International Journal of Smart Home
Vol. 9, No. 9 (2015), pp. 21-28
http://dx.doi.org/10.14257/ijsh.2015.9.9.03

Multiple Computation Models for the Prediction of Private Vehicle Ownership in Chinese Area

Jinbing Song

Department of Automobile Engineering, Changzhou College of Mechatronic Technology, Changzhou, 213164, Jiangsu, China
v.bin@163.com

Abstract

With the development of Chinese economics, there is an increasing tendency that people have the abilities to purchase private vehicles. However, the increase of private vehicles rapidly increases the air pollution. Therefore, it is necessary that we should study the change regulation of the private vehicle ownership in Chinese area. Due to the impact factors of the change regulation of the private vehicle ownership is various and uncertain, we should take various factors into consideration as much as possible. In this article, we take 11 indicators as the independent variables, while the private vehicle ownership as the dependent variable. Multiple linear regression (MLR) model and artificial neural networks (ANNs) models were developed respectively in order to predict the private vehicle ownership. As an alternative model, we developed grey model GM (1, 1) according to the regulation of the private vehicle ownership. Detailed comparisons among the MLR, ANNs and GM (1, 1) models were made and results show that they have different advantages respectively. Our results shows that all the three types of computation models can be used for the prediction of the private vehicle ownership in Chinese area.

Keywords: *Private vehicle ownership, multiple linear regression, grey model GM (1, 1), artificial neural networks*

1. Introduction

With the development of Chinese economics, there is an increasing tendency that people have the abilities to purchase private vehicles [1-3]. Nevertheless, the gas emissions of the private vehicles have generated relatively serious air pollution [4-6]. Previous research indicates that the ownership of private vehicles has a linear correlation with the air pollution. Therefore, it is crucial for scientists to study the change regulation of the ownership of private vehicles and put forward a series related solutions to air pollution.

However, how to measure the vehicles' ownership changes is also a big problem in the scientific research [7]. Due to the complexity of the social problems, we cannot directly confirm the impact factors to the change regulation of the private vehicle ownership. Therefore, in our study, we took all the potential factors as indicators as possible. The independent variables consists of 11 indicators, including per capita GDP, total retail sales of consumer goods of the whole society, total investment in fixed assets, number of public vehicles under operation, total number of bus operation, mean noise of city traffic arteries, total mileage of bus operation, road length, per capita disposable income of residents, residents savings balance and annual average price of gasoline. These 11 indicators are believed to have crucial influences to the change regulation of the private vehicles in the principle of sociology. Although the weights of these 11 indicators are uncertain, we can still obtain a highly robust prediction using computation techniques.

ISSN: 1975-4094 IJSH

We first developed a multiple linear regression (MLR) model in order to analyze the weights of different components. Then 15 artificial neural networks (ANNs) as a powerful non-linear machine learning techniques were developed on the basis on the same variable components as the MLR model. Finally, as an alternative and comparable approach, grey model GM (1, 1) was developed based on the private vehicle ownership in the time series, independent to those 11 indicators. By developing these three types of computation models, we aim at find out the suitable computation methods for the prediction of private vehicle ownership in Chinese areas.

2. Artificial Neural Network

Artificial neural networks (ANNs) are a common non-linear machine learning approach [8-11]. Usually, a complete ANN model consists of a series of "neurons", which is similar to human brain. Figure 1 illustrates a common structure of a general ANN model.

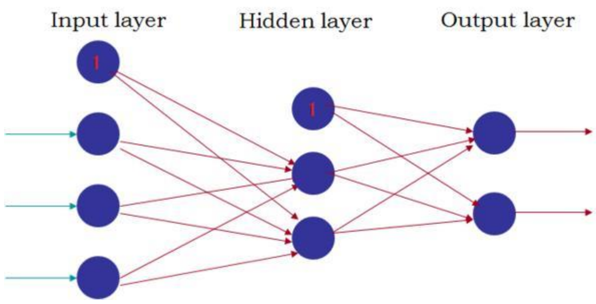


Figure 1. General Structure of an Artificial Neural Network

A complete ANN model consists of input layer, hidden layer(s) and output layer. The number of hidden layer may be different under different conditions. Users can choose different number of nodes and layers in hidden layer for the sake of finding out the best model for research.

Figure 1 is a common and conceptual structure of a complete artificial neural network. A general ANN model is made up of input layer, output layer and hidden layer (s). Figure 1 is an illustration of ANN models that have one input layer with four nodes (and one bias), one hidden layer with three nodes and one output layer with two nodes. Input layer is used for the input of the independent variables. Hidden layer is used for the computation of weights using certain functions from the input layer. After computation, results can be transferred to output layer.

3. Grey Model GM (1, 1)

Grey Model GM (1, 1) [12-15] is a mathematical approach that is currently widely used for the prediction in uncertain systems. It can undertake relationship analysis by determining the differences among different factors in the system. Afterwards, the original data can be changed into new forms for the sake of finding out regulations of the change of the system. The prediction work based on GM (1, 1) is completely independent to exterior independent variables. GM (1, 1) is frequently used for the prediction of the values which change with a certain gap of time.

In our research, because the private vehicle ownership is usually measured annually, and we aim at testing the robustness of the GM (1,1) models itself and make comparisons with MLR and ANN models, thus we can use GM (1,1) for predicting the ownership of private vehicles in Chinese areas.

4. Results and Discussion

Here, we develop the MLR; ANN models the GM (1, 1) model respectively, using the data provided by reference [7]. The establishing process is shown respectively in the following three sections.

4.1. Development of the MLR Model

Here, we use SPSS for develop an equation for the change regulation of private vehicle ownership. The 11 indicators were presented by x_1 to x_{11} respectively (in the order of the indicates listed in previous sections), and y is the private vehicle ownership.

$$y = 0.062x_2 - 0.1x_3 + 3.604x_5 + 0.007x_8 - 0.006x_9 - 0.14x_{10} + 22.274x_{11} - 353.734 \quad (1)$$

Equation (1) presents the MLR regression result, which shows that only x_2, x_3, x_5, x_8, x_9, x_{10}, x_{11} has significant impacts to y. Figure 2 shows the comparison between actual values and the predicted values using MLR.

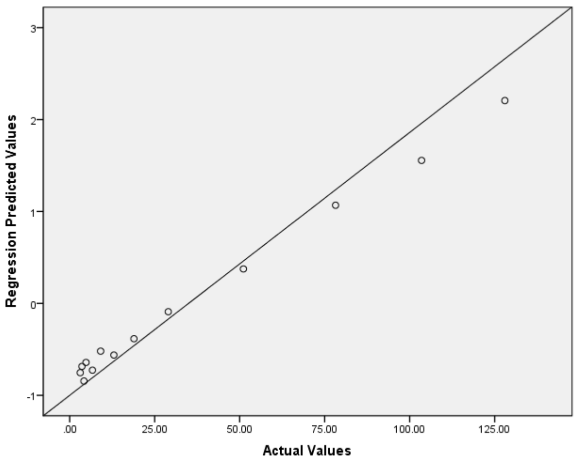


Figure 2. Regression Results of the MLR Model

Figure 2 indicates that MLR model has a very suitable result in the prediction. However, using MLR model cannot test the robustness due to the limited data scale. Therefore, we should use ANN and GM (1, 1) models as alternative models.

4.2. Development of ANN Models

In order to develop a series of ANN models, we set the same indicators and dependent variable as the MLR model. We used the general regression neural network (GRNN) [16-20] and multi-layer feed-forward neural network (MLFN) [21-24] to develop the models. The number of nodes of MLFN models was set from 2 to 15 in order to find out the most suitable nodes of MLFN model for the prediction.

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

Table 1. Best Net Search Results of Models for the Prediction of Private Vehicle Ownership in Chinese Area

ANN Model	Trained Samples	Tested Samples	RMS Error
GRNN	8	5	
MLFN with 2 Nodes	8	5	
MLFN with 3 Nodes	8	5	
MLFN with 4 Nodes	8	5	13.90
MLFN with 5 Nodes	8	5	38.48
MLFN with 6 Nodes	8	5	13.89
MLFN with 7 Nodes	8	5	54.71
MLFN with 8 Nodes	8	5	92.33
MLFN with 9 Nodes	8	5	53.61
MLFN with 10	8	5	22.19
Nodes	8	5	129.73
MLFN with 11	8	5	144.92
Nodes	8	5	53.17
MLFN with 12	8	5	61.89
Nodes	8	5	158.16
MLFN with 13			329.82
Nodes			98.02
MLFN with 14			296.05
Nodes			
MLFN with 15			
Nodes			

Table 1 show that the MLFN model with 3 nodes is the best model for prediction, with a lowest RMS error (13.89) in the result list. Figure 3 is used for illustrating the change regulation of the RMS errors of MLFN models with the change of nodes:

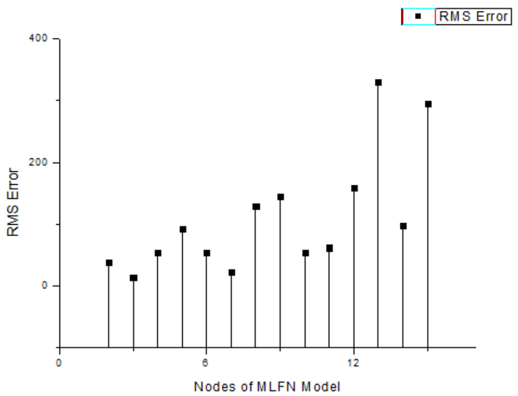


Figure 3. Change of RMS Errors with the Change of the Nodes during the MLFN Models

Figure 3 shows that there is a significant fluctuation of RMS errors when changing the nodes of MLFN. It is obvious that the RMS error is getting higher with higher nodes after that with 3 nodes in spite of the fluctuation.

Here, we present the results of the MLFN model with 3 nodes in Figure 4 to Figure 9:

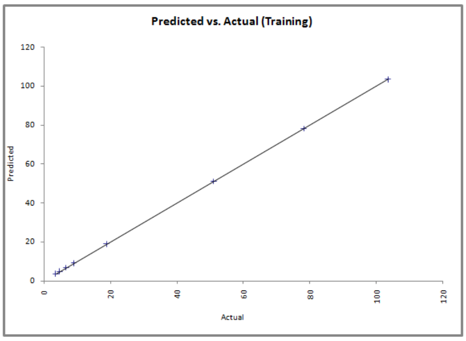


Figure 4. Predicted Values versus Actual Values after Training (MLFN-3 Model)

Fig 4 shows that the training process is extremely robust. The regression line is very similar to the proportional function. The result shows that the training process is correct and precise. The following results are reliable.

Figure 5. Residual Values versus Actual Values after Training (MLFN-3 Model)

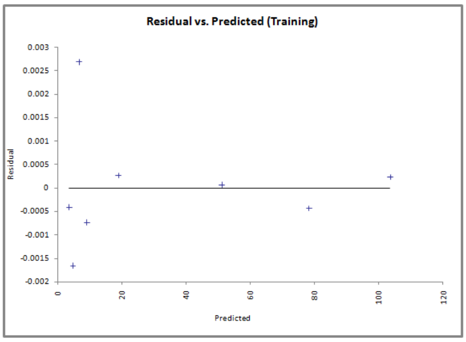


Figure 6. Residual values versus predicted values after training (MLFN-3 model)

Figures 5 and 6 shows that the residual values are relatively low. The training process is very robust, which indicates that the testing results are reliable because the training process is reliable.

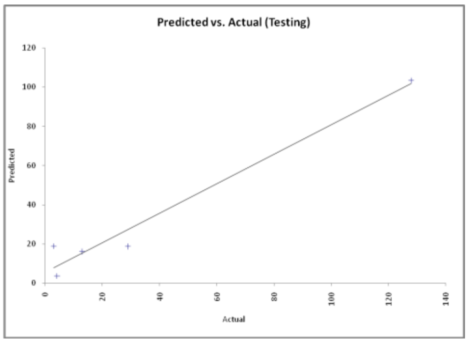


Figure 7. Predicted Values versus Actual Values after Testing (MLFN-3 Model)

Fig 7 shows that the training process is robust. The regression line is very similar to the proportional function. The result shows that the testing process is correct and precise. The following results are reliable.

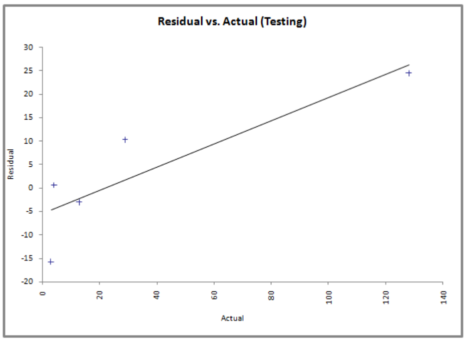


Figure 8. Residual Values versus Actual Values after Testing (MLFN-3 Model)

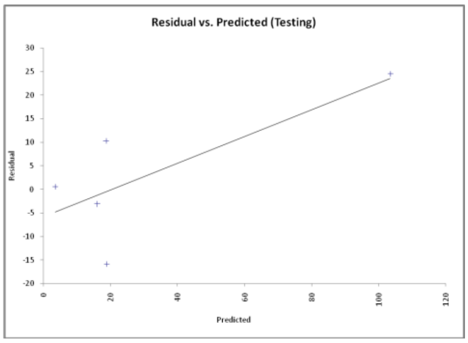


Figure 9. Predicted Values versus Actual Values after Testing (MLFN-3 Model)

Figs. 8 and 9 shows that the residual values are relatively low. The testing process is very robust, which indicates that the MLFN model with 3 nodes is robust in the prediction of private vehicle ownership in Chinese area.

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

We develop a GM (1, 1) model based on the sequence of numbers of private vehicle ownership. 8 data was used for the model development, while 5 data was used for testing. Results are presented as follows:

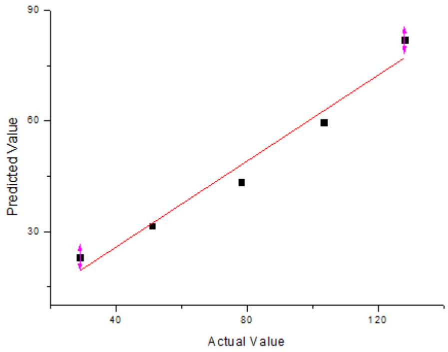


Figure 10. Testing Result of GM (1, 1) Model for the Prediction of Private Vehicle Ownership in Chinese Area

Figure 10 presents the results of GM (1, 1) model for the prediction of private vehicle ownership in Chinese area, which is a testing process based on a number of training set. Results show that the predicted values are highly close to the actual values. Results show that the prediction based on GM (1, 1) is effective.

According to all the results in Section 4, we can see that all the three models (MLR, ANN and GM (1, 1) can be used for the prediction of private vehicle ownership in Chinese area. We can clearly see that, on the one hand, 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. On the other hand, a suitable ANN model usually has a better result than that of GM (1, 1) model under most circumstances, with a comparatively lower RMS error. We cannot easily judge that which kind of model is the most suitable in our research. In practical applications, we should use different models under different circumstances. If the time is limited, GM (1, 1) model is obviously a good choice. If the research requires a precise result or it is aided by a super computer, ANN models may be 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. As for the MLR model, we can use it without a computer, which is an advantage compared to the ANN models and GM (1, 1). However, MLR model didn't consider some of the indicators among the totally 11 indicators, which may be very important and significant in non-linear fitting. So we still recommend that ANNs and GM (1, 1) are the first choices in the practical applications.

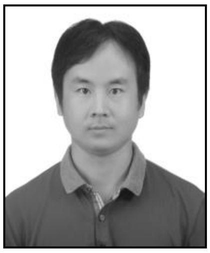
5. Conclusion

With the development of Chinese areas, there is an increasing trend that people has become more and more willing to purchase their private vehicles. Nevertheless, this increasing tendency sharply increases the air pollution. Hence, it is highly necessary that scientists should study the change regulation of the private vehicle ownership in Chinese area in order to find out the reason of the pollution and find out the regulation of the change. Due to the impact factors of the change regulation of the private vehicle ownership is various and uncertain, we should take various factors into consideration as much as possible. In this paper, we consider 11 indicators as independent variables, while the private vehicle ownership as the dependent variable. Multiple linear regression (MLR) model and artificial neural networks (ANNs) models were developed respectively in order to predict the private vehicle ownership. As an alternative model, we developed grey model GM (1, 1) according to the regulation of the private vehicle ownership. Comparisons among the MLR, ANNs and GM (1, 1) models were made and results show that they have different advantages respectively. Our results shows that all the three types of computation models can be used for the prediction of the private vehicle ownership in Chinese area. The MLR model has the advantage that we can obtain the prediction results using Equation (1), without a computer. The ANN model is precise, but it takes time to search the best network. And the GM (1, 1) model is quick, but it is less precise than that of ANN models. We should take all the circumstances into consideration in order to decide which model we should use in practical applications. In further research, we will definitely aim at using a large scale of date to modify the models and find out a common regulation of the change regulation of private vehicle ownership in Chinese areas. Solutions will be proposed in order to resolve related problems in order to improve the effectiveness of our society.

References

[1] L. Gan, "Energy policy", vol. 31, no. 6, **(2003)**.
[2] L. Tomba, "The China Journal", **(2004).**
[3] G. Montinola, Y. Qian and B. R. Weingast, "Federalism, World Politics", vol. 48, no. 1, **(1995)**.
[4] A. T. H. Chin, "Atmospheric Environment", vol. 30, no. 5, **(1996)**.
[5] N. KuÈnzli, R. Kaiser and S. Medina, "The Lancet", vol. 356, no. 9232, **(2000)**.
[6] B. Brunekreef, N. A. H. Janssen and J. de Hartog, "Epidemiology", **(1997)**.
[7] L. Liu and G. Zhang, "Journal of Chizhou College", vol. 12, no. 23, **(2009)**.
[8] J. Van Schependom, G. Nagels and W. Yu, "Schizophrenia Bulletin", **(2013)**.
[9] C. H. Aladag, A. Kayabasi and C. Gokceoglu, "Neural Computer App.", vol. 23, no. 2, **(2013)**.
[10] R. J. Kuo, S. C. Chi and S. S. Kao, "Computer Industry", vol. 47, no. 2, **(2002)**.
[11] E. C. Santos, E. D. Armas and D. Crowley, "Soil Bio. Bioche", vol. 69, **(2014)**.
[12] M. Mao and E. C. Chirwa, "Technological Forecasting and Social Change", vol. 73, no. 5, **(2006)**.
[13] L. Dang, L. Sifeng and D. Yaoguo, "Eng. Sci.", vol. 8, **(2003)**.
[14] T. A. N. Guan-jun, "Syst. Engineering-Theory & Practice", vol. 4, no. 18, **(2000)**.
[15] N. Xie and S. Liu, "Syst. Eng.-Theory & Practice", vol. 1, no. 014, **(2005)**.
[16] D. F. Specht, "Neural Networks, IEEE Transactions on", vol. 2, no. 6, **(1991)**.
[17] D. Tomandl and A. Schober, "Neural Networks", vol. 14, no. 8, **(2001)**.
[18] H. Li, W. Leng, Y. Zhou, F. Chen, Z. Xiu and D. Yang, "The Scientific World Journal", 2014, 478569 **(2014)**.
[19] H. M. Kandirmaz, K. Kaba and M. Avci, "International Journal of Photoenergy", 2014, 680596 **(2014)**.
[20] T. Masters and W. Land, "Computational Cybernetics and Simulation", IEEE, 1997, vol. 3, **(1997)**.
[21] D. Svozil, V. Kvasnicka and J. Pospichal, "Chemometr Intell Lab", vol. 39, no. 1, **(1997)**.
[22] J. R. M. Smits, W. J. Melssen and L. M. C. Buydens, "Chemometr Intell Lab", vol. 22, no. 2, **(1994)**.
[23] D. Yang, H. Li, C. Cao, F. Chen, Y. Zhou and Z. Xiu, "Journal of Spectroscopy", 2014, 901310 **(2014)**.
[24] A. Y. Shamseldin, A. E. Nasr and K. M. O'Connor, "Hydrology and Earth System Sciences Discussions", vol. 6, no. 4, **(2002)**.

Author



Jingbin Song, received the Master's degree in application engineering of vehicle from The Northeast forestry university, China in 2007. Currently, he is a lecturer at Changzhou Institute of Mechatronic Technology, China. His research interests include vehicle inspection and vehicle emission control.

