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# A Review of Low-Cost Embedded Acoustic and Vibration-Based Engine Misfire Detection for Real-Vehicle

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**Abstract**: Engine misfire is a combustion fault that results in one or more cylinders not contributing to the torque. It negatively affects the drivability, consumes more fuel, produces higher emissions and can cause damage to exhaust after-treatment systems if not detected. Conventional on-board diagnostics are primarily based on crankshaft speed variation, which is useful for regulatory monitoring, but can be less useful in retrofit maintenance systems, older engines and small marine engines that don't have advanced diagnostics. This review considers low cost, non-invasive misfire detection approaches based upon vibration and acoustic sensing, focusing on real vehicle and small marine applications. The paper compares crank-speed, exhaust-temperature, vibration, acoustic, acoustic-emission, and sensor-fusion methods, considers signal-processing and learning-based approaches, and addresses issues of embedded feasibility, noise robustness and sensor placement, data acquisition. The literature review reveals a high level of accuracy in the laboratory, but limited applicability of the practical deployment due to road vibration, ambient sound, mount repeatability, engine-to-engine variability and limited public datasets. Recent studies on acoustic-vibration fusion, frequency domain method and spectral analysis of marine diesel show the promising trend for low-cost embedded prototypes. The most practical near-term solution for practical application is a lightweight embedded system that includes an engine mounted vibration sensor, a body mounted reference vibration sensor, a digital microphone, and then windowed RMS/spectral features and transparent decision logic. The review ends by identifying gaps in the research and designing recommendations to build a strong and usable prototype that can alert operators at an early stage without relying on vehicle OBD infrastructure.

**Index Terms**: Acoustic sensing, embedded diagnostics, engine misfire detection, marine diesel engines, vibration analysis.

## 1 Introduction

An engine misfire is an absence, delay, incompleteness, or weakness of the combustion process in the cylinder that does not generate the usual torque production. In road vehicles, misfire detection becomes necessary because there is a relationship between mechanical reliability and emission control. In the USA, the requirements of OBD state that there should be detection of misfire which could lead to

catalyst failure or high emissions [1]. In California, the OBD system requirements dictate that the system must detect the misfire and identify the cylinder if possible [2]. It is clear from these requirements why misfire detection is included in emission detection in modern cars; however, this is not enough for other cases.

The traditional method of misfire detection is highly reliant on variations in the crankshaft angular velocity. In a study conducted by Kiencke [3], it is proven that there is a way to infer faults during combustion through the dynamics of the crankshaft since an unsuccessful combustion causes a change in the crankshaft speed curve. Another similar study conducted in more recent times involved applying a sequence learning model where Wang et al. [4] and Torres et al. [5] utilized crank-speed with LSTM recurrent neural network.

Literature has evolved in several branches. Pipitone et al. [6] explored the use of crankshaft angular speed to directly measure misfire, and Tamura et al. [7] proposed the low sampling rate exhaust gas temperature to identify abnormal combustion. Hmida et al. [8] analyzed the impact of misfire on crankshaft dynamic properties. Firmino et al. [9] made a comparison between vibration and acoustic analysis methods for the misfire detection in internal combustion engines. Rodrigues et al. [10] proposed the wavelet and chaos analysis of the misfire using a smartphone, and Ahsan et al. [11] and Ghazaly et al. [12 ]analyzed frequency domain misfire features using a MEMS accelerometer at different engine speeds. The literature in deep learning includes the highly noisy diesel engine by Qin et al. [13], the CNN based diesel misfire detection by Zhang et al. [14], and the combustion torque diagnosis by Zheng et al. [15]. Moreover, acoustic deep learning studies performed by Terwilliger et al. [16] prove that low-budget audio can be useful for off-board and extra-vehicular diagnosis. Recent work on vibration-acoustic ANN combination [17], placement optimization of sensors [18], and spectral fault detection in marine diesel engines [19] is particularly applicable to the practical embedded solution development. Hardware implementation is addressed based on INMP441 digital MEMS microphone, MPU-6050 inertial sensor, and ESP32 microcontroller documentation [20], [21], [22].

Thus, the goal of this work is not only the literature review and the summary of the algorithms used for misfires' detection, but also the transformation of the literature into a particular direction for designing such devices. Specifically, a device of low cost and embeddable type will be developed; it should be capable of being mounted on engines without the need for using any existing OBD systems. Such devices are especially required for old cars, generators and fishing boats when an early warning for drivers or the crew of the vessel is needed before going on a trip.

## 2 Review Method and Scope

This paper employs a narrative review approach. The articles chosen are based on conventional OBD and crank-speed techniques, non-invasive sensing, feature extraction through vibrations and acoustics, machine-learning algorithms, fault detection of marine diesel engines, and embedded hardware requirements. The literature review emphasizes peer-reviewed journal and conference papers that relate to misfire fault diagnostics or low-cost sensor applications. Manufacturer datasheets have been incorporated where they help the practical implementation of the sensors and microcontroller.

The scope of this review is deliberately practical. Laboratory techniques can be very precise, but a cost-effective misfire detector should also withstand noisy environments, different placement of sensors, electrical noise, and limited computing capabilities. For this reason, each technique has been evaluated on four parameters namely, information content for detection, ability to withstand real-world noise, ease

of installation, and feasibility of implementation in an embedded system. The reason behind this approach is that the most precise laboratory algorithm may not be the most practical algorithm in the field.

The study ignores engine control tuning, combustion chemistry models, and high-end instrumentation for test cell measurements. The above elements may be important for engine designers, although not quite relevant for a cost-effective mechatronics upgrade product. The focus is on the external data from the sensors, which are available for real-time display within a short period.

## 3 Misfire Mechanisms and OBD Limitations

An internal combustion engine with four strokes generates a periodic series of torque impulses. With no problems with the engine, every cylinder creates an identical torque pulse increase on the crankshaft because of ignition and combustion. A misfire causes the torque pulse to be eliminated or at least diminished. This means that the crankshaft will slow down more than usual, there will be unusual vibration in the engine, and the sound pattern of combustion and exhaust flow will differ. Thus, the problem is recognizable through different kinds of signals.

The use of OBD is successful since crankshaft position sensors are found in most contemporary engine designs. This is a key benefit in the field of mass production. However, the crank speed solution is inconvenient for the retrofit tool as it involves accessing car communication lines, trigger wheels, and specific diagnostic data from manufacturers. In cases where OBD information is available, it might still be difficult to analyze events due to low scan rates and filtering of diagnostic information. Small fishing vessels and old engine designs do not have an OBD interface.

In transient operating situations, crank speed approaches may also be affected by sensitivity issues. In situations where there is acceleration, deceleration, engagement of the clutch, propeller loading, and driving over rough terrain, the speed of the crankshaft is not only dependent on the quality of the combustion process. The difficult task lies in differentiating whether there is a genuine problem in the combustion process or whether it is simply a normal fluctuation in speed due to variations in loads. Research done on crank dynamics and torque estimation reveals that there is valuable information in the rotation system.

In summary [Table 1], for these reasons, external vibration and acoustic detection must be thought of as supplementary to, not as replacement of OBD systems. An on-road vehicle will use OBD to meet legal requirements for diagnostics, whereas a retrofit unit will offer additional maintenance alerts. A retrofit unit does not have to detect all regulatory misfires with the same level of accuracy that a certification process would require. Instead, the practical application will merely alert the driver to changes in the state of the engine.

*Table 1. Main misfire detection signal sources and practical limitations*

| Signal source | Main advantage | Main limitation for retrofit use |
|---|---|---|
| Crank-speed / OBD | Direct relation to torque contribution and already used in modern vehicles. | Often unavailable on older engines and may need vehicle-specific access. |
| Exhaust temperature | Simple low-rate signal and can indicate sustained cylinder power loss. | Slow response and less suitable for early detection of short intermittent faults. |

| | | |
|---|---|---|
| Engine vibration | Low-cost external measurement of mechanical imbalance and combustion shocks. | Sensitive to mounting, road vibration, engine age, and structural damping. |
| Acoustic signal | Non-contact or semi-contact measurement of abnormal combustion and exhaust sound. | Affected by wind, cabin noise, propeller sound, and nearby machinery. |
| Sensor fusion | Combines mechanical and acoustic evidence to reduce false decisions. | Needs synchronization, calibration, and careful embedded processing. |

## 4 Non-Invasive Sensing Modalities

### 4.1 Vibration sensing

Vibration sensing is one of the most attractive methods for a low-cost misfire detector. A misfire changes the balance of torque generation and introduces a mechanical disturbance through the crankshaft, mounts, and engine block. Accelerometers can measure this response without modifying the engine. MEMS sensors are also inexpensive and easy to interface with microcontrollers. In research work, vibration features such as RMS value, peak value, kurtosis, spectral peaks, order components, and wavelet coefficients have been used to distinguish normal and misfire states.

The main difficulty is that vibration signals are highly dependent on placement. A sensor attached to a rigid part of the engine block may capture combustion-related vibration strongly, while a sensor attached to the body or firewall may capture a mixture of engine vibration, road input, and structural resonance. Sensor placement work indicates that location can significantly influence classification performance. This finding is critical for a field product because boat engines and vehicle engines differ in available mounting positions, vibration isolation, and maintenance conditions.

One solution that can be utilized in an embedded system to tackle the above issue would be through the deployment of two vibration sensors. The first vibration sensor will be positioned near the engine to record vibrations generated by the engine through combustion. Meanwhile, the second vibration sensor can be attached to the body, chassis, or boat, in order to record any general vibrations that occur. Through measuring the difference or ratio of the two vibrations recorded, one can distinguish between vibrations originating from the engine and environmental vibrations.

### 4.2 Acoustic sensing

Acoustic sensing utilizes sounds that are produced by the process of combustion, exhaust pulses, intake, valves' operation, and mechanical impacts. Misfires will decrease the expected sound from combustion and change the periodicity of exhaust pulses. An acoustic sensing technique seems very attractive as a microphone is cheap and easy to install. The digital I2S microphone is an especially handy element for the ESP32-based system as it eliminates analogue wiring interference and provides a digital signal source directly.

The downside of acoustic sensing is its dependence on the environment. A microphone in the car may pick up sounds from the cabin, road, cooling fan, and airflow. A microphone in the fishing boat may record wave impact, propeller noise, wind, rain, and other engines' noises. Thus, a simple sound level cannot be used as an input; the signal must be processed through a window using such parameters as RMS level, band energy, dominant frequency, spectral centroid, and periodic energy variations. It is

most useful to combine an acoustic sensor with a vibration sensor: simultaneous changes in sound and vibrations from the engine increase the probability of the misfire.

Acoustic sensors can also be used in maintenance systems that are for operators since they match our perception. It is common that drivers or boat operators detect misfiring in their machines through unusual sounds made by the machine. These unusual sounds can be measured and verified using vibrations through an embedded system.

### 4.3 Sensor fusion

The fusion of sensor information is the most prospective direction for practical low-cost implementations. The vibration and acoustic signal reflect different physical aspects of the same fault. The vibration sensor reflects mechanical imbalance and structural reaction; the microphone reflects noise generated by combustion and the exhaust. False positives can be minimized if the decision layer makes use of consistency between the two domains or weighs their contribution depending on the rotational speed and operation mode of the engine.

Fusion can be performed in various ways. On a simple level, decision fusion employs independent acoustic and vibration thresholds that generate warning signals only when both exceed abnormality thresholds. Feature-level fusion integrates RMS, spectral, and time domain features into one vector before classification. The data level fusion merges with synchronous raw windows but requires more memory and processing capacity. For the microcontroller prototype, feature or decision level fusion is usually more implementable than raw-data level fusion.

Fusion is believed to enhance diagnostic reliability according to literature, but at the same time brings certain demands. The sampling intervals need to be aligned, the sensors need to be mapped, and the system needs to distinguish a loud outside sound from an engine sound. These demands justify the idea of having a design where the display will show not only the output state, but also live parameters like microphone RMS, engine vibration RMS, and body vibration RMS.

## 5 Signal Processing and Classification Approaches

### 5.1 Time-domain features

The time-domain features are advantageous in terms of microcontroller implementation due to computational simplicity. These include RMS value, peak-to-peak value, crest factor, impulse factor, variance, skewness, and kurtosis which can all be computed within limited windows. The RMS value is useful because it talks about the overall vibration/sound energy and peak values can tell about shocks. In case of misfire, there may be some irregular pattern of engine energy as compared to repeating one.

The biggest benefit of time-domain features lies in their ease of interpretation. If the vibration RMS increases in engine mounting but not in the body-mounted reference vibration, then there is some fault with the engine. If they both increase together, there may be something related to road shock or impact with the hull. Such logic is straightforward and easy to use in threshold ratios.

On the other hand, time domain features are subject to changes due to engine speed. A healthy engine operating at a high RPM will have a larger RMS value than an unhealthy engine operating at idle. Hence, the threshold values cannot be constant for all cases unless the system is limited to operating at a certain RPM. The thresholds could be designed separately for idling, low-speed, and high-speed operations in the prototype.

### 5.2 Frequency-domain and order-related features

The frequency domain approach is extensively employed due to the periodic nature of the signatures generated by rotating machinery. Fast Fourier Transform (FFT) allows for the detection of major frequency components and energy bands. Fault such as misfire will attenuate the expected frequencies in the combustion-order spectrum or cause modulation due to the non-firing cylinder signature. The frequency domain technique proves more effective whenever there is noisiness in the raw time signals and there is variation in the spectral energy distribution of the fault.

However, there is need to choose an appropriate FFT length for a small embedded system. Long windows yield better frequency resolution but increased memory requirement and latency. 256 or 512-point FFT may be adequate for a warning device whereas high resolution or crank-synchronous orders may be required for cylinder identification. In case of application in fishing boats, warning is more important than combustion analysis hence moderate FFT with band energy comparison will suffice.

The frequency domain analysis also aids in the comparison between the acoustic and vibration signals. The presence of abnormal energy in both signals indicates that the engine is faulty to a high degree of certainty. However, if the only signal showing any abnormality is that from the microphone at wind and voice bands, the whole event may be disregarded.

### 5.3 Machine learning and transparent rule-based decisions

Machine learning has yielded impressive results in several investigations, but mainly when large, labeled datasets and experiments have been used. ANN, CNN, SVM, random forest, and LSTM algorithms can detect patterns which are hard to define manually. Deep learning is particularly efficient when the signal comprises non-linear and multidomain information. However, the effectiveness of machine learning is contingent on the diversity of data. If the model is trained using one engine, one sensor location, and one testing environment, it might fail in another car or boat.

In case of a student research prototype and a cheap field product, the rule-based or feature thresholding approach remains relevant. It is simpler to develop such an approach using ESP32-class microcontroller, simpler to debug and present at conferences or in a PhD thesis. Rule-based model can make use of moving average, baseline training, RMS ratios, and spectral band thresholds. Additionally, it can have confidence measure which will be based on the consistency of microphone, engine vibration, and body vibration signals.

Recommendation of a balanced nature involves developing the prototype in two parts. First part will be that of deterministic real-time detection based on RMS and spectral features. In the second part, done either off-line or in future research, comparisons can be made between machine learning algorithms and the same data set. This way, immediate feasibility of the prototype is ensured without compromising on the possibilities of future research on improving the algorithm. Moreover, this is safer for marine application since warning logic can be reviewed.

*Table 2. Processing methods and suitability for low-cost embedded deployment*

| Method | Embedded suitability | Recommended use |
|---|---|---|
| Moving RMS / moving average | Very high; low memory and fast computation. | Live values, baseline tracking, first-level abnormality detection. |
| Peak and kurtosis features | High; simple operations but sensitive to impulses. | Shock-like misfire symptoms and rough-running indicators. |

| | | |
|---|---|---|
| FFT band energy | Moderate; needs buffers and careful window size. | Second-level confirmation and noise rejection. |
| Wavelet / chaos features | Moderate too low on small MCUs. | Offline analysis or higher-performance embedded boards. |
| CNN / LSTM models | Low to moderate depending on model size. | Future comparison after collecting a diverse labelled dataset. |

## 6 Sensor Placement, Data Acquisition, and Embedded Feasibility

### 6.1 Sensor placement

Sensor mounting location is one of the key variables in non-invasive misfire detection application. The same engine fault will be perceived differently depending on whether the sensor is mounted on the cylinder block, engine mount, bracket, body, or cabin surface. Mounting the sensor in the rigid cylinder block will provide stronger combustion-induced vibration; however, it will be harder and hotter to mount. Mounting in the body surface will be easier and safer, yet it will have more environmental vibration included. Considering this, literature suggests comparative testing.

In regard to a prototype built using two MPU6050 vibration sensors, a good approach will be placing the first sensor in the vicinity of the engine body and the second one in the body or boat structure in the vicinity of the first one. While the first sensor measures the vibration related to faults, the second one serves as a reference sensor for general motion of the boat. If the first sensor indicates significant change compared to the second one, the system will have grounds to increase misfire probability.

Proximity to the sound source needs to be sufficient for the detection of engine sound yet the microphone must not come into direct contact with heat, water, and air flow. It is recommended that an enclosure with acoustic holes and water resistance be considered for increased reliability. Microphone proximity to the sound source must remain constant since distance is a strong factor influencing sound level.

### 6.2 Data acquisition

A dataset with reliable synchronization involves the use of synchronous channels and repetition of operational parameters. As a bare minimum, the system is supposed to store microphone RMS or I2S window data, engine vibration RMS, body vibration RMS, and status output. In cases where there is enough memory, it is possible to keep raw windows to perform FFT offline. The test should include normal idle, normal accelerating, normal running, decelerating, changing loads deliberately, and conditions like a misfire situation. In case of marine applications, one should include tied-up idle, low-speed cruising, and high-load situations.

The choice of sampling methods should correspond to sensors used. INMP441 microphone produces digital audio data via I2S interface, featuring signal conditioning, analog-to-digital conversion, anti-aliasing filter, and 24-bit I2S data stream. The MPU6050 provides 3-axis accelerometer and gyroscope data and has the possibility to choose the range of the accelerometer. The ESP32 MCU has sufficient computing power to perform I2S data collection, read I2C sensors, calculate moving windows, update display and make simple decisions.

Data collection should not be affected by timing issues associated with the display. The time taken for TFT screen operations may affect data collection, as full refreshes of the screen may interrupt the

stability of the sample. A more elegant design involves updating of changes only in a controlled refreshing manner, as the sampling routine works separately. The use of timestamped serial output or SD/firebase data collection can be used to validate data, but real-time detection should not rely on connectivity to the cloud.

### 6.3 Embedded decision logic

The embedded decision algorithm will not declare misfire based on a one-off noisy signal. The algorithm needs to make use of windowing and persistence. For example, the algorithm may compute the RMS signals within a period of 100 ms to 250 ms, then smooth out using the moving average method before comparing with a learned baseline value. An alert will only be raised when the abnormal condition persists in several consecutive windows. This avoids the problem of false positives such as claps, knocks, waving, and gear shifting.

The decision-making process can be defined using a confidence level. The vibration abnormality of the engine, acoustic abnormality, and the engine to body vibration ratio each add to the points of confidence. A normal situation is indicated when confidence is low. A situation of suspected misfire is indicated when the confidence stays at a high level beyond a certain threshold. Warnings can also be issued when such suspected incidents happen repeatedly during a trip.

Another component of embedded feasibility is power and protection. Electrical systems of vehicles and boats are prone to voltage transients, reverse polarity danger, vibrations, and water exposure. A buck converter, fuse, switch, and cabling are not merely some additional devices that can be installed; rather, these components are integral parts of creating a field-relevant research prototype. Otherwise, a valid algorithm may not work in practice.

## 7 Gaps, Design Implications, and Research Direction

The reviewed literature highlights the significant gap between the laboratory and the field performance. Several papers have shown that the proposed algorithm had achieved high detection performance, yet the experiments were performed on a bench engine, at a few speed ranges, on a single sensor placement, or fault was artificially created. In practice, there is a need for real vibration, ship vibration, wind, rain, heat, improper installation, aging of the engine, and load variation by an operator. The above factors can compromise the performance and lead to false alarms, if not considered during validation.

The second gap is related to dataset availability. Misfire event dataset collection is complicated, as the induced misfire event could be dangerous and even could lead to the destruction of the engine or a catalyst. Therefore, several works perform very small, controlled experiments, which generate the problem of class imbalance, where normal operation takes the majority, whereas misfire is very rare. To perform proper research, one must include numerous normal data points and sufficient abnormal data to check whether the system is able to discriminate from normal events.

Another problem area lies in transferability. The model or threshold that works well on one engine will not necessarily be valid for another engine since engine configuration, stiffness of engine mounting, number of cylinders, kind of fuel, propeller loading, and maintenance conditions are all different for different engines. This means that the field diagnostic system should have a stage for baseline learning. It can use the normal RMS and spectral levels of the engine rather than predefined general thresholds for misfire detection by learning them during a short period.

The implications of the problem for a cheap prototype design become obvious. The first iteration should be focused on ensuring good data acquisition, proper display values, steady power supply, and correct

installation of sensors. The algorithm used should be simple enough for understanding and debugging. After acquiring reliable data from sensors, advanced models can be tested.

*Table 3. Research gaps and recommended design responses*

| Gap identified in literature | Effect on field use | Recommended design response |
|---|---|---|
| Bench-focused validation | High lab accuracy may not hold on to roads or boats. | Test idle, acceleration, load changes, and real environmental disturbances. |
| Limited sensor-placement guidance | Mounting changes can alter feature values. | Compare engine-mounted and body-mounted vibration sensors. |
| Ambient acoustic noise | False alarms from wind, hull impact, or nearby machinery. | Use acoustic-vibration agreement rather than microphone-only detection. |
| Engine-to-engine variation | Fixed thresholds may fail across engines. | Add baseline learning and adjustable thresholds. |
| Rare misfire events and class imbalance | Accuracy alone can hide poor fault sensitivity. | Report precision, recall, false alarms per hour, and detection latency. |

In terms of validation, some practical criteria must be considered. Accuracy is one but not the complete set of criteria. A device for use in the field should also give detection time, false alarms per hour of operation, missed event rate, stability of sensor readings, and loading conditions. A fishing boat can get distracted by a false alarm whereas a missed alarm may make the user unaware of any significant event before he sets sail to sea. Thus, the validation process should consider both sensitivity and reliability.

The research direction to be developed includes an affordable embedded audio-vibration system that will consist of one INMP441 microphone, two MPU6050 vibration sensors, ESP32 board, power source protection, and TFT display. The display is to output either raw or processed values along with the status message. This is important from the academic point of view as the researcher will be able to prove how the decision was reached. From the practical point of view, the operator will know what causes the alarm, whether sound or vibration.

This paper also offers a realistic contribution to scientific literature. Instead of making claims about how an inexpensive device can take the place of OBD devices, the paper needs to make a case for how it can serve as an additional maintenance tool. The innovation of the paper can come from its use of low-cost multi-sensor measurements, real-world testing, clear embedded decision-making process, and its applicability to old cars and Sri Lankan fishing boats.

## 8 Validation Strategy for an Embedded Prototype

Validation is an even more important aspect that turns the review paper into a better resource. In the case of a low-cost acoustic-vibration misfire detector, the process of validation would start with the repeatability assessment and not the final accuracy measurement. The first stage of validation would be repeatability test. The readings of microphone RMS, engine vibration RMS and body vibration RMS should stay within the stable boundaries with the normal operation of the engine in idle condition. In

case of significant drifting during touching of the sensor, shaking of the wire or refreshing of the display screen, the prototype will not be able to proceed to the next stage of validation.

The second criterion is separation of operating states control. Data logging must include normal idle, low throttle, medium throttle, and deceleration states. This is done to learn how changes in normal operating states affect the selected characteristics. A good classifier will not treat each RPM change as a misfire. Hence, the baseline should be defined for each state or normalized with the use of a ratio. For instance, engine vibration RMS divided by body vibration RMS helps to reduce the effect of vibrations caused by road or hull motion. Likewise, microphone band energy ratio will prove more stable than microphone volume in general.

The third test is disturbance rejection. Field conditions are clapping, knocking the body, engagement of equipment, close speaking, wind, waves, and other engines. They need to be added in an intentional manner during the work of an engine. The detector should maintain the normal state or detect a low-confidence abnormality but not raise a misfire warning alarm. It is necessary particularly in boats where vibrations caused by waves are significant and do not relate to combustion process. Body-mounted reference sensor is helpful in this test because non-engine disturbances are more prominent in body and engine channels.

The fourth test is fault sensitivity. True misfire must be induced only in safe and controlled conditions. It depends on engine model. In laboratory or stationary testing, short interruptions of spark or fuel supply or even cylinder cut-out can be used if there is no danger to the catalyst and engine. Where direct induction of misfire is impossible due to safety concerns, prototype can be initially verified with rough running simulation, historical recording or load disturbance and then tested in supervised manner. The key thing here is clear labeling of every test condition to separate it from disturbances.

The last evaluation will provide more than just one performance measure. It is dangerous to measure only accuracy since there are many more examples of normal data than misfires. The report should cover true positive rate, false positive rate, number of false alarms per hour, detection time delay, and repeatable detection day after day. If the device is designed to work to give warning signals to operators, then the number of false alarms per hour may be even more important than classification accuracy.

## 9 APPLICATIONS TO OLDER VEHICLES AND FISHING BOATS

Older cars and small fishing boats pose a different kind of challenge compared to modern cars. While modern cars generally have OBD systems calibrated by the manufacturers, along with standardized trouble codes and diagnostic software, there are a lot of older cars and marine engines that either lack the electronics altogether, do not have an OBD port available, or the operator relies primarily on engine noise, vibrations, smoke, and fuel consumption to tell if the engine is working properly. This opens the possibility of developing a low-cost solution to provide early warning for maintenance.

Fishing vessels are especially critical in this application as the reliability of the engine becomes safety-critical and income-related. Engine misfire or poor idling will most likely not be fixed until the operator quantifies the condition. In case the vessel goes out again with the combustion issue unfixed, it might result in fuel wastage, power loss, poor starting, increased emissions, or engine failure far offshore. A tiny display informing about good operation or possible misfire, along with real-time vibration values and engine sounds, may help to determine whether to check spark plugs, injectors, fuel lines, filters, wiring, or engine mounts prior to the next voyage.

Marine conditions require different approaches in the design of the device. It needs to be waterproof,

rustproof, resistant to vibrations, and protected against any unplugging. Engine sounds need to enter the microphone while being protected from splashes. The vibration sensors need to be firmly fastened since loose adhesion, or cable movements can provide wrong data. The power source needs to go through a fuse, relay, and buck converter, with the electronics being enclosed in a housing. Such considerations are not just the accessories of the design but also the essential elements influencing data quality and confidence.

The display interface should be straightforward. A boat operator does not require a sophisticated graph while controlling the vessel. The most effective display will be the status label, which can be NORMAL, CHECK ENGINE VIBRATION, CHECK ENGINE NOISE, or MISFIRE POSSIBLE. Below the status line, it is possible to include the values of microphone RMS, engine vibration RMS, body vibration RMS, and confidence percentage. This way the device will remain comprehensible while allowing sufficient information for research validation. The buzzer can be added later, but its sensitivity should not be excessive as otherwise, the false alarms will lead to user ignoring the system.

In terms of academic contribution, the fishing boat context enhances the originality of the work. The existing literature includes numerous controlled experiments, but there are fewer low-cost embedded examples that deal with practical maritime operation, user display, and low-maintenance installation. Thus, a paper based on this prototype can claim that the contribution is not only about the development of a new theoretical classifier but also the mechatronic implementation of misfire detection literature.

## 10 CONCLUSIONS

This review highlights techniques for detecting engine misfire, including the use of low-cost embedded acoustic sensors and vibration sensors. The classical OBD approach and crank speed technique are certainly valuable and well-established but are not always available for retrofit applications. Non-invasive vibration and acoustic techniques represent a valuable alternative since they can be mounted externally and computed using low-cost hardware. The literature presents high prospects for crank speed analysis, vibration analysis, acoustic analysis, sensor fusion, and machine learning; however, many experimental findings are still limited to ideal test conditions and limited datasets.

For real vehicle and small marine engines, the most valuable practical direction is sensor fusion with explicit embedded logic. One engine-mounted vibration sensor, one body-mounted reference vibration sensor, and one digital microphone are sufficient for gathering complementary evidence of misfire while filtering out road and hull noise and ambient noise. RMS, moving average, ratio, and frequency bands can be computed on ESP32-type microcontrollers and visualized in real-time. Machine learning can be used to improve future design, but the first prototype should focus on acquisition, mounting, calibration, and decision transparency.

However, the research gap does not lie in the lack of algorithm, but rather in the lack of low-cost systems that have been validated and tested under practical circumstances. A well-documented prototype for use in older automobiles and fishing vessels will make contributions to academia and practice by demonstrating how laboratory-based concepts on misfire detection can be turned into a warning system.

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