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A self-calibrating model to estimate average speed from AADT

M M Bruwer

MEGAN BRUWER (AMSAICE) is a transportation engineer. She joined the Civil Engineering Department of Stellenbosch University in 2015 as a lecturer, and as the project coordinator of the Stellenbosch Smart Mobility Laboratory (SSML). Prior to joining Stellenbosch University she worked as a transport engineering consultant, where she was involved in the implementation and operational design of public transport systems and road-based traffic accommodation for new developments. Her research interests include traffic-flow theory and the application of Intelligent Transport Systems to improve traffic data collection for transport planning and traffic management. She is currently completing a PhD in this field.

Contact details:
Lecturer and Project Coordinator:
Stellenbosch Smart Mobility Lab
Department of Civil Engineering
Stellenbosch University
Private Bag X1
Matieland
Stellenbosch 7602
South Africa
T: +27 21 808 4080
E: mbruwer@sun.ac.za

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Transport practitioners need a universally applicable speed prediction model to estimate average speeds on any road. Average annual speed is a key input to the economic assessment of transport infrastructure where reliable estimates of future average speeds are necessary to calculate economic costs and benefits. The relationship between Annual Average Daily Traffic (AADT) and average annual speed was investigated on higher-order roads across South Africa, revealing a high level of variability in this correlation at different locations. This variation is influenced by road characteristics, such as alignment and cross-section, complicating the formulation of a universal speed prediction model. Two novel speed prediction models are proposed in this article that use AADT to forecast future average annual speed. The speeds of heavy vehicles and light vehicles can be estimated separately, as well as the average speed of all vehicles simultaneously. Both models are self-calibrating, accounting for the variation in the AADT–speed relationship. This calibration step is unique to speed prediction models and increases the reliability of these models to estimate future average speeds considerably. Furthermore, self-calibrating average annual speed prediction models are universally applicable and will simplify economic assessment of transport infrastructure.

INTRODUCTION

New transport infrastructure is implemented only if it offers economically beneficial solutions to existing needs. The economic assessment of transport facilities requires reliable estimation of average annual speeds at future intervals to calculate economic costs and benefits. Currently, the few South African methods that exist to estimate the progression of average annual speeds are determined for – and are therefore only applicable to – particular roads. There is a need for a generic model to predict future speeds on higher-order roads for use in economic evaluation.

The annual progression of traffic volume is generally agreed upon, i.e. we anticipate an increase in traffic year-on-year, assumed to be related to population growth and development. The rate at which traffic increases annually is typically modelled using compound growth based on the economic principle of compound interest. In South Africa, annual traffic growth of below 3% per annum is considered low growth, and up to 4% as average growth (Committee of Transport Officials 2013). Fast-growing areas are associated with traffic growth of between 6 and 8% per annum, or even over 8% in exceptional cases. Traffic growth is particular to a certain road and depends on surrounding development, existing or future congestion, and the urban or rural nature of the road.

The impact of traffic volume on speed is also well established according to the principles of Traffic Flow Theory. As vehicle volume increases, drivers reduce their speed to cope with the increased density that brings with it additional complexity in the interactions between vehicles (Garber & Hoel 2015). The relationship between speed and volume is usually described for short time increments, with speed and volume aggregated in intervals of between 20 seconds and 5 minutes (Treiber & Kesting 2013).

The longer-term relationship between volume and speed, for example the impact of annual traffic growth on average annual speed, is less well understood. A study on major roads in South Africa found that average annual speed decreases annually on the majority of roads (Bester & Geldenhuys 2007). This speed decrease is likely due to an increase in traffic volume over time, but this influence was not quantified. There is significant variation in the relationship between volume and speed on different roads, influenced by road geometry and driver population. This variability complicates the formulation of a universal speed estimation model.

Average annual speed is important when conducting an economic assessment of a transport facility because it is used to estimate annual user costs (Margiotta *et al* 1999). An economic assessment considers whether the monetised economic benefits provided by a project will exceed economic costs. Many costs considered in the economic evaluation of road projects are directly associated with vehicle speeds. Road User Costs (RUCs) include the cost of operating a vehicle (fuel and oil consumption), travel time costs and emissions, with each component corresponding to speed.

This article considers the relationship between average annual speed and Annual Average Daily Traffic (AADT) on major roads, specifically with two or more lanes per direction and a speed limit of 120 km/h. The variability in the AADT–speed relationship is addressed by the formulation of self-calibrating speed prediction models developed from empirical data collected across South Africa, which are therefore applicable to a wide range of higher-order, high-speed roads. The speeds of heavy vehicles and light vehicles can be estimated separately, as well as the average speed of all vehicles simultaneously.

THE APPLICATION OF AVERAGE SPEED IN ECONOMIC EVALUATION

Transport economics assesses transportation projects in monetary terms to determine the economic benefit and cost to establish if the project should be implemented. The cost of transport infrastructure can be grouped into three subdivisions, namely the economic cost of infrastructure, user cost and external cost (Cape Metropolitan Transport 1994). Infrastructure costs are directly related to the transport facility, including construction and maintenance costs. User costs (RUCs for road projects) include all costs directly borne by road users, including Vehicle Operating Costs and Time Costs. External costs are not directly paid for by users or developers of the facility and include the cost of accidents, the social cost of traffic congestion, such as time away from family and environmental degradation (Quinet & Vickerman 2004).

Vehicle Operating Costs are a function of speed because speed affects fuel and oil consumption. Average speeds are used in economic evaluation because average operating costs for all vehicles are estimated (Thoresen & Roper 1996). Some literature indicates that a single average speed for all vehicle classes should be used (Heggie 1972), while other sources determine speed and Vehicle Operating Costs for each vehicle class separately (Pienaar & Bester 2008). Factors affecting speed and existing speed prediction models are discussed below to provide background to this article.

Factors affecting average speed

Four categories of factors affect vehicular speed – the driver, the vehicle, the roadway and the environment (Winfrey 1969). Drivers are influenced by driver age and alertness, while vehicle factors such as braking and cornering ability influence speed. The roadway and environment influence average speed through features such as horizontal and vertical alignment (affected by terrain), lane width, number of lanes, shoulder width, speed limit and pavement design.

Roadway features are used by the Highway Capacity Manual (Transportation Research Board 2000) to estimate Free Flow Speed, i.e. the speed selected by drivers in low-volume conditions when unhindered by other vehicles. Free Flow Speed is adjusted according to traffic volume to determine the average speed at particular flow rates.

Factors that influence speed, such as lane width, road alignment and speed limit, are unlikely to change over time, unless through infrastructure improvements. However, RUCs are required for each year of the economic analysis period (Pienaar & Bester 2008). Traffic volume is a dynamic factor that influences speed and is expected to vary annually. Traffic volume varies reliably with time and can be estimated in the future by well-established traffic demand forecasting models such as the Four-Step Model in urban areas (Institute of Transportation Engineers 2009) and traffic growth rates calculated from historical data for rural areas. Forecasted traffic volumes should therefore be used to estimate average speed, allowing RUCs to be calculated for all years of the economic analysis period.

Existing speed prediction models

Various international speed prediction models use AADT as an estimator variable to determine average speeds (Margiotta *et al* 1999; Lomax *et al* 1997; Schrank & Lomax 2009).

A linear model to estimate speed from Average Daily Traffic (ADT) on freeways was proposed for the National Cooperative Highway Research Program (NCHRP) in the USA (Lomax *et al* 1997). ADT is determined over a period shorter than a year, identifying it from AADT. The 1997 Lomax model (Equation 1) was based on empirical data and described average speed (mph) in terms of ADT per lane (1 000 veh/day/lane) and access frequency (freeway interchanges per mile). The speed prediction model was determined with a Coefficient of Determination (R^2) of 0.50.

$$U = 91.4 - 2.0(ADT) - 2.85(Access\ Frequency) \quad (1)$$

A later speed model, also developed in the USA, applies a stepwise prediction model to estimate average speed on freeways according to ADT as the only predictor variable (Shrank & Lomax 2009). This model estimates average speeds for peak and off-peak periods separately, and was developed from empirical data from freeways in 29 cities. The stepwise model predicts speed according to five congestion levels – uncongested (ADT < 15 000 veh/day/lane), medium congestion (15 000 < ADT < 17 500 veh/day/lane), heavy congestion (17 500 < ADT < 20 000 veh/day/lane), severe congestion (20 000 < ADT < 25 000 veh/day/lane) and extreme congestion (ADT > 25 000 veh/day/lane). The Schrank & Lomax (2009) model predicts that speeds along uncongested routes are unaffected by ADT. Speeds then decrease with increasing ADT up to the point where extreme congestion is encountered, after which the model assumes that speed will remain constant at 35 mph in the peak, and 40 mph in the off-peak period.

In South Africa, a speed prediction model that applies AADT was empirically derived for the N17, a two-way, two-lane road (Van As 2005). An adjustment factor $f_{c,}$ presented by Equation 2, is multiplied with Free Flow Speed to reduce speed according to congestion. The factor also takes road width into account through coefficient *a*, defined as 80 080 or 154 570 for "*lane plus shoulder width*" of 3.7 m or 6.2 m respectively.

$$f_c = e^{-AADT/a} \quad (2)$$

A method was developed by the South African National Roads Agency Limited (SANRAL) that makes use of a congestion factor to adjust RUC directly based on the ratio of AADT to daily capacity for various

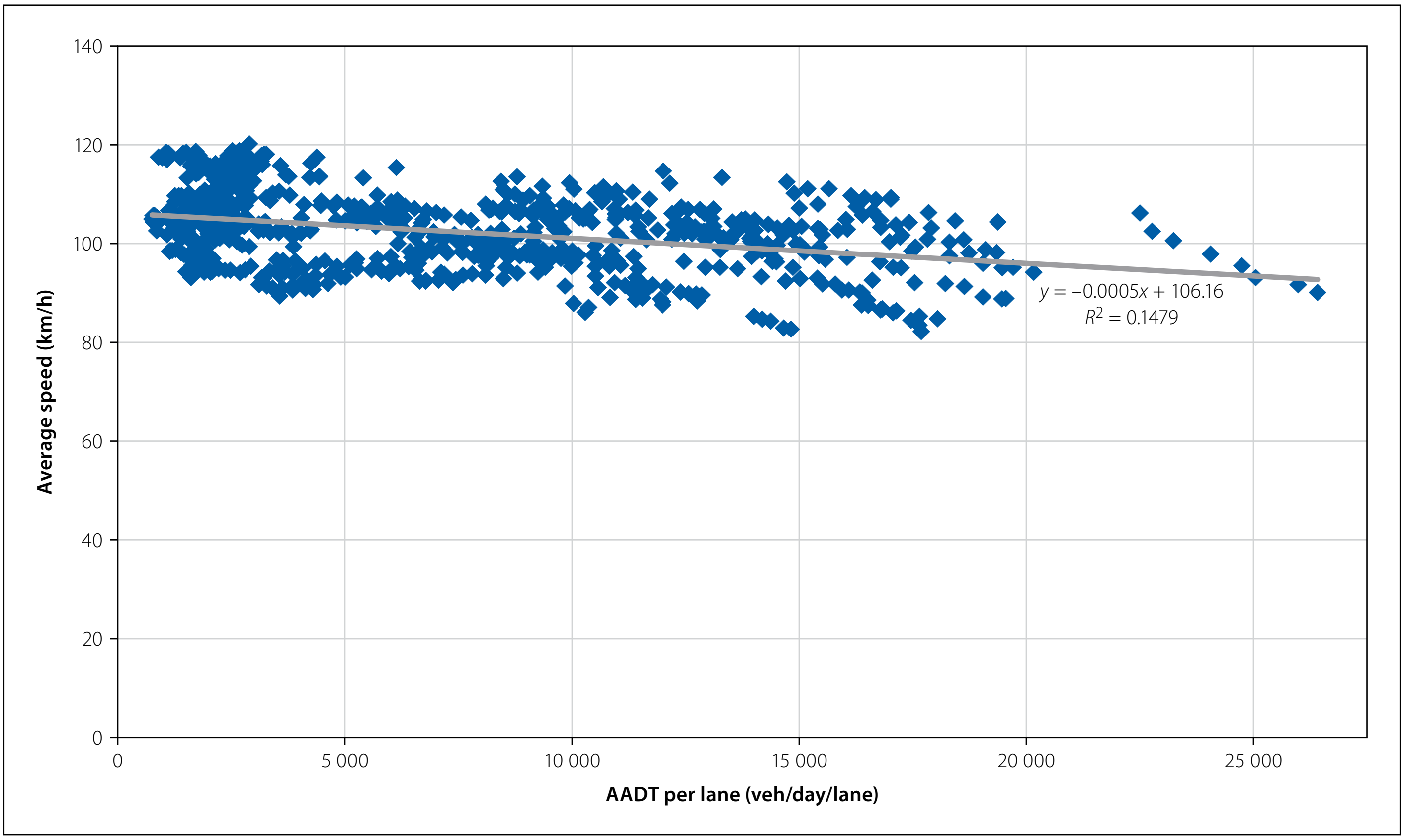

Figure 1 Relationship between Average Speed and AADT/ln "prediction" data (1994–2006)

road classes (Pienaar & Bester 2008). The stepwise function, presented in Equation 3, calculates a congestion factor *fc*, which is multiplied with RUCs and Time Costs to increase economic cost according to congestion levels (Pienaar & Bester 2008).

$$\frac{v}{c} \leq 0.4: f_c = 1.00$$

$$0.4 \leq \frac{v}{c} \leq 1.0: f_c = \left(\frac{v}{c} + 0.6\right)^{1.15} \qquad (3)$$

$$\frac{v}{c} > 1.0: f_c = 1.6^{1.15} = 1.72$$

In the function described in Equation 3, v is AADT (veh/day) and c is a daily capacity estimate attributed to a particular road class. Daily capacities are suggested to be 10 342 veh/day/lane for rolling terrain and 13 575 veh/day/lane for flat terrain (Pienaar & Bester 2008). No adjustment is made to user and time costs where AADT is less than 40% of the daily capacity, corresponding to AADT of around 5 500 veh/day/lane.

It has been suggested that congestion factors such as those described by Equation 3, which were formulated to be applied directly to RUC, can also be applied directly to Free Flow Speed to estimate average annual speed (Van As 2005). In order to adjust speed, an inverse of the congestion factor is multiplied with Free Flow Speed to estimate a lower average speed. This assumes that the decrease in speed is of the same order as the increase in both time costs and Vehicle Operating Cost, which may not be accurate and could be investigated in future research.

METHODOLOGY

This article empirically quantifies the relationship between average annual speed and AADT for multi-lane urban and rural freeways with a speed limit of 120 km/h across South Africa. Furthermore, generic models are empirically formulated to predict future speeds on higher-order roads for use in economic evaluation.

Empirical data

The traffic information used in this study was obtained from the Comprehensive Traffic Observation (CTO) database, collected by Mikros Traffic Monitoring (Pty) Ltd between 1994 and 2006 at CTO Stations (CTOSs) on major roads across South Africa. CTO data was also obtained from various CTOSs in 2008 and 2015 to test the accuracy of the proposed speed prediction models. Information provided at each CTOS includes the station location, number of lanes, speed limit, percentage of heavy vehicles and Average Daily Traffic (ADT). ADT is a daily traffic volume determined over a short time period such as a week or a month, rather than a full year as for AADT. Average annual vehicular speeds are also recorded for all vehicles, and for light and heavy vehicles separately.

All data entries not relevant to the study were removed, including data from roads with fewer than two lanes per direction and speed limits lower than 120 km/h. Additionally, roads with an inadequate representation of traffic data over a full year were excluded. The reported measured ADT was assumed to be a satisfactory representation of AADT if 60% of the year was observed.

The data from CTOSs within close proximity of toll plazas and freeway interchange ramps was also excluded from the dataset. A final set of 776 annual traffic surveys from 153 CTOSs from across South Africa was available to calibrate the speed prediction models ("prediction" dataset). The models were tested using data from 78 CTOSs around South Africa. Some of these "test" CTOSs were included in the "prediction" set (albeit at different years), while 45% were newly added.

Data analysis

Linear regression analysis and assessment of statistical significance using t-Test Hypothesis Testing were the primary tools

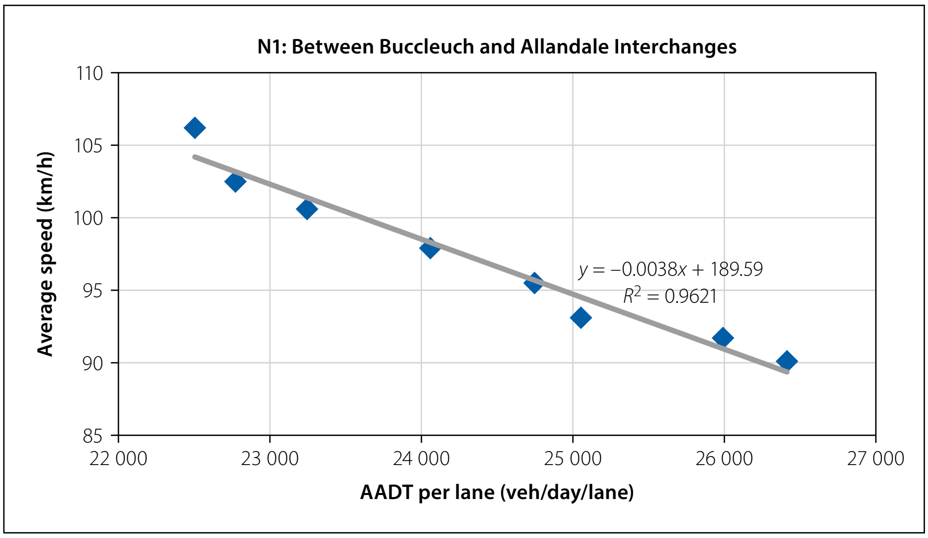

Figure 2 Relationship between Average Speed and AADT/ln at CTOS 565 along N1

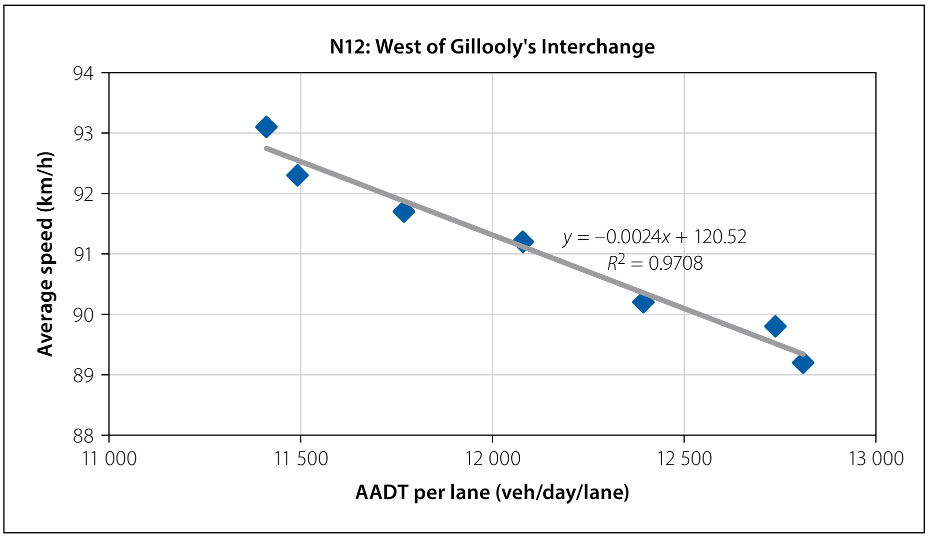

Figure 3 Relationship between Average Speed and AADT/ln at CTOS 581 along N12

applied to empirical data to evaluate the relationship between speed and AADT. A t-Statistic with an absolute value of greater than 1.960 indicates a statistically significant relationship at a 95% confidence level (Montgomery & Runger 2007). The Coefficient of Determination (R^2) was calculated for regression models to determine the applicability of the regression function to describe the variability of the data. Microsoft Excel was used for data analysis and statistical investigation.

The capacity of the speed prediction models to estimate future speed according to traffic volume was tested using two quality measures of error, namely Average Absolute Speed Error (AASE) and Speed Error Bias (SEB). These measures have been used extensively to compare speed results (Gwara 2017). Allowable error range for speeds compared with the AASE and SEB error measures are 10 km/h and ±7.5 km/h respectively.

Analysis and speed prediction models for average annual speeds of all vehicles are presented in detail in this article. Similar analysis methods were used to investigate the average speeds of heavy vehicles and light vehicles separately, and the main findings and speed prediction models for heavy and light vehicle speeds are summarised.

EMPIRICAL VOLUME-SPEED RELATIONSHIPS

Correlation between AADT and average annual speed

The relationship between AADT per lane (AADT/ln) and average speed observed on South African major roads is presented in Figure 1 for the "prediction" study period between 1994 and 2006. Average annual operating speeds range from 80 to 120 km/h. A maximum AADT/ln of 26 413 veh/day/lane was recorded in 2006 on the Ben Schoeman Freeway (N1) in Gauteng.

Figure 1 reveals the expected negative correlation between average annual speed and AADT/ln, i.e. average speed decreases as AADT/ln increases. This agrees with the finding of Bester and Geldenhuys (2007) that average annual speed decreases annually. A linear regression analysis indicated that the average annual speed of all vehicles is significantly correlated to AADT/ln, with a t-statistic of 11.590. The R^2 value is, however, low at 0.148, indicating that 14.8% of the variability expressed in the dataset is accounted for by the regression model. The significant scatter of data points and low R^2 value results from speed-influencing characteristics, such as lane width and road alignment, that are not controlled or accounted for in the dataset. Clearly, this regression model cannot be used directly to estimate speed from AADT/ln, as the predicted speeds would be too inaccurate.

An interesting observation can be made if Figure 1 is carefully considered, particularly that a number of distinct datasets are visible, forming discrete contours with relatively constant gradients. These discrete sets of data represent traffic information at particular CTOSs over a few years. A particularly visible dataset is isolated on the far right in Figure 1, measured at CTOS 565 on the Ben Schoeman Freeway (N1) in Gauteng between 1999 and 2006.

The relationship between AADT and average speed at two CTOSs (CTOS 565 on the N1 at Kyalami, and CTOS 581 along the N12 west of Gillooly's Interchange) are presented in Figures 2 and 3. Linear regression at these CTOSs yield R^2 values of 0.96 and 0.97 respectively.

Two problems are associated with these discrete datasets. Firstly, the regression equations indicate a large discrepancy in both the intercepts and the gradients, as can be compared between Figures 2 and 3. The second problem is related to the statistical integrity of the regression model for the entire dataset. In a regression analysis, each predictor variable must be independent of other predictor variables. This is not true for the regression model of the entire dataset, because the data points from distinct CTOSs are related to each other. This problem is consequently referred to as the "*time series error*" because it concerns annual information in a time series for each data group. Two options are available to eliminate the *time series error* – firstly, to consider the relationship between AADT/ln and speed at discrete CTOSs separately over the years of analysis, and secondly, to consider data for each year separately at all CTOSs.

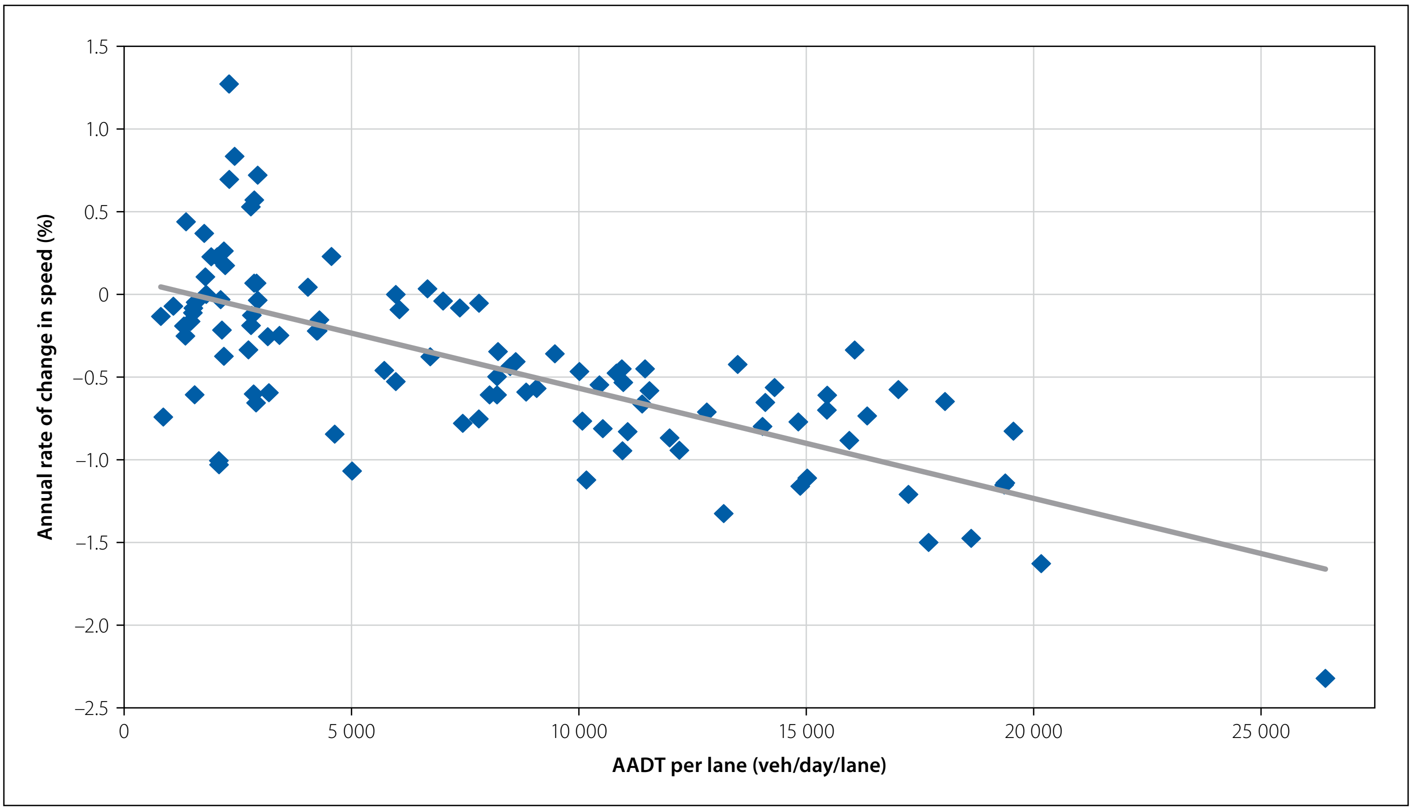

Figure 4 Annual rate of change in speed compared to AADT/ln

Analysis of the correlation between AADT/ln and average annual speed at discrete CTOSs

The first option to eliminate the *time series error* is to consider the relationship between speed and AADT/ln over time at each CTOS individually. The annual change in AADT/ln and speed at discrete stations is considered first, and then the results of independent regression analyses at discrete CTOSs are presented.

Annual traffic growth and change in speed at discrete CTOSs

Annual traffic growth rate and change in speed per annum were found to differ significantly at individual CTOSs. The annual change in AADT/ln and speed was analysed at all CTOSs with four or more years of data.

For the "prediction" dataset, the annual average traffic growth was observed to be 3.85%, in line with average traffic growth in South Africa of 3 to 4% (Committee of Transport Officials 2013). The minimum traffic growth observed was –0.09% per annum (N1 at the Mantsole CTOS between 1997 and 2001). A maximum growth rate of 9.2% was observed on the N2 close to the Umdloti Interchange between 2001 and 2006. The rate at which traffic increases per year was compared to AADT/ln, but no correlation was found, indicating that annual traffic growth rate is not influenced by traffic volume at the CTOSs investigated.

The average annual speed of all vehicles was observed to decrease at an average rate of –0.42% per annum. The minimum annual change in speed was –2.32% at the Kyalami CTOS on the Ben Schoeman Freeway (N1) between 1999 and 2006 (incidentally also the CTOS with the highest AADT). The maximum speed change was +1.27% per year (an increase in speed) between 1999 and 2006 measured along the N3 close to the Tugela Toll Plaza. The AADT/ln at this location was relatively low at 2 300 veh/day/lane in 2006.

There is a statistically significant correlation between the annual rate of change in average annual speed and AADT/ln (t statistic –10.44, R^2 0.51), as indicated in Figure 4. The most recent year's AADT/ln at each CTOS was used in the comparison. As can been seen in Figure 4, the annual rate of change in speed increases at higher AADT/ln. Speeds are therefore more significantly influenced by traffic volume at greater traffic levels.

From regression analysis of the relationship presented in Figure 4, it was found that the annual rate of change in average annual speed for all vehicles was –0.066% per 1 000 veh/day/lane. At low traffic volumes (less than 5 000 veh/day/lane), average annual speed is not significantly influenced by traffic volume, and speeds are equally likely to increase as they are to decrease at lower AADT/ln, as is evident in Figure 4. As AADT/ln increases, the influence of volume on speed becomes more pronounced. This finding is in line with the SANRAL model to estimate the impact of daily volume on RUC, where no adjustment is suggested for low volumes (Pienaar & Bester 2008).

AADT and average annual speed relationship at discrete CTOSs

According to the first option to eliminate the *time series error*, independent regression analyses were conducted at each CTOS with five or more years of data (96 individual stations).

The majority of CTOSs displayed a significant negative correlation between average speed and AADT/ln. In general, the regression analysis at discrete CTOSs resulted in high R^2 values, attributed to the fact that variables such as road alignment and lane width remain constant at each CTOS and therefore do not influence speed variability. Of the 96 CTOSs analysed, 58% produced an R^2 value of greater than 0.6. The majority of the CTOSs that presented a poor correlation between AADT/ln and average speed (R^2 value lower than 0.6) had a low AADT/ln of below 5 000 veh/day/lane. At some CTOSs, there was an increase in speed with increased AADT/ln, but all CTOSs displaying this positive correlation had a low AADT/ln (< 7 000 veh/day/lane). This links with the findings of Figure 4 that speeds may increase annually at low

Table 1 Annual Progression of the Speed vs AADT/ln Regression Models

Year	Intercept	Gradient	t-Statistic	R^2
2001	104.618	–0.000301	2.441	0.059
2002	104.913	–0.000395	3.221	0.099
2003	105.175	–0.000461	3.965	0.145
2004	104.581	–0.000536	5.029	0.190
2005	104.467	–0.000516	4.696	0.175
2006	106.017	–0.000693	6.085	0.322

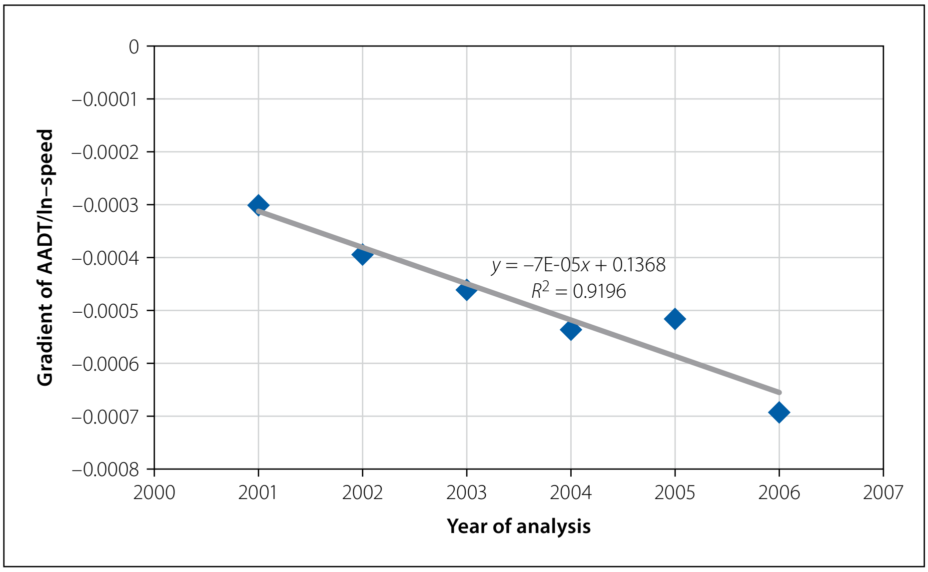

Figure 5 Annual progression of the AADT/ln–speed relationship gradient

AADT/ln because traffic density is not high enough to influence speed.

Annual progression of the AADT/ln and average annual speed relationship

This section considers the second method to eliminate the *time series error* by using only one data point per CTOS, but retaining time series information. Individual regression models were produced for each year from 2001 to 2006, using one data point from each CTOS corresponding to that year. This analysis does not consider traffic information from 1994 to 2000, because of the small sample of data available during these periods resulting in insignificant relationships. The results of the annual regression analyses are summarised in Table 1. The relationships are all significant according to the t-statistic while the R^2 values are low.

By considering traffic data for each year separately, the annual progression of the AADT/ln–speed relationship can be investigated. Table 1 reveals that, while the intercepts remain relatively constant (within 1.5 km/h), the gradients tend to become steeper. The intercept is representative of Free Flow Speed at low AADT/ln and is therefore expected to remain constant over time as there is no influence from traffic volume.

The annual progression of the gradient of the AADT/ln–speed relationship is graphically indicated in Figure 5. There is clearly a strong association between the annual gradients of the AADT/ln–speed relationship, with an R^2 value of 0.92.

Impact of heavy vehicles on speed progression

The CTO data includes Average Daily Truck Traffic (heavy vehicles per day), the percentage of heavy vehicles in the traffic stream, as well as the average annual speed of light vehicles and heavy vehicles separately, allowing the impact of heavy vehicles in the traffic to be evaluated.

Heavy vehicle population is described as a percentage of total vehicles. The minimum heavy vehicle percentage, 1.4%, was found on the N12 in Gauteng west of Gillooley's Interchange, and the maximum of 40.3% was observed on the N1 close to the Gariep Dam. An increase in heavy vehicle percentage was curiously found to be associated with an increase in average speed of all vehicles. It was determined, however, that roads with high percentages of heavy vehicles also had low AADT/ln and therefore higher speeds. Where heavy vehicle percentage exceeded 15%, AADT/ln was consistently lower than 5 000 veh/day/lane.

The speed of light vehicles and heavy vehicles was compared to AADT/ln separately. The average speed of heavy vehicles was found to be uncorrelated to AADT/ln. The average speed of heavy vehicles on all roads was maintained at an average of 80 km/h irrespective of traffic volume (heavy vehicle speeds ranged between 70 and 90 km/h on individual roads). This is likely due to additional speed limits imposed on heavy vehicles in South Africa of 80 km/h.

The speed of light vehicles was found to be significantly correlated to AADT/ln and was on average 2.7 km/h higher than the speed of all vehicles (including heavy vehicles). The correlation between light vehicle speed and AADT/ln is significant and is slightly steeper than the regression model for all vehicles. It was determined that the light vehicle speed regression model fits actual data better than for the speed of all vehicles, indicated by its higher R^2 value of 0.264 (0.148 for all vehicles).

SPEED PREDICTION MODELS

The derivation of two speed prediction models that estimate future average speed according to predicted AADT/ln values on higher-order roads in South African is described in this section. The first model uses findings from the investigation of the correlation between AADT/ln and the average annual speed at discrete CTOSs. The second model makes use of the findings of the annual progression of the AADT/ln and average annual speed relationship. Models to estimate the average speed of all vehicles (identified by subscript *A*) have been derived in detail in this article. Models to estimate the average speed of light vehicles (subscript *L*) are derived through a similar process and the resulting equations are presented at the end of this section.

Model from correlations at discrete CTOSs

The first speed prediction model considers the results of the evaluation of the relationship between AADT/ln and average annual speed at discrete CTOSs. The analysis identified that the rate of change in speed per year is correlated significantly to AADT/ln, according to Figure 3. The annual rate of change of average annual

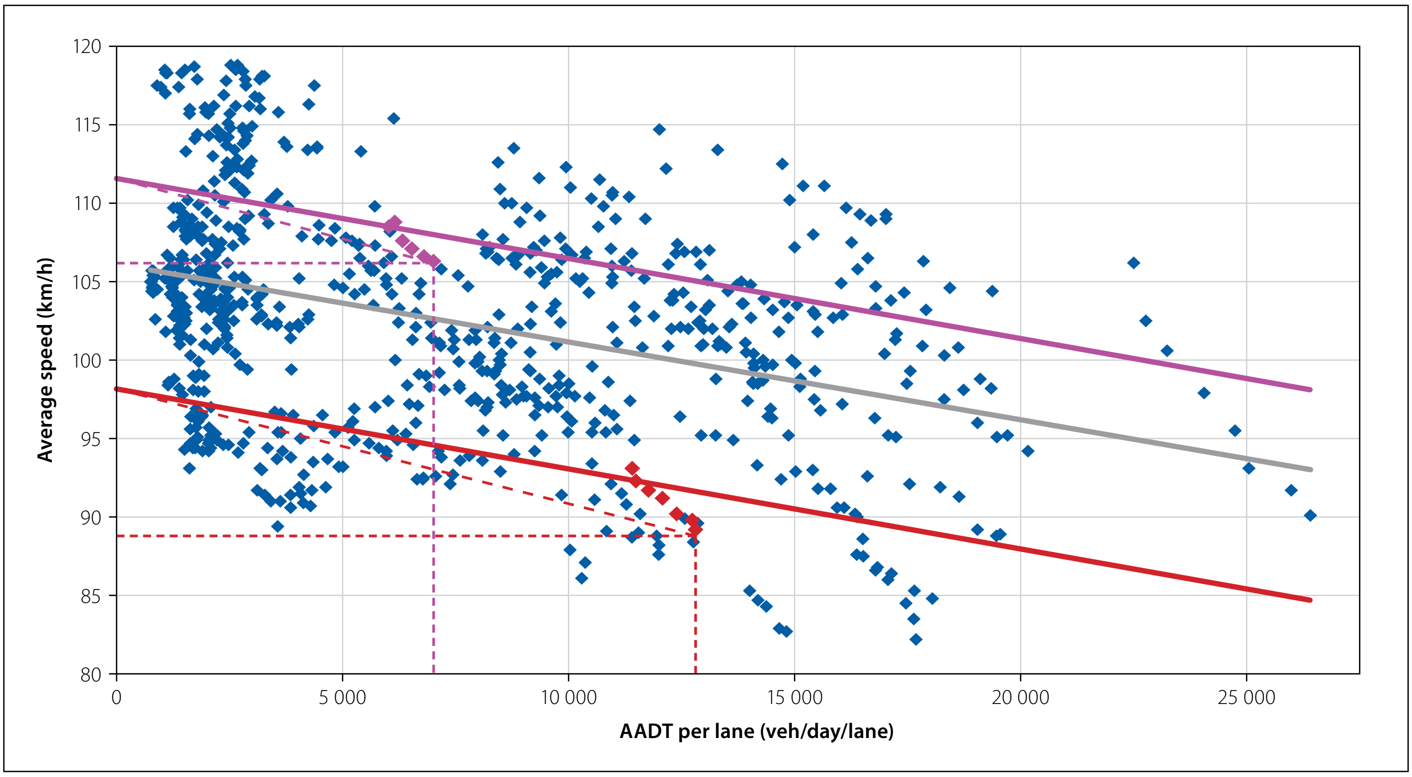

Figure 6 Graphical explanation of the prediction model for all vehicle speeds

speed of all vehicles was observed to be –0.066% per 1 000 veh/day/lane.

The relationship between annual change in speed and AADT/ln informed the formulation of an adjustment factor which can estimate future speed for a particular road. The adjustment factor is multiplied with the speed of all vehicles observed in a base year (U_{Ab}) to estimate the speed of all vehicles n years into the future (U_{Af}). The adjustment factor reduces base year speed according to a future AADT/ln estimate ($AADT_f$) described in Equation 4. Equation 4 is further referred to as "*Speed Prediction Model 1*".

$$U_{Af} = U_{Ab}\left[1 + \left(\frac{-0.066}{100} \times \frac{AADT_f}{1\ 000}\right)\right]^n \quad (4)$$

Model of annual progression of the AADT/ln and average annual speed relationship

The second speed prediction model is based on the annual progression of the statistically significant liner relationship observed between AADT/ln and speed. This relationship is described by Equation 5, which relates the average speed of all vehicles, U_{Ab}, at a particular base year b, to $AADT_b$ (which is input as AADT/ln) of year b using an intercept c_b (Free Flow Speed) and a gradient m_b. Equation 6 describes speed at some time in the future, denoted by subscript f.

$$U_{Ab} = c_{Ab} + m_{Ab} \,.\, AADT_b \quad (5)$$

$$U_{Af} = c_{Af} + m_{Af} \,.\, AADT_f \quad (6)$$

Investigation of the annual progression of the AADT/ln and average annual speed relationship identified that the intercepts remain relatively constant (refer to Table 1). It is therefore assumed that the intercepts describing base and future predicted speeds are equal, as per Equation 7.

$$c_{Ab} = c_{Af} \quad (7)$$

Further investigation showed that the gradient of the AADT/ln and average annual speed relationship decreases at a constant rate of -7.3877×10^{-5} per year. The gradient of the relationship for some future year f can therefore be determined by Equation 8 with n the number of calendar years between b and f.

$$m_{Af} = m_{Ab} - (7.388 \times 10^{-5})n \quad (8)$$

Equation 9 results from combining Equations 6, 7 and 8 to produce a model that estimates the average speed of all vehicles in year f, using base year and future traffic characteristics.

$$U_{Af} = U_{Ab} - m_{Ab} \,.\, AADT_b + [m_{Ab} - (7.388 \times 10^{-5})n] \,.\, AADT_f \quad (9)$$

It would be inconvenient to have to determine a specific gradient m_{Ab} for the particular base year in every analysis. In order to avoid having to define a gradient for each base year, the gradient (–0.00051) that describes the relationship between the average speed of all vehicles and AADT/ln (Figure 1), is used, resulting in Equation 10, which is further referred to as "*Speed Prediction Model 2*".

$$U_{Af} = U_{Ab} + 0.00051 \,.\, AADT_b - [0.00051 + (7.388 \times 10^{-5})n] \,.\, AADT_f \quad (10)$$

The first two terms of Equation 10 ($U_{Ab} + 0.00051 \,.\, AADT_b$) estimate a unique intercept for each road. The third term estimates a unique gradient depending on the number of years n. This procedure is graphically explained by Figure 6. The red points describe traffic on the N12 West of Gillooley's Interchange in Gauteng between 2000 and 2006, and the purple points on the N1 at Rand Show between 2001 and 2006. The solid red and purple lines indicate how unique intercepts are estimated from 2001 traffic data. The gradient of these solid lines is the same as the general regression equation (solid grey line). The second step determines a gradient based on the five years between 2001 and 2006, as indicated by the dashed lines, to estimate 2006 speed from a predicted AADT/ln value.

Speed prediction model 2 is self-calibrating. A particular intercept is not stipulated and so a unique model can be produced for every major road in South Africa. The model is calibrated for a particular road by using actual speed and AADT/ln values, providing information about the road's unique volume–speed relationship. This allows the prediction model to implicitly take roadway characteristics into account, such as terrain, lane and shoulder width, the number of interchanges and alignment.

Speed prediction models for heavy and light vehicles

The speeds of heavy vehicles (denoted by subscript *H*) are not affected by traffic volume. Heavy vehicle speeds observed during the base year can therefore be maintained throughout the analysis period according to Equation 11:

$$U_{Hb} = U_{Hf} \tag{11}$$

The annual rate of change of average annual speed of light vehicles was observed to be –0.071% per 1 000 veh/day/lane from evaluation of the relationship between AADT/ln and average annual speed of light vehicles at discrete CTOSs (t statistic –10.46, R^2 0.51). Similar to Equation 4 for all vehicle speeds, Equation 12 estimates the average speed of light vehicles according to "*Speed Prediction Model 1*".

$$U_{Lf} = U_{Lb}\left[1 + \left(\frac{-0.071}{100} \times \frac{AADT_f}{1\,000}\right)\right]^n \tag{12}$$

The annual progression of the relationship between AADT/ln and the average speed of light vehicles was analysed similarly to the speed of all vehicles. The gradient of this relationship decreases at a constant rate of -7.3298×10^{-5} per year. Similar to Equation 10 for all vehicles, Equation 13 estimates light vehicle average speed according to "*Speed Prediction Model 2*".

$$U_{Af} = U_{Ab} + 0.00077 \,.\, AADT_b - [0.00077 + (7.330 \times 10^{-5})n] \,.\, AADT_f \tag{13}$$

Model testing

The two speed prediction models to estimate future speed from AADT/ln were evaluated using a "test" dataset collected at 78 CTOSs around South Africa in 2008 and 2015. 2015 speeds were estimated from 2008 data, and then compared to actual speed measurements of 2015. In addition to the two models formulated for both all and light vehicle speeds, comparison is also made to speed estimates calculated using the SANRAL method (Pienaar & Bester 2008). This method was formulated to be applied on all higher-order roads in South Africa directly to RUC and not speed; however, Van As (2005) suggested that similar factors can be applied to speed directly.

Two quality measures of error, namely Average Absolute Speed Error (AASE) and Speed Error Bias (SEB) are used to evaluate speeds estimated by the prediction models. Allowable error range for speeds compared with the AASE and SEB error measures are 10 km/h and ±7.5 km/h respectively. The results of the error measures are presented in Table 2.

Table 2 Quality measures of speed prediction models

MODEL	AASE (km/h)	SEB (km/h)
Speed Prediction Model 1 (all vehicles)	3.463	–0.480
Speed Prediction Model 1 (light vehicles)	5.094	–2.216
Speed Prediction Model 2 (all vehicles)	4.028	–1.340
Speed Prediction Model 2 (light vehicles)	5.652	–3.003
Speed Prediction for heavy vehicles	2.574	0.298
SANRAL RUC adjustment factor	11.6989	–7.61942
Allowable error	10	±7.5

Both *Speed Prediction Model 1* and *Speed Prediction Model 2* (for all and light vehicles) estimate speeds that are well within the error allowances of both the AASE and SEB measures. *Speed Prediction Model 1* performs slightly better than *Speed Prediction Model 2* in both instances. The speed estimation for all vehicle speeds is slightly more accurate than speed estimation for light vehicles only. The error terms for the speed of heavy vehicles estimated according to Equation 11 are also presented in Table 2. The AASE and SEB for heavy vehicle prediction are very low, indicating that the assumption that speed of heavy vehicles remains constant irrespective of AADT/ln is valid. Estimates of speeds calculated from the SANRAL RUC adjustment factor do not adequately represent actual speeds; however, it must be remembered that this model was not formulated to predict future speeds, rather the increase in RUC.

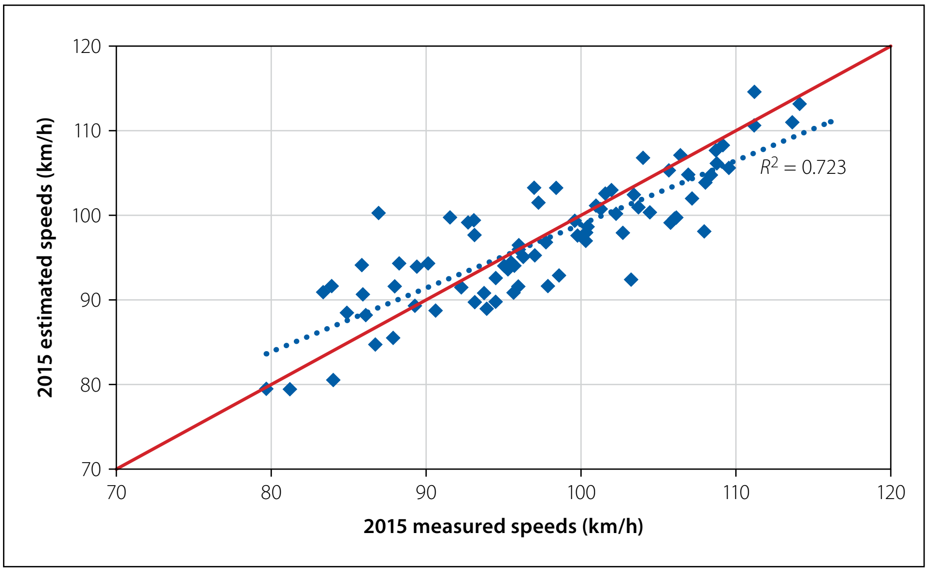

Figure 7 Comparison of speeds estimated using *Speed Prediction Model 1*

Comparison of 2015 actual speeds to 2015 estimated speeds for all vehicles is presented in Figures 7 and 8 for *Speed Prediction Model 1* and *Speed Prediction Model 2*, respectively. For *Model 1*, an R^2 value of 0.723 is determined, indicating a relatively good relationship between estimated speeds and those actually measured in 2015. *Model 2* resulted in a slightly lower R^2 value of 0.698, indicating marginally more variability between estimated and actual speeds. Considering the very high variation in observed speeds on higher-order roads across South Africa (refer to Figure 1), these models both do well in estimating future speeds. The red diagonal lines in Figure 7 and 8 indicate a gradient of 1.0. The regression lines of both *Speed Prediction Model 1* and *Speed Prediction*

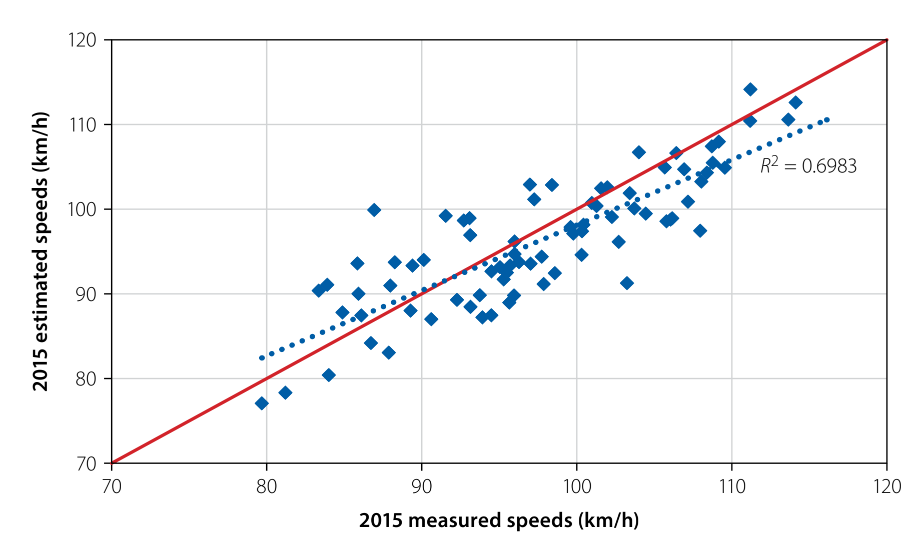

Figure 8 Comparison of speeds estimated using *Speed Prediction Model 2*

Model 2 are slightly less steep than the diagonal, indicating that both prediction models slightly overestimate speeds lower than 95 km/h and slightly underestimate speeds higher than 95 km/h.

CONCLUSIONS AND RECOMMENDATIONS

The objectives of this article were firstly to quantify the relationship between AADT and average annual speed on major highways, and secondly, to generate prediction models to forecast speed from AADT, applicable on a range of higher-order roads for use in economic analysis of road infrastructure.

A statistically significant relationship between AADT/ln and average annual speed was identified on major highways across South Africa. However, the relationship displayed a high level of variability and a *time series error* in which distinct groups of predictor variables (AADT/ln) were related. To eliminate this error, data was firstly considered at discrete positions on the road network, and secondly, the annual progression of the relationship between AADT/ln and speed was evaluated. At discrete locations, the AADT/ln–speed relationships were significantly less variable; however, each location presented a unique correlation, influenced by road characteristics, complicating the formulation of a universal speed prediction model. The annual progression of the AADT/ln–speed relationship revealed that, while Free Flow Speed remained relatively constant year after year, the rate at which speed is affected by AADT/ln increases annually at a constant rate.

Two novel speed prediction models were proposed in this article. Both models require the input of AADT/ln of the forecasted year to estimate a future average annual speed. Both models include a calibration variable, i.e. the average annual speed in the base year of analysis. The calibration step accounts for the variation in the AADT/ln–speed relationship resulting from specific roadway features. This calibration is unique to speed prediction models and increases the reliability of these models to estimate speed considerably. Separate prediction models were developed to estimate the average annual speed of all vehicles and light vehicles. The speed of heavy vehicles was found to remain constant throughout the analysis period, irrespective of AADT/ln.

The proposed speed prediction models can be used to estimate average annual speed for all vehicles and light vehicles from forecasted AADT/ln values for use in economic assessment. These models are applicable to all higher-order roads in South Africa with two or more lanes per direction and a speed limit of 120 km/h. It is recommended that further research be conducted to explore the applicability of these prediction models in other countries, and to calibrate the models for other types of roads.

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