DEVELOPMENT OF CLOSED LOOP EMISSIONS CONTROL FOR USE IN DISPATCHABLE, DISTRIBUTED GENERATION SYSTEMS USING A LOW COST, STATE-OF-THE-ART, SOLID-STATE NITRIC OXIDE SENSOR

THESIS

submitted in partial satisfaction of the requirements for the degree of

MASTER OF SCIENCE

in Mechanical and Aerospace Engineering

by

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2018
DEDICATION

To my beautiful fiancé Esther, the love of my life and my world

To my parents Brian and Christy Ehlig, whose love and support (spiritual, financial, moral, you name it) helped paved a road of success in my educational endeavors and journey in life

To my friends and family, without whom this road would have been far more difficult
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<tbody>
<tr>
<td>VG</td>
<td>Variable Generation</td>
</tr>
<tr>
<td>DAQ</td>
<td>Data Acquisition Device</td>
</tr>
<tr>
<td>DG</td>
<td>Distributed Generation</td>
</tr>
<tr>
<td>PV</td>
<td>Photovoltaics</td>
</tr>
<tr>
<td>CEMS</td>
<td>Continuous Emissions Monitoring Systems</td>
</tr>
<tr>
<td>NOx</td>
<td>Nitrogen Oxides</td>
</tr>
<tr>
<td>NO</td>
<td>Nitric Oxide</td>
</tr>
<tr>
<td>NO$_2$</td>
<td>Nitrogen Dioxide</td>
</tr>
<tr>
<td>N$_2$O</td>
<td>Nitrous Oxide</td>
</tr>
<tr>
<td>CO</td>
<td>Carbon Monoxide</td>
</tr>
<tr>
<td>OEM</td>
<td>Original Equipment Manufacturer</td>
</tr>
<tr>
<td>MTG</td>
<td>Microturbine Generator</td>
</tr>
<tr>
<td>CRMS</td>
<td>Capstone Remote Monitoring Software</td>
</tr>
<tr>
<td>QCL</td>
<td>Quantum Cascade Laser</td>
</tr>
<tr>
<td>SCR</td>
<td>Selective Catalytic Reduction</td>
</tr>
<tr>
<td>LDL</td>
<td>Lower Detectable Limit</td>
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</table>
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I would like to thank the California Energy Commission (CEC) for funding my project over the last two years.
ABSTRACT OF THE THESIS

Development of Closed Loop Emissions Control for Use in Dispatchable, Distributed Generation Systems using a Low Cost, State-of-the-Art, Solid-State Nitric Oxide Sensor

By Ryan A. Ehlig

Master of Science in Mechanical and Aerospace Engineering

University of California, Irvine, 2018

Professor G. Scott Samuelsen, Chair

Two commercially-available solid-state sensors, both capable of measuring nitric oxide and oxygen content in the exhaust of diesel automotive systems, were utilized in the present study to determine their potential as an inexpensive alternative to traditional continuous emission monitoring systems for distributed generation (DG) deployments. In order to assess their performance and real-time measurement capabilities, an extensive data acquisition network was developed to compare signals against an established reference instrument (Horiba PG-350) over an extended period of six to eight months. An existing experimental testbed, a 60 kW Capstone Gas Turbine engine, was utilized as the representative DG system in this study, and an exhaust test section was designed and fabricated. Three sensors of the two commercial brands were selected to measure the deviation among individual signals. After the measurement period was conducted, it was found within a 99% confidence interval or greater, the NTK sensor performed better in three of five measured sensor characteristics, specifically with respect to LDL, Accuracy, and Lag-Time and Rise-Time. An emissions map was then generated using a statistically-designed study in order to find the operating parameters of the engine that produce the lowest nitric oxide and carbon monoxide emissions. Using these results, a control algorithm was developed and demonstrated, capable of incorporating the NTK sensor signals, to allow the engine to adjust its performance to reduce nitric oxide emissions in real-time and at all operating conditions.
1. INTRODUCTION


1.1 California Electric Grid - Renewable Generation

As one of the most aggressive and expansive energy policies in the nation as well as the world that promotes the integration of renewable resources into the California electric grid, the Renewable Portfolio Standards (RPS) (established in 2002 by Senate Bill (SB) 1078) has led to an immense shift in California towards renewable sources of energy. The initial standards have been further improved under the leadership of Governor Arnold Schwarzenegger and subsequently Governor Edmund G. Brown in order to help fight climate change and bring about improvements in air quality. This is being done by enforcing standards that will reduce the greenhouse gas (GHG) emissions of the State by 40 percent below 1990 levels by the year 2030 [1]. Signed as SB 350 in October of 2015, the most recent updated standards have designated that “retail sellers and publicly owned utilities procure 50 percent of their electricity from renewable sources by 2030” [2]. California is currently on track to meeting 33% renewables by 2020, with an estimated 30% of electricity retail sales being served by renewable sources such as solar, wind, geothermal, biomass, and hydro as of November of 2017. It is estimated that 75,000 GW-hr of energy (out of 250,000 GWh total) from retail sales in 2017 was derived from renewable sources within the state, with the majority share coming from Solar and Wind (Fig 1). Small hydro remains an important part of California’s energy infrastructure as well, and it is established as a long-term viable plan for also
meeting the state’s energy storage needs as well. Whereas small hydro would be catered towards the energy storage needs of small local communities, large hydro serves the energy storage of the entire state, as 98% of installed energy storage infrastructure in California is in the form of pumped hydro [3]. Geothermal also remains important, but is limited largely by location. Biomass remains as the second smallest share of California’s total renewable sales at around 8%.

![Fig 1. 2017 Renewable Energy Sources, Retail Sales Breakdown (From In-state and Out-of-State) (Adapted from Ref. [1])](image)

In terms of total renewable capacity, California has a large variety of facilities serving both in-state and out of state. As of October 2017, California’s in-state operating renewable energy capacity was 27,800 MW, with more than 6,000 MW of self-generation (Fig 2). Self-generations refers to the concept of individual consumers that opt to install renewable resources (such as Solar PV) within their own homes or businesses, which helps to alleviate pressure off the local retail seller by lowering the total grid demand. Over 5000 MW comes from Solar PV [1].
Because of the large amount of variable generation (VG) resources within the state such as Solar and Wind, integration into the California electric grid has presented some difficulties; risk of overgeneration, where the supply of power exceeds demand, has grown and can cause significant damage by increasing the rotational speed of generators connected to the grid. This risk is mitigated by careful observation by the California Independent System Operator (CAISO). One technical solution is curtailment, which involves decreasing the output from a wind or PV resources below normal production; however, as the amount of curtailment increases, the overall benefits of additional solar installations drops [4],[5]. Solutions that increase the robustness of the electric grid and allow for the storage of energy from wind and solar are being aggressively pursued as California is on the path to achieving its goal of 33% renewable power generation by 2020.

1.2 Issue with Renewable Generation – The “Duck Curve”

First published by CAISO in 2013, the “Duck Curve” has raised awareness of the issues associated with curtailment and flexibility of the electric grid in California [4],[6]. Shown in Fig 3, the chart displays the net load over one day (total power demand minus the power supplied by renewables) from 2012 (actual) to 2020 (forecasted). Because of the increase in renewable VG
supplied during the day when Solar peaks in output, the overall netload is minimum around 1 pm. Later in the day, as Solar capacity and other VG capacity starts to decrease, the overall net load increases. With the decrease in renewable penetration from VG sources on the grid, the ramp steepens, and sources that are flexible in ramping capability must be utilized. With increasing renewable VG in order to meet California’s RPS goals, the ramp will only steepen, and the need for more flexible resources to meet this resulting net load will also increase.

![Duck Curve Chart](image)

*Fig 3. CAISO “Duck Curve” Chart (Adapted from Ref. [6])*

1.3 **Strategy - Distributed Generation and Microgrids**

One proposed strategy to increase the flexibility and robustness of the California electric grid is by installing small-scale distributed generation (DG). In this context, it is limited to generation that is less than 15 megawatts (MW) due to transmission system requirements and is
interconnected to the grid at the distribution voltage or at the point of use [7], [8]. It encompasses renewable technologies such as Solar and Wind as well as Combined Heat and Power-capable technologies such as Microturbines, Internal Combustion (IC) Engines, and Fuel Cells. DG is produced on-site and close to the load center while being interconnected to the grid [7]. It provides the ability to ramp-up and ramp-down output, shut-down and start-up quickly, and operate efficiently at low power output, which can help increase of the efficiency of the electric grid by delivering power directly to the user at the point of use. By meeting local demand for power, DG can help alleviate the burden placed on the grid operator.

It is estimated that around 5% to 10% of the electricity transmitted from centralized power sources is lost as heat due to resistance in the transmission and distribution (T&D) system [9]. In addition to reducing transmission losses, close proximity to the end user provides the opportunity to utilize any waste heat produced (i.e., combined heat and power—CHP) which can significantly increase the overall efficiency of these systems (total system efficiencies can achieve upwards of 60% to 80% efficiency) [3],[4]. Certain technology mixes along with CHP used for distributed generation can also potentially reduce the impact of emissions on air quality by spreading emitting sources over a larger cross-sectional area of land as opposed to larger localized emitting sources [11].

DG is commonly implemented within microgrids, which combine different DG resources (renewable VG as well as dispatchable generation) into a single controllable unit that can operate independently of the utility grid. Because gas-fueled DG can provide reliable baseload compared to other VG sources (such as solar and wind) and they can ramp-up and ramp-down on demand, these help increase the reliability and flexibility of microgrids [10].
1.4 Emissions Certification for Gas-Fueled Distributed Generation

California has established emissions certification requirements that DG technology, below permit levels in each air district, must undergo before being sold within California. This is done in order to facilitate the deployment of highly efficient and clean (low polluting) dispatchable generation throughout the state. Adopted by the California Air Resources Board in 2001 (required by Senate Bill 1298) with further amendments passed in 2007, the certification procedure is conducted at full load and at stable operation [12]. The 2003 requirements for fossil-fueled DG units is displayed in Table 1 as well as the stricter 2007 requirements in Table 2 for fossil-fueled power generation.

<table>
<thead>
<tr>
<th>Pollutant</th>
<th>DG Unit not Integrated with Combined Heat and Power (a)(1)</th>
<th>DG Unit Integrated with Combined Heat and Power (a)(1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oxides of Nitrogen (NOx)</td>
<td>0.5</td>
<td>0.7</td>
</tr>
<tr>
<td>Carbon Monoxide (CO)</td>
<td>6.0</td>
<td>6.0</td>
</tr>
<tr>
<td>Volatile Organic Compounds (VOCs)</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>Particulate Matter (PM)</td>
<td>An emission limit corresponding to natural gas with fuel sulfur content of no more than 1 grain/100 scf</td>
<td>An emission limit corresponding to natural gas with fuel sulfur content of no more than 1 grain/100 scf</td>
</tr>
</tbody>
</table>

Table 1. Emissions Standards (lb/MW-hr) for DG, 2003 (Adapted from Ref. [12])

<table>
<thead>
<tr>
<th>Pollutant</th>
<th>Emission Standard (lb/MW-hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NOx</td>
<td>0.07</td>
</tr>
<tr>
<td>CO</td>
<td>0.10</td>
</tr>
<tr>
<td>VOCs</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Table 2. Emissions Standards (lb/MW-hr) for DG, 2007 (Adapted from Ref. [12])
The certification procedure is conducted as outlined by the Air Resources Board (ARB) [12]. Highlights of the certification procedure related to emissions sampling are listed as follows:

1. Sampling methodology to conform to ARB testing procedures
   a. NOx, CO and Oxygen sampled according to ARB Test Method 100
   b. VOC’s sampled according to South Coast Air Quality Management District (AQMD) Method 25.3
   c. Gas Velocity and Flow Rate in accordance with ARB Test Methods 1, 2, 3, and 4

2. A minimum of three valid test runs are to be conducted and run consecutively.

3. Tests conducted after steady-state operation is reached.

4. Each run must be conducted at 100% output.

5. Emissions are specified in lb/MW-hr

6. Certification is valid for 5 years.

It becomes apparent from the highlights of the certification procedure listed above that emissions are not monitored during transient operation or when the output is less than 100% of full-load. As the need for deployment of more dispatchable generation within the state rises due the intermittent nature of renewables (Fig 3), emissions certification and monitoring designed for more transient behavior and lower power outputs will also be needed. Technology that could monitor engine operation and performance, make corrections in real-time, and that could lower the output of criteria air pollutants at all operating conditions would represent a significant improvement to the DG certification program. Such technology is already known in the power generation industry as traditional Continuous Emission Monitoring Systems (CEMS); however, it can present a costly solution to DG system manufacturers if the certification program is to be improved.
1.5 Traditional Continuous Emission Monitoring Systems

Continuous Emission Monitoring Systems (CEMS), defined by the Air Emissions Measurement Center (EMC), is “the total equipment necessary for the determination of a gas or particulate matter concentration or emission rate using pollutant analyzer measurements and a conversion equation, graph, or computer program to produce results in units of the applicable emission limitation or standard” [13]. The pollutant analyzers utilized by traditional CEMS within the power generation industry not only measure and report the effluent of the stationary source directly (according to the definition above), but they also adhere to established EPA measurement protocols and specific sampling methodologies. These devices can then be used to determine if emitting sources are in non-compliance of emissions standards.

Established by the Acid Rain Program (ARP) under Title IV of the 1990 Clean Air Act (CAA) Amendments, traditional CEMS became a necessary tool to limit the precursors to acid rain, primarily sulfur dioxide (SO$_2$) and nitrogen oxides (NO$_x$) from the power generation sector [14]. Applicable to systems with a nameplate capacity of over 25 MWe, stringent regulations for these systems are outlined in Title 40 of the Code of Federal Regulations (CFR) under Part 75 [15]. Because a well-representative sample of emissions from generating devices becomes necessary in order to prove compliance with the ARP, utilizing traditional CEMS can present a significant challenge to the engine operator; not only do analyzers utilized by traditional CEMS require constant maintenance and sampling systems to both pump and condition the sample before it can be analyzed, but it is necessary to choose a sampling location that avoids stratification of emissions within the exhaust ducting of the generating device. This is necessary to avoid a misrepresentation of the emissions sample that is being captured [16]. Stratification occurs when the effluent is not uniformly mixed near or at the point of sampling. See Fig 4 for the typical
configuration of traditional CEMS within a power plant. An emissions analyzer can also be utilized in parallel with flow metering devices, temperature and pressure meters, as well as dust meters to monitor the sampling conditions closely, all of which is a traditional CEMS configuration, as shown in the figure.

If an inexpensive, viable solution to traditional CEMs for the purpose of monitoring DG system performance during transient behavior and at lower power outputs was available, it would represent a significant improvement to the already existing requirements. The ability to measure emissions in real-time would give the advantage of knowing the engine performance historically and would allow ample opportunity for maintenance of the DG device if non-compliance was achieved. Such a solution will be explored in the following section.

Fig 4. Traditional CEMS Configuration, HORIBA (From Ref. [17])
1.6 Alternative to Traditional CEMS – Electrochemical Sensors

Because of the requirements the power generation industry must follow that utilize traditional CEM analyzers (outlined in section 1.5) and the stringent sampling methodologies they must adhere to [18], integrating traditional CEMS within existing DG systems requirements can present a costly and expensive solution to improving upon the standards. An inexpensive and viable alternative to traditional CEMS exists within the automotive industry as the solid-state electrochemical sensor. Developed by BOSCH in the 1960’s, the electrochemical sensor historically first saw use in the automotive industry to measure oxygen content in the exhaust of an automotive engine [19],[20]. These in-situ sensors are installed directly into the tailpipe of the automobile and operate by communicating with the Engine Control Module (ECM) using Controller Area Network (CAN) protocol to control air-fuel mixing centered at stoichiometric conditions. The largest single use of these sensors has grown (over 75% of usage in late 1990’s) and has expanded to include emissions control of CO and NOx as well as improvements in vehicle fuel economy [19]. Unlike traditional CEMS, they do not require sampling conditioning (they are able to measure on wet basis), require no maintenance (easily replaceable), and are fundamentally suited to the high exhaust temperatures due to high ionic conductivity of their electrolyte (Zirconia-based) material in these environments [19].

1.7 Research Scope, Goal, and Objective

The scope of this study involves quantifying the accuracy and robustness of several commercially-available solid-state electrochemical sensors (commonly used to measure nitric oxide emissions in the automotive industry for Light Duty (LD) and Heavy Duty (HD) diesel vehicles) within the context of measuring the emissions of a Distributed Generation system (i.e. a 60 kW Gas Turbine (Capstone C-60 Microturbine)). Subsequently, development of a closed-loop
algorithm capable of using the sensor information to optimize nitric oxide (ppm) emissions on a real-time basis will also be conducted. In order to accurately verify the performance of each electrochemical sensor, a traditional “CEM-like” analyzer will be used as reference device and as a comparison tool. The commercially-available sensor that performs more comparable to the referee instrument and presents promising trends regarding robustness and accuracy over the extended period of initial testing will be used to develop the algorithm.

The goal of this research is to:

- Develop a closed-loop control strategy, capable of utilizing a robust, accurate, and state-of-the-art electrochemical solid-state sensor, to mitigate the nitric oxide emissions from a 60 kW Gas Turbine operating on natural gas.

To accomplish this goal, the following objectives must be achieved:

1. **Develop Gas Turbine Testbed for Sensor Measurements.** A test-section capable of mounting the sensors in an environment with well-mixed and developed flow in order to avoid stratification of emissions measurements will be constructed. A system capable of powering and measuring the sensor signals will also be installed in order to record data over extended periods of time.

2. **Evaluate Sensor Robustness and Accuracy of Candidate Sensors.** Sensor signals will be recorded and measured over an extended period of time (six to eight months) and compared to an established referee instrument. The candidate sensor that performs best relative to other sensors will be utilized in the development of the control algorithm.
3. **Demonstrate a Control Algorithm.** Four distinct control algorithms will be developed using the most promising sensor resulting from Objective 2. These will be capable of operating independently of manual control and will be software-based (i.e. closed-loop control). The most practical approach of each of the four algorithms will be chosen to be implemented within the engine software and will be demonstrated in real-time.
2. BACKGROUND


2.1 Perspective

The following section will encompass an in-detail review of classical electrochemical sensors such as the oxygen sensor as well as recent technological advancements that have led to sensor technology capable of measuring nitrogen oxides, most of which are commercially-available today. These sections are intended to provide the necessary background in order to gain a better understanding regarding the performance of electrochemical nitric oxide sensors, which will be discussed in later sections. This section will also help to reinforce the idea that these sensors can also be applied to emissions monitoring for Distributed Generation systems.

2.2 Solid-State Electrochemical Sensor History

The emergence of the electrochemical sensor arose out of the need for monitoring hazardous gases resulting from combustion processes as well as concern for their environmental effects. Leakage of Liquid Petroleum Gas (LPG), and hydrogen (H₂) and carbon monoxide (CO) in syngas, which are commonly used for industrial processes, became an important concern for various health and safety reasons in the 1960’s [19]. Fuel-utilization also became a topic of concern due to efforts in increasing efficiency of industrial processes, so combustion products such as CO needed to be actively monitored. Oxides of sulfur, known as SOx (SO₂ and SO₃), as well as nitrogen oxides, known as NOx (NO and NO₂) became a cause for concern due to their
contribution to acid rain, which has a devastating environmental impact. Because of these numerous health, environmental, and safety concerns, a robust sensor capable of withstanding harsh environmental conditions and high temperatures of combustion reactions was needed.

Proposed as a strategy to satisfy the 1977 emissions standards on automobiles in California, BOSCH introduced the first Zirconium-Dioxide ($\text{ZrO}_2$) sensor (known as the lambda ($\lambda$) sensor) in 1976 with the intention of using it to help control vehicle exhaust emissions [21]. Lambda ($\lambda$), the air-fuel equivalence ratio, is defined as:

$$\lambda = \frac{A/F_{\text{actual}}}{A/F_{\text{stoichiometric}}}$$

Where $A/F_{\text{actual}}$ is the actual air-to-fuel ratio used in the combustion process and $A/F_{\text{stoichiometric}}$ is the stoichiometric air-to-fuel ratio, the ratio in which all the fuel is utilized in the combustion reaction with no excess air. Lambda greater than one indicates that the conditions of the combustion reaction are lean (excess air is available) whereas lambda less than one indicates the conditions are fuel rich (excess fuel is available).

Note that this is not to be confused with the fuel-air equivalence ratio, Phi ($\phi$), which can also be used to describe the conditions of the fuel and air in a combustion process and is defined as:

$$\phi = \frac{F/A_{\text{Actual}}}{F/A_{\text{stoichiometric}}}$$

The emissions in Fig 5 are shown for a 1976 vehicles (4-cylinder, 2-liter gasoline engine with electronic fuel injection). The graph on the left indicates NOx and CO emissions as a function of AFR without the implementation of the 3-way catalyst. Shown on the right is the shaded region being the intended operation region of the vehicle in order to minimize emissions with the 3-way catalyst. Note that the emissions are reported in grams per hour per power output of the engine in
order to allow for comparisons between vehicles with power output capabilities. The purpose of
the lambda sensor is to control the fuel injection so that operation is maintained within these limits;
the air-fuel ratio would be adjusted to $\lambda = 1$ to minimize the formation of CO and unburnt
hydrocarbons (UHC’s) and a three-way catalyst would be implemented to reduce NO and oxidize
remaining CO [22]. A control system capable of adjusting the quantity of injected fuel to near
stoichiometric conditions based on sensor feedback was tested and developed (Fig 6).

![Graph showing emissions levels vs lambda]

*Fig 5. Exhaust Emissions Before and After Implementation of 3-way Catalyst (Adapted from Ref. [23])*

![Diagram of engine and control system]

*Fig 6. Closed Loop Emissions Control (Adapted from Ref. [23])*
2.2.1 NOx and CO Formation

Before examining electrochemical sensors in further detail, it is important to first explain the mechanisms of NOx and CO formation in the combustion process. A general understanding of these emissions species will help solidify a background of better understanding for future sections of this thesis.

2.2.1.1 NOx Formation

As discussed in the Introduction, nitrogen oxides (NOx), which consists primarily of NO and NO₂, are precursors to acid rain and are regulated for stationary and mobile sources under the supervision of the Clean Air Act [24]. They are detrimental not only due to their impact on the environment but also to human health [25]. NO (nitric oxide), which consists of the majority of nitrogen oxides that leave the combustion process, oxidizes to form NO₂. This is particularly a problem in the urban airshed where it is formed after leaving the tailpipe of automobiles and mixes with other pollutant emissions to form smog. NO₂ contributes to the brown color found in chemical smog in the atmosphere and can also cause irritation to the eyes and to the lungs in the form of asthma.

There are four different (but not only) main mechanisms for NOx formation: Thermal NO, nitrous oxide mechanism, prompt NO, and fuel NO. Thermal NO is produced primarily in the high-temperature regions of a flame, occurring at significant rates when temperatures achieve ~1850 K and peaking slightly to the left of the stoichiometric point (ϕ = 1) [27]. This peak can be seen clearly in Fig 7, and is due to the competition between fuel and nitrogen for available oxygen. Its formation follows the extended Zeldovich mechanism in the reactions below:

\[ \text{O}_2 \leftrightarrow 2\text{O} \quad \text{Equation 2.3} \]
\[ \text{N}_2 + \text{O} \leftrightarrow \text{NO} + \text{N} \quad \text{Equation 2.4} \]
\[ N + O_2 \leftrightarrow NO + O \] \textbf{Equation 2.5}

\[ N + OH \leftrightarrow NO + H \] \textbf{Equation 2.6}

The Nitrous Oxide (N\textsubscript{2}O-intermediate) mechanism occurs primarily in fuel lean (\( \phi < .8 \)), low temperature, and high pressure conditions [28]. This is particularly applicable to lean premixed combustion systems, which will be summarized briefly in the next chapter (Section 4.1.1). The formation of nitrous oxide is initiated by the following reaction:

\[ N_2 + O \leftrightarrow N_2O \] \textbf{Equation 2.7}

Which is then oxidized in the following main reaction:

\[ N_2O + O \leftrightarrow NO + NO \] \textbf{Equation 2.8}

The Prompt NO (Fenimore) Mechanism is named so due to the rapid formation of NO very early in the flame region before the thermal pathway for NO is achieved. This is due to hydrocarbon radicals reacting with molecular nitrogen to form other intermediate compounds that then proceed to form NO. The following reaction initiates the mechanism:

\[ N_2 + CH \leftrightarrow HCN + N \] \textbf{Equation 2.9}

The reactions that then proceed to form NO are well understood for \( \phi < \sim 1.2 \), but reaction pathways become quite complex after this [28].

Lastly, Fuel NO is an important mechanism for NO formation when burning fuel with molecular-bound nitrogen, such as coal.

2.2.1.2 \textit{CO Formation}

Carbon monoxide is formed during incomplete combustion. The majority of CO in a combustion process is produced primarily in fuel rich regions where there is not enough oxygen present to complete the process that forms CO\textsubscript{2} (see Fig 7). It also can form during high
temperatures (>1800 K) where disassociation of CO$_2$ is significant [27]. The reaction that governs the removal of CO to CO$_2$ are as follows:

$$\text{CO} + \text{OH} \rightarrow \text{CO}_2 + \text{H}$$ \hspace{2cm} \text{Equation 2.10}

The reaction above occurs predominately at high temperature

$$\text{CO} + \text{H}_2\text{O} \rightarrow \text{CO}_2 + \text{H}_2$$ \hspace{2cm} \text{Equation 2.11}

This reaction occurs predominately in low temperatures

The formation of CO is minimized to the left in the fuel-lean region but then proceeds to increase again (see Fig 7). This is due to the slowed oxidation rates due to the low temperatures of the reactions.

![Diagram showing CO, NO, and Temperature Dependence on Equivalence Ratio](image)

*Fig 7. CO, NO, and Temperature Dependence on Equivalence Ratio (From Ref.[29])*

### 2.3 Solid-State Electrochemical Sensors – Design and Theory

Historically, two types of oxygen electrochemical sensors have been used in the automotive industry: potentiometric equilibrium sensors, where the response of the sensor varies
logarithmically with the partial pressure of oxygen in the exhaust stream (according to the Nernst equation), and limiting current amperometric sensors, where an the ionic current flowing through the electrolyte is a function of the concentration of oxygen that is present in the exhaust stream [20],[30].

Because Zirconia-based (ZrO$_2$) sensors have the ability to withstand the harsh environment and high temperatures of an automotive exhaust system, Yttria-Stabilized Zirconia electrolytes have been used extensively in both of these sensors.

2.3.1 Potentiometric Sensors

The classical stoichiometric sensor mentioned in section 2.2 is based on a potentiometric design [23]. Inside the sensors are two primary layers: a sensing cell and a heating layer. The heating element is primarily used so that the electrolyte remains above the 350 °C limit, remaining independent of the temperature of the exhaust [31]. A schematic of this design can be seen in Fig 8.

![Stoichiometric Sensor (Potentiometric)](Adapted from Ref. [32])

Exhaust O$_2$ is measured using the following manner (as outlined in [19], [21], [31]):
1. A yttria-stabilized zirconia (YSZ) thimble (sensing cell) with platinum electrodes on both sides is exposed to exhaust gas on the exterior side and air on the interior side. These electrolytes are usually chosen to be implemented within solid-state sensors due their high conductivity in high-temperature environments, as they can achieve a temperature range of 300°C - 900°C.

2. The sensing cell separates two region of different oxygen partial pressures: \( p^{I}O_2 \), corresponding to the partial pressure of oxygen in the exhaust gas, and \( p^{II}O_2 \), corresponding to the partial pressure of oxygen in the reference gas (air).

3. The sensing cell is an oxygen ion-conducting electrolyte that also acts a physical barrier and separates two half-cell reactions (forms an oxygen galvanic cell):

   \[
   4e^- + O_2 (p^{I}O_2) \rightarrow 2O^{2-} \quad \text{Equation 2.12}
   \]

   \[
   2O^{2-} \rightarrow O_2 (p^{II}O_2) + 4e^- \quad \text{Equation 2.13}
   \]

4. The resulting cell voltage obeys the Nernst Equation:

   \[
   V = \frac{RT}{4F} \log \left( \frac{p^{II}O_2}{p^{I}O_2} \right) \quad \text{Equation 2.14}
   \]

   Where \( R \) is the gas constant, \( F \) is the Faraday constant, and \( T \) is the temperature.

   This equation assumes the equilibrium partial pressure of oxygen has been achieved, otherwise significant deviation will be present.

   Fig 9 displays the partial pressure of oxygen and the resulting Nernstian voltage across the narrow operating window of engine conditions designed for the 3-way catalyst. Typically when an engine is operating rich, the partial pressure of oxygen in the exhaust is on the order of \( 10^{-15} - 10^{-46} \) atm, whereas when it is operating lean it is on the order of \( 10^{-2} \) atm [19]. The partial pressure of oxygen in air is near a constant value of .2 atm. Note that an increase in temperature also has a significant effect on the partial pressure and Nernstian voltages in the rich region.
The abrupt change in voltage around the stoichiometric region is independent of the Nernst equation, and is due to the abrupt change in equilibrium partial oxygen pressure of the exhaust around the stoichiometric region [33]. This results in high sensitivity and helps the sensor to detect the slightest changes around the stoichiometric point. Because of their poor sensitivity in lean environments as well as their short-life span (they can suffer from poisoning at the electrodes due to toxic exhaust species), the limitations of potentiometric sensor eventually were overcome with the development of diffusion-controlled limiting-current-type oxygen sensors (amperometric sensors).

![Fig 9. Voltage (mV) vs. $\lambda$ for Potentiometric Sensors (Adapted from Ref. [34])](image)

### 2.3.2 Amperometric Sensors

The amperometric sensor design not only arose out of deficiencies of the potentiometric sensor listed in section 2.3.1, but also arose out of the desire for a more fuel-efficient control system for automotive vehicles. Introduced by Toyota in 1984, a lean combustion system was developed
to improve fuel economy as well as to keep emissions low. Because of the limitations of potentiometric sensors (especially when the operating lean), a lean air-to-fuel ratio sensor was developed to detect the exhaust oxygen concentration over a wider range (15 ≤ A/F ≤ 23), which helped lead to a significant improvement in vehicle fuel economy for Toyota’s lean-burn systems [33]. Inside the amperometric sensor is a chip that includes 3 layers: two electrochemical cells (a pumping cell and sensing cell) and a heater. These three layers are stacked and formed together using green sheet laminating and co-firing technology that produce a very thin chip (5 mm wide by 1.5 mm thick) [21],[35]. Each yttria-stabilized zirconia electrochemical cell has porous platinum electrodes on both sides of the ceramic material and an insulating material is located between them. A metal powder paste is embedded into the bottom ceramic layer to form the heater. For a schematic showing the configuration of the layered chip inside the sensor, see Fig 10.

*Fig 10. Schematic of Amperometric Sensor and Cell (Adapted from Ref. [35])*

Exhaust O2 is measured in the following manner for a particular amperometric sensor [19],[21],[35]:

22
1. The pumping cell pumps oxygen through a hole in which exhaust enters. Exhaust diffuses across a narrow gap (at a thickness of tens of microns) and reaches the electrode on the underside of the pumping cell surface facing the gap. This electrode is positioning coincidentally around the hole.

2. The oxygen partial pressure of the gap is detected by the sensing cell. Air is guided in a duct with a closed-end in order to be measured as the reference gas. This is led to the reference electrode on the underside of the sensing cell facing the duct.

3. Unlike a potentiometric sensor, an external voltage is applied from the anode to the cathode of the sensing cell in order to pump oxygen. The resulting current is then limited by the diffusion of molecular oxygen across the electrolyte.

4. The resulting I-V characteristics are classified into three distinct regions (see Fig 11):
   a. The diffusion of oxygen ions through the electrolyte is a rate-determining step at small voltages.
   b. At the plateau region where there are intermediate voltages, the current is proportional to the concentration of molecular oxygen in the exhaust. This step is governed by the diffusion of molecular oxygen through the diffusion barrier (gas intake hole). The current can be written as:

   \[ I_p = 4F \frac{dN_{O_2}}{dt} \]

   Where \( F \) is Faraday’s constant and \( \frac{dN_{O_2}}{dt} \) is the diffusion of molecular oxygen across the diffusion barrier (gas intake hole).
The diffusion of molecular oxygen across the barrier is dependent upon the concentration gradient of oxygen molecules present \( \frac{dc_{O_2}}{dx} \), the effective cross-sectional area of the gap \( Q \), and the effective diffusion coefficient \( D_{O_2} \):

\[
\frac{dN_{O_2}}{dt} = -D_{O_2} Q \left( \frac{dc_{O_2}}{dx} \right) \tag{Equation 2.16}
\]

The limiting current condition (the plateau region) is when the oxygen concentration \( c_{O_2} \) at the cathode is 0 (i.e. oxygen is being completely used in the chemical reaction).

c. At high voltages, any increasing current is due to the electrochemical decomposition of zirconia, leading to damage of the ceramic material.

\( \text{Fig 11. I-V Characteristics of Oxygen Amperometric Sensor (Adapted from Ref. [21])} \)
2.4 Solid-State NOx Sensor

Solid-state sensor technology has been expanded in recent times to measure not only molecular oxygen but also to achieve multi-component analysis of different species, specifically NO, NO₂, CO, and HC’s in the exhaust systems of compression-ignition direct-injection engines. They can also operate either as amperometric or potentiometric, but stability has proven to be a problem for longer lifetimes of these sensors due to induced aging effects from the exposure to constant voltage and current [36]. New research has been looking into AC current measurements (impedancemetric signals). These rely on AC measurements at a specific frequency, which has shown promising results regarding higher sensitivity to NOx, better stability, and subtracting out background interferences [37].

2.4.1 Potentiometric NOx Sensors

It should be noted that the equation listed in section 2.3.1 (Nernst Equation) assumes that only molecular oxygen is involved in the chemical reaction occurring at the electrode, whereas in reality a series of reactions with different gases are involved, which all help to determine the potential at the electrode:

\[ \text{O}_2 + 4e^- \rightarrow 2\text{O}^{2-} \quad \text{Equation 2.17} \]
\[ 2\text{NO} + 4e^- \rightarrow \text{N}_2 + 2\text{O}^{2-} \quad \text{Equation 2.18} \]
\[ \text{CO} + \text{O}^{2-} \rightarrow \text{CO}_2 + 2e^- \quad \text{Equation 2.19} \]
\[ \text{CH}_4 + 4\text{O}^{2-} \rightarrow \text{CO}_2 + 2\text{H}_2\text{O} + 8e^- \quad \text{Equation 2.20} \]
\[ \text{H}_2 + \text{O}^{2-} \rightarrow \text{H}_2\text{O} + 2e^- \quad \text{Equation 2.21} \]

NO, NO₂, H₂O, CO, H₂, hydrocarbons (HC’s) and other gas species listed in the equations above appear in non-equilibrium gas mixtures in exhaust. Typical Zirconia-based Solid-state potentiometric sensors are designed with high catalytic material and achieve temperatures
exceeding 600°C in order to obtain equilibrium mixtures at the electrode surface; however, it is undesired for measuring these exhaust species. Because of this reason, Non-Nernstian (Mixed Potential) Potentiometric sensors are desired for measuring NO and NO₂ [38], [34].

In order to calculate the total mixed potential, standard electrode potentials ($\Delta \phi^{00}$) can be used for an estimate (for actual calculation, all current-voltage characteristics of all involved electrode reactions as well as kinetic constants must be known). $\Delta \phi^{00}$ can be calculated from standard thermodynamic data and is shown in Fig 12 for various electrode reactions.

![Fig 12. Standard Electrode Potentials with Reference to Oxygen Partial Pressures (Adapted from Ref. [38])](image)

In order to overcome the uncertainty of the mixed potential, these sensors incorporate a special outer electrode where catalytic activity is well defined. Once a defined level of oxygen covering the surface is known, a defined potential is also known. Electrode materials can then be chosen to be selective to other exhaust gas species other than oxygen, such as NO or NO₂ [34].

### 2.4.2 Amperometric NOx Sensors

At very low concentrations, especially for measuring nitric oxide after the 3-way catalyst, the Mixed Potential approach listed in the section above is not feasible [34]; the ability to distinguish between the gas components (especially within different exhaust gas species) becomes increasingly difficult due to various reasons [38]. Using voltammetric methods (see Fig 13),
amperometric sensors with single electrodes are able to achieve a separation of different electrode reactions and therefore are able to simultaneously measure different gas species.

For exhaust system requirements (fast response time and continuous operation), multi-electrode amperometric sensors are preferred. This allows for control over which reactions take place at different electrodes. This can be done by adjusting the gas composition; by carefully selecting electrodes in which different reactions to take place, the species of interest can be measured at a specific electrode \[38\]. As an example, in order to measure nitric oxide (NO) and oxygen (O\(_2\)), O\(_2\) would need to be chemically reduced at the first electrode and the reduction of NO to Nitrogen would need to be prevented until the second electrode. This is to ensure that the gas reaching the second electrode contains only nitric oxide and is absent of oxygen (see Fig 14). NGK Insulators, Ltd. has been at the forefront of the development for these sensors for direct implementation within lean-burn gasoline and diesel engines, specifically for measuring NO and O\(_2\) \[39\]–[41].
The disadvantage of using multi-electrode Amperometric sensors comes from the very low currents are produced, specifically when low concentrations of exhaust species are being measured; sometimes currents are in the nanoamperes to microamperes, so special insulation equipment is required to avoid current leakage [34],[38],[42].

2.4.3 Electrochemical Impedence Spectroscopy (EIS)

The problems presented in section 2.4.2 and 2.4.1 for amperometric and potentiometric sensors for NO, NO₂ sensing has led to the development of a new sensing technique that has shown promise for total NOx sensing (NO+NO₂). Previous sensor technologies have been sensitive to measuring only one of these components (mostly nitric oxide). An impedence spectroscopy based (impedancemetric) technique has been developed in which the magnitude of the measured complex impedance is the utilized sensing signal for the electrochemical device, allowing for multiple gas species to be measured [43].

The impedance of material Z can be measured when an AC signal is applied, and by measuring with respect to frequency \((f)\). Impedance is the opposition to current flow due to resistance, capacitance, and inductance effects at various frequencies. In order to measure impedance, the real component \((Re(Z))\) and imaginary component \((Im(Z))\) are used. A magnitude \((|Z|)\) or angle \((\theta)\) can then be used to quantify the response [43], [44]:

\[
Z(\omega) = Re(Z) + jIm(Z) \tag{2.22}
\]

\[
Re(Z) = |Z|\cos\theta \tag{2.23}
\]

\[
Im(Z) = |Z|\sin\theta \tag{2.24}
\]

Magnitude: \(|Z| = \sqrt{Re(Z)^2 + Im(Z)^2} \tag{2.25}\)

Phase Angle: \(\theta = \tan^{-1} \frac{Im(Z)}{Re(Z)} \tag{2.26}\)
Where $\omega = 2\pi f$. See Fig 15 and Fig 16 for typical Bode and Nyquist plots that are used to plot the sensor response.

**Fig 15. Typical Bode Plot for Impedancemetric Sensor Response (Adapted from Ref. [43])**

**Fig 16. Typical Nyquist Plot for Impedancemetric Sensor Response (Adapted from Ref. [43])**
If the magnitude (|Z|) and phase angle (θ) are known, these can be used at the sensing signal for either NO or NO₂. With this information, a Bode or Nyquist plot can be used to measure the amplitude of the resulting signal over a spectrum (range of frequencies). Studies by Woo et.al has shown that the phase angle can provide higher stability and higher sensitivity than by measuring the magnitude of impedance [43],[45]–[47]. It can serve as a sensing signal for the sensor at a specifically determined frequency and excitation amplitude.

Only a single YSZ electrolyte is needed for sensors utilizing EIS, where the following reactions take place at the electrode:

\[ \frac{1}{2} \text{O}_2 + 2e^- \leftrightarrow \text{O}^{2-} \quad \text{Equation 2.27} \]

\[ \text{NO}_2 + 2e^- \leftrightarrow \text{NO} + \text{O}^{2-} \quad \text{Equation 2.28} \]

Using this technique, sensitivity to NO and NO₂ can be reduced to less than 5 ppm, and similar responses to NO and NO₂ (total NOx sensing) have been measured [47].

2.5 Utilizing Solid-State Sensors for In-Situ Real-Time Monitoring

While much research and development has gone into NOx sensors for automotive applications, sensor literature is quiet vague on other applications, especially for implementation as a possible alternative to traditional CEMS. Current technology available for diesel passenger cars and commercial trucks (NO and NH₃ sensors for urea injection dosing within the SCR system) could provide a potential inexpensive alternative to traditional CEM analyzers for power generation systems (referenced in section 1.5). Implementation of solid-state sensors within Distributed Generation (DG) systems could allow for continuous, in-situ monitoring that could give the operator of these systems constant feedback regarding performance and emissions.

Wu et.al established that the “ideal” sensor for automotive application would have the following attributes [46]:
1.) Sensitive at less than 5 ppm
2.) Must be durable for 10 years/150k miles
3.) Must have a response time of time of \( \leq 2 \) seconds for 10 to 50 ppm
4.) Have an accuracy of 1 ppm
5.) Have low cross-sensitivity to O\(_2\), H\(_2\)O, and CO
6.) Operate in temperatures from 150°C - 650°C with potential excursion to 900°C

In 2016, commercially available NOx sensors have the following attributes reported by manufacturers [48],[49] :
1.) Have an accuracy of 10 ppm (BOSCH and NTK\(^\circledR\)) at low concentrations
2.) Response time varies (some less than 2 sec)

As a result, it is evident that additional development is still needed to develop sensors that meet these challenging criteria. None-the-less, the experimental work presented in this thesis utilizes current state-of-the art commercial devices to explore viability of implementation with DG devices.

2.6 Summary

Historically, the lambda (\( \lambda \)) electrochemical sensor has seen much development since the late 1970’s. First introduced by BOSCH as the oxygen sensor, its robust Zirconia-based electrolyte (ZrO\(_2\)) design allows it to operate in the harsh environment of an automotive vehicle’s tailpipe, where it can withstand temperatures between 300°C to 900°C. Designed to be integrated into the engine control system and coupled with a 3-way catalyst, it operates by adjusting the A/F ratio in order to operate within a narrow window in order to allow for the catalyst to effectively reduce NO and oxidize remaining CO. There two types of available lambda sensors: the potentiometric sensor, which relies on the Nernstian equation to correlate the measured voltage with the oxygen
partial pressure of the exhaust, or amperometric sensors, in which a fixed voltage is applied to a pumping cell and resulting current is used to measure the oxygen content. Within the last several decades, NGK insulators have helped lead the development of sensors (both potentiometric and amperometric and mostly recently, impedancemetric) that are capable of measuring NO as well as NO₂, or equal sensitivity to both (total NOx sensing). These sensors are designed to be integrated into Selective Catalytic Reduction (SCR) systems of Light Duty (LD) and Heavy Duty (HD) diesel vehicles. Even though these sensors have seen extensive used in the automotive industry, there is little known about other possible applications outside of the industry.

The goal of this thesis is to explore the potential concept of utilizing these devices for the purpose of monitoring and correcting the emissions performance (specifically the nitric oxide output) of DG devices; by investigating the robustness and accuracy of commercially-available solid-state sensor devices during the operation of a commercial DG system and developing an algorithm to help them maintain emissions performance in real-time, a potential viable solution to the lack of cost-effective monitoring devices for DG would be achieved.
3. APPROACH

Before proceeding, it is important to reiterate the current scope and tasks of this thesis in light of the background theory that was discussed in this previous section. These tasks will map directly to the objectives, listed at the end of Chapter 1.

3.1 Task 1: Develop Gas Turbine Testbed for Sensor Measurements

A test-section capable of mounting the sensors in an environment with well-mixed and developed flow in order to avoid stratification of emissions will be constructed. A system capable of powering and measuring the sensor signals will also be installed in order to record data over extended periods of time.

In order to support the first objective, various commercially-available sensors will need to be identified that can withstand the exhaust environment of the Gas Turbine (which will serve as a representative of DG devices for this thesis) for an extended period of time (six to eight months). As supported in the sections above, the Zirconia Oxide (ZrO2) electrolyte in the sensor housing has the ability to withstand the harsh environment of automotive exhaust systems (300°C - 900°C). Because of the lean-premix nature of Gas Turbine combustion, which will be explored in the next chapter, the exhaust temperatures should be fairly low compared to stoichiometric automotive exhaust conditions. Because of the ceramic heating element also built into the sensor housing that allows for continuous operation at required temperatures, these lean-conditions should not present a problem.

A Gas Turbine testbed will also need to be properly identified and a test-section will need to be constructed in such a way that the flow-field of each sensor does not impact the next. Ports for temperature measurements and emissions sampling for the referee instrument will also be constructed. This mounting section will need to be installed in a location such that the flow is as well-mixed and uniform as possible. At the UCI Combustion Laboratory (UCICL) testing facility,
there are numerous commercially-available Capstone Microturbine engines that can be used for testing with existing testbeds that can used for Task 2.

3.2 Task 2: Evaluate Robustness and Accuracy of Candidate Sensors

Sensor signals will be recorded and measured over an extended period of time (six to eight months) and compared to an established referee instrument. The candidate sensor that performs best relative to other sensors will be utilized in the development of the control algorithm.

Since the candidate sensors would have already been identified in task 2, an established referee instrument that can be used to quantify the robustness and accuracy of the sensor will have to be chosen. The latest available state-of-the-art analyzer available at UCICL is the HORIBA PG-350 instrument. This “CEM-like” instrument would represent the CEM analyzers commonly used to measure emissions for power generation systems over 25 MWe. For more on the analyzer’s specifications, Chapter 4 will detail this instrument more in depth.

With the established referee instrument and test bed for the sensor installation, a period of six to eight months would be needed to fully evaluate the sensor performance. Various sensor characteristics such as accuracy, lower detectable limit, lag time and rise time, and precision would need to be measured. A statistical comparison would then be used to differentiate the sensor readings within a 90% confidence interval or greater to confidently identify the most promising sensor. The sensor that performs better regarding measured sensor characteristics will be chosen for Task 3
3.3 Task 3: Demonstrate a Control Algorithm

Four distinct control algorithms will be developed using the most promising sensor resulting from Objective 2. These will be capable of operating independently of manual control and will be software-based (i.e. closed-loop control). The most practical approach of each of the four algorithms will be chosen to be implemented within the engine software and will be demonstrated in real-time.

First, an emission-map of the engine will need to be constructed at all operating conditions for the engine. Design Expert software will be utilized to model carbon monoxide and nitric oxide as a function of engine parameters for different load demands. This is pertinent in order to optimize the engine operating parameters to minimize nitric oxide formation. Once an emissions map is constructed, four different control algorithms will be developed with different techniques of reducing nitric oxide emissions. The most practical approach from the four possible algorithms will be chosen as the algorithm of choice. This algorithm will be subsequently programmed into the engine control software and will demonstrate its ability to reduce nitric oxide emissions in real-time.
4. EXPERIMENTAL DEVELOPMENT AND SETUP


4.1 Test Facility- Capstone 60 kW Gas Turbine

A Capstone C-60 Microturbine Generator (MTG) with CHP rated at 60kW output was utilized as a test bed in order to study two chosen candidate sensors (NTK and UniNOx®). These sensors were chosen due to their availability (easily obtained online from automotive OEMs) and because they represented the latest state-of-the-art nitric oxide sensor technology commercially available on the market. The engine operated on natural gas supplied from UC Irvine. Three “identical” solid-state sensors (3 NTK and 3 UniNOx®) of each model were used to allow evaluation of variability among individual sensors. This is important in order to assess a given device’s performance relative to the other. Sensors from different brands were installed 15° apart from each other, while sensors from the same brand were installed 120° apart in the same plane. This configuration ensures 1) each brand of sensor is placed around the entire diameter of the exhaust section, 2) different sensors are not interfering with the upstream flow of another sensor, and 3) that different sensors measure in the same region. Each sensor is capable of measuring either NO or NO₂ (cross-sensitive) and O₂. See Fig 17 for installation configuration. These NOx sensors were installed at a significant distance downstream intended to provide well mixed, fully-developed flow (see Fig 18).
Fig 17. Exhaust Section Installation Configuration

Fig 18. Layout of Testing Facility
4.1.1 C-60 Fuel Staging for NO Variation

To properly evaluate the sensor response, a relatively wide range of exhaust NO levels were desired. This was accomplished by varying the load demand on the engine, which was possible through the utilization of Capstone’s desktop software (Capstone Remote Monitoring Software (CRMS)).

The Capstone C-60 is a staged lean-premix combustion system capable of running various programmed load profiles [50],[51]. Lean-premixed combustion is a strategy that has been historically employed by OEMs of stationary gas turbine technology since the addition of more stringent regulations to the Clean Air Act in late 1980’s/early 1990’s. When this act was first passed, NOx was limited to 42 ppmvd (15% O2) under the Best Available Control Technology (BACT) strategy, and subsequently 25 ppmvd (15% O2) under the Top Down BACT strategy. Initially wet controls (injection of water and steam) were used to meet requirements but proved detrimental to the lifecycle of engine components, so an alternative method to achieving the emissions goals was needed. The lean-premix strategy works to reduce NOx by premixing fuel and air before they enter the combustor, which reduces the combustion flame temperature by utilizing excess air to help eliminate regions with high equivalence ratios (rich regions). The downside to this strategy resides in the CO/NOx tradeoff: as the temperature of combustion process decreases due to excess air, NOx decreases, but carbon monoxide (CO) increases due to incomplete combustion [52],[53]. Extensive research and development was performed in the 1990’s to help implement this strategy within stationary gas turbine technology that is widely used to this day [54]–[56].

Fig 19 and Fig 20 show the installation configuration of the injectors in the Combustor on planes A and B. It has 6 injectors total: 2 injectors (plane A) continuously supply fuel during
operation while 4 other injectors (plane B) are subsequently turned on and off to vary the power output depending upon the load demand. Varying local equivalence ratios are seen as load changes from 60 kW (6 injectors fired total) to down below 10 kW (2 injectors fired total). In order to expose the sensors to various levels of NO in which to measure, this staging of the engine was utilized.

![Diagram of C-60 Injector Configuration](image1)

*Fig 19. C-60 Injector Configuration (From Ref. [51],[57])*

![Diagram of C-60 Combustor and 3D Cross-section](image2)

*Fig 20. C-60 Combustor and 3D Cross-section (From Ref. [51],[57])*

Fig 21 illustrates how NO and NO$_2$ change with load demand for the C-60 engine. Standard error represents the variation in NO and NO$_2$ samples taken at each load. Note that the emissions samples were taken on a dry basis and are uncorrected. At 10 kW, NO levels are high due to the
high localized equivalence ratios for each injector. From ~22 kW to 35 kW the amount of NO₂ rises substantially, which can attributed to the overall cooling of the reaction due to the introduction of more air (albeit at ~1100 deg F from the recuperator). As the number of firing injectors increases and eventually reaches 6 injectors, the majority of NOx becomes NO due to the relatively high full load reaction temperature. At the lowest load demand, the NO₂ reading comes close to 10% of the total NOx output, and reaches close to 50% at around 22-35 kW.

A modified load profile (see Fig 22) was received from Capstone and was programmed using CRMS. Each load point was programmed to run for a minimum of 15 minutes each.

![Graph showing NO and NO₂ vs. Load](attachment:graph.png)

*Fig 21. NO/NO₂ (Uncorrected) vs. Load*
4.2 Sensor Data Acquisition System (DAQ) Setup

In order to collect relevant data pertaining to the sensors and the engine, an extensive data acquisition network was needed. This system needed to be robust enough to be able to record continuously without interferences and without the need for manual control of the need.

In order to accomplish this, a DAQ computer installed with the latest version of LabVIEW was also placed inside the controlled testing environment to collect relevant engine data, referee instrument data, data on ambient conditions, and automotive sensor signals at 1 Hz for 24 hours a day, 7 days a week for six to eight months of testing. Fig 23 illustrates the flow of communication from sensors and the engine to the DAQ computer. As shown, several steps are required to acquire information from the engine and the HORIBA PG-350 (referee “CEM-like” analyzer) as well as the automotive sensor signals. Data from another highly sophisticated analyzer (HORIBA MEXA-1400QL-NX) that utilizes a Quantum Cascade Laser (QCL) were also collected. The MTG outputs
information relevant to its operation (AFR, air flowrate, load demand, number of active operating injectors, and other useful parameters) and performance using serial communication that can be monitored by the user with CRMS. Because the MTG operates outdoors at the UC Irvine Distributed Technology Test Facility in an uncontrolled ambient environment, this information is sent to the DAQ computer with 150 feet of CAT 5e cable in order to preserve the signal integrity. The PG-350 includes an analog-output port that allows for configurable individual channels. Both the QCL and the PG-350 output in the form of 4-20 mA signals, which can be connected directly to a National Instruments (NI) USB DAQ device.

![Data Acquisition Communication Diagram]

*Fig 23. Data Acquisition Communication Diagram*

In order to collect and record the sensor signals using the LabVIEW program, the company EmiSense (subsidiary of CoorsTek) supplied the NTK and UniNOx® sensors and provided UCICL with the proper equipment to power the solid-state devices (see Fig 24 and Fig 25). The sensors are both commonly used in the Diesel Heavy Duty (HDV) and Light Duty Vehicle (LDV)
industry. Numerous other sensor types were also contenders to be evaluated (BOSCH EGS-NX sensor, Delphi Ammonia sensor, NTM sensors), but proved to be either difficult to obtain or were not chosen in favor of the NTK sensor and UniNOx® sensor. The equipment EmiSense provided with allows the NTK and UniNOx® sensors to operate simultaneously (up to 8 sensors possible) and sends one main signal to the DAQ computer in CAN-Bus protocol, which is subsequently interpreted as NO (ppm) and O₂ (%) data. This was accomplished using a USB signal using a NI-8473 CAN-to-USB converter. EmiSense also provided UCICL with a LabVIEW 2015 VI which served as a basis from which all data were received and stored.
The result is a somewhat complex network of devices and converters that ultimately allows for continuous monitoring of emissions using the solid-state sensors as well as the PG-350 (Fig 23).

4.3 Other Measurement Devices
4.3.1 Horiba Instruments – Referee Analyzer

A “CEM-like” instrument (HORIBA PG-350 analyzer) was utilized as a reference device so that the solid-state sensors’ performance could be measured and compared against a representative “true” value. The PG-350 (Fig 26) analyzer uses the cross-flow modulation chemiluminescence detection method to determine NO, which is an EPA approved sampling method. It utilizes a conversion device to determine the corresponding amount of NOx (see Table 3 for measurement specifications). Over the course of the testing period, it was spanned for a 0-250 ppm range of NO with an uncertainty of ±2.5 ppm. A response time of 10-seconds was utilized as well as 60-minute moving time average. To ensure the quality of data, the PG-350 was
calibrated using zero and span gases on a regular basis to account for drift and placed in a controlled environment.

Fig 26. HORIBA PG-350

Table 3. PG-350 Measurement Specifications

<table>
<thead>
<tr>
<th>Species</th>
<th>NO</th>
<th>O₂</th>
<th>CO</th>
<th>CO₂</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Range</strong></td>
<td>0-250 ppm</td>
<td>0-25% Vol</td>
<td>0 -500 ppm</td>
<td>0 – 10% Vol</td>
</tr>
<tr>
<td><strong>Accuracy</strong></td>
<td>Avg: ~ ± 2 ppm</td>
<td>± .125 %</td>
<td>± 2.5 ppm</td>
<td>± .05 %</td>
</tr>
<tr>
<td><strong>Method</strong></td>
<td>EPA Method 7E</td>
<td>EPA Method 3A</td>
<td>CARB Method 10</td>
<td>EPA Method 3A</td>
</tr>
<tr>
<td><strong>Response Time</strong></td>
<td>10 sec/30 sec</td>
<td>10 sec/30 sec</td>
<td>10 sec/30 sec</td>
<td>10 sec/30 sec</td>
</tr>
<tr>
<td><strong>Drift</strong></td>
<td>± 1.0 % of full scale/day</td>
<td>± 1.0 % of full scale/day</td>
<td>± 1.0 % of full scale/day</td>
<td>± 1.0 % of full scale/day</td>
</tr>
<tr>
<td><strong>Analog Output</strong></td>
<td>4 – 20 mA</td>
<td>4 – 20 mA</td>
<td>4 – 20 mA</td>
<td>4 – 20 mA</td>
</tr>
</tbody>
</table>
4.3.2 Horiba Instruments – MEXA-1400QL-NX

The HORIBA MEXA-1400QL-NX instrument was also utilized as a reference device (Fig 27). Shown in Table 4 are the species the instrument is capable of analyzing as well as the measurement specifications. It is capable of up to 10 Hz sampling.

Fig 27. HORIBA MEXA-1400QL-NX

This analyzer is able to measure four nitrogen species (NO, NO₂, N₂O, and NH₃) by utilizing Infrared Absorption Spectroscopy (IR Spectroscopy). The QCL (Quantum Cascade Laser) element inside the unit emits light within the mid-infrared (mid-IR) region with high resolution (< .05 nm) where many gases exhibit strong absorption tendency. Temperature of the element is controlled to allow the wavelength of the light to stay within the mid-IR region. This light is then measured by a photo-voltaic detector after passing through the sample gas of interest. Since the absorbance of the gas species is proportional to the concentration of gas (Beer-Lambert Law), a concentration can be calculated using a theoretical absorption spectrum of known concentration with the actual absorption spectrum of the target gas multiplied by a constant [58], [59]. Fig 28 shows a schematic of the gas cell inside the instrument during calibration. An initial intensity of
light, \( I_0 \), is emitted by the QCL element, which is then absorbed the different gas species. If a zero gas is used, the resulting intensity of the light should be similar to \( I_0 \) (due to the nearly no absorbance from nitrogen). When a span gas is used (which has a known absorbance), the resulting light (with intensity \( I \)) is used to measure the concentration of species of interest inside the cell. This general principle is then applied to measure different species inside exhaust gas.

![Diagram of gas cell and laser](image)

**Fig 28. HORIBA MEXA-1400QL-NX Cell Schematic (From Ref. [59])**

<table>
<thead>
<tr>
<th>Species</th>
<th>( NO )</th>
<th>( \text{NO}_2 )</th>
<th>( \text{N}_2\text{O} )</th>
<th>( \text{NH}_3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Measurement Range Used</strong></td>
<td>0-50 ppm</td>
<td>0-50 ppm</td>
<td>0-100 ppm</td>
<td>0 – 50 ppm</td>
</tr>
<tr>
<td><strong>Accuracy</strong></td>
<td>± .5 ppm OR 2% of Reading Zero Noise: .2 ppm</td>
<td>± .5 ppm OR 2% of Reading Zero Noise: .2 ppm</td>
<td>± 1 ppm OR 2% of Reading Zero Noise: .4 ppm</td>
<td>± .5 ppm OR 2% of Reading Zero Noise: .2 ppm</td>
</tr>
<tr>
<td><strong>Response</strong></td>
<td>&lt; 2 sec</td>
<td>&lt; 2 sec</td>
<td>&lt; 2 sec</td>
<td>&lt; 5 sec</td>
</tr>
<tr>
<td><strong>Drift</strong></td>
<td>± 1.0 % of full scale/8 hrs</td>
<td>± 1.0 % of full scale/8 hrs</td>
<td>± 1.0 % of full scale/2 hrs</td>
<td>± 1.0 % of full scale/2 hrs</td>
</tr>
</tbody>
</table>
Because the QCL is designed to validate the performance of SCR and Ammonia Injection devices in commercial diesel vehicles and because of its unique ability to measure NO, NO$_2$, and N$_2$O separately, it was chosen as an additional measurement analyzer. To see the results of the comparison of the instrument’s measurements relative to the PG-350 analyzer for the C60 system, please see Appendix Section 8.1.

4.3.3 Relative Humidity and Ambient Air Temperature Sensor

To measure fluctuations in ambient conditions on a day-by-day basis, the R.M. Young’s Relative Humidity and Ambient Air Temperature sensor (Fig 29) was used to measure the conditions of ambient air in close proximity to the engine. Incorporated into the design of this unit is a multi-plate radiation shield to protect measurements against solar radiation and rain. This was used specifically for measuring the impact of day-to-day fluctuations in ambient conditions on sensor performance. See Table 5 for measurement specifications.

<table>
<thead>
<tr>
<th>Relative Humidity</th>
<th>Ambient Temperature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Range 0-100%</td>
<td>-50 - 150°F</td>
</tr>
<tr>
<td>Accuracy ± 1% RH @ 23°C</td>
<td>± .54 °F at 73°F</td>
</tr>
<tr>
<td>Measurement Principle</td>
<td>Rotronic Hygrometer™</td>
</tr>
<tr>
<td>Response Time 10 sec</td>
<td>10 sec</td>
</tr>
<tr>
<td>Drift ± 1.0 % per year</td>
<td>N/A</td>
</tr>
<tr>
<td>Analog Output 4 – 20 mA</td>
<td>4 – 20 mA</td>
</tr>
</tbody>
</table>

Fig 29. R.M. Young’s Relative Humidity and Ambient Air Temperature Sensor

Table 5. R.M. Young’s Sensor Measurement Specifications
4.3.4  K-Type Thermocouples

An OMEGA® Type-K thermocouple (rugged heavy duty transition joint type) was used to measure the exhaust temperature near of the test section (see Fig 17 for configuration). This was used to monitor exhaust conditions and to study the impact of fluctuations in exhaust temperature on sensor performance.

![OMEGA Type-K Thermocouple](image)

Table 6. Type-K Thermocouple Specifications

<table>
<thead>
<tr>
<th>Probe Type</th>
<th>OMEGA Thermocouple</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measurement Range Used</td>
<td>Type K</td>
</tr>
<tr>
<td>-454 °F to 1650.2 °F</td>
<td></td>
</tr>
<tr>
<td>Accuracy</td>
<td>± 1.1 °C</td>
</tr>
<tr>
<td>Resolution</td>
<td>.1 °C</td>
</tr>
</tbody>
</table>

4.3.5  Sample Train Measurements – Water Dropout

A mini-refrigerator was utilized as part of the water dropout system for the gas sampling train. In order to effectively cool the sample and allow water to condense before the gas sample was analyzed (to avoid interference with NO measurements as well as damage to the analyzer’s internal equipment), a two-stage system was constructed. Two WHITEY® 304L Stainless Steel containers (each with 1 Liter capacity) that were used to collect the condensed water. This system was developed as a solution that enabled testing over long durations (24 hours a day, seven days a week in some cases) without the need for continuously adding cooling water or ice to the system. The two-stage system operates in the following manner:

1. The wet gas sample coming from the exhaust test section (Fig 17) is pumped into the dropout system using a GAST® vacuum pump. The inside of the refrigerator is chilled to around 40 °F (Fig 31).
2. A stainless steel tube routes the gas sample down into the container. The condensed water is collected at the bottom of the stainless steel basin while the gas sample is rerouted back up and out of a ¼ inch pipe T-fitting and into the next dropout container.

3. The gas sample is now routed out of the dropout and into the PG-350 sample port.

Temperature measurements inside the system as well as relative humidity measurements were taken using a thermocouple as well as the Young’s Relative Humidity and Ambient Air Temperature sensor (discussed in the preceding sections). These measured values can be seen in Fig 31 over the course of 3 days. At peak ambient temperature (12 P.M.), the system was able to achieve close to a 20°F drop between the sample temperature (coming out of the water dropout) and ambient temperature, and at other times close to a 10°F drop.

See Fig 32 for a schematic of the dropout system.
1. Wet Gas Sample Enters

2. Water condenses and collects in bottom of S.S. container

3. Gas Sample exits and is directed to next container

4. Dry Gas Sample exits to PG-350

Fig 32. WHITEY® 304L S.S. 1 L Containers
4.3.6 Sample Train Issues - Transient Analysis

Quantitative comparison of sensor readings with the reference instrumentation during transient operation presented a significant challenge. The sample time delay between the PG-350 and the in-situ sensors initially presented a problem when initially comparing the readings. Fig 33 shows the PG-350 NO output vs. the sensor output when the sample delay is left uncorrected. Because of a 10 second delay (150 foot sample line length) between the time the sample was analyzed by the PG-350 and when the sensor signals were recorded, a significant shift occurred during transient operation. During changes to a load in which significantly more nitric oxide is produced, the sensors will read higher than the PG-350, and the opposite will occur during changes to loads in which less nitric oxide is produced. This is because the sensors are installed directly into exhaust ducting and report measurements almost immediately. Once the 10 second sample delay was taken into account, the sensor signals were observed to be linear over the entire range of NO values (observed in Fig 34).

The most straightforward approach taken to address the problem of sample delay was to average the readings at each steady-state load and to filter out the data obtained during the transient phase of engine operation. This allowed for a fairer assessment of the sensor values vs. the PG-350 values due to inherently different signal processing techniques (see section 4.3.1 and 4.2). Table 7 shows the amount of sampling points collected at each load. Each point represents 10 seconds of time that has elapsed. 160 points is collected at a load point when the load goes down (80 points) and when the load goes back up (80 points). Once the transient parts of each load were filtered out (10 points taken out during transience), the sampling points at each load were averaged.
Fig 33. Before Sample Delay Correction

Fig 34. After Sample Delay Correction – 10 seconds
Table 7. Sampling Points for .1 Hz Data

<table>
<thead>
<tr>
<th>Load (kW)</th>
<th>Sampling Points</th>
<th>Load (kW)</th>
<th>Sampling Points</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>983</td>
<td>39</td>
<td>160</td>
</tr>
<tr>
<td>19</td>
<td>83</td>
<td>42</td>
<td>160</td>
</tr>
<tr>
<td>20</td>
<td>80</td>
<td>46</td>
<td>160</td>
</tr>
<tr>
<td>23</td>
<td>160</td>
<td>49</td>
<td>160</td>
</tr>
<tr>
<td>26</td>
<td>160</td>
<td>52</td>
<td>160</td>
</tr>
<tr>
<td>29</td>
<td>160</td>
<td>55</td>
<td>160</td>
</tr>
<tr>
<td>33</td>
<td>160</td>
<td>59</td>
<td>160</td>
</tr>
<tr>
<td>36</td>
<td>160</td>
<td>60</td>
<td>5285</td>
</tr>
</tbody>
</table>

4.4 Summary

A suitable experimental setup was achieved in order to actively collect data over a six to eight month period. Two different commercially-available sensors, the NTK and UniNOx® sensor, were chosen to represent the latest technological and state-of-the-art NO sensor technology in order to perform the objectives of this thesis. A sensor exhaust section, capable of installing up to 9 sensors, was constructed in such a way as to avoid measurement interference with other sensors and was installed in a location with well-developed and uniform flow. This was installed on an existing Gas Turbine testbed that incorporates a 60 kW Capstone Microturbine generator (MTG). This engine represents a common DG system that is commercially available on the market. An extensive data acquisition network was constructed, connecting various measurement devices, the referee analyzers, the solid-state sensors, and the MTG to a DAQ computer located in a closed, controlled environment. A water-dropout method for the referee instrument was also developed in order to condition the sample before analysis occurred. In order to correct for the delay of the sensor signals (situated in the exhaust environment) relative to the referee instrument (situated in a controlled environment), steady-state time averaging of sample data was conducted.
5. RESULTS

Portions from this chapter have been published in the following conference proceedings/reports:


Portions from this chapter have been published in the following California Energy Commission (CEC) report: R. A. Ehlig and V. G. McDonell, “Control System Demonstration Testplan,” 2018.

Portions from this chapter have been published in the following California Energy Commission (CEC) report: R. A. Ehlig and V. G. McDonell, “Control System Demonstration Report,” 2018.

5.1 Overview of Results

This chapter details the results from the two other main objectives of this thesis: to quantify the sensor characteristics of robustness and accuracy, and to demonstrate a control algorithm suitable (coupled with the best sensor) for optimizing the emissions performance of the DG system.

5.2 Solid-State Sensor Performance

5.2.1 Sensor Performance Overview

To quantify the performance of the solid-state sensors, 3 UniNOx® and 3 NTK sensors actively obtained readings throughout the entire testing period. NO and O2 readings from the
sensors were collected along with NO readings from the PG-350 on the same timestamp. The PG-350 reading was treated as the “true” value by which a comparison could be made.

The wet readings from the solid-state sensors (installed directly in the exhaust duct of the MTG) first had to be corrected to dry readings in order for a direct comparison with the PG-350 instrument to be made. Otherwise significant deviation from sample measurements would be observed. Finding the theoretical mole fraction of water in the exhaust was possible using the Air-to-fuel ratio information recorded from the CRMS software.

The following equations were used to correct the O$_2$ and NO readings of the solid-state sensors:

\[
NO_{ppmvd} = \frac{NO_{ppm}}{1 - x_{H_2O}} \quad \text{Equation 5.1}
\]

\[
O_2_{ppmvd} = \frac{O_2_{ppm}}{1 - x_{H_2O}} \quad \text{Equation 5.2}
\]

Where $x_{H_2O}$ is the mole fraction of water present in the exhaust. Once corrected from wet to dry, the readings from all sensors and the reference analyzer were corrected to a standard 15% O$_2$ concentration:

\[
NO_{ppmvd,15\%O_2} = NO_{ppmvd} \left(\frac{20.9 - 15}{20.9 - O_2_{ppmvd}}\right) \quad \text{Equation 5.3}
\]

Readings were subsequently averaged at each load and data taken during transient loads were filtered out (10 sampling points after load change were removed). A Matlab program was used to correct the sensor readings (see Appendix section 8.2) from data taken on a daily basis in order to streamline the process of analyzing the sensor results. Drift of the PG-350 instrument was also taken into account by spanning the instrument every 1-2 weeks over the course of the testing
period. Drift that was found to have occurred between these time periods was divided by the total number of days between calibrations and was accounted for in the PG-350 data by either adding (if the PG-350 drifted downward) or subtracting (if the PG-350 measurements drifted upward) from the analyzer’s measurements.

Because the solid-state sensors were exposed to exhaust conditions over a period longer than 6 months, seasonal variation, changes in ambient conditions, and exposure to different exhaust temperature conditions may have been an influential factor that impacted the sensor response over the course of testing. Exposure time (time spent in the exhaust) could also have had a profound impact on the results. In order to analyze the influence of these external factors on the data that were collected, a response-surface historical model was developed in Design Expert® 10 to analyze the effect of these factors. Ambient temperature (°F) and relative humidity (%) of ambient air were measured using the R.M. Young’s sensor (section 4.3.3) and exhaust temperature (°F) was measured using an OMEGA® Type K thermocouple (section 4.3.4). Time spent in the exhaust (from the initial period of observation) was recorded in the number of days the sensors were installed in the exhaust ducting.

5.2.2 Explanation of Accuracy and Precision

In order to gain a basic underlying understanding of the results that will be discussed, it is important to highlight the differences between accuracy and precision. This can be best illustrated with the dartboard analogy. The two dartboards (displayed in Fig 35) show the distinct differences.

In order to be precise, each dart that lands on the board must land close to the dart that came before it; however, in order to be accurate, each dart must land within a certain distance of the middle of the board. If the average distance between each subsequent dart is closer than to the middle (left board), than the shooter is precise but not accurate. If the average distance between
each dart is farther than the distance to the middle of the board, the shooter is accurate but not precise. By applying this analogy to the solid-state sensors, an accurate but imprecise sensor is one that measures close to the PG-350 response, but during repeated measurements it fails to achieve a similar response to what it measured before. A precise but inaccurate sensor would fail to measure close to the PG-350 response, but during repeated measurements would achieve a similar response to previous measurements. Because three sensors for each brand are utilized (3 NTK and 3 UniNOx® sensors), an average precision and average accuracy of the three will be found.

![Dartboard Analogy](image)

**Precise but not accurate**

**Accurate but not precise**

*Fig 35. Dartboard Analogy*

### 5.2.3 Accuracy

For sample calculations of Accuracy, please see Appendix Section 8.3

The accuracy of the sensor represents the closeness to which the sensor output represents the “true” levels of NO that are recorded by the reference instrumentation. It is the difference between the actual “true” value and the recorded value [60],[61]. By computing the maximum average deviation between the three duplicate sensor readings (NTK and UniNOx®) plotted against the one-to-one output of the PG-350 (Fig 37), the percentage accuracy can be found as:
\[
\text{Accuracy (\%) } = \frac{D_{\text{Max}}}{IN_{\text{f.s.}}} \cdot 100
\]

Equation 5.4

Where \(D_{\text{Max}}\) is the maximum average deviation from the reference instrument and \(IN_{\text{f.s.}}\) is the full-scale range of NO values reported by the PG-350 on each day of testing.

Fig 36 shows the averaged NOx output (measured during the week of 9/18/2017 – 9/24/2017) of the PG-350 compared against the solid-state sensor readings. There were some initial concerns that the sensors measured total NOx rather than specifically NO, which is shown not to be the case in the figure. The PG-350 reports close to twice what the solid-state sensors are reading at many of the measurements, which agrees with the figure that displays the NO and NO\(_2\) contribution to total NOx vs. load for the C60 (see Fig 21). Note that the individual corrections of PG-350 measurements as well as the sensor measurements to 15% O\(_2\) will also affect the differences between readings. Fig 37 shows the averaged NO output of the solid-state at various loads compared to the PG-350 analyzer over the course of a week of testing. Standard error for the NTK and UniNOx® sensors represents the variation among individual sensor measurements within a particular brand. This can also be attributed to the variation in measured oxygen percentage for each individual sensor, which can affect the corrected NO concentration. Standard error for the PG-350 measurement represents \(\pm 2 \text{ ppm}\) over the entire range of the span. It becomes clear that greatest deviation between the sensor readings and the PG-350 analyzer occurs when levels of NO are the highest. At higher levels of NO, the UniNOx® sensor underreports more consistently than the NTK sensors. The greatest deviation in results for the NTK sensor occurs when it over reports the NO levels in the exhaust (~140 ppmvd reading), which could be most likely be attributed to the background interference of NO\(_2\) in the sensor readings (cross-sensitivity to NO as well as NO\(_2\)); as the level of NO\(_2\) in the exhaust increases (see Fig 21), the sensors are
more likely to read a higher concentration of reported NO. In reality, this concentration being read by the sensors is a mixture of NO and NO₂, not just NO.

Fig 38 shows the calculated percentage accuracy over the course of the testing period from March to May and subsequently from September to mid-October when testing was resumed. Note that seasonal variation has an impact on the calculated accuracies, which will be explored in the next section (Section 5.2.3.1). Each blue and orange point represents the average of three sensor percentage accuracies (3 UniNOx® and 3 NTK sensors) for one day. Standard error represents the variation in individual accuracies calculated for each sensor. Table 8 shows the results of a t-test that was conducted that allows a statistical comparison of the reported accuracies for the two sensors. Given the differences between the mean variation of each sensor (comparing 12 % vs 14.8 %) compared to the variability among the three of each sensor (0.547 %) over the entire testing period, the t-test, with 132 degrees of freedom for the data set, indicates that the NTK sensor achieves better accuracy (lower percentage accuracy) than the UniNOx® sensor with more than 99% confidence.

For the MATLAB code that was used to calculate the sensor percentage accuracies, please refer to Appendix section 8.2.
Fig 36. PG-350 NOx One-One Output (Week of 9/18/2017 – 9/24/2017)

Fig 37. PG-350 NO One-One Output (late September/ early October)
5.2.3.1 Effect of External Parameters on Accuracy

A linear model was recommended and developed for both the NTK sensor and the UniNOx® sensor for accuracy as a function of Ambient air conditions, exhaust temperature, and exposure time over 170 days of non-consecutive testing testing. Although a higher order model generally would result in a highly accurate model of the results, a linear model was developed in order to more easily understand the impact of individual factors without complex multi-factor interactions. Data were collected from May to late June (typically warmer months) and from late
September to October (typically cooler albeit dryer months) in order to study the impact of external factors from different seasons of the year. Variance of Inflation (VIF) values, which is a measure of the lack of orthogonality in a model, were observed to be above 10 in some cases but kept below 20 (generally over 100 is a cause of concern for the validity of the model). Shown in Table 9 - Table 14 are the ANOVA results for each model. As the percentage accuracy decreases, the sensors agree more closely with the PG-350 instrument.

In order to measure the impact of each factor on accuracy, factors were measured and subsequently averaged at the load (usually ~ 10 kW) in which the largest significant deviation between the sensor values and the PG-350 values occurred; this is the load in which the accuracies are determined. The resulting maximum deviation was found by averaging the three signal deviations for each of the sensors. For the NTK sensor, the model shows that increases in exhaust temperature and time exposure impact the accuracy positively, whereas increases in relative humidity and ambient temperature impacts the accuracy negatively. For the UniNOx® sensor, increase in exposure times and exhaust temperature also impact the sensor positively, whereas increases in relative humidity and ambient temperature impact the sensor negatively.

For both these sensors, it appears that from looking at the accuracy over time (Fig 38) that both sensors do have improvements in accuracy relative to the beginning of the testing period; however, the effect of time exposure on accuracy has a greater impact on the UniNOx® sensor when looking at the figure (which started to deviated significantly in May-June towards worsening accuracy but increased in accuracy towards September-October). The NTK sensor also had an initial period of higher inaccuracy relative to later in the testing period, but towards March-Oct appears quite steady. Because these sensors drift overtime, the drift of the average signal response for both sensors appears to move closer relative to the PG-350 average signal, which is leading to
a higher reported accuracy. This is promising for these sensors as they are designed to be situated in an exhaust environment for their lifetimes without the need for calibration. Fig 39 shows the standard deviation of reported accuracies for each brand of sensor as well as the maximum range of NO measurements seen over the course of each testing day. For the NTK sensors, as time exposure increases the sensor accuracies appear to move closer together, leading to the conclusion that the drift of the individual sensors occur toward a direction of the PG-350 response. This is also reaffirmed by the average sensor accuracy increasing from March-April. The standard deviation of accuracies for the UniNOx® sensors appears relatively constant compared to the NTK sensor.

The maximum PG-350 measurements observed for each day (black line of Fig 39) also has a significant effect on accuracies observed. This is used in the accuracy equation as IN$_{fs}$; it is the full-scale range of inputs, corrected to 15% O$_2$, observed each testing day by the PG-350 instrument. This method of characterizing the full-scale range of inputs was chosen in favor over using a constant input of 200 ppm, which is the preselected range of the instrument, because it is not corrected and because the observed O$_2$ percentages vary from load to load over the course of a testing day. During the early March to early April period, the load profile of the engine was slightly modified to allow for a wider range of NO values to be observed. The lowest load initially programmed into the load profile was initially 19 kW and this was further reduced to 10 kW to allow for only 2 injectors to be active. Because this change exposed the sensors to more NO (from April onward) than what was previously detected (March – early April), the initial percentage accuracies are higher than what is calculated later on in the testing period. In September to October, the full-scale ranges are lower, so the impact on the reduced accuracy percentage is due to other factors.
For both relative humidity and ambient temperature, the results are definitive. Water concentration in the exhaust is also impacted by the relative humidity in the air, and the exhaust sensors are known to be cross-sensitive to water, which can lead to signal noise [62]. Relatively humidity and ambient temperature are also coupled factors (low relatively humidity generally means higher temperature and vice versa). This is proved true when looking at the factors over the course of testing (see Fig 40). Both models indicate that these sensors prefer a modestly warm and dry environment; the design expert numerical optimization tool found that at an Ambient Temperature of 73°F and at a Relative Humidity of 11%, the sensors achieve the best accuracies. Because wide fluctuations in relatively humidity and ambient temperature were not observed over the course of testing and from day-to-day periods (high and low factor levels), the impact of lower temperatures typical in a colder environment are not known.

For exhaust temperature, a general pattern is made clear: as exhaust temperatures rises, the accuracy of both sensors go up. Because the number of active firing injectors increases with load, the exhaust temperature also increases with load. Generally lower loads indicate lower exhaust temperatures, which significantly impacts the nitric oxide output of the engine (see Fig 21). Because more NO is observed by the sensors at lower loads, the variation in reported values tends to be much higher, which determines the reported accuracy of the sensors. Higher exhaust temperatures leads to high reported accuracies because the variation in reported values of NO seen will be generally lower.

For both models, Table 13 and Table 14 ANOVA results are indicative (with greater than 99% confidence) that both models are significant and show good understanding of accuracy, with the current factors utilized, for the sensors.
Fig 39. Standard Deviation of Sensor Accuracies

Fig 40. Design Expert Factors
Table 9. NTK Model for Accuracy (1)

<table>
<thead>
<tr>
<th></th>
<th>Std. Dev.</th>
<th>Mean</th>
<th>C.V. %</th>
<th>PRESS</th>
<th>-2 Log Likelihood</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-Squared</td>
<td>1.196E-3</td>
<td>8.414E-3</td>
<td>14.21</td>
<td>5.406E-5</td>
<td>-345.29</td>
</tr>
<tr>
<td>Adj R-Squared</td>
<td>0.8637</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pred R-Squared</td>
<td>0.8435</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adeq Precision</td>
<td>0.8091</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Likelihood</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BIC</td>
<td>-327.96</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AICc</td>
<td>-332.98</td>
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<td></td>
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</tbody>
</table>

Table 10. UniNOx Model for Accuracy (2)

<table>
<thead>
<tr>
<th></th>
<th>Std. Dev.</th>
<th>Mean</th>
<th>C.V. %</th>
<th>PRESS</th>
<th>-2 Log Likelihood</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-Squared</td>
<td>2.35</td>
<td>16.66</td>
<td>14.09</td>
<td>205.31</td>
<td>144.55</td>
</tr>
<tr>
<td>Adj R-Squared</td>
<td>0.6567</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pred R-Squared</td>
<td>0.6076</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adeq Precision</td>
<td>0.5432</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Likelihood</td>
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<td></td>
</tr>
<tr>
<td>BIC</td>
<td>162.03</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AICc</td>
<td>156.77</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 11. NTK Model for Accuracy (2)

\[
(\text{Accuracy NTK})^{2.11} = 
-0.097769 
-6.37487E-004 \times \text{Ambient Temperature} 
-9.85075E-005 \times \text{Relative Humidity} 
+3.44957E-004 \times \text{Exhaust Temperature} 
+4.17812E-005 \times \text{Time Exposure}
\]

Table 12. UniNOx Model for Accuracy (2)

\[
\text{Accuracy UniNOx} = 
+277.52886 
+1.16224 \times \text{Ambient Temperature} 
+0.12592 \times \text{Relative Humidity} 
-0.78056 \times \text{Exhaust Temperature} 
-0.022076 \times \text{Time Exposure}
\]

Where Temperature is in °F, Relative Humidity is in terms of percentage (%), and Time Exposure is in terms of days. Accuracy is expressed as a percentage (%).
5.2.4 Lower Detectable Limit

The Lower Detectable Limit (LDL) is defined as the smallest concentration level that can be statistically differentiated from a zero concentration level by a 99% confidence interval [63]. In terms of the sensors, it is the reported NO concentration that can be differentiated from a 0 ppm concentration with 99% confidence. It can be determined with the following equation:

$$\text{LDL (ppmv)} = \overline{NO}_{0,ppmv} + 3\sigma_{0,ppmv}$$  \hspace{1cm} \text{Equation 5.5}

Where $\overline{NO}_{0,ppmv}$ is the average first non-zero concentrations reported by each sensor and $3\sigma_{0,ppmv}$ is three times the standard deviation of the reported non-zero concentrations.

Fig 41 shows the average reported LDL for each sensor type over the entire testing period. Standard error represents the variation in the first non-zero concentrations that are reported. In order to measure LDL, a MATLAB code was written (Appendix section 8.2) to find the first non-
zero values of each sensor and subsequently use the reported measurement of the PG-350 at those values as the LDL for that individual sensor. This was done for each device and subsequently averaged with two other measurements, along with the calculated standard deviation of all three devices, to calculate the LDL of the particular brand. Table 15 reports the results of the t-test that was conducted for the average reported LDL of each brand. With greater than 99% confidence, the results indicate that the LDL of the NTK sensor (5.22 ppmvd) is lower than the LDL of the UniNOx® sensor (9.44 ppmvd). These results were shown to agree with results directly given by EmiSense for both of these sensors.

Fig 42 illustrates the sensor signals within the low emissions range (0-10 ppmvd) over the course of one week of testing (same as Fig 37). This range is where the LDL for each sensor is determined. Note that the PG-350 response is plotted on the y-axis, so a zero concentration from the solid-state sensor will be reported on this axis. From the 0 -3 ppmvd reported by the PG-350, the UniNOx® sensor signals are reporting at a concentration of 0 ppmvd; however, at around .5 ppmvd the NTK sensor begins to report its very first non-zero concentrations. This is the reason the NTK sensor has a lower LDL than the UniNOx® sensor. It isn’t until ~5 ppmvd for the UniNOx® sensors and ~ 2 ppmvd for the NTK sensors that a recognizable linear output is achieved in this case.
Fig 41. Lower Detectable Limit

Table 15. T-Test LDL Results

<table>
<thead>
<tr>
<th>Sensor Brand</th>
<th>Estimated Mean</th>
<th>Standard Error</th>
<th>Treatment</th>
<th>Mean Difference</th>
<th>df</th>
<th>Standard Error</th>
<th>Prob &gt;</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>NTK</td>
<td>5.22</td>
<td>0.33</td>
<td>1 vs 2</td>
<td>-4.22</td>
<td>131</td>
<td>0.46</td>
<td>&lt; 0.0001</td>
<td></td>
</tr>
</tbody>
</table>
5.2.5 Precision

For sample calculations of Precision, please see Appendix Section 8.3.

Sensor precision is a measure of the repeatability of measurements. It is commonly expressed in terms of a percentage, with a higher percentage associated with decreased precision [60],[61]. Precision can be measured in both upscale (increasing in NO measurement values) and downscale directions (decreasing in NO measurement values). This can be expressed as:

\[
Precision(\%) = \frac{\Delta S_{Max}}{IN_{f.s.}} \cdot 100
\]

Equation 5.6

Where \(\Delta S_{Max}\) is the maximum difference in reported output values at the same input for a given sensor in the upscale and downscale direction of measurements, and \(IN_{f.s.}\) is the full-scale range of NO values reported by the PG-350 for each day of testing.
Fig 43 shows the percentage precision for the NTK and UniNOx® sensors over the entire period of testing. Standard error represents the variation in reported values of percentage precision for different sensors within the same brand. Each blue and orange point represents the average of three sensor precision percentages (3 UniNOx® and 3 NTK sensors) for one day. Over the course of the testing period, the general trend indicates that precision is decreasing slightly for both sensor brands (increasing percentage). Because the sensors are installed directly into the exhaust environment, the exposure of different exhaust species to the electrodes could have an impact on precision loss over time.

The challenge with taking repeated measurements for these sensors is that input conditions are never truly identical; when individual sensor measurements are compared at the same input (same PG-350 measurement reported), the exhaust temperatures, ambient conditions, and other external factors may be dissimilar (all of which have an impact on the sensor according to section 5.2.3.1), which will lead to a larger standard deviations and subsequently larger differences between signals than may actually be the case. In order to truly assess the precision of the device, a controlled environment with close monitoring of input factors would be required; nonetheless, the large amount of data available from testing and the averaging of the three sensor signals are suitable in order to account for this fact.

Table 16 shows the results from t-test that was conducted. The results indicate that, with a confidence interval greater than 99%, the UniNOx® sensor is more precise than the NTK sensor for the duration of the testing period. This means that a measurement taken with the UniNOx® sensor is more likely to be the same at a given condition (given PG-350 measurement) than the NTK sensor.
To see the methodology of calculations used in the MATLAB code, please refer to Appendix section 8.2.

![Graph showing precision comparison between NTK and UniNOx sensors]

**Fig 43. Precision**

**Table 16. T-Test Precision Results**

<table>
<thead>
<tr>
<th>Sensor Brand</th>
<th>Estimated Mean</th>
<th>Standard Error</th>
<th>Treatment</th>
<th>Mean Difference</th>
<th>df</th>
<th>Standard Error</th>
<th>Prob &gt;</th>
<th>t</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>NTK</td>
<td>19.74</td>
<td>0.75</td>
<td>1 vs 2</td>
<td>4.56</td>
<td>132</td>
<td>1.06</td>
<td>0.0001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>UniNOx®</td>
<td>15.19</td>
<td>0.75</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

5.2.6 **Concentration-resolution**

Concentration Resolution is the smallest incremental change in nitric oxide that can be detected by the sensors [60], [61]. In the case of the UniNOx® and NTK sensors, both sensors can detect in incremental changes of 1 ppm (uncorrected and wet), as reported by the LabVIEW program.
5.2.7 Rise Time and Fall Time

Fall time and Rise time are important indicators of how fast the sensor can respond to changes in input parameters. According to the International Organization for Standardization (ISO), Rise time the time it takes to rise from 10% to 90% of the output signal step height (in the direction of increasing output). Fall time, the opposite of rise time, is the time it takes to fall 10% to 90% of the initial starting value. Because precise care was needed to measure fall time and rise time. A 10% NO concentration gas bottle was used to inject NO into the exhaust at a preset load (60 kW). Using a sonic orifice, a controlled amount of NO was injected such that a 100 ppm step increase in the exhaust NO occurred, as reported by the PG-350 instrument.

Sampling was conducted at 1 Hz to ensure sufficient time resolution of data (1 second increments compared to 10 second increments used for the other performance parameters). The fall and rise times were determined using the following equations were used:

\[ t_{rise} = t_{9F.V.} - t_{1F.V.} \]  \hspace{1cm} \text{Equation 5.7}

\[ t_{fall} = t_{1I.V.} - t_{9I.V.} \]  \hspace{1cm} \text{Equation 5.8}

Where \( t_{rise} \) represents rise time and \( t_{fall} \) represents fall time. To find the approximate fall time and rise time, linear interpolation is needed:

\[ \frac{NO_i - NO_{i-1}}{NO_{i+1} - NO_{i-1}} = \frac{t_i - t_{i-1}}{t_{i+1} - t_{i-1}} \]  \hspace{1cm} \text{Equation 5.9}

Fig 44 shows the results of the rise time and fall time tests and indicates that the NTK sensor responds more quickly than the UniNOx® sensor in both the rising and falling directions. The inherent 10-second sample delay for the PG-350 (configurable by the user for both a 10 second and 30 second response time) is the reason the instrument’s initial response time is longer relative to the solid-state sensors. The PG-350 also utilizes a time-averaging feature, which was preselected.
to 60 seconds. This has the ability to allow for an even faster, smoother, and more stabilized response by the PG-350 than if it were measuring raw values, which is particularly useful for the instrument since it is used mostly in applications where steady-state data are taken; nonetheless, the results agree with the configurable 10 second response time.

Table 17 shows the results of the test. The difference in the fall time and rise time of the NTK and UniNOx® sensors is significant.

![Figure 44. Rise Time and Fall Time Tests](image)

Table 17. Rise Time and Fall Time Results

<table>
<thead>
<tr>
<th>Test (5/19/17)</th>
<th>UniNOx</th>
<th>NTK</th>
<th>PG-350</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rise Time (sec)</td>
<td>8.26</td>
<td>3.70</td>
<td>11.02</td>
</tr>
<tr>
<td>Falling Time (sec)</td>
<td>6.83</td>
<td>4.02</td>
<td>10.41</td>
</tr>
</tbody>
</table>

5.2.8 Sensor Performance Results

Within a 99% confidence interval or greater, Precision, Accuracy, and LDL values were found to be significantly different among the NTK and UniNOx® sensors over the course of
testing. The NTK sensor was found to have a lower LDL (average of 5.22 ppmvd NO) and was found to have higher accuracy (average of 12.04% accuracy). The UniNOx® sensor was found to have greater precision (average of 15.91%). The NTK sensor was found to have a faster rise time and fall time (rise time of 3.70 seconds and fall time of 4.02 seconds) compared to the UniNOx® sensor. These results were validated with the physically measured rise and fall times of the PG-350, which was preset to a response time of 10 seconds (see Table 11). These results were also validated from sensor technical specifications directly given from EmiSense®, a developer of solid-state NOx sensor technology (LDL of 5 ppmvd for the NTK sensor and an LDL of 10 ppmvd for the UniNOx® sensor).

The impact of external factors such as relative humidity, ambient temperature, exhaust temperature, and time exposure (time that sensors were installed and measuring) were found and a linear model (significant within a 99% confidence interval or greater) for the NTK and UniNOx® sensor was developed. Increasing time exposure and exhaust temperature were found to positively impact accuracy and increasing relative humidity and ambient temperature were found to negatively impact the sensor response. These are important considerations to take into account when the sensors are installed in a harsh environment.

Because more of the measured sensor characteristics suggest the NTK sensor performs better than the UniNOx® sensor, the NTK sensor was designated as the sensor of choice for implementation in the control system of the Capstone MTG.
5.3  Control Algorithm Development for Emissions Optimization

5.3.1  Control Algorithm Development Overview

In order to implement the Ford NTK sensor within the control system of the engine, a total of four possible control algorithms were developed and an emissions map of CO and NO (ppmv, 15% O₂) at all possible operating conditions was generated. To generate the emissions map, open loop testing was performed using a Design of Experiments (DOEx) approach. Design Expert 10® software was utilized and a Response Surface User-Defined design was constructed. Using the results of the emissions map, optimized factor levels were found for each experimental model that minimized CO and NO emissions. These levels were subsequently used to develop the control algorithm with Capstone’s collaboration.

5.3.2  Experimental Design – Factors

A total of three factors (Turbine Exit Temperature (TET), Injector Staging, and Load (kW)) were used in the experimental design. The exit temperature coming out of the turbine (TET) is dictated by the total fuel flow going into the system, which is controlled through with the use of a 24V Proportional Valve (SPV) that feeds natural gas to the 6 injectors through a fuel manifold. Increasing the TET leads to an increase in efficiency of the system as each injector will operate with a higher fuel flow and higher local equivalence ratio, which leads to higher nitric oxide emissions; however, the staging of these injector, which dictates how many given injectors are firing at a given load, has the potential to decrease nitric oxide emissions and increase carbon monoxide by splitting the total fuel flow by an additional injector (see section 4.1.1 for information on Capstone’s Lean Premix system). Because the fuel flow from 0-60 kW is limited within a certain range, the ability to fire all six injectors at low loads (unstable flame) and only two injectors at high loads (choked fuel flow going into injectors) limits the staging to within one more or one
less injector than the default staging that is designed for the system. The fuel flow to each individual injector, which is determined by interactions between the load demand, the number of injectors turned on at any given moment, and the TET, all help to determine emissions and therefore an emissions map was needed at all possible operating conditions in order to understand the best way in which to optimize the system’s emissions performance.

Because the staging is physically dependent upon load, the experimental design was split up into 4 smaller designs (see Table 18 - Table 21) with 27 test points per design: 10-22 kW (a default of 3 injectors firing), 22-38 kW (4 injectors firing), 38-50 kW (5 injectors firing), and 50-60 kW (all 6 injectors firing). Overall centerpoint was established (1135.7 for TET) and the load was altered in increments of 2 kW for the study (Fig 45).

Table 18. 12-22 kW Factor Levels

<table>
<thead>
<tr>
<th>Units</th>
<th>Load</th>
<th>TET</th>
<th># of Injectors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type</td>
<td>kW</td>
<td>F</td>
<td>Continuous</td>
</tr>
<tr>
<td>Levels</td>
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<td>N/A</td>
<td>Discrete</td>
</tr>
<tr>
<td>L[1]</td>
<td>12</td>
<td>1100</td>
<td>2</td>
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<td>L[2]</td>
<td>22</td>
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<td>3</td>
</tr>
<tr>
<td>L[3]</td>
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Table 19. 22-38 kW Factor Levels

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<th># of Injectors</th>
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</thead>
<tbody>
<tr>
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<td>kW</td>
<td>F</td>
<td>Continuous</td>
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<tr>
<td>Levels</td>
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<td>N/A</td>
<td>Discrete</td>
</tr>
<tr>
<td>L[1]</td>
<td>22</td>
<td>1100</td>
<td>3</td>
</tr>
<tr>
<td>L[2]</td>
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<td>1175</td>
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</tr>
<tr>
<td>L[3]</td>
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Table 20. 38 - 50 kW Factor Levels

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<th># of Injectors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Units</td>
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<td>Type</td>
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<td>Levels</td>
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<td>Levels</td>
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<tr>
<td>L[2]</td>
<td>50</td>
<td>1175</td>
</tr>
<tr>
<td>L[3]</td>
<td>50</td>
<td>1175</td>
</tr>
<tr>
<td></td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>6</td>
</tr>
</tbody>
</table>

Table 21. 50-60 kW Factor Levels

<table>
<thead>
<tr>
<th>Load</th>
<th>TET</th>
<th># of Injectors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Units</td>
<td>kW</td>
<td>F</td>
</tr>
<tr>
<td>Type</td>
<td></td>
<td>Levels</td>
</tr>
<tr>
<td>Levels</td>
<td></td>
<td>Continuous</td>
</tr>
<tr>
<td>L[1]</td>
<td>50</td>
<td>1100</td>
</tr>
<tr>
<td>L[2]</td>
<td>60</td>
<td>1175</td>
</tr>
<tr>
<td></td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>6</td>
</tr>
</tbody>
</table>

Fig 45. Design of Experiments (DOEx) Test Points
5.3.3 Open Loops Commands – CRMS

In order to control staging and the TET settings through Capstone’s software that was installed on the DAQ computer (see Fig 23), open loop commands were issued to the engine using the command-line in CRMS. The default settings are shown in Table 22.

Table 22. Open Loop Commands - Default Settings for TET and Staging

<table>
<thead>
<tr>
<th>Inlet Temperatures (°F)</th>
<th>INJAT0</th>
<th>INJAT1</th>
<th>INJAT2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Setting</td>
<td>2</td>
<td>65</td>
<td>128</td>
</tr>
</tbody>
</table>

Table 23. Open Loop Commands - Default Settings for TET and Staging (2)

<table>
<thead>
<tr>
<th>3 Injectors</th>
<th>Turbine Exit Temperature (°F)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min</td>
</tr>
<tr>
<td>OFF (kW)</td>
<td></td>
</tr>
<tr>
<td>Steady State (kW)</td>
<td></td>
</tr>
<tr>
<td>ON (kW)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>4 Injectors</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>OFF (kW)</td>
<td>IJ3OF0 IJ3OF1 IJ3OF2</td>
</tr>
<tr>
<td>Steady State (kW)</td>
<td>IJ3SS0 IJ3SS1 IJ3SS2</td>
</tr>
<tr>
<td>ON (kW)</td>
<td>IJ3ON0 IJ3ON1 IJ3ON2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>5 Injectors</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>OFF (kW)</td>
<td>IJ5OF0 IJ5OF1 IJ5OF2</td>
</tr>
<tr>
<td>Steady State (kW)</td>
<td>IJ5SS0 IJ5SS1 IJ5SS2</td>
</tr>
<tr>
<td>ON (kW)</td>
<td>IJ5ON0 IJ5ON1 IJ5ON2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>6 Injectors</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>OFF (kW)</td>
<td>IJ6OF0 IJ6OF1 IJ6OF2</td>
</tr>
<tr>
<td>Steady State (kW)</td>
<td>IJ6SS0 IJ6SS1 IJ6SS2</td>
</tr>
<tr>
<td>ON (kW)</td>
<td>IJ6ON0 IJ6ON1 IJ6ON2</td>
</tr>
</tbody>
</table>
5.3.4  **ANOVA – Emissions Results**

The Horiba PG-350 (Section 4.3.1) was used to collect emissions data for the DOEx testing. NO, CO, and O₂ (used to correct the concentrations to 15% O₂) were the three primary responses of interest in this study. The following results below (Fig 46 - Fig 49) show the emissions over a variety of TET settings and different injector staging configurations. An overall centroid for the experimental design was also established (Fig 45). TET was altered between 1100°F (most stable TET before flameout became a predominate issue), 1137.5°F (the centerpoint of the experimental design), and 1175°F (the maximum TET setting that Capstone recommended). The injector staging was altered as described in section 5.3.2.

The results displayed in the figures below strongly indicate that the injector staging has the most profound impact on changing NO and CO emissions coming from the MTG. By increasing the amount of injectors firing at a given load, the amount of total fuel split up by the fuel injectors increases by 1 additional injector, leading to an increase in CO and decrease in NO due to changes in local equivalence ratios. The opposite occurs when decreasing the amount of injectors firing at a given load. The figures are also strongly indicative that altering the TET settings also has an impact on emissions but not as drastically as altering the staging of injectors; however, this provides an opportunity for more precise control and acts as a knob to “fine-tune” the NO and CO emissions if needed.

Fig 46 - Fig 48 show the effects of altering the injector staging relative to changes in TET for the TET = 1100 °F case and the TET = 1175 °F case. The injector +1 case, where one additional injector is added to the default staging, varies between 4 – 6 injectors. This results in some of the lowest observed nitric oxide levels (0- ~15 ppmvd) but has the worst CO levels, which are greater in excess of 1000 ppmvd. The opposite is true for the injector -1 case, where the CO levels are the
lowest observed (0-300 ppmvd), but the NO levels are the highest. The staging for this case is varied between 2-5 injectors. The balanced approach for CO and NO is shown for the default staging case. Increasing or decreasing the TET has a relatively small effect compared to altering the staging. This conclusion is also drawn when observing the magnitude of coefficients that are present in the models.

*Fig 46. Default Injector Settings, TET=1175 (left), TET=1100 (right)*
Fig 47. Injector +1 Settings, TET=1175 (left), TET=1100 (right)

Fig 48. Injector -1 Settings, TET=1175 (left), TET=1100 (right)
Fig 49 shows the results of the centerpoint case (TET = 1137.5 °F). The result of changing the staging is more easily seen when comparing the figures directly. NO is highest on the left and decreasing as one moves to the figure on the right, and vice versa for CO. If NO and CO are to be minimized, a modest and balanced approach for the algorithm will be needed; however, if NO were the only species to be minimized, CO will be very high (up to 2000 ppmvd, 15% O₂).

Using the results shown in the figures above, a model for each experimental design (Table 24 - Table 31) was developed. A quadratic model was recommended for analyzing each load range, with the exception of 50-60 kW (a linear model was recommended for this). In order to develop a more realistic (albeit more complicated) model of emissions, a quadratic model was preferred so that multiple factor interactions could be accounted for. In all cases, the number of injectors was found to be the most significant factor for the model within a 99% confidence interval or greater, followed by TET. This agreed with the initial observations supported from the graphs above. The
results of the statistical analysis and models for each experimental design are displayed below (Table 24 - Table 31). Each model shows good agreement with adjusted and predicted $R^2$ values.

**Table 24. 12-22 kW NO model - ANOVA**

<table>
<thead>
<tr>
<th>Stat.</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std. Dev.</td>
<td>0.98</td>
</tr>
<tr>
<td>Mean</td>
<td>5.56</td>
</tr>
<tr>
<td>C.V. %</td>
<td>17.61</td>
</tr>
<tr>
<td>PRESS</td>
<td>47.47</td>
</tr>
<tr>
<td>-2 Log Likelihood</td>
<td>62.95</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.9709</td>
</tr>
<tr>
<td>Adj R-Squared</td>
<td>0.9555</td>
</tr>
<tr>
<td>Pred R-Squared</td>
<td>0.9151</td>
</tr>
<tr>
<td>Adeq Precision</td>
<td>21.708</td>
</tr>
<tr>
<td>BIC</td>
<td>95.90</td>
</tr>
<tr>
<td>AICc</td>
<td>96.70</td>
</tr>
</tbody>
</table>

$$
\sqrt{NO + 0.50} = \\
+285.09390 \\
-0.27307 \times \text{Load} \\
-0.45631 \times \text{TET} \\
-13.12938 \times \# \text{ of Injectors} \\
-3.93550E-005 \times \text{Load} \times \text{TET} \\
-0.18184 \times \text{Load} \times \# \text{ of Injectors} \\
-8.29246E-003 \times \text{TET} \times \# \text{ of Injectors} \\
+0.023623 \times \text{Load}^2 \\
+2.17329E-004 \times \text{TET}^2 \\
+3.44009 \times \# \text{ of Injectors}^2
$$

**Table 25. 12-22 kW CO Model - ANOVA**

<table>
<thead>
<tr>
<th>Stat.</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std. Dev.</td>
<td>2.94</td>
</tr>
<tr>
<td>Mean</td>
<td>21.50</td>
</tr>
<tr>
<td>C.V. %</td>
<td>13.70</td>
</tr>
<tr>
<td>PRESS</td>
<td>396.82</td>
</tr>
<tr>
<td>-2 Log Likelihood</td>
<td>117.32</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.9736</td>
</tr>
<tr>
<td>Adj R-Squared</td>
<td>0.9587</td>
</tr>
<tr>
<td>Pred R-Squared</td>
<td>0.9244</td>
</tr>
<tr>
<td>Adeq Precision</td>
<td>23.615</td>
</tr>
<tr>
<td>BIC</td>
<td>149.90</td>
</tr>
<tr>
<td>AICc</td>
<td>151.99</td>
</tr>
</tbody>
</table>

$$
\sqrt{CO + 0.50} = \\
-1066.91380 \\
+0.98280 \times \text{Load} \\
+1.76296 \times \text{TET} \\
+65.60712 \times \# \text{ of Injectors} \\
-8.91904E-004 \times \text{Load} \times \text{TET} \\
-0.37298 \times \text{Load} \times \# \text{ of Injectors} \\
-0.040235 \times \text{TET} \times \# \text{ of Injectors} \\
+0.023617 \times \text{Load}^2 \\
-7.48197E-004 \times \text{TET}^2 \\
+0.53945 \times \# \text{ of Injectors}^2
$$

**Table 26. 22-38 kW NO Model - ANOVA**

<table>
<thead>
<tr>
<th>Stat.</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std. Dev.</td>
<td>0.17</td>
</tr>
<tr>
<td>Mean</td>
<td>0.56</td>
</tr>
<tr>
<td>C.V. %</td>
<td>29.89</td>
</tr>
<tr>
<td>PRESS</td>
<td>1.28</td>
</tr>
<tr>
<td>-2 Log Likelihood</td>
<td>-31.64</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.9818</td>
</tr>
<tr>
<td>Adj R-Squared</td>
<td>0.9715</td>
</tr>
<tr>
<td>Pred R-Squared</td>
<td>0.9484</td>
</tr>
<tr>
<td>Adeq Precision</td>
<td>27.023</td>
</tr>
<tr>
<td>BIC</td>
<td>0.94</td>
</tr>
<tr>
<td>AICc</td>
<td>3.03</td>
</tr>
</tbody>
</table>

$$
\log_{10}(NO) = \\
-26.01879 \\
-0.64938 \times \text{Load} \\
+0.089138 \times \text{TET} \\
-6.57475 \times \# \text{ of Injectors} \\
+6.39060E-004 \times \text{Load} \times \text{TET} \\
-7.96986E-003 \times \text{Load} \times \# \text{ of Injectors} \\
+2.62221E-003 \times \text{TET} \times \# \text{ of Injectors} \\
-3.42687E-004 \times \text{Load}^2 \\
-5.18733E-005 \times \text{TET}^2 \\
+0.33984 \times \# \text{ of Injectors}^2
$$
Table 27. 22-38 kW CO Model - ANOVA

<p>| | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Std. Dev.</td>
<td>1.94</td>
<td>Mean</td>
<td>20.49</td>
<td>C.V. %</td>
<td>9.45</td>
</tr>
<tr>
<td>PRESS</td>
<td>176.15</td>
<td>-2 Log Likelihood</td>
<td>91.20</td>
<td>Adj R-Squared</td>
<td>0.9795</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Pred R-Squared</td>
<td>0.9673</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adeq Precision</td>
<td>28.393</td>
<td>BIC</td>
<td>123.39</td>
<td>AICc</td>
<td>126.91</td>
</tr>
</tbody>
</table>

\[
\text{Sqrt}(\text{CO} + 0.50) = -531.78661 + 3.65427 \times \text{Load} + 0.45154 \times \text{TET} + 136.66794 \times \# \text{of Injectors} - 4.77444E-003 \times \text{Load} \times \text{TET} - 0.11545 \times \text{Load} \times \# \text{of Injectors} - 0.073718 \times \text{TET} \times \# \text{of Injectors} + 0.029328 \times \text{Load}^2 - 4.01916E-005 \times \text{TET}^2 - 4.84083 \times \# \text{of Injectors}^2
\]

Table 28. 38-50 kW NO Model - ANOVA

<p>| | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Std. Dev.</td>
<td>0.17</td>
<td>Mean</td>
<td>0.32</td>
<td>C.V. %</td>
<td>53.42</td>
</tr>
<tr>
<td>PRESS</td>
<td>1.18</td>
<td>-2 Log Likelihood</td>
<td>-29.89</td>
<td>Adj R-Squared</td>
<td>0.9499</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Pred R-Squared</td>
<td>0.9198</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adeq Precision</td>
<td>17.788</td>
<td>BIC</td>
<td>2.30</td>
<td>AICc</td>
<td>5.83</td>
</tr>
</tbody>
</table>

\[
\log_{10}(\text{NO}) = +51.46796 - 0.78093 \times \text{Load} - 0.026791 \times \text{TET} - 8.19065 \times \# \text{of Injectors} + 3.72860E-004 \times \text{Load} \times \text{TET} + 0.019215 \times \text{Load} \times \# \text{of Injectors} + 2.98810E-003 \times \text{TET} \times \# \text{of Injectors} + 2.94432E-003 \times \text{Load}^2 + 5.19224E-007 \times \text{TET}^2 + 0.32684 \times \# \text{of Injectors}^2
\]

Table 29. 38-50 kW CO Model - ANOVA

<p>| | | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Std. Dev.</td>
<td>3.24</td>
<td>Mean</td>
<td>20.01</td>
<td>C.V. %</td>
<td>16.17</td>
</tr>
<tr>
<td>PRESS</td>
<td>377.97</td>
<td>-2 Log Likelihood</td>
<td>128.03</td>
<td>Adj R-Squared</td>
<td>0.8915</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Pred R-Squared</td>
<td>0.8643</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adeq Precision</td>
<td>19.820</td>
<td>BIC</td>
<td>147.58</td>
<td>AICc</td>
<td>144.45</td>
</tr>
</tbody>
</table>

\[
\text{Sqrt}(\text{CO}) = -438.26240 + 1.95155 \times \text{Load} + 0.29510 \times \text{TET} + 127.37185 \times \# \text{of Injectors} - 0.47941 \times \text{Load} \times \# \text{of Injectors} - 0.087034 \times \text{TET} \times \# \text{of Injectors}
\]
\[ NO = -17.01774 + 0.077764 \times \text{Load} + 0.026865 \times \text{TET} - 2.70199 \times \# \text{of Injectors} \]

\[ \log_{10}(\text{CO}) = -94.73527 + 1.09357 \times \text{Load} + 0.078401 \times \text{TET} + 10.53181 \times \# \text{of Injectors} - 8.42787E-004 \times \text{Load} \times \text{TET} - 0.029820 \times \text{Load} \times \# \text{of Injectors} - 7.76025E-003 \times \text{TET} \times \# \text{of Injectors} \]

5.3.5 **Control Algorithm Concept – Optimized Settings**

Using the results of the statistical analysis presented in above, four algorithms were developed for possible implementation within the control system of the Capstone C-60 MTG. Results from each of the four load ranges shows that the number of injectors is the most significant factor for each model, within a 99% confidence interval or greater. All models show that an increase in TET increases nitric oxide (NO) and subsequently lowers carbon monoxide (CO), whereas an increase in the number of injectors increases CO and lowers NO. While nearly unlimited approaches could be considered, the situation was constrained by practicality associated with implementation into the Capstone engine control software. Essentially, new information (NO from sensor) could be
brought in and used to make decisions regarding manipulation of parameters that can be controlled. This ensures the algorithms presented can actually be implemented into the software without major restructuring of the current engine control software.

Each control algorithm developed had a different method for optimizing the emissions from the MTG. The optimized settings for the factor levels (TET and Injector staging) were found for each load using Design Expert 10® and varied depending upon the method (see Fig 50 and Fig 51 for optimized settings and expected emissions if the engine is operated under each algorithm). The following are the different control algorithms developed and their strategies:

1. **Control Algorithm #1: NO and CO Optimization by Adjusting TET and Staging** - The goal of this algorithm is to optimize NO and CO by adjusting the TET and Injector Staging.

   This algorithm is split up into 5 different ranges (49-60 kW, 39-48 kW, 30-38 kW, 11-29 kW, and <10 kW). The emissions ranges expected are as follows (ppmvd, 15% O2):

   a. **49-60 kW**: 1.9 – 2.4 ppmvd NO, 98 – 160 ppmvd CO
   b. **39-48 kW**: 1.9 – 2.4 ppmvd NO, 160 – 280 ppmvd CO
   c. **30-38 kW**: 7 – 9.2 ppmvd NO, 220 – 250 ppmvd CO
   d. **11-29 kW**: 10 – 27 ppmvd NO, 220 – 400 ppmvd CO
   e. **< 11 kW**: 30 – 100 ppmvd NO, 400 – 1000 ppmvd CO

2. **Control Algorithm #2: NO Optimization by Adjusting TET and Staging** – The goal of this algorithm is to minimize NO (but not CO) by adjusting the TET and Injector Staging.

   This algorithm is split up into 5 different ranges (49-60 kW, 39-48 kW, 30-38 kW, 11-29 kW, and <10 kW). The emissions ranges expected are as follows (ppmvd, 15% O2):

   a. **49-60 kW**: 1 – 2 ppmvd NO, 100 – 340 ppmvd CO
   b. **39-48 kW**: .2 – .4 ppmvd NO, > 1000 ppmvd CO
3. **Control Algorithm #3: NO and CO Optimization by Adjusting TET** – Control Algorithm #3 is designed to achieve lower nitric oxide (NO) and carbon monoxide (CO) by changing the TET setpoint (the injector staging is kept at the default settings). This algorithm is split up into 6 different ranges (49-60 kW, 40-48 kW, 29-39 kW, 23-28 kW, 12-22 kW, and <12 kW). The emissions ranges expected are as follows (ppmvd, 15% O2):

   a. 49-60 kW: .3–1 ppmvd NO, 500 – 1000 ppmvd CO
   b. 40-48 kW: .8 – 1 ppmvd NO, 500 – 730 ppmvd CO
   c. 29-39 kW: ~2 ppmvd NO, ~650 ppmvd CO
   d. 23-28 kW: 1 – 2 ppmvd NO, 450 – >1000 ppmvd CO
   e. 12-22 kW: 0 – 12 ppmvd NO, >1000 ppmvd CO
   f. <12 kW: 100 – 160 ppmvd NO, 50 – 90 ppmvd CO

4. **Control Algorithm #4: NO and CO Optimization by Adjusting Staging** – Control Algorithm #4 is designed to achieve lower nitric oxide (NO) and carbon monoxide (CO) by changing the injector staging (the TET setpoint is left at the default value). This algorithm is split up into 4 different ranges (39-60 kW, 22-38 kW, 6-21 kW, and 1-5 kW). The emissions ranges expected are as follows (ppmvd, 15% O2):

   a. 39-60 kW: 1-3 ppmvd NO, 20 – 550 ppmvd CO
   b. 22-38 kW: .2 – 1 ppmvd NO, 350 – 1000 ppmvd CO
   c. 6-21 kW: 2 ppmvd - 40 NO, >1000 ppmvd CO
   d. 0-5 kW: 50 – 100 ppmvd NO, >1000 ppmvd CO
When comparing the optimized factor levels in Fig 50, the optimized TET levels vary substantially for algorithm #2 and algorithm #3. Even though these algorithms would lead to substantially reduced nitric oxide output (Fig 51), the TET fluctuations are not feasible for the engine and will result in loss of performance as well as stability issues overtime. Algorithm #4 is a great choice in terms of stability (no fluctuating TET levels), but represents a poor choice with regards to CO emissions, which would reach up to 1000 ppmvd.

Out of the four control algorithms, Control Algorithm #1 was chosen to be implemented within the Capstone control software. Because NO and CO are both minimized, it is a practical approach to achieving acceptable emissions levels. For the current application, maps of CO emissions as a function of the parameters studied will be needed until a similarly robust sensor for exhaust CO is identified/developed.

*Fig 50. Optimized Settings for Algorithms 1-4 (left to right)*
5.3.6 Control Algorithm Logic

In order to take concept of the algorithm and implement it within the software of the Capstone engine, an initial Visio flow chart detailing the step-by-step procedure of the algorithm was first developed and improved upon. Control algorithm #1 was then simplified to make it easier to implement within the software by Capstone engineers (Fig 52). The final algorithm can be summarized in nine steps:

1. The system is started and the power demand is set. The amount of attempts the engine has tried to reduce emissions is zero (Attempt_cnt = 0)

2. The engine power output changes and steady-state is achieved (command DBTIME in CRMS sets defined steady-state time).

3. The emissions from the sensor are measured for a set amount of time (RT Emission 1). O\(_2\) (%) and NO (ppm) are measured.
4. The optimized TET and injector settings (Fig 50) found from DOEx testing are set.

5. After a steady-state period is achieved, the emissions will be measured from the sensor a second time (O2 (%) and N2 (ppm)). This variable is RT emission 2

6. Emissions are compared (RT emission 1 and RT emission 2), specifically NO (ppm). NO and O2 (%) should be recorded for 15% O2 correction.

7. If RT emission 1 is less than RT emissions 2, the algorithm has achieved its goal; however, if not, then the attempt counter will change to 1. This means the algorithm then has four attempts to achieve an emissions reduction. It attempts to do this by lowering the TET setpoint (TET_sp) by 15 °F each attempt. If maximum attempts are achieved and an emissions reduction hasn’t been achieved, the algorithm moves to step 8.

8. The engine has one additional attempt to change emissions. It does this by increasing the number of injectors by 1. If this step does not lower emissions, an error will be displayed.

The following commands were added by Capstone to be issued to the engine for this algorithm:

**DBFLAG** if the emission control is turned on

**DBATMP** attempts counter

**DBTIME** timer to wait for the system to be stabilized (600 = 1 minute)

The benefit of this algorithm is its universal approach to lowering nitric oxide emissions. This methodology can be applied to other Capstone engines regardless of their individual performance. The parameters used for lowering NO (TET and Injector Staging) will also have the same effect on emissions regardless of which engine utilizes the algorithm. This is because NO is intricately linked to TET and the injector staging, as observed in Section 5.3.4.
Run capstone SW to reach the steady state with the desired power output.

Start the system and enter the power demand. Attempt\_cnt = 0.

Measure RT emission 1.

Set optimized TET Setpoint and injector number (TET\_sp / inj\_num).

Wait until S. S (T > 1 min)? Measure RT emission 2.

RT emission 2 > RT emission 1?

Attempt\_cnt = 4.

TET\_sp - 15

Attempt\_cnt++

Attempt\_cnt = 5.

inj\_num + 1

Attempt\_cnt++

error

What to do with this condition, shutdown the engine or do nothing?

RAE: I would suggest a warning or some sort of message that will allow the engine to keep running. The engine can go back into its regular programming at this point for that specified load until the load is changed. Then the algorithm starts over again.

Fig 52. Control Algorithm #1 Simplified Flowchart
The downside to this algorithm is the inability of the system to directly measure or calculate inferred CO emissions for active optimization of both CO and NO. The Capstone User Control Board (UCB), where the sensor signals would be connected, has the ability to read with 10-bit precision but has minimal ability to perform complex calculations; this presents a problem when trying to calculate CO using quadratic equations shown in the tables in section 5.3.4. This also presents a problem when correcting emissions data with the oxygen concentrations observed, which cannot be performed by the C-60. In order to optimize both CO and NO, a similar and commercially-available CO sensor would need to be identified and utilized; however, the models for CO in the previous section could be potentially used as well if more processing power was implemented into the engine but are also linked directly to the performance of this particular Capstone engine. The inability of the engine control boards to perform calculations to predict CO levels or to measure CO directly with a sensor prevents this additional aspect of the algorithm from being realized.

5.3.7 Control Algorithm Sensor Communication

In order to integrate the sensor signals into the engine, a new Printed Circuit Board (PCB) was constructed in order to output Analog signals that are compatible with the C-60. Originally these sensors only output signals using CAN protocol.

A dedicated analog output (4-20 mA) line was adopted for the NO signal and a separate analog output (4-20 mA) line was adopted for the O2% signal. These signals are designed to “plug” into the Capstone User Control Board (UCB) in the AN-IN1 and AN-IN2 ports respectively. Because each signal outputs in a current loop, a 250 Ω precision resistor was placed between each ground and analog input port. See Fig 53 for the wiring schematic.
5.3.8 Control Algorithm Demonstration

In order to prove the capability of the algorithm to mitigate NO emissions in real-time by utilizing the NTK sensor feedback, a demonstration study was conducted at UCICL. Testing was conducted at each of four load ranges (12-22 kW, 22-38 kW, 38-50 kW, and 50-60 kW) in order to test the performance across a wide range of operating conditions. Upon loading the latest Capstone codeset (Codeset_C65_v5.40rc) and upgrading the fuel system with a Woodward control valve, the engine was able to read and response effectively to the NTK sensor feedback without issue (measured in the software as CHP Water Flow (GPM) and CHP Temperature Feedback for NO and O₂, respectively (see Fig 54). Software was built into the latest codeset to allow for configurable scaling for both analog outputs. The digital conversion device on the NTK board is 8-bit, and the User Control Board (UCB) in the communications bay of the MTG allows for up to
10-bit precision. The NTK analog board outputs information (actively averaging the 10 ms signals from the NTK sensor) at a 1 Hz rate, and CRMS outputs information every 5 seconds. See Fig 55 for the analog output board.

![Fig 54. CRMS Monitoring Screen](image)

![Fig 55. NTK Analog Output PCB](image)

For higher loads (20 kW and up) it was found that the best performance was obtained with a scaling of 0-30 ppm for NO and 0-21% for O₂. The wet, uncorrected readings of the NTK sensors were already quite low at loads higher than 30 kW (0-2 ppm reported from the PG-350). This presented a challenge for the algorithm to distinctly identify if the emissions had been lowered once the control logic took into effect; however, at the 16 kW load setting, a range of 0-100 ppm was employed for the NO output scaling as well as a 0-21% scaling for O₂. The injector staging
also remained the same below 20 kW, but was adjusted above 20 kW to allow for higher NO output before the onset of the initial control logic. This was done so the algorithm could more easily identify if a reduction in emissions had occurred.

The algorithm results for 16 kW and 29 kW are displayed below for NO, O₂, and CO. The PG-350 10 second sample delay was taken into account, and the data were shifted by 10 seconds. The longer response time of the PG-350 results in a slightly delayed response compared to the NTK sensor. Note that there are no figures for any loads higher than 30 kW, as the sensor was unable to resolve changes in NO at these points (less than 2 ppmvd measured the PG-350). Because the control board in the engine is unable to perform complex calculations, emissions were not able to be corrected in real time.

5.3.8.1 16 kW Results

The initial spike observed in Fig 56-Fig 58 for the 16 kW results represents the transient emissions during the change from a previous load to the current load condition (21 kW to 16 kW). If a 5 kW difference from the previous load is demanded, the control algorithm will take into effect for that load. For Fig 56, the algorithm first measures the emissions (RT Emissions 1) when the desired load is achieved. This occurs after a predetermined time has elapsed in order to achieve steady-state conditions. This predetermined time is governed by the variable DBTIME in CRMS, which is set to a maximum of 1 minute. The default settings (TET and default staging already preset in CRMS) are still utilized during this first period. Note the 1 ppm resolution of the NTK sensor, which results in the small spikes observed.

The algorithm’s first attempt to lower emissions is around the 16:49:26 mark. This is where the optimized settings from Control Algorithm #1 come into effect; however, there is no visible reduction in emissions because the optimized settings are nearly the same as the default settings.
programmed onto the engine. The TET is the same (1175°F) and the injector staging is similar as well. Note that the emissions are measured for a second time at 16 kW right before the 16:50:53 mark (RT Emissions 2). This drop in TET is the algorithm’s attempt to lower NO emissions, which is successful. The NO after the first drop (after 16:50:53) is visibly lower than before. The algorithm observes that after another steady-state period that the second emissions measurements are lower than before, so it continues to operate with the optimized settings.

![Graph showing NO results over time](image)

*Fig 56. 16 kW NO Results*

In Fig 57 and Fig 58, the CO and O₂ results are displayed. Note the 1% resolution of the NTK sensor, which results in two large spikes in Fig 57. The CO results in the figure also show that the algorithm is working. By decreasing the TET, the local equivalence ratios of each injector decrease, so NO decreases but CO increases.
Fig 57. 16 kW O₂ Results

Fig 58. 16 kW CO Results
5.3.8.2 29 kW Results

Fig 59 - Fig 61 below display the results for the 29 kW case. Note that from 14:54:14 – 14:57:07 the load had changed from 32 kW to 29 kW, so the algorithm had not reset to the initial logic. A minimum change of 5 kW is needed for control algorithm logic to start from the beginning. The first emissions measurements (RT Emissions 1) were taken sometime between 14:54:14 and 14:57:07. Right before the 14:57:07 mark, a large spike is observed, which is measured as RT Emissions 2. Because the algorithm sees a large increase in NO, it attempts to correct it by lower the TET by 15 degrees. A second and a third attempt also occur but eventually after the third attempt a reduction is seen and the algorithm continues to operate with the optimized settings.

The results for O₂ and CO are also displayed in Fig 60 and Fig 61. The sensor reports higher O₂ percentages than the PG-350 for this case. The CO results are also indicative of a change of TET as the emissions rise from ~140-160 ppm.
Fig 60. 29 kW O₂ Results

Fig 61. 29 kW CO Results
5.3.9  Summary of Control Algorithm Development

In order to develop an algorithm that utilizes the NTK sensor for minimizing nitric oxide emissions from the Capstone MTG, a Design of Experiments (DOEx) study was developed in order to generate an emissions map of the engine at all operating conditions from 10 kW – 60 kW. A piecewise study was generated and models for four load ranges (10-22 kW, 22-38 kW, 38-50 kW, and 50-60 kW) were developed. Using load (kW), Turbine Exit Temperature (TET), and the injector staging as factors in the study, CO and NO were measured as responses. Subsequently, model equations for CO and NO were developed for each load range.

Using the Design Expert® 10 optimization tool, optimized parameters for TET and injector staging were found such that NO and CO emissions were minimized at all loads between 10 kW – 60 kW. These results were then used to generate four distinct algorithms, albeit with different methods for optimizing the emissions. Control Algorithm #1, which adjust both TET and staging to optimize the performance with regards to CO and NO, was chosen as the algorithm of choice. This was subsequently used to develop a software revision by Capstone that allows the engine, coupled with the sensor signals, to measure the NO output of the engine in real-time and make adjustments to engine operating parameters if needed. An analog output PCB was also developed by EmiSense to allow the sensor signals to output in two compatible 4-20 mA signals, one for O₂ (%) and the other for NO (ppm), for the Capstone MTG.

The control algorithm was then successfully demonstrated and showed the ability to mitigate NO emissions in real-time. Although the NTK sensor reached its monitoring limits at loads above 30 kW and was unable to resolve any further improvements in NO (PG-350 measurements read 5 ppm or less), tests were successfully conducted at 16 kW and 29 kW.
6. SUMMARY AND CONCLUSIONS

6.1 Summary

The robustness and accuracy of two commercially-available and state-of-the-art Nitric-Oxide sensors, the UniNOx® and NTK sensors (designed and developed for Heavy Duty (HD) and Light-Duty (LD) Diesel vehicles), were characterized in order to determine if they could successfully be used in lieu of traditional Continuous Emission Monitoring (CEM) devices for Distributed Generation systems. This was completed by utilizing a HORIBA PG-350 (a traditional “CEM-like” instrument) as referee analyzer so that the sensor measurements could be properly compared against a representative “true” measurement. In order to test the sensors over an extended period of time, an existing gas turbine testbed consisting of a 60 kW Capstone Gas Turbine engine operating on natural gas was used. By varying the load demand from 60 kW to 10 kW and back up from 10 kW to 60 kW on a daily basis, the sensors were exposed to a variety of different nitric oxide levels in the exhaust. A suitable test-section was designed and constructed so that each sensor of a different type were installed 15° apart from one another and sensors of the same type were installed 120° apart respectively from one another. This was done in order to ensure individual sensors did not impact the flow-fields of other sensors in their proximity. An extensive network of devices, including an National Instruments (NI) USB DAQ and NI CompactRIO device, were installed to capture and record sensor signals (O2% and NO (ppm)) as well as Temperature (ambient and exhaust conditions) and Relative Humidity (%) data in order to understand the effects of external parameters on the sensors over the course of the testing period. Parameters such as AFR (Air-to-fuel ratio), load demand, and other pertinent engine operating conditions were also recorded through Capstone’s remote monitoring software (CRMS). A two-
state water dropout system was also constructed in order to allow the water to condense out of the sample-train so as to not interfere with measurement readings by the referee analyzer.

Over a six to eight month period of measurements, Accuracy, Precision, Lower Detectable Limit, Concentration Resolution, and Lag-Time and Rise-Time were measured and recorded. One-to-one comparisons of the PG-350 measurements plotted against the sensor signals initially showed much disagreement and irregularity among the signals. This was found to be due to a large sample delay between the sensor signals, which have immediate response because of the in-situ nature of their measurements inside the exhaust, and the delayed response of the PG-350, in which the exhaust sample must be preconditioned to avoid interference due to water. In order to account for this delay, a technique was developed in which to average sensor signals at each demanded load. Once this was performed, the sensor signals and the referee instrument measurements showed high agreement over the course of the testing period. An average sensor signal for each type of sensor was then used and compared against the referee instrument readings. Sensor measurements of each type also showed good agreement with each other during the testing period, so a well-mixed and developed exhaust flow was adequately achieved. Using a statistical comparison, the NTK was found to perform closer to PG-350 measured results on three of the five characteristics within a confidence interval of 99% or greater.

Upon identifying the most promising candidate sensor as the NTK sensor, four distinct control algorithms were developed. Using a user-defined response surface design, a piece-wise study was developed in order to generate an emissions map of the engine at all operating conditions (from 10 kW – 60 kW). Factors used in the study included Turbine Exit Temperature (TET), number of active injectors operating, and the load demand. By using a set of statistically-designed experiments, NO and CO emissions were modeled for every operating condition of the engine.
Because the total number of active injectors operating at a given load are constrained, the experimental study was split up into four smaller studies. Subsequently, the parameters for each developed model were then optimized, using different techniques, to produce four different control algorithms capable of minimizing NO at all operating conditions. Control Algorithm #1 was found to be the most favorable algorithm due to its simplicity and ability to minimize both NO and CO. This algorithm works by setting operating conditions to settings that favor the minimization of both NO and CO, and works to seek further improvements in reducing NO by adjusting TET and staging. Other algorithms require large fluctuations in TET, which is not suitable for prolonged operation of the engine. This algorithm was then simplified to be adapted into the engine software, and a special Printed Circuit Board (PCB) capable of allowing the sensor signals, which typical operate on CAN protocol in automotive vehicles, to output in 4-20 mA signals was developed for the engine. A software update was developed that enabled the control algorithm to be programmed onto the engine control board.

After upgrading the engine fuel system with the latest Woodward control valve, the algorithm was successfully tested and actively reduced nitric oxide emissions in real-time. Although the NTK sensor approached the limits of its monitoring capabilities above 30 kW where low emissions are already reported (less than 5 ppmvd of NO reported by PG-350), the algorithm showed successful operation at 16 kW and 29 kW as well as the ability to reduce emissions in real time by lowering the TET. Upon measuring the resulting feedback from the sensor (NO ppm), it made further corrections if they were necessary.

The following section summarizes the key observations and takeaways of this study.
6.2 Conclusions

- The latest commercially-available solid-state electrochemical NO sensors featured in this study were found to be well-suited for long-term, real-time emissions monitoring in DG systems; they are robust, accurate, and closely reflect the readings and measurement trends of the traditional “CEM-like” analyzer.

Even though NTK sensor performed better within a 99% confidence interval for three of the five measured sensor characteristics, both sensors were able to report consistently and accurately when compared with the PG-350 reference instrument over the six to eight months in which they were evaluated. The one-one comparison of the sensor readings with PG-350 instrument at the end of the testing period (over a week of testing results in late September/early October) showed that sensor measurements continued to consistently measure close to the “true” measurement value over the entire range of nitric oxide levels that were measured (0 - 150 ppmvd, 15% O₂). Sensor readings also showed great promise in reflecting the transient behavior of DG systems; they even showed the ability to respond more quickly to sudden changes in NO compared to the traditional “CEM-like” analyzer.

Because the sensors are a viable alternative to traditional CEM analyzers for monitoring the emissions of DG systems, this could lead to a long-term inexpensive solution for implementation of these solid-state devices (especially the NTK sensor) within dispatchable generation systems throughout the state. It could significantly improve monitoring capabilities of DG systems (at all loads), which is essentially non-existent except for during initial certification (only at 100% full-load).
Control Algorithm #1, coupled with the NTK sensor feedback, is a viable strategy and alternative to traditional CEMS for reducing the nitric oxide emissions of DG systems. Control Algorithm #1 demonstrated the ability to correct the NO emissions performance in real-time and without the need for manual adjustment by the operator. By utilizing the TET (°F) as a “knob” for adjusting NO, the nitric oxide emissions from the gas turbine decreased, and subsequent feedback was used to determine if further adjustments were required. Because the algorithm is capable of improving the NO emissions performance of the DG system in this study, a similar algorithm (utilizing NTK sensor feedback) could be developed for each DG systems throughout the state of California. Although the NTK monitoring capabilities and ability to resolve minute changes in NO (less than 5 ppmvd) are reached above 30 kW for the Capstone C60 MTG, the algorithm showed the ability to improve emissions performance where it is normally more poor (less than 50% full-load). This could have far reaching implications for the current certification process, which does not include a permanent nor corrective solution for poor emissions performance at other operating conditions other than 100% full-load. The certification process for DG systems in California could also be significantly improved by utilizing these solid-state devices as a permanent monitoring solution and as a corrective tool for continuous certification instead of traditional CEMS.
6.3 Recommendations

- **Characterize sensor performance when operating on other gaseous fuels**
  
  Because DG also operates on other renewable gaseous fuels such as gasified biomass and biomethane, the results from these analyses would be notable as well. These gaseous fuels may contain other contaminants that affect the performance and life of these sensors.

- **A carbon monoxide sensor capable of withstanding high temperature environments should be identified and properly characterized as well**
  
  If a sensor capable of measuring CO within the exhaust were to be implemented, it would lead to a significant improvement in the algorithm’s ability to minimize both CO and NO in real-time. The ability of the engine to perform calculations of inferred emissions levels is likely not to be realized, so a capable sensor that would output 4-20 mA signals for CO would improve the current algorithm immensely.

- **The latest commercially-available impedancemetric-based nitric oxide sensor capable of resolving changes in NO less than 5 ppm should be properly identified and utilized as a feedback device for the control algorithm**
  
  Because the NTK sensor had difficulty resolving improvements in NO at loads higher than 30 kW, the latest impedancemetric sensors mentioned in the Background section of this thesis could present a solution to this problem. These sensors have shown promise in resolving low NO emissions; however, when trying to contact the manufacturers of these devices, there weren’t any sensors available for evaluation.
7. REFERENCES


8. APPENDIX

8.1 HORIBA MEXA-1400QL-NX/ PG-350 Emissions Comparison

Fig 62. Default Injector Settings, TET=1175 (left), TET=1100 (right)

Fig 63. Injector +1 Settings, TET=1175 (left), TET=1100 (right)
Fig 64. Injector -1 Settings, TET=1175 (left), TET=1100 (right)

Fig 65. TET = 1137.5, Injector -1 (left), Default Staging (middle), Injector +1 (right)
8.2 MATLAB Code to Calculate Sensor Characteristics

clear;clc;
clf;
start = 1;

%C60 will be one less column that specified
%======Format time column to general%%
sheet = 1;
day = 1;
hour = 0;
DriftNO0 = 0;
DriftO20 = 0;
DriftNO = 0;
DriftO2 = 0;
DriftNO2 = 0;
DriftO22 = 0;
DriftNO3 = 0;
DriftO23 = 0;
DriftNO4 = 0;
DriftO24 = 0;
DriftNO5 = 0;
DriftO25 = 0;
DriftNO6 = 0;
DriftO26 = 0;
DriftQCLNO1 = 0;
DriftQCLNO21 = 0;
DriftQCLN2O1 = 0;
time = 1;
%for sheet = 2

%======================================================================
%ACCOUNT FOR DRIFT OF PG-350
%======================================================================
Sheet1 = ones(101,6); %Change Depending on the number of Days you have
Sheet2 = ones(101,7); %Change Depending on Number of Days you have
Sheet3 = ones(101,4); %For Relative Humidity and Temperature Data
R_SquaredData = Sheet1; %Initialize this matrix
ConResData = Sheet1; %Initialize this matrix
PrecisionDownscaleData = Sheet1;
PrecisionUpscaleData = Sheet1;
RealConResData = Sheet1;
NonLinearityData = Sheet2;
HistoricalData =Sheet3;
%62 not working
for sheet = [90:101]
   %1:59
   if sheet <= 5
      DriftNO0 = DriftNO0 + .06020023; % Drift saw -1.44 ppm/24 days
      DriftO20 = DriftO20 + .01244; %Drift saw -.361 ppm/24 days
   end
end
elseif sheet <= 26 & sheet > 5
DriftNO = DriftNO + .06020023; \% Drift saw -1.44 ppm/24 days
DriftO2 = DriftO2 + .01244; \% Drift saw -.361 ppm/24 days

elseif (sheet > 26) & (sheet <= 45)
DriftNO2 = DriftNO2 + .15131; \% Drift saw -4.388 ppm/29 days
DriftO22 = DriftO22 + .002355; \% Drift saw -.07065 ppm/29 days

elseif (sheet > 45) & (sheet <= 77)
DriftNO3 = DriftNO3 + .073; \% Drift saw +.8 ppm/11 days
DriftO23 = DriftO23 + .0091; \% Drift saw +.1%/11 days

elseif (sheet > 77) & (sheet <= 85)
DriftNO4 = DriftNO4 + .073; \% Drift saw +.8 ppm/11 days
DriftO24 = DriftO24 + .0091; \% Drift saw +.1%/11 days

elseif (sheet > 85) & (sheet <= 92)
DriftNO5 = DriftNO5 - .04; \% Drift saw -.4 ppm/10 days
DriftO25 = DriftO25 - .004\% Drift saw -.04%/10 days

elseif (sheet > 92) & (sheet <= 101)
DriftNO6 = DriftNO6 - .05; \% Drift saw -.55 ppm/11 days
DriftO26 = DriftO26 - .016; \% Drift saw -.18%/11 days
end

day

C60 = xlsread('All_Data_Spreadsheet_Engine_Macro.xlsx',sheet);
sensors = xlsread('All_Data_Spreadsheet_Sensors_Macro.xlsx',sheet);
%====================================================================
%FILTER OUT TRANSIENT DATA FROM C60
%====================================================================

for fil = 2
remind = 1;
star = 1;

if C60(fil,14) ~= C60(fil-1,14)
\% This means the data is transient
star(remind) = fil;
remind = remind+1;
end
end

\% how many intervals do you want taken out
intervals = 10; \% each step has 30 sample points (5 mins), take out 10 points
Step = zeros(1,numel(remind)*intervals);
% Create Matrix of transient data
for remind = 1:numel(star)
    Step(remind*intervals) = star(remind);
end

Step(end+1:end+(intervals - 1)) = Step(1:(intervals - 1));
Step = Step(intervals:end);

% Fill Matrix in with indices that you are taking out
for remind  = 2:numel(Step)
    if Step(remind) == 0
        Step(remind) = (Step(remind - 1)+1);
    end
end
Step = Step'

% Take indices out of data
C60(Step,:) = [ ];
sensors(Step,:) = [ ];

%=================================================================
% MAKE ROWS SAME LENGTH FOR C60 DATA AND SENSORS
%=================================================================
% Write if statement if one length is greater than the other
check1 = numel(sensors(:,1));
check2 = numel(C60(:,1));
if check1 > check2
    over = check1 - check2;
correct = check1 - over;
sensors = sensors(1:correct,:);
else
    over = check2 - check1;
correct = check2 - over;
C60 = C60(1:correct,:);
end

%=================================================================
% EDIT C60 DATA TO PUT 60KW DATA AT BEGINNING (easier for analysis)
%=================================================================
% Edit indices to align with data
% Make sure temperature data is last
index = 1;
i = 1;
% Put in the end of the load at the beginning
for i = 2:numel(C60(:,14))
    if C60(i,14) ~= C60(i-1,14) & C60(i,14) == 60000
        index = i:numel(C60(:,14));
    end
end
i = 1;  
index2 = 1;  
for i = 2:numel(C60(:,14))  
    if C60(i,14) ~= C60(i-1,14) & C60(i-1,14) == 60000  
        index2 = 1:i-1;  
    end  
end  

C60 = [C60(index2,:); C60(index,:); C60(index2(end):index(1)-1,:)];  
sensors = [sensors(index2,:); sensors(index,:); sensors(index2(end):index(1)-1,:)];  

%=========================================================================  
%THIS SECTION ABOVE MAY PRODUCE ERRORS  
%=========================================================================  
%FILTER SENSOR DATA AND DRIFT  
%=========================================================================  

%Establish sensors and account for drift  
UniNOx = sensors(:,2:4);  
NTK = sensors(:,5:7);  
UniNOxO2 = sensors(:,10:12);  
NTKO2 = sensors(:,13:15);  
humidity = sensors(:,16);  
temp = sensors(:,17);  
exhaust_temp = sensors(:,18);  

%====================DRIFT==================%  
if sheet <= 26  
    PG350data = sensors(:,8) + DriftNO;  
    PG35002 = sensors(:,9) + DriftO2;  
elseif (sheet > 26) & (sheet<= 45)  
    PG350data = sensors(:,8) + DriftNO2;  
    PG35002 = sensors(:,9) + DriftO22;  
elseif (sheet > 45) & (sheet <= 77)  
    PG350data = sensors(:,8) + DriftNO3;  
    PG35002 = sensors(:,9) + DriftO23;  
elseif (sheet > 77) & (sheet <= 85)  
    PG350data = sensors(:,8) + DriftNO4;  
    PG35002 = sensors(:,9) + DriftO24;  
elseif (sheet > 85) & (sheet <= 92)  
    PG350data = sensors(:,8) + DriftNO5;  
    PG35002 = sensors(:,9) + DriftO25;  
elseif (sheet > 92) & (sheet <= 101)  
    PG350data = sensors(:,8) + DriftNO6;  
    PG35002 = sensors(:,9) + DriftO26;  
end  

%Filter out data above 100 ppm  
Uni = UniNOx.*(UniNOx > 100);  
UniNOx = UniNOx - Uni;  
N = NTK.*(NTK > 100);
%===================================================================
%CORRECT FOR WET TO DRY CONCENTRATIONS AND O2%
%===================================================================

%AFR = C60(:,8);
alphpa = (8*AFR)./137.28;
H2Omofraction = 2./(1+2+(2*alpha*3.76)+(2*(alpha-1)));
UniNOx_dry = UniNOx./(1- H2Omofraction);
NTK_dry = NTK./(1- H2Omofraction);
UniNOx_O2dry = UniNOxO2./(1- H2Omofraction);
NTK_O2dry = NTKO2./(1- H2Omofraction);

%Correct for 15% O2 for Sensors and PG-350
UniNOx_O2_corrected = UniNOx_dry.*((20.99 - 15)./(20.99 - UniNOx_O2dry));

%===================================================================
%AVERAGE NO AT EACH LOAD (FOR CALCULATING LINEARITY)%
%===================================================================

i = 1;
j = 1;
a = 1;
b = 1;
c = 1;
start = 1;
PG350datamean = 1;
NTK_O2_correctedmean1 = 1;
NTK_O2_correctedmean2 = 1;
NTK_O2_correctedmean3 = 1;
UniNOx_O2_correctedmean1 = 1;
UniNOx_O2_correctedmean2 = 1;
UniNOx_O2_correctedmean3 = 1;
sample_points = 1;
humidity_mean = 1;
temp_mean = 1;
exhaust_temp_mean = 1;
Pre_PG350_downscale = 1;
Pre_NTK1_downscale = 1;
Pre_NTK2_downscale = 1;
Pre_NTK3_downscale = 1;
Pre_UniNOx1_downscale = 1;
Pre_UniNOx2_downscale = 1;
Pre_UniNOx3_downscale = 1;
Pre_PG350_upscale = 1;
Pre_NTK1_upscale = 1;
Pre_NTK2_upscale = 1;
Pre_NTK3_upscale = 1;
Pre_UniNOx1_upscale = 1;
Pre_UniNOx2_upscale = 1;
Pre_UniNOx3_upscale = 1;
Load = 1;

for i = 2:numel(C60(:,14))
    if C60(i,14) ~= C60(i-1,14) || i == numel(C60(:,14))
        if C60(i,14) < C60(i-1,14)
            %This means we are going downscale
            Pre_PG350_downscale(a) = max(PG350data(start:i-1)) - min(PG350data(start:i-1,1));
            Pre_NTK1_downscale(a) = max(NTK_O2_corrected(start:i-1,1)) - min(NTK_O2_corrected(start:i-1,1));
            Pre_NTK2_downscale(a) = max(NTK_O2_corrected(start:i-1,2)) - min(NTK_O2_corrected(start:i-1,2));
            Pre_NTK3_downscale(a) = max(NTK_O2_corrected(start:i-1,3)) - min(NTK_O2_corrected(start:i-1,3));
            Pre_UniNOx1_downscale(a) = max(UniNOx_O2_corrected(start:i-1,1)) - min(UniNOx_O2_corrected(start:i-1,1));
            Pre_UniNOx2_downscale(a) = max(UniNOx_O2_corrected(start:i-1,2)) - min(UniNOx_O2_corrected(start:i-1,2));
            Pre_UniNOx3_downscale(a) = max(UniNOx_O2_corrected(start:i-1,3)) - min(UniNOx_O2_corrected(start:i-1,3));
            a = a+1;
        elseif C60(i,14) > C60(i-1,14)
            Pre_PG350_upscale(b) = max(PG350data(start:i-1)) - min(PG350data(start:i-1,1));
            Pre_NTK1_upscale(b) = max(NTK_O2_corrected(start:i-1,1)) - min(NTK_O2_corrected(start:i-1,1));
            Pre_NTK2_upscale(b) = max(NTK_O2_corrected(start:i-1,2)) - min(NTK_O2_corrected(start:i-1,2));
            Pre_NTK3_upscale(b) = max(NTK_O2_corrected(start:i-1,3)) - min(NTK_O2_corrected(start:i-1,3));
            Pre_UniNOx1_upscale(b) = max(UniNOx_O2_corrected(start:i-1,1)) - min(UniNOx_O2_corrected(start:i-1,1));
            Pre_UniNOx2_upscale(b) = max(UniNOx_O2_corrected(start:i-1,2)) - min(UniNOx_O2_corrected(start:i-1,2));
            Pre_UniNOx3_upscale(b) = max(UniNOx_O2_corrected(start:i-1,3)) - min(UniNOx_O2_corrected(start:i-1,3));
            b = b+1;
        else
            Pre_PG350_upscale(b) = max(PG350data(start:i-1)) - min(PG350data(start:i-1,1));
            Pre_NTK1_upscale(b) = max(NTK_O2_corrected(start:i-1,1)) - min(NTK_O2_corrected(start:i-1,1));
            Pre_NTK2_upscale(b) = max(NTK_O2_corrected(start:i-1,2)) - min(NTK_O2_corrected(start:i-1,2));
            Pre_NTK3_upscale(b) = max(NTK_O2_corrected(start:i-1,3)) - min(NTK_O2_corrected(start:i-1,3));
            Pre_UniNOx1_upscale(b) = max(UniNOx_O2_corrected(start:i-1,1)) - min(UniNOx_O2_corrected(start:i-1,1));
            Pre_UniNOx2_upscale(b) = max(UniNOx_O2_corrected(start:i-1,2)) - min(UniNOx_O2_corrected(start:i-1,2));
            Pre_UniNOx3_upscale(b) = max(UniNOx_O2_corrected(start:i-1,3)) - min(UniNOx_O2_corrected(start:i-1,3));
            b = b+1;
        endif
    end
end
end
PG350datamean(j) = mean(PG350data(start:i-1));
NTK_O2_correctedmean1(j) = mean(NTK_O2_corrected(start:i-1,1));
NTK_O2_correctedmean2(j) = mean(NTK_O2_corrected(start:i-1,2));
NTK_O2_correctedmean3(j) = mean(NTK_O2_corrected(start:i-1,3));
UniNOx_O2_correctedmean1(j) = mean(UniNOx_O2_corrected(start:i-1,1));
UniNOx_O2_correctedmean2(j) = mean(UniNOx_O2_corrected(start:i-1,2));
UniNOx_O2_correctedmean3(j) = mean(UniNOx_O2_corrected(start:i-1,3));
temp_mean(j) = mean(temp(start:i-1));
exhaust_temp_mean(j) = mean(exhaust_temp(start:i-1));
humidity_mean(j) = mean(humidity(start:i-1));
sample_points(j) = numel(start:i-1);
Load(j) = C60(i-1,14);

% Find concentration resolution and LDL at the highest load
if (C60(i,14) < C60(i-1,14)) & (C60(i-1,14) == 60000)
  % Maximum P-P distance at full load
  SSNO = var(PG350data(start:i-1));
  SD = std(PG350data(start:i-1));
  ConResPG350 = max(PG350data(start:i-1)) - min(PG350data(start:i-1));
  ConResNTK1 = max(NTK_O2_corrected(start:i-1,1)) - min(NTK_O2_corrected(start:i-1,1));
  ConResNTK2 = max(NTK_O2_corrected(start:i-1,2)) - min(NTK_O2_corrected(start:i-1,2));
  ConResNTK3 = max(NTK_O2_corrected(start:i-1,3)) - min(NTK_O2_corrected(start:i-1,3));
  ConResUniNOx1 = max(UniNOx_O2_corrected(start:i-1,1)) - min(UniNOx_O2_corrected(start:i-1,1));
  ConResUniNOx2 = max(UniNOx_O2_corrected(start:i-1,2)) - min(UniNOx_O2_corrected(start:i-1,2));
  ConResUniNOx3 = max(UniNOx_O2_corrected(start:i-1,3)) - min(UniNOx_O2_corrected(start:i-1,3));
  % LDL at full load
  LDLPG350 = mean(PG350data(start:i-1) - PG350datamean(j)) + 3*std(PG350data(start:i-1) - PG350datamean(j));
  LDLNTK1 = mean(NTK_O2_corrected(start:i-1,1) - NTK_O2_correctedmean1(j)) + 3*std(NTK_O2_corrected(start:i-1,1) - NTK_O2_correctedmean1(j));
  LDLNTK2 = mean(NTK_O2_corrected(start:i-1,2) - NTK_O2_correctedmean2(j)) + 3*std(NTK_O2_corrected(start:i-1,2) - NTK_O2_correctedmean2(j));
  LDLNTK3 = mean(NTK_O2_corrected(start:i-1,3) - NTK_O2_correctedmean3(j)) + 3*std(NTK_O2_corrected(start:i-1,3) - NTK_O2_correctedmean3(j));
  LDLUniNOx1 = mean(UniNOx_O2_corrected(start:i-1,1) - UniNOx_O2_correctedmean1(j)) + 3*std(UniNOx_O2_corrected(start:i-1,1) - UniNOx_O2_correctedmean1(j));
  LDLUniNOx2 = mean(UniNOx_O2_corrected(start:i-1,2) - UniNOx_O2_correctedmean2(j)) + 3*std(UniNOx_O2_corrected(start:i-1,2) - UniNOx_O2_correctedmean2(j));
  LDLUniNOx3 = mean(UniNOx_O2_corrected(start:i-1,3) - UniNOx_O2_correctedmean3(j)) + 3*std(UniNOx_O2_corrected(start:i-1,3) - UniNOx_O2_correctedmean3(j));
end

%...
end

    start = i;
    j = j+1;
end

%FIND MIN OF LOAD
exhaust_temp_point = exhaust_temp_mean(find(Load == 10000));
temp_point = temp_mean(find(Load == 10000));
humidity_point = humidity_mean(find(Load == 10000));

sample_points = sample_points';
Load = Load';

%Precision_downscale =
[Pre_PG350_downscale',Pre_NTK1_downscale',Pre_NTK2_downscale',Pre_NTK3_downscale',Pre_UniNOx1_downscale',Pre_UniNOx2_downscale,Pre_UniNOx3_downscale']

%Precision_upscale =
[Pre_PG350_upscale',Pre_NTK1_upscale',Pre_NTK2_upscale',Pre_NTK3_upscale',Pre_UniNOx1_upscale',Pre_UniNOx2_upscale,Pre_UniNOx3_upscale']

UniNOx_O2_correctedmean = [UniNOx_O2_correctedmean1', UniNOx_O2_correctedmean2', UniNOx_O2_correctedmean3'];
NTK_O2_correctedmean = [NTK_O2_correctedmean1', NTK_O2_correctedmean2', NTK_O2_correctedmean3'];
PG350datamean = PG350datamean';

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%SORT SENSOR DATA INTO ASCENDING ORDER AND INTO UPSCALE AND DOWNSCALE DATA
%USED FOR PRECISION, LDL, AND CONCENTRATION RESOLUTION
%CALCULATE CORRESPONDING R^2 VALUES FOR SORTED DATA
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%sort rows of data vector
data = [PG350data,NTK_O2_corrected,UniNOx_O2_corrected,C60(:,14)];
%xlswrite("Issue.xlsm",data)
%pause
data1 = [PG350datamean,NTK_O2_correctedmean,UniNOx_O2_correctedmean];
data2 = sortrows(data1,1);
data3 = sortrows([data1,sample_points,Load],9);
%Corresponding R^2 Values
x = data2(:,1);
y = data2(:,2:end);
X = [ones(length(x),1),x];
b = X\y;
SensorCALC = X*b;
R_squared_NTK1 = 1 - sum((y(:,1) - SensorCALC(:,1)).^2)/sum((y(:,1) - mean(y(:,1))).^2);
R_squared_NTK2 = 1 - sum((y(:,2) - SensorCALC(:,2)).^2)/sum((y(:,2) - mean(y(:,2))).^2);
R_squared_NTK3 = 1 - sum((y(:,3) - SensorCALC(:,3)).^2)/sum((y(:,3) - mean(y(:,3))).^2);
R_squared_UniNOx1 = 1 - sum((y(:,4) - SensorCALC(:,4)).^2)/sum((y(:,4) - mean(y(:,4))).^2);
R_squared_UniNOx2 = 1 - sum((y(:,5) - SensorCALC(:,5)).^2)/sum((y(:,5) - mean(y(:,5))).^2);
R_squared_UniNOx3 = 1 - sum((y(:,6) - SensorCALC(:,6)).^2)/sum((y(:,6) - mean(y(:,6))).^2);

%numel(C60(:,14))
%C60(:,14)
%pause
for i = 2:numel(C60(:,14))
  if C60(i,14) ~= C60(i-1,14) & C60(i-1,14) == min(C60(:,14))
    downscale_data = data(1:i-1,:);
    upscale_data = data(i:end,:);
    break
  end
end
%Sort for precision calculations, LDL calculations, and Concentration Resolution
data_downscale = sortrows(downscale_data,1);
%xlsWrite('Show.xlsm',data_downscale)
data_upscale = sortrows(upscale_data,1);
%pause

%=========================================================================%
%DATA ROUNDING
%=========================================================================%
%round to nearest 10th if over 10 ppm for PG-350, nearest hundredth if under
%Changed to 2 due to errors
for i = 2:numel(data_downscale(:,1))
  if data_downscale(i,1) >= 10 & data_downscale(i-1,1) < 10
    data_downscale(1:i-1,1) = round(data_downscale(1:i-1,1),2);
    data_downscale(i:end,1) = round(data_downscale(i:end,1),1);
  end
end
for i = 2:numel(data_upscale(:,1))
  if data_upscale(i,1) >= 10 & data_upscale(i-1,1) < 10
    data_upscale(1:i-1,1) = round(data_upscale(1:i-1,1),2);
    data_upscale(i:end,1) = round(data_upscale(i:end,1),1);
  end
end

%=========================================================================%
LDLNTK1 = 1;
LDLNTK2 = 1;
LDLNTK3 = 1;
LDLUniNOx1 = 1;
LDLUniNOx2 = 1;
LDLUniNOx3 = 1;
ConResNTK1 = 1;
ConResNTK2 = 1;
ConResNTK3 = 1;
ConResUniNOx1 = 1;
ConResUniNOx2 = 1;
ConResUniNOx3 = 1;
i = 1;
j1 = 1;
j2 = 1;
j3 = 1;
j4 = 1;
j5 = 1;
j6 = 1;
j11 = 1;
j12 = 1;
j13 = 1;
j14 = 1;
j15 = 1;
j16 = 1;
for i = 2:numel(data_downscale(:,1))
    if data_downscale(i,2) ~= 0 & data_downscale(i-1,2) == 0
        ConResNTK1(j1) = data_downscale(i,1);
        if j1>1 & ConResNTK1(j1-1) ~= ConResNTK1(j1)
            RealConResNTK1(j11) = ConResNTK1(j1) - ConResNTK1(j1-1);
            j11 = j11+1;
        end
        j1 = j1+1;
    elseif data_downscale(i,3) ~= 0 & data_downscale(i-1,3) == 0
        ConResNTK2(j2) = data_downscale(i,1);
        if j2>1 & ConResNTK2(j2-1) ~= ConResNTK2(j2)
            RealConResNTK2(j12) = ConResNTK2(j2) - ConResNTK2(j2-1);
            j12 = j12+1;
        end
        j2 = j2+1;
    elseif data_downscale(i,4) ~= 0 & data_downscale(i-1,4) == 0
        ConResNTK3(j3) = data_downscale(i,1);
        if j3>1 & ConResNTK3(j3-1) ~= ConResNTK3(j3)
            RealConResNTK3(j13) = ConResNTK3(j3) - ConResNTK3(j3-1);
            j13 = j13+1;
        end
        j3 = j3+1;
    elseif data_downscale(i,5) ~= 0 & data_downscale(i-1,5) == 0
        ConResUniNOx1(j4) = data_downscale(i,1);
        if j4>1 & ConResUniNOx1(j4-1) ~= ConResUniNOx1(j4)
            RealConResUniNOx1(j14) = ConResUniNOx1(j4) - ConResUniNOx1(j4-1);
            j14 = j14+1;
        end
        j4 = j4+1;
end
elseif data_downscale(i,6) ~= 0 & data_downscale(i-1,6) == 0
    ConResUniNOx2(j5) = data_downscale(i,1);
    if j5>1 & ConResUniNOx2(j5-1) ~= ConResUniNOx2(j5)
        RealConResUniNOx2(j15) = ConResUniNOx2(j5) -
                                ConResUniNOx2(j5-1);
        j15 = j15+1;
    end
    j5 = j5+1;
elseif data_downscale(i,7) ~= 0 & data_downscale(i-1,7) == 0
    ConResUniNOx3(j6) = data_downscale(i,1);
    if j6>1 & ConResUniNOx3(j6-1) ~= ConResUniNOx3(j6)
        RealConResUniNOx3(j16) = ConResUniNOx3(j6) -
                                ConResUniNOx3(j6-1);
        j16 = j16+1;
    end
    j6 = j6+1;
end

%TAKE ONLY THE FIRST TERM (Concentration Resolution)
ConResNTK1 = ConResNTK1(1);
ConResNTK2 = ConResNTK2(1);
ConResNTK3 = ConResNTK3(1);
ConResUniNOx1 = ConResUniNOx1(1);
ConResUniNOx2 = ConResUniNOx2(1);
ConResUniNOx3 = ConResUniNOx3(1);

%========================================================================
%CALCULATE LINEARITY USING AVERAGED POINTS METHOD (AVERAGED AT EACH LOAD)
%========================================================================

j = 0;
i = 1;
diff = 0;
z = 1;
count = 1;
diffNTK1 = 1;
diffNTK2 = 1;
diffNTK3 = 1;
diffUniNOx1 = 1;
diffUniNOx2 = 1;
diffUniNOx3 = 1;
diffNTKmean1 = 1;
diffNTKmean2 = 1;
diffNTKmean3 = 1;
diffUniNOxmean1 = 1;
diffUniNOxmean2 = 1;
diffUniNOxmean3 = 1;

while i <= numel(data2(:,1))
    while count <= numel(data2(:,1))

        

    end
    count = count + 1;
end

while i <= numel(data2(:,1))
    while count <= numel(data2(:,1))

        

    end
    count = count + 1;
end
if data2(i,1) == data2(count,1)
    j = j+1;
    diffNTK1(z,j) = abs(data2(i,1) - data2(count,2));
    diffNTK2(z,j) = abs(data2(i,1) - data2(count,3));
    diffNTK3(z,j) = abs(data2(i,1) - data2(count,4));
    diffUniNOx1(z,j) = abs(data2(i,1) - data2(count,5));
    diffUniNOx2(z,j) = abs(data2(i,1) - data2(count,6));
    diffUniNOx3(z,j) = abs(data2(i,1) - data2(count,7));
    %j
    %pause
else
    break
end
count = count+1;

end

diffNTKmean1(z) = mean(diffNTK1(z,1:j));
diffNTKmean2(z) = mean(diffNTK2(z,1:j));
diffNTKmean3(z) = mean(diffNTK3(z,1:j));
diffUniNOxmean1(z) = mean(diffUniNOx1(z,1:j));
diffUniNOxmean2(z) = mean(diffUniNOx2(z,1:j));
diffUniNOxmean3(z) = mean(diffUniNOx3(z,1:j));

if i>numel(data2(:,1))
    break(data2(:,1))
end

end

%maximum deviation and location
[NTKmax1,index1] = max(diffNTKmean1);
[NTKmax2,index2] = max(diffNTKmean2);
[NTKmax3,index3] = max(diffNTKmean3);
[UniNOxmax1,index4] = max(diffUniNOxmean1);
[UniNOxmax2,index5] = max(diffUniNOxmean2);
[UniNOxmax3,index6] = max(diffUniNOxmean3);
range = max(PG350datamean) - min(PG350datamean);
LinearityNTK1 = (NTKmax1*100)/range;
LinearityNTK2 = (NTKmax2*100)/range;
LinearityNTK3 = (NTKmax3*100)/range;
LinearityUniNOx1 = (UniNOxmax1*100)/range;
LinearityUniNOx2 = (UniNOxmax2*100)/range;
LinearityUniNOx3 = (UniNOxmax3*100)/range;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%Finding Precision Downscale, LDL, and CONCENTRATION RESOLUTION
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%Find average deviation on curve
j = 0;
i = 1;
diff = 0;
z = 1;
count = 1;
preNTK1 = 1;
preNTK2 = 1;
preNTK3 = 1;
preUniNOx1 = 1;
preUniNOx2 = 1;
preUniNOx3 = 1;
preNTKmean1 = 1;
preNTKmean2 = 1;
preNTKmean3 = 1;
preUniNOxmean1 = 1;
preUniNOxmean2 = 1;
preUniNOxmean3 = 1;

while i <= numel(data_downscale(:,1))
    while count <= numel(data_downscale(:,1))
        if data_downscale(i,1) == data_downscale(count,1)
            j = j+1;
            preNTK1(z,j) = abs(data_downscale(i,2) - data_downscale(count,2));
            preNTK2(z,j) = abs(data_downscale(i,3) - data_downscale(count,3));
            preNTK3(z,j) = abs(data_downscale(i,4) - data_downscale(count,4));
            preUniNOx1(z,j) = abs(data_downscale(i,5) - data_downscale(count,5));
            preUniNOx2(z,j) = abs(data_downscale(i,6) - data_downscale(count,6));
            preUniNOx3(z,j) = abs(data_downscale(i,7) - data_downscale(count,7));
            %j
            %pause
        else
            break
        end
        count = count+1;
    end
    %preNTK1(z,1:j)
    %pause
    preNTKmean1(z) = mean(preNTK1(z,1:j));
    preNTKmean2(z) = mean(preNTK2(z,1:j));
    preNTKmean3(z) = mean(preNTK3(z,1:j));
    preUniNOxmean1(z) = mean(preUniNOx1(z,1:j));
    preUniNOxmean2(z) = mean(preUniNOx2(z,1:j));
    preUniNOxmean3(z) = mean(preUniNOx3(z,1:j));
    i = count;
    j = 0;
    z = z+1;

    if i>numel(data_downscale(:,1))
        break
    end
end
%maximum deviation and location
[preNTKmax1_downscale,index1] = max(preNTKmean1);
[preNTKmax2_downscale,index2] = max(preNTKmean2);
[preNTKmax3_downscale,index3] = max(preNTKmean3);

[preUniNOxmax1_downscale,index4] = max(preUniNOxmean1);
[preUniNOxmax2_downscale,index5] = max(preUniNOxmean2);
[preUniNOxmax3_downscale,index6] = max(preUniNOxmean3);

range2 = max(PG350data) - min(PG350data);

precisionNTK1_downscale = (preNTKmax1_downscale*100)/range2;
precisionNTK2_downscale = (preNTKmax2_downscale*100)/range2;
precisionNTK3_downscale = (preNTKmax3_downscale*100)/range2;
precisionUniNOx1_downscale = (preUniNOxmax1_downscale*100)/range2;
precisionUniNOx2_downscale = (preUniNOxmax2_downscale*100)/range2;
precisionUniNOx3_downscale = (preUniNOxmax3_downscale*100)/range2;

%=================================================================
%Finding Precision Upscale
%=================================================================

j = 0;
i = 1;
diff = 0;
z = 1;
count = 1;
preNTK1 = 1;
preNTK2 = 1;
preNTK3 = 1;
preUniNOx1 = 1;
preUniNOx2 = 1;
preUniNOx3 = 1;
preNTKmean1 = 1;
preNTKmean2 = 1;
preNTKmean3 = 1;
preUniNOxmean1 = 1;
preUniNOxmean2 = 1;
preUniNOxmean3 = 1;

while i <= numel(data_upscale(:,1))
    while count <= numel(data_upscale(:,1))
        if data_upscale(i,1) == data_upscale(count,1)
            j = j+1;
            preNTK1(z,j) = abs(data_upscale(i,2) - data_upscale(count,2));
            preNTK2(z,j) = abs(data_upscale(i,3) - data_upscale(count,3));
            preNTK3(z,j) = abs(data_upscale(i,4) - data_upscale(count,4));
            preUniNOx1(z,j) = abs(data_upscale(i,5) - data_upscale(count,5));
            preUniNOx2(z,j) = abs(data_upscale(i,6) - data_upscale(count,6));
            preUniNOx3(z,j) = abs(data_upscale(i,7) - data_upscale(count,7));
        end
    end
    count = count+1;
end
end
%preNTK1(z,1:j)
%pause
preNTKmean1(z) = mean(preNTK1(z,1:j));
preNTKmean2(z) = mean(preNTK2(z,1:j));
preNTKmean3(z) = mean(preNTK3(z,1:j));
preUniNOxmean1(z) = mean(preUniNOx1(z,1:j));
preUniNOxmean2(z) = mean(preUniNOx2(z,1:j));
preUniNOxmean3(z) = mean(preUniNOx3(z,1:j));
i = count;
j = 0;
z = z+1;
if i>numel(data_upscale(:,1))
    break
end
end
%maximum deviation and location
[preNTKmax1_upscale,index1] = max(preNTKmean1);
[preNTKmax2_upscale,index2] = max(preNTKmean2);
[preNTKmax3_upscale,index3] = max(preNTKmean3);
[preUniNOxmax1_upscale,index4] = max(preUniNOxmean1);
[preUniNOxmax2_upscale,index5] = max(preUniNOxmean2);
[preUniNOxmax3_upscale,index6] = max(preUniNOxmean3);
range2 = max(PG350data) - min(PG350data);
precisionNTK1_upscale = (preNTKmax1_upscale*100)/range2;
precisionNTK2_upscale = (preNTKmax2_upscale*100)/range2;
precisionNTK3_upscale = (preNTKmax3_upscale*100)/range2;
precisionUniNOx1_upscale = (preUniNOxmax1_upscale*100)/range2;
precisionUniNOx2_upscale = (preUniNOxmax2_upscale*100)/range2;
precisionUniNOx3_upscale = (preUniNOxmax3_upscale*100)/range2;

%=========================================================================
%PLOTS AND DATA
%=========================================================================%
%Correct for time/add data to matrices
%Time1 = datestr(C60(:,1),'HH:MM:SS');
%Time = datestr(sensors(:,1),'HH:MM:SS');
%Timeserial1 = datenum(Time1);
%Timeserial = datenum(Time);
%Data
%SensorData = [UniNOx_time,NTK_time,PG350_time];

%Time average NTK_mean
%Filters
a = 1;
b = (1/8)*ones(1,8);
c = (1/9)*ones(1,9);
d = (1/30)*ones(1,30);
e = (1/6)*ones(1,6);
g = (1/30)*ones(1,30);
f = (1/1)*ones(1,1);

PG350data = filter(g,a,PG350data);
NTK_O2_corrected = filter(g,a,NTK_O2_corrected);
UniNOx_O2_corrected = filter(g,a,UniNOx_O2_corrected);

%NTK_time = filter(f,a,NTK_mean);
%UniNOx_time = filter(f,a,UniNOx_mean);
%PG350_time = filter(f,a,PG350data);

Sensordata = [PG350data,NTK_O2_corrected,UniNOx_O2_corrected];

%Actual Power output to inverter
C60demand = C60(:,14)/1000;
%Injector Number
C60injector = C60(:,15);
C60turbine = C60(:,6);
C60compinlet = C60(:,7);

%Overalldata = [sensors(:,1),C60(:,2),Sensordata,TC_mean,C60demand,C60injector,C60turbine,C60compinlet];
%xlswrite('Data4_18.xlsm',Overalldata)
%Make series
Sensorseries = timeseries(Sensordata,Time,'name','NO');
%Sensorseries.TimeInfo.Units = 'hours';
%TCseries = timeseries(TC_mean,Time,'name','Temperature (F)');
%PGseries = timeseries(PG350_time,Time,'name','NO')
C60series1 = timeseries(C60demand,Time1,'name','C60 Power (KW)');
C60series2 = timeseries(C60injector,Time1,'name','C60 Injector Number');
C60series3 = timeseries(C60turbine,Time1,'name','C60 Turbine Exit');
C60series4 = timeseries(C60compinlet,Time1,'name','C60 Compressor Inlet');

%subplot(1,2,1)
figure(1)
hold on
scatter(data1(:,1),data1(:,5),10,'red','filled')
hold on
scatter(data1(:,1),data1(:,6),10,'blue','filled')
hold on
scatter(data1(:,1),data1(:,7),10,'black','filled')
hold on
plot(data1(:,1),data1(:,1),'black')
xlabel('PG350 NO (ppmvd)')
ylabel('UniNOx NO (ppmvd)')
legend('UniNOx1','UniNOx2','UniNOx3','Linear Response')
set(gca,'FontSize',18);

%plot(C60series1)

%subplot(1,2,2)
figure(2)
hold on
set(findall(gcf,'type','text'),'FontSize',30,'fontWeight','bold')
scatter(data1(:,1),data1(:,2),10,'red','filled')
hold on
scatter(data1(:,1),data1(:,3),10,'blue','filled')
hold on
scatter(data1(:,1),data1(:,4),10,'black','filled')
hold on
plot(data1(:,1),data1(:,1), 'black')
xlabel('PG350 NO (ppmvd)')
ylabel('NTK NO (ppmvd)')
legend('NTK1','NTK2','NTK3','Linear Response')
set(gca,'FontSize',18);

%RealConResData(sheet,:) =
[RealConResNTK1(1),RealConResNTK2(1),RealConResNTK3(1),RealConResUniNOx1(1),
  RealConResUniNOx2(1),RealConResUniNOx3(1)];
PrecisionUpscaleData(sheet,:) =
[precisionNTK1_upscale,precisionNTK2_upscale,precisionNTK3_upscale,precisionUniNOx1_upscale,precisionUniNOx2_upscale,precisionUniNOx3_upscale];
PrecisionDownscaleData(sheet,:) =
[precisionNTK1_downscale,precisionNTK2_downscale,precisionNTK3_downscale,precisionUniNOx1_downscale,precisionUniNOx2_downscale,precisionUniNOx3_downscale];
R_SquaredData(sheet,:) =
[R_squared_NTK1,R_squared_NTK2,R_squared_NTK3,R_squared_UniNOx1,R_squared_UniNOx2,R_squared_UniNOx3];
ConResData(sheet,:) =
[ConResNTK1,ConResNTK2,ConResNTK3,ConResUniNOx1,ConResUniNOx2,ConResUniNOx3];

%Day_data0 = [sample_points,Load,seconds];
NonLinearityData(sheet,:) =
[range,LinearityNTK1,LinearityNTK2,LinearityNTK3,LinearityUniNOx1,LinearityUniNOx2,LinearityUniNOx3];

%FOR AMBIENT TEMPERATURE, Humidity Data

%Day_data3 = [SSNO,SD];
xlswrite('Historical3_draft.xlsm',Day_data3,sheet)
xlswrite('Day_data_draft.xlsm',Day_data0,sheet)

    %xlswrite('Day_data3_draft.xlsm',Day_data2,sheet)
xlswrite('graphs.xlsm',data1,sheet)
HistoricalData(sheet,:) =
[hour(day),humidity_point,temp_point,exhaust_temp_point];

%Important for one-one comparison
day = day+1;
hour(day) = hour(day-1)+24;

end

%xlswrite('Data_new_3.xlsm',PrecisionDownscaleData,1)
%xlswrite('Data_new_3.xlsm',PrecisionUpscaleData,2)
%xlswrite('Data_new_3.xlsm',R_SquaredData,3)
%xlswrite('Data_new_3.xlsm',ConResData,4)
%xlswrite('Data_new_3.xlsm',NonLinearityData,5)
%xlswrite('Data_new_3.xlsm',HistoricalData,6)
8.3 Accuracy and Precision Sample Calculations

The table below (Table 32) displays a small segment of the daily measurements that are collected for the sensors as well as the PG-350 for Objective 1 of this thesis. The following is an explanation of the four circles in the table:

1. This is the PG-350 measurements that were recorded. At three times in the day (could be at different timestamps and at different conditions throughout the day), the PG-350 reported 5.06 ppmvd (15% O$_2$).

2. At the same time the PG-350 reported 5.06 ppmvd, the 3 NTK sensors also reported measurements as well. These are shown in the blue circle.

3. At the same time the PG-350 reported 5.06 ppmvd, the 3 UniNOx® sensors also reported measurements as well. These are shown in the yellow circle.

4. The purple circle represents the corresponding load (kW) the data were measured at.

Using these data, accuracy can be calculated using the following equation:

\[
\text{Accuracy (~)} = \frac{D_{\text{Max}}}{\text{IN}_{\text{f.s.}}} \cdot 100
\]

\text{Equation 8.1}

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|c|c|c|}
\hline
PG-350 & NTK 1 & NTK 2 & NTK 3 & UniNOx 1 & UniNOx 2 & UniNOx 3 & Load (kW) \\
\hline
5 & 6.728508 & 5.833674 & 5.614943 & 0 & 1.821652 & 1.855635 & 33 \\
5 & 0 & 1.788429 & 0 & 0 & 0 & 0 & 46 \\
5.04 & 1.61355 & 0 & 0 & 0 & 0 & 0 & 46 \\
5.06 & 3.082251 & 3.368874 & 1.690571 & 0 & 0 & 0 & 46 \\
5.06 & 5.137812 & 4.179985 & 3.830412 & 0 & 0 & 0 & 29 \\
5.06 & 3.464234 & 6.205357 & 3.873933 & 0 & 0 & 0 & 33 \\
5.07 & 3.484312 & 4.222372 & 3.905154 & 0 & 1.876998 & 0 & 29 \\
5.07 & 1.622051 & 1.775909 & 0 & 0 & 0 & 0 & 46 \\
5.14 & 3.077597 & 3.366685 & 1.691808 & 0 & 0 & 0 & 46 \\
\hline
\end{tabular}
\end{table}
To use this to calculate the accuracy of each individual NTK and UniNOx® sensor, $D_{\text{Max}}$ must first be calculated. Since each individual sensor has 3 responses at the same input, these differences will be averaged. These results are shown in the equations below and Table 33:

$$D_{\text{Max}} \text{NTK}_1 \text{ (ppmvd)} = \frac{|3.08 - 5.06| + |5.14 - 5.06| + |3.46 - 5.06|}{3} = 1.22$$  \hspace{1cm} \text{Equation 8.2}$$

$$D_{\text{Max}} \text{NTK}_2 \text{ (ppmvd)} = \frac{|3.37 - 5.06| + |5.14 - 5.06| + |3.46 - 5.06|}{3} = 1.24$$  \hspace{1cm} \text{Equation 8.3}$$

$$D_{\text{Max}} \text{NTK}_2 \text{ (ppmvd)} = \frac{|1.69 - 5.06| + |3.83 - 5.06| + |3.87 - 5.06|}{3} = 1.93$$  \hspace{1cm} \text{Equation 8.4}$$

$$D_{\text{Max}} \text{UniNOx}_1 \text{ (ppmvd)} = \frac{|0 - 5.06| + |0 - 5.06| + |0 - 5.06|}{3} = 5.06$$  \hspace{1cm} \text{Equation 8.5}$$

$$D_{\text{Max}} \text{UniNOx}_2 \text{ (ppmvd)} = \frac{|0 - 5.06| + |0 - 5.06| + |0 - 5.06|}{3} = 5.06$$  \hspace{1cm} \text{Equation 8.6}$$

$$D_{\text{Max}} \text{UniNOx}_3 \text{ (ppmvd)} = \frac{|0 - 5.06| + |0 - 5.06| + |0 - 5.06|}{3} = 5.06$$  \hspace{1cm} \text{Equation 8.7}$$

<table>
<thead>
<tr>
<th>Load (kW)</th>
<th>PG-350 NTK 1</th>
<th>NTK 2</th>
<th>NTK 3</th>
<th>UniNOx 1</th>
<th>UniNOx 2</th>
<th>UniNOx 3</th>
<th>Load (kW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>6.728508</td>
<td>5.836374</td>
<td>5.614943</td>
<td>0</td>
<td>1.821652</td>
<td>1.855635</td>
<td>33</td>
</tr>
<tr>
<td>5</td>
<td>6.728508</td>
<td>5.836374</td>
<td>5.614943</td>
<td>0</td>
<td>1.821652</td>
<td>1.855635</td>
<td>33</td>
</tr>
<tr>
<td>5.04</td>
<td>1.61355</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>46</td>
</tr>
<tr>
<td>5.06</td>
<td>3.082251</td>
<td>3.368874</td>
<td>1.690571</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>46</td>
</tr>
<tr>
<td>5.06</td>
<td>5.137812</td>
<td>4.179985</td>
<td>3.830412</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>46</td>
</tr>
<tr>
<td>5.06</td>
<td>3.464234</td>
<td>6.205357</td>
<td>3.873933</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>46</td>
</tr>
<tr>
<td>5.07</td>
<td>3.381506</td>
<td>3.912019</td>
<td>3.805154</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>29</td>
</tr>
<tr>
<td>5.07</td>
<td>1.622051</td>
<td>1.775909</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>46</td>
</tr>
<tr>
<td>5.14</td>
<td>3.077597</td>
<td>3.366685</td>
<td>1.691808</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>46</td>
</tr>
</tbody>
</table>

Once the averaged differences are computed, the maximum range of PG-350 data observed throughout the day are used to subsequently determine the accuracy.
Precision can be calculated using the following equation:

\[
Precision \% = \frac{\Delta S_{Max}}{I N_{f.s.}} \cdot 100
\]

To use this to calculate the precision of each individual NTK and UniNOx® sensor, \(\Delta S_{Max}\) must first be calculated. Since each individual sensor has 3 responses at the same input, these differences will be averaged. These results are shown in the equations below and Table 34.

\[
\Delta S_{Max \ NTK_1 (ppmvd)} = \frac{|3.08 - 5.14| + |3.08 - 3.46| + |3.08 - 3.08|}{3} = .813
\]  
Equation 8.9

\[
\Delta S_{Max \ NTK_2 (ppmvd)} = \frac{|3.37 - 3.37| + |3.37 - 4.18| + |3.37 - 6.21|}{3} = 1.22
\]  
Equation 8.10

\[
\Delta S_{Max \ NTK_2 (ppmvd)} = \frac{|1.69 - 1.69| + |3.83 - 1.69| + |3.87 - 1.69|}{3} = 1.44
\]  
Equation 8.11

\[
\Delta S_{Max \ UniNOx_1 (ppmvd)} = \frac{|5.06 - 5.06| + |5.06 - 5.06| + |5.06 - 5.06|}{3} = 0
\]  
Equation 8.12

\[
\Delta S_{Max \ UniNOx_2 (ppmvd)} = \frac{|5.06 - 5.06| + |5.06 - 5.06| + |5.06 - 5.06|}{3} = 0
\]  
Equation 8.13

\[
\Delta S_{Max \ UniNOx_3 (ppmvd)} = \frac{|5.06 - 5.06| + |5.06 - 5.06| + |5.06 - 5.06|}{3} = 0
\]  
Equation 8.14

<table>
<thead>
<tr>
<th>PG-350</th>
<th>NTK 1</th>
<th>NTK 2</th>
<th>NTK 3</th>
<th>UniNOx 1</th>
<th>UniNOx 2</th>
<th>UniNOx 3</th>
<th>Load (kW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>6.728508</td>
<td>5.833674</td>
<td>5.614943</td>
<td>0</td>
<td>1.821652</td>
<td>1.855635</td>
<td>33</td>
</tr>
<tr>
<td>5.04</td>
<td>1.61355</td>
<td>1.788429</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>46</td>
</tr>
<tr>
<td>5.06</td>
<td>3.082251</td>
<td>3.368874</td>
<td>1.690571</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>46</td>
</tr>
<tr>
<td>5.06</td>
<td>5.137812</td>
<td>4.179985</td>
<td>3.830412</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>46</td>
</tr>
<tr>
<td>5.06</td>
<td>3.464234</td>
<td>6.205357</td>
<td>3.873933</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>33</td>
</tr>
<tr>
<td>5.07</td>
<td>1.481312</td>
<td>4.222572</td>
<td>3.903154</td>
<td>0</td>
<td>1.876998</td>
<td>0</td>
<td>29</td>
</tr>
<tr>
<td>5.07</td>
<td>1.622051</td>
<td>1.775909</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>46</td>
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<tr>
<td>5.14</td>
<td>3.077597</td>
<td>3.366685</td>
<td>1.691808</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>46</td>
</tr>
</tbody>
</table>

Table 34. Explanation of Precision