Development and Validation of a Low Cost Data Acquisition System for Automotive Engine Sensors

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Abstract. This research presents the development and validation of an ESP32-based data acquisition system for an automotive engine stand in vocational engineering education. Conventional use of multimeters and oscilloscopes is restricted to single-channel, non-synchronised measurements, limiting students' ability to analyse dynamic engine-sensor behaviour. The proposed system interfaces with eight automotive sensors namely MAP, TPS, IAT, ECT, O_2, CKP, CMP, and knock, through dedicated signal-conditioning circuits and an ESP32 microcontroller. Firmware written in C/C++ using the Arduino IDE enables multi-channel sampling, real-time clock time-stamping, Bluetooth communication, and simultaneous logging to microSD and PLX-DAQ/Excel on a personal computer, together with Android-based monitoring. System performance was evaluated on a K3-VE engine stand by comparing measured voltages and waveforms with digital-multimeter and oscilloscope readings at idle, 2000, and 3000 rpm. For TPS, MAP, ECT, and IAT, the mean absolute percentage error generally ranges from 0% to about 3%, while the O_2 sensor shows larger errors of approximately 1–8% but still reproduces the correct operating range and trends. CKP, CMP, and knock channels successfully capture the essential digital and filtered waveforms for timing and knock demonstrations. These findings indicate that the platform provides sufficiently accurate, real-time multi-sensor monitoring for automotive diagnostics training and offers a scalable basis for future IoT-oriented instructional tools.

1 Introduction

Modern spark-ignition engines depend on an array of electronic sensors, including throttle position, manifold absolute pressure, intake air temperature, engine coolant temperature, oxygen, crankshaft position, camshaft position, and knock sensors, to facilitate accurate fuel and ignition management, comply with emission standards, and assist in onboard diagnostics [1][2]. Precise, time-synchronized collection of these sensor outputs on an engine test stand is crucial for analyzing transient engine behavior, validating control techniques, and facilitating diagnostic training activities. Nevertheless, numerous vocational and undergraduate laboratories continue to rely on handheld multimeters and standalone

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oscilloscopes, which offer only single-channel, non-synchronized measurements and minimal data logging functionality [1]. This circumstance limits data-informed instruction in engine management and condition monitoring, especially in institutions with limited financial resources.

To address these needs, various low-cost automotive data acquisition (DAQ) and logging systems have been proposed. Bedretchuk et al. developed an intelligent, low-cost ECU-level DAQ platform that acquires controller area network (CAN) data during on-road tests and streams it to an IoT server for AI-based analysis, demonstrating performance comparable to commercial systems but at a fraction of the cost [1]. A recent review by Melders et al. summarised architectures and communication protocols for engine-sensor DAQ systems and highlighted the importance of flexible, application-specific solutions that balance accuracy, connectivity, and cost for powertrain testing and diagnostics [2]. At the bench-testing scale, Amorim et al. presented an open-source data logger for real-time monitoring and fault detection, illustrating how low-cost hardware and open software stacks can support laboratory experimentation [3].

In parallel, Numerous domain-specific vehicle data acquisition solutions have been documented. Juwono et al. suggested an IoT-based diagnostic system for motor vehicles that extracts specific metrics from the ECU over the OBD-II interface and use fuzzy-logic algorithms to evaluate vehicle health [4]. Setiyawan et al. developed a wireless engine diagnosis tool on a Raspberry Pi platform as an educational resource for pre-service vocational teachers, highlighting the instructional significance of accessible diagnostic instruments [5]. In related local work, Putra et al. developed a portable diagnostic tester for EFI vehicle control systems, further highlighting the continuing need for affordable diagnostic instrumentation in automotive training environments [6]. These studies collectively demonstrate a keen interest in economic data acquisition and diagnostic tools; nonetheless, the majority of systems function at the ECU or OBD-II level, concentrate on a restricted range of characteristics, or are designed for particular powertrain types and educational contexts.

Concurrently, microcontroller architectures featuring integrated wireless connectivity, especially the ESP32, have gained appeal for constructing economical, IoT-enabled monitoring systems. Kalamaras et al. presented an ESP32-based IoT framework for the continuous monitoring of an anaerobic biogas reactor, incorporating various analog sensors and corroborating the readings with laboratory techniques [7]. Comparable ESP32-based systems have been used for dissolved-oxygen monitoring in aquaculture ponds and several environmental applications, substituting manual readings with continuous, remote logging and alert notifications. These studies demonstrate that ESP32-class microcontrollers can deliver dependable multi-sensor acquisition, local processing, and cloud connectivity in budget-conscious environments. Nonetheless, the application of simultaneous acquisition of diverse automobile engine sensors on a physical engine stand by integrating 0–5 V analog outputs with inductive crankshaft and camshaft signals, as well as a knock sensor, has garnered minimal attention in contemporary research.

From an educational standpoint, the majority of current low-cost options are either generic data acquisition platforms or ECU/OBD-II readers, which fail to provide students with direct exposure to raw engine-sensor behavior at the sensor connector level [2][4][5]. Additionally, at the component-training level, Pahlevi et al. developed a throttle position sensor practical trainer, indicating the pedagogical value of exposing students to direct sensor-level signals in automotive education [8]. Furthermore, Putra et al. also reported a compact motorcycle black box, showing that low-cost embedded vehicle data logging can be implemented in a standalone format [9]. Commercial multi-channel laboratory data acquisition systems offer this capability; but, their expense, reliance on proprietary software, and limited portability hinder widespread implementation in vocational laboratories.

Therefore, an integrated, cost-effective DAQ system is still required that can directly interface with the standard engine sensors on an instructional engine test stand, offer time-stamped multi-sensor logging, and facilitate both desktop and mobile visualization for versatile application in education and experimentation.

This study aims to bridge the existing gap by designing and empirically validating an ESP32-based data acquisition system for eight automotive engine sensors: throttle position, intake air temperature, manifold absolute pressure, engine coolant temperature, oxygen, crankshaft position, camshaft position, and knock, integrated into a K3-VE engine test stand. The proposed hardware incorporates analog signal-conditioning circuits and digital comparator stages to modify sensor outputs for the ESP32 input ports, while the firmware manages multi-channel sampling, real-time clock time-stamping, concurrent logging to microSD, and data streaming to a personal computer and an Android smartphone application via Bluetooth. The system's performance is assessed at idle, 2000, and 3000 rpm by comparing the measured voltages and waveforms to reference equipment, specifically a digital multimeter and a digital oscilloscope. The aim is to illustrate that an economical, microcontroller-driven architecture can deliver adequately precise and dependable real-time multi-sensor monitoring of automotive engines for diagnostic training and engine management experiments in vocational and undergraduate engineering laboratories.

2 Methods

This research adhered to a design–implementation–validation framework. A cost-effective data acquisition (DAQ) unit utilizing the ESP32 microcontroller was developed, incorporating signal-conditioning circuits for eight engine sensors and embedded code for synchronized data logging. The prototype was subsequently put on a pedagogical engine test stand and empirically evaluated against reference instruments under regulated running conditions, adhering to best practices in economical vehicular data acquisition design [1].

2.1 System Architecture

The DAQ system was built around an ESP32 development board that provides a 32-bit dual-core CPU, integrated Wi-Fi/Bluetooth, and multiple 12-bit SAR ADC channels suitable for real-time sensor networks [10]. The ESP32 reads five analog sensors such as throttle position (TPS), intake air temperature (IAT), manifold absolute pressure (MAP), engine coolant temperature (ECT), and oxygen sensor (O_2), and three high-speed sensors: crankshaft position (CKP), camshaft position (CMP), and knock.

Sensor outputs are directed through signal-conditioning boards before entering the ESP32. The microcontroller interfaces with (i) a DS3231 real-time clock (RTC) through I^2C for time-stamping, (ii) a microSD module via SPI for local CSV logging, and (iii) an Android smartphone via Bluetooth for real-time visualization. Comparable ESP32-based data acquisition architectures have been documented in recent economical and educational instrumentation devices [1]. A summary of the machine's sensors and acquisition channels is shown in **Table 1**.

Table 1. Summary of engine sensors and acquisition channels

Sensor	Measured quantity	Signal type (typical range in this study)	Conditioning and interface
TPS	Throttle opening	Analog voltage (~0.45–0.66 V)	Resistor divider to ESP32 ADC (0–3.3 V), optional RC anti-alias filter
MAP	Manifold pressure	Analog voltage (~1.22–1.82 V)	Resistor divider to ESP32 ADC, input protection
ECT	Coolant temp.	Analog voltage (~0.33–0.42 V)	Resistor divider and buffering to ESP32 ADC
IAT	Intake air temp.	Analog voltage (~1.24–1.27 V)	Resistor divider and buffering to ESP32 ADC
O_2	Exhaust λ (rich/lean)	Low-voltage analog (~0.78–0.93 V)	High-impedance buffer and scaling to ESP32 ADC
CKP	Crank angle	Inductive pulses, high dV/dt	LM393 comparator shaping to 0/5 V logic, then to ESP32 digital input
CMP	Cam angle	Inductive pulses	LM393 comparator shaping to 0/5 V logic, ESP32 digital input
Knock	Engine knock/vibration	Piezoelectric signal (kHz band)	LM324 amplification, band-pass filtering (~5–13 kHz), rectification, ESP32 ADC

2.2 Signal-Conditioning Hardware

For the analog sensors, simple passive networks were designed to map the native sensor outputs (nominally up to 5 V) into the 0–3.3 V input range of the ESP32 ADC, in line with the manufacturer's recommendations for external voltage dividers on higher-voltage signals. Each channel includes a series resistance and a shunt resistor to ground, forming a divider sized so that the expected maximum sensor voltage stays below the ADC limit, with optional small capacitors for noise reduction and anti-aliasing.

The CKP and CMP sensors produce high-frequency pulses whose amplitudes vary with engine speed. To convert these into clean logic-level transitions, each channel feeds an LM393 comparator configured with appropriate hysteresis and clamping, as is standard for translating analog or inductive signals to microcontroller-compatible logic inputs.

The knock sensor is a piezoelectric accelerometer that is mechanically attached to the engine block. The broadband output is amplified and subsequently transmitted through an active band-pass filter, focused on the typical knock-frequency range suggested in automotive knock-filter application notes, so allowing only combustion-related vibrations within approximately 5–13 kHz to be detected by the DAQ. The filtered signal is then rectified and scaled to the ESP32 ADC input range.

The DAQ module and conditioning circuits are powered from a regulated supply derived from the engine's 12 V electrical system, with separate regulation and decoupling for the ESP32 and analog front-ends to reduce coupling of switching noise into the measurement channels. Comparable low-cost, multi-channel DAQ systems adopt similar partitioning between power, conditioning, and acquisition boards.

2.3 Firmware and Data Logging

The firmware was developed in C/C++ utilizing the Arduino-compatible ESP32 toolchain. The program configures the ADC to sequentially sample five analog channels at about 100 samples per second per channel, which is adequate for slowly fluctuating engine sensor inputs and comparable to sample durations utilized in recent engine DAQ experiments.

Each acquisition cycle reads all analog channels, captures the current state of the digital CKP and CMP inputs, and optionally records brief knock-sensor bursts utilizing a higher-rate buffered mode. Time stamps are acquired from the DS3231 RTC and recorded alongside sensor voltages and engine speed in CSV format on the microSD card. When a Bluetooth connection is established, identical packets are transmitted to an Android application for real-time monitoring, adhering to prevalent protocols in contemporary ESP32-based monitoring systems.

2.4 Engine Test Bench and Operating Conditions

Validation studies were performed on a four-cylinder K3-VE engine installed on an educational engine stand. The stand preserves the original engine control unit and sensors, offering a realistic platform for data collecting studies akin to other laboratory engine test benches. The DAQ inputs were directly connected in parallel with the car harness, allowing the ECU to receive unaltered sensor signals while the DAQ passively observed them. Reference measurements were simultaneously acquired with a handheld digital multimeter for analog voltages and a digital storage oscilloscope for CKP, CMP, and knock waveforms, mirroring configurations from previous low-cost automotive data acquisition and validation investigations. The engine was ran at three steady-state conditions: idle, 2000 rpm, and 3000 rpm. Three repeated acquisition runs were conducted for each operating point. During each run, the engine was let to stabilize, after which both the DAQ system and the reference instruments documented data for a predetermined time interval. This methodology ensures repeatability and establishes a foundation for estimating measurement uncertainty.

2.5 Data Processing and Error Metrics

For each analog sensor and operating point, the recorded voltage samples from the DAQ and the multimeter were averaged over the acquisition window. The absolute percentage error at condition j was computed as:

$$APE_j(\%) = \left|\frac{V_{DAQ,j}-V_{ref,j}}{V_{ref,j}}\right| x100 \tag{1}$$

The mean absolute percentage error (MAPE) across the three repetitions at each rpm was then obtained as:

$$MAPE(\%) = \frac{1}{N}\sum_{j=1}^{n} APE_j \tag{2}$$

with N =3. MAPE is widely used to quantify relative error in low-cost DAQ systems and to compare them with higher-grade reference instrumentation.

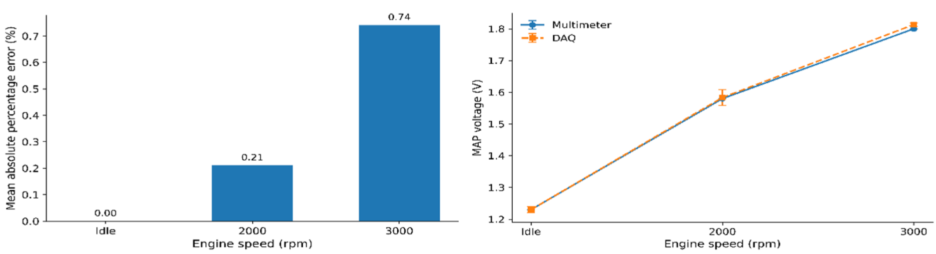
For the O_2 sensor, which has a switching behavior instead of a strictly linear voltage-load relationship, the identical error formulation was utilized for the average voltage throughout each time window. The assessment of CKP and CMP concentrated on (i) the quantity and distribution of pulses per engine cycle, (ii) the maintenance of waveform integrity, and (iii) the uniformity of timing patterns across iterations in comparison to oscilloscope traces. Comparisons for the knock sensor were conducted based on the existence or non-existence of knock-like bursts and the qualitative correlation between DAQ and oscilloscope envelopes within the specified band-pass frequency range.

3 Results and discussion

3.1 Results

The proposed DAQ system was evaluated by comparing its readings with a digital multimeter for the five analog sensors at idle, 2000 rpm, and 3000 rpm, each condition repeated three times. The mean values and mean absolute percentage errors (MAPE) for every sensor–speed combination were extracted from these datasets.

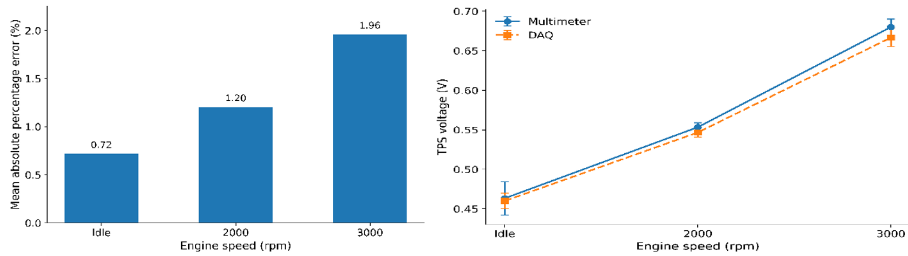
For the MAP sensor, the DAQ output was benchmarked against a digital multimeter at idle, 2000 rpm, and 3000 rpm, with three repetitions at each speed. Fig. 1 , (b) shows that the mean voltages from both instruments are almost coincident: about 1.23 V at idle, increasing to around 1.58 V at 2000 rpm and roughly 1.8 V at 3000 rpm. The error bars (standard deviation of three runs) are very small, on the order of 0.01–0.02 V, which indicates good repeatability of the DAQ measurements. The corresponding mean absolute percentage errors in **Fig. 1** (a) are negligible at idle (≈0%), and remain low at higher speeds, with values of about 0.2% at 2000 rpm and 0.7% at 3000 rpm. Overall, the DAQ tracks the manifold pressure sensor within well below 1% of the reference instrument over all tested operating conditions.



(a) (b)

Fig. 1. Validation of the MAP sensor channel: (a) mean absolute percentage error of DAQ readings relative to the digital multimeter; (b) mean MAP voltage versus engine speed measured by the DAQ and reference multimeter (error bars indicate ±1 standard deviation, n = 3).

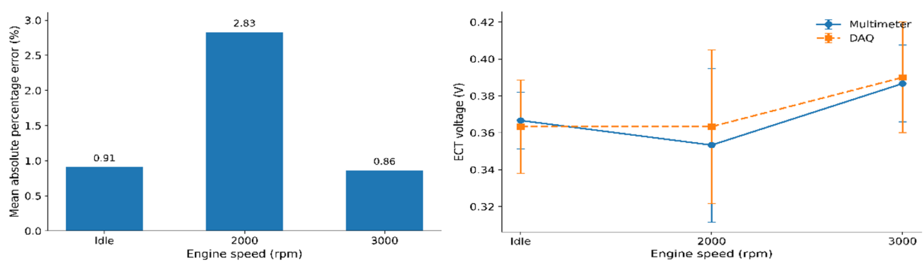
Furthermore, the throttle position sensor (TPS) readings from the data acquisition system were compared to those obtained from a digital multimeter at idle, 2000 rpm, and 3000 rpm, with three trials conducted for each condition. **Fig. 2** (b) illustrates that both instruments demonstrate a nearly linear increase in TPS voltage with engine speed, ranging from approximately 0.46 V at idle to about 0.55 V at 2000 rpm and around 0.68–0.69 V at 3000 rpm. At the three operating points, the DAQ curve consistently exhibits a slight deviation below the multimeter curve, suggesting a systematic under-reading rather than random variation. The small standard-deviation error bars indicate a high level of repeatability in the DAQ measurements. The mean absolute percentage errors, illustrated in **Fig. 2** (a), are relatively low: approximately 0.7% at idle, 1.2% at 2000 rpm, and slightly less than 2.0% at 3000 rpm. At maximum speed, the DAQ reproduces TPS voltage with an accuracy of approximately 2% relative to the reference instrument. The results indicate that the proposed low-cost DAQ effectively captures TPS signals with adequate accuracy and stability, confirming its suitability for engine test-stand monitoring and educational purposes.



(a) (b)

Fig. 2. Validation of the TPS sensor channel: (a) mean absolute percentage error of DAQ readings relative to the digital multimeter; (b) mean TPS voltage versus engine speed measured by DAQ and multimeter (error bars: ±1 standard deviation, n = 3).

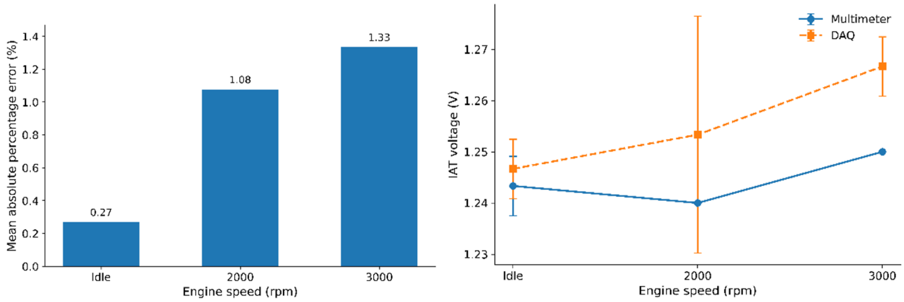
The engine coolant temperature (ECT) sensor measurements from the data acquisition system were compared to those obtained from the digital multimeter at idle, 2000 rpm, and 3000 rpm, with three repetitions conducted for each operating condition. **Fig. 3**(b) demonstrates that both instruments indicate low voltages between 0.33 and 0.42 V, corresponding to the characteristics of the thermistor-based sensor employed in the test stand. The mean ECT voltage decreases slightly from approximately 0.37 V at idle to 0.35 V at 2000 rpm, subsequently increasing to around 0.39–0.40 V at 3000 rpm as the coolant temperature rises. The DAQ curve reflects this non-monotonic trend and closely aligns with the reference curve; however, the variability of the DAQ readings at 2000 rpm is noticeably greater. The mean absolute percentage errors shown in **Fig. 3**(a) are approximately 0.9% at idle, 2.8% at 2000 rpm, and 0.9% at 3000 rpm. The maximum error for the ECT channel is observed at mid-speed; however, this worst-case scenario remains under 3%. The results demonstrate that the proposed DAQ system effectively captures minor variations in coolant-temperature voltage, exhibiting strong repeatability and satisfactory accuracy for laboratory engine-stand monitoring.



(a) (b)

Fig. 3. Validation of the ECT sensor channel: (a) mean absolute percentage error of DAQ readings relative to the digital multimeter; (b) mean ECT voltage versus engine speed measured by DAQ and multimeter (error bars: ±1 standard deviation, $n = 3$).

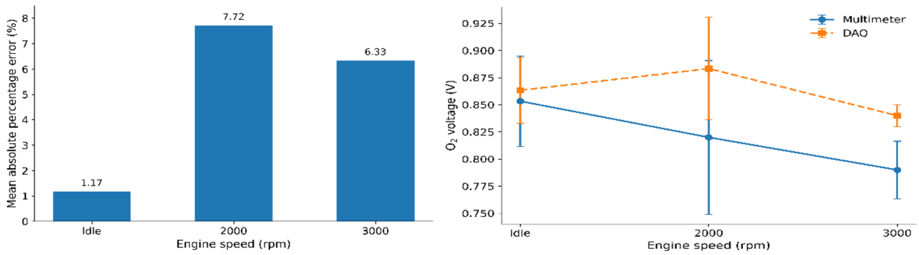
The intake air temperature (IAT) sensor's DAQ readings were compared to those of the digital multimeter at idle, 2000 rpm, and 3000 rpm, with three repetitions for each condition. **Fig. 4**(b) illustrates that the measured voltages exhibit remarkable stability: the multimeter reads approximately 1.24 V at idle, a minor reduction to 1.24 V at 2000 rpm, and an elevation to around 1.25 V at 3000 rpm. The DAQ exhibits a similar pattern but consistently yields somewhat elevated results, ranging from approximately 1.25 V at idle to roughly 1.26–1.27 V at 3000 rpm. The minimal error bars for both instruments signify excellent reproducibility, albeit the limited dynamic range of the signal. The mean absolute percentage errors depicted in **Fig. 4**(a) are minimal across all operating points. The inaccuracy is roughly 0.3% at idle, escalates to approximately 1.1% at 2000 rpm, and attains about 1.3% at 3000 rpm. Consequently, even at maximum velocity, the DAQ replicates the IAT voltage within approximately 1–1.5% of the reference value. The results validate that the suggested system can accurately acquire intake-air temperature information for engine monitoring and educational experiments.



(a) (b)

Fig. 4. Validation of the IAT sensor channel: (a) mean absolute percentage error of DAQ readings relative to the digital multimeter; (b) mean IAT voltage versus engine speed measured by DAQ and multimeter (error bars: ±1 standard deviation, $n = 3$).

The DAQ system for the oxygen (O_2) sensor was assessed in comparison to the digital multimeter at idle, 2000 rpm, and 3000 rpm, with three trials for each condition. **Fig. 5**(b) illustrates that both instruments measure voltages within the standard narrow range for a heated zirconia sensor, approximately 0.80–0.90 V. The multimeter reading diminishes marginally with increasing engine speed, from roughly 0.85 V at idle to around 0.79 V at 3000 rpm, while the DAQ output reaches a maximum of about 0.88–0.89 V at 2000 rpm before declining to approximately 0.84 V at 3000 rpm. The error bars are significantly larger than those of the other analog channels, indicating the greater cycle-to-cycle fluctuation of this dynamic signal. The typical absolute percentage errors depicted in **Fig. 5**(a) are around 1.1% at idle, escalating to about 7.7% at 2000 rpm and 6.3% at 3000 rpm. Consequently, the O_2 channel demonstrates the most significant relative deviations among all sensors, yet the DAQ accurately reflects the appropriate voltage range and qualitative trend. The results demonstrate that the economical DAQ can monitor the oxygen sensor's performance with satisfactory accuracy for instructional and diagnostic applications, while its precision is inferior to that of the other analog channels.



(a) (b)

Fig. 5. Validation of the O_2 sensor channel: (a) mean absolute percentage error of DAQ readings relative to the digital multimeter; (b) mean O_2 voltage versus engine speed measured by DAQ and multimeter (error bars: ±1 standard deviation, $n = 3$).

3.2 Digital Sensor

The digital inputs for the crankshaft position (CKP), camshaft position (CMP), and knock sensors were assessed by comparing DAQ recordings with oscilloscope traces at idle, 2000, and 3000 rpm, in conjunction with the analog channels. The processed CKP signal appears as a periodic 0–5 V pulse train in which the full tooth sequence and the missing-tooth region are clearly identifiable, consistent with typical ECU excitation signals that combine multitooth and missing-tooth segments for crank-angle referencing [11][12]. This behaviour indicates that the LM393 comparator stages and ESP32 digital inputs are able to digitize the inductive crank signal reliably for tooth counting and qualitative speed/phase observation, in line with applications where CKP and CMP signals are used to infer engine speed, crank position, and misfire events [11][12][13]. However, the chosen sampling strategy and concurrent logging tasks do not provide oscilloscope-level time-stamping on individual edges, so the present implementation is not intended for high-precision crank-angle or ignition-timing measurements. The CMP channel exhibits a lower-frequency pattern that remains phase-locked to the CKP sequence, enabling visualization of the cam–crank relationship and cylinder events in a qualitative manner, similar to recent studies that exploit sensor excitation signals for ECU analysis [11][12]. The knock channel, formed through LM324 amplification, band-pass filtering, and rectification, follows the envelope-based conditioning approaches reported for knock detection using piezoelectric vibration sensors [14][15]. Under the steady, non-knocking conditions of this study, the traces show low-amplitude fluctuations without distinct knock bursts, confirming correct operation of the conditioning chain while underlining the need for future quantitative knock-intensity calibration [14][15].

3.3 Discussion

The validation results indicate that the proposed ESP32-based DAQ fulfills the initial goal of delivering precise, multi-channel monitoring of the eight engine sensors enumerated in Table 1 across standard instructional operating points. The mean absolute percentage error (MAPE) across the five analog channels often stays below 2% (**Fig. 1–4**), with the exception of the dynamic O_2 sensor, which attains 6–8% at elevated speeds (**Fig. 5**). These values are equivalent to or inferior to the errors documented for other economical automotive and laboratory data acquisition platforms utilizing microcontroller-class hardware and basic conditioning circuits [1][3].

For the MAP and TPS channels (**Fig. 1** and **Fig. 2**), the DAQ accurately reflects the anticipated monotonic increase in sensor voltage corresponding to engine speed, exhibiting patterns that closely align with those of the multimeter. The slight, systematic underestimation of TPS and the incremental increase in MAPE with rpm align with fixed gain and offset uncertainties in the resistor dividers and ADC transfer function, as noted in prior ESP32-based data gathering investigations [7][10]. The ECT and IAT channels (**Fig. 3** and **Fig. 4**) demonstrate minimal absolute voltage fluctuations due to the constraints of brief, quasi-steady tests; however, the DAQ successfully detects these variations with a sub-3% MAPE, signifying that the 12-bit ADC resolution and sampling rate are sufficient for gradually changing thermistor-based sensors.

Furthermore, The O_2 sensor constitutes the most challenging analog input. Its narrow operational voltage band and rapid switching around stoichiometric conditions lead to larger scatter and relative error (**Fig. 5**). Similar behaviour has been reported in other low-cost loggers when bench-testing λ-sensors or other rapidly fluctuating electrochemical transducers [2][3]. In this context, the 6–8% MAPE observed here is still acceptable for educational purposes, because the DAQ reproduces the correct rich/lean transitions and overall trend, even if it does not match the reference instrument on a cycle-by-cycle basis.

At the same point, The qualitative agreement between CKP, CMP and knock-sensor waveforms recorded by the DAQ and those captured by the oscilloscope confirms that the LM393-based comparators and LM324 knock-conditioning stage preserve timing and pattern information required for phase detection and knock observation. Similar comparator-based front-ends are widely used in automotive and low-cost DAQ designs. The correct reproduction of the missing-tooth pattern in CKP and the phase-locked CMP pulses indicates that the system could be extended to support instructional activities on ignition timing, misfire diagnosis, or basic crank–cam correlation, complementing ECU- or OBD-II-level tools that dominate the literature [1][2][4][5].

Based an educational standpoint, the combination of accurate analog channels, reliable digital waveforms and multi-platform access (PC spreadsheet logging, microSD storage and Android visualization) addresses gaps identified in previous work, where systems were either generic laboratory DAQs or ECU-level recorders with limited transparency at the sensor connector [2][5]. The present results show that a relatively simple ESP32 architecture can expose students directly to raw engine-sensor behaviour while maintaining measurement quality close to that of standard instruments, thereby supporting data-driven learning scenarios in vocational and undergraduate laboratories. Remaining limitations, such as the higher relative error of the O_2 channel, the modest sampling rate and the focus on steady-state operating points, suggest clear directions for refinement, including improved O_2 conditioning, adaptive sampling strategies and extended transient testing in future studies.

4 Conclusion

This study has introduced the creation and experimental verification of an economic data gathering system based on the ESP32 for eight automotive engine sensors mounted on a K3-VE engine test bench. The system incorporates specialized signal-conditioning circuits, real-time clock time-stamping, microSD logging, and optional PC/Android interfaces inside a single small platform, fulfilling the demand for cost-effective, multi-channel instrumentation in vocational and undergraduate laboratories. The validation results indicate that, for the primary analog channels such as TPS, MAP, ECT, and IAT, the mean absolute percentage error relative to a digital multimeter typically ranges from 0% to around 2–3%, demonstrating consistent repeatability at idle, 2000 rpm, and 3000 rpm. The oxygen sensor, despite its low amplitude and dynamic behavior presenting greater challenges, remains within an error range that maintains the appropriate operating band and qualitative trends. The qualitative concordance between CKP, CMP, and knock waveforms captured by the DAQ and those documented by the oscilloscope substantiates that the comparator- and filter-based front-ends effectively maintain critical timing and pattern information. The findings indicate that a straightforward, microcontroller-based architecture can achieve measurement performance comparable to traditional laboratory instruments while offering direct access to raw engine-sensor information. The suggested method enhances the field of automotive instrumentation and engineering education by facilitating multi-sensor, time-synchronized experiments on conventional engine stands at a substantially lower cost. Future endeavors will concentrate on enhancing high-speed digital acquisition, optimizing the conditioning of low-voltage dynamic signals, and broadening validation throughout a more extensive array of operational settings and instructive scenarios.

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