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Impact of multi-lane pavement condition on passenger car traffic

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Scientific paper - Preliminary report

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Impact of pavement condition on passenger car traffic

The present paper explores the influence of pavement condition, roughness, and longitudinal grade on the operating speed (V_{85}) of passenger car traffic at multi-lane roads. The pavement condition is described as a pavement condition index, while pavement roughness is expressed as an international roughness index. The necessary data are collected at 67 tangent sections and the following three modelling approaches are adopted for analysis: linear regression, multiple regression analysis, and artificial neural network. The obtained results show that the artificial neural network modelling approach is the best one for estimating the operating speed V_{85} in terms of main statistical parameters.

Ključne riječi:
multi-lane road, roughness, pavement condition, operating speed, neural network

Prethodno priopćenje

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Utjecaj stanja višetračnih kolnika na promet osobnih vozila

U ovom radu istražen je utjecaj stanja kolnika, ravnosti kolnika i uzdužnog nagiba na iznos operativne brzine osobnih vozila (V_{85}) na višetračnim cestama. Stanje kolnika opisano je pomoću indeksa stanja kolnika, dok je ravnost kolnika opisana međunarodnim indeksom ravnosti. Podaci za ispitivanje prikupljeni su na 67 dionica ceste u pravcu, a u analizi tih dionica primijenjena su tri različita postupka modeliranja: linearna regresija, generalizirano linearno modeliranje te umjetna neuronska mreža. Rezultati istraživanja su pokazali da je primjena umjetne neuronske mreže najbolja za procjenu operativne brzine V_{85} s obzirom na glavne statističke parametre.

Ključne riječi:
višetračna cesta, ravnost kolnika, stanje kolnika, operativna brzina, neuronska mreža

Vorherige Mitteilung

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Einfluss mehrspuriger Fahrbahnen auf den Verkehr von Personenwagen

In dieser Arbeit wird der Einfluss von Fahrbahnzustand, sowie Ebenheit und Neigung in Längsrichtung auf die operative Geschwindigkeit von Personenwagen (V_{85}) auf mehrspurigen Straßen untersucht. Der Fahrbahnzustand wird mit dem Zustandsindex beschrieben und die Ebenheit mit dem internationalen Ebenheitsindex. Für die Untersuchungen benötigte Daten wurden auf 67 geraden Fahrbahnabschnitten verzeichnet und aufgrund drei verschiedener Modellierungsverfahren analysiert: mittels linearer und multipler Regression, sowie mit künstlichen neuronalen Netzen. Die Resultate haben gezeigt, dass mit künstlichen neuronalen Netzen die operative Geschwindigkeit V_{85} in Bezug auf die wichtigsten statistischen Parameter am besten beurteilt werden kann.

Ključne riječi:
mehrspurige Straßen, Ebenheit, Fahrbahnzustand, operative Geschwindigkeit, neuronale Netze

1. Introduction

The pavement condition and traffic speed are considered as operative and important factors that affect the efficiency of highway systems. The surface rehabilitation of multi-lane rural highways should be awarded a high priority by highway authorities, as this represents an important component of the rural network. The Traffic speed is an important parameter because it determines safety, time, comfort, convenience, and economics, and is an important indication for predicting pavement condition and surface roughness of roadways.

The present paper is mainly devoted to the study of the effects of surface roughness, pavement condition, and longitudinal grade on the operating speed of motor vehicles. The pavement roughness is expressed using the international roughness index (IRI), and the pavement condition is expressed via the pavement conditions index (PCI). The study of these features is beyond the scope of this paper.

The first part of the present study involves an investigation of the speed-pavement status relationship using traditional procedures such as the linear regression and generalized linear modelling (GLM). This is used to predict the operating speed under free flow conditions on rural multi-lane highways as applied in Egypt. In the second part, an artificial neural network (ANN), which is an advanced modelling technique, is used to predict the operating speed. The modelling of the operating speed - pavement status relationship by ANN models is also considered in this paper.

In the present study, empirical mathematical relations are developed between the operating speed and pavement status (pavement condition, surface roughness, and longitudinal grade) using traditional statistical models (linear and GLM), and the artificial neural network (ANN) model. The pavement data necessary for the development of models are readily available from the General Authority of Roads & Bridges and Land Transport (GARBLT) [1], which collects pavement data on four highways under study. The three models are evaluated for two-lane and three-lane sections individually, and also for combined data. Finally, a comparison is made between the two modelling techniques based on statistical parameters.

2. Literature review

The current study is only related to the free-flow speed, because the interactions among vehicles under non-free-flow conditions can significantly affect speed and make it an inconsistent value for a given set of road conditions. In a non-free-flow condition, a driver's desire to speed up on a good condition pavement will be impeded by traffic flow and will therefore not be reflected in the actual driving behaviour.

In this respect, Homburger et al. [2] recommended in the study of Fundamentals of Traffic Engineering four seconds as a minimum headway between the following vehicle and the vehicle travelling ahead to define free flow. Fitzpatrick et al. [3] concluded that vehicles with headway equal to or greater than five seconds are considered to be operating under free flow conditions.

In the Highway Capacity Manual (HCM) 2010 [4], the free-flow speed on a freeway segment is considered to be affected by lane width, lateral clearances, and total ramp density. This indicates that the model developers did not consider roughness, condition of pavement, and longitudinal grade in the development of their models.

In the study made by Karan et al. [5], a regression model of highway speed was developed using 72 sites near Ontario, Canada. The explanatory variables included the riding comfort index (RCI), pavement roughness (IRI), total capacity of roadway, traffic volume, and speed limit. The authors concluded that the speeds of motor vehicles on highways were significantly affected by pavement conditions. When the IRI increases from 1 to 2 m/km and all other variables are held constant, the speed drops by about 3.11 km/h.

Watanatada et al. [6] developed a speed model based on an approach named the Limiting Speed Model. In this model, pavement roughness is a major speed limiting factor. The IRI is converted to the maximum speed that a vehicle can reach at this roughness level by using the maximum average rectified velocity (ARVMAX), as shown in the following empirical equation (1), [6]:

where, a_o is the coefficient of equation.

$$\textbf{\textit{Ograničenje brzine ravnosti}} = \frac{\textbf{\textit{ARVMAX}}\,[\text{km/h}]}{(\textbf{\textit{a}}_o \cdot \textbf{\textit{IRI}})} \quad [\text{km/h}] \qquad (1)$$

It was found that roughness will be a constraining factor only when the IRI exceeds about 6 m/km, a condition which seldom exists on modern highway networks in the U.S. This result again indicates that the pavement roughness may not be a significant factor in the free-flow speed.

Elkins and Semrau [7] presented speed models for cars and trucks in the USA. based on data from analytical processes and data surveys conducted in Brazil and the USA. Cox [8], suggested that roughness has no impact on speeds for smooth roads, citing an Australian study showing that speeds were affected by roughness only above 5 IRI m/km. These results put into question the significance of any effect of pavement roughness on vehicle speed.

Chandra [9] investigated relationship between the pavement roughness, road capacity, and speed on a two-lane highway by establishing a simple linear relationship between the free-flow speed and roadway roughness. The experiments were conducted separately for cars and heavy vehicles. The IRI samples collected in this study ranged from 2 to 7 m/km. It was found that the roadway roughness negatively correlates with the free-flow speed, and that roughness is a significant variable in this relationship.

Wang et al. [10] built a linear regression model to estimate the free-flow speed on freeways in California. The explanatory

variables included the total number of lanes, day of the week, region (Caltrans district), gasoline price, and the pavement roughness as measured by the IRI. Data from the California freeway network from 2000 to 2011 were used to build the model. Ninety percent of the records had an IRI of 3 m/km or lower and an IRI change of 2 m/km or lower. The results showed that the pavement roughness had a very small impact on the free-flow speed within the range of this study. A 1 m/km change in the IRI resulted in the change of an average free-flow speed of about 0.48 to 0.64 km/h.
Ilić [11] presented a detailed literature review on the relationship between the road roughness and vehicle speed. It was found that the effect of pavement roughness on the vehicle speed was very small on the roads with the IRI values of less than 5m/km, which is usually the case for roads located in most developed countries. Unfortunately, no research has been done in Egypt concerning this point, which is due to the lack of field data. Egypt is classified as a developing country and, therefore, its transport systems suffer from many problems including a generally poor pavement condition. This problem badly affects vehicle speed and manoeuvring. Consequently, it leads to congestions, accidents, and pollution. Thus it is very important to explain and analyse the relation between the speed and pavement condition, the aim being to explore effective solutions and improvements to benefit road authorities in Egypt. Such study is beyond the scope of this pape

3. Study sites and field data

3.1. Study sections

Concerning the tangents at rural multi-lane highways in Egypt, the analysis of data uses 67 tangent sections that are distributed along four national highways in Egypt. Each section length is 100 m. Out of the sections under study, thirty-nine have two lanes in one direction of flow, and the others have three lanes. All studied sections have the same lane, lateral clearance, and median width to guarantee that their effect on V_{85} is negligible. These roads include the Cairo - Alexandria Agricultural Highway (CAA), Tanta - Damietta Agricultural Highway (TDA), Cairo-Alexandria Desert Highway (CAD), and Cairo-Ismailia Desert Highway (CID). Figure 1 shows the locations of these highways in the Egyptian road network.

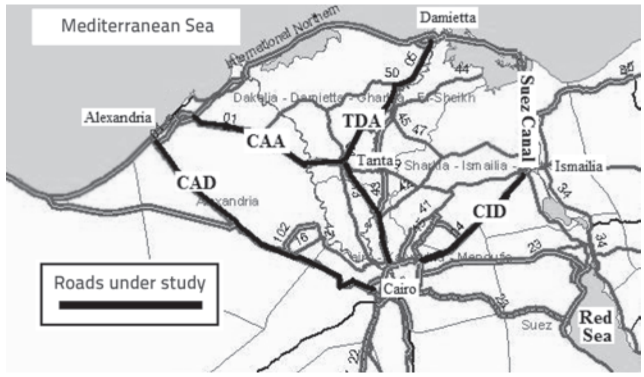

Figure 1. Multi-lane highways under study on Egyptian road network

3.2. Pavement data

Pavement data are key independent variables in the analysis. These data include the longitudinal slope of pavement (G), IRI, and PCI. For all studied sections, the G value was measured via survey tools proposed by Abdalla [12].
The PCI was calculated using the Micro PAVER procedure in which the pavement condition is based on a numerical value ranging from 0 to 100. The PCI numerical index ranges from 0 for a failed pavement to 100 for a perfect pavement condition. The PCI calculation is based on the operating conditions on the surface. Thus, it provides indications on pavement failure, as well as the maintenance and repair requirements. The Micro PAVER Software (PAVER 5.3.4 version) was used to calculate the PCI at all studied sections.
The surface roughness evaluation procedure is conducted by measuring the IRI as a road roughness index. The IRI indicator is measured by the equipment (Version ROMDAS) equipped with bump integrators to collect pavement profiles as raw data. The data are processed by the ROMDAS software package to identify the IRI for each section by traveling on it. The vehicle equipment is available from GARBLT [1].
A list of usable variables, their symbols, and statistical analysis results, are shown in Table 1.

3.3. Vehicles speed data

Passenger car speed data are the key dependent variables in the analysis. In the present paper, the driver's speed under free

Table 1. Symbols and statistical analysis results for studied variables

Variable	Symbol	Max.	Min.	Average	Standard deviation
Longitudinal slope [%]	G	4.95	-5.78	2.05	2.22
Pavement Conditions index	PCI	98	25	55.91	24.23
International roughness index	IRI	20.98	0.78	6.53	5.09
No. of lanes in one direction	NL	3	2	-	-

flow conditions avoids the effect of traffic flow on vehicle speed, and takes into account only the effect of surface roughness, pavement condition, and longitudinal grade on the operating speed. The passenger cars include taxis, private cars, vans, and jeeps. Spot speed data are collected using a radar gun (version LASER 500 with ±1km/h accuracy) that is placed at many points along each section at hidden spots outside the road so as to be invisible to the drivers, Abdalla [12]. Vehicles traveling in free-flow conditions are considered to have at least 5 seconds of headway. The recorded speeds collected at each site range from 100 to 160, which leads to a total number of 8,700 spot speeds. Speeds are measured during working days, at daylight hours. During collection of the data, the weather was clear and the pavements were dry and in good condition.

Table 2. Operating speed values for cars ($V_{85}C$) at all sections

Road name	Number of sections	Number of lanes in one direction	$V_{85}C$ [km/h]	Road name	Number of lanes in one direction	Lanes No. One dir.	$V_{85}C$ [km/h]
CAA	1	2	52.25	CID	35	2	106.62
CAA	2	2	73.83	CAD	36	3	98.3
CAA	3	3	66.45	CAD	37	3	95.55
CAA	4	3	74.2	CAD	38	3	92.5
CAA	5	3	44	CAD	39	3	93.63
CAA	6	3	92.32	CAD	40	2	67.36
CAA	7	3	66.42	CAD	41	3	111.9
CAA	8	2	49.59	CAD	42	2	68.35
CAA	9	3	67.23	CAD	43	3	110.27
CAA	10	2	58.03	CAD	44	2	73.13
CAA	11	2	50.15	CAD	45	3	109.66
CAA	12	2	60.7	CAD	46	3	91.13
CAA	13	2	83.75	CAD	47	3	40.2
CAA	14	2	83.23	CAD	48	3	85.33
CAA	15	3	66.73	TDA	49	2	71.61
CAA	16	3	35.7	TDA	50	2	73.59
CAA	17	3	96.26	TDA	51	2	53.622
CAA	18	2	76.21	TDA	52	2	72.65
CAA	19	2	77.25	TDA	53	2	98.75
CAA	20	2	56.7	TDA	54	2	93.73
CAA	21	2	28.53	TDA	55	2	94.73
CID	22	2	71.89	TDA	56	2	85.68
CID	23	3	39.08	TDA	57	2	102.68
CID	24	3	100	TDA	58	2	91.82
CID	25	2	62.5	TDA	59	2	101.15
CID	26	3	77.5	TDA	60	2	97.02
CID	27	2	57.25	TDA	61	2	94.64
CID	28	3	95	TDA	62	2	104.23
CID	29	3	68.33	TDA	63	2	95.24
CID	30	3	44.09	TDA	64	2	94.82
CID	31	3	38.13	TDA	65	2	93.28
CID	32	3	56.88	TDA	66	2	102.99
CID	33	2	39.92	TDA	67	2	87.65
CID	34	3	93				

Generally, to ensure validity of the Pearson correlation, each set of selected data should follow principles of normal distribution. Using the Kolmogorov-Smirnov test, it was established that the normal distribution of data could not be rejected at the 95% confidence level. The sample size requirements for the 85th percentile speed (V_{85}) were determined using the following well-known statistical equation (2).

$$N = \frac{\sigma^2 K^2 (2+u^2)}{2E^2} \tag{2}$$

where:
- N - the smallest sample size
- σ - estimated standard deviation of sample
- K - constant corresponding to the desired confidence level of 95% (1.96)
- E - permitted error in the average speed estimation (± 2 km/h)
- u - constant corresponding to the 85th desired percentile speed (1.04).

The operating speed values for cars ($V_{85}C$) at each section are provided in Table 2.

4. Methodology

The methodology used in the present study for predicting V_{85} was implemented by means of two main procedures: traditional procedure (linear and GLM), and non-traditional procedure (ANN). Many researchers found that the ANN provides a better model when being supported by better predictions for lower V_{85} values, which is due to the normality of the residuals and their independence from the predicted variable. Several authors have reported better performance of the ANN compared to the traditional methods. The advantage of the ANN is that it can directly take into account any non-linear relationships between dependent variables and each independent variable. Another advantage is that the ANN modelling approach is fast and flexible. Finally, the ANN model is simple and can be easily used by engineers.

4.1. Traditional modelling procedure

4.1.1. Linear regression

A mathematical form of linear regression is given by the following known equation:

$$Y = \beta_o + \sum_{i=1}^{n} \beta_i \chi_i \tag{3}$$

where:
- Y - V_{85} at each section
- χ_i - explanatory variables from 1 to n
- β_o - regression constant
- β_i - regression coefficient.

The stepwise regression analysis is used to select the most statistically significant independent variables with dependent variable in one model, while keeping only the statistically significant terms in the model. The selected model will have the smallest number of independent variables, the minimum infinity norm of error vector ($\|\delta\|$), the root mean square error (RMSE), and the highest R^2 value.

4.1.2 GLM

In this direction, the mathematical form includes all independent variables separately. This is performed by taking the natural logarithm of all these variables to produce a power relationship between V_{85} and each of the former items. This allows separate study of the effect all independent variables have on V_{85}. A normal distribution with a log link function is chosen to model these data. This form takes the shape given in equation (4), Varagouli et al. [13]:

$$V_{85} = \exp(\beta_0) \times X_1^{\beta 1} \times \ldots X_n^{\beta n} \tag{4}$$

where:
- X_n - explanatory variables from 1 to n
- β_o - regression constant
- βn - regression coefficient.

This model form is executed using the generalized linear model procedure PROC GENMOD and the SAS statistical software [14]. The SAS user's manual applies the maximum log-likelihood technique to estimate the regression coefficients, standard errors, Wald Chi-squared statistics, and p-values. The selected model has the minimum $\|\delta\|$, RMSE, and the highest R^2 value.

4.1.3. Multicollinearity

Multicollinearity is a common problem when estimating linear models or GLM. It occurs when there are high correlations among predictor variables, leading to unreliable and unstable estimates of regression coefficients. The most widely-used diagnostic factor in multicollinearity is the variance inflation factor (VIF), which estimates how much the variance of a coefficient is "inflated" by linear dependence with other predictors. It is emphasized that a VIF of 1.8 tells us that this predictor is completely uncorrelated to all other predictors. In general, care must be taken, when the VIF is greater than 2.50, which corresponds to an R^2 of 0.60, with regard to other variables, Allison [15].

4.2. Non-traditional modelling procedure (ANN)

In general, the ANN consists of 3 layers, namely, the input layer, the hidden layer, and the output layer. In statistical terms, the input layer contains independent variables, and the output layer contains dependent variables. The ANN procedure typically starts out with the randomized weights for all their neurons. When a satisfactory level of performance is reached, the training ends and the network uses these weights to make a decision.

The experience in this field is analysed according to Semeida [16] who established in his studies that the multi-layer perceptron (MLP) neural network models give the best performance compared to other models. In addition, this network is usually preferred in engineering applications because many learning algorithms could be used in the MLP.

One of the commonly used learning algorithms in ANN applications is the back propagation algorithm (BP), which is also used in this work (NeuroSolutions7), [17]. The overall dataset of sections is divided into a training dataset and a testing dataset. As in the literature, the training data set varies from 70% to 90 % , and the testing data set varies from 10 % to 30 % . Model performances are RMSE, $\|\delta\|$, and R^2 for testing and training data set on the one hand, and for all data sets on the other. Many trials have been made to reach a suitable percentage between the training and testing data that gives the best performance for operating speed models. In addition, overfitting can be avoided by randomizing all sections before training the network to reach the best performance for both training and testing of the data. The performance of testing data must be reliable as training data, (R^2 must not be smaller than 0.7), Tarefder et al. [18].

5. Analysis, results and discussions

5.1. Linear regression model results

After stepwise regression using the SPSS Package, the best three models that are statistically significant with $V_{85}C$ for two lanes, three lanes, and combined models, are presented in equations (5), (6) and (7), respectively. All variables are significant at the 5 % significance level for the selected models (P-value is < 0.05). Finally, many models are excluded due to poor significance with $V_{85}C$ or multicollinearity with predictor variables.

$$V_{85}C\text{ (2-lanes)} = 87.86 - 2.18 \cdot IRI + 0.17 \cdot PCI \quad (5)$$
(where $R^2_{adj} = 0.91$, RMSE = 5.74, $\|\delta\| = 0.14$)

VIF values for IRI and PCI are the same as 1.562 that are safe against multicollinearity (do not exceed 2.5), Allison [16].

$$V_{85}C\text{ (3-lanes)} = 96.07 - 4.11 \cdot IRI + 0.15 \cdot PCI \quad (6)$$
(where $R^2_{adj} = 0.82$, RMSE = 8.54, $\|\delta\| = 0,2$)

VIF values for IRI and PCI are the same as 1.103.

$$V_{85}C\text{ (kombinirana)} = 43.93 - 2.02 \cdot IRI + 20 \cdot PCI \quad (7)$$
(where, $R^2_{adj} = 0.87$, RMSE = 10.07, $\|\delta\| = 0.2$)

VIF values for IRI and NL are the same as 1.689.

The investigation of the 2-Lanes and 3-Lanes models shows that the negative coefficient sign for the IRI means that $V_{85}C$ decreases with an increase of the IRI. The increase in surface roughness causes considerable irregularities on the pavement surface. This uneven surface along road length enables drivers to clearly feel vibrations in the car body, and so they become worried and uncomfortable during driving. Accordingly, they prefer to reduce the car speed. In addition, the positive sign of the coefficient for the PCI means that $V_{85}C$ increases with an increase of the PCI. The pavement with less distress and better conditions enables drivers to feel balance of the car, which in turn enables them to be comfortable and safe, and so they become likely to increase the car speed with great safety. These results must be cogent.

For the combined model, it is concluded that the IRI is an effective factor on speed reduction. In addition, an increase in the number of lanes has a reasonable effect on speed increment. These results are in good agreement but need more accuracy to be included in statistical parameters.

5.2. GLM results

By using the GLM procedure PROC GENMOD in the SAS statistical software [15], the best three models that are statistically significant with $V_{85}C$ for two lanes, three lanes, and combined models, are presented in equations (8), (9), and (10), respectively.

$$V_{85}C\text{ (2-lanes)} = \exp(4.91) \cdot IRI^{-032} \quad (8)$$
(where, $R^2_{adj} = 0.92$, RMSE = 5.58, $\|\delta\| = 0.2$)

$$V_{85}C\text{ (3-lanes)} = \exp(4.87) \cdot IRI^{-035} \quad (9)$$
(where, $R^2_{adj} = 0.92$, RMSE = 8.96, $\|\delta\| = 0.15$)

$$V_{85}C\text{ (combined)} = \exp(4.44) \cdot IRI^{-025} \quad (10)$$
(where, $R^2_{adj} = 0.84$, RMSE = 26.89, $\|\delta\| = 0.28$)

Based on the three models, it can be concluded that the IRI variable is more effective for speed reduction compared to other variables. In the combined model, the lane number has a moderate effect on speed increment. These results are logical but have some problems with regard to validity and accuracy.

5.3. ANN model results

For the *2-lanes network*, the three independent variables (IRI, PCI, and G) are put in an input layer, one hidden layer is used, and one desired variable $V_{85}C$ is put in an output layer with 39 observations. The number of processing elements in the hidden layer approximately equals to one half of the total number of neurons in the input and output layers (two processing elements), which is based on the knowledge generally accepted in this field. The architecture of the ANN model is shown in Figure 2.

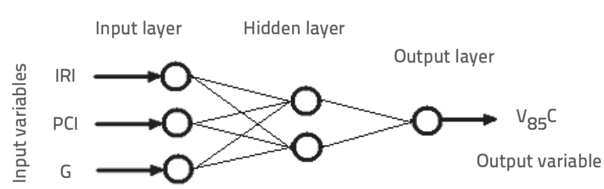

Figure 2. MLP network architecture of $V_{85}C$ modelSlika 2. Prikaz MLP mreže za $V_{85}C$ model

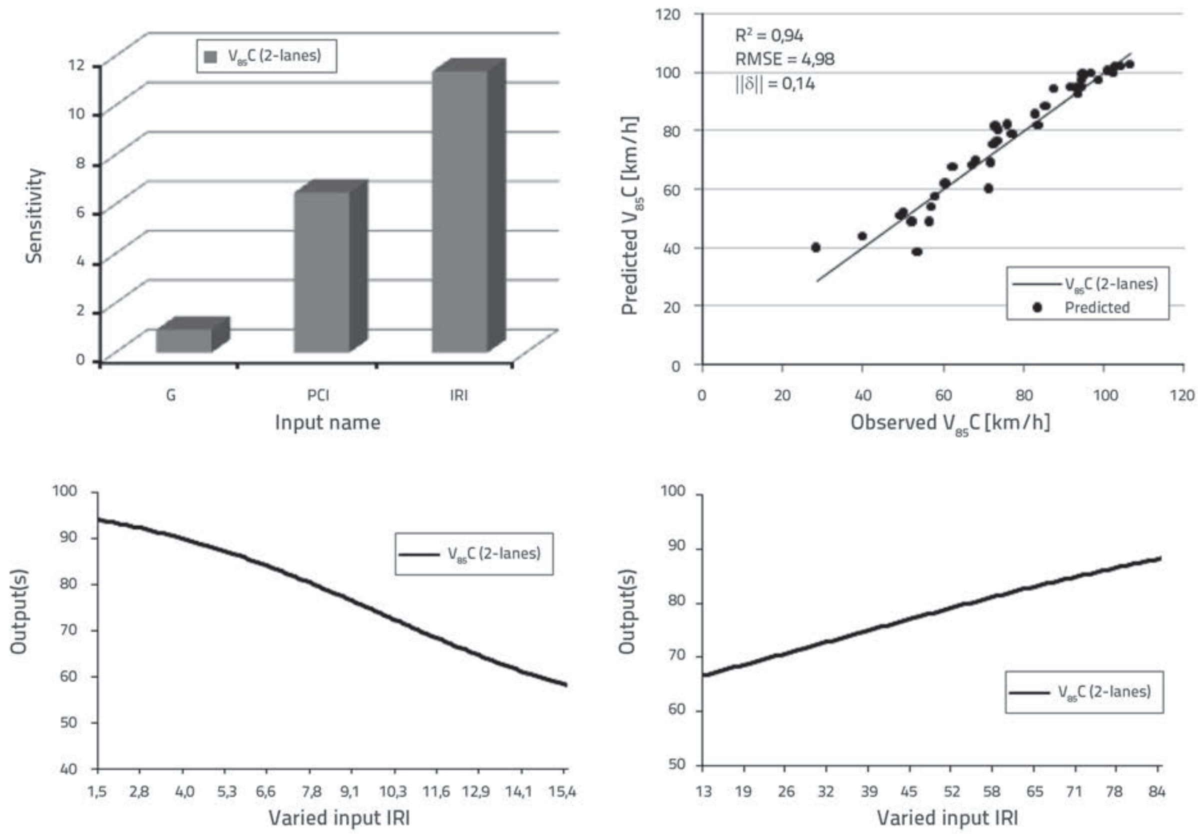

Figure 3. Validation and sensitivity analysis of $V_{85}C$ (2-Lanes) model by ANN

The use of the learning rule of momentum and the suitable number of iterations = 5000, is appropriate for quick convergence of the problem, as shown by Semeida [19] and [20]. In the present study, many trials have been made to reach the percentage between the training and testing data that gives the best model performance. However, for the best trial, the sections have been divided into a training data set formed of 32 sections (82 % of all sites), and a testing data set that has 7 sections (18 % of all sites).

In order to measure the importance of each explanatory variable, the general influence (sensitivity about the mean or standard deviation) is computed based on the trained ANN weights. For a specified independent variable, if this value (sensitivity about the mean) is higher than other variables, then the effect of this variable on the dependent variable ($V_{85}C$) is higher than that of the other variables. Figure 3 shows the sensitivity of each explanatory variable in the selected model. It has been established that the most influential variable on $V_{85}C$ (2-lanes) is the IRI, followed by the PCI. Also, the relationships between each effective input variable and $V_{85}C$ (2-lanes) are shown in the same Figure, indicating that the $V_{85}C$ (2-lanes) decreases with an increase of the IRI, and increases with an increase of the PCI. These results are more accurate, reasonable, circumstantial, and logical compared to those obtained by traditional models.

For the *3-lanes network*, the sections are divided into 23 sections (Training 82 %) and 5 sections (Testing 18 %) in the

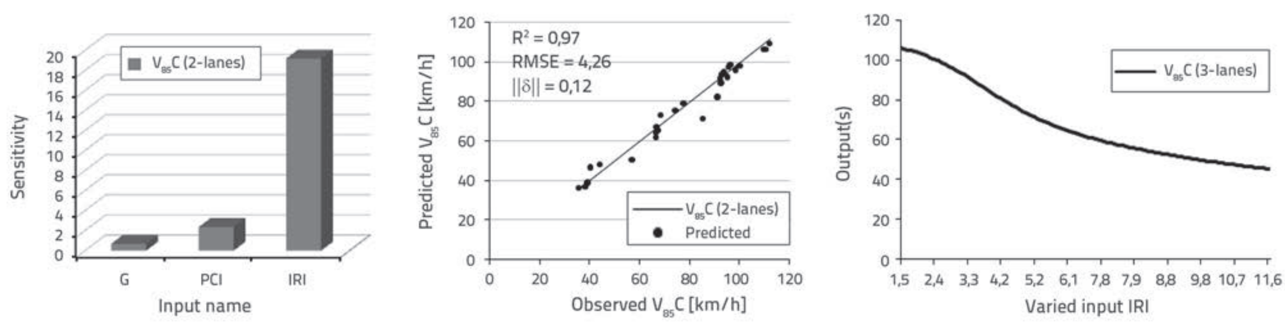

Figure 4. Validation and sensitivity analysis of $V_{85}C$ (3-Lanes) model by ANN

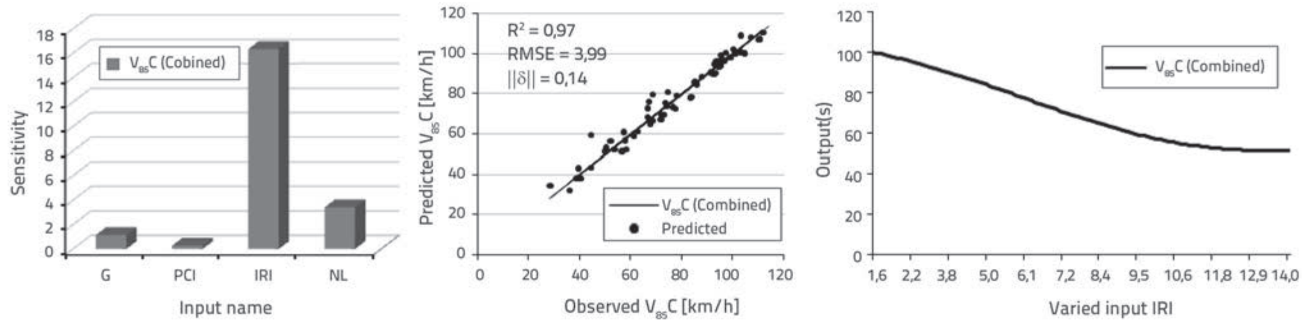

Figure 5. Validation and sensitivity analysis of $V_{85}C$ (Combined) model by ANN

Table 3. Performance for best trials for three ANN $V_{85}C$ models

Model	Performance	Training samples	Testing samples	Overall model
$V_{85}C$ (2-lanes)	R^2	0.96	0.93	0.94
	RMSE	4.15	7.72	4.98
	$\|\delta\|$	0.11	0.15	0.14
$V_{85}C$ (3-lane)	R^2	0.99	0.93	0.97
	RMSE	2.77	8.14	4.26
	$\|\delta\|$	0.05	0.13	0.12
$V_{85}C$ (combined)	R^2	0.98	0.92	0.97
	RMSE	3.12	6.89	3.99
	$\|\delta\|$	0.09	0.15	0.14

best model. Figure 4 shows the sensitivity of each explanatory variable in the selected model. It has been established that the most influential variable on $V_{85}C$ (3-lanes) is the IRI only. The relationship between the IRI and $V_{85}C$ (3-lanes) is also shown in the same Figure. It can be concluded that $V_{85}C$ (2-lanes) decreases with an increase of the IRI. These results are more reliable than the ones obtained by traditional models.

For the combined network, four independent variables (IRI, PCI, NL, and G) are put in the input layer. One hidden layer is used, and one desired variable $V_{85}C$ (Combined) is put in the output layer with 67 observations. The sections are divided into 56 sections (Training 84 %) and 11 sections (Testing 16 %) in the best model. Figure 5 shows the sensitivity of each explanatory variable in the selected model. It has been shown that the most influential variable on $V_{85}C$ (Combined) is the IRI only. The relationship between the IRI and $V_{85}C$ (Combined) is also shown in Figure 5. It can be noted that the $V_{85}C$ (Combined) decreases with an increase of IRI. These results are more accurate and rational compared to traditional models.

Finally, the best trial for training, testing and an overall data set for the three ANN models are presented in Table 3.

5.4. Comparison of results obtained by usable modelling techniques

The results of the three usable modelling techniques expressed in terms of R^2, RMSE, and $\|\delta\|$, are presented in Figure 6 for comparison purposes. It can be seen in this Figure that the ANN dominates over the linear regression and GLM in the three models (2-Lanes, 3-Lanes, and Combined). Therefore, this procedure should be applied in the future so as to gain more accurate and detailed results compared to traditional procedures.

6. Conclusion

This paper explores the influence of pavement condition, roughness, and longitudinal grade on the V85 at 67 tangent

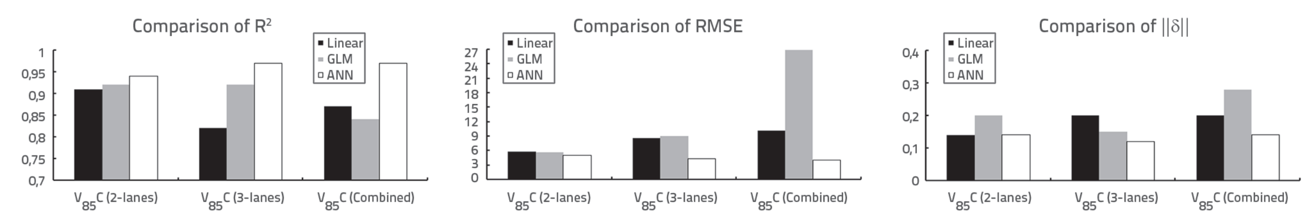

Figure 6. Comparisons between linear model, GLM, and ANN

sections situated along four national highways in Egypt. Three models are utilized and evaluated for two-lane sections (39 sections) and three-lane sections (28 sections), both individually and for combined data. Two modelling approaches are adopted for this purpose. The first consists of traditional procedures (linear regression and GLM) and the second involves a non-traditional procedure (ANN). The following important conclusions have been reached:

1. The ANN procedure gives better, more confident and consistent logical results compared to the linear regression and GLM in terms of computed statistical parameters.
2. For 2-Lanes model: The best ANN model gives R^2 equal to 0.94, while the best linear regression and GLM models give R^2 equal to 0.91 and 0.92, respectively. For 3-Lanes model: R^2 for the best ANN model is 0.97, while being 0.82 and 0.92 for the best linear regression and GLM models, respectively.
3. For the combined model, R^2 values are 0.97, 0.87, and 0.84, for the best ANN, linear regression, and GLM models, respectively. 3. The results of the best ANN for the 2-lanes model show that the most influential variable on $V_{85}C$ is the IRI, followed by the PCI. The increase of IRI by 1 m/km leads to a drop in $V_{85}C$ by 2.6 km/h. The increase of the PCI by 10 % leads to a rise in $V_{85}C$ by 3 km/h.
4. The results of the best ANN for the 3-lanes model indicate that the most influential variable on $V_{85}C$ is the IRI only. The increase of the IRI by 1 m/km leads to a drop in $V_{85}C$ by 6 km/h.
5. The results of the best ANN for the combined model reveal that the most influential variable on $V_{85}C$ is the IRI only. The increase of the IRI by 1 m/km leads to a drop in $V_{85}C$ by 4.5 km/h.
6. For all the models, the most important parameter is the IRI, except for the two-lane highway model which identifies the impact of the PCI. For the two-lane highway model, the correlation between the IRI and PCI is -0.6, which implies a moderate relationship between them. The sensitivity analysis points to this relation but the effect of the IRI on the operating speed is still greater than that of the PCI. On the other hand, the correlations between the IRI and PCI are -0.4 and -0.3, for the three-lane highway and combined models, respectively, indicating a weak correlation between them. However, in both cases the PCI impact on the operating speed can be neglected compared to the IRI.
7. The V_{85} results are highly important for controlling the operating speed on the multi-lane rural highways in Egypt. V_{85} can be controlled by targeting pavement roughness factor to improve the traffic performance of the highways. The surface rehabilitation of multi-lane rural highways should be awarded a high priority by the highway authorities, because this represents an important component of the rural network.

Finally, future research should be conducted and extended to include all aspects of this problem, including a greater emphasis on heavy vehicles, due to their impact on pavement surface. In addition, the impact of pavement distress on the capacity of multi-lane highways should also be a major target in future research related to Egyptian highways

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