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Research the Effect of Oxidation Catalytic Converter on Reducing Diesel Engine Particulate Emission Based on Artificial Intelligence

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Abstract: Diesel engines are widely used for their good power performance and economic performance, and the emission control technology of diesel engines has developed rapidly in recent years, not only for the health problems of everyone, but also for the sustainable development of a country. Amongst other things, NOX and particulate in-engine cleaning of diesel engines are a mutually constraining relationship and cannot well reduce the emissions of both at the same time. Therefore, this paper explores the reduction of diesel particulate emissions based on artificial intelligence research on oxidation catalytic converters. In order to reduce particulate emissions, three post-treatment methods are chosen in this paper: particulate trap (DPF), oxidation catalyst (DOC) and particulate oxidation catalyst (POC). The three technologies are used to analyse the factors influencing PM emissions, reduce diesel particulate emissions and achieve the goal of diesel exhaust gas compliance.

1. Introduction

Diesel engines are widely used for their good power and economic performance. Diesel exhaust emissions are one of the major sources of environmental pollutants and strict emission regulations are being implemented worldwide to improve and protect the environment [1-2]. As emissions regulations become more stringent, diesel engines need to use a variety of aftertreatment devices to enable their exhaust emissions to meet regulatory requirements, including selective catalytic reduction systems, diesel particulate traps, diesel oxidation catalytic converters, etc. [3-4]. Among them, diesel particulate traps, as the most direct and effective means to reduce carbon soot emissions, will become an important component of the future diesel engine aftertreatment system [7].

With the development of artificial intelligence technology, more and more researchers have conducted in-depth research on diesel particulate emissions. For example, experts such as Sergey Samokhin have studied the effect of EGR on engine emissions. EGR reduces CO emissions by decreasing the dissociation rate of carbon dioxide, and hot EGR can increase the intake air temperature to reduce NOX emissions, but it also affects the engine power [8]. John Shutty et al. studied the emission spectra during gas discharge through spectral diagnosis To investigate the mechanism of different discharge parameters and gas components on the uniform discharge of dielectric barrier, a new type of dielectric barrier discharge generator with large air gap coaxial cylindrical structure was designed and effectively matched with the driving power supply [9]. Through the study, it was found that using artificial intelligence to reduce diesel particulate emissions is a good research direction.

In the context of energy saving and emission reduction, this paper conducts an in-depth study on diesel engine particulate emissions based on artificial intelligence. The first part is a basic overview of the physical model of the diesel engine and the particulate trap trap, which introduces the knowledge about diesel engines. The third part is the analysis of the impact of the reformer, including the analysis of the impact of POC on PM emissions and the analysis of the impact of NO conversion.

2. Basic Overview

2.1. Physical Model of Diesel Engine

The internal structure of a diesel engine is complex and requires various systems to work together during operation.

(1) Engine module: the engine starts its operation in the relevant mode by entering the engine speed and calculating the engine torque [10].

(2) Air intake system: The air intake system consists of the compressor inlet, the upstream air duct and contains a simple model of the airbox. At the inlet and outlet of the airbox, conical orifice connections are used to simulate a smooth transition [11].

(3) Exhaust system: The exhaust manifold uses a heat transfer object to calculate the wall temperature. The orifice connecting the exhaust port to the flow pipe does not allow heat transfer between the walls of adjacent components [12].

2.2. Particle Trap Capture

The working process of the DPE is as follows: firstly, the particles in the exhaust gas are trapped by the filter wall of the clean particle trap under low temperature conditions, when the filter wall is saturated, the particles are deposited on top of the wall to form a filter cake layer, then under a certain condition, the passive regeneration rate is accelerated and the deposited particles are oxidised by NO2, after several iterations, the unburned part of the particles is covered on the wall or above the coating to form an ash layer, when the particles are trapped again When trapped again, the vast majority of particles form a cake layer, and then the particle trap regenerates the cake [13-14]. Differences in the capture process of a particulate trap can also affect the regeneration process [15]. Particle trap capture is generally divided into two categories: without catalytic coating and with catalytic coating [16]. Particle traps without a catalytic coating are divided into two stages: the particles enter the filter wall and are trapped, called deep bed trapping; after the filter wall is saturated, the particles are deposited on the channel surface, called filter cake trapping [17-18].

3. Factors Influencing Particulate Emissions

3.1. Particle Size Distribution

The particle size distribution of particle number concentration can be obtained from the relationship between the number of particles in the test results and the change in particle size. Similarly, the particle size distribution of the mass concentration of particles can be obtained by using the formulae shown in equations (1) and (2).

$$R_1 = \exp\left[\left(\sum a_i \ln R_{pi}\right) / K\right] \tag{1}$$

$$R_2 = \exp\left[\left(\sum b_i \ln R_{pi}\right) / L\right] \tag{2}$$

In this case, ai is the particle number concentration at the ith particle size interval, bi is the particle mass concentration at the ith particle size interval, Rpi is the characteristic particle size at the ith particle size interval, K is the total particle number concentration, L is the total particle mass concentration, the geometric mean particle size at the particle number concentration is R1 and the geometric mean particle size at the particle mass concentration is R2. For analytical purposes, the particles are divided into several different modes according to their size The particles are divided into several different modes. Particles with a particle size of 5nm-50nm are called nucleated; particles with a particle size of 50nm-1000nm are called aggregated; particles with a particle size of less than 100nm are called ultrafine.

3.2. Effect of Common Operating Conditions on Pollutant Conversion Rates

Based on the common operating conditions of non-road diesel engines, the conversion rates of CO, HC and NO under common operating conditions were investigated at an exhaust oxygen concentration of 15%. The four common operating conditions for off-road diesel engines were as follows: Condition 1: engine 1500r/min, 50% load; Condition 2: engine 1500r/min, 75% load; Condition 3: engine 1800r/min, 50% load; Condition 4: engine 1800r/min, 75% load. The temperature at the DOC inlet for these five operating conditions was obtained from the established engine model and fluid simulation calculations for the emission after-treatment unit. The results are shown in Table 1.

Table 1. Conversion rate of each pollutant at 15% exhaust oxygen concentration

Condition	Inlet temperature (℃)	CO conversion rate (%)	HC conversion rate (%)	NO conversion rate (%)
Condition 1	284	98.49	88.39	42.52
Condition 2	377	98.44	89.87	26.53
Condition 3	329	97.25	81.31	31.21
Condition 4	402	97.27	83.65	23.14

As can be seen from Table 1, under the common operating conditions, the CO conversion rate and HC conversion rate are good, while the NO conversion rate is slightly lower in working condition II and working condition IV. The NO conversion rate can be improved by increasing the oxygen concentration of the exhaust gas of Case 2 and Case 4 through secondary make-up gas. When the exhaust oxygen concentration is 20%, the CO, HC and NO conversion rate of working condition two and working condition four are shown in Table 2. The results show that when the exhaust oxygen concentration rises, the NO conversion rate increases significantly, so the NO conversion rate can be improved through the secondary gas supply.

Table 2. The conversion rate of each pollutant when the exhaust oxygen concentration is 20%

Condition	Inlet temperature (℃)	CO conversion rate (%)	HC conversion rate (%)	NO conversion rate (%)
Condition 2	377	98.45	90.07	30.58
Condition 4	402	97.31	84.24	27.11

3.3. Effect of Initial Soot Density in the DPF on Regenerative Energy Use

Let the initial soot density in the DPF be 4.5g/L, 5.5g/L, 6.5g/L, 7.5g/L, 8.5g/L, 9.5g/L and 10.5g/L respectively, adjust the injection rate in different cases so that the particle residue in the DPF is just less than 0.1g, calculate the total injection volume throughout the process and obtain the fuel required per unit of particle oxidation, resulting in The results are shown in Figure 1.

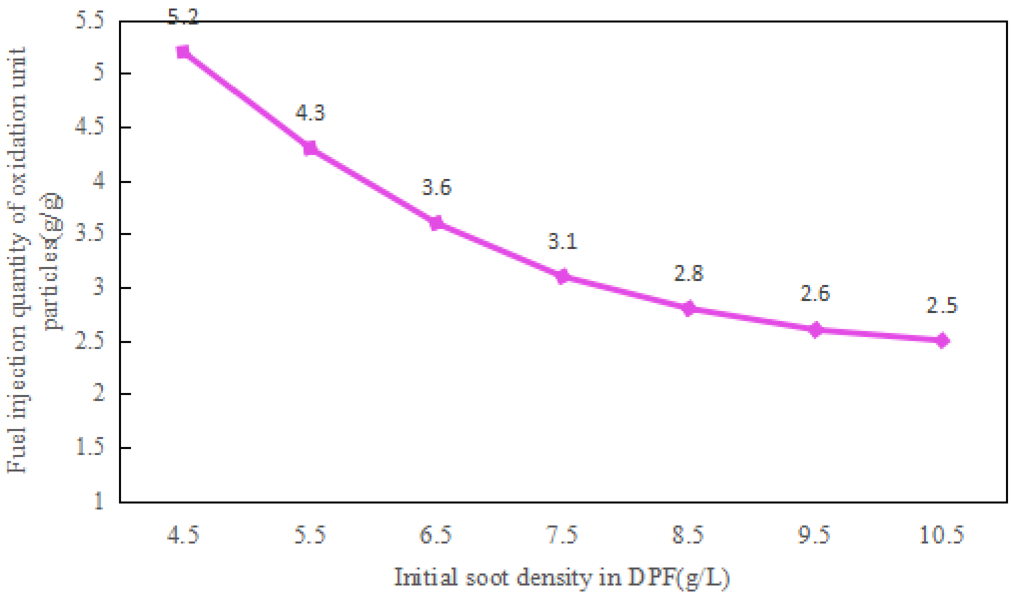

Figure 1. Variation in the amount of oil injected to oxidise a unit mass of particulates with the initial soot density within the DPF

As can be seen from Figure 1, although the amount of particulate inside the DPF increases, the amount of fuel injected per unit of particulate oxidation decreases in a hyperbolic pattern, particularly from 4.5 g/L to 7.5 g/L, with the amount of fuel required per unit of particulate oxidation decreasing by 2.1 g/L. The reason for this decrease is that the increase in initial soot density allows more particulate to oxidise and exothermise, requiring less external assistance. The amount of fuel injected per unit of particulate oxidation is also reduced. It can be seen that regeneration at higher carbon soot densities increases the efficiency of regeneration energy utilisation.

4. Transformer Impact Analysis

4.1. Analysis of the Effect of POC on PM Emissions

The results of the before and after particulate (PM) emission comparison of the P0C post-processor under the steady state cycle nine operating conditions are shown in Figure 2. It can be seen from Figure 2 that before the POC was installed, PM emissions from this diesel engine gradually increased with increasing load. At low speed and low load, the PM emission in the exhaust gas is low, 0.003g/kw·h at A25 operating condition, and 0.011g/kw·h when the load increases to A100 operating condition; at medium speed and low load, the PM emission in the exhaust gas is 0.003g/kw·h at B25 operating condition, and as the load increases, the PM ratio emission increases to 0.013g/kw·h at B100 operating condition. At high rpm, PM emissions are higher than at medium and low rpm, and PM emissions basically increase with load, from 0.007g/kw·h at C25 to 0.017g/kw·h at C100. After the engine is retrofitted with a POC after-processor, PM emissions are significantly reduced at low, medium and high rpm, while at the same time, PM emissions increase with load. The PM ratio emissions are significantly reduced as the load increases. In particular, at medium and high loads, the inlet temperature of the POC catalyst increases with increasing load. Under the higher inlet temperature, PM can be catalytically oxidised to CO by the catalyst, and the increase in temperature also enables the DOC catalyst in front to produce more oxygen and thus NO with stronger catalytic oxidation performance, ensuring that the POC catalyst can be regenerated continuously and passively, resulting in a reduction in PM in the exhaust of the POC catalyst. This ensures that the POC catalytic converter can be regenerated continuously and passively, resulting in a lower PM value in the POC catalyst exhaust.

Figure 2. Comparison of particulate emissions before and after POC

4.2. Analysis of NO Conversion Influencing Factors

From Figure 3, it can be found that the higher the exhaust flow rate, the smaller the NO conversion efficiency (i.e. NO2 concentration increase efficiency) and the narrower the temperature window for high conversion efficiency. This is because the higher the exhaust flow rate, the higher the air velocity, the shorter the residence time of the exhaust in the channel, and the NO conversion efficiency decreases, but the volume of gas handled increases. Therefore, in practical reactor design and matching, it is critical to select the right air velocity to achieve the goal of high NO conversion and small volume, and the right reactor volume and catalytic coating thickness for a given displacement engine. In addition, the exhaust gas flow rate has a strong influence on the NO conversion efficiency in the intermediate temperature region, less in the low temperature region and almost no influence in the high temperature region, due to the low reaction activity at low temperatures, the higher reaction activity at intermediate temperatures and the thermodynamic limitations received at high temperatures. The air velocity strongly influences the efficiency of NO oxidation, and obtaining high efficiencies at low temperatures requires relatively low air velocities, which is particularly important for the correct sizing of the oxidation catalyst. The size of the oxidation catalyst should be carefully and economically selected for each application, based on the expected flow rate and conversion efficiency requirements.

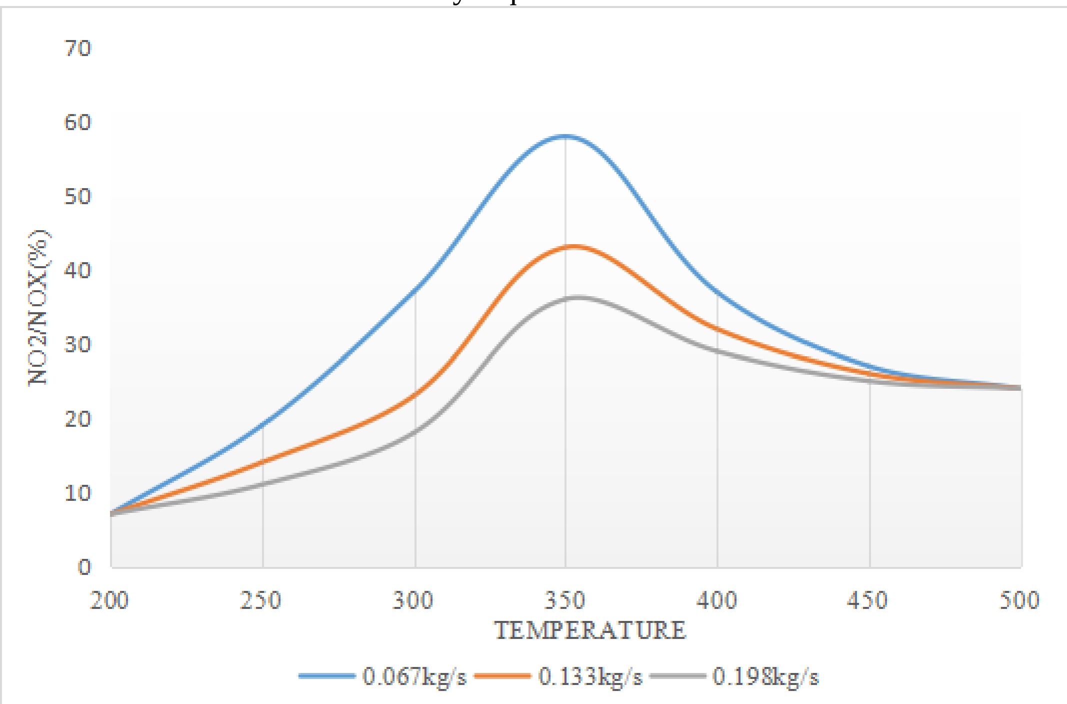

Figure 3. Effect of exhaust flow rate on NO conversion performance on DOC

The generation of NO2 in the oxidation catalyst is the focus of the study as the NO2 concentration is the main medium for the oxidation of particles deposited in the downstream particulate trap. Although there is a sufficiently large oxygen content in the diesel exhaust for NO oxidation, different oxygen levels still have an effect on the NO oxidation performance in the oxidation catalyst. As can be seen in Figure 4, with a constant total exhaust NOX, the NO2/NOX ratio at the DOC outlet increases and the NO conversion rate increases as the oxygen concentration in the exhaust increases, due to an increase in the concentration of reactive gases involved in the NO oxidation reaction. In addition, the thermodynamic equilibrium shifts towards higher temperatures, favouring better catalytic activity. At 200 ℃, the oxygen concentration has almost no effect on the conversion rate of NO due to the low activity. As the exhaust temperature increases, the degree to which NO is affected by the oxygen concentration of the conversion rate increases until it reaches a maximum at 350 ℃, and as the temperature continues to increase, the conversion rate of NO decreases slightly.

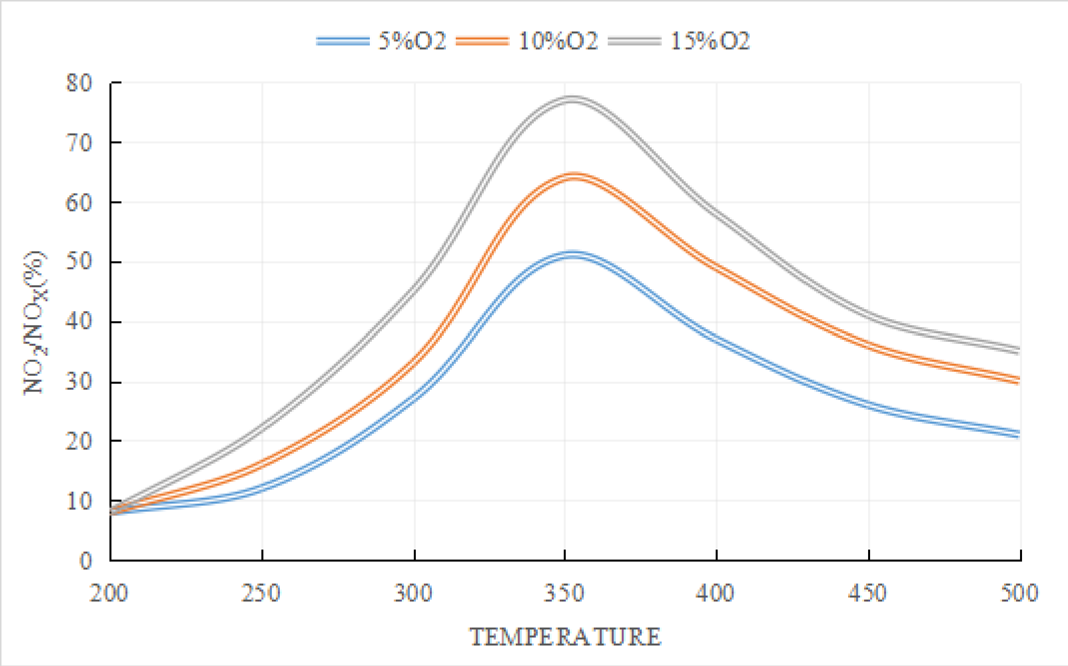

Figure 4. Effect of O2 concentration on NO conversion rate

5. Conclusion

With increasingly stringent emission regulations, in-engine cleaning alone is no longer sufficient to further reduce emissions of pollutants such as NOX and PM, and the necessary exhaust aftertreatment technologies are required. This paper uses artificial intelligence to study and analyse diesel particulate emissions, through the analysis of the following conclusions: through the analysis of the impact of POC on PM emissions found that the use of POC post-processors can reduce PM emissions; through the NO conversion factors found that the oxygen concentration has little effect on the conversion rate of NO, the exhaust temperature will affect the NO conversion rate oxygen concentration. Due to the professional and time constraints received, there are many shortcomings in this paper, which need to be improved and perfected.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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