2014

A novel particle swarm and genetic algorithm hybrid method for improved heuristic optimization of diesel engine performance

Aaron Bertram
Iowa State University

A novel particle swarm and genetic algorithm hybrid method for improved heuristic optimization of diesel engine performance

By

Aaron Michael Bertram

A thesis submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Major: Mechanical Engineering

Program of Study Committee:
Song-Charng Kong, Major Professor
Ganesh Balasubramanian
Gap-Yong Kim

Iowa State University

Ames, Iowa

2014

DEDICATION

This work is dedicated to my children, A. M. and L. R. We inherit each prior generation's doings, both good and bad, at the very moment that we are born into this world. I hope that this work may serve to improve the quality of life for all humanity as an investment in your future. Remember that during your life you are merely borrowing this Earth from the next generation and as such have already inherited my own footprints upon it. As wise men have said, "leave it better than you found it."

TABLE OF CONTENTS

Page

LIST OF FIGURES v

LIST OF TABLES vi

NOMENCLATURE vii

ACKNOWLEDGEMENTS x

ABSTRACT xi

CHAPTER 1 INTRODUCTION 1

1.1 Motivation 1
1.2 Objective 3

CHAPTER 2 THEORETICAL BACKGROUND 5

2.1 Particle Swarm Optimization 5
2.2 Genetic Algorithm 8
2.3 Engine Technology and Testing 11
2.4 Novel Hybridization of the PSO and GA 15

CHAPTER 3 EXPERIMENTAL SETUP 17

3.1 Overview of Testing 17
3.2 Particle Swarm Optimization 19
3.3 Genetic Algorithm 20
3.4 Hybrid Method and Objective 21
3.5 Exhaust Emissions Analysis 23
3.6 DAQ System 26
3.7 Engine Test Stand 29
3.8 Experimental Test Procedure 34

CHAPTER 4 EXPERIMENTAL RESULTS 36

4.1 Preliminary Studies 36
4.2 Pure PSO Results 37

4.3 PSO-GA Hybrid 41
4.4 PSO-GA PSO Objective Comparison 46
4.5 PSO-GA PSO Input Parameters Comparison 51

CHAPTER 5 CONCLUSION 56

5.1 PSO-GA Hybrid Improvements 56
5.2 Combustion Control for Emission Reduction using Heuristic Optimization .. 61

WORKS CITED 63

LIST OF FIGURES

Page

Figure 3.1 Horiba Mexa 7100D-EGR 24

Figure 3.2 AVL Reflective Smoke Meter 26

Figure 3.3 Kistler 6000 Series Pressure Transducer and 5000 Series Charge Amplifier 27

Figure 3.4 National Instruments PCI Card 28

Figure 3.5 BEI H25 Incremental Quadrature Shaft Encoder 29

Figure 3.6 John Deere 4045 Engine and GE Dynamometer.. 30

Figure 3.7 EGR Coding Manifold and Coolers 32

Figure 3.8 EGR System Supercharger and collection manifold 32

Figure 3.9 Fuel Flow Meter and Display Unit.. 33

Figure 4.1 NOx, PM and Total Objective Values for the PSO Method.. 37

Figure 4.2 NOx-Soot Objective Values for Generation 1 through 5 for the Basic PSO.. 38

Figure 4.3 Overall Objective Values for Generation 1 through 5 for the Basic PSO.. 39

Figure 4.4 Ave. and Min. Objective Values for Generation 1 through 5 for the Basic PSO 40

Figure 4.5 Minimum Objective Values for Generation 1 through 5 for the Basic PSO 40

Figure 4.6 NOx, PM and Total Objective Values for the hybrid PSO-GA Method. 42

Figure 4.7a NOx-Soot Objective Values for Generation 1 through 4 for the Hybrid PSO-GA 43

Figure 4.7b NOx-Soot Objective Values for Generation 1 through 4 for the Hybrid PSO-GA 43

Figure 4.8 Overall Objective Values for Generation 1 through 4 for the Hybrid PSO-GA 44

Figure 4.9 Ave. and Min. Objective Values for Generation 1 through 4 for the Hybrid PSO-GA 45

Figure 4.10 Minimum Objective Values for Generation 1 through 5 for the Basic PSO 46

Figure 4.11 Objective values of the PSO-GA and basic PSO method by time-equivalence 47

Figure 4.12 Objective values of the PSO-GA and basic PSO method without outliers 47

Figure 4.13 Average and Minimum Objective Values for the Hybrid and PSO methods 48

Figure 4.14a Minimum Objective Values for Hybrid PSO-GA and Basic GA 49

Figure 4.14b Minimum NOx Objective Values for Hybrid PSO-GA and Basic GA 49

Figure 4.14c Minimum PM Objective Values for Hybrid PSO-GA and Basic GA 50

Figure 4.15a Second order interaction between Pilot Percentage and EGR........ 52

Figure 4.15b Second order interaction between Pilot Percentage and Fuel Pressure 52

Figure 4.15c Second order interaction between EGR and Fuel Pressure........ 53

Figure 4.16a Second order interaction between SOI and Pilot timing........ 54

Figure 4.16b Second order interaction between SOI and Pilot percentage........ 54

Figure 4.16c Second order interaction between Pilot timing and Pilot percentage........ 55

LIST OF TABLES

Page

Table 3.1 Test Conditions 18

Table 3.2 Engine Control Parameter Limits 18

Table 3.3 PSO Factors 20

Table 3.4 GA Factors 21

Table 3.5 The Selected Objective Values 23

Table 3.6 Exhaust Gas Analysis Measurement Units 24

Table 3.7 Test Engine Specifications 31

Table 4.1 Qualitative Study of Unit Steps from Default Operating Conditions 36

Table 4.2 Settling Time Study Results 36

NOMENCLATURE AND VARIABLES

IC	Internal Combustion
ICE	Internal Combustion Engine
PSO	Particle Swarm Optimization
GA	Genetic Algorithm
DE	Differential Evolution
CAD	Crank Angle Degrees
TDC	Top Dead Center
ATDC	After Top Dead Center
SCR	Selective Catalyst Reduction
DI	Direct Injection
SI	Spark Ignition
CI	Compression Ignition
RCCI	Reactivity Controlled Compression Ignition
PCCI	Pre-mix Charge Compression Ignition
PPCCI	Partially Pre-mixed Charge Compression Ignition
HCCI	Homogeneous Charge Compression Ignition
Pbest	Individual particle best location in the PSO
Gbest	Globally best particle location in the PSO
C1	Factor in the PSO, social weight
C2	Factor in the PSO, individual weight
V_i	Velocity vector of particle i in the PSO

X_i	Position vector of particle i in the PSO
W	Inertia weight factor in the PSO
R_x	Random number, used in all methods
CO_2	Carbon Dioxide
CO	Carbon Monoxide
O_2	Oxygen
$BSNO_x$	Brake Specific NO_x Emissions
BSCO	Brake Specific CO Emissions
$BSCO_2$	Brake Specific CO_2 Emissions
BSHC	Brake Specific Hydrocarbon Emissions
BSPM	Brake Specific Particulate Matter Emissions
EPA	Environmental Protection Agency

ACKNOWLEDGEMENTS

I would like to thank my committee chair, Dr. Song-Charng Kong, and my committee members, Dr. Ganesh Balasubramanian, and Dr. Gap-Yong Kim, for their continued support throughout the course of this research. I specifically want to thank Dr. Kong for his continued patience with me as my mentor and guide through academia. His support, motivation, and intellectual stimulation has been the most powerful tool at my disposal. He has kept me grounded and guided through a most amazing experience. I also want to thank the students who have contributed work to the projects in the engines lab and created a stimulating and productive environment, specifically, George Zacharachis-Jutz, Jordan Tiarks, Nathan Beougher, Charles Mollenhauer, Ross Albert, Patrick Sanderson, and Katie Goebel. I would also like to recognize Prashanth Karra and Praveen Kumar for their inspiring work and motivation to succeed in this project.

Special thanks also to Dr. Kyung Hyun Ryu, for mentoring me and for teaching me a immeasurable wealth of information about engine dynamometer and engine operations, as well as James Dautremont, without whom operations in the lab would simply not be possible. His wealth of experience and knowledge in the lab has proved invaluable many times and his work on constructing large portions of the apparatus used is appreciated.

I would also like to thank my many friends, colleagues, and the department faculty and staff for making my experience at Iowa State University a truly amazing experience.

Finally, a very special thank-you to my family for their encouragement, and to my wife for her hours of patience, respect and love. Without her my work would not shine as brightly.

ABSTRACT

This study explores a novel application of the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) heuristic methods in a hybrid construction on a 4 cylinder medium-duty diesel engine at part-load conditions. The application of the hybrid PSO-GA approach is compared with a basic PSO in the optimization of the control parameters of a diesel engine utilizing high EGR capability, modestly high fuel pressure capability, and a two-injection fuel strategy.

The results indicate that the application of the GA to the basic PSO method improved the search breadth and convergence rate when compared to the basic PSO method alone. The novel approach of applying the GA to the fuel schedule is found to be worthy of further investigation. Applying the GA to specific parameters as way to improve optimizations on was effective in reducing the iterations and time taken to achieve satisfactory objective values. The hybrid method showed up to a 49% improvement in objective value over the basic PSO with less operational time in testing.

CHAPTER I INTRODUCTION

1.1 Motivation

Internal combustion engines (ICEs) have played a substantial role in the development of our modern world. Several industries rely on internal combustion engines to drive their productivity. Globally internal combustion engines are widely used in the sectors of transportation, power generation, construction, and agriculture. Almost every aspect of life in this age is dependent on ICEs [1]. IC engines are used widely and production is competitive. On the other hand, such widespread use of ICEs has been identified as a source of harmful emissions on a global scale [2] [3] [4].

Continued growth in industries which use ICEs is also a significant factor in the prediction of fuel use and emission production. As of 2012 87% of eligible Americans are licensed to drive an automobile, which represents a steady increase since licensing was introduced [4]. Furthermore, rapid growth and modernization in developing countries, such as China and India, are responsible for adding a large number of vehicles to the global fleet. Despite these trends, the predictions of gasoline consumption are somewhat steady to decreasing for the next 20 years. “Dieselization” of passenger cars and CAFE mileage standards imposed by recent American legislation both contribute to this prediction of gasoline use, while at the same time they contribute to the increased use of diesel engines [5].

On the other hand, increased attention towards diesel engine tailpipe emissions has created pressure for manufacturers to produce engines which pollute less [1] [3] [4]. Developments such as diesel particulate filters, selective catalyst reduction with diesel exhaust fluid, diesel oxidation catalysts, and NOx traps have been introduced to address emissions concerns by after-treatment of exhaust gasses. The U.S. Tiered emissions standards have required emissions to be reduced tenfold over the last decade [4]. The costs of these exhaust treatment systems are quite high since they often require rare earth metals and advanced manufacturing techniques [3] [6] [7] [8]. As new technologies are developed to both reduce emissions as well as increase fuel mileage, diesel engines become increasingly complex and more expensive to operate and develop [1] [3] [9].

As the vast majority of goods consumed in America are transported using diesel engines, improvements in fuel consumption can have a real impact on market prices of goods [1] [5]. Developments which improve the fuel consumption rate can also impact the fuel price itself. It is critically important to the economy that the issue of fuel efficiency in modern diesel engines is addressed [3].

Global environmental concerns over increasing atmospheric CO2 concentration are also another motivation for decreasing fuel use [4]. By decreasing the total fuel used CO_2 emissions are directly reduced [1] [3]. Although CO_2 emissions are not currently regulated by government agencies, a trend of advertising environmentally friendly technologies and practices has motivated agencies to further understand and limit resource consumption and CO_2 production [1].

Other pollution concerns come from the emission of hydrocarbons and nitrogen oxides which can contribute to acid rain and smog [1]. Smoke, or more technically particulate emissions, can also lead to substantial environmental impact as well as an immediate impact on humans [2]. In rapidly growing regions of Asia, pollution levels have reached dangerous levels for humans and rainfall onto the skin can harm people and objects.

Furthermore, small particulate matter has been implicated by the WHO in 3.7 million deaths in 2012 alone, attributed mostly to finer smoke particles which can easily enter the cardiovascular system and cause cancer [2]. This level of pollution requires rapid technology developments and such rapid changes in applied technologies are usually quite costly.

1.2 Objective

Computerized technology has allowed our society to advance at an astonishing pace since they were introduced [3]. Advancements in digital controls and communications, materials science, and manufacturing processes have provided opportunities to improve emissions performance in modern combustion engines [1] [3]. Optimizing such complex systems presents a problem in itself, however, as new technology must be thoroughly tested before it is considered viable for production. As each new device is added or changed the performance of the combustion system can become harder to predict and the combustion itself can become more difficult to control [1] [3]. Thus, efforts must be applied to improve the techniques of testing and control parameter optimization to enable new advancements to be rapidly evaluated and improved in the design process.

Modern optimization techniques have demonstrated that they can reduce the time and resources to identify solutions in complex systems with highly varied response characteristics [10] [11] [12] [13] [14] [15] [16]. The objective of this research is to apply new methodology to the heuristic optimization of control parameters in an experimentally tested diesel engine. A new hybrid of two established heuristic methods, the particle swarm optimization (PSO) and genetic algorithm (GA), which are commonly used in engine testing, is hypothesized to provide the benefits of both methodologies while avoiding compounding of the drawbacks [17] [16] [18]. This hybrid approach is expected to be broadly applicable applied to an experimental engine apparatus.

CHAPTER 2 THEORETICAL BACKGROUND

2.1 Particle Swarm Optimization

The particle swarm optimization (PSO) algorithm is a heuristic optimization algorithm, developed by Kennedy and Eberhart in 1995, wherein potential solutions are evaluated and improved using information exchange to produce improved solution values within a population [19]. As a heuristic method, of course, the PSO cannot guarantee the location a global optimum within the design space, although it does perform well on problems with non-differentiable space and with convoluted response variables [20]. PSO is just one example of a group of methods, classified as evolutionary methods, along with the genetic algorithm, which has been commonly applied to internal combustion engine optimization [3] [10] [17] [21].

Optimization of internal combustion engine operating parameters is a very complex and difficult problem. Heuristics in general, and specifically evolutionary methods, are an efficient way to optimize parameter selection within a particular test environment with such complexity [3] [11] [12]. The PSO and GA have both been shown to be effective methods for optimizing combustions systems, especially with a high number of variables in the design space and convolutions in the response characteristic which cannot be optimized with gradient search techniques [3] [10] [11] [17].

PSO has been used extensively since its emergence and many variations have been developed for specific applications and classes of problems [13]. Generalizations of the “social intelligence” factors have been developed into more modern methods such as neural network development and advanced topology structures within the PSO but these have tended to focus on well-studied test functions [11] [15]. Modern advancements in heuristic optimization have focused on generalized methods, computational systems, and standard test batteries, which have been widely used to evaluate the performance of optimization routines [3] [11]. On one hand we want the method to perform well on a wide range of problems, while on the other hand, performance in unrelated realms may actually serve as a detriment to the specific application, as illustrated by the “no free lunch” theorem [22] [23].

In experimental application an operator or designer has at hand a large amount of problem specific knowledge and potentially previously accepted test methods. The basic PSO algorithm is generally devoid of preference toward problem-specific knowledge and is widely applicable to almost all problem types, be they continuous or discrete, global or localized, etc. As applied to engine studies the basic PSO has performed well enough to be considered effective, though the PSO does have some drawbacks [3] [10] [21]. Drawbacks of the general PSO method include its single-objective arrangement, a likelihood of premature convergence by clustering in a local optimum, the inability to make vast leaps to isolated regions of the feasible design space, and stagnancy in late stages [3] [15] [19]. The advantages of the PSO method include rapid discovery of the approximate optimum, minimal objective evaluations when compared to other evolutionary algorithms, few tuning parameters, and relative simplistic methodology [11] [12].

The particle swarm algorithm is simple in construction and implementation requiring only a few lines of code to operate.

$$X_{i+1} = X_i + V_{i+1} \tag{2.1}$$

$$V_{i+1} = wV_i + C_1R_1(P_{best,i} - X_i) + C_2R_2(G_{best} - X_i) \tag{2.2}$$

The PSO algorithm uses two weight parameters to balance the individual and social confidence factors for the particle while stochastic elements are multiplied to those weights which vary the interest of the particles at each iteration. Another weight is used to either reduce the current velocity or reduce the impact of the previous velocity factor. These are called the constriction factor and the inertia weight respectively and in practice only one is applied, but almost all variations of the PSO use one or the other to prevent velocities of particles far from the global best from accumulating too much velocity and diverging [11] [14]. This basic PSO has been used successfully in combustion research and is the simple variation used in this study. Much work has been done on many PSO variations as well as parameter selection for the velocity reduction factor, social interest factor, and individual interest factor [11]. Such analysis is beyond the scope of this study and to emphasize the benefits of the methodology proposed no work beyond simply choosing well respected values for these parameters. Substantial work exists on not only the choice of the parameters themselves but on how to optimize even those parameter choices (a realm of optimization called meta-heuristics) [3]. Furthermore, the parameters were kept constant even if an improvement could be realized because the ultimate goal of the research presented here is to validate the construction and novel application of the method rather than compare the absolute performance of each method independently after meta-optimization of the optimization itself. While choosing different parameters can accelerate the optimization a relative comparison was made using $w=0.33$, $C_1=C_2=0.66$. This conforms well to parameter ranges presented in prior studies and literature [11] [12] [10] [19].

2.2 Genetic Algorithm

The Genetic Algorithm (GA) was originally presented in the 1960s and 70s by Rechenberg and Schwefel, and then through the work of John Holland at the University of Michigan, it became widely seen as a viable algorithm for optimization of a diverse array of problems. The use of genetic algorithms remained predominantly theoretical until the 80s when conferences began to be held on the subject. After some time academic interest grew and by 1989 commercial tools existed for computational optimization using desktop computers. The original software package is still in existence as “Evolver” which was its original moniker [3]. Such prevalence is rare in the computing industry and it speaks to the power of the genetic algorithm. Indeed, decades later even the basic GA serves as a powerful and proven tool for optimization [3] [10].

Modern variations in the structure of variants of the GA are so numerous that a concise study of GA methods is well beyond the scope of an application based work such as this. Many modern GA constructions have been reviewed and validated by computational researchers and work continues in combustion optimization with a focus on GA variants [3] [11] [12] [17].The GA is most commonly used in combustion chamber design as well as operating regime [3] [16] [24].

The genetic algorithm can be described simply as a set of functions which closely approximate natural selection and are performed on a set of individuals in order to improve the overall fitness of the population [11]. Beneficial traits are identified by their retention in the population as it evolves. Different implementations of the GA might examine individuals or the entire population, or typically some combination of the two. The functions used in the GA replicate those from natural evolutionary systems, specifically crossover, selection, and mutation [11] [12].

The GA has specifically been proven useful in determining optimal injection strategies in simulated experiments which revealed a prediction of PCCI combustion, a widely accepted strategy for reducing NOx and Soot emissions simultaneously [25]. The ability of the GA to find regions of the design space which are not contiguous with the initial search space is one of the primary reasons that the GA is so useful when discovering new modes of combustion, in particular, HCCI, RCCI, PCCI, as well as alternatively fueled engines, combustion modes wherein the earliest injections could be a full crankshaft rotation before the combustion event [3] [9] [25].

Generally speaking, the genetic algorithm can suffer from scalability issues as well as demanding a large number of evaluations to converge [11]. These limitations come with the advantage of being able to find disjoint areas of feasible solutions within a complex response space. The genetic algorithm can also naturally explore more of the design space as compared with the particle swarm method [11] [18]. Other potential shortcomings of the GA include failure to converge, destructive mutation, and genetic stagnancy. Many methods have been proposed for counteracting the shortcomings of the basic GA but each comes with its own new caveats; typically sacrificing simplicity in methodology and the increased difficulty of handling "problem-specific tuning parameters", such as with multi-objective methods or neighborhood PSOs.

While there are certainly plenty of GA variants that seek to add steps which push the solutions in particular directions using PSO like steps, however, as these methods become more convoluted they also become susceptible to bias and preferences toward certain problem specifics. Designers would like to use these methods to test unknown new technologies, some never before considered, and it would be unfair to expect methods which are highly conditioned to one system to perform effectively and efficiently on a new, totally unknown system [23]. This is underscored by the wide acceptance of the “no free lunch” effect. As a particular method becomes more convoluted the confidence in such a method to work as well when an unknown change is made in the system is reduced dramatically. Occam’s razor can be interpreted to mean a simple method which shows good success should always be preferred over a convoluted one which provides only similar performance. Certainly, though, some optimization methods and convolutions specific to combustion problems will be advantageous, they are beyond the scope of this study.

Another trend in optimization is toward multi-objective optimization techniques which can offer designers more feedback and explore spaces more fully. These have been commonly implemented in the GA and occasionally in the PSO, but as this study seeks to compare the GA, PSO, and hybridized PSO-GA method to each other it would have been unscientific to compare Multi-Objective GAs due to the fact that they have different performance metrics and goals in revealing relationships rather than seeking single optimums. Even as such, it is expected that improvements in the performance of single solution methods could be extended to such Multi-Objective methods as well as more complicated methods with enhanced logic, albeit with the potential for reduced enhancement due to overlap of the benefits. Furthermore, the coding of such multi-objective methods is often substantially different than that of single objective methods. The effect of the structure chosen for the particular objective function in this study is briefly explored in order to understand the impact of the choice, but conformity to prior studies and commonly used structure allows broader comparison and more accurate expectations. While the benefits of multi-objective methods are undeniable, they are simply a different class of optimizers and are better suited for design parameters rather than control parameters [3].

2.3 Engine Technology and Testing

Engine technologies constantly evolve as machining techniques and new materials become available, and as inventors develop novel technologies. The trend in recent times has been toward variability over fixed parameter selection. The results of this trend are that as-built engine calibration is several orders more complex than just a decade ago. New tools must be used to optimize these incredibly complex systems [3] [12] [26].

Examples of this include but are not limited to variable valve timing, variable valve lift, variable effective compression/expansion ratio (Miller cycle, Atkinson cycle), fuel pressure, fuel injection timing, fuel injection rate, fuel injection events, fuel reactivity, boost pressure / vane control, and exhaust recirculation rate. Considering that these parameters are actually all commonly available market technologies that were rare just a decade or two ago, and when they are combined and packaged into functional engines the complexity of the systems is dramatically large and parametric study is simply impossible. Even with discrete blocking and combustion mode prediction the order of such systems is incredible. Modern diesel engines can use from 5 to 8 injections during each combustion cycle alone, and in a rate shape controlled injector this would result in up to 4 parameters for each injection, potentially adding 32 variables to the necessary design space. The absurdity of such full parametric studies is quite clear [11].

Furthermore, the variable devices identified above would appear in the as-built condition of an engine, not its original design parameters, which could easily number into the hundreds. Given such complex systems which need to be tuned and calibrated for operation in the real world it is clear that optimization techniques need to be applied not only to computational design but also to operational testing of such engines. Validation of models, emissions testing, and rapid prototyping are just a few reasons that real engine testing must still occur despite so much progress in the realm of computational modeling. One example that underscores the need for using engine testing is the application of new fuels. Synthetic fuel developments have posed problems in multicomponent spray, vaporization, and combustion modeling requiring long periods of development and validation whereas engine studies can begin as soon as the fuel is available for testing. In this way, designers can use feedback from existing engines to validate and develop models as well as attempt preliminary designs using insight from the actual engine testing. The author sees the new paradigm of engine design as one in which engine testing and computational engine design are done in an integrated manner with feedback from testing apparatus able to be used immediately by designers to develop new designs. This new paradigm will require rapid discovery of optimum combustion parameters in order to be useful to design engineers. Thus, the necessity of adapting useful combustion optimization strategies from computational design to experimental apparatus is clear.

Another complexity involved with engine testing that is not a factor for computational design is the specific apparatus has a substantial impact on the time it takes to obtain results.

This would be paralleled in the computational realm by the comparison of a GPU calculation to a CPU calculation or the computational effort in floating point operation versus that of an integer operation. In common optimization problems, any single function evaluation is weighted the same as any other, whereas in an experimental apparatus, the time to obtain steady state equilibrium parallels the computational cost. The optimization of real systems should serve to minimize the time and real costs of operation rather than the specific number of data points taken. By increasing the speed of the data collection as well as the diversity of the population of data, value is added by the experiment in two ways; engineers can get feedback more quickly and at lower cost to iterate through the design process more rapidly, and secondly, within single objective methods still more information about tradeoff relationships can be discovered without the increased time penalty multi-objective methods can impose.

The focus of this study is on accelerating the optimization of injection schedule parameters in a two injection strategy with variable fuel pressure through applying the GA to an existing PSO method. As evidence indicates, the GA methodology has inherent benefits in developing injection strategy optimums [25] [3] [14]. The established particle swarm techniques work very well in problems where the response characteristics are nearly convex in the local region of the optimum and along any front which might be contiguous to that optimal region [10].

Multi-objective optimization research indicates that single objective function formulations for multi-objective problems are too restrictive and require more problem specific knowledge than those inherently designed for multi-objective optimization. Decisions in methods of applying appropriate objective functions to optimize problems which contain new constructions also complicate the process for single-objective methods in multi-objective problems [3]. The author posits that regardless of the multiple objective strategies used during an experimental engine study, the actual calculation of the objective value(s) itself is inconsequential in this study, due to the nature of collecting exhaust emissions and engine test data, and thus it can quickly be recalculated for all historical data points in the study at any time at effectively no iterative cost. In this way, the objective function can itself change during the testing such that a single objective methodology can still explore trade-offs between objectives and provide meaningful results without the added complexity of full multi-objective methods, while also maintaining some influence for engineering intuition and problem specific knowledge, by changing weight and order to specific the objectives. In this way the formulation of the single objective function can remain simple and construction minimized, while at the same time offering more exploration and broader information about the relationships between objectives and still allowing the designer to influence the priority of the objectives. This simplified approach to multi-objective optimization in an experimental engine study is proposed due to its simplicity and ability to illustrate clearly the benefits of the approach. The overall merit of multi-objective techniques in both the GA and PSO routines is not disputed, it is merely excluded and alternative approaches to simplify the construction are explored for viability. In practice multi-objective methods have been absolutely useful and are widely implemented but for the purposes of academic comparisons they interfere with this particular studies ability to test the application of the GA to particular parameters within another methodology. These multi-objective methods are excluded from this study but could be applied with the construction proposed here if deemed useful by designers of experiments. GA and PSO multi-objective variants have been shown to be effective developments in combustion optimization and are fundamental in modern engine design processes [3] [21] [25].

2.4 Novel Hybridization of the PSO and GA

Novel approaches to applying the PSO and GA methods simultaneously have been well researched and explored in computational studies [16] [24] [27]. Other hybrid approaches have also combined non-evolutionary methods with evolutionary ones, typically using gradients (or a numeric approximation of the gradient) combined with evolutionary methods [3] [11]. Hybrid gradient methods may improve the GA more than they improve the PSO due to the nature of the PSO to naturally seek out improved solutions in a path-driven approach, while the GA methods do not specifically reward individuals for improvement in objective value beyond the selection criteria. Other applied hybrid methods which have utilized regression techniques along with evolutionary methods and have been quite successful but typically require a large amount of data to be analyzed [3] [14]. Unfortunately, most current studies have neglected to compare the PSO-GA hybrid methods to basic PSO methods in order to determine if exploiting the advantages of hybrid methods can be realized on an experimental engine testing apparatus, especially one with a variable cost function in evaluation time. As indicated by prior research, it is expected that controllable design parameters can be optimized separately from hardware design parameters and while most recently research has focused on modeling and computational realms while optimization of control parameters in actual engine test platforms has been somewhat neglected. By investigating and applying hybrid concepts adapted from the computational realm, experimental methods will be sought to improve controllable parameter optimization on the experimental engine apparatus.

PSO and GA hybrids are often applied in novel ways using problem specific knowledge [21]. As identified by prior studies the PSO method advantage is primarily rapid convergence, especially in locally smooth regions. The GA advantages are primarily exploration and diversity, especially in convoluted and disjoint regions of feasible design space, and with highly complex response surfaces. Identifying which parameters are well suited to optimization by PSO and which are best suited to the GA requires engineering intuition, general problem-specific background knowledge, apparatus-specific knowledge, preliminary studies, or a substantial quantity of a priori decisions derived from prior explorations or research.

This study constructed a PSO-GA stepwise hybrid using a PSO “step” followed by a GA “generation” in order to exploit a settling time difference in the test apparatus. No function evaluation took place between the two different steps so the current objective value of the “parent” particle is unknown when compared to the current generation. In this evaluation, however, the parent particle location is tested to demonstrate the type of improvements expected.

CHAPTER 3 EXPERIMENTAL SETUP

3.1 Overview of Testing

This study aims to find a novel improvement of existing heuristic optimization methods for an experimental compression ignition engine by utilizing a hybrid of two existing methods. The goal of the test is to determine if the specific construction can improve the ability of the particle swarm method to find an optimum in less real-time, using less fuel and resources, and with improved diversity in near-optimum data points. The methodology implements the genetic algorithm functionality into the particle swarm method in order to diversify and improve results while exploiting the difference in settling time of the experimental apparatus

Initially a sensitivity study revealed the response level of the five parameters varied throughout the study while a second brief investigation revealed the safe feasible space for the main SOI and EGR on the apparatus. The apparatus also had limitations on fuel pressure and pilot injection parameters with respect to the absolute timing as well as the relative timing of the main SOI to the pilot timing. The initial study was used to guide the limiting factors in the primary study. Parameter sets with poor combustion quality were eliminated in this step to expedite testing and preserve the condition of the apparatus for continued testing without any loss of quality to the results. Poor combustion quality causes prohibitive HC emissions and instability in the apparatus preventing steady state conditions.

After initial tests were used to determine sensitive parameters, limits of operation, and response time of the system to step changes in each parameter, the final test arrangement was determined. Using the information from the initial studies the test parameters were set. Pump diesel fuel was used in order to best reflect operations as equipment would be used by end users in the marketplace and the fuel for the entire testing was reported to contain approximately 5% biodiesel and all of the fuel used for testing came from the same pump at the same time. No fuel density variations could be measured throughout the testing using both a specific gravity apparatus and a live measurement from the fuel flow apparatus.

The load condition chosen was approximately 50% of the rated constant duty load at 1400 RPMs which represented part-load conditions where control parameters play a critical role in determining emissions and fuel economy. Higher loads tend to be dependent more upon fixed design parameters while very low load cases are not as useful for real-world applications in medium to heavy duty engines applied in variable speed applications. These conditions replicated earlier studies on the apparatus and allowed validation of the operation prior to and following the study. Some parameters such as the intake temperature and fuel temperature may not be representative of average real-world conditions, however, they offered more consistent control over variation to control the test environment more effectively.

Table 3.1 Test Conditions

Speed	1400 RPM
Torque	110 Lb-ft (149 Nm)
Intake Temperature	80 F (26.7 C)
EGR Temperature	104 F (40 C)
Fuel Temperature	65 F (18.3 C)

Table 3.2 Engine Control Parameter Limits

Parameter	Minimum	Maximum
SOI	-15 CAD ATDC	5 CAD ATDC
EGR	2%	65.5%
Fuel Pressure	113 MPa	240 MPa
Pilot Timing	-40 CAD ATDC	0 CAD ATDC
Pilot Ratio	2%	65.5%

3.2 Particle Swarm Optimization

The particle swarm optimization routine requires parameters including limits on feasible design space in restricted domain problems as well as operational parameters for the method itself. The specific variant used in this basic PSO implementation is the inertia weight method which applies a velocity reduction factor to the previous velocity at each update. This is the most simple PSO variation and allows some velocity limitation without fully stifling the acceleration offered by the PSO. The factor was chosen to be very small in this study when compared with other PSO variants due to the desire for a more complete exploration of the local spaces after initialization. The alternate velocity restricting variation, the constriction factor, would have reduce the impact of new information to the particles and is more complex without providing clear benefits to this problem. The inertia weight factor chosen to be equal to 0.33.

The other PSO parameters were chosen to represent the social and individual motivation of each particle equally. The Gbest and Pbest influence was, on average, equal for each particle at each iteration by using a value of 0.66 for both the Gbest and Pbest scalar factor. This resulted in a new velocity term at each iteration which was on average one part each prior velocity, vector difference to Gbest location, and vector difference to Pbest location. Each factor had an equal influence with stochastic variation introduced to each of the Pbest and Gbest through the random number factor. The PSO factors used are summarized and presented in Table 3.3.

Table 3.3 PSO factors

C_1 – Social Factor	0.66
C_2 – Individual Factor	0.66
w – inertia weight factor	0.33

3.3 Genetic Algorithm

The generic genetic algorithm structure was modeled using an existing code and modifying the techniques to apply the three unique functions of crossover, mutation, and selection, to the method. The unique parameters for a GA include crossover rates and mutation rates as well as selection criteria. The selection criteria used was simply the objective function chosen. An opportunity exists to exploit a different objective function at each generation or specifically to the genetic algorithm rather than the PSO through the selection criteria. In this study the focus is on the construction rather than the individual exploits within each method. Two types of crossover were used to control the type of mixing referred to as “single point” and “switching” which traded either single points of genetic information or switched streams of genetic information are used as the recombination method. Two types of mutation were also implemented to control mutation referred to as “replacement” and “switching” with replacement involving replacement of the chosen point with a preset value and switching simply flipping the bit to the opposite value. The mutation rates were held quite low as this experiment did not have isolated design space islands or totally random starting points. In practice each problem requires tuning of such parameters and some test mutation and crossover was done on particular members to assure substantial variation in the design variables while selecting the parameters, summarized in Table 3-4 below

Table 3.4 GA Factors

Parameter	Crossover Rate	Crossover Type	Mutation Rate	Mutation Type
SOI	0	N/A	0	N/A
EGR	0	N/A	0	N/A
Pilot Timing	0.57	Switching	0.07	Switching
Pilot Percent	0.57	Switching	0.07	Switching
Fuel Pressure	0.34	Point	0.03	Replacement

3.4 Hybrid Method and Objective

The methodology applied herein was done as a two-step process, first taking a PSO update step, then producing offspring for each PSO point. The PSO was processed on the existing data points using the previous generations Gbest and Pbest locations, the genetic variants are taken by crossing over with random current generation PSO particles and exchanging selected fueling parameter information. The genetic variants are tested and the best performer is selected from each sub-population to represent the PSO particle. The resulting PSO position is then fed back to the PSO process so that a Gbest and Pbest can be identified from the selected population. The ratio of GA variants to test for each PSO particle was selected in order to maintain an equivalent ratio of GA and PSO searching with respect to evaluation time, rather than by the computational tradition of raw function evaluation counts.

The particle swarm and genetic algorithms used in the optimization were structured to work with single objective functions. The single objective function was normalized using the Tier 4 2014 final off-road standards set forth by the EPA as a guide. The study was not partial to this restriction however. An optimum utopia point was chosen, using knowledge of the apparatus and engineering intuition, which represented the center point of the NOx-Soot emissions area to explore the known NOx-Soot tradeoff. Targets for HC and CO emissions were set to the Tier IV emissions limits for the 75 HP to 175 HP range, which allowed 5.0 g/kw-hr CO production rather than the 3.5 g/kW-hr as required for larger engines from 175 HP to 560 HP. This particular engine is capable of producing 175 HP intermittently but it is not rated for continuous duty at such high power ratings and was not sold in such a configuration.

The objective function chosen was structured with NOx and Soot being prioritized higher than HC, CO, and specific fuel consumption, which were weighted equally as secondary objectives. This structure was chosen for simplicity and in compliance with prior examples from literature however the validity of the methodology and specific exhaust targets are not intrinsically related. Computational methods were also used to explore the impact of the weighting factors in order to determine if the weighting factors could have substantial impact on the study and validity of the methodology. The utopia point was chosen such that it was presumed to be impossible to achieve but reflected the design goals of modern engine designers. The objective function is as follows, denoted as F_{obj}, with ideal values taken from table 3.5

$$F_{obj} = \left[\left(\frac{NO_{meas}}{NO_{ideal}}\right)^2 + \left(\frac{PM_{meas}}{PM_{ideal}}\right)^2\right]^{0.5} + \left[\left(\frac{CO_{meas}}{3*CO_{ideal}}\right) + \left(\frac{HC_{meas}}{3*HC_{ideal}}\right) + \left(\frac{FC_{meas}}{3*FC_{ideal}}\right)\right] \quad (3.2)$$

Table 3.5 –Initially selected objective values

Emission / Objective	Tier 4 regulation	Objective Point Values
NOx	0.40 (g/kw-hr)	0.20 (g/kw-hr)
NMHC (THC-2%)	0.19 (g/kw-hr)	0.19 (g/kw-hr)
CO	5.0 (g/kw-hr)	5.0 (g/kw-hr)
Soot	0.02 (g/kw-hr)	0.01 (g/kw-hr)
Fuel Consumption	*	200

3.5 Exhaust Emissions Analysis

The exhaust emissions were measured using a Horiba MEXA 7100 DEGR 2 channel analyzer. Primary sampling and secondary sampling allowed for a live EGR calculation using the CO_2 ratio between intake and exhaust gasses. This is a common simplification of the EGR measurement and is provided directly by the Horiba analyzer. Figure 3.1 shows the Horiba analyzer in place as it was used. The analyzer was calibrated before each data session and atmospheric air was sampled at the end of each session to assure that drift errors were avoided. Exhaust gas measurements were given in terms of concentration or volume percentage. Table 3.6 shows the units of measure that the Horiba analyzer returned. The exhaust analyzer relies on several different technologies which can be found in corresponding data sheets. Of particular interest is the inclusion of methane in the hydrocarbon measurement, which, according to the EPA, represents a 2% increase in measured emissions versus controlled emissions. This difference only affects compliance to EPA standards, and since the test was not an EPA approved test the importance of including a scaled factor to correct the methane measurement was not necessary.

The Horiba exhaust gas analyzer measured emissions in two separate units with Nitric Oxides (NOx) and Total Hydro-carbons (THC) measured in an oven while the Carbon Dioxide (CO2), Carbon Monoxide (CO) and Oxygen (O2) were measured in a cooled gas analyzer. Both devices were part of the same measurement tool and used the same exhaust gas sampling sources.

Table 3.6 Exhaust Gas Analysis Measurement Units

Exhaust Gas Species	Unit of Measure
CO (H)	%
CO (L)	ppm
CO_2	%
O_2	%
HC	ppm C_6
NO_x	ppm

Figure 3.1 Horiba MEXA7100 DEGR Exhaust Gas Analyzer

The particulate matter emissions were measured using an AVL 415S smoke meter, pictured in figure 3.2. The particulate emissions were the most critical emission to control as the Tiered emissions are incredibly strict. The smoke meter operated fundamentally by drawing a known sample volume of exhaust gasses through heated line and filter to capture the emission. Then, a light of known reference intensity was reflected off of the sample to determine its blackening level and this was correlated and reported by the machine in volume-specific mass units (g/m^3) and in FSN, a customized unit representing the Smoke Number sometimes used in industry. Since the EPA currently uses the brake-power specific mass production, the measurement was converted from volume specific units into mass specific units using exhaust gas properties and exhaust mass flow rates. This methodology allowed the total particulate emissions to be measured and represented in the same units as the gaseous emissions for direct comparison. The AVL sampling was set to sample 3.5L of exhaust gas and five samples for each data point, which allowed high confidence in the precision of the smoke tests, which can be naturally somewhat varied.

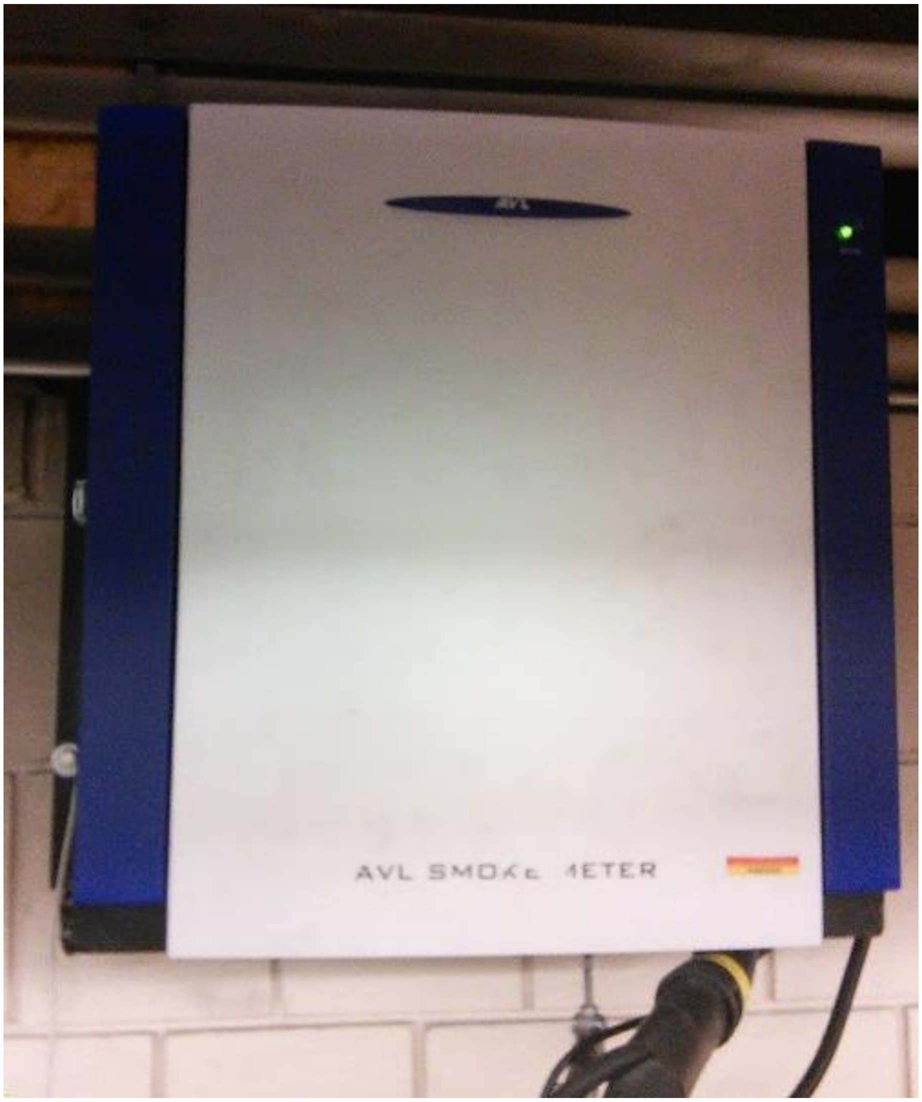

Figure 3.2 AVL 415S Reflective Smoke Meter

3.6 DAQ Systems

National Instruments PCI data cards were used to capture data from SCB-68 breakout boxes. Thermal data was acquired through one unit while dyno and engine pressure data were taken through another. Thermocouple junctions and pressure transducers were placed at critical locations in the fuel and air flows. Differential pressure was measured across a laminar air flow meter and converted into a corrected airflow volume and mass. The cylinder pressure measurements were made using a Kistler 6125A pressure transducer and a Kistler 5010A charge amplifier. Figure 3.3 shows the pressure transducer and charge amplifier used, while figure 3.4 shows a PCI series DAQ card representative of the computer hardware used in this test.

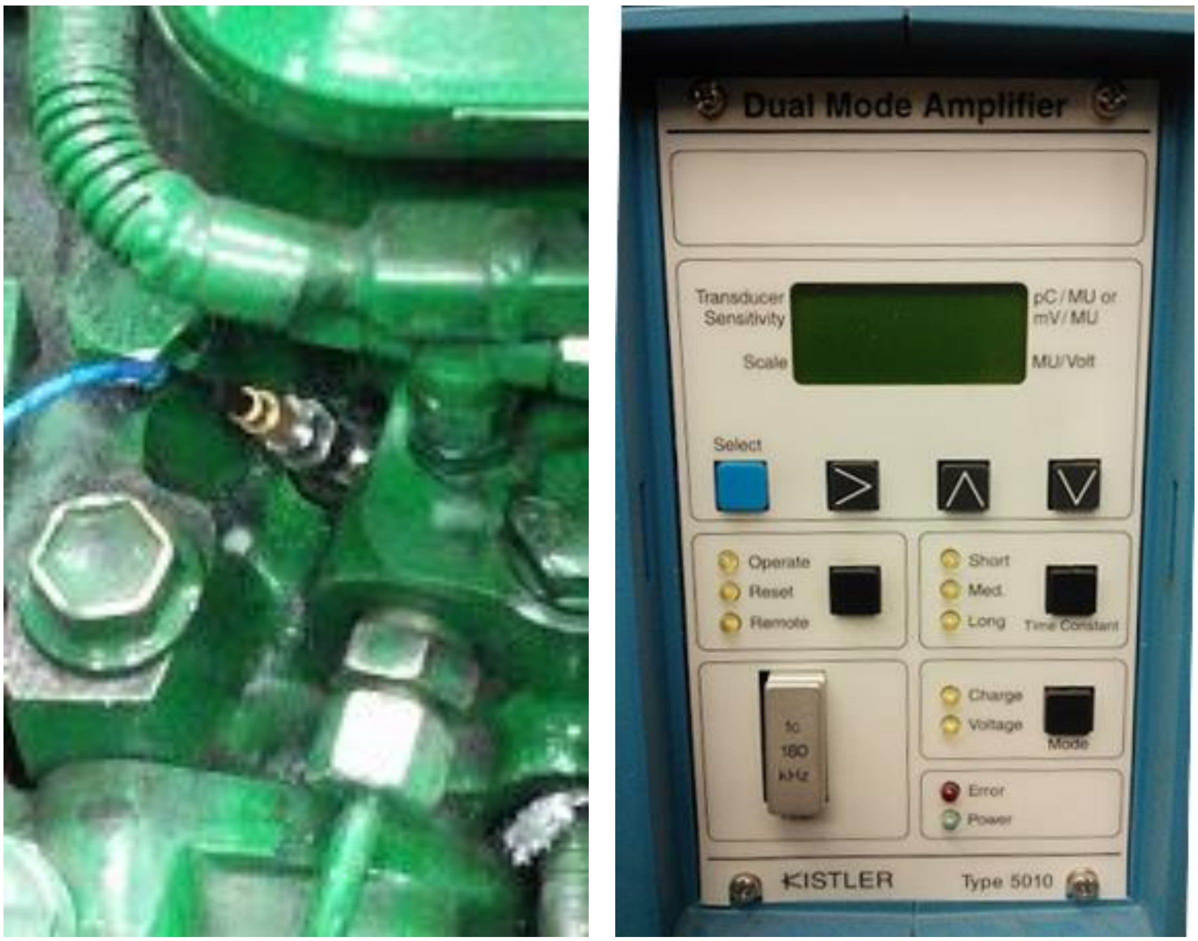

Figure 3.3 Kistler 6000 Series Pressure Transducer and 5000 Series Charge Amplifier

Figure 3.4 National Instruments PCI

Data was captured at discrete crank angle degree increments by a BEI H25 Incremental shaft encoder, pictured in figure3.5. The encoder was set up to trigger data collection of the DAQ system by using the clock input on the DAQ hardware. This method has been commonly used in academia and the research community as it produces smooth dense data at almost any RPM and does not need to be validated at each RPM value. It was also the same methodology that the other engine measurement and control devices used inherently, including the John Deere ECU. This also prevents the system from capturing different data densities when the rotational speed was varied, allowing the LabView data acquisition code to function the same for all speeds.

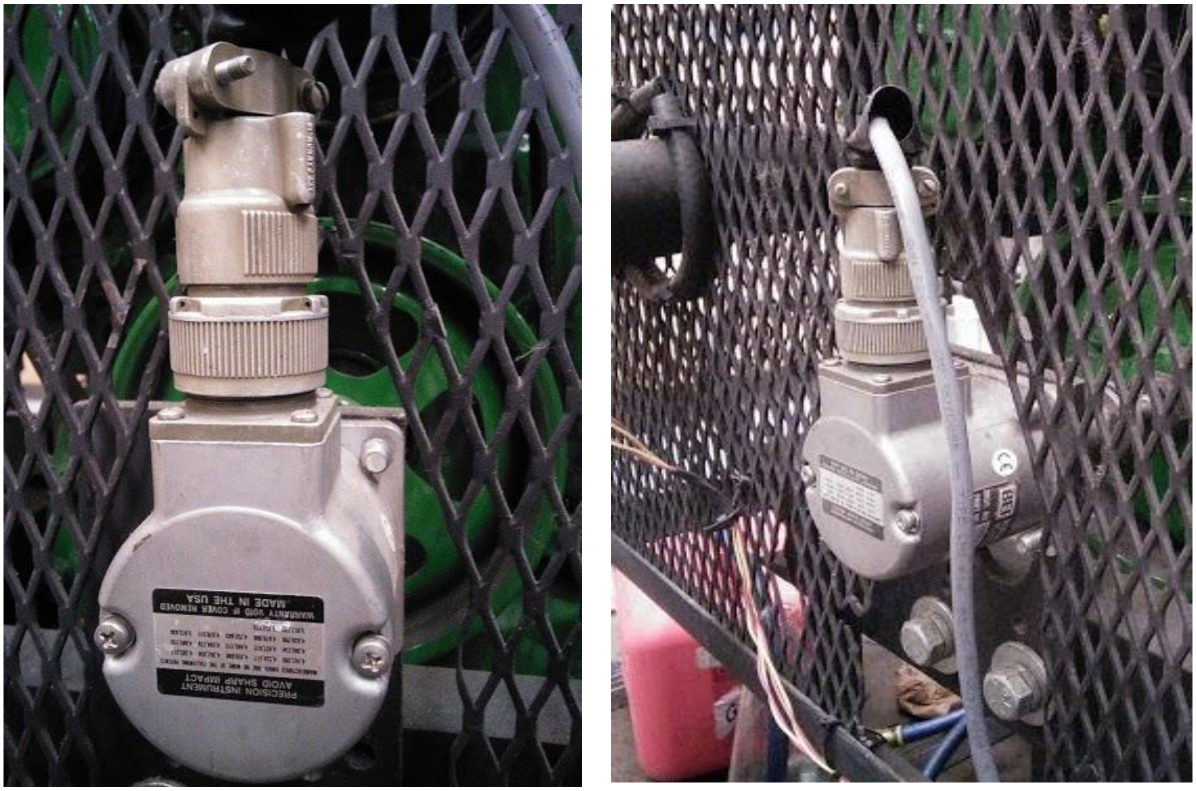

Figure 3.5 BEI H25 Incremental Quadrature Shaft Encoder

The data was processed using a customized LabView program which captured and averaged cycle data and produced representative curves for heat release rate and cylinder pressure. The program provided additional data that was not used by the study specifically though it was captured and archived as part of an effort to archive data on the particular apparatus as fully as possible, either for expansion of this study or for alternate analysis of this precise study.

3.7 Engine Test Stand

The test apparatus used in this study was a 4-cylinder medium duty John Deere 4045T engine utilizing a high-pressure common rail injection system. The engine was equipped with a fixed geometry turbocharger and a customized low-pressure cooled EGR system. The engine was coupled to a GE dynamometer which was able to motor the engine delivering up to 120 HP and absorbing up to 150 HP. The test stand measured torque using a torque arm and force transducer which was calibrated using internal dynamometer skew and scale factors and a fixed weight. The dynamometer and engine are pictured in figure 3.7. The Engine geometry specifics are listed in Table 3.6 and were common or similar to almost all John Deere 4045 engines manufactured over the last decade. The engine represented a typical engine in its current configuration, with exception to the EGR system used.

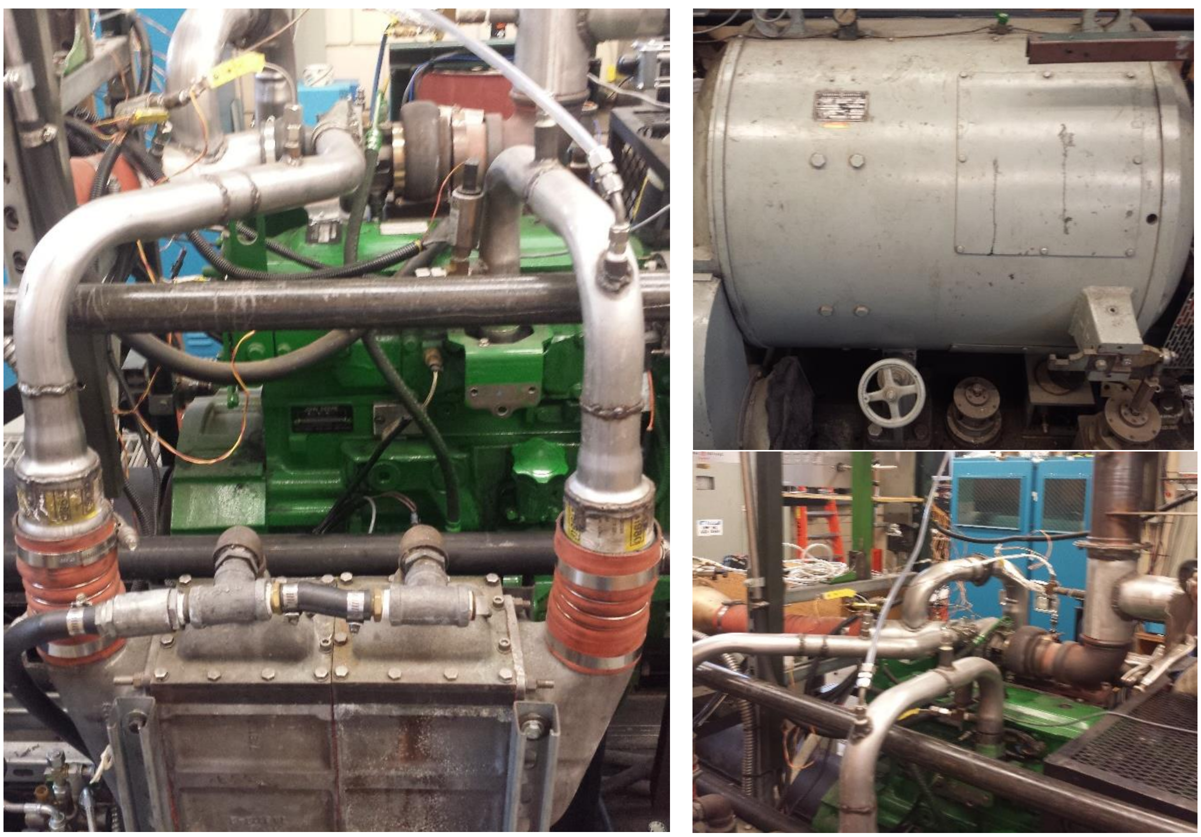

Figure 3.6 John Deere 4045 Engine and GE Dynamometer

Table 3.7 Test Engine Specifications

Parameter	Specification
Bore	106 mm
Stroke	127 mm
Compression Ratio	17.0:1
Injection System	Common Rail
Intake Valves	2
Exhaust Valves	2
Firing Order	1-3-4-2
Piston Shape	Bowl in Piston
Model	HF475-4

The EGR system applied to the engine was a customized apparatus utilizing a small positive displacement supercharger driven by an externally controlled 3 phase motor. The current to the motor was adjusted to vary the speed of the supercharger to further motivate the EGR gasses to enter the intake flow. This allowed precise and wide control of the EGR parameter without needing to send parameters to the engine ECU separately. The EGR system was capable of delivering EGR rates well above typical operating limits for combustion engines, up to 80% or more, and such substantial EGR rates require substantial cooling. Three John Deere EGR coolers were employed in parallel with variable cooling water flows to cool the exhaust gasses prior to entry to the turbocharger. Figure 3.7 shows the EGR manifold and coolers employed by the system while figure 3.8 shows the supercharger system used to motivate the EGR gases into the intake flow.

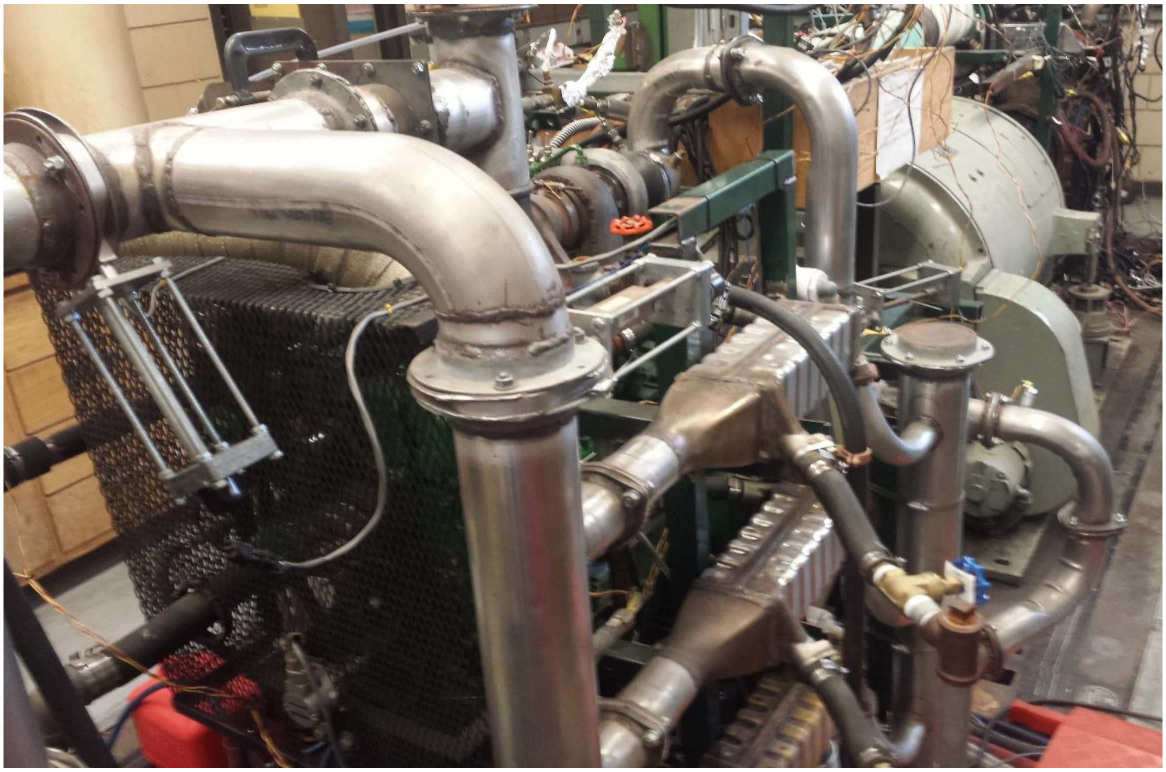

Figure 3.7 EGR Cooling Manifold and Coolers

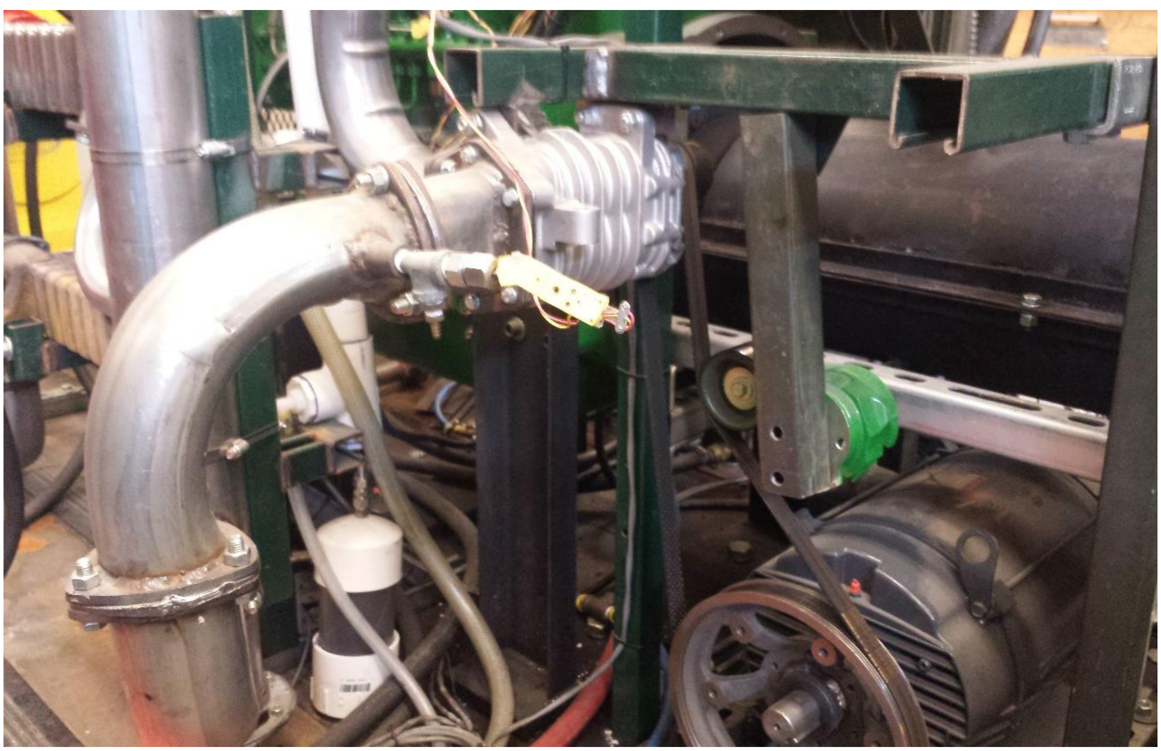

Figure 3.8 EGR System Supercharger and Collection Manifold

The fuel flow was measured using a high precision flow meter, which relied fundamentally on the Coriolis effect to measure the flow, and the measurement was repeated 4 times during each data point collection. The meter utilized an integrated temperature and density measurement while it reported flow in terms of mass flow rate (g/s). Figure 3.9 shows the flow meter and its associated display unit.

Figure 3.9 Fuel Flow Meter and Display Unit

The John Deere DevX development tool was used to send and receive communications with the engine ECU. The fuel event timing and fuel pressure were confirmed using the feedback from the ECU via the CANBUS using the DevX tool. The tool also allowed other engine operating parameters to be observed while the engine was operated for consistency. The DevX software and John Deere ECU had a substantial effect on the testing. The configuration files associated with the DevX and the ECU limit fuel control parameters and were important factors in determining the operational limits of the engine for the study.

3.8 Experimental Test Procedure

The test procedure for the study involved sending operational parameters to the ECU and setting manual controls for the EGR system and engine throttle to meet the test specifics and then waiting for steady state operation to take exhaust, fuel, air, and performance data. After each adjustment some time was taken before the controls were adjusted a second time to achieve the precise operating point. Settling time for the apparatus varied based on the specific changes made to the operating condition, but observations were made as the apparatus settled to discern steady state operation. Since the turbocharger was of the fixed geometry type the exhaust gas temperature was a good feedback tool for determining steady state conditions. The emissions were also measured live and were used to determine the steady state readiness of the apparatus. Once steady state was achieved the apparatus was initialized and data collection was started. Naturally, manually collected data took a few minutes and over the course of the test some measurements had significant variability, such as fuel flow rate. These measurements were measured and averaged to decrease the variability introduced by their measurement.

Once the test data was captured for an entire generation the engine was motored and motoring data was collected. The data was passed to the optimization handler and new data points were returned to the test supervisor. Then the next generation of particles was tested.

This process was repeated several times for both methods and comparisons were made between the variations.

Each day the apparatus was run using prior data points which were initially collected and compared to expectations in order to qualitatively judge the operational status of the engine. This was done to detect major defects and not to study the day to day repeatability in a scientific process. The day to day variability is a major factor in testing, but was relatively minor in observation. This was due to the use of highly effective temperature controls for the intake, EGR, fuel, and coolant systems, which kept most temperatures consistent regardless of the weather conditions. Temperature, humidity, and pressure measurements were made each session so that the ambient conditions could be factored into the airflow measurements specifically.

Each session the exhaust gas analyzer and particulate matter analyzer were also self-calibrated and validated using the qualitative observation discussed previously. The gas analyzer utilized complex internal calibrations which required very precise calibration gases and the smoke meter used internal blackening and white measuring utilities to self-calibrate. These processes were performed at a minimum of every 4 hours as well as any time a data session was started.

CHAPTER 4 EXPERIMENTAL RESULTS

4.1 Preliminary Studies

The results of the sensitivity and response studies indicated that the parameters which were most sensitive were the fuel schedule parameters, SOI, pilot timing, and pilot percentage, while the parameters which caused the longest delay in system readiness were SOI and EGR. The parameters for the PSO included all variables, allowing the PSO to rapidly accelerate the optimization, while the GA was only processed on the pilot timing, pilot percentage, and fuel pressure. The fuel pressure sensitivity was modest, as was the sensitivity, and a smaller rate of crossover was chosen in order to minimize the amount of variation while all parameters possible in the GA for more rapid and diverse exploration.

The engine was initially operated during the first stages of the PSO and GA codes in unison while timing the apparatus and data collection process. The time required to measure the system after a large jump in all 5 input parameters was approximately 10 minutes while the time required for a pilot change and modest fuel pressure change was approximately 2.7 minutes.

Table 4.1 Qualitative Study of Unit Steps from Default Operating Conditions

Parameter	Delay in Settling	Effect on Combustion
SOI	High	High
EGR	High	Medium
Pilot Timing	Low	Medium
Pilot Quantity	Low	Medium
Fuel Pressure	Medium	High

Table 4.2 Settling Time Study Results

	Average	Std. Dev.
PSO Change	2.64 (min)	0.64 (min)
GA Change	10.73 (min)	2.96 (min)

4.2 Pure PSO Results

The initial population was distributed and tested and both algorithms were initiated using the test parameters from section 3. The initial test points had an average objective value of 28.52 and a minimum value of 11.66. The basic PSO method showed a decrease in the average objective function value, which indicated a tendency toward rapid clumping, while the minimum remained stagnant during the third generation. This highlights the PSO methods aggressive acceleration toward the optimum as a whole, while early exploration was inhibited by the strong drive towards one optimum value. Figure 4.1 shows the particle history for the objective values of NOx, PM, and the total of the complete objective function.

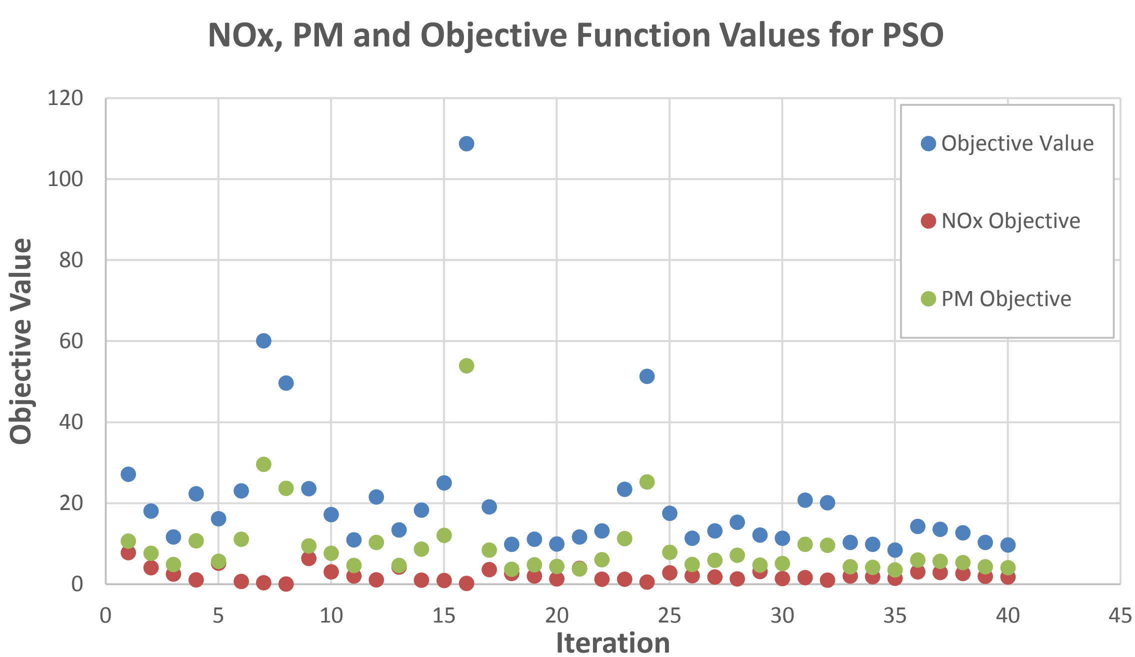

Figure 4.1 NOx, PM and Total Objective Values for the PSO Method

The NOx-Soot trade was explored, as it was well known in the apparatus, and the generations were examined to observe the qualitative character of the spread as well as observe the movement from generation to generation. Shown by figure 4.2, the later generations of the PSO were improved in general but the showed little deviation from the known relationship. No points compliant to the desired region were observed. Only one point of the final generation demonstrated non-dominated properties which indicated that the PSO had not found the optimum neighborhood precisely by generation 5 and 40 particle evaluations.

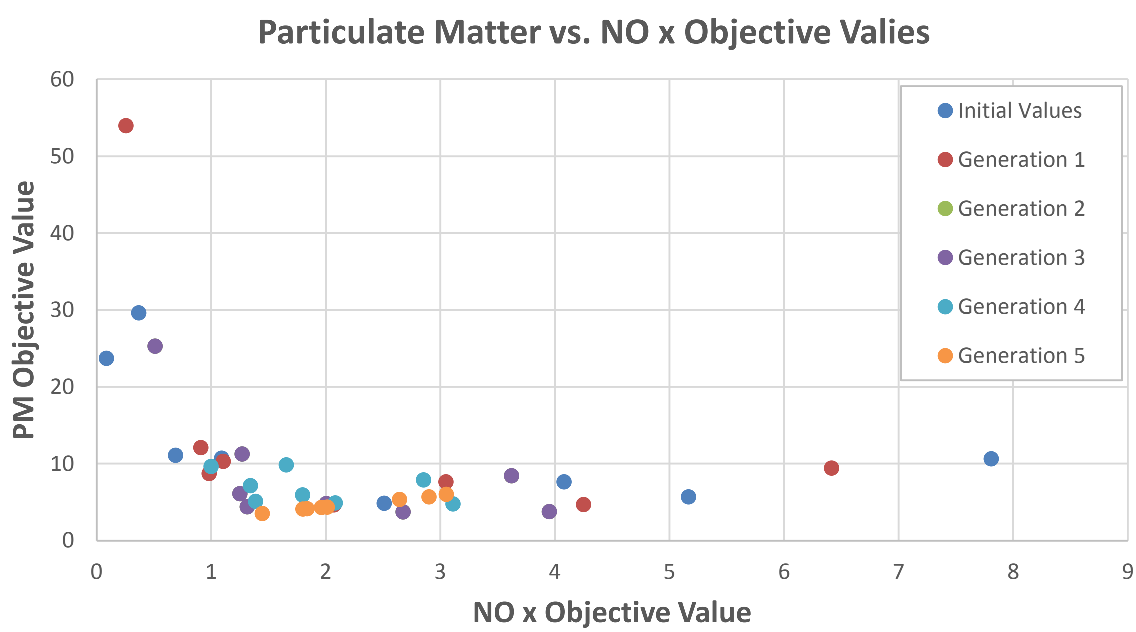

Figure 4.2 NOx-Soot Objective Values for Generation 1 through 5 for the Basic PSO

The overall improvement which occurred in the PSO can be seen in figure 4.3 which illustrates the relatively slow improvement in the best value of the population while the average and variation between population members was reduced continually.

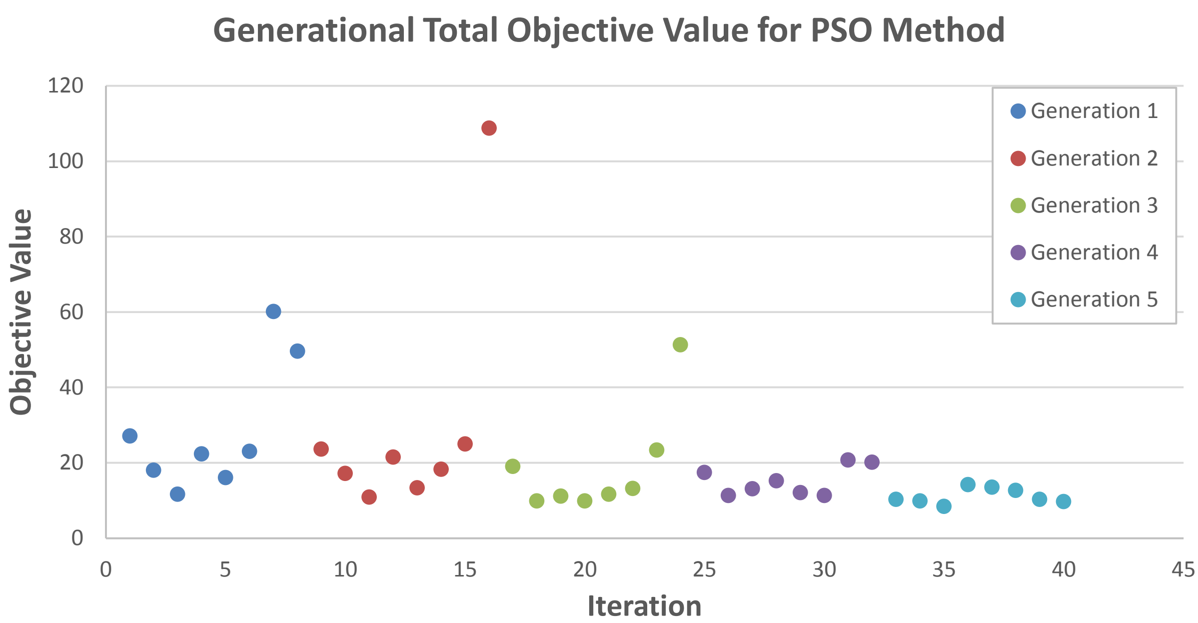

Figure 4.3 Overall Objective Values for Generation 1 through 5 for the Basic PSO

The PSO method showed a clear trend of consistently decreasing the objective value of the best member and the population as a whole, but as the PSO population approached the minimum distance from the desired region the convergence was somewhat slow. The minimum value found after 5 generations of the PSO was 8.5 and the final average of the particles was 11.15. Figure 4.4 shows the progression of the best value found and the average of the swarm by generation while figure 4.5 shows the particle evolution of the best overall, NOx, and Soot objective values.

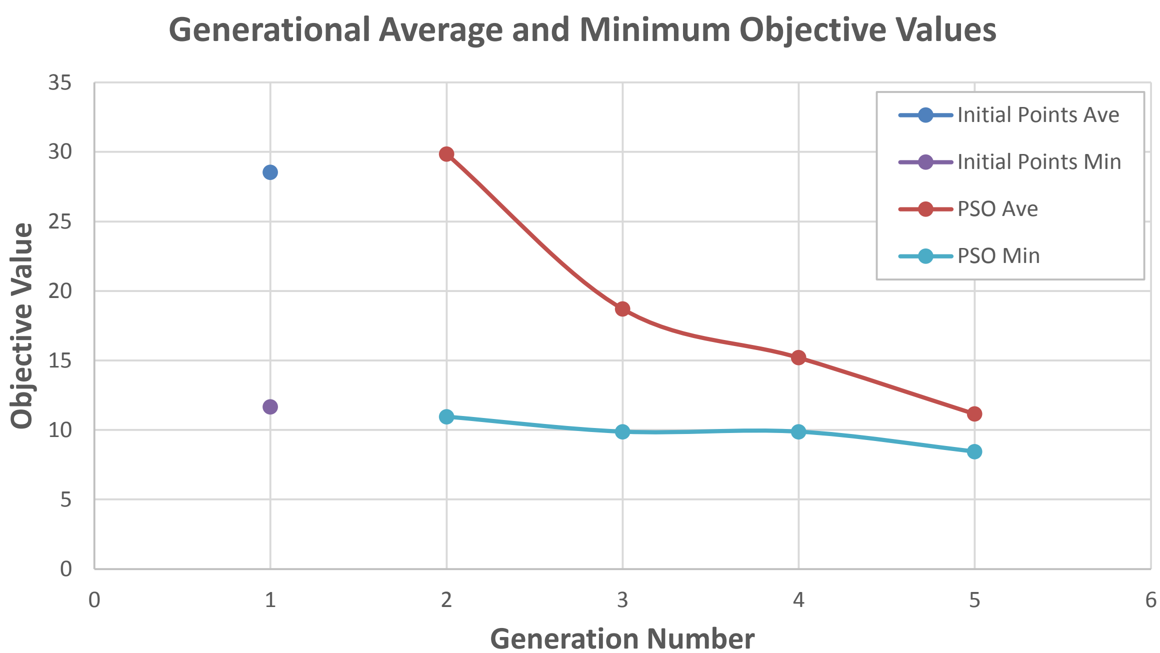

Figure 4.4 Ave. and Min. Objective Values for Generation 1 through 5 for the Basic PSO

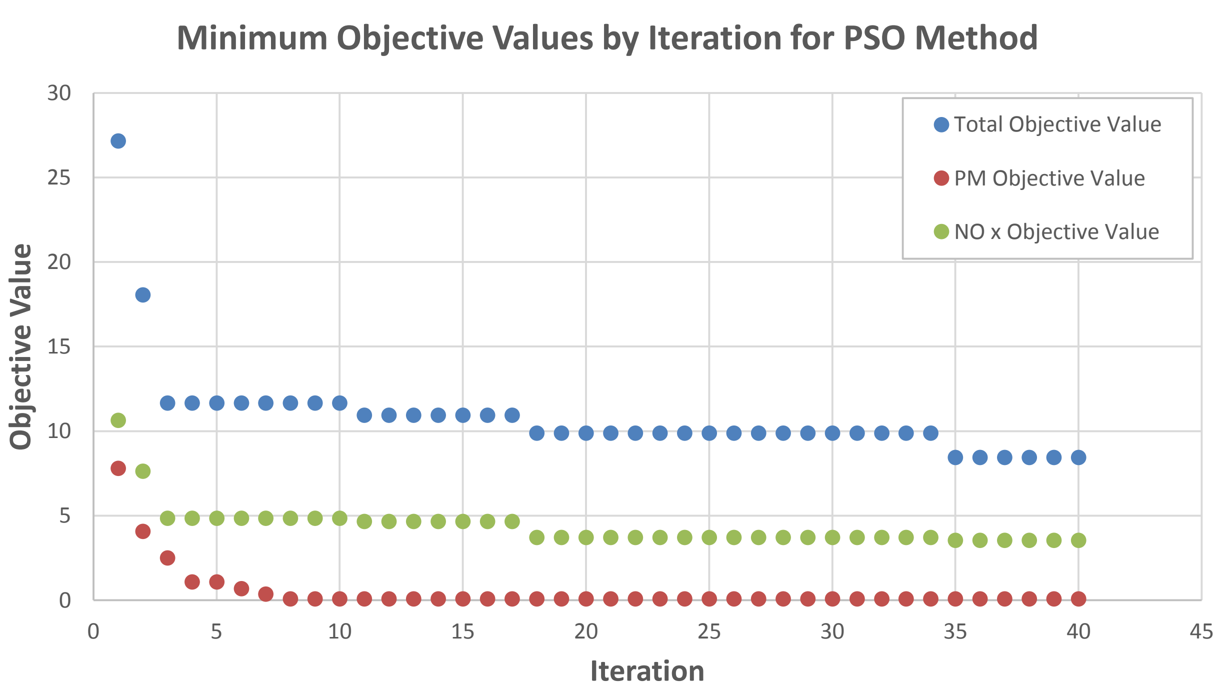

Figure 4.5 Minimum Objective Values for Generation 1 through 5 for the Basic PSO

The particle swarm method showed a clear tendency to improve over generations even when the progress was slow and the drive was lowered by clumping and approach to the optimum.

4.3 PSO-GA Hybrid

The hybrid PSO-GA method showed a decrease in the average objective function value, which indicated a tendency toward rapid clumping, while the minimum remained stagnant during the third generation. This highlights the PSO methods aggressive acceleration toward the optimum as a whole, while early exploration was inhibited by the strong drive towards one optimum value. Figure 4.6 shows the particle history for the objective values of NOx, PM, and the total of the complete objective function. Clearly evident was the ability of the hybrid method to maintain exploration and diversity into the later evaluations of generation 3 due to the combined overshoot of the PSO and the diversity influence of the GA.

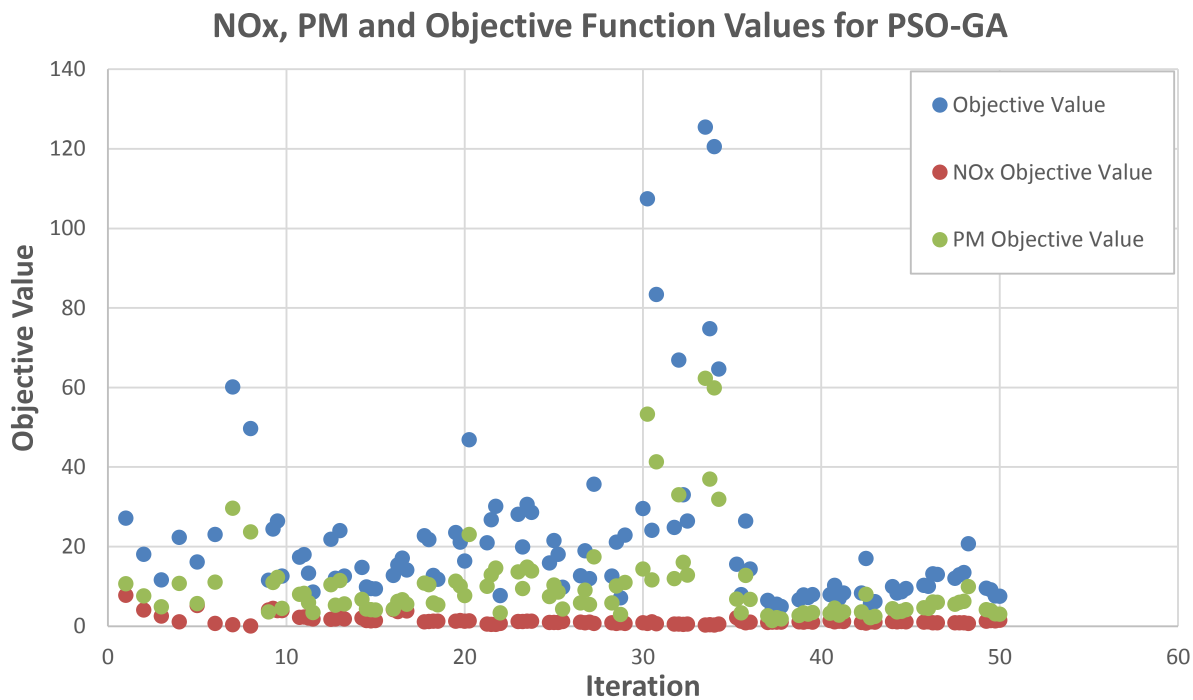

Figure 4.6 NOx, PM and Total Objective Values for the hybrid PSO-GA Method

The NOx-Soot trade was explored for the hybrid method, as it was for the basic PSO, and the generations were examined to observe the spread of the population as well as the progression as the generations evolved. Shown in figure 4.7a and 4.7b, the majority of the selected survivors achieved results which dominated the initial data set and the complete set of PSO-GA points produce many non-dominated points which penetrate the previously discovered NOx-Soot limit, bearing the traditional curved and angled “V” shape. The complete set of PSO-GA hybrid produced many members below the previously understood limit proving that there were operational points that were highly sensitive to pilot parameters which would have easily been missed in a course refined parametric study.

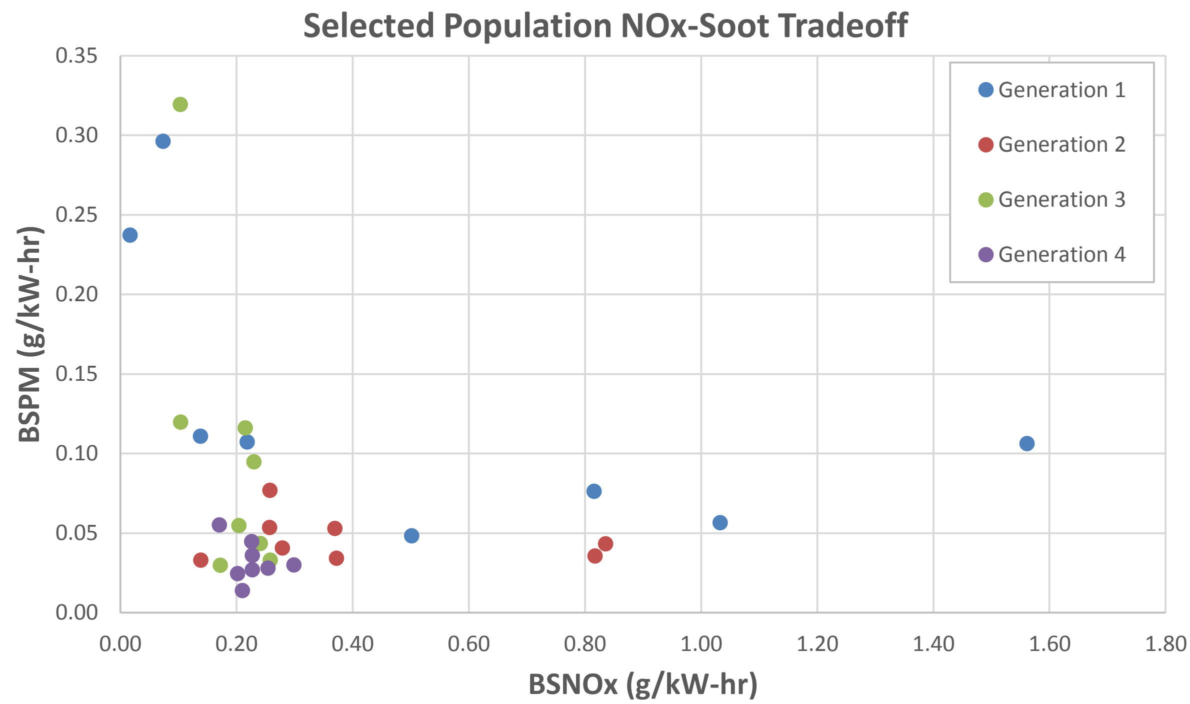

Figure 4.7a NOx-Soot Objective Values for Generation 1 through 4 for the Hybrid PSO-GA

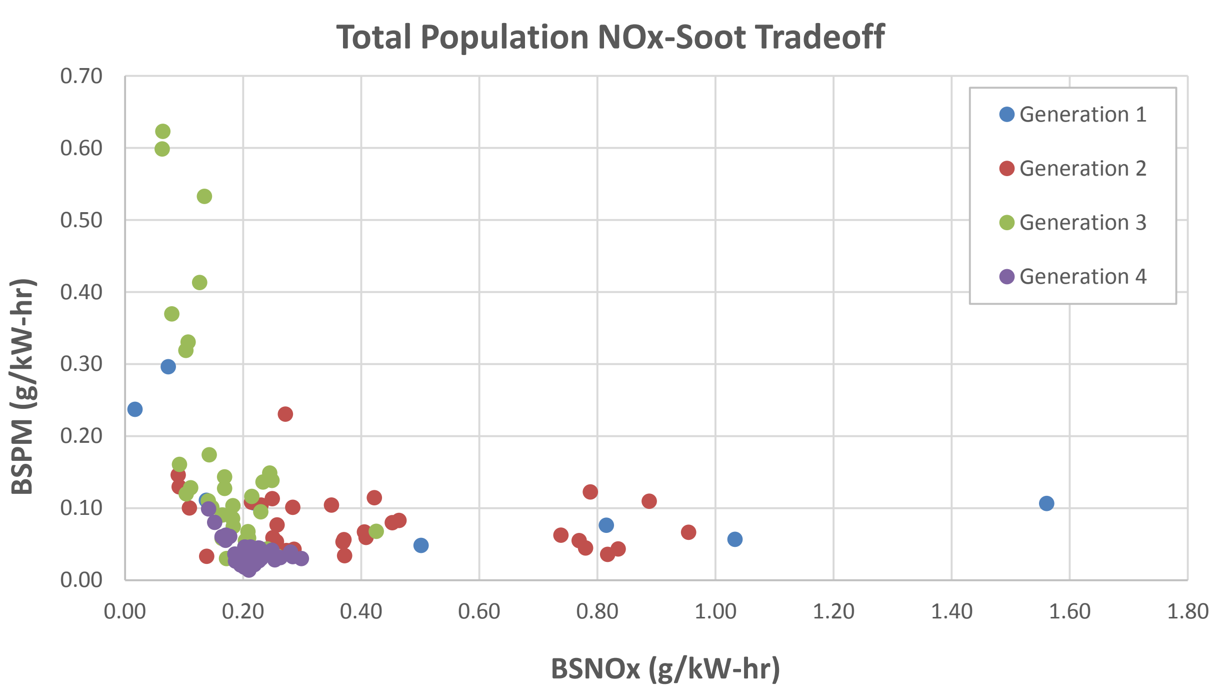

Figure 4.7b NOx-Soot Objective Values for Generation 1 through 4 for the Hybrid PSO-GA

The overall improvement which occurred in the hybrid method can be seen in figure 4.8 which shows that while the average value decreased reasonably the minimum value decreased more consistently through evolutions and the spread of particles maintained a range which was greater than 3 times the minimum value. This illustrates that the hybrid method more aggressively reduced the minimum function value by exploiting a region on the NOx-Soot tradeoff curve while it maintained more complete exploration of the space late into the optimization. Also, it is further evident that while the hybrid method did not consistently reduce the average and spread at each generation, it did reduce the minimum value which indicated that the method was indeed exploring more fully while more rapidly finding the optimum neighborhood.

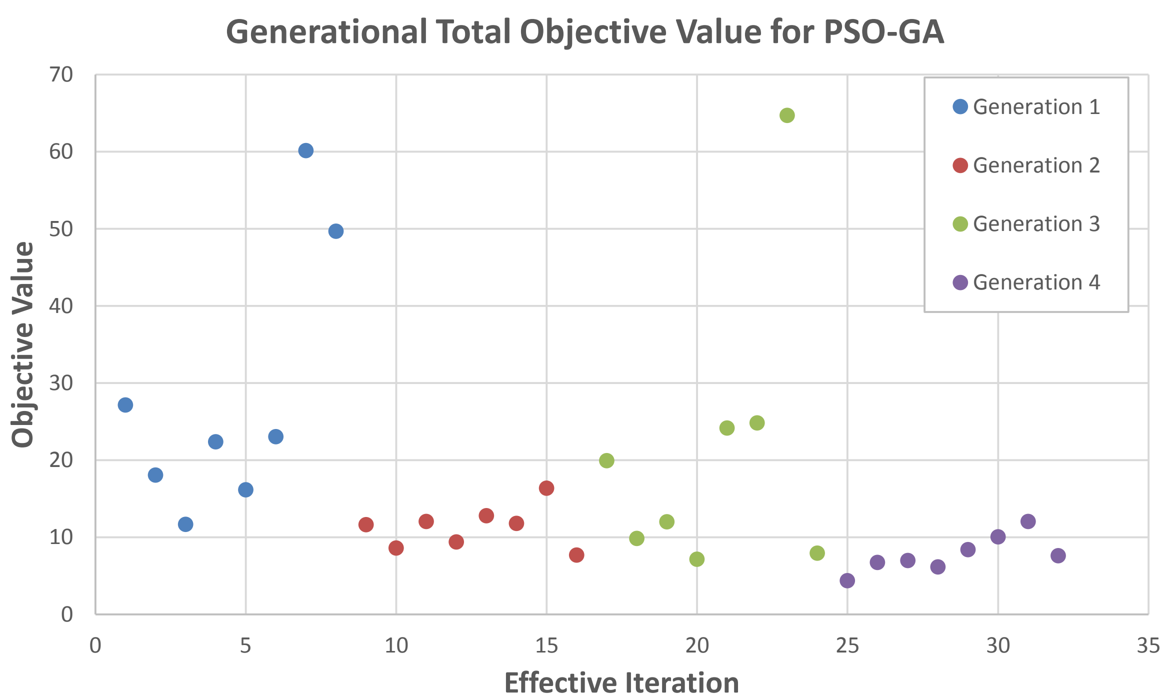

Figure 4.8 Overall Objective Values for Generation 1 through 4 for the Hybrid PSO-GA

The hybrid method consistently decreased the objective value of the best member even as the hybrid population approached the minimum distance from the objective minimum. The minimum value found after 4 generations of the hybrid was 4.34 and the final average of the particles was 7.77. Figure 4.9 shows the progression of the best value found and the average of the swarm by generation and figure 4.10 shows the evolution of the best overall, NOx, and Soot objective values.

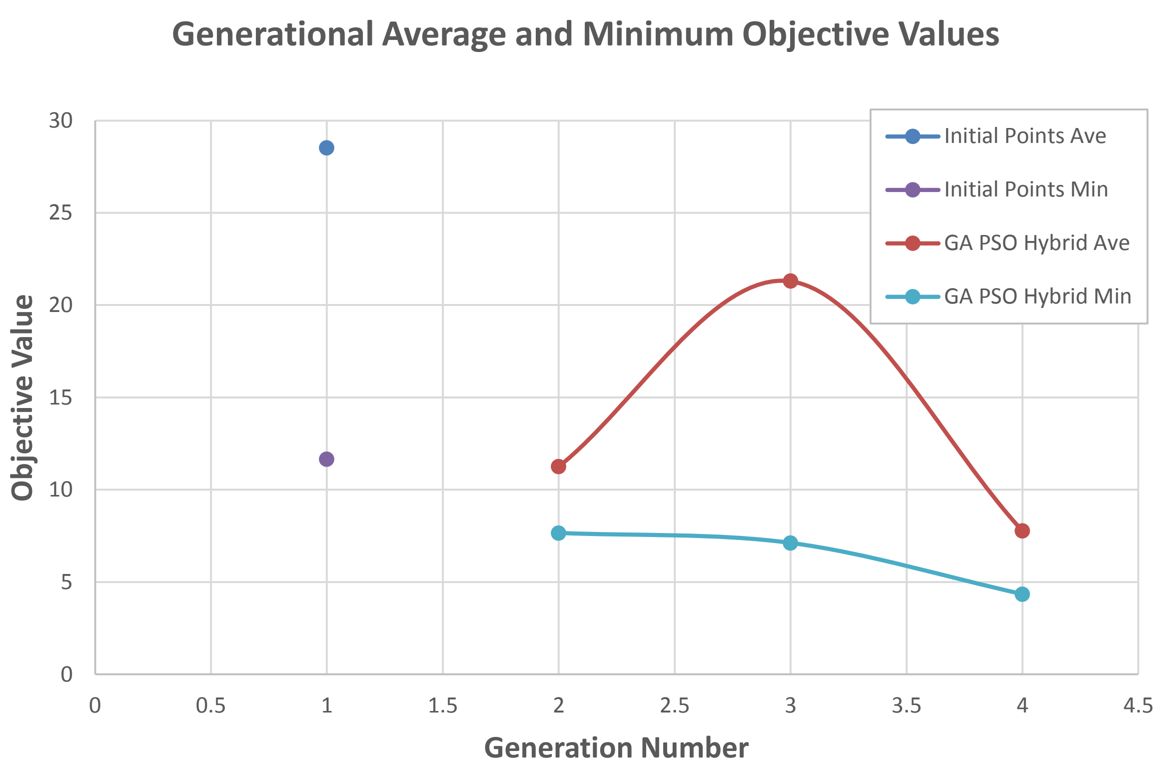

Figure 4.9 Ave. and Min. Objective Values for Generation 1 through 4 for the Hybrid PSO-GA

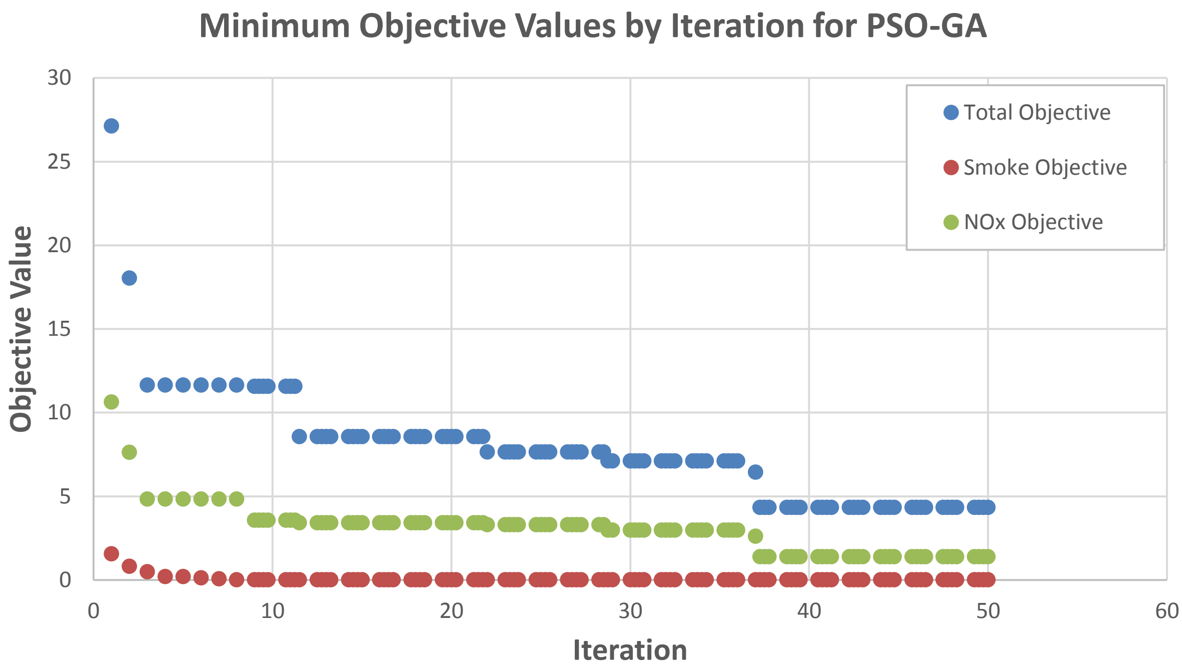

Figure 4.10 Minimum Objective Values for Generation 1 through 5 for the Basic PSO

Figure 4.10 illustrates how the hybrid method maintained substantial decreases in smoke objective and overall objective value each generation, even as convergence was approached. This illustrated the ability of the hybrid methods GA step to maintain diversity and aggressive searching even as the drive of the PSO was reduced near the optimum.

4.4 PSO-GA Objective Comparison

The hybrid method was compared with the basic PSO method and a relative reductions in NOx, PM, and overall objective values were examined. The acceleration of the hybrid method was observed and the overall objective value was compared in terms of test time equivalence. Figure 4.11 shows the hybrid method achieving lower function values earlier in the test schedule. Figure 4.12 excludes points which fell outside the desirable range and shows the improvements of the hybrid method more clearly.

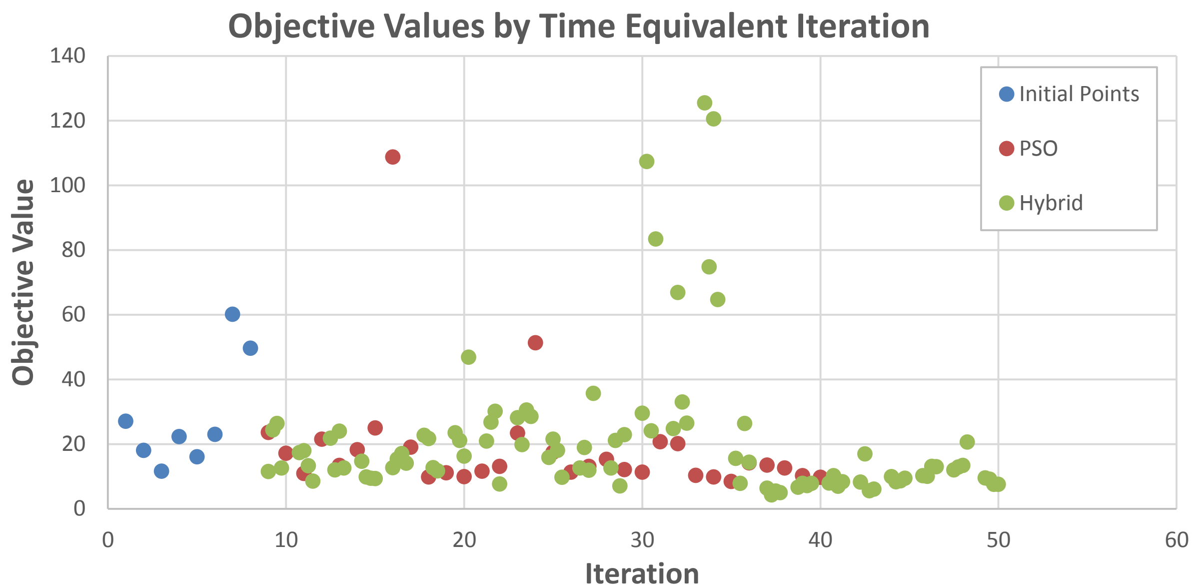

Figure 4.11 Objective values of the PSO-GA and basic PSO method by time-equivalence

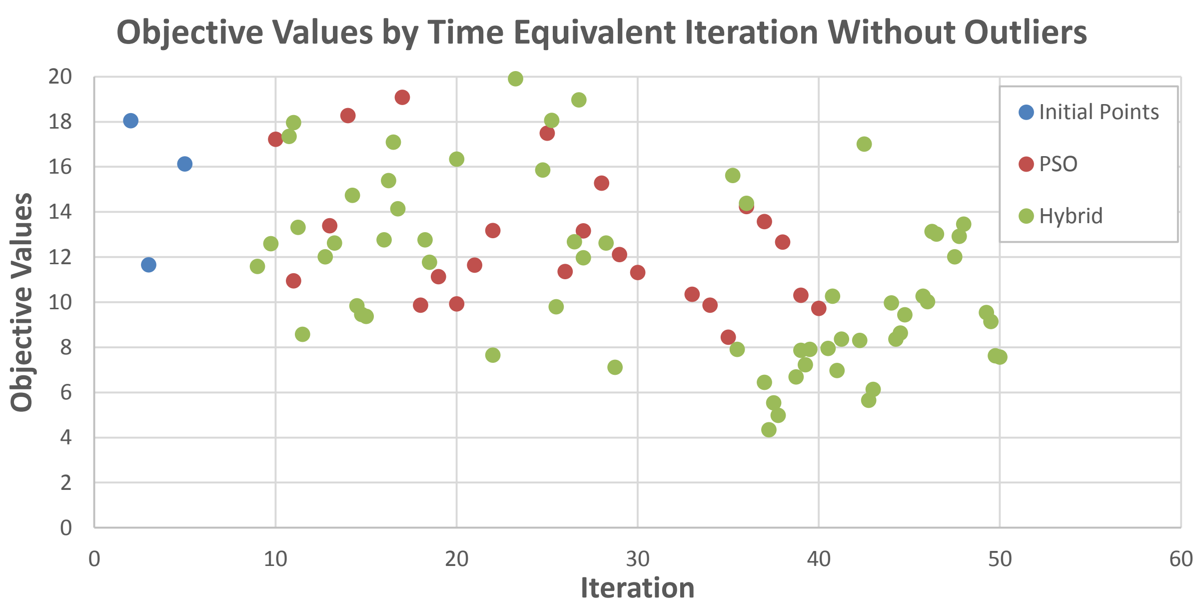

Figure 4.12Objective values of the PSO-GA and basic PSO method without outliers

The hybrid method increased the rate of improvement showing an advantage in the first step that nearly exceeded the best value found by the basic PSO method over a full 5 generations. The hybrid method also showed a higher rate of improvement over successive generations, as figure 4.13 illustrates, when compared with the basic PSO method. Also visible is the rapid reduction in average values of the PSO method versus the spreading evidenced by the hybrid method. The observed trend illustrates the benefits of the hybrid method clearly. The relative gap between the average objective value and the minimum value discovered highlight the simultaneous benefits of the hybrid method as the particles avoided clumping.

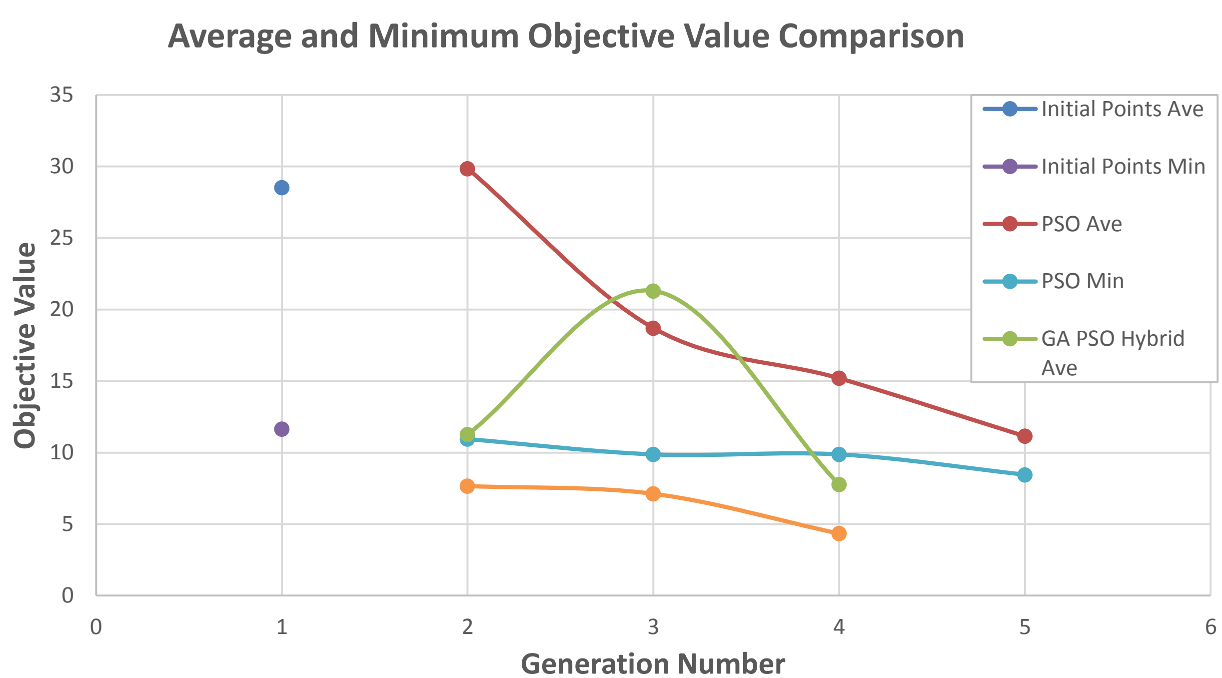

Figure 4.13 Average and Minimum Objective Values for the Hybrid and PSO methods

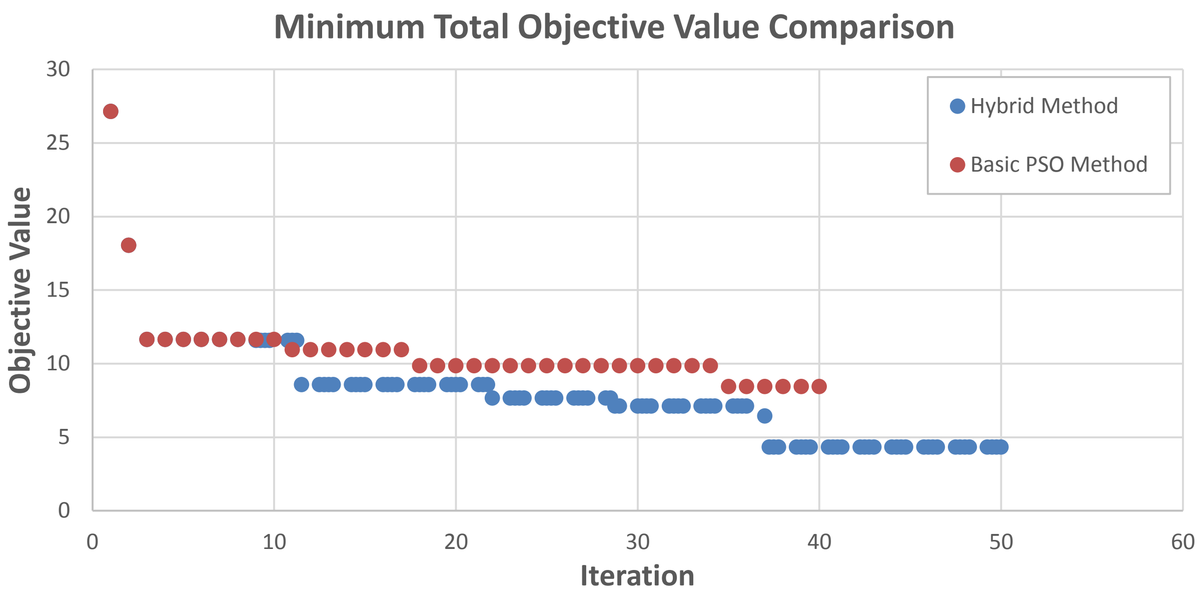

Figure 4.14a Minimum Objective Values for Hybrid PSO-GA and Basic GA

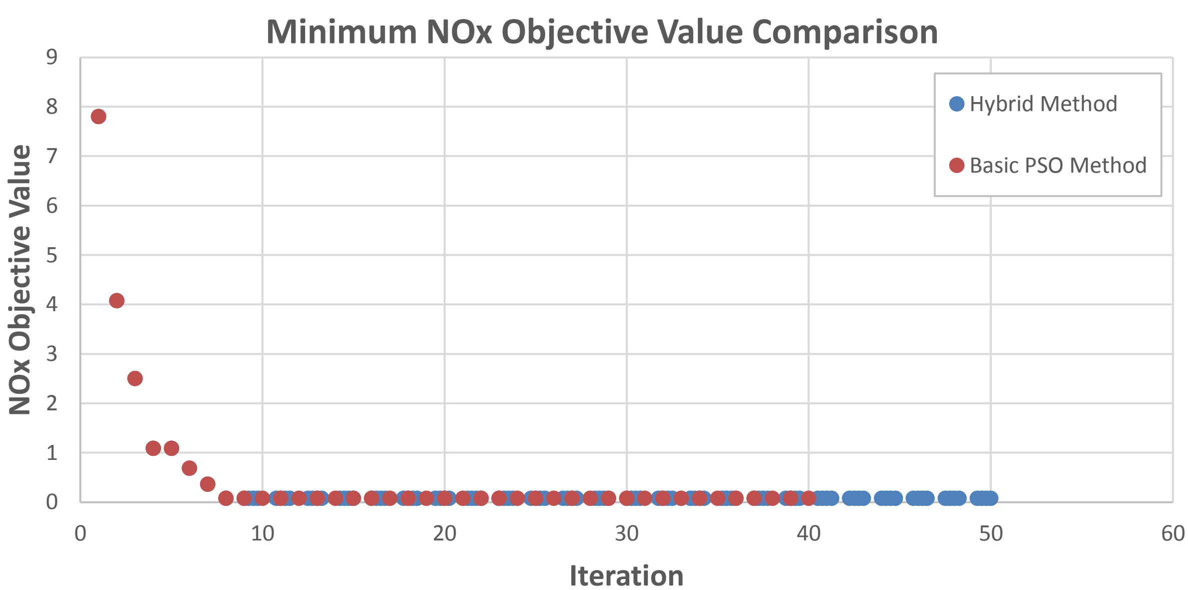

Figure 4.14b Minimum NOx Objective Values for Hybrid PSO-GA and Basic GA

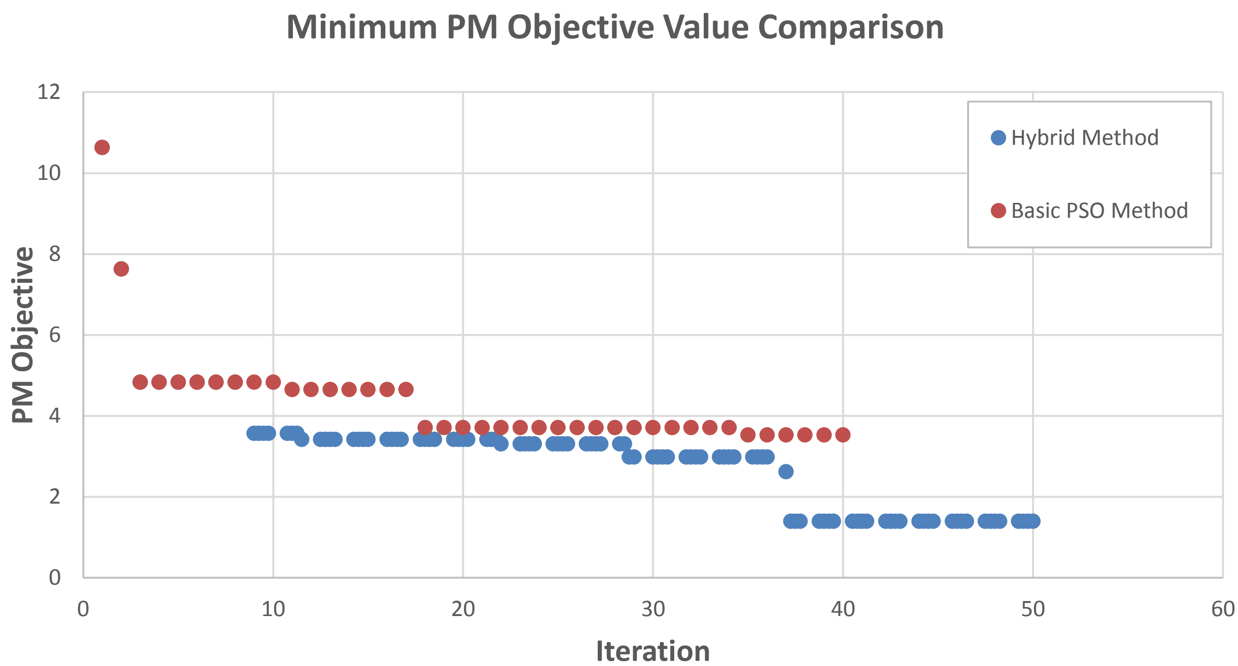

Figure 4.14c Minimum PM Objective Values for Hybrid PSO-GA and Basic GA

Figures 4.14a, b, and c reflect a reduction of 48% in overall objective value, an insignificant reduction in the lowest NOx objective value, and a 60% reduction in the best PM objective value by the same time-weighted iteration. The significant reductions in the two most critical emissions as well as the overall value of the objective function reveal the substantial impact the hybridized method had on the rapid optimization of the engine apparatus.

The HC objective value minimum was reduced by 13%, the CO objective value minimum was reduced by 28%, and the fuel consumption objective was reduced by 14%.

4.5 PSO-GA PSO Input Parameters Comparison

In order to garner information about the input parameters and their interactions two sets of data were trimmed from the whole dataset. Those points whose objective value was above an upper limit and those which were below a lower limit were taken to represent the best and worst conditions. Several graphs were produced to represent the second order interactions between the input parameters to reveal the combinations of parameters which had positive and negative relationships. A complete second order interaction analysis was not the intention of the study, though the desire to discover prudent second order interactions was always a goal set forth by the methodology improvement through particle diversity.

The precise values chosen as cutoffs were taken to be less important than the information captured within them. The upper limit was chosen to be 40 while the lower limit was chosen to be 7.5 which produced approximately 10 points for each in the upper portion and lower portion. The selected points represented the upper and lower quadrant of the data informally and were used to simply to understand if the optimization technique caused enough variation to discern important relationships for tuning and further study. The important negative relationships discovered are presented below in figures 4.15a, b and c and the positive relationships are presented in figure 4.16a, b, and c. The negative relationship discovered involved three parameters, specifically the pilot percentage, the fuel pressure, and the EGR rate, and are highlighted by the figures.

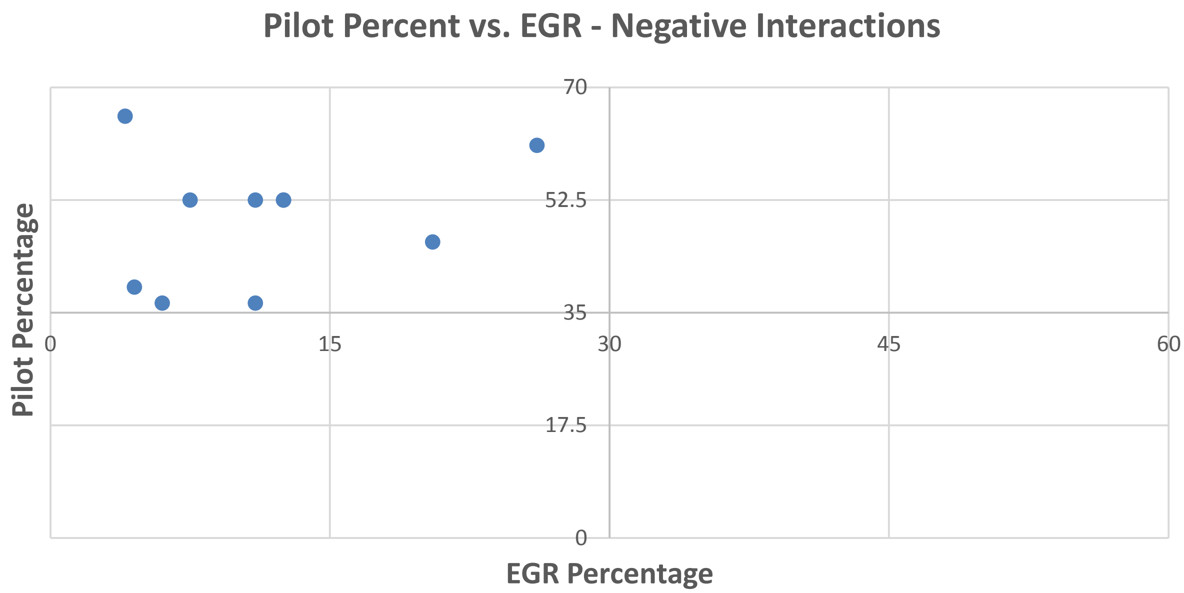

Figure 4.15a Second order interaction between Pilot Percentage and EGR

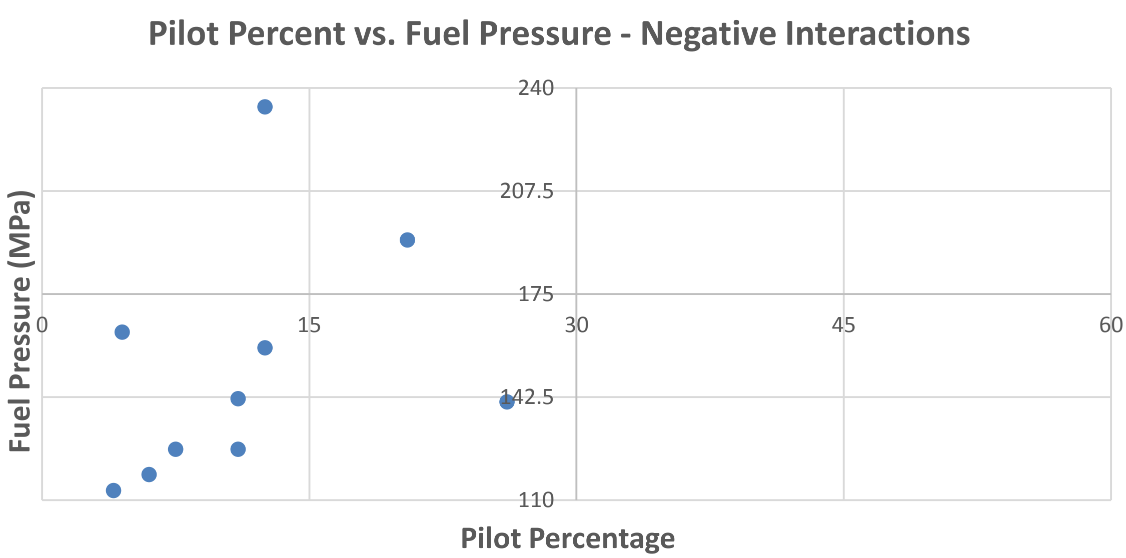

Figure 4.15b Second order interaction between Pilot Percentage and Fuel Pressure

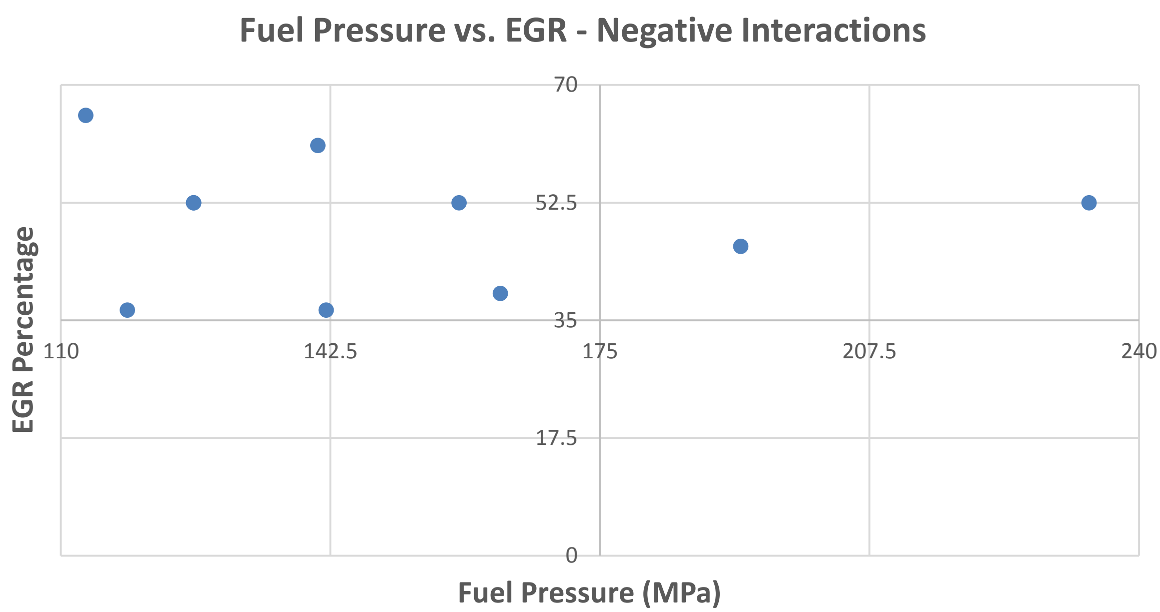

Figure 4.15c Second order interaction between EGR and Fuel Pressure

Figure 4.15a shows that there was a strong interaction between high EGR levels and small pilot amounts while figure 4.15c shows a slightly weaker interaction between low fuel pressure and high EGR levels. In both cases, high EGR levels was interacting with the fuel pressure and pilot delivery. Figure 4.15b shows that both low pilot percentage and low fuel pressure combined in a modestly strong interaction to reduce performance. All three figures 4.15a, b, and c present the understanding that there is likely a strong interaction between very high EGR, low pilot quantity, and low fuel pressure.

Figures 4.16a, b and c show the primary positive interactions, which were generally more evident and stronger in nature. Figure 4.16a shows the pilot timing and main SOI and figure 4.16b shows the main SOI and pilot percentage. Figure 4.16c shows the pilot percentage and pilot timing interaction that completes the set of three second order interactions between the main SOI and two pilot parameters.

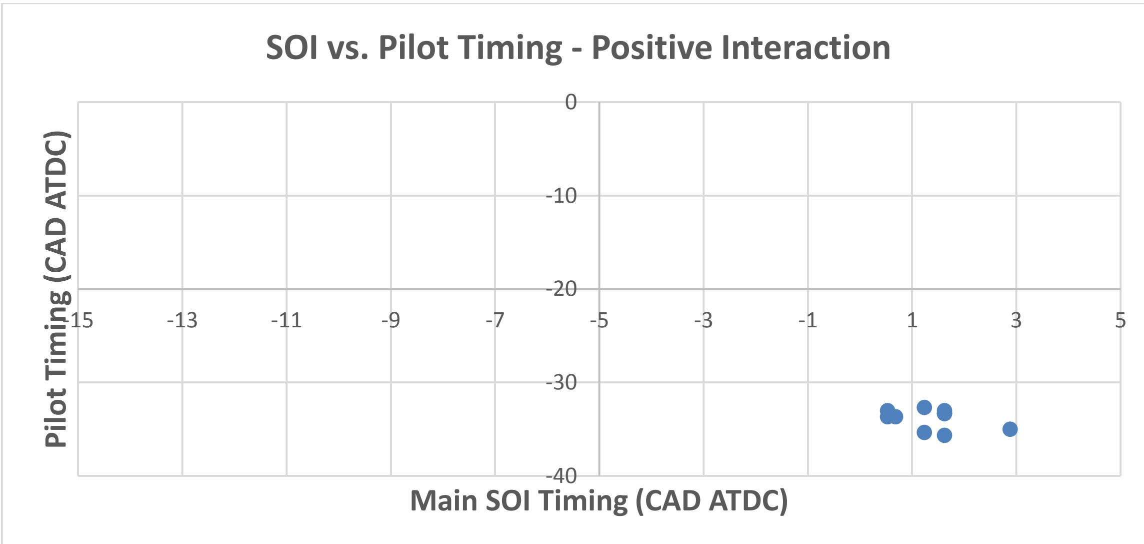

Figure 4.16a Second order interaction between SOI and Pilot timing

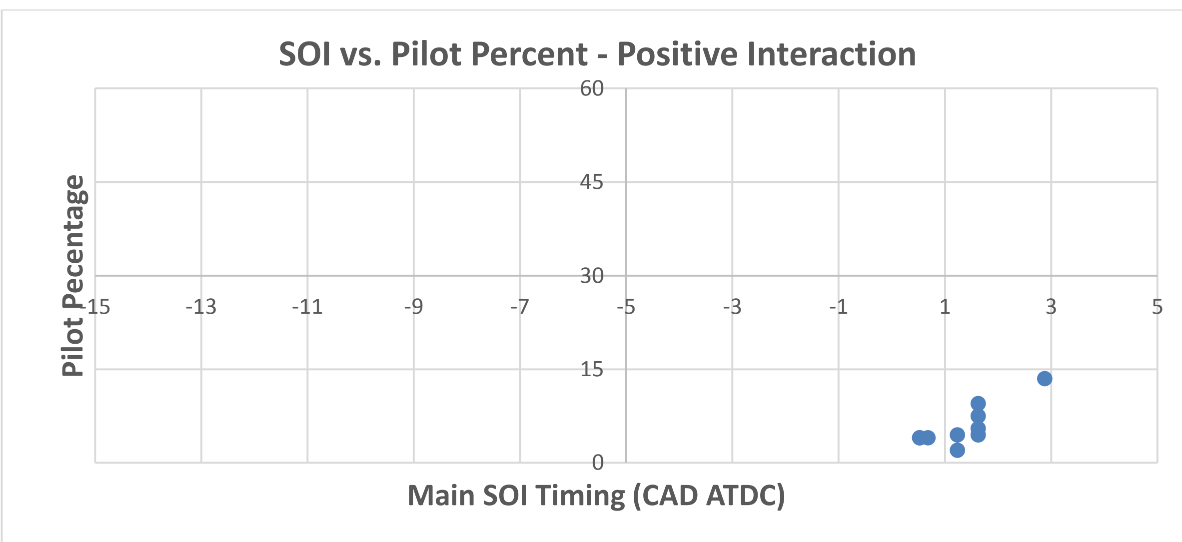

Figure 4.16b Second order interaction between SOI and Pilot percentage

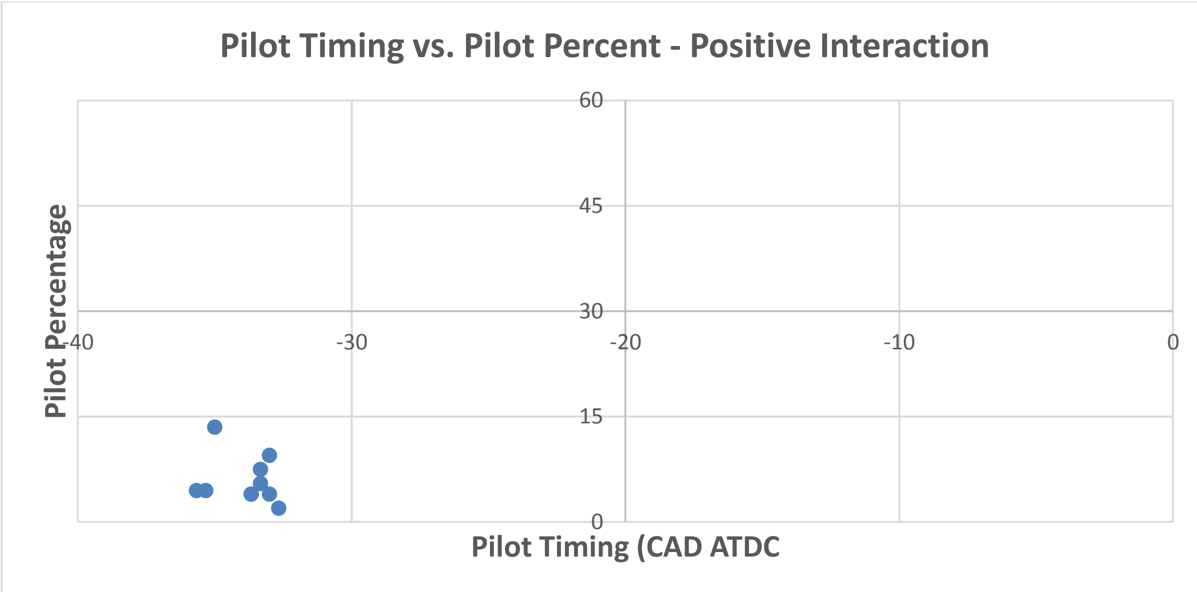

Figure 4.16c Second order interaction between Pilot timing and Pilot percentage

In all three interactions there was a strong indication that late SOI, early pilot timing, and a modestly small pilot percentage produced the best results. The results of this explorative study of second order interactions are clearly strong and while not a full DoE study they were useful to gain useful information from the data as the optimization highlights the regions where engineers have been most interested in.

Further results from the interaction study showed that EGR was best held at a mid-level value near 30% while fuel pressure was moderately high near 190 MPa. Results of the EGR and fuel pressure interactions complete the identification of the traits present in the optimum region. As these values have coalesced in a complete set of strong positive interactions it can be said that all high performing test points were near mid-level EGR of 30%, modestly high fuel pressure between 175 and 205 MPa, main SOI between TDC and +3 CAD ATDC, a pilot timing between -36 and -30 CAD ATDC, and a pilot percentage between 2 and 15%.

CHAPTER 5 CONCLUSIONS

5.1 PSO-GA Hybrid Improvements

The data gathered during this experiment indicate that the novel hybrid approach selected did show improvement in the convergence speed and spread of exploration simultaneously. The PSO-GA hybrid method produced data which allowed some negative interactions to be isolated and some positive attributes to be identified in the region of the optimum value. The data revealed that there was a subtle region of improvement over the standard NOx-Soot tradeoff curve which could be explored rapidly using the novel approach.

The hybrid approach used applied the genetic algorithm specifically to parameters which had an unpredictable effect on the system and yet did not cause unsettling of the balance in the large fluid and heat transfer devices used for EGR cooling and return, turbocharger, or in-cylinder temperature. The main SOI timing and EGR rate had a substantial impact on the thermal and fluid systems and required a several extra minutes to reach equilibrium and measure and yet they did not have an unpredictable effect with regards to system response. Typical main SOI sweeps and EGR sweeps are rather smooth until the functional limits of the engine to sustain combustion are reached. With regards to pilot timing, pilot percentage, and fuel pressure, some trends are less smooth and the results have distinct mode changes mid-sweep. Several possible reasons exist for these sensitivities including spray interactions with the piston and cylinder wall, the pattern of spray circulation, spray-spray interactions, squish-spray interactions, combustion regime change from rapid low temperature blue-flame combustion to typical high temperature yellow-flame combustion.

The application of the Genetic Algorithm to the fuel delivery schedule was a natural one due to the discrete computer control of the injection event as well as the consistent angular position-based injection event timing. Modern engine controls are beginning to vary the fuel delivery in ways never seen before, including injection rate shaping, high number of injections, and pressure variation during different injection events during a single cycle. The rapid developments which have taken place in fuel injection technology give rise to viewing the fuel injection events as a single massive variable known as the fuel injection schedule, which contains information about the pressure during the injection events, the time of each discrete injection as well as it's duration, and the ramp slope of the opening and closing of each event. Current state of the art technology is capable of delivering between 5 and 8 injection events per cycle with highly variable combustion modes including HCCI and PCCI as well as secondary fuel injection with RCCI. Considering an engine with 8 injections of one fuel at one pressure, there would still be 8 individual start times, 8 relative ratios of fuel delivery or end times, 8 opening ramp rates, and 8 close ramp rates, along with a single fuel pressure, results in 33 parameters for fully characterizing the fuel flow schedule.

The novel approach, which follows from the application of the genetic algorithm, views the fuel flow into the cylinder as a single long schedule of discrete events. Simply put, the time-based discrete control of the injector is naturally represented by the gene structure in the GA while the response sensitivity to the injection schedule is another key to exploiting the GA search diversity. In this way the fuel schedule demanded and the fuel schedule which can be delivered can be resolved for each system independently, such that a system with 4 injections could similarly apply a fuel schedule demand as a 5 injection system, though the performance of such a system would be expected to be somewhat different. A tendency for fuel schedule parameters to follow varied standards of definition also convolutes how optimization can be applied whereas allowing designers the freedom to interpret a fuel schedule demanded by the optimization in whatever way the combustion system uses rather than convoluting the optimization structure with restrictions imposed by fuel injector technology, which may itself vary as part of the study.

Another novel advantage of the GA is its ability to reach disjoint sections of the fuel injection strategy such as HCCI combustion modes wherein the fuel charge is injected during the intake stroke and mixed fully before combustion. In these modes of combustion there is not a smooth feasible space which lies between the HCCI region, PCCI region, and normal combustion region, and this could prevent a pure PSO method from being able to reach the remote combustion regime when it is not initialized into the neighborhood of that combustion regime. Given the prevalence of these modern combustion regimes the PSO methodology needs to be updated in order to maintain prudence and applicability. Retaining the characteristic rapid convergence of the PSO method in a hybridized approach requires that the PSO is augmented in the best way possible to overcome these barriers in applying new combustion regimes.

The results of the study indicated that the novel hybrid technique of applying the GA to the selected fuel injection parameters was capable of providing improvements in convergence speed as well as diverse feedback about the design space related to the optimum region over the standard PSO. When the ability to reach disjoint areas of feasibility is also considered the novel approach of adding GA operators to the PSO, with specific application to fuel injection schedule, the benefits of the hybrid approach are substantially significant.

Another aspect of the hybridized approach in experimental apparatus is that by using genetic algorithm structures the objective function structure can actually be changed throughout the optimization with an emphasis on explorative effects without actually implementing complex multi-objective methods. It can be seen here that NOx and PM can both be reduced simultaneously, as well as other emissions and fuel consumption. Single objective methods are sufficient to discover and characterize the optimum neighborhood in this study and the additional time required to re-calculate the objective values based on a different weight or ordering scheme is considered to be effectively zero. Global optimum value improvements could also be seen by randomizing the weights of the objective function and recalculating the objective function for all historical points during each generation of the PSO. This would allow any design prejudice to be removed and reveal the true Pareto front while using single objective function methods such as the hybrid one proposed here. This functionality was implemented in the code but not utilized by the study due to the entirely different nature of true multi-objective studies while this study was focused on comparing the PSO and hybrid methods. Casual investigations were done on individual generations and populations which showed that the global best particle rarely ever changed and when it did it often was the nearest neighbor who inherited the global best position, and thus little changed about the vectoring for the subsequent generations of the PSO. This technique would be more prudent if the weight preference of the designer was unknown or if true multi-objective characterization was desired. This adaptation further extends the novel hybrid methodology here to a more robust multi-objective method without the need to restructure the method into a complicated new multi-objective version. This also allows single objective variations of the PSO and GA to be incorporated into the respective steps of the algorithm, especially in cases where they have been established as effective on the particular apparatus prior to the implementation of the hybridized approach.

The novel hybrid approach is clearly an improvement over the standard PSO which offers benefits of both the PSO and the GA while avoiding the shortcomings of either method alone. Additionally, further variations on structure have allowed multiple objectives to be studied using single objective methods more robustly than in the past. Additionally, the approach taken in this study is open to a wider range of variations for improving results on individual experimental apparatus than the existing multi-objective techniques, which are often quite complex and require major recoding to apply established variations. Methods which are expected to show additional improvement in the hybrid model include multiple swarming, neighborhoods, specific topologies applied in the PSO method, GA elitism, and non-dominated population analysis in the GA. Using these simple tools combined with the novel hybrid methodology applied herein improvements in the optimization of control parameters on experimental engines can be seen.

As new technology becomes ready for market optimization will play a larger role in integrating that new technology into an already complex system. Improved optimization techniques mean that more equipment can be applied simultaneously and more complex systems can be optimized using the newly developed methods. This methodology serves to improve the optimization of complex fuel delivery strategies which are an important emerging technology which also has retrofit potential.

5.2 Combustion Control for Emission Reduction using Heuristic Optimization

Tier 4 final emissions standards are difficult to achieve using traditional in-cylinder control approaches such as EGR and combustion phase control. Improved methodologies which accelerate and improve the ability of optimization to reveal tightly curved portions in the response surface may have been hidden as older technology was not necessarily designed for operation in the particular design space discovered by the optimization.

The control parameters varied in this study were well adapted to the technique used and by the 4th generation the optimization revealed points compliant with general Tier 4 emissions standards with respect to NOx and Smoke. Specific techniques used in analysis of exhaust gas measurements for Tier 4 compliance were not followed specifically while the results are expected to be both accurate and precise, confidence in the results to say that this engine would be able to produce Tier 4 compliant emissions under an FTA test cycle or in the field is not sufficient. A specific uncertainty is also not attributed to the measurements because of a large number of unknown factors, as is commonly the case with engine studies, however, since data which was repeated on different days showed less variation than the margin of error given by the measurement equipment and data concurred with prior data taken on the apparatus throughout previous studies the measurements are valid. The results indicated that a few Tier 4 compliant operating points with regard to NOx and Soot were found on an engine which was manufactured using technology a decade older than the Tier 4 emissions standards themselves. The emissions data resulting from this optimization study show that diligent optimization strategies can produce dramatically reduced emissions during steady state operation. This is more useful as an academic tool for exploration and as a feedback tool for designers rather than as a test bed for validation of emissions compliance.

Based on the results of this study the new hybrid PSO-GA methodology is expected to perform as an effective tool for rapid optimization of control parameters in multiple objective engine studies. The hybrid approach offered faster convergence and wider spread, allowing interactions to be discovered at the same time as finding a very high performing optimum neighborhood. The tests are however, limited in scope and application and further study is necessary to validate the approach. Continued research on the same apparatus as well as new apparatuses will be required to give full confidence to the results of the improvement but conference with computational results is reassuring. This hybrid approach will give engine research experimentalists a basis for designing their own unique combinations of the PSO and GA while offering the simplicity of single-objective function structures with freedom to utilize existing variations of the PSO and GA already discovered.

Works Cited

[1] C. K. Ferguson and A. T. Kirkpatrick, Internal Combustion Engines: Applied Thermosciences, New York: Wiley, 2000.

[2] WHO, World Health Organization, "WHO, World Health Organization," 13 March 2014. [Online]. Available: http://www.who.int/mediacentre/factsheets/fs313/en/. [Accessed July 2014].

[3] Y. Shi, R. D. Reitz and H.-W. Ge, Computational Optimization of Internal Combustion Engines, London: Springer-Verlag, 2011.

[4] U.S. Environmental Protection Agency, "Nonroad Diesel Engines," US EPA, [Online]. Available: http://www.ecfr.gov/cgi-bin/text-idx?SID=ce19e4f40381388d99fccef4a71f67d5&tpl=/ecfrbrowse/Title40/40cfr1039_main_02.tpl. [Accessed 11 July 2014].

[5] U.S. Energy Information Administration, "Annual Energy Outlook 2013 - Oil/Liquids from Excecutive Summary," U.S. Energy Information Administration, Washington D.C., 2013.

[6] J. Ambs and B. McClure, "The Influence of Oxidation Catalysts on NO2 in Diesel Exhaust," SAE, 1993.

[7] E. Rohart, V. Belliere-Baca, K. Yokota, V. Harle and C. Pitois, "Rare earths based oxides as alternative materials to Ba in NOx-trap catalysts," *Topics in Catalysis,* Vols. 42-43, no. 1-4, pp. 71-75, May 2007.

[8] S. Verdier, V. Harle, A. Huang, E. Rohart and e. al., "Doped Zirconia with High Thermal Stability, for High Sulfur Resistance Diesel Oxidation Catalysts," SAE, 2006.

[9] G. E. Zacharakis-Jutz, "Performance characteristics of amonia engines using direct injection strategies," Self Published, Ames, IA, 2013.

[10] P. Karra and S. Kong, "Application of Particle Swarm Optimization for Diesel Engine Performance Optimization," 2010.

[11] G. N. Vanderplaats, Multidiscipline Design Opimization, Monterey, CA: Vanderplaats Research and Developement, 2007.

[12] J. S. Arora, Introduction to Optimum Design, Waltham, MA: Academic Press, Elsevier Inc., 2012.

[13] F. V. D. Bergh, "An Analysis of Particle Swarm Optimizers, PHD Thesis," University of Pretoria, 2001.

[14] P. K. Karra, "Parametric Study and Optimization of Diesel Engine Operation for Low Emissions Using Different Injectors," Self Published, Ames, IA, 2009.

[15] M. Clerc and J. Kennedy, "The Particle Swarm explosion, stability, and convergence in a multidimensional complex space," *Transactions on Evoluyionary Computation, Vol. 6,* pp. 58-73, 2002.

[16] S. Jeong, S. Obayashi and Y. Minemura, Application of hybrid evolutionary algorithms to low exhaust emission diesel engine design, Yokohama: Taylor & Francis, 2008.

[17] S. Jeong, S. Hasegawa, K. Shimoyama and S. Obayashi, "Development and investigation of efficient GA/PSO-hybrid algorithm applicable to real-world design optimization," in *Eleventh* , Proceedings of the Eleventh conference on Congress on Evolutionary Computation, 2009.

[18] R. Hassan, B. Cohanim and O. d. Weck, "A Comparison of Particle Swarm Optimization and the Genetic Algorithm," Vanderplaats Research and Developement Inc, Colorado Springs, 2004.

[19] J. Kennedy and R. Ebert, "Particle Swarm Optimization," in *{roceedings of IEEE Inernational Conference on Neural Networks IV.*, 1995.

[20] J. Kennedy, "The partical swarm: socail adaptation of knowledge.," in *International Conference on Evolutionary Computation* , Indianapolis , 1997.

[21] R. Poli, "Analysis of the Publicaitons on the applications of particle swarm optimization," *Journal of Artificial Evolution and Applications,* pp. 1-10, 2008.

[22] M. E. H. Pedersen, "Tuning & Simplifying Heuristical Optimization," School of Engineering Sciences, Univerity of Southampton, 2010.

[23] D. H. Wolpert and W. G. Macready, "No Free Lunch Theorems for Optimization," *Transactions on Evolutionary Computations, Vol. 1,* pp. 67-82, 1997.

[24] A. Kaveh and S. M. Rad, "Hybrid Genetic Algorithm and Particle Swarm Optimization for the Force Method-Based Simultaneous Analysis and Design," *Iranian Journal of Science & Technology, Transaction B: Engineering Vol. 34, B1,* pp. 15-34, 2010.

[25] M. Kim, M. Liechty and R. and Reitz, "Application of Micro-Genetic Algorithms for the Optimization of Injection Strategies in a Heavy-Duty Diesel Engine," *SAE,* 2005.

[26] R. Thangaraj, M. Pant, A. Abraham and P. Bouvry, "Particle Swarm Optimization; Hybridization perspectives and experimental illustrations," *Applied Mathematics and Computation,* pp. 1-19, 2011.

[27] Y.-T. Kao and E. Zahara, "A hybrid genetic algorithm and particle swarm optimization for multimodal functions," *Applied Soft Computing,* pp. 849-857, 2008.

[28] J. B. Heywwood, Internal Combustion Engine Fundamentals, Singapore: McGraw-Hill, 1988.

[29] M. Pedersen and A. Chipperfield, "Simplifying Paricle Swarm Optimization," *Applied Soft Computing,* pp. 618-628, 2010.