Using PLSRGM (0, N) Method to Predict China's Transportation Sector Energy Demand

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Abstract: Because the transportation sector consumes more and more energy, it is important to predict future transport energy demand for sustainable transport. In this paper, a new method PLSRGM (0, N) is proposed by integrating PLSR (partial least square regression) into GM (0, N). Then TEDM (transport energy demand model) based on PLSRGM(0,N) will be activated using GDP, population, urban per capita disposal, rural per capita net income, passenger-kilometers and freight ton-kilometers with historical energy data available from 1997 to 2006. The results of posteriori checks show that the model is more reliable and has higher forecasting accuracy. The projections are made with two scenarios until 2030. It is expected that this paper will provide an effective tool to develop energy model that will greatly assist policy-makers.

Keywords: Transport energy demand; Socio-economic indictors; PLSRGM (0, N).

1. Introduction

The transportation sector plays an important role in the national economy developm ent and social activities. Since China's reform and opening up to the outside world, passenger (freight) traffic has been increasing rapidly undertaken for all modes of transport, which provide strong support to national economic and social development. At the same time, transportation energy consumption has been rising year by year. Transport energy consumption came to 18583×10^4tce in 2006, compared to 4541×10^4tce in 1990, with an average annual growth rate of 9.21%. In particular, petroleum product consumption is increasing rapidly. At present the consumption of petroleum products in transportation accounts for approximately 30% of the total petroleum products consumed in China. As petroleum resources are limited in China, imported petroleum accounted for 11.28% of the total primary energy consumption in 2006 [1].

Trends in other countries indicate that the world is becoming more and more similar in material production and consumption patterns. At present the rapid development of transportation and popularization of private car promotes transport energy consumption, which accounts for about 1/4~1/3 of total energy consumption in developed countries. With the development of society, transport energy demand still shows a rising trend. In the United States, transport energy consumption accounts for 33.91% of total energy consumption in 1980, but 38.3% in 1993. Furthermore, over 2/3 of the petroleum is consumed in transportation.

Along with sustained economic growth and the rise in living standards, the transformation of transportation is progressing towards a highly effective, comfortable, and rapid system in China. Moreover, the number of owners of family cars will rapidly increase. Thus, future transport energy demand will grow quickly, and its share of total energy consumption will increase unceasingly. It can be foreseen that the transportation sector will become China's primary energy consumer. Moreover, transport is the main area of growth in energy-related greenhouse gas emission. In such a situation, it is extremely important to predict future transport energy demand for China's energy security and sustainable development of transportation.

So far, many energy models on China have been investigated by a number of studies [2-5]. There are many methods which have been applied in the analysis of energy demand, such as multiple linear regression model [6]; fuzzy theory [7]; times series analysis [8]; neural network [9]; grey theory [10]; genetic algorithm [11]; input-output framework [12] etc. However, little effort has been specialized in transport energy model. And statistical data related to transport is more deficient. But Grey System theory (GM) and Partial Least Squares Regression (PLSR) can excellently deal with data of small sample, inadequate information. In this paper, a new method PLSGM (0, N) has been developed by integrating PLSR into GM (0, N), and we use this method to predict the future transport energy demand based six socio-economic indicators: GDP, population, urban per capital disposal, rural per capital net income, passenger-kilometers and freight ton-kilometers.

This paper is organized as follows. In section 2, we will briefly introduce the PLSR and GM (0, N), then develop the PLSRGM (0, N) method. Next, we will analyze the data related to the transport energy consumption from 1993 to 2006, and develop a TEDM (transport energy demand model), based on the PLSRGM (0, N) method. We will forecast the transport energy demand until 2030, using TEDM under two scenarios in section 4. Finally, we will conclude our paper.

2. Experimental

2.1 The PLSR principle

The PLSR method was first introduced by S.Wold. It is a novel multivariate data analysis method, which was developed from practical application in the real world. This method is mainly used for modeling linear regression between multi-dependent variables and multi-independent variables. Moreover, this method has some other advantages, which ordinary multiple linear regressions do not have. For example, it avoids the harmful affection in modeling, due to the multi-collinearity and regressing, when the number of observations is less than the number of variables. In addition, PLSR method combines the basic functions of regressing models, principal components analysis and canonical correlation analysis, and so on. For more details about this method, the reader can refer to the book written by Wang [13]. In general, the PLSR method is usually represented as an algorithm, and divided into a calibration and a prediction step. In the following section, it will be briefly introduced.

Let the basic data $X=[x_1, x2,\ldots x_m]$ and y, where each of $x_1,x_2,\ldots x_m$ and y is a n dimensional vector. And the data matrix X can be decomposed into a bilinear form as Eq.(1),

$$X = t_1 p_1^T + t_2 p_2^T + \cdots + t_h p_h^T + E_h \,, \qquad (1)$$

where $p_i(1\leq i\leq h)$ is a loading vector, $t_i(1\leq i\leq h)$ is a latent variable (factor), and E_h is the residual matrix of X, when the first h latent variables are included in the PLSR method. The basis for the PLSR method is that the relation between X and y is conveyed through the latent variables. This means that y also has a decomposition as Eq.(2),

$$y = t_1 q_1 + t_2 q_2 + \cdots + t_h q_h + f_h \,, \qquad (2)$$

where the scalar $q_i(1\leq i\leq h)$ is the loading value of y, and f_h is the residual vector of y, when the first h latent variables are included in the PLSR method.

2.1.1 The calibration step

The algorithm specifies how to calculate the scores and loadings, which is formalized as follows:

Step 1: Scale the process variables. Both X and y is scaled to unite variances, which are divided by their standard deviations, and centered by subtracting their averages. This corresponds to giving X and y the same weights, and same prior importance in the analysis

$$x_{ij}^* = \frac{x_{ij} - \bar{x}_j}{s_j}, \qquad y_i^* = \frac{y_i - \bar{y}}{s_y},$$

where $\bar{x}_j = \frac{1}{n}\sum_{i=1}^{n} x_{ij}$ is the average of x_j,

$s_j = \sqrt{(x_j - \bar{x}_j)^T (x_j - \bar{x}_j) / (n-1)}$ is the standard deviation of x_j. Analogously, $\bar{y}$ and s_y are the average and standard deviation of y, respectively.

And then let $h = 1$, $E_0 = (x_{ij}^*)_{n*m}$ and

$f_0 = (y_i^*)_{n*1}, i = 1,2,\ldots n, j = 1,2,\cdots,m$.

Step 2: Calculate the weight vectors (ω_h) : $\omega_h = E_{h-1}^T f_{h-1}$;

Step 3: Calculate the score vectors (t_h): $t_h = E_{h-1} w_h$;

Step4: Calculate the loading values of X and y: $p_h = E_{h-1}^T t_h / (t_h^T t_h)$, $q_h = f_{h-1}^T t_h / (t_h^T t_h)$;

Step 5: Find the residuals: $E_h = E_{h-1} - t_h p_h^T$,

$f_h = f_{h-1} - q_h t_h$;

Step 6: Determine the stopping point.

Cross-validation (CV) is often used to fix the stopping criterion.

$$RSS_h = \sum_{i=1}^{n} (y_i - \hat{y}_{hi})^2 \,,$$

$$PRESS_{hi} = \sum_{j=1}^{n_i} (y_i - \hat{y}_{h(-i)})^2 \,,$$

$$Q_h^2 = 1 - \frac{PRESS_h}{RSS_{h-1}} \,,$$

where h is the number of the latent variables included in the PLSR model, y_i is the target value, $\hat{y}_{hi}$ is the PLSR prediction value of the ith observation, $\hat{y}_{h(-i)}$ is the PLSR prediction value, without the i th sample point. In practice normally, if $Q_h^2 \geq (1 - 0.95^2) = 0.0975$, continue extracting factors (repeat steps 2-6), otherwise stop.

2.1.2 The prediction step

Suppose the operation stops after h iterations, and then we obtain h principal components, $t_1,t_2,\ldots t_h$, so that f_0 can be expressed with them, written as;

$$f_0 = q_1 t_1 + q_2 t_2 + \cdots + q_h t_h \,.$$

Because the principal components are the linear combinations of the original descriptors, the factor model indirectly describes the effect of each descriptor on activity.

$$\begin{aligned} f_0 &= q_1 E_0 w_1 + q_2 E_1 w_2 + \cdots + q_h E_{h-1} w_h \\ &= q_1 E_0 w_1^* + q_2 E_0 w_2^* + \cdots + q_h E_0 w_h^* \end{aligned}$$

where $w_h^* = \prod_{j=1}^{h-1} (I - w_j p_j^T) w_h$, and I is the identity matrix with size $n*n$.

Finally, we have

$$\hat{y}^* = \alpha_1 x_1^* + \alpha_2 x_2^* + \cdots + \alpha_m x_m^* \,,$$

where $\alpha_j = \sum_{h=1}^{k} q_h w_{hj}^*$ is the coefficient of x_j^*, and w_{hj}^* is the j th element of w_h^*.

We perform the anti-operation of normalization, and we have

$$y = \bar{y} + s(y)(\sum_{i=1}^{m} \alpha_i x_i^*) = \bar{y} + s(y)(\sum_{i=1}^{m} \alpha_i \frac{x_i - \bar{x}_i}{s_i}) \,,$$

which is called the PLSR model. We can obtain the corresponding results, when we feed in a new vector of X.

2.2 GM (0, N) principle

Grey system theory was formulated by Deng [14]. According to this theory, a system, whose internal information, such as architecture, operation mechanism, system characteristics and parameters -are completely known is called a white system. In contrast, a system is defined as a black system if one cannot obtain any information and characteristics about the system. Grey space is thus defined as a system defined between the white and black systems. It seems that, the information and messages of the grey system are partially clear, but some are not. The grey model is generally described as GM (n, h), where n is the rank of differential equation, and h is the number of variables. For different n and h, a different grey model can be generated, for example GM (1, 1), GM (1, N) and GM (0, N) etc. In this paper, the GM (0, N) model is only considered.

The GM (0, N) model, which is similar to multiple linear regression in shape, has essential differences with it. The basis of multiple linear regressions is the original data serial, but GM (0, N) is one accumulation of the original data serial. The calculated steps are given as follows.

2.2.1 Data accumulation

Let $X_i^{(0)}=(x_i^{(0)}(1),x_i^{(0)}(2),\ldots, x_i^{(0)}(n)),(i=1,2,\ldots,h)$ be non-negative original data series. $X_i^{(1)}=(x_i^{(1)}(1),x_i^{(1)}(2),\ldots, x_i^{(1)}(n))$ is the one accumulation (1-AGO) to $X_i^{(0)}$ ($i=1,2,\ldots,h$), where $x_i^{(1)}(k)=\sum_{j=1}^{k} x_i^{(0)}(j)$, k=1,2,…$n$. Obviously, the new series $x_i^{(1)}$ ($i=1,2,\ldots,h$) are monotonous increasing. Compared with the original series $x_i^{(0)}$ ($i=1,2,\ldots,h$), the regularity of data is enhanced and the randomness is reduced.

2.2.2 Forecast equation

The GM (0, N) model reflects the influence of the other *h-1* variables on the change of the dependent variable. If $X_1^{(0)}$ is regarded as a dependent variable and $X_2^{(0)}, \cdots X_h^{(0)}$ are regarded as variables, the GM (0, N) model can be laid out as follows.

$$x_1^1(k) = b_2 x_2^{(1)}(k) + b_3 x_3^{(1)}(k) + \cdots + b_N x_N^{(1)}(k) + a \quad (3)$$

Let $\hat{a} = [b_2, \ldots, b_N, a]^T$ be the coefficient matrix, and its least square solution is;

$$\hat{a} = (B^T B)^{-1} B^T Y,$$

where

$$B = \begin{bmatrix} x_2^{(1)}(2) & x_3^{(1)}(2) & \cdots & x_N^{(1)}(2) & 1 \\ x_2^{(1)}(3) & x_3^{(1)}(3) & \cdots & x_N^{(1)}(3) & 1 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_2^{(1)}(n) & x_3^{(1)}(n) & \cdots & x_N^{(1)}(n) & 1 \end{bmatrix},$$

$$Y = \begin{bmatrix} x^0(2) \\ x^0(3) \\ \vdots \\ x^0(n) \end{bmatrix};$$

a is growing grey value of system; $b_2, b_3, \ldots, b_h$ is the internal controlling grey value; B is the accumulated generating matrix; and Y is the constant vector.

Subsequently, we plug $\hat{a}$ into Formula (3), in order to calculate the simulation value for $X_1^{(1)}$. By

$$\hat{x}^0(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1), k = (2,3,\cdots,n)$$

the simulation value for $X_1^{(1)}$ can be converted into the simulation value for $X_1^{(0)}$.

2.2.3 PLSRGM (0, N) principle

In GM (0, N), the parameter vector $\hat{a}$ is calculated by least square method. Since the data disposed by the GM(0, N) model is a small sample, poor information, and the number of variable N is bigger, there exists multiple correlation among the variables of Formula (3). And that least square method does not overcome the negative effects of multicollinearity, so the least square method cannot be used here. However, PLSR combines the basic functions of regressing model, principal components analysis and canonical correlation analysis, which is an effective tool to deal with the multicollinearity problem. Thus, we use the PLSR method instead of the least square method to calculate the coefficient matrix, and the PLSRGM (0, N) method is developed. The posterior check is adopted as a test of the reliability of the model. The test standards are given as follows.

Let $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n))$ and $\hat{X}^{(0)} = (\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \ldots, \hat{x}^{(0)}(n))$ be the original series and simulation series, respectively. And the residual series is $\varepsilon^{(0)} = (\varepsilon(1), \varepsilon(2), \ldots, \varepsilon(n)) = (x^{(0)}(1) - \hat{x}^{(0)}(1), x^{(0)}(2) - \hat{x}^{(0)}(2), \ldots, x^{(0)}(n) - \hat{x}^{(0)}(n))$.

Assuming that S_1 and S_2 are the standard deviations of the original series and residual series, the posterior check ration C, the probability of small error p and the average relative error ε, can be obtained by the following formulas:

$$C = \frac{S_1}{S_2}, \qquad p = P\left\{\left|\varepsilon(i) - \bar{\varepsilon}^{(0)}\right| \le 0.6745 S_1\right\},$$

$$\varepsilon = \frac{\sum_{i=1}^{n} \frac{\left|x_i^{(0)} - \bar{x}_i^{(0)}\right|}{x_k^{(0)}}}{n};$$

where $\bar{\varepsilon}^{(0)}$ is the average relative error.

Based on these values, the accuracy grade of the model can be assessed according to the criteria listed in Table 1. *G* (Grade) stands for the accuracy grade of the model. The smaller the *C* value is, the higher the accuracy grade of the model is. On the other hand, the higher the *p* value, the higher the accuracy grade of the model. The smaller the ε value is, the higher the accuracy grade of the model is.

Table 1. Assessing criteria for the accuracy grade of the model.

Grade	ε	C	p
1	< 0.01	< 0.35	> 0.95
2	< 0.05	< 0.50	> 0.80
3	< 0.10	< 0.65	> 0.70
4	< 0.20	< 0.80	> 0.60

In the following section, we will establish a TEDM-based on the above PLSRGM (0, N) method. In this paper, let *X* represent the socio-economic indicator matrix with size *n*m*, and *y* is the transport energy consumption vector.

3. TEDM Development

3.1 Data description

Data relating to the transport energy model from 1997 to 2006 has been collected from the China Statistical Yearbook [1], as shown in Table 2. Here $x_1, x_2, \ldots x_6$ and y represent GDP, population, urban per capital disposal, rural per capital net income, passenger-kilometers, freight ton-kilometers and transport energy consumption, respectively. The year 2005 is set as the base year.

Table 2. The related data of the transport energy model.

Year	x_1 (10^9Y)	x_2 (10^6P)	x_3 (Y)	x_4 (Y)	x_5 (10^9P-km)	x_5 (10^9P-km)	y (10^4tce)
1997	9246.9	1236.3	5388.2	2279.2	1005.6	3838.5	7543
1998	9971.3	1247.6	5699.1	2377.2	1063.7	3808.9	8245
1999	10732.3	1257.9	6229.5	2467.9	1129.9	4056.8	9340
2000	11635.7	1267.4	6628.5	2519.5	1226.1	4432.1	10067
2001	12601.9	1276.3	7191.7	2625.3	1315.5	4771.1	10363
2002	13747.2	1284.5	8155.7	2751.4	1412.6	5068.6	11171
2003	15125.3	1292.3	8889.9	2869.7	1381.1	5385.9	12819
2004	16650.4	1299.9	9573.9	3064.7	1630.9	6944.5	15104
2005	18386.8	1307.6	10493.1	3254.9	1746.7	8025.8	16629
2006	20426.3	1314.5	11586.5	3495.7	1919.7	8895.2	18583

Y denotes yuan, P denotes person.

For convenience, we also use $x_1,x_2,\ldots x_6$ and y to denote the one accumulation series of all related variables.

3.2 Multiple correlation diagnosis

We can obtain the following results regarding correlation coefficients on independent variables and dependent variables, which are shown in Table 3. Let $X=[x_1,x_2,\ldots x_6]$.

From Table 3, we can see that there are a number of multiple correlations between X and y, which is in accordance with the results computed by variance inflation factors. Thus a transport energy demand model based on PLSRGM (0, N) has been developed.

Table 3. The correlation coefficients between X and y.

	x_1	x_2	x_3	x_4	x_5	x_6	y
x_1	1.000	0.994	0.999	0.998	0.999	0.999	0.999
x_2		1.000	0.994	0.998	0.996	0.990	0.992
x_3			1.000	0.998	0.999	0.999	0.999
x_4				1.000	0.999	0.996	0.997
x_5					1.000	0.998	0.999
x_6						1.000	0.999
y							1.000

3.3 TEDM

First, the variables ($x_1,x_2,\ldots x_6$) and the dependent variable (y) are disposed in standardization. Next we use the PLSR approach to develop the model. Through the cross-validation analysis, shown in Table 4, two main components will be able to better explain the changes in the dependent variable.

Table 4. The value of cross-validation.

Q_1^2	Q_2^2	Q_3^2
0.999	0.942	-1.611

The form of the PLSRGM (0, N) is

$$y = 0.221x_1 - 1.284x_2 + 0.363x_3 + 0.332x_4 + 1.461x_5 + 0.861x_6 - 188.595 \quad (4)$$

The result of posterior checks of the PLSRGM (0, N) model is shown in Table 5.

Table 5. The result of posterior checks.

	ε	C	p
	0.0221	0.0064	0.999
Grade	2	1	1

The result indicates that PLSRGM (0, N) method is more reliable. Because of China's large population base and effective implementation of family planning policy, population growth rate is far lower than other factors'. Therefore, the coefficient of x_2 (-1.284) is negative in the model. At the same time it also shows that transport energy consumption per capita is lower than others. The coefficients of x_5, x_6 are 1.461, 0.861, respectively, which truly score the influenced weights on y. These are consistent with the facts of actual situations. Thus, the model can be used to predict the future transport energy demand.

4. Forecasting Transport Energy Demand

In order to make the future projections for the transport energy demand by PLSRGM (0, N), all parameters need to be estimated first for each year. Then the demand can be obtained. In this paper, we aim directly at two scenarios, to predict transport energy demand until 2030.

4.1 Scenarios

4.1.1 Economic development and population

So far, some institutions and scholars [2,5,15] have predicted China's economic growth. In this paper, we will use the economic growth rate given by the State Council Development Research Center, which identifies two types of economic development as shown in Table 6.

Regarding future population, this paper utilizes the forecasts of the Chinese Population Information Research Center [16], as shown in Table 6.

4.1.2 Urban per capita disposal and rural per capita net income

Yong and Li [17] have studied the correlations between economic growth and urban per capita disposal (UPCD), rural per capita net income (RPCNI), respectively, and then established an econometric model. In this paper, the following formulas are used to predict the future urban per capita disposal and rural per capita net income.

UPCD =a×GDP+b

RPCNI =c×GDP+d

Here, a,b,c,d are regression coefficient. See the results in Table 7.

4.1.3 Transport demand

According to the results of the World Bank [5] and other agencies, transport demand and GDP have the following correlation:

passenger-kilometers(PK)= =a×GDP+b

freight ton-kilometers (FTK)=c×GDP+d

Here, a,b,c,d are regression coefficient. See the results in Table 8.

4.2 Forecast results and policy recommendations

The forecast results of the transport energy demand under two scenarios until 2030 are shown in Figure 1. In 2030, total transport energy demand will reach a level of about 87008.47×10^4 tce for scenario 1, and about 101991.48×10^4 tce for scenario 2. The two scenarios show that the transport energy demand in 2030 will be 4.68-5.49 times that of in 2006. If there are no control measures imposed on the use of vehicles, we cannot attain sustainable transport.

Along with China's sustained economic growth and the improvement in living standards, China's future transport energy demand will increase rapidly. So its proportion of energy consumption will rise. Therefore, this will affect the entire national energy supply, and need and environmental protection. In order to control excessive growth of transport energy demand, the state should draw up relevant policies and take effective measures. In our opinion, the following policy recommendations are necessary by virtue of the above analysis on the forecast results.

(1) Optimizing transport structure and accelerating the promotion of new energy-saving technology.

(2) Carrying out the construction of public transportation infrastructure.

(3) Optimizing energy structures from the development of strategic perspective to accelerate the construction of oil and gas network and reduce the total transport demand.

(4) Road transport is the largest consumer of transport energy consumption. It is as imperative soon as possible to draw up the suitable requirements for the strategy of sustainable development of energy efficiency standards for motor vehicles, in order to reduce energy consumption from the source.

Table 6. The future scenarios of population and GDP.

Contents		2006*	2010	2015	2020	2025	2030
Population(10^8)		13.15	13.77	14.31	14.72	15.04	15.25
GDP growth rate(%)	Scenario 1	11.1	8.1	7.5	6.8	5.4	4.5
	Scenario 2	11.1	8.5	8.2	7.7	6.2	5.1

* Statically values.

Table 7. The future scenarios of UPCD and RPCNI.

Contents		2006*	2010	2015	2020	2025	2030
UPCD(yuan)	Scenario1	11586.5	15906.6	22762.9	31563.5	41006.7	51060.5
	Scenario2	11586.5	16140.8	23855.6	34492.2	46536.6	59629.8
RPCNI(yuan)	Scenario1	3495.69	4265.7	5559.6	7220.4	9002.4	10899.7
	Scenario2	3495.69	4309.9	5765.7	7773.1	10045.9	12516.8

Table 8. The future scenarios of transport demand.

Contents		2006*	2010	2015	2020	2025	2030
PK(10^9p-km)	Scenario 1	1919.7	2507.3	3480.1	4728.8	6068.7	7495.1
	Scenario 2	1919.7	2540.5	3635.1	5144.3	6853.2	8711.1
FTK(10^9t-km)	Scenario 1	8895.2	12192.1	17963.5	25371.5	33320.5	41783.5
	Scenario 2	8895.2	12389.3	18883.2	27836.8	37975.4	48996.9

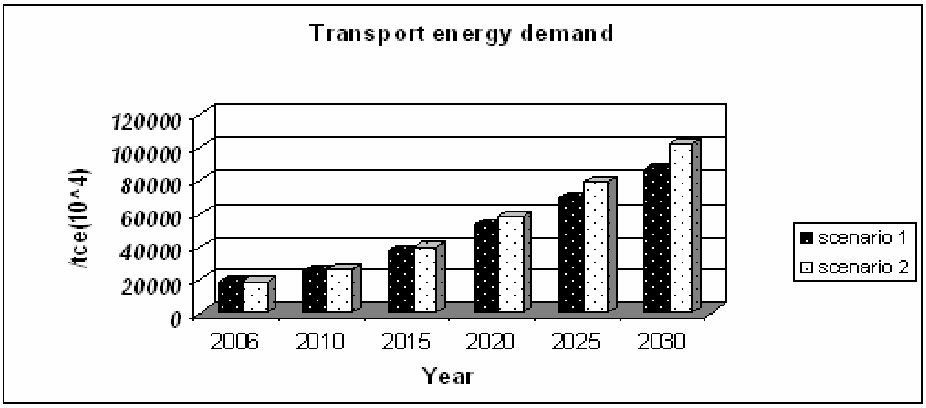

Figure 1. Forecast results of transport energy demand based on two scenarios.

5. Conclusion

In this paper, a new PLSRGM (0, N) method has been developed by integrating the PLSR method and GM (0, N). The analysis using socio-economic data from 1997 to 2006 adequately confirms the validity of our model, which shows that the precision accuracies of forecast models are higher. Moreover, we use this model to forecast the transport energy demand until 2030. If there are no valid measures imposed on the use of vehicle to attain the sustainable transport, the future transport energy demand in 2030 will be 4.68-5.49 times in 2006. As a developing country, we need a robust planning and /or approaches to utilize energy sources for the future. The projections may help planners to plan their future energy needs.

This study provides an effective tool, which can be used as an alternative solution and estimation techniques for the transport energy demand. Furthermore, future studies should take into account the various parameters in order to estimate the transport energy demand, such as energy price, environmental effects and technological developments, etc.

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