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Prediction of Exhaust Contaminant of Gasoline Vehicles Based on Grey Model GM (1,1) and Artificial Neural Networks

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Abstract

Exhaust contaminant of gasoline vehicles is a crucial aspect to measure the vehicle performances and the air pollutions. According to the feature of vehicles, the emission of exhaust contamination of a vehicle is different as time goes by, which shows an increase tendency in most of the cases. Measuring the changes of a vehicle's exhaust contaminant emission is of great importance in the field of vehicle engineering. However, it is hard to determine and find out the regulations of the emission, needing a long time for regular determination and advanced relevant machines. In this article, we aim at providing two novel methods for the prediction of exhaust contaminant of gasoline vehicles, using grey model GM (1,1) and artificial neural networks (ANNs) models respectively. Results show that both the GM (1,1) model and ANN models are comparatively precise for the prediction. The GM (1,1) model can quickly obtain the predicted values of exhaust contaminant, but it is less precise than ANN models. However, ANN models need more time for the training process, compared to GM (1,1) model. Results indicate that the two kinds of models can be used for different circumstances.

Keywords: *Exhaust contaminant, gasoline vehicles, grey model GM (1,1), artificial neural networks*

1. Introduction

With the development of the economics in many developed and developing countries, gasoline vehicles are currently widely used in many families [1-4]. However, there come many problems with the wide use of vehicles. Air pollution is one of the most severe problems that are extremely harmful to environments [5-7]. Therefore, how to control the air pollution has become a crucial topic all over the world. In order to control the pollution of the exhaust contaminant, the first step is to measure the gas emissions of the vehicles. And this measure should be undertaken in a series year in order to obtain the changes of the emissions and then put forward the control method. Only by understanding to the emission changes of the gasoline vehicles, can we put forward a more targeting policy and strategy to the control of air pollution.

However, how to measure the vehicles' emission changes is also a big problem in the scientific research [8-11]. A different kind of exhaust contaminant has different change regulation because of the feature of the vehicles. One cannot only consider one kind of exhaust contaminant or take all the exhaust contaminants as a united object because these two kinds of ideas will make scientists trap into the problems. Here, we take the CO, HC and NO as the main study object, developing models for each kind of the exhaust

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contaminant independently. Taking the usage of years as an independent variable, we can establish a series of models for predicting the emission of these gases.

Because the emission scale of the exhaust contaminants could change with time, we can regard the emissions as the sequence for grey model prediction GM (1,1). Here, we firstly used GM (1,1) to predict the emissions of the exhaust contaminants, and then we used artificial neural networks (ANNs) to develop non-linear models to predict the same emissions of the exhaust contaminants. By using these two prediction techniques, we can help people understand the change regulation of the emissions of exhaust contaminants. Utilization these two models, we can do further research and discussions on how to control the air pollution caused by the gasoline vehicle emissions.

2. Grey Model GM (1,1)

Grey Model GM (1,1) [12-15] is a mathematical method that can be used for the prediction in the uncertain system. It can undertake the relationship analysis by determining the differences among different factors in the system. And then the original data can be transformed into the new forms in order to find out the regulation of the change of the system. Generating a novel and regulated sequence, differential equation model can be established so as to predict the future trend of the study object. Usually, GM (1,1) is used for the prediction of the values on the basis of the original data listed in an equal interval sequence.

Here, because the determination of the emissions of exhaust contamination is usually undertaken once a year, and what we are really concerning about is the yearly change of the emissions of those gases, based on the prediction principle of grey model, we can use GM (1,1) for predicting the emissions of exhaust contaminants.

3. Artificial Neural Network

Artificial neural network (ANN) is a powerful non-linear fitting machine learning technique [16-19]. An ANN model is made up of various neurons. Figure 1 shows a schematic structure of a general ANN model.

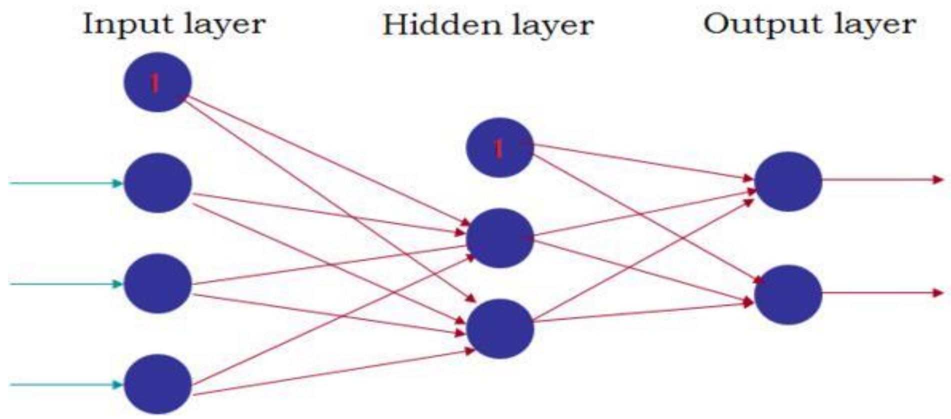

Figure 1. General Structure of an Artificial Neural Network

Figure 1 is a schematic structure of an artificial neural network. A general ANN model consists of the input layer, the output layer and the hidden layer (s). Figure 1 is an example of an ANN model that owns one input layer with four nodes (including one bias), one hidden layer with three nodes and one output layer with two node. Input layer is usually what we call independent numeric variables. Hidden layer is used for computing the weights from the input layer. After the calculation, results can be conveyed to the output layer, which determines the output values of the ANN model.

4. Results and Discussion

Here, we develop the GM (1,1) and ANN models respectively, using the data provided by reference [20]. The establishing process is shown as follows. We chose two series of results for the use of the prediction. In each kind of model, we used two groups of data from different systems. Hence there will be totally six groups of results of the emission prediction.

4.1. Development of Grey Model GM (1,1)

We develop six GM (1,1) models respectively. In each of the model, we left four values in the last of the sequence as the testing set. Figures 2 to 7 present the comparisons between the actual values and predicted values of the testing set.

Here, we first develop the model for the prediction of the emission of HC in the first system. Testing results are shown in Figure 2:

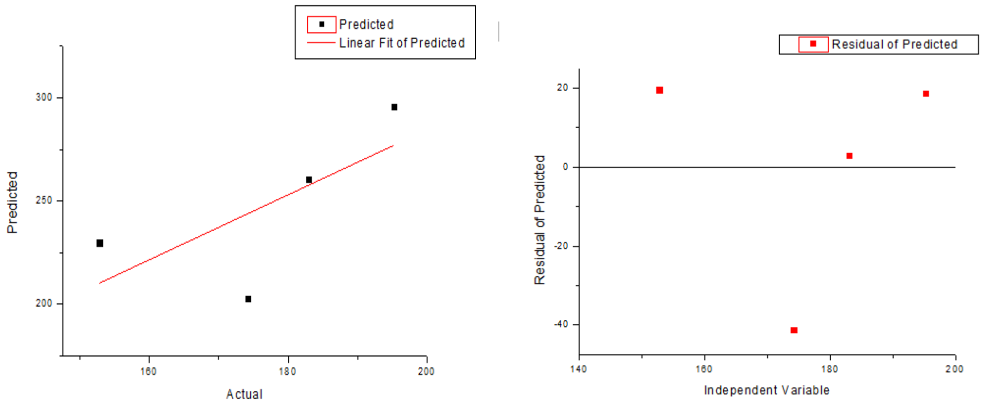

Figure 2. Testing Results of GM (1,1) Model for the Prediction of the Emission of HC in the First System

Figure 2 present the results of GM (1,1) model for the prediction of the emission of HC, which is a testing process based on a number of training set. Results show that only one point that is slightly deviate the regression line, showing that the model is comparatively precise.

The results of the GM (1,1) model for the prediction of the emission of CO in the first system are shown in Figure 3:

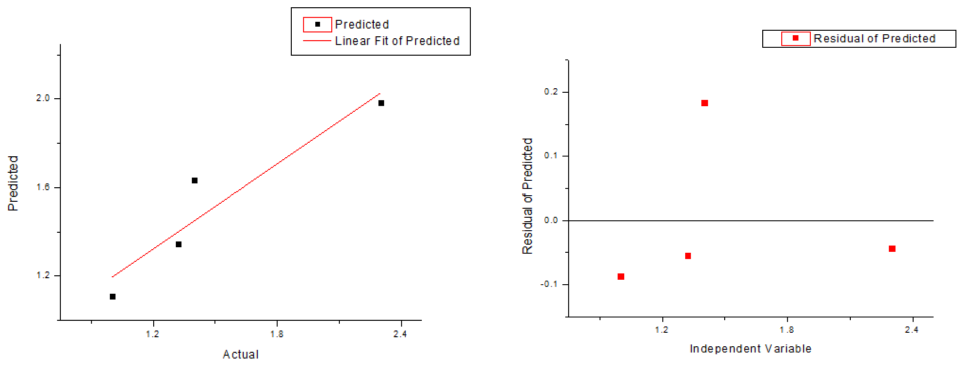

Figure 3. Testing Results of GM (1,1) Model for the Prediction of the Emission of CO in the First System

Figure 3 shows that the predicted values are very close to the actual values. And the residual errors of the predicted values are comparatively low, indicating that the GM (1,1) model for CO in the first system is a very suitable model.

The results of the GM (1,1) model for the prediction of the emission of NO in the first system are shown in Figure 4:

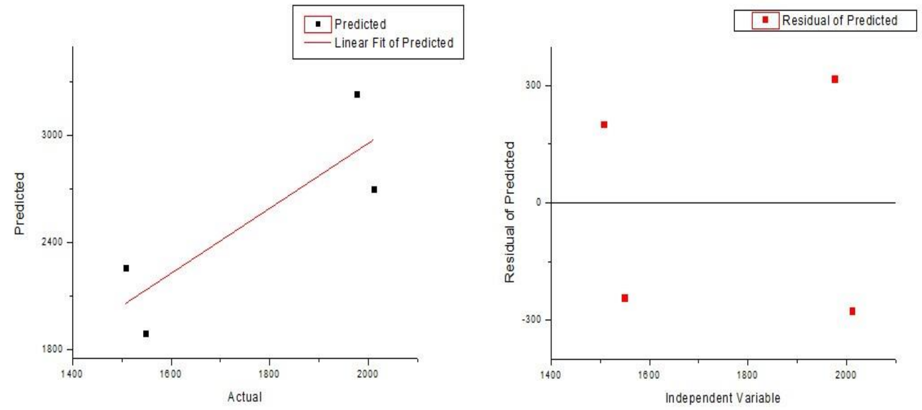

Figure 4. Testing Results of GM (1,1) Model for the Prediction of the Emission of NO in the First System

Figure 4 shows that the predicted values are also very close to the actual values. And the residual errors of the predicted values are comparatively low, indicating that the GM (1,1) model for NO in the first system is quite robust.

In the second system, we also use the same mode to develop the GM (1,1) models. Figure 5 illustrates the testing results of GM (1,1) model for the prediction of the emission of HC.

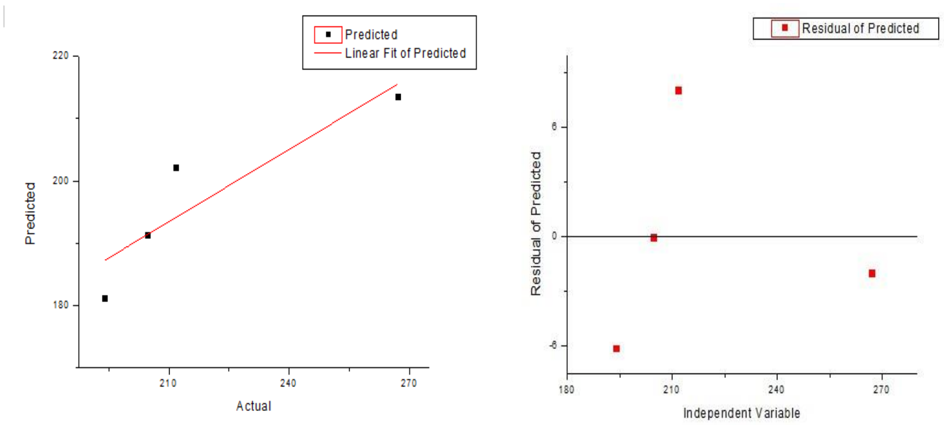

Figure 5. Testing Results of GM (1,1) model for the Prediction of the Emission of HC in the Second System

Figure 5 shows that the predicted values are quite similar to actual values. Residual errors also confirm the robustness and correctness of the GM (1,1) model in the prediction of HC in the second system.

Figure 6 shows the testing results of GM (1,1) model for the prediction of the emission of CO in the second system.

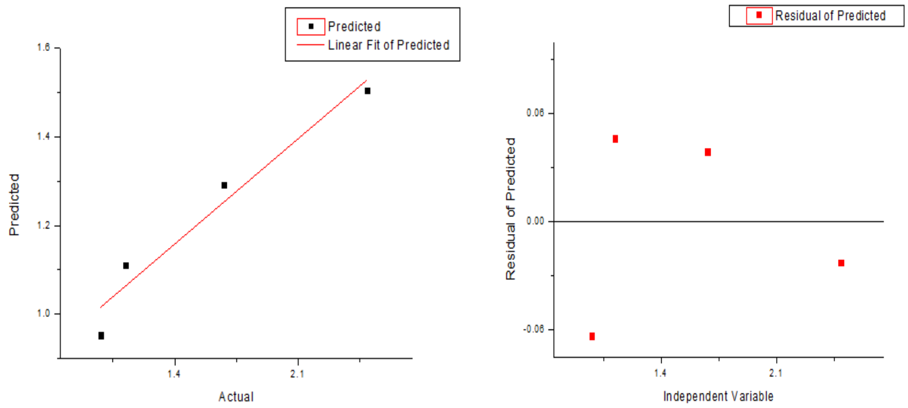

Figure 6. Testing Results of GM (1,1) model for the Prediction of the Emission of CO in the Second System

Figure 6 shows that the predicted values are also quite similar to actual values. Residual errors also confirm the robustness and correctness of the GM (1,1) model in the prediction of CO in the second system.

Figure 7 shows the testing results of GM (1,1) model for the prediction of the emission of NO in the second system.

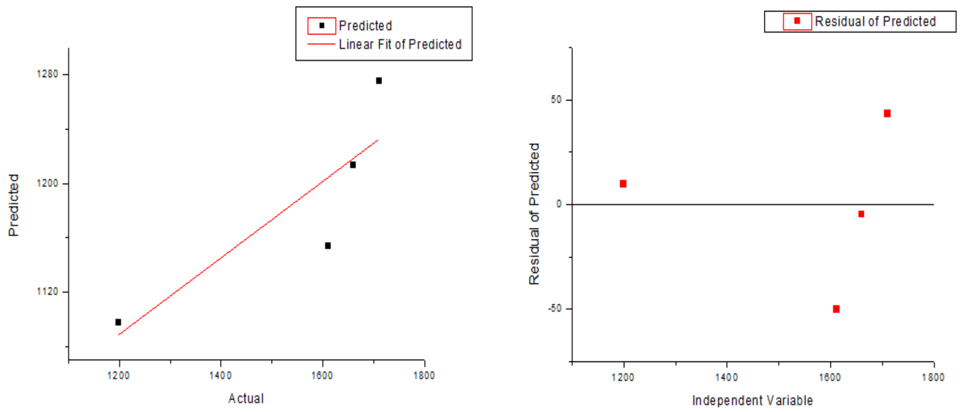

Figure 7. Testing Results of GM (1,1) Model for the Prediction of the Emission of NO in the Second System

Figure 7 shows that only one point which is slightly deviates the regression line, which we consider as the fluctuation of the GM (1,1). In general, results are also robust.

4.2. Development of ANN Models

Here we set the year of the use of a vehicle as the independent variable, while we set the emission of gas as the dependent variables. Similar to the development method of GM (1,1) models, we developed six groups of ANN models respectively. We mainly used the general regression neural network (GRNN) and multi-layer feed forward neural network (MLFN) to develop the models.

Table 1 shows the training results of ANN models for the prediction of the emission of HC in the first system:

Table 1. Results of Models for the Emission of HC in the First System

ANN Model	Trained Samples	Tested Samples	Average RMS Error
Linear Regression	9	5	8.90
GRNN	9	5	10.95
MLFN with 2 Nodes	9	5	11.65
MLFN with 3 Nodes	9	5	10.53
MLFN with 4 Nodes	9	5	9.72
MLFN with 5 Nodes	9	5	16.97
MLFN with 6 Nodes	9	5	8.72
MLFN with 7 Nodes	9	5	21.83
MLFN with 8 Nodes	9	5	13.26
MLFN with 9 Nodes	9	5	35.05
MLFN with 10 Nodes	9	5	31.86

Table 1 show that the MLFN model with 6 nodes is the best model for prediction, with a lowest RMS error (8.72) in the result list.

Table 2 shows the training results of ANN models for the prediction of the emission of CO in the first system:

Table 2. Results of Models for the Emission of CO in the First System

ANN Model	Trained Samples	Tested Samples	Average RMS Error
Linear Regression	7	5	0.40
GRNN	7	5	0.43
MLFN with 2 Nodes	7	5	0.41
MLFN with 3 Nodes	7	5	0.40
MLFN with 4 Nodes	7	5	0.43
MLFN with 5 Nodes	7	5	0.40
MLFN with 6 Nodes	7	5	0.39
MLFN with 7 Nodes	7	5	0.45
MLFN with 8 Nodes	7	5	0.39
MLFN with 9 Nodes	7	5	0.45
MLFN with 10 Nodes	7	5	0.74

Table 2 shows that both the MLFN model with 6 nodes and 8 nodes are the best model for prediction, with the lowest RMS errors (0.39) in the result list. However, although the RMS errors of the two models are equal, we still consider that the MLFN model with 6 nodes is the best model during the training and testing process because the training time will increase with the increase of the number of nodes in the MLFN model. The training time of MLFN model with 8 nodes is obviously longer than that of MLFN model with 6 nodes.

Table 3 shows the training results of ANN models for the prediction of the emission of NO in the first system:

Table 3. Results of Models for the Emission of NO in the First System

ANN Model	Trained Samples	Tested Samples	Average RMS Error
Linear Regression	7	5	150.86
GRNN	7	5	112.30
MLFN with 2 Nodes	7	5	470.65
MLFN with 3 Nodes	7	5	1939.60
MLFN with 4 Nodes	7	5	5714.71
MLFN with 5 Nodes	7	5	737.94
MLFN with 6 Nodes	7	5	371.50
MLFN with 7 Nodes	7	5	1455.54
MLFN with 8 Nodes	7	5	4504.65
MLFN with 9 Nodes	7	5	1522.72
MLFN with 10 Nodes	7	5	1594.25

Table 3 shows that the GRNN model is the best ANN model for the prediction, which have a clearly overwhelming advantage, compared to other models during the computation experiments. Also, it should be mention that although the RMS errors shown in Table 3 is much higher than those of other tables, we still consider that the GRNN model is available because the emission of NO in modern vehicles are obviously higher than other exhaust contaminants.

Table 4 shows the training results of ANN models for the prediction of the emission of HC in the second system:

Table 4. Results of Models for the Emission of HC in the Second System

ANN Model	Trained Samples	Tested Samples	Average RMS Error
Linear Regression	8	5	16.09
GRNN	8	5	23.87
MLFN with 2 Nodes	8	5	15.66
MLFN with 3 Nodes	8	5	17.44
MLFN with 4 Nodes	8	5	12.49
MLFN with 5 Nodes	8	5	12.81
MLFN with 6 Nodes	8	5	62.62
MLFN with 7 Nodes	8	5	10.96
MLFN with 8 Nodes	8	5	80.05
MLFN with 9 Nodes	8	5	14.48
MLFN with 10 Nodes	8	5	132.89

Figure 4 shows that the MLFN model with 7 nodes is the best model for the prediction, with an RMS error 10.96. Without considering the training time, the MLFN model with 7 nodes is a quite suitable ANN model for the prediction of the emission of HC in the second system.

Table 5 shows the training results of ANN models for the prediction of the emission of CO in the second system:

Table 5. Results of Models for the Emission of CO in the Second System

ANN Model	Trained Samples	Tested Samples	Average RMS Error
Linear Regression	8	5	0.47
GRNN	8	5	0.14
MLFN with 2 Nodes	8	5	0.19
MLFN with 3 Nodes	8	5	0.15
MLFN with 4 Nodes	8	5	0.17
MLFN with 5 Nodes	8	5	2.24
MLFN with 6 Nodes	8	5	1.31
MLFN with 7 Nodes	8	5	0.17
MLFN with 8 Nodes	8	5	0.67
MLFN with 9 Nodes	8	5	0.52
MLFN with 10 Nodes	8	5	1.41

Table 5 shows that the GRNN model is the best model for this prediction, with an RMS error 0.14. It should be mentioned that the training time of the GRNN model is very quick, which is a very suitable model for the research which need a "quick result".

Table 6 shows the training results of ANN models for the prediction of the emission of NO in the second system:

Table 6. Results of Models for the Emission of NO in the Second System

ANN Model	Trained Samples	Tested Samples	Average RMS Error
Linear Regression	8	5	150.56
GRNN	8	5	110.76
MLFN with 2 Nodes	8	5	127.83
MLFN with 3 Nodes	8	5	808.73
MLFN with 4 Nodes	8	5	120.33
MLFN with 5 Nodes	8	5	220.84
MLFN with 6 Nodes	8	5	6363.47
MLFN with 7 Nodes	8	5	160.84
MLFN with 8 Nodes	8	5	499.85
MLFN with 9 Nodes	8	5	325.67
MLFN with 10 Nodes	8	5	370.56

Table 6 shows that the GRNN model is the best model during the experiments, with an lowest RMS error (110.76), showing that GRNN model is a very strong ANN model for relevant researches.

According to all the results in Section 4, we can see that both the GM (1,1) model and the ANN models can be used for the prediction of the gas emissions of the gasoline vehicles. We can clearly see that GM (1,1) model is very quick to achieve the results, while the ANN models need to make comparisons among various results of different ANN models. However, the robustness and correctness of ANN models are usually higher than those of GM (1,1) models. Of course, one cannot easily judge that which kind of model is the best. In practical applications, we should use different model under different circumstances. In the quick-test research, GM (1,1) model is undoubtedly a better choice than ANN models. But in the research which requires a precise result or the research with advanced computers, ANN models are obviously better than GM (1,1) models. Now we can draw a conclusion that both GM (1,1) model and ANN models can be used for the prediction of exhaust contaminant of gasoline vehicles.

5. Conclusion

Exhaust contaminant of gasoline vehicles is of great importance to measure the vehicle performances and the air pollutions. In accordance with the iner-function of vehicles, the emission of exhaust contamination of a vehicle can be different, which shows an increase trend. Measuring the changes of a vehicle's exhaust contaminant emission is a crucial duty in relevant fields. However, due to the limitations of the techniques, it is quite difficult to determine and find out the regulations of the emission, requiring a relatively long time for regular determination. Here, we aim at providing two novel methods for the prediction of exhaust contaminant of gasoline vehicles, using grey model GM (1,1) and artificial neural networks (ANNs) models respectively. Results show that both the GM (1,1) model and ANN models are comparatively precise for the prediction. The GM (1,1) model can quickly obtain the predicted values of exhaust contaminant, but it is less precise than ANN models. However, ANN models need more time for the training process, compared to GM (1,1) model. Results indicate that the two kinds of models can be used for different circumstances.

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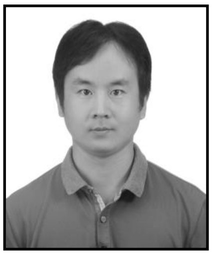

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