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REPORT

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Next Generation NGV Driver Information System

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Acknowledgements

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Executive Summary

Measuring the amount of fuel contained in the tank of a Natural Gas Vehicle (NGV) is not as straightforward as it is for a liquid-fueled vehicle. The fuel in an NGV is a compressed gas at pressures up to 4200psig, and its pressure changes with temperature. The current state-of-the-art, which is used on most NGVs, is a simple pressure gauge as a rough guide for remaining fuel. This presents a high degree of error because pressure varies widely depending on temperature. Immediately following refueling, the temperature in the vehicle's cylinders is often greater than 150°F. As the driver pulls out of the fueling station and begins consuming gas, the pressure drops at a very fast rate due to expansion cooling of the gas. This pressure drop appears to the driver to be a very rapid decrease in fuel level, reducing trust in the fuel level indication and leading to concern about the distance the vehicle can travel before refueling again, which is known as "range anxiety."

To address the fuel volume and range anxiety issues in NGVs, GTI Energy (GTI) formed a project team that included Argonne National Laboratory (ANL), Ozinga Brothers, Inc (Ozinga), and Chicago Area Clean Cities (CACC) to develop and demonstrate a next-generation natural gas vehicle (NGV) driver information system. This system is aimed at accurately predicting the remaining distance-to-empty (DTE) of any NGV based on information from the fuel system and engine, as well as real-time traffic and turn-by-turn directions for the planned route. The project involved a combination of laboratory testing, modeling, algorithm development and deployment, data collection, and assessment of DTE prediction accuracy.

The laboratory testing addressed two different aspects of the project. The first was to measure and model the heating and cooling effects of natural gas during the filling and emptying of high-pressure storage tanks. The second involved assembly and testing of two different data logger and communication systems for subsequent installation on trucks. The selected data loggers were tested and then installed along with sensors on 12 trucks to relay pressure, temperature, vehicle speed, and distance travelled information for over a year to a central location for analysis. Algorithms were created to calculate the mass of gas and to provide DTE predictions.

The objective of this project was to develop and demonstrate a driver information system (DIS) that predicts the remaining DTE for any NGV within 5% or 25 miles (whichever is greater) any time during vehicle operation. GTI and ANL developed and demonstrated methods to measure remaining fuel mass more accurately and make DTE predictions and tested them against real-world data in a wide range of duty cycles. We confirmed that more accurate estimations of usable remaining fuel and DTE for NGVs are possible if well-defined information about CNG pressure and temperature is known and combined with information about upcoming vehicle use (route, speed, stops, etc.).

The goal was to determine whether a simple, cost-effective system can provide NGV drivers with the information they need to overcome range anxiety. The project produced prototype sensing and communications hardware and software that underwent rigorous testing in the field. It also produced a design for a fuel gauge that can be mounted in a truck to display the amount of fuel remaining and high and low DTE estimates to the driver. These items are not ready for commercial use, but they represent initial, experimental products developed under the project. The next step in the development of the DIS is the commercialization of the system.

I. Background – Need for a better fuel gauge

Measuring the amount of fuel contained in the tank of a Natural Gas Vehicle (NGV) is not as straightforward as it is for a liquid-fueled vehicle. The fuel in an NGV is a compressed gas at pressures up to 4200psig, and its pressure changes with temperature. If the gas temperature goes up – for the same amount of gas in a tank – then the pressure goes up. If the temperature goes down, then the pressure goes down. To complicate matters further, the temperature of the gas does not simply vary in response to the ambient temperature, but it also changes as a function of filling or emptying the tank. It warms during filling through what is called the heat of compression, and it cools during emptying as it is the reversal of the compression process. Whereas knowing a liquid level in a gasoline or diesel vehicle will provide an accurate measure of the volume of fuel, there is no corresponding single-value indicator of NGV fuel volume or mass.

The current state-of-the-art, which is used on most NGVs, is a simple pressure gauge as a rough guide for remaining fuel. This presents a high degree of error because pressure varies widely depending on temperature. Immediately following refueling, the temperature in the vehicle's cylinders is often greater than 150°F. The pressure gauge indicates a 'full' cylinder even though the vessel is under-filled compared to the target fill capacity. As the driver pulls out of the fueling station and begins consuming gas, the pressure drops at a very fast rate due to isentropic cooling of the gas. This pressure drop appears to the driver to be a very rapid decrease in fuel level, reducing trust in the fuel level indication and leading to concern about the distance the vehicle can travel before refueling again, which is known as "range anxiety."

The cost of range anxiety is difficult to quantify due to dependence on driver experience. However, initial discussions with vehicle operators indicated they return for fueling when their vehicle tanks are still 20-40% full. Decreasing the remaining fuel content to below 10% before refueling would result in significant time and cost savings. The simplest way to quantify these savings is with fuel system costs. NGV fuel systems are typically oversized in response to full-fill difficulties and range anxiety. By increasing confidence in the fuel status of the vehicle, the fuel storage capacity can be reduced, which can lower fuel system cost by as much as 20%.

II. Introduction

To address the fuel volume and range anxiety issues in NGVs, GTI Energy (GTI) formed a project team that included Argonne National Laboratory (ANL), Ozinga Brothers, Inc (Ozinga), and Chicago Area Clean Cities (CACC) and submitted a proposal to DOE to develop and demonstrate a next-generation natural gas vehicle (NGV) driver information system. This system is aimed at accurately predicting the remaining distance-to-empty (DTE) of any NGV based on information from the fuel system and engine, as well as real-time traffic and turn-by-turn directions for the planned route.

GTI has vast experience in the thermodynamics and mechanics of delivering gaseous fuels onto vehicles, including the development of several proprietary fueling algorithms for hydrogen and natural gas vehicles, which are built on the fundamental thermodynamics of the fuel. ANL has extensive experience with vehicle Controller Area Network (CAN) decoding and data acquisition. The team at ANL previously developed a phone-based application (app) that evaluates driver behavior and preferences based on a range of route choices. Ozinga owns and operates a fleet of compressed natural gas (CNG) ready mix concrete delivery trucks in the Chicago area. They have incurred significant costs due to range anxiety, reporting their drivers routinely exit the vehicle to check CNG system pressure gauges to estimate remaining fuel levels. These practices result in refueling when a significant amount of fuel remains on the vehicle. CACC has a history of working with owners of CNG fleets and of helping transfer technology and information to NGV owners.

Early in the project GTI and Chicago Area Clean Cities (CACC) conducted a survey of NGV fleets/fleet drivers about fueling behaviors and concerns around fueling and predicted range. The survey was created using Microsoft Forms and emailed to 22 contacts at 16 organizations. Ten responses were received, representing fleets that operate from 2 to 190 vehicles, primarily in the Midwest. Three respondents stated that there is no added information that would be helpful, two wanted generally “better fuel gauges”, three wanted DTE added, and one said the fuel gauges in their vehicles are worthless. A full report on the survey is contained in Appendix A.

The project involved a combination of laboratory testing, modeling, algorithm development and deployment, data collection, and assessment of DTE prediction accuracy. Each of these activities, and their associated problems and results, are described in this report. The laboratory testing addressed two different aspects of the project. The first was to measure and model the heating and cooling effects of natural gas during the filling and emptying of high-pressure storage tanks. The second addressed assembly and testing of two different data logger and communication systems for subsequent installation on trucks. The modeling activities involved taking gas temperature and pressure information and combining it with known characteristics of the gas and the tank volume to calculate the amount of gas in the tank. Data collection involved the use of sensors installed on 12 trucks to relay pressure, temperature, vehicle speed, and distance travelled information to a central location for analysis and storage as well as to execute on-board DTE calculations. Algorithms were updated or created to calculate the mass of gas and to provide the DTE predictions.

GTI held regular meetings with internal staff and external partners. These included weekly status meetings, bi-weekly meetings with additional GTI staff involved with the DAS design and testing, and bi-weekly phone meetings with subcontractors and with Thomas Wallner and Michael Pamminger of ANL.

III. Objectives/Goals/Milestones – DTE predictions

The objective of this project was to develop and demonstrate a driver information system that predicts the remaining DTE for any NGV within 5% or 25 miles (whichever is greater) any time during vehicle operation. The predictive model of DTE for a planned route was to be based on real-time traffic conditions and weather, among other parameters. However, the vehicle’s duty cycle (speed profile and time spent idling) proved to have a larger influence on DTE than traffic or weather conditions. Also, our fleet partner at Ozinga was unable to share destination data with the team as it was considered proprietary customer data. Without destination data, traffic conditions could not be included. Using measured information such as fuel tank temperature and pressure, we showed that predictions of DTE can be improved to within 5%, allowing vehicle fuel capacity to be reduced, lowering fuel system and operating costs by as much as 20%.

The main goal of this project was supported by many interim goals that were spaced quarterly throughout the program. The interim goals for each budget period are listed in the Tables below.

Table 1 - Milestone List for Budget Period 1

Milestone Log – Smart CNG Station Deployment				
Budget Period 1 – October 1, 2019 – June 33, 2021 (Extended Date)				
Milestone Title	**Planned Completion Date**	**Status**	**Method of Verification**	**Comments**
Complete design of data acquisition system (DAS)	3/30/2020	Completed	DAS Specifications and Drawings	**Goal:** Design meets data collection requirements while minimizing modification to vehicle **Progress:** GTI completed the data acquisition systems by identifying the number and types of sensors and other data inputs, the number of channels needed, and potential sources of the hardware.
Installation of DAS	6/30/2020	Completed	Photos of Hardware in Trucks	**Goal:** Completed installation of at least 10 data acquisition systems. **Progress:** Successfully completed
Completed parametric modeling of fuel consumption process.	9/30/2020	Completed	Technical Report	**Goal:** Modeling shows which measurements offer the most increase in accuracy over simple pressure gauge. **Progress:** Successfully completed
Validation of model	12/31/2020	Completed	Comparison of Model Results vs Data	**Goal:** Validation of parametric modeling with data from laboratory in controlled testing **Progress:** Successfully completed
Economic viability	12/31/2020	Completed	Go/No Go	**Goal:** Parametric modeling shows accuracy capable of improving prediction of usable fuel remaining with a small investment per vehicle. **Progress:** Modeling across a range of extreme compositions showed an error of less than 5% at all times. Testing in a laboratory environment showed less than 3.5% error. These results fulfilled the Go/No-Go requirement for BP1.

Table 2 - Milestone List for Budget Period 2

Milestone Log – Next Generation NGV Driver Information System				
Budget Period 2 – July 1, 2021 – June 30, 2022				
Milestone Title	**Planned Completion Date**	**Status**	**Method of Verification**	**Comments**
Beta test version of application completed	12/31/2021	Completed	App created, shared with team	**Goal:** Beta-test version of the application completed and presented to fleet drivers for initial testing **Progress:** Application completed
Application functionality validated	3/30/2022	Completed	Demonstrated ability of app to learn	**Goal:** Recalculation of model parameters using new data improves predictions **Progress:** Completed
Validate usable fuel model with fleet data	5/30/2022	Completed	Calculated remaining fuel from P and T measurement	**Goal:** Experimental data and modeling results incorporated into a usable-fuel prediction model as an input into the application. **Progress:** Completed
Deploy system in fleet vehicles	6/30/2022	Completed	Data collection initiated	**Goal:** Systems installed on at least 10 fleet vehicles. **Progress:** Completed. Hardware installed on 12 vehicles for data collection and communications.
Usable fuel model accurate	6/30/2022	Completed	Go/No Go	**Goal:** Model predictions within 5% of true fleet vehicle operation. **Progress:** Completed. Collected data on multiple vehicles, not whole fleet.

Table 3 - Milestone List for Budget Period 3

Milestone Log – Next Generation NGV Driver Information System				
Budget Period 3 – January 1, 2023 – December 31, 2023				
Milestone Title	**Planned Completion Date**	**Status**	**Method of Verification**	**Comments**
Complete functionality testing	5/31/2023	Completed	Verified data integrity	**Goal:** Test driver information systems installed on each vehicle and verify performance **Progress:** Completed
Validate 'distance-to-empty' prediction	9/30/2023	Completed	Calculated DTE range	**Goal:** Prediction is within 5% of witnessed fuel range during operation of fleet vehicles. **Progress:** Completed.
Quantify changes in driver behavior	3/31/2024	Completed	Technical Report	**Goal:** Measure the percentage of fuel remaining at beginning of refueling events. Compare to before driver information system was implemented. **Progress:** No appreciable improvement noted due to short term use and extensive experience of drivers.
Commercialization Plan Complete	6/30/2024	Completed	Results shared with industry	**Goal:** Develop a commercialization plan with commercial partner input to include next steps for fabricating and marketing driver information system **Progress:** Completed

The calculation of the remaining distance-to-empty depends on the usable fuel quantity in the vehicle and on the average fuel economy along the upcoming route. These two values must be properly measured and predicted, respectively, to accomplish the goal of this project. GTI addressed the estimation of the usable fuel remaining on the vehicle with the development of a new model with inputs of CNG tank pressure, ambient temperature, on-board gas temperature, and historic engine fuel consumption data. Fuel consumption rate is an often-overlooked factor, but it dramatically affects the temperature, and hence pressure, of the remaining gas due to the cooling effects of gas expansion. To predict the expected average fuel economy for a given route GTI's partner, ANL developed a second, predictive model of the required fuel based on powertrain efficiency and speed profile.

Once the usable fuel status on-board the vehicle is obtained, the DTE is calculated by dividing the amount of usable fuel by an estimation of the fuel economy. Fuel economy strongly depends on future route information. Unfortunately, Ozinga could not share information about upcoming routes with GTI. Instead, the route had to be characterized with backward-looking data collected by the mobile app. The original plan was to divide the planned route into different segments according to traffic conditions and geography and calculate the fuel economy for each one. The overall estimated fuel economy of the route would be the average value of the segments. However, for the vehicles and routes that were part of the project we found the terrain was not variable and the fuel economy was determined more by traffic type (urban, suburban, or rural) and the duty cycle of the vehicle (i.e., time spent idling). Using these inputs, fuel economy on the route was calculated with two different approaches, an analytical approach estimating the impact of each parameter and an empirical approach based on machine learning. The two values could be averaged to obtain a fuel economy estimate. In practice, as the machine learning model received more input and improved its predictions, it was used more in estimating the final fuel economy.

Once the two models were developed, they were implemented in a mobile app to display a real-time DTE prediction to the driver. This app was also to be used for driver guidance and fleet management. Ozinga expressed interest in using the information on truck fuel efficiency to measure and reward driver performance. This could be an added benefit of the NGV Driver Information System. The values of the parameters in the analytical model, the training of the machine learning model, and the weighting of each model on the average final fuel economy estimation were calculated from the data collected during the baseline stage of the project.

The activities conducted to develop a next-generation fuel gauge for NGVs - laboratory testing of gas tank charging and discharging, testing and selection of sensors and data acquisition systems, modeling and algorithm development and deployment, data collection and analysis, and DTE fuel gauge evaluation – are described in the following sections.

IV. Gas Compressibility Tests

a. Approach

The usable fuel status model utilizes a heat balance between the tank and the atmosphere to predict the amount of fuel that will remain stranded in the vehicle tank when the minimum operating pressure is reached. As fuel is consumed, the gas in the tank expands and cools. This isentropic expansion cooling causes a reduction in tank pressure and results in more gas stranded on board the vehicle as the low pressure lacks the driving force to provide sufficient gas flow to the engine. Fortunately, the CNG storage vessel walls act as a thermal buffer, providing heat from the atmosphere to the gas, which mitigates some of the pressure drop effect.

Two processes were modeled to accurately predict the usable fuel status of the vehicle:

1. Isentropic decrease in gas enthalpy as the pressure is reduced
2. Heat transfer from the atmosphere to the vessel and from the vessel to the gas

The first of these issues, the isentropic enthalpy decrease, determines how much the gas cools as it expands and how much heat needs to be transferred from the atmosphere to bring the gas back up to ambient temperature. Although enthalpy decrease for isentropic expansion is a well-studied and understood phenomenon, the amount of cooling varies with the composition of the gas. The team determined how much variability is possible from this cooling for a range of gas compositions and pressures encountered by typical NGVs. We then estimated the impact this variability has on the fuel status prediction. Real-time estimation of gas composition using micro-electromechanical sensors (MEMS) was considered but was not needed.

The second process, heat transfer, occurs in several steps and requires modeling the heat flow between the tank liner, carbon-fiber wrapping, and the outer tank wall, which absorbs heat from the atmosphere. Previously developed modeling for H2 tanks, based on fundamental physics, was used as a starting point for predicting heat transfer from the wall of the cylinder to the gas during fuel consumption. A natural convection heat transfer correlation was used to estimate heat transfer between the ambient air and the external surface of the vessel. GTI conducted experiments in the laboratory to verify and refine the algorithm that was previously developed for calculating CNG mass in a tank as a function of the tank's internal pressure and temperature.

b. Results

Previous research at GTI measured the average temperature of the vessel wall and compared it to the gas temperature and ambient temperature during a fuel-consumption process over the course of three hours. **Error! Reference source not found.** shows these temperatures. As expected, the vessel wall temperature sits between the gas and ambient temperatures. The temperature of the gas in the vessel depends on both the starting conditions and on how fast the gas in the tank is being consumed. If the vehicle is traveling at high speeds and consuming fuel quickly the temperature will decrease faster, resulting in a more drastic pressure decrease and leaving more fuel stranded in the vessel below the minimum operating pressure. The mobile app that was developed estimated how fast the fuel will be consumed and how fast the temperature will

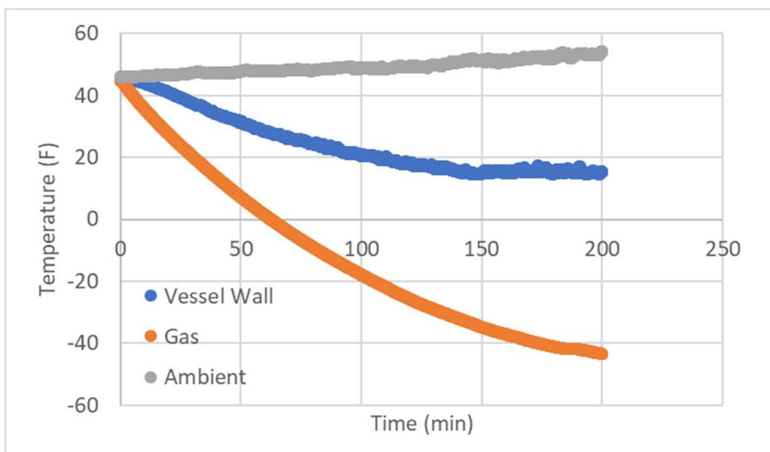

Figure 1 - Test result showing CNG and tank cooling during de-fueling over 3 hours

decrease.

There are two main requirements to accurately determine the usable fuel left on the vehicle: 1) determining the total amount of gas contained on board the vehicle, and 2) predicting how much of that gas will be 'stranded' or unusable. We satisfy the first requirement with the real gas equation (PV = ZnRT), but difficulties can arise with variability in the composition of natural gas, which determines the compressibility factor Z and the molecular weight that is needed to convert gas quantity into a mass. GTI conducted a survey of gas composition across the US in 2013. The extremes from this analysis were used as boundaries in the model. With these inputs, a surface plot and equation were created to calculate compressibility factor as a function of pressure and temperature (**Error! Reference source not found.** below). The surface created from these data is very accurate at temperatures above -60F.

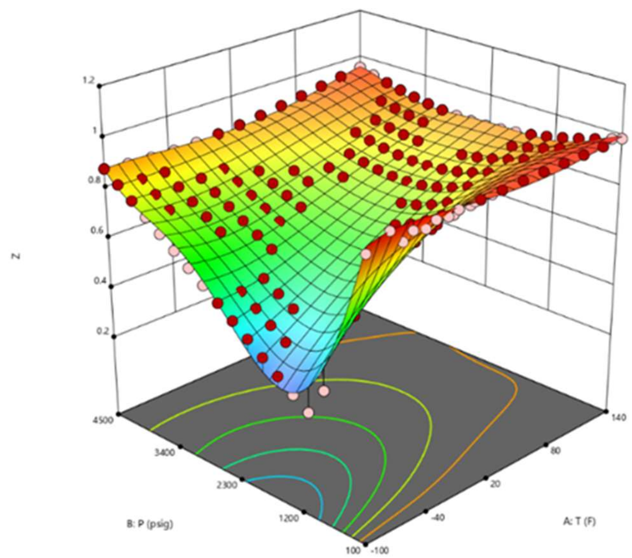

Figure 3 - Dependency of compressibility factor on pressure and temperature

GTI conducted experiments to determine the impact of heat transfer between the tank and the environment on the temperature inside the tank at the 'empty' condition. Figure 2 shows the temperature inside the tank (relative to ambient) for several different de-fueling experiments. While the temperatures are very different from ambient, they are similar for widely different de-fueling rates. The ultimate temperature is dependent on the tank size, positioning, whether a shroud is present around the tank, and other factors. This data, with additional input from gathered data from the Ozinga vehicles, was used to determine the stranded fuel onboard the vehicles.

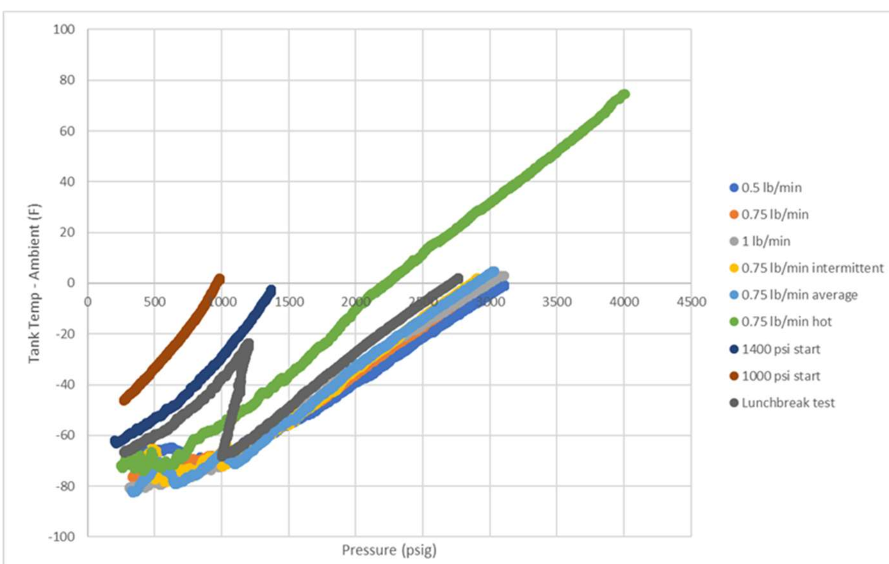

Figure 2 - In-tank temperature behavior during de-fueling

Significant spatial and temporal variations in gas temperatures inside the tanks were observed. However, controlled experimentation coupled with real-world fleet testing ensured that an accurate model of gas temperature was developed. Experimental work at GTI found the cylinder centerline temperature could predict the gas density within 1.5% at any time during a fill, when the gas is warming. The accuracy of predictions based on this centerline temperature is likely to be even better for the much slower fuel-consumption-driven cooling process.

V. Selection of Sensors

a. Approach

GTI evaluated temperature sensor devices for installation in the on-board tanks. The choices included thermocouples, thermistors, and RTDs (Resistance Temperature Detectors). Each one has slightly different characteristics and advantages. The critical parameters include length, accuracy, durability, and response time. Thermocouples do not require an input voltage to operate but their durability and signal strength were questioned for use on board a heavy-duty vehicle. RTDs are passive devices usually made of platinum wire whose resistance varies with temperature. The benefit of RTDs is reliability, but they suffer from relatively slow response times. Thermistors are also passive devices whose resistance varies with temperature, but there were issues finding them rated for high pressure service. RTDs and thermistors need an excitation voltage of 5 volts to operate.

GTI contacted McNeilus (the manufacturer of Ozinga's base trucks) to discuss design aspects of the vehicle that could influence installation of temperature sensors in the CNG tank system and to identify an acceptable location and method for installation of temperature and pressure sensors on the trucks. The temperature sensor must penetrate to the center of the tank to get a true, representative gas temperature and it must not protrude so far outside of the tank that it will get damaged during normal operation. Of course, it must not introduce leaks into the system.

b. Results

A thermocouple was chosen as the preferred temperature sensing device. GTI selected appropriate fittings and probes and

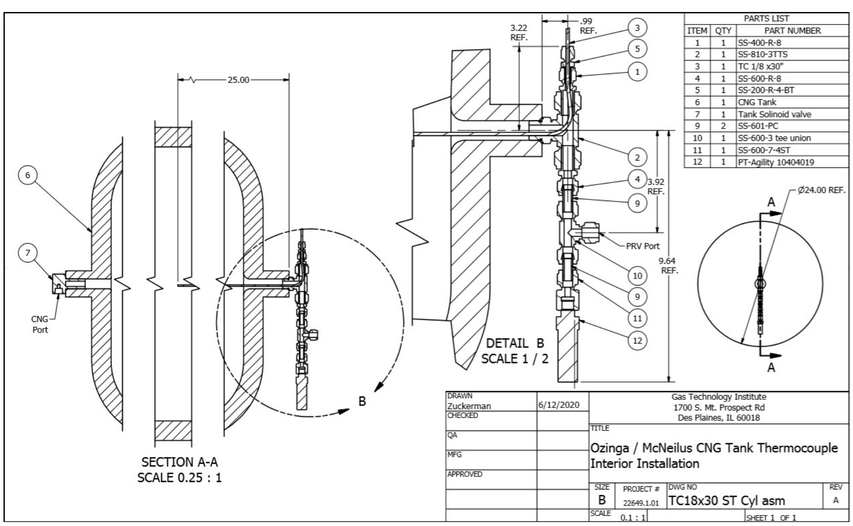

Figure 4 - Thermocouple and pressure probe mounting design

prepared drawings of the planned system which were sent to McNeilus for review and comment (Figure 4 and Figure 6).

The selected thermocouple location on the truck is shown in a diagram and photograph in Figure 5.

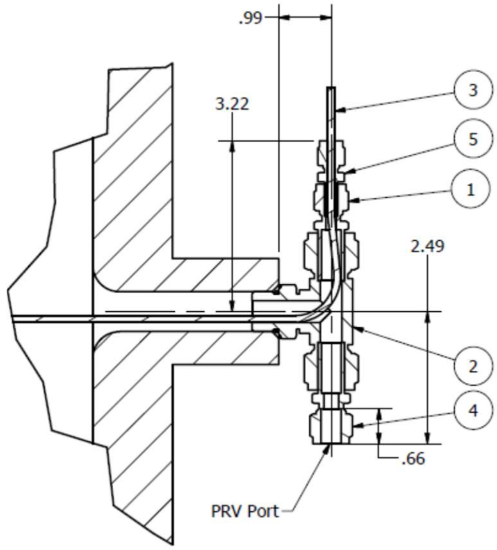

Figure 6 - Diagram showing details of thermocouple insertion assembly

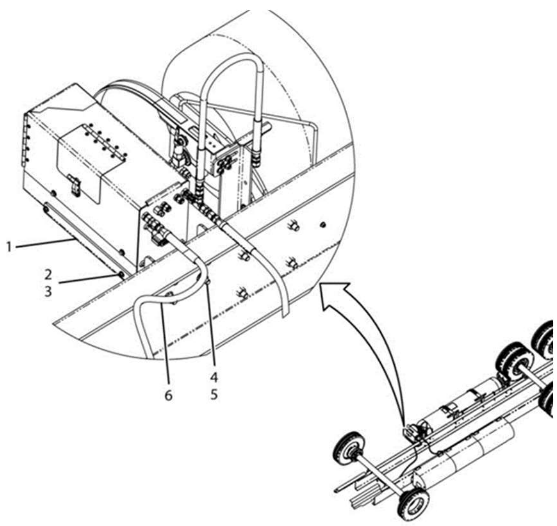

Figure 5 - Thermocouple insertion location shown in a diagram (left) and photograph (right)

The installed pressure sensor needed an excitation voltage of 5V to operate. The HEM hardware does not provide any excitation voltage channels, so additional hardware was required. GTI calculated the power drain imposed by the HEM system and it is between 300 and 350 mA. In 24 hours, the DAS would consume about 8.5 amp-hours or about 10% of the power in a typical truck battery (usually about 75 amp-hours). GTI and ANL did not think this power draw should be a problem, but the issue was discussed with Ozinga. We installed a time-delayed relay in the system that would disconnect the DAS from the truck battery when the truck is idle for long periods of time to avoid draining the battery.

VI. Selection of Data Collection and Transfer Devices

a. Approach – Two systems assembled and tested in laboratory

The requirements and specifications for the data acquisition systems were reviewed, discussed, and selected by the team early in the project. It was agreed that we would build and test two different systems at GTI before selecting one system to replicate and install on multiple trucks. Hardware providers were contacted, and parts that included data loggers, analog-to-digital converters, and data streamers were ordered and received from two suppliers. One system used parts from HEM Data that were designed for vehicle applications but have data-handling limitations. The other system used components from Campbell Scientific Inc. (CSI) that are commonly used in industrial applications and have more programming capability that provide data handling flexibility. GTI assembled one system first using the parts from HEM Data. It was undergoing testing in GTI's laboratory when GTI's management ordered that all our facilities be closed on March 16, 2020, due to the Coronavirus outbreak. Testing was completed after a delay of several months. The HEM system used for laboratory testing is shown in Figure 7.

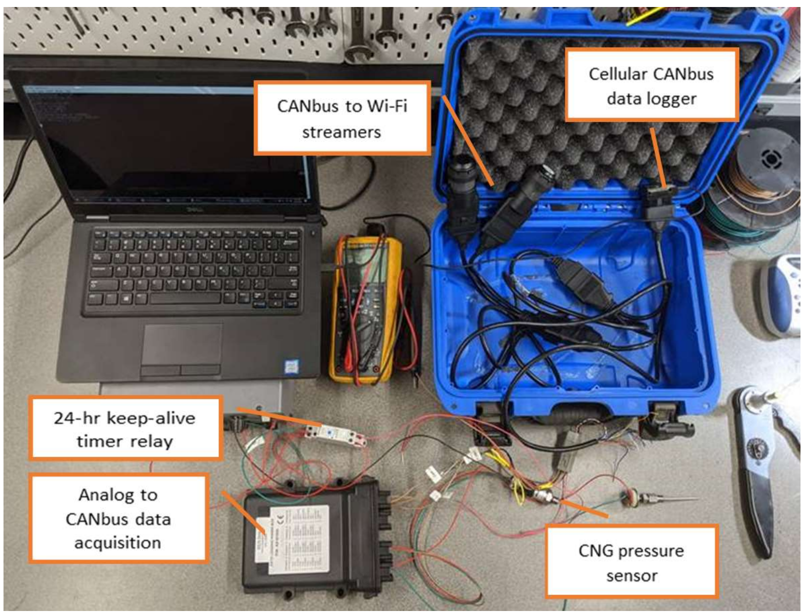

Figure 7 - HEM data acquisition system on laboratory bench

Parts from Campbell Scientific Inc. (CSI) were ordered, received, and assembled into a second system that is shown in Figure 8. A sketch of the Campbell DAS is shown in Figure 9. The Campbell datalogger has programmable excitation voltage outputs that can be turned on or off to conserve battery life by idling external sensors. The Campbell system also has a battery-backed power supply to support it when vehicle power is shut down. These attributes were considered when selecting between the two units. A Cummins engine control module (ECM) identical to those used on the test trucks was borrowed from Ozinga and used to provide inputs to the DAS during laboratory testing.

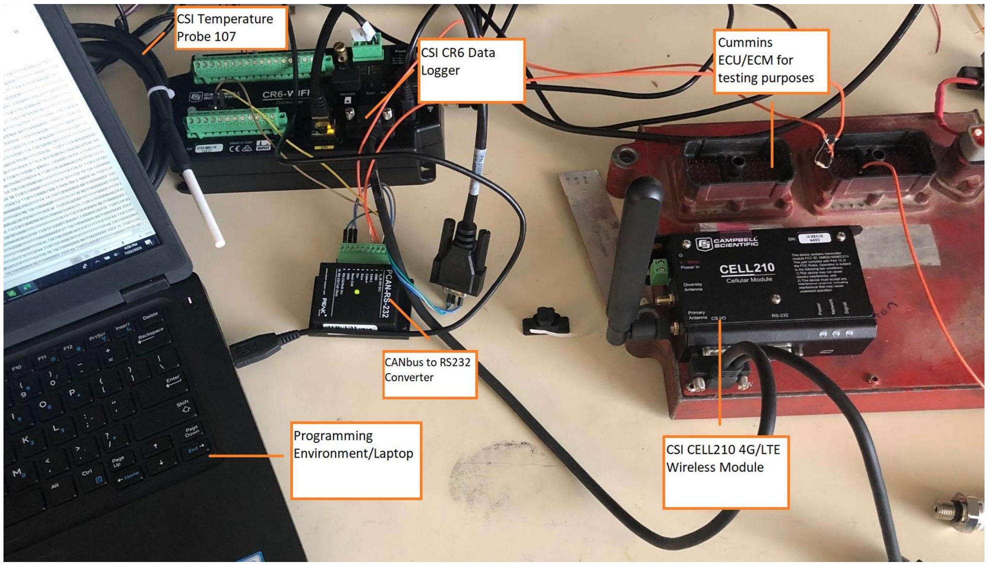

Figure 8 - Campbell Scientific data acquisition system

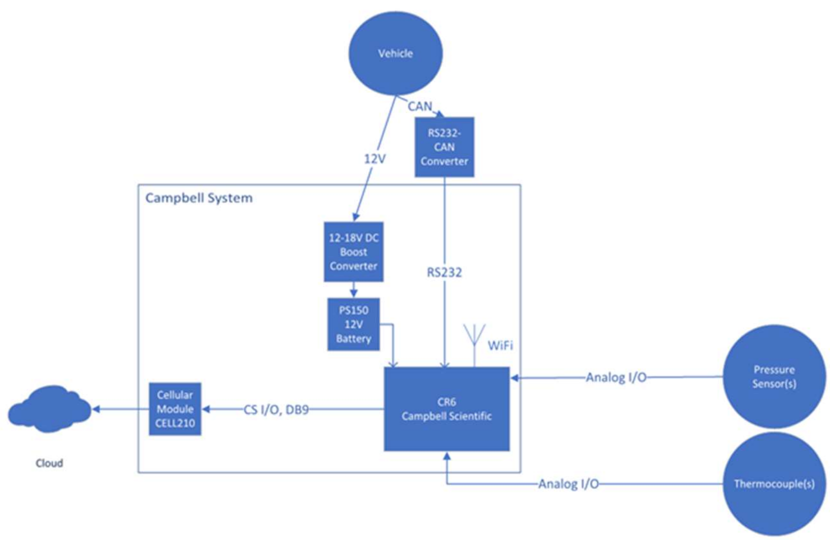

Figure 9 - Concept sketch of Campbell Scientific data acquisition system

One of the differences between the two systems is how they interact with the vehicle's Controller Area Network (CAN) Bus. A CAN bus is a standardized robust vehicle communications network designed to allow microcontrollers and devices to communicate with each other's applications without a host computer. It is a message-based protocol, designed originally for multiplex electrical wiring within automobiles. Every vehicle uses a CAN Bus to send messages to various system controllers on the vehicle. Because GTI and ANL needed vehicle information during operation, we had to connect to the existing CAN bus. The HEM system sends all data to the CAN bus and then transmits it off the vehicle for analysis. The Campbell system records select CAN bus data and then combines that with the measured pressures and temperatures from the truck's fuel system before transmitting. The Campbell system can filter and process data onboard the unit and can also be programmed with additional data about the vehicle such as VIN number, tanks sizes, etc. These are benefits of the Campbell system.

b. Problems

The issue with the Campbell system was an inability to accurately capture all the CAN bus data at the rate it is provided. Both the data converter and Campbell hardware have bandwidth limitations that prevented the system from capturing all the CAN bus data at the full rate that it is broadcast. The team was concerned that the slower data acquisition rate of the Campbell unit would be an issue. It is a shortcoming compared to the HEM system. Data filtering was explored as a possible option for reducing the amount of transmitted data and thereby resolving the bandwidth issue.

One of the main questions for data transfer, as mentioned above, relates to data filtering. The CAN Bus transmits more messages than are needed for the Driver Information System. The data needs to be filtered so that only the needed data are stored and analyzed, but whether that filtering takes place on the vehicle (prior to transmission to the Cloud) or takes place in the Cloud (prior to storage and analysis) was an issue. GTI evaluated both options for each of the HEM and Campbell systems.

c. Results – Down selected to HEM Data system

GTI evaluated differences in cost, performance, ease of programming, and communication format before committing to one system. The analysis of the HEM and Campbell systems ultimately ended with the selection of the HEM system partly because it was functioning properly earlier and there were still data filtering and sampling issues with the CSI system. However, the biggest issue was the cost, which was twice that of the HEM system. The HEM system is composed of a data logger and a streamer for sending the data off the vehicle.

To test the performance of the HEM system on a vehicle, the team at ANL used an Argonne delivery truck for app development. Data was successfully streamed via an IOSix data streamer from HEM Data onto a development phone via a WiFi connection. Some of the streamed CAN messages were picked out and decoded and are shown on the phone screen in Figure 10. The phone screen displays a snapshot of pedal position, fuel injection rate, engine coolant temperature, and engine

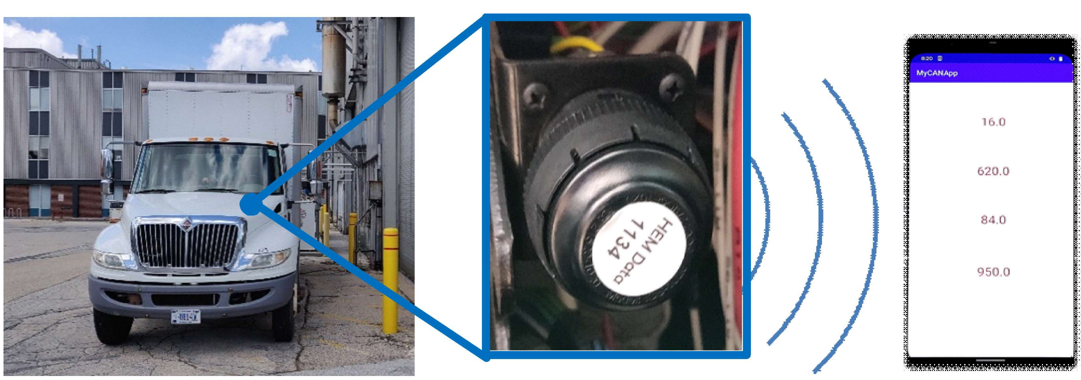

Figure 10 - Demonstration of initial data transfer from truck to phone at ANL

speed (from the top down) of a real-time data stream. Core functionalities, including data transmission to a cloud service, data on traffic conditions and more, required for the initial data collection phase, were implemented and tested on the app.

VII. Data Collection/Storage/Transfer with Data Loggers and Cell Phones

a. Approach – Installation on trucks

GTI built and installed the system that used parts from HEM Data on 18 trucks, as shown for reference in Table 4 - Ozinga Trucks providing data to GTI and ANLTable 4, owned and operated by Ozinga Brothers, a major concrete provider in the Chicago area. GTI installed thermocouples and pressure transducers to the CNG tanks on 11 of the trucks. The remaining 7 vehicles had fuel storage system configurations which made thermocouple installation very difficult. This gave the team the opportunity to test accuracy of systems using ambient temperature as a guide instead of in-tank temperature. We used two methods of retrieving data: one through the HEM datalogger with a cellular connection and the second through a Google Pixel phone which carries the app developed by ANL, with both sending data to a cloud server.

Table 4 - Ozinga Trucks providing data to GTI and ANL

Truck #	Engine Location	Builder	Built	Location	CAN DAQ Box #	Install Date
1331	Rear	KNWRT	2013	Des Plaines	2	Oct-21
1332	Rear	KNWRT	2013	Des Plaines	3	Oct-21
1338	Rear	KNWRT	2013	Des Plaines	13	Oct-21
1340	Rear	KNWRT	2013	Des Plaines	14	Oct-21
1923	Rear	KNWRT	2019	Chinatown	4	Jun-21
1924	Rear	KNWRT	2019	Chinatown	5	Jun-21
1925	Rear	KNWRT	2019	Chinatown	15	Jun-21
1926	Rear	KNWRT	2019	Chinatown	16	Jun-21
1416	Rear	KNWRT	2014	Chinatown	1	Sep-20
1341	Rear	KNWRT	2013	Montgomery	6	Oct-21
1415	Rear	KNWRT	2014	Montgomery	17	Oct-21
1590	Rear	KNWRT	2016	Montgomery	7	Oct-21
1591	Rear	KNWRT	2016	Montgomery	18	Oct-21
1825	Rear	PTRBL	2018	Mokena	8	Aug-21
1380	Front	OSHKS	2013	Mokena	9	Dec-21
1381	Front	OSHKS	2013	Mokena	10	Dec-21
1821	Front	ADVNC	2018	Gary	11	Jul-21
1884	Front	TERXX	2019	Gary	12	Jul-21

One HEM DAS was installed on a concrete truck by Ozinga Brothers technicians for initial testing. It sent data over the cellular interface for storage and review as designed. A photograph of the HEM DAS mounted in a Pelican case for protection and the location of the Pelican case in the truck are shown in Figure 11 .


Figure 11 - HEM data acquisition system in Pelican case (left) and mounted in truck (right)

After successful testing of the first DAS, GTI assembled multiple HEM data acquisition systems in Pelican cases as shown in Figure 12.


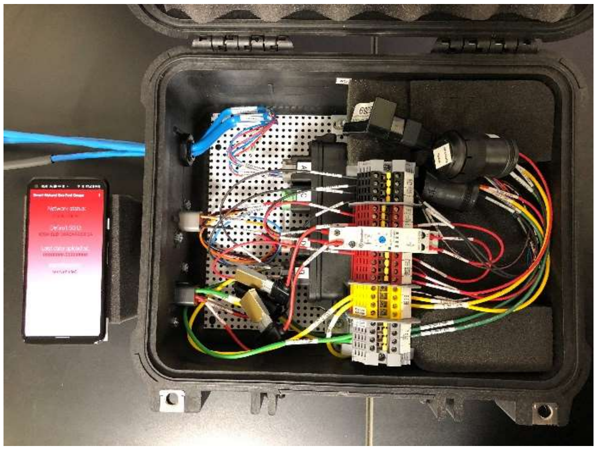

Figure 12 - Multiple HEM data acquisition system: In Pelican case (left) and components (right)

After the data collection and communications hardware was installed, we examined the data received from each truck and made adjustments to the software or hardware, as needed, to provide the necessary data on a consistent basis. Thermocouples and pressure transducers were installed on the CNG tanks on some of the trucks, starting with trucks #1340 and 1341. Eventually, only 11 trucks had both temperature and pressure sensors and GTI was troubleshooting these systems frequently to resolve any communications issues, some of which involved getting the data streamers to communicate properly with the base HEM unit. Some of the trucks experienced trouble with alarms going off when the new systems were installed, but this was subsequently resolved.

Data was transferred from the vehicle to the Cloud. GTI then collected and analyzed the data to measure and evaluate the driver information system performance. Data was also transferred from the data logger to a phone in the cab so that the tanks' fill status could be communicated, and the remaining range calculated for the driver. GTI purchased 21 4G system data loggers from HEM Data. After the 4G systems were received and tested there were problems with slow data transfer. GTI switched to a new Cloud platform and downloaded new software for the loggers. As stated above, multiple systems were then assembled in their Pelican cases by GTI's technical team members and installed in a variety of trucks owned by Ozinga. One day's worth of data took about 3 to 5 minutes to transfer into an Excel file. During this period, we calculated the volume of data that would be collected and selected a cost-effective way to collect and store that data. This was important because of the cost and complexity of collecting and storing data from twelve trucks for over one year in various driving conditions.

GTI also evaluated options for data logging and transfer from the vehicle to other devices. Data needed to be transferred from the vehicle to the Cloud so that GTI can then collect, interrogate, and analyze the data to measure and evaluate system performance. Data also had to be transferred from the vehicle to the fill station during filling of the CNG tanks and from the data logger to a tablet or other device in the cab so that the tanks' fill status can be communicated and the remaining range can be calculated for the driver. The options included Wi-Fi and Cellular service. Both options were explored to determine the optimal solution for this project. Wi-Fi was chosen for real-time, short-range data transfer and cellular was used for data transfer to the cloud. GTI set up a cloud server that was used to store and organize the data collected from each truck.

Figure 13 shows the overhead location in the truck cab that was used initially for storing the phone.

Figure 13 - Overhead bin in Ozinga truck where ANL phones were originally stored while in use

GTI developed a software tool for automated conversion and analysis of the large volumes of data expected from the fleet of dataloggers. In the meantime, the group at ANL began analyzing the data received from the first truck in detail, troubleshooting installation/communication issues, and establishing data processing procedures. Eighteen data acquisition systems were delivered to Ozinga and installed. Twelve of the systems were for this project and six were for the parallel DOE-funded Smart Station project. That project is developing a methodology for assuring full filling of CNG tanks during refueling.

b. Problems

Several problems were encountered in the process of installing and commissioning the data acquisition systems. The nature of these problems and the actions that were taken to resolve them are summarized in the sections below.

i. De-bugging

GTI purchased 21 data loggers from HEM Data. They all operated initially on 3G, which AT&T does not support any longer. When we learned this, we sent all 21 data loggers back to HEM Data in exchange for 4G systems. After the 4G systems were received and tested there were still problems with slow data transfer through AT&T. GTI switched to a new Cloud platform and downloaded new firmware for the loggers, which resolved most of the issues. Some issues with transferring data to the cloud persisted for the duration of the project. The transmission of data suffered from timeout errors, which resulted in the loggers filling up with un-transferred data and stopping data collection. This was only corrected by manually downloading and erasing data from the loggers, which wasn't always possible. One of the conclusions from this project is that vehicle data collection and transmission is difficult and needs further improvements.

ii. Interference between CAN bus and data loggers – resetting

After GTI installed thermocouples and pressure transducers to the CNG tanks on the trucks, GTI had to troubleshoot these systems to resolve communications issues, some of which involved getting the data streamers to communicate properly with the base HEM unit. Although data was received from 11 trucks for storage and analysis, it was not sent on a consistent basis. Interference between the GTI-installed data loggers and the normal CAN Bus communications on the trucks caused many of the trucks to stop transmitting data. Some of the trucks experienced trouble with alarms going off when the new systems were installed. After the data collection and communications hardware was installed, we examined the data received from each truck and adjusted the software or hardware, as needed, to provide the necessary data on a consistent basis. However, many of the systems stopped working and it was difficult to get access to the trucks for repairs because they were very busy throughout the spring and summer.

iii. CAN Bus identification

Another issue that had to be resolved was finding the right data source on the CAN bus. Some trucks required multiple connection attempts before the correct bus contacts were identified and a data link was established. There were several reasons for this. First, the Ozinga trucks used in the project represented several different vintages. They had different engines and fuel storage systems (either from Agility or Momentum) with CAN bus arrangements that varied widely. The newer trucks (2018 and later) have multiple CAN systems and the location of specific data sources varied between trucks and was not always clearly marked, making data identification a time-consuming process of trial and error among tens or hundreds of data signals. Finding the right data source and transmitting large volumes of data reliably were continuing problems that affected progress and data analysis efforts.

iv. Data management and security

The volume of data that was transferred from the trucks to the Cloud was quite large and initially overwhelmed GTI's existing systems for receiving, storing, and displaying the data. The data management group at GTI built a new process for collecting and storing the truck data to help alleviate these issues by making the data easier to organize and view. However, data security issues complicated the data transfer and storage process. When we started collecting data we had a simple script, but this eventually raised security concerns. It created a large "surface area" without adequate protection for the data. We migrated to Azure from Amazon Web Services (AWS). Azure is a Microsoft-based application for managing data in the Cloud while AWS is a similar product/utility offered by Amazon. The GTI IT department added computer and IP filtering plus additional steps to reduce the risk of a data breach. A Windows machine handled data conversion because we didn't want to keep all the data in the Cloud. They also added the ability to change the data logger configuration using individual configuration files, which adds functionality. These changes helped improve the reliability of the systems and added the ability to make changes remotely, which was very valuable as access to the vehicles was a consistent issue throughout the project.

v. HEM reliability

The HEM dataloggers proved to be unreliable in sending data to the server and were not able to provide consistent, long term data collection. This was largely due to a datalogger communication issue with the cloud server which was never fully resolved. As planned in the early stages of the project, the phones installed by ANL would include a datalogging and transmitting function as a secondary transmission option. This redundant function was extremely valuable during the project and also provided the ability to see truck location in real-time, which helped locating the trucks when the dataloggers needed maintenance.

c. Cell phone option

i. Ozinga management discussion

As stated above, the trucks ultimately included two methods of retrieving data: one through the HEM datalogger with a cellular connection sending data to a cloud server, and the second method through the Google Pixel phone carrying the App developed by ANL, which also sends data to a cloud server. Therefore, even when not collecting data from the loggers GTI still retrieved data through the phone application and some of this data is presented below. While the phones were initially stored in an overhead compartment, the team thought that the phones could also be used to display relevant information about DTE to the drivers if they could be mounted in a prominent location in the cab. This use of a phone as a fuel gauge was proposed to Ozinga management.

Ozinga has a strict policy that forbids their drivers from having cell phones in their trucks. This is a work rule that must be followed to prevent misuse of phones during working hours and to avoid distracted driving. For these reasons there was initial resistance by Ozinga management to the idea of using cell phones in the cabs, but when GTI and ANL assured Ozinga that the drivers would not have access to the phones and would only be able to see a portion of the screen they approved their use. GTI and ANL fabricated the needed phone cases and worked with Ozinga staff to install them on trucks. The initial focus was on installing the phones on trucks that were also providing CNG tank temperature and pressure measurements via the data loggers installed earlier.

ii. Phones overheating – charging rates/location

Since the phone needs to be constantly charging, overheating within the cab was a concern that had to be managed by limiting charging current. The problem was worse when the phones were kept in the overhead storage compartment, which had no air motion for cooling. GTI identified acceptable charging rates that avoided overheating and a proper phone charger was ordered by ANL.

iii. Results – Cell phones used for data collection

After spending many months debugging the HEM DAS and resolving data collection and transfer issues the team decided to use the cell phones as the primary source of data. Part of the task was focused on designing and fabricating a phone case that would restrict driver access to the phone while also providing enhanced cooling. The devices used for this task were Google Pixel 4a and Pixel 4XL phones, which were able to process data as they tracked multiple vehicle-specific parameters, such as natural gas consumed, as a function of time. The factors that needed to be considered when designing the case were the thermal rejection capability and physical size. As the phone processed data, the battery and processor in the phone could reach the maximum operating temperature. Therefore, alternative cooling had to be implemented within the case to maintain a lower temperature. Figure 14 shows a preliminary design concept and a 3-D printed version of the case, respectively.


Figure 14 - Version 1 Case 3D Design (left) and Version 1 Case Printed and Assembled (right)

Included with the case was a Peltier cooler that contains two semiconductive materials located within the fan enclosure that transfers electrical current between the plates. It creates a temperature gradient between those plates of the fan and transfers heat through the applied area. As shown in Figure 14, beneath the rectangular copper plate is a thermal compound that ensures heat is efficiently transferred through each copper plate. With the modifications and equipment implemented within the phone case, it was necessary to test for parameters of thermal rejection. Therefore, once testing commenced, the temperature of the phone began at 31.2°C and dropped towards 22.3°C, about a 9°C reduction in device temperature. Figure 15 provides the dimensions of the initial design.

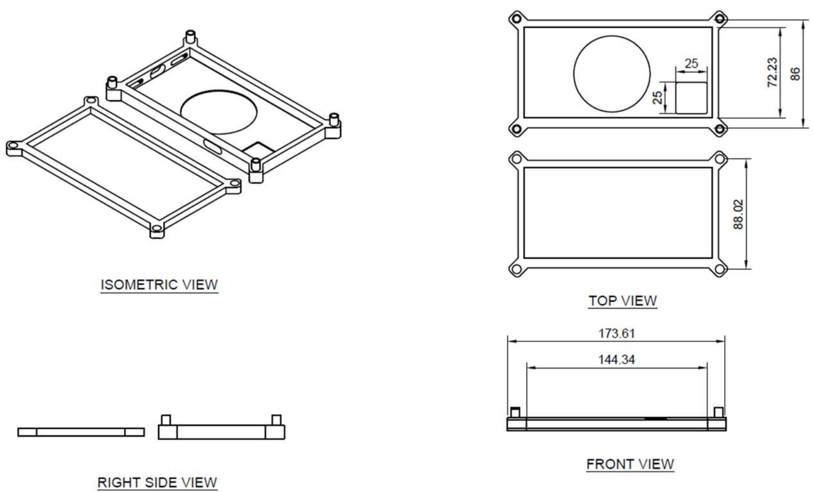

Figure 15 - Version 2 case CAD drawings with access to power button and dowel pin attachment

After the initial testing with the version 1 case was completed, the design of a more compact version 2 began. The focus was improving access to the power button, which is shown in Figure 15. In addition, integration of tubular dowel pins was included to provide the user with effortless attachment of both parts of the case. Unlike version 1, the version 2 phone case was much smaller

Figure 16 - Version 1 case temperature at beginning (left - 20°C) and after 5 min (right - 10°C)

and easier to attach in the driver's cabin. The width of the phone was reduced by 25%, which minimized the area covered to allow enhanced positioning within the vehicle.

The final version of the case and its use with the phone as a fuel gauge are shown in section IX. Large amounts of data were still collected using the HEM systems and this data was stored and is available for future analysis, but most of the data shown in the following sections was collected using the phones.

VIII. Data Analysis

To predict DTE more accurately, GTI and ANL collected and studied large amounts of data from the 12 trucks operating in various traffic environments with different duty cycles and rates of fuel consumption on these duty cycles. From this data we developed methods to determine the quantity and properties of the fuel in the tank (through measurement and estimation) and the likely future fuel consumption rate in miles per diesel-gallon-equivalent (DGE) (through knowing recent fuel economy trends and expected future route conditions). With better information on the remaining mass of fuel and expected fuel consumption rate we were able to calculate DTE. We then evaluated the accuracy of these DTE estimates, compared them with predictions based on pressure measurements alone, and devised a useful method for displaying this information to the driver. These steps are described in the following sections.

a. Calculating remaining fuel mass

As noted in the Background section, the major reason for the uncertainty of the fuel mass in natural gas vehicles is that it is a function of tank temperature. Historically, pressure alone has been used to gauge remaining fuel on most NGVs. This project included the measurement of gas storage temperature as an important factor. But the mass of gas on the vehicle at any moment is also a function of the tank volume, gas chemical composition, and real gas factor. Tank size is unknown because tanks vary from vehicle to vehicle, the precise tank size may not have been measured, and it would not include the volume contained in the valves and tubing. Gas composition is also an unknown because it varies seasonally and geographically. However, both factors are relatively constant during normal operations of most vehicles. To that end, an algorithm was established to estimate the initial mass of gas and other parameters.

The algorithm contains the real-gas equation as shown in Equation (1). Equation (1) was rearranged to obtain molar mass over volume and further mass over volume times molar mass as shown in Equation (2). Rearranging Equation (2) again reveals that in-tank gas mass scales linearly with tank volume times molar mass, which are the two unknowns in this equation, as shown in Equation (3).

$$PV = ZnRT \qquad (1)$$

$$\frac{n}{V} = \frac{P}{ZRT} = \frac{m}{VM_{NG}} \qquad (2)$$

$$m = VM_{NG}\frac{P}{ZRT} \qquad (3)$$

Additional relations necessary to estimate the initial fuel mass, m_0, and tank volume times molar mass divided by the universal gas constant, $(VM_{NG})/R$, are that the initial fuel mass is a constant, as well as the fact that fuel mass consumed since the last refill is the difference between the initial fuel mass and the current fuel mass, as shown in Equations (4) and (5).

$$m_0 = \frac{P_0}{Z_0 T_0}\frac{VM_{NG}}{R} = c_1 \frac{VM_{NG}}{R} \tag{4}$$

$$m_{consumed} = m_0 - m_k = m_0 - \frac{P_k}{Z_k T_k}\frac{VM_{NG}}{R} \tag{5}$$

Combining Equations (4) and (5), plus the fact that VM_{ng}/R_{ng} does not change, allows us to describe the system in state-space form, shown in Equation (6) and (7). The parameter c_1 describes the conditions after the last refill and c_2 the current tank conditions, which are calculated based on pressure, temperature, and real gas factor. A Kalman filter was used to estimate the states, with Equations (6) and (7) describing the dynamic and the measurement model of the system.

$$x = Ax = \begin{bmatrix} 0 & c_1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} m_0 \\ \frac{VM_{NG}}{R} \end{bmatrix} \tag{6}$$

$$z_k = Hx = \begin{bmatrix} 1 & -c_2 \end{bmatrix} \begin{bmatrix} m_0 \\ \frac{VM_{NG}}{R} \end{bmatrix} \tag{7}$$

A measurement update rate of 1 minute was assumed for the algorithm with initial estimation results shown in Figure 17. Figure 17 shows the initial fuel mass m_0 (the first state) in the top plot and the second state (the tank volume times molar mass divided by the universal gas constant) in the middle plot. A dataset collected on October 14th, 2021 with truck 1416 operating out of Chinatown was used for an initial evaluation of the estimation algorithm. The bottom plot shows the real gas factor Z, which was computed as a function of tank temperature and pressure based on a sixth-order polynomial that was fitted to a surface plot, which was shown in Figure 2. The estimator was initialized with an initial tank mass of 230kg and the second state as 0.002.

Apparent from the figure is the substantial uncertainty at the beginning of the estimation. However, after a few minutes, the algorithm starts approaching reasonable values and oscillates, in this case, around 197kg. The initial uncertainty results in a long converging time of about 120 minutes. The difference between the blue and orange line in the top plot is the fuel consumed. Since the second state, shown in the middle plot, is directly connected to the first state, the shape of the oscillations is similar for both states.

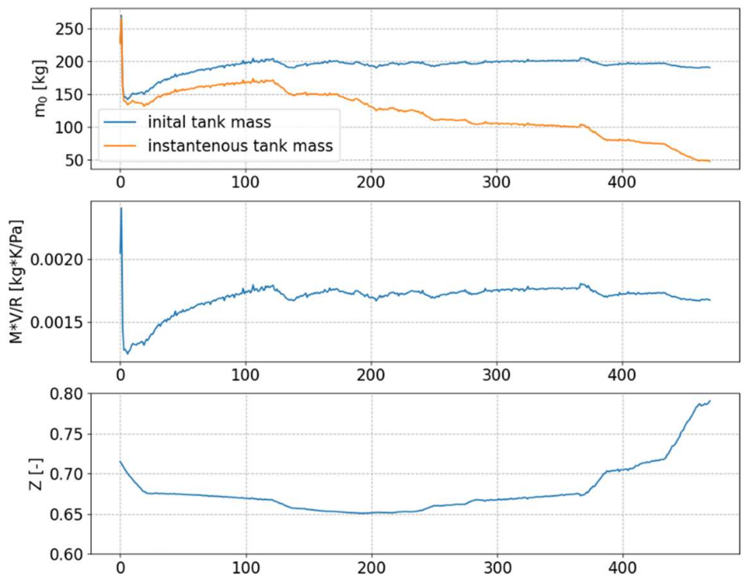

Figure 17 - Kalman filter state estimation results and real gas factor overtime (400+ minutes)

However, while adding this algorithm to the existing Android application, it became clear that Java does not have supporting libraries for matrix and vector multiplication, which are a significant part of the Kalman filter algorithm. Therefore, the initial algorithm was replaced by a slightly simpler estimation algorithm, a recursive least-squared estimator. Leveraging this algorithm is possible because only one parameter is required to be estimated. The estimated parameter, VM_{ng}/R_{ng}, which combines the tank volume as well as the gas properties.

Equations 8-10 below provide an explanation of how this parameter is related to the mass estimation process. Equation 8 shows the relationship between this parameter, the measured tank conditions (c_0, c_k), and the consumed fuel mass flow (m_f) obtained from the CAN bus. Equation 9 relates the tank pressure (p_k), temperature (T_k) and real gas coefficient (Z_k) to VM_{ng}/R_{ng} through a least squares estimation algorithm. The parameter, $c_0 - c_k$, accounts for the temperature and pressure change in the tank associated with the fuel mass consumed between two instances i.e., c_o after the last refueling event and c_k, the current tank conditions, where c_k is computed according to Equation 9. The tank pressure and temperature conditions are represented by p_k and T_k, which are measured; while Z_k reflects the real-gas coefficient of natural gas, which is itself a function of pressure and temperature. A more general representation of Equation 8, with an added catch-all error term, is shown in Equation 10. Equation 10 can be used with VM_{ng}/R_{ng} to compute the instantaneous natural gas tank mass (m_k). The individual parameters shown in Equation 10 are detailed in Equation 11, 12, and 13.

$$(c_0 - c_k)\frac{VM_{ng}}{R_{ng}} = m_{f\_consumed} \tag{8}$$

$$c_k = \frac{p_k}{T_k Z_k} \tag{9}$$

$$\phi_k^T \theta_k = y_k + \varepsilon_k \tag{10}$$

$$\theta_k = \frac{VM_{ng}}{R_{ng}} \tag{11}$$

$$\phi_k = c_0 - c_k \tag{12}$$

$$y_k = m_{f\_consumed} \tag{13}$$

Rearranging Equation 10 results in Equation 14, which explicitly expresses the error between measurement and estimation. To leverage that information, the covariance matrix and the updated gain need to be computed first, as illustrated in Equation 15 and 16, with λ being a calibration factor to adjust the influence of historic estimates on the current estimate. Equation 17 illustrates the correlation between Equations 14, 15, and 16, and the estimated value of the current sample.

$$\varepsilon_k = y_k - \phi_k^T \theta_k \tag{14}$$

$$P_k = \frac{1}{\lambda}\left(P_{k-1} - \frac{P_{k-1}\phi_k \phi_k^T P_{k-1}}{\lambda + \phi_k^T P_{k-1}\phi_k}\right) \tag{15}$$

$$L_k = \mathrm{P}_k \phi_k \tag{16}$$

$$\theta_k = \theta_{k-1} + L_k \varepsilon_k \tag{17}$$

These equations enable calculation of the tank mass even when we do not know the exact size of the tank or the composition of the gas. By starting the App with an estimated value for VM_{ng}/R_{ng} the App will adjust this value through a learning process. Knowing θ (or VM_{ng}/R_{ng}) allows us to compute the fuel mass in the tank from current T and P values.

Figure 18 illustrates how VM_{ng}/R_{ng} can be estimated and the App will utilize the learning process for the individual truck to adjust the value of VM_{ng}/R_{ng} to a more accurate value. The data shows that trucks 1331, 1332, 1415 and 1590 started at a similar value for VM_{ng}/R_{ng} of 0.001975 at the beginning of the month. The application stores the estimated values over the last 10 days and calculates the average for a given day. Truck 1416 was installed at the end of 2022 and thus starts at a lower value of 0.00182, which remained constant across the data shown for the month of March

2023. Once a constant value for VM_{ng}/R_{ng} has been determined the mass of gas can be calculated as shown in Equation 3. Figure 18 shows the VMWdR estimation for several trucks from

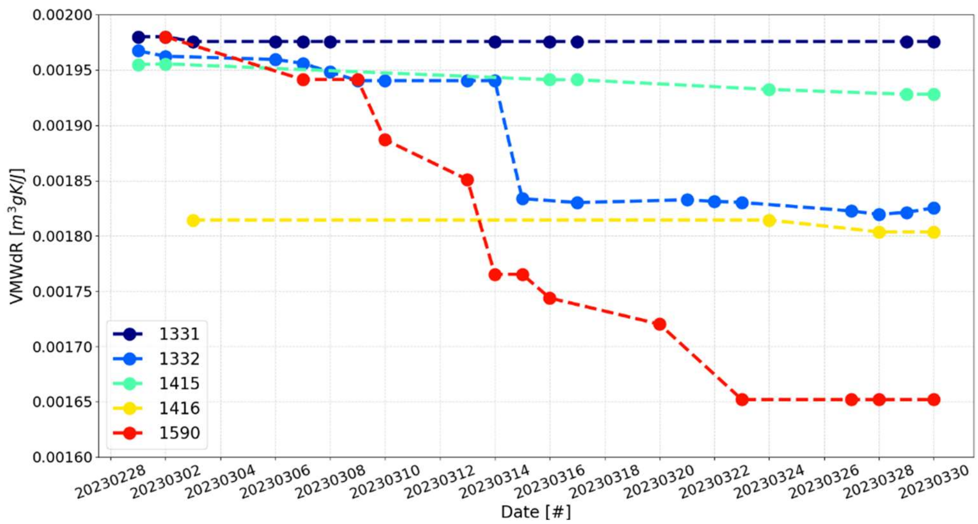

Figure 18 - Variation of VMWdR over time for trucks equipped with DTE prediction interface

the start of their service. For truck 1590, shown in red, the default values were the same as truck 1416, which has a fuel storage volume almost 40% greater than that of truck 1590. This was a test of how quickly the algorithm could correct this huge error in the volume estimation. The data show that this correction occurs within 10 operating days.

b. Estimating fuel consumption rate

To understand fuel consumption and what factors affect it most, large volumes of data were collected from truck #1416 and analyzed by ANL. Data from the entire 12-truck fleet were collected and analyzed later, including vehicles stationed in urban, suburban and rural areas. This overview

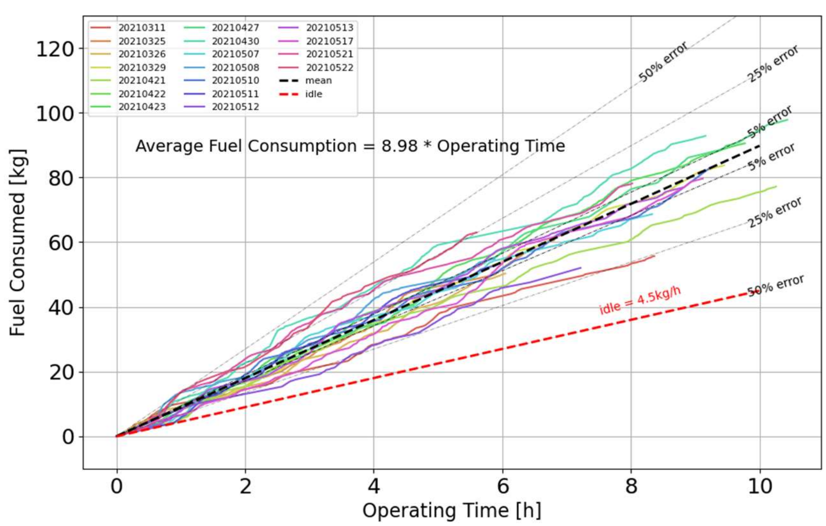

Figure 19 - Fuel consumed versus operating time for a single cement truck; 18 operating days

outlines the analytical process based on select, limited data from this single truck operated in an urban environment. For this analysis, a dataset of 18 operating days was reviewed, with Figure 19 showing the accumulated fuel consumption over the operating time. The average operating time was around 8 hours per day with a standard deviation of 1.72 hours for the dataset shown. The distinct black dashed line illustrates the average fuel consumption across all 18 samples with a slope of 8.98 kg/h.

A prediction error of 5% for total fuel consumed is also shown in Figure 19, represented by the two dashed lines close to the mean value. If the prediction were based on an average fuel consumption value, the error can be as high as 50% within the first three to four hours of operating the truck on a given day, but the error is shown to fall within the 25% error lines as the operating time increases. It's worth noting that the lower bound of the 50% error line coincides with the average fuel consumption at idle, indicated by the red dashed line at the bottom of Figure 19, which is on average about 4.5kg/h. This illustrates that the cement truck spends on average about 50% of the total fuel while idling. This fact is also confirmed when dividing the duty cycle up into various operating modes, as illustrated in Figure 20.

Figure 20 shows the total fuel consumed across different modes of operation. While idling is the predominant mode in terms of fuel consumed (with 52% of the fuel used during idling), another 21% is used at less than 20km/h and 18% at speeds between 20 and 40km/h. To understand factors influencing the total fuel consumption, the effect of the vehicle weight was estimated, with the results being presented next.

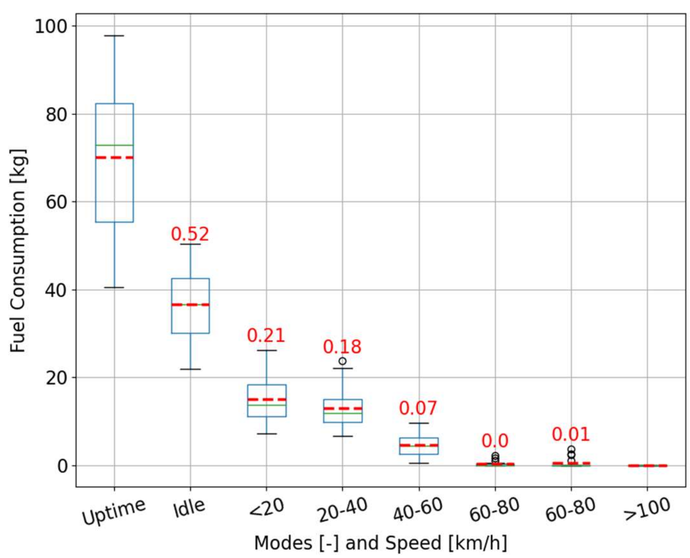

Figure 20 - Total fuel consumed at uptime, idle and various speed ranges

Figure 21 illustrates the normalized total fuel consumed for a set of 49 trips. The bars reflect the fraction of fuel consumed for an outbound trip compared to the total fuel amount consumed for an inbound trip. The probability density function peaks at around 55%, meaning 55% of the total fuel mass consumed for a given round trip is used on outbound trips. If the assumption is made that a cement truck is fully loaded with concrete on an outbound trip and returns empty, the difference in fuel consumption can be mostly attributed to the difference in truck weight. This analysis indicates that on average about 22% more fuel is consumed on an outbound trip (55%) versus an inbound trip (45%). Other influences such as grade to and from the Ozinga plant were deemed negligible due to the flat terrain.

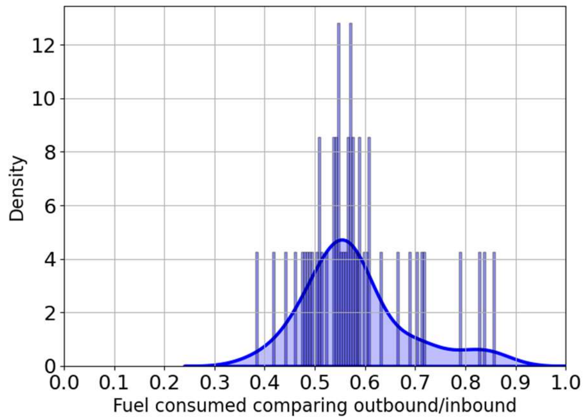

Figure 21 - Normalized fuel consumption comparing outbound and inbound trips

This result was not unexpected because the difference in weight between a cement truck with a fully loaded drum and an empty drum can be as high as a factor of ~4 (30000kg vs 7500kg). To investigate this further, Figure 22 shows the fuel consumption of three outbound trips (blue) and inbound trips (green) along the same route to and from a site on a given day. The blue bars represent the fuel consumed during an outbound trip while the green bars show the same for an inbound trip (returning to the Ozinga plant). The yellow bar on the left shows the average fuel consumed for all outbound trips and the pink bar for all inbound trips. The black bars on top illustrate the standard deviation. The mean values across these three trips are represented by the bars on the left of Figure 22. The average fuel consumption of the outbound trips is 1.94 kg, while the fuel consumption for the inbound trips is on average 1.57kg, which translates into a difference of about 24%.

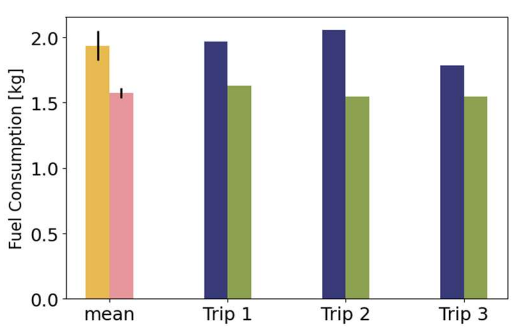

Figure 22 - Fuel consumption for 3 trips to a given site along the same route

The data also confirmed that the Ozinga trucks spend a significant fraction of their operating time idling while the concrete mixer is turning or dispensing product. This increases the uncertainty in DTE predictions because the truck is not moving while idling and yet the fuel consumption can be great because of the load represented by the turning drum. Therefore, GTI and ANL decided to predict and display a range of DTE values that the driver can use based on their knowledge of the expected upcoming duty cycle.

c. Calculating average speed and its importance in calculating DTE

Because Ozinga could not share information about upcoming routes, and because factors such as weather and traffic conditions were minor when compared to the duty cycle of the truck (i.e. idling time), GTI and ANL needed another parameter to help predict fuel consumption rate. The best parameter for this purpose was average vehicle speed, which was determined by a careful analysis of data from several trucks.

To better understand the variability in measured fuel consumption at a given average vehicle speed, the team developed a statistical model based on data from truck #1416 by means of a first-order Markov model. It uses two independent states - vehicle speed (v) and total fuel consumed (m_{fuel}). Truck #1416 is stationed in Chinatown and serves customers in the downtown area as well as suburbs close to Chicago.

The main idea behind a first-order Markov model is that the state in the next timestep is only a function of the state at the current time step plus some added noise, while the added noise is based on conditional probabilities of the parameters involved. This is formulated in Equation 18, where x represents the current and next time steps, which are expressed by the subscript k (current) and k+1 (next), respectively. The parameter ω represents the random variables that are associated with each state. The states - vehicle speed (v) and total fuel consumed (m_{fuel}) - are identified in Equation 19. The random variable related to the first state, v, is acceleration, while the fuel consumption is conditioned on vehicle speed as well as acceleration, as shown in Equation 20, which is called the transition probability function.

$$x_{k+1} = x_k + \omega dt \quad (18)$$

$$x = \begin{bmatrix} v \\ m_{fuel} \end{bmatrix} \quad (19)$$

$$\omega \sim p(f(v,a)) \quad (20)$$

The probability distribution for the random variables (acceleration and instantaneous fuel mass flow) was determined by the data collected from #1416. To simulate multiple days of operation for truck 1416, the statistical model was exercised multiple (over 1000) times using sampled variables from distributions in actual trips. Every simulation started with a velocity and acceleration of zero. By leveraging Equation 18 and sampling from the distributions shown in Figure 23, which are mathematically represented in Equation 20, many simulated trips were generated. A single simulated day represents an 8-hr duration as this roughly reflects the average daily operating time observed for #1416.

Figure 23 illustrates how the distributions were determined based on real world data. The left plot in Figure 23 shows a scatter plot with acceleration over vehicle speed with the area around 5m/s being

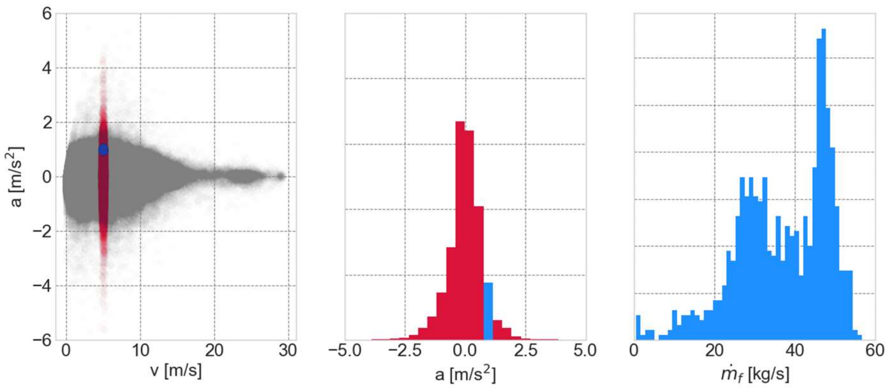

Figure 23 - Scatter plot showing 144 days of acceleration and vehicle speed conditions (left)
Discrete distributions for acceleration at 5m/s.(middle)
Fuel mass flow rates at 5m/s vehicle speed and 1m/s2 acceleration (right)

highlighted. The middle plot illustrates the acceleration distribution found for 5m/s (cross section of the left plot). The right plot shows a histogram for all fuel mass flows for a given condition, in this case a vehicle speed of 5m/s and an acceleration of 1m/s^2.

The results obtained from this procedure are illustrated in Figure 24. The top two plots show the histories of the states - vehicle speed and total fuel consumed - for 1000 simulations. The bottom plot illustrates the distance traveled, which is the integrated vehicle speed.

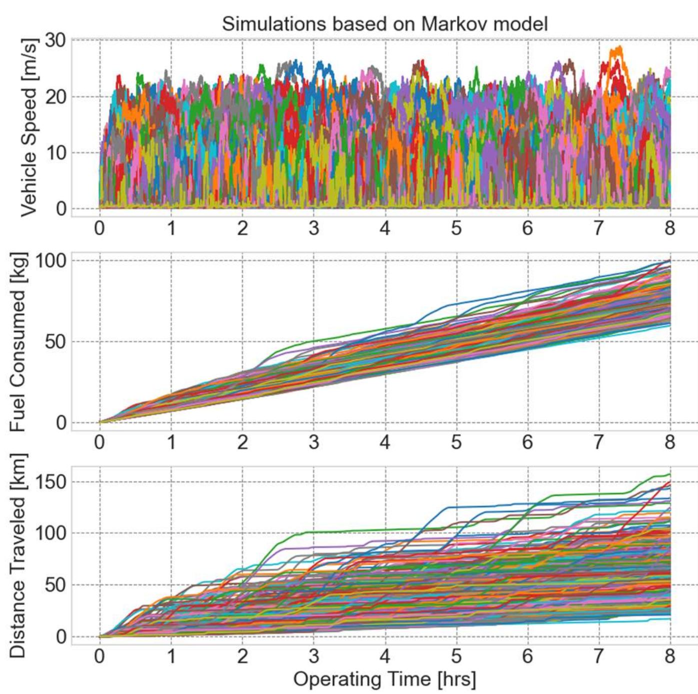

Figure 24 - Vehicle speed, fuel consumed, & distance traveled vs. time for 1000 simulations

The results obtained from this procedure allowed for a comprehensive analysis of the relationship between fuel consumption and distance traveled. One parameter was found to consistently predict distance traveled for a given fuel mass: average speed. The relationship between these three parameters is shown in Figure 25. Distance traveled was found to be linearly dependent on fuel mass and non-linearly dependent on average speed, as shown in equation 21 below and in the top left in Figure 25.

$$\text{distance traveled} = m_{fuel}\,(c_1\, v^{C_2} + c_3\, v) \qquad (21)$$

This equation contains three calibration parameters, c_1, c_2, and c_3, with m_{fuel} being the fuel mass and v being the average vehicle speed across the timeframe that a given fuel mass was consumed.

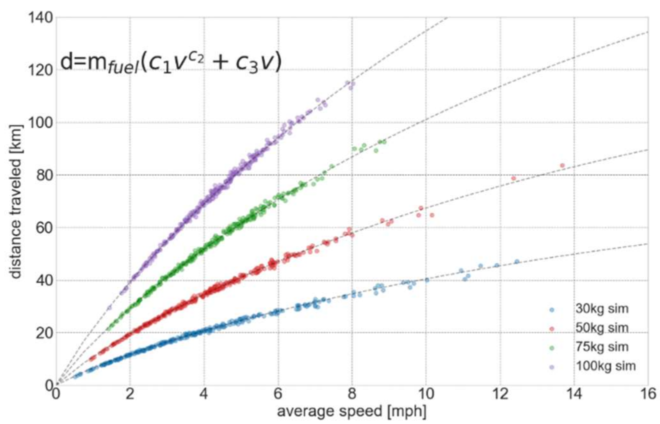

Figure 25 – Relationship of fuel mass, average speed and distance traveled from simulations

Figure 25 shows distance traveled as a function of average speed for 30kg, 50kg, 75kg and 100kg of natural gas. The analysis confirms that distance traveled versus average speed increases non-linearly as the average speed is increased. This is the mathematical result of the speed measured with time in the denominator and the fuel consumption being measured with fuel consumed in the denominator. This creates an inverse relationship with the fuel economy approaching the maximum value as the average speed increases. Eventually, this value will reach a maximum and start declining as powertrain losses and drag at high speeds negatively impact fuel economy. However, this is not relevant at the speeds shown on this plot.

A comparison of simulated and real data is presented in Figure 26. It shows the data presented in Figure 25 in a slightly different fashion, with the ordinate illustrating the distance traveled normalized by fuel mass. In addition to normalizing the distance traveled by fuel mass, the natural gas mass was converted to diesel gallon equivalent (DGE) which allows plotting fuel economy on the ordinate. The abscissa reflects average velocity. A difference between simulation and experimental data was found in the sense that the dispersion around the dashed line is more significant for the experimental results compared to the simulated data, and this trend becomes even more pronounced as the average speed increases. This can most likely be attributed to the fact that different speed traces can result in the same average speed, with the differences in operating efficiency not being accounted for. The probability of the Markov model sampling from the higher or lower end of the speed spectrum for a longer period is unlikely and thus the results remain close to the average, the dashed line.

The GTI/Argonne team used the relationship between average speed, fuel mass, and distance traveled to implement the distance-to-empty (DTE) prediction algorithm. Deviations from the dashed lines in Figure 26 (i.e., deviations from Equation 21) were addressed by displaying a range of DTE rather than a single value. The range of DTE was then adjusted based on actual fuel economy values computed as a function of recent driving conditions. Examples of how the DTE predictions were determined are provided in the next section.

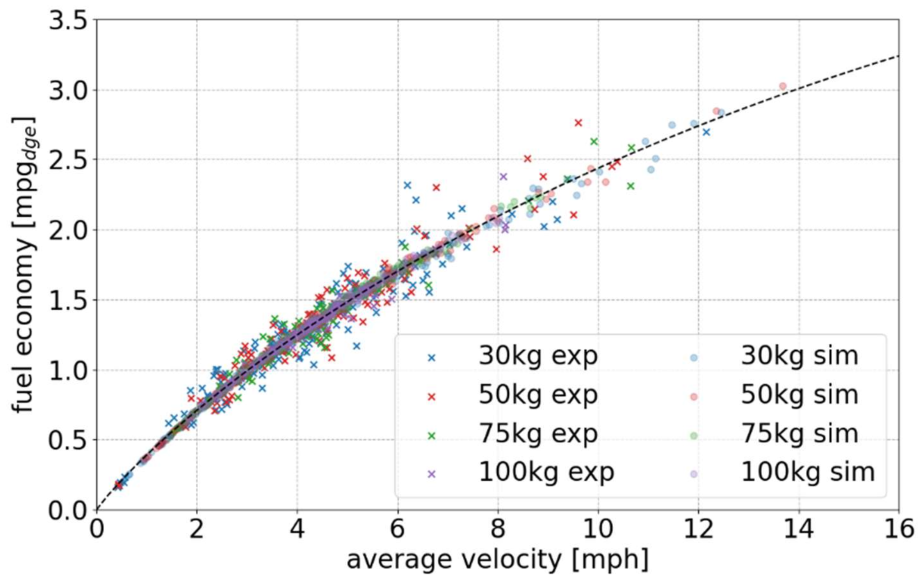

Figure 26 - Relationship between average speed and distance traveled from results in Figure 25 Experimental data are illustrated by the x markers

d. Predicting fuel consumption rate from average vehicle speed

The distance a vehicle travels during its workday is the determining factor in calculating average speed, but this includes time spent in traffic and time spent idling. Figure 27 displays the distance traveled per day (typically eight hours of operation) for four trucks from both urban and suburban areas, with the bars representing the density of days ending in each bin, with a bin-width of 10km each. The continuous trace represents the cumulative distribution function on the right. Truck 1416 shows the shortest distances traveled (attributable to its urban location) while truck 1825 covered a median distance more than 2.5 times as much as truck 1416 due to its operation in more rural and suburban areas. On average, truck 1416 covered around 55km/day and truck 1825 around 145km/day. The distances traveled by trucks 1331 and 1332, which both operated in the same

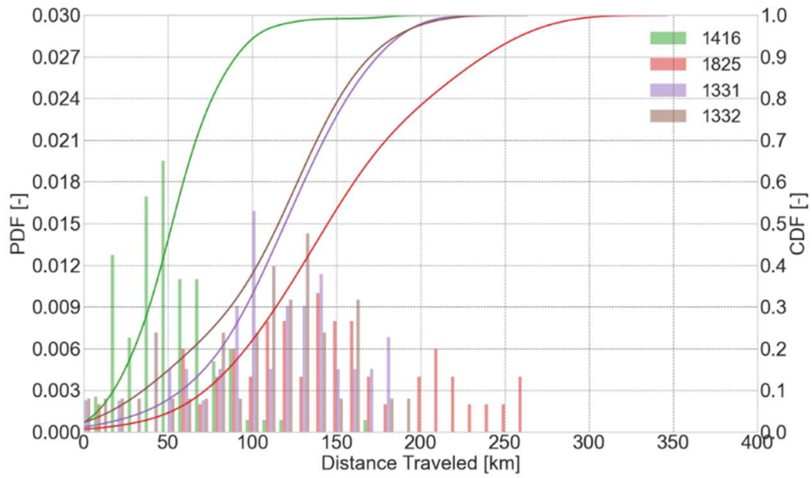

Figure 27 – PDF and CDF across distance traveled for trucks 1416, 1825, 1331, and 1332
PDF - Probability density function; CDF - Cumulative density function
Truck 1416 - Chinatown; Truck 1825 – Mokena; Trucks 1331 and 1332 - Des Plaines

suburban area, are between those for trucks 1416 and 1825, at 120km/day and 115km/day respectively.

The influence of these different distances driven by these four trucks, and the effect on fuel consumption, is shown in Figure 28. Operating a vehicle over longer distances (and at higher average speeds) is associated with better fuel economy. Improved fuel economy at higher engine

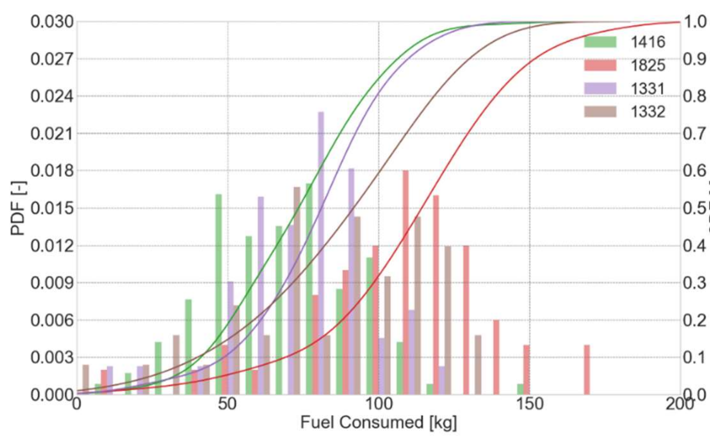

Figure 28 - PDF and CDF of fuel consumed for trucks 1416, 1825, 1331, and 1332
PDF - Probability density function; CDF - Cumulative density function
Truck 1416 - Chinatown; Truck 1825 – Mokena; Trucks 1331 and 1332 - Des Plaines

load conditions is indirectly shown in Figure 28, as the median fuel consumption for truck 1825 is only about 1.6 times higher than truck 1416 (~114kg versus ~70kg) although it travels typically more than 2.6 times as far. While trucks 1331 and 1332 operated in the same area and covered almost the same distance on average, Figure 28 shows that truck 1331 operated more efficiently than truck 1332, with an average daily fuel consumption of 81kg versus 91kg.

The results presented in Figure 29 show fuel economy for these four trucks in diesel gallon equivalent (mpgdge) versus average truck speed, with each marker representing a given day. The trend in Figure 29 clearly indicates that higher average speeds also resulted in higher mpgdge values and thus higher fuel economy. The highest average speeds were found for truck 1825 at just below 20mph, resulting in mpgdge of 3-3.5, while average speeds of around 4.1mph for truck 1416 resulted in fuel economies of only around 1.4 mpgdge. The trend of fuel consumption over average speed also shows that the relation starts to top out as the average speed increases. The average speed of any truck could be affected by driving conditions (urban/suburban/rural) and by idling time at a job site (more idling produces a lower average speed). Fuel consumption rate can be affected by engine load, vehicle speed, and driver performance. These factors combine to produce the variability in fuel consumption shown in Figure 29. The figure shows that if we know average speed we can predict fuel consumption within certain bounds. The more information available on the future route, driving conditions, and duty cycle of the vehicle the more accurate will be the estimate of average vehicle speed.

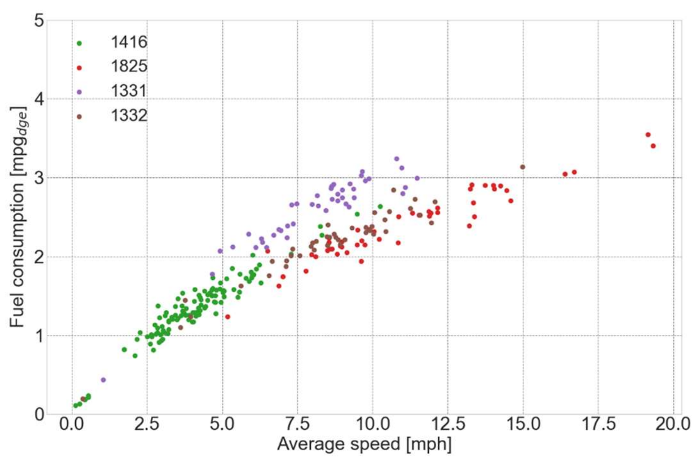

Figure 29 - Fuel consumption in diesel gallon equivalent (mpgdge) versus average speed for 1416 (Chinatown) and 1825 (Mokena) as well as 1331 and 1332 (Des Plaines)

e. Implementation of the Distance-to-Empty estimation algorithm

To test our ability to predict DTE we collected data on actual distances traveled by the trucks and compared that with the distances predicted by the algorithm. Figure 30 exhibits the upper and lower limit of the estimated DTE in blue as well as the mean value in red across one single day for truck #1416. The colored traces (blue and red) in Figure 30 are the filtered traces of the actual estimated values (gray). The spikes in the estimated distance to empty values stem from a bad connection of one of the two available temperature sensors in the tank, which directly influences the estimation of the tank mass and DTE. The Android application was initialized with average historic values for VM_{ng}/R_{ng}, reflecting the tank size and gas property estimate, as well as for fuel efficiency and the standard deviation thereof. Having VM_{ng}/R_{ng} available allows an estimate of the natural gas mass in the tank. Utilizing this with the fuel efficiency and the standard deviation allows calculation of the mean DTE estimate and the upper and lower limit of DTE, reflecting a 2σ (or 95%) confidence interval. The Android application was initialized with the average value of the last 10 days for the parameters mentioned. New estimated values at the end of the day were saved locally on the phone and affected the average parameter values the next time the application was initialized.

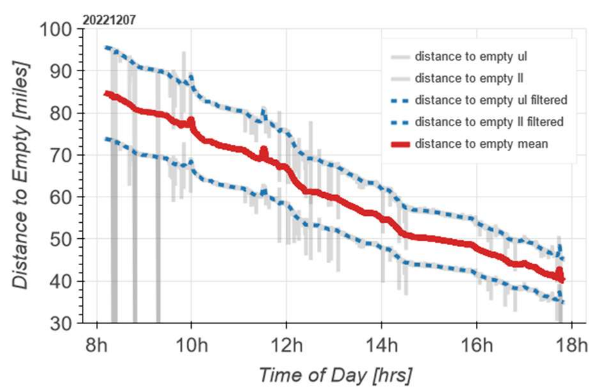

Figure 30 - Distance to empty estimates across one single day
Blue traces reflect the upper and lower estimates (2σ confidence interval). Red trace shows the mean value.

Figure 31 compares the predicted DTE and the actual traveled distance across a single day. The initial mean DTE estimate at the beginning of the day (initial value of the red trace in Figure 31) was set as the reference and the remaining mean DTE value was subtracted from that across the day. The actual distance covered as a function of time is shown in black. The blue traces show the upper and lower limit of distance to empty (2σ confidence interval) with the red line reflecting the mean value.

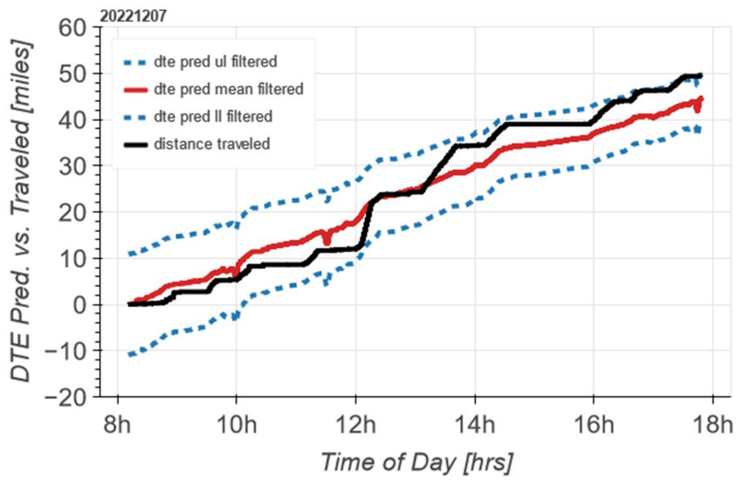

Figure 31 - Comparison of predicted distance to empty and traveled distance

For this given day, the distance traveled was close to the lower limit of the DTE estimate in the morning and changed course around noon to approach the upper limit. The reason for this behavior is based on the duty cycle for this specific day. The truck covered little distance in the morning with significant idling times (horizontal sections in black trace). While significant idling periods can also be seen in the afternoon, the truck spent a substantial amount of time at higher speeds, in this case on the highway, with the engine operating under more efficient conditions than one would encounter in stop-and-go traffic. At the end of the day around 6pm the accumulated distance traveled was close to the upper limit of the estimated DTE.

To evaluate further the accuracy of the algorithm, Figure 32 compares the predicted ranges with the actual distance driven for two select trucks, 1332 and 1590. The algorithm calculates the mean distance-to-empty and the upper and lower bounds, which are based on computed standard deviations of the vehicle efficiency over the past 10 operating days. All values in Figure 32 are displayed with respect to their initial value at the beginning of the day, starting at zero. For

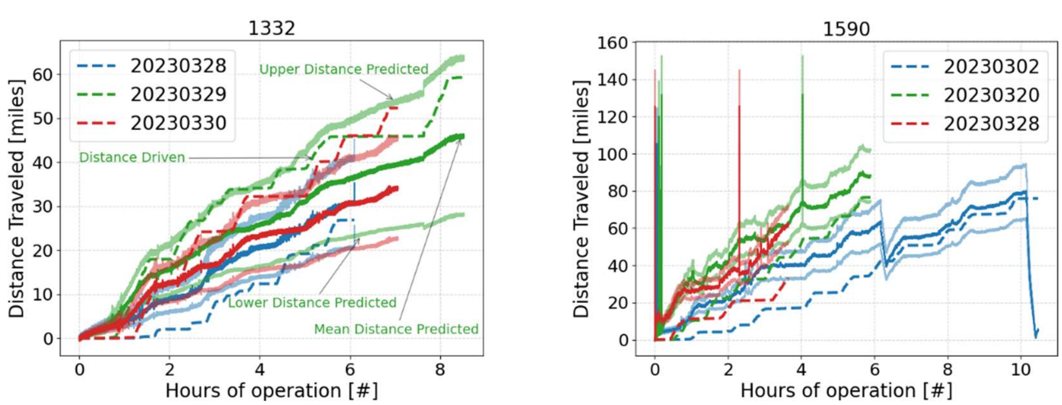

Figure 32 - Estimated and actual distances driven vs. hours of operation; trucks 1332 and 1590

additional context, Figure 32 presents the distance-to-empty prediction interface showing the upper and lower bounds as well as the mean distance-to-empty estimates.

In Figure 32, the dashed lines represent the actual distance driven as obtained from the vehicle's CAN bus. The dark-colored noisy signal indicates the mean distance-to-empty predicted by the algorithm, while the light-colored region represents the upper and lower boundaries of the 2σ confidence interval. For instance, on March 28 (20230328), after about 6 hours of operation, truck 1332 traveled 27 miles, which is slightly below the mean predicted distance of 30 miles represented by the noisy blue line. However, on 20230329, after more than 8 hours of operation, the truck traveled about 59.5 miles, while the mean predicted distance was only 46 miles. This indicates that the truck operated more efficiently than usual that day, with the actual distance driven staying close to the upper distance predicted for the entire day. On 20230330, the truck operated even more efficiently, with the actual distance driven after 7 hours being above the upper bound of the predicted distance.

The right plot of Figure 32 shows the results for truck 1590, which was equipped with only one fuel tank, unlike the other trucks which have two. As a result, there are refueling events during the day, as shown for 20230302 at around 6 hours of operation. However, the application did not detect these events properly and thus overestimated the tank size. While the application does estimate that the tank is smaller than that of the other trucks, as shown in Figure 33, VM_{ng}/R_{ng} should be about 50% compared to the other trucks. This discrepancy leads to the algorithm estimating longer DTE ranges than is actually feasible, as seen in the distance driven on 20230302 at around 6 hours and 20230328 after 3.5 hours of operation. The spikes shown for truck 1590 are associated with application resets that occurred when transmission to the WiFi streamer was lost.

The data in Figure 33 is repeated from Figure 18 and shows the algorithm learns and improves the value for VM_{ng}/R_{ng} over time. Trucks 1331, 1332, 1415 and 1590 started at a similar value for VM_{ng}/R_{ng} of 0.001975 at the beginning of the month. This value was found to be accurate for most two-tank systems. The DTE gauge on 1415 was installed previously and had updated the tank and natural gas properties slightly from the initial value of 0.001975. The values shown appear to trend

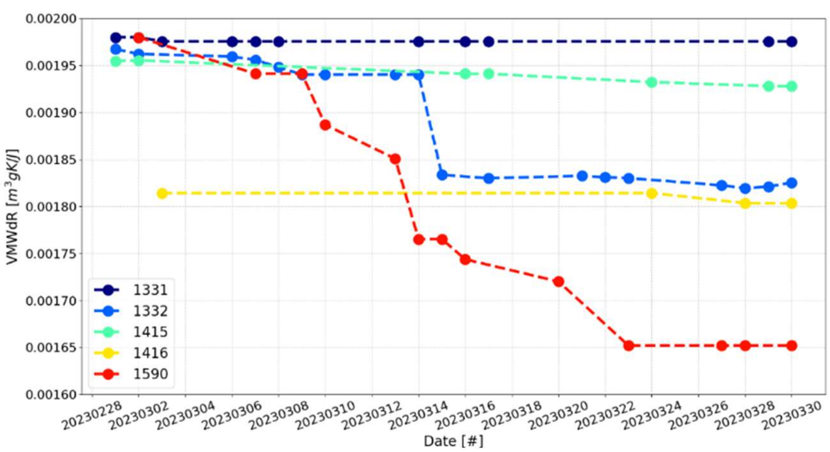

Figure 33 - Variation of VMWdR over time for trucks equipped with DTE prediction interface

to the average value of 0.001949. Truck 1416 started at a lower value of 0.00182, which remained constant across the data shown for the month of March 2023. The application stored the estimated values over the previous 10 days and calculated the average for a given day. Figure 33 shows how the App improves the value for VM_{ng}/R_{ng} as usage data is accumulated and can even adjust the value to account for trucks that have different numbers and sizes of tanks.

The Android application utilizes an algorithm that predicts the range of distances a vehicle can travel based on the estimated tank mass and vehicle efficiency. To confirm the accuracy of the algorithm, Figure 34 compares the predicted ranges with the actual distance driven for the two selected trucks, 1415 and 1590. The algorithm calculates the mean distance-to-empty and the upper and lower bounds, which are based on computed standard deviations of the vehicle efficiency over the past 10 operating days. All predicted distances (upper limit, mean and lower limit) in Figure 34 are displayed with respect to their initial value at the beginning of the day.

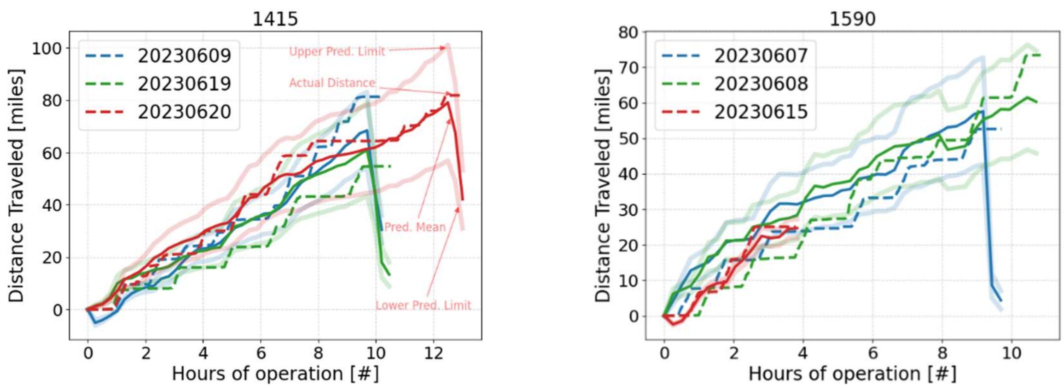

Figure 34 - Estimated and actual distances driven vs. hours of operation; trucks 1415 and 1590

In Figure 34, the dashed lines represent the actual distance driven, obtained from the vehicles' CAN buses. The light-colored traces indicate the upper and lower boundaries of the 2σ confidence interval, while the continuous line reflects the predicted distance with respect to the predicted distance shown at the beginning of the day when the truck was first started up. For truck 1415, it is shown that the predicted mean distance (solid line) and the actual distance driven (dashed line) show good agreement most of the time. The algorithm had estimated the correct tank mass and gas properties for truck 1415. Looking at the right graph for truck 1590, the data from June 7th and 8th suggest there is a significant difference between the predicted mean distance (solid line) and the actual driven distance (dashed line), especially within the first few hours of operation. This was attributed to the fact the initial tank properties were set for two-tanks while 1590 has a single tank.

However, by June 15th, the underlying values utilized for the distance to empty estimation are closer to the true values, compared to the beginning of the month, and thus June 15th shows better agreement between prediction and actual distance. Of note are the dips below zero that can occur within the first hour of operation. This can be attributed to changes in temperature and pressure in the tank right after start-up that led to slightly more estimated tank mass than when the engine was first started up, leading to a slightly higher DTE prediction.

f. Benefit of P/T measurements

This section provides a comparative analysis between tank mass estimates derived solely from pressure readings versus those obtained from both pressure and temperature. In the absence of the phone-based gauge, that estimates the distance to empty, drivers default to using an analog pressure gauge to approximate the remaining fuel in the tank. This traditional method fails to consider the temperature's impact on the gas mass within the tank. The effect of temperature on the actual tank mass, when combined with pressure readings, is shown in Figure 35.

The initial pressure reading was calibrated to correspond with the fuel mass at the start of each day. This alignment was determined by the estimation algorithm of the phone-based gauge. The graph highlights two traces: the orange trace represents the method based purely on pressure, while the blue trace shows the tank mass estimated using both pressure and temperature. Relying solely on pressure to ascertain mass presents challenges. Its accuracy is notably dependent on the tank's internal temperature, being accurate only in the rare event that the tank temperature remains

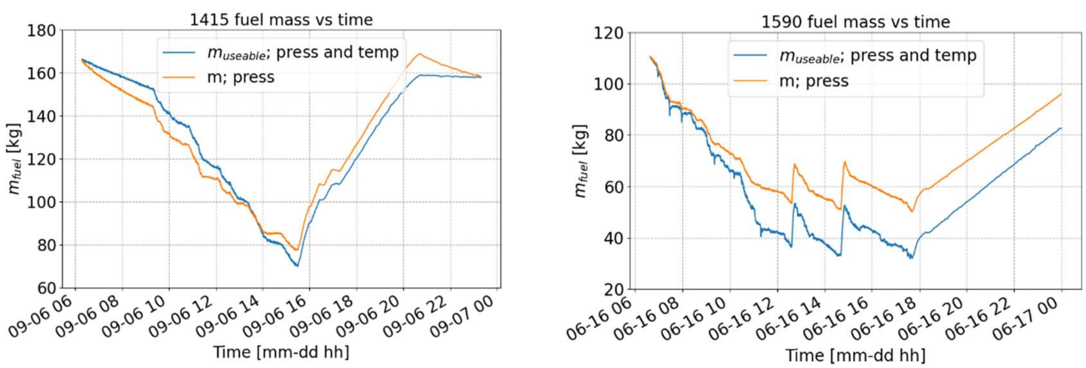

Figure 35 - Comparison of fuel mass with and without accounting for the effect of temperature

constant—a rare occurrence. Consequently, this approach often yields discrepancies, with potential errors reaching up to 20kg (44lbs) in the NG fuel mass measurement.

IX. Implementation of DTE Algorithm

a. Methods to display DTE results

GTI and ANL staff had discussions about how to display the remaining range information and whether to use the phones installed in the trucks or an independent gauge to be added later. The team decided to build and implement a new phone case that would provide the driver access to only the processed information needed (e.g., DTE predictions), restrict the driver's access to the phone, and provide needed supplementary cooling of the phone.

After deciding to use the existing phones as displays rather than a separate gauge, this effort focused on designing and fabricating a case that can be mounted on the dashboard for easy viewing and enhanced cooling while still restricting driver access to the phone. Google Pixel 4a and Pixel 4XL phones were used to process data and track the vehicle and multiple vehicle-specific parameters, such as natural gas consumed, as a function of time.

As discussed in Section VII.c, augmented cooling had to be implemented within the case to maintain a lower temperature. Included with the case is a Peltier cooler that contains two semiconductive materials that transfer electrical current between two plates. It creates a temperature gradient between those plates and transfers heat away from the phone. After a meeting with the managers at Ozinga Brothers, it was decided that the front cover would be made a part of the phone case, with a cutout at the bottom showing the distance-to-empty gauge, so that the driver cannot remove or utilize the phone. The redesigned phone case is shown in Figure 36.

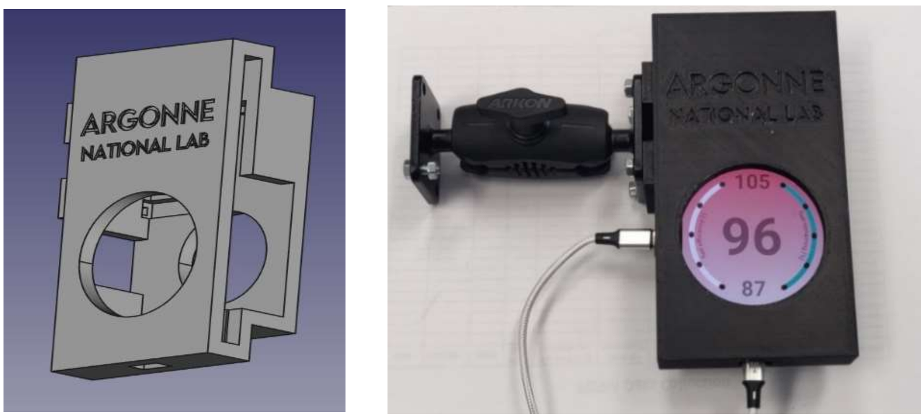

Figure 36 - Virtual mockup of the phone case created in FreeCad (left).
3D printed phone case and phone displaying the fuel gauge (right).
USB connections supply power to the phone and an integrated fan.

Making an accurate prediction of DTE is made difficult by the varying amount of time the trucks idle during their operation. It was noted that many DTE predictions suffer from poor accuracy, particularly when driving conditions have large effects on the expected range, as is the case in many electric and hybrid vehicles. Using the range prediction displays in those vehicles as a reference, we decided to display the DTE with upper and lower range estimates as well as the average estimate. This additional information would allow the driver to relate the expected operating conditions that day to the range predictions. We expect the distance between the upper and lower bounds to be greater in duty cycles that include large amounts of idling. Duty cycles that involve more continuous movement will result in a narrower band of range prediction.

The range of distance-to-empty can be adjusted based on actual fuel economy computed as a function of recent driving conditions. The values displayed on the fuel gauge (right picture in Figure 37) represent distance-to-empty values based on different driving scenarios. As the truck is being driven, the Android app keeps track of fuel consumed and distance covered. This information is used to calculate the covariance in fuel efficiency.

The DTE range is demonstrated in Figure 37. The values displayed on the fuel gauge represent DTE values based on different driving scenarios. The app keeps track of fuel consumed and distance covered, and this information is used to calculate the covariance in fuel efficiency. Multiplying the remaining fuel mass by the average fuel efficiency per distance traveled results in the bold number in the middle, 156. The top number, 215, illustrates a driving scenario with the fuel efficiency is one standard deviation above the mean, while the number at the bottom, 98, reflects a driving scenario with fuel efficiency one standard deviation below the historic mean. The indicator on the left side illustrates vehicle efficiency while the indicator on the right shows tank mass. The algorithm adjusts to parameter changes that occur, such as changes in gas properties, driving behavior, or duty cycle.

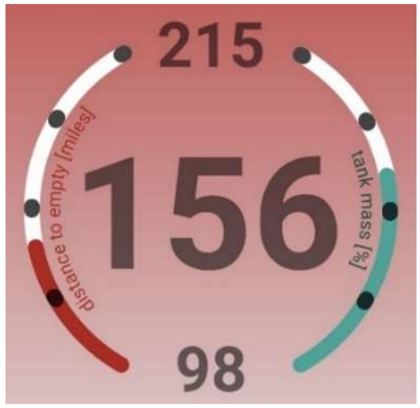

Figure 37 - Distance to empty interface showing upper, mean, and lower values

The entire assembly, consisting of a Google Pixel 4a phone, phone case, and a fan (shown on the left in Figure 38) were installed in 12 trucks, as illustrated in the photo on the right in Figure 38.

Figure 38 - Position of Fuel Gauge in vehicle

b. Impact on Driver Behavior

The final Study in this project was to be an assessment of the impact of the fuel gauge on driver behavior to see if the enhanced information changed the frequency of refueling stops. Unfortunately, the team underestimated the experience the drivers had with their vehicles. They widely reported that refueling of the vehicles was required when the fuel system pressure reached 1500psig. The reasoning for this was based on engine stalls that had occurred when fuel systems were drained to lower pressures. Manufacturers stand by engines being able to operate with fuel systems as low as 500psig. This discrepancy is an opportunity for improvement in NGV operations but is outside the scope of this project. Because of these challenges, this project was unable to quantify changes in driver behavior due to the implementation of the Driver Information System.

X. Commercialization/Technology Transfer Efforts

GTI conducted several activities to communicate the results of this work and to expand awareness within the industry regarding the potential for more accurate DTE predictions as described below.

a. Presentation at Green Drives Conference

GTI made a presentation at the annual Green Drives Conference and Expo on May 9, 2024. Green Drives is one of the largest clean-transportation conferences held in the Midwest. It is sponsored by the Illinois Alliance for Clean Transportation and is attended by government officials, commercial and municipal fleet managers, corporate sustainability officers, and clean-tech and clean-energy professionals who want to learn how to use cleaner, lower emissions fuels and technologies while saving money. Advanced vehicle technologies, electric vehicles, and alternative fuels were showcased, including dozens of green vehicles and exhibitors. Attendees not only had a chance to network with experts from throughout the nation and the region, but they learned of first-hand experiences from fleets currently using alternative fuels and electric vehicles. GTI's presentation on the next generation Driver Information System and related work was well received. Many fleet owners confirmed the need for an improved gauge and expressed interest in our results. Ultimately, however, they want a product they can test on their own vehicles.

b. Discussion/issues with Digital Fleet/Cummins/Momentum

Ozinga expressed interest in integrating the DTE and fuel efficiency information into their fleet dispatch software (Digital Fleet), which is used by Ozinga as well as other ready-mix concrete and construction material vehicles. Integration into the Digital Fleet system would allow the dispatcher to select dispatch routes to optimize the remaining fuel of the trucks as well as monitoring fuel status and fuel efficiency of all vehicles. This would give the dispatcher a way to assess a driver's performance with respect to driving efficiency and unnecessary idling. However, discussions with the providers of the Digital Fleet software ended when ANL filed for a copyright on the DTE prediction software. Digital Fleet did not want to keep track of ANL's code amidst their own proprietary code. This was a learning experience for GTI and ANL regarding integration of our code into commercial software.

c. NGV America Annual Meeting and future efforts

GTI prepared a 2-page flyer summarizing the results of this project and distributed these flyers at the annual meeting of NGVA. GTI also secured a project with the Utilization Technology Development program sponsored by members of the US gas industry. This project will focus on the transfer and commercialization of the results of this project and the parallel smart dispenser project. The value proposition of this technology increases significantly when combined with the Smart Station sister project, also funded under this same FOA. When that project concludes at the end of 2024, there will be more interest from fleets and equipment vendors in this technology.

XI. Conclusions/ Impact - Performance vs Objectives

GTI and ANL developed methods to measure remaining fuel mass more accurately by using both temperature and pressure measurements on NGVs and used this information to make DTE predictions and tested them against real-world data in a wide range of duty cycles. GTI and ANL developed and installed DTE models and data acquisition systems and tested them on twelve trucks to determine whether a simple, cost-effective system can provide NGV drivers with the information they need to calculate fuel economy, estimate remaining fuel on board, estimate DTE, and overcome range anxiety.

We confirmed that more accurate estimations of usable remaining fuel and miles-to-empty for NGVs are possible if well-defined information about CNG pressure and temperature is known and combined with information about upcoming vehicle use (route, speed, stops, etc.). The project produced prototype hardware and software that underwent testing in the field. These included algorithms for calculating the amount of natural gas remaining in the tank at any time and for calculating the distance the vehicle can travel with that amount of gas before it is empty. It also produced a design and hardware for a fuel gauge that can be mounted in a truck to display the amount of fuel remaining and high and low DTE estimates. These items are not ready for commercial use, but they represent initial, experimental products developed under the project. The following conclusions were derived from this work.

- DTE can be predicted accurately from remaining fuel mass and knowledge of the future route and driving conditions.
- Estimating the average vehicle speed is effective because it captures virtually all aspects of the vehicle's duty cycle, including traffic issues and idling.
- Calculating the remaining fuel mass from both temperature (T) and pressure (P) measurements improves the accuracy of this estimate by as much as 20%.
- Vehicle fuel economy can be calculated in real time and shared with both the driver of the vehicle and the fleet dispatcher.
- The HEM data loggers could be made to interface with the existing CAN bus systems but were not sufficiently reliable for long-term operation and would need improvements or upgrades to be used in a driver information system.
- A DTE prediction app and phone-based fuel gauge system were demonstrated that could provide a useful range of DTE values, but driver acceptance could be improved by incorporating these innovations into the conventional driver information system.
- The new DIS can be used to assess both driver and vehicle performance.
- The DTE app could be integrated into the Digital Fleet software. However, copyright issues prevented demonstration of this on this project.

XII. Recommendations for Future Work

The next step in the development of the Driver Information System (DIS) is the commercialization of the system. For this to occur, the system needs to have two advancements:

1. A component is needed to place a temperature sensor in the end of a CNG vessel opposite the fill valve. This component, likely a modified end plug, must have the Duetsch connection for the temperature sensor as well as a port for connection of the temperature relief device often connected to this opposite end of the tank.

2. The DIS algorithm needs to be housed either in an Electronic Control Unit in the vehicle or in some other device.

For an initial deployment, we have decided to design and fabricate an end plug that has temperature measurement and relief capabilities. We currently have an initial design and are finalizing details for the electrical pass-through and temperature sensor.

List of Acronyms

Acronym	Description
ALA	American Lung Association
ANL	Argonne National Laboratory
AWS	Amazon Web Services
CACC	Chicago Area Clean Cities
CAN	Controller Area Network
CNG	Compressed Natural Gas
CSI	Campbell Scientific Incorporated
DAS	Data Acquisition System
DGE	Diesel Gallon Equivalent
DIS	Driver Information System
DTE	Distance to Empty
NGV	Natural Gas Vehicle
NGVA	Natural Gas Vehicles America

Appendices

Survey of Truck Fleet Drivers

A subcontract between GTI and the Chicago Area Clean Cities Coalition (CACC) was executed in 2021, which kicked-off of their survey activities. CACC outsourced a portion of their scope to the American Lung Association (ALA), which has considerable experience in working with truck fleets on health and operation issues. In partnership with GTI, Chicago Area Clean Cities (CACC) conducted a survey with NGV fleets/fleet drivers about fueling behaviors and concerns around fueling and predicted range. This survey was created using Microsoft Forms and distributed using an emailed link to the Form. Initial emails were sent on March 7th, 2022, a first reminder to take the survey was sent on March 16th, 2022, and final reminder was sent on March 28th, 2022. Emails were sent to 22 contacts representing 16 organizations.

There were 37 questions on the survey with three sections: Vehicle and Fleet Information (14 questions), CNG Fueling/Filling Questions (14 questions), and Fuel-gauge Questions (9 questions). There were 20 short answer and 17 multiple choice questions. There were ten responses to the survey, and it took an average of 22 minutes and 37 seconds to complete. The number of natural gas vehicles (NGV) that a responding fleet operates ranged from 2 to 190 vehicles. The domicile state(s) for fleet operation of respondents was primarily Illinois (7 out of 10) and the others included California, Colorado, Idaho, New York, Ohio, Utah, and Washington. The states that fleets operate in were primarily in the Midwest including Illinois (9), Wisconsin (5), Indiana (5), Michigan (4) but also included all answers indicating operation across the entire United States.

Vehicle classes 1 through 8 were represented in the survey results. Five respondents stated having multiple class types in their fleets. Seven of the fleets answered “no” to “Do your vehicles include substantial power take-off systems?”. The power take-off systems mentioned for those that answered “yes” include refuse bodies and ready mix trucks. Respondents were split on “Do your vehicles spend a substantial portion (>20%) of their operation time idling?” with five answering “Yes” and five answering “No”.

There was a lot of variety in the answers to how the vehicle CNG fuel systems are sized. Some noted that their fleets had all the same capacity for the fuel systems or that there are no options for sizing them differently. Some fleets mentioned that they sized based on their daily fuel usage needs. Fuel storage for the fleet vehicles ranged from 8-gallon gasoline equivalent (GGE) to 245 GGE. The highest external temperatures at which the vehicles operate ranged from 90 to 120 degrees Fahrenheit with most fleets answering that they operate in over 100 degrees Fahrenheit. The lowest external temperatures ranged from -35 to 10 degrees Fahrenheit. Eight of the ten respondents use dedicated CNG and two use Bi-fuel.

Most respondents (7) refuel their vehicles daily, with one filling multiple times a day, and two filling every few days. Seven of the ten respondents use pressure to determine if the tank is full, with two using the fuel system percent full reading and one using the “Blue IQ system read-out and pressure gauge”. Five of the respondents chose “Often” for how often they are able to get a full tank fill, one chose “Never”, two chose “Sometimes”, and two chose “Always”. Eight of the respondents chose that there is “Some variation” in their experience with an ability to get a full take and two choosing “No variation between fill ups”. According to most respondents, weather conditions impact the fueling level of their vehicles. Three respondents noted that they find that in colder temperatures there is less fuel per fill-up due to lower pressure and one respondent felt that colder weather has a better fill. One respondent noted that there is some impact on fueling with a more noticeable impact seen on the vehicle fuel economy. Eight of the respondents said that there is no difference in performance based on where they fuel their vehicles.

There was a range of answers for how close to empty the fleets were willing to drive with CNG. Specific PSI answers ranged from 500 to 1,500. Two answers mentioned that because their vehicles run on bi-fuel they are not concerned with running out of CNG fuel to use or they purposefully run out of CNG so that the additional fuel is used and does not go “stale”. There were not many comments addressing weather, but one fleet did mention that drivers are less likely to run close to empty when it is cold outside. Multiple fleets mentioned “distance to empty” for what additional information would be most useful on the fuel gauge. It was also mentioned that having information from the fuel system displayed in the instrument cluster would be helpful.