Dual-layered Multi-Objective Genetic Algorithms (D-MOGA): A Robust Solution for Modern Engine Development and Calibrations

Pragalath Thiruvengadam Padmavathy

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Dual-layered Multi-Objective Genetic Algorithms (D-MOGA): A Robust Solution for Modern Engine Development and Calibrations

Pragalath Thiruvengadam Padmavathy

Dissertation Submitted
to the Benjamin M. Statler College of Engineering and Mineral Resources
at West Virginia University

in partial fulfillment of the requirements for the degree of

Doctor of Philosophy in
Mechanical Engineering

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Abstract

Dual-layered Multi-Objective Genetic Algorithms (D-MOGA):
A Robust Solution for Modern Engine Development and Calibrations

Pragalath Thiruvengadam Padmavathy

Heavy-duty (HD) diesel engines are the primary propulsion systems used within the freight transportation sector and are subjected to stringent emissions regulations. The primary objective of this study is to develop a robust calibration technique for HD engine optimization in order to meet current and future regulated emissions standards during certification cycles and vocational activities such as drayage operations. Recently, California - Air Resources Board (C-ARB) has also shown interests in controlling off-certification cycle emissions from vehicles operating in the state of California by funding projects such as the Ultra-Low NOx study by Sharp et. al [1]. Moreover, there is a major push for the complex real-world driving emissions testing protocol as the confirmatory and certification testing procedure in Europe and Asia through the United Nations - Economic Commission for Europe (UN-ECE) and International Organization for Standardization (ISO). This calls for more advanced and innovative approaches to optimize engine operation to meet the regulated certification levels.

A robust engine calibration technique was developed using dual-layered multi-objective genetic algorithms (D-MOGA) to determine necessary engine control parameter settings. The study focused on reducing fuel consumption and lowering oxides of nitrogen (NOx) emissions, while simultaneously increasing exhaust temperatures for thermal management of exhaust after-treatment system. The study also focused on using D-MOGA to develop a calibration routine that simultaneously calibrates engine control parameters for transient certification cycles and vocational drayage operation. Several objective functions and alternate selection techniques for D-MOGA were analyzed to improve the optimality of the D-MOGA results.

The Low-NOx calibration for the Federal Test Procedure (FTP) which was obtained using the simple desirability approach was validated in the engine dynamometer test cell over the FTP and near-dock test cycles. In addition, the 2010 emissions compliant calibration was baselined for performance and emissions over the FTP and custom developed low-load Near-Dock engine dynamometer test cycles. Performance and emissions of the baseline calibrations showed a 63%
increase in engine-out brake-specific NO\textsubscript{x} emissions and a proportionate 77\% decrease in engine-out soot emissions over the Near-Dock cycle as compared to the FTP cycle. Engine dynamometer validation results of the Low-NO\textsubscript{x} FTP cycle calibration developed using D-MOGA, showed a 17\% increase brake-specific NO\textsubscript{x} emissions over the FTP cycle, compared to the baseline calibrations. However, a 50\% decrease in engine-out soot emissions and substantial increase in exhaust temperature were observed with no penalties on fuel consumption.

The tools developed in this study can play a role in meeting current and future regulations as well as bridging the gap between emissions during certification and real-world engine operations and eventually could play a vital role in meeting the National Ambient Air Quality Standards (NAAQS) in areas such as the port of Los Angeles, California in the South Coast Air Basin.
Acknowledgements

“The more I learn, the more I realize how much I don’t know”

-Albert Einstein

These words have resonated with me throughout my PhD program. Although I don’t quite comprehend what it means to have a doctorate degree at this moment, I have realized what Albert Einstein meant. He means that one does not cease to learn.

First and foremost, I would like to thank Amma, DaDa and Arvi for their love, compassion and endless support. Neither words nor actions can describe how I truly feel. You three have believed in me as a child, even when I myself had my doubts. My dyslexia made it difficult for me to get through school and I’m sure it was especially difficult on my family as well. They past the baton of responsibility from one to the other, starting with Amma followed by Dada and then finally to Arvi. I thank you for this from the bottom of my heart, it’s my turn now...

I sincerely thank Dr. Mridul Gautam for being a wonderful advisor. He was there when I truly needed his advice, whether it was regarding work or life. Mridul, I will always have the utmost gratitude for giving me the opportunity to work with CAFEE. Joining CAFEE was the best thing that has ever happened to me up until now. Dan Carder, you have always watched over me and supported me, I thank you for that. Working with you and your elite group of individual has been an eventful and memorable experience, but like all good things it has come to an end. I must thank Chris and Jason who taught me everything about being hands-on. Chris, WMATA is and I’m sure will always be the best and the worst test campaign I have been involved. I would also like to thank Brad, Richard and Zac without whom this study wouldn’t have simply been an untested concept.

Like all research groups, there are sub-groups of people who prefer to work together, CAFEE is no exception. ODB group is what it later turned out to be called, I still wonder why. Saroj, Berk, Marc and Arvind it has been a pleasure working with you guys. It was a lot of fun whether it was engine testing at ERC or Chassis work at Sacramento. It was always work hard
and play with you guys. Berk you need to calm down man, all is well. Marc I thank you for guiding me from the day I joined WVU as a graduate student. Arvind and you thought me everything I know about emissions, engines, and this black magic called PM.

I must thank my committee members, Dr Perhischi, Dr. Ryskamp and Dr. Besch who have been an integral part of this research work, as well as Dr. Nix, Dr. Wilhelm and Dr. Cozzolini for their time and effort in vetting this document.

I have been blessed with a family away from home whom I have known for almost 6 years now but it seems like we met only yesterday. Greg, Anna, Peter, Marc, Sukanya and saving the best to the last ‘the wolf pack’. You guys have been and will continue to be part of my family, and I thank you for all your support, motivation and inspiration. I was able to get through the last two years of my PhD only thanks you to all of you guys. I would like especially thank the wolf pack for being there when I was lost, not sure how things would have turned out if you guys weren’t there. Peter, thanks to you I have a second hobby of travelling now. I look forward to more exciting trips like the Nepal, Switzerland and India, perhaps South America?

Thank you very much to my longtime friends Diya, Nandini, Preetham, Sharanya, Zee, Manasvinee, Lakshmi, Vikram, and of course the one who always manages to stand out in the group, Gops. I would also like to thank Wicky, Vaidy, Vaishnav and Syed. I would also like to thank Babu and Balu for their endless compassion they have shown towards me and my family. I always look forward to having intellectual discussions with you guys. I would also like thank my friends from Cummins namely Mike, Chet, Sam, Avinash, Abhishek and Bala. Last but not the least, I would like thank RKS sir for inspiring me throughout my undergraduate program.
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<tr>
<td>ADECS</td>
<td>Advanced Diesel Emissions Control System</td>
</tr>
<tr>
<td>A-TEAM</td>
<td>After-Treatment Exhaust Availability Model</td>
</tr>
<tr>
<td>AI</td>
<td>Artificial Intelligence</td>
</tr>
<tr>
<td>ANN</td>
<td>Artificial Neural Networks</td>
</tr>
<tr>
<td>Patm</td>
<td>Atmospheric Pressure</td>
</tr>
<tr>
<td>bar/°CA</td>
<td>bars per degree crank angle</td>
</tr>
<tr>
<td>BDL</td>
<td>Below Detection Limits</td>
</tr>
<tr>
<td>BI</td>
<td>Best Individual</td>
</tr>
<tr>
<td>bhp</td>
<td>brake horse power</td>
</tr>
<tr>
<td>bhp-hr</td>
<td>brake horse power - hour</td>
</tr>
<tr>
<td>bsFC</td>
<td>Brake-Specific Fuel Consumption</td>
</tr>
<tr>
<td>bsNOₓ</td>
<td>Brake-Specific NOₓ Emissions</td>
</tr>
<tr>
<td>bsPM</td>
<td>Brake-Specific PM emission</td>
</tr>
<tr>
<td>bsSoot</td>
<td>Brake-Specific Soot Emissions</td>
</tr>
<tr>
<td>bTDC</td>
<td>before Top Dead Center</td>
</tr>
<tr>
<td>C-ARB</td>
<td>California Air Resources Board</td>
</tr>
<tr>
<td>CO₂</td>
<td>Carbon Di-Oxide</td>
</tr>
<tr>
<td>CO</td>
<td>Carbon Mono-Oxide</td>
</tr>
<tr>
<td>°C</td>
<td>degree Celsius</td>
</tr>
<tr>
<td>DOJ</td>
<td>Department of Justice</td>
</tr>
<tr>
<td>DOT</td>
<td>Department of Transportation</td>
</tr>
<tr>
<td>Escore</td>
<td>Desirability of Exhaust Gas for maintain the after-treatment at 250°C base A-TEAM</td>
</tr>
<tr>
<td>DOC</td>
<td>Diesel Oxidation Catalyst</td>
</tr>
<tr>
<td>DPF</td>
<td>Diesel Particulate Filter</td>
</tr>
<tr>
<td>D-MOGA</td>
<td>Dual-layered Multi Objective Genetic Algorithms</td>
</tr>
<tr>
<td>ECM</td>
<td>Engine Control Module</td>
</tr>
<tr>
<td>ECU</td>
<td>Engine Control Unit</td>
</tr>
<tr>
<td>EEPS</td>
<td>Engine Exhaust Particle Sampler</td>
</tr>
<tr>
<td>ExhT</td>
<td>Engine Out - Exhaust Temperature</td>
</tr>
<tr>
<td>ESC</td>
<td>European Steady-State Cycle</td>
</tr>
<tr>
<td>EGR</td>
<td>Exhaust Gas Recirculation</td>
</tr>
<tr>
<td>FTP</td>
<td>Federal Test Protocol</td>
</tr>
<tr>
<td>ft-lbs</td>
<td>foot pounds (unit of torque)</td>
</tr>
<tr>
<td>FTIR</td>
<td>Fourier Transform Infrared</td>
</tr>
<tr>
<td>FC</td>
<td>Fuel Consumption</td>
</tr>
<tr>
<td>GA</td>
<td>Genetic Algorithms</td>
</tr>
<tr>
<td>g/bhp-he</td>
<td>grams per brake horse power - hour</td>
</tr>
<tr>
<td>g/cc</td>
<td>grams per cubic centimeter</td>
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<td>GHG</td>
<td>Green House Gas</td>
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<td>Q_Loss</td>
<td>Heat Transfer to the control volume</td>
</tr>
<tr>
<td>HD</td>
<td>Heavy-Duty</td>
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HEPA filter
kJ/kg
kPa
LFE
L-MOGA
CH₄
mg/stroke
MOGA
NAAQS
NHTSA
N-m
N₂O
NMHC
NTE
NOP
OEM
NOₓ
PN
PM
ppm
PI
PEMS
RBF
RSM
rpm
SCR
SOI
SET
T, P
THC
TPM
US-EPA
U-MOGA
UDDS
VGT
Wcv

High Efficiency Particulate Air filter
kilo Joules per kilogram
kilo Pascal
Laminar Flow Element
Lower level GA of D-MOGA
Methane
milligrams per power stroke of the piston
Multi-Objective Genetic Algorithms
National Ambient Air Quality Standards
National Highway Traffic Safety Administration
Newton-meter (SI unit of torque)
Nitrous Oxide
Non-Methane Hydrocarbons
Not-to-Exceed
Nozzle Opening Pressure
Original Equipment Manufacturers
Oxides of Nitrogen (excluding Nitrous Oxide)
Particle Number Count
Particulate Matter
parts per million
Performance Index
Portable Emissions Measurement System
Radial basis Function
Response Surface Methodology
revolutions per minute (unit of engine speed)
Selective Catalytic Reducer
Start of Injection
Supplement Emissions Test
Temperature, Pressure
Total Hydrocarbons
Total Particulate Matter
United States - Environmental Protection Agency
Upper level GA of D-MOGA
Urban Dynamometer Driving schedule
Variable Geometry Turbo
Work done by the control volume
INTRODUCTION

Engine calibration and certification is primarily focused on optimizing engines for performance and emissions over the certification cycles. Although, there are in-use regulations and confirmatory testing programs that urge engine/vehicle manufacturers to operate within emissions certification limits on road, it becomes a bigger challenge when including real-world engine operations in vocations such as the near dock drayage operation that are characterized by low load engine operations and decreased after-treatment activity [2]. The growing complexities of diesel engine combustion and control strategies with large numbers of engine control parameters and advanced after-treatment thermal management control strategies make it a highly complex and challenging task to locate the optimal control strategy. Although there are statistics-based techniques such as the Taguchi method used by Ardanese et al. [3] and the steepest ascent/descent method [4], these methods primarily depend on the initial location of the optimization process and do not explore the entire search space. Evidently, there is a lack of a robust approach to simultaneously optimize the engine for performance and emissions over certification cycles and different vocations of the engine application [2, 5, 6].

Genetic Algorithms (GAs) are search algorithms that are based on Darwin’s theory of evolution, they use natural selection and mutation of genetic information (parameter strings) of the artificial creatures. The existence of these artificial creatures is governed by the survival of the fittest principle, after which genetic information from one generation is passed to the other by a process of selection with the added random mutation. GAs are widely used in many fields of study and have wide range of applicability, however their major field of application is in parameter optimization [7-13]. GAs are empirically and theoretically shown to provide robust searches in complex multidimensional spaces. This is mainly because, unlike traditional optimization and search methods that are carefully designed to move from a single initial point to another which could lead to locating false peaks in complex multi-modal search spaces [8]. GAs are designed to heuristically search the entire search space using a probabilistic transition rule over a deterministic one [9]. This process of natural selection, mutation and reproduction can be used as a robust tool for multi-objective engine parameter optimization and to explore the entire search space without any need for additional information about the parameters themselves [9, 11, 14, 15]. The mathematical models or representation of the system response allows GAs to search
for optimal solutions in more than one direction at a time which is not possible with traditional optimization techniques [8, 9]. GAs are capable of handling large number of parameters and objectives efficiently. The simplicity, elegance and robustness of GAs allow them to have a wide range of application in engineering and in other science and technological fields [8].

Since the introduction of the first federal emissions limits for heavy-duty (HD) vehicles in 1974, HD engine emissions standards have tightened over the years. Currently, the emission limits for on-road HD diesel engines are set at 0.2, 0.01, 0.14 and 15.5 g/bhp-hr for oxides of nitrogen (NOₓ), total particulate matter (TPM), non-methane hydro carbons (NMHC) and carbon mono-oxide (CO) emissions respectively, and are defined over the federal test protocol (FTP) engine dynamometer test cycle [16-19]. In 2014, California-Air Resources Board (C-ARB) introduced the “Optional Low NOₓ Standards,” where engine manufacturers can choose to certify their engines under three optional lower NOₓ standards [20]. In addition to this, beginning in 2017 HD engine manufacturers must also comply with the green-house-gas (GHG) CO₂ standards set at 460 g/bhp-hr over the FTP cycles for heavy-heavy diesel (HHD) engines used for goods movement applications [19, 20]. This possesses significant challenges for engine manufacturers in developing cleaner and greener vehicles/engines because reducing NOₓ emissions from diesel engines typically involve strategies that incur fuel consumption (FC) penalties such as employing after-treatment thermal management strategies to maintain SCR temperatures and in-cylinder NOₓ reduction that typical increases soot emission rates that will result higher in diesel particulate filter (DPF) soot loading.

1.1 PROBLEM STATEMENT

Recent comprehensive studies conducted on vehicle technologies operating in the South Coast Air Basin of California by Thiruvengadam et al. [2, 5] and Bishop et al. [21] show that current model year HD diesel engines used for drayage applications produced 5 to 7 times higher brake-specific NOₓ emissions than the certified emissions limits [5]. The higher emissions levels from vehicles operated in these vocations can primarily be attributed to after-treatment temperatures below 250°C, at which point selective catalytic reducer (SCR) efficiency decreases [21]. In-use chassis dynamometer studies have also shown that exhaust gas temperatures from these vehicles were below 250°C for 95% of the duration when operating over the local and near-
dock driving cycles [2, 22, 23]. Additionally, the use of DPF in modern diesel after-treatment systems has changed the conventional NO\textsubscript{x}-versus-PM trade-off into a NO\textsubscript{x}-versus-CO\textsubscript{2} trade-off. This could be attributed to the high filtration efficiency of DPFs, over 95% on a mass basis, with the fuel penalty incurred due to increased engine back pressures with DPFs. As a result, manufacturers are challenged by meeting increasingly strict NO\textsubscript{x} standards while meeting newly imposed GHG CO\textsubscript{2} standards that are directly related to better fuel efficiency.

The central hypothesis of this study is that there exist one or more solutions for simultaneously meeting the required NO\textsubscript{x} and CO\textsubscript{2} emission target over the certification cycles as well as vocation specific test cycles such as the near dock drayage applications. The hypothesis is mainly driven through industry experience and a lack of literature available for transient cycle-based engine calibration approaches. GAs such as the one developed in this study can be used to virtually test, optimize and calibrate the engine and after-treatment system in order to obtain the best possible outcome of performance, emissions and fuel economy during transient engine operation.

1.2 OBJECTIVE

The **global objective** of this study is to develop a robust calibration process for engine optimization in order to overcome the NO\textsubscript{x}-versus-CO\textsubscript{2} trade-off and meet current and future regulated emissions limits during the certification cycles, in addition to lower emissions during duty-cycles specific to certain vocations. The **rationale** for this study is that there is a lack of a viable technical approach to meet the current “Optional Low NO\textsubscript{x}” standards set forth by CARB while simultaneously trying to meet the current and future GHG CO\textsubscript{2} standards promulgated by the US-EPA, over certification cycles and vocation specific test cycles. The following are **specific objectives** to accomplish the global objective of this study:

1. **Establish baseline engine performance** for regulated emissions for 2010 compliant engine calibrations developed by Ardanese et al [3] over the certification and drayage engine dynamometer cycles. Since this study aims to improve upon the work done in the past by demonstrating that off-cycle emissions levels can be reduced while also complying with emissions standards over certification cycles it is necessary to benchmark the previous work, evaluate the engine performance and brake-specific emissions during
the certification cycle such as the FTP cycle and real-world low-load drayage vocation specific cycles such as the Near-Dock cycle.

2 Develop an engine model for virtual parameter optimization using Dual-layered Multi-Objective Genetic Algorithms (D-MOGA). Since D-MOGA works by performing population based searches, analyzing several candidate solutions simultaneously and improving upon the best performing candidates, it is necessary for the engine and after-treatment to be represented as a mathematical model or function. The mathematical data-driven models are an integral part of the genetic algorithm based optimization process. The performance of the candidate solutions is evaluated with the help of these virtual data-driven engine and after-treatment models.

3 Obtain a global optimal solution(s) using D-MOGA that will meet the current (2017) regulated emissions levels over the certification cycles as well as have lower regulated emission levels over the port drayage engine test cycle. D-MOGA has the potential to search and obtain an optimal solution based on specific objectives such as Low-NOₓ, Low-FC, Low-NOₓ and FC and Low-FC, NOₓ and Soot. The study also aims to develop a method to reduce off-certification cycle emissions while still complying with 2010 US-EPA regulated emission standards.

4 Test cell validation the Low-NOₓ optimal calibrations obtained using D-MOGA and evaluate its performance and emissions over certification and off-certification cycle engine operation. D-MOGA has the potential to search and obtain more than one optimal solution to the problem at hand. The candidate calibrations obtained from D-MOGA will be ranked based on performance, emissions and fuel consumption during off-cycle drayage activity. The proposed study aims to lower off-cycle emissions while still maintaining baseline certification levels.
LITERATURE REVIEW

The constant advancement in HD diesel engine technology that is driven by regulatory policies is an increasingly complex task for engineers to manually develop engine calibrations that can simultaneously reduce fuel consumption and NO\textsubscript{x} emissions. This calls for unique, robust and possibly autonomous approaches to develop engine calibrations that can meet current and future regulated emissions limits being lower in emission rates during real-world engine operation. The literature review in this work will consider current and future emissions regulatory trends and how these regulations can be achieved through engine parameter optimization as well as the trade-offs in achieving these targets.

2.1 REGULATED EMISSIONS

Engine manufacturers are constantly subjected to ever changing regulations set forth by the United States Environmental Protection Agency (US-EPA) and California Air Resources Board (C-ARB). In December 21, 2000 the US-EPA officially set forth the 2010 emissions standards which were phased in from 2007-2009. The 10 fold decrease in NO\textsubscript{x} and PM emissions as compared to the previous 2004 standards, forced all the engine and truck manufacturers to ultimately install diesel oxidation catalysts (DOC), diesel particulate filters (DPF) and selective catalytic reducers (SCR) after-treatment systems as the primary emissions control devices. The DOC and DPF systems enabled the OEMs to meet the regulated emissions limits for TPM, CO, NMHC and in the process breaking the NO\textsubscript{x}-versus-PM trade-off [24]. This however, shifted the NO\textsubscript{x}-versus-PM trade-off to a NO\textsubscript{x}-versus-CO\textsubscript{2} trade-off due to decreased brake thermal efficiency on the engine as well as the need to have higher exhaust temperatures to bring the aftertreatment to light-off temperature quickly, especially during cold engine starts [25, 26]. Figure 1 shows the NO\textsubscript{x} versus FC trade-off between two different model year engines. Although the 2007 model year engine exhibited a 2.5\% gain in fuel economy, it can be clearly noted the slope of the trade-off curve is steeper as compared to the earlier model year engine, implying that the NO\textsubscript{x} versus FC trade-off is becoming more aggressive for modern engines.
Figure 1: Fuel consumption versus NOx trade-off for the 2004 and 2007 EGR engines [26].

Furthermore, on October 21st 2014, C-ARB introduced the “Optional Low-NOx Standards” for heavy-duty engines to further reduce tailpipe emissions from vehicles operating in South-Coast air basin of California [27]. The primary reasons behind these regulations were to try and meet the NAAQS standards for ozone and NO2 in this area. Engine families that are certified under these NOx limits can be included in the Averaging, Banking and Trading (ABT) program for NOx where the engine/truck manufacturers may use them to generate credits. Table 1 shows a list of all the current regulated emissions limits that engine/truck manufacturers must meet. Additionally, the table also shows European regulated emissions limits that were set into effect in 2013. The European EURO-VI regulation also includes total particle number count limits which add further design specifications on DOC-DPF porosity and platinum group metal (PGM) loading.
Table 1: Current Regulated Emissions Standards [18, 19].

<table>
<thead>
<tr>
<th>Regulations</th>
<th>Test Cycle</th>
<th>CO</th>
<th>NMHC</th>
<th>HC</th>
<th>NOx</th>
<th>TPM</th>
<th>PN</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010 US EPA</td>
<td>FTP</td>
<td>15.5</td>
<td>0.14</td>
<td>-</td>
<td>0.2</td>
<td>0.01</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>SET</td>
<td>15.5</td>
<td>0.14</td>
<td>-</td>
<td>0.2</td>
<td>0.01</td>
<td>-</td>
</tr>
<tr>
<td>EURO VI</td>
<td>WHTC</td>
<td>2.983</td>
<td>0.55</td>
<td>0.119</td>
<td>0.373</td>
<td>0.007</td>
<td>6.0×10^{11}</td>
</tr>
<tr>
<td></td>
<td>WHSC</td>
<td>1.119</td>
<td>-</td>
<td>0.097</td>
<td>0.298</td>
<td>0.007</td>
<td>8.0×10^{11}</td>
</tr>
<tr>
<td>C-ARB Low-NOx</td>
<td>FTP</td>
<td>15.5</td>
<td>0.14</td>
<td>-</td>
<td>0.1</td>
<td>0.01</td>
<td>-</td>
</tr>
<tr>
<td>(Option-1)</td>
<td>SET</td>
<td>15.5</td>
<td>0.14</td>
<td>-</td>
<td>0.1</td>
<td>0.01</td>
<td>-</td>
</tr>
<tr>
<td>C-ARB Low-NOx</td>
<td>FTP</td>
<td>15.5</td>
<td>0.14</td>
<td>-</td>
<td>0.05</td>
<td>0.01</td>
<td>-</td>
</tr>
<tr>
<td>(Option-2)</td>
<td>SET</td>
<td>15.5</td>
<td>0.14</td>
<td>-</td>
<td>0.05</td>
<td>0.01</td>
<td>-</td>
</tr>
<tr>
<td>C-ARB Low-NOx</td>
<td>FTP</td>
<td>15.5</td>
<td>0.14</td>
<td>-</td>
<td>0.02</td>
<td>0.01</td>
<td>-</td>
</tr>
<tr>
<td>(Option-3)</td>
<td>SET</td>
<td>15.5</td>
<td>0.14</td>
<td>-</td>
<td>0.02</td>
<td>0.01</td>
<td>-</td>
</tr>
</tbody>
</table>

*Euro 6 limits have been converted to g/bhp-hr units.

In addition to these ever changing regulations, starting 2014 the US GHG regulation took effect. The regulation was jointly developed by the US-EPA, the National Highway Traffic Safety Administration (NHTSA), and Department of Transportation (DOT) which introduced emission limits for carbon-di-oxide (CO₂), nitrous oxide (N₂O) and methane (CH₄) and is planned to be phased in at different levels between 2014 and 2027. Table 2 shows current and proposed future GHG regulations for engines on vocational HD trucks.

Table 2: Current and proposed future GHG emission trends for vocational HHD engines in the United States [19, 20].

<table>
<thead>
<tr>
<th>Year</th>
<th>CO2 Emissions</th>
<th>Fuel Consumption</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>g/bhp-hr</td>
<td></td>
</tr>
<tr>
<td>2014**</td>
<td>567</td>
<td>177</td>
</tr>
<tr>
<td>2017*</td>
<td>555</td>
<td>173</td>
</tr>
<tr>
<td>2021*</td>
<td>513</td>
<td>160</td>
</tr>
<tr>
<td>2024*</td>
<td>506</td>
<td>158</td>
</tr>
<tr>
<td>2027*</td>
<td>627</td>
<td>196</td>
</tr>
</tbody>
</table>

** GHG standards were on voluntary basis
*Standards also include N₂O and CH₄ limits, not shown in table.

These ever-changing regulations have been one of the prime motivating factors that helped diesel engines constantly evolve in technology as well as complexity over the years. Diesel engines are currently equipped with advanced after-treatment technologies that have made them cleaner and greener than their predecessors. After-treatment systems on MY’ 2010+
Engines/vehicles are primarily comprised of DOCs to help mitigate CO and NMHC, DPFs to reduced TPM emissions and finally urea-based SCR systems to reduce NOx emissions. The following discussion will detail how these aftertreatment systems work together and to what degree their performance affects emissions during real-world driving conditions.

2.2 IN-USE AND REAL-WORLD EMISSIONS

Following the Consent Decrees in 1998 between US-EPA, C-ARB, DOJ and HD engine manufacturers (Caterpillar Inc., Cummins Engine Company, Detroit Diesel Corporation, Mack Truck, Incorporated, Navistar International Transportation Corporation, Renault Vehicules Industriels, Volvo Truck Corporation) [28], emissions limits for the SET cycle were introduced along with in-use emissions compliance requirements [17-19]. In-use compliance requirements included Not-to-Exceed (NTE) limits, which are 1.25 times that of certification limits for TPM and 1.5 times that of certification limits for NOx. The in-use compliance is evaluated using on-road PEMS testing.

Although the use of DPFs in current model year diesel engines have contributed to near zero PM mass emission levels [5, 29-31], a study conducted by Thiruvengadam et. al. [5] showed that NOx emissions from 2010 and later model year engines equipped with urea-SCR after-treatment systems were 5-7 times higher than in-use certification limits during chassis dynamometer testing even though these engine/vehicles were compliant with the applicable in-use regulations as well as engine certification standards. The study showed that their emission levels were above the brake-specific certification limits during off-cycle goods movement activities such as regional, local, and near-dock chassis dynamometer driving cycles [5, 23]. Figure 2 shows the difference in off-cycle emissions for category V vehicles equipped with DOC, DPF and SCR after-treatment systems. The brake-specific emissions are higher during vocational operations as compared to the UDDS chassis dynamometer cycle which is more representative of the FTP engine certification test.
Figure 2: Comparison of distance-specific NOx emissions, brake-specific emissions, and percentage after-treatment activity over the UDDS, regional, local, and near-dock drayage driving cycles [5].

The higher NOx emission rates were primarily attributed to SCR catalysts being below the light-off temperature of 250°C [5]. Remote sensing studies conducted by Bishop et al. also showed similar emission rates from port-trucks operating in the South-Coast Air Basin [21]. The study also showed that most of the trucks exhibited lower after-treatment temperatures and higher NOx emission rates as shown in Figure 3. In addition to this, a study conducted by Quiros et al. further substantiated this observation [6].
A closer look at the in-use regulations shows that engine/vehicle manufacturers are also allowed exclusions for in-use NTE operating regions, where higher emissions were allowed when after-treatment temperatures were below 250°C while operating in the NTE zone. This leads to differences between emissions during certification tests, in-use compliance tests and real-world emissions. This situation also leads to inaccuracies in emission inventory models that are used as benchmark for future regulations. This study shows the difference between emissions during certification tests and vocation specific off-certification cycle engine operation and aims to develop a robust approach to mitigate these differences.

2.3 ENGINE CONTROL PARAMETERS AND THEIR EFFECTS

Modern HD diesel engines technology has advanced greatly in the past two decades and produce regulated emissions that are an order of magnitude lower than their predecessors. These engines feature electronic fuel injection; air handling and emissions control systems that are controlled with the use of a central brain. The central brain is known as the engine control unit (ECU) otherwise commonly known as engine control module (ECM). The ECU is an electronic device with a microprocessor or microcontroller that is programmed with all the control algorithms for electronically controlling the engine hardware and components in a safe and efficient manner. ECU’s equipped modern engines are programmable, that is the control
algorithms and/or control parameters can be changed with the help of suitable ECU software. The ECU controls the various engine control parameters with the help of look-up tables some of which are a function of engine speed and torque demanded by the driver through pedal position. These look-up tables are essentially a set of control instructions for the engine ECU and are also known as engine maps which comprise the ECU calibration.

Modern diesel engines employ a comprehensive set of look-up tables and feed-forward, feed-back, open-loop and closed loop controllers that are sensor based as well as model-based. Rakapoulus et. al [32] discusses in detail, the complexities and intricacies of diesel engine controls during transient operation [32-34]. Figure 4 shows a simplified diagram of the controllable parameters for air-handling and fueling systems in a modern diesel engine and highlights the complexities of a modern diesel engine powertrain control, illustrated by Rakopoulus et. al [32]. More recently, there has been significant work done by Varsha et. al [35] at the engine development center of TATA Motors, Ltd., for more robust approaches in engine modelling and calibration using AVL GmbH’s Global COR iDOE methodology [35].

![Figure 4: Simplified diagram showing controllable inputs for air-handling and fuel systems [32].](image-url)
The value or position to which a certain actuator, valve or injector is being commanded to operate at by the ECU is known as the engine control parameter and the method in which these parameters are controlled are based on inputs from one or more physical and virtual sensors, known as the control algorithm. There are many engine control parameters on current model engines; however, with respect to the engine used in this study there are four main control parameters that have the largest engine effect on performance and emissions. These four control parameters are variable geometry turbocharger (VGT) rack position, exhaust gas recirculation system (EGR) valve position, start of injection (SOI) and nozzle opening pressure (NOP) and are discussed in detail in the following sections. The parametric effects on engine performance as well as emissions and their trade-offs are also discussed in these sections.

2.3.1 Variable Geometry Turbo (VGT)

Turbochargers are commonly used in diesel engines to increase the intake charge air pressure, commonly known as boost. Increasing the boost in an internal combustion engine increases the total mass of intake charge air in-cylinder. As a result, this increases the volumetric efficiency of the engine as well as the brake-thermal efficiency of the engine [36].

![Figure 5: Pivoting vane (left) and moving wall (right) variable geometry turbochargers (1-Turbine housing; 2-Variable angle vanes; 3-Adjusting ring)](image)

There are two main types of turbochargers, fixed geometry or waste-gated turbochargers (WGT) and VGTs. More recently HD diesel engines have used VGTs to meet increasingly stringent emissions regulations and customer demand for improved fuel economy. This is
because, better matching of combustion parameters can be achieved using VGTs as compared to WGTs over a wide range of steady-state and transient engine operation that result in better overall fuel economy [37]. Figure 5 shows the two main types of VGT currently used in HD diesel engines. The test article used in this study employs a pivoting vane type VGT manufactured by Honeywell Garrett®.

The engine performance and emissions response due to VGT position or VGT performance cannot be explained separately without also studying the effects of EGR. This is because EGR valve position and VGT position have strong parametric interactions. This can be attributed to the design of the air-handling system of the engine. Typically, closing the VGT vanes by requesting a smaller VGT position value results in higher exhaust back pressure which in-turn drives more EGR and also increases turbo spool speed which also increases the boost. Liu et al. [37] explains the trade-off between brake-specific fuel consumption and brake-specific engine out NO\textsubscript{x} with increasing VGT position, as shown in Figure 6 where the influence of VGT position on the NO\textsubscript{x} and FC trade-off can observed.

![Figure 6: Trade-off between BSFC and EO-bsNO\textsubscript{x} with varying VGT position [37].](image)
2.3.2 Exhaust Gas Recirculation (EGR)

EGR as the name suggests, is a NO\textsubscript{x} control technique where a portion of the exhaust gas is taken, cooled and routed back into the intake as shown in Figure 11. This is an effective method for in-cylinder NO\textsubscript{x} reduction, because it reduces combustion temperatures with the presence of diluents such as H\textsubscript{2}O and CO\textsubscript{2} in the charge air. This also decreases the availability of free oxygen which limits the formation of in-cylinder NO\textsubscript{x} during combustion. Figure 7 shows the effect of intake oxygen concentration in reducing in-cylinder NO\textsubscript{x} formation [26, 36].

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{figure7.png}
\caption{Effect of intake oxygen concentration on NO\textsubscript{x} reduction with increasing EGR [26].}
\end{figure}

EGR reduces the in-cylinder NO\textsubscript{x} formation by reducing combustion temperatures. However, this leads to combustion in-efficiencies that result in an increase of in-cylinder soot formation due to the presence of unburnt fuel [38]. This has led to the famous NO\textsubscript{x}-versus-PM trade-off that challenges diesel engine manufacturers. Figure 8 shows the NO\textsubscript{x}-versus-PM trade-off with varying levels of EGR rates, the same trade-off can also be observed in the response of the test article used in this study, shown in Figure 56 of Appendix I. The in-cylinder emissions control methods in current MY’ engines also include VGTs and high pressure fuel injection systems.
2.3.3 Nozzle Opening Pressure (NOP)

The test article used in this study is equipped with Delphi’s proprietary E3 diesel electronic unit injector (EUI), as shown in Figure 9. Contrary to a common rail fuel injection system where a single pump pressurizes the fuel to 1000 to 2000 bar on a common fuel rail from which fuel is supplied to the injectors, Delphi’s Unit injector receives fuel at significantly lower pressure of 100 to 200 bar and pressurizes the fuel with the help of a camshaft that drives the plunger on the tail of the injector to compress a small portion of a fuel to pressures up to 2500 bar [19, 39]. As a result, each cylinder possesses a separate injection pumping mechanism that can attain desired injection pressures at a higher response rate which cannot be achieved in a common rail system due to the larger dead volume of the common rail system [39-41].

**Figure 8**: NOx and PM emissions trade-off with varying EGR rates [26].
The E3 EUI is comprised of two solenoid valves, namely, the Spill Control Valve (SCV) and Needle Control Valve (NCV). Energizing the normally open SCV allows the injector to build pressure when the cam actuated plunger/pump on the tail end is compressed. Energizing the normally closed NCV allows the fuel to be sprayed into the cylinder. Essentially, the timing of energizing the NCV is the SOI timing angle and the duration of advanced timing of the SCV is the NOP angle. Increasing the NOP angle provides more duration for the pressure to build up thus increasing injection pressures, as shown in Figure 10. This study refers to NOP as an angle as opposed to an equivalent injections pressure that can be obtained from Volvo’s EUSIM® model. The work done by Chaufour et al. [40] also explains in detail the modeling of the EUI and its role in the engine design process. This is primarily due to the non-parametric approach to engine calibration used in this study.
Figure 10: Effect of increasing NOP on injection pressure and injection profile [42].

Delphi’s EUIs are commonly used for HD applications by various manufacturers such as Volvo and DDC. The injector has continuously evolved over the years reducing in size and increasing in fuel delivery pressures. It must be noted that the injector used in this study was a production system for a MY 2007 engine. The system was able to meet 2010 and later regulated emissions standards such as NOₓ, THC, CO, and TPM; the system was also able to meet the current GHG CO₂ standards.

A number of studies conducted in the past have ascertained the effects of injection pressures on in-cylinder combustion, a few important ones are discussed here.

a) The work done by Huang et al. [42] at Southwest Research Institute shows that increasing NOP on the E3 EUI was highly effective in reducing soot emissions when running EGR rates greater than 50%.

b) Rente et al. [43] discusses in detail the formation of in-cylinder emissions due to effects NOP in his work. He shows that increasing NOP reduced ignition delay but increased brake-specific NOₓ emissions. The study also pointed out that higher injection pressures improved brake-specific fuel consumption and simultaneous NOₓ and soot reduction can be achieved with high EGR rates.

c) Ehleskog and et al. [44] showed that increasing NOP resulted in high soot formation and higher soot oxidation which in turn resulted in lower soot emissions with no
EGR. He also showed the opposing and negating effects of increasing NOP on NO\textsubscript{x} and soot emissions.

2.3.4 Start of Injection (SOI)

With respect to internal combustion engines, there are various definitions of the start of injection. Many researchers discuss start of injection as the timing or crank angle when the fuel injector solenoid is energized. Other literature defines SOI as the crank angle when mass fraction burned achieves 5\% of total combustion event. Others define it as the crank angle at which the fuel injector needle is fully open. Regardless, the holistic effect of SOI shows that reducing or delaying SOI will lower combustion temperatures and reduces peak in-cylinder pressures which decrease in-cylinder NO\textsubscript{x} formation also reduces brake-specific fuel consumption and increases soot formation. Advancing or increasing the SOI angle has the opposite effect on these combustion parameters, fuel consumption, NO\textsubscript{x} and soot emissions [3, 19, 36, 41, 44-46].

2.4 AFTER-TREATMENT EMISSIONS CONTROL DEVICES

In addition to the in-cylinder emissions control strategies employed in modern diesel engines to mitigate NO\textsubscript{x} and soot while trying to get the best fuel economy, modern diesel engines also use after-treatment systems to further mitigate particular emissions to meet regulatory emissions limits. Figure 11 shows the typical engine and after-treatment architecture of a 2010 on-highway vehicle. After-treatment emissions control solutions includes DOC for CO and THC mitigation, catalyzed DPFs or continuously regenerating traps (CRT) for TPM emissions, and Urea-SCR system for NO\textsubscript{x} mitigation. An ammonia cleanup catalyst is also often used in the SCR system to mitigate any excess ammonia [26].
The following subsections briefly explain the different roles each of these units play in emissions control and their interdependence as well as their performance trade-offs.

2.4.1 **Diesel Oxidation Catalyst (DOC)**

Diesel oxidation catalysts as the name suggest, are oxidation catalysts used to oxidize carbon monoxide (CO) and hydrocarbons in the gas phase as well as the soluble organic fraction of diesel particulates which are typical by products of diesel combustion. The DOC chemically oxidizes the pollutants present over the active catalytic sites to convert them to CO$_2$ and water vapor (H$_2$O). The chemical oxidation process is explained in the chemical reaction equations shown below:

$$[\text{Hydrocarbons}] + O_2 \rightarrow CO_2 + H_2O$$

$$CO + 1/2O_2 \rightarrow CO_2$$

In addition to this, DOC also plays a secondary role of oxidizing the NO emissions produced during in-cylinder combustion. DOCs are typically designed such that the NO/NO$_2$...
ratio at the outlet of the DOC has reached 1:1. This is done in order to promote the catalytic oxidation of soot trapped in the DPF using NO₂ pollutants formed in the DOC. Figure 12 by Stanton [26] shows how NO₂ production influences soot oxidation in the DPF as well as the chemical equations that help explain reaction. NO₂ gets consumed in the DPF through catalytic oxidation of soot in the DPF producing NO and CO₂ in the process.

![Figure 12: NO₂/NOₓ molar fraction through the DOC and DPF [26].](image)

2.4.2 Diesel Particulate Filter (DPF)

Diesel particulate filters are typically wall flow filters, where the exhaust gas passes through a porous catalyzed substrate that is ceramic based. As the exhaust gas passes through the porous substrate, the soot particles produced from diesel combustion are trapped in the porous walls and a reduction in the TPM emissions occurs. As the soot loading on the DPF increases, the exhaust backpressure on the engine also increases, thus over time the soot loaded on the DPF has to be burned off in a process known as active regeneration. This process varies depending on the type of DPF material and the amount of PGM loading on the substrate. Koltsakis et al. [47] made use of advanced models to synergistically optimize DOC and DPF systems. The study also explains the inter-dependencies between and DOC and DPF after-treatment systems, over-sizing or under-sizing of the DOC would affect the catalytic oxidation soot due to imbalances in NO/NO₂ ratio and availability of oxygen during passive and active regeneration.

2.4.3 Selective Catalytic Reduction (SCR)

SCRs systems are primarily used to reduce NOₓ emissions produced during diesel combustion and they are the most complex amongst the three after-treatment systems as well.
Urea-SCR systems use a 32.5% solution of urea in water (\((\text{NH}_2\text{H})_2\text{CO}\)), that is injected in the exhaust stream prior to the SCR catalyst. The urea mist in the exhaust goes through thermal decomposition known as hydrolysis to finally produce ammonia (\(\text{NH}_3\)), \(\text{CO}_2\) and steam. \(\text{NH}_3\) is trapped in the activity sites of the SCR catalyst is subsequently used to catalytically reduce NO/NO\(_2\) emissions. The test article used for this study makes use of a vanadium based SCR that has a low light-off temperature and equivalent deNO\(_x\) potential to the more commonly used Cu-Zeolite SCR catalysts. The low light-off temperature increases the deNO\(_x\) activity of the Urea-SCR system during low load engine operations which is typical to vocations such as drayage.

In addition to this, SCR systems also have short falls when reducing NO\(_x\) emissions in the presence of hydrocarbons. Hydrocarbons occupy the activity sites on the SCR catalyst and reduce the deNO\(_x\) potential of the system as shown in a study by Girard et al. [48, 49]. Vanadium based SCR catalysts are less prone to hydrocarbon contamination as compared to Iron-Zeolite or Cu-Zeolite catalysts [48-50]. Figure 13 shows the difference between the deNO\(_x\) potential for an aged Cu-Zeolite and Vanadium SCR system.

![Figure 13: Difference in NO\(_x\) conversions at 30k hr\(^{-1}\) for Cu-Zeolite (left) and Vanadium catalyst with various hydrocarbons [50].](image)

In studies such as, Staton’s systematic development of a commercial vehicle that will meet future regulations [26] and Girard et. al’s study analyzing the technical advantages of vanadium SCR systems for diesel NO\(_x\) control in emerging markets [48], the temperature dependencies of SCR de-NO\(_x\) potential have been pointed out well defined. Stanton also provides a comparison of how SCR performance is associated with in-use activity and
temperature distribution for Copper-Zeolite SCR, as shown in Figure 14. This temperature dependency can also be observed in a study by Cavataio et al [51]. The bar chart shows the frequency distribution of exhaust temperatures of a heavy-duty engine operating in a line haul truck application.

![Graph showing SCR NOx conversion efficiency as a function of SCR gas temperature.](image)

**Figure 14:** Copper zeolite SCR catalyst performance as a function of SCR exhaust gas temperatures observed in line haul truck applications [26].

In the study by Cavataio et al. [51], the effect of thermal aging at exhaust temperatures above 670°C was observed. In this study the vanadium SCR catalyst de-NOx potential was decreased significantly after exposing the catalyst to 64 hrs of hydrothermal aging to gas temperatures of 670°C. However, the de-NOx potential of Iron-Zeolite and Copper-Zeolite SCR catalysts was still observed to be over 90% after the same hydrothermal treatment [49, 51]. Even though vanadium based SCRs have superior performance in reducing NOx emissions from engine exhaust, they thermally deteriorates over time faster than the Zeolite-based catalysts [48, 49, 51]. Since HD engine/vehicle manufacturers need to show emissions compliance for the
useful-life of 435,000 miles or 11 years [16], Copper-Zeolite is a more logical choice for durability.

One must also consider the urea dosing system’s performance in addition to the SCR catalyst performance. Currently, urea-dosing systems are open loop dosing systems which consume more urea than required [26]. This is primarily due to the lack of real-time feedback information such NH₃ slip through the SCR catalyst to tighten the dosing control. Although there have been many advancements on-board NH₃ sensor measurements it is still a work in progress in order to make it a more robust and cost-effective solution [52, 53]. Figure 15 explains the role of Urea-dosing system on reducing fuel consumption and the impact of using closed-loop Urea dosing systems with NH₃ sensors for feedback.

![Figure 15: Relationship between fuel consumption benefits and SCR conversion efficiency [26].](image)

(Average of 14 drive cycles: Span 27 hp/L to 52 hp/L)
2.5 ENGINE AND AFTER-TREATMENT MODELS

Currently, the step-by-step development of an engine and after-treatment greatly relies on the development of either robust computer models or computer simulations. This section attempts describes some of the techniques that have been developed in the past in order to model the engine and after-treatment systems. These modelling techniques are essential tools that are used in the development and calibration of modern engines.

Physical models or phenomenological models make use of actual physics or chemistry-based governing equations that explain a certain phenomenon or process. These models are usually very computationally intensive and require large computational power and time. Tools such as Gamma Technologies’ GT-Suite, AVL’s Drive, and ANSYS ICE are some examples that are commercially available currently. These models do not explicitly require experimental data but they do require a fair amount of good engineering judgement to make assumptions which could lead to differences between simulated and actual results. Studies such as the assessment of the predictive capabilities of combustion models for modern common rail diesel engine by Piano et. al [54], are one such good examples of the numerous physical engine simulations work that has been performed in the past.

Analytical models are models that make use of an analytical function that describes the responses of the system under study. These functions may be derived from the actual physics of the system or maybe a function with similar response behavior as the system. These models are faster and require less computational resources but require the use of experimental data in order to reduce prediction error and optimize the function parameters to match actual system response. Cioffi et. al [55] study explains one such methods of representing after-treatment system performance as well as the behavior using a control system approach.

In addition to this, there are several methods of data-driven approaches involve developing analytical models using comprehensive experimental data collected during controlled tests or real-world applications. Approaches such as response surface methodology (RSM) and artificial neural network (ANN) modeling are some of the popular and more robust approaches to develope data-driven models. The parametric study and optimization using RSM by Ganji et. al [56] shows how RSM can be used in the development of diesel engines. ANNs are currently a
more popular non-parametric approach to develop models that can better represent non-linear and multi-model system responses. Since current model year engines are becoming more and more complex, the use of ANN in engine and after-treatment models have become prevalent [57, 58]. This study makes use of a unique approach in developing a data driven ANN steady-state engine model.

### 2.6 OPTIMIZATION TECHNIQUES

Over the years, many optimization techniques have been developed, each specific to the optimization problem encountered at the time. Professor Astolfi from Imperial College London broadly classifies optimization methods into three categories [59, 60]. They are as follows:

1. **Mathematical Programming Methods.** These methods include calculus of variations and optimal control; linear, quadratic and non-linear programming; geometric programming; integer programming; network methods (PERT); as well as game theory.

2. **Stochastic Process Techniques.** These methods include simulated annealing, stochastic tunneling, parallel tampering, stochastic hill climbing, swarm algorithms and evolutionary algorithms such as GAs and evolution strategies.

3. **Statistical Methods.** These methods include steepest ascent/descent method, linear search, Newton-Raphson algorithm, Quasi-Newton method, graduate gradient method and more.

In the field of engine development and optimization, many of these optimization techniques have been used due to their robustness in obtaining the best solution with minimal test cell time for data collection. Varsha et. al [35] work with the DOE process which makes use of K-means clustering of vehicle or engine activity to select test points for engine calibration. Additionally, the Taguchi optimization method was used by Ardanese et. al [3] to meet current emissions standards using a 2007 model year heavy duty diesel engine.

#### 2.6.1 Autonomous Optimization Techniques

The use of artificial intelligence processes in optimizing complex problems has been sought after since the development of the first super computer. In Badar et. al [61], some of the
autonomous optimization techniques are discussed for minimizing active power loss in electrical power systems. These methods include genetic algorithms, particle swarm optimization, ant colony optimization, Tabu search, simulated annealing and differential evolutions. Amongst these, genetic algorithms are the most commonly used process due to their population based search technique that yields a robust optimal solution in complex multi-modal search space.

Conventional optimization or search methods such as the statistical Taguchi method are a sequence of step by step instructions that asymptotically approach an optimal point. Most of these optimization techniques according to Gen et. al [8] begin with a single point in the search space and then improve through methods such as steepest ascent/descent. However, this point-to-point approach has the probability of approaching local optima as opposed to the global optima in a multi-modal search space. GAs on the other hand, heuristically approach a global optima by maintaining population of potential solutions and undergo simulated evolution in the search and solution space. This population-to-population approach allows GAs to escape local optima [8]. Since GAs are a population based search method, one of the most basic and important requirements is a model or mathematical function that represents the systems response. The accuracy and representativeness of the model or mathematical function primarily governs the ability of the GA to provide an accurate optimal solution. GAs also provide great flexibility to hybridize and modify the GA functionality to make them more efficient for implementation to a specific problem [8].

2.6.2 Genetic Algorithms

Genetic algorithms attempt to mimic Darwin’s theory of evolution in order to obtain an optimal solution. They begin by randomly selecting candidate solutions from the search space. The candidate solutions or individuals in the populations are encoded into chromosomes where the combinations in the domain of the search space make the genes of the chromosome. The chromosomes are typically encoded in to a binary vector but this is not always the case since the chromosomes can be in real representations as well for certain problems. The ‘0’ or ‘1’ value in binary representation mimic the DNA protein adenine(A), guanine (G), cytosine (C) and thymine (T).
Figure 16: The general structure and flow chart for genetic algorithms.
Performance index are the scores given in reference to their closeness to an optimal solution. They are evaluated for all the individuals in the population. The individuals ranked based on their performance index are put through a selection process such as a roulette wheel or tournament selection, where those individuals that performed better are encouraged to move forward. The selected individuals are modified using genetic operations that mimic the process of heredity of genes to create new off-springs that make the population for the subsequent generation. This process is then repeated for each generation followed by a new generation [8-10]. Figure 16 shows the general structure of a genetic algorithm.

Gen et. al [8], discusses in detail how genetic algorithms can be used to navigate through complex search spaces such as the Ackley function. The Ackley function is a multi-modal function that is used typically as a test function for GAs. The work also aims to show how GAs can be used also to obtain global optimal solutions in such complex search spaces where methods such as hill climb also known as the steepest ascent/descent methods, would surely get trapped in local optima. GAs have a wide range of real world applications in optimization processes such as controller design for autonomous helicopter models, duty cycle creation using evolutionary algorithms by Perhinschi et. al [62] and many more [9-11, 13, 15].

A wide verity of work on optimization of internal combustion engines for performance and emissions have been done in the past. Some of the significant works are by Munnannur et. al [13] on intake valve timing optimization using GA which made use of multi-dimensional engine simulation code KIVA-3V models and Thiel et. al [11] who used micro-genetic algorithms to optimize a HD diesel engine equipped with the EUI fuel injection system for engine performance and emissions. The later study made use of AVL’s statistical CAMEO tool to obtain a RSM model. Both these studies made use of the objective function developed by Montgomery et. al [4]. Donateo et. al [12] also used GAs to optimize common rail Electro-Injector design in their study that made use of different techniques and strategies in the GA development process.
2.7 CLOSING STATEMENT

Clearly, the process of engine calibration is a complex task that involves comprehensive knowledge of engine architecture, control system basics, control algorithms employed as well as an understanding of the numerous model and sensor-based inputs used for the control algorithms and their limitations. The calibration engineer also requires a reasonable amount of experience and thorough understanding of the complex engine and system response in order to achieve future emissions targets. Furthermore, the systematic improvements of the diesel engine performance every year have made engine calibration an increasingly difficult problem to optimize. A problem that may not necessarily have a unique solution in the trade-off between and mitigating NO\textsubscript{x} emissions and CO\textsubscript{2} emissions is illustrated by Figure 17.

Figure 17: Multi-modal simulated trade-off curve between engine-out NO\textsubscript{x}, FC and PM for the MY2007 Volvo MD11 test article.

Moreover, with the phase in of EPA GHG CO\textsubscript{2} standards and the introduction of “the optional Low NO\textsubscript{x}” standards by C-ARB, novel and robust calibration techniques and tools such as the one developed in this study can play an essential role in simultaneously meeting the current and future regulated emissions standards. This study also aims to lay down the ground
work for a robust calibration process that will help mitigate engine emissions over the
certification cycles and mitigate engine emissions over specific vocational applications. This
could allow engines such as those that operate in the ports of Los Angeles (LA) which have been
reported to emit 5-7 times higher levels of regulated NOx emissions to be optimized for lower in
emissions during real-world activity while complying with the current certification standards set
forth by the US-EPA. This could also have a direct impact on the ambient air quality of that area.
Additionally, the use of tools and search techniques such as D-MOGA will reduce the need for
manufacturer negotiated exclusions and AECDs for engine operations outside the FTP cycle.
Bridging the gap between certification emissions levels of these engines and off-cycle real-world
emissions levels would reduce the need for correction factors currently employed to CARB’s
data driven inventory models EMFAC and US-EPA’s GEM. This study discusses in detail the
development of a robust approach for calibrating or optimizing the emissions and performance of
modern heavy-duty diesel engines using a novel technique known as D-MOGA. The study will
also use a DOE based approach for test point selection and engine testing. This was done in order
to develop an engine response model using ANN which will be used for the offline calibration
process.
APPROACH

The measurements for developing the data-driven engine and aftertreatment models as well as baselining the engine were conducted at the WVU Center for Alternative Fuels, Engines and Emissions (CAFEE) Engines and Emissions Research Laboratory (EERL). The EERL is equipped with multiple engine dynamometers including a 500 horsepower General Electric transient DC dynamometer. The following sections the test article, laboratory and instrumentation, test point selection, parameter screening, engine baselining and the test cell validation process.

3.1 TEST ARTICLE

A model year 2007 Volvo MD11 equipped with a DOC, DPF and SCR after-treatment system was used for this study. The study however did not make use of the after-treatment system, instead an exhaust back pressure valve simulated the after-treatment backpressure. Table 3 shows detailed specifications regarding the engine and after-treatment system hardware.

<table>
<thead>
<tr>
<th>Table 3: Hardware Specifications of the engine for proposed work [3]</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Engine Make/Model</strong></td>
</tr>
<tr>
<td><strong>Engine Perfromance</strong></td>
</tr>
<tr>
<td><strong>Base Configuration</strong></td>
</tr>
<tr>
<td><strong>Exhaust Aftertreament</strong></td>
</tr>
<tr>
<td><strong>Aspiration</strong></td>
</tr>
<tr>
<td><strong>Injection System</strong></td>
</tr>
<tr>
<td><strong>Displacement, cu.in. (L)</strong></td>
</tr>
<tr>
<td><strong>Compression Ratio</strong></td>
</tr>
<tr>
<td><strong>Bore and Stroke, in. (mm)</strong></td>
</tr>
<tr>
<td><strong>Cylinder Spacing, in. (mm)</strong></td>
</tr>
</tbody>
</table>

Full access to the ECU using the Volvo VAT2000 software allowed for engine control parameters to be changed, specifically EGR, VGT, NOP and SOI. This is the same engine used
in the Advanced Diesel Emissions Control System (ADECS) study by Ardanese et. al [3], a predecessor to the current study.

3.2 LABORATORY AND INSTRUMENTATION

The test cell is compliant with recommendations provided in the Code of Federal Regulations (CFR), Title 40, Part 1065 [18]. The test article was tested on a 500hp DC General Electric transient engine dynamometer. Figure 18 shows the laboratory setup of this study.

The study made use of MKS MultiGas™ FTIR to characterize raw engine-out emissions. Engine-out PM emissions were characterized using TSI EEPS™ 3090 using a two stage dilution system. Dilution air supply for the two stage dilution system was HEPA filtered and dehumidified to avoid artifacts from the dilution air contributing to PM mass measured. Figure 19 shows schematic diagram of the laboratory setup for this study.

![Test cell setup at WVU CAFEE's EERL facility](image)

**Figure 18:** Test cell setup at WVU CAFEE's EERL facility

The study made use of MKS MultiGas™ FTIR to characterize raw engine-out emissions. Engine-out PM emissions were characterized using TSI EEPS™ 3090 using a two stage dilution system. Dilution air supply for the two stage dilution system was HEPA filtered and dehumidified to avoid artifacts from the dilution air contributing to PM mass measured. Figure 19 shows schematic diagram of the laboratory setup for this study.
PM mass concentration is calculated using Integral Particle Size Distribution (IPSD) method from the particle number count size distribution measured by the TSI EEPS™ 3090 instrument. A constant density function of 1.26 g/cc was used for the IPSD calculation for this study, based on the inferences made in Thiruvengadam et al. [63]. Additionally, the study made use of a Kistler High Temperature Pressure Sensor Type 6125C-U20 was used to measure in-cylinder pressures. The pressure rise rates were kept below 10 bar/°CA and peak cylinder pressures below 150 bars during the parameter screening experiments. This was done to ensure safety and longevity of the engine and to be within the measurement range of the pressure transducer.

3.3 TEST POINTS SELECTION

Test points were selected based on the FTP and Near-Dock engine test cycles at which engine performance and emissions were characterized. The speed and load from both the cycles...
were combined and partitioned in 26 clusters or groups using the k-means cluster method. The centroid location in the lug curve for these 26 clusters points were used as the test points for the parameter screening experiments. K-means clustering is a method of grouping a number of observations or data points into a certain number of groups or clusters such that they belong with nearest neighboring points. A heuristic search algorithm is used to find the location of these points such that Equation-1 shown below is minimized.

\[ J = \sum_{j=1}^{k} \sum_{i=1}^{n} \| x_i^{(j)} - c_j \|^2 \quad (Eqn.1) \]

Where, J is the sum of squared errors for the centroids which is being minimized heuristically. Figure 20 shows the K-means clusters and their centroids for the Near-Dock and FTP engine test cycle. Appendix-II shows the speed-torque time trace for the FTP and Near-dock cycle. Color bar indicated the number of the cluster and the points are colored accordingly.

**Figure 20:** K-means clustering of FTP and Near-dock points.
Additionally, the A, B, C speed points at 100% load from the ESC were also included in order to account for engine performance and emissions over the ESC steady-state cycle. Since GHG limits are prescribed over the ESC cycle, it is important to include the 3-ESC points in the calibration test points. Figure 21 shows test points chosen for the parameter screening experiments. The hexagrams coloured in yellow are speed and load points are the centroids of the k-means cluster and are selected based on the two transient cycles (FTP, Near-dock) used in this study. The circles coloured in red are the three ESC A, B and C speed points at 100% load. Idle point is marked using a green box. The points are number in order of test schedule but the points were tested in no specific order. The speed-load points for FTP and Near-dock engine dynamometer cycle are shown using blue and brown dots respectively. These 29 test points shown in Figure 21 will be optimized by the D-MOGA for performance and emissions. The lug curve shown in Figure 21 represents the maximum brake torque trace of the 2010 US-EPA emissions compliant baseline calibration developed by Ardanese et. al [3]. Whereas, the lug curve shown in Figure 20 represents the maximum brake torque trace of the original MY’ 2007 calibration. This unique approach to selecting speed and load points for testing and calibration serves as a robust way to account for the engines duty cycle during certification as well as off-cycle operation. Moreover, the engine was also baselined for emissions and performance over the FTP and the off-certification Near-Dock engine dynamometer cycle on the Low-NOx calibrations developed by Ardanese et al. [3]. This heuristic method used for selecting test points for engine modelling and calibration is similar to the approach used in AVL GmbH’s Global COR iDOE methodology [35]. The Near-Dock engine test cycle used in this study was created by normalizing engine speed and load measured during real-world activity from a goods movement vehicle operating in the port of LA. A 30 minute cycle was then created based on the normalized points and maximum speed and load curve of the test article.
Figure 21: Test points selected for engine parameter screening in this study.

3.4 ENGINE PARAMETER SCREENING

A Design of Experiments (DOE) approach was used for the engine parameter screening tests. Parameter sweeps consisting of three levels were performed for the four engine parameters, EGR, VGT, SOI and NOP. The parameter sweeps were performed using a fractional factorial test matrix design of VGT, SOI and NOP at three levels over three different EGR levels. Table 4 shows the four engine control parameters and their unit of measure used in this study.

Table 4: Engine control parameters used for screening experiments

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Acronym Used</th>
<th>Parameter Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exhaust Gas Recirculation Opening</td>
<td>EGR</td>
<td>%</td>
</tr>
<tr>
<td>Variable Geometry Turbo Opening</td>
<td>VGT</td>
<td>%</td>
</tr>
<tr>
<td>Start of Fuel Injection</td>
<td>SOI</td>
<td>° (degrees) CA bTDC</td>
</tr>
<tr>
<td>Nozzle Opening Pressure</td>
<td>NOP</td>
<td>° (degrees) CA bTDC</td>
</tr>
</tbody>
</table>
A face centered central composite design (CCD) was used for the fraction factorial design of the test matrix with 6 repeats at the central location. The engine controller did not allow changes in EGR positions at pedal positions less than 25%, thus for those load points the EGR was left unchanged and sweeps were done only for the three parameters. Figure 22 shows the CCD test matrix design used the parameter screening experiments. The screening experiments were performed for each of the 29 test points used in this study.

![Face centered CCD design](image)

**Figure 22:** Face centered CCD design used for engine parameter screening [64].

The maximum and minimum limits were defined for each test points and for each EGR level. The limits were defined during engine operation based on active limiters such as turbo-speed limiter, burn-fraction limiters as well as smoothness of engine operation based on operator experience, peak in-cylinder pressures and in-cylinder pressure rise rate. Appendix-III describes the 3-level parameter sweeps CCD test matrix used in this study.

Once, the maximum, minimum and midpoint levels were defined, the main reason for having repeats in the central location is to obtain the mean variability and error of the experiments. This is done only at the central location as opposed to doing it on all the test points in the experimental design. Additionally, to account for the change in volumetric and/or brake thermal efficiency due to changes in these four engine control parameters, the indicated torque value was also adjusted and recorded to ensure the same brake torque was developed by the
engine during each screening experiment. The indicated torque was later used as the reference torque position in the look-up tables while creating the final engine calibrations.

3.5 BASELINE AND VALIDATION

The 2010 regulated emission limits compliant Low-NOx calibration developed by Ardanese et. al [3] was used as the baseline calibrations for this study. The engine was exercised over the federal test protocol (FTP) and the custom Near-Dock cycle. Each test cycle comprised of three hot starts with 10 minute soak times in between tests. Engine was instrumented for temperature, pressure and intake flow was measured using a calibrated laminar flow element (LFE). MKS MultiGas™ FTIR was used for raw exhaust gas emissions measurement and soot emissions were characterized using TSI EEPS™ 3090 as discussed in Section 3.2.

Once the D-MOGA had converged and no significant improvement was observed over several generations, the results from the most recent generation were obtained. The best individual of the generation was chosen as the candidate for validation. Three different look-up tables were created using the optimal setting for each of the four control parameters as discussed in Section 4.3. The look-up tables or maps were updated on to the engine’s original MY 2007 calibration. This is because, during the parameter screening experiments the original MY’ 2007 calibrations were loaded. As a result, any other un-altered maps relative to fueling and/or limiters would still be in effect and will be representative of the test data using which the engine models were developed in this study. The engine was subsequently exercised over 3 hot starts of the FTP and Near-Dock engine dynamometer test cycles for validation. Test setup and conditions remained the same as of engine baseline experiments and were performed soon after baselining the engine.
METHODOLOGY

The D-MOGA code implementation was written in MATLAB. MATLAB is a proprietary fourth-generation programming language developed by MathWorks®. This chapter details the structure and design of D-MOGA, in addition to the various properties used for the genetic algorithms. This chapter also discusses the various models developed using artificial neural networks for obtaining the optimal engine calibrations.

4.1 D-MOGA

D-MOGA was developed as a novel approach to engine calibration, so as to optimize engine performance and meet emissions certification levels, while providing lower off-certification cycle real-world emissions rates. This section discusses the basic structure of D-MOGA and how various components of the optimization tool were developed and setup for duty-cycle based engine parameter optimization.

4.1.1 Structure:

D-MOGA is essentially a double layered Multi-Objective Genetic Algorithms (MOGA) cluster with two distinct optimization processes. The first layer or the upper level is a target based MOGA where of engine-out NOx, soot, exhaust energy availability and fuel consumption are optimized for transient engine dynamometer cycle. Individual weights provided by upper level MOGA (U-MOGA) are sets of four real numbers between 0 and 1 for each of the 29 test points. The weights are used to target the objectives of the parameter optimization process in the lower level. These weights provided by U-MOGA are optimized for the four objectives and over all the test points. The transient engine and after treatment performance model is used to virtually evaluate the performance index using the results obtained from the lower layer MOGA (L-MOGA) as well as each of the 4 sets of 29 weights assigned to the candidates at this layer, over transient test cycles, specifically to this study the FTP and Near-Dock engine dynamometer cycles. The second layer or the lower level performs multi objective parameter optimization using GA, based on the 4 weights assigned by the U-MOGA for each of the 29 test points under the lug curve. The L-MOGA obtains the most optimal combination of engine control parameters (SOI, NOP, EGR, VGT) based on the target weights assigned for each of the 29 test points. D-
MOGA developed in this study made use of 100 individuals at each layer for the optimization processes. These 100 individuals are candidate solutions of the optimization process that heuristically evolve over every generation of MOGA. Figure 23 shows a general schematic representation of D-MOGA and its internal working.

![Figure 23: Schematic structure of D-MOGA](image)

An artificial neural-net model was developed for the engine control model and the engine parameter response model. It is detailed in section 4.2. In addition to this, an exergy based after-treatment model was developed; section 4.2.1 discusses this in detail.

4.1.2 Genetic Representation

The double layered MOGA cluster of D-MOGA comprises of the first layer (U-MOGA) aims to provide optimal targets through weighting factors for the objective functions to NOx, FC, soot and exhaust temperature. The second layer (L-MOGA) aims to provide optimal engine control parameters (SOI, NOP, EGR and VGT) and responses based on target obtained from upper level GA. As a result, the two MOGA layers require two different genome definitions to
compile the information (properties) of the individual into the chromosome. The chromosome consists of all the attributes of the individuals. The chromosome of the U-MOGA was comprised of four weights ranging between 0-1 for the 29 test points discussed in section 3.3. The four weights assigned for each point were for the four responses with resolution of 0.00001, as shown in Table 5.

Table 5: Responses and their objectives

| Optimized Response         | Acronym Used | Units Used (U-MOGA || L-MOGA) | Response Goal |
|----------------------------|--------------|-------------------------------|---------------|
| NO$_x$ Emissions           | NO$_x$       | g/bhp-hr || ppm              | Minimize      |
| Fuel Consumption           | FC           | Grams || mg/stroke            | Minimize      |
| Soot Emissions             | Soot         | g/bhp-hr || g/cc             | Minimize      |
| Exhaust Flow Exergy        | Exergy       | # || kJ/kg                   | Maximize      |

The chromosome for the L-MOGA was comprised of a simpler gene structure containing information regarding the four engine control parameters. These four engine control parameters are the settings that need to be optimized for the best engine performance based on the targets provided from the U-MOGA. Table 6 shown below, describes the four engine control parameters and their units of measure. The L-MOGA optimization is performed for each of the 29 optimization points using the sets of four weights from the U-MOGA.

Table 6: Engine control parameters used for optimization at the lower level

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Acronym Used</th>
<th>Parameter Unit</th>
<th>Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exhaust Gas Recirculation Opening</td>
<td>EGR</td>
<td>%</td>
<td>0.01</td>
</tr>
<tr>
<td>Variable Geometry Turbo Opening</td>
<td>VGT</td>
<td>%</td>
<td>0.1</td>
</tr>
<tr>
<td>Start of Fuel Injection</td>
<td>SOI</td>
<td>°CA (degrees)</td>
<td>0.01</td>
</tr>
<tr>
<td>Nozzle Opening Pressure</td>
<td>NOP</td>
<td>°CA (degrees)</td>
<td>0.01</td>
</tr>
</tbody>
</table>

D-MOGA developed for this study made use of a real representation of the genome for the individuals as opposed to the conventional binary representation. This was done in order to reduce the computational time incurred in converting the binary represented genome to real values that are used in the engine and parameter response models. The genetic operators such as crossover and mutation were modified accordingly to suit the real representation of the genome.
4.1.3 Population Initialization

The initial population for each level of the D-MOGA was selected randomly with the help of a random number generator. Constraints for engine control parameters used in L-MOGA were generated randomly within the bounds of the parameters screening experiments to form the individual’s chromosome. Each of the 29 test points had predefined constraints that defined the search space of L-MOGA, as shown in Table 7.

**Table 7: Engine parameter constraints used for L-MOGA**

<table>
<thead>
<tr>
<th>Point</th>
<th>Speed</th>
<th>Load</th>
<th>EGR</th>
<th>VGT</th>
<th>SOI</th>
<th>NOP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>rpm</td>
<td>ft-lb</td>
<td>Max</td>
<td>Min</td>
<td>Max</td>
<td>Min</td>
</tr>
<tr>
<td>#</td>
<td></td>
<td></td>
<td>%</td>
<td>%</td>
<td>%</td>
<td>%</td>
</tr>
<tr>
<td>Idle</td>
<td>650</td>
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<td>43.0</td>
<td>16.0</td>
<td>95.2</td>
<td>3.7</td>
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<tr>
<td>2</td>
<td>765</td>
<td>44.4</td>
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<td>20.0</td>
<td>95.2</td>
<td>3.7</td>
</tr>
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<td>3</td>
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<td>19.0</td>
<td>95.2</td>
<td>3.7</td>
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<tr>
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<td>42.4</td>
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<td>95.2</td>
<td>10.2</td>
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<td>45.4</td>
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<td>10.2</td>
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<tr>
<td>6</td>
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<td>19.8</td>
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<td>0.0</td>
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<td>30.1</td>
</tr>
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<td>0.0</td>
<td>95.2</td>
<td>30.1</td>
</tr>
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<td>19.9</td>
</tr>
<tr>
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<td>963.6</td>
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<tr>
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</tr>
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</tr>
<tr>
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<td>30.1</td>
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<tr>
<td>27</td>
<td>1817</td>
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<td>0.0</td>
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<tr>
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<td>0.0</td>
<td>95.2</td>
<td>24.7</td>
</tr>
</tbody>
</table>
4.1.4 Evaluation Functions

Once the system response was evaluated using the artificial neural network engine response model, it was necessary to score each individual in the population based on their performance. These performance indices are a quantitative measure for each of the candidate solutions that emphasize the characteristic responses using a single value. Two methods were used to perform this task. Firstly, the use of desirability function approach was used since it is one of the best methods for multi-objective optimization processes [65] for both levels of D-MOGA. The function used to define the performance index of the individual which is known as the objective function, is essential in the optimization process. Accurately defining the function so it represents the search surface governs the way the overall performance index is obtained. Thus, an alternate method for evaluating the performance index at the upper level was also considered as developed by Montgomery et al. [4]. In addition to this, the objective function for the lower level desirability was also defined as a second order function and analyzed as an additional case. These two methods are explained in detail below:

**Desirability Method for Performance Index** is based on the idea that the response of a process or a system is considered completely unacceptable if they fall outside the defined desired limits. For each response \( \hat{y} \) (NO\(_x\), FC, soot, exhaust exergy), the desirability function assigns a value between 0 and 1; where, 0 represents completely undesirable and 1 the most desirable. This value was used as the performance indices of the individual [65]. The desirability function was defined as follows:

\[
P_I = \begin{cases} 
1.0 & \hat{y} < T \\
\frac{(\hat{y} - U)}{(T - U)}^{x} & T \leq \hat{y} \leq U \\
0 & U < \hat{y} 
\end{cases} \quad \text{Desirability function for minimizing a response [65]} \quad (\text{Eqn.2})
\]

\[
P_I = \begin{cases} 
0 & \hat{y} < L \\
\frac{(\hat{y} - L)}{(T - L)}^{x} & L \leq \hat{y} \leq T \\
1.0 & T < \hat{y} 
\end{cases} \quad \text{Desirability function for maximizing a response [65]} \quad (\text{Eqn.3})
\]
\[
P_I = \begin{cases} 
1.0 & \hat{y} < T \\
\left(\frac{\hat{y} - L}{T - L}\right)^x & T \leq \hat{y} \leq L \\
\left(\frac{\hat{y} - U}{T - U}\right)^x & T \leq \hat{y} \leq U \\
0 & U < \hat{y}
\end{cases} 
\]

Desirability function for targeting a response [65] (Eqn.4)

Where, L, T, U and PI are the lower value, target values, upper values and performance indices, respectively and x is the order power used for second order desirability. These values were defined based on the range of the NO\textsubscript{x}, FC, soot and exhaust exergy responses observed during the parameter screening experiments for lower level GA. On the other hand, the values for L, T and U for the upper level GA were based on 2017 NO\textsubscript{x}, GHG and PM emissions standards. For defining engine out NO\textsubscript{x} levels, 95\% reduction efficiency was assumed for the after-treatment. Moreover, the desirability for the flow exergy made use of the targeting method described in Equation 4. A desirability of 1 was assigned when the flow exergy equivalent to engine exhaust temperature at 250°C and desirability of 0 was assigned if the flow exergy was equivalent to exhaust temperatures less than equal to the catalyst light-off temperatures (160°C) or greater than 500°C. The 500°C temperature limit was chosen because it is the temperature at which the vanadium based catalyst begins to undergo thermal deterioration [48, 50].

**Figure 24:** Desirability function representation for lower level MOGA with first order curves.

The overall performance index of the individuals in the population is determined based on the cumulative performance of the four responses evaluated from the combination of engine
parameters (SOI, NOP, EGR, and VGT). Equation 5, found below, represents the fitness function for the GA to evaluate the performance for every individual in each generation.

\[
FF = w_{NOx} PI_{NOx} + w_{FC} PI_{FC} + w_{soot} PI_{soot} + w_{ExhT} PI_{ExhT} \quad (Eqn.5)
\]

Where, \( w_{NOx}, w_{FC}, w_{soot}, \) and \( w_{ExhT} \) are the weighted factors of the corresponding responses. A similar approach for defining the performance index was also used for U-MOGA however the performance index was evaluated for the brake-specific emissions and fuel consumption over the FTP cycle and Near-Dock cycle. A cycle average of the performance index was used to obtain an overall cycle performance for flow exergy or exhaust temperature. This method yields an overall performance index between 0 and 1.

**Montgomery Method for Performance Index:** The method developed by Montgomery et al. [4] and used by Senecal et al. [66] for combustion modeling and optimization was also used in this study. This was done in order to ascertain the sensitivity of D-MOGA to the optimization process and the resulting optimal solution. Since the Montgomery et.al method for evaluating the performance indices uses only one target value as compared to the two or three values in the desirability method, the performance index can be easily defined without biasing the function towards a specific target if incorrectly defined. Equation 6 below shows how this function was defined. It must be noted that this method for evaluating the overall performance index obtains a value between 0 and 1000. An overall performance index of 1000 is obtained when all the target values are achieved.

\[
PI = \frac{1000}{W_{NOx} \left( \frac{bsNOx}{bsNOx_{target}} \right)^2 + W_{soot} \left( \frac{bsSoot}{bsSoot_{target}} \right)^2 + W_{FC} \left( \frac{bsFC}{bsFC_{target}} \right)^2 + W_{ExhT} \left( \frac{1}{EScore} \right)}
\]

... (Eqn.6)

Where \( bsNOx_{-target}, bsSoot_{target} \) and \( bsFC_{target} \) are engine-out brake-specific NOx target (0.4 g/bhp-hr); 2010 tailpipe total PM emissions limit (0.01 g/bhp-hr); and 2017 EPA GHG brake-specific CO2 limit (143.75 g/bhp-hr is the corresponding brake-specific diesel fuel consumption)
targets, respectively. The bsNO\textsubscript{x} emission target was set at 0.4 g/bhp-hr because with a 95% efficient DOC. DPF and SCR after-treatment system, the tail-pipe brake-specific NO\textsubscript{x} emissions can meet the optional C-ARB Low-NO\textsubscript{x} emission limit of 0.02 g/bhp-hr. The transient cycle desirability of A-TEAM (Escore) is defines in Equation 7 for U-MOGA. This score that represented the performance index for thermal management is the cycle weighted average of the desirability of the flow exergy obtained from L-MOGA’s desirability function. Where, d\textsubscript{i}(\hat{e}) is the performance index of exhaust flow exergy obtained using the targeting desirability function shown in Equation 4.

\[ Escore = \frac{\sum d\textsubscript{i}(\hat{e}) \cdot t}{\sum t} \quad \text{...(Eqn.7)} \]

### 4.1.5 Genetic Operators

The genetic operators consist of three main operations, specifically selection, crossover and mutation. Selection is considered as the evolutionary operation that mimics the process of *Darwinian evolution* to create a new and possibly better population from one generation to the next. D-MOGA makes use of the roulette wheel selection method. The roulette wheel selection, also known as fitness proportionate selection, works by selecting an individual solution for mutation and crossover based on the probability proportional to the fitness or performance index of the individual. Roulette wheel selection methods are defined in such a way that there is a higher probability of individuals with a higher performance index being carried over to the next generation or at least some of their properties are carried over to the next generation. The probability of an individual being selected for mutation and cross over is defined as follows:

\[ p\textsubscript{i} = \frac{P\textsubscript{I\textsubscript{i}}}{\sum_{j=1}^{N} P\textsubscript{I\textsubscript{j}}} \quad \text{...(Eqn.8)} \]

Once 100 individuals are selected from the previous generation using the roulette wheel method with the probability of repetition, two of these individuals are randomly chosen as parents for the crossover operation to produce two new candidate solutions for the next
These two new candidate solutions which are formed by a combining part of the parents are also known as off-springs. D-MOGA makes use of single point crossover in real representation of the chromosome. This means that a single point is randomly chosen to split both parent’s chromosome and is combined such that two new off-springs are created. Figure 25 shows an illustration of how the parents form the off-springs for the next generation during crossover operation in the L-MOGA. The same operation is carried out in a similar manner for the U-MOGA that consists of 4x29 long chromosomes. Crossover is one of the main genetic operators in GA-based optimization processes, since the performance of this operator greatly defines the performance of the GA [8]. D-MOGA makes use of a crossover rate of 50%. Crossover rate is defined as the percent of individuals in the new generation that are produced as a result of the crossover genetic operator. A higher crossover rate would encourage exploration; on the other hand, a lower crossover rate would encourage exploitation. The measure of exploration and exploitation is subjective and varies for every genetic algorithm. The definition of crossover rate used in D-MOGA was defined by Gen et al. [8].

Selection and crossover operations transfer good heredity from one generation to the next which allows the convergence of the search algorithm to a global solution, while the mutation operator is used to produce random changes in the candidate properties. Mutation operation is the random change of the locus or the position of the gene in one direction of the search space. Thus an individual’s single gene (values of chromosome in real representation) is randomly changed to form the new individual as shown in Figure 25.

\[\text{Figure 25: Illustration of crossover and mutation in D-MOGA for the lower level MOGA}\]
D-MOGA made use of a 50% mutation rate to explore the search space more rigorously and prevent the best solution to be trapped in local minima of the multi-modal solution space. Mutation rate for D-MOGA was defined as the probability of mutating the remaining \( \{N*(1-crossover\_rate)+1\} \) parent individuals to the next generation. Both levels of D-MOGA made use of the same set of genetic operator properties illustrated in Table 8.

<table>
<thead>
<tr>
<th>Algorithm Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
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</tr>
<tr>
<td>Number of Mutation Digits</td>
<td>1</td>
</tr>
<tr>
<td>Crossover Type</td>
<td>Single Point</td>
</tr>
<tr>
<td>Mutation Rate</td>
<td>50%</td>
</tr>
<tr>
<td>Crossover Rate</td>
<td>50%</td>
</tr>
<tr>
<td>Elitism</td>
<td>Best Individual</td>
</tr>
<tr>
<td>Selection</td>
<td>Roulette-Wheel</td>
</tr>
</tbody>
</table>

Finally, D-MOGA also made use of the best individual elitism selection method, where the chromosome and phenotype (decoded solution) of the best individual was transferred from one generation to the next unchanged. The use of elitism in the selection process made sure exploitation was enforced as a result forcing D-MOGA to always look for better solution. The definitions of these genetic operators vary from GA to GA, author to author, and based on the application. However, these differences do not affect the results obtained by the GAs due to their high flexibility.

4.2 ARTIFICIAL NEURAL NETWORK ENGINE MODELS

One of the primary and most important requirements for GAs are the need of a mathematical representation of the system that is to be optimized. Previously, in section 4.1.4 the objective function used for evaluating the performance index was discussed in detail. This section discusses the development of engine response model used for the L-MOGA and the transient engine response model developed for the U-MOGA using artificial neural networks. The responses obtained from these models are used for evaluating the performance indices of the individual by both levels of D-MOGA.
Mixed activation function Artificial neural network (ANN) models were built for the two levels of D-MOGA to evaluate the engine response factors for the different engine control parameter combinations. Four engine parameter response models were developed using ANN for estimating the response of NO\textsubscript{x}, fuel consumption, soot and exhaust energy based on engine speed, engine load, VGT position, SOI, NOP and EGR valve position. Two different approaches were used for developing the models, one of which was used solely for the soot model. The ANN models that were developed consisted of two hidden layers with combinations of three different activation functions. Single neuron of ANN provides a single output based on an activation function of the weighted sum of the inputs as shown in Figure 26.

![Figure 26: Schematic diagram of neuron for ANN model [57].](image)

The NO\textsubscript{x} and FC models as well as the after-treatment energy availability model (A-TEAM) consisted of two layers; each layer consisted of 1 neuron with a sigmoid activation function, 2 neurons with a linear activation function, and 4 neurons with the Gaussian (Radial Basis Function -RBF) activation function. The mathematical representation of these activation functions is explained in detail in the work by Turkson et al. [57]. The reasons for choosing these activation functions were to encapsulate the linear response of the factors with the linear activation function as well as the non-linear responses of the factors with the Sigmoid and Gaussian activation functions. The output layer consisted of an aggregate function operated on the outputs of the second layer of the neurons. The neural network model was trained using the training data obtained from the engine parameter sweep testing performed over the 29 test points.
and validated against baseline data over these 29 test points which consisted of the engine operated without enforcing any ECU overrides. This was done in order to separate the validation data set from the training data set and so that the validation data set represents normal engine operation. The training algorithms for neural network made use of a sum of the square errors penalty method where the sum of the squared error of the predicted responses were minimized.

For the soot response model, the neural network that was developed consisted of two layers; each layer consisting of 1 neuron with sigmoid activation function, 2 neurons with a linear activation function and 5 neurons with a RBF activation function. The validation method used for this model made use of a holdback method where 33% of the training dataset was randomly chosen and used for the validation. This was done to improve the accuracy of the soot response model as the technique applied to the other models did not work for the soot response model. In addition to engine parameters such as engine speed, engine load, VGT position, SOI, NOP and EGR valve position used in the other neural network models, the soot response model also made use of the prediction from the FC response model. Figure 27 shows the connectivity diagram for the two kinds of neural network models developed for this study.

![Figure 27: Neural net connectivity diagram used for fuel consumption, engine-out NOx and A-TEAM (left); as well as the neural net connectivity diagram for the soot response model (right).](image)

The use of FC in the soot response model allowed the neural networks to inherently account for pumping and parasitic losses as well as combustion inefficiencies that lead to the
formation of soot inside the cylinders. The use of FC as one of the input modelling parameters in the soot response model greatly increased the accuracy of the model. It must also be noted that the accuracy of the soot response was quite low as compared to the other models which is attributed to several factors. First, the formation of soot emissions from modern diesel engines greatly varies between steady-state operation and transient operation. This is primarily due to the formation of locally rich air and fuel mixtures in the combustion chambers during transient operations such as accelerations.

These locally rich regions of air and fuel mixtures result in poly-aromatic hydrocarbons (PAH) from unburned fuel which leads to the formation of soot. The phenomenology of soot formation due to PAH emissions from unburned fuel is discussed further by Mansurov’s review of combustion processes [67]. Additionally, Rakopoulos et al. detailed how the effects of engine speed, boost pressure or turbo speed lagging the fueling response to throttle to position [33] result in this momentary rich periods of air-fuel mixtures. In essence, Rakopoulos et.al explains that during transient responses such as accelerations, locally rich regions of air and fuel ratios are prevalent in the combustion chambers which are a consequence of meeting the torque demanded as well as increasing the engine speed. This leads to excessive soot formations when compared to steady-steady engine operation.

DPFs after-treatment equipped in current model year engines are highly efficient and reducing tailpipe soot emissions rates to nearly zero. This reducing soot formation by the engine is less of concern compared to NO\textsubscript{x} or FC. As a result, this study mainly aims to optimize engine operations for NO\textsubscript{x}, fuel consumption and thermal management of after-treatment alone. The use of the soot model is to provide the D-MOGA a metric to estimate the amount of soot density for a specific combination of engine control parameters qualitatively. D-MOGA aims to reduce soot emissions at both levels of the GA to reduce FC incurred by active regeneration of the DPF in addition to increased pumping losses from increased back pressure due to soot loading on the DPF.

The identification of the number of neurons and the types of neurons used for the neural network model as well as the inputs to the models were heuristically determined through trial and error. The response models were developed using data obtained from steady state testing and
are more representative of steady state engine operation than transient engine operation. However, the general trends of engine control parameter effects on performance and emissions for steady-state and transient engine operation are similar. Appendix I shows the engine control parameter trends on steady-state performance and emissions at speed-load point-18 (engine speed of 1310 rpm; brake torque of 974.1 ft-lbs).

Figure 28 consists of scatter plots between actual and predicted responses for the four steady-state engine response models developed in this study. The scatter plots also provide a visual representation of the accuracy of the model prediction in reference to its measured value. The plots include both training as well as validation data sets.

![Figure 28: Measured Vs Predicted plots for the artificial neural network engine steady-state engine response model for NOx, FC soot and A-TEAM.](image-url)
The steady-state engine parameter response model was used for parameter optimization by the L-MOGA. A modified version of the EO-NOx steady-state engine model was developed to better represent transient engine responses. Moreover, a novel and unique approach to model the quality of heat available in the engine exhaust to heat up the after-treatment was developed. The following subsections will discuss in detail how these models were designed and developed.

4.2.1 After-Treatment Energy Availability Model (A-TEAM)

A-TEAM was developed for both layers of the D-MOGA to evaluate a performance index in regards to the specific exergy available for heating up the after-treatment to an optimal temperature as opposed to the conventional exhaust enthalpy approach which estimates the rate of heat energy in the exhaust that is available for the after-treatment. A-TEAM used the concept of exergy to estimate the energy available for heating up the after-treatment to an optimal temperature. Exergy is defined as the maximum theoretical work obtainable from an overall system consisting of a system and the environment as the system comes into equilibrium with the environment by Moran et.al [68].

The A-TEAM estimates the specific flow exergy through the after-treatment such that the exit conditions of the after-treatment are at an optimal exhaust temperature of 250°C and atmospheric pressure of 101.325 kPa. Figure 29 shows the system diagram and control volume for estimating the flow exergy for the given inlet exhaust temperature. The specific flow exergy calculated is an estimate for the theoretical energy required for optimal catalyst temperatures of 250°C. This is done to maximize the NOx conversion efficiency of the SCR during the D-MOGA’s optimization process. The objective function for this purpose is defined in Section 4.1.4. The flow exergy was modeled using artificial neural networks using inputs such as engine speed, engine load, VGT position, SOI, NOP and EGR valve position. Exergetic analysis is a robust technique to analyze the maximum potential of a thermodynamic system. Mass-specific flow exergy was utilized for the A-TEAM instead of an exergy rate balance to ensure that exhaust mass flow did not affect the model accuracy.
4.2.1 Transient Response Engine Model

A transient engine response model was developed in order to estimate the brake-specific FC, brake-specific engine-out NO\textsubscript{x} emissions and total engine-out soot emissions over the transient cycle. The same steady-state engine model was used for predicting the FC, because minimal difference was observed between steady-state fueling predictions and transient fueling predictions when operating in the same engine control parameter look-up tables. Figure 30 shows the plot of ECU estimated fueling versus ANN predicted engine response for FC and the measured versus ANN predicted engine response for NO\textsubscript{x} emission concentrations over the FTP cycle. The blue line indicate actual value measured for NO\textsubscript{x} and ECU value reported for fuel consumption; brown line indicates predicted values.
The steady-state NO\textsubscript{x} response neural network model was used for the transient response NO\textsubscript{x} model. However, a six second moving median filter was applied to the transient NO\textsubscript{x} response model. The median filter simulate the phenomenology of engine control parameters lagging responses one from to the other. Although, a more robust approach for simulating control parameter lag is to use the actual response lag of these parameters as opposed to a median file, such simulation would require more computational time as well as more information regarding response times such as $t_{50}$ or $t_{90}$ for the control parameters used in this study. The use of the median filter was negligible during steady-state engine operation. A similar approach was also used for the estimation of the soot density over the cycles.

Once the transient response model for FC, engine-out NO\textsubscript{x} concentrations, and engine-out soot concentration was developed, it was necessary to obtain the exhaust flows during engine operation over the cycle to calculate the total mass of emissions during the transient cycle. Given that exhaust mass flow is simply the sum of intake fuel mass flow, intake mass flows was
predicted with the help of another neural network model. The intake mass flow model consisted of the same neural net structure as the steady-state FC model shown in Figure 27, where the prediction was a function of engine speed, engine load, VGT position, SOI, NOP and EGR valve position. Brake-specific NO\textsubscript{x} emissions and total soot emissions were calculated using average NO\textsubscript{x} and soot concentration over the cycle, times the integrated exhaust flow over the cycle. Figure 31 shows the predicted intake flow using neural network model which is plotted against measured intake flow by the ECU.

![Figure 31](image.png)

**Figure 31:** Predicted values of the intake flow model plotted against the ECU reported intake flow over the FTP cycle.

### 4.3 ENGINE CALIBRATION MAP CREATION

The best individual’s optimal parameter combination for the 29 points under the lug curve after 500 generation of D-MOGA simulation was used for creating the Low-NO\textsubscript{x} FTP calibration. Three maps were created for each of the four different engine parameters, them being NOP, SOI, EGR valve position and VGT position. The three maps correspond to the three modes of engine operation, transient mode, dynamic mode and static mode. No information was available on how the ECU transitions from one map to the another during transient operation, therefore it was difficult to account for it in the transient engine response modeling. As a result, the same optimal settings were used for all three maps.
During the engine parameter screening experiments, discussed in Section 3.4, a indicated torque value override that was used to manage fueling rate and ensure that the brake torque was kept constant. This indicated torque override value was recorded during the experiments and later was estimated for the new combination of best individual’s optimal parameter settings. Since the maps were a function of indicated torque and engine speed, A thin plate spline (TPS) interpolation method was used to interpolate and obtain settings between the test points. This is the same method employed by U-MOGA. TPS is a poly-harmonic spline based interpolation technique who’s splines can be represented using RBF. To prevent the interpolation method from extrapolating to unrealistic settings outside the bounds of the test data, maps where created only between engine speed of 700 RPM to 1900 RPM and 0 to 2200 Nm of indicated torque. The original MY 2007 calibrations setting were used for the speed and load points outside of the bounds of the test data.

4.4 PARETO FRONT SELECTION METHOD

After performing several D-MOGA simulations, it was observed that the convergence of the average performance index to the best individual was inadequate. It was also observed that the distribution of the performance index for a randomly generated population was non-uniform. As a result, the probability of selection of each was similar, irrespective of the objective function employed. As shown in Figure 32, the cumulative probability distribution line was observed to be a straight 45° line for the randomly generated population, which indicates the small differences in probability of selection between the individuals of the population. These small differences in the probability of selecting from one individual to the other reduced the chances of having more individuals with higher performance index thus leading to longer convergence times.
Figure 32: Selection probability distribution of a randomly generated population

In light of this, the Pareto frontier method was implemented to the roulette-wheel selection methodology and to the elitist strategy. It was evaluated using the validated Low-NO\textsubscript{x} objective D-MOGA 3 simulation run. Developed by Vilfredo Pareto (1848-1923), the Pareto frontier method established the concept of optimality with multiple objective functions with trade-offs.

Ge et al. [69] provides a formal definition to Pareto optimality or Pareto front in his work. It is the set of points with the lowest NO\textsubscript{x} emissions, lowest FC, or both such that there are no better points in the solution space. This concept is illustrated by Figure 33. The Pareto optimality criterion is commonly used in engineering, economics, and life sciences where cases with multi-objective functions with trade-offs are considered.
Figure 33: Scatter plot showing the random initial population and the pareto individuals evaluated based on the NO$_x$-FC trade-off

In this study, D-MOGA estimates the Pareto front individuals in the U-MOGA based on their performance over the transient cycle. These individuals are carried over to the next generation using the elitist selection strategy. Moreover, these individuals are also added to the parent population for crossover and mutation genetic operations. This is done to increase the probability that the new generation of these individuals will inherit the properties of the Pareto front individual. Since, there exists at least one Pareto front individual for a given population and there is a chance that all the individuals of the populations can be part of the Pareto front, this improves the convergence of D-MOGA to find the global optima. This method promotes exploration of the next generation of individual based on the NO$_x$-versus-CO$_2$ trade-off, forcing the off-springs to have genes that had a lower NO$_x$, CO$_2$ or both.
RESULTS AND DISCUSSIONS

The D-MOGA was successfully developed and implemented to perform transient test cycle-based engine calibration. This chapter discusses the baseline performance of the 2010 US-EPA emissions standards compliant Low-NO\textsubscript{x} engine calibration developed by Ardanese et. al [3]. The results obtained from the virtual D-MOGA simulations that were performed to investigate the influence of different objective functions for evaluating the performance index of the individual are also discussed. Moreover, the Low-NO\textsubscript{x} FTP calibration obtained using the desirability method (D-MOGA 3) was validated on the engine dynamometer for performance and emissions. Additionally, this chapter also discusses the parametric study performed on L-MOGA to estimate the best genetic operator properties and the Pareto front selection strategy.

5.1 BASELINE ENGINE PERFORMANCE AND MODEL VALIDATION

The performance and emissions levels of the baseline 2010 EPA emissions standards compliant Low-NO\textsubscript{x} calibration developed by Ardanese et. al [3] was evaluated. This was essential to ascertain how well conventional single point optimization approaches such as the Taguchi method used in previous studies [3], performed over certification cycles and also over off-cycle transient engine activity.

Figure 34 shows engine out brake-specific NO\textsubscript{x} (bsNO\textsubscript{x}) and soot (bsSoot) emissions as well as brake-specific fuel consumption (bsFC) of the test article with the baseline Low-NO\textsubscript{x} calibration developed by Ardenese et al [3], over the FTP cycle and Near-Dock, cycle. It can be observed that during non-regulatory cycle activity, such as the Near-Dock cycle, a 63% increase in engine out bsNO\textsubscript{x} emissions was observed with minimal changes in bsFC. A significant decrease in bsSoot emissions was also observed which could be attributed to the conventional NO\textsubscript{x}-versus-PM trade-off discussed by Zelenka et. al [24].
Figure 34: Transient engine model prediction compared against measured baseline results.

Figure 34 also shows the transient model predictions over the two transient cycles as well as the percent difference between the actual and predicted. The baseline Low-NOx calibration developed by Ardanese et. al [3] was used for evaluating prediction accuracy of the transient engine model. It can be observed that the steady-state response model used to develop the transient response model was able to predict engine operation during FTP and Near-Dock cycle within 3% of the actual results for bsFC. This could be attributed to the transient behavior of the main parametric effects and them being speed, torque, NOP and SOI. For a specific indicated torque and engine speed the ECU determines the duration of injection pulse from SOI based on the NOP, request Air-Fuel ratio map and Burned-Fraction of fuel map and these commands are executed by actuating solenoids on the injectors. During transient engine operation fueling parameters such as NOP and SOI have an instantaneous response to demand. As a result, fueling parameters respond quicker than air handling of parameters such as EGR rate and boost pressure even when the actuator position adjustment is performed instantaneously as requested. This is
because, there is a delay for the VGT to change speed and subsequently boost pressure. The strong interaction between VGT and EGR also influence the transient responses of EGR rate effecting decreasing Air and Fuel ratio to rich stratified combustion regimes during accelerations as shown by Rakopolous et. al [32, 33] in their study. This out of phase between fuel parameters such as NOP and SOI and air-handling parameters such as EGR and VGT causes a significant increase in soot emissions and decrease in NO\textsubscript{x} emissions when compared to steady-state engine operation as a result, there are discrepancies between steady-state and transient engine responses. In an attempt to match NO\textsubscript{x} emissions between the steady-state and transient models, this study made use of a median filter to reduce the response of the NO\textsubscript{x} emissions during highly transient engine speed or load changes while predicting a reasonable response during pseudo steady-state operation. However, this method failed to accurately predict non regulatory cycle engine activity, resulting in higher prediction errors of approximately 23% for NO\textsubscript{x} emissions during the Near-Dock cycle.

In regards to soot emissions, Figure 35 shows the differences in the measured and predicted engine-out soot mass concentrations during the FTP cycle. Although the predicted brake-specific soot emissions are on average 68% lower than the measured emissions, continuous traces of engine-out soot mass concentrations between the FTP and the Near-Dock cycle follow the same trends. In other words, even though the model did not yield the exact location of an optimal point in the solution space it would locate the general vicinity of the optimum point. It can also be inferred from this figure that the general shape and complexity of the search space was estimated approximately.

![Image](image-url)

**Figure 35:** Actual versus predicted engine out soot concentration with baseline calibrations over the FTP cycle
5.2 SOLUTION SPACE FOR TRANSIENT ENGINE CALIBRATION

Many engineering optimization problems are very complex in nature and the problem of engine calibration of modern HD diesel engines is no exception. The transient engine model developed for this study was able to estimate the general topology of the engine response surface. Figure 36 shows the multi-modal topology of the response surface for the engine operating over the FTP cycle and Figure 37 shows the topology of the response surface for the engine operating over a combined FTP and Near-Dock cycle, as a function of bsNO\textsubscript{x} and bsSoot emissions, as well as bsFC.

![Figure 36: Topology of transient engine response surface space for the engine operating over the FTP cycle.](image-url)
**Figure 37:** Topology of transient engine response surface for the engine operating over the combined FTP and NearDock cycle.

Figure 36 and Figure 37 demonstrate the complexity of the multi-modal behavior of the test article which is significantly different from an engine operating over the FTP cycle alone than an engine operating over a combined FTP and Near-Dock cycle. This elucidates the complexities of optimizing the engine operation simultaneously for certification cycles and a variety of real-world off-certification cycle engine operations. Moreover, Gen and Cheng [8] in their work scrupulously discuss with examples, the ergodic nature of evolution in genetic algorithms at performing robust global search where the convergent stepwise procedure of traditional approaches would fail, especially in cases where system responses resemble the multi-
modal Ackley function, fortifying the need for D-MOGA to be used during the engine development and calibration process.

5.3 LOWER LEVEL MOGA PERFORMANCE

Because the L-MOGA (lower level) is performing 29x100 optimizations for every generation of the U-MOGA (upper level), it is important to ensure convergence is met for every single run with minimal evolutionary iterations to reduce computing time. It was also necessary to ensure that the D-MOGA made use of the best combination of genetic operator properties to get the most robust solution for every run of the L-MOGA. This section describes the performance of the L-MOGA that performs steady-state engine parameter optimization. The results obtained during some of the preliminary parametric studies performed on the L-MOGA during development are also discussed.

During the development of the D-MOGA, a parametric study on the L-MOGA was performed to discern the best combination of genetic operator properties necessary to yield robust solutions. Table 9 shows the results obtained from a systematic parameter screening performed on varying levels of mutation and crossover rates. The results were compared to optimal solutions obtained from a statistical modelling program developed by SAS known as JMP® Statistical Discovery™. JMP® makes use of the step-wise gradient descent/ascent algorithm to minimize/maximize the overall desirability. Figure 38 shows the JMP® profiler window used for this study at test point number 18. It can be seen in Table 9 that amongst the different genetic operator properties used, employing a high mutation rate and crossover rate yielded optimal solutions. As explained by Gen and Cheng [8], having a high crossover rate promotes exploration of the solution space and reduces the chances of settling in a false optimum. On the other hand, having a high mutation rate allows the GA to try probable solutions that have not been tried before. Although, having a high mutation rate also means losing the heuristic nature of the GA that allows it to learn from the past, the algorithm was modified and strategies such as elitist selection were used to compensate for this effect during genetic operations.
Figure 38: JMP®’s Profiler used as the benchmark tool for desirability profiling and optimization of several response variables

Table 9: MOGA results for test Point 18 with varying crossover rate and mutation rate

<table>
<thead>
<tr>
<th>Cross-over Level</th>
<th>Mutation Level</th>
<th>Cross-over rate</th>
<th>Mutation rate</th>
<th>Population size</th>
<th>NOx (ppm)</th>
<th>FC (g)</th>
<th>ExhT (°C)</th>
<th>MOGA Observation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>Medium</td>
<td>0.3</td>
<td>0.4</td>
<td>100</td>
<td>48.00</td>
<td>198.7</td>
<td>408.4</td>
<td>Optimal Solution</td>
</tr>
<tr>
<td>Low</td>
<td>High</td>
<td>0.0</td>
<td>0.6</td>
<td>100</td>
<td>159.4</td>
<td>181.2</td>
<td>414.4</td>
<td>Local Min/Max</td>
</tr>
<tr>
<td>Medium</td>
<td>Low</td>
<td>0.4</td>
<td>0.3</td>
<td>100</td>
<td>158.5</td>
<td>181.3</td>
<td>414.9</td>
<td>Local Min/Max</td>
</tr>
<tr>
<td>Medium</td>
<td>Medium</td>
<td>0.3</td>
<td>0.3</td>
<td>100</td>
<td>159.1</td>
<td>181.9</td>
<td>415.0</td>
<td>Local Min/Max</td>
</tr>
<tr>
<td>High</td>
<td>High</td>
<td>0.6</td>
<td>0.6</td>
<td>100</td>
<td>48.00</td>
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<td>408.4</td>
<td>Optimal Solution</td>
</tr>
<tr>
<td>High</td>
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<td>High</td>
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<td>100</td>
<td>48.00</td>
<td>198.7</td>
<td>408.4</td>
<td>Optimal Solution</td>
</tr>
</tbody>
</table>

Once a suitable combination of genetic operators was selected, they were used in both levels of the D-MOGA. These properties were enumerated in Table 8. Additionally, a comparison between optimal solutions obtained from JMP® and the solution of the best individual after 100 generations of the L-MOGA were made. The comparison was performed on 12 points of the 13 mode SET test cycle. The L-MOGA made use of a RSM model developed using a preliminary dataset collected by Ardanese et. al [3]. The results obtained from this comparative analysis are shown in Table 10. GA properties used include a population size of
100%, mutation of one parameter in real representation at the rate of 50%, single point crossover at the rate of 50% and one individual for elitism. Results obtained using MOGA are results of the best individual after 100 generations. They provide confidence in the ability of the L-MOGA to determine optimal parameter combinations irrespective of the modelling accuracy of the system.

**Table 10:** Response optimization results of gradient based search method and the L-MOGA over 12 modes of the SET test cycle points

<table>
<thead>
<tr>
<th>Modes</th>
<th>Gradient Search Optimal Response</th>
<th>MOGA Optimal Response</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NOx (ppm)</td>
<td>FC (g)</td>
</tr>
<tr>
<td>2</td>
<td>71.61</td>
<td>264.1</td>
</tr>
<tr>
<td>3</td>
<td>96.69</td>
<td>138.9</td>
</tr>
<tr>
<td>4</td>
<td>31.78</td>
<td>221.4</td>
</tr>
<tr>
<td>5</td>
<td>59.74</td>
<td>118.9</td>
</tr>
<tr>
<td>6</td>
<td>63.10</td>
<td>193.6</td>
</tr>
<tr>
<td>7</td>
<td>62.29</td>
<td>67.20</td>
</tr>
<tr>
<td>8</td>
<td>112.3</td>
<td>313.1</td>
</tr>
<tr>
<td>9</td>
<td>33.73</td>
<td>80.10</td>
</tr>
<tr>
<td>10</td>
<td>134.0</td>
<td>325.8</td>
</tr>
<tr>
<td>11</td>
<td>BDL</td>
<td>82.4</td>
</tr>
<tr>
<td>12</td>
<td>68.19</td>
<td>238.5</td>
</tr>
<tr>
<td>13</td>
<td>37.26</td>
<td>153.1</td>
</tr>
</tbody>
</table>

**5.4 EFFECT OF OBJECTIVE FUNCTION ON OPTIMAL SOLUTIONS**

For all the D-MOGA simulation runs, the optimal solutions were reached between 500 and 600 generations when the changes in the performance index of the best individual were no longer observed. Figure 39 shows the evolution of the best individual’s performance index and average performance of the Low-FC objective using the Montgomery et. al [4] objective function for the U-MOGA and second order desirability for NOx and soot at the L-MOGA (D-MOGA simulation # 23 in Table 12). Additionally, the optimization histories for the remainder of the D-MOGA simulation runs are illustrated in Appendix-IV.
Three different objective functions were analyzed along with four different improvement targets. Additionally, the D-MOGA simulations also included single cycle runs with the FTP certification cycle and a combined FTP and Near-Dock cycle, totaling 24 simulations. Table 12 and Table 13 in Appendix-V shows the results and the statistics of the different D-MOGA simulation runs that were performed in this study, respectively. There was little to no correlation found between the definition of the objective function used to evaluate the performance index and the number of generations required by the D-MOGA to reach the optimal solution.

Figure 40 and Figure 41 show the variability charts of the percent difference between the FTP and Near-Dock engine-out bsNOx emissions and bsFC, respectively. The mean diamonds in these charts indicate the mean and confidence intervals of the group that is based on simulated test cycle results. The horizontal line of each group shows the mean percent difference between certification and off-cycle activity after D-MOGA optimization.
Figure 40: Variability chart of percent difference in engine-out brake-specific NOx emissions between the FTP and Near-Dock D-MOGA simulation results.

Figure 41: Variability chart of percent difference in brake-specific FC showing between the FTP and Near-Dock D-MOGA simulation results.
To evaluate the capabilities of the D-MOGA to perform simultaneous optimization during certification cycle and off-certification cycle engine activities, the combined dual-cycle optimization was investigated in this study. It can be observed in Figure 40 that the combined dual-cycle optimization method is able to significantly reduce off-cycle emissions by approximately 50%, when compared to optimizing the engine solely over the FTP cycle. However in doing so, there is also a significant increase in bsNO\textsubscript{x} emissions over the FTP certification cycle. One the other hand, there is minimal improvement in off-cycle brake-specific FC between the two cycle calibration methods.

The definition of the objective function at both levels of the D-MOGA plays an important role in the optimality of the solution which concurs with Montgomery et. al [4] and with Thiel et. al [11]. Applying a second order power (x=2) to the desirability function defined previously in Equation 2 and Equation 3 for bsNO\textsubscript{x} and bsSoot emissions in the L-MOGA, in addition to the use of the objective function defined by Montgomery et. al [4] in the U-MOGA, resulted in the best optimization results based on the transient engine model developed in this study, as shown in Figure 40.

Figure 42 shows a scatter plot of the D-MOGA simulation that was aimed at simultaneously lowering bsNO\textsubscript{x} emissions over the FTP and the Near-Dock cycle (D-MOGA simulation # 23 in Table 12). Points shown in the graph are a function of bsFC in the Y-axis and bsNO\textsubscript{x} emissions in the Y-axis, over the combined FTP and Near-Dock cycle. The plot shows the randomly generated initial population as well as the population after 500 generations of the simulation along with the location of the best individual after 500 generations. The X and Y axis indicate the bsNO\textsubscript{x} emissions and bsFC, respectively, over the combined FTP and Near-Dock cycle.
5.5 LOW-NOX FTP CALIBRATION MAP (D-MOGA 3)

The Low-NOx FTP calibration developed in this study using the desirability objective function at both levels of the D-MOGA (D-MOGA simulation # 3 in Table 12) was chosen as the candidate calibration for the final validation study. Optimal points obtained from the best individual of the D-MOGA 3 simulation after 500 generations were used to generate the transient, dynamic and static maps. All three sets of maps were updated using the same optimal points. The optimal points were converted to standard maps using the thin-plate spline interpolation method. Figure 43 through Figure 46 show the transient maps obtained and used for the validation experiments in this study. During validation experiments, it was found through trial and error that the transient look-up table played the biggest role in engine performance over the FTP cycle, followed by the dynamic maps.
Figure 43: EGR valve position optimized transient map from the D-MOGA 3 Low-NO\textsubscript{x} calibration

Figure 44: VGT position optimized transient map from the D-MOGA 3 Low-NO\textsubscript{x} calibration
Figure 45: NOP CA angle optimized transient map from the D-MOGA 3 Low-NO\textsubscript{x} calibration

Figure 46: SOI CA angle optimized transient map from the D-MOGA 3 Low-NO\textsubscript{x} calibration
The dual-level multi-objective approach to transient engine optimization yielded engine maps that were counter-intuitive and were more complex in shape compared to maps developed by Ardanese et. al [3] in their work. The maps developed by Ardanese et. al, resembled plateaus and were a result of optimizing a wide area of the map around each optimized engine speed and load point as well as having the same objective or target over the entire area under the lug curve. However, the D-MOGA does multi-objective optimization on each engine speed and load point using targeting weight. This is done even when the objective function in U-MOGA is reduced to a single objective. This results in a more complex, but robust optimal solution. Figure 47 and Figure 48 shows the NOx, FC, soot and Escore targeting weight contributions to engine operation over the FTP and the combined FTP and Near-Dock cycles respectively, for Low-NOx FTP calibration obtained using D-MOGA simulation #3. This is important in understanding the role that the test point’s play in the process of calibrations and to understand how the D-MOGA optimizes the targeting weights with the use of genetic algorithms. The pie charts for 29 test points are located based on the engine speed and brake torque they represent. The size of each pie chart is proportional to the frequency of the engine operations in the vicinity of these points multiplied by the exhaust mass flow. The blue solid line indicates the baseline lug-curve of the engine.
Figure 47: Weight contribution of the optimized test points to transient cycle operation showing the targeting weights assigned by D-MOGA for Low-NOx FTP calibration.
Figure 48: Weight contribution of the optimized test points to transient cycle operation showing the targetting weights assigned by D-MOGA for Low-NOx FTP calibration.

Idle engine operation played a significant role in both the FTP and the Near-Dock cycle and is represented by the large pie chart size. This is due to high frequency of idle operation in both the FTP and Near-Dock engine test cycles. On the other hand, there are apparent differences between the contributions of these test points in the FTP and the Near-Dock cycles. In addition to this, both figures show few points highlighted in red that did not play any role in the overall performance during transient engine operation. Thus, it is evident that simultaneously optimizing the engine operation over certification cycles and off-cycle real-world activity poses a very complex challenge due to the varying activity of engines. Moreover, the activity of an
engine/vehicle varies based on geographical location, its vocation, and the ambient conditions it is operating in. Thus it is would pose a very complex challenge for manufacturers to optimize every single engine model or a fleet of engines/vehicles based on their real-world activities.

The conventional approach of using the AVL 8 Mode points in conjunction with the 13 mode ESC points as used by Ardanese et. al [3], simply facilitates optimization over a larger area under a wider area under the lug curve. This study as well as the study performed by Varsha et al [35] both employ a similar method of clustering important points under the lug curve based on vehicle activity. This is a more robust approach to calibrating the vehicle performance over certification as well real-world off-cycle activity. This is primarily because, rather than simply covering a wider area under the lug curve, the D-MOGA allows the optimization process to target specific regions under the engine’s speed and torque lug curve that play a vital role in the performance and emissions of the engine/vehicle during transient operations.

5.5.1 Validation

This section discusses the experimental validation of the engine calibration developed with the D-MOGA 3. The engine was exercised over the FTP and the Near-Dock cycle. This activity evaluated the performance of the engine in comparison to the baseline Low-NOx 2010 calibration developed previously by Ardanese et. al [3]. Figure 49 is a scatter plot showing the randomly generated initial population indicated using a grey dot (•), population after 500 generations indicated with black circles (○), the population with the best individual’s location after 500 generations indicated using green diamond (◇), and the location of the validated point as function of bsNOx and bsFC indicated using a red triangle (△) over the FTP cycle.
Figure 49: Scatter plot of D-MOGA 3 simulation and validation results shown as function of bsNOx and bsFC

From an initial observation of Figure 49, it can be noted that there is significant difference between the estimated and the validated bsNOx and bsFC results. In addition to this, off-cycle brake-specific emissions are considerably higher when compared to the performance of the baseline calibrations, as shown in Figure 50. This is primarily attributed to the modelling inaccuracy during transient engine operation discussed in Section 5.1 of this study. Moreover, the D-MOGA 3 was aimed at obtaining low bsNOx emissions over the FTP cycle alone and did not make use of the combined cycle optimization method.
Upon further investigation into the validation results, exceptional improvement in the VGT outlet exhaust temperatures was observed for both cycles. Figure 51 shows the exhaust temperature profile, measured several inches downstream of the VGT turbine, between the baseline 2010 compliant calibration developed Ardanese et al [3] and the calibration obtained from the D-MOGA 3. Increased exhaust temperature provided by the D-MOGA 3 calibration validated the robustness of the A-TEAM model used in this study. Additionally, the calibration developed in this simulation also produced 50% lower engine-out brake-specific soot emissions with only a 17% increase in brake-specific NO\textsubscript{x} emissions. Although there is a discernible increase in brake-specific NO\textsubscript{x} emissions of 1.0235 g/bhp-hr, the increased thermal energy during the FTP and the Near-Dock cycles is more than sufficient for the tailpipe emissions to be lower than the 2010 regulated emission limits set forth by the US-EPA, with the use of a DOC-DFP-SCR after-treatment system. This is primarily because, urea-SCRs like the one discussed by Ardanese et. al [3] are typically 95% to 99% efficient in reducing NO\textsubscript{x} emissions when catalyst
temperatures are above 250 °C [5, 26, 49]. Furthermore, the increase in exhaust temperature would help the urea-SCR system reach catalyst light-off temperatures sooner and promote frequent passive regeneration of the catalyzed DPF. More passive regeneration of the DPF could provide reduced engine out brake-specific soot emissions and result in bsFC benefits due lower engine exhaust back pressure. Results shown in Figure 50 also show minimal improvement in bsFC over the FTP cycle. However, further improvements to bsFC can be made by reducing the overall weight on Escore which was set to one in this simulation and setting the overall weight for FC to a value that is greater than zero. This would reduce the aggressive thermal management employed by the calibration developed in the D-MOGA 3 simulation while improving bsFC.
Figure 51: Measured turbine-out exhaust temperatures for certification (FTP) and off-cycle (Near-Dock) engine operation showing apparent improvement in exhaust temperatures for thermal management.
5.6 PARETO FRONT SELECTION METHODOLOGY

In an effort to further improve the D-MOGA in optimizing engine emissions and performance during transient operations, Pareto front selection methodology was successfully augmented to the genetic operations performed by the U-MOGA. This was demonstrated using the validated D-MOGA 3 simulation run. Figure 52 shows the evolution history of best individual’s performance index and average performance index of the population for the D-MOGA 3 simulation, with and without including Pareto individuals. The influence of this methodology augmented to the evolutionary search algorithm is discussed in this section.

Figure 52: Evolution of best individual’s performance index and average performance index of the population for the D-MOGA 3 simulation, with and without including Pareto individuals

Figure 52 shows the influence on the performance index of the best individual with and without forcefully including Pareto front individuals to the population and parents of the next generation. Figure 52 also shows the visible improvement in the average performance index of
the population over the next generation of the D-MOGA simulation. Figure 53 shows the location of the final population with Pareto front selection method in comparison to the non Pareto elitist and roulette wheel selection strategy used in the D-MOGA 3 simulation. The initial population (Δ) is shown in grey triangles, population after 500 generations without Pareto Individuals are indicated with an x (x), population after 500 generations with Pareto Individuals are indicated in red dots (●), best individual after 500 generations amongst Pareto individuals are shown in green diamonds (◊) and best individual after 500 generations are shown in blue diamonds(◊).

Figure 53: Scatter plot of the D-MOGA 3 simulation with and without Pareto individuals evaluated over the FTP cycle.
The improvements in the average performance index of the population over every generation insinuated that the majority of the individual had better performance indices and are clustered around the best individual. This is evident when observing the location of individuals in the population after 500 generations, as shown in Figure 53. Although there is no significant improvements observed in the bsNOx, bsFC and overall performance index of the best individual after 500 generations, it can be observed that the population after 500 generation have explored more regions with lower bsNOx and bsFC response regions as compared to the non Pareto front selection method and thus ensuring these regions are explored during the D-MOGA simulation. Ge et. al [69] used a similar approach with Pareto front design in their MOGA that optimized HD diesel combustion using multi-dimensional modeling, yielding concurrent results. Gen and Cheng in their work, proposed several approaches to exploit the set of Pareto solutions to the genetic search [8]. However, this study used simpler selection strategies with regard to the involvement of the Pareto front individuals, in order to achieve this goal.

Figure 54 displays bar plots that present the simulated bsNOx and bsSoot emissions as well as the bsFC and Escore in comparison to the simulated D-MOGA 3 results that did not make use of the augmented Pareto front selection methodology. Small but clear improvements are observed in the simulated results over the FTP and Near-Dock cycle. Due to modelling inaccuracy of the transient engine response model, speculation on the validation results cannot be made on the actual performance of this calibration. However, from a qualitative stand point improvements were made by the D-MOGA based on the mathematical representation of the complex transient engine response that it used to optimize transient engine performance in this study.
Figure 54: Bar plot showing results of DMOGA 3 simulations, with and without Pareto individuals.
CONCLUSIONS AND RECOMMENDATIONS

The key objective of this research was to develop a robust calibration methodology and approach for transient engine calibration. The results further established the importance of objective functions and their representativeness to the solution space, in solving optimization problems using evolutionary genetic algorithms. This chapter recapitulates the results of this study and further provides recommendations for further improvement of the work done in this study. Additionally, this chapter also discusses the future applications of the D-MOGA that has been instituted in this study.

6.1 CONCLUSIONS

This study performed 24 different the D-MOGA simulations to investigate and determine the best objective function for obtaining robust solutions for transient engine calibration using the D-MOGA. The ability to simultaneously reduced emissions and fuel consumption over the certification cycle and off-cycle near dock activity was also evaluated. Each of these simulations were able to efficiently optimize engine operation for 50,000 simulations of the FTP or combined the FTP and the Near-Dock cycles over 500 generations of the D-MOGA simulations. D-MOGA was able to heuristically learn from one generation and improve upon it for the next generation. Each of the 29 points where optimized for about 5,000,000 times over 500 generations of the D-MOGA simulation runs, in order to arrive at the best calibration. The following conclusions were based on the study.

- The 2010 emissions compliant baseline engine calibration developed by Ardanese et. al [3], showed a 63% increase in engine-out bsNO_x emissions and a proportional 77% decrease in engine-out bsSoot emissions, during off-cycle activity leaving more work for the de-NO_x urea-SCR after-treatment system.
- The ANN-based transient engine response model developed for NO_x and soot emissions in this study was found to be inaccurate during off-cycle activity and for alternate calibrations. This is attributed to lack of information regarding the ECU control strategy and not incorporating the delayed response of boost and EGR flows in the transient modelling process.
The solution space analyzed using the randomly generated optimized individuals of the U-MOGA, was found to have complex multi-modal transient engine response behavior for the trade-off between bsFC, bsNO\(_x\) and bsSoot emissions. This behavior was different for different engine test cycle as exhibited by the combined the FTP and the Near-Dock cycle.

A parametric study, performed to find the best properties to obtain robust solutions within 100 generations was analyzed and demonstrated using the L-MOGA during the development process. Having a high crossover rate and high mutation rate allowed the L-MOGA to explore more of the search space, yielding a better solution every time.

The definition of the objective function played a vital role in arriving at the optimal solutions based on the targets provided. Amongst the three methods tested in this study, it was found that using the objective function developed by Montgomery et. al [4] with second order power on NO\(_x\) and soot emissions was found to be the best suited for simultaneously optimizing the engine over the FTP and the Near-Dock cycle.

The combined cycle calibration approach was virtually tested using the D-MOGA. A test cycle developed by simply joining the two cycles together during the calibration process was analyzed to see if it was an effective technique to calibrate the engine over multiple test cycles such as the FTP certification cycle and the real-world Near-Dock cycle simultaneously. This method was virtually proved to be very effective in conjunction with the use of the D-MOGA.

A Low-NO\(_x\) FTP calibration was developed using the desirability method (D-MOGA 3). The simulation resulted in more smooth transitioning surface maps for the four parameters SOI, NOP, VGT position and EGR valve position, as compared to the calibration maps developed by Ardanese et. al [3].

The Low-NO\(_x\) FTP calibration map developed in this study using the desirability approach was validated and the results where compared to the baseline 2010 compliant calibrations developed by Ardanese et. al [3]. It was found that even though the engine produced 17% higher emissions than the baseline Low-NO\(_x\) calibration (1.0235 g/bhp-hr), however the engine-out NO\(_x\) emissions were still
within the capabilities of the urea-SCR system 95% reduction efficiency to meet the 2010 certification limits.

- Additionally, a substantial increase in thermal exhaust energy was also achieved without incurring any fuel penalties due to increased thermal management of SCR during certification and off-certification cycle engine operation.

- A substantial increase in off-cycle brake-specific NO\textsubscript{x} emissions was observed. Although the D-MOGA simulated results showed a decrease in off-cycle emissions, the validated results where 102% higher than the baseline results during the validation process. This was attributed to the lack of prediction accuracy of the transient engine model over the certification cycle and more so during off-cycle engine activity.

- However, exceptional improvement in the VGT outlet exhaust temperatures was observed for the FTP and the Near-Dock cycles during the engine dynamometer validation experiments. This additional exhaust energy available to the after-treatment will help the SCR system reach light-off quicker and be active during a longer period the FTP and the Near-Dock cycle for actively reducing engine-out NO\textsubscript{x} emissions.

- It was observed that the A-TEAM served as an effective metric for offline optimization of exhaust thermal management. Since the transient fuel consumption model developed in this study was accurate, the D-MOGA with the use of A-TEAM, was able to exhaust thermal energy without incurring any fuel penalties in the process.

- The heuristic search algorithm for the D-MOGA was further improved by forcefully including the Pareto front individuals to the roulette-wheel and elitist selection process. This method was augmented to the D-MOGA 3 simulation and results after 500 generations were compared. The results showed small improvements in the optimal solutions of the best individuals, between the two individuals.

- The augmentation of the Pareto front individuals to the selection process proved to be an effective technique in directing the heuristic search process in the direction of specifically lowering bsNO\textsubscript{x} emissions and bsFC.
Typically, thermal management strategies employed to bring after treatment temperatures up to speed quickly, incur significant fuel penalties, as demonstrated in the CARB funded research program performed by Sharp et. al [1] to achieve ultra-low brake-specific NO\textsubscript{x} emissions. This phenomenon, over the years has shifted the focus of engine and vehicle manufacturers, from the NO\textsubscript{x}-versus-PM trade-off to a NO\textsubscript{x}-versus-CO\textsubscript{2} trade-off [70]. However, the results obtained in this study show that there exists a possibly unexplored global optimum for every engine and after-treatment architecture ever designed developed in the past and for those that will be in the future. This global optimum can be characterized by low tail-pipe brake-specific emissions that are achieved without incurring any significant penalties in brake-specific fuel consumption. Robust optimization techniques such as the D-MOGA developed in this study are more efficient way of reaching optimal engine and after-treatment performance and in return pushing the limits of engineering further. Moreover, the new Real-Driving Emissions (RDE) test procedures that the European Commission legislated [71, 72] presents big challenges in this respect to manufacturers to meet consumer and regulatory demands. The D-MOGA can be utilized as a robust tool in such instances to perform engine optimizations for real-world engine/vehicle activity and as tool that can streamline the engine calibration process.

6.2 RECOMMENDATIONS

This study discussed the some of the first iterations in developing the D-MOGA for creating robust engine calibrations. The experience and knowledge gained during this first iteration will be used to make improvements for the next iteration of model developments, simulation and validation processes. Thus, the D-MOGA is a tool that can streamline and fool-proof the process of engine and after-treatment calibration, where the calibration engineer/s learns from every step of the optimization process and imparts his knowledge to the D-MOGA in the form of computer or mathematical models. This interaction between human and GAs is what makes the D-MOGA truly a robust technique that evolves over the timeline of engine development. Some of the recommendations for improvements for the next iteration of the human and GA process are discussed below:

- Further improvements can be made to the transient engine model accuracy. Due to the apparent lag of boost and EGR flow rates respective to commanded VGT
position and EGR position, it would be a better approach to create the transient cycle model as a function of the boost and EGR flow rates and simulate the delayed response of these values based on the VGT and EGR valve positions.

- Having more knowledge regarding ECU control algorithm as well as the engine torque limiters can help employ suitable reward and penalties schemes in U-MOGA would improve the robustness of the final calibration.

- To improve the smoothness of engine operation and engine performance and durability, it would be essential for the D-MOGA to account for combustion characteristics such as cycle to cycle variations at the lower level of the D-MOGA. This would help to avoid combinations of engine control parameters that could lead to rough idles or unsteady engine operation thus requiring the need for validation experiments to be performed by the engineer.

- As opposed to creating four individual maps for each engine control parameter using the same optimal control parameter configurations, a more robust approach would be to have individual optimal settings for the four transient, dynamic, static and steady-state maps. In newer MY’ engines, there could be many more sets of individual maps for each control parameter that could be optimized by D-MOGA efficiently, due to the ergodic nature of the GA-based optimization process.

- Incorporating a fast computing model for the U-MOGA to estimate the aftertreatment activity in conjunction with the A-TEAM at the lower level would allow the D-MOGA to obtain better FC when employing different thermal management strategies to improve SCR activity.

- Modelling, combustion characteristics, engine emissions and performance when engine is cold and as a function of engine oil and coolant temperatures could improve cold start performance of the engine calibration obtained from the D-MOGA.

- Providing rewards and penalties to candidate calibrations based on in-use performance such as NTE or work-based window approaches could reduce the need for small adjustments during vehicle integration and in-use compliance processes.
6.3 FUTURE WORK

The D-MOGA approach is a virtual calibration routine. Once the engine and after-treatment system can be represented with fast and reasonably accurate models, the calibration routine can be performed during earlier stages of engine development, thus greatly reducing the engine test cell and calibration time. Moreover, parts that could fail due to durability issues that are a result of operating the engine in a particular and possibly optimal manner can be redesigned and manufactured to be stronger and more durable. Since the D-MOGA is basically an evolutionary search algorithm it can be coupled to empirical engine models such as GT-Power (GT-SUITE®) and can be used for engine and parameter optimizations. Also, to meet the NAAQ standards in areas such as the South Coast Air Basin or port of LA, the calibration tool could be used as a retrofit technology to update the existing engine calibration and reduce emissions from drayage fleets operating in these areas. Although this may require a few minor hardware upgrades due to the durability of engine components, this could still prove to be a viable and cost effective solution to simultaneously meeting in-use HD confirmatory standards while achieving lower real-world off-cycle emissions. Figure 55 shows some of the real-world applications of the D-MOGA for optimizing the performance and emissions of current model year engines and vehicles.
Figure 55: Applications and capabilities of the D-MOGA calibration tool and scope of future work
REFERENCES


42. Huang, Y. and J. Leet, *Investigation of In-cylinder NOx and PM Reduction with Delphi E3 Flexible Unit Injectors on a Heavy-duty Diesel Engine.* 2008.


Appendix I - Interaction of Engine Parameters and Responses

Figure 56: Interaction plot showing the effects of engine control parameter on engine response factors for test article operating at a speed of 1310 rpm and 974.1 ft-lbs of brake torque (POINT 18). The horizontal axis comprises on the varying engine control parameters plotted against the vertical axis comprising of engine response factors. The red line indicates varying trend of response with change in input control parameters.
Appendix II - Test Cycles

Figure 57: Speed and Torque trace for FTP certification cycle

Figure 58: Speed and Torque trace for Near-dock cycle.
Appendix III - Central Composite Design Test Matrix

**Table 11:** Parameter sweep test matrix for 3-level CCD test matrix. EGR is at three levels and each level of EGR position comprises of a face centered CCD test matrix of VGT, SOI and NOP at three levels. ‘0’ indicates center or moderate level; ‘-1’ indicate lowest level of parameter sweep; and +1 indicate highest level of parameter sweep. The actual position of VGT, NOP and SOI engine parameter are subjective and varies at every test point, this test matrix primarily used to provide directions for parameter sweeping. At speed-loads below 25% throttle, the parameter sweeps for VGT, NOP and SOI was performed for a single default level of EGR due to lack of EGR control.

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Appendix IV - Optimization History for D-MOGA

Figure 59: Evolution of BI’s PI and average PI of the population for D-MOGA 1

Figure 60: Evolution of BI’s PI and average PI of the population for D-MOGA 2.
Figure 61: Evolution of BI’s PI and average PI of the population for D-MOGA 3.

Figure 62: Evolution of BI’s PI and average PI of the population for D-MOGA 4
Figure 63: Evolution of BI’s PI and average PI of the population for D-MOGA 5

Figure 64: Evolution of BI’s PI and average PI of the population for D-MOGA 6
Figure 65: Evolution of BI’s PI and average PI of the population for D-MOGA 7

Figure 66: Evolution of BI’s PI and average PI of the population for D-MOGA 8
Figure 67: Evolution of BI’s PI and average PI of the population for D-MOGA 9

Figure 68: Evolution of BI’s PI and average PI of the population for D-MOGA 10
Figure 69: Evolution of BI’s PI and average PI of the population for D-MOGA 11

Figure 70: Evolution of BI’s PI and average PI of the population for D-MOGA 12
Figure 71: Evolution of BI’s PI and average PI of the population for D-MOGA 13

Figure 72: Evolution of BI’s PI and average PI of the population for D-MOGA 14
**Figure 73:** Evolution of BI’s PI and average PI of the population for D-MOGA 15

**Figure 74:** Evolution of BI’s PI and average PI of the population for D-MOGA 16
Figure 75: Evolution of BI’s PI and average PI of the population for D-MOGA 17

Figure 76: Evolution of BI’s PI and average PI of the population for D-MOGA 18
Figure 77: Evolution of BI’s PI and average PI of the population for D-MOGA 19

Figure 78: Evolution of BI’s PI and average PI of the population for D-MOGA 20
Figure 79: Evolution of BI’s PI and average PI of the population for D-MOGA 21

Figure 80: Evolution of BI’s PI and average PI of the population for D-MOGA 22
Figure 81: Evolution of BI’s PI and average PI of the population for D-MOGA 23

Figure 82: Evolution of BI’s PI and average PI of the population for D-MOGA 24
## Appendix V - D-MOGA Simulation Results and Analysis

### Table 12: Simulation run results after 500 generations for the different objective functions investigated in this study

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<td>bsFC</td>
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Table 13: Simulation statistics for the different DOMGA simulation runs performed.

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<td>Near-dock Average</td>
<td>Difference during Off-cycle activity</td>
<td>Mean difference during Off-cycle activity</td>
<td>FTP Average</td>
<td>Near-dock Average</td>
<td>Difference during Off-cycle activity</td>
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<td>Difference during Off-cycle activity</td>
<td>Mean difference during Off-cycle activity</td>
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<tr>
<td>Low-NOx, Soot &amp; FC</td>
<td>D-MOGA 1</td>
<td>0.4947</td>
<td>0.9510</td>
<td>156.7%</td>
<td>109.6%</td>
<td>196.4</td>
<td>218.0</td>
<td>9.637%</td>
<td>11.07%</td>
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<td>Low-NOx &amp; FC</td>
<td>D-MOGA 2</td>
<td>0.5845</td>
<td>0.9269</td>
<td>79.28%</td>
<td>58.68%</td>
<td>197.9</td>
<td>214.8</td>
<td>8.269%</td>
<td>8.676%</td>
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<td>Low-FC</td>
<td>D-MOGA 3</td>
<td>0.5143</td>
<td>0.9025</td>
<td>189.0%</td>
<td>101.9%</td>
<td>200.4</td>
<td>216.1</td>
<td>5.34%</td>
<td>7.964%</td>
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<td>Low-NOx, Soot &amp; FC</td>
<td>D-MOGA 4</td>
<td>0.8366</td>
<td>0.8135</td>
<td>-22.0%</td>
<td>-16.6%</td>
<td>206.1</td>
<td>205.6</td>
<td>-2.146%</td>
<td>-0.031%</td>
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<td>Low-NOx &amp; FC</td>
<td>D-MOGA 5</td>
<td>0.4760</td>
<td>1.0218</td>
<td>57.82%</td>
<td>127.1%</td>
<td>200.6</td>
<td>214.0</td>
<td>3.091%</td>
<td>6.806%</td>
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<td>Low-FC</td>
<td>D-MOGA 6</td>
<td>0.5406</td>
<td>0.6933</td>
<td>15.23%</td>
<td>26.33%</td>
<td>205.1</td>
<td>218.5</td>
<td>2.870%</td>
<td>6.696%</td>
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