Enhancing internal combustion engine fault detection through co-simulation with piezo-electric pressure measuring chains

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Abstract. This study undertakes a proof-of-concept investigation, employing a combination of physics-based and empirical models to analyze an in-cylinder pressure piezo-electric measurement chain. The primary objective is to systematically characterize and comprehend deviations arising from the components within the measuring chain. The method implemented elucidates the real-time capabilities of the measuring chain model, thereby refining raw measurement data to discern deviations (errors) in the measuring chain components. This endeavor is geared towards facilitating effective condition monitoring and enhancing system reliability. We detail our approach, which integrates co-simulation techniques with piezo-electric pressure measuring chains, to detect and mitigate faults within internal combustion engines. Through this approach, we develop a comprehensive understanding of the underlying dynamics of the measuring chain, allowing for automated parameter estimation using genetic algorithms. Our key findings reveal significant improvements in fault detection accuracy, with a notable reduction in in-cylinder pressure errors. This study not only contributes to advancing fault detection methodologies but also holds promise for optimizing engine performance and reliability in various applications.

1 Introduction

In-cylinder pressure analysis stands as a well-established and widely applied technique in the research and development phase of internal combustion engines. While the use of in-cylinder pressure measurement chains during engine operation runtime is a relatively recent introduction, its adoption has been hindered by the considerable expense associated with the measurement equipment. However, the landscape is evolving with increasingly stringent emission regulations and the reduction of hardware costs due to production scaling factors. Consequently, in-cylinder pressure measurement during engine runtime emerges as a pivotal enabler for the next generation of clean engine combustion systems.

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The paramount performance factor of measurement systems is the quality of pressure data. A significant challenge lies in maintaining data quality within defined limits over extended, unmonitored periods. The stability of pressure data quality under dynamically changing operating conditions facilitates the application of closed-loop combustion control systems during engine runtime. In conventional research and development systems, measurement data is typically monitored or examined after the measurement process, rather than in real-time.

Priority design targets for high-performance propulsion systems development include emissions and fuel efficiency. By meticulously measuring and characterizing combustion system performance, it becomes feasible to operate the engine at an enhanced level of efficiency. Specific areas of focus for high-performance/efficiency engine applications encompass motorsports, marine, and stationary engines. In-cylinder pressure values, indicative of both abnormal and normal combustion modes, can be directly utilized in the engine control-loop. Piezo-electric measurement chains have firmly established their presence in in-cylinder pressure measurement, both in research and runtime applications.

1.1 Background

The selection of engine in-cylinder pressure as a primary driver for the development of an engine fault detection modeling technique is underpinned by a multitude of considerations, with the target application area standing as the predominant factor. Complexities associated with accuracy, simulation speed, functionality, cost, and other influencing factors emerge as pivotal constraints in this discerning choice.

In the work conducted by Al-Durra et al. [1], a noteworthy contribution was made through the development of a model capable of estimating in-cylinder pressure traces for a 2499cc 4-cylinder diesel engine. The resulting pressure trace model underwent rigorous comparison with empirical test data, demonstrating a commendable degree of accuracy in mirroring the engine's test data.

Korres [2], in his study, delved into the potential enhancements achievable in engine fault diagnosis, with a specific focus on in-cylinder pressure, employing closed-loop engine models. Recognizing indicators such as the point of peak pressure, pressure inclination after inlet valve closure, and pressure during the compression phase proved instrumental in identifying the root cause of engine faults.

Kao et al. [3] posited in their research that in-cylinder pressure traces could serve multifaceted purposes, including estimations for fuel burn rate, heat release rate, and air-fuel ratio. Consequently, the in-cylinder pressure trace emerges as a valuable tool in the detection of engine faults such as misfires.

The imperative nature of combustion fault detection in large-scale marine engine applications was underscored by Watzenig et al. [4]. Large-scale marine engines, operating for prolonged periods at high seas, are susceptible to increased downtimes. The authors developed a model-based in-cylinder pressure approach, successfully detecting changes in the compression ratio and increased blow-by effects, thereby signaling the need for maintenance before potential failures.

Contributing to the field, Casoli et al. [5] developed an in-cylinder pressure model-based approach for engine optimization, diagnostics, and the reduction of development time. Their approach seamlessly integrated crank-based modeling with a real-time technique, resulting in a validated real-time 4-cylinder diesel engine model that exhibited noteworthy agreement with validation test data.

A critical consideration in fitting in-cylinder pressure measurement hardware to commercial engines revolves around the substantial challenges posed by cost, durability, and reliability of the measurement system.

Lui et al. [6] innovatively introduced a software-based in-cylinder pressure estimation model designed to operate without additional measurement hardware, leveraging the engine's crankshaft kinematics. While proving to be a viable approach, they encountered accuracy issues at in-cylinder peak pressures.

To address the challenge of in-cylinder pressure estimation, Kulah et al. [7] integrated a software-based approach with a pressure transducer fitted to a single cylinder of a 6-cylinder diesel engine. Utilizing data from the pressure transducer and crankshaft kinematics, they successfully estimated and corrected the pressure in the remaining 5 cylinders via a feedback loop. The model demonstrated robust performance across a wide range of engine operational points, overcoming the challenge of pressure prediction for transient operating conditions.

2 Aim and objectives

This study meticulously examines the feasibility of developing a model-based in-cylinder pressure monitoring system tailored for large-scale marine or stationary engines, aiming to ensure uninterrupted and reliable operation. To achieve this overarching aim, the study meticulously outlines the following specific objectives:

- Development of a Crank-Resolved, Physics-Based Engine Model:

This objective entails the creation of a comprehensive and intricately detailed crank-resolved engine model based on fundamental principles of physics. The model aims to provide a thorough representation of engine behavior, serving as a foundation for subsequent analysis.

- Development of a Simulink-Based, Piezo-Electric Pressure Measuring Chain Model:

This objective involves the construction of a Simulink-based model specifically tailored for a piezo-electric pressure measuring chain. The model is designed to simulate the intricate interactions within the measuring chain, ensuring a nuanced representation of the in-cylinder pressure measurement process.

- Integration and Co-Simulation of the Two Models:

This objective focuses on the seamless integration and co-simulation of the crank-resolved engine model and the Simulink-based piezo-electric pressure measuring chain model. The successful amalgamation of these models is crucial for obtaining a comprehensive understanding of the in-cylinder pressure dynamics.

- Development of an Optimization Procedure for Automated Measuring Chain Model Parameter Estimation:

This objective centers on the formulation and implementation of an optimization procedure aimed at automating the parameter estimation process for the piezo-electric pressure measuring chain model. This step is pivotal for enhancing the accuracy and reliability of the model's predictions.

- Calibration and Validation of the Piezo-Electric Pressure Measuring Chain Model with Experimental Data:

The final objective involves a rigorous calibration and validation process for the Simulink-based piezo-electric pressure measuring chain model, utilizing empirical experimental data. This step is crucial for verifying the model's accuracy and aligning its predictions with real-world measurements.

The outlined objectives collectively form a structured and sequential framework, guiding the research process toward the attainment of the overarching aim. Each objective addresses a specific aspect critical to the development and validation of the proposed in-cylinder pressure monitoring system.

3 Modelling and co-simulation

3.1 Measurement chain modelling

The measuring chain comprises essential components, including a piezo-electric transducer, connecting cable, and a charge amplifier. A representation of a typical set of measuring chain components is illustrated in Figure 1. The piezo-electric transducer, charge amplifier, and connecting cables are presented as a comprehensive measuring chain, represented by an equivalent circuit schematic in Figure 2.

Piezoelectric Transducer *Connecting Cables* *Charge Amplifier* *Data Acquisition*

Fig. 1. Piezo-electrical measurement chain for in-cylinder pressure measurements.

The output voltage of the chain, denoted as V •, based on the equivalent circuit model (neglecting the effects of resistors), is described by Equation (1):

$$V_o = \frac{-q}{C_r} \times \frac{1}{1+\frac{1}{A\,C_r}(C_t+C_r+C_c)}. \tag{1}$$

By introducing a large gain level "A" to the open loop, Equation (1) can be simplified to:

$$V_o = \frac{-q}{C_r}, \tag{2}$$

here, the output voltage is directly proportional to the charge "q" produced by the transducer.

In the current study, the modeling of the measuring chain is approached [8, 9] as a comprehensive standalone system rather than a modular one. This modeling structure allows for a simplified and robust evaluation of combined components errors.

An evolutionary algorithm-based procedure is developed for the automated parametrization and verification of the model using test data. In the process of developing the measuring chain model, the real in-cylinder pressure is presumed to align with the pressure predicted by a well-calibrated and validated crank-based engine model.

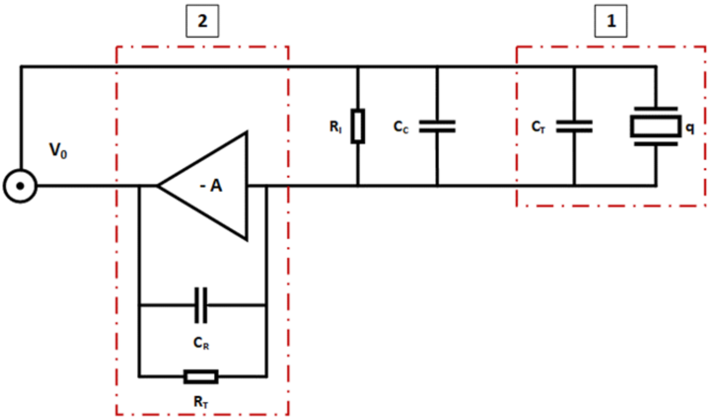

Fig. 2. Simplified schematic of the equivalent circuit of the measuring chain.

3.2 Internal Combustion Engine Modelling and Validation

A baseline physics-based engine model was meticulously crafted using the commercially available internal combustion engine modeling software, Ricardo WAVE. The real-life counterpart specifications and performance parameters of the baseline engine model are comprehensively presented in Table 1.

Table 1. Summary of key data for the experimental test engine.

Parameter	Value
Type	Gasoline
Number of cylinders	4, in line
Displacement	1487 cc
Bore	78.0 mm
Stroke	82.3 mm
Conrod Length	134.5 mm
Compression Ratio	10 ± 0.2 :1
Firing Order	1-3-4-2
Maximum Power	124 kW @ 5,400 rpm
Maximum Torque	230 Nm @ 1,600-5,000 rpm
Intake Valve Clearance	0.24-0.31 mm
Exhaust Valve Clearance	0.35-0.41 mm

To parameterize the Ricardo WAVE engine model, a series of engine tests were systematically conducted. These tests were specifically designed to collect the requisite experimental data essential for the precise calibration and validation of the engine model. A steady-state operating point at 1,000 RPM was judiciously selected as a benchmark. The in-cylinder pressure data obtained at this operating point served as a crucial dataset for both the parameterization and validation of the measuring chain model.

3.3 Baseline Internal Combustion Engine Test Procedure

The baseline engine underwent testing at a controlled speed of 1,000 RPM, accompanied by a normalized load of 0.75. This load value was strategically chosen to position within the mid-range of the engine's load capacity. To ensure the precision of recorded performance parameters during changes in engine test points, a brief period was allocated for the engine to reach its new steady-state operational condition before data recording commenced. To mitigate the effects of cyclic variation, the in-cylinder pressure was diligently recorded and subsequently averaged over 300 cycles to derive the pressure trace. All additional measured parameters were documented over a standardized period of 10 seconds, with parameter values estimated through meticulous averaging of the test data. The comprehensive layout of the test environment, including systems connections and interactions, is elucidated in Figure 3. Furthermore, Figure 4 presents the experimentally obtained, averaged in-cylinder pressure curves at 1,000 RPM as a function of the crankshaft angular position.

These detailed test procedures were crucial for obtaining reliable data to facilitate the subsequent calibration and validation processes of both the baseline engine model and the measuring chain model.

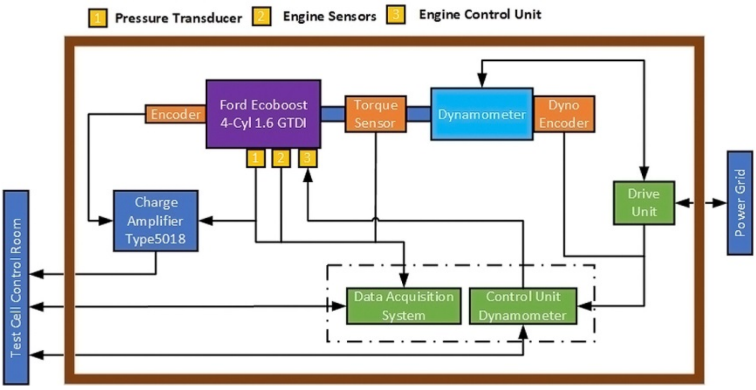

Fig. 3. Test environment layout and main measurement modules.

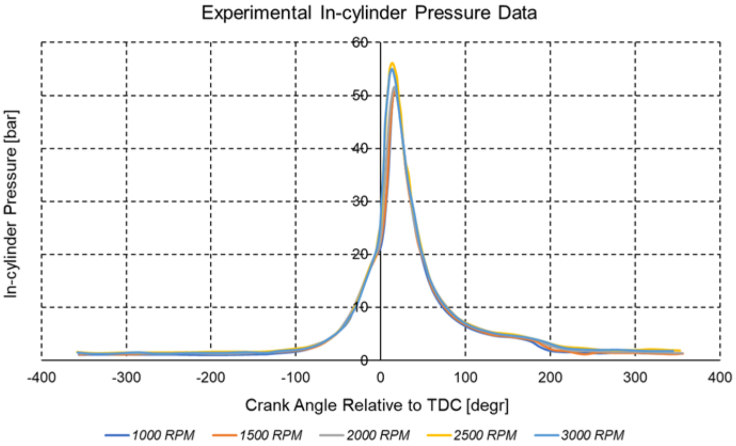

Fig. 4. Experimentally measured in-cylinder pressure curves.

3.4 Co-simulation Environment

The co-simulation modeling technique serves as a pivotal approach for integrating models across diverse software domains, facilitating the development of comprehensive computational tools [10]. In this study, the in-cylinder pressure output is derived from a one-dimensional (1D) crank angle-based Ricardo WAVE engine model, while the performance of the measuring chain is represented in MATLAB-Simulink using a second-order transfer function. The structure of the measuring chain second-order transfer function is delineated in Figure 5. This transfer function establishes the relationship between the 1D physical engine model (PS1) and the measuring chain output (PE2). Initial parameter values for the second-order transfer function-based measuring chain model are presented in Table 2.

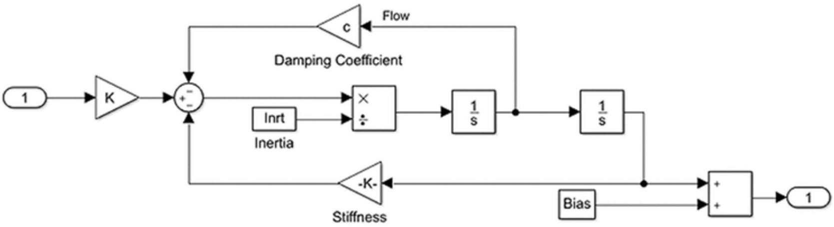

Fig. 5. Second order transfer function representing the measuring chain.

Table 2. Initial transfer function parameter estimates at 1,000 RPM.

Gain K	Second order coefficient	First order coefficient	Zero order coefficient	Constant Bias
1.05	7.0000 x10^{-8}	3.000 x10^{-4}	1.05	0.3

Figure 6 offers a comparison between the crank-based physics engine model, the non-calibrated measuring chain piezo-electric model, and the experimental in-cylinder pressure curves at 1,000 RPM. Notably, the region of highest error between the experimental and estimated measuring chain model output corresponds to the peak in-cylinder pressure. The estimated peak exhibits an offset and higher value compared to the experimental data, a discrepancy that can be mitigated through precise estimation of the measuring chain transfer function parameters via an evolutionary algorithm optimization procedure.

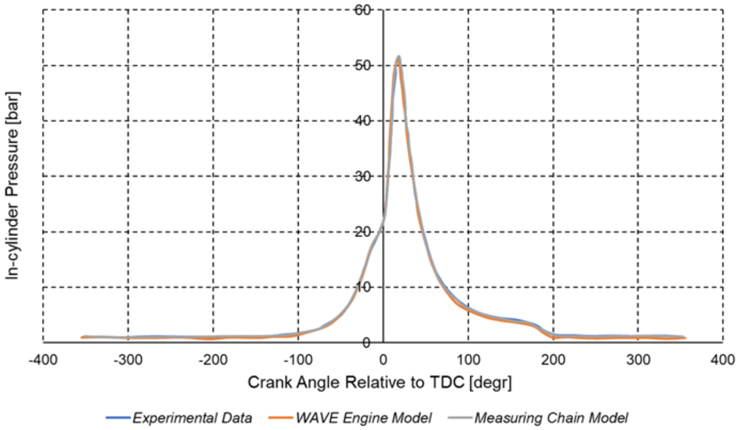

Fig. 6. Comparison of crank-based engine physics model, non-calibrated measuring piezo-electric chain model and experimental in-cylinder pressure curves at 1,000 rpm.

The comparison between the measuring chain model and the experimental in-cylinder pressure trace reveals disparities between simulation and test results. The theoretical pressure peak occurs approximately 1 degree before top dead center (TDC) with a lower peak pressure of 0.4 bar compared to the test data. It is observed that the estimated pressure values during the intake and exhaust strokes are lower compared to the test.

The identified discrepancies can be attributed to the cumulative error within the measuring chain model. The errors stemming from individual components due to assumptions, limitations, and operating conditions propagate through the system. This error propagation is elucidated in Figure 7. To minimize the combined model error, an evolutionary-based parameter estimation procedure is employed.

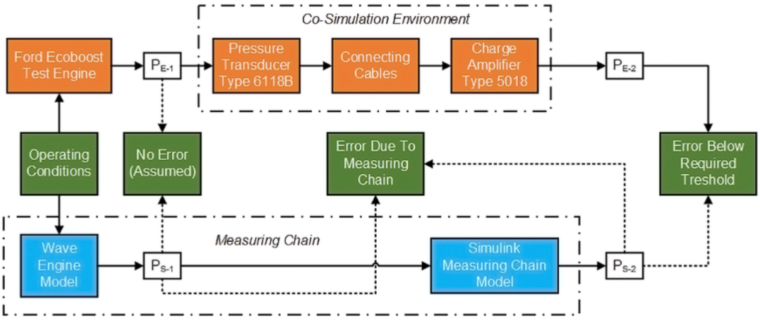

Fig. 7. Top level schematic describing the error propagation and comparison between the co-simulation WAVE engine + measuring chain model (blue) and the experimental measurement (orange).

Table 3. Definition of the outputs shown in Figure 7.

Output	Description
P_{E1}	The actual experimental in-cylinder pressure (unobtainable through measurement)
P_{E2}	The recorded experimental in-cylinder pressure outputted by the measuring chain
P_{S1}	The in-cylinder pressure outputted by the engine model
P_{S2}	The corrected in-cylinder pressure outputted by the engine model after passing through the modelled measuring chain

4 Measuring Chain Model Automated Parameter Estimation

A MATLAB-based genetic algorithm procedure is employed to systematically estimate the parameters of the measuring chain model. The evolutionary algorithm initiates by generating an initial population of random solutions, each assigned a 'fitness' value representing an estimate of its accuracy compared to the test data. Subsequently, the algorithm utilizes fitness-based selection to recombine the best solutions and generate the next generation, continuing this process iteratively until the algorithm's stopping criteria are met.

The parameter estimation procedure commences with the co-simulation between the Ricardo Wave engine model and the Simulink measuring chain model. Following the completion of co-simulation, the model results are exported to the MATLAB workspace, initiating the genetic algorithm optimization. The top-level structure of the optimization procedure is depicted in Figure 8.

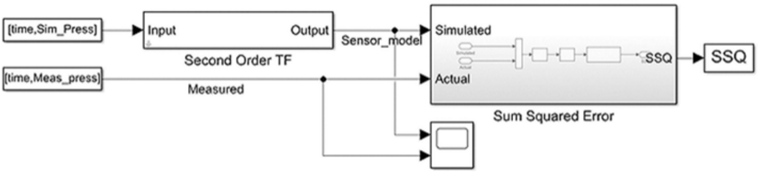

Fig. 8. Reference model for the optimisation algorithm.

The estimated in-cylinder pressure produced by the measuring chain model is then compared to the experimental data, and the sum squared error is calculated. The optimization algorithm iterates until the sum squared error is minimized, resulting in the estimation of the optimal set of measuring chain model parameters. The optimized set of parameters, crucial for enhancing the accuracy and reliability of the measuring chain model, is presented in Table 4.

Table 4. Optimised transfer function parameters at 1,000 RPM.

Gain K	Second order coefficient	First order coefficient	Zero order coefficient	Constant Bias
1.3172	7.0016 x10^{-8}	1.9050 x10^{-4}	1.3408	0.3329

5 Results and discussion

The refined set of measuring chain model parameters significantly improves the accuracy of in-cylinder pressure estimation. As illustrated in Figure 9, the estimated in-cylinder pressure curve exhibits commendable agreement with the experimental curve. The peak in-cylinder pressure error between the model and the test data undergoes a substantial reduction from 0.8% to 0.3% (equivalent to 0.15 bar) following the evolutionary optimization procedure. This improvement highlights the effectiveness of the genetic algorithm-based parameter estimation method in fine-tuning the measuring chain model parameters to better match experimental data.

One of the most significant errors, previously marked at 33.3% between the model and the test pressure data around the crankshaft angular position of 205 degrees, experiences a substantial amelioration, diminishing to 13.3% after the optimization procedure. The resultant pressure differential before and after optimization at this specific point is estimated to be approximately 0.2 bar. Post-optimization, all other operational points exhibit negligible differences when compared to the test data, underscoring the robustness of the optimization approach.

The comparison of simulated engine physics model, experimental data, and the optimized measuring chain model pressure curves, as depicted in Figure 9, provides a comprehensive visualization of the improvements achieved through the optimization process. These results underscore the efficacy of the applied methodology in enhancing the fidelity of the measuring chain model.

The evolutionary algorithm's success in parameter optimization can be attributed to its ability to systematically explore the solution space and converge on an optimal set of parameters that minimize the sum squared error between the model and experimental data. This process ensures that the measuring chain model accurately captures the dynamic behavior of in-cylinder pressure, which is crucial for reliable engine diagnostics and performance optimization.

The substantial reduction in peak in-cylinder pressure error is particularly noteworthy as it directly impacts the accuracy of engine performance assessment. Peak pressure is a critical parameter for evaluating engine efficiency and detecting potential faults. The optimization method's ability to reduce this error enhances the model's utility in real-world applications, such as predictive maintenance and fault diagnosis.

Furthermore, the reduction in the notable error at the crankshaft angular position of 205 degrees demonstrates the model's improved capability to accurately represent the pressure dynamics during specific phases of the engine cycle. This phase is critical for combustion analysis and ensuring optimal engine operation. The evolutionary optimization procedure effectively addresses the cumulative errors that arise from individual components and operating conditions, resulting in a more reliable and accurate measuring chain model.

The negligible differences observed in all other operational points post-optimization indicate that the model maintains its accuracy across the entire range of engine operation. This consistency is essential for the model's application in various engine conditions, including different loads and speeds. The ability to generalize across different operational scenarios makes the model a valuable tool for continuous engine monitoring and diagnostics.

The developed procedure represents a robust proof of concept, demonstrating its efficacy as a valuable tool for detecting in-cylinder pressure errors arising from both combustion irregularities and faults within the measuring chain. By formulating this process based on a simplified second-order transfer function for the measuring chain model, we have established a practical approach that balances accuracy with computational efficiency. Our study not only offers a practical framework for in-cylinder pressure monitoring but also opens avenues for further research and refinement in the field of internal combustion engine diagnostics and optimization.

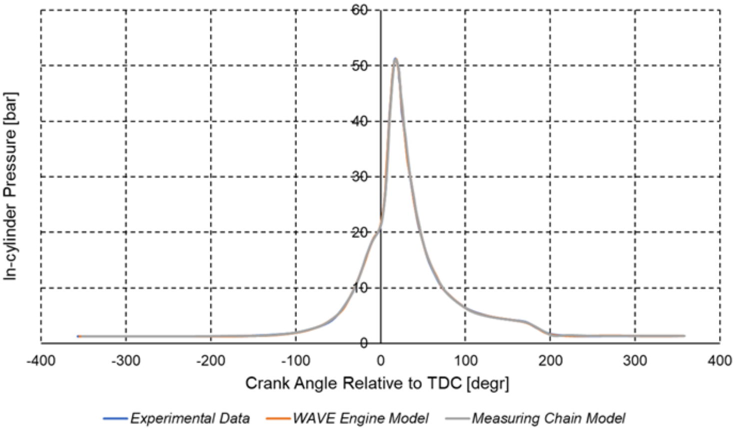

Fig. 9. Comparison of simulated engine physics model, experimental and optimised measuring chain model pressure curves.

6 Conclusion

The developed procedure represents a robust proof of concept demonstrating its efficacy as a valuable tool for detecting in-cylinder pressure errors arising from both combustion irregularities and faults within the measuring chain. By formulating this process based on a simplified second-order transfer function for the measuring chain model, we have established a practical approach that balances accuracy with computational efficiency.

To validate the effectiveness of our proposed method, we employed a 4-cylinder gasoline crank-resolved engine model as the basis for our experiments. Operating under a baseline test scenario with an engine speed of 1000 RPM and a load of 0.75, we rigorously tested the measuring chain model for its capability in detecting pressure faults. The parameterization of the measuring chain model was a critical aspect of our procedure, and we achieved this through the implementation of a genetic algorithm procedure. This optimization method allowed us to fine-tune the model parameters to enhance its accuracy and reliability.

The results clearly demonstrate the success of our approach in simulating the in-cylinder pressure distribution as a function of the crankshaft angular position. By effectively capturing pressure variations and deviations, our developed tool showcases its potential to aid in diagnosing engine faults and optimizing engine performance.

Specifically, the optimization procedure led to a significant reduction in the peak in-cylinder pressure error from 0.8% to 0.3%, and the notable error at the crankshaft angular position of 205 degrees was reduced from 33.3% to 13.3%. These improvements underscore the effectiveness of the genetic algorithm in refining the measuring chain model parameters, thereby enhancing the fidelity of in-cylinder pressure estimations.

The present study not only offers a practical framework for in-cylinder pressure monitoring but also opens avenues for further research and refinement in the field of internal combustion engine diagnostics and optimization. The integration of a simplified second-order transfer function with a genetic algorithm for parameter optimization provides a balanced approach that ensures both accuracy and computational efficiency. Future work could explore the application of this method to different engine types and operational conditions, as well as the integration of real-time monitoring capabilities for on-board diagnostics systems.

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