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Review

A Review of Recent Advancements in Knock Detection in Spark Ignition Engines

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Abstract: In gasoline engines, the combustion process involves a flame's propagation from the spark plug to the cylinder walls, resulting in the localized heating and pressurization of the cylinder content ahead of the flame, which can lead to the autoignition of the gasoline and air. The energy release from the autoignition event causes the engine cylinder to resonate, causing an unpleasant noise and eventual engine damage. This process is termed as knock. Avoiding knock has resulted in limiting the maximum engine pressures, and hence limiting the maximum efficiencies of the engine. Modern engines employ knock sensors to detect resonances, adjusting the spark plug timing to reduce pressures and temperatures, albeit at the expense of engine performance. This paper sets out to review the different signals that can be measured from an engine to detect the start of knock. These signals traditionally consist of the in-cylinder pressure, the vibrations of the engine block, and acoustic noise. This paper reviews each of these techniques, with a focus on recent advances. A number of novel methods are also presented, including identifying perturbations in the engine speed or exhaust temperature; measuring the ion charge across the spark plug leads; and using artificial intelligence to build models based on engine conditions. Each of these approaches is also reviewed and compared to the more traditional approaches. This review finds that in-cylinder pressure measurements remain as the most accurate for detecting knock in modern engines; however, their usage is limited to research settings. Meanwhile, new sensors and processing techniques for vibration measurements will more accurately detect knock in modern vehicles in the short term. Acoustic measurements and other novel approaches are showing promise in the long term.

Keywords: engine knock; signal processing; vibration measurements; audio measurements; pressure measurements

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1. Introduction

A critical design challenge in all spark ignition (SI) engines, whether it is for a Model T or a modern hybrid vehicle, is preventing engine knock. Engine knock, an occurrence stemming from the rapid autoignition of the end-gas preceding a flame front, leads to an irritating noise, and severe knocking can result in engine damage. This autoignition process is governed by the chemical reactions within the cylinder, typically happening under elevated pressures and temperatures. Since the peak temperatures and pressures in the cylinder establish the thermal efficiency of an engine, avoiding knock is the limiting factor for the maximum engine efficiency. Modern engines employ knock sensors to detect when knock is occurring and then adjust the spark timing of the engine to lower the pressures and temperatures, thus avoiding knock, albeit at a lower engine performance.

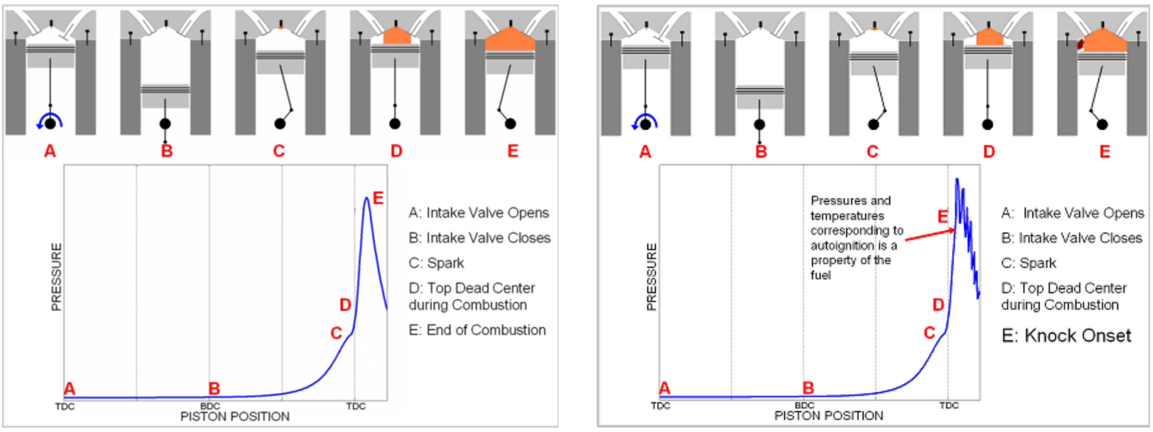
This paper aims to comprehensively examine the different signals that are typically measured from an engine to forecast the onset of knock. Both conventional and novel methods for measuring knock are discussed in this paper, including the in-cylinder pressure, engine block vibrations, and acoustic noise. While the in-cylinder pressure is the most precise detector of knock, it necessitates intrusive access to the combustion chamber. Meanwhile, vibration and acoustic measurements might not adequately capture knock in contemporary engines. The paper also reviews a number of new methods for detecting and predicting knock. The present paper critically evaluates advancements in measuring these signals, discussing their strengths and limitations.

2. Background

2.1. Overview of Knock

SI engines currently power the majority of passenger automobiles in the world. Although alternatives, such as fuel cells and advanced batteries, are becoming available, the SI engine is still positioned to be the primary means of powering both consumer and commercial vehicles, especially in rapidly growing emerging markets [1]. In particular, as the global fleets start to move to electrification, hybrid vehicles that combine an electric powertrain with an SI engine will become increasingly prevalent [2]. Therefore, it is imperative that the field of SI engine technology be advanced further. Since the maximum efficiency of an engine is limited by knock, advancing the knock limits is crucial to advance ICE technology.

The term “knock” signifies the engine noise resulting from the rapid self-ignition of unburned fuel and air as the flame traverses the combustion chamber [3]. Figure 1 displays a regular engine cycle and a knocking engine cycle. Initially, in Figure 1, the intake valve opens at point A, allowing for the entry of fuel and air into the cylinder. The piston’s downward movement draws this mixture through the open valve into the cylinder, followed by the closure of the intake valve at point B, trapping the fuel and air inside. Subsequently, as the piston moves upwards, compressing the fuel–air mixture leads to an increase in the in-cylinder pressure due to a decreased cylinder volume. At point C, the spark plug initiates combustion by creating a flame kernel. This flame propagates across the chamber, elevating the pressure from point C to point D. In Figure 1a, the combustion ends at point E, with the flame being quenched against the cylinder walls. The resultant pressure surge from the combustion thrusts the piston downward, generating mechanical work.



(**a**) (**b**)

Figure 1. (**a**) Image and pressure trace for a standard SI engine cycle and (**b**) a knocking cycle.

The knocking cycle, illustrated in Figure 1b, follows a similar progression to the normal cycle from point A to point D. However, with the increasing cylinder pressure, the temperature within the end-gas, comprising unburned fuel and air ahead of the flame front, rises. At point E, the heightened pressure and temperature of the end-gas lead to autoignition. This rapid autoignition results in a pressure increase within the region, outpacing the expansion rate of that region. Consequently, the energy release manifests as a rapid pressure rise, followed by pressure fluctuations resonating within the combustion chamber’s frequencies. These pressure oscillations induce vibrations in the engine block, generating engine noise—a characteristic knocking sound that is emitted by the engine [4].

2.2. Signals for Measuring Knock

Since knock is a compilation of a chemical event triggering pressure oscillations inside the combustion chamber, inducing engine block vibrations and resulting in an audible sound, there are a number of different signals that can be measured to detect and study knock. These different signals were first measured by Draper in 1928, who measured the pressure oscillations associated with a knocking engine and found that they relate to the resonance frequencies of the engine cavity [5]. Today, the same signals are used, albeit with more advanced equipment. The three most common signals for detecting knock are measuring the in-cylinder pressure, detecting block vibrations, and audible detection [6]. Each of these three methods, with their advantages and disadvantages, are given in Table 1.

Table 1. The most common methods for measuring knock in SI engines.

Signal	Instrument	Advantage	Disadvantage	Usage
Pressure Oscillations	In-Cylinder Pressure Transducer	High sensitivity	Expensive	Knock Studies
Engine Block Vibrations	Accelerometer	Easy to mount	Less accurate	Knock sensors in automobiles
Engine Noise	Microphone or Human Ear	Cheap	Arbitrary and not accurate	Engine calibrations

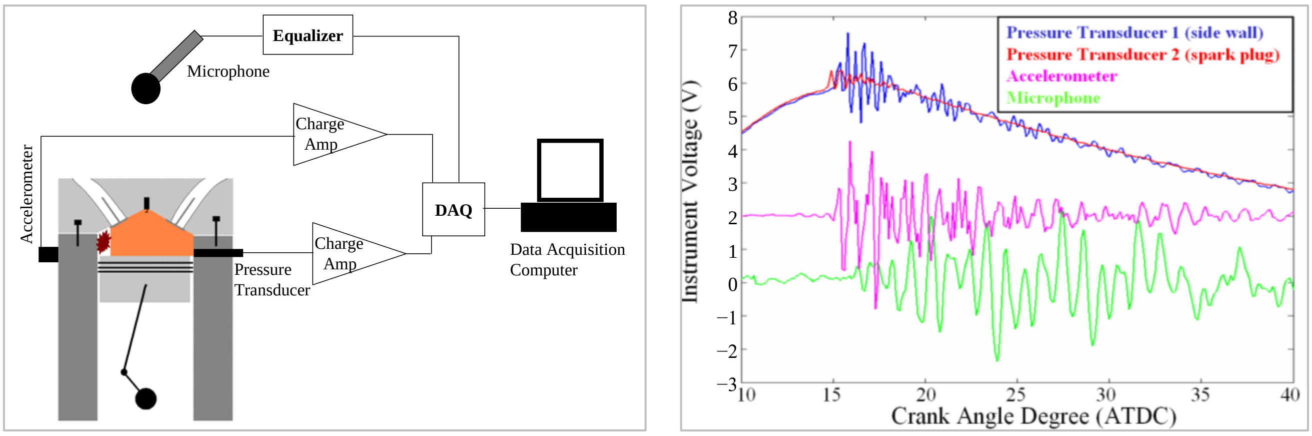
For engine research, the primary method to assess knock is through in-cylinder pressure transducers, which precisely track the initial pressure changes and oscillations due to fuel autoignition [7]. However, pressure transducers are expensive and require being placed with direct access to the inside of the engine cylinder. Moreover, fast-response pressure transducers are required, given that the frequencies associated with knock are between 6 kHz and 30 kHz, further driving up the cost [8]. Also, these expensive pressure transducers are exposed to the engine conditions, so they must be able to withstand significant heat.

An alternative approach for evaluating knock involves using accelerometers that are affixed to the engine block. These devices capture block vibrations that are linked with knock and are relatively cost-effective. While a number of different types of accelerometers are available, most knock sensors in modern automobiles are piezoelectric devices that convert engine vibrations into electrical signals. Typically, knock sensors tend to implement a bandpass filter to focus on a set of frequencies between 3 and 25 kHz, which are primarily associated with knock [9].

Prior to the inclusion of knock sensors, audible noise was the most common metric for assessing if an engine is knocking. Indeed, knock is by definition a noise, and the primary goal of avoiding knock is to avoid an unpleasant sound that would annoy the vehicle users. In older vehicles, prior to the inclusion of knock sensors, the engines would be calibrated based off engineers listening for knock. While this was somewhat arbitrary, there is a sharp sound at 6 kHz which is easy for most people to detect even at low knocking levels [10].

Figure 2 illustrates the unprocessed signals obtained from two pressure transducers, a high-speed accelerometer and a microphone, during a cycle bordering on knock in an engine. Positioned on the engine block's side, the accelerometer and the microphone, situated 1 cm from the block, registered data. Autoignition occurs around 15° after the top dead center (ATDC), causing in-cylinder pressure oscillations. The accelerometer's vibration measurement initiates very soon after the onset of pressure oscillations, recorded by the transducers in the cylinder. Subsequently, the microphone detects noise after the accelerometer commences vibration measurement.

Furthermore, the signals shown in Figure 2 illustrate the progression to audible knock. Autoignition induces gas pressure fluctuations within the cylinder, which are promptly captured by the pressure transducers. These gas oscillations within the cylinder engender vibrations throughout the engine block. The accelerometer captures these vibrations, characterized by a slower buildup and decay compared to the rapid pressure oscillations. Consequently, these vibrations from the engine block emit an audible noise, which is then detected by the microphone.



(**a**) (**b**)

Figure 2. (**a**) Schematic of an experimental setup recording different knock signals including in-cylinder pressure, block vibrations, and audible noise. (**b**) Raw pressure signals from the different instrumentations.

2.3. Knock in Modern Vehicles

Figure 3 plots the number of scholarly publications related to engine knock that have been published by the Society of Automotive Engineers (SAE) from 2000 to 2022 [11]. Several general trends are readily apparent: First, over this time, there was a total of 118,000 publications from SAE; 6300 of them were related to knock, equating to approximately 5.4 percent of publications. While this value might seem small, it is important to note that there are many other automotive research fields. Second, the number of publications steadily increased from 2000 to 2017. These publications were focused primarily on better modeling of the autoignition process, characterizing the signals to enhance knock detection, and identifying new additives to mitigate knock. From 2012 to 2017, an issue termed mega-knock became a key area of research. Mega-knock is an intense knock event that particularly occurs with high-ethanol-content fuels [12]. From 2017 to 2022, the number of articles started to decrease, in part as the automotive industry began focusing more on electrification, moving away from traditional combustion engines. However, it is important to note that in 2022, 5.1 percent of the articles published by SAE were still related to knock, indicating that it is still an issue that is being actively researched. Much of the current research is looking at knock mitigation for bio-fuels or for new engine operating regimes that are common for hybrid operations.

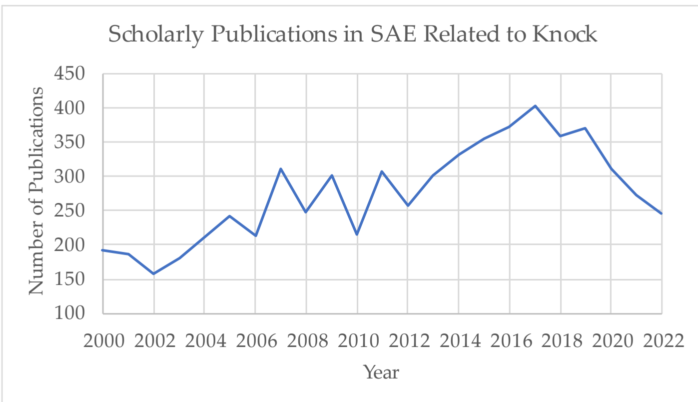


Figure 3. Scholarly publications in the Society of Automotive Engineers (SAE)'s journals and conference proceedings from 2000 to 2022 related to engine knock.

Knock remains a pertinent concern in contemporary engine design due to its implications across diverse technological advancements, notably in the context of engine downsizing, boosting, and hybrid powertrains. While downsizing involves reducing the engine displacement to enhance fuel efficiency without compromising power output, it increases the risk of knock due to increased thermal and mechanical loads in the cylinder of smaller engines [13]. Simultaneously, an increasing number of SI engines are turbocharging or supercharging, which increases the in-cylinder pressures and temperatures, hence increasing the propensity of the engine to knock.

Moreover, the integration of hybrid powertrains introduces new complexities in engine operation, impacting their knock propensity. Hybrid engines combine internal combustion engines with electric propulsion, allowing the vehicle to operate in different modes. Typically, under high-load conditions, hybrid vehicles will use the engine, sometimes in conjunction with the motor. Under such conditions, the engine is operating at full load, resulting in the high temperatures and pressures associated with knock [14].

Knock has also been a topic of research for Homogeneous Charge Compression Ignition (HCCI) engines [15]. HCCI engines operate at higher pressures and temperatures than SI engines; as such, rather than using a spark plug, the content of the engine autoignites. This autoignition event is a controlled event, which is different from knock, which is an abnormal event that can lead to engine damage. However, HCCI engines can still experience knock at high loads. HCCI engines typically use an SI scheme over a certain operating range and an HCCI scheme over a specific operating range. Therefore, for an HCCI engine, it is increasingly imperative that knock can be detected and predicted. Accurate knock detection and prediction are vital for HCCI engines to optimize combustion timing, prevent abnormal combustion events, and enhance the overall engine efficiency while ensuring that the engine operates within safe and reliable parameters [16].

3. Advancements in Knock Detection

Despite knock being fairly established and understood, it is still a critical factor that must be accounted for in SI engine design. As such, there have been continual advances in the measuring and assessment of engine knock. Knock research has progressed significantly since Draper's first measurement of knocking pressure signals, with better sensors and analysis algorithms. This section will detail the most recent advances.

Generally, these advances can be categorized into two primary categories, advances in sensors and advances in processing. While some of the advancements discussed in these sections are related to new sensors, the bulk of the advancements relate to advances in processing techniques. In particular, many studies are focused on the use of machine learning algorithms to more accurately process the different signals associated with knock. Machine learning involves the use of algorithms and statistical models to analyze and extract meaningful patterns from each signal. This approach enables the development of systems that can automatically learn and adapt to complex signal characteristics, including those with high levels of noise, such as those that are used for detecting knock.

3.1. Pressure Signals

Pressure traces provide the most reliable method for identifying if an engine is knocking. It is important to note that pressure measurements have historically been used in research settings to understand the fundamentals of knock and determine knock mitigation techniques. Figure 4 shows how pressure signals are currently collected and processed to determine knocking conditions.

Figure 4 also displays the two general trends in the collection and processing of pressure signals to detect knock. The first is the development of new sensors that would allow for pressure signals to be integrated into production automobiles. The second trend is new processing algorithms to be able to detect knock, especially at borderline knock conditions. The ability to detect knock is especially difficult given new engine trends, including the use of turbocharged downsized engines [17]. Studies by Attard et al. [18] and Deva et al. [19] found that the pressure oscillations associated with knock in these engines are substantially different from those in conventional engines, with more cycle-to-cycle variation.

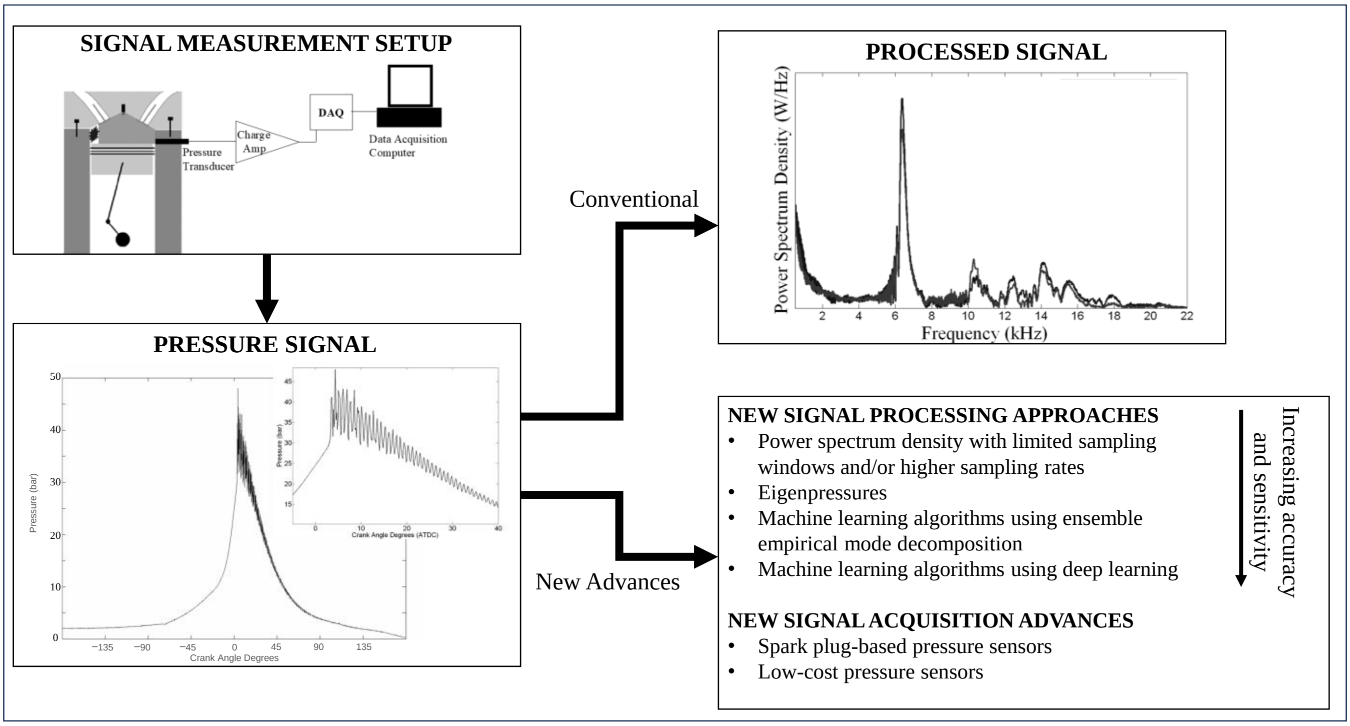


Figure 4. Summary of current and new advances in signal acquisition and processing of pressure data for the detection of knock.

3.1.1. Acquisition of In-Cylinder Pressure Signals

Several efforts have been made to reduce the cost and intrusive nature of pressure transducers in order to allow them to be used in production automobiles. Sellnau et al. [20] introduced a low-cost engine control system utilizing a non-intrusive cylinder pressure sensor in the spark plug. Their study found that by measuring pressure variations through a pressure transducer that was mounted in the spark plug, they could more accurately detect knock onset, allowing the engine control unit to better control the ignition timing. A similar study by Corti et al. [21] also used a spark plug-based pressure transducer. While their results were similar to those reported by Sellnau et al. [20], they noted challenges associated with thermal and vibration issues affecting the sensor readings.

Haertl et al. [22] introduced a low-cost, series-produced in-cylinder pressure sensor, which enabled the engine control unit to detect knock. Comparisons with structure-borne vibration sensors showed the feasibility of implementing cylinder-pressure-based knock control in the engine control unit, resulting in a 0.5–0.7 percent increase in engine efficiency. This increase in engine efficiency comes from more optimal spark timing, which results in higher pressures and a higher overall thermal efficiency of the engine. Although more accurate, this technique is more expensive than conventional knock sensors and requires the sensor to have access to the combustion chamber, which could lead to durability and cooling issues for the engine.

3.1.2. Processing of Pressure Signals

For both the lab setting and potential use on roads, it is necessary to advance the algorithms for detecting knock from pressure signals, especially at borderline knock conditions. Although knock pressure waves are characterized by pressure oscillations at set frequencies, the exact frequencies and amplitudes are dependent on a number of parameters and vary from cycle to cycle.

Several studies have identified modified methods to calculate the power spectrum density calculations which capture the frequency contributions of pressure oscillations associated with knock. Zhang et al. [23] improved the detection of knock in standard gasoline engines by analyzing a narrow window around 20 crank angle degrees after the expected start of knock combustion. During this window, the raw pressure signal is less noisy, resulting in an increased ability to differentiate the oscillations associated with knock. However, in borderline knock cases, the pressure oscillations associated with knock in this window have a very low amplitude and are difficult to detect. Meanwhile, Deva et al. [19] found that pressure signals should be sampled at a higher frequency rate in order to be able to detect the higher frequencies that play a more prominent role in knock in modern boosted engines. This technique requires a faster response pressure transducer and increased processing capabilities, but better captures high frequency oscillations.

Panzani et al. [24] presented a novel knock detection approach using in-cylinder pressure principal component analysis, which moved away from traditional bandpass filtering. The study introduced "eigenpressures", which effectively allowed for the modeling of an engine cycle without the oscillations associated with knock. The "eigenpressures" are based on a singular value decomposition based on experimental pressure traces. Their technique was then able to isolate the oscillations associated with knock. The proposed method outperformed standard techniques, including bandpass filtering, exhibiting better knock classification performance with few easily tunable parameters. While promising, such an approach may be difficult when considering the broad range of engine operating conditions that are associated with knock.

Several studies introduced more advanced processing techniques to detect knock signals, especially at borderline knock conditions, when the pressure oscillations have a low amplitude. A study by Kim [25] developed a machine learning model using in-cylinder pressure data to distinguish knock from normal cycles. The model presented in the study used Wavelet Packet Decomposition and Ensemble Empirical Mode Decomposition, which effectively identify the primary oscillation modes of the pressure signals and decompose the pressure signal into its frequency components. The algorithm is able to adjust to different engine operating conditions and identifies the relevant frequencies for detecting knock. This approach, as outlined in the study, allowed for a higher level of accuracy in detecting knock at borderline knock conditions while requiring less processing.

Tajima et al. [26] conducted research on predicting knock occurrences using deep learning with the in-cylinder pressure history. Deep learning involves using neural networks to better identify complex patterns, which are then used to train a model. In this case, the form of the pressure trace prior to the onset of knock could be used to predict whether or not knock would occur. The study concluded that deep learning is effective in predicting knock occurrences using the in-cylinder pressure history, even across multiple operating conditions. Offner et al. [27] performed a similar study that used a 1D convoluted neural network trained on pressure data. Their study concluded that the algorithm had a fast response time, making it applicable for real-world engine control. Another study by Shin et al. [28] used deep learning algorithms to develop a model to predict knock at steady-state conditions. Their study found that at steady-state conditions, they were able to achieve a 99 percent prediction accuracy; however, it was unclear if this technique would work at the transient conditions that are often associated with knock.

3.2. Vibration Signals

While pressure data are more reliable for measuring knock, almost every vehicle on the road uses a vibration sensor to determine if its engine is knocking [29]. This is due to accelerometers being less expensive and intrusive than pressure sensors. As shown in Figure 5, the noisy vibration signals are bandpass-filtered, and knock is determined to occur when the oscillations are above a threshold value. While straightforward, this process can be inaccurate, as discussed by Cavina et al. [30], who found that this process was not able to adequately detect knock at high engine speeds.

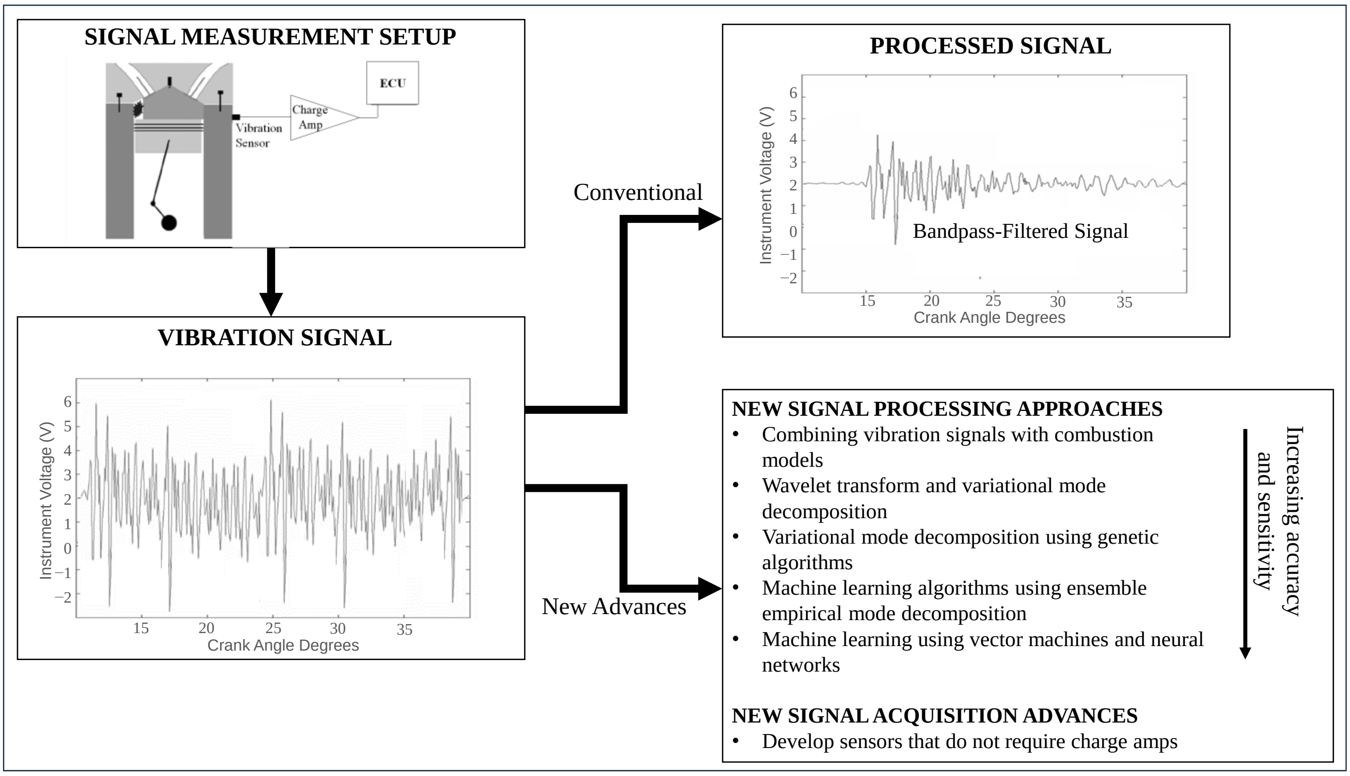


Figure 5. Summary of current and new advances in signal acquisition and processing of vibration data for the detection of knock.

Given that most modern knock sensors use vibration sensing, it is a key signal for knock detection. Figure 5 also shows the advances that are being made in vibration sensing technology. While there has been limited work in the advancement of new vibration sensors, an extensive amount of work related to the processing of the signals to achieve higher levels of accuracy has been carried out.

3.2.1. Acquisition of Vibration Signals

Since vibration sensors are used throughout the industry, and knock sensors are not exposed to the extreme conditions of the combustion chamber, the automotive sector is able to generally leverage advances in accelerometers used from other industries to achieve higher frequency responses and faster response times. These technologies are widely available and have been used in many of the studies identified throughout this paper. However, for widespread usage, the cost of high-precision accelerometers is somewhat prohibitive when compared to the vibration-based knock sensors that are used in every production gasoline automobile.

Regardless, work is underway to further decrease the cost of vibration-based knock sensors. This is key, since as engine powertrains are becoming hybridized and more expensive, it is necessary to reduce the cost and complexity of the more conventional components. Arominski [31] presented a preliminary concept of utilizing piezoelectric accelerometers for detecting engine knocking. While it is common for most knock sensors to require external amplification, Arominski [31] presented a sensor with a strong enough signal that it did not require signal amplifications, hence reducing the cost of the sensor. Initial tests without external amplification devices showed promise, and future research aims to explore the full potential of these cost-effective sensors for precise measurements of the knock combustion phenomenon in prototype internal combustion engines.

3.2.2. Processing of Vibration Signals

Numerous studies have looked at new processing techniques for the signals from vibration-based knock sensors, with a primary goal of increasing the accuracy of knock determination.

Pla et al. [32] proposed a novel knock recognition method that uses a combustion model to estimate the mass fraction that is burned when vibrations are sensed by a knock sensor. The amplitude of the vibration wave depends on the amount of fuel and air that autoignite. The threshold values for the vibration sectors to indicate that a cycle is knocking were then modified to reflect when in the cycle the vibrations were detected. Vibrations detected late in the cycle had a lower threshold than ones earlier in the expansion stroke when there was a larger mass of unburned fuel in the cylinder. It is important to note that the amount of non-knock vibrations for an engine follows a similar pattern, since there are considerably more vibrations at the top of the expansion stroke than later in the stroke. Compared to the commonly used fixed threshold approach, the proposed method demonstrated a significant improvement of over 10% in knock detection accuracy, as validated against cylinder pressure data. While promising, such an approach could be difficult to implement given the need for combustion models for a range of operating conditions.

Meanwhile, Sun et al. [33] proposed a knock recognition method using wavelet transform and variational mode decomposition to process knock sensor signals. This approach, similar to how pressure data are processed, is more precise than bandpass filtering, which maintains a fairly wide range of frequencies. Rather, the approach by Sun et al. [33] allowed the engine control unit to focus on a narrow set of frequencies, allowing for decreased noise and increasing the ability to extract knock features. The proposed method increased the accuracy of knock measurements compared to traditional bandpass filtering, but also required increased processing.

Another study, performed by Yang et al. [34], also performed a spectral analysis of the vibration signal to determine the frequencies of interest associated with knock. The study then proceeded to use genetic algorithms to expand the range of frequencies that are considered for detecting knock, setting the appropriate threshold values for determining the onset of knock. The signals were then reconstructed using only the frequencies of interest; the denoised signals were then trained using a sparse Bayesian extreme learning machine. While this multi-step algorithm is much more complex than what is commonly used, Yang et al. [34] were able to achieve a classification accuracy of 98.3 percent, which is significantly higher than conventional processing techniques.

Another method was developed by Moshrefi et al. [35], who used machine learning with a similar Empirical Mode Decomposition method. This study introduced a quantum threshold method to reduce the signal noise in the vibration sensor. The model was trained by comparing vibration data to pressure data to identify knocking cycles. The approach by Moshrefi et al. [35] then actively varied the filter parameters of the vibration data to reduce the engine noise. The study found that this technique enhanced the detection accuracy compared to previous wavelet transform methods. Their models showed a 3.4% improvement in accuracy for simulated signals and a 13.2% improvement in actual signals, emphasizing the effectiveness of their approach. However, similar to the other studies, it does require the engine control unit to have significantly higher processing capabilities.

Aramburu et al. [36] used both supervised and unsupervised ML approaches to process vibration signals to detect knock in heavy-duty engines. The evaluated methods encompass a One-Class Support Vector Machine and Convolutional Neural Networks. Notably, both approaches exhibited robust knock detection capabilities, surpassing 80% sensitivity levels compared to current approaches, which are based on the amplitude of the filtered signals. The analysis found that the location of the vibration sensors on the engine block and the quantity of sensors used only had minor impacts on the ability of their algorithm to detect knock.

3.3. Audio Signals

Knock is primarily an engine noise issue, although heavier knock, especially when sustained over long periods of time, can result in engine damage. As such, it would make sense that a direct measurement of the noise should provide a good indicator of a knocking engine. The challenge arises from the cost of audio sensors, coupled with having to detect a low-amplitude sound in a relatively noisy environment. Regardless, the human ear is well tuned for detecting engine knock; however, most audio sensors lack the same capability. As shown in Figure 6, when audio sensors are used, the signals are typically bandpass-filtered to take out the low-frequency and high-frequency noises, while maintaining the 6 kHz signal that is traditionally associated with knock.

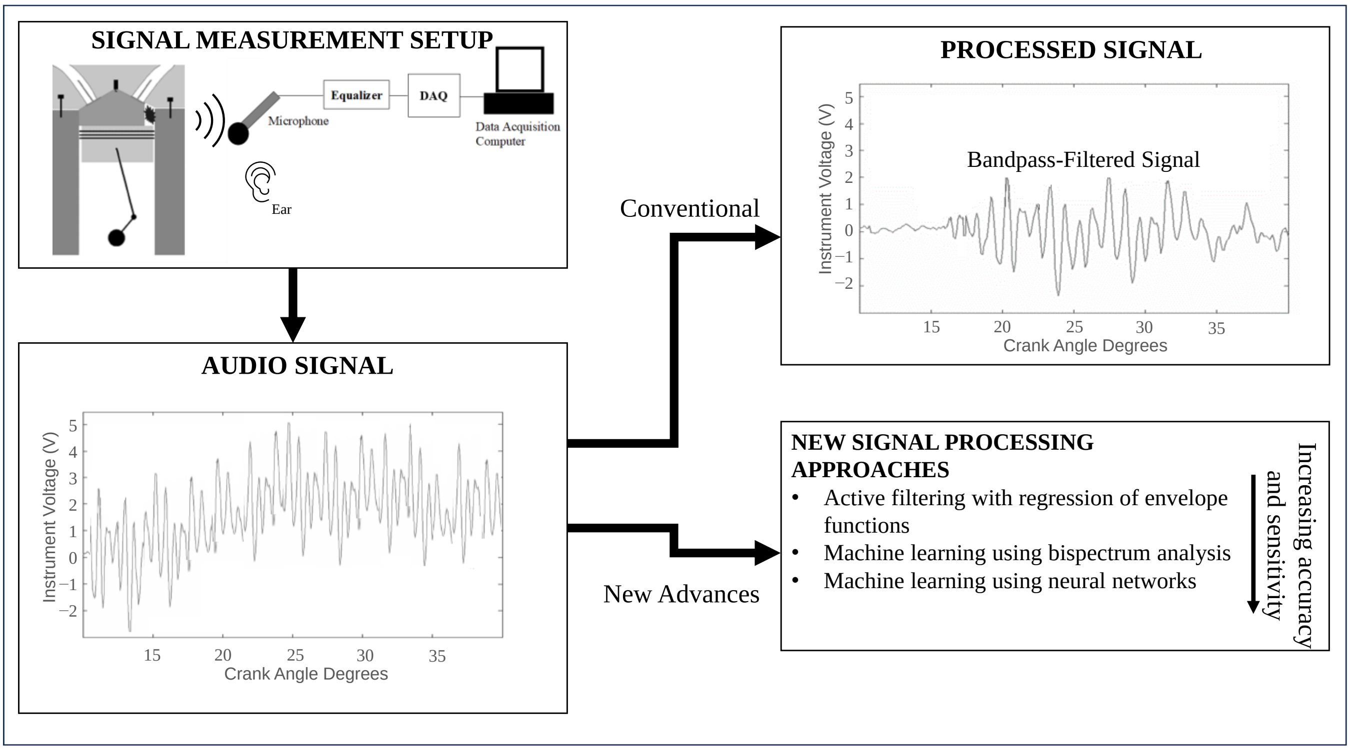


Figure 6. Summary of current and new advances in signal processing of audio data for detection of knock.

Figure 6 displays the different advances that have been made in detecting knock through audio signals. The advances in this area are fairly limited, since this technique is not commonly used compared to vibration and pressure sensors. Regardless, different research groups have attempted to better capture knock through audio signals, with a focus on processing.

One novel approach was presented by Sujono et al. [37], who sought to use pattern recognition for knock detection, incorporating a microphone sensor, active filter, regression of the normalized envelope function, and Euclidean distance calculation. This approach actively filtered the audio signal from the engine, focusing on specific frequencies of interest. The filtered microphone data from four cycles were recorded and compared to each other to look for differences between the four cycles. If the signals were suitably different, it indicated an anomalous combustion event, and likely knock occurred in one of the cycles. The study then proceeded to use this approach to drive a fuzzy logic controller to adjust the spark timing based on the output from their algorithm. This approach showed promise in a lab setting; however, it would likely be difficult on the road, where the contribution of external noises is significantly higher.

Meanwhile, a study by Otaka et al. [38] employed a bispectrum analysis of microphone data to detect knock even in very noisy conditions. While traditional power spectrum analysis looks at the frequency contributions to a signal, bispectrum analysis also considers the phase of each frequency relative to each other. They extracted features from the bispectrum analysis that indicated knock, and then trained a model using machine learning algorithms. The results coincided well with knock experts audibly listening for knock. Furthermore, their study found that with only one microphone, they were able to differentiate between which cylinder was knocking in a multi-cylinder engine.

Shaik [39] performed an analysis of using machine learning to detect engine knock, with a goal of being able to replicate a human's ability to detect knock. In particular, their study collected audio signals and processed them through Fourier transforms to determine the contribution of different frequencies to the overall audio signal. They then applied convolutional and artificial neural networks to determine if the engine was knocking. Neural networks are computational models inspired by the structure and functioning of the human brain, consisting of interconnected nodes (neurons) that are organized in layers to process and learn complex patterns from data. The study was able to achieve over an 90 percent efficiency with this approach.

3.4. Other Signals

A number of studies are evaluating novel techniques for detecting knock in engines. Such techniques generally use sensors and components that are already in the engine, with a goal of being able to replace the knock sensors by simply processing other signals from the engine, as shown in Figure 7, which provides an overview of other signals that are being researched for knock detection. The ultimate goal of many of these studies is to allow for the assessment of knock using sensors that are already in the engine and take advantage of the increased computational power that is available in modern vehicles.

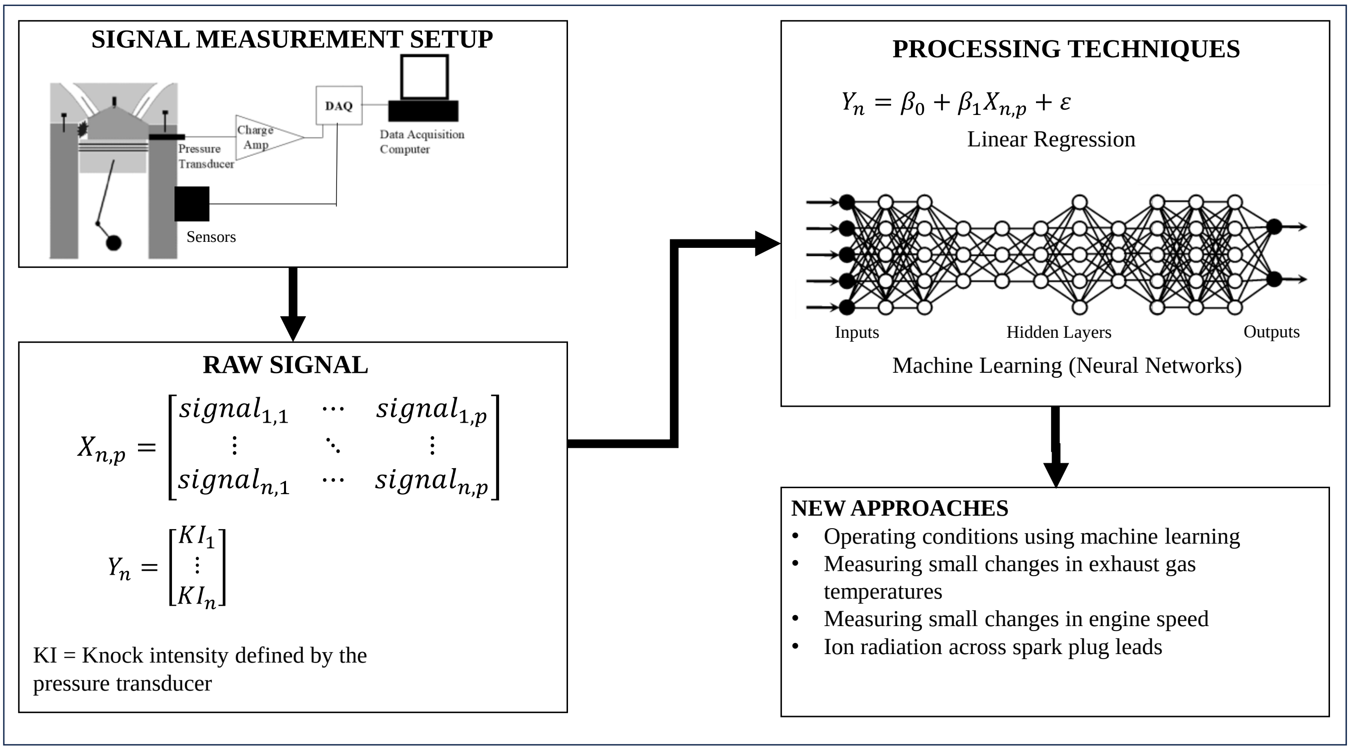


Figure 7. Summary of advances in signal collecting and processing of different sensor data to detect knock.

It is important to note that these studies typically base their models on pressure trace data to identify if an engine cycle was knocking or not. Given that these studies use the pressure data to train their models, they are naturally not as accurate as in-cylinder pressure measurements for predicting knock. Regardless, they show promise compared to accelerometer data, perhaps reducing the need for knock sensors in future engines.

3.4.1. Engine Operating Conditions

Francis et al. [40] developed a system that used five different machine learning techniques to predict knock. Their study collected engine data from a number of sensors on the engine, including the data from the vibration knock sensor. They then used different machine learning algorithms, including AutoEncoder Dense and Convolutional, Feature Extraction Classifier, Support Vector Machines, and Isolated Forest. Of these techniques, the Feature Extraction Classifier, which involves extracting relevant features from the raw data and using them to train a model for classification tasks, achieved the highest level of precision; however, they found that even with this technique, they were only able to detect 81 percent of the knocking cycles.

Petrucci et al. [41] tried an alternative approach, using three machine learning approaches to detect knock in the racing field. These models incorporated factors such as the engine speed, air–fuel ratio, internal cylinder pressure, combustion timing, and air conditions. Their study found that they could accurately predict knocking conditions through these models, concluding that they could enhance the engine performance under diverse operating conditions without extensive computational efforts or the need for a knock sensor.

3.4.2. Exhaust Gas Temperatures

In two studies, Hosseini and Chitsaz [42,43] presented a novel approach for knock detection using a combination of traditional engine sensors and an exhaust gas temperature sensor as inputs for an artificial neural network. The underlying premise of their model was that pressure and temperature fluctuations in the engine resulted in autoignition and, hence, knock; these fluctuations, in turn, modify the heat transfer out of the engine, resulting in changes in the exhaust gas temperature. Experimental tests on a turbocharged gasoline-powered vehicle generated around 5 million data sets, which were filtered and used for network optimization. The neural network achieved a 92 percent precision in detecting knock occurrences. This approach appears promising, especially since the exhaust gas temperature is a signal that is already measured in all production vehicles.

3.4.3. Engine Speed

Baskar et al. [44] explored the possibility of engine knock detection based on small variations in the engine speed that can be associated with knock. Their experiments were conducted on a single-cylinder, air-cooled, port-fuel-injection spark-ignition engine at 3000 rpm with wide-open throttle conditions. Baskar et al. extracted the speed oscillations using a high-pass filter. The study found that the amplitude of speed oscillations correlated with the knock intensity. Hence, through precise measurement of the engine speed, they found that they could detect knock in the limited operating conditions used in their study.

3.4.4. Ion Radiation across Spark Plug Gap

One area that has gained significant traction over the years is related to measuring the ion current across the spark plug leads, with a number of studies exploring this possibility. In 2007, Yoshimura et al. [45] performed a feasibility analysis and found that knock could be predicted by using this approach. Combustion events generate ionized particles in the air–fuel mixture, forming a conductive path between the spark plug electrodes. The autoignition event that results in knock causes changes in the composition of the ionized particles. As such, analyzing changes in the ion current signal in real time provides insight into the occurrence of knock.

Wang et al. [46] further analyzed this method, correlating knocking cycles to changes in the ion current signal. This approach was able to accurately classify 95.7 percent of knocking cycles. In a separate study, Wang et al. [47] improved the accuracy to 98.4 percent through the use of artificial neural networks. Similar analyses were used by Xinke et al. [48] and Kumano et al. [49]. Another study by Zhou et al. [50] analyzed the results from a number of development efforts related to using ion detection to assess engine knock, then successfully implemented this technique in a Formula SAE racing car for Chongqing University in 2020. Regardless of this success, it is likely that significant development is required for the integration of this technique into a commercial vehicle.

4. Discussion

Figure 8 displays a high-level summary of the advances in different signal processing approaches for the detection of knock in SI engines. Each of the signal processing approaches has a different goal. The use of pressure signals is to help develop better tools for fundamental knock research, since in-cylinder pressure measurements are unlikely to be used on commercial vehicles. Meanwhile, the research into vibration signals is aimed towards creating cheaper and more accurate knock sensors for commercial vehicles, especially as vehicles start to transition to operating in downsized, turbocharged, hybrid configurations with alternative fuels. The research into audio signals and the other approaches are intended for the long-term replacement of the traditional vibration-based knock sensor.

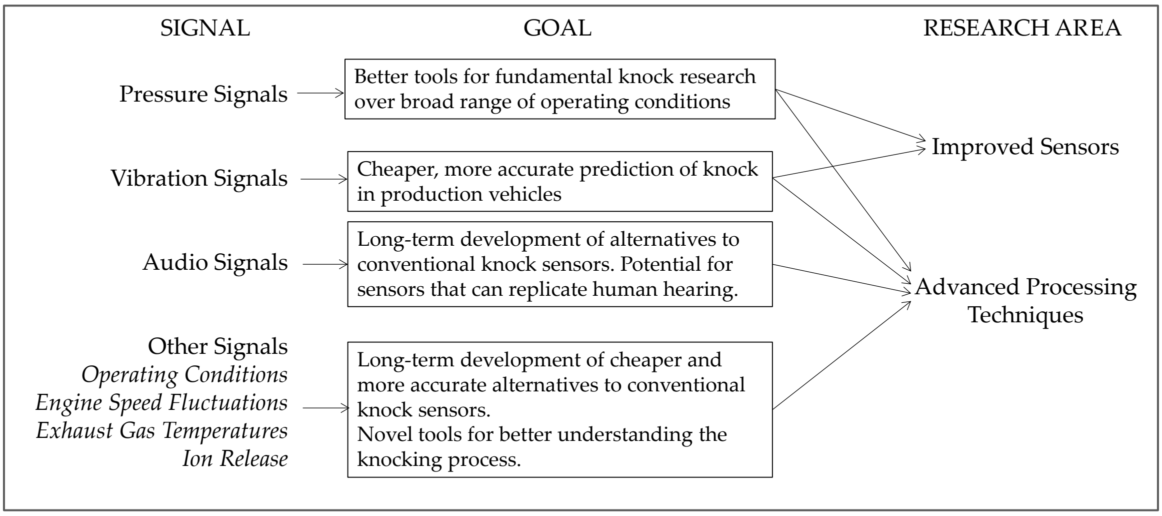


Figure 8. Summary of the different studies being conducted to understand knock signals, the overarching goals of the studies, and the focus of the studies.

The research trends generally demonstrate that the assessment of knock through the spectral analysis of pressure traces remains the gold standard for knock detection. Indeed, almost every study used pressure signals as the "ground truth" in their studies to determine if the cycle is knocking. The advancements in the pressure sensors and processing yielded only marginally better results from what can currently be measured.

Meanwhile, the research into vibration signals indicates that there are improvements that can be made on commercial knock sensors. Indeed, as engines enter hybrid configurations and become increasingly turbocharged, knocking frequencies will likely be over a broader frequency range than what a conventional knock sensor may be able to detect. Many of the studies in this area focused on new processing techniques, most of which would take advantage of the increased computational power that is available in hybrid vehicles. The studies showed improvements and have the potential to be integrated into vehicles in the short term to decrease the cost and increase the reliability of knock sensors.

The other signal processing approaches for the detection of knock are still relatively immature. While they can support in a lab setting to fundamentally understand knock, they are unlikely to be integrated into vehicles in the short term. However, over the long term, many of these approaches show promise for replacing the traditional knock sensor, especially through the processing of signals that are already collected by the engine's processing unit, such as the engine speed or exhaust gas temperature, or by using equipment that is already included in the engine, such as the spark plug.

This review article also provided insights into the expected future trends of knock research. Since knock will remain a problem in automotive design, there will be continued research into how to detect knock more accurately in an engine, especially at borderline knock conditions. Studies will continue to leverage new advances in signal processing and data analytics and apply them to the different knock signals. In particular, research will likely focus on how to detect knock from other signals that are collected by the engine, in order to avoid needing a separate knock sensor. For example, measuring small perturbations in engine speed, exhaust gas temperature, and the voltage across the spark plug gap, coupled with other signals that are collected by the engine (e.g., intake conditions, emissions, coolant temperatures) could provide a new method that is more accurate and cheaper than conventional knock sensors and less intrusive than pressure transducers.

5. Conclusions

Knock has been a key issue in engine design since the inception of the SI engine. As engines evolved, the damage and noise associated with knock became less of an issue due to the ability to accurately assess when an engine is starting to knock and then modify the engine's operating conditions to avoid knock. Future SI engines, including downsized, turbocharged engines that may be used in hybrid configurations, will still require active monitoring of signals from the engine to mitigate knock. As such, although the automotive market is moving to electric vehicles, there is still a substantial amount of research being carried out on knock detection.

This paper reviewed advances in different knock detection techniques. It initially focused on the primary detection techniques, including in-cylinder pressure, engine block vibrations, and audible noise. The paper also addressed a number of new knock detection approaches, including measuring the exhaust gas temperature, perturbations of the engine speed, and ion measurements across the spark plug. The study found that these detection techniques are being combined with new processing techniques, including artificial intelligence and machine learning algorithms, to more accurately determine if an engine is knocking.

Regardless of the advances, this review indicated that in-cylinder pressure measurements with spectral analysis remain the most reliable method for assessing knocking cycles. Further, advances in vibration sensors and signal processing will result in less expensive and more accurate knock sensors being integrated into vehicles in the short term. While a number of other methods for assessing knock are under development, these technologies require further advancement before being integrated into vehicles. However, they have the benefit of being able to use components that are already in the engine.

As engines continue to evolve, the ability to detect knock must evolve as well. Research trends show that there is continued research in this field, improving vibration-based sensors in the short term, while developing novel processes for the longer term.

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