

COMPARATIVE ANALYSIS OF ANPR AND TIRTL SYSTEMS USING ARTIFICIAL NEURAL NETWORKS FOR TRAFFIC SPEED MANAGEMENT

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Abstract

Transportation networks are struggling with increased traffic due to mixed flows and the unregulated growth of private vehicles. Over-speeding and congestion are critical issues for urban planners. Effective speed management and enforcement are essential to mitigate excessive speed, which is a major cause of traffic accidents. This study aims to develop efficient traffic speed management measures by evaluating the performance of Automatic Number Plate Recognition (ANPR) and The Infra-Red Traffic Logger (TIRTL) in data collection and the detection of excessive speeding. The results show ANPR detected only 51% of the vehicle classes, while TIRTL detected 96% of them. A maximum speed reduction of 20 km/h was observed in the vehicles, with an average reduction of 8 km/h. The ANN model developed can help urban planners devise new speed management techniques by accurately estimating their effectiveness in an urban setting.

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Key words

- Artificial neural network,
- Automatic Number Plate Recognition,
- Intelligent transport flow,
- Infra-Red Traffic Logger
- Traffic speed management.

1 INTRODUCTION

India emerged as the fifth-largest market for automobiles in 2020, with a total of 3.49 million units sold in the passenger and commercial vehicle segments. Between 2009 and 2019, the annual compound growth rate of road traffic in India increased by 9.9%, with two-wheelers constituting nearly 74% of all registered vehicles (Chaudhary, 2019; Bari et al., 2019). This has led to a surge in road congestion and instances of excessive speeding by drivers attempting to arrive at their destinations on time. Excessive speeding refers to driving above the posted speed limit or driving too quickly for the road conditions. According to a 2020 report by the National Crime Records Bureau (NCRB) of India, over 60% of all road accidents were caused by excessive speeding, resulting in

75,333 fatalities and 2,09,736 severe injuries (Tandon, 2020). To address this issue, it is imperative to implement an effective enforcement mechanism to regulate vehicle speeds and mitigate their harmful effects. Therefore, the implementation of a speed management system in urban areas is necessary to combat excessive speeding and alleviate traffic congestion.

A speed management strategy refers to a collection of policies and measures aimed at mitigating the adverse impacts of excessive speeding within a transportation system. This requires a systematic and deliberate approach to address the issue of speeding, starting with the implementation of appropriate speed limits for different types and categories of roads. Speed control measures have been adopted in various countries, and some of these measures are outlined below:

- **Introduction of speed limits:** The establishment of speed limits for different categories of vehicles and various types of roads, such as highways, roads in residential areas, and roads in urban areas, is a common method for regulating speed. A study conducted by Hadiuzzaman et al. (2013) showed that speed limits can significantly reduce congestion and improve traffic flow, particularly during peak traffic hours. However, an inherent limitation of this approach is the potential for non-compliance by some drivers, which can lead to hazardous situations on the road. Moreover, in certain circumstances, speed limits may be set too low or too high, resulting in frustration or confusion among drivers (Jin et al., 2011; Tientrakool et al., 2011).
- **Speed cameras:** Several studies have reported a reduction in the number of injuries sustained by individuals through the implementation of speed cameras, with estimates ranging from 4% in London, England, to 51% in New South Wales, Australia. In one assessment of the French speed camera program, Carnis and Blais (2013) found evidence of a reduction in both fatal and non-fatal traffic injuries, with a reported 21% decrease in the fatality rate per 100,000 vehicles. However, a potential limitation of this approach is the possibility of inaccuracies in the speed camera system, leading to the imposition of fines on drivers who were not actually exceeding the speed limit. Furthermore, some drivers may be able to circumvent detection by briefly slowing down and then resuming their previous speeds (Tavolinejad et al. 2021).
- **Traffic calming measures:** Many cities and towns across the world use a range of traffic calming measures to reduce vehicle speeds including, but not limited to, speed bumps, roundabouts, chicanes, and raised crosswalks. A recent study by Sanka et al. (2021) investigated the effectiveness of installing speed humps on local streets in China to measure the speed variations of 3000 vehicles. The study found that mean speed reductions of 6.7 km/h and speed reductions of 8.7 km/h were observed. Another study by Distefano and Leonardi (2019) evaluated the efficacy of chicanes in reducing vehicle speed and reported an average vehicle speed reduction of up to 50% as well as a 40% reduction in crash fatalities. In addition, a study by the U.S. Federal Highway Administration (FHWA, 2000) found that roundabouts can decrease total collision rates by 37%, injury collisions by 75%, and fatal collisions by 90%. One potential drawback of traffic calming measures is that they increase travel times for drivers, which may lead to frustration. Moreover, some drivers may attempt to avoid these measures by using alternate routes, which could potentially cause congestion in other areas.

Forecasting the efficiency of speed management techniques is of great significance to planners and designers; hence, the accuracy of various speed enforcement systems has to be evaluated. Data-mining technology known as predictive modelling solutions analyse both recent and historical data to create a model that can be used to forecast future events (D'Apuzzo et al. 2021). These mathematical models can be used to carry out in-depth research, create hypotheses, and make predictions. However, creating a mathematical model is difficult because engineering and mathematics frequently

require expertise in other fields. Recently, the use of artificial intelligence, “big” data, and self-driving vehicles has proven effective in reducing traffic congestion. Researchers have successfully used artificial intelligence (AI) tools such as artificial neural networks (ANN), fuzzy logic models, and genetic algorithms to not only reduce vehicle traffic flow at intersections, but also reduce accidents, congestion, etc. But no work has focused on implementing these AI tools, particularly in highway speed management (Olayode et al., 2020).

Artificial neural networks (ANN) are machine learning algorithms that can be taught using input-output data to understand patterns and connections within the data. These nonlinear statistical modelling algorithms are an innovative alternative to logistic regression, the most widely used method in engineering for creating predictive models for discrete outcomes. The effectiveness of ANNs has been demonstrated by Kumar and Chowdary (2023) and Liu et al. (2018), who developed road safety prediction models utilizing an ANN and regression approaches. The ANN approach was found to be satisfactory even with limited data. Another study employed an ANN model to estimate the fuel consumption and emissions of a diesel engine under transient conditions. The model was trained and tested using data from a test vehicle (Abdelwahab and Abdel-Aty 2001). Additionally, an ANN model was used to control vehicle speed by utilizing data from a real vehicle. The results showed that the model was capable of accurately controlling the vehicle's speed. Finally, a study compared the effectiveness of ANN and support vector machine (SVM) techniques for predicting vehicle speeds. The models were trained using data collected from a real vehicle, and the outcomes demonstrated that the ANN model performed better than the SVM model (Şentaş et al. 2018).

The use of Automatic Number Plate Recognition (ANPR) in transportation systems has become widespread in urban and highway settings. ANPR is a technology used to automatically identify and read the license plate numbers of vehicles passing through an area. ANPR systems use cameras and image processing software to capture images of license plates, recognize the characters on the plates, and convert them into a text format (Hounsell et al. 2009). In recent years, numerous large-scale License Plate Recognition (LPR) systems have been deployed in various countries. Beijing, for example, has 1958 ANPR cameras covering the entire metropolitan area, and this number is expected to increase. LPR systems gather data such as departing timestamps of vehicles and license plate numbers and use them in law enforcement, vehicle monitoring, and access control applications (Han et al. 2015). LPR data can also provide detailed estimates of traffic information, such as link travel time and queue lengths. Compared to other data sources, LPR data can model an entire traffic flow due to the high penetration rate of LPR cameras recording the information of nearly all the vehicles. However, LPR data still face limitations such as low matching rates of license plate numbers between upstream and downstream intersections, despite the increasing accuracy of LPR recognition (Saha et al. 2015). On the other hand, the Infra-Red Traffic Logger (TIRTL) is a device that uses infrared technology to measure the speed and volume of traffic on a particular road. It consists of two components, i.e., a sensor that is installed on the road and a data logger that records the data collected by the sensor. The data collected by TIRTL can be used to monitor traffic

flow and identify areas where speed management measures may be necessary.

To address the issue of excessive speeding vehicles and their impact on traffic accidents, a comprehensive speed management method is necessary. This study aims to evaluate the performance of two speed enforcement systems, namely Automatic Number Plate Recognition (ANPR) and the Infra-Red Traffic Logger (TIRTL), in identifying speeding vehicles. In addition, the study will explore the use of regression-based and ANN models for speed predictions and compare the performance of Multiple Linear Regression (MLR) with ANN. Various research studies have explored the speed prediction sector, with different models and methodologies being developed. This study will analyse the predicted results of the different models and compare them with both historic and real-time data. The implications of the findings can be far-reaching, with the potential to inform policy and decision-making on the local, national, and even global levels.

2 STUDY METHODOLOGY

This section provides a comprehensive discussion of diverse approaches utilized for speed measurements in the field, together with the methodologies employed for data analysis. Moreover, it includes an overview of the appropriate techniques for data processing and information transmission in addition to the aforementioned information. The methodology adopted for the present study is presented in Fig. 1.

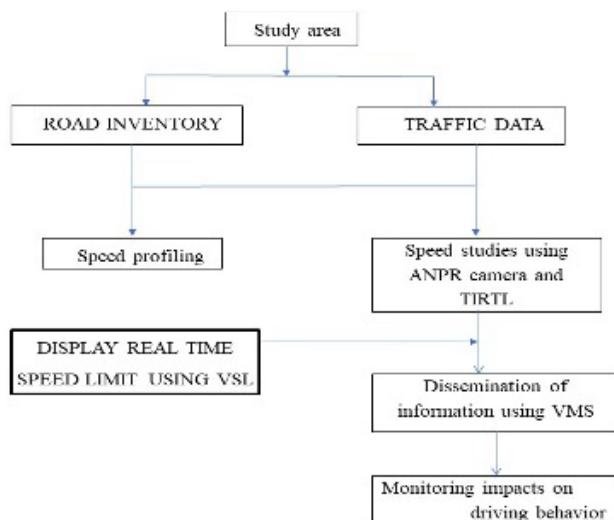


Fig. 1 Flow chart showing the methodology of the project

2.1 Selection of study area

The urban highways of India function unpredictably due to an inadequate transport infrastructure and a lack of adherence in most of the cities to good road condition standards. As a result, the effectiveness of Intelligent Transportation Systems (ITS) in such environments is doubtful. A study was therefore conducted to evaluate the applicability of ITS measures in an urban setting with a deficient transportation infrastructure. The study selected the city of Tiruchirappalli in Tamil Nadu as the study region for investigating and assessing the

implementation of ITS speed management. Specific road sections were chosen for the ITS technology implementation, (see Fig. 2). The selection of the study region was critical to ensuring the precision and relevance of the results to other Indian cities. The study was conducted over a period of six months, during which data from a total of 12,345 vehicles were intercepted and analyzed. The vehicles intercepted were categorized into various classes, including two-wheelers, auto-rickshaws, cars, light commercial vehicles (LCVs), and heavy commercial vehicles (HCVs).

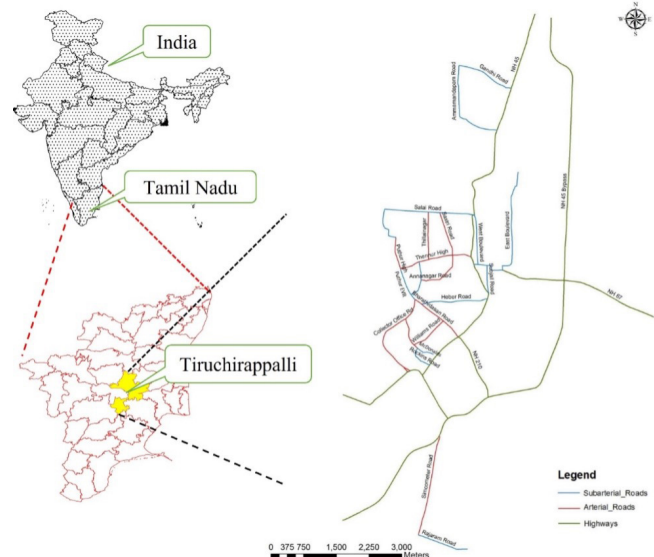


Fig. 2 Digitized road network map in the study area

Understanding the characteristics of a road is essential for picking the optimal site for ITS measures. To produce an inventory, a preliminary site assessment was undertaken on 24 roads as shown in Fig. 2, and details such as the nature and length of the road, its quality, and existing traffic control measures were noted.

The present study assessed the effectiveness of traffic speed control measures on 24 roads. The only measures identified were speed breakers and traffic signals. However, when the distance between these measures is short, it may disrupt traffic flow, causing drivers to reduce speed, which could affect research results. To ensure the deployment of automated systems such as ANPR and TIRTL, uninterrupted road stretches are required where vehicles can move freely. For the investigation of variable speed limits, a straight stretch of road without any speed management measures is necessary. Thus, the concept of "maximum free length" was introduced; it refers to the longest uninterrupted road stretch where vehicles can move without external hindrances. Multilane highways are ideal for the implementation of variable speed limits. This information may assist in the development of effective traffic speed control strategies. A comprehensive manual count was conducted to verify the accuracy of the automated systems. The manual count was cross-referenced with the data obtained from the Automatic Number Plate Recognition (ANPR) and the Infra-Red Traffic Logger (TIRTL) systems. Out of the 12,345 vehicles, the ANPR system correctly identified 6,297 vehicles (approximately 51%), while the TIRTL

system correctly identified 11,841 vehicles (approximately 96%). Errors in the assessment of vehicle classes and speed detection were systematically categorized. For instance, the ANPR system showed a higher error rate for two-wheelers and auto-rickshaws due to the smaller size of their license plates, whereas the TIRTL system maintained a high degree of accuracy across all the vehicle classes.

2.2 Setup of Instrument for ANPR and TIRTL

The Automatic Number Plate Recognition (ANPR) system consists of a camera that observes a vehicle number plate and a speed gun that is paired with the camera through KLiPR software. The complete setup is illustrated in Fig. 3, with the camera and speed gun positioned on a tripod to face the traffic from the opposing direction. The KLiPR software generates a structured output, as depicted in Fig. 4, which includes the images of a vehicle, its speed, and the number plate extracted using the optical character recognition (OCR) system. Furthermore, the output includes the date and time of the observation and the information about the number plate. These components work collaboratively to offer an efficient and precise ANPR system for various applications.

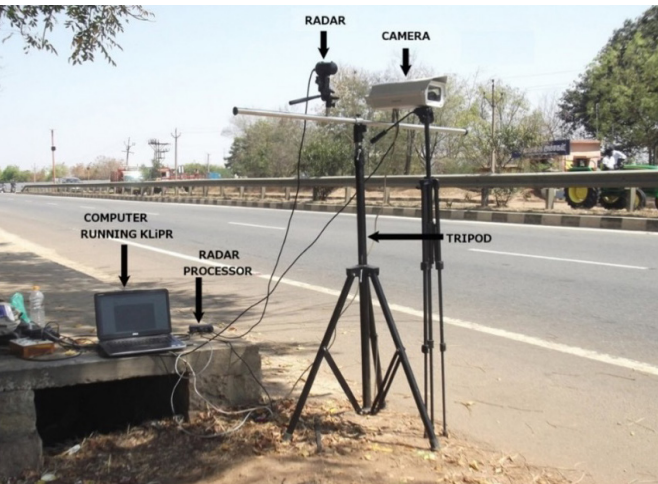


Fig. 3 Setup of an ANPR system



Fig. 4 KLiPR software interface

The TIRTL is a traffic monitoring device that does not intrude on traffic. It consists of a receiver (Rx) unit and a transmitter (Tx) unit on opposite sides of the road and is positioned perpendicular to the traffic flow as shown in Fig. 5. The transmitter (Tx) emits two cones of infrared light across the road, so that when a vehicle passes through, the cones break, and the receiver (Rx) records the broken cone data. The TIRTL's infrared cones form two straight and two diagonal beam paths by crossing each other. When a vehicle passes through these beams, two events occur: - one, when the vehicle enters the beam path, and the other, when it exits. All four beam paths record both of these events, thereby resulting in eight time-stamped events per axle. By knowing the velocity of each wheel and the time-stamp for each axle crossing, the inter-axle spacing can be calculated. This information is then compared to a table of inter-axle spacing ranges to correctly categorize the vehicle.

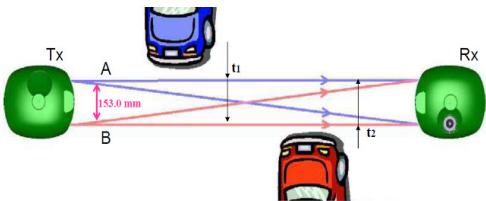


Fig. 5 Speed measurement using TIRTL (Tx – Transmitter, Rx – Receiver)

3 RESULTS AND DISCUSSION

The TIRTL instruments were put to a test to see how efficiently they worked. The performance was assessed in two ways using the typical parameters given by the developer:

- 1. Percentage of vehicles detected
- 2. Accuracy of speed detected

3.1 Percentage of vehicles detected

To determine the accuracy of the vehicle detection using the ANPR and TIRTL systems, a manual count of the traffic passing on a road was conducted, and the outputs of the two systems were compared with the manual count. The results are presented in Fig. 6. Out of 206 vehicles, the ANPR system correctly identified only 51% of the total vehicle classes, with heavy vehicles such as buses and trucks being identified more accurately. In contrast, the TIRTL system demonstrated a higher accuracy rate i.e., 96% of identifying the vehicle classes.

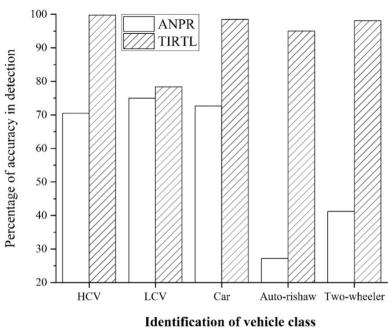


Fig. 6 Comparison of ANPR and TIRTL data in vehicle class identification

3.2 Accuracy in speed detection

Fig. 7 displays a comparison of the accuracy of speed detection using the ANPR and TIRTL systems. The TIRTL system demonstrated a significantly higher speed detection accuracy rate of 91%, as compared to the ANPR system's accuracy of 68%. The speed of heavy commercial vehicles (HCV) and light commercial vehicles (LCV) was accurately detected across all the classes of vehicles. However, two-wheelers and auto-rickshaws showed a relatively low accuracy rate in speed detection. It was observed that the magnification level, focusing, viewing angle, and camera height were critical components that affected the precision of speed detection using the TIRTL system.

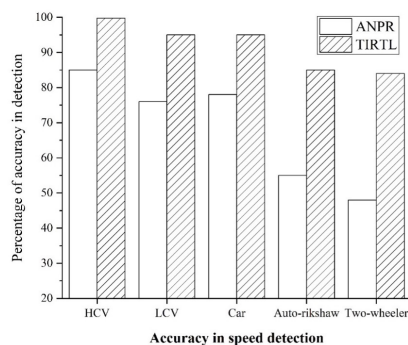


Fig. 7 Comparison of ANPR and TIRTL data in detecting the vehicle speed

3.3 Effect of VMS message with ANPR setup on reduction of speed of road users

In the field study, VMS was utilized to assess the efficiency of ANPR in managing speed. The long base method was implemented to identify vehicles exceeding the speed limit, and an ANPR camera was used to capture the license plate. A 27-meter section of the road was selected as it was clear of obstacles that could hinder vehicle speed. As the vehicle approached the marked 27-meter line, the ANPR camera recorded its license plate. A video camera synchronized with the ANPR was employed to determine the speed of the identified vehicle. To display the license number of the over-speeding vehicle, the VMS board was placed 200 meters away from the designated line. A second video camera was placed 300 meters away from the VMS board to monitor the speed variations of over-speeding vehicles. The entire setup in the field is depicted in Fig. 8.

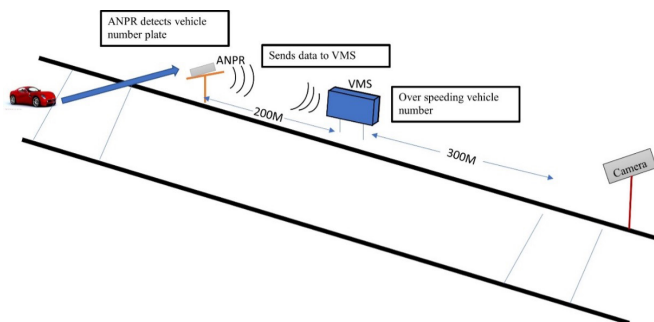


Fig. 8 Test setup model of ANPR and VMS

As the testbed is situated in a suburban area, the maximum speed of vehicles is restricted to 80 km/h, and they must cross a specific 27-meter line in a minimum of 1.2 seconds. Any vehicles that exceed this limit and cross the line in less than 1.2 seconds have their license plate numbers displayed on the Variable Message Sign (VMS) Board. The message that appears on the VMS Board is illustrated in Fig. 9. The speeds of the vehicles were determined by analysing video graphic surveys, and the resulting speed variations were examined. The differences in speed caused by the dissemination of the message through the VMS are shown in Table 1.



Fig. 9 The VMS's number plate display for a speeding vehicle

Tab. 1 Percentage of excessively speeding vehicles that reduced their speed on seeing the VMS

Vehicle Type	No. of excessively speeding vehicles observed	No. of vehicles that reduced their speed after the VMS	Percentage (%)
HCV	21	16	76.1
Car/LCV	53	34	64.1
Auto-rickshaw	25	18	72.0
Two-Wheeler	19	15	78.9
Overall	118	83	70.3

Tab. 1 indicates that cars and auto-rickshaws are the most frequently detected vehicles for excessive speeding, whereas two-wheelers are detected less frequently by automated number plate recognition (ANPR) due to their small license plates which pose problems in identification. The message that was disseminated via the variable message sign (VMS), resulted in responses from approximately 64% of the cars and 79% of the two-wheelers, which constituted 70% of all the excessively speeding vehicles during the observation period. It was interesting to note that the speed of a car without a displayed number plate reduced after perceiving the displayed

vehicle number, which led to deceleration for examination purposes. Further analysis demonstrated that two-wheelers experienced greater speed reductions compared to cars, which could potentially be attributed to their higher deceleration rates and allowed them to decrease speed over shorter distances than cars. The maximum speed reduction in cars was recorded as 20 km/h, with an average reduction of 8 km/h, while the maximum speed drop of 32 km/h was observed in a car, with a typical average speed reduction of 12 km/h.

3.4 Effect of the VMS message with the TIRTL setup on the speed reduction of the road users

The impact of the message display on Variable Message Sign (VMS) boards was studied using a TIRTL setup interconnected with the VMS board. The posted speed limit was adjustable based on the traffic flow, and the TIRTL setup was installed to determine the speed of vehicles. The VMS board was then placed 100m away from the TIRTL setup, and a video camera was used to survey the speed of passing vehicles for an hour, during which 601 vehicles were detected, with 72 vehicles observed to be traveling above 80 km/h. The complete test setup is shown in Fig. 10. A sample size of 100 vehicles (70 cars and 30 two-wheelers) was selected, representing 15% of the total vehicles observed; their speeds were compared before and after the VMS board. The percentage and range of speed reduction achieved are presented in Tab. 2.



Fig. 10 Test setup of TIRTL to identify the over-speeding vehicles

Tab. 2 Percentage of cars and two-wheelers with speed variations

Difference in Speed	CARS		TWO-WHEELERS	
	Numbers	Percentage (%)	Numbers	Percentage (%)
Increase in speed	6	8.6	4	13.33
Constant speed	47	67	8	26.66
Reduced by 0-5 km/h	9	12.8	5	16.66
Reduced by 5-10 km/h	5	7.14	6	20
Reduced by 10 km/h and above	3	4.3	7	23.33

The TIRTL data revealed that the vehicles that predominantly exceeded the speed limit were cars and two-

wheelers. The message conveyed through the VMS was acknowledged by around 24.3% and 60% of the cars and two-wheelers, respectively. Notably, even the vehicles moving at a speed of less than or equal to 80 km/h displayed reduced velocity subsequent to the display of the message, which was due to the driver's deceleration in response to the displayed message. The deceleration rate of two-wheelers being higher than that of cars, they were observed to reduce their velocity over shorter distances compared to the cars. As a result, two-wheelers showed a greater decrease in speed, with an average velocity reduction of 12.4 km/h compared to 6.8 km/h for cars.

4 DEVELOPMENT OF THE MODELS

4.1 Multiple Linear Regression (MLR) models

A Multiple Linear Regression (MLR) analysis was used to identify the strength of the relation between the variables and to estimate the change in the dependent variable when there was a change in the independent variables such that the future trends in the speed management could be predicted. In the present study, the MLR model was developed for accuracy in detecting speed for ANPR and TIRTL with input variables such as increased, constant and reduced speed. Eqs. (1) and (2) show the empirical relationships for predicting the speed using ANPR and TIRTL.

$$V_{ANPR} = 40 + 1.35 * (\text{increased speed}) + 0.72 * (\text{constant speed}) + 0.58 * (\text{decreased speed}) - 2.52. [R^2 = 0.72] \quad (1)$$

$$V_{TIRTL} = 45 + 1.85 * (\text{increased speed}) + 0.85 * (\text{constant speed}) + 0.71 * (\text{decreased speed}) - 1.55. [R^2 = 0.81] \quad (2)$$

V_{ANPR} – Speed forecasting using ANPR, V_{TIRTL} – Speed forecasting using TIRTL

Tab. 3 Linear Regression results for V_{ANPR}

V_{ANPR}	Coefficients	Std. Error	t-stat.	p-value
Intercept	42	2.2135	45.85	0.657E-2
Increased speed	2.52	0.00765	23.65	0.0758
Constant speed	1.35	0.00425	4.69	0.0082
Decreased speed	0.85	0.00053	1.57	1.636E-22

Tab. 4 Linear Regression results for V_{TIRTL}

V_{TIRTL}	Coefficients	Std. Error	t-stat.	p-value
Intercept	47	3.1254	60.32	0.8723E-2
Increased speed	3.24	0.00365	20.54	0.0745
Constant speed	1.53	0.00987	3.65	0.0032
Decreased speed	0.96	0.00619	2.87	1.525E-23

The findings of the regression analysis are presented in Tabs. 3 and 4, which report the regression coefficients, standard errors, t-statistics, and p-values. The regression coefficient of 2.52 in Tab. 3 indicates that a one-unit change in the independent variable results in a corresponding change of 2.54 units in the dependent variable. The t-values, which are obtained by dividing the regression coefficients by the standard errors, have all yielded p-values below the 0.05 threshold, thereby indicating that the three variables under consideration exert a statistically significant influence on the predicted model.

4.2 Development of an Artificial Neural Network

Artificial Neural Networks (ANN) are a class of soft computing techniques used for forecasting mathematical models; they draw inspiration from the structure and functionality of the human brain. ANNs are capable of predicting complex nonlinear relationships between dependent and independent variables. Once trained, ANNs can compute outputs for a given set of inputs; however, the connections between inputs and outputs are not immediately discernible (Xu et al., 2018). The back-propagation (BP) algorithm is the most common technique used for training ANNs, whereby weights and bias variables are updated using the Levenberg-Marquardt optimization technique. The Levenberg-Marquardt algorithm combines the steepest descent method and the Gauss-Newton algorithm, thereby inheriting the speed advantage of the latter and the stability of the former (Nasr et al., 2012). Feed-forward ANNs propagate information in a forward direction and can be categorized into two types: single-layer neuron networks and multi-layer neuron networks. Multi-layer neuron networks have the added benefit of handling non-linear functions (Puri et al., 2016). Hence, ANNs consist of interconnected artificial neurons arranged in multiple layers, which comprise an input layer, one or more hidden layers, and an output layer, as depicted in Figure 11.

The ANN network developed in this study consists of the following:

- Four neurons in the input layer ($N_i = 3$); the input parameters in each neuron represent an increase in speed, constant speed, and reduced speed.
- A hidden layer with 8 or 12 neurons in ANN1 for ANPR and ANN2 for TIRTL.
- One output layer with a single neuron corresponding to the predicted value of the accuracy of detecting an over-speeding vehicle (%).

The performance validation of the ANN1 and ANN2 models developed was estimated using the criteria below:

- Root Mean Square Error (RMSE): The RMSE that can be estimated by using the following function is used to assess the error values that occurred during the training, testing, and validating of ANN models (Zollanvari and Dougherty, 2014)

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (O-P)^2}{n}}$$

Where O = experimented value
P = predicted value
n = number of samples

- Mean Absolute Percentage Error (MAPE): The following equation can be used to determine the average of the absolute percentage error (Draper et al., 2013):

$$MAPE = \frac{\sum_{i=1}^n |(O-P)/O|}{n} * 100$$

- Coefficient of determination (R^2): The absolute percentage of variance in a model is represented by the R-square coefficient. The following function can be used to determine R^2 :

$$R^2 = 1 - \frac{\text{square of residuals}}{\text{square of predicted values}}$$

The network structure for the current investigation was created using the MATLAB Neural Network Toolbox. Figs. 11 and 12 illustrate the schematic representation of the ANN's structure. The Levenberg-Marquardt back-propagation algorithm was used as a training function, and a hyperbolic tangent sigmoid was used as a transfer function. The training rate, which indicates how frequently connection weights are altered during training, was calculated in relation to the network's performance. The training rate and momentum for each ANN were altered to produce the best results. Seventy percent of the data sample is utilized for training; 15% is used for testing; and the remaining 15% is used for validation.

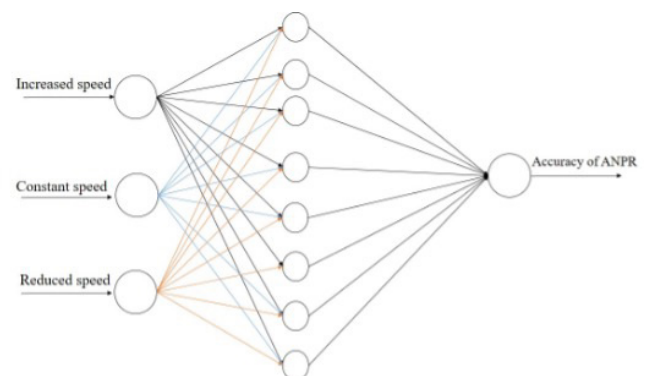


Fig. 11 ANN₁ model structure (3-8-1) for predicting the accuracy of ANPR

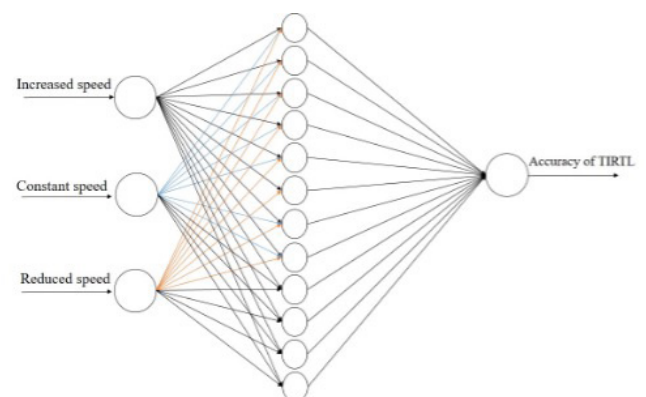


Fig. 12 ANN₂ model structure (3-12-1) for predicting the accuracy of TIRTL

Tab. 5 ANN model results

MODEL	Training			Testing			Validating		
	R ²	RMSE	MAPE	R ²	RMSE	MAPE	R ²	RMSE	MAPE
ANN1	0.9875	0.1865	1.536	0.9841	0.1758	1.658	0.9832	0.1825	1.423
ANN2	0.9932	0.1325	1.256	0.9958	0.1356	1.324	0.9921	0.1345	1.336

The statistical values for evaluating the performance of the ANN model to forecast the accuracy of various speed management techniques using ANPR and TIRTL were shown in Tab. 5. The model was trained using 70% of the data sample, and the RMSE values of 0.1865 and 0.1325 were achieved for predicting the accuracy of the speed management technique, as well as the MAPE values of 1.536 and 1.256. It was determined that the RMSE and MAPE values for testing and validation were low, thereby demonstrating the model's accuracy. Among all three data sets (training, testing, and validation), the training data set produced the best outcomes by offering very low RMSE, MAPE, and R² values that were extremely close to one. It is also important to note that the accuracy of ANN models can be ranked according to RMSE, MAPE, and R² in the following manner: reduced speed, increased speed, and constant speed.

It was observed that the ANN exhibits higher values of “R” in comparison to MLR. This observation suggests that ANN effectively characterizes the problem and that the estimated output error falls below the acceptable limits. Consequently, the ANN model consistently ensures greater precision than the regression model suggested.

4.3 Comparison of the MLR and ANN models

The suitability of both the ANN and MLR models for predicting vehicle speed in an urban area was evaluated by comparing their performances. Tab. 6 presents a comparison of the VANPR and VTIRTL values for both the measured and predicted data using the two models. A random sample of the data points was removed, and the error values for the two models were calculated; on the one hand the MLR model displayed an average deviation of 2.56 km/h and 1.52 km/h in V_{ANPR} and V_{TIRTL}. On the other hand, the ANN model demonstrated an average deviation of 1.46 in V_{ANPR} and 0.72 in V_{TIRTL}. Therefore, the ANN model outperformed the MLR model in terms of the mean-squared error and coefficient of determination between the measured and predicted data. Furthermore, ANN models are more versatile and proficient at forecasting extreme speed levels, whereas MLR models are better suited for capturing the linear pattern of time series data. However, MLR models have limitations in their adaptability and require correction factors to account for any extreme values. In summary, current ANN models can be effectively utilized to provide accurate vehicle speed estimates and forecasts.

Tab. 6 Comparison between the measured and predicted results of the models

Testing trial	Results					Error values			
	Measured speed in the field	Regression		ANN		Regression		ANN	
		V _{ANPR}	V _{TIRTL}	V _{ANPR}	V _{TIRTL}	V _{ANPR}	V _{TIRTL}	V _{ANPR}	V _{TIRTL}
1	50.5	47.6	48.1	48.8	49.4	2.9	2.4	1.7	1.1
2	62.3	59.3	60.5	60.8	61.8	3	1.8	1.5	0.5
3	68.9	65.3	67.4	66.7	68.1	3.6	1.5	2.2	0.8
4	75.8	77.1	74.8	76.5	75.1	-1.3	1	-0.7	0.7
5	82.6	84.6	81.7	83.8	82.1	-2	é.9	-1.2	0.5

5 CONCLUSIONS

Speed management aims to improve the safety and mobility of traffic in an area by developing, implementing, and enforcing appropriate management strategies. Intelligent Transportation Systems (ITS) are currently playing an important role in speed management in developed countries and have been shown to significantly improve the safety and efficiency of transportation systems. However, the use of ITS in India has been limited due to factors such as a mixed traffic system, a lack of proper town planning, and irregular road patterns etc. The study's objective is to evaluate the feasibility of various ITS measures in

Tiruchirappalli, the study area. Speed management equipment such as an ANPR camera, TIRTL, and VMS were used. The study concludes that ANPR correctly detected only 51% of the total vehicle classes, whereas the TIRTL correctly detected 96% of the vehicle classes. The TIRTL detected 91% of the vehicle's speed, while the ANPR detected only 68%. The HCV and LCV speed detection were accurate across all the vehicle classes, but the speeds of the two-wheelers and auto-rickshaws were not detected to the same degree. The speed of a car whose license number was not displayed dropped their speed after the notification was displayed on VMS. This occurred as a result of the car slowing down to inspect the visible vehicle number.

Two-wheelers experienced larger speed reductions than automobiles, according to the research. A maximum speed reduction of 20 km/h was observed with a car, with an average speed reduction of 8 km/h. A maximum speed reduction of 32 km/h was recorded with a two-wheeler; however, the typical average speed reduction was only 12 km/h. The VMS message was received by approximately 24.3% of cars and 60% of two-wheelers, respectively. It was evident that the ANN models outperformed MLR in terms of forecasting vehicular speed, with high R values and low mean-squared error. Finally, the ANN model generated might aid urban planners in creating new speed management techniques by properly estimating the correctness of the speed management techniques in an urban setting. As a result, ANN can be a useful alternative to analytical models for predicting the performance of any ITS technology.

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REFERENCES

- Abdelwahab, H. T., & Abdel-Aty, M. A. (2001) *Development of artificial neural network models to predict driver injury severity in traffic accidents at signalized intersections*. Transportation research record, 1746(1), 6-13.
- Bari, C., Navandar, Y., Dhamaniya, A. (2019) *Service Time Variation Analysis at Manually Operated Toll Plazas under Mixed Traffic conditions in India*. J. East. Asia Soc. Transp. Stud. 13, 331–350. <https://doi.org/10.11175/easts.13.331>
- Carnis, L., & Blais, E. (2013) *An assessment of the safety effects of the French speed camera program*. Accident Analysis & Prevention, 51, 301-309. <https://doi.org/10.1016/j.aap.2012.11.022>
- Chaudhary, R. (2019) *Green human resource management in Indian automobile industry*. J. Glob. Responsib. 10, 161–175. <https://doi.org/10.1108/JGR-12-2018-0084>
- D'Apuzzo, M., Santilli, D., Evangelisti, A., Fusco, G., Nicolosi, V., Pernetti, M., & Isaenko, N. (2021) *Toward the development of a hybrid approach to speed estimation in urban and rural areas*. Traffic Injury Prevention, 22(6), 449-454. <https://doi.org/10.1080/15389588.2021.1935904>
- Distefano, N., Leonardi, S. (2019) *Evaluation of the benefits of traffic calming on vehicle speed reduction*. Civ. Eng. Archit. 7, 200–214. <https://doi.org/10.13189/cea.2019.070403>
- Draper, C., Reichle, R., de Jeu, R., Naeimi, V., Parinussa, R., Wagner, W. (2013) *Estimating root mean square errors in remotely sensed soil moisture over continental scale domains*. Remote Sens. Environ. 137, 288–298. <https://doi.org/10.1016/j.rse.2013.06.013>
- FHWA. (2000) *Roundabouts: An Informational Guide*. Report 672. Federal Highway Administration. Virginia, USA.
- Hadiuzzaman, M., Qiu, T. Z., & Lu, X. Y. (2013). *Variable speed limit control design for relieving congestion caused by active bottlenecks*. Journal of Transportation Engineering, 139(4), 358-370.
- Han, Y., Wang, G., Yu, J., Liu, C., Zhang, Z., & Zhu, M. (2015) *A service-based approach to traffic sensor data integration and analysis to support community-wide green commute in China*. IEEE Transactions on Intelligent Transportation Systems, 17(9), 2648-2657.
- Hounsell, N. B., Shrestha, B. P., Piao, J., & McDonald, M. (2009) *Review of urban traffic management and the impacts of new vehicle technologies*. IET intelligent transport systems, 3(4), 419-428. DOI: 10.1049/iet-its.2009.0046
- Jin, Y., Wang, X., Chen, X. (2011) *Evaluating the Speed Reduction Effectiveness of Speed Bump on Local Streets*. ICCTP 2011, ASCE 2011 346–359.
- Kumar, B. S., & Chowdary, V. (2023) *Use of artificial neural networks to assess train horn noise at a railway level crossing in India*. Environmental Monitoring and Assessment, 195(3), 1-19. <https://doi.org/10.1007/s10661-023-11021-2>
- Liu, Q., Wang, B., & Zhu, Y. (2018) *Short-term traffic speed forecasting based on attention convolutional neural network for arterials*. Computer-Aided Civil and Infrastructure Engineering, 33(11), 999-1016. <https://doi.org/10.1111/mice.12417>
- Nasr, M. S., Moustafa, M. A., Seif, H. A., & El Kobrosy, G. (2012) *Application of Artificial Neural Network (ANN) for the prediction of Artificial Neural Network (ANN) for the prediction of EL-AGAMY wastewater treatment plant performance-EGYPT*. Alexandria engineering journal, 51(1), 37-43.
- Olayode, O.I., Tartibu, L.K., Okwu, M.O., (2020) *Application of Artificial Intelligence in Traffic Control System of Non-autonomous Vehicles at Signalized Road Intersection*. Procedia CIRP 91, 194–200. <https://doi.org/10.1016/j.procir.2020.02.167>
- Puri, M., Solanki, A., Padawer, T., Tipparaju, S. M., Moreno, W. A., & Pathak, Y. (2016) *Introduction to artificial neural network (ANN) as a predictive tool for drug design, discovery, delivery, and disposition: Basic concepts and modeling*. In Artificial neural network for drug design, delivery and disposition (pp. 3-13). Academic Press.
- Saha, S., Basu, S., & Nasipuri, M. (2015) *An Indian license plate recognition system*. Multimedia Tools and Applications, 74, 10621-10656.
- Sanka, A.I., Irfan, M., Huang, I., Cheung, R.C.C. (2021) *A survey of breakthrough in blockchain technology: Adoptions, applications, challenges and future research*. Comput. Commun. 169, 179–201. <https://doi.org/10.1016/j.comcom.2020.12.028>
- Şentaş, A., Tashiev, İ., Küçükayvaz, F., Kul, S., Eken, S., Sayar, A., & Becerikli, Y. (2020) *Performance evaluation of support vector machine and convolutional neural network algorithms in real-time vehicle type and color classification*. Evolutionary Intelligence, 13, 83-91. <https://doi.org/10.1007/s12065-018-0167-z>
- Tandon, R. (2020) *COVID-19 and mental health: Preserving humanity, maintaining sanity, and promoting health*. Asian Journal of Psychiatry, Volume 51. doi: 10.1016/j.ajp.2020.102256
- Tavolinejad, H., Malekpour, M. R., Rezaei, N., Jafari, A., Ahmadi, N., Nematollahi, A., & Farzadfar, F. (2021) *Evaluation of the effect of fixed speed cameras on speeding behavior among Iranian taxi drivers through telematics monitoring*. Traffic injury prevention, 22(7), 559-563. <https://doi.org/10.1080/15389588.2021.1957100>
- Tientrakool, P., Ho, Y.C., Maxemchuk, N.F. (2011) *Highway capacity benefits from using vehicle-to-vehicle communication and sensors for collision avoidance*. IEEE Veh. Technol. Conf. 0–4. <https://doi.org/10.1109/VETECF.2011.6093130>
- Xu, Y., Ye, Z., Wang, Y., Wang, C., & Sun, C. (2018) *Evaluating the influence of road lighting on traffic safety at accesses using an artificial neural network*. Traffic injury prevention, 19(6), 601-606. <https://doi.org/10.1080/15389588.2018.1471599>
- Zollanvari, A., Dougherty, E.R. (2014) *Moments and root-mean-square error of the Bayesian MMSE estimator of classification error in the Gaussian model*. Pattern Recognit. 47, 2178–2192. <https://doi.org/10.1016/j.patcog.2013.11.022>