A Model-based Method of Monitoring Combustion Pressure Measurement Chains for Closed-loop Combustion Control Applications

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Abstract Significant research is ongoing into the use of carbon neutral fuels for combustion engines. In order to fully exploit these new fuel technologies, alongside existing carbon based fuel types, the engine requires a sophisticated level of control for the combustion event based upon a cyclic feedback loop (i.e., a preceding cycle provides the optimization data for the following cycle). This then allows the engine and combustion controller to have the capability to respond and optimise, normal and abnormal combustion phenomena, based on information gained during run-time (as opposed to inferred or indirectly derived parameters). An essential element is the in-cylinder pressure sensor and its measuring chain, that supplies the raw in-cylinder pressure curve for real time analysis within the control system. This paper describes a model-based method for monitoring such a dynamic system, in which the condition of the physical system is represented in a dynamic model consisting of the engine itself, plus the measuring chain, as coupled models. The intent is to mimic the condition of the complete physical system in the model, allowing comparison of model and physical systems to observe residuals and identify fault conditions with all, or part of the measuring chain components.

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1. Introduction

The ability to accurately monitor in-cylinder pressure in reciprocating combustion engines, has a variety of advantages and potential real-world uses. The engineering required to develop control systems during the design phase of internal combustion engines is time consuming. If realistic and representative models of engines and subsystems can be produced, the calibration time of control systems can be significantly shortened. Internal combustion engines and their control systems have become increasingly more complex in order to meet the demands of legislation and competition, augmenting the requirement for feedback systems and diagnostic monitoring. This has resulted in further development of Engine Control Unit (ECU) modules and the fitment of complex systems such as advanced turbocharging, Exhaust Gas Recirculation (EGR) and exhaust emission after treatment. Future stages of development are likely to demand an increase in the use of smart sensor technology, including the fitment of in-cylinder transducers, which can provide continuous closed-loop feedback to the engine control model and loop [1].

1.1. Problem Statement

Piezo-electric measurement chains are well established for in-cylinder pressure measurement - both for research and run-time applications but there are a number of factors that can affect the overall accuracy and quality of the data provided by the measuring chain. The installation of the transducer itself can have a significant effect on its performance, mainly due to temperature shifts at different engine operating conditions. A major effect to be considered is thermal shock of the transducer itself. This is due to the temperature difference across the sensor diaphragm when exposed to the combustion flame front - which in turn causes a non-permanent change in material property of the diaphragm; this causes an intra-cycle change in sensitivity that can significantly affect the accuracy of certain derived results. The signal generated by the sensor is an electrical charge - this needs to be transferred via high impedance cables and connectors to avoid charge leakage and signal drift. In addition,

electrical noise and tribo-electrical effects can distort the sensor signal considerably.

An issue with existing measurement chains for in-cylinder pressure measurement is that electronics hardware requires calibration for the complete operating range of the engine. With a temperature envelope that depends on many variables – such as fuel type, engine condition, combustion strategy. Temperature conditions are difficult to establish unless a temperature sensor is fitted, and this requires additional effort and expense. Such that in order to be effective, each measurement chain must be adapted to its particular installation and environment. The installation of the temperature sensor still cannot compensate for pressure sensor hysteresis, or real-time sensor drift.

1.2. Aims and Objectives

This paper proposes a fundamental framework and technical concept for a Model based monitoring system for in-cylinder pressure measuring chains, for engine control systems employing engine cylinder pressure measurement, used for closed loop combustion control. The aim is to create a mechanism to be able to observe real time data from the system and compare it with reference data, for diagnostic purposes. This will allow system faults to be observed and identified during run-time, such that fault conditions can be recognised and evasive action taken by the control system, to protect the engine and operational state.

The main objective is to create a deployable, co-simulation environment that is able to run in parallel during engine operation, to provide reference data relating to any operational condition, to which real-time measurement data can be compared during every engine operational cycle. For this purpose, a co-simulation environment must be developed and optimised in order to validate the system concept. A sensitivity analysis should be performed, and fault detection logic must be defined, to support the working system concept. Additionally, a calibration and optimisation workflow should define how a working system could be optimised prior to deployment.

1.3. Innovation

This work supports the fundamental requirements for the application of using engine physics-based models, in control loops with closed loop optimisation, based on cylinder pressure feedback. The work suggests the development of an analytically based pressure sensor and measuring chain model, that can be used in a feedback loop, along with a physical measuring chain. The measuring chain model, along with an engine physics-based model, are used during runtime in an observer-based strategy. This approach is also able to compensate for dynamic inaccuracies and drift over the engine operating life. In order to optimise the measuring chain, a Genetic Algorithm (GA) was utilised, and this facilitates an efficient mechanism to calibrate a model that does not required detailed information about measuring chain components, thus a model can be calibrated and made useable in a very efficient manner with minimal system information required.

The expected benefit of this work is to create robust system monitoring mechanism, specifically for the measurement chain, so that cylinder pressure measurement can be deployed with greater confidence and thus be adopted more widely for engine run time applications. This technology will support the use of advanced fuels and combustion systems, in future IC engine concepts and as such, be an enabler for reduced carbon emissions and increased engine efficiency.

2. Literature

There are a variety of motives for modelling in-cylinder pressure and the chosen method of model development depends on the application. There are numerous factors that determine this including cost, required accuracy, simulation speed and function. Considerable previous research has been undertaken to create engine and component models which are of sufficient accuracy to partially replace real time measurements of laboratory-based engine development. Work carried out by Al-Durra et al. [2] involved the development of a model which could estimate the in-cylinder pressure trace of a 2499cc 4-cylinder diesel engine. The model was compared to the actual pressure trace produced from engine testing. The trace was acquired over 70 engine cycles and incorporated low-pass signal filtering and pegging to the intake manifold pressure. The results proved that the model-based estimator was of sufficient accuracy to represent the engine. While the purpose of the model in this particular work was aimed to reduce development time, it proves the possibility of accurately calculating in-cylinder pressure using a parameterised model.

In addition to the prospect of engine development time and cost reduction, Korres [3] discussed how closed-loop engine models have the potential to improve the diagnosis of engine faults. With regards to in-cylinder pressure, knowing the point of peak pressure, pressure inclination after inlet valve closure and pressure during the compression phase are all useful indicators for identifying the root cause of an engine fault.

Kao et al. [4] noted specific information that can be obtained from the cylinder pressure trace, including fuel burn rate, heat release rate and estimation of air-fuel ratio. This data is useful in the detection of engine faults such as misfires.

Combustion fault detection is of particular importance in a large-scale marine engine application. The work of Watzenig et al. [5] recognised that these specific engines often operate in the high seas for prolonged periods of time and suffer from very high downtime costs. Their work focused on using a model-based in-cylinder pressure approach to detect changes in the compression ratio and increased blow-by. The results successfully found that although challenges with measurement noise and transducer drift were encountered, their model-based approach was capable of identifying both changes in compression ratio and blow-by, signalling the need for maintenance before a failure occurred.

Casoli et al. [1] recognised the benefits of engine optimisation, diagnostics, and development time reduction by modelling in-cylinder pressure. However, they noted

that with increasingly complex engine control systems, engine modelling has increased in difficulty and must overcome new challenges in order to remain advantageous in future engine development. New control technologies, such as in-cylinder pressure monitoring, require intra-cycle models which estimate changes within each cycle. While crank-based models are able to model this complexity, they are generally too slow to run in real-time. Mean value models (MVM) are capable of running in real-time but are restricted to inter-cycle modelling. The work of Casoli et al. aimed to combine the benefits of crank-based model detail with MVM real-time speed capability. Using a 4-cylinder diesel engine and in-cylinder pressure measurement as a parameter comparison, a model was built using experimental data provided by the OEM to define look-up tables. While model assumptions were made (such as using a homogenous gas mixture), it was found that a model could be built which provided a good representation of the experimental data at 48 different test points (at a frequency of 1 degree of crank angle) and it was capable of running in real-time on a standard dual-core computer.

A significant drawback of fitting in-cylinder pressure measurement hardware to commercial engines is cost and durability. The work of Lui et al. [6] aimed to develop a model capable of predicting in-cylinder pressure with enough accuracy for a purely software-based system to be implemented without the need for hardware. Rather than directly measuring the in-cylinder pressure, their model estimated it using crankshaft kinematics. While this proved to be largely robust, there were still issues accurately predicting peak pressure.

The work of Kulah et al. [7] combined this software-based approach with a pressure transducer fitted to a single cylinder of a 6-cylinder test diesel engine. Using data from this pressure transducer and crankshaft kinematics, pressure in the remaining 5 cylinders was estimated and corrected using a feedback loop. The model proved to be robust over a wide range of operating points and overcame the challenge of predicting pressure for transient operating conditions as well as steady-state conditions.

There are several papers available that highlight specific shortfalls in the classical approaches for condition monitoring of complex machinery. Zhou et al. [8] suggested a method whereby a combination of data-driven and probability-base prognostics could be used to solve the issue of a lack of historical or trend data. In this work a combination of modelling and predicting the failure probability curve using the Weibull Proportional Hazard Model was applied to a marine engine application (monitoring of oil elements for failure prediction). Validating this curve with some test data showed good correlation test data and the ability predict, with reasonable accuracy, the actual RUL (Remaining Useful Life).

HaiJun [9] suggested a combination of spectrometric oil analysis in combination with a Back Propagation Neural Network to predict the complex trends and interactions between the monitored variables that are used to assess an impending failure (metal components in the oil). HaiJun suggests that this approach is required due to the fact that it is difficult to describe the content of metal trend, in lubricating oil, in a traditional mathematical model (such as a linear regression forecast). This method showed some promising results, but it could be suggested that further work would be required in order to ensure validity for the multiple applications, that would occur in the suggested application field.

A similar approach to the above, i.e., modelling ferro graphic analysis of engine oil was suggested by Wang et al. [10]. However, in this instance the unit under observation was an aircraft engine. The same issues were cited (i.e., difficulty in modelling the responses of the metal compounds in the oil with respect to engine wear) however this approach involved the use of a different mathematical method – using a combination of time series and greys theory. Again, a promising approach for a single instance but further validation would be required to prove the robustness of the approach

Watzenig et al. [11] suggested a method by which blow-by losses and compression ratio could be derived from in-cylinder pressure data (follow on from the previously mentioned paper). This is an interesting topic as both of these values are important metrics for the overall health of a combustion engine. Thus, if these can be derived with reasonable accuracy, they can be monitored during run-time - and over operation time - for condition monitoring purposes. Watzenig et al. suggested that the assessment of engine states from a limited amount of measurement data - with the possibility of reliable assignment of failure causes and effects - are an active research field. The main focus of this work was based on a developing an identification method - with the possibility of clear separation of two common failures of large diesel engines - that cause very similar changes in the cylinder pressure, these being:

- Changes in the compression ratio
- Increased blow-by flow rate

It was suggested possible that following a model-based approach, the symptoms due to these faults could be determined. The study involved the use of simulation data to perform thermodynamic modelling and non-linear parameter estimation. In addition, a noise sensitivity analysis was performed. By minimizing the residual error between sample measured and calculated cylinder pressure data, the optimal parameter configuration for blow-by and compression ratio was found. Based on the prior known limits of the parameters, the engine state could be assessed and potentially monitored. Estimation robustness and reliability was achieved by excluding the combustion phase and signal parts with high noise level. The non-linear parameter identification problem is solved in terms of a constrained optimization.

Method and results were validated using real engine data - with known physically determined failure modes - two measured data sets of different engines, containing single blow-by and single compression ratio failures were used in the study.

Watzenig et al. suggested that this approach was a success and that the desired metrics could be identified and separated successfully, and robustly. Thus, useable for detecting failures that could be used to predict maintenance intervals.

Fog et al. [12] used a non-invasive approach to try to characterise the condition of exhaust valves in large

marine diesel engines. This was implemented via an Acoustic Emission approach to collect relevant data which was then processed to gain useful information regarding the actual valve condition via a Principal Component Analysis (PCA). A test subject was used where exhaust valves faults could be applied at different engine speed and load conditions. The results gained showed good sensitivity to mechanical and fluid mechanical events that can be isolated down to individual cylinders. Another advantage is the ease with which these measurements could be applied, due to the non-invasive nature. However, considerable data processing and pattern recognition is required to be able to extract value from the data, which is time consuming and computationally expensive.

Wang et al. [13] suggested the importance of condition monitoring for a number of transportation sectors. He used a set membership condition monitoring framework, applied to a dual fuel marine engine. The purpose was to improve identifiability of potential engine health problems. A set-membership, specific example case study was developed where the changes in volumetric efficiency, compressor isentropic efficiency and turbine isentropic efficiency were monitored as health parameters. To improve health parameter identifiability, transient data from mode transitions between the diesel mode and gas mode were utilised. The simulation results were based on a non-linear mean-value model of the engine. The overall results claimed that the proposed set-membership estimation algorithms can provide good approximation of the of the health parameters. However, it was cited that further work was required in order to generalise the proposed framework, to accommodate more health parameters

Badgley [14] discussed the potential for Smart condition monitoring systems for large engine applications in his 1985 paper. He discussed the benefit of embedding diagnostic capability into control systems, that would be capable of determining the possible cause of an engine failure. The system proposed in the work would form the basis of an intelligent condition monitoring – allowing the potential for more efficient operation due to optimised maintenance scheduling, increased reliability, and robustness due to lower probability of failure and better definition of duty cycles for design component selection

In his work, Badgley [14] suggested that a data-based, fault-symptom matrix (which was innovative at the time of writing) would provide a framework for cause-effect information to be stored and classified. Using trend gradient analysis approach on the measured signals available from the engine instrumentation, small levels of signal drift could be identified and utilised to conduct comparisons - well before any critical level is approached. In effect, the computer logic can anticipate the onset of problems by noticing gradual increases or decreases in the signals being monitored. The numerical characteristics stored in the knowledge base permits this to be performed. Deviations from running averages by specified percentages can be used to emphasize the stored knowledge base values, thereby giving them more importance in the evaluation. This causes the deviating parameter and its associated relationships with various faults to be highlighted - well in advance of failure. This

anticipatory capability could be used to provide significant value in identifying departure of engine operation from optimum conditions. Badgley [14] suggested that in a working application, corrections of such departures can provide significant cost savings through reduction of fuel usage, as higher efficiency is achieved over long operating times. It is clear that any form of predictive monitoring can bring some benefits to the user or operator – in this approach, a simple data-based method was deployed and this has now been superseded by artificial intelligence and machine based learning, in combination with much larger sample data sets.

Grill et al. [15] proposed in their work the use of in-service remote monitoring of vehicle operation and health. Then using knowledge from this data to improve lifecycle and services during vehicle life. The basic idea of such distributed system is to acquire vehicle sensor data and to frequently transfer processed and aggregated data to off-board servers for further processing, archiving and analysis. The system concept consists of:

- On-board data acquisition via controller systems
- Communication system for data transfer
- Off-board storage and back end
- Access for internal and external users

This paper was written 15 years ago - its content mirrors current state of the art monitoring systems that are in use today in many domains. Industry 4.0, Digitalisation and Artificial Intelligence based analyticals are all now in service. For example, for the marine engine industry, condition monitoring of engines with remote data transfer and central monitoring is a current standard - and this will develop further in the near future. This paper describes the scenario, but it is clear that reliable, physical sensors are still required to provide the basic input to any monitoring system. The performance of which is fundamental to the success of the system overall.

Dandge [16] proposed a simple engine condition monitoring system, for use in vehicles for emerging markets. Basic engine state was defined by simple component monitoring of existing engine warning systems (oil pressure, coolant temperature etc.). It was suggested that such a system would reduce the risk of failure – which is important even for low technology applications in price sensitive markets

Wallin et al. [17] discussed the potential and benefits - with respect to condition monitoring - for engine monitoring based on direct torque measurement. In this particular application, a Formula 1 engine was the target. Wallin et al. suggested that tuning of the engine in this application is usually carried out on an engine test rig before the engine is mounted in the race car. It was stated that, from experience, it has been proven that the conditions in a test rig do not entirely reflect the environment in the vehicle for this application, and this means that the engine may not perform at its absolute optimum. With a torque sensor permanently installed for run-time use, the engine can be tuned under actual race conditions and can also be monitored throughout the entire race. This means that reliable engine torque sensing is a most desirable feature for race engines. The sensor presented in this paper is based on a robust and compact magneto-restrictive sensor concept, that has been further improved to match the demanding requirements of a

Formula 1 race engine. The main discussion in this paper related to the design of the specific sensor type, how it was integrated into the powertrain, and the benefits provided by the measurement data.

Engine torque is also desirable value to have in a production operational situation. Most vehicle engine control system provide this value to the control system - but generally indirectly, via a software function based on engine fuelling - rather than a physical sensor. Operators of stationary type, large engines are interested in engine out shaft torque and power, and sensor technology is now being adopted in this market to allow this measured torque data to be continuously available for control and optimisation purposes. The measurement of torque is highly complementary to in-cylinder measurements - as the combination of this data allows engine efficiency, friction losses, cylinder balancing and many other aspects of the engine operation to be studied and optimised during run-time.

Model based approaches lend themselves well to the process of understanding and characterising complex systems. Radwan et al. [18] applied a statistical, local approach method within a model-based framework in order to diagnose component related faults in the air intake system of an automotive combustion engine. The main focus was on the detection and isolation of component faults, as opposed to sensor/actuator faults. This approach uses a stochastic Fault Detection and Isolation (FDI) algorithm as a general methodology. The challenge is to provide robust on-board diagnostics, regardless of the inherent non-linearities in a system, and the random noise that could be present. The technique was demonstrated using a mean value engine model (as used for control and diagnostic purposes). The dynamics of one single sub-system were the focus (the air intake system) with an aim to detect and isolate faults in two parameters: the volumetric efficiency and throttle discharge coefficient. For further simplification, other boundary conditions were set (for example, no EGR, no faulty sensors etc.). This approach showed the capability of the diagnostics, even in the presence of noise and modelling errors. The main feature of the local approach is that it reduces complex detection problems to a standard one, of monitoring the mean of a Gaussian vector, with a constant covariance matrix. It was suggested that this method is computationally low cost compared to other approaches that demand the design of numerous nonlinear observers and inverse models. It was suggested by the authors that this method could be developed further, to cover EGR dynamics in the intake manifold, allowing detection of component faults in the EGR system.

Schwarte et al. [19] also applied model-based fault detection method to the air system of a production passenger car diesel engine, where model inputs were to be from the existing production sensor array. This seems to be a common approach currently, mainly due to the increased calculation power available in modern engine control units, in combination with the fact of increasing pressure for emissions compliance and detection of fault conditions. Five reference model types were explored in real time, running at an engine test stand, on a rapid prototyping system. The reference models were approximated by a neural network LOLIMOT (Local Linear Model Tree) with continuous mathematical functions. In the online application, maps are employed for the reference models to reduce computational effort. The maps can be generated by the identified neural network with any desired rating. In summary, the work concluded that fault detection covering the full engine operating range was possible and sensor faults with greater than 3% error could be identified robustly (although it was found that some adjustment of the volumetric efficiency model thresholds may be required in practice to allow for production tolerances of components and sensors). This level of sensitivity would be suitable for a production-based error detection application but for run-time control applications, greater sensitivity would be required.

Yoo et al. [20] demonstrated the use of a simple model of an engine cooling system that could operate in real time based on available inputs from a production engine control unit. The motivation for this development was emissions compliance and improved response and diagnostic capability of the engine controller to recognise and respond to fault conditions in the cooling system. Alongside the model a diagnostic algorithm was developed to identify four main failure modes. The model consisted of two base parts running in parallel, an engine model (heat generation) and a radiator model (heat rejection). A Sankey type breakdown of the losses gave an approximation of heat generated as a function of mass air flow. For the radiator model, the coolant temperature at the inlet of the engine needs to be formulated from the energy balance between the lost energy through the radiator and the lost energy of coolant. The heat transfer coefficient of the radiator is dependent on the vehicle speed and cooling fan operating status. It was suggested that the capability of this model could be extended, although at the time of paper publication, this development fulfilled the CARB (California Air Resources Board) requirements.

Gribble [21] explored the use of a model-based approach in order to access relevant tuning parameters and unmeasurable metrics for an aviation gas turbine during run time. He suggested that the steady-state values of the tuning parameters are indicators of the health of the engine's components and their trends. They can be followed to monitor the progress of deterioration within the engine over a long period of time. The model parameters were divided into measured/unmeasured and input/output – the unmeasured inputs were used as tuning parameters. By tracking the difference between model and measured outputs, and adjusting the tuning parameters, the model accuracy could be adjusted "on the fly" via tracking and compensating automatically with a control algorithm. The results from this study showed a good capability to adjust the model in a short space of time so that variables to assess engine health and for use in control algorithms were quickly available – depending upon the model complexity (within a few seconds). The solution was proposed as scalable with respect to input/output requirements. In addition, the approach could be used for offline analysis and was as such, quite flexible.

Vanraj et al. [22] made a detailed study of state-of-the-art approaches for condition monitoring techniques. A suggested trend from this work being that a complex

machine condition monitoring system has become more important with ever-increasing requirements on productivity and cost saving. This is due to the fact that complex machines have many parts, each with individual failure modes. So accurate and robust failure detection is a challenge.

Vanraj et al. [22] suggests that Predictive Maintenance (PM) is normally applied to changes in operational parameters that are observed during run time (vibration, oil quality, noise etc.). Combining this information with advanced analysis techniques employing data science, in real time, can provide a robust approach to augment traditional signal monitoring techniques.

Krogerus et al. [23] suggested in their survey of state-of-the-art diagnostic techniques for diesel engines, that the most significant sub-system of the diesel engine is the fuel injection system; even minor faults can compromise combustion efficiency, with a subsequent increase in acoustic noise and particle emissions. It was stated in the work that the analysis of modern diesel fuel injection systems is complicated by the high fluid pressure levels and the short time constant of the fuel injection event that must be precisely controlled. Gaining health information from the system components is mentioned as a challenging task. The work suggests that the characteristic values that best provide the status and condition of the fuel injection system can be difficult to measure due to the operational environment. In summary this work collates and suggests the methods that have been employed for diesel engine diagnostics and what the future requirements will be. It provides a useful overall study for reference purposes.

3. Methodology

Due to the complexity of closed-loop engine control using a real time in-cylinder pressure measurement system, there is great difficulty in identifying and isolating sub system failures using current diagnostic systems. The ability to precisely flag sub-component degradation and failures within the CPMC (Combustion Pressure Measurement Chain) has the potential to considerably minimise system downtime. A monitoring method that is appropriate to the complexity of the CPMC system is a MIMIC system (Multiple Indicator-Multiple Cause).

MIMIC is a method for monitoring dynamic systems in which the condition of the physical system is represented (and can be repeatedly updated) in a dynamic qualitative model. In the case discussed in this text, this involves observing the discrepancies between the output of the CPMC, and a representative dynamic model of the measuring chain running in parallel. Various parameters within the dynamic model can be adjusted to isolate faults within the CPMC chain if they occur. The outputs of the model are directly compared to outputs from the physical process and residuals can be observed. From analysing these residuals, symptoms can be generated and subsequently used in fault diagnosis or fault trees. The residuals have a zero value in ideal situations but in practice this rarely happens. The deviations of these values are a combined result of the noise and parameter changes in the theoretical model, and/or faults in the physical system. If the deviation due to noise is negligible, the residuals can be analysed directly for a threshold. If the residual is greater than the threshold, a fault occurrence can be declared. By adjusting the parameters in the theoretical model and observing the residuals, specific faults within the physical system can be identified and isolated. Figure 1 shows a basic schematic for a model-based monitoring fault diagnosis system.

4. Combustion Pressure Measurement Chain Overview

A transducer can be simply described as a device which converts a physical or mechanical quantity into an electrical signal [24]. When considering the measuring chain of a piezoelectric pressure transducer, its fundamental purpose is to convert a mechanical stress input into an electrical voltage output. Measurement of in-cylinder pressure is dynamic, meaning the value is a continuous function of time. Piezoelectric transducers are ideally suited to this application due to their wide dynamic range, but they only produce an electrical output when there is a change in the applied load. The complete measuring chain includes the transducer itself, the connecting cable, and the charge amplifier. This is of importance when considering the sources of resistance and capacitance of the representative electrical circuit. A typical set of measuring chain components is shown in Figure 2.
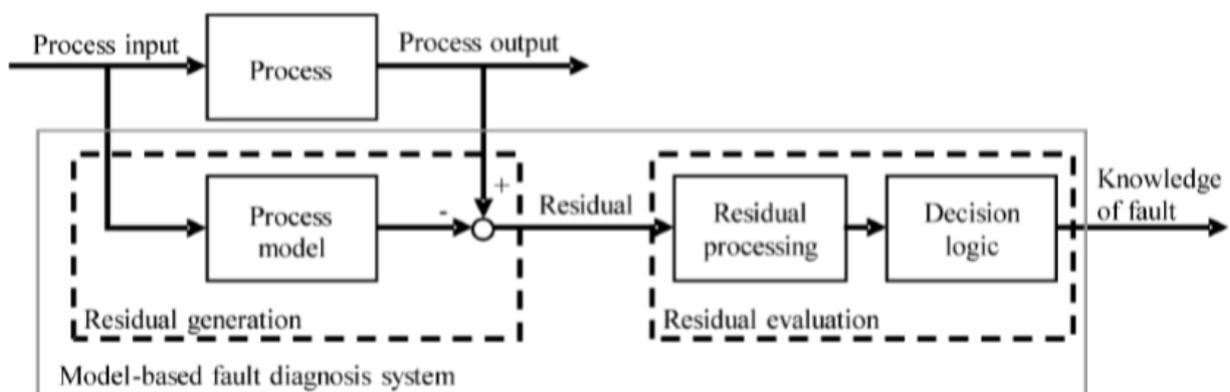

Figure 1. Generic model-based monitoring fault diagnosis system schematic
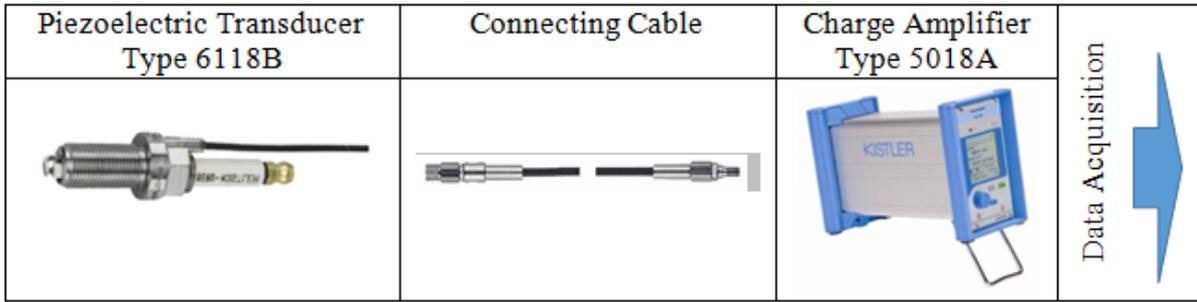
Figure 2. Piezo-electrical measurement chain for cylinder pressure measurements

When modelling the piezoelectric transducer, it is possible to consider it simply as a current source, i.e., a derivative of charge with respect to time. When stress is applied to the piezoelectric material within the transducer, a charge (in the magnitude of Pico coulombs per newton) is introduced to the circuit through two electrodes which form a capacitor. The voltage produced from the measuring chain can be established from Equation (1) below.

$$V = \frac{1}{C} \int \frac{dQ}{dt} dt = \frac{Q}{C} \qquad (1)$$

The piezoelectric material causes a leak of charge since it forms a closed circuit with resistance. Therefore, the complete model of the transducer can be considered as a current source in parallel with both a capacitor and a resistor as shown in Figure 3 below:
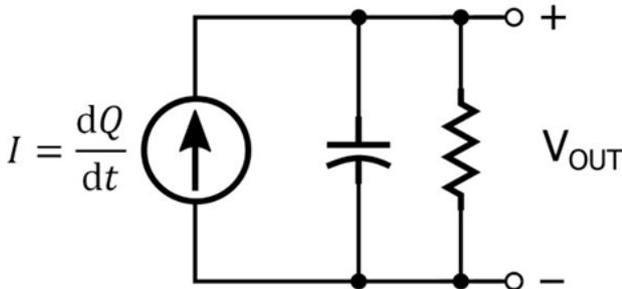

Figure 3. Electronic model of a charge amplifier

Since the charge produced by the piezoelectric material is very small, it is necessary to incorporate a charge-to-voltage converter. The task of which is to convert the small charge into a useful voltage output. The charge is converted into voltage using an integration function, whilst high internal impedance of the circuitry prevents the small charge being lost through leakage [25]. From Equation (1), it can be seen that introducing a capacitor enables a means of converting charge into voltage - using a method that ensures the pressure induced by the transducer is directly proportional to the output voltage. This results in a capacitor being connected in parallel with the amplifier. Therefore, it is then necessary to connect a resistor in parallel, to prevent charging of the capacitor. The amplifier therefore compensates for the transducer's electrical charge using a charge of equal magnitude and opposite polarity. This produces the voltage across the range capacitor.

In addition to the charge amplifier and the transducer, it is important to incorporate the connecting cable into any electrical model. The resistance and capacitance of the cable can be represented by a further resistor and capacitor connected in parallel. Since the transducer produces a charge in the magnitude of Picofarads, small changes to the cable (such as replacement or even movement) can alter the output of the measuring chain - which is a further reason why the charge amplifier is required. There can be generation of a small charge on the surface of the cable conductor caused by moving the cable - this is known as the triboelectric effect. Specific cables are available to avoid this - they are of high impedance and low noise and employ PTFE insulation to reduce drift effects and graphite sheathing to minimise the triboelectric effect. The measuring chain can now be considered as transducer, cable, and charge amplifier – this is represented by the following simplified model shown in Figure 4 below.
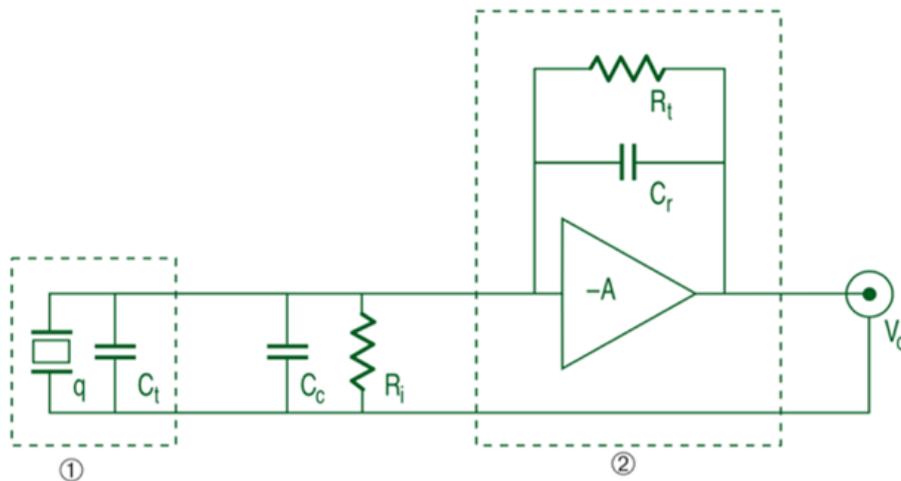

Figure 4. Simplified electronic model of the measuring chain

Based on this model, the output voltage V_o (neglecting the effects of the resistors) is given by Equation (2) below:

$$V_o = \frac{-q}{C_r} \times \frac{1}{1 + \frac{1}{AC_r}(C_t + C_r + C_c)} \qquad (2)$$

Using a sufficiently high open loop gain A, enables this to be reduced to Equation (3) below:

$$V_o = \frac{-q}{C_r} \qquad (3)$$

Where the output voltage V_o is directly proportional to the small charge q produced by the transducer. Due to the dynamic nature of the measurement, it is important to consider the time constant of the system. For the model shown in Figure 4, the time constant is defined as the discharge time for the step input of the AC coupled circuit to decay to 36.8% of the original value. The time constant τ is determined by the capacitance of the range capacitor C_r and its insulating resistor R_t:

$$\tau = R_t C_r \qquad (4)$$

For engine measurement applications, it is generally recommended that a short time constant is used although, in order to prevent low engine speeds being attenuated with errors, a time constant of at least ten times the duration of the measured cyclic signal should also be selected [26].

State of the art piezo electric measuring chains utilise numerous technologies to overcome the many sources of error that can be associated with various components within the measuring chain - and the measurement process itself. Typical problems in engine measurement applications are associated with signal drift, frequency response, noise, and transducer diaphragm degradation (caused by the harsh environment of the combustion chamber).

5. Measurement Chain Modelling Development

5.1. Model-Based Monitoring System

For modern road vehicles to conform to the stricter emissions regulations, the adoption of more advanced electronic powertrain control strategies, that can enable further harmful emissions reductions are required. This usually requires the implementation of new sensors. A vehicle control system is highly dependent on the performance of these sensors, so they must be monitored by the vehicle's on-board fault detection systems (OBD) to detect faults as early as possible and prevent run-time failures or emission limit violations. Current vehicle OBD methodology is based on various approaches that monitor the condition of these sensors. As long as the raw data from the sensor is maintained within a certain threshold range, the sensor is considered healthy. As the deviation between the raw data and threshold values are used as the basis for detecting faults, a good understanding of the raw data during different engine operating modes is required for a robust traditional diagnostic algorithm. Traditional diagnostic algorithms check the limit or trend, of measurable output variables, thus limiting their ability for precise fault diagnosis. To improve upon this, model-based monitoring methods have been developed which compare the raw data from a sensor and outputs from a dynamic model (such as MIMIC). By adjusting the parameters in the dynamic model and observing the deviation, faults within the physical system can be identified and isolated more reliably.

A simple schematic of the dynamic model of the measuring chain and how this operates in co-simulation can be seen in Figure 5.
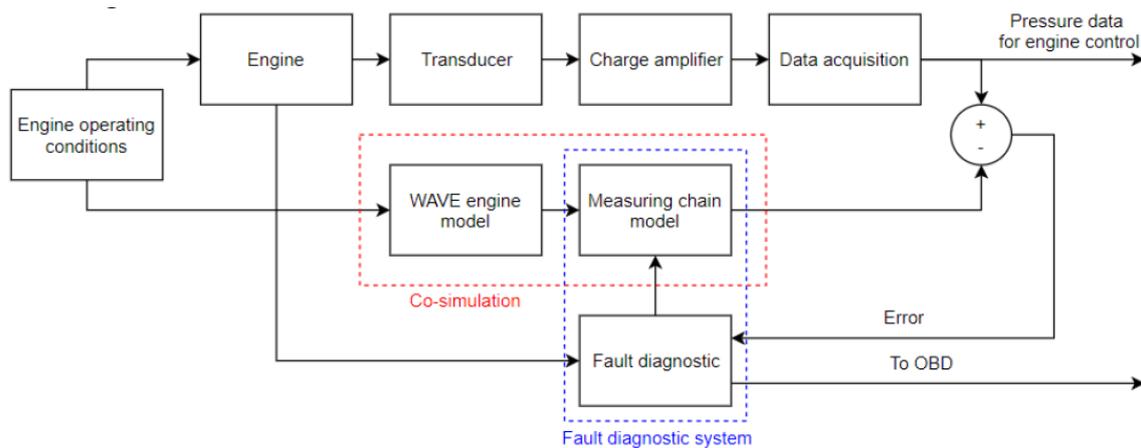

Figure 5. Overview of co-simulation environment

5.2. Analytical Function Based Measuring Chain Model (AMCM)

In this part of the work, a model of the components of the measuring chain, as a complete system was created (using sub-system models). Important to note is that this modelling approach was able to provide access to the connection points between the main sub-system element models, such that monitoring residual values at these points was possible. This allows more diagnostic detail to be gained when a failure occurs. An overview of the system model is shown graphically in Figure 6 below:
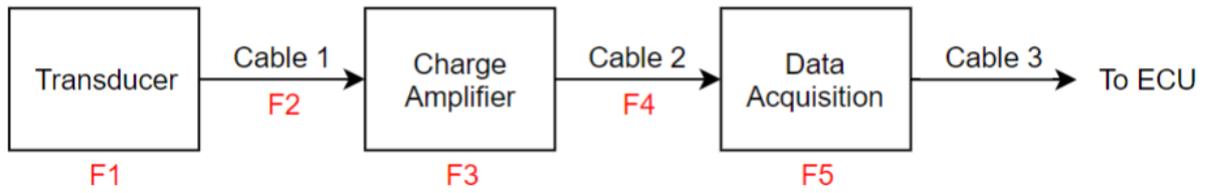
Figure 6. Faults in Transducer (F1), Charge transfer cable (F2), Charge amplifier (F3), Analogue cable (F4), Data acquisition (F5)

The pressure transducer simulation consists of a virtual measuring element, that is modelled as a simple, under damped, spring-mass system. The pressure input signal flow is as follows. The input takes the in-cylinder reference pressure curve and adds the additional pressure acting on the piezoelectric element due to thermal shock (analytically defined). This model assumes the diagram temperature is proportional to the in-cylinder pressure and fluctuates between 200 to 400°C. In general, thermal shock induces pressures errors of 0.3 to 0.6 Bar to the piezoelectric element at peak temperatures. The polarity of this error can vary as a function of the sensor design itself.

The signal is then converted to a force that is applied to measuring element where parameters for diaphragm mass, damping and stiffness are adjustable. The measuring element simulation takes the total pressure applied to the piezoelectric element (combustion pressure + thermal shock) and calculates the reaction pressure inside the element due to its spring damper properties. A second order spring-mass damper transfer function was used to achieve this. Next, the pressure to current conversion considers the pressure occurring inside the piezoelectric element and converts it to the output current produced by the sensor. Piezoelectric transducers have a charge sensitivity which describes the relationship between the applied pressure and output charge. A current output from the pressure transducer model was required for the rest of the AMCM model to function. This was achieved by using a discrete derivative to convert the charge output of the transducer model to current. A signal flow overview is provided in Figure 7.
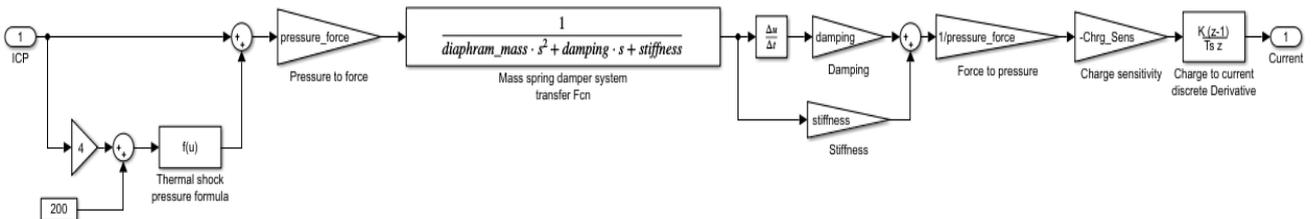

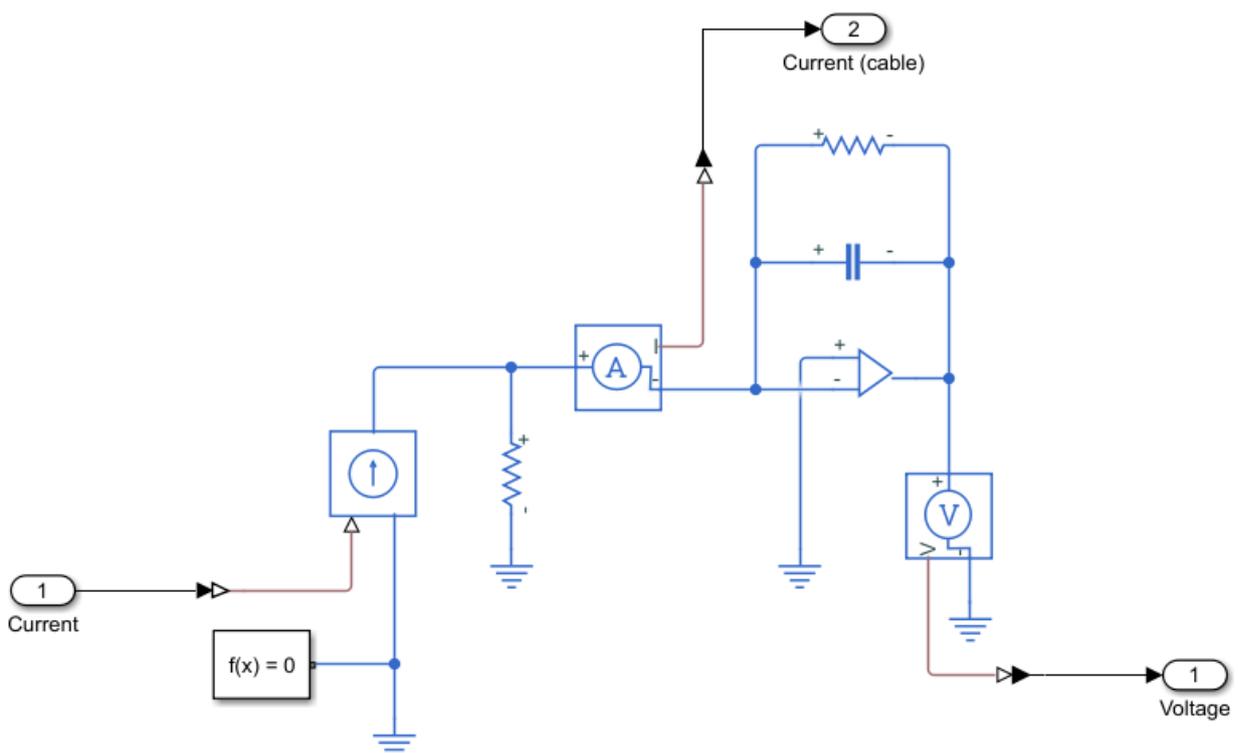**Figure 7.** Pressure transducer sub-model

Figure 8. Charge amplifier sub-model

The charge amplifier model (Figure 8) forms a charge current to voltage converter, with adjustable time constant and resistive charge leakage paths (on the input side), these are both adjustable parameters that represent typical "in service" variations that could affect the data quality in the signal flow of a real, hardware-based system. The output current from the sensor model provides the calculated current output from the pressure transducer as electrical current into the charge amplifier circuit. The connecting cable simulation consists of a resistor connected to ground, to model the insulation resistance of the cable and pressure transducer. An insulation resistance value of 100 MΩ for the specific transducer and connecting cable used in the engine testing was obtained from literature. A virtual ammeter was positioned in the model between the insulation resistor and charge amplifier to monitor the current flowing through the connecting cable. The output of this ammeter can be used for fault diagnostics of the connecting cable. The charge amplifier sub-system takes the input current from the connecting cable and converts it to a useable voltage for data acquisition (between 0 - 10 volts). It consists of a feedback capacitor and range resistor which determine the gain and time constant of the charge amplifier (as discussed in previous section).

This simulation set-up allowed the possibility of stimulation of the model, using reference data, over the course of a number of repeated engine cycles in order to be able to evaluate the effect and significance of any specific parameters. The overall measurement chain simulation block as created in Matlab Simulink is shown below in Figure 9 below.

The simulation was run over a number of cycles for a fixed period both in the time and angle domain. The analysis and output of the model takes the number of zero crossings, the measured pressure signal and the actual pressure signal and returns:

- The angle of shift of the maximum pressure occurrence between measured and actual
- The error of maximum value between measured and actual at the first cycle
- The signal drift (difference in measured max between the first and last simulated cycles)

This provides the basic form of errors that can typically occur due to the measurement chain components, these being shift of the pressure curve in the X and Y axis per cycle, plus drifting of the signal over the measurement time.
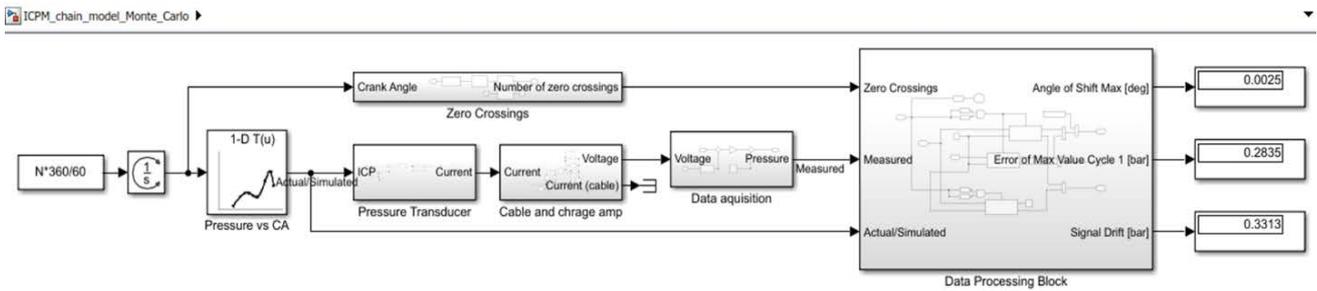

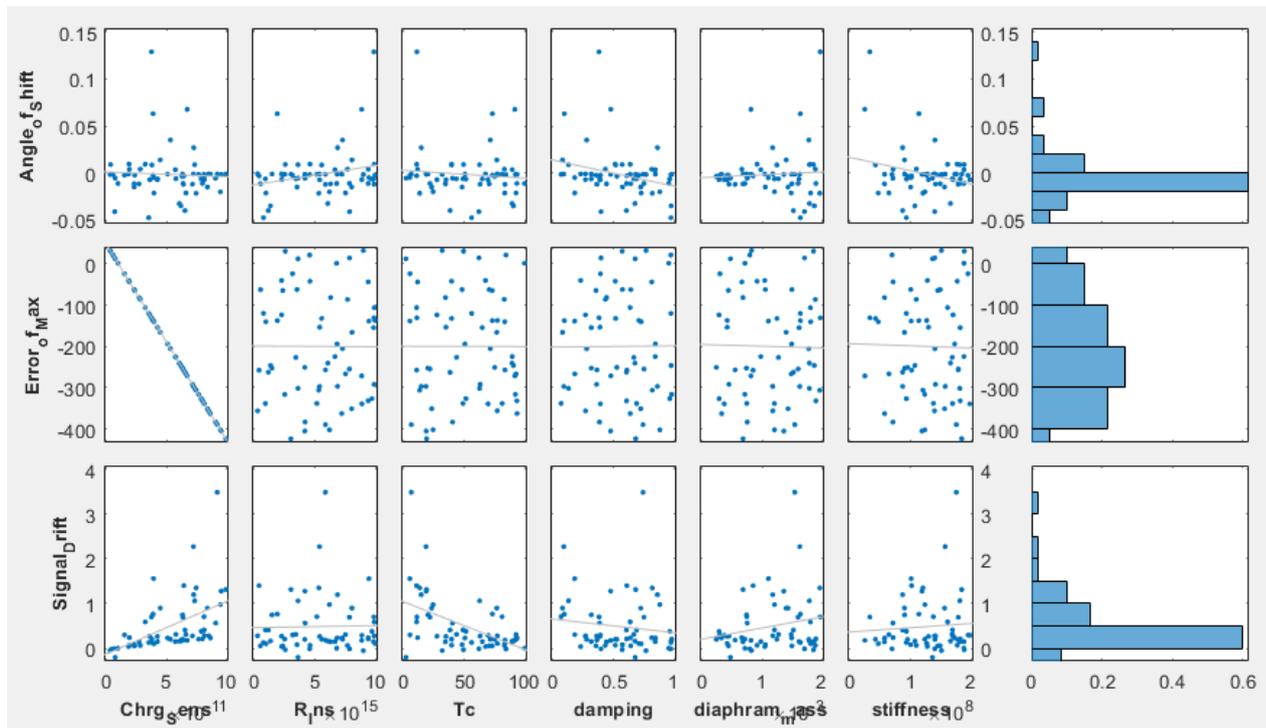**Figure 9.** Analytical measurement chain simulation model overview

Figure 10. Sensitivity Analysis - Monte Carlo Simulation Setup - 1000rpm
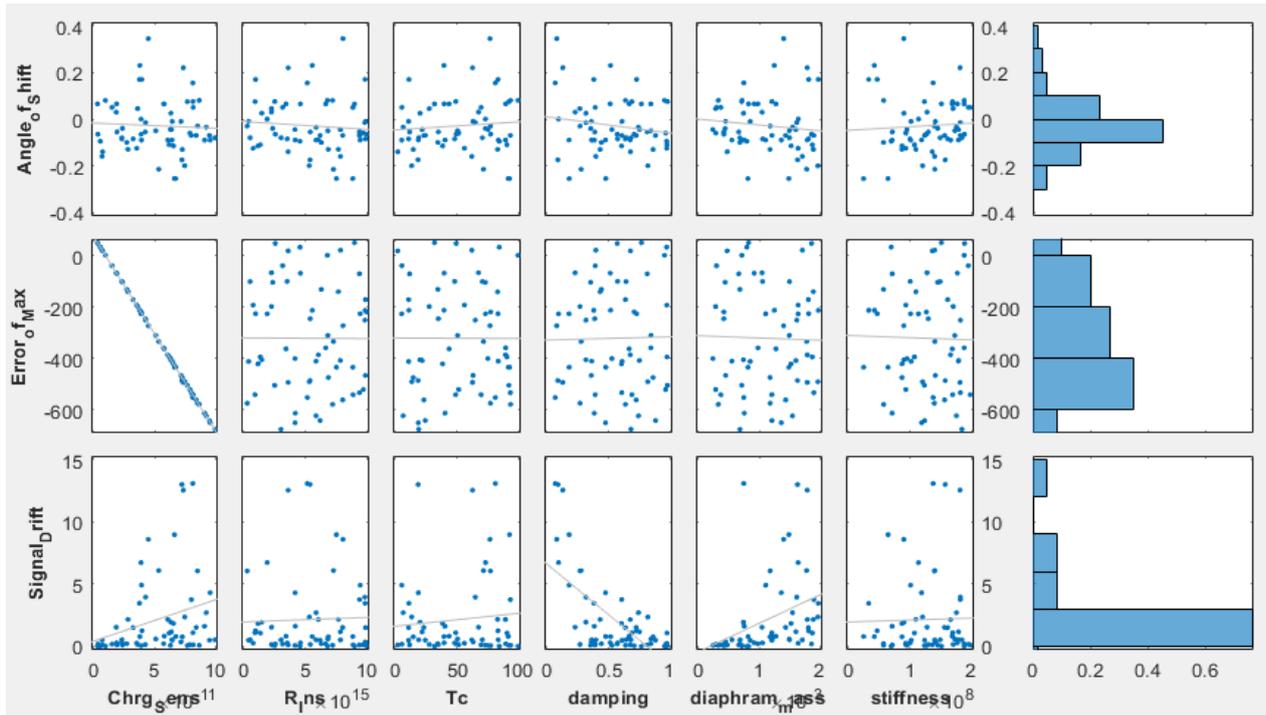
Figure 11. Sensitivity Analysis - Monte Carlo Simulation Setup – 6000rpm

5.3. Parameter Optimisation of the Measuring Chain Model

In order to be able to establish the optimum parameters for any given system, an optimisation procedure was developed. This consisted a sensitivity study to allow discovery of the "fittest" parameter set, in order to front load and reduce the time required for subsequent numerical optimisation.

A sensitivity analysis was undertaken using a design of experiments (DoE) based approach with a monte-carlo based parametric study. The optimal criteria based on observation of the SSQ value compared between input (reference curve) and output of the model (simulation response of the AMCM). Initial simulation runs were executed at 2 operational points based on engine speed (1000rpm and 6000rpm). Results are shown in Figure 10 and Figure 11 as a scatter plot of variations versus responses.

The same data is presented as Tornado plots in Figure 12 and Figure 13 below. These show more clearly the sensitivity of each measuring chain parameter with respect to each of the output parameters. It can be clearly seen that the charge sensitivity has significant correlation to the error of maximum, irrespective of speed. This is to be expected as the charge sensitivity has a significant impact to the input/output gain of the measuring chain.
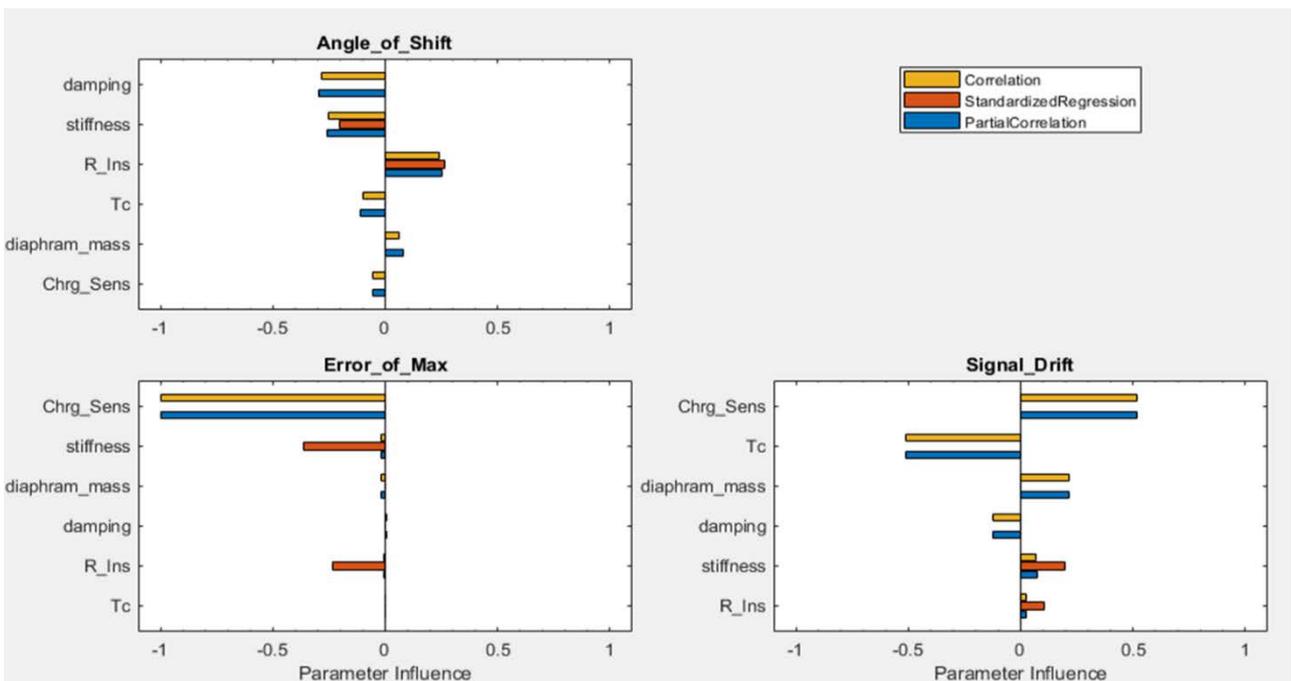

Figure 12. Sensitivity Analysis - Monte Carlo Simulation - Evaluation of Results 1000rpm – Tornado Plot
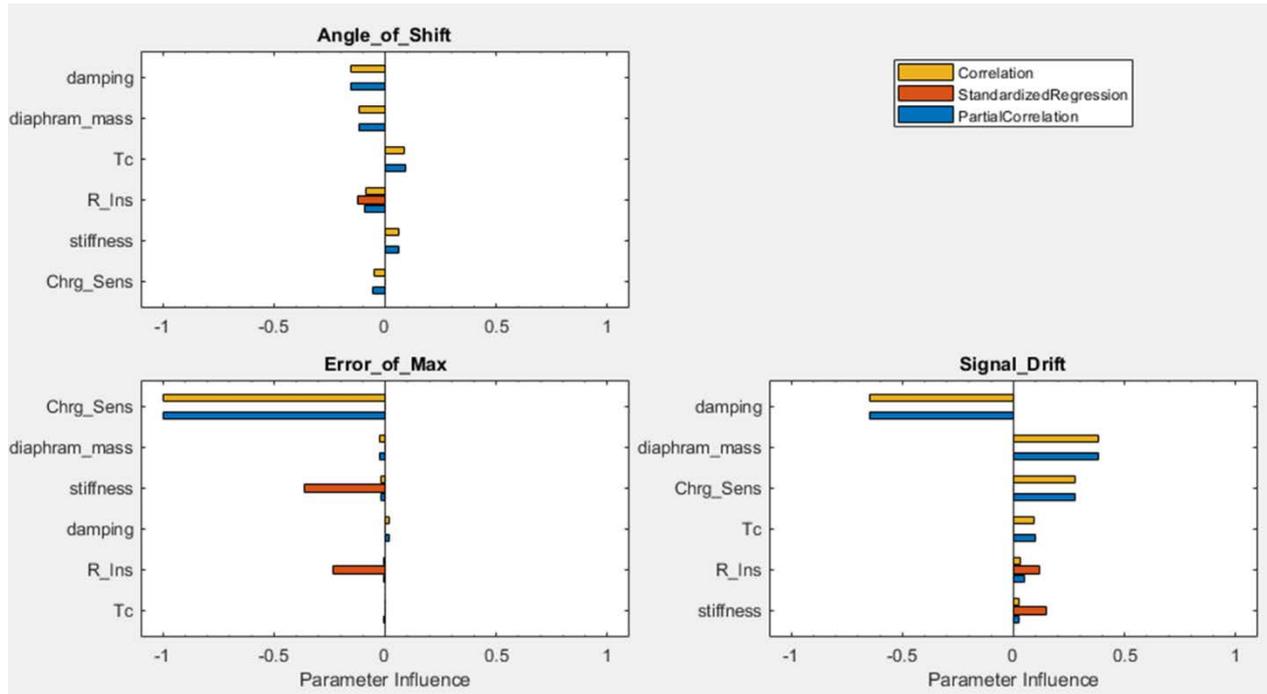
Figure 13. Sensitivity Analysis - Monte Carlo Simulation – Evaluation of Results 6000rpm – Tornado Plot

At this point, the sensitive parameters could be identified. But it is necessary to optimise those parameters in order to provide good model performance that could allow the optimisation of the AMCM such that measured data can be matched to reference data efficiently. For this purpose, a workflow to allow for optimisation of the AMCM was undertaken. The idea being that using pre-optimised parameter set from the sensitivity analysis (with the lowest SSQE) would reduce the calculation runtime, also, allow a better starting point for the optimisation with less chance of the operation getting "stuck" in a local optima loop.

The procedure was as follows:

- Fittest parameter set from sensitivity analysis now used as the starting point of the optimization
- Deploying the LSQNONLIN (Least-squares, non-linear) optimization algorithm in Matlab Simulink
- The optimizer further reduced the SSQE resulting to a better fit between the simulated and measured pressure curves

The optimizer was run and stopped with the parameter values shown below as final in Table 1. It is worth noting that TC and damping attained the values of their constraint limits. Thus, it may be necessary to investigate and

possibly repeat the procedure.

Figure 14 shows the curve produced by the simulation using the optimum parameters suggested, compared to the measured curve.

5.4. Fault Identification Method

A schematic to illustrate how the co-simulation is utilised for diagnostics can be seen in Figure 15.

Figure 15 highlights the possibility in the system for isolating subcomponent faults. The monitoring system deploys the engine and measuring chain models in combination. The residual outputs of each AMCM chain subcomponent (R1, R2, R3) are evaluated by fault decision logic where they are referenced against the model-based components at the given operational condition (hence dynamic observation). Tolerance bands are used as thresholds to observe and identify if the physical components are operating as intended, or if a fault condition is detected. Tolerance band thresholds can be determined from experimental testing and general knowledge of the system undergoing fault diagnosis. Threshold values must be chosen that minimize the occurrence of false alarms.

Table 1. Parameter Estimation of the AMCM using the Simulink Parameter Estimation Toolbox

| Input parameter	RangeMin	RangeMax	Sensitivity analysis – Lowest SSQ	Optimised value
Diaphragm Mass M [gram]	0.2	2	0.0017	0.0016927853838270251
Piezoelectric Element Stiffness K [MN/m]	20	200	6.505e07	64824164.1141022
Piezoelectric Element Damping Coefficient R [Ns/m]	0.05	1	0.8955	0.999999999...
Pressure Transducer Charge Sensitivity Qpt [pC/Bar]	1	100	1.0206e-11	9.84729725893669e-12
Pressure Transducer and Connecting Cable Insulation Resistance [MΩ]	10e13	10e15	1.5247e14	152469245388119
Charge Amplifier Time Constant [Tc]	1	100	93.3144	99.99999999...
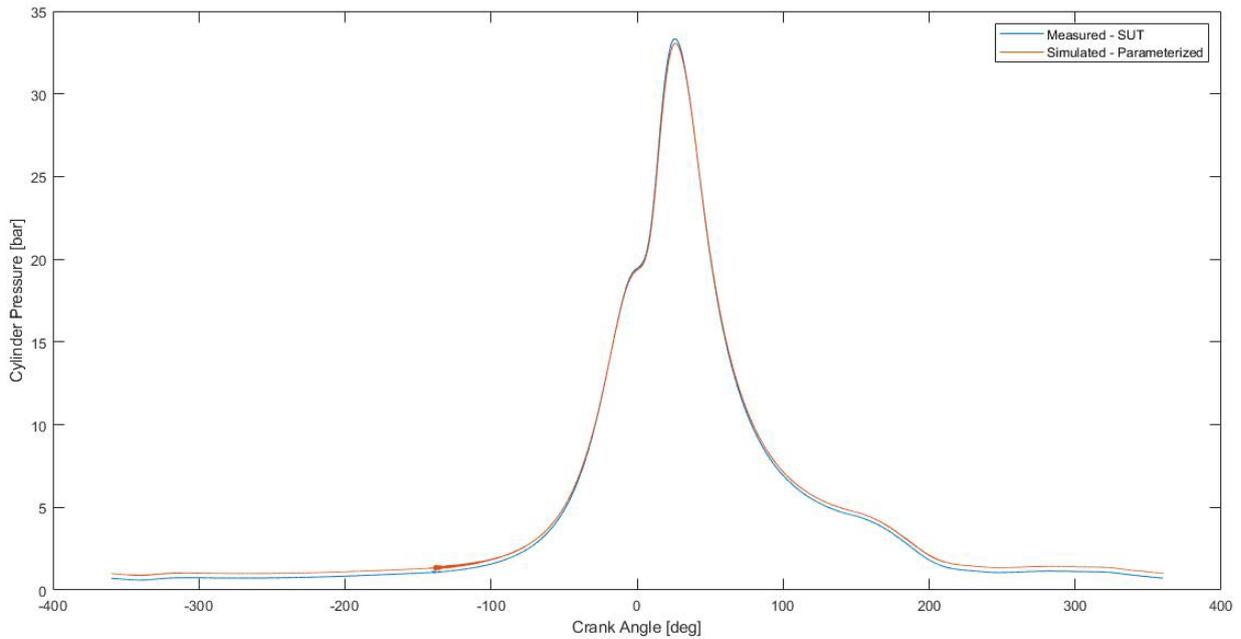
Figure 14. Comparison of the pressure curve resulting from the optimal parameter set and the measured (SUT) pressure curve showing good correlation and agreement between physical and virtual measurement chain, for the given operational point
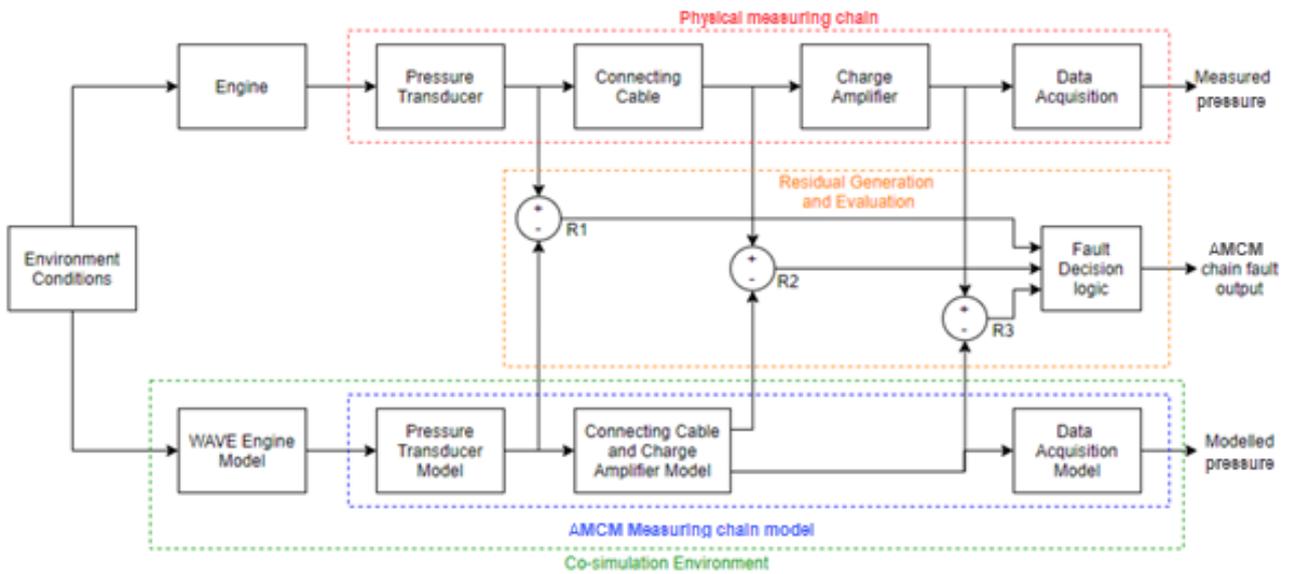

Figure 15. Co-simulation environment showing node points for residual monitoring for diagnostic purposes

Timer and counter based strategies, for fault handling are well known methods in common use. They are based on the simple logic of "X of Y" fault filtering. Where "Y" is the samples of the sensor state, if greater than "X" exceeds a given fault threshold or state, then a failure state is deemed to occur. There are 2 continuously running counters required (failures X and samples Y) with associated thresholds for sample size and failure counts within a sample. For each diagnostic cycle during run time, the sample counter will increment accordingly until it reaches the threshold value of sample size (Y). For each of these events, if a threshold violation occurs, the failure counter triggers and advances by 1 (X), once the fail counter reaches the threshold set for the maximum number of tolerated failures within a sample, a status of test complete and test failed will be set. If the sample counter reaches the set limit, without the failure counter exceeding its limit, then the test considered as complete and passed. At this point all counters are reset and the monitoring time (over samples) is restarted. This is a continuous loop while the system is in operation. A disadvantage of this approach is that due to its inherent simplicity, it requires considerable training or pre-knowledge of the system responses during operation, in order to robustly define the sample counts and thresholds. Typically, diagnostic algorithms will run in parallel with different cycle times according to the specific application, relative to required monitoring frequency for the occurrence of the expected sub-system fault. Due to the complexity of closed-loop engine control using a real time in-cylinder pressure measurement system, there is great difficulty in identifying and isolating sub system failures using current diagnostic systems. The fault decision logic shown in Figure 16 makes use of simple static thresholds in the form of look up tables to easily present the concept.
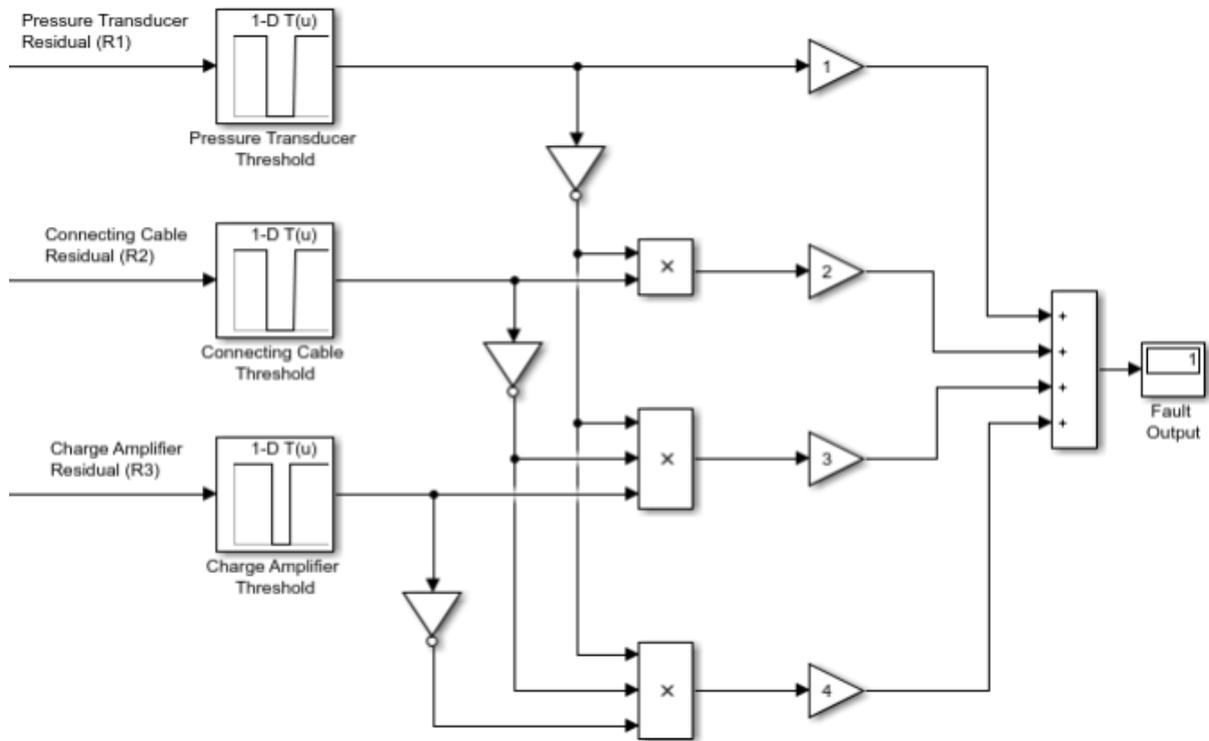
Figure 16. Fault decision logic with static thresholds

Although static thresholds are simple to implement, they require large threshold values and small residual operating ranges in order to distinguish the faults from the disturbances and uncertainties. As combustion pressure measurement results in very transient readings, and the measurements made using a physical system are required to be precise for optimal combustion feedback control, static thresholds may not provide the required accuracy for a combustion measurement chain fault detection system. Instead, adaptive thresholds are proposed that could be implemented which use the input signal to actively adjust the threshold values to extend the residual operating range, thus allowing for tighter threshold values to be implemented. Adaptive thresholds have been shown to considerably reduce false alarms without losing fault detection sensitivity.

6. Results and Discussion

The purpose of this work was to develop the concept of a measuring chain model, to improve data quality with respect to combustion pressure measuring chains. A dynamic model was created to monitor the physical measuring chain's performance that consists of an engine model and measuring chain model in co-simulation. The engine model takes Throttle position, torque demand and environmental factors (ambient temperature etc.) as inputs and outputs in-cylinder pressure and the corresponding crank position. The outputs of the engine model serve as inputs for the measuring chain model.

6.1. Parameter Sensitivity Observations

The following observation were notable from the sensitivity analysis at the 2 engine speed points that were

observed, that gave a clear indication of which parameters were significant. No parameters appeared to be more significant with respect to phase shift (X axis errors) Charge sensitivity had a strong connection to maximum values (Y axis errors)

- Time constant is significant with respect to "timing" based results especially where the integrity pressure volume relationship is important and becomes most significant with respect to energy conversion points.
- Charge sensitivity and time constant are significant for drift over cycles

With respect to the actual calculated results used for combustion closed-loop control, observations were:

- Charge sensitivity has an effect on IMEP, PMax and RMax as it is effectively a gain setting applied to the curve and so affects the whole measured curve. However, this is a fixed parameter depending on the sensor properties. Therefore, this parameter would be useful to monitor for diagnostics to detect engine or sensor failures
- Rise values are connected to stiffness and damping parameters, and therefore are connected to measuring element properties these are as such fixed values.
- Energy conversions points (MBFs) are mostly connected to the time constant parameter, the time constant is in effect a filter property so this relationship would have to be explored at other engine operating points

6.2. Results Summary

Some of the relationships that are observed can be difficult to quantify absolutely. However, what can be stated is the using this measuring chain model, then tuning the parameters using a numerical optimiser to train the

model, allows the possibility to closely match the model to reference data at any given engine operation point. It should be stated that there are many dynamic processes at play within in a combustion pressure measuring chain. The measuring chain model developed in this work aimed to model the major dynamic effects such as thermal shock, the spring damper properties of the piezoelectric element, and the drift effects of the charge amplifier but in general the measuring chain model was simplified for the purpose of proving the fault diagnostic concept proposed.

The main parameter values affecting the behaviour of the dynamic processes were either directly obtained from literature or estimated using data from literature. The estimated model parameters underwent parameter estimation to best "fit" the measuring chain model output to that data obtained from experimental testing. Even though parameter values were obtained directly from literature, or were optimised, they still may not have truly represented the behaviour of the dynamics occurring in the physical measuring chain, resulting in some discrepancies observed.

6.3. Review of the Process

A 2-step procedure to developing the models was deployed in order to allow iterative monitoring of the process, and achievement of the intended goals. A workflow process was developed and used in order to optimise the models that were created. The measuring chain components were modelled at sub-system level. This meant a more detailed model, including the sub-system components was created. Critical parameters were identified in the sub-systems and these were used as model tuning (optimisation) parameters. Using the genetic algorithm-based approach, these parameters could be optimised such that the data from the measuring chain model could be matched to the simulation data perfectly for a given condition. This workflow is important as to establish the required model parameters accurately could be very time consuming or even impossible to get the required information. The genetic algorithm could tune the system with approximate values and find the "fittest" set of parameters in order to match data output from the engine and measuring chain simulation to the experimental, measured data. This process was discussed and demonstrated in the relevant chapter and could be considered as a calibration process that could be triggered automatically during run time, or at each start-up, in order to keep the model-based monitor and the physical system well matched, ready for in-service monitoring of the system. A sensitivity analysis was also performed in order to try to understand the system responses compared to stimulation of inputs, in order to be able to try and understand the most significant parameters, also parameter interactions, such that system modelling and characterisation could be better understood, and that system optimisation could be executed more efficiently based on this information. The sub-system models provide mathematical representation of the system behaviour and were constructed as to provide the appropriate level of fidelity for system monitoring.

Once the measuring chain models had been optimised, a mean squared error of 0.1021 between the modelled and experimental in-cylinder pressure traces was observed showing a strong correlation between the co-simulation and experimental measurements. With a complete measuring chain model capable of calculating representative in-cylinder pressure readings during steady state engine operation, the measuring chain model-based monitoring fault diagnostic system had all the necessary components needed to generate residuals. Fault decision logic was proposed that processed the residuals via the use of thresholds and a series of logic gates which in turn generated an integer that corresponded to a specific measuring chain subcomponent fault. The proposed decision logic made use of static thresholds as they were simple to implement and served as a place holder to prove the concept. However, as in-cylinder pressure measurements are very transient even during steady state operation, adaptive thresholds were proposed to maximise fault detection sensitivity and minimise false alarms.

7. Conclusions

The aim of this project was to explore the concept of combustion pressure measuring chain modelling for the purpose of data quality improvement. A real application being foreseen for alternative fuel engine applications where closed-loop combustion control is already being deployed for run-time optimisation of fuel, air, and combustion systems. At the time of writing there are no known monitoring systems specifically for these combustion pressure measuring chains that are being used for runtime applications, and therefore no monitoring of the feedback loop that includes the sensor and signal conditioning. It should also be noted that the cost of engine combustion sensors is a barrier to a wider adoption of the technology - which is particularly relevant and useful where alternative, environmentally friendly fuels types can be used to reduce harmful combustion engine emissions. The adoption of this measuring chain model-based optimisation could facilitate the use of lower cost sensors, that are less accurate or robust, whereby the required level of precision can be provided by model-based enhancement of the data with optimally tuned parameters.

The premise of the model-based monitoring fault diagnostic system was to generate residuals between the physical measuring chain components and their corresponding mathematical models. The AMCM could be applied for fault diagnostics where residuals from the sensor and measurement chain components can be observed. The most important aspect is to be able to optimise the model such that the data from the reference source can be adjusted to take account of the errors in the measurement chain, at specific operational points, so that reference data can be compared objectively with real-time data for run time monitoring. In the work, a method of model training has been used that could be widely applied using a sensitivity analysis, along with a genetic optimisation algorithm. This approach proved robust and provided the required improvement in data precision for this application. In order to validate the performance of the AMCM in full, additional experimental data for each measuring chain subcomponent needs to be obtained. This

will then allow for quantifiable residuals to be generated, in turn allowing for appropriate threshold values to be chosen for diagnostic purposes. The additional data would also enable the measuring chain sub-component models to be further verified against component specific data, which may result in the error between the co-simulation and experimental data reducing further.

In practice, it could be necessary to train and parameterise the model for measurement over a large number of points within the engine operating envelope. This is feasible as the required data vectors (i.e., reference curve) and model (function) with parameters (scalars) have minimum computational overheads and thus would be feasible to implement during run time on a suitable signal processing platform of an engine controller.

It is suggested that the ability to precisely flag subcomponent degradation and failures within the physical measuring chain would minimise system downtime and assist in maintenance. A monitoring method that responds to the complexity of the physical measuring chain system using model-based monitoring is shown as a practical possibility in this work. Observing the discrepancies between the output of the physical chain and a dynamic model running in parallel. A workflow was demonstrated in this work that allows efficient optimisation of the various parameters within the dynamic model in order to be able to isolate faults within the physical measuring chain if they occur.

8. Further Work

This work could be usefully extended as follows:

- The ability for the co-simulation to calculate in-cylinder pressure for transient operating conditions (as well steady state condition) would be an interesting further investigation. Most engine applications operate with regularly changing engine loads, speeds, and environmental conditions - meaning the in-cylinder pressure curve varies significantly between cycles.
- In order to differentiate between a combustion fault and measuring chain component fault, a measurement chain monitoring system could need to communicate with other sensors in the engine control loop. For instance, a discrepancy in in-cylinder pressure in combination with a discrepancy detected by another sensor could indicate a genuine combustion fault, whereas a sole in-cylinder pressure discrepancy is likely to be due to a measuring chain component fault causing a false reading. Incorporating software to communicate between the monitoring system and other ECU sensors would be a key aspect of the system's commercial application.
- The engine model is capable of calculating useful values that could be used to optimise the measuring chain model "in the loop". Cylinder temperature values can be easily obtained that could then be used with the sensor thermoshock analytical characterisation (within the sensor model) – in order to improve accuracy from the engine model by decoupling thermoshock effects (a major source

of inaccuracy for in-cylinder sensors). A similar approach can be adopted for other factors e.g. sensor drift over time, hysteresis etc.) this would allow an improvement of the overall accuracy even when low cost components were used in the measuring chain.

9. Summary

The further work suggested here would allow an extension of the function of the measuring chain model such that is could be used to improve signal and data quality available from the measurement system. This model-augmented data quality improvement would be of high interest as it would be an enabler for lower cost sensors and signal conditioning electronics. Raw data could be improved in software and made more widely useable and reliable for engine control applications. Sensor modelling is of particular interest, and the method suggested for calibration of the sensor model using a GA based approach means that detailed design information about the sensor is not necessary, as well as the fact that production and sensor-to-sensor design variations can be compensated for. Inversion of the model once calibrated allows the extrapolation of the data to compensate for all influencing factors that compromise data quality with respect to the measurement chain itself.

Nomenclature

Alternating current	AC
Analytical Measuring Chain Model	AMCM
After Top Dead Centre	ATDC
Cubic Capacity	CC
Combustion Pressure Measurement Chain	CPMC
Design of Experiment	DoE
Engine Control Unit	ECU
Exhaust Gas Recirculation	EGR
Fault Detection and Isolation	FDI
Genetic Algorithm	GA
Kilowatt	kW
Least Squares Non Linear	LSQNONLIN
Multi Indication - Multi Cause	MIMIC
Mean Value Model	MVM
Newton-Metres	Nm
On-board Diagnostics	OBD
Original Equipment Manufacturer	OEM
Principal Component Analysis	PCA
Polytetrafluoroethylene	PTFE
Revolutions per minute	RPM
Sum-Squared error	SSQ
Top Dead Centre	TDC
Transfer Function Measuring Chain Model	TMCM

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