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Data-Driven Misfire Detection in Hydrogen Gen-sets using a Production Exhaust Pressure Sensor

Aharishkumar Muswathi Babulal * **Jelle Heijne** ** **Peter Wezenbeek** *** **Maarten Vlaswinkel** * **Frank Willems** *,****

* *Control Systems Technology, Eindhoven University of Technology, The Netherlands (e-mail: a.muswathi@student.tue.nl)*
** *NPS Driven, Eindhoven, The Netherlands*
*** *Lumipol Group, Eindhoven(e-mail:p.wezenbeek@lumipolpower.com)*
**** *TNO Mobility & Built Environment, Helmond, The Netherlands*

Abstract: With the growing demand for climate-neutral powertrains, hydrogen combustion gen-sets are emerging as cleaner alternatives to diesel gen-sets. However, spark-ignited hydrogen engines are prone to misfires, impacting performance and engine lifespan. This study presents a novel approach for detecting misfires and identifying the misfiring cylinder using exhaust pressure signals from the production sensor, enabling a cost-effective, real-time diagnostic solution. Unlike complex feature extraction methods, the proposed approach is optimized for constant-speed gen-sets, ensuring computational efficiency and seamless integration within an Engine Management System. The technique utilizes exhaust pressure and crank angle signals to compute a tracking error feature—the squared deviation between the actual pressure signal and a reference signal. A common reference signal is modeled using normalized normal combustion exhaust pressure data from the training set and can be used for different loads. The method is validated at a 6° crank angle resolution in the hardware across multiple misfiring patterns, including single, continuous, and multiple cylinder misfire events, and the results demonstrated excellent performance under steady-state conditions. Finally, validation on the research engine demonstrated the method's feasibility for real-time implementation.

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Keywords: On-board diagnostics, Spark ignition engine, fault detection

1. INTRODUCTION

Efforts to establish a sustainable, pollution-free environment have led to adopting alternative fuels such as ethanol, dimethyl ether, and biodiesel. Current research focuses on hydrogen-powered engines due to their zero carbon emissions. Replacing diesel gen-sets with hydrogen alternatives is key to cutting carbon emissions, especially in high-demand gen-set applications. The impact is even greater when using hydrogen from sustainable sources, supporting net-zero emission goals. Due to its wide flammability limits (4%–74%) by volume in air), hydrogen is particularly well-suited for spark ignition engines. This property allows for lean combustion, making hydrogen an alternative for existing genset applications.

1.1 Hydrogen Combustion Anomalies

Similar to the combustion anomalies observed in conventional Spark Ignition (SI) and pre-ignition for Port Fuel Injection (PFI) engines, hydrogen internal combustion engines (H2-ICE) can also experience issues such as misfires, post-fires, knock, and backfires. Misfires occur when in-cylinder combustion is absent, caused by ignition failure, a lean air-fuel mixture, dirty and broken spark plug, or non-optimized spark timing (Marwaha and Subramanian, 2023). Misfires lead to a drop in output torque (Boudaghi et al., 2015) and hydrogen slip, where unburned hydrogen exits the exhaust, posing an uncontrolled combustion risk. Repeated misfires can cause hydrogen-air accumulation, with around 13% of hydrogen escaping through the exhaust (Marwaha and Subramanian, 2023), potentially resulting in post-fire and backfire events. Post-fire occurs when ignition happens in the exhaust manifold during the exhaust stroke, with flames moving back toward the combustion chamber. This can ignite the accumulated hydrogen-air mixture, leading to a backfire in the next cycle. Backfire happens when flames travel toward the intake manifold during the suction stroke. Therefore, misfires, or a combination of misfires, post-fires, and backfires, can disrupt engine operation by reducing the indicated mean effective pressure (IMEP)(Marwaha and Subramanian, 2023).

1.2 Misfire Detection

This study primarily focuses on misfire detection, since early detection helps to prevent post-fires and backfires, thereby extending engine life. Various Engine Misfire Detection (EMD) methods, characterized by different features derived from multiple sensor measurements, have been investigated over the past few decades. Based on that, EMD can be grouped into in-cylinder combustion diagnosis and post-cylinder combustion (outside the combustion chamber) diagnosis (Boudaghi et al., 2015).

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Typical in-cylinder combustion events can be measured directly using in-cylinder pressure, ionization current, and optical sensors installed in individual cylinders. Integrating an optical sensor with a spark plug allows misfire diagnosis by monitoring the wide-band light radiation intensity, indicating misfires when it drops below a certain level (Piernikarski and Hunicz, 2000). While post-processing in-cylinder pressure data from conventional piezoelectric sensors can provide accurate real-time combustion information (such as IMEP, torque, and CA50), this method is primarily used for offline diagnosis (Lujan et al., 2010). Ion current sensing can detect missing and partially burned combustion (Cavina et al., 2016) but is unsuitable for hydrogen engines due to lacking charge carriers like hydrocarbons. While accurate, these techniques are impractical for On-Board Diagnostics (OBD) due to high sensor costs (Boudaghi et al., 2015).

The second category of EMD methods focuses on parameters like exhaust gas temperature or pressure, engine block acceleration, and engine speed fluctuations. Temperature-based detection is effective only under certain load conditions with noticeable temperature differences (Tamura et al., 2011), while oxygen sensors and vibration signals face limitations due to high noise and low sensitivity to single misfires (Amadou et al., 2013). Most effective EMD strategies rely on crankshaft speed signal analysis, correlating speed fluctuations (Iida et al., 1990; Pipitone et al., 2007; Naik, 2004) with combustion events. The misfire detection based on the engine roughness index developed by Klenk et al. (1993), evaluates crankshaft rotation time through angular sectors related to combustion. However, in multi-cylinder engines, detecting misfiring cylinder is difficult due to overlapping expansion strokes and inconsistent combustion energy, which increase background noise (Cavina et al., 2016). Standard OBD techniques, which are primarily focused on speed variations, are unsuitable for generator sets. Gen-set applications rely on engine speed control, which can counteract the effects of misfire events. On the other hand, exhaust pressure can reveal misfire events through pressure drops, provided the sensor is correctly positioned (Chiavola, 2003).

1.3 Research Objectives

This research develops a misfire detection method for production engines that identifies misfiring cylinders while addressing the technological constraints of the Engine Management System (EMS), including computational load, complexity, and reliance on available sensors. Existing OBD techniques based on crankshaft speed are unsuitable for speed-controlled gensets, as misfire-induced speed fluctuations are often suppressed. Current exhaust pressure-based methods, such as Chiavola (2003), usually rely on frequency-domain features, which impose high computational demands and slow detection times, hindering real-time implementation. A novel data-driven method is developed to overcome these limitations, enabling efficient extraction of misfire characteristics directly from economical production sensor data, without reliance on complex physics-based models. Since exhaust pressure is a viable alternative to in-cylinder pressure for combustion control and diagnostics, this study focuses on detecting misfires within the same cycle using a tracking error feature in the crank angle (CA) domain. Ultimately, this research aims to establish a validated approach for real-time misfire detection through testing on a research engine setup.

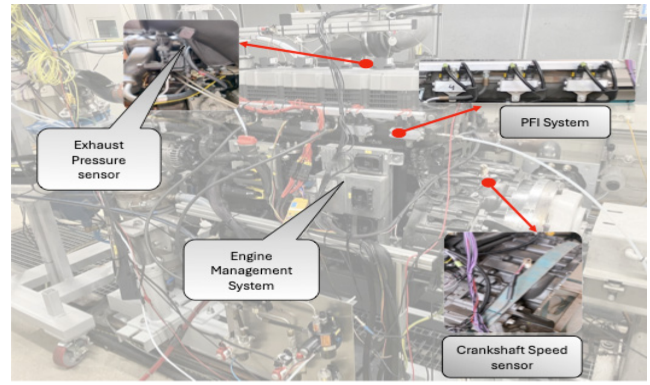

Fig. 1. Experimental setup

1.4 Outline

The paper is structured as follows: the experimental setup and data acquisition section describes the data collection process. The methodology section outlines the exhaust pressure-based EMD method and the procedure for identifying and locating misfires. The results section presents validation of the EMD method with a separate dataset. Finally, conclusions and a summary of results are provided.

2. EXPERIMENTAL SETUP AND DATA ACQUISITION

A modern euro-VI diesel engine is modified to operate on hydrogen using a Port Fuel Injection (PFI) system with a centrally located spark plug in each cylinder head. The compression ratio is modified to suit the requirements of hydrogen combustion. Key specifications of the research engine setup are listed in Table 1, and the experimental setup is shown in Fig.1. The research engine is a six-cylinder inline configuration with a 12.9 L displacement, equipped with in-cylinder pressure sensors for each cylinder. It also has exhaust pressure and crank angle sensors. A magnetic pickup sensor on the flywheel measures engine speed with a 0.5° CA resolution. An exhaust pressure sensor is located between the exhaust manifold and the turbocharger, sampling at 90 kHz frequency. However, production engines typically use a standard 60-tooth design, therefore all the acquired samples are down-sampled to 6° CA aligning with the resolution of the production engine.

Table 1. Engine Specifications

Parameter	Value
Compression ratio (-)	11.25
Operational speed (rpm)	1500
Max. Power (kW)	275 @1500 rpm
Firing order	1-5-3-6-2-4
Ignition type	Spark Ignited

2.1 Data acquisition and separation

Data acquisition is initiated with a measurement plan to cover the engine's full operating load range at a constant speed of 1500 rpm. Misfires are artificially induced during data acquisition by injecting fuel without igniting it. Hence, the misfires are defined as a fouled spark plug scenario. This method is chosen because it is simpler to implement than other methods such as lowering the intake temperature, which is challenging to control for individual cylinders, or diluting the incoming charge with the excess air due to the wide flammability range - a unique property of hydrogen. A dynamometer applies loads based on torque control, ensuring a constant load on the engine. The measurement plan is designed to collect a dataset used for data labeling for modeling and validation testing, as listed in Table 2. Measurements are taken across various misfiring patterns detailed below.

(1) Single cylinder misfire.
(2) Two consecutive cylinders in the firing order (1-5) misfire.
(3) Two cylinders misfire in firing order with one-cylinder interval (1-3).
(4) Two cylinders misfire in firing order with two-cylinder interval (1-6).

Table 2. Measurement Plan

● - 25% Load * - 50% Load ◇ - 75% Load

Pattern	Cyl 1	Cyl 2	Cyl 3	Cyl 4	Cyl 5	Cyl 6
Single cylinder	● * ◇	●	●	●	●	●
1-5	● * ◇					
1-3	● * ◇					
1-6	● * ◇					

A total of 17 datasets were acquired, each containing 200 cycles, resulting in a cumulative of 3,400 cycles, including 340 misfiring cycles. Of this, 65% (2,200 cycles, including 220 misfiring cycles) is allocated for training. The training dataset includes single-cylinder misfires across all loads and multiple-cylinder misfiring patterns at 25% load. The remaining 35% (1,200 cycles, including 120 misfiring cycles) is reserved for validation and comprises multiple-cylinder misfiring patterns at 50% and 75% loads.

2.2 Data labelling

All acquired data is categorized into two groups: misfires and normal combustion. Each dataset is labeled based on the Workdone, calculated by integrating the area under the P-V diagram. The Workdone for each cylinder can be determined using the corresponding in-cylinder pressure trace from the research engine setup. Workdone is calculated for the power stroke, which occurs between Inlet Valve Closing (IVC) and Exhaust Valve Opening (EVO). Misfiring cycles are identified by negative work done, as the absence of combustion results in work being done on the system (negative) rather than by the system (positive). This categorization helps distinguish between normal operation and misfiring events, as defined by the following equation:

$$W = \int_{V_i}^{V_f} p\,dV, \tag{1}$$

where - V_i and V_f are the initial volume and final cylinder volume [m^3] respectively, p is the in-cylinder pressure at each volume V [bar].

3. MISFIRE DETECTION METHOD

3.1 Background

During each combustion cycle, the exhaust valve of each cylinder opens once for gas exchange, generating pressure waves in the exhaust manifold due to the sudden release of combustion gases and piston motion. These exhaust pulsations are influenced by the pressure of the cylinder at the time of valve opening, which is determined by the combustion process. In addition, factors such as standing pressure waves from reflections and wave propagation, depending on the characteristics of the exhaust system, also play a role. The primary oscillation frequency of the exhaust gas pressure in each exhaust strand corresponds to the ignition frequency. At a constant engine speed of 1500 rpm in a six-cylinder, four-stroke engine, three cylinders fire per crankshaft revolution, resulting in an ignition frequency of 75 Hz. Misfires or combustion anomalies disrupt this exhaust rhythm as shown in Fig.2. The figure compares the exhaust pressure during a normal firing cycle with a misfiring cycle in cylinder 1, showing a significant decrease in the exhaust pressure for the misfiring cycle compared to the normal firing cycle.

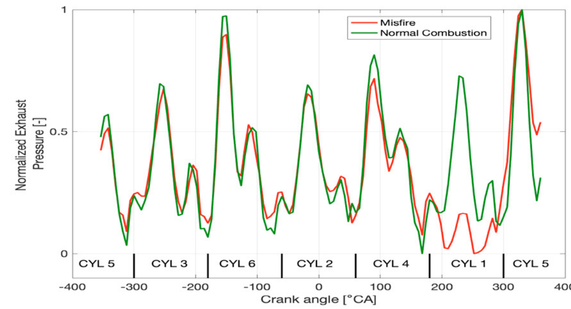

Fig. 2. Measured exhaust pressure waveform without misfires and with a misfire in cylinder 1, @25% load

The placement and selection of the exhaust pressure sensor are critical for accurate misfire detection. To effectively capture misfire frequencies, the sensor must have a cut-off frequency of at least 75 Hz (or twice the ignition frequency of 150 Hz per the Nyquist criterion) without attenuation. Furthermore, optimal positioning of the sensor along the exhaust path must minimize the transport delay (t_d), caused by the time delay as the exhaust pressure waves travel to the sensor. This delay varies for each cylinder due to differences in the length of the exhaust path, as detailed in Table 3. For example, assuming that the exhaust pressure waves travel at the speed of sound (520 m/s at exhaust manifold temperature 400°C), a sensor placed 1245 mm from the exhaust manifold of cylinder 1 results in a transport delay of

$$t_d = \frac{1.245}{520} = 0.00239\text{s} = 21.54^\circ \tag{2}$$

Table 3. Transport delay calculation

Cylinder	Manifold to sensor distance (mm)	Transport delay (deg)
1	1245	21.54
2	1085	18.77
3	930	16.09
4	742	12.84
5	703	12.16
6	830	14.36

For the detection and localization of misfires by exhaust pressure gas analysis, various approaches can be used, including frequency-domain analysis through spectral amplitudes and time-domain methods. This paper focuses on

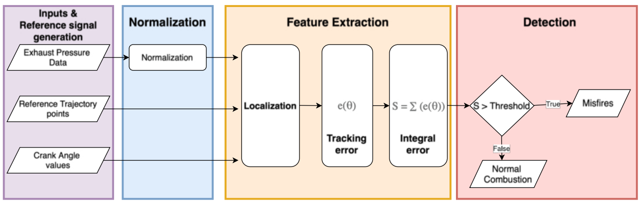

Fig. 3. Schematic of the Reference-Based Method

a CA domain-based diagnostic system that uses tracking error features derived from exhaust pressure measurements at each CA value. This approach is hereafter referred to as the reference-based method.

3.2 Exhaust pressure reference - based

Fig.3 shows the scheme for the developed reference-based misfire detection method. Exhaust pressure patterns exhibit consistent rises and drop at each crank angle across different loads, as seen in Fig.2. During normal operation, each combustion cycle (two crankshaft revolutions) generates six peaks in the exhaust pressure signal, corresponding to an ignition frequency of 75 Hz, indicating combustion in all six cylinders. However, during a misfire, the peak of the misfiring cylinder is absent. As the exhaust gas travels along a fixed path, the acoustic characteristics remain unchanged, allowing the calculation of deviations between a reference pressure signal and the actual pressure signal at each CA value. This deviation, termed the tracking error, is the primary feature for misfire detection. The methodology includes four stages: reference trajectory generation, normalization, feature extraction, and detection, which are detailed in the following sections.

3.3 Reference signal generation

Joseph Fourier's principle states that "Any signal x(t) of infinite length can be represented as a sum of harmonics." This principle is particularly relevant to exhaust pressure signals, where acoustic wave dynamics—traveling and reflecting within the exhaust pipe—shape the pressure buildup into a multi-sine pattern. The Fourier transform decomposes the pressure signal into its fundamental frequency components, offering essential insights for parameterizing the reference trajectory in relation to the engine's operating speed. Unlike simple averaging, which can obscure critical frequency-dependent characteristics, this approach preserves key exhaust pressure dynamics, making it highly effective for the intended engine applications.

Fig.4 shows the Fast Fourier Transform (FFT) of the exhaust pressure signal, converting it to the frequency domain to extract key components for reference signal generation. The dominant peak at 75 Hz corresponds to the ignition frequency at 1500 rpm, while an additional peak at 37.5 Hz arises from the acoustics of cylinders 4, 5, and 6, occurring three times per cycle (cycle frequency: 12.5 Hz). The remaining frequencies are integer multiples of these primary components. Unlike cycle averaging, which may introduce delays, Fourier analysis allows the reference trajectory to be predefined for corresponding engine speeds by directly substituting the known fundamental frequency components. Reference trajectory constructed using the sum of sines given by

$$x_{\mathrm{r}} = \sum_{n=1}^{5} a_{\mathrm{n}} \sin(2\pi f_{\mathrm{n}} t + c_{\mathrm{n}}) = a_n \sin(\omega_{\mathrm{n}} t + c_{\mathrm{n}}), \tag{3}$$

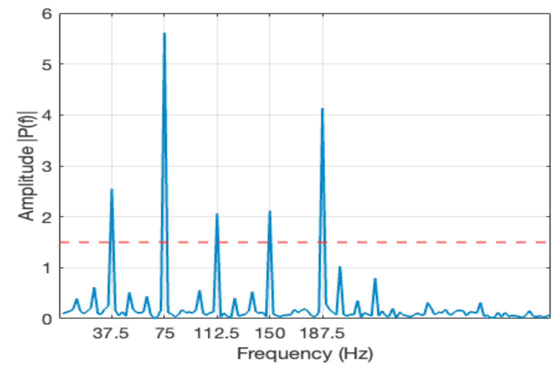

Fig. 4. Exhaust pressure signal in frequency domain

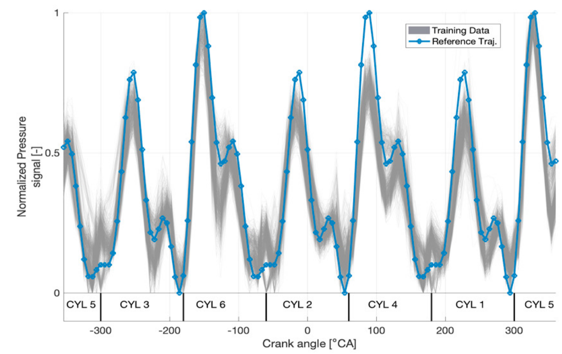

Fig. 5. Reference signal

This time-domain signal is then translated to the crank angle (CA) domain, as the time interval between two consecutive teeth is same (at constant speed) by

$$\Delta\theta = \frac{2\pi N_{\mathrm{e}}}{60} \Delta t, \tag{4}$$

hence,

$$x_{\mathrm{r}} = \sum_{n=1}^{5} a_{\mathrm{n}} \sin\left(\left(\frac{60 f_{\mathrm{n}}}{N_{\mathrm{e}}}\right)\theta\right) + c_{\mathrm{n}}, \tag{5}$$

where - x_r is the reference value at a crank angle [-], θ is the crank angle [deg], a_{n} is the amplitude of n^{th} harmonic[-], f_{n} is the frequency of n^{th} harmonic [Hz], N_{e} is the engine speed [rpm], c_{n} is the phase of n^{th} harmonic [rad].

In this study, the reference trajectory is constructed using the dominant frequency components that exceed an amplitude threshold of 1.5 as shown in Fig.4. Five key frequencies are crucial for constructing the reference trajectory, closely replicating the exhaust pressure behavior across various loads with a fitting R-squared value of 81.25% as shown in Fig.5. Including additional frequencies below the threshold does not improve the fitting accuracy further.

3.4 Normalization

Normalization addresses variations in exhaust pressure amplitude across different engine loads, which complicates error tracking with a single reference. This technique scales all incoming pressure values between 0 and 1, ensuring consistent detection across varying loads. Online normalization uses a 20-element buffer array to accommodate samples for every 120° CA (at 6° CA sampling), minimizing the initial delay. Once filled, the buffer updates

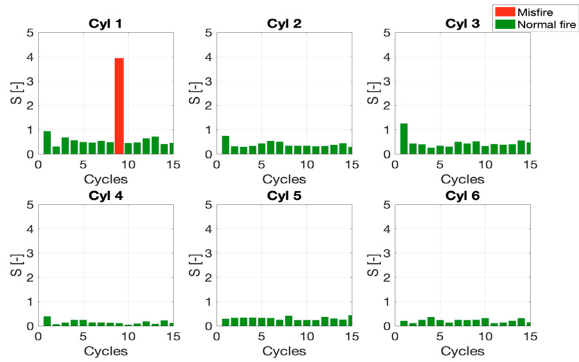

Fig. 6. Intergral error (cylinder 1 misfiring) @25% load

with each incoming sample, updating the minimum and maximum values.

$$p_{\mathrm{norm}}(\theta) = \frac{p_{\mathrm{i}}(\theta) - p_{\min}}{p_{\max} - p_{\min}}, \tag{6}$$

where $\mathrm{p}_{\mathrm{norm}}$ is the normalized pressure value at a crank angle [-], p_{i} is the actual pressure value at a crank angle [kPa], $\mathrm{p}_{\min}$ and $\mathrm{p}_{\max}$ are the minimum and maximum pressure value in a buffer array [kPa] respectively.

3.5 Cylinder localization

Each cylinder is localized by dividing the engine cycle into six segments, corresponding to 120° CA for a six-cylinder engine. In this study, the engine cycle begins when the piston is at the Bottom Dead Centre (BDC) at the start of the compression stroke for each cylinder. Each cylinder is assigned a specific range of crank angles, calculated using the Exhaust Valve Opening (EVO) angle and the transport delay. For example, the starting angle for cylinder 1 is calculated by adding the EVO angle of 145° aTDC and the transport delay of 22°, resulting in 167°. The ending angle is then obtained by adding 120° to the starting angle, giving 287°. Thus, each cylinder is associated with a specific CA range.

3.6 Feature extraction

After normalizing the pressure values, the tracking error (e)—calculated as the squared deviation between the normalized pressure and the reference trajectory—is determined at each crank angle. Squaring the error signal ensures that all values are positive, effectively addressing cases where the error signal might be negative, thereby eliminating irregularities and ensuring a consistent representation of deviations. Then, the integral error value (S) is obtained by summing the tracking errors across the CA range for each cylinder, yielding a single value per cycle (for two revolutions of the crankshaft), as shown in Fig.6. This integration minimizes the impact of short-term fluctuations and noise, resulting in a stronger signal for distinguishing misfire events based on certain thresholds. Integral error (S) is calculated by

$$S_{\mathrm{j,c}}(\theta) = \sum_{\theta_{\mathrm{start,j}}}^{\theta_{\mathrm{end,j}}} (\mathrm{x_j}(\theta) - \mathrm{x_r}(\theta))^2 = \sum_{\theta_{\mathrm{start,j}}}^{\theta_{\mathrm{end,j}}} \mathrm{e}(\theta), \tag{7}$$

where $\mathrm{x_j}$ and $\mathrm{x_r}$ represent the normalized pressure and reference pressure values at that crank angle, respectively. $\theta_{\mathrm{start,j}}$ and $\theta_{\mathrm{end,j}}$ denote the starting and ending CA segments for the j^{th} cylinder during the c^{th} cycle respectievely.

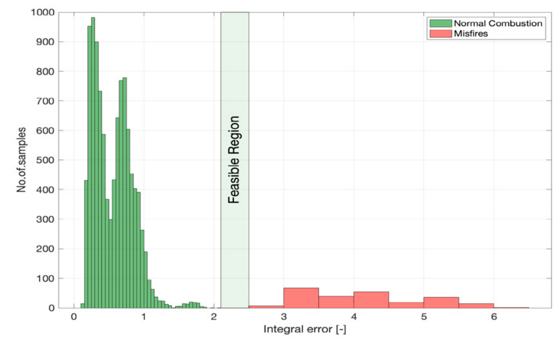

Fig. 7. Estimation of $\mathrm{C_T}$ using the training dataset

3.7 Calibration

Misfires are detected and located when the integral error $\mathrm{S_{j,c}}$ exceeds the critical threshold ($\mathrm{C_T}$) in the specified CA range designated for that particular cylinder, which is calibrated using the integral error values from the training dataset. The $\mathrm{C_T}$ value is specifically determined based on integral error values from cylinders 1, 2, and 3, as sensor sensitivity varies with its position relative to these cylinders' exhaust manifolds. Considering these factors, the $\mathrm{C_T}$ is set at 2.2—the median value within the feasible domain that effectively differentiates misfires from normal combustion, as illustrated in Fig. 7. At this threshold, all misfire events across different cylinders and load conditions are accurately detected without false alarms.

4. HARDWARE-IN-LOOP TEST RESULTS

The proposed EMD method is validated on hardware by embedding the C-code, generated from the Simulink model, into the Engine Management System (EMS). Exhaust pressure measurements, crank angle values, and single-cycle reference trajectory points are provided as inputs. The output is a Boolean indicator representing the combustion state, where 0 denotes normal combustion and 1 indicates a misfire.

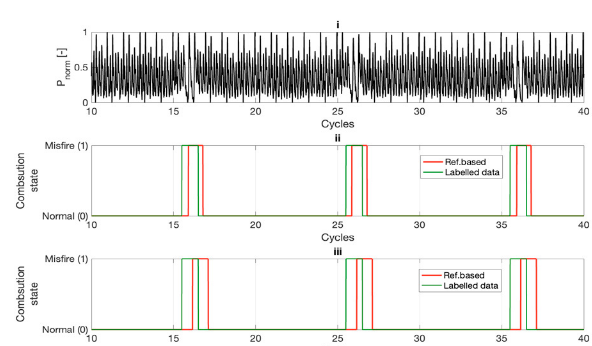

Fig. 8. Simulation results (i) Exhaust pressure readings (ii) Cyl 1 Combustion State (iii) Cyl 3 Combustion State

A Hardware-in-Loop (HiL) test is conducted using a validation dataset with a fixed step size of 5 ms (the interval between consecutive samples) to account for the unknown computation time of the EMS in real-time. Each test incorporates pressure measurements for 200 cycles, sampled at a 6°CA. The validation results for cylinder 1 and 3 misfiring patterns at 50% load are presented in Fig. 8,

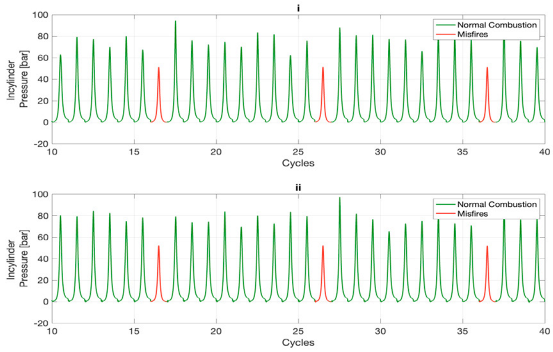

Fig. 9. In-cylinder pressure trace (i) Cylinder-1 (ii) Cylinder-3

which displays exhaust pressure measurements alongside the Boolean outputs of cylinders 1 and 3. The figure illustrates that misfires in these cylinders are accurately detected, as indicated by the Boolean signal transitioning from normal combustion to misfire upon identifying a pressure drop. The detected misfire events in each cylinder are compared with pre-labeled data using in-cylinder pressure traces. Fig. 9 confirms the detection accuracy, showing a decrease in in-cylinder pressure in cylinders 1 and 3 due to the absence of combustion in that particular cycle. Similarly, the proposed method is validated for additional cases, including cylinder 1-5 and cylinder 1-6 misfiring at 25% and 75% loads. The detection method consistently achieved 100% accuracy under steady-state conditions. The proposed EMD method addresses key technological challenges by enabling seamless EMS integration and achieving high detection speed, identifying misfire events within the same cycle while remaining within the permissible detection range of one cycle after the misfiring event. Finally, the method is validated on a research engine by inducing misfires at various loads under steady-state conditions. The results confirm its accuracy and reliability, supporting its potential for real-time deployment in production engines.

5. CONCLUSION AND FUTURE WORKS

This study presents a novel, data-driven, and cost-effective method for detecting and localizing misfiring cylinders in hydrogen-fueled generator sets. The method extracts a tracking error feature from the exhaust pressure signal of a production sensor to classify combustion anomalies. It achieved high detection accuracy under steady-state conditions across varying loads while satisfying all imposed constraints. Additionally, a single threshold, enabled by a simple normalization technique, successfully captured all misfiring events across different load conditions.

To further enhance its robustness, the method can be improved through an adaptive threshold, making it more effective under changing speed conditions. Although the new EMD-based approach showed superior accuracy, certain limitations remain, particularly in handling backfire events due to updates in pressure parameters used for normalization. This issue might be mitigated by smoothing the normalized pressure trace to counteract sudden pressure drops during backfires.

Overall, this new EMD method demonstrated reliable misfire detection for a six-cylinder engine and presents significant potential for future research in three key directions:

- Validation under Transient Conditions – Validating the proposed method during load transitions ensures greater robustness across a broader range of real-world gen-set applications.
- Application to Larger Engines – Expanding the method's applicability to larger engines with higher cylinder counts, such as eight, ten, or twelve cylinders.
- Adaptive Reference Trajectory Development – Developing an adaptive reference trajectory to enhance the method's applicability across varying engine speeds and wider range of operational conditions.

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