	Diesel	**Received on:**	**8/4/2011**
		Completed:	**8/16/2011**

Test	**Method**	**Result**	**Unit**	**ASTM limit**	**Pass/Fail**
Flash point, closed cup	D 93	63	^oC	52, min	P
Water and Sediment	D 2709	<0.005	% volume	0.050, max	P
Distillation at 90% rec.	D 86	297.8	^oC	338, max	P
Kinematic Viscosity cSt@40□C	D 445	2.15	mm^2/sec.	1.9-6.0	P
Ash	D 482	0.000	% mass	0.010, max	P
Sulfur	D 5453	2.75	ppm	15, max	P
Copper Corrosion at 50□C	D 130	1a	n/a	No. 3, max	P
Cetane Number	D 613*	51.6	n/a	40, min	P
Cloud Point	D 2500	-21	^oC	Report	Report
Carbon Residue	D 4530		% mass	report	
Other Tests:					
Visual Inspection	D4176		haze	2	
Cold Filter Plug Point	D 6371		^oC	Report	
Low Temperature Flow Test	D 4539		^oC	Report	
Density	D 4052		g/mL	0.85-0.90	
Moisture by Karl Fisher	E 203		% mass	0.040, max	
Biodiesel Content	D7371	0.03	%(V/V)	0.0-5.0	P
Notes:					
Ramsbottom Carbon Residue	D 524**	0			Report

* Denotates done by outside laboratory.

Approval: Title: QMR or designee Date: August 17, 2011

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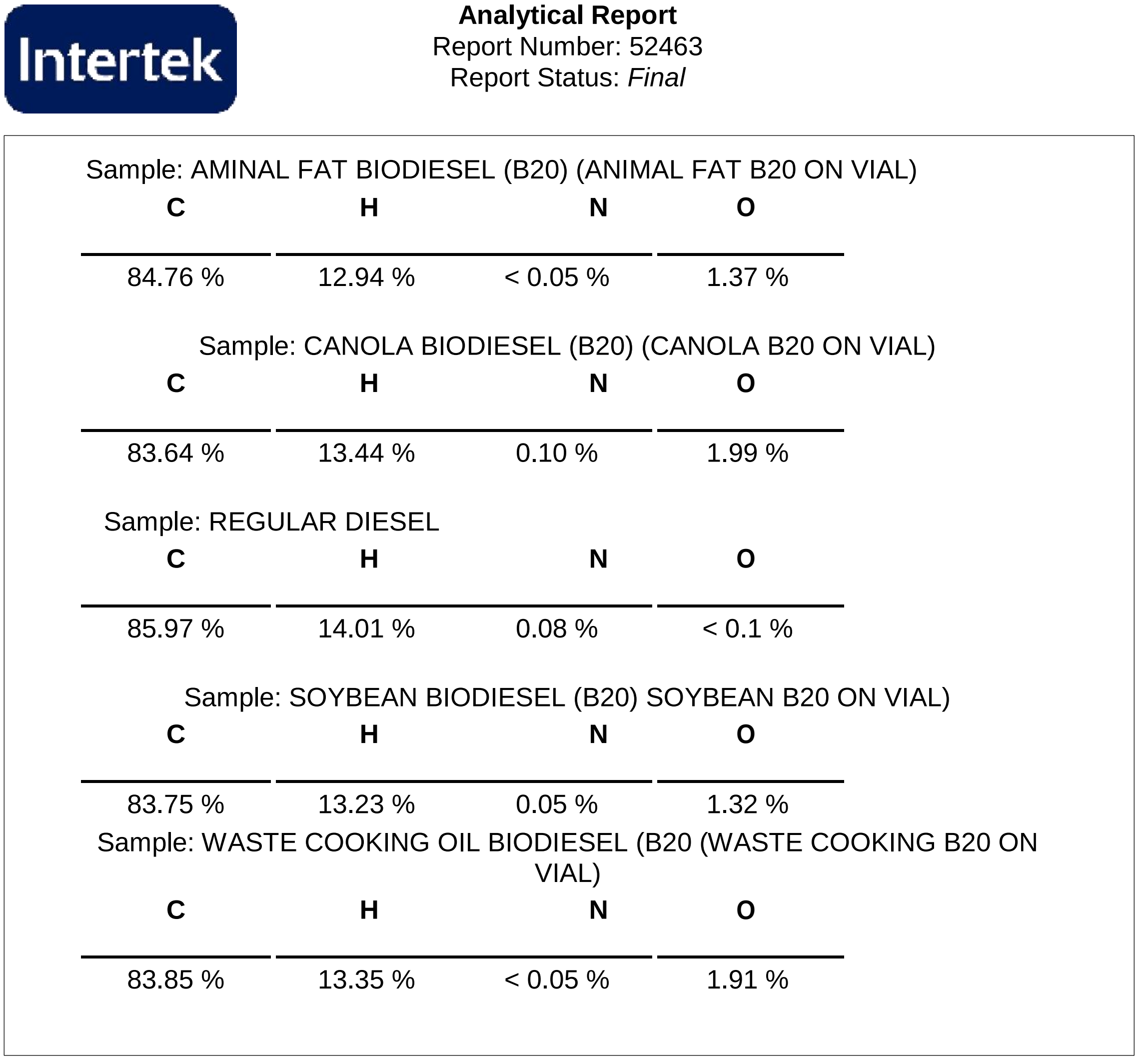
Table A.6 C H O N elemental analysis results



Analytical Report
Report Number: 52463
Report Status: *Final*

Sample: AMINAL FAT BIODIESEL (B20) (ANIMAL FAT B20 ON VIAL)

C	**H**	**N**	**O**
84.76 %	12.94 %	< 0.05 %	1.37 %

Sample: CANOLA BIODIESEL (B20) (CANOLA B20 ON VIAL)

C	**H**	**N**	**O**
83.64 %	13.44 %	0.10 %	1.99 %

Sample: REGULAR DIESEL

C	**H**	**N**	**O**
85.97 %	14.01 %	0.08 %	< 0.1 %

Sample: SOYBEAN BIODIESEL (B20) SOYBEAN B20 ON VIAL)

C	**H**	**N**	**O**
83.75 %	13.23 %	0.05 %	1.32 %

Sample: WASTE COOKING OIL BIODIESEL (B20 (WASTE COOKING B20 ON VIAL)

C	**H**	**N**	**O**
83.85 %	13.35 %	< 0.05 %	1.91 %

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Natchanok Pala-En received a bachelor of science degree in Public Health (Environmental Sanitary) and master's degree in Public Health (Environmental Health) from Khon Kaen University, Khon Kaen, Thailand. She went on to the Ph.D. program at UTA in the Department of Earth and Environmental Sciences in order to gain a broad knowledge of air pollution control, and biofuel in particular. Her research topic focuses on emissions from biodiesel with different feedstocks.

At present, she works as an environmental officer at the Pollution Control Department, Thailand.