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# *The Harm and Countermeasures of Automobile Exhaust Pollution Based on Deep Reinforcement Learning*

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***Abstract:*** With the improvement of people's living standards, the number of automobiles has increased rapidly, and the problem of exhaust pollution has become more and more serious. Automobile exhaust emits a large amount of nitrogen oxides, hydrocarbons and fine particle pollutants, resulting in enhanced atmospheric oxidation and hazy weather in cities. The purpose of this paper is to study the hazards and countermeasures of automobile exhaust pollution based on deep reinforcement learning. Combining the perception ability of deep learning and the decision-making ability of reinforcement learning, it has the ability to solve complex control problems, and tries to apply it to the energy management problem of hybrid electric vehicles. Compared with the total average emission factors of various pollutants of traditional gasoline cars, the average emission factors of CO, HC and NOX of clean cars based on deep reinforcement learning have obvious advantages compared with traditional gasoline cars, indicating that the deep reinforcement learning of clean cars Has good emission reduction performance.

## 1. Introduction

A motor vehicle is a wheeled vehicle that is pulled or driven by a power unit and is driven on the road for riding, transporting goods or performing special operations, including automobiles, wheeled special mechanical vehicles, tractor transport units, motorcycles and mopeds and trailers Wait. Automobiles account for a high proportion of the total number of motor vehicles in cities. The appearance of automobiles has brought significant changes to people's transportation and living and production methods. Its speed and convenience have improved people's work efficiency, accelerated economic development, and changed However, it also brings huge pollution to people's living environment, affecting people's physical and mental health and the sustainable development of the natural environment [1].

The increasing number of vehicles and other means of transport has had a serious negative impact. Air pollution refers to the pollution of the atmosphere due to the presence of certain substances and gases (from man-made or natural sources) with harmful and toxic effects. It is one of the most dangerous forms of pollution. Mukhitdinov, O pointed out that clean vehicle and fuel technologies provide us with an affordable and usable way to reduce transportation-related air pollution and climate change emissions. These include fuel-efficient vehicles that use less oil; cleaner fuels that produce fewer emissions; and electric vehicles and trucks that can completely eliminate tailpipe emissions [2]. Achmad analyzed the road network performance and vehicle emissions of the road network in the Beringin Janggut area of Palembang through traffic simulation using Vissim software and vehicle exhaust emission calculations using EnViver software, and compared the results with ambient air measurements. As well as providing alternative solutions to existing traffic conditions [3]. Exploring the energy management strategies of electric and renewable new vehicles will further stimulate the enthusiasm of automotive enterprises for technological innovation [4-5].

This paper introduces the types of automobile exhaust pollution and the principle of harm, puts forward the countermeasures for automobile exhaust pollution, describes the principle of the deep reinforcement learning algorithm, designs the Loss function based on the energy management algorithm, and uses the gradient descent method to update the network. Parameters, the prevention and control measures discussed in this paper are specific and clear, and have operability. The research aims to guide policy practice, effectively reduce the long-term quality of vehicle exhaust emissions, and improve the urban atmospheric environment.

## 2. Research on the Harm and Countermeasures of Automobile Exhaust Pollution Based on Deep Reinforcement Learning

### 2.1. Types and Hazards of Automobile Exhaust Pollution

(1) Sulfur dioxide

Sulphur dioxide can seriously damage soil and water bodies and throw the ecology out of balance. Although some catalytic and purification equipment is usually installed in motor vehicles, sulfur dioxide usually accumulates on its surface, which makes the use of catalytic equipment inconvenient [6-7]. With the rapid development of industrial desulfurization technology, the sulfur dioxide produced by vehicle exhaust will be greatly reduced, but the pollution situation has not disappeared [8].

(2) Carbon monoxide

The formation of carbon monoxide is formed by the incomplete combustion of fuel in motor vehicles, and the main source of carbon monoxide in the atmosphere is the exhaust gas of motor vehicles. After carbon monoxide is inhaled by the human body, carbon monoxide reacts with hemoglobin in the human body to produce carboxyheme [9-10].

(3) Nitrogen oxides

The emission of nitrogen oxides usually comes from two sources: one is produced by the combustion of nitrogen-containing compounds, and the other is produced by the combustion reaction of nitrogen and oxygen in the air [11]. Most of the nitrogen oxides emitted directly from the exhaust are nitric oxide, which is then oxidized to nitrogen dioxide in the atmosphere after a few hours. The nitrogen oxide that mainly harms the human body is nitrogen dioxide, which can weaken the oxygen supply capacity of the human blood and cause adverse effects on the visceral tissues of the human body [12-13].

## 2.2. Countermeasures for Automobile Exhaust Pollution

(1) Unify and improve local emission standards

There is still a certain gap between the development level of my country's automobile manufacturing industry and foreign developed countries, and it is still difficult to meet the European and American emission standards in terms of exhaust emission control technology. The non-uniformity of vehicle emission standards has caused regions with higher emission standards to be easily affected by provinces with lower emission standards in neighboring regions when preventing and controlling vehicle exhaust pollution, resulting in continuous disputes over vehicle exhaust pollution between regions. Unifying regional emission standards is not only conducive to improving the same access level of regional emissions and reducing vehicle exhaust emissions, but also conducive to reducing law enforcement costs, improving law enforcement efficiency, and avoiding cross-regional law enforcement confusion [16].

Due to the unbalanced economic development in my country, although the developed areas are more advanced in economy, technology and legal awareness, their automobile exhaust pollution is relatively serious, and it is the best choice to apply more stringent local emission standards [17].

(2) Increase the market share of clean energy vehicles

From the perspective of the car itself, the fundamental way to reduce exhaust emissions is to develop clean energy, develop clean energy vehicles, increase the market share of clean energy vehicles in the Beijing-Tianjin-Hebei region, and reduce the use of high-pollution and high-emission vehicles in the region ratio [18].

At present, clean energy vehicles mainly include battery vehicles, electric vehicles, and hybrid energy vehicles. The development of clean energy vehicles is to prevent and control vehicle exhaust pollution from the source, which requires a lot of investment and social support. As far as the Beijing-Tianjin-Hebei region is concerned, the regional advantages should be fully utilized to jointly support the development and use of clean energy vehicles and increase the market share of clean energy vehicles. The proposed measures mainly include: First, tax incentives for clean energy vehicles. Secondly, the inclusion of clean energy vehicles in the government procurement plan will play a role; thirdly, policy incentives such as a lottery-free policy and unlimited travel for clean energy vehicles should be adopted; finally, the supporting infrastructure for clean energy vehicles should be improved, such as Build charging stations, battery recycling, etc.

## 2.3. Reinforcement Learning

Reinforcement learning is one of the fields of machine learning. It is inspired by behavioral psychology. It is different from supervised learning. The training samples of supervised learning are labeled, while the training of reinforcement learning is not labeled. It is based on rewards and punishments given by the environment. study. Reinforcement learning mainly focuses on how the agent can take different actions in the environment to maximize the cumulative reward. Reinforcement learning has made remarkable achievements in the fields of Go game, robot control, and unmanned driving. The basic block diagram of reinforcement learning is shown in Figure 1.

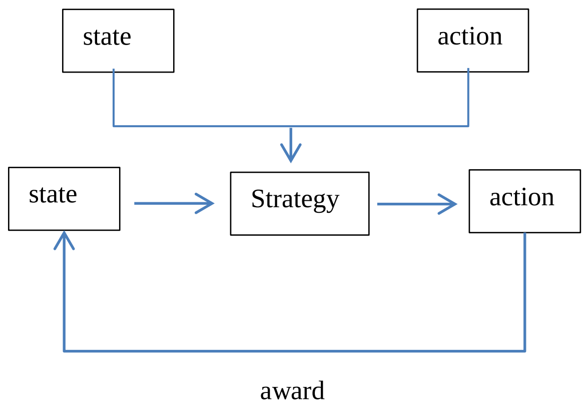


*Figure 1. Reinforcement learning block diagram*

The basic concepts of reinforcement learning include the following parts:

(1) Status

The state refers to various data of the system at the current moment.

(2) Action

Actions that the agent can produce in the current state. An action set is all the actions an agent can produce.

(3) Rewards

Reward refers to the feedback (positive or negative) obtained by the agent after performing the action at the current moment, indicating the pros and cons of the action in the current round, and all the rewards obtained by the agent in one round are called cumulative rewards.

(4) Strategy

Reinforcement learning is the mapping learning from environmental states to actions, and this mapping relationship is called a policy. That is, the process of how the agent chooses an action in the current state is called a policy.

(5) Goals

The agent automatically finds the optimal policy in a continuous time series, and the optimal policy usually refers to maximizing the long-term cumulative reward. We use the value function (Q function) to measure the quality of the strategy and update the Q value through the reward function.

## 3. Energy Management Strategy for Clean Energy Vehicles Based on Deep Reinforcement Learning

### 3.1. Design of Energy Management Strategy Model

In the DQN algorithm, instant rewards can directly affect the adjustment of deep network parameters. The DQN algorithm tends to maximize the immediate reward at each moment. In this paper, the inverse of the instantaneous fuel consumption of the engine is selected as the immediate reward function, and at the same time, the setting of the reward function is adjusted according to the change of SOC. The instant reward function looks like this:

$$r=\begin{cases}\dfrac{1}{C_{ICE}} & C_{ICE}\neq 0\cap 0.5\leq SOC\leq 0.8\\ \dfrac{1}{C_{ICE}+C} & C_{ICE}\neq 0\cap SOC<0.5 or SOC>0.8\\ \dfrac{2}{Min_{C0}} & C_{ICE}=0\cap 0.5\leq SOC\\ -\dfrac{1}{C} & C_{ICE}=0\cap SOC<0.5\end{cases} \quad (1)$$

In the formula, r——the immediate reward from action a to state s' in state s

CICE——The instantaneous fuel consumption value of the engine, the unit is L/100km

MinC0——The minimum non-zero value of the engine instantaneous fuel consumption, the unit is L/100km

The so-called activation function is a function that is further enhanced after summing the inputs of each path. The activation function of the hidden layer of the neural network usually adopts the ReLU (Rectified Linear Unit) function, and the output layer adopts the linear activation function. Among them, the ReLU function is shown in Equation 2:

$$f(x)=\max(0,x) \quad (2)$$

### 3.2. Energy Management Algorithm Based on Deep Reinforcement Learning

The algorithm flow integrates the principle of the DQN algorithm and the transfer characteristics of parameters such as input and output. The algorithm designed in this paper participates in two parts: the outer loop and the inner loop: the outer loop is the part where the algorithm participates in the simulation, and the relevant parameters will follow the simulation settings. Perform corresponding updates; the inner loop is the training and parameter update of the algorithm itself, and the parameters that need to be optimized will be updated according to the termination conditions of the algorithm.

At the beginning of the algorithm, the parameters are initialized synchronously. The specific operation steps are: initialize the experience pool D, the experience pool can store n state action pairs s-a; initialize the Q network, the weight parameter is $\theta$; initialize the target Q network, the weight parameter is $\theta$_= $\theta$; Randomly initialize a state s, initialize the experience pool, and set the observation value s_. After that, the traversal loop of the DQN algorithm is performed.

### 3.3. Parameter Setting

Set the number of discrete control actions n_actions to 24, the number of n_features feature state space to 2, which are Tdem and SOC respectively, and the number of steps to update the Q reality network parameters replace_target_iter=200. The experimental parameters need to be determined through experience summarization and adjustment. The selected parameters can ensure the stability of the algorithm and ensure the training efficiency. The specific parameter settings are shown in Table 1:

*Table 1. DQN algorithm parameters*

| Parameter name | Set value |
|---|---|
| Minimum number of samples | 30 |
| Experience pool sample size | 800 |
| Minimum number of samples in experience pool | 100 |
| Attenuation factor | 1 |
| Learning rate | 1 |

## 4. Comparative Analysis of the Average Emission Factors of Clean Cars and Traditional Cars Based on Deep Reinforcement Learning

In order to quantitatively analyze the exhaust emissions of clean energy vehicles based on deep reinforcement learning, traditional gasoline cars are selected as reference models. The reference vehicles are comparable to clean energy vehicles in dimensions, curb weight and displacement. The specific parameters are shown in Table 2. The main road is the test route, and the average emission factors of pollutants CO, HC and NOX emitted by hybrid cars and traditional gasoline cars are compared. The results are shown in Figure 2.

*Table 2. Parameters of traditional gasoline sedan*

| Parameter | Curb weight/kg | Car length/mm | Engine power/kw | Displacement/t |
|---|---|---|---|---|
| Traditional gasoline sedan | 1462 | 3499 | 107 | 1.5 |

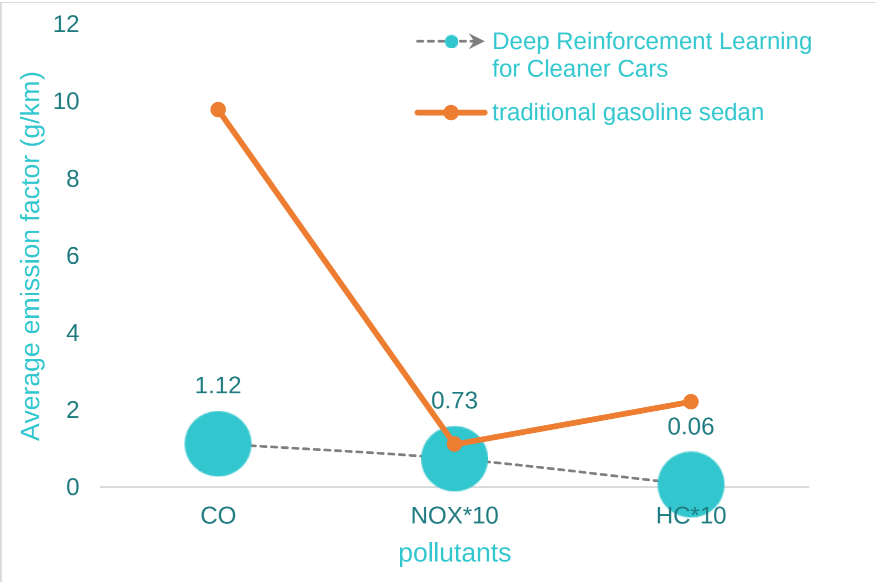


*Figure 2. Comparison of the average emission factors of pollutants between the two cars*

The overall average CO emission factor of clean energy vehicles based on deep reinforcement learning is 1.12g/km, and that of traditional gasoline cars is 9.79g/km (equivalent to 8.7 times the emissions of clean energy vehicles); as shown in Table 3. The total average emission factor of NOX of clean energy vehicles is 0.73g/km, and that of traditional gasoline cars is 1.11g/km (equivalent to 1.5 times the emission of clean energy vehicles); the total average emission factor of HC of clean energy vehicles is 0.06g/km km, the traditional gasoline car is 2.21g/km (equivalent to 36.8 times that of clean energy vehicles). The CO, HC and NOX emissions of clean energy vehicles are significantly lower than those of traditional gasoline cars. This generally reflects the good emission reduction performance of clean energy vehicles based on deep reinforcement learning.

*Table 3. Comparison results*

| Pollutants | Deep Reinforcement Learning for Cleaner Cars | Traditional gasoline sedan |
|---|---|---|
| CO | 1.12 | 9.79 |
| NOX*10 | 0.73 | 1.11 |
| HC*10 | 0.06 | 2.21 |

## 5.Conclusion

The main body of this paper is derived from the theoretical framework of deep learning, combined with the characteristics of the life cycle of the automobile industry, and divergent policy paths. There are still many parts of this article that deserve further study. First, a more in-depth political system analysis can be carried out on the causes of the existing problems. The research needs to further classify the problems, and the cause analysis can be more systematic and comprehensive. Second, in the final analysis of countermeasures, new ideas for energy management of hybrid vehicles will be further explored in the future, and more diversified means will be used to solve problems. Finally, with the improvement of the social governance system and the enhancement of public participation ability, the use of voluntary tools such as social organizations and the public in the field of automobile exhaust pollution prevention and control needs to be further studied in the future.

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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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