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Prediction of Transport Energy Demand Using Statistical Modelling

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ABSTRACT

The paper illustrates a statistical modelling approach based on gross domestic product (GDP), population, and the total number of cars along with historical energy data available from 1976 to 1999 for the transport energy demand forecasting using socio-economic and transport related indicators. . The percentage error range between the actual and predicted energy demand based on statistical modelling were -1.4 to +5.4. The prediction results obtained bear out the suitability of the adopted methodology for the transport energy-forecasting problem.
KEY WORDS: Transport energy demand; statistical modelling; GDP

1. INTRODUCTION

Energy demand has rapidly been increasing because of developments in the industrial, agricultural, and transportation. The population rise and improved life style are other reasons for the increase in energy demand. The fast growth on the GDP leads to increase a number of cars owners and hence to increase in energy demand in transportation sector.

Various methods regarding modelling and predicting energy demands have evolved [1-15]. Wohlgemuth [1] estimated and examined the transport energy and factors affecting it based on the International Energy Agency (IEA). The IEA also analyzed the price elasticity between income and transportation demand for the OECD and non- OECD countries.

Ediger and Tatlidil [2] illustrated the total energy demand in Turkey. They found that the additional amount of energy consumption per year gives much better results for energy demand performance analysis than the total amounts and the rates. This is mainly because the additional amounts reflect the capability to consume and to meet it by production or import. They applied several statistical methods to such historical curves to estimate the future by examining the past, the simplest on being the best fit curves obtained by regression analysis.

The UK energy demand was also investigated by Hunt et al. [3] using Timeseries (TS) approach. The STSM was used to estimate energy consumption considering the change of seasons. The analysis emphasized the empirical relevance of evolving trends and seasonal for energy demand. There were clear signs that the nature of the trend was typically not linear and deterministic but stochastic in form, with its pace and even direction altering over time. The results also pointed to the risks of obtaining biased price and income elasticities if inappropriately constrained model formulations are used.

The trends of the energy demand and corresponding socio-economic and transport indicators are not linear and deterministic in nature but are stochastic in form which alters over time. Using the genetic algorithm, approach Ceylan and Ozturk and Haldenbilen and Ceylan [4, 5] were able to estimate the energy demands of turkey. The SSE between the estimated values and observed values were minimized in the modelling process. The results show considerable energy savings were obtained when the demand was controlled on transportation sector when compared with MENR findings [6].

Duangjai Intarapravich et al. [7] had developed the Asia-Pacific energy supply and demand model to 2010 for high, low and base cases that take into account variations in economic performance, prices and fuel substitution in individual nations and in the region as a whole. Michalik et al. [8] had formulated the structural models to predict the energy demand in the residential sector. Bala [9] had presented projections of rural energy supply and demand and assess the contributions to global warming. The output of the dynamic system model had been used in the LEAP model and overall energy balances are compiled using a bottom–up approach.

Iran expects a very large growth in energy demand in the future as its economy expands, especially for petrol in transportation sector. The main objective of this paper is to present a statistical approach for the transport energy prediction using a multiple regression based on population, GDP and number of cars in Iran.

2. PROCESS MODELING

In this study, regression method was used to determine the relationship between input and output variables. Because the form of the relationship between the response and the independent variables is often unknown, the first step is to find a suitable approximation to the true functional relationship between the response ‘y’ and a set

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of independent variables {x1, x2 … xn}[17]. A multiple regression model is employed when the response function is unknown:

$$\mathrm{Y} = \beta_0 + \sum_{i=1}^{k} \beta_i \mathrm{X}_i + \cdots + e \tag{1}$$

Where i enumerates the linear coefficients, β represents the regression coefficients, k is the number of experimental factors, and e is the random error [18].

In this study, the Transport energy demand is the response, while the population, GDP and number of cars are the independent variables.

3. RESULTS AND DISCUSSION

The results and discussion are categorized into two segments: the modelling results and the prediction of results.

3.1 Modelling results

Data related with transport energy modelling is collected from different sources. The transport energy demand, GDP, and population are collected from the Ministry of Energy (Iran). The numbers of cars is collected from the Ministry of Industries and Mines (Iran). Data is given in Table 1.

Table 1: The GDP, population, cars, and energy demand from 1976 to 1999

Years	Energy demand (10^6 barrels of oil equivalent)	GDP (10^9 IRR)	Population (10^3)	Number of cars
1976	57.2	242326	33709	635003
1977	57.5	236645	35025	819104
1978	58.3	219191	36393	2036756
1979	54.1	209919	37814	2123493
1980	53.6	178149	39291	2211019
1981	55.4	170281	40826	2313433
1982	58.7	191667	42420	2401071
1983	72.3	212877	44077	2558797
1984	104.0	245036	55837	3011331
1985	109.5	254823	56963	3115405
1986	122.1	258601	58114	3177836
1987	144.6	259876	59290	3239692
1988	141.9	267534	59151	3326451
1989	147.9	283807	60056	3438418
1990	153.2	291769	61070	3598860
1991	161.2	300140	62103	3789752
1992	170.3	304941	63152	4015888
1993	183.4	320069	64219	4298243
1994	194.4	330565	65301	4661605
1995	208.9	355554	66300	5175401
1996	220.9	379838	67315	5898617
1997	234.0	398234	68345	6759831
1998	254.3	420928	69390	7724445
1999	270.4	446880	70496	8819366

In this study, a regression method was exploited in order to find out the relationship between The GDP, population (Pop), number of cars (No), and transport energy demand (E). Statistical model based on nonlinear polynomial equation were developed for transport energy demand (E) using MINITAB software. The model is used for prediction of results. Equation (2) is the final empirical model.

$$\mathrm{E} = -159 + 0.000001\ \mathrm{No} + 0.00228\ \mathrm{Pop} + 0.000587\ \mathrm{GDP} \tag{2}$$

The summary of model is given in Table 2. The value of R^2 for transport energy demand is 98.8% which means that the regression model provides a perfect description of the relationship between the GDP, population (Pop), number of cars (No) and the transport energy demand (E).

Table 2: Summary of model

R-Sq	R-Sq(adj)
98.8%	98.6%

Figure 1 shows normal probability plots for residual against the predicted response for transport energy demand. It is found from Figure 1 the residual generally fall on straight line and it indicates the errors are normally distributed. Therefore, the proposed model is acceptable.

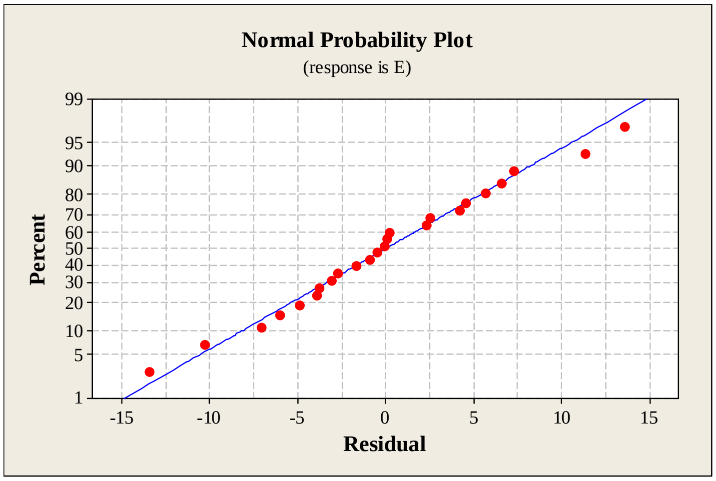

Figure1 Normal Plot of Residuals for transport energy demand

Table.3 shows that final empirical model is valid. Performance of predicted energy demand was compared with the actual one for 5 different years and a good agreement was made. Since the amount of errors was proved to be negligible, so this model can be selected for prediction of energy demand in future.

Table 3: Results of Confirmation Test

Years	GDP (10^9 IRR)	Population (10^3)	Number of cars	Actual energy demand (10^6 barrels of oil equivalent)	Predicted energy demand (10^6 barrels of oil equivalent)	Error (%)
1977	236645	35025	819104	57.5	60.59	+5.4
1986	258601	58114	3177836	122.1	128.48	+5.2
1990	291769	61070	3598860	153.2	155.11	+1.2
1995	355554	66300	5175401	208.9	206.05	-1.4
1999	446880	70496	8819366	270.4	272.87	+0.9

3.2 predictions of results

In this study, using trend analysis is projected the GDP, population (Pop), and number of cars (No) for future transport energy demand predictions during the years 2013 to 2020.
The estimation of GDP, population (Pop), and number of cars (No) is given in Figures. 2, 3, 4, respectively.

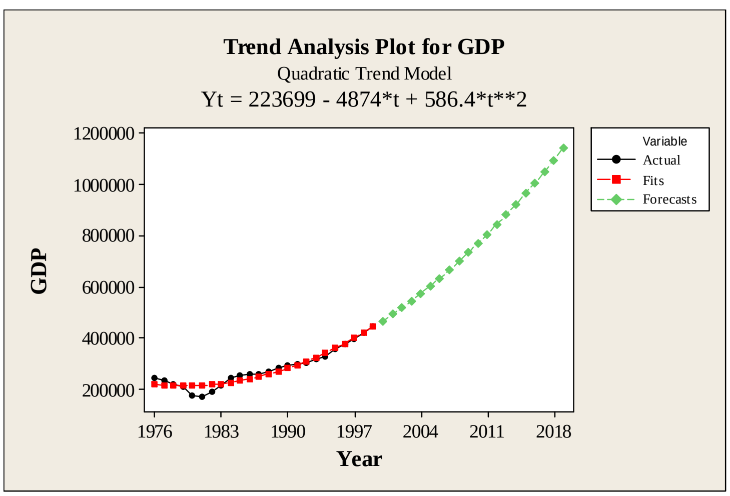

Figure 2 Estimated GDP.

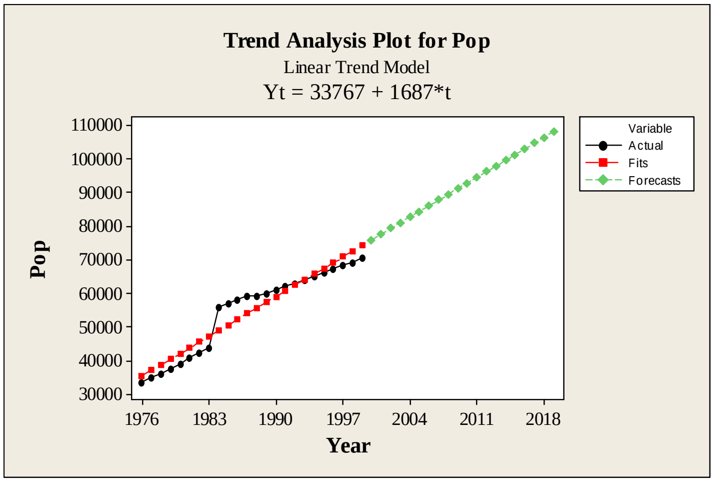

Figure 3 Estimated population (Pop).

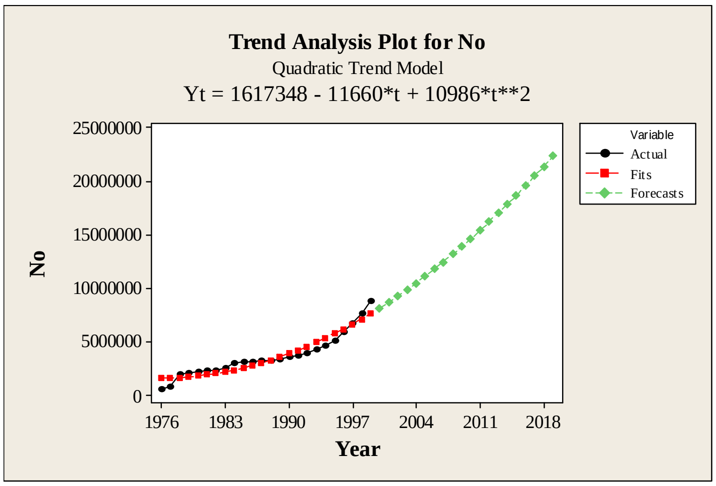

Figure 4 Estimated numbers of cars (No).

Using the final empirical model for transport energy demand (Eq.2) and the estimation of GDP, population (Pop), and number of cars (No) is predicted future transport energy demand during the years 2013 to 2019. Table 4 shows the forecasted transport energy demand.

Table 4: Forecasted transport energy demand

+	Energy demand (10^6 barrels of oil equivalent)
2013	600.8
2014	629.1
2015	658.2
2016	687.9
2017	718.4
2018	749.5
2019	781.4
2020	814

4. Conclusions

This study seeks to a way of possible application of the statistical modelling to forecast transport energy demand for next 8 years. Transport energy demand is modelled for the period of 1976–1999 based on population, GDP and number of cars as independent variables. The following conclusions can be drawn from this study.

1. It is proved that the statistical modelling applied in this research is an effective tool for prediction of transport energy demand.
2. The population, GDP and number of cars as independent variables are important parameters which influence transport energy demand significantly.

3. The quadratic model developed using statistical modelling is suitable for prediction with the limits of factors studied.
4. The summary of model certifies that the developed mathematical model is accurate and there is a close agreement between predicted values and actual values.
5. Future studies therefore should take account the various parameters, such as import, export and technological developments, etc., to estimate the energy demand.

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