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Development and applications of various optimization algorithms for diesel engine combustion and emissions optimization

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Development and applications of various optimization algorithms for diesel engine combustion and emissions optimization

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NOMENCLATURE

GA: Genetic Algorithm

PSO: Particle Swarm Optimization

ABC: Artificial Bee Colony

EGR: Exhaust Gas Recirculation

NOx: Oxides of Nitrogen

PM: Particulate Matter

HC: Hydrocarbon

CO: Carbon Monoxide

CO_2: Carbon Dioxide

BSFC: Brake Specific Fuel Consumption g/kW-h

SOI: Start of Injection

CAD: Crank Angle Degree

TDC: Top Dead Center

ATDC: After Top Dead Center

BTDC: Before Top Dead Center

ABSTRACT

For this work, Hybrid PSO-GA and Artificial Bee Colony Optimization (ABC) algorithms are applied to the optimization of experimental diesel engine performance, to meet Environmental Protection Agency, off-road, diesel engine standards. This work is the first to apply ABC optimization to experimental engine testing. All trials were conducted at partial load on a four-cylinder, turbocharged, John Deere engine using neat-Biodiesel for PSO-GA and regular pump diesel for ABC. Key variables were altered throughout the experiments, including, fuel pressure, intake gas temperature, exhaust gas recirculation flow, fuel injection quantity for two injections, pilot injection timing and main injection timing. Both forms of optimization proved effective for optimizing engine operation. The PSO-GA hybrid was able to find a superior solution to that of ABC within fewer engine runs. Both solutions call for high exhaust gas recirculation to reduce oxide of nitrogen (NOx) emissions while also moving pilot and main fuel injections to near top dead center for improved tradeoffs between NOx and particulate matter.

ACKNOWLEDGEMENTS

CHAPTER 1 INTRODUCTION

1.1 Motivation

As Gross Domestic Product and population expand, more energy is required to meet increasing demands for transportation and electricity production. Due to the continued use of fossil fuel combustion to meet this need, the corresponding emissions from this process has come under scrutiny due to rising atmospheric CO_2 and global surface temperatures (Vanic et al 2012). Further, other possible products of combustion such as oxides of nitrogen and particulate matter can be hazardous to human health. Over the last 30 years emission standards have been set in countries throughout the globe designed to reduce emissions from all forms of combustion related to power production (Turns 2012). In the US, the Environmental Protection Agency (EPA) has set stringent standards for both diesel and gasoline engines in Tiers that decrease allowed emissions per kilowatt-hour (kW-h) progressively over time.

1.2 Objective

The focus of this work is on modern diesel engines, which utilize a vast swath of technologies to minimize emissions and maintain power output. These technologies include but are not limited to EGR, injection pressure, injection timing, turbo-charging and intercooling. A small change in any of these parameters can introduce vast differences in heat release, emissions, and efficiency. In order to best utilize these technologies to reduce emissions and fuel consumption, new engines are tested on a dynamometer stand and connected to a variety of state-of-the-art equipment to read emissions data for each operating condition of interest. As noted by Perhinschi et al. 2011, traditional parametric studies are costly and require exhaustive strain on

equipment and labor. Artificial intelligence (AI) in the form of optimization algorithms can be used to vastly reduce the number of required experiments saving money and time.

Mathematically, the way in which air and fuel are mixed and burned in an engine can be represented as inputs to a complex multimodal, non-separable function producing power and emissions as outputs. Optimization of diesel engines is a balancing act of interconnected variables and tradeoffs between emissions and power output. Given variable limits and an overall objective, optimization algorithms produce a new set of experimental trials based on the results of previous experiments, rather than by a step-by-step change in each of the input parameters. These algorithms are typically based on evolution or swarm intelligence which can both be found in nature.

The following chapters will review current optimization algorithms and give examples as to how they can be improved and used to solve real world problems in shorter time. Two of the algorithms discussed below are modified, tested against standard benchmark functions and then applied to real world engine operation. Chapter 2 provides a literature review covering the numerous diesel engine pollution reduction strategies and the many varieties and applications of optimization. Chapter 3 encompasses the process and testing of a Particle Swarm-Genetic Algorithm hybrid as well as a modified version of Artificial Bee Colony algorithm. Chapter 4 displays and discusses the results of both applications to a John Deere diesel engine. Finally, Chapter 5 summarizes key results and provides recommendations for future experimental optimization with ABC.

CHAPTER 2 LITERATURE REVIEW

2.1 Modern Diesel Engine Emission Reduction Strategies

Exhaust Gas Recirculation (EGR)

EGR involves the recirculation of combustion product exhaust gas back into the intake manifold. The CO_2 and H_2O in the exhaust gas increases the specific heat of the charge gas and decreases the local equivalence ratio (Turns 2012). These effects work to decrease overall in-cylinder temperatures and reduce thermal NOx emissions whose production are a strong function of temperature. EGR is especially important for the combustion of biodiesel which produces fewer emissions of incomplete combustion but increased NOx comparatively to that of regular diesel (Mueller et al. 2009). Products of incomplete combustion include CO, HC, and PM. The increase in NOx when using biodiesel and its blends has been well studied and has been strongly correlated with increased local equivalence ratio near the fuel jet due to the oxygen content of the fuel. This accelerates combustion and increases cylinder temperatures earlier in the cycle than regular diesel, especially at low or partial load conditions where mixing controlled combustion is less prevalent (Mueller et al. 2009). While EGR decreases NOx emissions it also can increase PM emissions due to decreasing local equivalence ratio which must be taken into account to meet EPA and Euro regulation standards (Turns 2012).

Fuel Injection Strategies

The modern, high pressure, common rail, diesel fuel delivery system allows for more than one fuel injection at any crank angle, theta, at constant pressure. Increasing fuel injection pressure increases the momentum of fuel within the charge gas and has been shown in previous studies to improve mixing between air and fuel and thus lower PM emissions (Karra and Kong

2008). In Karra and Kong 2008, it was found that fuel pressure could be increased from 150-180 MPa under moderate EGR to reduce PM without a large penalty in NOx emissions. Pilot injections split the overall fuel between an early and main injection. Pilot combustion produces heat and radical species which allow for a decreased ignition delay for main injection and thus a decrease in soot emissions (Karra and Kong 2008, Shi et al 2010).

2.2 Optimization Algorithms

Genetic Algorithm (GA)

The Genetic Algorithm (GA) is modeled after the evolution of species and represents potential solutions as parents and children. A given set of potential parents with specific genes (solution elements) are trialed as generation one. Similar to evolution, only the best parents survive or are 'good enough' relative to the utopia to combine their positive characteristics in the form of an offspring. Similar to human genetics children differ from their parents through random mutations. Children with superior mutations for their environment survive to eventually become parents thus continuing the cycle. Due to its ability to thoroughly explore the search space, convergence time is a common concern with GA, requiring careful consideration of parameters affecting selection of the best results, mutation rate, population, and crossover of genes (Angelova and Penchevea, 2011). Experimental applications typically employ the micro-Genetic algorithm (µGA) which allows for a much smaller population of 5 or less compared to that of the standard GA, which can require populations of up to 200. In µGA, tournament selection and elitism strategies work with crossover and mutation in an effort to ensure that only the best potential solutions participate in the optimization routine (Karra and Kong 2010).

Particle Swarm Optimization (PSO)

Particle Swarm optimization (PSO) models a swarm of beings, each individual has information about their distinct location (P_{best}) in the search space as well as the position of the leader (G_{best}). This could represent a swarm of birds, ants, or even robots. In the PSO process starting particles are given initial positions X_i. Following the evaluation of initial positions the vector X_i is modified by means of an updated velocity V_{i+1}, using equations 2.1 and 2.2. In the PSO equations, i is the current iteration, w is an inertia weight for the previous velocity, and C_1 and C_2 represent interest factors for both local and global solution information. R_1 and R_2 are randomly chosen numbers in [0,1] that serve to enhance exploration (Karra, 2009).

$$X_{i+1} = X_i + V_{i+1} \qquad (2.1)$$

$$V_{i+1} = wV_i + C_1 R_1 (P_{best} - X_i) + C_2 R_2 (G_{best} - X_i) \qquad (2.2)$$

Artificial Bee Colony Optimization (ABC)

ABC optimization, introduced by Dervis Karaboga in 2005 is another form of swarm optimization that mimics the way in which bees find and develop food sources. In a real honey bee hive only a portion of the bees will leave in search of food sources. In the first step of the ABC, a quantity of initial food sources or parameter vectors are trialed. The fitness of each food source in reference to a given utopia point is recorded. Initial food sources are produced based on the upper and lower bounds (UB and LB respectively) of the problem according to equation 2.3. Equation 2.3 is conducted in a loop where each food source, i, is given an element j, until the dimension of the food source, D, has been reached (Karaboga and Akay, 2009, Karaboga, 2005).

$$Food_{ij} = X_{LB} + Rand[0,1](X_{UB} - X_{LB})_j \qquad (2.3)$$

Following the initialization and testing of initial food sources employed bees return one

by one to a point very near each source. The employed bee phase will add one random mutation

to their source based off of another randomly chosen food source in the group, regardless of

fitness. Following their selection, each employed bee evaluates the mutated food source's

wealth in comparison to the initialized source and remembers only the better one. In the hive,

employed bees will return from a given food source and conduct the waggle dance in the hope of

recruiting onlooker bees to the food site. The quality of the dance communicates the quality and

location of the food source to the hive. The onlooker bee phase uses probability based on the

fitness of the previous solutions to mimic the waggle and dance and thus decide which food

sources are most likely to receive onlooker bees (tests). The food source that received the best

fitness value is most likely to be selected at each step in the onlooker bee phase. The onlooker

bee will again apply a random mutation to the visited source based off of a randomly selected

neighbor and will remember only the food source with the better result. During the onlooker

phase it is possible that a food source will be visited more than once or not at all. Each time a

food source is not improved by the onlooker or employed bee phase its trial counter is increased.

Equation 2.4 below prescribed by Karaboga, is used at both the employed and onlooker bee

phases, where $\varnothing$ is a random number in the interval [0,1]. The first subscript identifies the food

source, and the second, the parameter (dimension) to be changed (Karaboga and Akay, 2009).

$$V_{ij} = x_{ij} + \varnothing_{ij}\left(x_{ij} - x_{kj}\right) \qquad (2.4)$$

Following the conclusion of the onlooker bee phase the scout bee is called. Should a

food source have been modified (trialed) more than a specified limit value without improvement,

it is replaced by the scout bee with a newly initialized food source. If the limit value has not been

reached by any food source than the cycle repeats with the employed bees visiting each source in

succession. Only one scout bee is allowed, per iteration, in standard ABC. The amount of times

the cycle repeats in application is referred to as maximum cycle number (MCN) (Karaboga and

Akay, 2009).

2.3 Modifying the Standard ABC Algorithm

Because of the small number of input parameters, ABC optimization can be applied to a

large host of problems. Standard ABC has been applied to numerous benchmark functions in

Karaboga and Akay 2009, and shows better if not competitive performance against PSO and GA

in standard benchmark tests. The primary shortcoming of traditional ABC in comparison to

other evolutionary algorithms is time to convergence (Zhu and Kwong, 2010; Imanian et. all,

2014; Gao and Liu, 2011). Gau and Liu, 2011 also point out that traditional ABC can also

become trapped in local minima, when optimizing multi-modal functions.

Exploration and exploitation describe the ability of an algorithm to both find and utilize a

trend to its full potential. A lack of exploration could lead an algorithm to settle at the bottom of

local minimum. An endless search could be result of a lack of exploitation, where the algorithm

is not able to follow the shortest route to the bottom of the valley. Zhu and Kwong 2010 and

Yuan et al. 2014, determine that the ABC algorithm is very effective in exploration but lacking

in exploitation. Therefore, a term inspired by PSO is prescribed for the modification of food

sources which considers the global best solution in equation 2.5. In this addition to equation 2.4,

ω is a random number in the interval [0,1.5] and y represents the current global best solution

(Zhu and Kwong 2010). This modification increases the convergence speed of the algorithm by

pulling all potential solutions toward the global best, similar to that of PSO in equation 2.2. By

applying Equation 2.5 to both the employed and onlooker bee phases, Zhu and Kwong were able

to improve the exploitation of ABC in standard benchmark tests and thus decrease convergence

time. Imanian et al. 2014, employs this technique as well, but restrict the use of Equation 2.5 to

the onlooker phase only, using Equation 2.4 in the employed bee phase.

$$V_{ij} = x_{ij} + \varnothing_{ij}\left(x_{ij} - x_{kj}\right) + \omega_{ij}\left(y_j - x_{ij}\right) \tag{2.5}$$

A further modification can be made to the employed bee phase in order to increase

exploration. In Gao et. al. 2011, several modifications are made to ABC in an effort to avoid

local minima. The work suggests the mutation of multiple elements of a food source at both the

employed and onlooker phases. At each modification step, based on a constant probability P,

additional elements of a food source are mutated using a random number generator in a loop

(until the random number is larger than P). If P is selected too large, than it becomes highly

possible that all elements of a food source vector will be changed in one step. Using P equal to

0.25, the algorithm is able to explore further mutations, allowing it to achieve better fitness than

standard ABC in the same number of iterations (Gao et. al 2011). Fitness refers to the fraction of

actual solution value to that of the ideal.

2.4 Hybrid Algorithms

It is possible to combine optimization algorithms in order to produce a hybrid with the

intent to use the positive attributes of one algorithm to cancel out the negative attributes of

another. Hybrid algorithms can also be designed in order to 'seed' or lead another algorithm into

a narrow search space. In Araújo et al. 2013, PSO is employed to the first 30% of function

iterations to perform a global search while for the final 70% of iterations, Differential Evolution

(DE) algorithm is employed to perform a local search. DE is similar to PSO, however it has

been shown to perform a more thorough exploration of the search space than PSO which can become entrapped in local minima. Using PSO to first seed the more explorative DE allows for a thorough search in a higher quality area of the search space (Araújo et al. 2013). The Genetic Algorithm is powerful search tool, however this ability can lead to long convergence times when it is used alone. In Muñoz et al. 2013, GA is first given three iterations followed by the use of a local search tool; the Nelder Mead Method. By coupling GA with a local search method the computational time is greatly decreased for the same accuracy gained with pure GA (Muñoz et al. 2013).

PSO and GA have been, and can be combined, to take advantage of the exploration of GA as well as the exploitation of PSO. Shi et al. 2005 and Jeong et al. 2009, apply algorithms which employ PSO and GA simultaneously at each iteration. In Jeong et al. 2009, solutions are split half and half at each iteration to PSO or GA operators. By combining the two methods both authors report improved search capability of the hybrid algorithm, resulting in better solutions in shorter time.

2.5 GA and PSO Engineering Applications in Literature

GA and PSO have the ability to optimize multiple objectives at the same time and have been used in numerous engineering problems. Hardy and Reitz 2006, Ge et al. 2009, Ge et al. 2010, and Lee et al. 2012 all use Genetic algorithms for the optimization of diesel engine piston design and injection parameters for emissions and fuel consumption. Duan et al. 2014 uses multi-objective PSO to optimize the efficiency, power-output, and entropy production of a numerically modeled Stirling Engine. Karra and Kong 2010, use PSO optimization through direct experiment to minimize emissions by balancing fuel injection strategies with EGR.

2.6 ABC Engineering Applications in Literature

ABC has been used for a multitude of problems extending outside of the standard benchmark tests. In Şahin et al. 2011, ABC is employed for the optimization of shell and tube heat exchanger design to minimize overall cost. In Saif et al. 2014, ABC is used successfully to optimize assembly line task planning. Finally, M. Basu 2011 utilizes Bee Colony algorithm to find the best combination of heat and electric power dispatch to minimize fuel costs. The above simulation based works, show bee colony optimization to converge to Pareto regimes of higher optimality than those found through traditional GA and PSO methods. A Pareto regime represents the solutions with optimum tradeoff between multiple objectives.

CHAPTER 3 EXPERIMENTAL SETUP

3.1 Experiment Overview

This work examines the applications of a PSO-GA hybrid algorithm and modified ABC algorithm to experimental diesel engine optimization. Based on the literature review this chapter provides an overview of how both algorithms were constructed, used, and tested both computationally and experimentally. For the PSO-GA experiment 100% soy biodiesel was used as fuel with 5 input dimensions as seen in Table 3.9. For the ABC experiment, pump diesel was applied as fuel with 6 input dimensions as seen in Table 3.10. Chapter 4 shows the progression of results for both algorithms and discusses tradeoffs between emissions and efficiency. The resulting best condition and algorithm performance are also discussed.

3.2 Combining GA and PSO

By combining PSO and GA, one can get the exploration of GA coupled with the exploitation abilities of PSO. In this work a unique pairing of PSO with GA was used, where PSO and GA are operated sequentially at each iteration using a small population. Each iteration begins with PSO using Equations 2.1 and 2.2 for N potential solutions. Following PSO, the best n solutions, evaluated by fitness value, are submitted to a μGA process (small population). The μGA operator randomly mates pairs of these solutions whilst also applying a mutation to a randomly chosen offspring to be brought back to PSO at the next iteration. A small population N is desired to minimize dynamometer time. The best population size was found to be 8 in the interval [6,10] in order to minimize time to convergence in standard benchmark tests. N and n are therefore set to 4 for simplicity. PSO constants C1 and C2 along with the μGA mutation rate

can be found in Table 3.1 (Qiang et al. 2015). The full PSO-GA hybrid process steps can be seen below and by use of a flow chart in Figure 3.1.

Table 3.1: PSO-GA Parameters Defining the Dimension and Limits of the Problem

PSO-GA Hybrid Parameters	
Population Size (N)	8
Tournament Selection (n)	4
PSO Constants: C1, C2	2
GA Mutation Rate	0.1

Step 1: Randomly generate initial positions $X(i)=\{x_j\,(i)\}$ and velocities $V(i)=\{v_j\,(i)\}$ of particles, where j is the dimension of the particles, $j=(1,2,\ldots, N)$ where N is the size of the swarm.

Step 2: Calculate the value of the objective function. If the termination condition is met, the algorithm terminates.

Step 3: Obtain the new velocities $V\,(i+1)$ and positions $X\,(i+1)$ of particles using Equations 2.1 and 2.2, and update P_{best} and G_{best}.

Step 4: Identify the best n members and discard the rest of the $N–n$ members.

GA steps:

Step 5: Tournament selection based on n members. Select these n individuals from $X(i+1)$ to form the mating pool with a population of $X_s(i+1)$.

Step 6: Crossover. Perform crossover operation on population $X_s(i+1)$ to form a population $X_c(i+1)$.

Step 7: Dynamic mutation. Mutate a single element of an individual with the mutation rate of p_m to form a population $X_m(i+1)$ and output $N–n$ offspring.

Step 8: Form the new generation $i+1$ which includes n members from PSO and $N–n$ members from GA. Return to step 2.
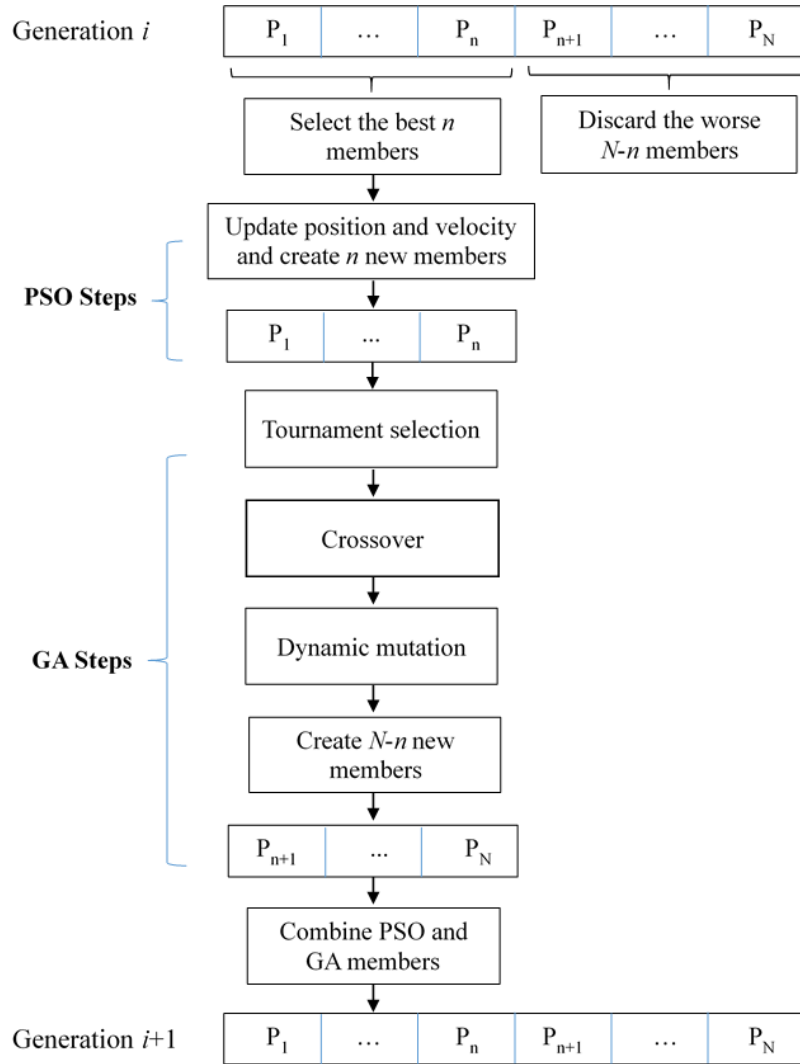
Figure 3.1: PSO-GA Hybrid Flow Chart

3.3 Modified ABC Algorithm

Testing a new engine requires a large amount of capital and time, therefore, it is important that testing time be minimized and that a satisfactory solution is found. Therefore, modifications from the literature were made to the standard ABC algorithm in an attempt to increase convergence speed and avoid local minima. In this work, in order to maintain individual exploration of the employed bee stage, a PSO inspired term was only applied in the Onlooker Bee phase similar to that of Imanian et al. 2014. Inspired by Gao et al 2011, the

employed bee phase is designed to involve two mutations using Equation 2.4, for each food source. The probability scheme from Gao et al. was not employed.

The value of Limit for ABC was found using equation 3.1 from Karaboga and Akay 2009, where D is the number of elements in each food source. No food sources in the experiment reached the limit value. The number of food sources (population) to be memorized was chosen arbitrarily in an effort to minimize experimental time. A larger number of initialized sources could slow down convergence time which is of careful consideration when working to minimize dynamometer time. The MATLAB program for ABC was designed per Gao and Liu 2011, to move any mutations outside of table 3.10 to within the specified upper or lower bounds automatically. Table 3.2 shows input parameters to the Modified ABC algorithm.

$$Limit = (\#\,Foods)(D) \qquad\qquad (3.1)$$

Table 3.2: ABC Parameters Defining the Dimension and Limits of the Problem

ABC Parameters	
Colony Size	8
Number of Food Sources	4
Food Source Dimensions (D)	6
Maximum Cycle Number	200
Limit	24

The complete list of steps in the modified algorithm are below followed by the overall flowchart used though the experiment in Figure 3.2.

Step 1: Use equation 2.3 to generate four random initiate food sources.

Step 2: Initial food sources are tested and assigned a fitness value.

Step 3: Employed bees visit each food source in succession changing two random parameters at

a time at each food source based on equation 2.4.

Step 4: Altered food sources from step 3 are tested and assigned a fitness value.

Step 5: A greedy selection is made whereby only the best condition of each food source is

memorized, if the fitness value of a food source does not improve its trial counter

increases.

Step 6: A probability value is assigned to each food source based on its current fitness value

relative to the group.

Step 7: A random number generator is used in tandem with food source probability to determine

which sources will be visited by each of the 4 onlooker bees.

Step 8: Each food source selected by the onlooker bees is altered using equation 2.5.

Step 9: Altered food sources from step 8 are tested and assigned a fitness value.

Step 10: A greedy selection is made whereby only the best condition of each food source is

memorized, if the fitness value of a food source does not improve its trial counter

increases.

Step 11: If any food sources have exceeded the trial Limit value, they are considered abandoned

and a new food source is generated by the scout bee using equation 2.3. Only one scout

bee is allowed per trial

Step 12: If optimum conditions have not been met return to Step 3.
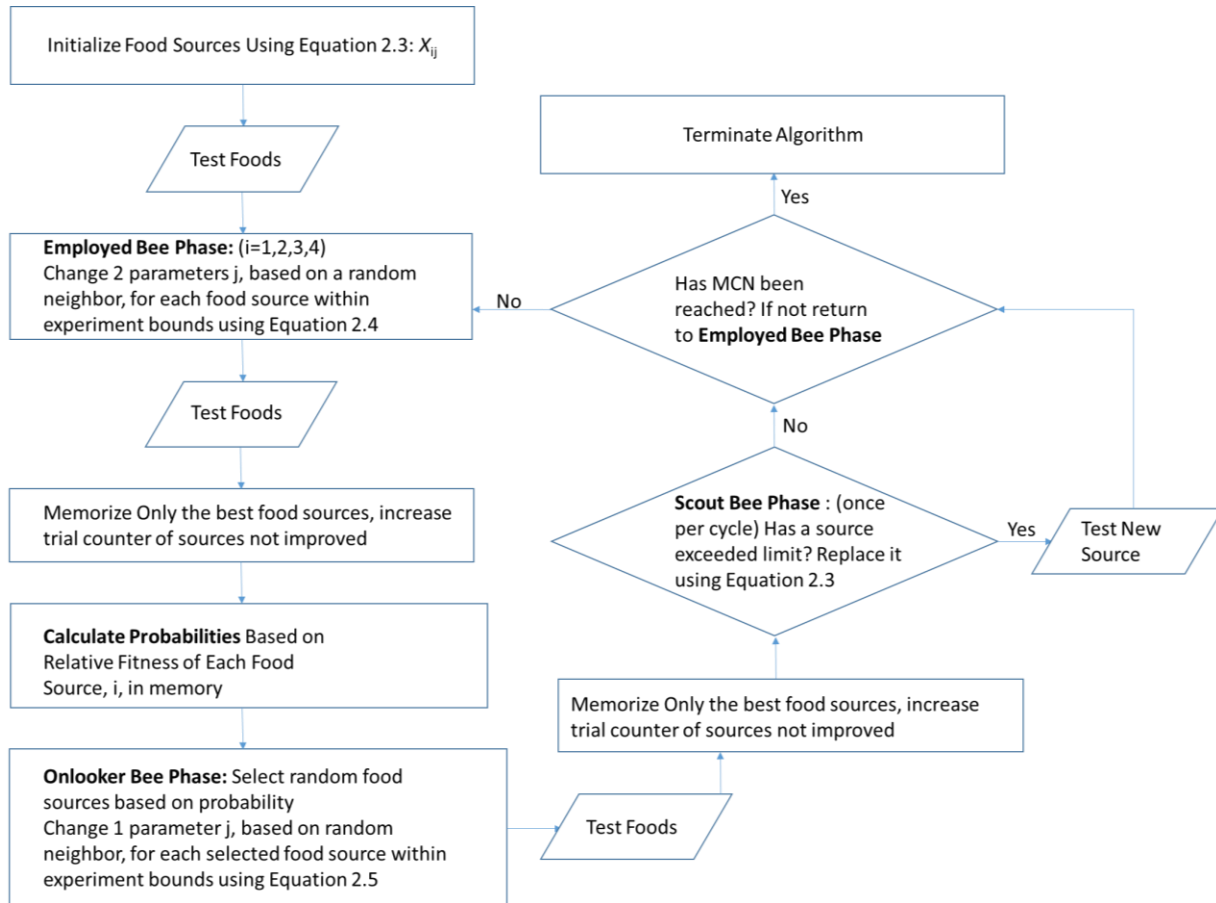
Figure 3.2: Modified Artificial Bee Optimization Flow Chart

3.4 Benchmark Tests

As was done in the previously stated literature (Karaboga and Akay 2009; Imanian et. al., 2014; Zhu and Kwong 2010; Gao and Liu 2011) the PSO-GA hybrid and modified ABC algorithm were tested against PSO and GA in the minimization of three test functions. Equations 3.2, 3.3, and 3.4 represent optimization test functions and are referred to as Styblinsky-Tang, Rastrigin, and Ackley respectively. Each algorithm was given a maximum of 200 iterations for each of 30 trials. Tables 3.4 and 3.6 give the average minimum of 30 trials for each algorithm and test function. Tables 3.3 and 3.5 give the range of each test function along with its respective minimum value. The optimum value of the Styblinsky-Tang function changes with

the dimension of the input. PSO and GA were given the same dimensional input as PSO-GA and ABC in order to increase similarity to the experimental work. A population size of 4 and 8 with dimensions of 5 and 6 for PSO-GA and modified ABC respectively were applied. The ABC algorithm was given the extra dimension of intake temperature experimentally, therefore this addition is reflected in the additional dimension given to ABC in the benchmark tests.

$$f(x) = \sum_{i=1}^{D} \frac{1}{2}(x_i^4 - 16x_i^2 + 5x_i) \qquad (3.2)$$

$$f(x) = 10D + \sum_{i=1}^{D}(x_i^2 - 10\cos(2\pi x_i)) \qquad (3.3)$$

$$f(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{D}x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{D}\cos(2\pi x_i)\right) + 20 + e \qquad (3.4)$$
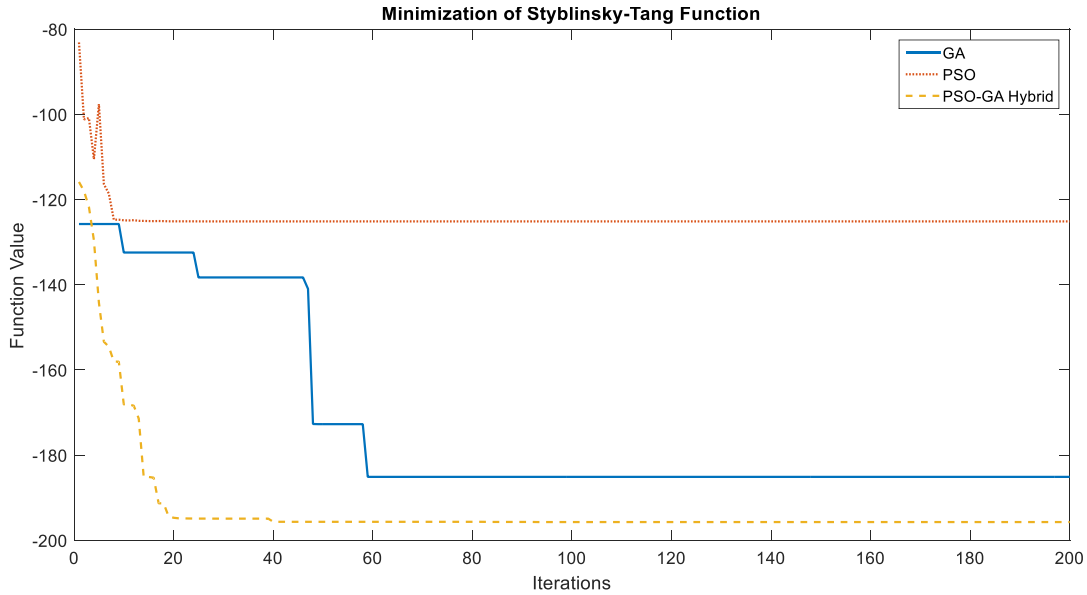
Figure 3.3: Minimization of Stablinksy-Tang Function for PSO-GA
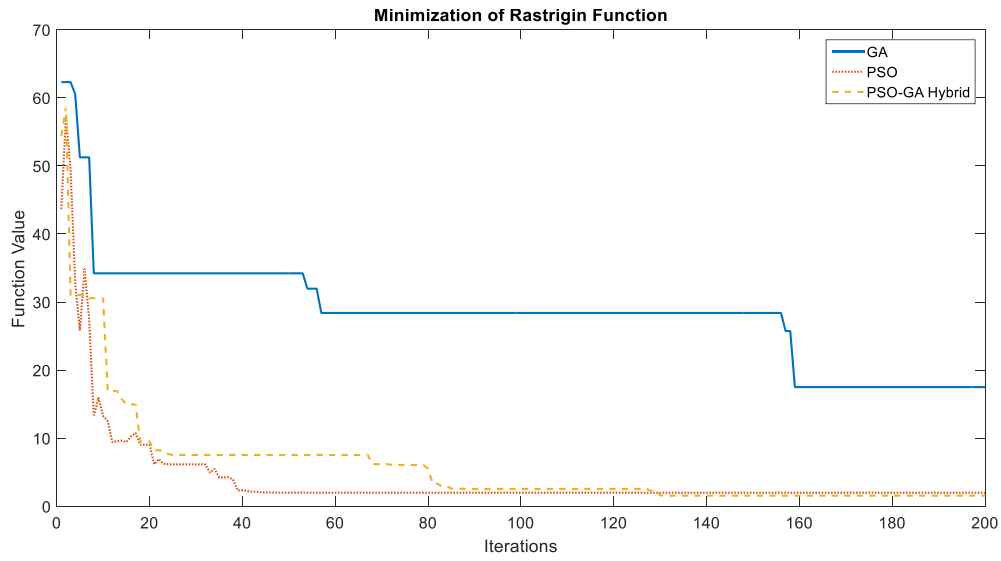
Figure 3.4: Minimization of Rastrigin Function for PSO-GA
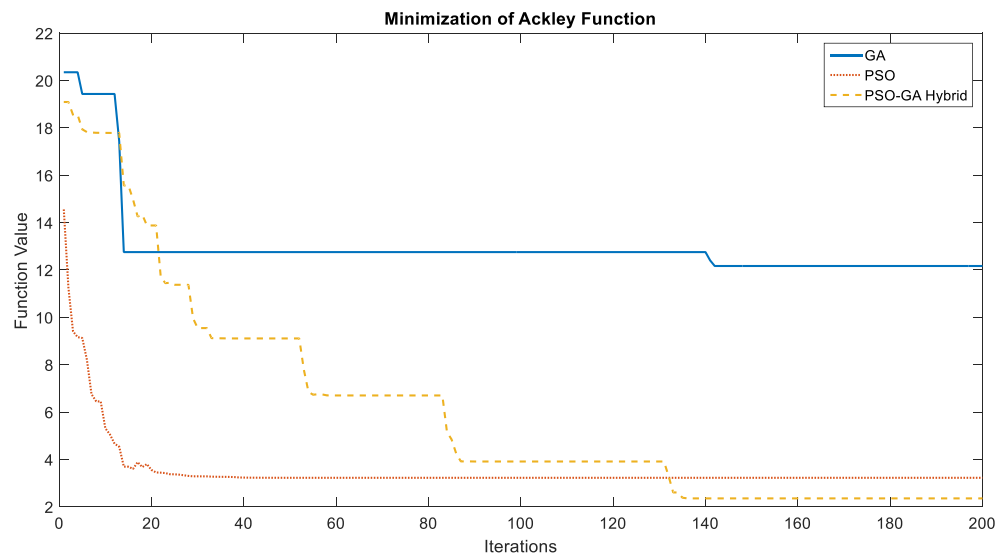
Figure 3.5: Minimization of Ackley Function for PSO-GA

Table 3.3: 5 Dimension Benchmark Function Details

Benchmark Function Details			
Function	Dimensions	Domain	Minimum F(x)
Syblinski-Tang	5	[-5.0, 5.0]	-195.829
Rastrigin	5	[-5.12, 5.12]	0
Ackley	5	[-32.768, 32.768]	0

Table 3.4: Average Minimum Values for Benchmark Functions Using Each Algorithm for 30 Trials at 200 Iterations per Trial

Algorithm	Styblinksy-Tang Min. Value	Rastrigin Min. Value	Ackley Min. Value
GA	-158.5758	19.3020	11.8823
PSO	-165.6725	5.3463	1.6228
PSO-GA Hybrid	-195.7331	1.8890	2.1473

The PSO-GA hybrid is able to converge closer to the objective value than GA for each test and performs competitively with PSO. Figures 3.3, 3.4 and 3.5 show the increased exploration of the hybrid against PSO. The improved exploration of the hybrid slows down convergence in some trials but also helps the algorithm to avoid local minima. This is due to the fact that at each iteration the GA performs a wide global search based on the best four PSO particles. The same PSO and GA inputs for the hybrid algorithm found in Table 3.1, were used for the individual algorithms as well.
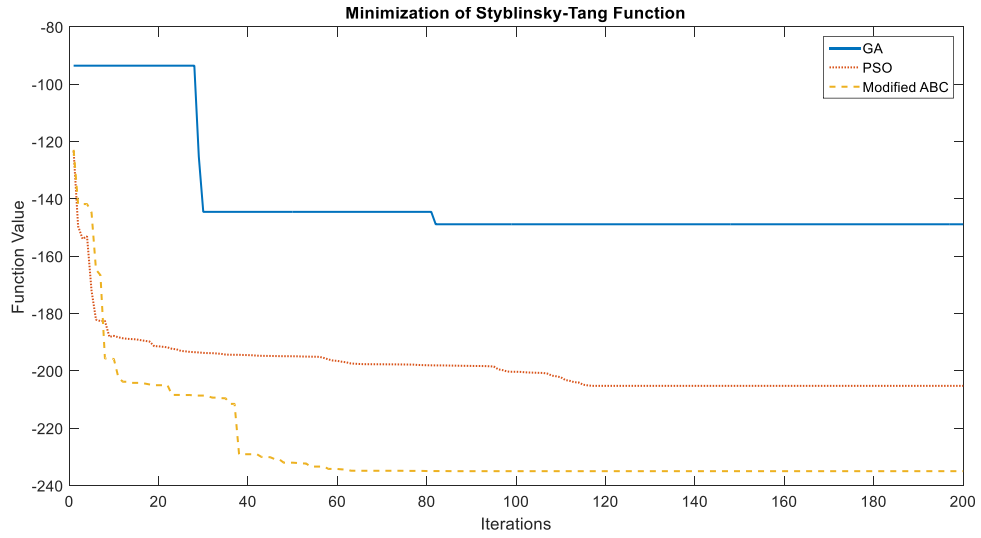
Figure 3.6: Minimization of Stablinksy-Tang Function for Modified ABC
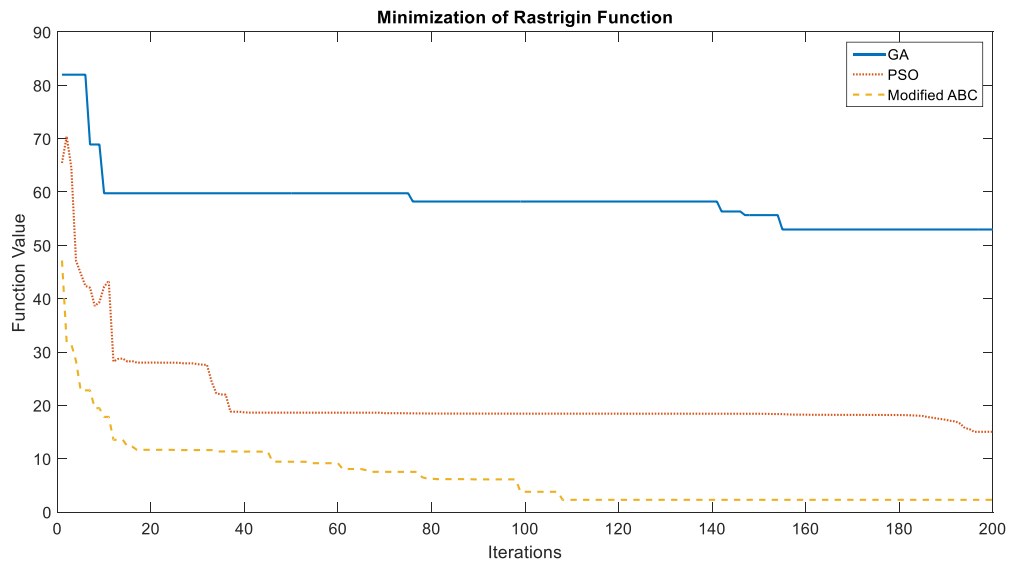
Figure 3.7: Minimization of Rastrigin Function for Modified ABC
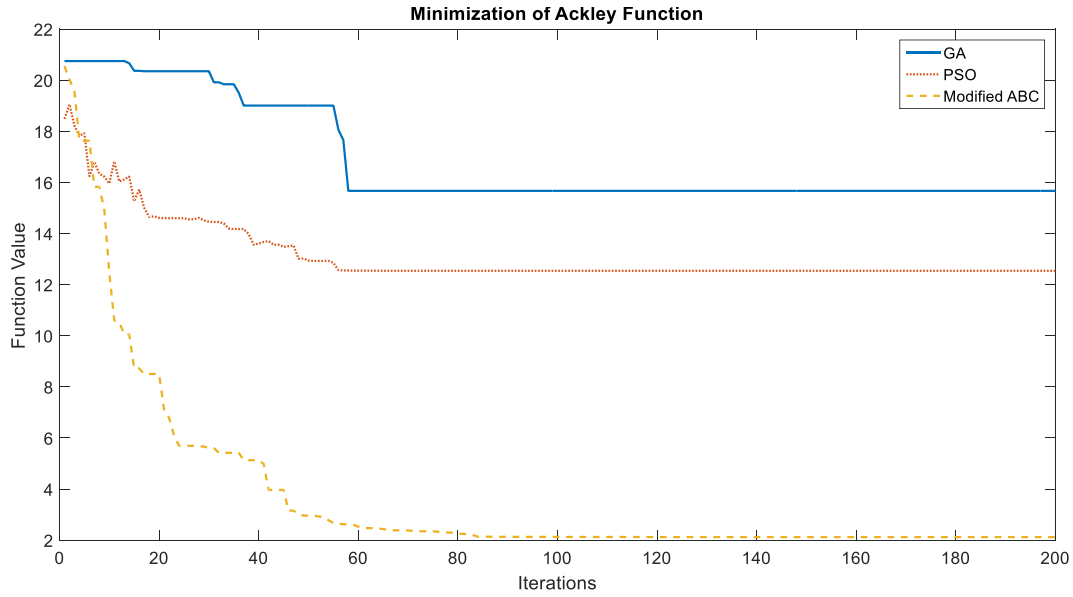
Figure 3.8: Minimization of Ackley Function for Modified ABC

Table 3.5: 6 Dimension Benchmark Function Details

Benchmark Function Details			
Function	Dimensions	Domain	Minimum F(x)
Syblinski-Tang	6	[-5.0, 5.0]	-234.996
Rastrigin	6	[-5.12, 5.12]	0
Ackley	6	[-32.768, 32.768]	0

Table 3.6: Average Minimum Values for Benchmark Functions Using Each Algorithm for

30 Trials at 200 Iterations per Trial

Algorithm	Styblinksy-Tang Min. Value	Rastrigin Min. Value	Ackley Min. Value
GA	-177.9695	32.3384	14.6464
PSO	-192.3975	17.9791	10.3603
ABC	-234.9970	0.0613	0.0238

Figures 3.6, 3.7 and 3.8 show the performance of ABC vs PSO and GA against the benchmark functions. Within the limited number of trials, ABC consistently out-performed GA and PSO in finding values closest to the global minimum. The same PSO and GA inputs for the hybrid algorithm found in Table 3.1, were used for the individual algorithms as well. Settings for modified ABC for the benchmark tests as well as for the experimental work can be found in Table 3.2. The decrease in population to 4 vs the value of 8 used in PSO-GA benchmark functions may have been detrimental to the performance of the PSO and GA algorithms.

3.5 Engine Stand Setup

This work utilized a 4-cylinder, 4.5 liter turbo-charged diesel engine with a high pressure common rail injection system and long route EGR. Table 3.7 gives exact metrics for the engine. A General Electric, DC dynamometer was used to load the engine through all trials. John Deere ECU control software DevX was used to command fuel injection pressure, injection timing, and fuel distribution for two injections. EGR flow to the intake was controlled by means an externally driven EGR pump. Intake gas temperature was controlled via a heat exchanger using city water as the cold flow. Cylinder pressure was measured using a Kistler 6125A pressure transducer and a Kistler 5010A charge amplifier. Cylinder pressure data was processed through a customized Labview program which captured and averaged cycle data for pressure and heat release analysis. MATLAB was used to program the Hybrid PSO-GA and modified ABC algorithms throughout both experiments.

Exhaust emission species and intake CO_2 were quantified using a Horiba MEXA-7100DEGR analyzer. The Horiba analyzer captured emissions of CO_2, CO, O_2, HC and NOx. The percentage of EGR was monitored by comparing the amount of CO_2 in the exhaust to that of

the intake gas. An AVL 415S smoke meter was used to quantify particulate matter (PM) in the

exhaust stream.

Table 3.7: Test Engine Metrics

John Deere Power Tech Diesel Engine	
Number of Cylinders	4
Bore (mm)	106
Stroke (mm)	127
Compression Ratio	17.0:1
Injection System	High Pressure Common Rail
Intake/Exhuast Valves	2 Each per Cylinder

3.6 Testing Process:

The results for each trial in the experiment were taken at steady-state conditions. This

was done first, by giving the engine thirty minutes start up time each day to warm the oil, and

second, by allowing a minimum of ten minutes to pass after each set of conditions had been

input. Parameters kept constant for both experiments are given in Table 3.8. The test conditions

and control parameter limits for PSO-GA and ABC testing can be found in tables 3.9 and 3.10

respectively.

Table 3.8: Engine Testing Conditions Held Constant for All Trials

Speed (RPM)	1400
Brake Mean Effective Pressure (Bar)	16.7
Avg. Fuel Temperature (^{o}C)	20

Table 3.9: PSO-GA Optimization Parameter Limits; Any Generated Mutation Outside of the Bounds Was Programmatically Placed Inside, Near the Limit

Parameter	Minimum	Maximum
EGR %	2	50
Intake Gas Temperature (°C)	40	40
Fuel Pressure (Mpa)	113	200
Pilot Injection Timing (CAD ATDC)	-40	0
Pilot Fuel %	2	65
Main Injection Timing (CAD ATDC)	-15	5

Table 3.10: ABC Optimization Parameter Limits; Any Generated Mutation Outside of the Bounds Was Programmatically Placed Inside, Near the Limit

Parameter	Minimum	Maximum
EGR %	2	50
Intake Gas Temperature (°C)	20	55
Fuel Pressure (Mpa)	113	200
Pilot Injection Timing (CAD ATDC)	-40	0
Pilot Fuel %	2	65
Main Injection Timing (CAD ATDC)	-15	5

3.7 Objective Function:

In order to optimize multiple objectives at once for both PSO-GA and ABC an objective function was designed such that each trial's fitness was evaluated based on the cumulative fitness of 5 variables. The objective function took inputs from brake specific (g/kW-h) CO, HC, NOx, PM and fuel consumption. Similar to Hardy and Reitz 2006 and appropriated from Bertram 2014, Equation 3.5 below shows the overall objective function which is weighted to respond most quickly to changes in PM and NOx. Ideal values were prescribed using the EPA Tier 4 off-road standards illustrated in Table 3.11 (Non-road Compression-Ignition Engines-Exhaust

Emission Standards). In order to monitor the tradeoff between PM and NOx emissions, separate

objective functions that only consider these pollutants are taken from Equation 3.5 and can be

seen below in equations 3.6 and 3.7. In the following discussion in Chapters 4 and 5 the term

fitness will be used as a qualifier for a given solutions objective value. Decreasing fitness refers

to a decrease in objective value while increased fitness refers to an increased objective value or

poor solution development.

$$F_{obj} = \left[\left(\frac{NOx_{meas}}{Nox_{ideal}}\right)^2 + \left(\frac{PM_{meas}}{PM_{ideal}}\right)^2\right]^{0.5} + \left[\left(\frac{CO_{meas}}{3CO_{ideal}}\right) + \left(\frac{HC_{meas}}{3HC_{ideal}}\right) + \left(\frac{FC_{meas}}{3FC_{ideal}}\right)\right]$$ (3.5)

$$PM_{obj} = \left(\frac{PM_{meas}}{PM_{ideal}}\right)$$ (3.6)

$$NOx_{obj} = \left(\frac{Nox_{meas}}{Nox_{ideal}}\right)$$ (3.7)

Table 3.11: Engine Performance Ideal Values, All Units in g/kW-h

Engine Performance Objectives		
Engine Out	Tier 4 Regulation	Objective Point Values
Nox	0.4	0.2
PM	0.02	0.01
CO	5.0	5.0
HC	0.19	0.19
Fuel Use	N/A	200

CHAPTER 4 RESULTS AND DISCUSSION

4.1 PSO-GA Optimization Results

Fitness Evolution

Figure 4.1 below shows the evolution of particles by generation throughout the PSO-GA experiment. The figure is organized by overall fitness found by Equation 3.5. As seen in the above benchmark tests the algorithm was able to quickly reduce the overall objective function. Generations 5 and 6 represent highly similar input parameters that lie in a close tradeoff between NOx and PM. Figure 4.2 shows the global minimum value for each generation (iteration) of the PSO-GA hybrid. Due to its oxygen content, biodiesel produces comparatively low PM and HC emissions to that of regular diesel fuel in the absence of EGR, therefore the global minimum PM objective function never decreased as EGR was added to reduce NOx. Trials were stopped at 48 due to a lack of further decrease in overall global minimum fitness value.
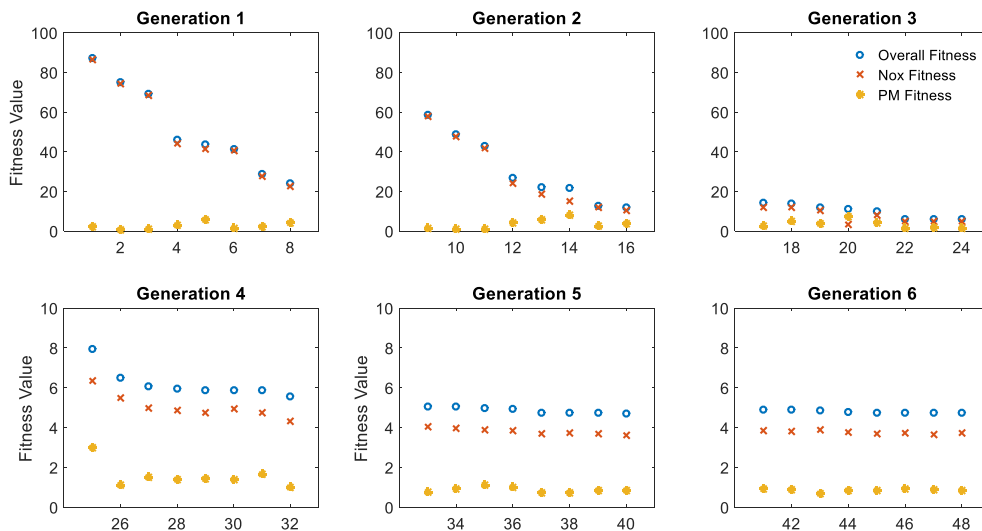
Figure 4.1: Evolution of Fitness Values for Overall, NOx, and PM, Fitness Over 48 Total PSO-GA Engine Runs
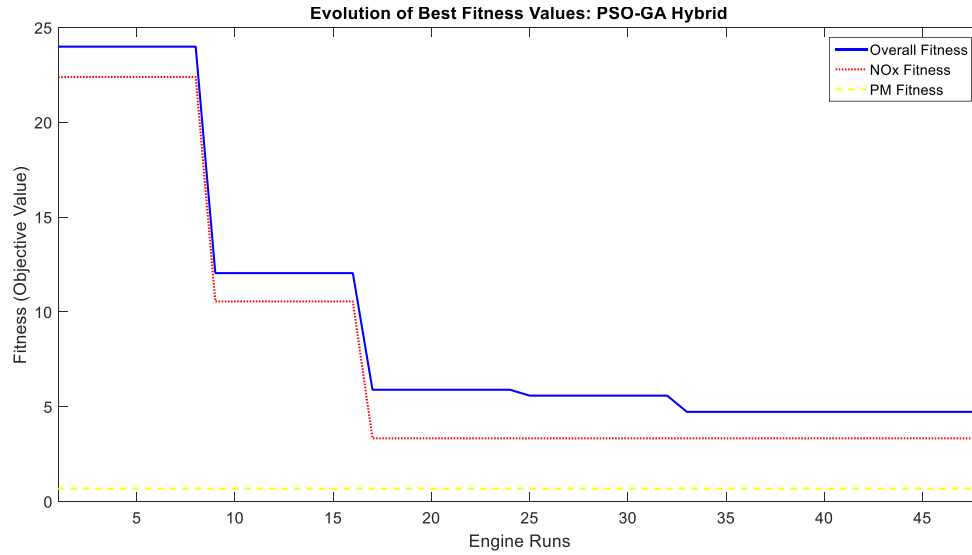
Figure 4.2: Evolution of Global Minimum Fitness Values for Overall, NOx, and PM, Fitness Over 48 Total PSO-GA Engine Runs

Best Conditions

Table 4.1 shows the best solutions for overall objective function (minimum fitness) while Table 4.2 displays the best solutions for PM and NOx emissions. Emissions and input values for points from generations 4 and 5 are very similar and differ primarily from main injection timing. The algorithm evolved with fitness to move main injection and pilot injections near top dead center with a small offset between injections. The additional oxygen content and density of biodiesel allows for the application of increased EGR without large increases in PM emissions compared to regular diesel fuel (Zhang et al. 2006). Referring to Table 4.2, injecting a large, early pilot, effectively burns the fuel during the compression stroke reducing PM under moderate EGR but at the expense of BSFC and increased NOx. Increasing EGR with an early pilot decreased NOx but increased HC and CO emissions, this could be due to poor mixing of air and fuel at this condition.

Table 4.1: Parameters for Best Global Objective Value Obtained through 48 Trials of PSO-GA

Trial	Fuel Injection Pressure (Mpa)	Exhaust Gas Recirculation (%)	Pilot Timing Offset (CAD)	Main Injection Timing (CAD BTDC)	Pilot/Main Fuel (%)	Intake Gas Temperature (°C)
40	173.67	48.53	4.90	-3.13	45.06	40.0
39	173.83	49.48	4.90	-3.23	44.88	40.0
48	173.86	49.41	4.90	-2.99	44.88	40.0

Table 4.2: Parameters for Best PM (Top) and NOx (Bottom) Objective Value Obtained Through 48 Trials of PSO-GA

Trial	Fuel Injection Pressure (Mpa)	Exhaust Gas Recirculation (%)	Pilot Timing Offset (CAD)	Main Injection Timing (CAD BTDC)	Pilot/Main Fuel (%)	Intake Gas Temperature (°C)
2	157.02	14.42	13.54	-0.03	60.09	40.0
20	168.91	48.55	38.28	-3.74	44.85	40.0

Table 4.3: Emissions, Fuel Consumption and Overall Fitness for Best Overall Fitness, PM, and NOx Results

Trial	NOx (g/kW-h)	PM (g/kW-h)	CO (g/kW-h)	HC (g/kW-h)	Fuel Consumption (g/kW-h)	Overall Fitness
40	0.72	0.008	3.02	0.18	296.10	4.72
39	0.74	0.009	3.01	0.14	293.37	4.73
45	0.73	0.009	3.09	0.17	293.71	4.74
2	14.88	0.007	0.37	0.07	304.89	75.08
20	0.67	0.074	11.01	0.99	300.36	11.04

Tradeoffs

     Figure 4.3 shows the non-dominated (best tradeoff) solutions found for NOx VS BSFC. The filled squares represent the optimum tradeoffs between the two objectives. Trials from Table 4.3 correspond to those on the Pareto front. By design, the objective function was highly sensitive to changes in NOx and PM, thus moving the algorithm toward and along the front. The following discussion will discuss changes in NOx through the latter half of the experiment.

     Within generation 3 the algorithm began to center around solutions whose fitness varied most with main injection timing. Table 4.4 gives the bounds for this 24 trial regime while Figure 4.4 displays sweeps of SOI VS NOx and SOI VS PM. Trials with SOI 1.72 CAD ATDC in Figure 4.4 display the effect of increasing EGR within the bounds of Table 4.4. The data shows however that retarding Main SOI with the same pilot offset has a much greater impact on reducing both PM and NOx together. Furthermore, at SOI > 2.8 CAD ATDC, increasing EGR to the edge of the bound of table 4.4 allows for further NOx reduction while keeping PM below the EPA tier 4 limit of 0.01 g/kW-h. Retarding main injection timing, along with the use of a late pilot injection near TDC reduces the maximum cylinder pressure which will be discussed further in section 4.3. With a large pilot near TDC an effective radical pool may be developing with increased heat that aids in reducing PM (Shi et al. 2010).

Table 4.4: Bounds for Majority of Trials in Generations 4-6 for PSO-GA

Fuel Injection Pressure (Mpa)	Exhaust Gas Recirculation (%)	Pilot Timing Offset (CAD)	Main Injection Timing (CAD ATDC)	Pilot/Main Fuel (%)
[173.67-174.19]	[47.88-49.97]	4.909	[1.72-3.31]	[44.79-45.66]
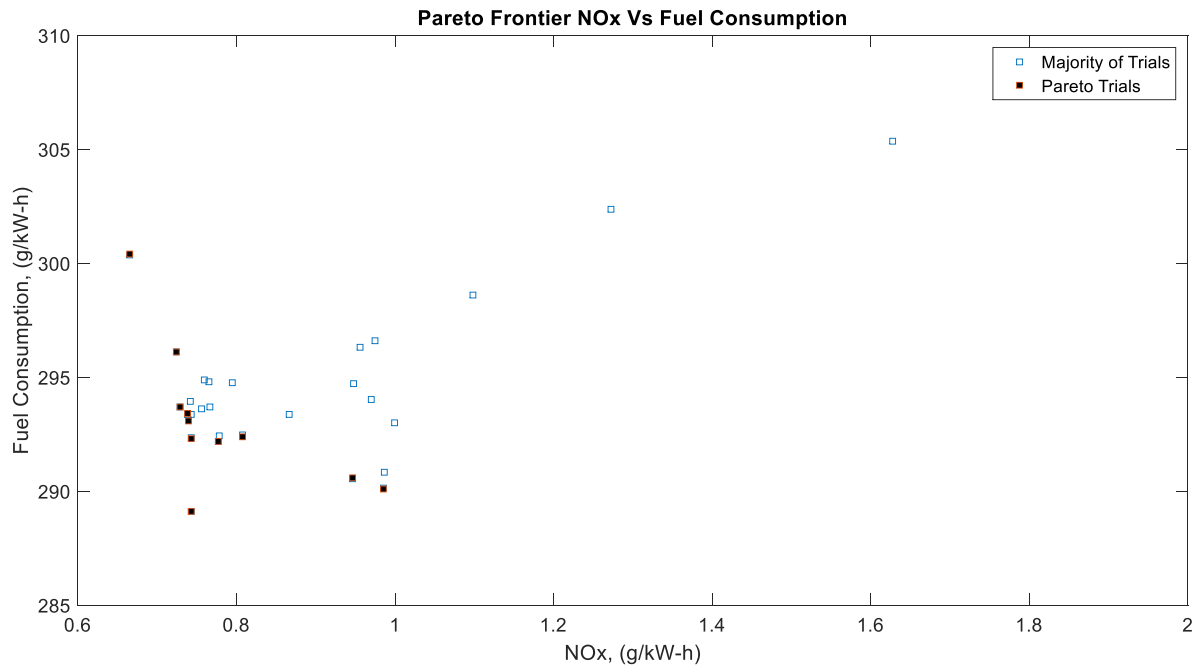
Figure 4.3: Pareto Frontier for NOx VS BSFC
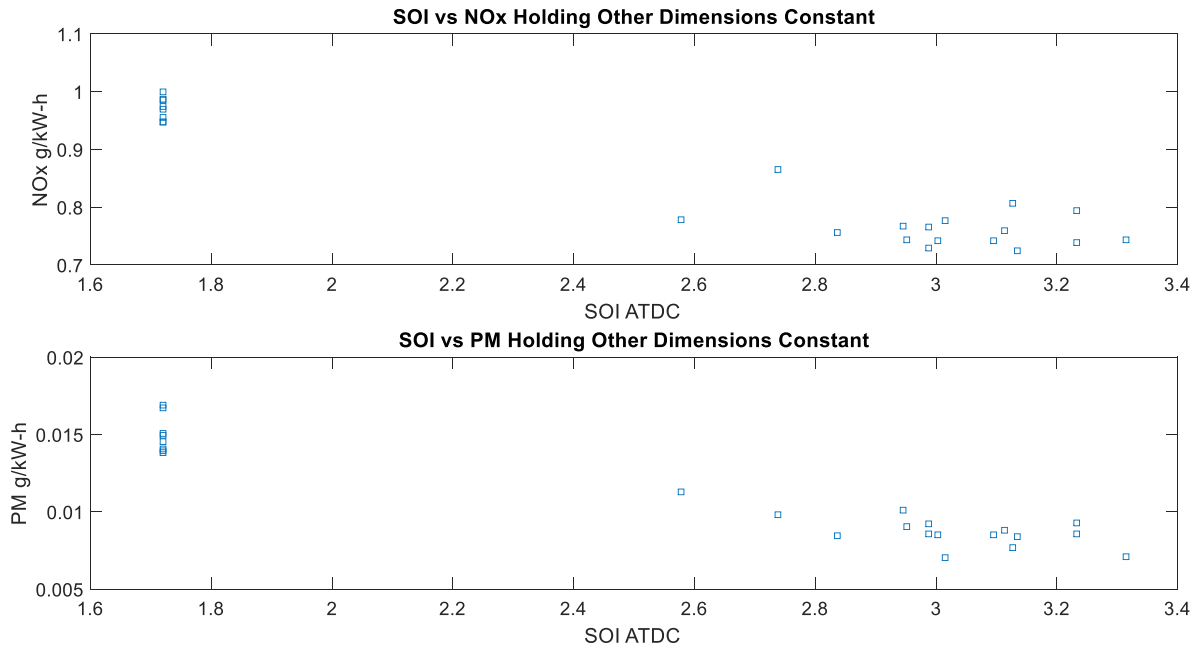
Figure 4.4: SOI ATDC VS NOx (Top) and PM (Bottom) Holding all Other Variables Near Constant

4.2 ABC Optimization Test Results

Fitness Evolution

The evolution of fitness based on Equations 3.5, 3.6, and 3.7 can be seen below in Figure 4.5. Generations 1-7 represent full cycles of ABC through the Employed and Onlooker phases of the algorithm (4 for each phase). Trials in Figure 4.5 are ordered by decreasing overall fitness in each generation. Trial 37 in generation 5 exhibited PM and overall fitness values outside the range of the graph at 104 and 107 respectively. The outlier is due to a mutation increasing fuel pressure causing spray impingement with the cylinder wall (Lee et. all 2012). The tradeoff between NOx and PM is illustrated in figure 4.5 where large reductions in NOx are accompanied by an increase in PM, this can especially be seen in Generations 6-7. Figure 4.6 shows the global minimum values for overall fitness, NOx and PM. Trials were stopped at 65 total engine runs due to a lack of further decrease in overall global minimum fitness. This can be seen in the lower half of figure 4.5 and in figure 4.6. The global minimum for all three objectives remains almost constant from trials 45 to 65. Decreasing exploration eluded that the algorithm may have become trapped in the Pareto regime of a local minimum where within this search area, small advances in one objective came with the equal loss of another.
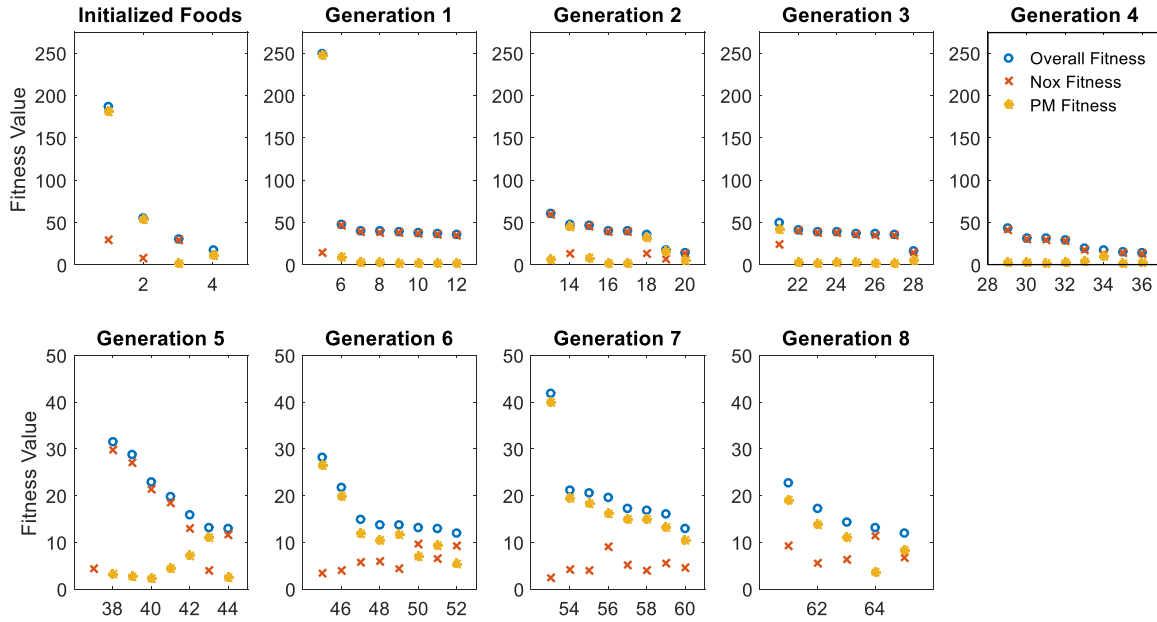
Figure 4.5: Evolution of Fitness Values for Overall, NOx, and PM, Fitness Over 65 Total ABC Engine Runs
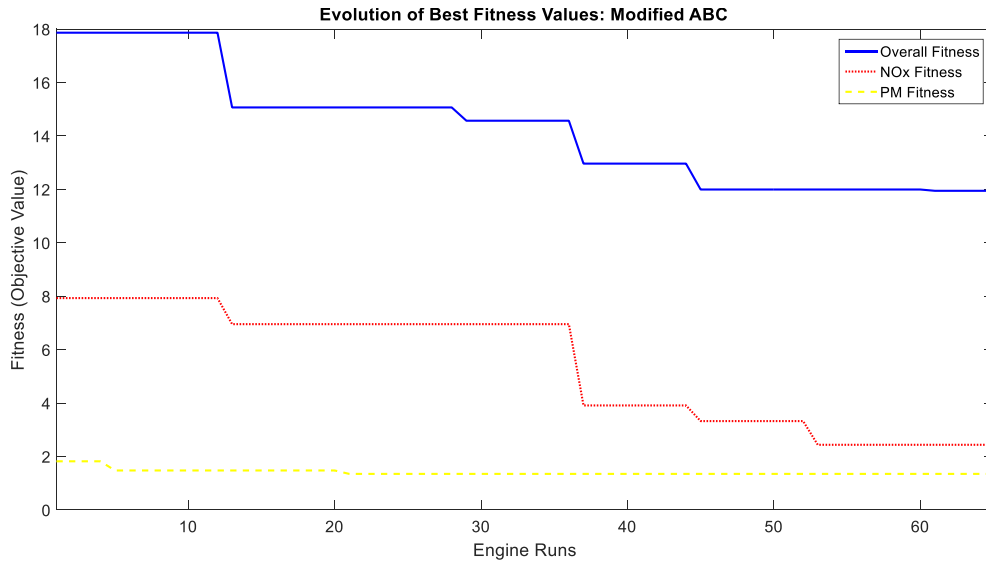
Figure 4.6: Evolution of Global Minimum Fitness Values for Overall, NOx, and PM, Fitness over 65 Total ABC Engine Runs

Best Conditions

The details of the best results can be observed in Table 4.5 while parameters for best PM

and NOx can be found in Table 4.6. The best results for overall fitness call for main injection

timings near TDC with almost 20 CAD between injections and high EGR. Changes in intake

temperature did not have as large an effect as the other five variables. Therefore, most

discussion will concentrate on changes in injection timing, pilot fuel ratio, fuel pressure and

EGR. Trail 45 in Table 4.6 shows the progression of Trial 44 in Table 4.5. Increasing EGR with

the same injection timings greatly reduced NOx emissions while at the same time increasing PM

and fuel consumption due to incomplete combustion. Table 4.7 shows the resulting emissions,

and fitness data for Tables 4.5 and 4.6.

Table 4.5: Parameters for Best Global Objective Value Obtained through 65 Trials of ABC

Trial	Fuel Injection Pressure (Mpa)	Exhaust Gas Recirculation (%)	Pilot Timing Offset (CAD)	Main Injection Timing (CAD BTDC)	Pilot/Main Fuel (%)	Intake Gas Temperature (°C)
65	163.50	43.40	19.79	2.06	23.75	46.8
52	174.60	45.50	21.88	8.24	28.75	47.3
44	182.60	20.64	16.80	-3.80	25.68	46.7

Table 4.6: Parameters for Best PM (Top) and NOx (Bottom) Objective Value Obtained

through 65 Trials of ABC

Trial	Fuel Injection Pressure (Mpa)	Exhaust Gas Recirculation (%)	Pilot Timing Offset (CAD)	Main Injection Timing (CAD BTDC)	Pilot/Main Fuel (%)	Intake Gas Temperature (°C)
27	169.35	6.88	29.79	-0.304	36.39	52.5
45	182.61	50.88	20.64	-3.80	25.68	46.7

Table 4.7: Emissions, Fuel Consumption and Overall Fitness for Best Overall Fitness, PM,

and NOx Results

Trial	NOx (g/kW-h)	PM (g/kW-h)	CO (g/kW-h)	HC (g/kW-h)	Fuel Consumption (g/kW-h)	Overall Fitness
65	1.33	0.08	3.59	0.33	256.54	11.94
52	1.85	0.05	3.63	0.38	261.92	11.99
44	2.34	0.02	2.09	0.25	257.14	12.96
27	6.96	0.01	3.36	0.56	260.91	36.47
45	0.49	0.40	5.95	0.63	265.50	41.92

Tradeoffs

ABC optimization is unique from other algorithms because of its ability to memorize and forget food sources based on fitness. Further, of the four sources in memory at one time in this experiment, only the best of these received an increased number of mutations due to the probability component of the Onlooker phase. Several, distinct, food sources in this experiment received repeated mutations improving overall fitness while also applying memorization of positive elements. Due to their similarity, these food sources can be compared through sweeps of EGR and fuel pressure. Tables 4.8 and 4.9 show the details of the food sources whose trial results are illustrated in Figures 4.7, 4.8 and 4.9. The selected conditions are split up by main injection timing occurring before and after TDC. Brackets indicate the bounds of input variables affecting overall fitness, NOx, and PM as sweeps of EGR and fuel pressure are conducted. Trials in the below tables do not represent the entire population of food sources, only repeated similar sources that can be relatively compared in a six dimensional hyperspace.

**Table 4.8: Food Sources with Main SOI ATDC and Various Pilot Timing Offset**

Condition	Fuel Injection Pressure (Mpa)	Exhaust Gas Recirculation (%)	Pilot Timing Offset (CAD)	Main Injection Timing (CAD *ATDC*)	Pilot/Main Fuel (%)	Intake Gas Temperature (°C)
1	[176-183]	[2-42]	11.85	3.80	28.26	[22-46]
2	[183-200]	[28-50]	20.64	3.80	[25-27]	46.7
3	[150-169]	[2-9]	29.78	0.30	36.58	[47-55]

Table 4.9: Food Sources with Main SOI BTDC and Various Pilot Timing Offset

Condition	Fuel Injection Pressure (Mpa)	Exhaust Gas Recirculation (%)	Pilot Timing Offset (CAD)	Main Injection Timing (CAD *BTDC*)	Pilot/Main Fuel (%)	Intake Gas Temperature (°C)
4	[126-167]	[10-42]	29.78	2.06	[23-45]	[46-48]
5	[135-174]	45.52	21.88	6.50	[48-65]	47.3
6	[157-192]	10.95	7.56	2.06	[44-48]	47.10

Table 4.8 conditions are shown in Figure 4.7 for NOx and PM vs EGR. Of these conditions timings with 11 and 20 CAD offsets and 30-50% EGR perform the best in terms of balancing NOx and PM. Increasing EGR, decreases exhaust gas temperature resulting in less NOx but increased PM.

Table 4.9 conditions for main SOI before TDC are shown in Figure 4.8 for NOx and PM VS fuel pressure. Decreasing pilot fuel allows for a simultaneous decrease in NOx and PM emissions for the same EGR and fuel pressure (blue triangles). This could be due to less heat being produced during the compression stroke and a leaner air-fuel mixture. The algorithm did not explore high EGR with condition 6 (red square short offset) which may have performed better with increased EGR similar to that of the triangles in Figure 4.7.

NOx Emissions for Similar Foods With Main SOI ATDC

PM Emissions for Similar Foods With Main SOI ATDC
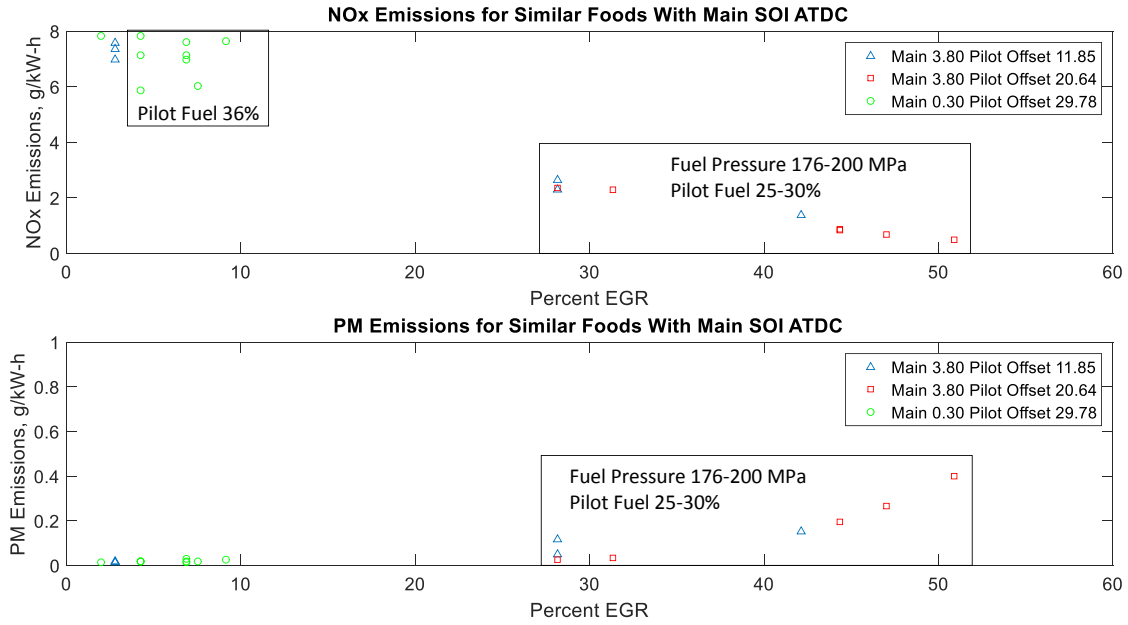
Figure 4.7: Comparison of NOx and PM for Similar Food Sources, With Main Injection Timing ATDC

NOx Emissions for Similar Foods With Main SOI BTDC

PM Emissions for Similar Foods With Main SOI BTDC
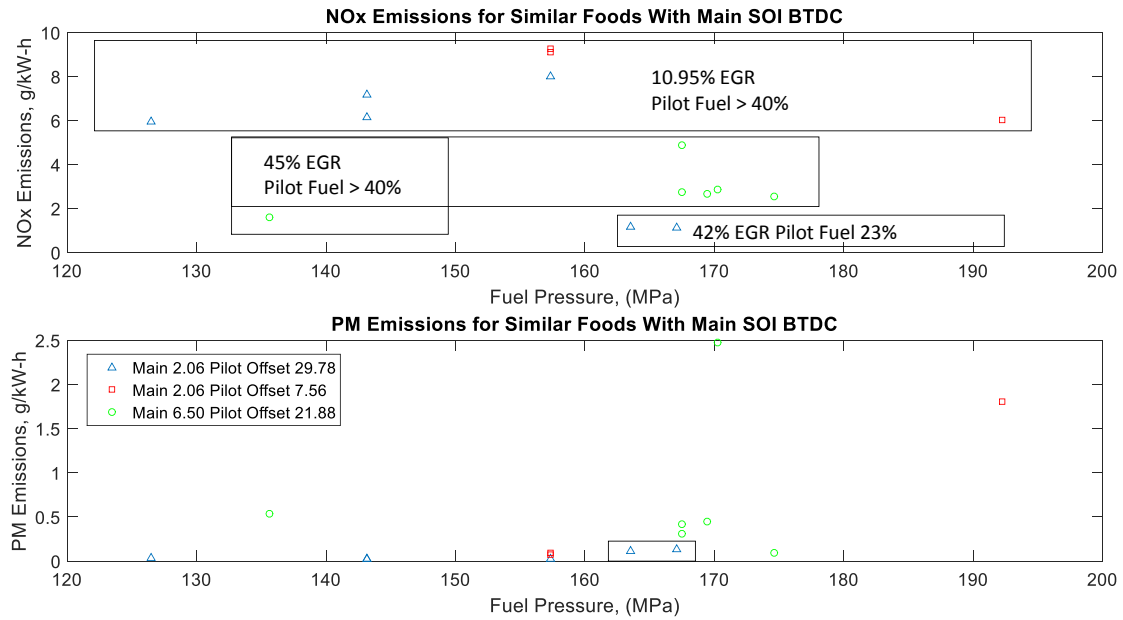
Figure 4.8: Comparison of NOx and PM for Similar Food Sources, With Main Injection Timing BTDC
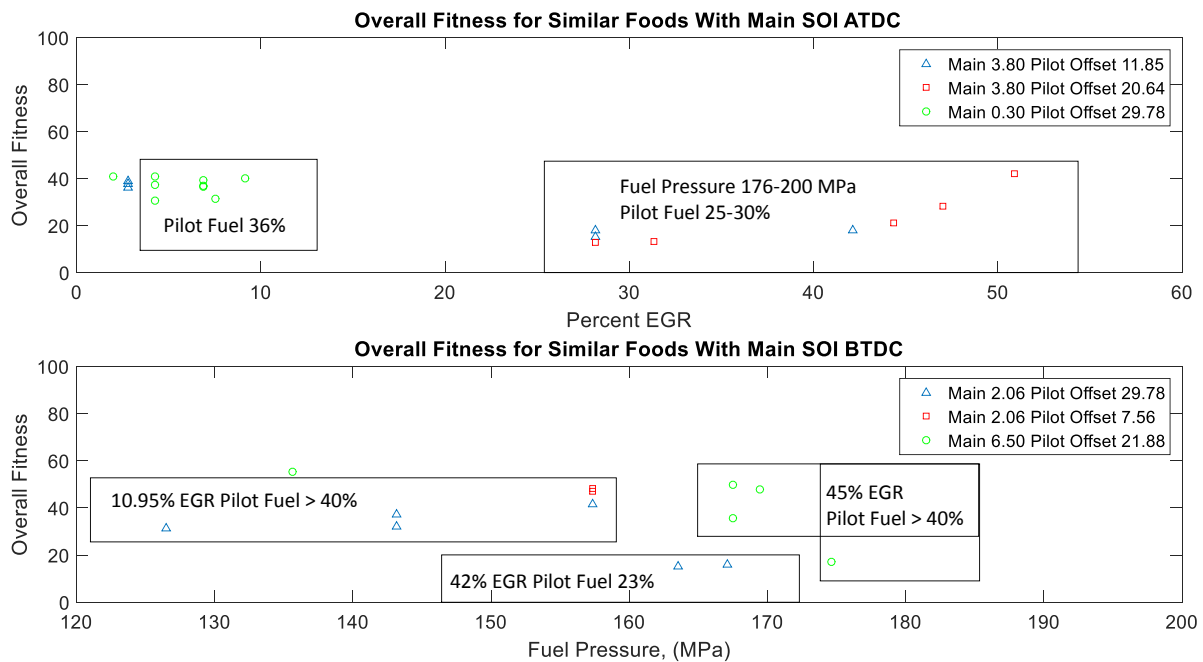
Figure 4.9 compares the overall fitness of conditions 1-6 in Tables 4.8 and 4.9. Decreasing pilot offset is shown as beneficial for main SOI after TDC similar to that of the PSO-GA results. For main SOI before TDC the larger offsets show better performance under high EGR and decreased pilot fuel in conditions 4 and 5. Pilot fuel between 20 and 30% showed the best fitness for both sets of injection timings. Increasing pilot fuel beyond 30% percent at these timings resulted in increased fuel consumption and poor tradeoff between NOx and PM. The trends seen here are reflective of the best final conditions found in Table 4.5.

Figure 4.9: Comparison of Overall Fitness for Similar Food Sources, With Main Injection Timings Before, and After TDC

By definition, a Pareto front defines a regime with the optimum tradeoff between inversely proportional objective variables (Ge et. all 2009). Several fronts of interest were formed by the best solutions of the Modified ABC algorithm that are shown in Figures 4.10 and 4.11. Increasing EGR cools combustion gasses decreasing NOx, but increasing CO and PM. As

stated above the best balance between PM, CO, and NOx was found through decreased pilot fuel and high EGR for large pilot offsets and through comparatively lower EGR with smaller pilot offsets. Both variations are shown in Table 4.4 to have produced the best overall fitness for the ABC experiments. Fuel consumption is best served in, tandem with NOx and PM reduction, with main SOI near TDC as is discussed in the heat release data analysis.
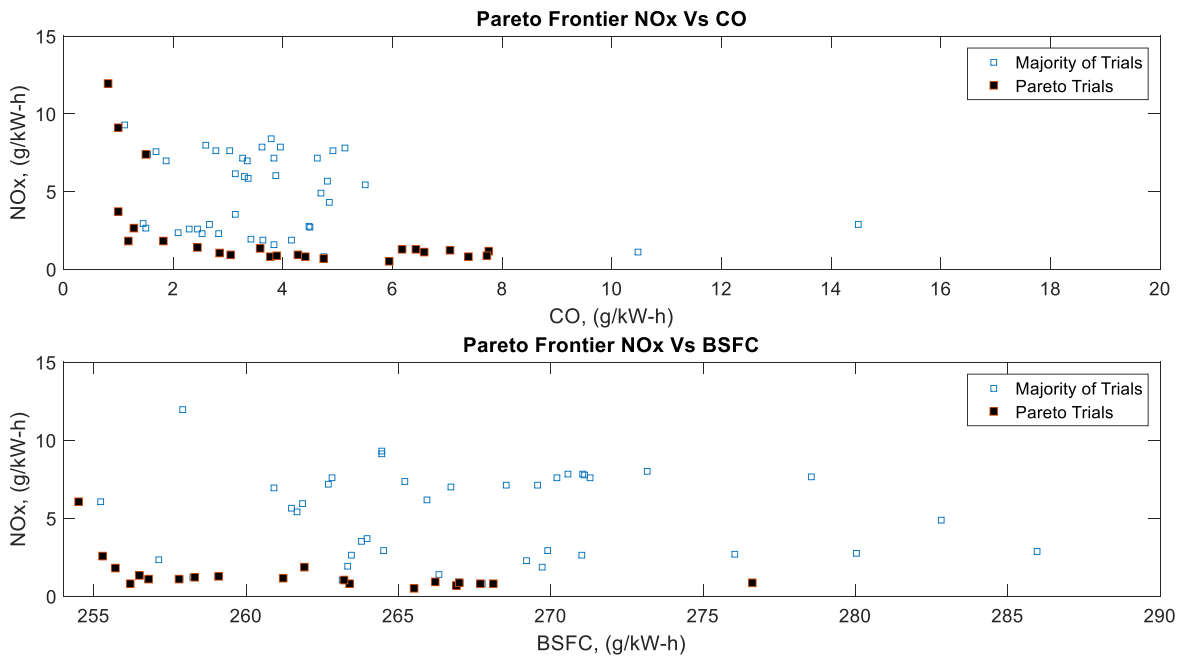
Figure 4.10: Pareto Frontier for NOx VS CO (Top) and NOx VS BSFC (Bottom)
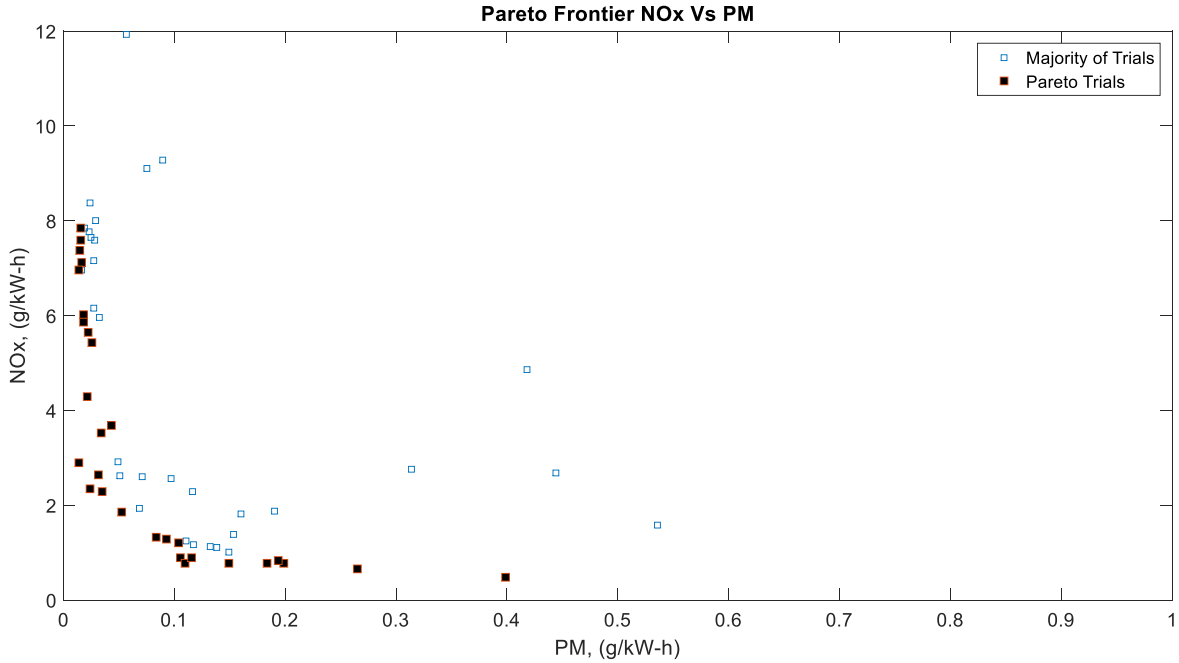
Figure 4.11: Pareto Frontier for NOx VS PM

4.3 In-Cylinder Heat Release and Pressure Analysis

Heat Release Calculation Details

Using cylinder pressure data, the ideal gas law, and conservation of energy the heat release rate was calculated and plotted for the global best (fitness value) solutions from PSO-GA and ABC. As in Karra 2009, the heat loss (HL) through the cylinder wall was modeled assuming a constant cylinder gas temperature of 600K, and Nusselt number from the Taylor correlation in Ferguson, C.R. 2001. The final heat release rate equation is shown below as Equation 4.1 where gamma is the ratio of specific heats. Instantaneous pressure and volume change with CAD were found using cycle averaged pressure data and three-point forward-difference.

$$\frac{dQ_n}{d\theta} = \frac{\gamma}{\gamma-1}P\frac{dV}{d\theta} + \frac{1}{\gamma-1}V\frac{dP}{d\theta} + HL \qquad (4.1)$$

PSO-GA Best Conditions Heat Release

Heat release rate in J/CAD and cylinder pressure in MPa are shown below in Figure 4.12 for some of the best operating conditions given by the PSO-GA hybrid algorithm. Due to the convergence of the algorithm into one area of the search space, heat release rates and pressure for the best three points are highly similar. Therefore, Figure 4.12 shows the effect of moving main SOI with constant pilot offset as discussed in the PSO-GA tradeoffs section. The combustion phases with main SOI resulting in decreased peak cylinder pressure. Reducing cylinder pressure for the same amount of air and fuel reduces bulk average cylinder gas temperature by the ideal gas law and thus reduces thermal NOx (Mueller et al. 2009). Phasing combustion to later in the cycle reduces NOx and PM simultaneously to the best solution with Main SOI 3.13 CAD ATDC for the same size pilot.
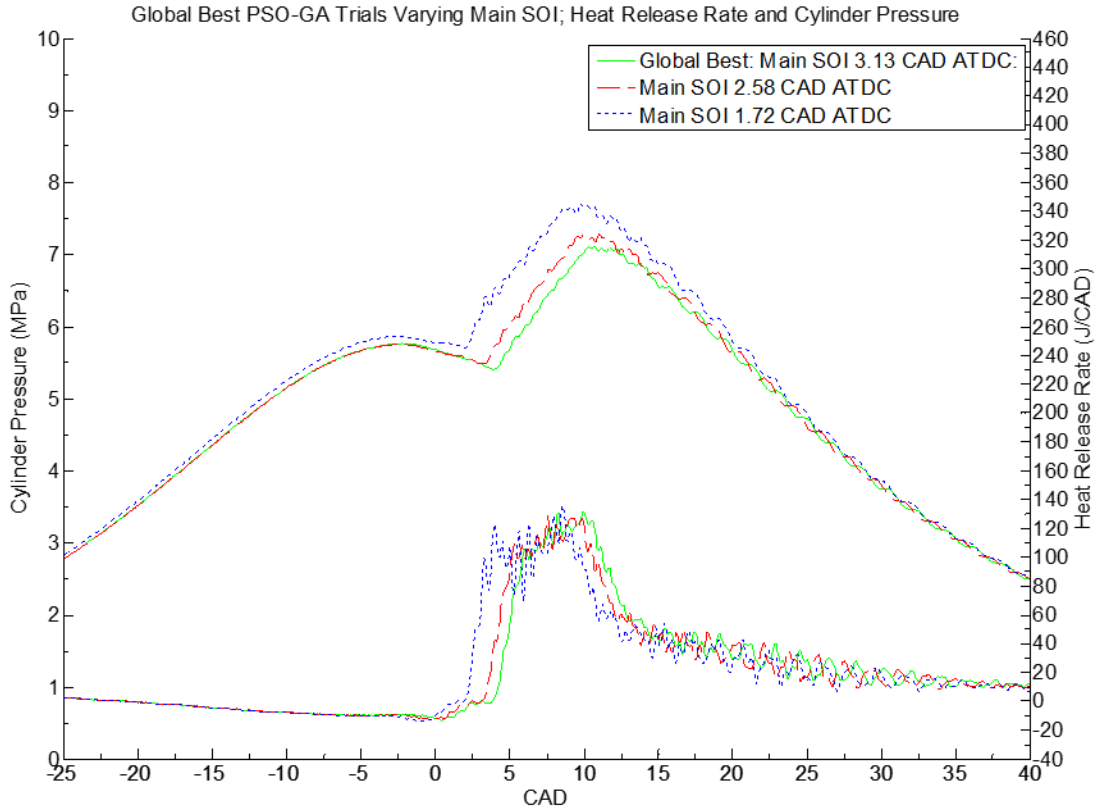
Figure 4.12: PSO-GA Best Global Food Sources Heat Release Rate in J/CAD and Cylinder Pressure in MPa

ABC Best Conditions Heat Release

The best three food sources differ largely in injection timing and EGR. The small dotted line shows the third best source. Decreasing EGR increases temperature and pressure from pilot fuel combustion, however, because this occurs before TDC fuel efficiency is negatively impacted and NOx emissions are higher than in the other cases. Comparatively high EGR for the first and second best cases reduce cylinder temperature decreasing NOx for more PM. Moving Main SOI closer to TDC allows for the most heat release to occur just after TDC. The increased offset of the second best condition and earlier timing mean the piston is forced to compress more hot combustion gases rather than use them for work while also vastly increasing peak cylinder

pressure. Retarding injection timings under high EGR phases combustion and decreases peak pressure giving the best tradeoffs between PM, BSFC and NOx. As in the PSO-GA experiments the decrease in peak cylinder pressure for the best source, decreases temperature and thus NOx emissions.
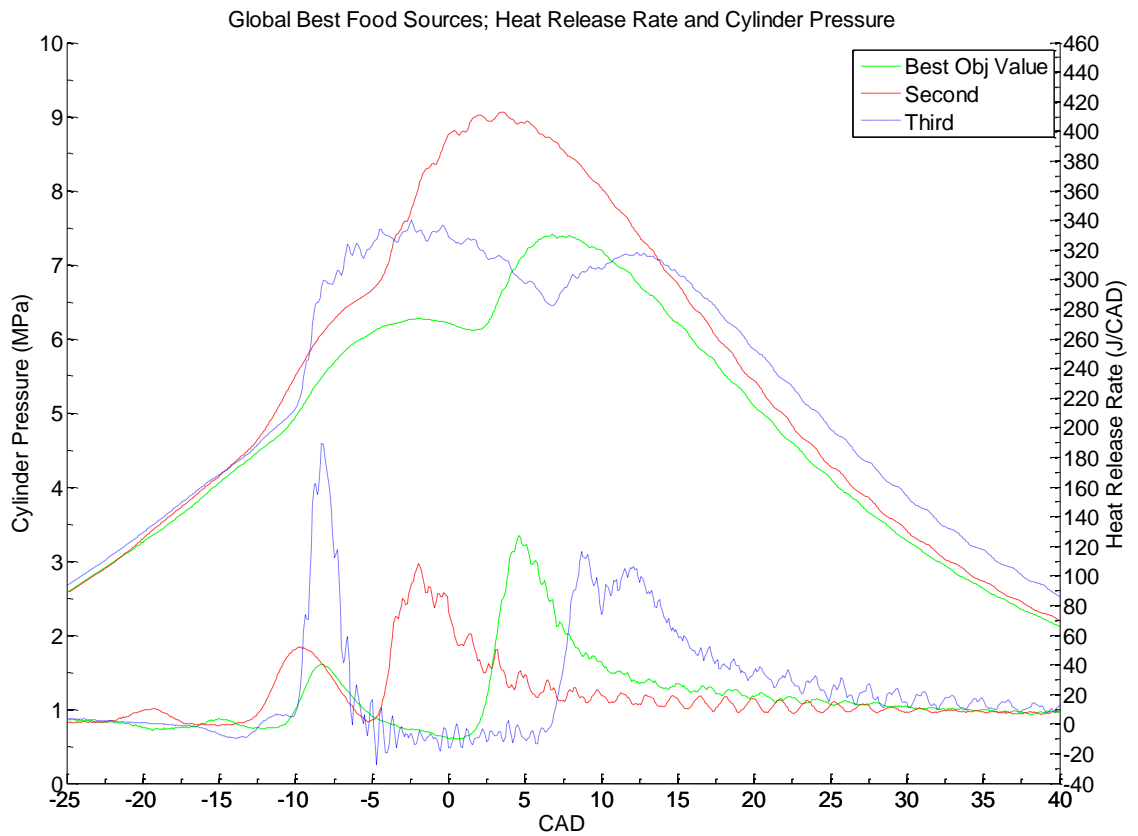
Figure 4.13: ABC Best Global Food Sources Heat Release Rate in J/CAD and Cylinder Pressure in MPa

4.3 Comparing PSO-GA and ABC Results

Comparison of Objective Value Reduction

Both PSO-GA and ABC were able to reduce multiple engine performance objectives simultaneously. Below, the algorithms are compared based on their ability to reduce NOx, PM, HC, CO, and fuel consumption. Table 4.10 shows the percent reduction in these objectives based on their minimum values within the first and last generations tested. The presence of EGR increases PM emissions, however in the case of PSO-GA, as seen in Table 4.3, PM is still within the EPA limit of 0.01 g/kW-h. In terms of overall objective value reduction, PSO-GA showed superior performance in decreasing NOx and BSFC while still keeping PM, HC, and CO within the EPA limits.

Table 4.10: Objective Value Reduction, From First Generation to Last

Objective	% Increase	% Decrease	% Increase	% Decrease
Nox	N/A	**83.7**	N/A	**29.6**
PM	4.1	N/A	93.4	N/A
CO	6.7	N/A	N/A	**10.8**
HC	2.4	N/A	N/A	**0.01**
BSFC	N/A	**2.54**	19.5	N/A

Comparison of Heat Release

The Heat Release Rate in J/CAD and cylinder pressure in MPa can be seen below in Figure 4.14 for the best conditions of PSO-GA and ABC. The conditions feature increased EGR and differ most in injection timing. Looking at the pressure curves, the earlier injections of the ABC condition greatly increase cylinder pressure over that of the PSO-GA. Increased heat decreases emissions of incomplete combustion but increases thermal NOx. The Heat release and corresponding early pilot of ABC is detrimental to BSFC as well, due to increased pumping

losses for compression of hot gasses. Finally, retarding both injections toward TDC allows for

increased useful heat release with fewer pollutants, as main injection is burned more completely

in this region with increased EGR. If injections continue to move forward passed TDC however,

this phasing could begin to negatively impact BSFC.
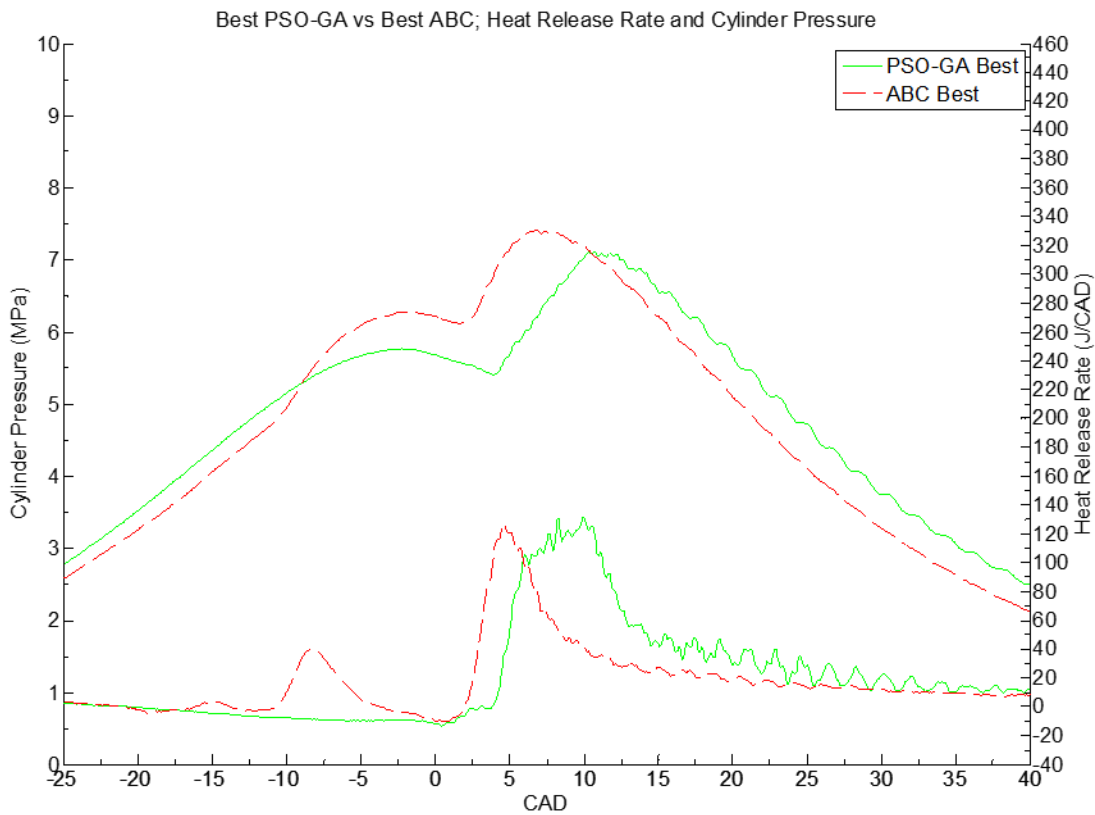
Figure 4.14: PSO-GA VS ABC Comparison of Best Condition Heat Release Rate in J/CAD

and Cylinder Pressure in MPa

CHAPTER 5 CONCLUSION

5.1 Key Results

The hybrid PSO-GA and modified ABC algorithms successfully optimized engine performance for 5 and 6 input variables respectively. Both algorithms moved pilot and main injections closer to TDC in order to improve tradeoffs between NOx, PM, and BSFC. Of the two algorithms, PSO-GA was able to best reduce NOx emissions and BSFC while keeping other objectives below the Tier 4 limit set by the EPA. Both algorithms produce effective and useful data in less time than a comprehensive parametric study, by using evolutionary theory and swarm intelligence behaviors seen in nature. Saving time reduces cost, making it easier to make the most of new and established methods of increasing engine performance.

5.2 Future Work: ABC Algorithm

The ABC algorithm was successful in reducing 3 of the 5 objectives through the second experiment. Its advantages over PSO and GA, are its simplicity of application and ability to memorize only the best solutions. The benchmark tests in this work show that it is superior to PSO and GA when applied to small populations. Its ability of exploration is also of great advantage. Future, experimental applications of ABC where time is in itself an objective should look into further reductions in population or decrease in limit value. This could increase exploration and exploitation at the same time by reducing the amount of 'less viable' solutions. Similar to that of Araújo et al. 2013 and Muñoz et al. 2013, ABC optimization in its standard form could be used to perform a wide search after some amount of iterations of PSO or PSO-GA. This would help ensure the avoidance of local minima, and provide further trends in areas of higher optimality.

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