

Computational Optimization of a Heavy-Duty Compression Ignition Engine Fueled with Conventional Gasoline

2011-01-0356

Published
04/12/2011Adam B. Dempsey and Rolf D. Reitz
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doi:10.4271/2011-01-0356

ABSTRACT

The potential of low temperature combustion to yield low NO_x and soot while maintaining diesel-like thermal efficiencies has been demonstrated through countless studies. Methods of achieving low temperature combustion are just as numerous and they range from using high cetane number fuels, like diesel, with large amounts of exhaust gas recirculation, to completely premixing a high octane number fuel, like gasoline, and approaching an HCCI-like condition. The potential of operating a heavy-duty compression ignition engine fueled with conventional gasoline in a partially premixed combustion mode to have high thermal efficiency and low emissions has been demonstrated in this study. The objective of this work was to optimize the engine using computational tools. The KIVA3V-CHEMKIN code, a multi-dimensional engine CFD model was coupled to a Nondominated Sorting Genetic Algorithm (NSGA II), which is a multi-objective genetic algorithm. Two engine operating conditions were investigated in this study, a mid-load and a high-load point, 11 bar and 21 bar IMEP, respectively. The goal of the optimization study was to simultaneously reduce six objectives, which are soot, NO_x, unburned hydrocarbons, carbon monoxide, indicated specific fuel consumption, and ringing intensity, which is related to maximum pressure rise rate. The genetic algorithm was allowed to vary eight engine design parameters that included pilot injection parameters, main injection parameters, injector included angle, number of injector nozzle holes, and swirl ratio. A non-parametric regression analysis tool was used to post-process the optimization results in order to illustrate the effects of the design parameters on the objectives. The results show that gross indicated thermal efficiencies of 50% with low emissions and low ringing intensity are possible at the mid-

load condition. The high-load condition yields low NO_x emissions, and an efficiency of 50% as well, but indicates that meeting soot emissions and ringing intensity constraints will be a challenge.

INTRODUCTION

The direct injection compression ignition (DICI) engine has a superb reputation for its fuel economy, reliability, and durability. However, due to the heterogeneous nature of conventional diesel combustion, particulate matter (soot) and nitric oxide (NO_x) emissions have been a challenge for diesel engines. In 2010 the United States regulates exhaust emissions at 0.268 g/bkW-hr and 0.013 g/bkW-hr, for NO_x and soot, respectively, from new on-highway, heavy-duty diesel engines [1]. This is approximately a 100% reduction in both NO_x and soot from the time when the regulations were put in place in 1988. In addition, improving fuel efficiency is always a goal because of its direct connection to CO₂ emissions and crude oil usage. Hence, the heavy-duty diesel engine has been a topic of massive research and development over the last two decades.

In the conventional DICI engine diesel fuel is injected near the top of the compression stroke via a high pressure spray, which can be upwards of 200 MPa. The liquid jet breaks up very rapidly into small droplets that begin to vaporize and mix with the surrounding hot air. Due to the high reactivity of diesel fuel (low octane number) the mixture auto-ignites readily. Considering that there is little time for mixing before ignition occurs, the mixture is quite rich during this initial premixed combustion ($\Phi \sim 4.0$). In the relatively hot, fuel rich region of the jet, fuel is pyrolyzed into fragmented hydrocarbons that are precursors for soot nucleation [2]. Following the pre-mixed combustion event, a diffusion flame

is established in which the fuel burns at stoichiometric mixture conditions, which yields high temperatures and thus high NO_x formation rates [3]. The emissions consequences of this mixing limited combustion can be best illustrated on a local Φ - local Temperature space diagram, which is shown in Figure 1 [4]. The “Conventional diesel” line in Figure 1 represents a snapshot in time of a burning diesel spray in a 21 % O₂ environment. It can be seen that there is a diffusion flame (i.e., mixing controlled burning) at stoichiometric mixture, which yields high NO_x formation rates, and a region of $2 < \Phi < 3$ with $T \sim 1800$ K, which can produce unacceptably high soot formation rates.

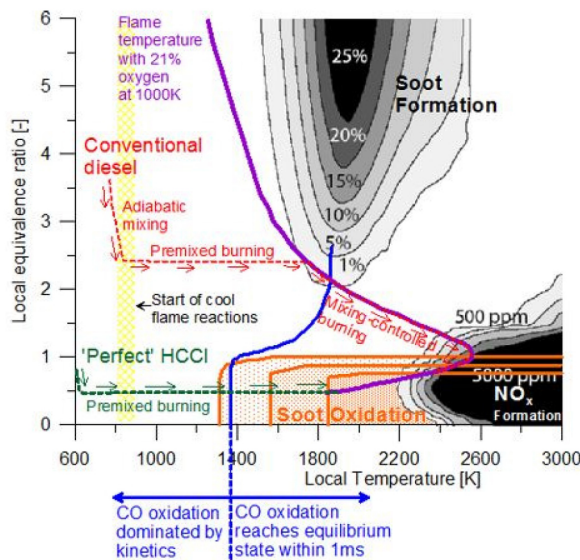


Figure 1. Local Equivalence Ratio vs. Local Temperature for Conventional Diesel Combustion [4].

In an effort to reduce NO_x and soot emissions, while maintaining high thermal efficiency, many new compression ignition combustion strategies have been proposed. Homogeneous Charge Compression Ignition (HCCI) is a concept that has been researched for over 20 years. It was initially studied in four-stroke engines by Foster et al. in 1983 [5]. The HCCI process essentially involves a completely premixed fuel/air charge that is inducted into the cylinder at equivalence ratios that are typically lean ($\sim \Phi < 0.5$). Once within the cylinder, the mixture is compressed until autoignition occurs. HCCI combustion has been shown to have superior characteristics in terms of thermal efficiency, which result from lower heat transfer losses and shorter combustion durations [6]. In addition, the lean, low temperature combustion process yields near zero NO_x and soot emissions, which are depicted in Figure 1 as ‘perfect’ HCCI. Although HCCI combustion appears thermodynamically attractive, the HCCI concept presents a

controllability challenge as it gives up two combustion control aspects. First, the timing of ignition is not controlled, either by fuel injection, as in a DICI engine, or by the spark, as in a SI engine. Second, the rate of heat release is not controlled, either by the rate of fuel injection, as in a DICI engine, or by finite turbulent flame propagation, as in a SI engine. As a result, the near constant volume combustion event can lead to a very rapid rate of heat release, and hence a very rapid rate of pressure rise. Finally, considering that the fuel/air charge in HCCI engines is completely premixed, unburned hydrocarbon (UHC) and carbon monoxide (CO) emissions from the partially combusted gases of the crevice volumes can be an issue.

A second alternative combustion strategy to conventional DICI diesel combustion is Partially Premixed Compression Ignition (PPCI). This concept is a hybrid between HCCI and conventional DICI combustion. As indicated in Figure 1, to avoid the high NO_x and soot formation rates, the fuel must have sufficient time to mix before ignition takes place. However, being completely premixed, as in the case of HCCI, leads to unacceptably high pressure rise rates and thus limits the maximum engine load. In the case of PPCI the fuel is injected either very early or late in the cycle to promote mixing before ignition. This type of diesel combustion strategy has been successfully implemented by several researchers using diesel fuel, under a variety of names, including PREDIC [7], Modulated Kinetics (MK) [8], and UNIBUS [9].

Diesel PPCI was characterized by researchers at Lund University at 8, 12, and 15 bar gross indicated mean effective pressure¹ (IMEP) [10]. They found that the traditional NO_x-soot trade-off that exists with conventional DICI diesel combustion can be defeated with diesel PPCI, but at the cost of a decline in combustion efficiency. They presented an EGR sweep at 12 bar gross IMEP, which is shown in Figure 2 [10]. It can be seen that at EGR rates of 65% and higher, the NO_x emissions are near zero and the soot emissions begin to decline sharply. Unfortunately, this high EGR level resulted in combustion efficiencies below 90%, which can be seen in the dramatic rise in CO and UHC emissions. Also, in order to achieve PPCI operation, the compression ratio had to be reduced to 12.4, which combined with poor combustion efficiency resulted in low thermal efficiency.

¹Gross refers to the compression & expansion strokes only (–180° ATDC to 180° ATDC). Indicated means the cycle work was calculated from the cylinder pressure, neglecting engine friction. Mean Effective Pressure is equal to the cycle work divided by the engine displacement volume.

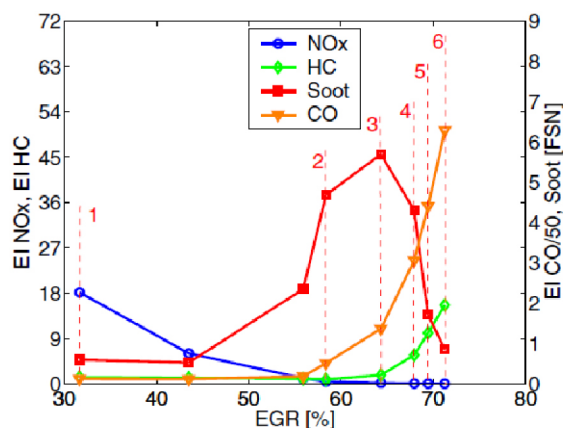


Figure 2. Diesel PPCI emissions at 12 bar gross IMEP with a CR of 12.4 [10].

As indicated above, the concept behind partially premixed combustion is to control the combustion phasing with direct fuel injection and to separate the injection event from high temperature heat release so as to avoid the soot formation island shown in Figure 1. This is achievable with diesel fuel, but as illustrated in Figure 2, requires EGR rates upward of 65% and leads to poor combustion efficiency.

Another approach is to use low reactivity fuels to allow for more mixing time before ignition. Johansson was one of the first to operate a heavy-duty compression ignition engine with a low cetane number diesel fuel to obtain PPCI operation [11]. Kalghatgi et al. [12] did a thorough comparison of DICI using gasoline and diesel fuel. Experiments were conducted in a single cylinder engine with a CR of 14 and single injections near TDC. Using different EGR rates three diesel-like fuels (cetane number > 30) and a gasoline (RON ~ 95) were tested at 1200 rev/min. It was discovered for a given set of operating conditions and the same combustion phasing, the gasoline produced a much longer ignition delay which facilitated premixed combustion, resulting in lower NOx and soot [12]. Kalghatgi et al. [13] continued to develop the gasoline PPCI concept by using multiple injections. With gasoline it was found that a pilot injection early in the compression stroke helped reduce the maximum heat release rate for a given engine load and enabled combustion to occur later in the cycle with low cyclic variation compared to a single injection. They were able to extend the load range of gasoline PPCI to 16 bar IMEP with low NOx and soot emissions and with fuel consumption comparable to conventional diesel.

More recently, researchers at Lund University have been studying gasoline PPCI in a heavy-duty engine from low to high load. Manente et al. [14, 15] have developed an operating strategy very similar to UNIBUS to operate a heavy-duty DICI engine with gasoline. Their strategy utilizes two direct injections, high boost, and approximately 50%

EGR. At 18 bar gross IMEP they were able to achieve soot in range of 1-2 FSN, gross indicated efficiency of 56%, NOx below 0.3 g/kW-hr, and peak pressure rise rates around 15 bar/deg. These results are promising as they were achieved essentially across the entire load range.

Computational studies of gasoline PPCI are not as numerous as the experimental investigations. Shi and Reitz performed a computational optimization of a heavy-duty compression ignition engine fueled with gasoline-like fuels [16]. They found that gasoline-like fuels exhibit great potential for cleaner combustion as compared to diesel fuel because of their low reactivity, which leads to longer ignition delays and PPCI operation. This is consistent with the findings of the experimental studies discussed above. However, the optimization was carried out a fixed EGR rate of only 30%, which made it difficult to find designs that yield proper combustion phasing for good efficiency and acceptable peak pressure rise rates.

In this work gasoline PPCI operation in a heavy-duty compression ignition engine was optimized using computational tools at mid and high-load. As will be shown, the mid-load condition results show promise with low emissions, gross indicated thermal efficiency of 50%, and low ringing intensity. The results at the high-load condition, while achieving low NOx emissions and an efficiency of 50% as well, indicate that soot and ringing intensity are a challenge for gasoline PPCI combustion.

COMPUTATIONAL TOOLS

MULTI-DIMENSIONAL ENGINE CFD

Multi-dimensional engine CFD codes are an important part of the engine development process today. Powerful simulation tools, like chemically reactive CFD models allow engineers and researchers develop combustion strategies in a timely and cost effective manner. In this work the KIVA-ERC code, which is based on the KIVA3V Release 2 code, was used [17,18,19]. The KIVA3V code uses the most popular approach for modeling engine sprays, the Lagrangian-Drop Eulerian-Fluid method, in which liquid fuel is treated as Lagrangian parcel and the ambient gas is discretized into cells. The physical properties of conventional gasoline (for spray break-up, evaporation, and mixing) are taken to be that of iso-octane ($i-C_8H_{18}$). Once evaporated, the chemical reactivity of the fuel is modeled as a mixture of iso-octane and n-heptane ($n-C_7H_{16}$). The KIVA-ERC code has been coupled to the CHEMKIN II libraries for detailed combustion chemistry calculations [20]. Several sub-model improvements have been made to the KIVA3V code, including fuel droplet break-up, droplet evaporation, droplet collision modeling, turbulence modeling, adaptive chemistry models, and the development of primary reference fuel chemical mechanisms.

Beale and Reitz implemented a hybrid spray break-up model, namely the KH-RT model [21]. The droplet collision model is from the original KIVA3V code and is based on O'Rourke's model. However, a radius of influence method was implemented to reduce the mesh dependency of the collision process [22]. The interaction of the liquid fuel parcels with the wall was modeled with the standard KIVA3V wall film model developed by O'Rourke and Amsden [23]. Ra and Reitz made improvements to the droplet vaporization sub model [24]. The RNG k- ϵ turbulence model was modified and implemented into the KIVA3V code by Han and Reitz [25]. An adaptive neighbor search method, namely Adaptive Multi-Grid Chemistry (AMC) model, was used to speed-up the computations by reducing the calling frequency to the chemistry solver [26]. Finally, to further reduce the simulation time, a dynamic maximum timestep strategy was implemented, which is briefly discussed in [Appendix A](#).

Conventional gasoline and diesel fuels are multi-component fuels and consist of a wide range of hydrocarbon species. It is not practical in engineering applications to kinetically model each species in the real fuel. Therefore, the ignition and combustion characteristics of automotive fuels are typically represented by blends of the primary reference fuels (PRF), namely iso-octane and n-heptane. It is widely accepted that the ignition and combustion characteristics of iso-octane and n-heptane can represent gasoline and diesel fuel, respectively. A reduced PRF mechanism consisting of 45 species and a 142 reactions, which includes NO_x chemistry, was utilized in this study to represent the autoignition and subsequent combustion of conventional gasoline [27]. As can be seen in [Figure 3](#), this mechanism accurately captures the homogeneous ignition delay of PRF blends in shock tubes at 40 atmospheres pressure. The experimental data presented in [Figure 3](#) is that of homogeneous shock tube experiments performed by Fieweger et al. [28]. Note the PRF number is defined as the volume percent of iso-octane in a mixture of purely iso-octane and n-heptane.

Soot emissions were predicted using a phenomenological soot model. Two competing processes are considered in the model, namely soot formation and soot oxidation. Acetylene (C₂H₂) is used as the soot inception species in the formation rate equation [29]. The NO_x formation chemistry is represented by 4 species and 12 reactions, which is a reduced version of the GRI NO_x mechanism [30].

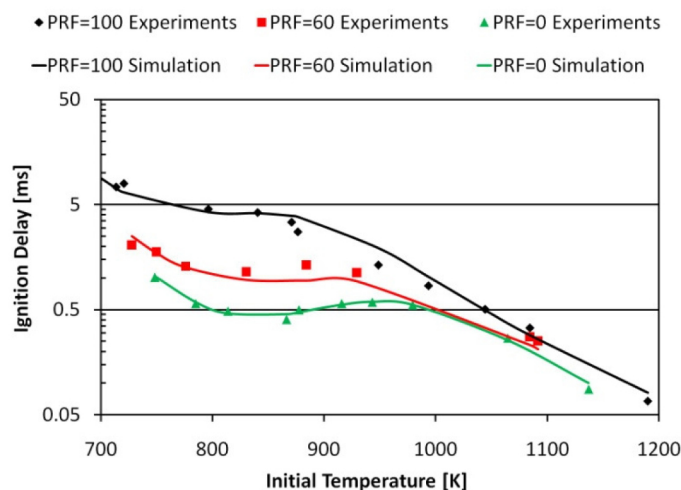


Figure 3. Homogeneous Ignition Delay of Stoichiometric Mixtures ($\Phi = 1.0$) of Primary Reference Fuels at 40 atm.

OPTIMIZATION METHODOLOGY

Previous studies have shown that the combustion characteristics and magnitude of pollutant formation for DICI engines are predicted well by the current CFD models. In addition, the major trends in combustion characteristics and emissions are adequately captured as engine design parameters are changed [29, 31]. Thus, it is feasible to perform engine optimization using numerical simulation [32,33,34].

In this work the optimization tool used was based on genetic algorithms (GA). Genetic algorithms are mathematical algorithms that are designed to simulate the evolutionary process of an ecosystem, which obeys the Darwinian idea of “survival of the fittest”. It is a search-based algorithm that utilizes the “fittest” attributes of previously simulated designs to generate new designs. The goal is to create designs that move the evolutionary process towards better solutions. In an attempt to mimic natural evolution and to avoid localized optimization, random changes of genes are introduced as well. Therefore, GAs are considered global optimization techniques because they explore the entire design space.

Shi and Reitz [34] assessed the performance of three different Multi-Objective Genetic Algorithms (MOGA) used in DICI diesel engine optimization. Considering the goal of the optimization is to find a set of designs that are as close as possible to the true Pareto front and have solutions that are diverse as possible, they defined four quantities for assessing MOGAs. Their analysis concluded that the Nondominated Sorting Genetic Algorithm II (NSGA II) of Deb et al. [35] with a large population size displayed better performance in approaching the true Pareto front and spreading the optimal solutions over all the objectives.

The algorithm randomly creates the first generation of designs which contains 32 citizens [34]. Then these designs are evaluated using 32 simultaneous KIVA runs. Once all of these simulations have finished, the objectives (i.e., performance and emissions) are passed to the NSGA II code. All the citizens undergo conventional selection, crossover, and mutation procedures to produce offspring for the next generation. From the second generation onward, the parent generation competes with its offspring to introduce elitism.

When studying multi-objective problems trade-offs exist from design to design. For example, an engine design that yields low fuel consumption and low acoustic noise might have high emissions. This raises the question, what is an optimal solution in a multi-objective problem? The most common definition for “optimum” used in these types of problems is referred to as Pareto optimal, which was developed by Vilfredo Pareto. In words, a solution set (i.e., all the objectives) is Pareto optimal if there exists no other solution set which would decrease one of the objectives without causing a simultaneous increase in any other objective. This idea is illustrated for an optimization with only two objectives in Figure 4 [34].

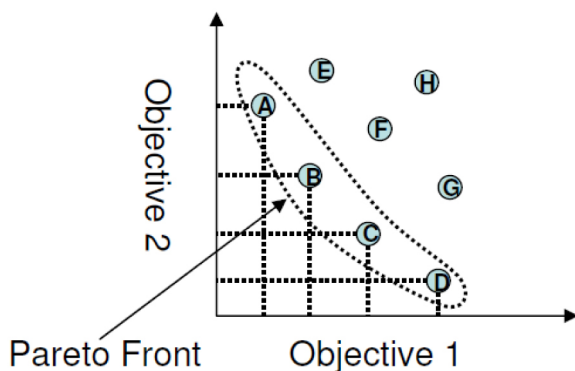


Figure 4. Concept of Pareto Optimal Solutions for a Two Objective Optimization.

In Figure 4 A-H are solutions to a two objective optimization problem. It can be seen that solutions A-D are Pareto optimal because they provide a simultaneous decrease in both the objectives, as compared to solutions E-H. This “front” of optimum solutions is typically referred to as the Pareto front. In addition to understanding what an optimum solution is, quantifying when the optimization has converged on a set of optimal solutions is necessary. The convergence of the GA was monitored in this work as was done in an earlier optimization by Kokjohn and Reitz [36]. Essentially, when the Pareto front stops advancing towards the origin in Figure 4, the optimization is said to have converged. The convergence parameter that quantifies the movement of the Pareto front is presented later.

Considering that GA optimizations are searched based and the goal is to find diverse solutions, typically there are a large number of evaluations that are not on the Pareto front. However, these evaluations are not necessarily wasted because they contain valuable information about the effects that design parameters have on the objectives across the entire design space. Unfortunately, it can be difficult to visualize this information in problems that contain more than two objectives, as in this study. Therefore a non-parametric regression technique was utilized to post-process the optimization results. A non-parametric regression tool is simply a curve fitting technique that can be applied to an irregular set of data where the functional form is unknown. The tool used in this study is known as the Component Selection and Smoothing Operator (COSSO), which was developed by Lin and Zhang [37] and successfully demonstrated on CFD engine simulation results by Liu and Reitz [38]. The response function used in COSSO is of the form

$$f(x) = c + \sum_{i=1}^n f_i(x_i) + \sum_{i<j} f_{ij}(x_i, x_j) + \dots \quad (1)$$

where c is a fitting constant that COSSO is allowed to vary to make the response surface best fit the data, n is the total number of CFD evaluations, f_i are the main effects for each engine design variable x_i , and f_{ij} are the two-way interactions for each pair of design variables. This notion could be extended to higher order terms, but in this study it was truncated to two-way interactions for the sake of simplicity and, as will be shown in the results section, the regression model captures the trends in the optimization data. COSSO determines $f(x)$ by minimizing

$$\frac{1}{n} \sum_{i=1}^n [(y_i - f(x_i))^2] + \lambda J(f) \quad (2)$$

where y_i is the CFD result of the current objective to be fit. The second term, $J(f)$, quantifies the roughness of the response function and λ is used as a smoothing parameter. By minimizing the above equation, COSSO discourages a lack of fitness to the data (the first term) and penalizes for roughness to avoid an excessively noisy fit (the second term). COSSO does require the specification of a “center point” design. Therefore, the resulting response curves should be thought of as a sensitivity analysis about a particular design.

ENGINE CFD MODEL VALIDATION

Before the genetic algorithm optimization study was started, the KIVA-ERC code was validated against experimental data of gasoline PPCI combustion in a heavy-duty compression ignition engine. Hanson et al. [39] used a high octane number

gasoline and operated a Caterpillar 3401E Single Cylinder Oil Test Engine (SCOTE) in PPCI mode. This was accomplished using multiple direct injections at 1500 bar injection pressure. The pilot injection was fixed at -137° ATDC and contained 30% of the total fuel by mass for all cases shown here. The main injection timing was varied as EGR increased to maintain a fixed combustion phasing (CA50²) of 13° ATDC. The intake temperature and pressure were 40°C and 200 kPa absolute, respectively. The engine geometry specifications are shown in Table 1. The fuel was a commercially available gasoline with a pump octane number (PON) of 91. The PON is defined as the average of the research (RON) and motored (MON) octane number. The authors conducted a sweep of the EGR rate at a fixed load and speed of 11.5 bar net³ IMEP and 1300 rev/min, respectively.

Table 1. Caterpillar Engine & Injector Specifications [39].

Engine Geometry	
Displacement [L]	2.44
Bore x Stroke [mm]	137.2 x 165.2
Connecting Rod [mm]	261.6
Compression Ratio	16.1
Squish Height [mm]	1.57
IVC/EVO [deg ATDC]	-85/130
Swirl Ratio [-]	0.7
HEUI Fuel Injector	
Number of Holes	8
Hole Diameter [micron]	229
Included Spray Angle [deg]	154

In the model validation study the fuel was chemically modeled as 91 PRF, to match the PON of the experimental fuel. Two different KIVA computational grids were utilized in the model validation, namely a coarse grid and a fine grid. The specifications for these grids are shown in Table 2.

The cylinder pressure and apparent heat release rate (AHRR) for a representative case is shown in Figure 5. The fine grid predicts the experimental start of combustion and pressure rise rate (PRR) quite accurately. The coarse grid accurately predicts the start of combustion, however it over-predicts the PRR.

Table 2. Computational Grids at TDC (45 degree sector mesh).

Coarse Grid	
Cells at BDC	8,300
Average Cell Size	~ 3 mm
Azimuthal Resolution	3 degrees
Run Time	~ 15 hrs

Fine Grid	
Cells at BDC	34,000
Average Cell Size	~ 1.5 mm
Azimuthal Resolution	2 degrees
Run Time	~ 120 hrs

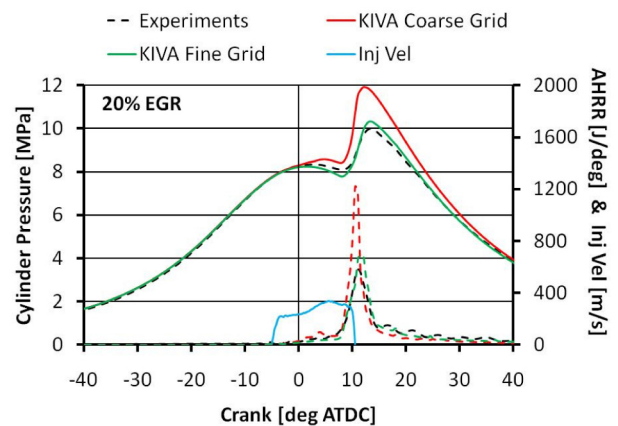
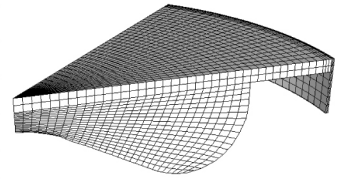
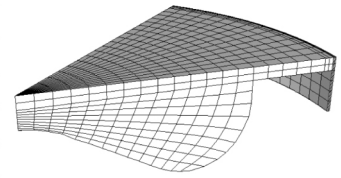


Figure 5. Experiments & Simulation of Gasoline PPCI at 20% EGR.

Figure 6 shows the emissions predictions against the experimental results. For both computational grids, the trends in emissions that result from sweeping the EGR rate are captured reasonably well. The NO_x emissions are predicted very accurately by the fine grid and slightly over-predicted by the coarse grid. This is expected considering the peak cylinder pressure, and hence peak cylinder temperature, are over-predicted by the coarse grid. The predicted soot emissions do not show as much sensitivity to changes in the EGR rate as the experiments do. Nevertheless, both grids show that the soot emissions begin to decrease at approximately 15% EGR. However, the present soot validation results suggest that the model predicted soot will under-estimate experimental measurements. Additionally, by comparing Figure 6 and Figure 2, the advantage of using of a low reactivity fuel, like gasoline, as opposed to a high reactivity fuel, like diesel, in the PPCI regime become apparent. With gasoline, the soot/NO_x trade-off that traditionally exists as EGR is increased is dominated over at an EGR rate of approximately 20%. As EGR is further

²Crank angle degree at which 50% of the total chemical heat release has been reached.

³Net refers to the entire 4-stroke cycle (-360° ATDC to 360° ATDC).

increased, both NO_x and soot decrease simultaneously. This trend was not observed with diesel fuel until 65% EGR. In addition, because the charge is lean overall at these EGR levels, the CO and UHC still have sufficient oxygen to oxidize and remain at low levels, leading to good combustion efficiency.

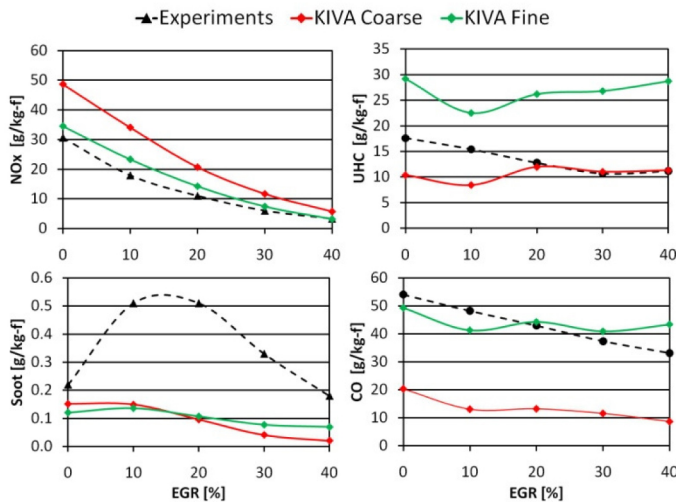


Figure 6. Hanson's et al. 11.5 bar gross IMEP Gasoline PPCI EGR Sweep Compared to Simulation Results.

The grid dependence that exists in the simulation results was traced to differences in the predicted fuel distribution created by the main injection, which can be seen in Figure 7. It can be seen that the coarse grid has a thicker region of high equivalence ratio relative to the fine grid. This can be attested to the fact that an artificial numerical viscosity is introduced when solving the Navier-Stokes equations numerically. This adds to the actual molecular viscosity and over predicts the diffusion term. This artificial viscosity increases as the grid size increases.

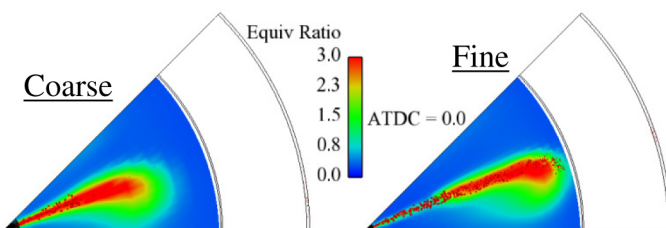


Figure 7. Equivalence Ratio Contours of 40% EGR case. The plane coincides with the spray axis.

Using the coarse grid the optimization study could be completed in approximately 30 days. However, if the fine grid were used, at least 150 days were required for convergence. Considering the computational time benefit, the

accurate prediction of combustion phasing, and reasonably accurate emission trends yielded by the coarse grid, it was selected for the optimization study. Optimal designs determined by the optimization were then reevaluated with the fine grid to ensure that the results were grid independent. It should be noted that grid effects were most notable for mixing controlled combustion cases, such as shown in Figure 5. As will be shown later, chemistry controlled cases showed much less grid dependence.

GENETIC ALGORITHM OPTIMIZATION

The genetic algorithm optimization was conducted on the same Caterpillar engine as discussed previously, with the exception of a different intake valve closure (IVC) time. Two engine operating conditions were investigated in this study, a mid-load and a high-load point, which are approximately 11 bar and 21 bar gross IMEP, respectively. The conditions that were fixed throughout the optimization are shown in Table 3⁴. The genetic algorithm was allowed to vary eight engine design parameters that included pilot injection parameters, main injection parameters, injector included angle, number of injector nozzle holes, and swirl ratio. These parameters and their respective ranges are shown in Table 4.

Table 3. Fixed Engine Operating Conditions for Optimization.

Operating Conditions	Mid-Load	High-Load
Speed [rpm]	1300	1300
Fuel [mg/cycle]	135	270
IMEP [bar]	~ 11	~ 21
Intake Temperature [C]	60	60
Boost Pressure [bar abs.]	2	4
IVC/EVO [ATDC]	-143/130	-143/130
IVC Press. [bar abs.]/Temp. [K]	2.3/372	4.5/373

Table 4. Engine Design Parameters & Ranges for both Mid-Load & High-Load.

Design Parameter	Range
Pilot SOI [ATDC]	-143 to -55
Pilot Injection Press [bar]	300 to 3000
Pilot Injection Amount [%]	0 to 100
Main SOI [ATDC]	-35 to 10
Main Injection Press [bar]	500 to 3000
Injector Included Angle [deg]	120 to 170
EGR [%]	0 to 58
Swirl Ratio [-]	0 to 4
Number of Nozzle Holes [-]	6 to 11

The EGR rate was allowed to vary from 0% to 58% for both the mid-load and the high-load operating conditions. In this study the EGR gases were assumed to be complete

⁴The IVC pressure and temperature were determined by GT-POWER [43] simulations of the CAT SCOTE single-cylinder engine lab.