Optimization of Diesel Engines by Means of Multi-Orifice Asynchronous Fuel Injection

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ABSTRACT
A multi-orifice asynchronous injection system permits independent timing and duration of the injected fuel pulses, where each orifice has its own diameter and injection direction. Fuel pulses can be separated by a dwell, as in the traditional split injection, or they can overlap. In this study, a gradient-based optimization algorithm is used in conjunction with a CFD code to explore the asynchronous injection technique in order to find optimal operating conditions of a medium-speed diesel engine. It has been found that this asynchronous fuel injection method leads to considerable reductions in emissions while the fuel consumption remains low.

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INTRODUCTION

One of the main objectives in today's engine research is to find operating conditions which minimize the fuel consumption while meeting legislative emission standards. In this study, a computational approach is taken to find optimal injection strategies which realize these goals. This leads to a constrained optimization problem where an appropriate cost function is minimized over a high-dimensional parameter space. The parameters are the engine input data which, in this study, include injection-specific quantities and nozzle properties. The cost function to be minimized is computed from engine output data such as the specific fuel consumption (SFC), the nitric oxides (NOx), and particulates (PM), i.e., soot.

The relationship between engine input variables and their influence on the emissions and fuel economy is very complex, and in general, is not explicitly known. Typically, a reduction in nitric oxide is associated with an increase in the soot formation, referred to as the soot-NOx trade-off, and is usually at the expense of fuel consumption. This complex dependence between engine input and output data, and the fact that engine simulations are computationally very expensive, plays a major role in motivating the development of an efficient optimization tool.

A well-suited optimization method for input-output systems with unknown dynamics, is based on the genetic algorithm (GA). GAs are modeled on the principle of natural selection, where an optimal state is determined over many generations of successful outcomes, subject to possible mutations. A variation of the GA, called the micro-genetic-algorithm (µGA), has successfully been developed and applied in engine optimizations by Reitz and co-workers (e.g. [1-5]). The main feature of the µGA is the efficient selection process used in the determination of the next generation, which allows a drastic reduction in the population size. As a consequence, the number of time-intensive engine simulations is greatly reduced, which makes the µGA applicable to engine optimization for present-day computers. Still, the hundreds of engine simulations required by a µGA optimization lead to enormous computational costs, which can be a considerable drawback of this optimization strategy.

Computationally more efficient are gradient-based minimization methods, where an optimum is obtained by minimizing the cost function along a sequence of search directions. The main drawback of gradient methods is the fact that they are less likely to reach a global minimum in the presence of local minima.

In previous studies by these authors (cf. [6, 7]), a conjugate gradient method in conjunction with a backtracking algorithm had been introduced and tested for an experimental, non-road Sulzer S20 DI diesel engine utilizing a KIVA-3-based CFD code [8]. Both studies showed that the conjugate gradient method is highly efficient in terms of the number of engine simulations, and yield considerable improvements in terms of emissions. However, this approach suffered from the disadvantage that although the monotonic cost function descent can lead to very low emissions, it also can result in unacceptably high fuel consumption. Therefore, in a further development, a steepest descent method in combination with an adaptive cost function has been developed and tested to improve injection configurations for the S20 (cf. [9, 10]). This approach had the advantage that the emission targets were attained more accurately while maintaining a low fuel consumption. Thus, eliminating the disadvantage of the monotonic cost function used in the conjugate gradient method.

The steepest descent method has also been used in this study, where a multi-orifice asynchronous injection system of the S20 is optimized. Multi-orifice in this context means that the fuel is injected via two orifices per 30 deg cylinder sector (instead of one, as for conventional injectors), and asynchronous indicates that the timing of the two fuel pulses is totally independent, allowing, for example, a temporal overlap of the two fuel pulses. Also, each orifice has its own diameter and injection direction, which makes this system very flexible in supplying fuel into the combustion chamber. The optimizations have been performed for a two fuel pulse strategy, where the optimization parameters include the start of injections, the injection durations, the nozzle orifices and the downward injection directions. The emission mandates used in this study are the ones prescribed by the United States Environmental Protection Agency (EPA) for stationary engines [11].

OPTIMIZATION METHOD

The optimization approach taken in this study is based on the steepest descent method which utilizes an adaptive cost function in conjunction with a backtracking strategy for the line search. The backtracking algorithm utilizes quadratic and cubic polynomials to accelerate the convergence, and the initial backtracking step employs an adaptive step size mechanism which depends on the steepness of the search direction. The actual optimizations are performed on a normalized parameter space, where each optimization parameter is first mapped onto the unit interval [0, 1], which leads to an optimization problem over the unit cube in higher dimensional space. Following a more precise problem statement, these algorithms are summarized. More detailed descriptions can be
found in [9].

**Problem Formulation**

We consider the constrained optimization problem where the specific fuel consumption is minimized subject to prescribed emission levels. More formally, this is expressed as minimizing the objective function, i.e., the specific fuel consumption, \( s : X \rightarrow \mathbb{R} \) subject to the constraints \( g(x) = 0 \). Here, \( X \subset \mathbb{R}^n \) represents the admissible set of engine input parameters and \( g : X \rightarrow \mathbb{R}^2 \) denotes the emissions, which, in our case, are the nitric oxide and the particulate mass.

This problem can be reformulated as an unconstrained optimization problem by introducing the penalty term \( g(x)^T D g(x) \), where \( D \) is a positive definite matrix, usually taken to be diagonal, and the superscript \(^T\) denotes the transpose. This leads to the unconstrained optimization problem of minimizing the cost function (also called merit or penalty function) over the admissible parameter set \( X \), i.e.,

\[
\min_{x \in X} f(x; \zeta) = \min_{x \in X} [s(x) + \zeta g(x)^T D g(x)]. \tag{1}
\]

Here, \( \zeta > 0 \) is a penalty parameter such that if \( x^* = \min_{x \in X} f(x; \zeta) \) then \( \lim_{\zeta \to \infty} x^*_\zeta = x^* \), where \( x^* \) is the solution of the original constrained optimization problem (cf. [12]). In practice this means that the choice of \( \zeta \) yields a solution \( x^*_\zeta \) which is as close to the optimum \( x^* \) as desired.

**The Adaptive Steepest Descent Method**

In each iteration step, \( k \), the steepest descent method determines a search direction, \( p_k = -\text{grad } f(x_k; \zeta_k) \), at the pivot, \( x_k \). (The gradient, \( \text{grad} \), is taken with respect to \( x \), keeping \( \zeta \) fixed.) The cost function, \( f \), is then minimized along this search direction, using the backtracking algorithm described below. This minimization process, called line search, yields a new pivot \( x_{k+1} \) and a new penalty parameter \( \zeta_{k+1} \) (see below), which allows the determination of the new search direction \( p_{k+1} \). This iteration process is continued until either the target is reached or a minimum is encountered.

**The Backtracking Algorithm**

The backtracking algorithm used in this study is a modified version of the one presented in [13]. It is equipped with an additional adaptive initial step size for the first backtracking step and minimizes either a quadratic or a cubic polynomial to find the subsequent step sizes. Note that during the backtracking phase the penalty parameter \( \zeta \) remains constant and, therefore, in order to simplify the notation, the dependence of \( f \) on \( \zeta \) is ignored in this subsection, i.e., \( f(x) = f(x; \zeta) \).

In this algorithm, a new pivot, \( x_{k+1} \), is determined such that the cost function, \( f \), is minimized in the descent direction, \( p_k \), starting from the present pivot, \( x_k \). The endpoint of the first backtracking interval, \( x_s \), is given by \( x_s = x_k + \frac{\lambda}{||p_k||} ||p_k|| \), where \( \lambda \) is a user input constant and \( \delta_k = \min \{ \text{grad } f(x_k), p_k > ||p_k|| \} \) is the derivative of \( f \) at \( x_k \) in the direction \( p_k \). If \( x_s \) lies outside the parameter space (the n-dimensional unit cube) then it is projected onto its boundary. Using the slope \( \delta_k \) at \( x_k \), a parabola is fitted through the three points \( (x_k, f(x_k)), (x_s, \delta_k), (x_{k+1}, f(x_s)) \) and its minimum, \( x_m \), is determined. Again, if \( x_m \) lies outside the parameter space then it is projected onto its boundary. This gives the new backtracking step \( \Delta x = ||x_m - x_s|| \).

If \( f(x_m) \) is larger than the difference between \( f(x_k) \) and the tolerance, \( \beta ||p_k|| \Delta x \), where \( \beta \) is a constant, then the backtracking step is changed (usually reduced) as follows: a cubic polynomial is fitted through the four points \( (x_k, f(x_k)), (x_s, \delta_k), (x_m, f(x_m)), (x_{k+1}, f(x_{k+1})) \) and its minimum, \( x_r \), is determined. Once more, if \( x_r \) lies outside the parameter space then it is projected onto its boundary. Next, the new interval endpoint is set to \( x_s = x_m \), and the new pivot candidate becomes \( x_{k+1} = x_r \). This new pivot candidate, \( x_m \), determines the new step size, \( \Delta x = ||x_m - x_k|| \), and the associated change in the tolerance. This iterative process is continued until \( f(x_m) \) is smaller than the difference between \( f(x_k) \) and the tolerance; this then qualifies \( x_m \) as the new pivot for the next search direction.

The first step in the backtracking algorithm is normally the largest distance used for finding a new pivot. In each subsequent iteration this distance is usually reduced. The backtracking algorithm in this study is equipped with an adaptive initial step size control to make this first step as large as possible. This is achieved by linking the first step size to the steepness of the cost function derivative in the search direction, \( \delta_k = \text{grad } f(x_k) / ||p_k|| \). This has the effect that if \( \delta_k \) is very steep then a small step size is chosen, and if the gradient is flat, then the first step size is taken to be large. This behavior is achieved by taking the initial backtracking interval as \( \Delta x = \lambda / ||p_k|| \).

Note that the parabola fit during the first backtracking step serves the purpose of accelerating the cost function minimization. A heuristic argument shows that in most cases, except possibly in some pathological situations, the cost function at the parabola minimum \( x_m \) satisfies \( f(x_m) < f(x_k) \) and \( f(x_m) < f(x_r) \) if \( x_r \) is a solution of the quadratic fit. The cubic polynomial fit is used in the subsequent backtracking steps to increase the speed of the cost function minimization even further.

The positive constant \( \beta \) helps to control the toler-
In the search of the new pivot, and \( \lambda \), also positive, provides a user-control for the initial backtracking step. Both of these constants influence the convergence rate and the number of function evaluations. The values taken in this study are \( \beta = 0.01 \) and \( \lambda = 0.5 \).

### The Adaptive Cost Function

An optimal engine performance means that the fuel consumption is minimized subject to prescribed emission targets. As discussed in the Problem Formulation, this constrained optimization problem can be reformulated as an unconstrained optimization problem by minimizing the cost function given in Eq. (1). In this study, the fuel consumption is expressed in terms of the normalized specific fuel consumption, \( SFC/SFC_0 \), as is discussed below in more detail. The emissions, which constitute the penalty terms, are the nitric oxides, \( NOx \), and the particulates, \( PM \). Therefore, based on Eq. (1), the cost function is given by

\[
f(x; \zeta) = \frac{S}{2} \left( \frac{SFC}{SFC_0} \right)^\rho + \frac{\zeta}{2} \left( C \left| \frac{PM - PM_0}{PM_0} \right|^\rho \right) + N \left| \frac{NOx - (NOx)_0}{(NOx)_0} \right|^\rho,
\]

where \( x \) denotes the engine input, \( \zeta \) the penalty parameter, and the subscripts \( 0 \) the target values. The positive weights \( C, N \) and \( S \), and the positive exponents \( \rho, n \) and \( s \), determine the importance of each of the terms. In this study, all the weights and exponents were set to one except for \( s \), which was set to two. (As discussed below, the factors of \( \frac{1}{2} \) are used to set \( f(x_i; \zeta_i) = 1 \) at the start of each line search.) Notice that the dependence between the engine output quantities, \( SFC, PM \) and \( NOx \), and the engine operating parameters, \( x \), are not known explicitly.

As discussed in the Problem Formulation, the penalty parameter, \( \zeta \), determines the closeness of the minimum \( x^*_c = \min_{x \in \mathbb{X}} f(x; \zeta) \) to the actual solution, \( x^* \), of the original constrained optimization problem. This suggests that \( \zeta \) can be updated after every line search. This \( \zeta \)-update uses the appropriate values at the new pivot, \( x_{k+1} \), according to the following expression

\[
\zeta_{k+1} = \zeta_k \left( \frac{SFC(x_{k+1})}{SFC_0} \right)^\rho \left( C \frac{PM(x_{k+1}) - PM_0}{PM_0} \right)^\rho + N \left| \frac{NOx(x_{k+1}) - (NOx)_0}{(NOx)_0} \right|^\rho.
\]

With this expression for \( \zeta_{k+1} \), the cost function in Eq. (2) satisfies \( f(x_{k+1}; \zeta_{k+1}) = 1 \). Note that with the choice of \( \zeta_{k+1} = \max(\zeta_k, \zeta_{k+1}) \), used in the adaptive steepest descent algorithm, the sequence \( \{\zeta_k\} \) is non-decreasing which gives the penalty terms more and more weight, and thus the optimization parameters approach the constrained minimum.

The EPA mandated values for \( NOx \) and \( PM \) were chosen to meet the Tier 3 2006 (Blue Sky Series) standards of stationary engines as given in Ref. [11]. These mandates are \( PM_0 = 0.12 \) g/KW-hr and \( (NOx)_0 = 4 \) g/KW-hr. The specific fuel consumption is normalized with the tuning case value of \( SFC_0 = 194.13 \) g/KW-hr. These values are summarized in Table 1.

<table>
<thead>
<tr>
<th>EPA Mandates</th>
<th>Targets</th>
</tr>
</thead>
<tbody>
<tr>
<td>( PM_0 \ [g/KW-hr] )</td>
<td>0.12</td>
</tr>
<tr>
<td>( (NOx)_0 \ [g/KW-hr] )</td>
<td>4</td>
</tr>
<tr>
<td>( SFC_0 \ [g/KW-hr] )</td>
<td>—</td>
</tr>
</tbody>
</table>

In the simulations the SFC has been determined as

\[
SFC = \frac{\dot{m}_f}{P},
\]

where \( \dot{m}_f \) is the injected fuel mass rate and the power output \( P \) has been computed from

\[
P = \frac{RPM}{120} \int_{IVC}^{EVO} p dV - L.
\]

In this expression, \( RPM \) is the engine speed in revolutions per minute, \( p \) is the cylinder pressure, \( dV \) is the differential volume increment, \( IVC \) denotes the inlet valve closure and \( EVO \) is the exhaust valve opening. \( L \) denotes the power losses due to friction, scavenging, and operation of peripherals such as the turbocharger and the injection system.

The power losses, \( L \), have been estimated from the difference of the experimental power output of 157.62 kW and the tuning case integral

\[
\frac{RPM}{120} \int_{IVC}^{EVO} p dV = 169.62 \text{ kW as } L = 12 \text{ kW. This value of } L \text{ has been used in all the simulations in this study. It should be noted that the computations have been performed at full engine load where changes to } L \text{ are small in comparison to the power output. Therefore, using a constant } L \text{ in all the simulations is expected to have a negligible effect on the final optimization results.}
\]

\(^1\text{The regular Tier 3 2006 EPA mandates are } PM_0 = 0.20 \text{ g/KW-hr and } (NOx)_0 = 4 \text{ g/KW-hr.}\)
### Computational Details

The optimization code is a fully automated control unit for the entire optimization procedure including the engine simulations. The latter have been performed for the Sulzer S20 DI diesel engine with a modified version of the KIVA-3 code [8]. This code is equipped with the RNG k-ε turbulence model as implemented by Han and Reitz [14], the CAB atomization and drop breakup model [15], the LIT auto ignition model [16], and the LTL characteristic time combustion model [9]. The nitric oxide is predicted with the extended Zeldovich mechanism, the soot production is modeled according to Hiroyasu and Kadota [17], and the soot oxidation is computed with the model of Nagle and Strickland-Constable, as presented in Chan et al. [18]. All other models used in the simulations are the standard KIVA-3 models. Detailed model descriptions can be found in the respective references, and the model constants used in this study are obtained from an elaborate tuning process which is described in [9].

The computations start at inlet valve closure at 144 CA before top dead center (TDC) and stop at 129 CA after TDC when the exhaust valves open. All simulations have been performed at full load at 1000 RPM with a total injected fuel mass of 1.02 g. Additional engine specifications are listed in Table 3.

The cylinder flow is assumed to be periodic with respect to the number of nozzle orifices, and therefore, only the sector of the combustion chamber which corresponds to one nozzle orifice was simulated. The computational domain of the tuning case corresponds to a 30 deg sector mesh with $23 \times 7 \times 14$ cells in radial, azimuthal and axial direction at TDC.

As shown in Table 1, the actual target values for particulates, $PM_{10}$, and nitric oxide, $NOx_{0}$, used in the computations in Eq. (2) are smaller than the EPA values. The reason for this is that the EPA mandates
are approached from above and can only be reached to within a certain accuracy. Therefore, since these mandates cannot be exceeded, the use of lower actual target values in Eq. (2) increases the likelihood that the EPA values can be satisfied.

### Optimization Parameters and Computation Cases

The objective of this study is to obtain new injection strategies which minimize the specific fuel consumption subject to given nitric oxide and particulate constraints. It is assumed that the engine is equipped with a common rail injection system utilizing a multi-nozzle, asynchronous injector. More precisely, in each 30 deg sector of the cylinder, the fuel is injected over two nozzle orifices (instead of one, as in the actual engine) each with different diameters and different injection directions, using totally independent injection timings. This means that, in opposition to the traditional split injection, the start of injection of the second fuel pulse (through the second orifice) can occur before the first pulse is finished. The different injection directions are characterized by the vertical and azimuthal spray angles. Note that the vertical injection angle, i.e., the angle of the spray axis with the cylinder axis, is zero when the spray is injected downward onto the cylinder.

In order to make the asynchronous injection agreeable with a common rail injection system, the injection pressures of the two orifices are assumed to be the same. This requires that the injection velocities of the two orifices are identical. Therefore, the fuel mass, \( m_i \), delivered through nozzle, \( i \) (\( i = 1, 2 \)) has been determined from the nozzle cross-sections, \( A_i \), the discharge coefficients, \( c_i \), and the injection durations, \( \Delta t_i \), assuming the same constant injection velocity for both pulses. As is discussed in more detail in [9], this leads to the fuel mass fraction ratio

\[
\frac{m_i}{m_{tot}} = \frac{c_i A_i \Delta t_i}{c_1 A_1 \Delta t_1 + c_2 A_2 \Delta t_2},
\]

where \( m_{tot} \) is the total injected fuel mass.

Observe that in each engine simulation the injection pressure, hence the injection velocity, is adjusted to reflect the given injection parameters such that the correct total fuel mass is delivered. Finally, it should be noted that the injection velocities have been limited such that the injection pressure does not exceed 210 MPa.

Four different optimization runs have been performed, each exhibiting a two pulse injection strategy. The starting conditions, together with the corresponding increments used in the computation of the gradients, are listed in Table 2.

The first computation case, Split, corresponds to a normal split injection with one nozzle orifice and two fuel pulses, possibly separated by a dwell. The other computation cases utilize the asynchronous injections, where the fuel is injected via two independent pulses through two different nozzle orifices. In these cases, the timing of the two pulses can (and does) overlap.

The second case, VAI (vertical asynchronous injection), in addition to the injection timings, also allows for variations of the vertical injection angle and a change in the diameter of the second orifice. The corresponding quantities of the first orifice are fixed at 80 deg\(^2\) and 0.285 mm, respectively. The azimuthal injection directions are the same for both orifices. Also, the starting conditions of this case is identical to the Split computation case.

The third and the fourth computation cases, AA11 and AA12 (azimuthal asynchronous injection 1 and 2), inject both fuel pulses at a fixed vertical injection angle of 80 deg, and in the azimuthal direction, the sprays are separated by a fixed angle of 10 deg. The AA11 case permits variations only for the injection timings, while the orifice diameters were fixed. The AA12 case, in addition to the injection timings, also allows for variations of the two nozzle diameters. It should be noted that both azimuthal asynchronous injection cases, AA1 and AA12, have the same starting conditions, namely, the first and second fuel pulses start at the same time. This is different from the VAI case, where at the starting point, the two fuel pulses are injected sequentially.

### RESULTS AND DISCUSSION

The results of the four optimization cases, together with the starting point values, are summarized in Table 4. The paths to the optimal emissions are illustrated in Figs. 1–3 for the NOx-soot, the NOx-SFC and the soot-SFC, respectively. In these figures, each symbol denotes the appropriate values at a pivot, and the

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**Table 3. Specifications for the Sulzer S20.**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bore [mm] x stroke [mm]</td>
<td>200 x 300</td>
</tr>
<tr>
<td>Compression ratio</td>
<td>13.6</td>
</tr>
<tr>
<td>Engine speed [rev/min]</td>
<td>1000</td>
</tr>
<tr>
<td>Orifices x diameter [mm]</td>
<td>12 x 0.285</td>
</tr>
<tr>
<td>Injection start [CA ATDC]</td>
<td>~10.5</td>
</tr>
<tr>
<td>Injected fuel mass [g]</td>
<td>1.02</td>
</tr>
<tr>
<td>Power output [kW/cylinder]</td>
<td>157.62</td>
</tr>
</tbody>
</table>

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1 The vertical injection angle is the angle between the spray axis and the cylinder axis. Zero degrees means that the spray is injected onto the piston.
**Figure 1.** NOx and soot values at the pivots of the search path.

**Figure 2.** NOx and SFC values at the pivots of the search path.

It is well known that split injections can be very effective in reducing emissions (cf. [19–21]). This has also been shown for the S20 in a previous study (cf. [7]) where both emission targets were met. However, that study also showed that split injection by itself can lead to high fuel consumption. Because the cost function in the present study is such that the SFC is weighted stronger with respect to the emissions than in [7], the optimization lead to an operating point with a considerably better fuel consumption, but at the cost of higher soot.

The VAI case—the asynchronous injection with variable vertical injection angle and orifice size for the second pulse—meets both EPA emission mandates after the second line search. The SFC value is only 3.1% higher than the starting value and 2.5% lower than the standard split injection case. The start of the first injection is at -2.3 CA with a duration of 16.6 CA. The second injection starts already at 5.9 CA and lasts for 15.4 CA, resulting in an overlap of 8.4 CA. The optimal vertical angle remained almost unchanged from its starting position, and the second nozzle diameter was just slightly reduced from 0.285 mm to 0.281 mm. Thus, there were only two parameters that experienced a significant change from their starting values, namely the start of injection and the overlap of the pulses. This shows that an asynchronous injection can achieve considerable emission reductions and improved fuel efficiency over a standard split injection. This is discussed in more detail below.

Both azimuthal asynchronous injection cases, AA11 and AA12, meet the EPA emission mandates after the third and fourth line search, respectively. In fact, the particulate values, PM, are considerably lower than in the previous two cases and lie well below the EPA mandate of 0.12 g/KW-hr. The SFC values are in-
increased by only 2.8% and 2.2%, respectively, over their starting values. In comparison with the VAI case, however, the SFC values are increased by 3.2% and 2.6%, respectively. Both of the AAII cases exhibit a temporal overlap of the two fuel pulses, the AAII overlap is 12.8 CA and the AAII2 is only 2.9 CA.

In the AAII case, the only parameters varied are the injection timings. As discussed below, the large injection overlap is the cause of the observed reduction in soot and NOx.

The shorter injection overlap of the AAII2 case, which presumably would lead to higher emissions, is partly compensated with the nozzle size variations. The first pulse, which lasts for only 7.8 CA, is injected through a nozzle orifice with diameter 0.32 mm, whereas the second fuel pulse, which lasts 26.3 CA, is injected through a hole with diameter 0.25 mm. As discussed below, the smaller diameter of the second orifice makes a significant contribution to the soot reduction, despite the relatively late injection into the expansion stroke.

The maximum cylinder pressures of the starting points and the four optimal points are also listed in Table 4. It can be seen that the starting points, which have low SFC values, exhibit the highest peak cylinder pressures. It is interesting to observe that the lowest maximum cylinder pressure is associated with the best SFC cases VAI and AAII2. This is quite unexpected and is a direct consequence of the asynchronous injection, where the relatively long injection delay of the first pulse is partly compensated by the overlapping injection of the second pulse.

**Split Injection versus Asynchronous Injection**

Split injection can be an effective means for reducing emissions, but in the absence of additional measures, it can lead to high fuel consumption (c.f. [7]). In a regular split injection, a limited amount of fuel is injected relatively early via the first fuel pulse, which is usually short enough to avoid generating too much heat, thus limiting the formation of nitric oxide. The subsequent dwell delays the supply of additional fuel which further limits the heat release, and thus leads to an additional suppression of NOx formation. In addition, the combustion products of the first pulse act as NOx-suppressant for the delayed second pulse in the same way that exhaust gas recirculation (EGR) does. This internal EGR effect, in combination with the delay of the second pulse, is responsible for the reduced NOx formation. On the other hand, this internal EGR effect leads to increased soot formation, and the lower temperatures of the late combustion phase are insufficient for an adequate soot oxidation. Consequently, the net soot is considerably increased. The mechanisms just described explain the relatively low NOx but high soot of the split injection case Split.
In contrast to the split injection, the asynchronous injection allows an overlap of the two injected fuel pulses. Thus, the total injected fuel can be supplied in a much shorter time interval (without the need for overly high injection pressures). In fact, the start of injection of the first pulse can be delayed further than in the split injection case, which helps in the suppression of NOx. For the computations under investigation, the start of the asynchronous injection in the VAI case is delayed by 4.4 CA in comparison with the split injection case, Split, but it stops 5 CA earlier. The fact that the fuel injection into the expansion stroke is shorter than in the split injection case works in favor of the soot suppression, hence explaining the better soot results in the VAI case. Further, the second pulse experiences an internal EGR effect, caused by the combustion products of the first pulse, which contributes to the observed NOx reduction.

The asynchronous injection provides an additional mechanism for the reduction of soot in the late combustion phase, namely through the use of a smaller diameter of the second injection orifice. Because of mass conservation, a reduced nozzle orifice leads to an increased injection velocity which improves the atomization, hence results in a better evaporation and an improved combustion. In turn, this leads to an increased soot oxidation, i.e., a reduction in the net soot. This is particularly prevalent for the second pulse, because, as is well known, a poorly atomized fuel spray injected into the expansion stroke leads to a large soot formation. This phenomenon explains the low emissions, soot in particular, in the AA12 case, where the overlap is smaller but the second nozzle orifice is considerably reduced. Note that this phenomenon also applies to the VAI case, but to a lesser degree.

In summary, the computed results illustrate the potential of the asynchronous injection to reduce emissions while maintaining high fuel efficiency.

**Computational Costs**

The computational cost is measured in terms of the number of cost function evaluations which correspond to the number of engine simulations. As can be seen in Table 4, these numbers lie between 19 for the VAI case, and 37 for the AA12 case. Each computation case depends on the number of parameters to be optimized, and how close the starting point is to the respective optimal point, i.e., the number of line searches. In other optimization methods such as in the µGA, typical numbers of reported cost function evaluations lie between 250 (cf. Senecal and Reitz [1]) and 400 (cf. Wickman et al. [2]). It must be pointed out, however, that in the cited µGA studies the cost function and the parameters that were optimized were quite different, and, as mentioned earlier, the optimal values are likely to correspond to a global optimum. Nevertheless, this study shows that gradient methods are computationally very effective in exploring new optimal injection strategies for engines, even though only a local minimum may have been reached.

**SUMMARY AND CONCLUSIONS**

In this study, a gradient-based optimization tool has been developed and, in conjunction with a CFD code, utilized in the search of new optimal fuel injection strategies. The approach taken uses a steepest descent method with an adaptive cost function, where the line search is performed with a backtracking algorithm. The backtracking algorithm utilizes quadratic and cubic polynomials to accelerate the convergence, and the initial backtracking step employs an adaptive step size mechanism which depends on the steepness of the search direction. The adaptive cost function is based on the penalty method, where the penalty parameter is increased after every line search. The parameter space is normalized and thus, the optimization is performed over the unit cube in higher-dimensional space.

The engine simulations were performed with a KIVA-3-based code which is equipped with well-established spray, combustion and emission models. The computations have been done for a Sulzer S20 diesel engine which, for the simulations, is equipped with a multi-orifice, asynchronous injection system. This system permits an independent timing of the fuel pulses, and each orifice has its own diameter and injection direction. Optimizations have been performed for a two-pulse injection strategy, and the optimization parameters include the start of the injections, the injection durations, the size of the nozzle orifices and the vertical injection angles.

The computations showed that, in opposition to the conventional split injection method, the asynchronous injection scheme meets the EPA mandates while keeping the fuel consumption low. The reasons for the improvement over the standard split injection lies in the fact that the asynchronous injection allows an overlap of the two injection pulses, which supplies the total fuel in a much shorter time to the cylinder (without the need of overly high injection pressures). This allows a long injection delay which, together with the internal EGR effect, leads to low NOx. At the same time, the short overall injection time prevents fuel from being injected too late, a fact which acts favorably in the reduction of the net soot. In addition, as in the AA12 case, a smaller nozzle orifice diameter of the second pulse can lead to a considerable improvement of the atomization process and hence a reduction in the soot formation.
In conclusion, this study illustrates that the adaptive steepest decent method applied to engine optimization is a computationally very effective tool to explore new optimal injection strategies.

REFERENCES


