Optimization of Operating Parameters for a 2-stroke DI Engine with KIVA 3V and a Genetic Algorithm Search Technique

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Abstract

An optimization study utilizing multidimensional engine modeling and a global search technique known as the Genetic Algorithm has been carried out. The subject of the study is a 2-stroke, single-cylinder, gasoline direct injection engine with a centrally located pressure swirl injector and two spark plugs. The goal was to optimize the part load operating parameters of the engine in order to achieve the lowest possible emissions, reduced wall heat transfer, and improved fuel efficiency. Parameters subject to permutation in this study were start of injection (SOI), injection duration, spark timing, injection angle, dwell between injections, and the percentage of mass in the first injection.

INTRODUCTION

Gasoline Direct Injection is emerging as the technology of choice for achieving superior fuel economy in spark ignition engines. At light load, the fuel is injected late in the cycle, creating a stratified charge suitable for stable ignition in the vicinity of the spark plug. This enables overall ultra-lean operation and the elimination of losses from throttling.

The challenge is to control the emissions from GDI engines. High local temperatures and spray impingement are respectively, the primary causes of high nitrogen oxides and unburned hydrocarbons in the exhaust. As an added challenge, three-way catalysts for exhaust gas after-treatment perform poorly under the lean conditions created by stratified operation.

Multidimensional engine modeling with the use of complex CFD codes like KIVA is becoming more and more widespread as engineers and scientists work to find solutions to increasingly more stringent emissions standards and the need for environmental preservation. Such codes are now widely used at national laboratories, universities and research institutes, and within the engine industry. These models continue to get better as understanding of the physics and chemistry of engine processes improves and as computer technology and CPU speed increases [1].

In an engine optimization problem, the CFD code uses a mathematical scheme to dictate the manner in which the optimum will be sought out. The Genetic Algorithm is one such search technique. Senecal and Reitz [2] applied this technique with multidimensional modeling to successfully optimize the operating parameters of a Catepillar 3400 series diesel engine. They were able to simultaneously reduce both soot and NOx emissions, while improving fuel consumption. The reductions in emissions were quite significant; a 70% reduction in NOx and a 50% reduction in soot. A similar study was conducted by Wickman *et al.* [3], in which nine parameters corresponding to combustion chamber geometry, injection and spray parameters, swirl ratio, EGR fraction and nozzle hole diameter were subject to permutation with the Genetic Algorithm. The spray and combustion calculations were performed in KIVA 3V. The study yielded substantial improvements in emissions and fuel economy for both the small-bore and large-bore diesel engines studied.

MODEL SUMMARY

The engine CFD calculations for this study have been performed with an expanded version of the standard KIVA 3V [4] engine CFD code produced at Los Alamos National Laboratories. The code has been adapted to include submodels and improvements developed at the University of Wisconsin Engine Research Center. The following is a summary of the major models used in this study:

SPRAY MODEL: The Linearized Instability Sheet Atomization (LISA) Model is applied to describe transition from the flow inside the injector to the fully atomized spray droplets. There are three distinct phases in the spray formation process: film formation, sheet breakup, and atomization.

IGNITION MODEL: The discrete particle ignition kernel model proposed by Fan et al. [5] is utilized in this study to model the ignition and early flame propagation processes. The model is shown schematically in Figure 1, and depends on the laminar flame speed, S_L, and the turbulence kinetic energy, k.

COMBUSTION MODEL: Once the ignition kernel reaches a critical diameter, the calculation switches to a fully turbulent combustion model. The critical diameter is given by:

$$d_k \geq C_{m1} l_l = C_{m1} \cdot 0.16 \frac{k^{1.5}}{e}; \quad C_{m1} = 2.1$$

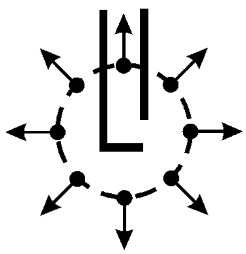
C_{m1} is set to 2.1 in this study, and ε is the rate of dissipation of turbulent kinetic energy.

The fully turbulent combustion model uses characteristic time treatment to determine species conversion rates:

$$\frac{d\, r_i}{dt} = -\frac{r_i - r_i^*}{t_c} = -\frac{r_i - r_i^*}{t_l + t_t}$$

where ρ_i is the species density and * indicates thermodynamic equilibrium.

The characteristic time is the combination of laminar (τ_l) and turbulent (τ_t) timescales and is the same for all the species considered. Seven species are considered in this study: Fuel, O_2, N_2, H_2O, CO_2, CO, and H_2 [7].



$$u_{k,rad} = \left[\frac{T_{ad}}{T} s_L + \sqrt{\frac{2}{3} k} \right]$$

Figure 1: Discrete Particle Ignition Kernel Model

OPTIMIZATION METHODOLOGY

The micro-Genetic Algorithm is a global search technique based on the laws of natural selection. The micro-Genetic Algorithm utilizes 5 individuals as opposed to the larger population sizes seen in the Simple Genetic Algorithm [6]. Five individual designs are created by random sampling of the parameter space. These designs are then subjected to some kind of evaluation to determine the merit or 'fitness' of the individuals. Successful individuals are maintained and the less successful ones are dispensed of. The traits of the successful individuals are then combined to produce a new generation of individuals. This new generation is then evaluated for 'fitness' and the procedure continues. Successful individuals can be seen as parents, and the individuals derived from them, as children. In the creation of 'children' from 'parents,' mutations are permitted. These mutations take the form of random changes to a small portion of the population. The reproduction continues until there is no further improvement in merit or fitness. Then the best individual is maintained and the other four are generated randomly. This is referred to as a micro-population restart. The reproduction is then continued. This process continues to evolve better and better designs. If no improvement is seen after continuous population restarts and reproduction, it can be concluded that an optimum has been reached.

The merit function is the mathematical expression that embodies the quantities or values of interest. These quantities can be viewed as qualities, or traits of individuals. The merit function is a means to combine the quantities of interest into one overall value that describes the fitness of an individual design. The form of the merit function utilized in this study is as follows:

$$Merit = \frac{1000}{\left[\frac{NO_x + HC}{NO_{x,m} + HC_m} \right]^2 + \frac{ISFC}{ISFC_0} + \frac{WHEAT}{WHEAT_0}}$$

where :

NO_x + HC are the nitrogen oxides and hydrocarbon emissions lumped together. Units are g/kW-hr.

$NO_{x,m}$ + HC_m are the equivalent EPA mandated values for outboard and personal watercraft engines under 4.3kW (81 g/kW-hr).

ISFC is the indicated specific fuel consumption in units of g/kW-hr.

$ISFC_0$ is the indicated specific fuel consumption in units of g/kW-hr as calculated from simulation of the baseline operating case, taken as 261.95 g/kW-hr.

WHEAT is the total cylinder wall heat transfer in units of ergs.

$WHEAT_0$ is the total cylinder wall heat transfer in units of ergs as calculated from simulation of the baseline operating case, taken as $5.21e^8$ ergs.

The Genetic Algorithm (GA) code is coupled to the CFD code, but the two codes are distinct entities. Individual designs received from the GA are sent to KIVA as input parameters. The simulation is then carried out. Statements have been added to the KIVA code to calculate the merit function value from the various results of the simulation (HC, NOx, etc.). The merit function value for each individual is then sent back to the GA code where it is used to determine the successful 'parents.' Reproduction then takes place and new individuals are created within the GA code. These individuals, in turn, get sent to KIVA and simulations are carried out. The simulations are done in parallel, and so the entire population is simulated at the same time – each one on an individual CPU, taking about 12 hours per case on an SGI origin 2000 computer.

SIMULATION DETAILS

The computational mesh employed in the simulation is shown in Figure 2. It is comprised of about 11000 computational cells.

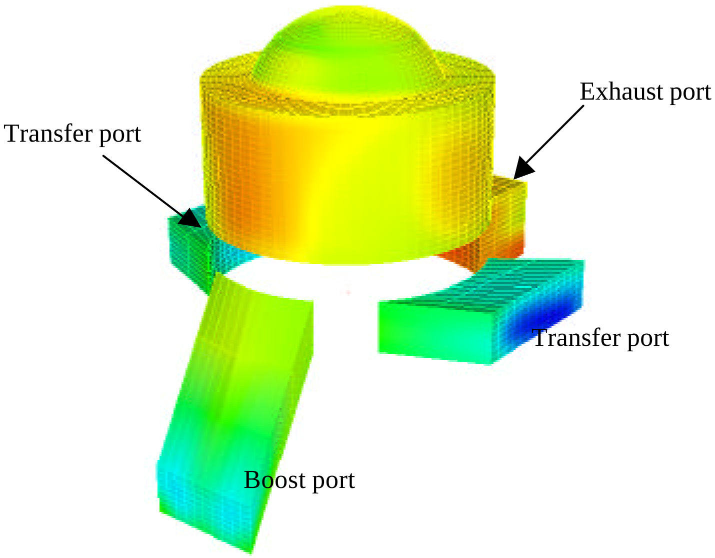


Figure 2: Computational Mesh. Colors depict Surface temperature.

Bore [mm]	85.8
Stroke [mm]	67.3
True Compression Ratio [-]	7.4
Exhaust Port Timing [°ATDC]	95
Boost Port Timing [°ATDC]	117
Transfer Port Timing [°ATDC]	117
Speed [rpm]	2000
Load [Nm]	11.4
Ignition Timing [°ATDC]	-26
Injection Timing [°ATDC]	-80
Spray Cone Angle [°]	54
Injection Pressure [MPa]	5.17

Table 1: Engine Specifications and Operating Conditions for the Baseline Case

The engine specifications and operating conditions for the baseline case are given in Table 1. Experimental data of the baseline operating case has been matched very well by simulation results in previous studies [7,8]. Good agreement of cylinder pressure was obtained through the entire cycle including the scavenging period. The same CFD code used in those studies is being used in the current study.

RESULTS AND DISCUSSION

The evolution of the maximum merit function value is shown in Figure 3. This plot of maximum merit function versus generation shows the development of the fitness of individuals as the optimization process proceeds. It can be seen from the plot that initially there is a rapid improvement in fitness. By generation 3, the fitness of the baseline operating condition is exceeded. After this point growth continues, but at a slower pace. By generation 5, the merit function has achieved a value of 479.50. There is then a short plateau where no better designs emerge from the process. Generation 12 breaks the stalemate with a design having a merit function value of 479.76. No improvement is seen in Generation 13, but in Generation 14 the merit climbs to 481.26. After this point, no improvement in the design is seen despite continuing the process until Generation 53. This is a very long plateau and it is thus arguable that the design has converged upon an optimum. Figure 4 parallels Figure 3 in time, giving the improvement in emissions with the successive generations. It can be seen that the nitrogen oxide and hydrocarbon emissions are lowered substantially. By Generation 3, the emissions had superseded that of the baseline operating case. Continued improvement is seen after that point until the long lasting plateau begins at generation 14. It is also evident from the plot that the emissions predicted in all cases are far lower than the EPA mandated emissions corresponding to the year 2006 and after.

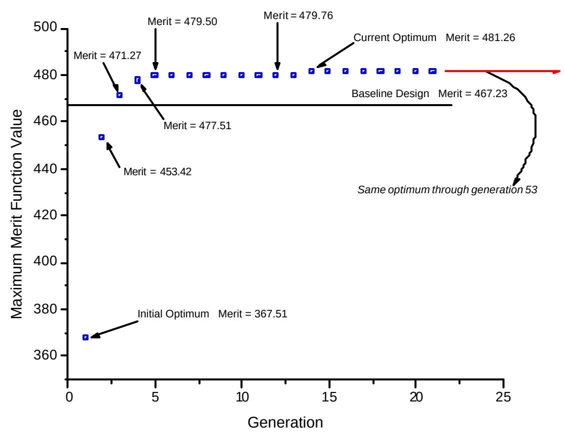


Figure 3: Maximum Merit Function vs Generation

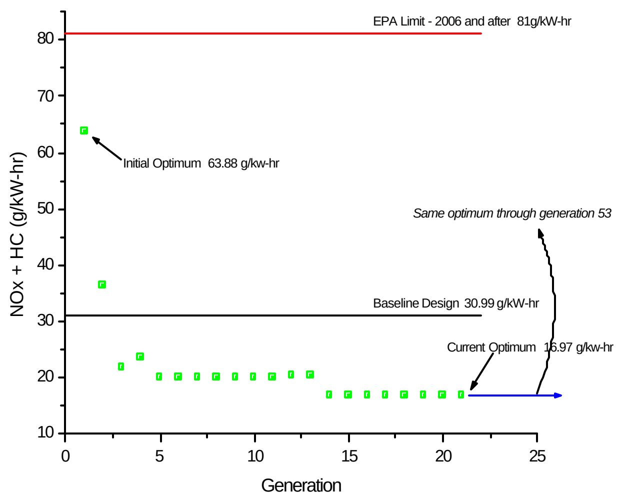


Figure 4: NOx + HC vs Generation

Table 2 is a comparison of the characteristics of the current best design and the baseline design.

	Baseline	Current Best
SOI(CA)	280	323.4
Duration(CA °)	12.42	7.74
Spark Time(CA)	334	324.8
Spray Angle(°)	54	142.86
Dwell(CA °)	0	19.68
% Mass in 1st Pulse	100	70.9

Table 2: Comparison of Baseline Case and Current Best Design

Table 2 shows that the optimum employs a totally different injection and ignition strategy than the baseline case. Fuel is injected very late in the cycle. This first pulse comprises over 70% of the total fuel. The fuel is injected at a much higher pressure than for the baseline. This can be seen by comparing the injection duration of the two cases. In the baseline case, fuel is injected for about 12 crank angle degrees but in the current best design it is only injected for about 7 degrees. The amount of fuel is held constant for all individuals in this study. In other words, all cases have the same, fixed load. While the first pulse of fuel is being injected, the dual spark plugs begin to discharge their electrical energy, starting an ignition process that occurs while the spray event is still in progress. The fuel is injected at an extremely wide angle of about 143 degrees. In the baseline case, the cone angle of the fuel spray is only 54 degrees. In the current best design, there is a pause of about 20 crank angle degrees before the second pulse, comprising the remaining 30% of the fuel, is injected into the cylinder.

Table 3 shows the improvements in emissions, heat transfer, and fuel economy attained by the new design as compared to the baseline operating case.

	% Change
NOx	3.84% reduction
HC	54% reduction
ISFC	0.43% reduction
Wall Heat Transfer	3.76% increase

Table 3: Reductions Achieved in Emissions and Fuel Consumption

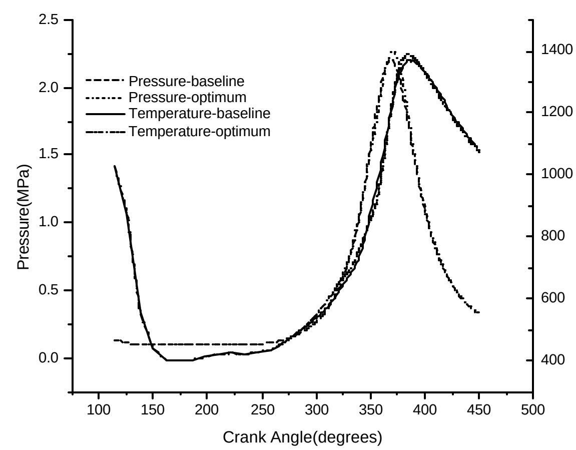


Figure 5: Comparison of Cylinder Pressure and Temperature

It can be seen that there is a tremendous 54% reduction in emissions of unburned hydrocarbons. Nitrogen oxides are reduced by almost 4% and fuel consumption is improved marginally. All this is accomplished with a small total heat transfer penalty of about 4%.

Figure 5 shows a comparison of the cylinder pressures and temperatures between the two cases. It can be seen that the optimum design has slightly higher peak pressures and temperatures, as compared to the baseline operating case. This, in turn, results in a small increase in power in the new design. This is seen in the decreased specific fuel consumption. The increased power also plays a reducing role in the hydrocarbon and nitrogen oxide emissions as these are both normalized with respect to the power (i.e. given in g/kW-hr). Another reason for the reduction in nitrogen oxides is probably a reduction in the number of hot spots or in the magnitudes of such local temperatures [7]. The higher average peak temperatures and pressures are responsible for the greater overall wall heat transfer seen in the optimum design. The large reduction in hydrocarbon emissions is probably attributable to excellent atomization and vaporization in the cylinder. This is due to the extremely high injection pressures imposed by this design. Table 2 shows that the injection duration for the new design is almost one half that of the baseline case. This high injection pressure creates very small, highly atomized spray particles that evaporate quickly and mix well with the surrounding air.

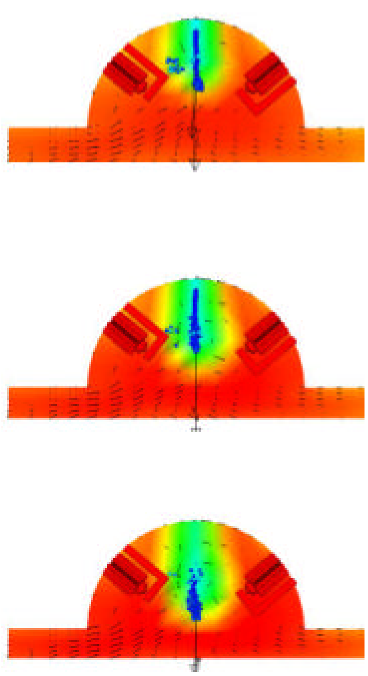


Figure 6: Development of Fuel Spray
(Pilot Injection)

Figure 6 shows the development of the fuel spray. It can be seen that despite having a cone angle of 142 degrees, the lack of momentum of the small droplets and the heavy entrainment of air into the spray cause the spray plume to collapse into a slug like jet that penetrates into the cylinder.

SUMMARY

An optimization study based on multidimensional spray and combustion modeling, coupled with a genetic algorithm search technique has been successfully conducted. The operating parameters of a 2-stroke, direct-injected, single cylinder research engine have been subjected to Darwinian-type evolution, and an optimum design has emerged from this process. The optimum design offers a substantial reduction in regulated emissions, and a small fuel efficiency gain. In-cylinder heat transfer is increased slightly. The results for this particular engine, at the given speed and load, seem to point toward higher injection pressures, extremely late, split injections and simultaneous injection and ignition.

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