Towards an AI-Based Approach for Adaptive Emission Control and Sensor Diagnostics: A gasoline engine case study

Latifa Heroual[1,*], Mohamed Lamine Berkane[1] and Nour El Houda Bouzerzour[1]

[1]LIRE Laboratory, Faculty of information and communication technologies, University of Abdelhamid Mehri - Constantine 2, Ali Mendjeli Campus, 25000 Constantine, Algeria

Abstract

The integration of ML (Machine Learning) techniques and predictive maintenance strategies has revolutionized various fields, including the automotive industry. The intersection of the automotive sector and computer science has long been a focal point of research, with numerous studies directed towards enhancing the reliability of vehicles and implementing effective emission control strategies as well as diagnosing various malfunctions, thereby emphasizing the significance of predictive maintenance in ensuring optimal performance. Oxygen sensors and Catalytic converter play a significant role in monitoring and reducing the emissions produced by a vehicle's engine, which contribute to environmental protection and regulatory compliance. Regardless of that, the attention towards identifying and diagnosing malfunctions of these components has been limited in the literature. In this paper, we propose an innovative pipeline framework design to identify faulty oxygen sensor and Catalytic converter. Our framework combines data-centric and algorithm-centric features, we aim to optimize the vehicle's performance and improve fuel efficiency by predicting sensors malfunction based on real-time data and adapting to keep the engine running at or near the stoichiometric air-fuel ratio, which is the most fuel-efficient condition for many gasoline engines. Our method harnesses the capabilities of XGBoost (Extreme Gradient Boosting) and LSTM (Long Short-Term Memory) algorithms to analyze data extracted from the car's Electronic Control Unit (ECU). This analysis allows us to identify anomalies related to vehicle emission control systems and trigger adaptive measures.

Keywords

Machine learning, Predictive maintenance, Data-centric, Algorithm-centric, Automotive diagnostics, Lambda sensors, Emission Control.

1. Introduction

The automotive industry has always been at the forefront of adopting technology, beginning with the integration of on-board electronic components and systems within vehicles during the 1970s [1], which was primarily triggered by the implementation of emissions regulations. This played a major role in the widespread utilization of electronic engine controls. As a result, technological

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*Corresponding author.
latifa.heroual@univ-constantine2.dz (L. Heroual); mohamed_lamine.berkane@univ-constantine2.dz (M. L. Berkane); nourelhouda.bouzerzour@univ-constantine2.dz (N. E. H. Bouzerzour)
0009-0000-9087-1384 (L. Heroual); 0000-0001-8781-0257 (M. L. Berkane); 0000-0002-8785-6631 (N. E. H. Bouzerzour)

evolution eventually led to the establishment of On-Board Diagnostics (OBD) systems in vehicles, which now has become a standard that most of the Electronic Control Units (ECUs) are equipped with [2]. Today, with the emergence of Artificial Intelligence (AI), the automotive industry is undergoing a revolutionary transformation [3]. Over the years, IT *(Information Technology)* has brought significant advancements to the field of automotive industry, such as emission control [4] and predictive maintenance [3] enhancing real-time diagnosis and decision-making. According to statista.com (August, 2023)[1], during the second half of 2019, the number of registered [2] and re-registered vehicles in Algeria was approximately 400,000 using gasoline with only around 200,000 vehicles powered by diesel, creating a significant impact on the country's fuel consumption and emissions landscape. As the automotive industry continues to grow and gasoline-powered vehicles remain prevalent, addressing emissions becomes paramount. The high number of gasoline vehicles on the road implies a substantial contribution to air pollution and greenhouse gas emissions. This scenario emphasizes the urgency to develop efficient and adaptive strategies for emission control, utilizing the advancements in technology, such as AI-driven diagnostics and optimization algorithms. In this paper, we propose an innovative approach that combines data-centric and algorithm-centric features to retrieve and process a set of parameter's values from a vehicle's OBD-II system with the aim of diagnosing malfunctions associated to oxygen sensor and Catalytic converter. Through this study, we aspire to make a meaningful contribution to the automotive industry by advancing the diagnostic capabilities, improving emission control, optimizing engine performance and thus contributing to the overall environmental sustainability and performance optimization of modern vehicles.

The remainder of the paper is organized as follows: In section 2, we provide foundational concepts to establish overall understanding of the context. Section 3 offers a comprehensive literature review. In section 4 we present our proposed solution for malfunction prediction and emission optimization. Finally, section 5 provides perspectives and concludes this paper.

2. Related concepts

To establish the foundation for both the context and significance of our study, it is essential to explore the following key related concepts:

2.1. Electronic Control Unit

Every automobile is equipped with an electrical instrumentation panel that is used as a driver information centre, formerly known as a dashboard [5]. It contains various gauges and indicators that provide valuable information to the driver. The information displayed on the dash board is retrieved from the Electronic Control Unit (ECU) of the vehicle [6].

[1] https://www.statista.com/statistics/1261249/vehicle-registrations-and-re-registrations-in-algeria-by-type-and-fuel/

[2] A vehicle registration officially certifies that a vehicle can be driven on public roads and connects a vehicle to both a state and an owner. Each state requires vehicles to be registered with the appropriate government agency, which then issues a vehicle registration certificate that shows who's responsible for it and signifies that it's legal to drive. https://www.progressive.com/answers/what-is-vehicle-registration/

2.2. On-Board Diagnostics

On-board diagnostics (OBD) is an automotive term that pertains to a vehicle's self-diagnostic and reporting capability. OBD systems empower vehicle owners and automobile repair technicians to access the status of various vehicle sub-systems. The OBD-II standard defines the diagnostic connector's type, pinout, electrical signaling protocols, and message format. This standard is upheld internationally by the International Organization for Standardization (ISO).

2.3. Oxygen sensor

Oxygen sensors are not limited to automotive applications; they are used in a wide range of contexts beyond cars. They are in fact vital in environmental monitoring, chemical processes, remote sensing in space, agriculture, and medicine [7]. In the automotive industry, oxygen detection is used to control combustion by measuring the concentration of gases in the exhaust [8], a process that is generally done by an Exhaust Gas Oxygen (EGO) sensor known as the "Lambda" sensor from the greek letter (λ) [9]. This component is an essential element of the modern automobile's on-board diagnostic (OBD) system. It is a key parameter that measures the non-dimensional air–fuel ratio (AFR) which is defined as the ratio of the mass of air to that of fuel and is mathematically equivalent to the equation depicted in (1). The air-fuel ratio significantly influences performance, horsepower, emissions (including Nitrogen Oxides and Carbon Monoxide), and fuel consumption. Therefore, maintaining the appropriate ratio is crucial to prevent engine pinging and knocking, and it also contributes to the longevity of the catalytic converter [10]. Conditions related to this ratio will be discussed in section **??**. Lambda value can also be calculated using the equation in (2).

$\frac{AFR}{AFR \text{ at stoichiometry}}$ (1)	$\frac{\frac{m_{\text{air}}}{m_{\text{fuel}}}}{14.7}$ (2)

Table 1
Air-Fuel Ratio Expressions

2.4. Catalytic Converter

Catalytic vehicles equipped with three-way catalysts mark a significant advancement in reducing automotive emissions, especially urban pollution. Maintaining the exhaust and fuel control systems through routine lambda sensor and catalytic converter maintenance is critical [9]. The oxygen sensor collaborates with the catalytic converter to simultaneously reduce hydrocarbons (HCs), carbon monoxide (CO), and nitrogen oxides (NOx), playing a pivotal role in emission reduction [7].

When engine emissions surpass OBD thresholds due to a degraded oxygen sensor, the fault indicator lamp is triggered, and fault codes are recorded. However, confirming a malfunctioning lambda sensor requires professional inspection [11].

The catalytic converter, in conjunction with the oxygen sensor, provides an effective solution for reducing CO, HC, and NOx emissions in gasoline vehicles [12]. Using two oxygen sensors to measure oxygen concentration before and after the catalytic converter, the air-to-fuel ratio is computed as the basis for regulation by the fuel injector controller [13].

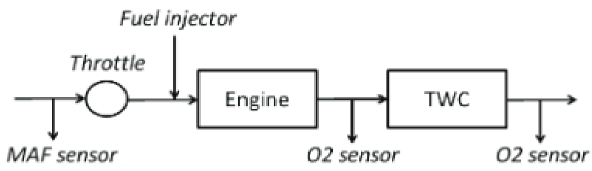

Figure 1: Diagram of engine showing air and fuel path.[13]

2.5. Motivation

Few research have addressed emission control involving the oxygen sensors, some have suggested the use of AI to predict its malfunction, while others proposed monitoring methods. However, lacking aspects within all of them are (i) diagnostic aspects involving the combined interaction between the catalytic converter and oxygen sensor; and, (ii) taking adaptive measures i.e. the implementation of adaptive strategies to reduce emission in vehicles equipped with faulty Lambda sensors.

In addition to aforementioned limitations, our research is driven by several key motivations:

2.5.1. Inconclusive OBD Codes

The Diagnostic Trouble Codes (DTCs) generated by On-Board Diagnostics (OBD) systems often lack definitive insights into the specific issues affecting catalytic converter and oxygen sensors, requiring more analysis.

2.5.2. Environmental concern

As the transportation sectors stands as the largest contributor to greenhouse gases [14], catalytic converters and oxygen sensors are pivotal in emission control, making their efficient functioning indispensable for both environmental preservation and regulatory compliance.

2.5.3. Predictive maintenance demand

The growing demand for predictive maintenance practices necessitates robust diagnostic tools that can identify potential issues in these critical automotive components well in advance and act upon the results of these predictions.

3. Related works

Predictive maintenance has been a topic of interest and gained attention, recently. While the computing science domain has witnessed significant advancements in various aspects, including AI-driven diagnostics, there remains a distinct limitation in the exploration of specific topics such as the combined effect of components like upstream and downstream oxygen sensors and the catalytic converter on emission. However, some notable contributions, such as those by Giordano et al [15] applying a prognostic pipeline in the context of automotive field to detect deviations from nominal behavior in high pressure fuel (HPF) systems. In a subsequent study [16], they employed the pipeline approach to predict and anticipate potential clogging status of the oxygen sensor in diesel engines. Both studies were data-driven. Another work was proposed by Ekinci and Ertuğrul [17], in their study, they focus on developing a model-based methodology to monitor and diagnose oxygen sensors precisely and accurately with the aim to meet legislations and performance benchmarks while reducing calibration effort. Table 2 depicts a comparison between the two works from different perspectives.

Study	scope	Engine type	variables	models used
Giordano et al (2022)	Predictive maintenance	Diesel	Fuel injection, Test bench, Exhaust gas temperature, Engine airflow, Catalytic converter, Exhaust manifold, Torque control, Diagnostic Trouble Codes (DTC), Accelerator, Engine temperature, Pressure, Fuel rail, NOx emissions, Oxygen sensor, Combustion mode , Other.	Decision Trees, Random Forest (RF), Suport Vector Machine (SVM), Neural Networks (NN), (Multilayer Perceptron), MLP
Ekinci and Ertuğrul (2019)	Diagnostics, O2 monitoring system	Gasoline	Oxygen sensor	NN (Nueral Networks), NARX (Nonlinear Autoregressive Exogenous), PCA (Principal Component Analysis)

Table 2
Comparison of computer science works involving Lambda sensor

In addition to its close predictions and better classifications, the combination of LSTM with XGBoost has already been proven as valid and effective in terms of: overfitting avoidness, improved generalizability as well as feasability and efficiency in works such as [18, 19, 20, 21, 22, 23]. [18] have tried the combination of LSTM with XGBoost to predict traffic flow while [18] used the same combination to detect abnormal behaviour from normal. On the other hand, research around Lambda sensors exist in other fields such as physics, applied science, automation, electronics and mechanical engineering as well as state laboratories in the U.S and China. Botsaris and Polyhroniadis [9] describe a new design for a microprocessor controlled exhaust gas lambda sensor device. Authors claim that portability and interaction could have been integrated by using an external keyboard. Also, higher storage capacity would enhance the statistical processing of more data. Amato et al [24] examined the possibility of employing a Virtual Lambda Sensor (VLS) mode through a Fuzzy Inference System (FIS), they designed a model to predict the engine air-fuel ratio using the cylinder pressure signal from a gasoline engine. The authors of this paper acknowledged the necessity for enhancing both accuracy and robustness. De Lima et al [25] presented a simple and low-cost method to determine oxygen concentration in the exhaust gases of combustion more specifically, in the industrial combustion by mounting a combustion chamber with a heated lambda sensor in its chimney. A drawback of this study is the nonlinear outputs of the sensor preventing their conversion to meaningful oxygen concentration values. Wang Dongliang et al's [22] study defines three forms of oxygen sensor degradation and analyses the influence of oxygen sensor degradation on both emission and air-fuel ratio. This study used response signals of a good oxygen sensor and simulated the signals of a degraded oxygen sensor using a signal generator. The TWC's functionality relies on maintaining the correct combustion mixture AFR and oxygen storage levels. To achieve precise control, Mallik et al. [13] integrated measurements from oxygen sensors (UEGO) positioned before and after the catalytic stage. The objective is to enhance AFR control performance by utilizing data from both UEGO sensors. Di Maio et al [26] investigated the effect of deviations in Lambda values, among other conditions on the efficiency of the catalytic converter. However, oxygen storage phenomena and perturbations in AFR were not considered. Al-Arkawazi [27] dedicates his study to understanding "the relationship between the AFR, lambda (λ) and the exhaust emissions of gasoline-fueled vehicles", according to the author "it is connecting the actual field measurements and results with theoretical relation between AFR, Lambda (λ) and the gasoline-fueled vehicles exhaust emissions percentages and values". Data for this study consisted of exhaust gas composition and were collected directly from the exhaust shaft of several vehicles by an emission measurement device.

In the context of automation, Meng, Lei, et al [28] developed an adaptive AFR regulation controller and proposed a generalized predictive control method to address nonlinearities, time delays, parameter changes, and uncertainties in the AFR closed loop. The controller is based on a predictive control method and the data was obtained from an experimental engine system and experiments were conducted on an engine test bench. Selvam et al [4] proposed a physics-aware AI model leveraging the concepts of variability of driving scenarios, co-occurrence patterns, and a low-order combustion-physics-based model . In this study, data from the OBD of a transit bus in a metro transit were used to evaluate the model and a nonlinear regression method to predict NOx emission values. This paper focuses on the prediction of NOx emissions from vehicles, however, the authors did not consider other vehicular emissions nor did they address Lambda sensors. Salehi et al [29] introduced a Nonlinear Auto Regressive with eXogenous inputs (NARX) model designed to simulate the nonlinear output voltage of the oxygen sensor located after the catalyst (a.k.a the upstream Lambda sensor). The authors proposed a real-time applicable algorithm. However they only considered the upstream Lambda sensor and the exhaust gas flow as input for their system.

Aside from [4], the above-mentioned works did not use AI which resulted in drawbacks in terms of accuracy and robustness in [24] and [25] due to non-linearity issues. The aforementioned studies did not consider the oxygen sensor as a key component in emission, whereas [29] focused on the upstream Lambda sensor only. The obvious diversity of research across various fields as well as its chronological extent highlights the sustained interest in this topic. The fact that different disciplines continue to explore and innovate this area reflects both the significance and complexity of the technological aspect of such components.

4. Proposed solution: AI based approach for predictive maintenance and emission control

In this section, we present our innovative approach, which blends data-centric and algorithm-centric (a.k.a model-centric) features to: (i) forecast Lambda sensor malfunction; (ii) make automatic suitable adaptive adjustments on these sensors and the catalytic converter in order to optimize performance, reduce emission; and, (iii) achieve fuel efficiency.

4.1. Overview

The data-centric aspect of our approach follows the principle of «systematically engineering the data needed to build an effective AI system» (Andrew Ng, 2022) [1]. The prevailing approach in many projects is centered around obtaining and downloading datasets, with a primary focus on enhancing the code to achieve better performance [30]. In contrast, a data-centric approach emphasizes the significance of data engineering. By dedicating efforts to process, clean, and enrich the data, we can unleash the full potential of the ML algorithms. Data engineering allows us to handle large volumes of information, handle missing values, and create relevant features that lead to more accurate and robust models. We recognize the importance of data engineering as a foundation for success [31]. We prioritize the effective preparation and transformation of dataset before applying sophisticated algorithms. By doing so, we can maximize the value of the data and achieve more accurate and meaningful results in predicting Lambda sensor malfunctions. The model-centric aspect acknowledges the maturity of existing algorithms [32].

Instead of solely relying on data-centric methods, we recognize that some algorithms, like LSTM and XGBoost, have already proven their effectiveness in various domains. Thus, we adopt a model-centric perspective as well by selecting suitable performing models that align with our objectives.

XGBoost is an ensemble learning technique known for its efficiency and effectiveness in handling both numerical and categorical data and excelling in feature importance analysis. This technique would particularly be useful for control strategies optimization, such as finding the optimal air-fuel mixture for emission reduction while maintaining engine performance [33]. LSTM as a recurrent neural network designed for sequential data analysis [34] is suitable for time-series data from ECUs. Its ability to capture temporal dependencies and patterns in the data would also help the prediction process based on historical sensor readings. It would also be valuable for detecting gradual changes or anomalies and deviations. Leveraging the power of XGBoost and LSTM models, we have devised a comprehensive pipeline that enables to continuously learn from data, predict malfunctions and adapt strategy to reduce emission and achieve fuel efficiency.

4.2. Proposed framework

Our proposed framework is depicted in figure 2, and it has the following steps:

- **Data acquisition:** Data is primarily obtained from car sensors. Due to limited storage space in the embedded car processing unit, an eventual historization process on a cloud-based database using Python scikit-learn library[1] is necessary. This process would serve as continuous learning. The same process applies to driving profiles[2].

[1]https://mitsloan.mit.edu/ideas-made-to-matter/why-its-time-data-centric-artificial-intelligence
[1]https://scikit-learn.org
[2]A driver profile represents a group of drivers with similar behaviors.[35]

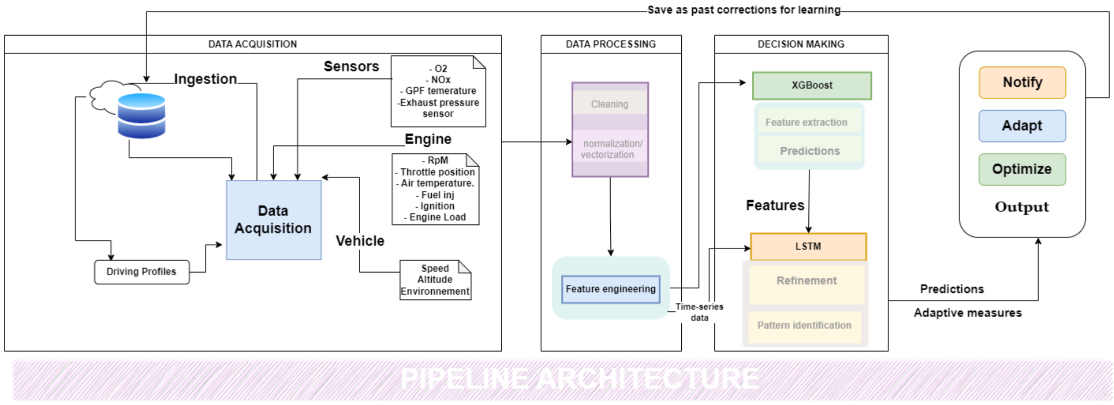

Figure 2: Proposed framework.

- **Data processing:** This step involves handling missing values and outliers and removing irrelevant data. Vectorization is needed for LSTM. Engineered features are: time since the last emission change, cumulative emissions and difference between upstream and downstream Lambda values. Table 3 shows the most significant features to include in both the prediction and adjustment measures process, where:
  - Time since last emission change: Duration since the previous significant change in emissions.
  - Cumulative emissions: Total sum of emission values over a certain period.
  - Δ_λ: Disparity between upstream and downstream lambda sensor values.

From ECU	Engineered features
Upstream Lambda, Downstream Lambda, Engine temperature, RPM	Time since the last emission change, Cumulative Emissions = $\sum$ Emission Values, Δ_λ = $\lambda_{\text{upstream}}$ - $\lambda_{\text{downstream}}$

Table 3
Most relevant features

- **Decision-making:** Structured data are extracted using XGBoost and embeddings are then fed into the LSTM model. At this level, features including RPM (Revolutions Per Minute), both upstream and downstream lambda sensor values, NOx levels, engine temperature as well as, the previously mentioned engineered features which are: time since last emission change, cumulative emissions, disparity between upstream and downstream lambda sensor values. It is worth mentioning that our approach takes into consideration both upstream and downstream lambda sensors for more accurate air-fuel ratio adjustments, especially that difference in values read from these two components may trigger a false positive, while in fact it can be used to determine whether the catalytic converter is effectively consuming oxygen and doing a good job burning harmful pollutants to facilitate the emission reduction process. Detecting similar downstream and upstream values indicates incomplete combustion and suggests faulty catalytic converter.

- **Output:** Based on the predictions made in the preceding step, the output will include notifying the driver of a possible clogged catalytic converter. Additionally, it will involve making auto-adaptive adjustments on the actuators to optimize emissions.

4.3. Adaptive measures

Figure 2 illustrates the decision making process and the different actuators affected by the adaptive measures. Adaptive measures encompass a set of rules to be applied using the actuators in case a malfunction leading to more harmful emission due to incomplete combustion.

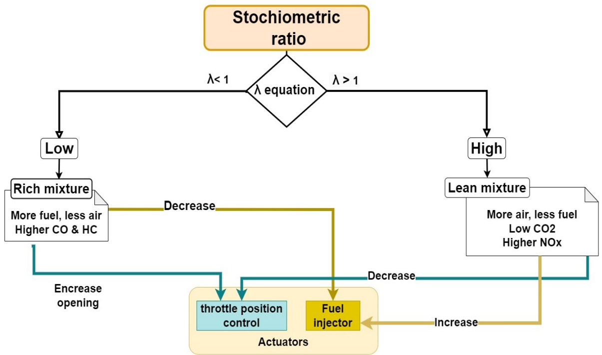

Figure 3: Auto-adaptive measures.

If one of the Lambda sensors is faulty, the lambda value is calculated using the equation: If $\lambda < 1$, this means that the combustion is low and thus mixture is rich i.e. contains more unburnt fuel and insufficient oxygen to completely burn all the fuel. In this case, the ECU must adjust the air intake opening to allow more air to enter and decrease the opening of fuel injectors (the ECU can achieve this by manipulating the duration of time the fuel injectors stay open during each engine cycle) to reduce fuel wastage and achieve efficiency.

Algorithm 1 Categorization of Catalytic Converter Clogging

function CategorizeCC(UpstreamLambda, DownstreamLambda, Tolerance, Thresholds)
  Difference $\leftarrow$ UpstreamLambda $-$ DownstreamLambda
  if Difference $< -$Tolerance **then**
    return "Severely Clogged"
  else if $-$Tolerance $\leq$ Difference $\leq$ Tolerance **then**
    return "Normal Operation"
  else if Difference $>$ Tolerance **and** Difference $\leq$ Thresholds[1] **then**
    return "Reduced Efficiency"
  end if
end function

As an adaptive measure, algorithm 1 leverages the delta lambda value, which represents the difference between the upstream and downstream lambda sensor values, to determine the potential clogging in the catalytic converter. This algorithm categorizes Catalytic Converter health into three states - Severely Clogged, Normal, or Reduced Efficiency. It does this by analyzing the difference between upstream and downstream lambda sensor values. This classification aids real-time monitoring of Three-Way Catalytic Converter performance. Physically, unclogging the catalytic converter could either be controlled by the engine ECU or simply instructing the driver to use the acceleration pedal.

5. Conclusion

The evolution of ML and the automotive industry today is reshaping how we optimize vehicle performance and emissions control, marking a significant shift in the industry's landscape. In our paper, we aimed to predict malfunctions in the oxygen sensor, considering both upstream and downstream oxygen sensors and the catalytic converter, to reduce harmful emissions. To achieve this, we proposed a framework that capitalizes on XGBoost's high accuracy and decision-making capabilities for auto-adaptive adjustment measures and leverages LSTM's proficiency in processing time-series data and learning over time. XGBoost assists in implementing auto-adaptive adjustments, while LSTM aligns with the data historization process during acquisition and processing time-series data. This combination ensures a comprehensive approach that effectively addresses both prediction and adaptation.

Our proposed solution of a pipeline framework seamlessly integrates algorithm-centric and data-centric methodologies, suitable for both prediction and decision-making. It's important to note that problems requiring ML models to solve are unique and finding suitable public datasets can be challenging. Focusing on model architecture alone doesn't guarantee a significant increase in performance. Our study is, to the best of our knowledge, the first to use AI to predict malfunctions in these two components and apply adaptive strategies to achieve greener and more efficient gasoline engine performance. No prior research has explored the combined effects and interactions between lambda sensors and the catalytic converter in the context of the vehicle emission control system

Looking ahead, future potential advancements and areas of innovative exploration could involve the generalizability of our adaptive algorithm across various engine types and operating conditions and exploring how it could be integrated with autonomous driving systems. The potential of large-scale data collection through collaborations with automotive manufacturers or organizations could lead to more generalized models applicable to a wider range of scenarios, including the expansion towards the internet of things. Extending the study to include hybrid and electric vehicles and adapting the algorithm to their specific emissions control systems could contribute to the eco-friendliness of alternative propulsion technologies.

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