Multi-Objective Optimization of Fuel Consumption and NOx Emissions for a Heavy-Duty Direct Injection Diesel Engine

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Table of Content

- Motivation
- Numerical Tools
- Objectives
- Computational Test Cases
- Results
- Conclusions
Simulation Supported Engineering Process

modeFRONTIER and SRM coupling

- Mixing time calibration

Process automation

1. Perform engine model training
2. Perform catalyst model training
3. Perform engine + catalyst simulation

Engine optimization

- In-cylinder content as ensemble of particles
- Local in-homogeneities ($T, Y$) and detailed chemistry
- Transport equation for Mass Density Function ($ρ_\text{FD}$)
Phenomenological Turbulence Modeling

\[
\frac{dk}{d\varphi} = \left( -\frac{2}{3} \cdot \frac{k}{V_{cyl}} \cdot \frac{dV_{cyl}}{dt} - \mathbf{e} + \left[ C_{sq} \cdot k_{sq}^{\frac{3}{2}} \right] \right) + C_{\text{inj}} \cdot \frac{dk_{a}}{dt} + C_{\text{sw}} \cdot C_{m}^{3} \cdot \frac{1}{6 \cdot n} \quad \text{(Eq. 1)}
\]

Source: P. Kozuch; Phenomenological model for a combined nitric oxide and soot emission calculation in DI diesel engines; 2004

\[
\mathbf{e} = C_{diss} \cdot \frac{k^{\frac{3}{2}}}{l} \quad \text{(Eq. 2)}
\]

\[
\tau_{\phi} = C_{t} \cdot \frac{k}{\mathbf{e}} \quad \text{(Eq. 3)}
\]

Multi-Objective Optimization

Dominated design: exist solutions with better (lower) values of both objectives

Pareto front: there doesn’t exist solutions with better values for both objectives

\((X,Y)\) belongs to Pareto front if: \(\forall i \not\exists (x^*, y^*): f_i(x^*, y^*) \leq f_i(X, Y)\)
Incremental Space Filler

Augmenting algorithm considering the existing points and adding new points sequentially by maximizing the minimum distance from the existing points
✓ Suitable for RSM training and GA optimization
✓ Uniform space filling
✓ Rejects unfeasible designs

Initial DOE

Points added using ISF
Uniform Latin Hypercube

✓ Stochastic space-filler DOE algorithm
   (advanced Monte Carlo sampling)
✓ Generates random numbers conforming to the uniform distribution
✓ Achieves high uniformity levels for each variable
✓ Tries to minimize correlations between input variables
   and maximize the distance between generated designs
✓ Suitable for RSM training and GA optimization
Genetic Algorithms

Genetic and Evolutionary Algorithms use the analogy of natural selection and reproduction as optimization target.

- Initial population
- Select the most fit individuals
- Crossover/mutation of genes
- Form new generation
- Display results

$n$ generations

Environment = Objectives/Constraints
Individual/genes = Design/values
Dominance = Solution Fitness
Genetic Algorithms

✓ Each individual (design) is coded by a binary string

✓ Best individuals are selected (by fitness or dominance criteria), and operators are applied to generate a new population
FAST Optimization Algorithm

Metamodels are Polynomials, Radial-Basis-Functions, Kriging and Neural Networks.

Evaluation of the real and virtual optimization results running them in SRM.
What is the objective of this work?

MULTI-OBJECTIVE OPTIMIZATION

COMBUSTION CONCEPT

Fuel Consumption

NOx emissions

0D SRM TRAINING
Engine Map Measurements

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type</td>
<td>Heavy-Duty Diesel</td>
</tr>
<tr>
<td>Displacement</td>
<td>6.7l</td>
</tr>
<tr>
<td>EGR</td>
<td>No external EGR</td>
</tr>
<tr>
<td>Injector</td>
<td>Direct Injection</td>
</tr>
<tr>
<td>Cylinders</td>
<td>6</td>
</tr>
</tbody>
</table>

Operating Conditions

- Single Main Injection
- Pilot+Main Injection
0D SRM Training

<table>
<thead>
<tr>
<th>RPM</th>
<th>Bar</th>
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</thead>
<tbody>
<tr>
<td>1700rpm</td>
<td>18bar</td>
</tr>
<tr>
<td>1300rpm</td>
<td>21.5bar</td>
</tr>
<tr>
<td>1300rpm</td>
<td>12.5bar</td>
</tr>
<tr>
<td>1300rpm</td>
<td>5.7bar</td>
</tr>
<tr>
<td>1200rpm</td>
<td>5.7bar</td>
</tr>
<tr>
<td>1200rpm</td>
<td>12.5bar</td>
</tr>
<tr>
<td>1200rpm</td>
<td>21.5bar</td>
</tr>
<tr>
<td>1000rpm</td>
<td>5.7bar</td>
</tr>
<tr>
<td>1000rpm</td>
<td>10.2bar</td>
</tr>
<tr>
<td>1000rpm</td>
<td>21.5bar</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>$C_{sq}$</th>
<th>$C_{inj}$</th>
<th>$C_{sw}$</th>
<th>$C_{diss}$</th>
<th>$C_{\tau}$</th>
<th>$C_{h}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.0</td>
<td>1.7</td>
<td>7.4</td>
<td>1.6</td>
<td>0.5</td>
<td>15</td>
</tr>
</tbody>
</table>
0D SRM Training

Normalized $x = \frac{x_i}{\bar{x}}$
Algorithm Selection

✓ The FAST NSGA-II predicts a well defined Pareto Front compared to NSGA-II, and needs less designs to do so.

✓ The Uniform Latin Hypercube (ULHC) is faster than the Incremental Space Filler algorithm.

✓ The Radial Basis Function is not used for the virtual optimization because it is computational too expensive.

✓ The FAST NSGA-II algorithm together with the Uniform Latin Hypercube space filler algorithm is selected for optimization.
Optimization Task

1. Minimize **ISFC and sNOx emissions** for each operating point.

2. Do not exceed **200bar peak cylinder pressure** (PCP) and **1000K turbine inlet temperature** (TIT). The **air-fuel-ratio** (AFR) is allowed to change between **-3.0 and +3.0**.

3. Optimize the operating parameters of each operating point individually:
   A. Start of Injection: **-16°CA aTDC to +6°CA aTDC**,  
   B. Injection Pressure: **800bar to 2000bar**,  
   C. Compression Ratio: **15 to 21**,  
   D. Initial Temperature: **340K to 390K**,  
   E. External EGR: **0% to 20%** (mass-based).
How the results are presented

\[ \Delta x = \left( \frac{x_{\text{exp}} - x_{\text{sim}}}{x_{\text{exp}}} \right) \cdot 100\% \]

Average of all operating points:

-5%
Optimization Results

-5%  
58%  
+40%  
12%

BMEP /bar  
Speed / rpm

1700 1300 1300 1300 1200 1200 1200 1000 1000 1000 1000

18 21.5 12.5 5.7 5.7 12.5 21.5 5.7 10.2 21.5

1700 1300 1300 1300 1200 1200 1200 1000 1000 1000 1000

18 21.5 12.5 5.7 5.7 12.5 21.5 5.7 10.2 21.5

1700 1300 1300 1300 1200 1200 1200 1000 1000 1000 1000

#estecoUM18
Optimization Results

+23%

+38%

+322%

+1.22°CA
The compression ratio is most effective for part load operating point efficiency.

Full load operating points are highly limited by PCP and TIT.
Conclusions

✓ Simulation Supported Engineering Process based on modeFRONTIER and SRM is successfully established.

✓ Global SRM mixing time training is 60% faster due to process automation.

✓ Tabulated chemistry accelerates the SRM simulation by factor 1000 compared to online chemistry.

✓ The modeFRONTIER and SRM based optimization process takes 1.8min/design and is faster compared to a CFD based optimization approach (up to 16h/design).

✓ The FAST NSGA-II algorithm with the ULHC space filler performed the best for the Heavy-Duty Diesel engine optimization.

✓ The ISFC could be reduced by 5% in average and the sNOx emissions are reduced by 58% in average.
THANK YOU FOR YOUR ATTENTION