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Preventive Diagnostics of Internal Combustion Engines Based on Setpoint-to-Actual Deviation Using Artificial Intelligence and a Standardized 3/5/7 Data-Collection Protocol

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ABSTRACT

Preventive engine diagnostics needs a signal that appears before a diagnostic trouble code and remains interpretable across engine types. This article proposes a conceptual and methodological framework for internal combustion engines in which the diagnostic primitive is the deviation between the electronic control unit setpoint and the actual realized value across regulated loops. The aim is to define how this deviation can support early fault recognition when engineers combine it with artificial intelligence and a standardized 3/5/7 data-collection protocol covering idle, urban, and highway phases. The study uses a structured review of ten recent sources on OBD-II analytics, fault detection, predictive maintenance, residual diagnostics, and explainable AI. The analytical part substantiates the diagnostic value of setpoint-to-actual deviation, specifies the data collection logic, and outlines validation through detection lead time. The framework supports workshops and fleets seeking traceable pre-DTC monitoring without proprietary software details and with field validation reserved for later studies.

Keywords: preventive diagnostics, internal combustion engines, setpoint-to-actual deviation, OBD-II data, artificial intelligence, predictive maintenance, diagnostic trouble codes, residual analysis, 3/5/7 protocol, engine health monitoring

INTRODUCTION

Internal combustion engines rely on electronic control units that calculate target values, move actuators, and measure the response of regulated systems. Workshop diagnostics still often begins after the system crosses a calibrated threshold and records a diagnostic trouble code. This logic suits standardized fault reporting, but it leaves the intermediate zone without a stable method for preventive interpretation. In that zone, the engine still runs, the ECU still compensates, fuel consumption may rise, and emissions may increase before a code appears.

The diagnostic signal selected for early recognition determines the quality of the whole method. A single observed value rarely explains early degradation because load, speed, temperature, traffic, driving style, and control strategy change the same parameter. This article treats the deviation between the ECU setpoint and the actual realized value as the basic diagnostic unit. The gap between the requested state and the achieved state reflects the effort needed to keep the engine near the commanded operating point. A growing gap marks drift before the fault reaches a code threshold.

The aim of this article is to develop a conceptual and methodological framework for preventive diagnostics of internal combustion engines based on setpoint-to-actual deviation, artificial intelligence, and a standardized 3/5/7 data-collection protocol. The research objectives are to substantiate the setpoint-to-actual gap as a diagnostic primitive across regulated engine loops, to define a comparable data-collection logic for idle, urban, and

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highway phases, and to formulate an AI-supported validation strategy based on early drift detection and detection lead time.

The proposed framework combines three elements that current research often treats in separate lines: regulatory deviation, reproducible operating phases, and multivariate AI interpretation. The same logic covers diesel and gasoline engines. The list of controlled pairs changes with architecture, while the diagnostic operation remains stable: compare the target state with the achieved state under comparable measurement conditions.

The working hypothesis is that a standardized setpoint-to-actual deviation vector, collected through the 3/5/7 protocol and interpreted by an AI layer, provides a stronger methodological basis for pre-DTC diagnostics than code-based reading or raw-parameter interpretation alone. Since this article does not contain an empirical field dataset, the hypothesis receives conceptual assessment through source-based synthesis and becomes a validation plan for later field testing.

MATERIALS AND METHODS

The literature search followed a focused narrative screening of recent work on vehicle OBD-II analytics, internal-combustion-engine fault detection, AI-based predictive maintenance, explainable predictive maintenance, residual diagnostics, and engine benchmark datasets. Search terms combined “OBD-II machine learning”, “internal combustion engine fault diagnosis”, “predictive maintenance vehicles artificial intelligence”, “setpoint actual deviation”, “residual fault detection”, “explainable predictive maintenance”, and “engine fault benchmark”. Screening covered publisher and indexing platforms such as MDPI, SpringerLink, IEEE Xplore, Nature, TRID, arXiv, Crossref, and Google Scholar. Thirty-four candidate records were inspected at the title, abstract, and bibliographic level. Twenty-four records were excluded because they fell outside the 2021-2026 window, addressed electric drivetrains without ICE relevance, lacked stable bibliographic metadata, duplicated another record, or covered generic industrial maintenance with weak transfer value for engine diagnostics. The final corpus retained ten sources. This corpus covers the diagnostic signal, data comparability, AI interpretation, validation difficulty, explainability, and transfer across operating conditions.

The study uses comparative source analysis, source-based interpretation, conceptual synthesis, typologization of diagnostic signals, and analytical generalization. Comparative analysis connects OBD-II analytics with residual diagnostic logic. Conceptual synthesis combines the setpoint-to-actual primitive, the 3/5/7 protocol, and an AI decision layer. Typologization separates raw readings, diagnostic codes, residuals, and multivariate deviation vectors. Analytical generalization converts these elements into an implementation and validation model suitable for later empirical testing.

RESULTS

Recent OBD-II research supports a wider reading of the vehicle diagnostic interface. Modern studies use OBD-II streams as sources of real-time operational parameters and diagnostic trouble codes, while machine learning expands their application to vehicle safety, efficiency, sustainability, and state interpretation (Michailidis et al., 2025). Research on vehicle trajectory prediction based on OBD and GPS data adds a related methodological point: analysts can use OBD data for real-time and offline tasks when they process it as structured time-series information rather than a static service record (Navali et al., 2023). Preventive diagnostics needs this temporal reading. A fault code marks a threshold event. A deviation trajectory records movement toward that event.

Fault detection research explains why the proposed primitive should be a deviation rather than a raw parameter. Residual-based diagnostics detects abnormal behavior through the difference between expected and observed system behavior (Mercorelli, 2024). In an electronically controlled engine, the setpoint-to-actual pair creates a practical residual-like structure inside the control process. The ECU commands boost pressure, injection pressure, throttle position, EGR rate, camshaft phase, idle speed, and mixture-related targets. Sensors and feedback loops then record the realized response. A growing distance between the requested and achieved values carries more diagnostic meaning than the achieved value alone because it preserves the direction of control effort.

ICE-specific diagnostic studies support the same decision from another angle. Recent work on internal combustion engine fault detection reviews model-based and data-driven approaches and shows that engine faults appear through many signals under varied operating conditions (Srinivaas et al., 2025b). Acoustic predictive models classify several fault types from selected signal channels, showing the value of pattern recognition in non-invasive diagnostic data (Torres et al., 2025). The framework proposed here occupies another diagnostic layer. It starts from the engine controller's own target and asks whether the mechanical, air, fuel, combustion, and aftertreatment systems still realize what the controller requests.

Four strands of prior research converge on one requirement for the proposed method. OBD-II machine learning studies emphasize standardized access to vehicle parameters and the need for high-quality temporal data (Michailidis et al., 2025). Vehicle predictive maintenance reviews identify data quality, scalability, integration, and health monitoring as recurring barriers (Mahale et al., 2025). AI-based predictive maintenance literature describes data acquisition, preprocessing, decision support, trustworthiness, explainability, and validation in real operating settings (Ucar et al., 2024). Explainable predictive maintenance research adds the maintenance user: predictive systems used for operational decisions need outputs that technicians can inspect and challenge (Cummins et al., 2024). A setpoint-to-actual signal loses diagnostic force if engineers collect it under inconsistent conditions. An AI alert loses workshop value if the technician cannot trace the deviation to a regulated loop and an operating phase.

The standardized 3/5/7 protocol answers this measurement problem. The protocol divides one session into three operating phases: three minutes at idle, five minutes in urban driving, and seven minutes in highway driving. Idle records low-load stability and closed-loop regulation without driver demand. Urban driving exposes transient regulation, repeated acceleration and deceleration, and medium-load response. Highway driving records more stable high-load behavior, where boost, air mass, injection pressure, aftertreatment, and thermal behavior become more visible. The LiU-ICE benchmark supports the broader need to collect nominal and faulty engine data under relevant operating settings because it provides data and a model from an internal combustion engine test bench under nominal and faulty modes (Jung et al., 2024). The 3/5/7 protocol adapts this comparability requirement to a workshop-oriented field procedure. Figure 1 presents the proposed workflow. It does not report empirical results. It specifies the movement from control-loop measurement to preventive diagnostic decision.

ECU setpoints and actual values → 3/5/7 protocol phases → phase-specific

Figure 1. Setpoint-to-actual preventive diagnostic workflow
Prepared by the author based on Mercorelli (2024), Michailidis et al. (2025), Mahale et al. (2025), and Jung et al. (2024)

The workflow fixes the diagnostic object before the AI layer enters the process. The model does not receive unstructured raw parameters and then assign meaning after the fact. Engineers first build a phase-specific deviation vector. Each phase records the operating state attached to the deviation. The AI layer then interprets a vector across loops. A small airflow deviation, a delayed boost response, and an atypical fuel correction may remain ambiguous in isolation. The same signals can gain diagnostic meaning when they appear together under the same phase pattern.

The universality of the primitive has a technical boundary. Gasoline and diesel engines do not expose identical regulated pairs. A gasoline engine gives more weight to mixture control, lambda-related behavior, throttle response, ignition correction, knock-control adaptation, and fuel trims. A diesel engine gives more weight to injection pressure, rail regulation, air mass, boost, EGR, DPF-related pressure, and torque-related corrections. The operation remains the same: command, response, deviation, phase, persistence, and comparison with a reference. ICE fault diagnosis reviews show that model-based and data-driven families already operate in this domain, while recent cross-domain studies test transfer, federated learning, transformer-based models, and generalization across engine datasets (Srinivaas et al., 2025a, 2025b). The proposed framework uses that research direction with restraint. It does not claim that one trained model will fit all vehicles. It claims that a comparable deviation representation gives later generalization a stronger technical base.

The controlled pairs in the framework cover mixture or fuel-air regulation, injection pressure and cylinder balance, boost, airflow, throttle position, EGR, ignition and combustion quality, VVT, idle control, and aftertreatment-related indicators. Their value depends on phase sensitivity. EGR drift may stay weak during some operating states and become visible in others. Boost deviation needs load. Idle instability carries more meaning in low-load phases. DPF backpressure and regeneration behavior require thermal and load interpretation. For this reason, the protocol standardizes more than duration. It assigns diagnostic meaning to the phase in which a deviation appears.

The AI layer is justified by the size and structure of the diagnostic task. One 3/5/7 session can generate a dense time-stamped record of many regulated and contextual variables. A technician can read a few parameters, but manual reading becomes fragile when several small deviations remain individually ambiguous. Predictive maintenance literature reports that AI processes multivariate sensor data for anomaly detection, fault diagnosis, and maintenance decision support, while field deployment still faces integration and trust barriers (Mahale et al., 2025, Ucar et al., 2024). The proposed model gives AI a bounded task. It quantifies deviation, compares it with a healthy reference, grades drift persistence, and presents the suspected loop.

The validation strategy follows from the absence of empirical data in the present article. The first validation layer collects healthy references by vehicle family, engine type, ECU generation, and protocol phase. The second layer collects before-after pairs, where the first measurement records suspected drift and the second follows confirmed repair or independent diagnostic verification. The third layer compares the AI drift signal with later DTC appearance. Detection lead time then becomes the main planned metric: the interval between the preventive signal and the later fault-code threshold. This metric belongs to future empirical work and should not be phrased as a completed result.

The reviewed literature sets a realistic boundary for the claim. ICE fault diagnosis research demonstrates the value of machine learning and deep learning for classification under controlled datasets, acoustic signals, vibration features, and cross-domain conditions (Srinivaas et al., 2025a, 2025b, Torres et al., 2025). OBD-II research demonstrates the availability and analytical value of standardized vehicle data (Michailidis et al., 2025, Navali et al., 2023). Residual diagnostics explains why comparison against expected behavior gives more information than a standalone measurement (Mercorelli, 2024). Predictive maintenance and

XAI reviews explain why field systems require data quality, integration, transparency, and human-readable outputs (Mahale et al., 2025, Ucar et al., 2024, Cummins et al., 2024). This combination supports the conceptual feasibility of the framework and leaves performance estimates to later field validation.

DISCUSSION

Previous studies develop several adjacent lines: OBD-II analytics, predictive maintenance, residual diagnostics, explainable AI, and ICE fault classification. Their limitation for the present problem lies in fragmentation. One group of works focuses on vehicle data access. Another group focuses on fault classification. A third group studies predictive maintenance governance and interpretability. The proposed framework connects these lines through one diagnostic object: setpoint-to-actual deviation under standardized operating phases.

The authorial position is deliberately conservative. The framework should not be presented as a proven diagnostic system until field data are available. Its current value lies in the ordering of the diagnostic process. A workshop or fleet operator first needs a comparable signal, then a phase-stable dataset, then a reference structure, then an AI interpretation layer. Only after these steps can the operator make a claim about early detection. If developers start from a model before defining the diagnostic object, the system may classify data without giving the technician a traceable reason for inspection.

Implementation begins with parameter mapping. For each supported engine and ECU family, the diagnostic team identifies regulated pairs available through diagnostic access: target and actual boost, target and actual rail pressure, commanded and actual EGR, expected and measured air mass, target and actual throttle position, target and actual idle speed, requested and measured camshaft phase, fuel trims, combustion-related counters, and aftertreatment indicators. Engineers should not replace unavailable parameters with artificial proxies unless they document the technical meaning of the substitute. Missing access remains a limitation of the vehicle or diagnostic interface.

The second step enforces the protocol. A healthy reference and a suspected-fault record become comparable only when both pass through the same phase structure. A pause function can protect the session from traffic interruptions, but the software has to log every pause. An unmarked pause contaminates interpretation because the phase length no longer reflects the intended operating exposure. The session record should contain timestamp, phase, pause state, vehicle identifier, engine type, ECU family, current DTC status, temperature state, and the full deviation vector.

The third step designs the deviation features. The system calculates absolute deviation, relative deviation where the unit permits it, phase-specific persistence, return speed after transient load changes, and co-movement between loops. A short deviation during acceleration has a different diagnostic meaning from a stable offset across a full phase. An isolated gap differs from a joint pattern linking boost, air mass, EGR, and fuel correction. This logic lowers the risk of excessive alerts and keeps the technician’s attention on repeatable drift.

The fourth step constrains the AI output. The system should not produce a bare message such as “fault likely.” It should assign the drift to a loop family, state the phase where the drift appears, describe persistence or transience, compare the signal with the healthy reference, and recommend verification. A useful workshop output could state: “air-path regulation drift under highway load, persistent target-achieved gap, EGR and airflow co-movement, no DTC at collection time.” This phrasing does not replace mechanical inspection. It directs inspection toward a plausible loop and shows the basis for that direction. Table 1 translates the implementation logic into a decision sequence. The table compares what each decision block contributes to a preventive diagnostic decision and how the output should be interpreted before a repair recommendation appears.

Table 1. Diagnostic decision logic for setpoint-to-actual deviation in the 3/5/7 protocol

Decision block	Operational meaning	Diagnostic output
Signal construction	Pair each available ECU target with its actual realized value	Deviation vector by controlled loop
Protocol normalization	Attach each deviation to idle, urban, or highway phase	Comparable phase-specific record
Reference comparison	Compare current deviation with healthy record from the same protocol	Distance from healthy behavior
Pattern recognition	Detect persistence and co-movement across loops	Drift signature before DTC threshold
Alert grading	Separate weak, moderate, and strong deviation patterns	Priority level for inspection
Human verification	Link AI output to workshop checks and repair confirmation	Confirmed cause or rejected alert

Prepared by the author based on Mercorelli (2024), Michailidis et al. (2025), Mahale et al. (2025), and Ucar et al. (2024)

The table indicates that algorithmic sophistication alone cannot carry the framework. AI improves pattern detection, but the diagnostic decision depends earlier on pair selection, phase labeling, reference quality, and technician feedback. The framework has methodological value before a production model exists because it defines the data structure required for a defensible preventive claim.

A second implementation issue concerns validation and monitoring. The framework needs metrics that reflect its preventive purpose. Accuracy alone would be too narrow. A system may classify known faults well and still fail to identify drift early. The central question is whether the system produces a reliable signal before the DTC threshold, whether the alert remains interpretable, and whether technician verification confirms the suspected loop. Table 2 specifies metrics for field implementation. The table compares detection timing, stability, localization, false alerts, and feedback quality. Pilot deployment should collect these metrics before any strong claim about economic or environmental benefit.

Table 2. Validation and monitoring metrics for field implementation

Metric	Definition in the proposed framework	Implementation use
Detection lead time	Time between AI drift alert and later DTC appearance or confirmed fault escalation	Measures preventive value
Deviation persistence	Duration and recurrence of the setpoint-to-actual gap within a phase	Filters transient noise
Phase stability	Whether the same drift appears under comparable idle, urban, or highway conditions	Supports repeatability
Localization agreement	Match between suspected loop and technician-confirmed cause	Evaluates diagnostic usefulness
False alert rate	Share of alerts rejected after inspection or repeat measurement	Controls workshop burden
Repair feedback closure	Presence of before-after records after confirmed repair	Builds labeled learning pairs
Explanation adequacy	Technician assessment of whether the output supports inspection	Measures practical interpretability

Prepared by the author based on Cummins et al. (2024), Jung et al. (2024), Srinivaas et al. (2025a), Srinivaas et al. (2025b), and Torres et al. (2025)

The metrics in Table 2 limit premature success claims. A preventive diagnostic framework earns credibility through lead time, repeatability, localization, and repair feedback. Economic and environmental benefit then become downstream outcomes. Earlier confirmed drift detection can reduce the period of degraded operation and may lower repair cost, but field data must verify that chain.

The study has several limitations. First, the article does not generate or analyze an empirical dataset. It presents a conceptual and methodological framework. Second, ECU parameter access differs across manufacturers, models, engine generations, and diagnostic tools. Some vehicles expose target and actual values clearly. Others provide partial or manufacturer-specific data. Third, engine control systems compensate for moderate degradation, so early deviations may be small and sensitive to noise. Fourth, driver behavior, temperature, fuel quality, road slope, traffic, and regeneration events can distort measurement if the diagnostic system does not log them. Fifth, a labeled database of confirmed before-after cases grows slowly because high-quality labels require technician verification, repair documentation, and repeat measurement.

Generalization creates a separate limitation. The framework is universal at the level of diagnostic logic, but not at the level of identical variables or thresholds. Diesel and gasoline engines share the principle of controlled regulation, yet their diagnostic signatures differ. A diesel air-path drift and a gasoline mixture-control drift require separate interpretation. The AI layer should learn within structured engine families and use cross-family transfer only where variables and operating conditions have technical comparability.

The discussion of previous research leads to a practical conclusion. The field already has strong components: OBD-II data access, AI-based predictive maintenance, residual diagnostics, explainable AI methods, ICE fault datasets, and classification models. A workshop-ready measurement logic can connect these components to early drift recognition before a code appears. The 3/5/7 protocol gives the deviation vector an operating-phase structure. Without such structure, a measured gap may reflect ordinary driving variation. With it, engineers can compare the same gap against a healthy reference and decide whether inspection is justified.

CONCLUSION

The proposed framework defines setpoint-to-actual deviation as the diagnostic primitive for preventive internal combustion engine monitoring. This primitive gives technical meaning to early drift because it compares what the ECU requests with what the engine realizes. The principle applies to diesel and gasoline engines within one diagnostic logic, while the concrete controlled pairs differ by engine type and ECU architecture.

The 3/5/7 protocol converts the primitive into a comparable data-collection procedure. Idle, urban, and highway phases create a structured measurement environment in which healthy references and suspected-fault records can be compared without treating all operating states as equivalent. The protocol supports a labeled database suitable for AI interpretation and later validation.

The AI layer should be evaluated through detection lead time, persistence, phase stability, localization agreement, false alert rate, repair feedback, and explanation adequacy. The hypothesis receives conceptual support: a standardized deviation vector interpreted by AI offers a stronger methodological basis for pre-DTC diagnostics than raw readings or fault codes alone. Empirical confirmation remains pending and requires field datasets collected under the described protocol.

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