THE MALAYSIAN GOVERNMENT'S ROAD ACCIDENT DEATH REDUCTION TARGET FOR YEAR 2010

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Objective: This paper makes a projection of the vehicle ownership rate to the year 2010 and to use this projection to predict road accident deaths in year 2010. The projection served as an indicator for the Malaysian government to achieve a 4 road accident deaths per 10,000 vehicles safety target in year 2010.

Method: The study included the prediction of vehicle ownership and the analysis of past trends in the road accident death rate. Gompertz growth model was used to project vehicle ownership and the prediction of road accident death rate was done using Autoregressive Integrated Moving Average (ARIMA) model with transfer noise function.

Results and Conclusions: The Gompertz model predicted that vehicle ownership would be equal to 0.4409 by the year 2010. The road accident death rate is projected to decrease to 4.22 in year 2010, at an average decline rate of 2.14% per annum. This result suggests that a minimum 2.18% reduction per annum is required to achieve the national target in year 2010.

Key Words: Road safety target, Autoregressive Integrated Moving Average (ARIMA), Gompertz growth model, Vehicle ownership rate, Transfer noise function

1. INTRODUCTION

In the year 1996, the Malaysian government established a 5-year national road safety target to reduce road accident deaths by 30% by the year 2000[1]. During the 5-year period, several road safety initiatives from national to community levels were initiated. A series of intervention programs on strategic issues, such as lack of conspicuity and protection, speeding, bad driving behavior and unsafe road conditions, were proposed. An integrated safety program was introduced to both prevent and reduce future traffic accidents, as well as to reduce injuries during and after accidents. Strategies were categorized into: (a) accident prevention and reduction, (b) injury control and (c) post injury reduction. Targeted televised motorcycle safety campaigns, more stringent traffic legislation, national accident blackspot programs, road safety auditing, construction of new motorcycle lanes and better protection for motorcyclists were among the integral components of this comprehensive approach.

By 2001, the concerted efforts resulted an 11%, 10.7% and 29% decrease in the number of deaths, serious and slight injuries, respectively, in spite of a dramatic increase in vehicle ownership in the same period[2]. The road accident death rate dropped from 6.2 deaths per 10,000 vehicles in year 1999 to 5.6 deaths per 10,000 vehicles in year 2001. However the nation's safety performance is still far behind world-class standard, which is below 3 deaths per 10,000 vehicles. Hence, in year 2001, the Malaysian government adopted a new national road safety target of 4 road accident deaths per 10,000 vehicles by year 2010.

This paper makes a projection of the vehicle ownership rate to the year 2010 and to use this projection to predict the road accident death in 2010. This was undertaken using an Autoregressive Integrated Moving Average (ARIMA) model with transfer noise function, developed to project road accident deaths in year 2010. The projection takes into account changes in population and the vehicle ownership rate. The relationship between death rate and population, vehicle ownership rate, are described utilizing transfer noise function in ARIMA analysis. Prior to road accident death rate projection, the prediction of vehicle ownership rate using the Gompertz growth model was done separately. The projection may be served as an indicator for the Malaysian Government to achieve the 4 road accident deaths per 10,000 vehicles safety target in year 2010.

2. QUANTIFIED ROAD SAFETY TARGETS: OTHER COUNTRIES' EXPERIENCE

Of all modes of transport, transport by road is the most dangerous and most costly in terms of human lives. Although extensive efforts has been made in many countries in reducing both risk and the absolute number of accidents, the present number of accidents is still far too high in most countries. Improved road safety is achievable if suitable safety targets in respect to time frame, as well as ambitiousness are adopted[3]. This is supported by Elvik[4], who pointed that the best performance in road safety was achieved by countries with highly ambitious quantified targets.

The European Union countries with the best road safety records, such as Sweden, the United Kingdom and the Netherlands, were the first to set quantified targets to reduce the number of victims to derive maximum benefit from potential improvements in road safety from increased knowledge, accumulated experience and technical progress. It is broadly accepted that targeted road safety programs are more beneficial in terms of effectiveness of action, the rational use of public resources and reductions in the number of people killed and injured than non-targeted programs.

In 1997, Sweden adopted an ambitious road safety program to aim to achieve zero deaths and serious injuries on the road for the country as a whole. The program addresses all areas in which local authorities and companies have a leading role to play. Systematic improvements to the road network have been undertaken to reduce the severity of accidents, and incentives have been provided in conjunction with the private sector, to reduce the demand for road transport and thus the exposure of road users to risk.

Australia has adopted a national target to achieve a 40% reduction in the number of fatalities per 100,000 population, from 9.3 in 1999 to no more than 5.6 in 2010. A series of two-year Action Plans was developed to monitor the road safety program and a review with recommendations for a new Action Plan is required. This target provides a framework for coordinating the road safety initiatives of the federal, state, territory and local governments and of others capable of influencing road safety outcomes.

3. THE VEHICLE OWNERSHIP MODEL

Growth in vehicle ownership is often seen as an inevitable outcome of increasing per-capita Gross Domestic Product (GDP)[5]. In this study the Gompertz growth model, proposed by Dargay and Gately[6] is used to describe the growth of vehicle ownership as a function of per-capita GDP. The main advantage of this equation is that its asymmetric sigmoidal nature can fit a vehicle growth curve well. It was proven to be highly effective in generating the growth curve and for relating the impact of variables on different vehicle ownership growth phases. Of particular significance is that the Gompertz growth function allows a slow vehicle ownership growth in the lowest per-capita GDP level, followed by an increasing rate of growth as per-capita GDP rises, and finally reaches a saturating level. The vehicle ownership model is expressed by:

$$V_t = \theta(\gamma \exp(\alpha \exp(\beta GDP))) + (1-\theta)V_{t-1} \qquad (1)$$

where V_t is the rate of vehicle ownership at time t, θ is the adjustment of vehicle ownership and per-capita GDP growth ($0<\theta<1$), and γ is the asymptotic vehicle ownership as t increases indefinitely. Parameters α and β are curvature parameters. Analogously, the parameter α determines the value of Gompertz growth function at per-capita GDP is equal to zero and the parameter β plays a role in determining the per-capita GDP value at vehicle ownership saturation level. The smaller the value of β, the greater the per-capita GDP at saturation level.

Long-run elasticity of the vehicle per population ratio with respect to per-capita GDP varies with economic performance. Long-run per-capita GDP elasticity is presented as,

$$\tau^{LR} = \alpha\beta.GDP.e^{\beta.GDP} \qquad (2)$$

Fitting of data for the Gompertz growth model was performed by the Marquardt-Lebenberg algorithm[7]. The algorithm calculates the regression coefficient α, β, γ and θ. The goodness of fit was checked by the estimation of the regression coefficient, coefficient of determinant (R-Square) and the associated *p*-values for the model parameters.

4. ROAD ACCIDENT DEATH RATE PROJECTION MODEL

Many statistical methods are available to explain accident-related variables, such as log-linear model, generalized linear model and multiple-linear model. Data observed over time usually have strong correlations among neighboring observations. Therefore the ordinary methods are not appropriate for this analysis because these methods assume that the observations over time are independent[8].

In light of the problem associated with ordinary methods, several researchers have turned to the ARIMA model as a means to better predict accident variables. The ARIMA model is a useful statistical method for analyzing longitudinal data with a correlation a1mong neighboring observations. This method has proven to be very useful in the analysis of multivariate time series[9-11].

In ARIMA analysis, there are two simple components for representing the behavior of observed time series processes, namely the autoregressive (AR) and moving average (MA) models. The AR model is used to describe a time series in which the current observation depends on its preceding values, whereas the moving average (MA) model is used to describe a time series process as a linear function of current and previous random errors. It is possible that a time series model will consist of a mixture of AR and MA components. In this case the series are said to be computed by an autoregressive moving average process of order (p,q), where p and q are the orders of the AR and MA components, respectively. The selection strategy for such models was developed and selected by the Box and Jenkins method[12]. A general ARIMA model can be written as:

$$B^d N_t = \frac{\theta(B)a_t}{\phi\ (B)} \quad (3)$$

where a_t is assumed to have white noise, B is the backshift operator, N represents stochastic part, d is the order of regular differencing needed to achieve time series stationarity, and other parameters in the model are defined as follows:

$$\theta_q(B) = 1 - \theta_1 - \theta_2 B^2 - ... - \theta_q B^q \quad (4)$$

$$\phi_P(B) = 1 - \phi_1 - \phi_2 B^2 - ... - \phi_P B^P \quad (5)$$

where $\phi_1 \ldots \phi_p$ are autoregressive (AR) parameters, $\theta_1 \ldots \theta_q$ are moving average (MA) parameters.

ARIMA model development consists of a three-stage iterative process, which consists of identification, model parameters estimation, and diagnostic checking of the residuals of the fitted model[13]. In the process of identification, the first step is to determine whether the time series is stationary or not stationary. If the series indicates nonstationarity, the time series is first converted to a stationary series by appropriate transformative and differencing operations. TheDickey and Fuller test[14] was used to examine the time series data staionarity. The Augmented Dickey-Fuller regression is given as follows:

$$y_t = \alpha + \rho y_{t-1} + \beta t + \sum_{i=1}^{k} \phi_i \Delta y_{t-i} + \varepsilon_t \quad (6)$$

where t is a time trend, y_t represents the road accident death rate, $\Delta\ y_{t-i}$ is the lagged change in road accident death rate, and ε_t is a white noise error term. Null hypothesis $\rho=0$ versus alternative hypothesis $\rho<0$ was tested. Failure to reject the null hypothesis is evidence that the series y_t is non-stationary.

At the identification stage, the appropriate AR and MA parameters are found by examining autocorrelation function (ACF) and partial autocorrelation function (PACF) of the time series. Autocorrelation and partial autocorrelation analyses were conducted on the stationary time series. Autocorrelation measures the unconditional relationship of values between time lags, while partial autocorrelation measures the conditional relationship between series observations. Based on the characteristics of ACF and PACF, a variety of possible ARIMA models was established for the road accident death rate in the first stage, and then estimated in the second stage.

In contrast to the ARIMA model, which describe the behavior of single time series, ARIMA model with transfer noise function model can represent more complex systems which are able to connect one series not only with its own past values, but also with past and present values of other, related time series. In this study, ARIMA with transfer noise function was used to assess the effect of vehicle ownership and population on altering the trend of the road accident death rate (per 10,000 vehicles). The general form of the transfer function ARIMA model comprises a part relating to the transfer function and a part relating to the error terms, is defined as:

$$Y_t = v_1(B)x_{1t} + v_2(B)x_{2t} + N_t \quad (7)$$

where Y_t is the road accident death rate, x_{it} is the explanatory variable (x_{1t} represents population number; x_{2t} represents vehicle ownership) and N_t is the stochastic component assumed to follow a general ARIMA structure. In equation (7), $v_i(B)$ is the transfer noise function determining the nature of the influence of the backward shift operator. Specifically $v_i(B)$ can be expressed as:

$$v_i(B) = [\omega(B)/\delta(B)]B^b \tag{8}$$

where the numerator can be expanded to $\omega(B) = (\omega_0 - \omega_1 B - \ldots - \omega_s B^s)$, the denominator can be expanded to $\delta(B) = (1 - \delta_1 B - \ldots - \delta_r B^r)$, "s", "r" and b represent the orders of the polynomials and the degree of seasonality, respectively. Combining equation (3) and (7) yields:

$$Y_t = \frac{\omega_1(B)B^b}{\delta_1(B)}x_{1t} + \frac{\omega_2(B)B^b}{\delta_2(B)}x_{2t} + \frac{\theta(B)}{\phi(B)}a_t \tag{9}$$

The identification of a transfer function ARIMA model was accomplished by calculating the sample cross correlation function ($r_{xy}(k)$) at various lags, k, and then comparing it to theoretical impulse response functions of different orders in order to obtain some idea of the delay parameter b and the orders r and s of the operators in the transfer noise function between an output and an input series. In the modeling effort presented in this paper, the model error term was estimated using the least square estimation method[15], in which the least square function is calculated via non-linear least-squares iterations.

Diagnostic check is needed to determine the best model among the tentative 'adequate' models. A number of criteria for model comparisons have been proposed. The diagnostic tools used include the statistical significance of the parameters, the Box-Ljung (Q) statistic and the Akaike information criterion (AIC). The best model should have the lowest AIC value, a statistically insignificant Q statistic at a lag of about one-quarter of the sample size. After carrying out the complete identification, estimation and diagnostic iterative scheme of Box-Jenkins, the final ARIMA model can be used for predictions of the future road accident death rate (per 10,000 vehicles).

5. DATA

Registered vehicle number data from 1976 to 2001 were taken from the Malaysia Traffic Police annual statistics[2] while the per-capita Gross Domestic Product (GDP) and population data were obtained from the Central Bank of Malaysia.

Per-capita GDP and population projection figures were obtained from Malaysia Third Outline Perspective Plan 2001–2010[16]. Per-capital GDP and population were expected to grow at 2.3% and 7.5% per annum between 2000–2010, respectively.

6. RESULTS AND DISCUSSIONS

6.1 Projections of vehicle ownership

Projection of vehicle ownership rate was made on the basis of the Gompertz growth model of vehicle ownership described above and assumptions concerning population and per-capita GDP growth. Fitted parameters for all the growth models are shown in Table 1.

Table 1 Estimated parameters of vehicle ownership model

Parameter	Parameter Definition	Coefficient
θ	Speed of adjustment	0.2671
γ	Saturation level	0.9621
β	Shape or curvature of the function	90.8862
α	Shape or curvature of the function	2.2921
R-square		0.9612

(Significant level, $p<0.05$)

The estimated Gompertz growth model for vehicle ownership was significant at a significance level of 0.05. The Gompertz growth model yielded the best fit to data, as shown by the high R^2 value (0.9612). Based on the Gompertz growth equation, the adjustment parameter, θ, is estimated to be 0.267, indicating that 26.7% of the total response could be attributed to per-capita GDP changes in that particular year. The estimated saturation level is 0.96 vehicles per population and vehicle ownership saturation occurs when per-capita GDP reaches 0.066 million annually (Figure 1).

Value β determines the maximum per-capita GDP elasticity level. The smaller the β, the greater the per-capita GDP required to reach saturation level. In this analysis β is equal to 90.8862 and maximum per-capita GDP elasticity is estimated to occur when per-capita GDP is 0.014 million (Figure 2).

The GDP is assumed to increase by 2.2% per year for the entire forecast period[16]. The resulting projections yield an estimate of 0.4409 vehicles per capital in year 2010 (Table 2). The estimated relationship between vehicle ownership and per-capita GDP is illustrated in Figure 3.

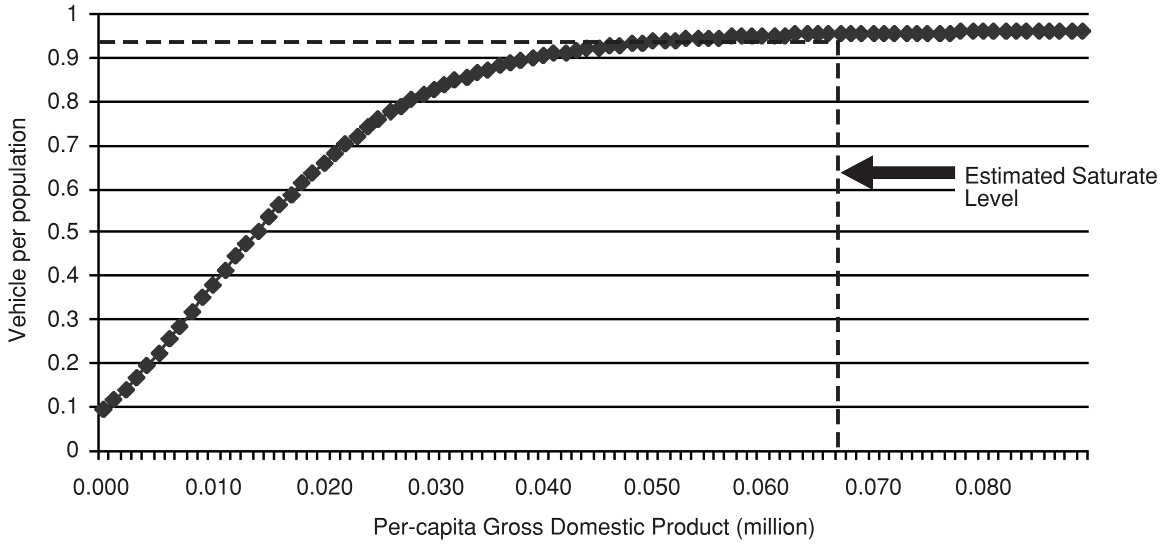

Fig.1 Estimated vehicle ownership function

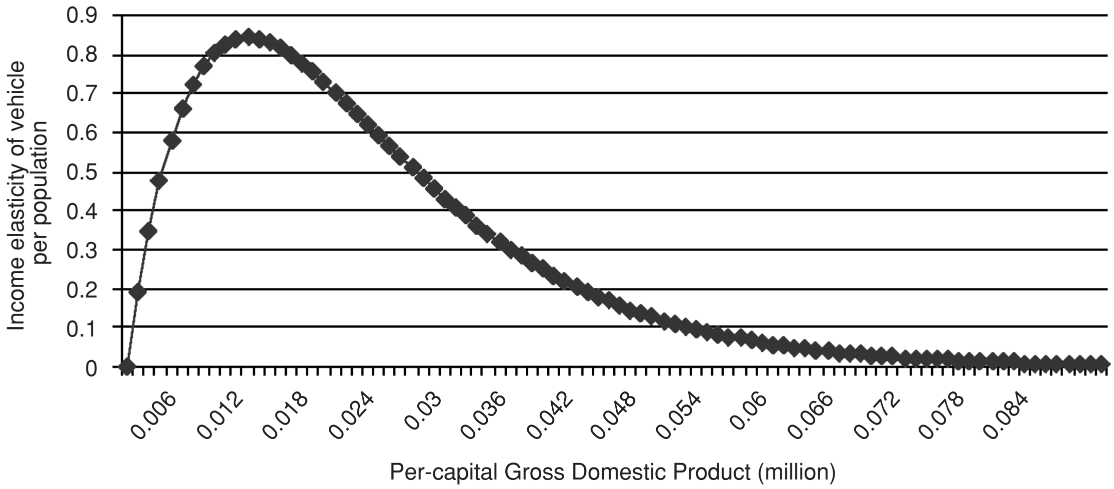

Fig. 2 Estimated per-capita Gross Domestic Product elasticity for vehicle ownership

Table 2 Projection of vehicle ownership, 2001–2010

Projection Year	Per-capita GDP	Vehicle per population
2001	0.0157	0.4603
2002	0.0149	0.4856
2003	0.0142	0.4985
2004	0.0135	0.5023
2005	0.0129	0.4998
2006	0.0122	0.4926
2007	0.0117	0.4822
2008	0.0111	0.4696
2009	0.0105	0.4556
2010	0.0100	0.4409

6.2 Projection of road accident death per 10,000 vehicles

The results of the Augmented Dickey Fuller (ADF) stationarity test are summarized in Table 3. The ADF test statistic is compared with the critical values from the Dickey-Fuller distribution with a trend at the 5% significance level. Since the absolute value of ADF statistics for road accident deaths series are more than the critical value of 2.86. Thus, the null hypothesis of the ADF test is rejected. This result reveals that the road accident death series is stationary.

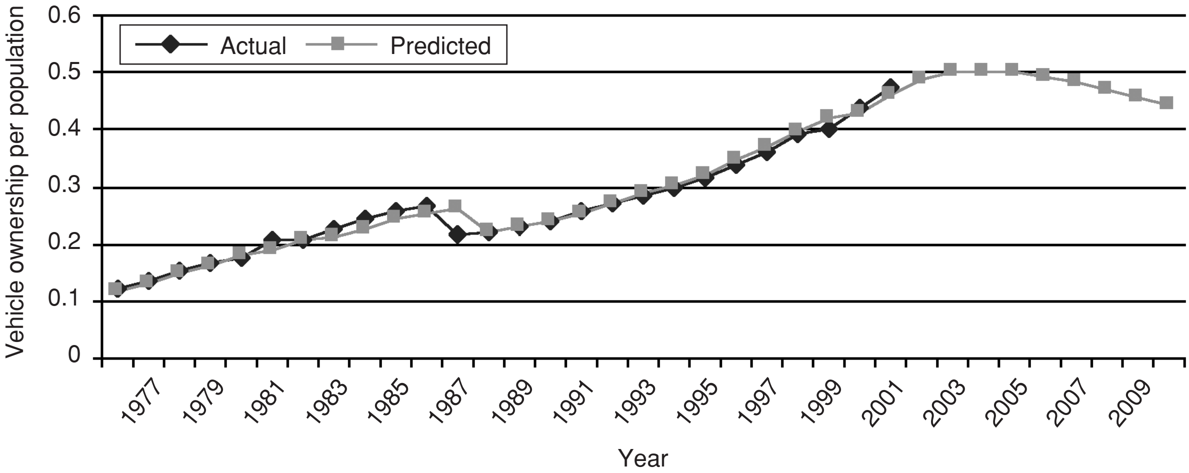

Fig. 3 Vehicle ownership estimation and projection, 1976–2010

Table 3 Result of Augmented Dickey Fuller (ADF) test for road accident death rate

Variable	ADF statistic	5% Critical value
Road accident death	−4.123	−2.86

From the plots in Figure 4, the autocorrelation function appears to be dying down exponentially, while the partial autocorrelation function cuts off to zero after lag 1, thus suggesting a Moving Average MA(1) model.

The cross-correlation plot between input and output series shows a positive correlation at lag 0 (Figures 5 and 6). This result implies that the road accident death rate increases with the growth in population and vehicle ownership. Based on the above autocorrelation and partial autocorrelation functions observation, the ARIMA model with transfer noise function is established as follows:

$$Y_t = 3.0332 + 2.0694\times10^{-8} X_{1t} + 1.8825 X_{2t} + \frac{N_t}{(1-0.4288B)} \quad (10)$$

A diagnostic check was performed using Q-statistic, which tests for the non-randomness of the residual autocorrelations. The model had insignificant Q-statistics at the 10% level, implying that the residual autocorrelations are independent. Hence, it may be inferred that the residual autocorrelations are not significantly different from zero. The Box-Ljung analysis implies that the model is adequate. This is further enhanced by the lowest AIC value and the model parameters are significant at 10% significant level (Table 4).

The road accident death rate is projected to decrease to 4.22 in 2010, at an average decline rate of 2.14% per annum (Figure 7). This result suggests that to achieve a new national target of 4 deaths per 10,000 vehicles, the decline rate has to be 2.18% per annum.

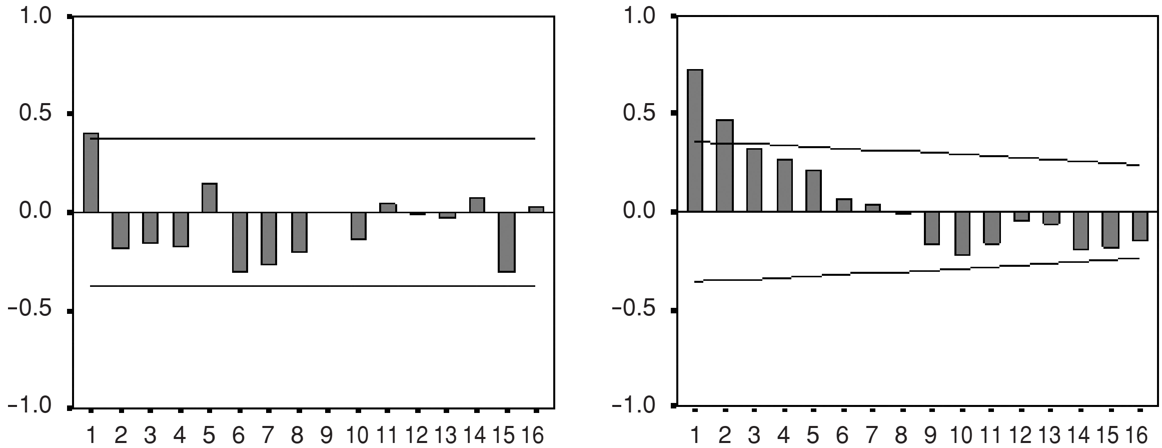

Fig. 4 Partial autocorrelation (left) and autocorrelation (right) functions of road accident death rate

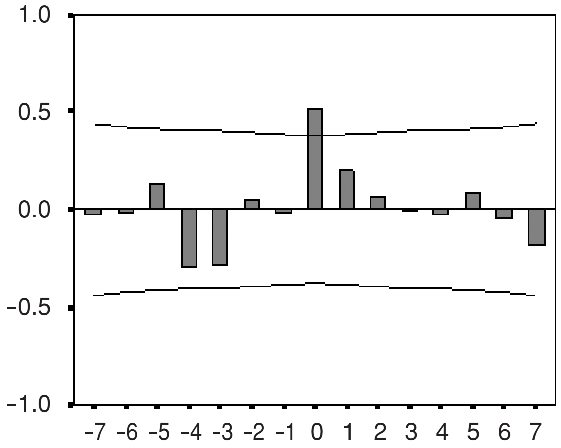

Fig. 5 Cross-correlation functions of the pre-whitening time series between road accident death rate and population series

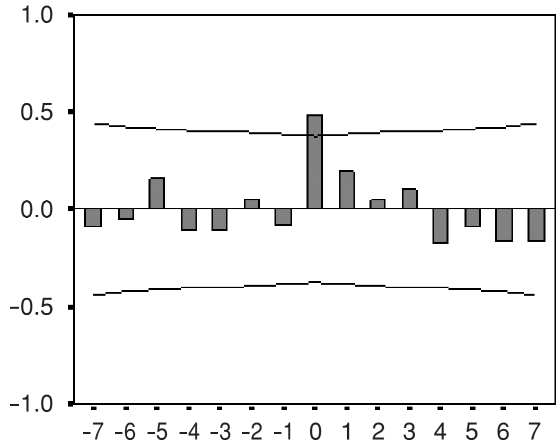

Fig. 6 Cross-correlation functions of the pre-whitening time series between road accident death rate and vehicle ownership series

Table 4 Estimation for the model of annual road accident death rate

Conditional Least Squares Estimation				
Parameter	Estimate	Std Error	T-value	Lag
Constant	3.0332	0.1376	22.05	0
Moving Average (1)	−0.4288	0.2336	−1.84	1
Population	2.0694×10^{-8}	1.4733×10^{-8}	1.40	0
Vehicle Ownership	1.8825	0.5542	3.40	0
Q-Statistic	Prob Q(6) = 0.869	Prob Q(12) = 0.897	Prob Q(18) = 0.435	

(Significant level, $p < 0.10$)

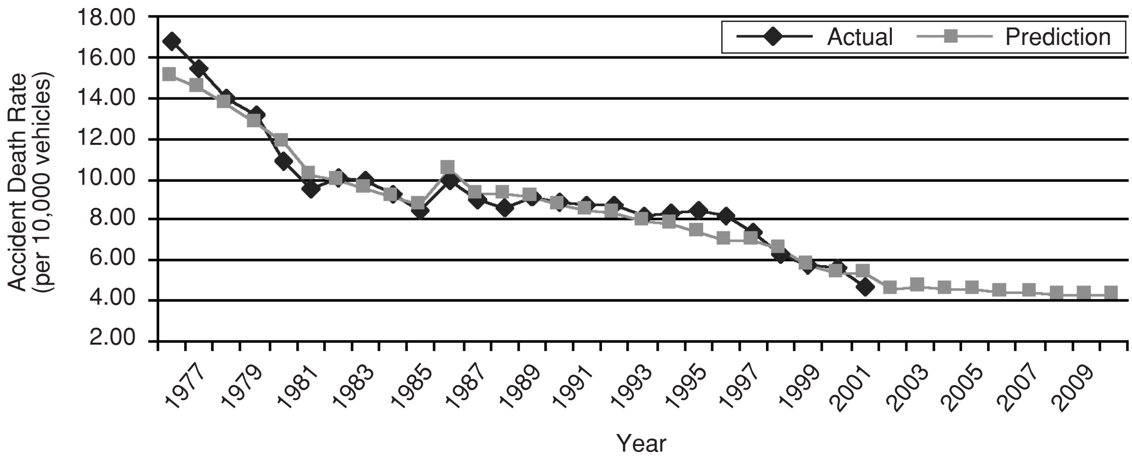

Fig. 7 Road accident death per 10,000 vehicles estimation and projection, 1976–2010

7. CONCLUSION

This paper provides the numerical context for recommendations for the reduction target of the road accident death rate for the year 2010 that was announced in the Malaysian Road Safety Council annual meeting in 2002. The research included the prediction of vehicle ownership and the analysis of past trends in the road accident death rate. Projections of the road accident death rate were undertaken for 2010 taking into account the assumption of per-capita GDP, vehicle ownership and population growth.

The Gompertz model predicted that the vehicle ownership per population would be equal to 0.4409 by the year 2010 while the ARIMA model with transfer noise function reveals that a minimum 2.18% reduction per annum is required to achieve the national target in year 2010.

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