Cylinder Pressure Sensor based Engine Combustion and Fuel System Diagnostics

MICHAIL KORRES
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Abstract

Nowadays, the developed diagnostics models and software are not capable of locating the root cause of an emerging malfunction, or in other words the responsible component, while the vehicle is up and running. In most cases they are solely able to provide the driver with indications that a fault has been detected within a group of components. Subsequently, it is unavoidable that the vehicle returns to the workshop for a number of standardized tests to be performed, in order to evaluate the condition of the potentially faulty components.

The new era in combustion engines and the attempt to fully incorporate closed-loop combustion control can facilitate the diagnostics procedure and especially the process of fault isolation. By harnessing signals from both real and virtual sensors, it can be feasible to diagnose or even prognose faults, averting the return of the vehicle to the workshop. Moreover, the down-time of the vehicle, can be radically decreased, since there will be an indication on which components to focus. Taking into account the fast-pace steps and improvements on the respective hardware, such as sensors, one can understand that this endeavour can actually be successful in the future.

In the spectrum of this thesis it is assessed whether or not fault detection and isolation can be achieved, through comparison of sensors’ output signals for a number of engine parameters to a stored set of nominal values for these parameters (reference values). Towards that goal, virtual sensors have been developed with the aid of measurement data, in order to increase the reliability of the system. Subsequently, a network of dependencies between parameter values and consequent malfunctions has been constructed, in the form of flowcharts, rudimental for fault isolation. In addition to that and despite the fact that no finalized production code for the model is provided, pseudocode charts have been created as well.

Finally, significant effort was made to derive precise tolerances for the reference values, as this is of great importance for the results of the diagnostics model.
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Last but not least, I am really thankful to all my friends both in Stockholm and Greece. Despite the long distance, I could feel their support and encouragement during difficult times, or when things did not seem to be turning out well for me.

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# Nomenclature

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<th><strong>Abbreviation</strong></th>
<th><strong>Description</strong></th>
</tr>
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<tbody>
<tr>
<td>CA</td>
<td>Crank Angle</td>
</tr>
<tr>
<td>CAD</td>
<td>Crank Angle Degree</td>
</tr>
<tr>
<td>CAx</td>
<td>Crank angle at X % heat released</td>
</tr>
<tr>
<td>CBR</td>
<td>Case Based Reasoning</td>
</tr>
<tr>
<td>CCV</td>
<td>Cycle-to-Cycle Variation</td>
</tr>
<tr>
<td>CHR</td>
<td>Cumulative Heat Release</td>
</tr>
<tr>
<td>CI</td>
<td>Compression Ignition</td>
</tr>
<tr>
<td>CLCC</td>
<td>Closed-Loop Combustion Control</td>
</tr>
<tr>
<td>D</td>
<td>Diesel</td>
</tr>
<tr>
<td>DTC</td>
<td>Diagnostic Trouble Codes</td>
</tr>
<tr>
<td>ECU</td>
<td>Engine Control Unit</td>
</tr>
<tr>
<td>EVC</td>
<td>Exhaust Valve Closure</td>
</tr>
<tr>
<td>EVO</td>
<td>Exhaust Valve Opening</td>
</tr>
<tr>
<td>FDI</td>
<td>Fault Diagnosis and Isolation</td>
</tr>
<tr>
<td>FFT</td>
<td>Fast Fourier Transform</td>
</tr>
<tr>
<td>FT</td>
<td>Fault Tree</td>
</tr>
<tr>
<td>HP</td>
<td>High Pressure</td>
</tr>
<tr>
<td>HPP</td>
<td>High Pressure Pump</td>
</tr>
<tr>
<td>HRR</td>
<td>Heat Release Rate</td>
</tr>
<tr>
<td>ICE</td>
<td>Internal Combustion Engine(s)</td>
</tr>
<tr>
<td>IMV</td>
<td>Inlet Metering Valve</td>
</tr>
<tr>
<td>IVC</td>
<td>Inlet Valve Closure</td>
</tr>
<tr>
<td>IVO</td>
<td>Inlet Valve Opening</td>
</tr>
<tr>
<td>LHV</td>
<td>Lower Heating Value (of the fuel)</td>
</tr>
<tr>
<td>LP</td>
<td>Low Pressure</td>
</tr>
<tr>
<td>LPP</td>
<td>Low Pressure Pump</td>
</tr>
<tr>
<td>MDV</td>
<td>Mechanical Dump Valve</td>
</tr>
<tr>
<td>OBD</td>
<td>On-board Diagnostics</td>
</tr>
<tr>
<td>PDF</td>
<td>Probability Density Function</td>
</tr>
<tr>
<td>RME</td>
<td>Rapeseed Methyl Ester</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root Mean Square Error</td>
</tr>
<tr>
<td>RPM</td>
<td>Rotations Per Minute</td>
</tr>
<tr>
<td>SI</td>
<td>Spark Ignition</td>
</tr>
<tr>
<td>SOC</td>
<td>Start of Combustion</td>
</tr>
<tr>
<td>SOI</td>
<td>Start of Ignition</td>
</tr>
<tr>
<td>SnR</td>
<td>Signal to noise Ratio</td>
</tr>
<tr>
<td>TDC</td>
<td>Top Dead Centre</td>
</tr>
<tr>
<td>XPI</td>
<td>EXtra-high-Pressure Injection</td>
</tr>
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</table>
1 Introduction

1.1 Thesis definition and objectives

The incentive for this thesis is the possibility of diagnosing malfunctions in a compression ignition engine’s fuel injection system through thorough evaluation of signals from both real and virtual sensors (providing values for parameters such as the heat release rate, in-cylinder pressure, etc.). Virtual sensors are widely employed to provide “artificial” signals, through acquisition and processing of data obtained from real sensors. The parameters or quantities, which were utilized and assessed are enumerated in the Methodology chapter. Their traces, can potentially provide an indication of the condition of various components. Components under evaluation comprise the injectors, fuel pipeline, inlet metering valve etc. In addition, sensors’ condition and errors are subject to assessment as well.

The primary challenge of the thesis is to perform on-board diagnostics. This can prove beneficial from both the engine lifetime and economical aspect. As far as the first is concerned, it can be understood that the diagnosis of the root cause of an eventual malfunction, can allow direct actions to avert further damage to the engine. Taking the economical perspective into consideration, the vehicle’s down time can be significantly shortened (as time spent at the workshop can be reduced).

Statistics theory consideration and integration in the developed diagnostics model is vital to define the thin boundaries between random error and actual component failure. Moreover, under the same scope, both component (such as real sensors) and model tolerances (Virtual Sensor models) have to be considered. Thus, an important aspect of this study is the determination of the probabilistic uncertainty, or more specifically the probability that a malfunction occurred. At a subsequent stage of the study, the possibility of predicting a malfunction will be evaluated as well.

Virtual sensors mentioned above play a major role in the diagnostics endeavor. A representative example is the virtual sensor employed to ‘reconstruct’ the pressure trace, obtained as output from the in-cylinder pressure sensor (P_cyl). This procedure comprises three major tasks:

- Elimination of spikes because of high signal to noise ratio
- Identification of the sensor gain through correlation of the received pressure trace to a reference pressure
- Determination of sensor zero-drift

Another vital quantity that can be provided by the virtual sensor is the Heat Release Rate. The Heat Release Rate (HRR) is derived based on the methodology deployed below concerning Wiebe functions. After an initial estimation for the Wiebe function parameters is performed, the resulting HRR curve is compared to the HRR obtained through the first law of thermodynamics. Subsequently, an optimization procedure is investigated to achieve optimum fitting between them, and hence the final parameters of the Wiebe functions can be determined.

Most of the work mentioned in the bullet points above, along with the HRR calculation and other quantities estimation is already done by T. Johansson [1] and to reproduce the methodology employed is not the aim of this thesis. However in the frame of the current study, virtual sensors were developed as well for the parameters of interest in order for the diagnostics procedure to be facilitated.

The core of the diagnostics system is the definition of whether or not any of the engine’s components of interest are malfunctioning. For this purpose, pseudocode diagrams concerning every evaluated component were employed, to describe the diagnostics algorithm and additionally flowcharts were
An attempt was also made to quantify the magnitude of malfunction that is detected in a single component. However, the aforementioned task is very complex, as the different parts of the engine interact with each other and faulty behavior can emerge as a result of superposition of malfunctions. Random errors, cycle to cycle variations and tolerances are not negligible as well and they should be taken into account.

An important characteristic of the model is its adaptability. It should provide reliable and consistent results not for one engine solely, but for a variety of engines with different specifications and under different operating conditions.

1.2 Delimitations

Delimitations setting is rudimental, to ensure that the scope of this thesis is not overwhelmingly broad and that it does not trespass into the research territory of the other thesis conducted simultaneously at SCANIA. Furthermore, some limitations are imposed due to the limited amount of time at disposal for the completion of the thesis. More specifically:

- The diagnostics model is confined to the fuel/injection system. It is solely slightly extended to investigate the potential of diagnosing sensors’ errors (and more specifically CAD encoder, in-cylinder and rail pressure sensor errors)
- Components, whose condition is not evaluated during the diagnostics procedure, are considered fully functional (e.g. high pressure pump, fuel filters, etc.)
- Incomplete combustion (e.g. due to blow-by) is not assessed, unless concrete indications that the blow-by magnitude is significant emerge
- No consideration is made on emissions
- No Wiebe functions-based HRR model was constructed. Virtual sensors already developed at SCANIA are solely employed
- Even though the engine control unit (ECU) computational capabilities are acknowledged as a major factor of influence in this study, no specific limitations were set. Reason for this omission is the continuously increasing potential of the ECU
- Code should be plausible to implement on an embedded system but no investigation on the possibility was part of the thesis. Hence, no finalized code is included
- It is assumed that no deformation of the cylinder interior surfaces occurs due to combustion phenomena (volume is considered to be known). In case the opposite is inferred somehow, it will be treated as an error of the diagnostics system. Another thesis is conducted in parallel to this one, concerning volume deviation from ideal cycle
- Matlab/Simulink environment is solely employed for data processing and model construction
- It is assumed that no failure in the ECU and CAN system occurs (fault-free mode)

1.3 Literature survey

1.3.1 Virtual sensors and Diagnostics

An ever-increasing legislation stringency concerning emissions produced by the combustion of hydrocarbons-fuels, has forced manufacturers to put substantial effort into emissions control and reduction. In order to achieve that, uninterrupted monitoring and control of various combustion parameters is more than crucial. The latter gave rise to endeavors to develop and integrate a closed-loop combustion control system (CLCC), able to optimize the functionality of the engine at every single
moment (in terms of efficiency, fuel consumption and performance for different ambient conditions and road demands). CLCC can also contribute to the engine robustness against disparities due to external conditions (e.g. fuel-type) and against internal variations, such as cycle-to-cycle variation (CCV).

Research towards this direction has created fertile field for development and enhancement of the currently existing diagnostic techniques. On-board Diagnostics (OBD) evolution can be significantly accelerated, by monitoring and estimating quantities and parameters of interest. In the long run, not only more accurate fault diagnostics will be feasible, but also prediction of probable malfunctions. This can prove to be very beneficial not only to the vehicle components lifetime but also for maintenance cost reduction [2, 3]. Another perspective worth mentioning is the vehicle’s availability, as the down-time can be diminished significantly (Down-time is defined as the time that the vehicle remains inactive, e.g. in the workshop).

Monitoring of combustion parameters however, could not be feasible without harnessing the advanced capabilities of sensors mounted on the engine body, e.g. pressure, temperature and flow sensors. Along with the aforementioned ones, during the last decade there has been an attempt to inaugurate and use virtual sensors on board as well [1, 4, 5, 6]. The advantage of virtual sensors compared to their counterparts lies on the fact that they can provide modelled values for important parameters, non-measurable by the ordinary sensors. One of these parameters that are assessed extensively in this thesis is the HRR. Several scientific papers have approached the HRR closely and have proposed ways of estimating it, employing different strategies and models [1, 7, 8, 9, 10, 11, 12].

One of the most common approaches to the problem of determining the HRR, is provided by the single-zone heat release model [7]. This model is governed by the first law of thermodynamics, but its simplicity is neutralized by inaccuracies that emanate from over simplified specific heat ratio and heat transfer from charge to wall values [1].

Consequently, more sophisticated multi-zone models have also been developed [8, 9]. However, they bear a major disadvantage: They require substantially higher computational capability from the ECU, if they are to be employed in real time on-board applications. Given the fact that computational capacity of commercial vehicles is limited, implementation of multi-zone models is currently hindered [10, 12].

The aforementioned restriction applies to HRR models based on neural networks and machine learning as well. This technique is quite intriguing and has already been investigated by Cesario N. et al [10]. It presents great potential and margins for improvement, but it is not widespread. Primary advantage is its adaptability: More specifically, the fact that once implemented on a machine, it has the capability of ‘learning’ its behavior under different operating conditions. Nevertheless, prerequisite is that a large volume of data concerning engine’s parameters is available and stored in the ECU. Otherwise, the result can be unreliable sometimes, which is not acceptable for production. Another drawback of the model is that there is a tradeoff between accuracy and universality [11].

Finally, the utilization of Wiebe functions to parametrize the HRR, whose advantage is the relatively low computational cost, was evaluated. The parameters of the Wiebe function are merely constants, which lack physical consistency. For that reason, some papers have attempted to discover correspondences between these constants and engine’s operational parameters [12].

A functional and accurate virtual sensor for the HRR requires an accurate pressure signal. However, pressure traces extracted from the in-cylinder pressure sensor can be either slightly distorted due to high signal to noise ratio (SnR), or in need of calibration-referencing (sensor gain and sensor drift present) [1, 13, 14].
1.3.2 Engine and combustion Diagnostics

Intensive literature research was conducted on techniques currently employed to detect faults and malfunctions in the fuel/injection system. Two different approaches were primarily encountered:

- **Case Based Reasoning (CBR):** This method relies on a big database of recorded past issues encountered on vehicles and their respective solutions, in order to detect emerging malfunctions. Diagnostic Trouble Codes (DTC) subsequently indicate if there is a problem (triggered by a system’s failure of deteriorated performance). Finally, a developed DTC model locates the root cause of the malfunction [15, 3]

- **Sensor based Diagnostics:** A widespread method today in the industry and the one implemented in many cases for diagnostics. Harnesses a conglomeration of real and virtual sensors’ signals providing values about variables of interest. Subsequently, these values are processed and evaluated by a model, in order to detect deviations from nominal performance, and ultimately track potential malfunctions.

The current thesis mostly emphasizes on the second category, but harnessing the advantages of CBR when feasible. In case of implementation in the ECU, a combination with the first one would be ideal: a DTC can be saved when a problem is encountered, instead of constantly running the algorithm. Below, the most commonly employed techniques are enumerated, along with the respective referenced papers.

Many authors have looked into the possibility of detecting problems with the aid of accelerometers mounted on strategic positions on the components of interest [16, 17]. Despite the fact that this method looks promising, it encounters the following issue: the exact source of excitation is difficult to be located.

A similar strategy is harnessing the engine speed, and after subjecting the signal to Fast Fourier Transform (FFT), it utilizes the amplitude spectrum derived [18, 19]. The shape of the amplitude versus frequency curve can provide adequate information on whether injection misfire occurs. However, this method is prone to inaccuracies, due to low sampling speed, measurement resolution, distorted signal due to exogenous excitation (load disturbance from the gearbox) [19] and crankshaft torsion effects (because of reciprocating masses).

Apart from the aforementioned strategies, optical diagnostics are widely implemented as well, because they can provide insight to the phenomena that occur in the cylinder [20, 21], or even detect cavitation in the fuel pipeline [22].

Finally, it is worth mentioning that most applicable techniques can solely allocate the problem source, but are incapable of quantifying the extent of malfunction. Lamaris et al. [23] attempted to estimate the magnitude of an eventual malfunction, by comparing a modelled characteristic parameter of a component to a reference value.

1.3.3 Diagnostics Model

The most thought-provoking task in the endeavor of diagnosis is probably the development of an accurate model. The model proposed usually comprises three discrete steps [24, 25] in order of execution:

- Fault detection
- Fault isolation
- Fault identification

Most diagnostics models follow the same procedure to detect the root cause of a malfunction, which is based on residuals generation [25, 26, 27, 24, 28, 29] (detection of discrepancies between values derived from a reference model and values extracted from a real process). More intricate models harness the
power of Neural Networks [11], a fact that constitutes them very efficient and adaptive. However, in case a large number of input and output variables is involved, the computational load, as well as the risk of overfitting, cannot be neglected.

Ultimately, an integral part of the diagnostic models is the level of reliability, which can be estimated by the use of the statistics and probabilistic analysis [30, 31, 32, 33]. Kirillov S. et al evaluate the possibilities not only to diagnose, but also to prognose problems with the aid of statistics [32]. A separate section in the following chapter is devoted to the respective theoretical background.

1.4 Structure/ Outline:

The structure of the thesis and the procedure employed consists of the following discrete steps that constitute the main chapters:

- Theoretical background
- Methodology employed (comprising parameters of interest, reasoning process for the construction of the flowcharts and tolerances)
- Results
- Conclusions

Due to confidentiality reasons both the flowcharts and pseudocode for each of the evaluation tests are not included.
2 Theoretical background

2.1 Fuel/Injection System

The developed diagnostic model emphasizes on and assesses the functionality of the fuel/injection system. Therefore, before advancing to the core diagnostics procedure, an overview of the aforementioned system and its components is rudimental. Moreover, this section comprises and analyzes common encountered faults together with the symptoms emanating from them.

2.1.1 System layout

Continuous research and development in internal combustion engines (ICE) over the last few decades have imposed new trends for engine design and its respective subsystems. Improvements and enhancements are abetted as well by major breakthroughs in material science and control engineering, sectors that are firmly affiliated to the automotive industry. Especially for the case of the fuel/injection system, which is a determining factor of the engine’s performance and efficiency, evolution has been quite rapid. Nowadays, a range of different configurations are used, depending on the application and customer demands.

In the current thesis solely compression ignition (CI) engines are investigated: simultaneous description and assessment of both compression and spark ignition (SI) engines would be a time-consuming task, as they yield major disparities between them. Hence, the main principle of the CI engine is the compression of air in the cylinder. Fuel is injected in the cylinder around the top dead centre (TDC) and subsequently evaporated, when mixed with the compressed air. After evaporation the heat generated by the compression process facilitates the ignition of the air fuel mixture and subsequently combustion occurs.

Rudimental prerequisite for the whole procedure is that the injected fuel disperses rapidly and in the correct timing. That is where the injection system comes in play. Nozzle geometry of the injectors subjects the fuel to immensely high pressures, a fact that guarantees the shift dispersion of the fuel droplets. Once the diameter of the droplets is small enough, evaporation can be facilitated. The second criterion (correct timing) is fulfilled by the advanced manufacturing of the injector body together with the increased capabilities of the ECU. Towards that goal, XPI (eXtra-high Pressure Injection) technology was developed, which complies with the standards and demands of the new generation CI engines.

![Figure 1: XPI Injector](image)
Structure of an XPI injector is presented in Figure 1. Moreover, a brief description of the parts it comprises and their functionality follows below.

For simplification, the injector can be regarded as an on/off valve. On condition denotes that the lower plunger is lifted and ‘reveals’ the hole pattern of the nozzle. Then, fuel flows through the opening and subsequently is sprayed into the cylinder. On the contrary, when this route is sealed by the plunger head no injection takes place. Injection timing and duration interval are regulated by the current supplied to the coil, according to the signals from the ECU and a trim code (individual calibration programmed in the Engine Management System).

The whole process is analysed in sequential order:

- Initially, the coil is energized when current runs through it and drives the armature up. This movement drifts and overpowers the armature spring
- Armature plunger is dragged together with the armature and allows fuel flow from the control volume to the return through the pilot valve. This phenomenon is followed by a radical pressure drop in the control volume (as the fuel is drained at a higher pace than refilled)
- When the pressure decrease surpasses a specific threshold, the lower plunger spring is contracted back to its nominal length and subsequently the lower plunger is lifted
- Pressure difference between the cylinder interior and the fuel in the injector forces the fuel mass through the nozzle into the cylinder. Since the pressure magnitude (in the cylinder) due to the compression is extremely high, one can imagine how difficult the task of securing this aforementioned pressure difference is: holes of microscopic diameter (order of µm) are more than crucial
- According to the predetermined injection tuning, current ceases to be supplied from the ECU. Consequently, the pilot valve is blocked and pressure in the control volume starts building up
- This forces the lower plunger to seal the nozzle opening and halt the injection

However, this thesis is not aiming to diagnose solely problems in the injectors, but to address malfunctions in the whole fuel/injection system. Hence, a brief introduction to the joint configuration is included. In Figure 2 that follows, one can observe a complete fuel/injection system, affixed in a EuroVI diesel engine.

The main parts depicted in the figure are:

- Low pressure pump (LPP)
- Fuel filters
- Inlet metering valve (IMV)
- High pressure pump (HPP)
- Accumulator (rail)
- Rail pressure sensor
- Mechanical dump valve
- Return rail
- XPI injector
- Pipeline

The figure does not include main and tech-tank, where the fuel is saved. A conceptual analysis of the functionality of each component follows, in ascending order (from 1 to 8).
The LPP communicates directly with the tech-tank and drains fuel, which flows through the fuel filters towards the HPP. This flow is regulated by the IMV and has a direct impact on the pressure in the accumulator. Subsequently, the HPP is responsible for transferring the fuel to the accumulator through the high pressure circuit. A mechanical dump valve (MDV) is attached to the rail and secures that the in-rail pressure does not overcome a prearranged threshold value (pressure values are monitored by the rail pressure sensor). In this undesirable case, the MDV opens and releases fuel to the return rail, in order to ensure that the mechanical parts are out of jeopardy. Fuel entering the injector, but not sprayed in the cylinder is accumulated in the return rail as well. Ultimately, injection occurs when the pulse signal from the ECU energizes the injector armature coil (explained above).

### 2.1.2 Potential Malfunctions

Possible malfunctions that pertain in the fuel/injection system, are enumerated in the list below. The magnitude of severity varies, according to the root cause of the fault and the extent of damage (e.g. extent of leakage). Indicatively, the following can be encountered:

- Fuel Pump malfunctions (HP, LP)
- Accumulator pressure loss (leakage, dump valve issue)
- Clogged or malfunctioning fuel filters (clogged, ageing, very low pressure difference between inlet and outlet)
- Pipeline issues: cavitation, leakage
- Sensor error (rail pressure sensor)
- Leakage in the tanks
- IMV fault
- Erroneous injection timing
- Failure in the injectors

As far as the last bullet point is concerned, it is separately assessed in Table 1.
### Table 1: Possible injector failures

<table>
<thead>
<tr>
<th>Injector part</th>
<th>Root cause</th>
<th>Possible reason</th>
</tr>
</thead>
</table>
| Pilot valve   | Damaged pilot valve seat | • Cavitation  
• Debris |
|               | Damaged check ball       | -              |
|               | Shifted stroke length    | Ageing         |
| Lower plunger | Plunger stuck at lowest position | • Debris  
• Thermal expansion |
|               | Plunger stuck in open position | • Debris  
• Thermal expansion |
|               | Lower plunger sealing    | Crack due to loads |
|               | Fuelling gain orifice     | Blocked by debris |
|               | Lower plunger stroke change | Lower plunger seat wear |
| Nozzle        | Tolerances between nozzle and body | - |
|               | Nozzle wear/ cracks       | • cavitation  
• High stresses, fatigue |
|               | Nozzle retainer not perfectly fitted | - |
|               | Lower plunger seat        | • Debris  
• Wear |
| Spray holes   |                         | • Erosion  
• Corrosion  
• Cavitation  
• Clogging  
• Carboning |
| Sac           |                         | Cavitation     |

Apart from the failures presented in the table above, injection timing is also an extremely influential factor. Incorrect injection timing can be triggered by several reasons, such as an ECU failure, an error in the trim code, a failure in a fuel injection system component or a sensor error (e.g. CAD sensor).

Moreover, this thesis covers a broader spectrum of components subject to evaluation, and not strictly components comprising the fuel/injection system. More specifically, techniques for estimating the condition of sensors (in-cylinder pressure, RPM and CAD sensor) are also proposed.

The current OBD methods harness the sensors’ output, in order to detect and isolate the very root cause of a system failure. When an erroneous value or sequence of values is recorded from one or more sensors, a DTC is stored.

#### 2.2 Malfunctions pertaining in the combustion and gas exchange process

The current thesis spectrum is not restricted in the fuel/injection system malfunctions, but also evaluates issues occurring in the cylinder during the combustion and gas exchange phases. The development of virtual sensors facilitates this attempt and together with the real sensors mounted on-board valuable conclusions can be extracted.

The three primary faults inside the cylinder domain that are addressed in the present thesis (and affect combustion and gas exchange) are:
• pre-ignition
• blow-by
• valve issues

Pre-ignition is not so common in CI engines, due to the fact that only air is initially compressed and not a mixture of air and fuel, as in SI engines. However, fuel deposits in the injector’s nozzle outlet or on the cylinder liner can cause the phenomenon in some cases, as well as lubricant oil leakage into the cylinder. Pre-ignition is detrimental for engine efficiency and produced torque.

A regular malfunction phenomenon is blow-by: loss of a certain amount of air through the crevices between the piston head and cylinder liner. Loss of air can also be detected because of inadequately sealed valves in 4 stroke CI engines. Reason for the first category is a fault or deterioration of the piston rings due to ageing. Blow-by can severely affect the output torque, as the loss of air results in diminished in-cylinder pressure and less air available for combustion.

Finally, valve issues are to be addressed as well, as they are very influential for the engine operation. Inlet and exhaust valves’ opening (IVO and EVO respectively) and closing (IVC and EVC respectively) are the parameters mainly employed for evaluation procedure.

2.3 In-Cylinder Pressure and Heat Release Rate

2.3.1 In-Cylinder Pressure

A major objective of this study, as already stated in the first chapter, is to harness the in-cylinder pressure trace along with the heat release rate (HRR) virtual sensor output, in order to diagnose malfunctions in the fuel/ injection system.

The pressure trace can provide noteworthy information on the combustion process inside the cylinder and indications on whether a failure in an engine component has occurred. Particularly, the following values are of interest:

• Maximum pressure ($P_{\text{max}}$)
• Pressure inclination after IVC
• Pressure at compression phase for a specific crank angle (CA) value between the IVC and TDC

Equally essential to the aforementioned pressure values are the respective crank angle values, from which valuable conclusions can be drawn (e.g. regarding injection timing and start of combustion, as well as CAD for maximum in-cylinder pressure). Due to page budget restrictions and thesis delimitations, no in-depth analysis of the pressure signal reconstruction procedure is included. The interested reader can refer to [1, 13, 14] for more details.

2.3.2 Heat Release Rate

The developed HRR model in [1] is utilized as basis for the virtual sensor based diagnostics. Reason for that is the importance of this specific quantity and the fact that rudimental parameters can be directly derived from it - such as the CA at which a specific fuel percentage is burned (CAx) and the cumulative heat release (CHR).

The HRR model employs Wiebe functions for parametrization, which are of the following form:
\[ x_b = 1 - \exp\left[-a\left(\frac{\theta - \theta_{SOC}}{\Delta \theta}\right)^{m+1}\right] \] (1)

where:
- \( x_b \) is the fraction of the burned fuel amount
- \( a \) (efficiency parameter) and \( m \) are constant parameters
- \( \theta \) and \( \theta_{SOC} \) are current CA and CA at which start of combustion occurs

According to [1] the number of Wiebe functions utilized to obtain the HRR curve is \( n+1 \), where \( n \) denotes the number of injection events. Addition of one accounts for the main combustion event that comprises both premixed combustion and diffusion and late combustion ensemble (two Wiebe functions in total for main combustion). Hence, total mass fraction burned in main combustion is:

\[ x_b = \beta \cdot x_{b1} + (1 - \beta) \cdot x_{b2} \] (2)

Parameter \( \beta \) is a weight factor and \( x_{b1} \) and \( x_{b2} \) are the fractions of the fuel amount burned in premixed and diffusive combustion respectively.

The derivative of the mass fraction is subsequently calculated (mass fraction burning rate) and encapsulated in equation (4) below, in order to obtain the HRR.

\[ \frac{dx_b}{d\theta} = a(m+1)\left(\frac{\theta - \theta_{SOC}}{\Delta \theta}\right)^m \exp\left[-a\left(\frac{\theta - \theta_{SOC}}{\Delta \theta}\right)^{m+1}\right] \] (3)

Ultimately, total Heat release rate is defined as the superposition of the distinct HRR curves obtained through equation above:

\[ \frac{dQ_{net}}{d\theta} = \sum_{i=1}^{N} m_{inj,i} \cdot LHV \cdot \frac{dx_{bi}}{d\theta} \] (4)

where:
- \( \frac{dQ_{net}}{d\theta} \) is the total heat release
- \( m_{inj,i} \) is mass of injected fuel per each cycle
- \( LHV \) is the lower heating value of the injected fuel

The challenging part of the HRR calculation is the determination of the parameters that pertain in equation Fel! Det går inte att hitta någon referenskälla.(3). That can be achieved through an optimization procedure: more specifically the task can be to minimize the least square error of the difference between the aforementioned HRR curve and the respective one obtained from the first law of thermodynamics according to equation (5) below.

\[ \frac{dQ_{net}}{d\theta} = \frac{1}{\gamma-1} \cdot V \cdot \frac{dp}{d\theta} + \frac{\gamma}{\gamma-1} \cdot P \cdot \frac{dV}{d\theta} \] (5)
The equation takes into account pressure (p), cylinder volume as function of θ (V) and heat capacity ratio (γ). A typical curve for the HRR with solely one main injection occurring is presented. Combustion phases along with start of ignition (SOI) can be observed in Figure 3.

Once HRR is finally delivered, the major parameters of interest that can be extracted through it are:

- CHR by merely integrating the HRR over the interval around the TDC (integration over the whole cycle would be computationally demanding)
- CA10, 50, 90. These quantities can approximately indicate start, location and duration of combustion

2.4 Model Based Diagnostics

Model based diagnostics can be divided in two main sub-categories, according to the analysis carried out and the methodology employed:

- Quantitative model based
- Qualitative model based

Both methods are capable of detecting and isolating the root of a malfunction. However, the first one bears the advantage of fault quantification: it does not solely detect the cause of the fault, but it can also provide an estimation of its magnitude.

Despite the fact that the two methods are discrete, they can be jointly employed in a model, in order to harness the advantages of both. Their rationale is scrutinized below.

2.4.1 Quantitative model based diagnostics

Quantitative model based diagnostics are grounded on quantitative evaluation of parameters and variables of interest, in order to detect and identify faults, according to the fault diagnosis and isolation (FDI) rationale [24]. As implied by the term itself, for the model based diagnostics to be applicable a
model has to be constructed. Subsequently, estimated values for the variables of interest are outputted from the model and they are compared to the respective values obtained from sensors in the frame of a concept called residual generation.

2.4.1.1 Diagnostics system layout

The function of the FDI system can be adequately described from the scheme below (Figure 4). An input vector is initially subject to a two-way ‘processing’. The first route is the upper branch of the scheme, which constitutes the graphical representation of the system (e.g. fuel/injection system). It comprises actuators, the system itself and sensors. The lower branch solely contains a group of non-linear or linear observers, which provide an estimation for the major system states.

Afterwards, the output vector from the sensors (measurable output) along with the output vector from the observers (estimated states) is employed as input in the residual generator block. The residual generator merely performs an one to one comparison of the respective inputs: values of measurable variables are deducted from the corresponding estimated variables values or vice versa.

The final step of the FDI procedure is fault detection and isolation. Fault is initially detected through direct comparison of the residuals to threshold values, which are not constant, but rather dynamic, depending on the operating conditions. These values denote the magnitude of acceptable error and are a function of the monitored system’s functional parameters. At this point it has to be highlighted that the system reliability is also considered (e.g. in the IC engine case the cycle-to-cycle variations and the hardware tolerances).

![Figure 4: FDI system layout](image)

Once a single residual value surpasses the aforementioned thresholds, then it is ascertained that a fault has occurred. Consequently, fault isolation is feasible, through evaluation of which residual thresholds are breached. However, in the majority of occasions a single residual infringement is not sufficient to provide the root cause. The reason is that for a dynamic system like the CI engine, failures emerge as the outcome of an agglomeration of residuals. A matrix defining all the relationships between residuals and failures in the form of Table 2 is usually employed to facilitate the diagnostics procedure. 1 denotes that a failure $f_i$ is correlated to a residual $r_i$, while 0 denotes the opposite [24, 25].
### Table 2: Dependencies between faults and residuals

<table>
<thead>
<tr>
<th>Residuals</th>
<th>( r_1 )</th>
<th>( r_2 )</th>
<th>( r_3 )</th>
<th>( r_4 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( f_1 )</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
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<td>1</td>
<td>1</td>
</tr>
<tr>
<td>( f_3 )</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>( f_4 )</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

#### 2.4.2 Qualitative model based diagnostics

The qualitative model differs significantly from the quantitative one. A typical tool employed for qualitative analysis is the fault tree (FT), which is a graphical representation of the system’s structure. The form of the FT can be observed in Figure 5.

![Fault Tree](image)

**Figure 5: Fault Tree**

The FT comprises the aggregate of the system’s components and hardware that can be erroneous (e.g. injectors, sensors, when ICE system is assessed), along with Boolean gates optionally (usually OR and AND) and fault events. The different blocks, which can be seen in Figure 5 are interconnected in a way that represents physical dependencies. The shapes of the blocks vary, according to the events they impersonate.

For example, in the FT presented a variety of primary and secondary fault events (through observations or residuals) result in an input event, for instance a component failure. Definition of primary or secondary for the fault events depends on the degree of importance and the probability of occurrence.

#### 2.4.3 Pseudocode algorithms

Pseudocode algorithm constitutes a feasible solution to detect and describe malfunctions using logical commands and cause-and-effect relationships. Since the rationale is similar to the FT, only a brief introduction into the system is included.
Pseudocode algorithm can receive 2 forms: a) language form, but simplified compared to the conventional programming languages (in order for it to be easily perceptible by humans and not machines), b) flowchart, which serves as a graphical alternative. The latter is deployed in the following figure:

![Figure 6: Pseudocode basic flow chart](image)

Pseudocode flow chart is based on the same rationale as the FT, with one major difference. Pseudocode examines both eventualities of a condition (two different branches for true and false respectively), while FT assesses only the eventuality of interest.

2.5 Statistics theory and reliability

Tolerances of the sensors along with model/observers’ uncertainties and cycle to cycle variations imposes the incorporation of statistics theory and reliability in the developed diagnostics model.

Every variable can be treated as a sample of values confined between specific intervals. The most characteristic quantities of a sample are the mean value and the variance of the sample values around the mean (in the case they are modelled as a normal distribution variable). Once they are determined, the probability density function (PDF) can be defined, which expresses the likelihood that the variable receives a specific value. The integral of the PDF over an interval represents the probability of a random value to be found inside this interval.

One of the most widely employed probability distributions is the Normal or Gaussian distribution, which can adequately represent random variables. For this specific distribution the mean value $\mu$ and variance $\sigma^2$ can be calculated respectively from the following formulas:

$$\mu = \frac{1}{n} \sum_{i=1}^{n} x_i$$  \hspace{1cm} (6)
\[ \sigma^2 = \frac{1}{n} \sum_{i=1}^{n} (x_i - \mu)^2 \] (7)

Subsequently the probability density of the normal distribution is defined from equation (8). The square root of variance \( \sigma \) is called standard deviation.

\[ f(x | \mu, \sigma^2) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \] (8)

Below, the form of the PDF can be observed along with the tolerance intervals, obtained from the PDF’s integral. Tolerance interval diagram is a rudimental tool for statistics, as it provides the probability that a random value pertains into a specific interval of a variable distribution and simultaneously sets the limitations for a variable’s value range.

![Figure 7: PDF for different mean values and variances (left) and tolerance interval (right)](image)

Nevertheless, standard normal variables are not always the case. Hence the PDF that characterizes them is not of the form observed in Figure 7. Additional distributions usually employed are the Gamma and Boltzmann distributions (for semi-infinite random positive values).
3 Methodology employed

3.1 Developed diagnostics model

3.1.1 Description of the procedure followed

The principle of the diagnostics model is to detect whether or not a malfunction has occurred in the system and subsequently attempt to locate the defective component or root cause of the problem. For that reason, the parameters mentioned in the previous chapter are constantly monitored and evaluated. The evaluation procedure is established on the comparison of the parameters’ values recorded by the real and virtual sensors configuration to their respective ‘normal’ or nominal values.

Determination of the normal value margins for the aforementioned parameters requires the utilization of statistics theory, and major prerequisite is that the reference measurements are conducted on a healthy engine. Moreover, model tolerances (e.g. Virtual sensor for CAx, CHR, SOC detection etc.) as well as sensors tolerances need to be considered and incorporated. Then, since data concerning the parameters of interest is accumulated, the diagnostic procedure can be inaugurated.

It is easily understood that the term normal is abstract and usually vague. Its vagueness emanates from the fact that a ‘normal’ parameter value differentiates from engine to engine: the margins of normal operation vary according to engine specifications, operating conditions, driving modes and driver demands. Thus, a principle difficulty of the model is adaptability, or the ability to determine the threshold, beyond which engine operation ceases to be normal or fully functional for different conditions.

The procedure described above is depicted in the following figure (Figure 8), which comprises two main levels:

1. Data acquisition and processing to determine nominal values and tolerances for the parameters of interest (reference values).

2. Consequently, comparison is made between data recorded from both real and virtual sensors and reference values obtained from level 1. This process leads to fault detection and subsequently fault isolation.

![Figure 8: Schematic of the diagnostic system](image-url)
The possible malfunctions considered (erroneous components and processes) in the frame of the present diagnostics model are deployed below, along with the respective subchapter, where the reasoning process for each of them is explained.

- In-cylinder pressure sensor error (3.2.2.1)
- CAD encoder error (3.2.2.2)
- Valve issues (3.2.2.3)
- Blow-by issues (through crevices between the cylinder liner and piston head) (3.2.2.4)
- Rail pressure sensor error (3.2.2.5)
- Inlet metering valve fault (3.2.2.6)
- Pipeline issues (clogged pipeline, pipeline leakage) (3.2.2.7)
- Mechanical dump valve fault (3.2.2.8)
- Injector related fault (comprising injector trim code error, injector body error, disconnected injector) (3.2.2.9)

Finally, in order to determine the root cause of the malfunction (fault isolation), simultaneous evaluation of parameters is required. Based on that and employing a network of logical dependencies (observations and resulting possible causes) the flowcharts for each of the malfunctions considered above were constructed.

An analytical description of the whole procedure (data acquisition and processing, fault detection, fault isolation, flowchart construction) follows in the next sections.

3.1.2 Data acquisition and processing

For the diagnostics procedure to be feasible, measurement data acquisition for different operating points is a major prerequisite. This is performed offline, e.g. during engine calibration, in order to ensure both fully controlled conditions and that a “healthy” engine is employed as reference.

The reference values for the model were obtained after processing of measurement data from a SCANIA D13 inline 6-cylinder engine. In overall 36 operating points in stationary conditions were recorded, each one a combination of fixed rotational speed (RPM) and load. Six different RPM levels were chosen along with five load levels ranging from full load to zero. The last six operating points recorded are with the engine motored (no fuel is injected). The sequence of operating points was as follows in Figure 9. The exact values of engine load and speed are hereby omitted due to confidentiality.

![Operating Points Tested](image)

*Figure 9: Sequence of operating points*
For each of the operating points, data from 50 cycles were gathered, in order to average out cycle-to-cycle variation effect. To diminish the effect of transient conditions, when shifting from one operating point to another, smooth transition was important. For that purpose, a minimum time interval of two minutes under constant speed and load conditions for each operating point was rudimental before data was recorded. The type of fuel used was Euro VI reference fuel with 7% RME.

Two in-cylinder pressure sensors were mounted to the cylinders, one in cylinder 1 and the other in cylinder 6. Subsequently, the output signals to be evaluated are deployed as well. These are split in two main categories: parameters directly obtained from real sensors and parameters obtained from virtual sensors, after post-processing. It must be highlighted here that the “raw” signals from the real sensors undergo high frequency sampling and processing as well (e.g. pressure pegging for the in-cylinder pressure traces).

**Real sensors output:**

- In-cylinder pressure (In-cylinder pressure sensor)
- Rail pressure (Rail pressure sensor)
- Crankshaft speed and CAD (CAD encoder)
- Boost pressure (Intake manifold pressure sensor)
- Boost temperature (Intake manifold temperature sensor)
- Current in the armature coil (to determine injector’s on-time)

**Virtual sensors output:**

- Maximum in-cylinder pressure (P$_{\text{max}}$)
- CAD at which P$_{\text{max}}$ is observed (CAD$_{P_{\text{max}}}$)
- Heat release rate
- Cumulative heat release (CHR)
- CA10, 50, 90
- Start of combustion (SOC)
- Heat capacity ratio
- Injected fuel quantity (m$_{\text{f}}$)
- Average rail pressure
- IVO, IVC, EVO, EVC

The majority of the virtual sensors have been already developed by SCANIA. However, for the diagnostics system to function properly, estimations for parameters such as IVO, IVC, EVO, EVC, adiabatic pressure, etc. had to be created as well. In chapter 3.2 the interested reader can have more insight on the logic behind the calculation of the aforementioned parameters.

These data serve as the basis for the fault detection and isolation algorithms through reference to nominal (past) engine operation. Once the engine operates under a specific load and engine speed already encountered in the past, the diagnostics system is run and compares the parameters of interest to the respective ‘normal’ values. As it easily understood, the specific strategy bears a major disadvantage: operation under specific operating points is not usually feasible, when the vehicle is up (because the load and subsequently engine speed is determined by the driver), and hence OBD is hindered in that case. Furthermore, it demands a significantly high amount of data as reference, which is translated into ECU space occupied. Perhaps these strategies can be deployed during motoring cycles or idling, when load or RPM remain relatively steady.

For that reason, reference of parameters to a predetermined rule of thumb correlation (function) between different operating points can be regarded as the most reliable strategy, able to provide diagnostic results for virtually any combination of RPM and load. Initially, a correlation curve can be determined for each
of the engine’s parameters of interest versus load and rpm. This is usually performed offline and subsequently the outcome is stored in the engine’s ECU. Due to time restrictions, the current thesis does not focus on development of functions for nominal parameters values versus load and RPM.

The major issue that has to be always considered is the effect of transient operating conditions in the reliability of the diagnostic procedure verdict. Thus, the diagnostics system requires steady state conditions to function adequately: a minimum amount of cycles, e.g. 50 is rudimental to obtain assessable values of the parameters of interest. In every case, the intermediate cycles are evaluated, to eliminate transient conditions interference (e.g. given a pool of 100 cycles at steady conditions the first cycles have to be ruled out from consideration).

3.1.3 Fault detection

Fault detection is the core of the diagnostics procedure. An erroneous situation is assumed when a 5% or more out of the total recorded values for one of the parameters evaluated above is abnormal (e.g. from a pool of 50 cycles if a parameter is abnormal for 3 cycles). Abnormality is determined by whether or not the parameter values received are between the normal operation margins. These margins depend on the engine, the operating point and the parameter nature itself. A more profound analysis along with results can be observed in 3.3. The 95% confidence is employed in order to ensure that the model is robust enough.

Reference of parameters to a predetermined rule of thumb correlation between different operating points can also be utilized. However, that is not attempted in the current thesis.

Primarily two different evaluation strategies to identify potential malfunctions are employed and listed below:

1. Reference of the parameters to a healthy past engine operation

2. Simultaneous comparison of components’ parameters (e.g. in-cylinder pressure for all the cylinders) for a single operating point.

Each of the aforementioned strategies bears its own advantages, which are harnessed properly to provide an adequate diagnostics system.

The layout of the fault detection system is illustrated in Figure 10 below.

![Figure 10: Fault detection system layout](image)

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Once value discrepancy is sensed, a fault code is emitted and consequently fault isolation can be initialized. Unless this is a case, no fault isolation code is run, as it is easily perceived that it would require computational power without any benefit. Thus, fault detection and isolation are not proceeded in parallel.

3.1.4 Fault isolation

Once a fault detection code has been triggered, fault isolation is commenced immediately. The system is structured according to already developed diagnostic systems and follows the same fundamentals. Hence, when a malfunction is detected, a DTC is triggered. Fault isolation has modular character: more specifically, each component to be tested is evaluated individually. However, interactions between the different components of a dynamic system are not negligible, so it is really important that the order of evaluated components is chosen wisely.

As far as the evaluation tests are concerned, only one is independent of others (sole prerequisite is the recording of parameters and the existence of reference nominal values). This is the in-cylinder pressure evaluation test. The others do not pertain in this category, as they are to some extent dependent on the result of evaluation tests performed already.

However, the system is designed in a way that no previous knowledge of the condition of some components is required: Starting from the in-cylinder pressure sensor evaluation test, a malfunction verdict is feasible, merely by employing parameter values recorded. Towards that goal, the order with which the tests are run is essential.

Below one can observe that the tests are categorized in groups, according to the dependencies between them:

- **Group 1** at the bottom of the pyramid comprises of the following evaluation tests:
  - In-cylinder pressure sensor
  - CAD encoder
  - Valve issues
  - Blow-by

- **Group 2** contains:
  - Rail pressure sensor test
  - Inlet metering valve test
  - Pipeline issues test (clogged pipeline, pipeline leakage)
  - Mechanical dump valve test

- **Finally, the top of the pyramid consists of the**:
  - Injector test (comprising injector trim code error, injector body error, disconnected injector), which is dependent from most of the previous evaluation tests

When the condition of the in-cylinder pressure sensor has been assessed, the tests of Group 2 are not run randomly, but follow a predetermined sequence, which is designated from the descending listing order. Hence, the CAD encoder evaluation test is performed second and subsequently the CAD encoder, valve issues and blow-by test with this order. The same is the case for Group 3, after the components of group 2 are assessed.
At this point it is worth mentioning that if a component has been diagnosed with an issue, then the evaluation procedure is not interrupted, but can be continued. For instance, in case an in-cylinder pressure sensor is found to be faulty, then only the tests regarding the respective cylinder can be hindered or affected: e.g. blow-by of this cylinder, respective injector. However, the CAD encoder test can be performed normally, as the signals received from the remaining functional sensors are more than enough.

Moreover, the system can conform to eventual malfunction in some cases and will attempt to search for an alternative way to locate a malfunction. Considering the same scenario for example (in-cylinder pressure sensor fault) and given that the CAD encoder is fully functional, the model bypasses the erroneous pressure trace provided by the sensor and employs the CAD encoder output to proceed.

Finally, the system can adapt to ‘shortage’ of required number of steady state cycles, by demanding a lower number than the threshold of 50 cycles for the evaluation tests to run. In that case however, the lack of adequate number of cycles has to be compensated for, by ‘enlarging’ the margins of nominal values (as CCV has to be taken into consideration). More discussion about that is included in the respective chapter (3.3.1).

3.2 Evaluation tests and parameters of interest

In order for the diagnostics model to be functional and detect one or more of the potential malfunctions mentioned in 3.1.1 an evaluation test for each of them has to be constructed. Evaluation tests consist of if conditions, testing whether or not a parameter of interest receives normal values, and subsequent paths depending on whether or not the conditions are sustained. At the end of each path (or branch when flowcharts are concerned), there is a conclusion of faulty or no faulty engine operation.

The reasoning process followed for each evaluation test can be found in subchapter 3.2.2 below. However, before this analysis is commenced, it is important to describe the algorithms developed to estimate some of the parameters of interest employed in the evaluation tests. For the sake of simplicity, reference is solely made to algorithms developed by the writer. The interested reader can recur to the work of T. Johansson [1] for more feedback on the algorithms already developed (concerning heat capacity ratio, CHR, CAx, etc.).
3.2.1 Parameters of interest

3.2.1.1 SOC detection

The SOC detection is a valuable tool in the attempt to distinguish the root cause of a malfunction. Prerequisite for trustworthy results to be extracted from it, is that the in-cylinder pressure sensor is not extremely noisy. SOC detection is able to provide an answer to whether or not combustion occurs. Moreover, a fair approximation of the CAD value at which SOC is detected (CAD_{SOC}) is extracted.

The only input inserted to the algorithm for SOC detection is the P_{cyl} and for that reason this signal was manipulated and evaluated for both motoring and normal operation cycles. Two different techniques were developed, one computationally light and one computationally heavy, both analysed below.

- **Computationally heavy**: The concept for SOC detection is based on one simple observation: When combustion occurs the derivative of the pressure trace presents two peaks around TDC (Figure 12*Fel! Det går inte att hitta någon referenskälla.*). The first comes before the TDC and can be employed as an estimation for CAD_{SOC}. The other one is generated from the change of inclination (decrease) in the pressure trace, as we approach the maximum pressure, and is present in every cycle independently of whether or not combustion takes place.

![Figure 12: Raw and smoothed pressure first derivative for highest load and engine speed](image)

During the whole procedure the signal utilized is not the ‘raw’ pressure derivative, but the smoothed curve of it, in order to get rid of the spikes created by high frequency noise. For that purpose, a moving average filter is used. Smoothing the curve bears the major disadvantage of phase delay and hence the peak/s are shifted slightly towards higher CADs. The curve is subject to smoothing only for the CAD interval containing all the necessary information, or more specifically the interval where SOC and maximum pressure can be located. A typical dynamic value range is [minimum (CAD_{IVC}, CAD_{Pmax}−100): CAD_{Pmax}], as shown in the figure above.

The pressure derivative can be derived from the reformed Eulerian derivative:

\[
p_{cyl}(i) = p_{cyl}(i+1) - p_{cyl}(i)
\] (9)

However, the two peaks phenomenon is not detectable for cycles at low load (reference is made in 4.1.1) and in that case the method analyzed below has to be employed.
• **Computationally light:** Provides a verdict on whether or not combustion happens, by measuring the maximum of the ‘raw’ pressure derivative in an interval around the TDC (±30 CAD indicatively)

In contrast with the aforementioned technique, the light SOC detection method cannot provide an approximation for CAD_{SOC}. It exploits the fact that after the turning point (premixed combustion initiation point), the pressure signal oscillates to a great extent and subsequently more noise can be observed. However, this results in the method being prone to disturbing factors such as excessive noise that may not be originating from combustion (sensor error or even blow-by or valve issues).

### 3.2.1.2 IVC, EVO, IVO, EVC along with duration of the IVC and EVO actions [34] [34]

Calculation of inlet valve closing and exhaust valve opening is performed as well by harnessing the in-cylinder pressure sensor and more specifically the first and second order derivatives of the pressure trace.

![In-cylinder pressure vs CAD for cylinder 1 motoring](image)

*Figure 13: In-cylinder pressure vs CAD for motoring cycle, highest RPM (cylinder 1)*

In the case of IVC, evaluation of the first order derivative is enough to locate the correct CAD at which the inlet valve closes. That is because the violent closure of the valve creates a pulse that propagates in the cylinder and can be sensed by the pressure sensor. Subsequently, the pressure fluctuates right before the ‘bell’ in the region depicted in Figure 13 and a peak in the absolute of the first derivative can be observed (Figure 14). The CAD region of interest is marked with red colour in both figures.

IVC and EVO are not instantaneous and both actions require some time (negligible though) to be completed. The duration of these actions is an important quantity and can potentially designate a malfunction in the valves. It can be determined by the CAD interval, where disturbance in the pressure derivative is intense. Since the word intense is vague, the procedure followed is described analytically below. As fas as the IVC is concerned:

1. CAD_{IVC} or the CAD at which IVC occurs is assumed to be the location of the maximum pressure derivative in the interval [100: CAD_{P_{max}}] of the x axis (P_{IVC})

2. To define the start of IVC (CAD_{IVCS}), a reference value of the pressure derivative is required. That value is the maximum pressure derivative in the interval [100: CAD_{IVC-30}], i.e. before
fluctuations emerge ($P'_{\text{REF,IVC}}$). Subsequently the $\text{CAD}_{\text{IVC,S}}$ is defined as the first CAD value in the interval [100; $\text{CAD}_{\text{Pmax}}$] at which $P' = (P'_{\text{IVC}} + P'_{\text{REF,IVC}})/2$.

3. The same procedure is followed for the determination of the completion of the IVC action ($\text{CAD}_{\text{IVC,C}}$): $\text{CAD}_{\text{IVC,C}}$ is defined as the last CAD value in the interval [$\text{CAD}_{\text{IVC}}$;($\text{CAD}_{\text{IVC}} + \text{CAD}_{\text{Pmax}}$)/2] at which $P' = (P'_{\text{IVC}} + P'_{\text{REF,IVC}})/2$.

4. Finally the duration of the IVC action ($\text{CAD}_{\text{IVC,D}}$) is obtained by subtracting $\text{CAD}_{\text{IVC,S}}$ from $\text{CAD}_{\text{IVC,C}}$.

\[\text{Figure 14: Absolut first derivative of the pressure vs CAD for motoring cycle, highest RPM (cylinder 1)}\]

As far as EVO is concerned, it is noticeable that the pressure derivative in the corresponding region (CAD around 500, marked in Figure 14) is not as high as the respective one for the IVC. Actually its value is comparable to the pressure derivative values nearby (for CAD around 450). Hence the exact location of the EVO cannot be detected with desired degree of accuracy.

This obstacle can be surpassed by employing the second order derivative of the pressure and more specifically its absolute value. Evaluation of this quantity clearly shows that the peak value of the second derivative is substantially higher than the respective values in its vicinity (interval in Figure 15 marked with red coloured circle).

Consequently, based on the reasoning process for IVC:

1. $\text{CAD}_{\text{EVO}}$ or the CAD at which EVO occurs is assumed to be the location of the maximum pressure derivative in the interval [$\text{CAD}_{\text{Pmax}}+50$; $\text{CAD}_{\text{Pmax}}+250$] of the x axis

2. To define the start of EVO ($\text{CAD}_{\text{EVO,S}}$) a reference value of the pressure derivative is required. That value is the maximum pressure derivative in the interval [$\text{CAD}_{\text{Pmax}}+50$; $\text{CAD}_{\text{EVO}} - 30$], i.e. before fluctuations emerge. Subsequently the $\text{CAD}_{\text{EVO,S}}$ is defined as the first CAD value in the interval [$\text{CAD}_{\text{Pmax}}+50$; $\text{CAD}_{\text{Pmax}}+250$] at which $P' = (P'_{\text{EVO}} + P'_{\text{REF,EVO}})/2$.
3. The same procedure is followed for the determination of the completion of the EVO action (CAD_{EVO,C}): CAD_{EVO,C} is defined as the last CAD value in the interval [CAD_{EVO,C}\text{CAD_{EVO,C}+50}] at which \( P' = \frac{(P'_{EVO} + P'_{REF,EVO})}{2} \)

4. Finally the duration of the EVO action (CAD_{EVO,D}) is obtained by subtracting CAD_{EVO,S} from CAD_{EVO,C}.

![Figure 15: Absolute second order derivative of the pressure vs CAD for motoring cycle, highest RPM (cylinder 1)](image)

Estimation of IVC and EVO is hampered for low engine speed, because the maximum of the first (Figure 14) and second order (Figure 15) derivative in the designated areas is of similar magnitude to the respective values in their vicinity.

As far as the IVO and EVC are concerned, precise estimation cannot be succeeded for motoring cycles, but only for cycles recorded with high load and RPM conditions: in order to enhance gas exchange at high engine speed valves overlap is employed. Hence the IVO occurs several CAD prior to EVC.

A cycle recorded at maximum load and highest RPM conditions is presented in figure 16, in order to demonstrate the valves overlap. Both IVO and EVC peaks are marked with red and the CAD distance between them is obvious.
3.2.1.3 Average Rail Pressure

The rail pressure signal ($P_{\text{Rail}}$) is rudimental for the evaluation of a large number of components, ranging from the IMV to the injectors. However, the fuel in the rail is subject to transient phenomena and actions (injectors’ opening and closure, pump strokes, IMV opening, water-hammer effect [34]), a fact that constitutes precise pressure measurement a very challenging task even with the most sophisticated hardware.

Due to the fact that the pressure signal has a significantly high signal to noise ratio (SnR), a moving average filter was chosen again to smooth the signal. In the following figure the pressure in the rail is plotted for two operating points and both ‘raw’ and smoothed rail pressure trace ($P_{\text{Rail,S}}$) are included.
The previous figure constitutes clear that some operating points can be more easily assessed compared to others and consequently they can aid more in the evaluation procedure. For that reason, engine cycles measured at high load were selected.

### 3.2.1.4 RPM estimator

The RPM estimator is primarily employed to review the functionality of the CAD encoder. Estimation of engine speed can be achieved merely by deploying the pressure traces from all the cycles recorded for one cylinder and for a single operating point continuously (or in other words in the order in which they were recorded).

Provided that the in-cylinder pressure sensor and the CAD encoder are both functional, the CAD distance between consecutive pressure peaks is obtained and subsequently converted into RPMs through the following formula:

\[
RPM_{ \text{seg} } (i) = \frac{60 \cdot 2 \cdot n}{\text{time}} \cdot \frac{k}{k - CAD_{ \text{seg} } (i)}
\]

where:

- \( \text{time} \): the total time recorded (gives average RPM when divided from \( 60 \cdot 2 \cdot n \))
- \( n \): number of cycles
- \( k \): number of steps per cycle (usually equal to 7200, one every 0.1 CAD)
- \( CAD_{ \text{seg} } \): segment distance between two consecutive pressure peaks (CAD distance divided to 0.1)

The result is the average engine speed of one cycle.

### 3.2.1.5 Signal Noise estimation

This parameter can prove very important in the attempt to diagnose a potential malfunction in the in-cylinder pressure sensor. The first order derivative of \( P_{ \text{cyl} } \) and specifically its maximum is employed as an indication of noise in the signal.

However, in order to evaluate correctly the sensors functionality, noise has to be investigated in specific CAD intervals (where ideally under non-faulty operation signal noise is low). These are usually the two regions around the CAD at which maximum \( P_{ \text{cyl} } \) is located (\( CAD_{ \text{max} } \)): more specifically the first between IVC and \( CAD_{ \text{max} } \) and the latter between \( CAD_{ \text{max} } \) and EVO.

More feedback concerning the noise estimation and how this is correlated to sensors evaluation can be found in the respective sub-chapters (3.2.2.1 and 3.2.2.5) of rail pressure sensor and in-cylinder pressure sensor evaluation tests.

### 3.2.1.6 Area segments \( W_1, W_2 \) separated by the \( CAD_{ \text{max} } \) abscissa below \( P_{ \text{cyl} } \) and above IVC pressure

In the attempt to distinguish an eventual blow-by fault from other possible malfunctions (in-cylinder pressure sensor fault) this parameter was developed, again as a result of the elaboration on the \( P_{ \text{cyl} } \) trace. More specifically the ratio \( (r_{W}) \) of the two aforementioned segments is believed to be a useful tool, an assumption based on observations from traces recorded with significant blow-by.
Prerequisites for the area to be determined are:

- IVC and EVO have already been located
- CAD\text{P}_{\text{max}} has been determined

The reason why the area above IVC pressure is assessed, is the attempt to avoid noisy pressure signal intervention in the calculations. Hence, firstly the base pressure threshold or base of the area segments is set: CAD at which IVC happens is defined (CAD\text{IVC}) and then the pressure measured at an adjacent point (indicatively CAD\text{IVC}+15 CAD) serves as a first approximation for the base pressure. Subsequently the pressure just before the EVO is measured as well and if it comes higher than the first approximation then this is finally established as the base pressure. The area segments are depicted in Figure 18 below.

![Figure 18: W1 and W2 for a motoring cycle at highest RPM](image)

It is rudimental to not set a very high threshold or base pressure, because that would result in a number of points ruled out from the calculation. Hence, the ideal situation is to adjust the aforementioned value as low as possible and simultaneously as close as possible to the CAD at which there are no pressure fluctuations emanating from valve opening and closures. For that reason, the pressure at (CAD\text{IVC}+20) CAD has been selected as base pressure, based on measurement data for the different operating points.

3.2.1.7 Pressure slope P_{slope} right after CAD\text{IVC}

The P_{slope} evaluation is an alternative way to distinguish a blow-by related issue from an in-cylinder pressure sensor fault. The concept is quite simple and the only requirement for the method is that the IVC position has been detected beforehand.

The P_{cyl} curve is subsequently fitted to a fourth order polynomial for the interval defined by an adjacent point to CAD\text{IVC} and a point between the aforementioned and CAD\text{P}_{\text{max}}. To be more precise the interval selected was:

\[ [\text{CAD}_{\text{IVC}}+5; ((\text{CAD}_{\text{IVC}}+5) + \text{CAD}_{\text{P}_{\text{max}}})/2] \]
Figure 19 below presents the pressure slope at CAD_{IVC}+5 along with the raw and smoothed pressure signal.

![Figure 19: Pressure slope (P_slope) for a motoring cycle at highest RPM](image)

The fitting is performed with a least root mean square error (RMSE) optimization procedure that defines optimum coefficients for the fourth order polynomial. Alternatively, a computationally heavier method is proposed: Initially smoothing the raw \( P_{cyl} \) trace using a moving average filter and then fitting the curve to the fourth order polynomial.

A discrepancy in the result could be observed between the two methods, when the \( P_{cyl} \) signal is very noisy. However, the latter deployed method does not significantly enhance the calculated inclination’s accuracy and thus the first method can be employed.

3.2.1.8 Adiabatic pressure

The adiabatic pressure (\( P_{pol} \)) can be employed to detect any gain errors related to the in-cylinder pressure sensor. Reliable results can solely be extracted if the boost pressure and temperature sensors are functional, as their signals are utilized as input for the model.

For the sake of simplicity only motoring cycles are considered (the charge only consists of air) and hence calculations are facilitated. The procedure followed to construct the adiabatic pressure curve versus CAD is described below:

1. Initially, the heat capacity ratio (\( \gamma \)) is determined, with the aid of the developed virtual sensor by T. Johansson [1]. This parameter is a function of in-cylinder temperature and CAD. However, the temperature cannot be directly calculated and an initial value is needed for the algorithm to proceed. An approximation is provided by the boost temperature at CAD_{IVC}, assuming that the temperature in the intake manifold is equal to the actual charge temperature just before the inlet valve closes. This estimation is quite realistic under motoring conditions and low engine speed, because there is sufficient time for the charge to cool down to intake air comparable temperature values per cycle.
2. Utilizing the adiabatic process equation below from thermodynamics (Equation (11) ) the temperature in every step can be calculated:

\[ T_{\text{cyl},1} \cdot V_1^{\gamma-1} = T_{\text{cyl},2} \cdot V_2^{\gamma-1} \]  

(11)

, where:
- \( T_{\text{cyl}} \) is the in-cylinder temperature
- \( V \) is the ideal volume of the charge assuming no blow-by through valves and crevices between cylinder liner and piston head

A convergence algorithm had to be incorporated in the model, as the second part of the previous equation is non-linear. It can be easily understood that an inherent issue of the adiabatic model is the demanding calculations with an increasing number of iterations in case high accuracy is required

3. With the temperature and consequently the heat capacity ratio defined for every step, the pressure can be determined through Equation (12) :

\[ P_{\text{cyl},1} \cdot V_1^{\gamma} = P_{\text{cyl},2} \cdot V_2^{\gamma} \]  

(12)

Boost pressure can be employed as an initial estimation for \( P_{\text{cyl}} \) at the first step, as long as low engine speed cycles are considered

3.2.2 Evaluation tests

An analytical description of the rationale behind every evaluation test is deployed in the order proclaimed in Figure 11. Due to confidentiality, the respective flowcharts are not included, so unfortunately no reference can be made to them.

3.2.2.1 In-cylinder pressure sensor evaluation test

The test is based on the evaluation of the following parameters obtained during motoring cycles.

1. Signal to noise ratio for normal operation cycles (preferably high load and engine speed) in the following intervals: compression and expansion strokes excluding the TDC (noise is usually observed around the TDC). Indicated values for the lower and upper interval limits in CAD are \( \text{CAD}_{\text{IVC}}+30 \) and \( \text{CAD}_{\text{Pmax}}-60 \) for compression and \( \text{CAD}_{\text{Pmax}}+40 \) to \( \text{CAD}_{\text{Pmax}}+100 \) for expansion respectively, considering recorded pressure at a sample rate of 0.1 CAD
2. Adiabatic pressure for motoring cycles and low engine speed
3. In-cylinder pressure and especially the maximum value of the in-cylinder pressure trace (for every cylinder assessed)
4. \( W_1 \) and \( W_2 \) (area segments before and after the \( \text{CAD}_{\text{Pmax}} \) respectively analyzed in 3.2.1.6), or \( r_W \) for motoring cycles with adjustable value of base pressure
5. The \( P_{\text{Slope}} \) as a complementary parameter to \( r_W \)
6. Start of Combustion (SOC) point detected

In each of the aforementioned quantities tolerances are considered and incorporated, according to chapter 3.3.

Once a fault is detected, this is designated either as “other fault” in case it does not pertain in the component or phenomenon under evaluation, or as “Component fault” otherwise. For instance, in the
In-cylinder pressure sensor evaluation test that follows below, when an error in this specific component is encountered then an “In-cylinder Pressure Sensor Fault” is ‘emitted’.

The process followed in the flowchart is explained in steps:

1. Initially the signal noise is evaluated for the closed intervals mentioned above (compression and expansion strokes excluding the TDC). If it surpasses a set value, then there is strong indication that the sensor is erroneous.

2. Independently of whether or not high SnR is noticed, the evaluation is continued. Second step is to view the condition of the boost pressure sensor. If it is functional, branch 1 is followed and the recorded pressure trace from the in-cylinder pressure sensor is compared to the respective adiabatic pressure trace (data no.2 of the list above). If not another branch is followed (branch 2), where the \( P_{\text{max}} \) of all the cylinders is evaluated.

3. Considering the first branch and in case the adiabatic pressure maximum value is lower (taking tolerances discussed in chapter 3.3 into account) than the respective \( P_{\text{max}} \) outputted from the sensor, then it is assumed that either the sensor is erroneous, or another fault has occurred (e.g. injector fault). In order to untwist the dilemma, a SOC detected condition is inserted. Subsequently, SOC detection would denote that unintended injection may have occurred. If that is not the case an “In-cylinder pressure sensor fault” is emitted.

4. When the adiabatic pressure maximum value is equal (within a margin of error, in order to account for model errors, CCV and other phenomena affecting the pressure trace) to the respective \( P_{\text{max}} \) outputted from the sensor, then the \( r_W \) value is assessed. Similar values of recorded \( r_W \) and nominal (reference) \( r_W \) (having accounted for uncertainties) would be the normal observation and hence no specific error can be spotted. The opposite reveals that both blow-by and a sensor fault is encountered, except for the case that the calculated \( P_{\text{Slope}} \) is not lower than the nominal one: then a combination of blowby and other issue is inferred.

5. Considering the first branch and in case the adiabatic pressure maximum value is higher than the respective \( P_{\text{max}} \) outputted from the sensor, \( r_W \) is again compared to its nominal value. In the event that similar values are derived, an “In-cylinder pressure sensor fault” is emitted. Otherwise, the \( P_{\text{Slope}} \) is assessed as well, and if its value is less than the nominal one a combination of in-cylinder pressure fault along with blowby is assumed.

6. Considering the second branch, \( P_{\text{max}} \) is considered as a criterion, along with \( r_W \). The first sub-branch is formed after the observation that \( P_{\text{max}} \) of a cylinder is lower to the others (having accounted for uncertainties). A supplementary condition is inserted: whether the \( P_{\text{max}} \) for this cylinder is lower than its past values or not. If it is not lower, then there might be an issue with the CAD encoder, or a model error. “In-cylinder pressure sensor fault” is designated when \( r_W \) receives nominal values. In any other case, the result of the evaluation points to another fault, unless the \( P_{\text{Slope}} \) is lower than the respective reference value.

7. When \( P_{\text{max}} \) of a cylinder is higher compared to the average of the other cylinders and simultaneously higher compared to its respective past values (having accounted for tolerances), then there are two eventualities: Either the sensor is faulty, or another fault is the case (injector related). To derive the actual problem root, SOC detection shall be employed. When SOC is not noticed the sensor is liable. However even if SOC is noticed, there might be an undercurrent sensor fault, as a faulty sensor could affect the SOC detection as well. Thus, the values of \( r_W \) and the pressure slope are assessed once more.
8. When the $P_{\text{max}}$ of all cylinders is similar, then there is a probability of pressure sensor fault in the case that $W_1$ and $W_2$ for a cylinder/s are deviating significantly from each other (and hence $r_W$ is outside the nominal margins. Furthermore, in the rare case that the $P_{\text{Slope}}$ is lower than its reference value, following a sustained condition of normal $r_W$ values, the same result is inferred.

**Noteworthy:** Since no information is available concerning the condition of the CAD encoder, the nominal deviation values (e.g. $P_{\text{max}}$ of a cylinder to the average $P_{\text{max}}$ of the others) are considered as the highest recorded in the past for any RPM. Alternatively, the estimated RPM from 3.2.1.4 can be utilized.

### 3.2.2.2 CAD encoder evaluation test

The CAD encoder evaluation test runs right after the in-cylinder pressure sensors condition has been determined. Evaluation is hindered by the fact that observations are affected by many phenomena, such as sensors’ tolerances and noise, as well as torsion interference. Especially the $CAD_{P_{\text{max}}}$ is influenced by all the above reasons, which can alter significantly the expected values (e.g. from the measurement data $CAD_{P_{\text{max}}}$ is not observed at TDC, but slightly before, because of thermal effects).

Nevertheless, the magnitude of influence of torsion interference and thermal effects is lower during motoring cycles, which are solely considered for this evaluation test.

The parameters assessed are:

1. $P_{\text{max}}$ of cylinders with functional in-cylinder pressure sensors
2. $CAD_{P_{\text{max}}}$
3. SOC detection
4. Estimated RPM ($RPM_{\text{seg}}$)

Four evaluation strategies are employed:

1. Comparison of the maximum cylinder pressure for a cylinder to the average of the others and to its past values for a value given from the CAD encoder. This technique is shift and can provide a good indication of whether or not malfunction has occurred. It is based solely on $P_{\text{max}}$ evaluation. Initially the $P_{\text{max}}$ for a cylinder with functional pressure sensor is compared to its respective past values for a specific RPM value. If it is lower the next step is to compare it to the average $P_{\text{max}}$ of the other cylinders. In case it is not lower to that value as well, then that would imply that all the cylinders or at least some of them have reduced maximum compared to their respective past one. Subsequently, the actual RPM must be less than the one outputted from the CAD encoder.

   The same reasoning procedure is followed in case the $P_{\text{max}}$ for a cylinder is higher than its respective past value.

2. Comparison of the estimated RPM for the time interval between two consecutive pressure peaks for a single cylinder ($RPM_{\text{seg}}$) to the average RPM value over this specific time interval outputted from the CAD encoder. In case these values deviate significantly, erroneous behavior is concluded for the CAD encoder. Evaluation refers only to cylinders with functional in-cylinder pressure sensors and cycles where no combustion occurs (no SOC is detected).

   The most reliable RPM estimation is the one harnessing the pressure trace of the cylinder closest to the encoder, as this cylinder is not subject to substantial torsion interference. $RPM_{\text{seg}}$ derived from the evaluation of the pressure trace of other cylinders can only reinforce a conclusion already derived.
Provided that the CAD encoder is functional all the time intervals can be transformed into corresponding CAD intervals.

3. Initially, the in-cylinder pressure signal obtained from the sensor closest to the CAD encoder is assessed, as it 'suffers' less from torsion interference (always provided that the sensor is functional).

The first parameter to be investigated is the $\text{CAD}_{P_{\text{max}}}$- In case $\text{CAD}_{P_{\text{max}}}$ for this cylinder receives nominal values then subsequently SOC detection is employed. When SOC is observed, there are three possible faults depending on the magnitude of $P_{\text{max}}$ of this cylinder compared to that of the others (in case all the pressure sensors are functional) or compared to its past values for given engine speed (cylinders with functional sensors are considered only).

- Combination of CAD encoder and other fault (injector) is diagnosed if the $P_{\text{max}}$ of the cylinder is higher than the average of the others/ its past value
- Other fault (blowby) is diagnosed when the $P_{\text{max}}$ of the cylinder is lower than the average of the others/ its past value
- SOC model error in case $P_{\text{max}}$ of the cylinder is equal to the average of the others/ its past value

Engine speed estimated from the previous branch is employed and not the one provided from the CAD encoder, since the condition of this component is under assessment.

If no SOC is detected, $P_{\text{max}}$ of this cylinder is again compared to the average $P_{\text{max}}$ of the other cylinders or its past value depending on the condition of the pressure sensors. Equal $P_{\text{max}}$ for every cylinder denotes that probably no fault has occurred. Otherwise, there is indication for a CAD encoder fault. In any case, the evaluation process is not interrupted, but continued with evaluation of the parameters of the other cylinders.

In case $\text{CAD}_{P_{\text{max}}}$ for the cylinder closest to the encoder is higher than the respective nominal value for the estimated RPM and no SOC is spotted simultaneously, that points to a CAD encoder malfunction.

Finally, in the occasion that $\text{CAD}_{P_{\text{max}}}$ for the cylinder closest to the encoder is lower than nominal for the estimated RPM, SOC and $P_{\text{max}}$ are subsequently evaluated once more. This “branch” comprises the following combinations designating encoder malfunction:

- $P_{\text{max}}$ of this cylinder is higher than the average of the others/ its past value and SOC is detected: combination of encoder fault and injector fault
- $P_{\text{max}}$ of this cylinder is higher than the average of the others/ its past value and no SOC is detected: combination of encoder fault, injector fault and SOC model error
- $P_{\text{max}}$ of this cylinder lower than the average of the others/ its past value and SOC is detected (rare occasion): combination of encoder fault and other fault (either SOC model error and blowby, or a less feasible combination of injector and blowby)
- $P_{\text{max}}$ of this cylinder lower than the average of the others/ its past value and no SOC is detected: combination of encoder fault and blow-by
- $P_{\text{max}}$ of this cylinder equal to the average of the others/ its past value regardless if SOC is detected: combination of encoder fault and other fault

Eventually, the evaluation continues further to strategy-branch 4, which was created assuming that the pressure sensor for the cylinder closest to the encoder is faulty.

4. Branch 4 allows tangible results to be received regarding a potential error in the CAD encoder, even if the pressure sensor of the cylinder closest to the encoder is faulty. $\text{CAD}_{P_{\text{max}}}$ is the primary criterion: Nominal values for every cylinder with a functional sensor denote a no fault condition, given the
assumption that unintended injection cannot be occurring at all cylinders simultaneously (scenario that would indicate concurrent injector’s fault for all cylinders and CAD encoder fault).

If a single divergent from the nominal CAD_{P_{\text{max}}} value is observed, SOCA detection is run for all cylinders. In the event that combustion is detected for a cylinder and the CAD_{P_{\text{max}}} for that cylinder is equal or lower than the CAD_{P_{\text{max}}} nominal, a implies a CAD encoder fault is implied.

3.2.2.3 Valve issues evaluation test

Measurements employed from 4 stroke engine with poppet valves. For this evaluation technique to be employed for a 2 stroke engine’s valves assessment, adjustments are needed.

This evaluation test considers the following parameters, measured preferably at high engine load and speed, in order to guarantee that the valves overlap and a better estimation for CAD_{IVO} and CAD_{EVC} is acquired:

- CAD_{IVO}, CAD_{IVC} along with CAD_{IVC,D}
- CAD_{EVO}, CAD_{EVC} along with CAD_{EVO,D}

The test begins with the assessment of high engine load and speed normal operation cycles (branch 1). In case a sufficient number of steady state cycles at normal operation conditions is not available, then motoring cycles can be evaluated (branch 2). However, in the second case tangible results can only be extracted for IVC and EVO. Moreover, the duration of IVO and EVC actions (CAD_{IVO,D}, CAD_{EVC,D} respectively) cannot be calculated accurately and hence these quantities cannot be employed as tools for this test (unless concrete data is provided).

Every branch is split in two sub-branches, the first one devoted to the assessment of the inlet valves condition and the second to the evaluation of the exhaust valves.

For the valve timing evaluation, the pressure trace is employed for each of the cylinders with functional sensors. The assessment can be trustworthy only with this prerequisite. The only case when valve timing is not detectable and the sensor is seemingly functional is disconnection of the sensor around normal CAD_{IVO}, CAD_{IVC}, CAD_{EVO} and CAD_{EVC} values. Moreover, the CAD encoder must be functional as comparison of the CAD parameters of interest to the reference ones is made for a given RPM value.

The first branch comprises the assessment of inlet valves, through observing CAD_{IVO} and CAD_{IVC}. Depending on that, four possible cases exist:

1. Inlet valve malfunction, when both CAD_{IVO} and CAD_{IVC} are abnormal given known engine speed, and are not shifted equally from the nominal values, or when CAD_{IVC,D} or CAD_{IVO,D} is not within normal values for the tested engine speed
2. Inlet valve malfunction when either the CAD_{IVO} or the CAD_{IVC} solely is abnormal
3. Different calibration, when both CAD_{IVO} and CAD_{IVC} are abnormal for a specific engine speed, but are equally shifted from normal value range by a small extent (difficult to determine)
4. Inlet valve functional when CAD_{IVO} and CAD_{IVC} are within nominal values range for the studied engine speed.

Same process is followed for the exhaust valves as well. The second branch is constructed based on the reasoning process described above and harnesses motoring cycles. Consequently CAD_{IVC}, CAD_{EVO} values are only available along with CAD_{IVC,D}, CAD_{EVO,D}.
3.2.2.4 Blowby evaluation test

The blowby evaluation test bears the CAD encoder evaluation test as prerequisite for its operation and harnesses the following parameters:

1. Adiabatic pressure for motoring cycles and low engine speed
2. In-cylinder pressure and especially the $P_{\text{max}}$ (for every cylinder with functional pressure sensor)
3. $W_1$ and $W_2$ or $r_w$ for motoring cycles with adjustable value of base pressure
4. $P_{\text{slope}}$
5. Start of Combustion (SOC) point detected

Two strategies are employed:

1. Comparison of the in-cylinder pressure trace obtained from the sensors (max pressure specifically) to the max adiabatic pressure estimated from the boost pressure
2. Comparison of the maximum cylinder pressure for a cylinder to its respective past value for the given RPM

Initially the first strategy is used (branch 1) with the prerequisite that both the boost pressure and the boost temperature sensor are functional sustained. First case is that the $P_{\text{max}}$ from the sensor is higher than the respective maximum from the adiabatic estimation. The first thing to evaluate is whether the observed $r_w$ is equal to the nominal one. If there is a discrepancy between the aforementioned values and more specifically if the first is higher than the latter, then the next step would be to try and detect possible combustion incident (through SOC detection). In the event that SOC is not observed, then an injector related fault is ruled out from the possible root causes and the in-cylinder pressure sensor is most probably responsible. Since the $r_w$ is abnormally high as well, blow-by occurs (pressure sensor fault solely creates a positive pressure gain, meaning that if that was the only malfunction then the ratio would have been equal to the nominal). On the other hand, when SOC is detected then the predominant reason for this combination of events would be a fault in the injector.

When the pressure sensor maximum output is equal to the respective adiabatic maximum this does not necessarily imply that no fault has occurred. Subsequently, the $r_w$ parameter is employed again in collaboration with the $P_{\text{slope}}$. If the $r_w$ value is within normal intervals, no fault condition is assumed only when the pressure slope is normal as well. In the opposite case ($P_{\text{slope}}$ is abnormal) a combination of other faults is the conclusion. When $r_w$ is found to be above the nominal values spectrum, then blowby is responsible, accompanied by another malfunction in parallel depending on the value of $P_{\text{slope}}$.

- $P_{\text{slope}}$ equal to nominal denotes blowby and an injector fault
- $P_{\text{slope}}$ higher than nominal denotes blowby and a scaling error in the pressure sensor, which amplifies the pressure around TDC
- $P_{\text{slope}}$ lower than nominal results in a combination of blowby and other faults (pressure sensor negative gain error and injector) which is a rare occasion

Finally, when the pressure sensor maximum output is less than the respective adiabatic maximum, the same criteria ($r_w$ and $P_{\text{slope}}$) are investigated once more. In the event that the recorded $r_w$ is equal to the nominal one, blowby is inferred when the $P_{\text{slope}}$ is abnormally high. Actually, the magnitude of the blowby is considerable, since it cancels out the positive gain error of the pressure sensor. Excessive blowby is also the logical assumption when the both the $r_w$ and $P_{\text{slope}}$ receive higher values than the respective normal ones, as well as when the $r_w$ is lower than normal (blowby accompanied by injector related fault).

As long as the evaluation based on the first strategy is finished, the second strategy is employed as well (branch 2). Same reasoning process is followed, but with the comparison of $P_{\text{max}}$ of different cylinders being the criterion for determination of malfunction, instead of the adiabatic pressure.
Three strategies are employed to evaluate the condition of the rail pressure sensor. The first one is based on the evaluation of rail pressure values recorded during motoring, while the second one harnesses the respective values during normal operation (preferably with the following conditions: Load ≥ 75 % and engine speed ≤ 1000 RPM) The last strategy considers the time needed to drop the rail pressure from one higher value to a commanded value.

1. The first strategy (branch 1) assesses the noise in rail pressure. During motoring no injection should occur. Hence, by utilizing the SOC detection one can check whether injection actually occurs or not. Provided the second is the case, then extensive noise could indicate an issue with the rail pressure sensor. Noise is measured per cycle by employing the maximum and the minimum values provided by the rail pressure sensor.

   The ideal ‘background’ for evaluation is a series of motoring cycles (to avoid rail pressure fluctuations from fuel injections) when the actual rail pressure is higher than the commanded or target rail pressure (to avoid IMV intervention).

   The initial step of this method is to compare the smoothed rail pressure signal (using moving average filter) to the respective one from the past and take separate cases according to the result. When the processed (smoothed) signal is almost steady, or decreases with a lower rate compared to the past, as leakage cannot be totally averted, then the maximum and minimum raw values can reveal a malfunction: abnormally high discrepancy between the two latter values per cycle denotes an eventual issue with the sensor, when no combustion is detected (SOC detection).

   To enhance robustness, abnormal behaviour is assumed when the phenomenon (or the observation that the discrepancy between the maximum and minimum rail pressure values in a cycle is higher than the nominal one) repeats itself for 5% of the steady state cycles considered. On the other hand, if SOC is detected and this is not observed in the smoothed signal (rail pressure not decreased accordingly) again a fault can be assumed.

2. Strategy 2 (branch 2) also deals with the noise in the rail pressure signal at the time injection occurs. At that point usually the noise in the rail is not significant since there is constant fuel flow towards the injector’s nozzle. Noise could indicate an issue in the rail sensor, or a valve issue, or even an injector fault. To rule the last two out, the Pmax is assessed. If the value is normal for the given operating conditions and no blowby or valves issues have been indicated from the respective evaluation tests, this clearly points to a rail pressure sensor fault.

   Moreover, the extreme case that the rail pressure is steady, despite injections (rail sensor disconnected) is also considered for the diagnostics process.

3. The last branch (branch 3) can also indicate an incident of disconnected rail pressure sensor. This is the case when the pressure drops abnormally fast from a higher value to a lower one during motoring conditions.

Since the condition of the rail pressure sensor is determined, the IMV evaluation test can be performed. Four different strategies are used, the first two based on the output signal of the rail pressure sensor and the other two on the time needed from one rail pressure value to another.
1. Evaluation of the IMV functionality can be succeeded by assessing the values of the rail pressure sensor (branch 1). When the pressure is higher than the target rail pressure, the valve should by default remain closed. Hence, if there is a raise in the rail pressure during motoring cycles (no injection), then a fault is very probable. The evaluated rail pressure signal is smoothed to avoid significant noise interference.

There can be a possibility that the pressure in the rail is steady but an IMV malfunction is still probable: when unintended injection occurs the pressure in the rail should drop. So the fact that it is not dropping but remains steady indicates a minor fault (leakage) in the IMV.

The advantage of this method is the fact that tangible conclusions can be extracted even if the engine speed is constantly changing and not sufficient number of steady conditions cycles can be recorded (branch 2).

2. Idling conditions are tested (branch 2), and the pressure in the rail is once more employed. If by any means the final pressure in the rail (smoothed signal) is higher than or equal to the initial one for the whole timespan or for a number of cycles, then an IMV fault is probably the cause.

3. The third strategy (branch 3) assesses the time interval from a certain rail pressure value to a higher one (command value) during motoring conditions. If the time needed is more than the respective past time value, then either IMV is faulty, or injection/s happen (subsequently minor drops in rail pressure are observed). To distinguish the root cause, SOC detection is employed, along with the P_max values for each cylinder.

NOTE: In this work all components prior to the IMV valve, such as the HP pump and fuel filters, are considered error immune (fully functional).

4. The final strategy (branch 4) is based on the time evaluation once more, but from a certain rail pressure value to a lower one, during idling conditions. More time than usual spent could either indicate an IMV fault or an injector malfunction (injection of less fuel).

Due to lack of relevant data, strategies 3 and 4 can be regarded as an expansion of the test in the future, when more measurements are acquired.

3.2.2.7 Pipeline issues evaluation test

This test resembles the previous one in structure - four similar strategies- and parameters assessed. That is why isolation between pipelines issues and an IMV fault is sometimes impossible by solely utilizing specific strategies (e.g. strategy 3 above).

The spectrum of pipeline issues comprises pipeline leakage and clogged pipeline incidents between rail and injectors.

1. The first strategy (branch 1) deals with the evaluation of the rail pressure signal obtained during motoring cycles. When the pressure in the rail is more than the commanded rail pressure and it decreases with a higher pace than normal (smoothed signal inclination) two eventual malfunction may be the root cause: unintended injection/s or leakage. To ascertain the exact reason SOC detection and P_max values are employed. If a P_max value for a cylinder is significantly higher than its respective past value or than the average of the others, then injection is happening. It must be highlighted that in case P_max is normal for all cylinders the result of the blowby test is additionally employed (in order to avoid fallacious results in extreme cases when blowby and unintended injection occur in parallel).
An observation that could also point towards pipeline leakage is a drop in the rail pressure, when the actual pressure is lower than the target one. The leakage can be either of great or low magnitude depending on if the IMV is functioning or not. Functional IMV together with the pressure drop denotes excessive leakage.

2. An alternative strategy (branch 2) similar to the above would be to record the time needed for the pressure to drop from a certain initial value (significantly higher than the target rail pressure) to another one slightly lower, when the engine is motoring. Diminished time could indicate pipeline leakage fault provided that none of the injectors is opening.

3. Strategies 3 and 4 (branches 3 and 4 respectively) involve time evaluation as well from a specific rail pressure to another, similarly to the ones described in the IMV evaluation test. They are incapable however, of providing reliable fault isolation if they are employed individually, as they cannot distinguish between a group of potential malfunctions (e.g. injector problem, pipeline issues or IMV fault).

3.2.2.8 Mechanical dump valve test

This test solely evaluates the pressure in the rail, provided by the rail pressure sensor. In case it surpasses the pressure threshold for mechanical dump valve (MDV) activation, a fault code is emitted. A functional rail sensor is a prerequisite.

3.2.2.9 Injector evaluation test

The injector evaluation test is the most complicated one and harnesses the results of the aforementioned tests. It consists of two main sections, injector fault detection during engine motoring and during normal operation (for operating points of Load>75%, engine speed<1200 RPM as well as for idling cycles).

The following injector related problems can be encountered:

- faulty injector’s trim code assuming that the current in the armature coil is solely determined on that, or in other words that erroneous current magnitude can only be caused by this reason
- Injector body fault comprising issues with the pilot valve, the lower plunger, nozzle, armature spring or the spring of the plunger
- Disconnected injector

As far as motoring cycles are concerned, three strategies have been developed, the first based on the in-cylinder pressure evaluation, the second on rail pressure sensor evaluation and the last one on the time needed for the rail pressure to decrease from a certain value to another.

1. The first strategy (branch 1) primarily assesses $P_{\text{max}}$ in collaboration with SOC detection and the result of the blowby test, to identify a problem in the injector. Even in the case of ‘concealed’ (or difficult to identify) cases, e.g. when $P_{\text{max}}$ is normal and seemingly there is no error, the model is able to reveal faults, by utilizing already performed tests such as the blowby test. The model is also able to adapt to different conditions, like providing a verdict even if some rudimental sensors have already been diagnosed with a fault (CAD encoder for instance).

Separation between injector body and injector trim code fault, which are the possible root causes diagnosed from this strategy, can be achieved through observation of the current in the armature coil (or the on-time, assuming no issue with the armature spring).
2. In case the rail pressure sensor is functional, the second strategy (branch 2) can be employed as well. It can work well for cycles recorded with both steady and unsteady RPM: by employing $P_{\text{max}}$ when the CAD encoder is functional and RPM is steady and SOC detection if the opposite is the case. The smoothed rail pressure signal is the first criterion to decide whether or not an injector fault has occurred.

3. Ultimately, time passed for the pressure in the rail to drop from a certain value to a slightly lower one is assessed (branch 3). If time is less than normal and SOC is detected ($P_{\text{max}}$ is employed as well to increase certainty and to avoid fallacious results from a possible SOC model error) subsequently injector fault can be presumed.

Once the motoring cycles evaluation is completed, specific operating points (Load>75% and engine speed<1200 RPM) along with idling conditions are evaluated. Five methods are employed this time:

1. The first (branch 1, sub-branch 1) is based on $P_{\text{max}}$ comparison of a cylinder to the average of the others provided that all in-cylinder pressure sensors are functional, or to its past values. In the event that a sensor is diagnosed as faulty, the crankshaft speed can be employed (sub-branch 2), or the CHR along with CA10 (sub-branch 3). CA10 is employed instead of CAD$_{\text{SOC}}$ in order to employ the output of the virtual sensor, when the in-cylinder pressure sensor is not functional.

2. The virtual sensor for heat release and specifically for CA10, 50, 90 (CAx) and for total fuel amount (branch 2) can substantially contribute towards diagnosis of injector related malfunctions as well. Deviation of the CAx values from the nominal ones can indicate injection timing issues: delayed injection (positive offset) or early injection (negative offset). The estimated total fuel amount on the other hand can provide information about the injector body condition. Combined with the evaluation of current in the armature coil, injector trim code and injector body faults are distinguished.

3. The third step (branch 3) would be to check the crankshaft speed during engine idling to observe whether or not it remains around idle RPM. If the minimum falls below a specific value and no blowby or valve issues have been previously recorded nor pipeline issues, then injector fault is probably the case. Moreover, the evaluation of the crankshaft speed maxima for each cycle can point to a malfunction as well (higher maximum for a peak compared to the others or to the past).

4. Time from a certain average crankshaft speed to idling conditions is recorded and evaluated (branch 4). More time compared to past can lead to the conclusion that one or more of the injectors is ‘over-performing’.

5. Finally, in branch 5, two more separate cases (rare) are considered: i) Engine speed is fluctuating above idle speed even if clutch is disengaged and ii) Average RPM is increasing above idle RPM even if gas pedal and clutch are disengaged. An alternative feasible explanation for the aforementioned extreme cases is that the pressure in the rail is extremely high and hence more fuel is injected in the cylinders.

Due to lack of data, strategy 3 for motoring cycles and strategy 4 for normal operation can be regarded as an expansion of the test in the future, when more measurements are acquired.
3.3 Tolerance analysis

3.3.1 Margins of normal operation

For the needs of the diagnostics model a tolerance analysis had to be made, in order to incorporate components tolerances (mainly sensor tolerances), cycle-to-cycle variations (CCV) and model tolerances in the system. This analysis enlarges the nominal values range for the parameters of interest, thus averting the phenomenon of a faulty DTC emission.

The tolerance analysis did not address tolerances for heat release related parameters (CHR, CAx and \( m_f \)), due to lack of data and restricted time.

As far as the sensor tolerances are concerned, usually there are two sources of error: offset or drift and gain error. Drift is more significant when low values of the measured quantity are recorded. Gain error is more significant close to the maximum of the output signal. Typical values for each of the sensors employed are cited in Table 3 below:

<table>
<thead>
<tr>
<th>Sensors</th>
<th>Rail pressure</th>
<th>In-cyl. pressure</th>
<th>CAD encoder</th>
<th>CAD encoder</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensor tolerances</td>
<td>Offset &amp; gain combined</td>
<td>Offset &amp; gain combined</td>
<td>Offset</td>
<td>Drift</td>
</tr>
<tr>
<td></td>
<td>± 1 % of the average value</td>
<td>± 3 % of the average value</td>
<td>± 2-4 RPM</td>
<td>+ 0.5 CAD</td>
</tr>
</tbody>
</table>

Due to confidentiality, the exact values for the sensor tolerances had to be ‘masked’; less accurate values are included. The same applies to Table 4 and Table 5, which are presented below.

Most of the parameters of interest (cited in Table 4 below) are affected by a single sensor tolerance: for instance, \( P_{\text{max}} \) by the in-cylinder pressure sensor, \( CAD_{\text{Pmax}} \) by the CAD encoder, etc. However, parameters such as the adiabatic pressure \( P_{\text{pol}} \), are subject to deviations emanating from multiple sensor tolerances. More specifically the \( P_{\text{pol}} \) is affected by both the boost pressure and boost temperature sensor tolerances.

Reference is made to the reasoning process for determining the effect of sensor tolerances (tol\(_s\)) on the \( P_{\text{pol}}, \) Noise and \( r_W \).

- The respective tolerance for \( P_{\text{pol}} \) (tol\(_{s,p}\)) is provided by Equation 13:

  \[
  \text{tol}_{s,p} = \sqrt{\text{tol}_{s,1}^2 + \text{tol}_{s,2}^2}
  \]  

  , where tol\(_{s,1}\) is the tolerance of the boost temperature sensor and tol\(_{s,2}\) is the tolerance of the boost pressure sensor, both given as a percentage of the mean or average value.

- As far as noise is concerned, this quantity was defined as the first order derivative of the in-cylinder pressure trace. Noise is measured in the vicinity of the TDC, where pressure receives relative high values and hence it cannot be significantly influenced by the in-cylinder pressure sensor tolerance (assuming that the tolerance value is constant for a small time interval). Consequently, for simplicity the respective tol\(_s\) is selected to be zero.

- Finally, a similar issue is encountered for the determination of the effect of sensor tolerances on the \( r_W \). Assuming that the CAD\(_{\text{IVC}}, \) CAD\(_{\text{EVO}} \) and CAD\(_{\text{Pmax}} \) are equally influenced by the CAD
drift the CAD intervals for the calculation of $W_1$ and $W_2$ remain the same. Consequently, the only factor that can provoke a deviation is the in-cylinder pressure sensor tolerance. However, since this value merely creates a 3% gain, which is negligible in terms of area ($W$) below the pressure trace, the $t_{ol}$ for the $r_w$ can be considered zero with a good approximation.

**Table 4: Effect of sensor tolerances ($t_{ol}$) on each the parameters of interest**

<table>
<thead>
<tr>
<th>Variable</th>
<th>$P_{\text{max}}$</th>
<th>$P_{\text{pol}}$</th>
<th>CAD$<em>{\text{Pmax}}$, CAD$</em>{\text{SOC}}$</th>
<th>CAD$<em>{\text{IVC}}$, CAD$</em>{\text{EVO}}$, CAD$_{\text{EVC}}$</th>
<th>$r_w$</th>
<th>Noise</th>
<th>$P_{\text{slope}}$</th>
<th>$P_{\text{Rail}}$, $P_{\text{Rail,S}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of the mean</td>
<td>CAD</td>
<td>% of the mean</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$t_{ol}$</td>
<td>$\pm 3$</td>
<td>$t_{ol_{p}}$</td>
<td>$+0.5$</td>
<td>$+0.5$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>$\pm 1$</td>
</tr>
</tbody>
</table>

Finally, the limits can be further expended, by adding a term for the model tolerances ($t_{ol_{m}}$). This comprises:

- Mechanical tolerances due to the mounting position of sensors (e.g. CAD encoder). Mechanical tolerances pertain in all CAD estimations and are adjusted differently for each cylinder’s parameter of interest (CAD$_{\text{Pmax}}$ for the cylinder furthest from the CAD encoder can be shifted by $d_{\text{CAD}}$ due to torsion interference).

- Safety tolerance ($t_{ol_{saf}}$) to compensate for disturbing factors, such as noise in the output of the signals, or CCV (e.g. when the available recorded cycles are less than 50), which can significantly affect the results. Depending on the complexity of the model this term can be either arbitrary, or an estimate defined from past measurements. Ultimately, it was decided that the safety tolerance is defined as a function of available cycles for each operating point:

$$t_{ol_{saf}} = k \cdot \frac{50}{Z}$$

for $Z \leq 50$, else $t_{ol_{saf}} = k$

where $k$ is a constant (see first row of Table 5) and $Z$ is the number of available cycles.

**Table 5: Model tolerances (maximum values)**

<table>
<thead>
<tr>
<th>P$<em>{\text{max}}$, Noise, $P</em>{\text{Rail}}$, $P_{\text{Rail,S}}$ and $P_{\text{slope}}$</th>
<th>CAD$<em>{\text{Pmax}}$, CAD$</em>{\text{SOC}}$</th>
<th>CAD$<em>{\text{IVC}}$, CAD$</em>{\text{EVO}}$, CAD$_{\text{EVC}}$</th>
<th>$r_w$</th>
<th>Noise</th>
<th>$P_{\text{slope}}$</th>
<th>$P_{\text{Rail}}$, $P_{\text{Rail,S}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of the mean</td>
<td>CAD</td>
<td>% of the mean</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Safety tolerance</td>
<td>$\pm 1$</td>
<td>$\pm 2$</td>
<td>$\pm 1$</td>
<td>$\pm 2$</td>
<td>$\pm 3$</td>
<td>$\pm 2$</td>
</tr>
<tr>
<td>Mechanical tolerance</td>
<td>-</td>
<td>-</td>
<td>$\pm 1$</td>
<td>$\pm 0.5$</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Total model tolerance ($t_{ol_{m}}$)</td>
<td>$\pm 1$</td>
<td>$\pm 2$</td>
<td>$\pm 2$</td>
<td>$\pm 3$</td>
<td>$\pm 3$</td>
<td>$\pm 2$</td>
</tr>
</tbody>
</table>

From the aforementioned quantities in Table 5 some are dependent on the output of a single sensor (P$_{\text{max}}$, Noise, $P_{\text{Rail}}$, $P_{\text{Rail,S}}$ and $P_{\text{slope}}$) and others on the output of multiple sensors and tolerances of other quantities (e.g. $r_w$, CAD$_{\text{Pmax}}$ etc.). The ones that pertain in the second category are given higher safety tolerances in general, as they can be significantly affected by error propagation: for instance, CAD$_{\text{IVC}}$ can be affected from the mounting position of both the in-cylinder pressure sensor and the CAD encoder.

As far as the mechanical tolerances are concerned, the following values are used:

- $\pm 1$ for the CAD$_{\text{Pmax}}$, CAD$_{\text{SOC}}$ and CAx of the cylinder furthest from the CAD encoder
- $\pm 0.5$ for the CAD$_{\text{IVC}}$, CAD$_{\text{EVO}}$, CAD$_{\text{IVO}}$ and CAD$_{\text{EVC}}$
Pressure trace is not influenced by the mounting position of the in-cylinder pressure sensor and subsequently zero mechanical tolerance is assigned to $P_{\text{max}}$ and noise.

$\pm 0.5\%$ of the mean recorded value for $P_{\text{Rail}}$ and $P_{\text{Rail},S}$

For the $P_{\text{pol}}$ the total mechanical tolerance ($\text{tol}_{m,n}$) is extracted from the following formula:

$$tol_{m,n} = \sqrt{tol_{m,1}^2 + tol_{m,2}^2}$$

(14)

where $\text{tol}_{m,1}$ is the mechanical tolerance depending on the relative position of the boost temperature sensor to the cylinder and $\text{tol}_{m,2}$ is the mechanical tolerance depending on the relative position of the boost pressure sensor to the cylinder. To simplify the tolerance analysis both terms are considered equal to zero.

As far as the mechanical tolerance for $r_w$ is concerned, its calculation is an extremely difficult task, since it is a complex function of the aforementioned mechanical tolerances (according to 3.2.1.6): CAD$P_{\text{max}}$, CAD$_{IVC}$ and CAD$_{EVO}$. Consequently, a decision was made to incorporate it in the safety tolerance and chose a value according to observations of recorded measurements.

Regarding tolerance analysis, two different approaches were considered:

- The first approach is the determination of the average value from the pool of 50 measurement cycles for every operating point. Then the standard deviation, $\sigma$ is calculated according to the theory in chapter 2. The CCV effect is countered by adjusting the limits of nominal operation to the mean value plus minus 6 standard deviations:

$$CCV = [\bar{X} - 6\sigma, \bar{X} + 6\sigma]$$

(15)

The total margin is refined after sensor tolerances ($\text{tol}_s$) and model tolerances ($\text{tol}_m$) are considered as well. Ultimately, the tolerance intervals with the first approach are set as:

$$\text{Tolerance}_1 = [\bar{X} - 6\sigma - 2\text{tol}_s - \text{tol}_m, \bar{X} + 6\sigma + 2\text{tol}_s + \text{tol}_m]$$

(16)

The multiplication of sensor tolerance with number 2 is to take into consideration the case in which reference measurements and evaluation measurements were performed with opposite sign of sensor tolerance (stochastic approach).

- The second approach does not focus on the average values, but on the calculation of the upper and lower limits of each parameter. Assuming that the number of 50 reference cycles for each operating point is adequate to secure a good estimation of the maximum and minimum values that can be encountered for each parameter of interest, the tolerance intervals are:

$$\text{Tolerance}_2 = [\min - 2\text{tol}_s - \text{tol}_m, \max + 2\text{tol}_s + \text{tol}_m]$$

The minimum threshold is determined from the minimum value that has been measured from the reference data deducting the sensor tolerance and model tolerance contribution. Likewise, the maximum is obtained from the maximum value encountered plus the appropriate tolerance addition.

It can be seen that the second approach would result in more DTCs, as the tolerance intervals are not so broad compared to the respective ones of the first approach. Consequently, to alter that some adjustments can be made in the model tolerances ($\text{tol}_m$).
3.4 Flowchart construction

The flowcharts created reflect the procedure followed for the diagnostics system and can be broken down into three major categories:

- Fault detection flowchart
- Evaluation test flowcharts
- Functional flowcharts

The first one comprises blocks that represent parameters, events, conditions, and results (Figure 10). The flowchart should demonstrate a chronological sequence: starting with the evaluation of the theoretically most ‘influential’ parameter, an if condition is set (whether or not this parameter is within the margins of normal operation) and depending on the verdict, either the next parameter is examined, or a fault code is triggered. The procedure ends when all of the parameters of interest have been evaluated. If conditions are depicted as rhombus shaped blocks and action or subsequent events as rectangular blocks.

After the fault detection test has been performed and an error/fault code is emitted, fault isolation commences. The respective flowchart is appended (Figure A.1) and consists of all the individual evaluation tests. The blocks shape observed in that figure is the one selected to demonstrate that an evaluation test is conducted, as well as fault detection and fault isolation.

The evaluation test flowchart is more intricate, since its purpose is to determine the root cause of the fault code triggered through the fault detection process. As already mentioned previously, the character of the system is modular and hence one flowchart corresponds to each component. If conditions are again depicted as rhombus shaped blocks but two different shapes are employed for the event blocks depending on the probability of occurrence: rectangular for common subsequent event and oval for a rare one. Moreover, when a fault concerning the respective test is detected (e.g. injector body fault during the injector evaluation test), this is distinguished and is defined using a block of orange colour, as depicted in the next figure. Identification of any other fault pertains to the ‘other fault’ category and is depicted with a blue colour block, as well as the no fault conclusion.

However, if there is a slight indication for a failure of another component, the system emits a secondary fault code (block of oval shape). At some point, the flowchart of the ‘suspect’ component is deployed for confirmation (always following the sequence referred in sub-chapter 3.1.4). In case the latter evaluation concludes in a fault, then the indication is sustained and a primary fault code for the specific engine part is triggered.

A characteristic that has to be analysed as well, is that there is a sequence determining the scanning order of different branches. Hence, numbers define the priority: for instance, in case an if condition or a statement is followed by two or more branches, branch number one is run first and when a dead end-conclusion (independently of fault or no fault) is reached, the simulation continues from the beginning of branch number two.

Finally, except for fault detection and evaluation test, functional flowcharts are additionally employed to depict a logical iterative procedure. This can be the storage of values when stationary conditions are detected.

The following figure constitutes a representative example of a typical functional test flowchart.
The reasoning process of the flowchart in Figure 20 is described in steps:

1. Initially the functional parameter $M$ is defined. $M$ is employed as a safety factor to ensure that the results are not affected by transient conditions. Thus, in case the desired number of steady state cycles for evaluation is 50, factor $M$ is added and the prerequisite is that $50 + M$ steady state cycles are recorded for a single operating point. Then the first $M$ cycles are excluded and not taken into account for calculation of the parameters of interest. An indicative value for $M$ can be 20.

2. Parameter $K$ is defined. It is used as a threshold value established in order to decrease the required number of steady state cycles, when this number cannot be reached. More specifically after $K$ failed attempts to obtain $Z + M$ consecutive steady state cycles, the $Z$ value is readjusted from 50 to 40. The $i$ value is compared to the $K$ one and needs to be reset every time the $Z$ value is decreased. The algorithm works in such a way that the $Z$ cannot be decreased more than two times (below 30). In case this is the case the algorithm starts from the very beginning.

3. Once parameters are stored for a single operating point the procedure is repeated for another operating point.

4. Figure 20 refers to storage of normal operation cycles. However, when a sufficient number of operating points has been recorded, the exact same process is employed for motoring cycles as well.

Conclusions regarding the required number of steady state cycles to be recorded and the diagnostics model in general are included in section 5.1.
4 Results

4.1 Parameters of interest

4.1.1 SOC model

Results for CAD_{SOC} are cited in the following table for both cylinders 1 and 6, during different operating points. The computationally heavy method is employed. Due to confidentiality reasons, the mean values in Table 6 are omitted and the ones concerning the standard deviations are rounded to the first decimal. The same procedure applies to Table 7 (two decimals accuracy instead of one however).

<table>
<thead>
<tr>
<th>SOC</th>
<th>Cyl. 1</th>
<th>Standard Deviation</th>
<th>Cyl. 6</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Highest load</td>
<td>Highest load</td>
<td>High load</td>
<td>Average load</td>
</tr>
<tr>
<td></td>
<td>Highest RPM</td>
<td>Lowest RPM</td>
<td>Highest RPM</td>
<td>Highest RPM</td>
</tr>
<tr>
<td>CAD</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.3 0.1</td>
<td>0.3 0.3</td>
<td>0.2 0.2</td>
<td>-</td>
</tr>
</tbody>
</table>

From the evaluation of the mean value and standard deviation, it was clarified that the SOC detection algorithm (3.2.1.1) is not adequate for providing reliable results for CAD_{SOC} for medium values of engine load or below. Furthermore, with the technique employed (moving average filter) a delay in the smoothed signal and subsequently to the CAD_{SOC} is unavoidable. Despite that, the SOC detection is able to serve its primary purpose: to define whether or not combustion occurs.

In addition to the computationally heavy method, the noise in the pressure trace (or the maximum first order derivative) around the TDC is measured as well. However, due to confidentiality reasons, the standard deviation values are solely cited in Table 7.

<table>
<thead>
<tr>
<th>Noise</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>CAD</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.05 0.04 0.04 0.04 0.02 0.02</td>
</tr>
</tbody>
</table>

From the evaluation of measurement data, a strong correlation between noise and engine speed was observed: for higher RPM the maximum noise increases in general.

4.1.2 IVC, EVO and duration of actions

According to the algorithm described in 3.2.1.2, results for CAD_{IVC}, CAD_{EVO} as well as for CAD_{IVC,D} and CAD_{EVO,D} were obtained. In Table 8 values for CAD_{IVC} and CAD_{EVO} standard deviation are presented, for three operating points. Again, the values have been ‘masked’ or rounded off, similarly to
the process explained in section 4.1.1 above. This is the also the case for the values cited in Table 9 to Table 14.

**Table 8: CAD\textsubscript{IVC} and CAD\textsubscript{EVO} standard deviation for different operating points (cylinder 1)**

<table>
<thead>
<tr>
<th>Operating points (motoring cycles)</th>
<th>Highest RPM</th>
<th>Very high RPM</th>
<th>High RPM</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>IVC (CAD)</strong> Standard Deviation</td>
<td>1.9</td>
<td>0.3</td>
<td>1.4</td>
</tr>
<tr>
<td><strong>EVO (CAD)</strong> Standard Deviation</td>
<td>4.4</td>
<td>3.5</td>
<td>4.9</td>
</tr>
</tbody>
</table>

The most tangible conclusion extracted from the table, is that there is a high level of uncertainty in the calculation of EVO with the method analysed in 3.2.1.2. The standard deviation values as far as the EVO is concerned, are more than double compared to the respective IVC values. Reason for that is the magnitude of pressure fluctuations recorded during IVC, because of the pressure wave intensity: the pressure trace oscillates more during IVC compared to EVO.

As far as the duration of IVC and EVO actions is concerned, the algorithm cannot provide a satisfactory result, due to difficulties encountered in estimating the exact CAD for start and completion for each of the actions.

4.1.3 Ratio \( r_w \) between the area segments \( W_1 \) and \( W_2 \)

The calculation of \( r_w \) is of great importance for both the in-cylinder pressure sensor and the blowby evaluation tests, as it is the predominant tool in the attempt to distinguish these malfunctions.

Motoring cycles were employed for the engine speed values referred in 3.1.2 and the results for the ratio standard deviation are deployed in the following table:

**Table 9: Ratio (\( r_w \)) between the area segments \( W_1 \) and \( W_2 \) for motoring cycles**

<table>
<thead>
<tr>
<th>Operating points (motoring cycles)</th>
<th>Highest RPM</th>
<th>Very high RPM</th>
<th>High RPM</th>
<th>Average RPM</th>
<th>Low RPM</th>
<th>Very low RPM</th>
</tr>
</thead>
<tbody>
<tr>
<td>( r_w ) Standard Deviation</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.02</td>
<td>0.03</td>
<td>0.03</td>
</tr>
</tbody>
</table>

The ratio presents significant standard deviation for all operating points. This can be justified by the fact that the base pressure is quite close to the IVC pressure and consequently the values for \( W_1 \) are affected by signal noise (pressure fluctuations).

4.1.4 Pressure slope right after CAD\textsubscript{IVC} (\( P_{slope} \))

The pressure slope right after IVC (more specifically at CAD\textsubscript{IVC}+5) is employed as an alternative technique to distinguish between an in-cylinder pressure sensor fault and blowby. Typical nominal values for the \( P_{slope} \) cannot be presented in the table below, due to confidentiality. Nevertheless, the respective standard deviation values are included.
Table 10: Standard deviation of the pressure slope right after CAD_{IVC} (@ CAD_{IVC}+5) for motoring cycles

<table>
<thead>
<tr>
<th>Operating points (motoring cycles)</th>
<th>Highest RPM</th>
<th>Very high RPM</th>
<th>High RPM</th>
<th>Average RPM</th>
<th>Low RPM</th>
<th>Very low RPM</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_{slope}$ Standard Deviation</td>
<td>$2 \cdot 10^{-4}$</td>
<td>$1 \cdot 10^{-4}$</td>
<td>$1 \cdot 10^{-4}$</td>
<td>$2 \cdot 10^{-4}$</td>
<td>$2 \cdot 10^{-4}$</td>
<td>$2 \cdot 10^{-4}$</td>
</tr>
</tbody>
</table>

The most important conclusion extracted from the data processing is that the standard deviation of the slope values is of the same order compared to the mean value. This is caused by the decision to measure the slope at a point adjacent to the IVC (CAD_{IVC}+5). In case a latter point is selected e.g. CAD_{IVC}+10, then the ratio of the mean value to the respective standard deviation is increased.

4.2 Tolerances

Indicatively the tolerances for $P_{\text{max}}$ and $r_w$ according to section 3.3 are analytically presented below (for motoring cycles at six different values of engine speed).

4.2.1 Nominal values for $P_{\text{max}}$

Initially, the $P_{\text{max}}$ standard deviation values for the 50 recorded cycles at each engine speed were calculated (both for cylinder 1 and cylinder 6).

Table 11: Standard deviation for $P_{\text{max}}$ at each engine speed (50 recorded cycles)

<table>
<thead>
<tr>
<th>Operating points (motoring cycles)</th>
<th>Highest RPM</th>
<th>Very high RPM</th>
<th>High RPM</th>
<th>Average RPM</th>
<th>Low RPM</th>
<th>Very low RPM</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_{\text{max}}$ Cyl. 1 Standard Deviation</td>
<td>0.10</td>
<td>0.10</td>
<td>0.11</td>
<td>0.10</td>
<td>0.09</td>
<td>0.14</td>
</tr>
<tr>
<td>Cyl. 6 Standard Deviation</td>
<td>0.07</td>
<td>0.06</td>
<td>0.06</td>
<td>0.07</td>
<td>0.07</td>
<td>0.15</td>
</tr>
</tbody>
</table>

Hence employing Equation (16) and Equation (17) deployed in the tolerance analysis section, and replacing tol$_a$ and tol$_m$ with the respective values cited in Table 4 and Table 5 the nominal values for $P_{\text{max}}$ are determined in the following table (for both approaches).

Table 12: Tolerance intervals for $P_{\text{max}}$ using both tolerance strategies (motoring cycles, cyl. 1 and 6)

<table>
<thead>
<tr>
<th>Operating points (motoring cycles)</th>
<th>Highest RPM</th>
<th>Very high RPM</th>
<th>High RPM</th>
<th>Average RPM</th>
<th>Low RPM</th>
<th>Very low RPM</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_{\text{max}}$ Appr. 1 Cyl. 1</td>
<td>60.2</td>
<td>59.5</td>
<td>57.8</td>
<td>56.1</td>
<td>55.7</td>
<td>55.2</td>
</tr>
<tr>
<td>Cyl. 6</td>
<td>53.9</td>
<td>53.6</td>
<td>51.6</td>
<td>50.1</td>
<td>49.8</td>
<td>48.8</td>
</tr>
<tr>
<td>Appr. 2 Cyl. 1</td>
<td>55.7</td>
<td>57.9</td>
<td>55.5</td>
<td>53.7</td>
<td>53.2</td>
<td>52.4</td>
</tr>
<tr>
<td>Cyl. 6</td>
<td>52.9</td>
<td>52.4</td>
<td>50.0</td>
<td>48.3</td>
<td>47.8</td>
<td>46.2</td>
</tr>
<tr>
<td>Cyl. 6</td>
<td>59.9</td>
<td>59.2</td>
<td>57.5</td>
<td>55.7</td>
<td>55.3</td>
<td>54.7</td>
</tr>
<tr>
<td>54.3</td>
<td>53.8</td>
<td>51.9</td>
<td>50.5</td>
<td>50.2</td>
<td>49.4</td>
<td></td>
</tr>
<tr>
<td>58.5</td>
<td>57.8</td>
<td>55.2</td>
<td>53.4</td>
<td>52.88</td>
<td>51.9</td>
<td></td>
</tr>
<tr>
<td>53.0</td>
<td>52.6</td>
<td>50.2</td>
<td>48.5</td>
<td>48.0</td>
<td>46.9</td>
<td></td>
</tr>
</tbody>
</table>
It can be seen that the second approach would result in more DTCs, as the tolerance intervals are not so broad compared to the respective ones of the first approach. However, the margins of normal operation for both strategies are broad enough to guarantee robustness in the model.

These two strategies for the nominal intervals definition ensure high confidence, not only as far as $P_{\text{max}}$ is concerned, but for all the parameters of interest. Subsequently, the confidence interval can be set to 95% (see chapter 3.1.3), i.e. when the fault detection is conducted, in case 5 % or more of the recorded measurement values deviates from the nominal, malfunction can be assumed.

4.2.2 Nominal values for $r_w$

The results of the tolerance analysis for the ratio $r_w$ are cited below. Initially the standard deviation values for motoring cycles and the six different speeds are presented (Table 13), and then the tolerance intervals employing each of the two aforementioned approaches (Table 14).

Table 13: Standard deviation for $r_w$ of cylinder 1 at each engine speed (50 recorded cycles)

<table>
<thead>
<tr>
<th>Operating points (motoring cycles)</th>
<th>Highest RPM</th>
<th>Very high RPM</th>
<th>High RPM</th>
<th>Average RPM</th>
<th>Low RPM</th>
<th>Very low RPM</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r_w$ Standard Deviation</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
<td>0.02</td>
<td>0.03</td>
<td>0.03</td>
</tr>
</tbody>
</table>

The average value of $r_w$ (omitted deliberately due to confidentiality) is more than one for each of the different engine speeds when motoring cycles are recorded. This can be justified by the fact that the blowby effect cannot be completely eradicated.

As far as the standard deviation is concerned, it is significantly high compared to the mean value (ranging from 2 to 4 percent). Reason for that is the noise in the pressure signal close to IVC, which influences significantly the magnitude of $W_1$ and subsequently the $r_w$.

Table 14: Tolerance intervals for $r_w$ employing both tolerance strategies (motoring cycles, cylinder 1)

<table>
<thead>
<tr>
<th>Operating points (motoring cycles)</th>
<th>Highest RPM</th>
<th>Very high RPM</th>
<th>High RPM</th>
<th>Average RPM</th>
<th>Low RPM</th>
<th>Very low RPM</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r_w$ Appr. 1</td>
<td>1.26</td>
<td>1.22</td>
<td>1.23</td>
<td>1.20</td>
<td>1.24</td>
<td>1.24</td>
</tr>
<tr>
<td></td>
<td>0.82</td>
<td>0.87</td>
<td>0.85</td>
<td>0.89</td>
<td>0.86</td>
<td>0.86</td>
</tr>
<tr>
<td>$r_w$ Appr. 2</td>
<td>1.11</td>
<td>1.13</td>
<td>1.13</td>
<td>1.11</td>
<td>1.14</td>
<td>1.14</td>
</tr>
<tr>
<td></td>
<td>0.93</td>
<td>0.97</td>
<td>0.96</td>
<td>0.98</td>
<td>0.97</td>
<td>0.96</td>
</tr>
</tbody>
</table>

In contrast with the $P_{\text{max}}$ tolerance, in this case it can be observed that there is a substantial discrepancy between the respective margins of the two tolerance approaches. More specifically the first approach ($6\cdot\sigma$) provides broader nominal values interval compared to the second one.
5 Conclusions

5.1 Conclusions on diagnostics model

The primary purpose of the diagnostics model, as already stated from Chapter 1, is to diagnose the root cause of a malfunction as early as possible, even when the vehicle is up. This can be variously beneficial and not solely from the logistics and economical perspective. The lifetime of components can be significantly prolonged and that will contribute in the long run to the sustainability of the environment, a factor that is sometimes underrated. Moreover, proper and fully controlled operation of the engine will avert potentially higher fuel consumption as well: a faulty injector for example can be responsible for redundant fuel combustion.

Focusing on the structure of the developed diagnostics model itself, this is primarily based on two main pillars, as described in the main corpus of the report:

- Parameter evaluation
- Network of flowcharts

As far as the flowchart diagrams are concerned, priorities related to parameters evaluation had to be set. Throughout the model algorithm, the $P_{\text{max}}$ is given more gravity than the SOC detection (or in other words it is considered more reliable) as a criterion for the diagnosis procedure. Nevertheless, when the evaluation of a component’s condition is not feasible through the assessment of $P_{\text{max}}$ (e.g. for the injector evaluation test, in case the CAD encoder and at least one in-cylinder pressure sensor are not functional), then the SOC detection is employed, along with the estimated injected fuel quantity through the heat release rate.

This hierarchy in the evaluated parameters provides the model with the ability to assess the SOC detection method employed and retract it in case it is found to be erroneous (injector evaluation test, branch 1).

Desired accuracy can be achieved only if there are reference measurements available for a large number of different operating points. Alternatively, a function connecting the margins of normal operation to the load and engine speed can be developed and employed, by interpolating existing data. However, in this case as it is easily understood, there is a trade-off between accuracy and computational cost. If an intricate fitting technique is to be employed, that can solely be achieved by a computational heavy model.

Finally, in case the safety threshold of 50 steady state cycles for each operating point is not sustained, due to transient conditions, evaluation is conducted employing a lower number of cycles. Nevertheless, this number cannot be less than 30 (section 3.4), because the error emanating from CCV will become more significant.

5.2 Conclusions on parameter evaluation

From the analysis carried out in the Methodology employed chapter, it is constituted clear that the results and the robustness of the diagnostics model in general depend to a great extent on the tolerances of the evaluated parameters.

The strategy employed for the definition of tolerances (model tolerances comprising an additional term of safety), can contribute significantly to the robustness of the model. Robustness is further enhanced
due to the following: abnormal behaviour is assumed when the discrepancy between an observed value of a parameter (e.g. P_{\text{Rail}}) and the nominal one occurs for more than 5% of the steady state cycles considered (already discussed in 3.2.2.7).

However, there is a trade-off between unnecessary DTCs emitted and delayed fault diagnosis: since the margins of nominal operation for the parameters of interest are enlarged, subsequently the number of diagnosed faults will be diminished. Then once the fault aggravates, the malfunction will be eventually detected, but with a time delay, that may be proved detrimental for the component’s lifetime.

Two strategies are referred in 3.3 for the determination of tolerances and can be employed in the model. The first approach based on $\pm$ 6 standard deviation defined margins can offer robustness, but it is less accurate when the distribution of the parameter values is far from the normal distribution norm. Especially when the majority of the values is concentrated in the proximity of the median, but there are some values deviating significantly from the median value.

The second approach for the tolerances is more trustworthy in case there is a considerably large pool of measurements, so that even extreme values can be encountered and hence incorporated in the model as respective maxima and minima of a parameter. On the other hand, this method lacks theoretical or ‘scientific’ support, and should not be employed if there is not a large number of reference values available.

Finally, another term was added to the model tolerances, in order to compensate for the influence of sensors positioning on the results (mechanical tolerances). The mounting position of the CAD encoder and in-cylinder pressure sensors in the engine body has to be considered always and the mechanical tolerances values have to be adjusted accordingly.

5.3 Future work

Future work should primarily focus on the universality of the model, so it can cover a broader spectrum of engines. Despite the fact that the model is versatile as far as its structure and logic is concerned, there is a factor hindering its direct implementation to a variety of engines. Nominal values for the parameters of interest were defined after thorough evaluation of past (reference) measurements conducted in a single engine and hence they can be employed for that engine solely. Along with that, a set of arbitrary constants based on measurements has been assumed and incorporated in the corresponding virtual sensors. Thus, it is unavoidable that the model will run into erroneous results and conclusions, in case it is employed with absolutely no adjustments in another engine. It is rudimental that when another engine is assessed, the nominal values of the parameters of interest are adapted to the respective reference measurements from that engine.

Another beneficial enhancement of the model would be the ability to redefine tolerances in order to account for components replacement or relocation: whenever a single component is replaced or mounted to a different location (sensors for instance), the tolerances and subsequently the nominal values have to be altered. Both the sensor tolerances and the mechanical tolerances are affected by a potential change in the sensors configuration, according to what has already been discussed in 3.3.

Moreover, as far as the parameters evaluation is concerned, the SOC detection can be also subject to improvements. The main goal is to eradicate the phase delay described in 3.2.1.1. This issue may be addressed if the pressure derivative signal is smoothed not only once but twice, the second time with a negative phase filter.

Finally, the next venture in the diagnostics procedure would be the prognosis of an eventual fault. Detection of components in the verge of malfunction, is crucial from all the perspectives mentioned in
5.1. Nevertheless, the prognosis task is not an easy one, as the borderline between random error and error induced from a defective component is very slim. The attempt will be futile unless significant amelioration in hardware accuracy is succeeded.
Figure A.1: Flowchart diagram for fault isolation
7 Bibliography


