Fast response surrogates and sensitivity analysis based on physico-chemical engine simulation applied to modern compression ignition engines

Owen Parry, Julian Dizy, Vivian Page, Amit Bhave, David Ooi

Abstract
Virtual engineering that combines physico-chemical models with advanced statistical techniques offers a robust and cost-effective methodology for model-based IC engine calibration and development. The probability density function (PDF)-based Stochastic Reactor Model (SRM) Engine Suite is applied to simulate a modern diesel fuelled compression ignition engine. The SRM Engine Suite is coupled with the Model Development Suite (MoDS) to perform parameter estimation based on the engine measurements data at representative load-speed operating points. The fidelity of the SRM Engine Suite is further tested by carrying out blind tests against measurements for combustion characteristics (heat release rate, in-cylinder pressure profile, etc.). The comparison between the calculated (software evaluated) and the measured combustion characteristics shows good agreement. Furthermore, the model evaluations for engine-out soot and NOx emissions agree relatively well with those measured over the entire engine load-speed operating window. Fast response computational surrogates are generated using High Dimensional Model Representation (HDMR), the performance of which are then compared with the validated SRM Engine Suite. The associated global sensitivities are also evaluated to understand the influence of the engine operating conditions and the model parameters on combustion metrics such as ignition delay, maximum heat release rate, maximum pressure rise rate and peak in-cylinder pressure. The benefits of the proposed methodology, comprising formulation of physico-chemical model-based surrogates and its application to software-in-loop (S-i-L) and control in compression ignition engines, are also discussed.

1 Introduction

Demonstrating continuous reduction of vehicular/machine and powertrain development costs and time through the use of model-based engineering analyses is key to the wider adoption of innovative virtual or digital engineering workflows that augment experimental analyses. The variability and complexities of the modern powertrain control calibration with the increasing degrees of freedom offer significant opportunities for model-based engineering to yield cost-reduction benefits, while developing vehicles and non-road machines that comply with stringent CO2 and other gas phase as well as particulate phase emissions regulations.

Traditionally, engine calibration has relied on engine dynamometers and vehicle testing. The Engine Control Unit (ECU) development has conventionally been dependent on look-up table based approaches, or on cost-intensive closed-loop control strategies that rely on several production-level sensors [1]. Measurement-driven engine calibration methodology involves the generation of engine data, generally dictated by a design of experiments (DoE) strategy. The data points are then used to build statistical meta-
models, or response surfaces, of various combustion characteristics; for instance, engine performance and emissions as a function of engine load and speed. Optimisation techniques are then applied to these fitted meta-models to identify optimal actuator settings at individual load-speed points, followed by interpolation in order to generate smooth actuator maps.

The powertrain system complexity and the necessary design iterations within the measurement-driven calibration provide further impetus to augment the calibration with model-driven methods. Model-based methodology with calibrated zero dimensional (0D) models that incur low computational expense have been widely applied to control applications. For example, recently a 0D model was applied towards prediction and optimisation of combustion and engine performance parameters such as the angle corresponding to 50% of fuel mass fraction burnt (MFB50), the maximum in-cylinder pressure and indicated mean effective pressure (IMEP) for model-based combustion control [2]. The same combustion and performance characteristics were also estimated elsewhere for feed-forward control within the ECU [3,4,5]. In another study, based on test measurements from a 4-cylinder compression ignition engine, mean value models for fuel consumption and emissions were used for model-based optimal calibration [6]. However, adequate model-accuracy is crucial to the design of an optimal, fast-response and robust control system [7]. Using physics-based models is hence necessary to ensure the accuracy of the results and importantly the applicability of the model to a wide range of driving conditions, and even other engines [8].

To exploit the predictive capability of combustion characteristics offered by 3D computational fluid dynamics (CFD) models, a two-step methodology can be adopted. First, a detailed CFD simulation is run in order to populate the training datasets, followed by regression analysis to construct the response surfaces. The potential for various regression techniques, such as K-nearest neighbours, Kriging, Neural Networks and Radial Basis Functions to replace or partially substitute CFD evaluations has been studied by [9]. The efficiency of the methodology still largely depends upon the number of CPU-intensive CFD evaluations, which is dictated by the Design of Experiment (DoE) method adopted and the number of design parameters. Simulating an individual load-speed operating point using 3D CFD with detailed chemical kinetics can take up to a day or two, making it impractical to cover the whole design space.

To realise efficient model-based engineering, it is vital to combine the predictive capability of simulation with practical computational overhead. Furthermore, to shorten powertrain development cycles, it is important to equip simulation engineers with systematic methodologies that make predictive simulation-based workflows more robust and more accurate.

Recently, Extremum Seeking (a gradient-based optimisation approach) was used to calibrate the heat transfer coefficient in a semi-empirical, simplified engine model in order to minimise the error between the measured and modelled in-cylinder pressure [7]. Initial model parameter values were selected based on experience and on studies in the literature in order to improve the likelihood of finding a global, rather than local, minimum in the cost function.

A hybrid calibration method based on a combination of physics-based models and optimisation methods has been proposed [10]. The entire IC engine simulation model was divided into sub-systems and the parameters calibrated using measurement data on the sub-system level. This step was then followed by performing calibration with a reduced number of the most dominating parameters in several loops, while using the entire IC engine simulation together with optimisation methods. In another study, [11]
has also demonstrated automated calibration of combustion and heat transfer parameters, such as the radiation coefficient, the combustion terminal angle, combustion speed, etc., using a combination of ant colony and genetic algorithms. The aim of this paper is to present a methodology for developing IC engine models with high predictive capability and low computational expense, making them ideal candidates for model-based engineering workflows such as model-in-loop or software-in-loop.

To achieve this objective, the probability density function (PDF)-based SRM Engine Suite was chosen for simulating fuels, combustion and emissions in modern IC engines [12-15]. The physico-chemical simulator was then coupled with an advanced statistical toolkit, Model Development Suite (MoDS) [16-18], to calibrate the model “automatically” based on the measurements data. This represents a significant improvement over previous attempts involving manual calibration [19]. MoDS was then used to generate fast-response surrogates and perform sensitivity analysis of key combustion characteristics and emissions as a function of engine operation variables.

The paper is organised as follows: First, the Tier 4 capable IC engine geometry and operating conditions are presented. Then, the two software toolkits that were used, i.e. the SRM Engine Suite and MoDS, are introduced. Both have been applied in numerous studies elsewhere, hence, to avoid repetition, only the features unique to the present paper are explained. The automated base model calibration in terms of the in-cylinder pressure profile, soot and NOx emissions performed over the representative engine load-speed operating points is presented, followed by the results of the blind tests carried out on additional engine operating points. This is followed by the discussion on the quality of the computational surrogates generated and the sensitivity of the combustion and emissions characteristics of interest on engine operating variables.

1.1 Engine

The data used for model validation has been obtained from a Cat® C4.4 ACERT turbocharged Diesel-fuelled Compression Ignition (CI) engine. In total, 146 steady state operating points with single and double injection strategies were obtained during the present study. Table 1 provides the basic engine geometry data, whereas the steady state load-speed operating points are displayed in Figure 2. Please note that the load-speed points used in this study are not representative of the engine’s final calibration.

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Table 1 – Engine geometry for the Cat® C4.4 ACERT single-turbocharged Diesel-fuelled Compression Ignition (CI) engine.
Figure 1 – The Cat® C4.4 ACERT single-turbocharged Diesel-fuelled Compression Ignition (CI) engine.

1.2 SRM Engine Suite

The SRM Engine Suite is an advanced toolkit to simulate fuels, combustion and emissions in IC engines. Figure 2 presents a snapshot of the software graphical user interface (GUI). The GUI offers the users an intuitive workflow for creating a new engine model based upon engine templates and a fuels library. The main inputs concern basic engine geometry, operating conditions, and fuel characteristics, with advanced features to account for characteristic k-ε turbulent mixing time profiles, injection mass rate profiles, etc.

Figure 2 – A screenshot showing the SRM Engine Suite graphical user interface.

The software has been successfully applied to simulate unsteady spark ignition (SI) combustion [20-22], conventional compression ignition [23] including dual-fuel (natural gas with Diesel pilot), partially premixed charge compression ignition (PPCI) as well as other low temperature combustion modes of engine operation [24-27]. In addition, engine breathing (intake and exhaust) and EGR (including the species concentrations) are also accounted for by the software. However, other powertrain components such as heat exchangers, turbocharger, etc. are not modelled within the SRM Engine Suite. In such instances, the SRM Engine Suite offers a coupling for co-simulation with 1D and 3D toolkits [28,29].

The SRM (Stochastic Reactor Model) Engine Suite uses a Probability Density Function (PDF) transport equation [30,31] based approach and accounts for the detailed chemistry of fuel oxidation and the emissions formation pathways. The model also accounts
for the inhomogeneities in the $\phi$-T space (chemical equivalence ratio; temperature) by mimicking the sub-processes of turbulent mixing, wall heat transfer, multiple direct injections, etc. For variable density flows, an MDF (mass density function) rather than a PDF is used to describe the SRM. This MDF is then solved using a Monte Carlo particle method with a second-order operator splitting algorithm [31].

The SRM Engine Suite provides four model parameters which have been calibrated to represent the experimental heat release rate (HRR) and the in-cylinder pressure:

- The liquid fuel evaporation coefficient which influences the atomisation of the injected spray into the turbulent flow ($\lambda_{\text{evap}}$).
- The heat transfer coefficients which impact the heat transfer between the flow within the cylinder and the combustion chamber surface ($C_1$, HRC$_2$)
- The characteristic turbulent mixing time ($k/\varepsilon$) parameter used to control frequency of mixing events ($C_\Phi$).
- The injector spray distribution term, directly related to the injected spray angle within the cylinder ($\alpha_{\text{inj}}$).

Additional calibrated parameters include:

- The turbulent mixing time during injection ($C_\Phi_{\text{inj}}$).
- The stochastic heat transfer constant ($C_{\text{HT}}$).
- The Sauter Mean Diameter constant ($\text{SMD}_A$).

The empirical soot sub-model has four input parameters. The rates of soot formation and oxidation are controlled by pre-exponential multipliers ($C_{\text{sfe}}$ and $C_{\text{soe}}$ respectively) and exponential multipliers ($C_{\text{sfe}}$ and $C_{\text{soe}}$ respectively).

Finally, the NO$_x$ sub-model has a single scaling coefficient ($C_{\text{NO}_x}$) which was applied globally (for all operating points studied).

1.3 MoDS

MoDS is a highly flexible software package designed to simplify model development using an advanced suite of numerical and statistical tools. Models can take a variety of different forms, including virtually any executable that can be run from the command line and reads (writes) its inputs (outputs) outputs from (to) file. The key features of MoDS include:

- **Automatic parameter calibration** - Calibrate a model against an existing data set.
- **Uncertainty analysis** – Find the parameters with the largest uncertainties and/or propagate those uncertainties through a model.
- **Fast response/surrogate models** – Generate surrogates to approximate results from a detailed model, but which can be evaluated in a tiny fraction of the time. The user can choose between polynomial, HDMR and Kriging.
- **Sensitivity analysis** – Quantify how much of the variance in the model outputs is due to each model input.
- **Multi-processor support** – Parallelise workflows via MPI.
- **An intuitive GUI** - Supports the design process and guides the user through the work-flow (see Figure 2).

The features of automatic calibration, surrogate construction and sensitivity analysis form much of the basis for this work and are described in more detail in the following section.
1.4 SRM-MoDS Coupling

1.4.1 Base Model Calibration

The twelve model parameters described in the previous section were calibrated automatically through MoDS using data from experiments performed at \( N = 30 \) operating points. The operating points were defined via 10/13 (single/double) injection process conditions, \( x \). 300 points on the pressure profile, together with \( \text{NO}_x \) and soot emissions data, \( y \), were used to compare the model and the experiments.

The goodness of the model parameters, \( \theta \), was calculated using a least-squares objective function,

\[
\Phi(\theta) = \sum_{i}^{N} \left( \frac{y_i - f(x_i, \theta)}{\sigma_i} \right)^2
\]

(1)

To initialise the calibration, a high-dimensional uniform sampling method, based on Sobol sequences [32], was used to select suitable starting values for the model parameters being calibrated [33].

The local optimisation was then carried out using Hooke and Jeeves’ algorithm [34]. This algorithm was chosen in preference to gradient-based methods which were previously found to perform poorly on similar model systems. At each iteration of the optimisation process, MoDS provides inputs to the SRM Engine Suite, runs it, and evaluates Equation (1) for each output. MoDS then modifies the model inputs according to Hooke and Jeeves’ algorithm, with the aim of minimising \( \Phi(\theta) \), and begins the next iteration.

1.4.2 Blind Tests

To test the predictive capability of the calibrated model, its output at a further 30 operating points was compared to corresponding experimental data.

1.4.3 Surrogate Construction and Sensitivity Analysis

MoDS was used to fit surrogate models to the SRM Engine Suite data in order to enable rapid evaluation at new operating points. The high dimensional model representation (HDMR) method was used to fit the surrogates, as it allows for the automatic selection of the polynomial order of the surrogate. Another benefit of the HDMR method is that the coefficients can be used to calculate the global sensitivity of each output.
variable to each input variable. The foundation of the HDMR method is the series decomposition of each model output (response) using orthonormal basis functions.

2 Results and Discussion

This section examines results from the three main phases of the study: the calibration of the SRM Engine Suite to experimental data, testing of the model against data not included in the calibration (blind tests) and the construction of surrogates to approximate the detailed model results. In each case, simple metrics are used to compare the in-cylinder pressure profiles, raw concentrations of NO\textsubscript{x} and soot emissions.

2.1 Base Model Calibration

The base model calibration yields a global set of model parameters applicable over the entire load-speed operating window. The results in this section assess the quality of the calibration by directly comparing with experimental data for in-cylinder pressure, NO\textsubscript{x} and soot emissions. This validation is a necessary step before testing the model under other process conditions.

2.2 In-cylinder pressure profile

In order to quantify how well the calibrated SRM Engine Suite reproduces the experimentally-measured in-cylinder pressure profiles (as a function of crank angle), a positive fractional difference was computed for each profile. That is, the average error at an operating point with process conditions \( \mathbf{x} \) was defined as

\[
P_{\text{err}}(\mathbf{x}) = \frac{\sum_{i}^{N} \text{abs}[P_{\text{exp},i(\mathbf{x})} - P_{\text{SRM},i(\mathbf{x})}]}{N} \tag{1}
\]

where \( N = 30 \) is the number of operating points. The torque-speed map of \( P_{\text{err}} \) presented in Figure 4 shows that the SRM Engine Suite is able to match the experimental pressure data well – differences are less than five per cent at all operating points and typically less than three per cent in the upper halves of the speed and torque ranges.

![Figure 4 - A torque-speed map of the average fractional difference in In-cylinder pressure between the SRM Engine Suite and experimental data. The average is computed over 300 points in the pressure profile. The grey labelled circles show the 30 operating points used in the model calibration.](image-url)
2.3 NO\textsubscript{x} emissions

In this section, the raw concentrations of engine-out NO\textsubscript{x} (i.e. NO + NO\textsubscript{2}) will be presented as a comparison between the experimental data and the SRM Engine Suite predictions.

Figure 5 shows the experimentally-measured raw NO\textsubscript{x} output concentration from the C4.4 engine, as a function of torque and speed. There is a clear trend for increased NO\textsubscript{x} emission at low speeds.

![Figure 5 - A torque-speed map of the experimentally-measured raw NOx emissions. The grey labelled circles show the 30 operating points used in the model calibration. Redder colours correspond to higher NOx emissions.](image1)

Figure 6 depicts the raw NO\textsubscript{x} output concentration predicted by the SRM Engine Suite as a function of torque and speed. The calibrated model is able to capture the trend in the experimental data for higher NO\textsubscript{x} emissions at lower speeds and torques.

![Figure 6 - A torque-speed map of the NOx emissions predicted by the SRM Engine Suite. The grey labelled circles show the 30 operating points used in the model calibration. The scale used to map NOx values to colours is the same as in Figure 5.](image2)

Figure 7 illustrates the difference in the raw NO\textsubscript{x} output concentration predicted by the SRM Engine Suite and that measured experimentally for the C4.4 engine. The model...
matches the experimental NO\(_x\) data to within 40 per cent at all operating points, and to better than 20 per cent at most of the steady state load-speed operating points. Almost invariably, the discrepancies between the model and the experiments are due to an underprediction of the raw NO\(_x\) by the model compared to the experimental data.

Figure 7 - A torque-speed map of the fractional difference in NO\(_x\) emissions between the SRM Engine Suite and experimental data. The grey labelled circles show the 30 operating points used in the model calibration.

### 2.4 Soot emissions

Following the same format as the previous section, the engine-out soot concentration will be analysed as a function of load and speed, including assessing the accuracy of the SRM Engine Suite predictions relative to the experimental measurements. Figure 8 plots the experimentally-measured soot output from the C4.4 engine as a function of torque and speed. Soot emissions are relatively constant across all operating points, increasing only slightly with engine speed. We note that the elevated emissions observed at point 27 could be explained by the fact that the engine is not being operated optimally; the operating points shown here do not exactly match those used in the final engine calibration.

Figure 8 - A torque-speed map of the experimentally-measured soot emissions. The grey labelled circles show the 30 operating points used in the model calibration. Note that no colour scale is included here in order to protect data confidentiality. Redder colours correspond to higher soot emissions.
Figure 9 shows the soot output predicted by the SRM Engine Suite as a function of torque and speed. Similar to the experimental data, the model predictions are relatively flat across the speed-torque plane, but the calibration is able, to an extent, to capture the increased emission at operating point 27.

![Figure 9 - A torque-speed map of the soot emissions predicted by the SRM Engine Suite. The grey labelled circles show the 30 operating points used in the model calibration. The scale used to map soot emission values to colours is the same as in Figure 7.]

The difference in the soot output predicted by the SRM Engine Suite and that measured experimentally for the C4.4 engine is shown in Figure 10. The model typically underestimates the measured soot output by 10-50 per cent at low speed and high torque, and by a factor of two at low torque.

![Figure 10 - A torque-speed map of the fractional difference in soot emissions between the SRM Engine Suite and experimental data. The grey labelled circles show the 30 operating points used in the model calibration.

2.5 Blind Tests

While the model is relatively successful at matching the calibration data, it is of course important to validate its performance with data not included in the calibration. For these blind tests, 30 more operating points were selected and the model re-evaluated under
the new conditions. In the following section, the results of these tests are presented in the form of model-experiment difference maps for in-cylinder pressure, NO\textsubscript{x} and soot emissions.

2.5.1 In-cylinder pressure (blind tests)

A torque-speed map quantifying the average model-to-experiment discrepancy for in-cylinder pressure, $P_{\text{err}}$, (See Equation 2 for calculation) at the 30 blind test operating points can be seen in Figure 11. Comparing with Figure 4, it is clear that the model performs as well at the blind test points as it does at the calibration points. There is a similar trend for larger discrepancies at low engine speeds, but even in those cases the model remains accurate to within four or five percent.

![Figure 11 - A torque-speed map of the average fractional difference in in-cylinder pressure between the SRM Engine Suite and experimental data for 30 operating points not included in the model calibration (labelled grey circles).](image)

2.5.2 NO\textsubscript{x} emissions (blind tests)

Figure 12 depicts the difference in the NO\textsubscript{x} output predicted by the SRM Engine Suite and the experimental data for the 30 blind test operating points. The performance of the model at the test points is similar to the calibration points (Figure 7) except for very low torques where the model-experiment discrepancy is between 50 and 90 per cent.
2.5.3 Soot emissions (blind tests)

The difference in the soot output predicted by the SRM Engine Suite and the experimental data for the 30 blind test operating points is plotted in Figure 13. Both the magnitude of the difference between experiment and model and the trend with speed and torque is very similar to the calibration points (Figure 10).

2.6 Surrogate and Sensitivities

The HDMR surrogate was constructed using 1000 Sobol points sampled from within the process-condition space containing all 60 operating points (those used in the initial calibration, and those used to test the calibrated model). Separate surrogates were generated for the single and double injection cases. The motivation for treating the two separately was that three extra process conditions are required to describe the double injection cases. While the model could have been made to mimic single injection cases by (for example) setting one injection mass to zero, this effectively makes all single
injection operating points edge cases of the surrogate model, which is not desirable from a numerical point of view. To assess the quality of the surrogates, they were evaluated at the 30 engine load-speed points used in the original MoDS calibration. The soot and NOx results from the surrogates were then compared with the results obtained from the SRM Engine Suite. The performance of each surrogates relative to the SRM Engine Suite is shown in Figure 14 and Figure 15. The surrogates capture NOx trends relatively well across most of the 30 operating points. However, at the low speed, single injection points (13 to 15), the surrogate fails to reproduce the trend in NOx emission predicted by the SRM Engine Suite. Both surrogates provide a reasonable match to the soot emissions predicted by the detailed model across the majority of the operating points. Once again, the largest discrepancies are seen at the mid to low speed operating points (9 to 15).

A useful characteristic of HDMR surrogates is that the coefficients of each term in the decomposition can be used to compute the global sensitivity of each output to each input. In Figure 16 the sensitivity of the in-cylinder pressure to different process conditions is shown. Note that, since the pressure profiles comprise 300 data points, each of which requires its own surrogate model, the sensitivity values quoted here are averages across the whole profile. Figure 16 reveals that the predicted pressure profile is most affected by the initial pressure and the injection parameters, which together explain more than 90 per cent of the total variance.

Figure 14 - A comparison of NOx results between the SRM Engine Suite and surrogates for both single and double injection operating points. Note that no scale is included here to protect data confidentiality.

Figure 15 – A comparison of soot results between the SRM Engine Suite and surrogates for both single and double injection. Note that no scale is included here to protect data confidentiality.
Sensitivities are also shown here for NO\textsubscript{x} (Figure 17) and soot (Figure 18). Where there are two parameters shown, this represents the sensitivity of the model output to varying both of the parameters simultaneously. In both cases, emissions are shown to be most sensitive to the injected mass of fuel. In addition, NO\textsubscript{x} emissions are sensitive to the EGR fraction and to the injection parameters, whilst soot is affected more by the initial pressure. These factors account for around 70 and 80 per cent of the total variance in NO\textsubscript{x} and soot emissions respectively.
2.7 Parameter sweeps

In order to rigorously assert the robustness of the calibration and the performance of the model, a set of parameter sweeps on the full load rated speed operating point has been performed. The parameters being swept include EGR fraction, injection timings and boost pressure. Due to confidentiality reasons, the ranges used in these swings and the specific configurations of each case cannot be disclosed. The output measures that will be considered in this study are, as in the previous sections: in-cylinder pressure, NO\textsubscript{x}, and soot.

The automated calibration procedure employed for this study is described in Section 2.1; it uses 18 calibration points and 42 blind test points. The concatenated pressure profiles, together with a zoomed-in profile for a single case, are plotted in Figure 19. These are composed of all of the individual control points that are accounted for in the objective function during the calibration. From the individual profile, it is clear that the SRM model is able to capture not only peak cylinder pressure, but also the start of combustion for both the pilot and the main, the total duration and the correct amount of heat transfer throughout the cycle, in particular in the expansion stroke. To this end, a few pressure control points have been added to the objective function just before EVO in order to ensure that the total heat transferred to the walls is accurate.

![Pressure profile](image)

*Figure 19 – Upper panel:* The in-cylinder pressure profiles for the calibration and blind test points, concatenated into a single series. The SRM Engine Suite profiles are plotted as red lines and the experimental data as blue lines and points. The vertical dashed line separates the calibration cases (left) from the blind tests (right). *Lower panel:* The pressure profile for case 14 as a function of crank angle. The colours and line styles are the same as those used in the upper panel.

Looking at the NO\textsubscript{x} emissions, shown in Figure 20 and covering a wide range of values (the highest value shown is 1250ppm larger than the smallest one), one can observe that both the trends and the absolute values are reflected in the SRM predictions, not only for the calibrated cases, but also in the blind tests.
Figure 20 - The NO\textsubscript{x} emission measured experimentally (blue lines with points) and predicted by the SRM Engine Suite (red line) for each of the 60 combinations of the sweep parameters. The vertical dashed line separates the calibration cases (left) from the blind test cases (right).

Finally, considering soot emissions, it is worth noting that this heavy-duty engine utilises a highly-optimised combustion system that produces very little soot at full load, making it remarkably difficult to simulate and predict trends and absolute differences from point to point. Nonetheless, the calibrated Hiroyasu model included in the SRM Engine Suite, using acetylene (C\textsubscript{2}H\textsubscript{2}) as a precursor in each stochastic parcel, generates very satisfactory values which contain the majority of the trends and can be scaled successfully to account for the magnitude of these differences too, as evidenced in Figure 21.

Figure 21 - The soot emission measured experimentally (blue lines with points) and predicted by the SRM Engine Suite (red line) for each of the 60 combinations of the sweep parameters. The vertical dashed line separates the calibration cases (left) from the blind test cases (right).
3 Conclusions

The SRM Engine Suite was used to simulate the C4.4 diesel-fuelled compression ignition engine. It was calibrated automatically via MoDS software using experimental data taken at thirty representative engine load-speed operating points. The calibrated model matches in-cylinder pressure profiles and NO\textsubscript{x} emissions well, soot emissions to a lesser extent (factor of two). Blind testing of the SRM Engine Suite produces similar results, broadly validating its use at the full load-speed operating window. One exception is NO\textsubscript{x} emissions at low torque where the errors are significantly larger than for the calibrated points. In a parameter sweep test, where boost pressure, EGR percentage and injection timings are largely perturbed, the physics included in the SRM Engine Suite account well for the underlying phenomena and predicts the aforementioned measures (in-cylinder pressure, NO\textsubscript{x} and soot) to a high degree of accuracy. Surrogates provide a reasonable approximation to the full SRM Engine Suite results, particularly for the double injection operating points. The worst surrogate performance for NO\textsubscript{x} and soot is for single injection at mid-to-low speed, where differences are approximately a factor of two.

The coupling of SRM Engine Suite and MoDS to perform automatic calibration of a detailed engine model to experimental data, followed by the generation of fast-response surrogates and associated sensitivities, constitutes a powerful tool for automotive engineers.

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6 Definitions/Abbreviations

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<td>EGR</td>
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<td>Indicated Mean Effective Pressure</td>
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References


7 Appendix

Figures 22 and Figure 23 show in-cylinder pressure profiles for the two sets of 30 operating points used to calibrate and test the model.

![Pressure Profiles](image)

Figure 22 - Pressure profiles for each of the 30 operating points used to calibrate the model. The blue dashed and red solid lines correspond to the experimental data and SRM Engine Suite predictions respectively.
Figure 23 - Pressure profiles for the 30 operating points used to blind-test the model. The blue dashed and red solid lines correspond to the experimental data and SRM Engine Suite predictions respectively.
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