ASSESSING THE IMPACT OF THREE-WHEELERS ON TRAFFIC FLOW IN INDIA: A CASE STUDY USING ANN

Malaya Mohanty*, Madhu Lisha Pattanaik, Satya Ranjan Samal, Shivam

School of Civil Engineering, KIIT Deemed to be University, Bhubaneswar, India

*E-mail of corresponding author: malaya.mohantyfce@kiit.ac.in

Malaya Mohanty 0000-0002-6116-782X, Madhu Lisha Pattanaik 0000-0003-0835-9694, Satya Ranjan Samal 0000-0001-8675-453X

Resume

This study explores the significant role of three-wheelers (3W) on urban road traffic, focusing on the reduction in average vehicle speeds and its consequential impact on the Level of Service (LOS) of the road. Data collected from various traffic volumes reveal significant speed reductions ranging from 4% to 35% due to the movement of 3Ws on the road. To model this phenomenon, Artificial Neural Network (ANN) is employed. The resulting reductions in speed, induced by the 3W, trigger LOS degradation, leading to congestion and delays. A noteworthy finding is that the traffic flow naturally gravitates towards the LOS C, underscoring the substantial role played by the 3W in diminishing the overall LOS of the road. This research offers critical insights into the dynamics of urban traffic influenced by the 3W, providing a valuable foundation for traffic management and urban planning efforts.

Available online: https://doi.org/10.26552/com.C.2024.033

Article info

Received 27 February 2024
Accepted 23 May 2024
Online 31 May 2024

Keywords:

three-wheelers (3W)
traffic flow
average speed reduction
congestion
level of service (LOS)
artificial neural network (ANN)
speed modelling

ISSN 1335-4205 (print version)
ISSN 2585-7878 (online version)

1 Introduction

The world's urban landscapes are constantly evolving, with transportation playing a pivotal role in shaping the dynamics of cities and the flow of traffic [1]. Among the diverse array of vehicles that traverse the streets of bustling metropolises and tranquil towns, the three-wheelers hold a unique position. These small vehicles with three wheels are commonly found in parts of the world with a unique impact on traffic flow. Understanding how three-wheelers affect the traffic is essential for city planners, policymakers, and commuters alike.

Urban transportation systems are continuously evolving, and one essential aspect of this transformation is the role of three-wheelers (3W) in influencing the traffic dynamics [2]. This study sets the stage for a comprehensive exploration of how the 3W impacts urban road traffic. The study delves into the reduction in average vehicle speeds caused by 3W and its subsequent repercussions on the Level of Service (LOS) of roads.

Increase in buildings over the years have increased pressure on the existing infrastructure leading to the building of new roads, flyovers, and expressways [3-8]. India, being a developing country has seen a wave of rapid growth in the road infrastructure over the last few years [9-10]. The major objective of constructing new and wider roads is usually to reduce the time of journey between any two locations, while also keeping in view the safety of the road users. However, in developing countries like India, the problem of heterogeneity or mixed traffic acts as an obstruction in achieving these objectives completely [11]. On the roads of developing countries, various categories of vehicles like two-wheelers, cars, and heavy vehicles are observed. One such category, which is predominately observed as public transport in developing countries are the auto-rickshaws or three-wheelers (3W). While these vehicles offer advantages such as affordability, maneuverability, and accessibility, they also raise concerns regarding their impact on traffic flow. The 3Ws have several advantages as they can easily change lanes [12], are much more affordable, and can provide door-to-door service, which is not possible for other public transportation systems. However, their frequent stop-and-go feature, along with less operating speed as compared to the traffic stream, along with an appreciable composition in traffic flow, makes it a potential cause for reducing the overall quality of service on roads, thereby increasing the probability of congestion and delays to road users [5, 13-16].

Therefore, in the present study, the effect of the 3Ws as slow-moving vehicles (SMVs) has been assessed utilizing artificial neural network (ANN). Data is collected across various traffic volumes and proportions of vehicles influenced by 3W unveil a significant slowing of traffic, with cars and two-wheelers experiencing the most substantial speed reductions. The modelling of this phenomenon is facilitated by Artificial Neural Networks (ANN). Further, the consequences of these speed reductions reflect through congestion and delays, altering the LOS of roads. The present study leads to a deeper understanding of the role of three-wheelers in the broader traffic ecosystem, which is essential for crafting effective urban transportation policies and planning for a more sustainable and efficient future of mobility.

2 Literature review

Not many studies have been found to address the effect of 3W as slow-moving vehicles on the traffic stream in developing countries. However, there are some studies [11, 17-18], which have studied the traffic congestion in developing countries and have indirectly considered the effect of slow-moving vehicles (SMVs) like 3W, and heavy vehicles (HVs) while analyzing the congestion or calculating heterogeneity index. Pinzke and Lundqvist (2004) [14] conducted a comprehensive study on accidents involving slow-moving vehicles on Swedish roads. Another research studied the patterns of elephant racing at moving bottlenecks and explained the non-linear features of complex interactions among vehicles. However, the authors did not specify any single category of vehicle [19]. Slow-moving vehicles are defined as vehicles, which move at speeds between 10-40 km/h [20]. The authors developed a macroscopic model to assess the effect of slow-moving vehicles on traffic congestion where the input parameters consisted of the flows in both directions, the percentage of trucks, the speed and journey length of the slow-moving vehicle; and the outputs provided by the model are number of overtakes; size and duration of disturbance; number of affected vehicles and their delay, etc. Although the speed is a better parameter to judge slow-moving vehicles, developing one model might not apply to different categories of vehicles. Wickes and Nelson (2000) [21] had described the complete physics behind the slow-moving vehicles, their requirement, the necessary emblems to be put on them to prevent hazards and their speed limits. However, since the study was conducted 23-25 years ago, it considered only farm vehicles as slow-moving vehicles. Recently, Del Serrone et al. (2023) [22] assessed the effectiveness of providing climbing lanes to slow-moving vehicles while climbing hills using VISSIM. Although the results exhibited by the authors are positive, however, unlike the study, in developing countries heavy vehicles are not the only slow-moving vehicles. Further, their study was limited to hilly terrain only. A similar study suggested providing passing bays every 2-4 km for slow-moving agricultural vehicles on 2-lane rural roads [23]. Garvey (2003) [24] addressed the shortcomings of the SMV emblem that was used as a safety feature for more than 40 years in the US. He interviewed over 100 male and female drivers on the identification of the SMV emblem, which surprisingly showed that although older drivers understood the meaning of the safety emblem, the understandability of younger counterparts was under 30%. The study was meant for developed countries and talked about poor driver education. Its utilization in developing countries seems to be sparse. Sylla (2021) [25] proposed a model to understand the effect of SMVs on traffic. However, the model although accurate was hugely dependent on the downstream traffic density. Further, the SMVs were defined as vehicles moving in bottlenecks only. Gaur and Sachdeva (2022) [26] opined that SMVs reduce the capacity of the road. The study reported that an increase in HVs from 5 to 15% on the road reduces the capacity of the road by 20%. Another literature [27] studied the effect of SMVs on young drivers at night in Malaysia. All the literature seems to address only HVs or agricultural vehicles as SMVs, whereas, in developing countries like India, selective 3Ws are also SMVs as their average speeds are usually less than 40 km/h. Similarly, machine learning (ML) and deep learning methods have not been used much to study the aspect of SMVs.

A study at a small roundabout in Hlohovec, Slovakia [28], reflected that changing the traffic organization would result in shorter travel times, better traffic flow permeability, and fewer collision points. The study also highlighted the impact of the proposed changes on traffic characteristics, such as stop times, speed, and travel times. Lizbetin and Stopka (2016) [29] proposed a solution for a specific traffic operation in the city of Pilsen. They focused on analyzing traffic survey results in the field. The goal of their study was to increase traffic fluency, safety, and environmental protection in urban areas. Neural networks has also been used in a study to forecast the number of road accidents and the authors opined that neural networks are an effective tool to study traffic scenarios [30]. In a dated study [31], the authors reviewed and suggested various traffic scenarios/contexts, which should be studied in detail; and one of them was to address the travel time by various categories of vehicles. Another research studied the two types of behaviours exhibited by drivers: one being aggressive and another being cooperative. While aggressive behaviours might lead to crashes, excessive cooperative behaviours can lead to long queues and congestion [32]. These drivers need to be studied as they always slow down the traffic stream. Although the study by Metelski (2018) [33], examined various traffic events on the road, the researcher has opined that it

Figure 1 *Snapshot from one of the sites illustrating the temporary road markings*

does not delve into all the types of traffic problems related to various categories of vehicles. Authors of [34] presented that cars emit maximum Carbon Di-Oxide to the environment. They also found that standing vehicles and at speeds below 15th percentile speeds produce much higher CO_2 to the environment and the reason is attributed to intersections and SMVs. An increase in EVs and autonomous vehicles can decrease the proportions of SMVs like 3-wheelers, which impact the traffic flow, [35]. Therefore, it can be said that many researchers have directly or indirectly addressed the problems faced by SMVs on the road, but have not much assessed it as their objectives were different. Further, with advancements in active learning (AL) and machine learning, the studies need to apply them to make evaluation easier on roads. Therefore, the present study attempts to evaluate the effect of 3Ws in Indian conditions on urban road traffic scenarios utilizing ANN.

3 Site selection, data collection and methodology

Data from various mid-block sections on 6-lane divided urban roads within the city of Bhubaneswar, India, were gathered via video recording technique. Bhubaneswar, classified as a tier-II smart city, boasts a population of approximately 1.5 million residents. The selection of this city for our study is based on its representation of a typical tier-II city in India, sharing similar demographic characteristics with many other cities in this category. The test sections were specifically chosen to ensure that the traffic flow at these locations remains unaffected by factors such as horizontal curvature, the presence of intersections downstream or upstream, bus stops, parked vehicles, pedestrian activity, or any form of side friction. Data was collected from various locations at mid-block sections within the urban area, and these collections were carried out at different time intervals for a comprehensive analysis. Temporary road markings were applied to the road section, as depicted in Figure 1. For the study, data were acquired through video recording techniques, and subsequently retrieved with the aid of Kinovea software, ensuring accuracy and efficiency in the extraction process. The recorded videos were played back on a monitor using Kinovea video editing software, and the following parameters were extracted.

a) Traffic Volume.
b) Operating speeds of vehicles
c) Composition of vehicles.

The extracted data were subjected to various statistical analyses to study the effect of 3W on other categories. The detailed methodology of the study is presented in the form of a flow chart in Figure 2. To identify vehicles following the 3-wheelers (3Ws) for the study, certain criteria were established. This included identifying vehicles that consistently followed 3Ws without the availability of space for overtaking them and exhibited a regular pattern of brake light usage, observed through the tail lamp lights. Additionally, in instances where a queue is formed, vehicles within the queue were considered only if the leading vehicle was a 3W. Analyzing the speeds of both regular vehicles and those following 3Ws offered valuable insights into the impact of 3Ws on the traffic flow, presenting an intriguing avenue for research.

3.1 Artificial neural network

Artificial neural networks (ANN), recognized as one of the foremost data mining techniques for addressing intricate challenges across diverse fields such as fluid mechanics, signal processing, transportation studies, nanotechnology, and atomic physics [36], serve as prevalent nonlinear estimation models [37]. The ANN methodology involves data processing through

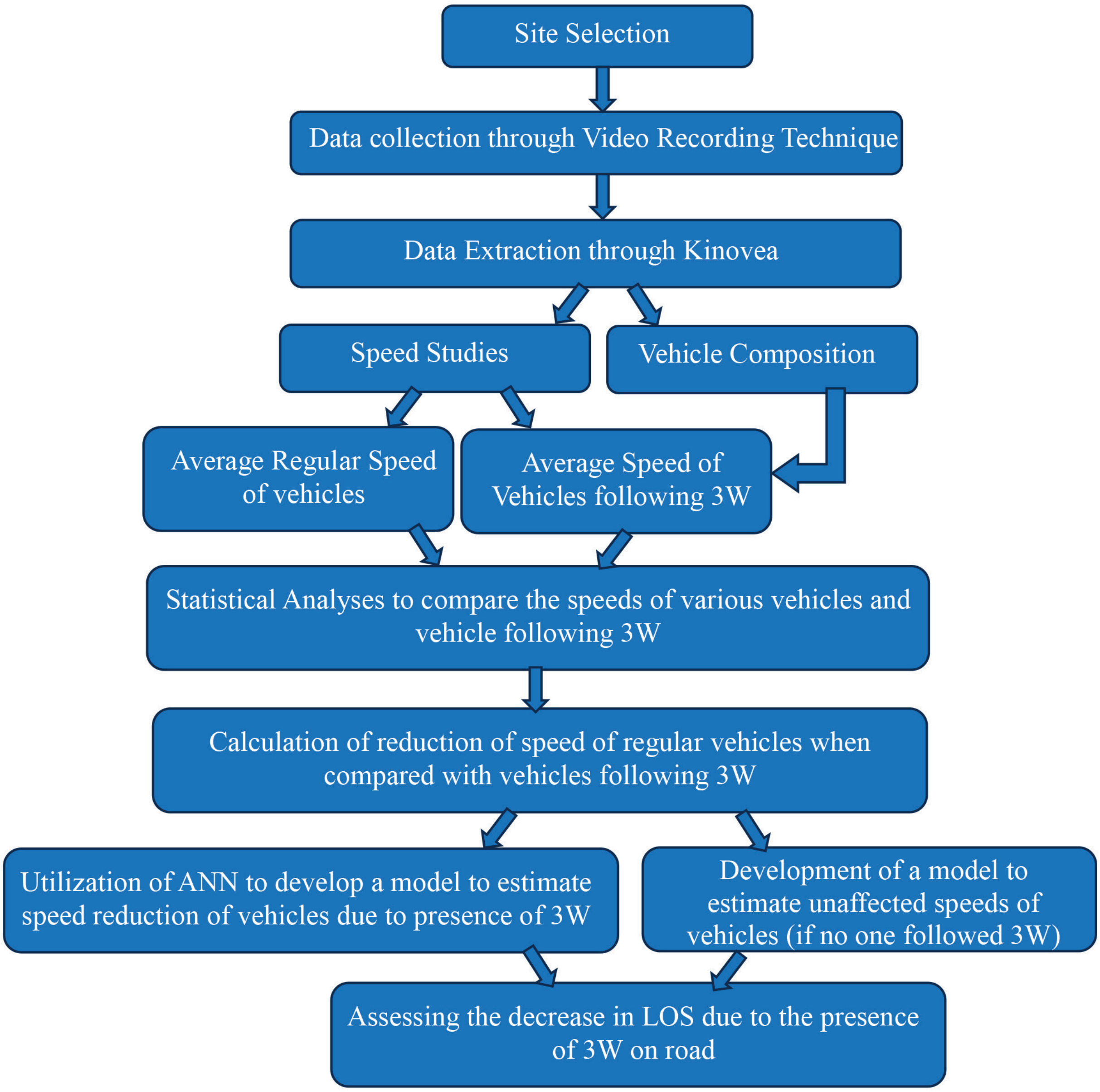

***Figure 2** Flowchart for methodology*

interactions among virtual neurons, arranged in a layered structure with numerous interconnections [38]. Each neuron's output in each layer serves as input to multiple neurons in the subsequent layer, thus establishing the transfer functions applied to each neuron's input signal.

Numerous studies attest to the ANN's adeptness in accurately predicting various traffic incidents, establishing its reliability [39]. Typically, the ANN configurations with two hidden layers are widely employed in transportation engineering problem-solving. However, inappropriate neuron counts in hidden layers may result in over-fitting or under-fitting, compromising the network's performance and accuracy. Shallow networks with one or two hidden layers represent the most fundamental ANN structures. With more than one hidden layer, ANN models transition into deep models, enabling the learning of multiple representation levels and enhancing their capacity to model complex real-world data.

Given the intricate nature of the data handled by ANNs, introducing non-linearity into the model is crucial, which is achieved through activation functions. These functions facilitate the neural network in emphasizing pertinent information, while disregarding irrelevant data points. Various sigmoid activation functions, including TanH, linear, and Gaussian, can be utilized in developing ANN models. TanH non-linearity is commonly favored, particularly when the data structure is entirely unknown. In the present study, ANN has been utilized to estimate the speed of the traffic stream at different traffic volumes, based on the categories of vehicles and the percentage of vehicles following 3Ws. This in turn can accurately determine how LOS is being affected due to the presence of slow-moving 3Ws.

4 Results and analysis

The study revolves around the assessment of operational effects of 3-wheelers on the flow of traffic on urban roads. To examine this effect, first the classified traffic volume along with speeds of various motorised category of vehicles have been extracted as mentioned in section 3. The data has been knowingly collected during the working hours of 8 AM to 8 PM, when the most of the public is active to ascertain the true effect of 3-wheelers. During this time, the lowest volume on the studied locations has been found to be around 1500-2000 v/h, which can reach up to 5000 v/h. The consolidated data of average speeds of various categories of vehicles during different traffic volumes is presented in Table 1.

The data provided in Table 1 is a compilation of more than 20000 vehicles across various traffic volumes at different times of the day. It can be observed that the average speeds remain statistically the same up to 3500-4000 v/h ($p > 0.05$ for speed values from 1500-4000 v/h in t-tests comparison). However, at traffic volumes above 4000 v/h, the road is moving towards congestion, therefore the average speeds decrease suddenly in the range of 25-37%. The t-test comparing speeds of vehicles within 1500-4000 v/h and >4000 v/h also gave similar results as the p-value was obtained to be <0.05. The effect of traffic congestion is seen more in the case of cars, jeeps, and HV as compared to 2W and 3W due to the dimensions of vehicles. From Table 1 can be observed that the 3-W and HVs have lesser speed as compared to other 2 categories of vehicles, which is in similar lines with the objective of the present study. The proportion of HVs is much lesser (0.5-1% of total traffic), as compared to other categories and HVs mostly comprises city buses and school buses in the present study. However, out of every 100 vehicles on the studied road, 11-12 vehicles are 3Ws, and therefore they affect the flow of other vehicles more, as compared to HVs due to their inherent lesser operating speed and higher traffic composition. Secondly, it is observed that due to bigger dimensions, buses are visible from a distance and that is why other road users take appropriate measures while driving, from a distance (like lane changing manoeuvres, or overtaking manoeuvres) based on the traffic condition. The same does not apply in the case of vehicles following the 3Ws. Moreover, due to their design of 1 wheel in front, they suddenly change their lane towards the curb side for picking up passengers or drop them off. Before divulging that assessment, Table 2 showcases the average change in speed as compared to 3W for various categories of vehicles across different volumes.

The positive values in Table 2 represent an increase in speed over 3Ws, while a negative value represents a decrease in speed. As can be seen from Table 2, the 2W and cars and jeeps have higher speeds as compared to 3Ws at any traffic volume. The difference in speeds is bigger at lower traffic volumes. As the traffic goes towards higher volumes and congestion, the difference in speed decreases. Although the 3Ws are the slowest vehicles on the road, in 3 instances, HVs have shown

Table 1 *Descriptive statistics of classified speeds at different traffic volume levels*

Volume (v/h)	Average Speeds (km/h)			
	2W	3W	Cars and Jeeps	HV
1500-2000	34	27	40	27
2000-2500	33	26	39	26
2500-3000	35	28	40	27
3000-3500	35	30	41	30
3500-4000	36	32	41	27
4000-4500	29	24	29	23
4500-5000	27	24	26	23

Table 2 *Percentage increase of operating speeds as compared to 3W*

Volume (v/h)	% of increase/decrease of speed as compared to 3W		
	2W	Cars and Jeeps	HV
1500-2000	25.93	48.15	0
2000-2500	26.92	50	0
2500-3000	25.00	42.86	-3.57
3000-3500	16.67	36.67	0
3500-4000	12.50	28.13	15.63
4000-4500	20.83	20.83	-4.17
4500-5000	12.50	8.33	-4.17

Table 3 *Grubb's test to determine outlier speed values for different categories of vehicles*

	Mean Speed (km/h)	Std. Deviation	Min.	Max.	G	P
2W	34.05	9.80	14.75	80.00	4.69	0.001
3W	28.50	7.28	13.00	50.70	3.05	0.703
Cars and Jeeps	36.55	8.72	16.36	63.16	3.05	0.746
HV	31.11	9.22	8.43	54.55	2.54	0.406
2W (post outlier removal)	33.70	8.98	14.75	66.67	3.67	0.073

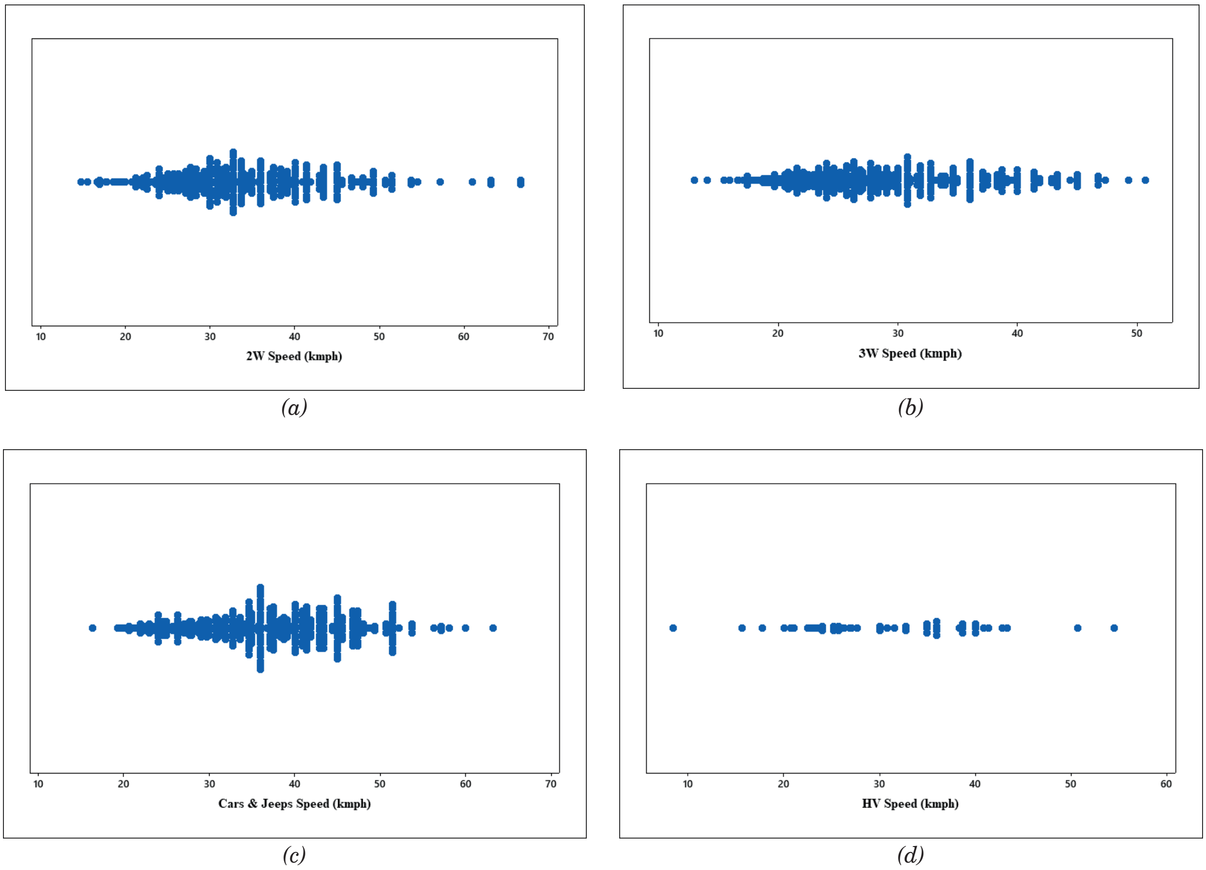

Figure 3 *Outlier charts for speeds of different categories of vehicles*

smaller speeds than 3Ws. However, this speed decrease of 3-4% as compared to 3W is statistically insignificant at 5% significance level. Moreover, the number of these HVs is very small due to which this observed smaller speeds can be analysed to be the same as that of 3Ws' speeds. Post this initial analysis, Grubb's outlier tests were performed to delete outliers (if any) present in the data. It is observed that only one speed variable in 2W (a speed of 80 km/h) was an outlier. Table 3 showcases the results of Grubb's test where it can be observed that the p value > 0.05 for all the other categories except for 2W. The result for the 2W after, removing the outlier, is also shown in Table 3. The outlier charts, based on Grubb's test, are shown in Figure 3.

Since the present study has attempted to examine the effect of slow-moving vehicle (SMV) i.e., 3W, the data was extracted to calculate the speeds of vehicles, which follow the 3W, and are not able to overtake them. The speeds of various category of vehicles, which are exclusively following the 3W, at different traffic volumes, are presented in Table 4.

It is obvious that every category of vehicle shall move at a speed near to or slower than the average speed of 3W, for any specific traffic volume, and this is evident from Table 4. For example, at 2000-2500 v/h, the average speed of 3W was found to be 26 km/h and therefore the vehicles following 3W are observed to be moving at similar average speeds i.e., between 25-28 km/h. Now, if we see the average speed of a regular car (From Table 1) is found to be 39 km/h at 2000-2500 v/h. Thus, the average reduction in speed of cars is around 11 km/h (39-28 km/h), which amounts to a reduction of 28.2%. The reduction in speeds of each category of vehicles due to following a 3W is provided in Tables 5-8.

Table 4 Average speeds of vehicles exclusively following 3W

Volume (v/h)	Average Speeds (km/h) while following 3W			
	2W	3W	Cars and Jeeps	HV
1500-2000	28	26	29	25
2000-2500	28	25	28	26
2500-3000	26	28	29	27
3000-3500	28	28	29	26
3500-4000	27	30	31	26
4000-4500	22	23	23	23
4500-5000	21	23	22	22

Table 5 Comparison between speeds of regular 2W and 2W following 3W

Volume (v/h)	Average Speeds (km/h)		
	2W regular speed	2W following 3W	% reduction in speed
1500-2000	34	28	17.64
2000-2500	33	28	15.15
2500-3000	35	26	25.71
3000-3500	35	28	20.00
3500-4000	36	27	25.00
4000-4500	29	22	24.14
4500-5000	27	21	22.22

Table 6 Comparison between speeds of regular 3W and 3W following 3W

Volume (v/h)	Average Speeds (km/h)		
	3W regular speed	3W following 3W	% reduction in speed
1500-2000	27	26	3.70
2000-2500	26	25	3.84
2500-3000	28	28	0.00
3000-3500	30	28	6.67
3500-4000	32	30	6.25
4000-4500	24	23	4.17
4500-5000	24	23	4.17

Table 7 Comparison between speeds of regular cars and jeeps and those following 3W

Volume (v/h)	Average Speeds (km/h)		
	Cars and Jeeps regular speed	Cars and Jeeps following 3W	% reduction in speed
1500-2000	40	29	27.50
2000-2500	39	28	28.21
2500-3000	40	29	27.50
3000-3500	41	29	29.27
3500-4000	41	31	24.39
4000-4500	29	23	20.69
4500-5000	26	22	15.38

***Table 8** Comparison between speeds of regular HVs and those following 3W*

Volume (v/h)	Average Speeds (km/h)		
	HV regular speed	HV following 3W	% reduction in speed
1500-2000	27	25	7.41
2000-2500	26	26	0.00
2500-3000	27	27	0.00
3000-3500	30	26	13.33
3500-4000	27	26	3.70
4000-4500	23	23	0.00
4500-5000	23	22	4.35

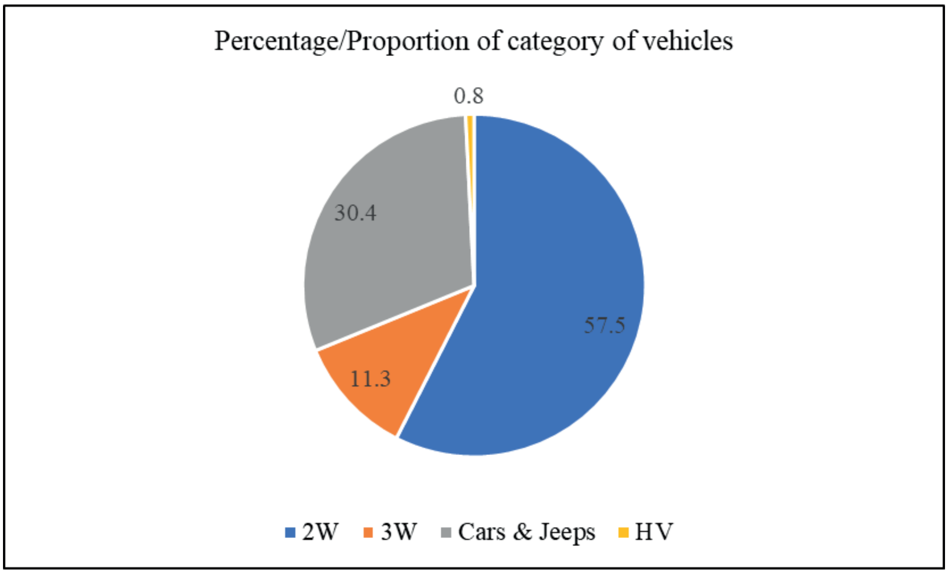

***Figure 4** Proportion of various category of vehicles*

***Table 9** Proportion of vehicles affected by 3-Wheelers (forcibly following 3W)*

Traffic volume (v/h)	Percentage of vehicles affected (%)			
	2W	3W	Cars and Jeeps	HV
1500-2000	17.5	13.3	20.2	10
2000-2500	22.6	17.6	22.8	-
2500-3000	23.8	22.4	23.4	-
3000-3500	23.6	28.6	24.6	16.6
3500-4000	21.2	30.9	25.1	14.4
4000-4500	20.5	30.8	25.3	-
4500-5000	20.2	31.1	25.2	15.6
Average	21.3	25.0	23.8	8.1

NB - Since number of HVs are too small on the studied road, the percentage values of HVs affected by 3W is on a higher side.

As can be seen from Tables 5-8, the vehicles are forced to slowdown when following a 3W. The cars and jeeps, being the fastest are affected the most, followed by 2W. While the cars and jeeps are forced to reduce their speeds in the range of 15-29% while following a 3W forcibly, 2W have to reduce their speeds in the range of 15-26%. It is also observed that since the regular speeds of 2W do not change much with increase in volume, therefore, the higher reduction in speeds is observed at higher volumes. However, due to bigger size, the regular speeds of cars and jeeps decrease with increase in volume. Therefore, their forced reduction is higher at lower traffic volumes. The HVs are usually not seen to be following the 3W. Even when the HVs follow 3W, due to their regular speeds being smaller, they do not usually get affected by them. Similar is the case of 3W following 3W. The present study is conducted on an urban arterial road where the highest allowable speed is marked at 50 km/h for cars and jeeps, and 40 km/h for motorised 2W. For urban arterials, the LOS can be determined based on operating speeds (OS) as percentage of free flow speeds (FFS) [40-41].

It is evident from Tables 5 to 8 that due to the prevalence of 3W, the 2W, 3W, cars and jeeps are forced to reduce their speed to an extent, which will certainly cause a reduction in LOS leading to undesirable delays and congestion. However, the magnitude of the effect of this forced reduction on traffic flow completely depends on the number of vehicles that are getting affected/ have to forcefully follow 3W. If more vehicles are getting affected by 3Ws, then the regular speeds of 2W and cars and jeeps will also increase if 3W are removed from road or are provided a special lane. Therefore, the composition of traffic, the unaffected percentage, and the affected percentage (following 3W) must be obtained. Figure 4 showcases the average proportion of vehicles on the road. Next, Table 9 shows the percentage of affected vehicles, which forcibly follow 3W.

Table 9 provides an insight that on an average 20-25% of vehicles across all categories of vehicles (except HV) are getting affected by 3Ws. For 3W and cars and jeeps, general trend can be observed that with increase in traffic volume, the proportion of affected vehicles increases, as well. For 2W, this number increases with volume, but up to a certain extent. Thereafter, the number marginally decreases and remains constant. Since, the vehicles who follow the 3W also affect the regular speeds and their proportion is not less, therefore, it can be noted that without 3W on the road, or the vehicles that are not following the 3W, the average speeds of the vehicles shall increase, which can be calculated based on the available data. If the average regular speed of i[th] category of vehicle is V_i^r, the average forced reduced speed of same category of vehicle is V_i^f, and the proportion of affected vehicles is P_i, then the average unaffected speed of the i[th] category of vehicle (V_i^u) can be obtained by applying:

$$V_i^u = \left(\frac{V_i^r - P_i \cdot V_i^f}{1 - P_i} \right) \tag{1}$$

The regular and forced reduction in speed is already provided in Tables 5 to 8. Tables 10 to 13 provide an addition to the above data where the unaffected average speeds of each category of vehicles are also presented.

From Tables 10 to 13 can be observed that the average speed of each category of vehicles is affected by the presence of 3W. The speeds of 2Ws and cars and jeeps reduce in the range of 18% to 35% and are the

***Table 10** Comparison of speeds for regular 2W, unaffected 2W, and 2W following 3W*

Volume (v/h)	Average Speeds (km/h)			
	2W regular speed	2W following 3W	2W unaffected	% Reduction in unaffected speed percentage as compared to following 3W speed
1500-2000	34	28	35.3	20.68
2000-2500	33	28	34.5	18.84
2500-3000	35	26	37.8	31.22
3000-3500	35	28	37.2	24.73
3500-4000	36	27	38.4	29.69
4000-4500	29	22	30.8	28.57
4500-5000	27	21	28.5	26.32

***Table 11** Comparison of speeds for regular 3W, unaffected 3W, and 3W following 3W*

Volume (v/h)	Average Speeds (km/h)			
	3W regular speed	3W following 3W	3W unaffected	% Reduction in unaffected speed percentage as compared to following 3W speed
1500-2000	27	26	27.2	4.41
2000-2500	26	25	26.2	4.58
2500-3000	28	28	28	0.00
3000-3500	30	28	30.8	9.10
3500-4000	32	30	32.9	8.81
4000-4500	24	23	24.5	6.12
4500-5000	24	23	24.5	6.12

Table 12 *Comparison of speeds for regular Cars and Jeeps, unaffected Cars and Jeeps, and Cars and Jeeps following 3W*

Volume (v/h)	Average Speeds (km/h)			
	Cars and Jeeps regular speed	Cars and Jeeps following 3W	Cars and Jeeps unaffected	% Reduction in unaffected speed percentage as compared to following 3W speed
1500-2000	40	29	42.8	32.24
2000-2500	39	28	42.3	33.81
2500-3000	40	29	43.4	33.18
3000-3500	41	29	44.9	35.41
3500-4000	41	31	44.4	30.18
4000-4500	29	23	31.0	25.81
4500-5000	26	22	27.4	19.71

Table 13 *Comparison of speeds for regular HV, unaffected HV, and HV following 3W*

Volume (v/h)	Average Speeds (km/h)			
	HV regular speed	HV following 3W	HV unaffected	% Reduction in unaffected speed percentage as compared to following 3W speed
1500-2000	27	25	27.2	8.09
2000-2500	26	26	26	0.00
2500-3000	27	27	27	0.00
3000-3500	30	26	30.8	15.58
3500-4000	27	26	27.2	4.41
4000-4500	23	23	23	0.00
4500-5000	23	22	23.2	5.17

most affected by the presence/movement of 3Ws on road. Even other 3Ws and HVs on the road also get affected by the slow moving 3Ws on few instances where they are forced to reduce their speeds to 15% for HVs following 3Ws and 9% for 3Ws following 3Ws. The speeds of cars and 2W are drastically reduced as they usually travel faster on roads, while 3W and HV are affected less. This phenomenon not only affects their travel times and contribute to congestion, but also decreases the overall LOS of the road. Further, the results obtained are only for the present study area and will differ from place to place, with different proportions of 3W on the road.

To present this reduction in speed via a model, Artificial Neural Network (ANN) has been used, where percentage reduction in speed for any category of vehicles can be predicted by knowing the average traffic volume on the road and how much percentage of that category of vehicles are affected by 3W (or following 3W). The JMP SAS software has been used to conduct the ANN. For the analysis, 3 hidden layers were considered. Shallow networks were not considered, since 3 independent variables, where one of them is nominal (category of vehicle), have been used for prediction. TanH activation function, which is the default activation function in the software has been directly employed. This is because the TanH provided very good prediction accuracies in the first attempt, and secondly TanH is usually preferred over other activation functions, like Sigmoid, as it gives better performance for multi-layer neural networks [42-43]. Random Holdback validation technique is used for the validation. Figure 5 showcases the general ANN framework followed by the statistics for training and validation in Table 14.

Values from Table 14 show how good the model is at predicting the reduction in speed. The R-square values are more than 0.95 for both training and validation. Similarly, the values of Root Average Squared Error (RASE) and mean absolute deviation are in the range of 1 and 2. While calculating the average percentage reduction in speed, the calculated error, as compared to the field data, is in the range of 1-2% only. Figure 6 shows a screenshot of the profiler for determining the percentage reduction in speed utilising the independent variables. The vertical red lines can be adjusted dynamically to get the speed reduction values. The figure also shows how Cars and Jeeps is the category that are forced to reduce their speed by a higher margin as compared to other categories. The first graph shows that at lower volumes the speed reduction is high since the regular vehicular speeds are high at low traffic volumes. The regular speed decreases with increase in volume, which reflects in the graph that the speed reduction also decreases. For example, a car travels at 45-50 km/h at 2000-2500 v/h whereas it travels at around 40 km/h at 3000 v/h. Thus, when following 3W in both volumes, if the car's speed reduces to 30 km/h,

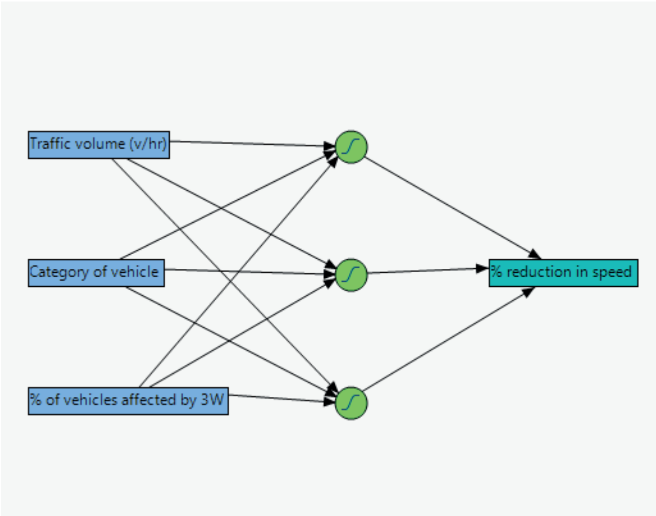

Figure 5 *ANN architecture for predicting percentage reduction in speed*

Table 14 *Statistical values for ANN training and validation*

Training (70% data)		Validation (30% data)	
Measures	Value	Measures	Value
R-Square	0.954	R-Square	0.968
RASE	2.262	RASE	2.150
Mean Absolute Deviation	1.861	Mean Absolute Deviation	1.332

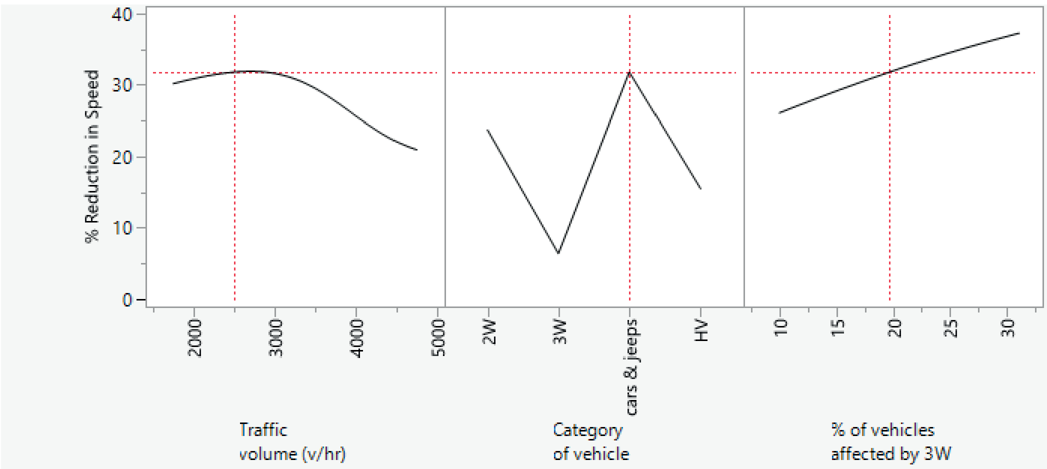

Figure 6 *Profilers to determine the reduction in speed*

the reduction is higher at lower traffic volume. The last graph tells the major point that higher the vehicles that get affected by 3W, higher is the reduction in speed. Indirectly, it hints towards the fact that, higher the number of 3W on road, more vehicles will get affected by them, ultimately leading to higher reduction in overall speed of traffic.

Figure 7 shows the interaction profilers, representing the trends in a very clear way. The figure shows the trends for 2 extremes of traffic volumes and percentage of vehicles getting affected by 3W/following 3W. As can be seen from the first row of Figure 7, at lower volumes (1750 v/h), speed reduction for vehicles is high as compared to higher volumes (4750 v/h). Similarly, though cars and jeeps are the ones whose speed reduces the highest, however at higher volumes, speed of 2W is reduced more as opposed to other category of vehicles. This is because of the flexibility to change lanes while manoeuvring is high for 2W, which significantly decreases with an increase in traffic volume. The same phenomenon is observed in the first graph of the second row of Figure 7.

The ANN can be used effectively to determine the average reduction in speed for each category, at different traffic volumes and the percentage of vehicles getting affected by 3W. Utilising this speed, and proportion of

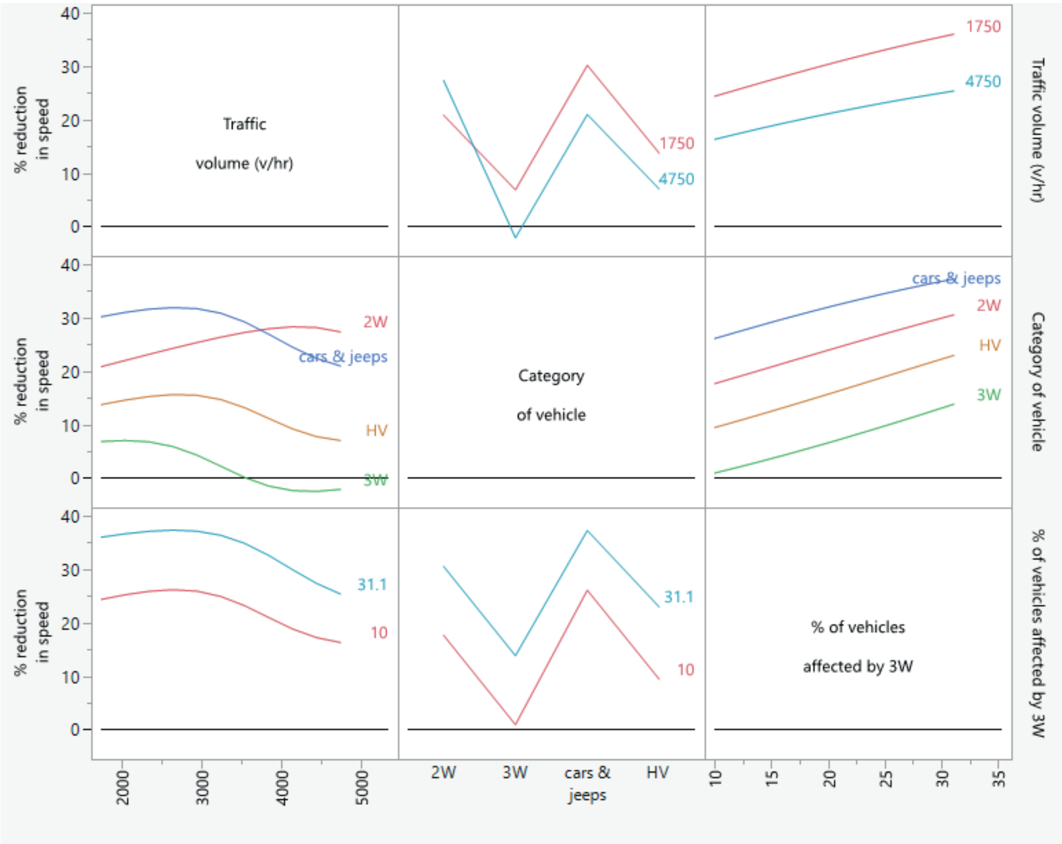

Figure 7 *Interaction Profilers to determine the reduction in speed*

Table 15 *LOS for urban roads*

LOS	Percentage of free flow speed
A	> 84
B	83-76
C	75-59
D	58-41
E	40-22
F	< 22

Table 16 *Average LOS at different traffic volumes*

Average Traffic Volume (v/h)	Average operating speed (km/h)	% of free flow speed (60 km/h)	Designated LOS
1500-2000	36.9	0.62	C
2000-2500	35.9	0.60	C
2500-3000	37.6	0.63	C
3000-3500	38.4	0.64	C
3500-4000	38.9	0.65	C
4000-4500	30.0	0.50	D
4500-5000	28.0	0.47	D

vehicles, the overall average reduction in speed on any road stretch, at any time of the day can be obtained by a simple equation as provided in:

$$ORS = (P_{2W} \cdot RS_{2W}^{ANN}) + (P_{3W} \cdot RS_{3W}^{ANN}) + \\ + (P_{Cars\&Jeeps} \cdot RS_{Cars\&Jeeps}^{ANN}) + (P_{HV} \cdot RS_{HV}^{ANN}) \quad (2)$$

where:

ORS = Overall percentage reduction in speed of traffic flow,

P_i = Proportion of ith category of vehicle in the traffic,

RS_i^{ANN} = Percentage reduction in speed for ith category of the vehicle obtained from ANN model.

This reduction in speed due to 3W shall cause a decrease in the Level of Service of the road leading to congestion and undesirable delay. According to [40], the LOS for urban roads can be determined using the operating speed as a percentage of free flow speed. Table 15 presents the LOS levels for urban roads.

On the studied road, the safe speed limit or the 85th percentile speed is 50 km/h. The observed free-flow speed on the road is around 60 km/h. Based on those numbers, it can be said that the road usually remains under LOS C for most traffic volumes, which slowly goes towards LOS D at very high traffic volumes. Details about the same is provided in Table 16.

Applying the unaffected speed data, it is observed that the traffic stream naturally goes to LOS C, but not worse, like up to LOS D, which proves the fact that 3Ws decrease the speed of whole traffic, thereby decreasing the overall LOS of the road.

5 Discussion

The focus of the present study lies in evaluating the operational impact of the three-wheelers on urban road traffic flow. To investigate this impact, the study initially extracted data concerning the classified traffic volume and the speeds of various categories of motorized vehicles across weekdays during the active hours of 8 AM to 8 PM, when the public is most engaged. Observations reveal that the average speeds exhibit consistency up to traffic volumes ranging from 1500 to 4000 vehicles per hour (v/h), with minor fluctuations likely attributed to the diversity of vehicles and varying times of the day. However, beyond the 4000 v/h threshold, as traffic congestion becomes more apparent, average speeds undergo a sudden decline within the range of 25% to 37%. Notably, it becomes evident that three-wheelers (3Ws) and heavy vehicles (HVs) tend to operate at much lower speeds, compared to the other vehicle categories.

It was observed that when vehicles follow a three-wheeler, they are compelled to reduce their speeds forming a queue in the process if a lateral gap for overtaking is not available. Cars and jeeps, which are the fastest category, experience the most significant impact, with speed reductions ranging from 15% to 29% when tailing a 3W. Similarly, two-wheelers (2W) need to reduce their speeds by approximately 15% to 26% when following a 3W. These reductions inevitably result in a decrease in the Level of Service (LOS), causing undesirable delays and congestion. Artificial Neural Network (ANN) has been employed to model and quantify this speed reduction. The ANN model predicts the percentage reduction in speed for any vehicle category, based on knowledge of the average traffic volume on the road and the proportion of that category affected by 3W, with high accuracy (R-square > 0.95 for both training and validation). It is worth noting that as the number of 3Ws on the road increases, a larger number of vehicles are affected by them, resulting in a more substantial overall reduction in traffic speed. This reduction in speed, attributable to the presence of 3Ws, invariably leads to a decrease in the Level of Service (LOS) of the road, resulting in congestion and undesirable delays. It is noted that the road typically operates at LOS C for most traffic volumes, gradually transitioning to LOS D at peak traffic volumes. Had there been less 3Ws on the road, the other categories could also have travelled at higher speeds (4-35% higher than forced reduced speeds), and LOS levels would not have gone down so much.

6 Conclusion

The presence of three-wheelers in urban traffic systems is a phenomenon that warrants careful examination due to its multifaceted impact on traffic flow. The presented study explored the dynamic influence of three-wheelers on traffic flow, encompassing both the positive and negative repercussions of their integration into urban transportation networks. Three-wheelers often provide essential last-mile connectivity, reducing the need for private car usage for short trips and thereby potentially easing congestion. Additionally, their smaller footprint demands less parking space, which can alleviate the burden on urban parking infrastructure. However, a surge in the number of three-wheelers in certain regions can contribute to traffic congestion and safety concerns due to their lower engine capacities leading them to travel at a lower speed as compared to other categories.

The present study has illustrated several key findings that shed light on the effect of 3W on the traffic ecosystem. The analysis, based on data collected at various traffic volumes and proportions of vehicles affected by 3W, has revealed substantial reductions in average speeds, ranging from 4% to 35% for the vehicles following 3W, which are unable to change their lanes. Notably, vehicles like cars and two-wheelers experience the most significant speed declines due to their typically higher speeds on the road. This phenomenon has been effectively modelled using the Artificial Neural Networks (ANN), exhibiting the high levels of prediction accuracy. By quantifying these speed reductions, it becomes possible to ascertain the broader implications on the on-road performance. The decrease in speed instigated by the presence of 3Ws invariably results in a degradation of the Level of Service (LOS), leading to congestion and delays.

These findings carry critical implications for the traffic management and urban planning. Recognizing the significant role of 3Ws in shaping the traffic dynamics enables policymakers to devise strategies that enhance the road efficiency, mitigate congestion, and improve overall transportation systems. As urban areas continue to evolve, understanding and addressing the complexities introduced by 3Ws will be instrumental in fostering efficient and sustainable mobility solutions for the future. Introducing more public buses can reduce the number of 3Ws on the road, which should help in improving road traffic conditions. Similarly, 3W can be given a specific lane towards the kerb side for their manoeuvres, so that they do not interfere with the general flow of traffic. Although the study has assessed all the vehicles following a 3W, which are not able to overtake the vehicle, the study has not talked about the queues, which might form because of more than one vehicle where the leader might not be a 3W but may be a direct follower is a 3W. Similarly, the congestion due to the presence of 3Ws is not directly measured and can be determined in future studies. Lane changing behaviour of 3Ws can also be studied in the future, which should provide more insights into their movement on the road. Further, the studies can be expanded to include the results for rural roads and roads with other lane configurations.

Acknowledgment

The authors received no financial support for the research, authorship and/or publication of this article.

Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] WEN, L., KENWORTHY, J., MARINOVA, D. Higher density environments and the critical role of city streets as public open spaces. *Sustainability* [online]. 2020, **12**(21), 8896. eISSN 2071-1050. Available from: https://doi.org/10.3390/su12218896

[2] ABDULAMER, S. H., EEDAN, H. A. Effect of three-wheeled vehicles on the capacity of a traffic stream. *Journal of Engineering and Sustainable Development (JEASD)* [online]. 2021, **25**(Special_ Issue_2021), p. 3-165-3-173. ISSN 2520-0917, eISSN 2520-0925. Available from: https://doi.org/10.31272/jeasd.conf.2.3.16

[3] MOHANTY, M., SARKAR, B., PATTANAIK, M. L., SAMAL, S. R., GORZELANCZYK, P. Development of congestion severity index for uncontrolled median openings utilising fundamental traffic parameters and clustering technique: a case study in India. *International Journal of Intelligent Transportation Systems Research* [online]. 2023, **21**, p. 461-472. ISSN 1348-8503, eISSN 1868-8659. Available from: https://doi.org/10.1007/s13177-023-00365-1

[4] MOHAPATRA, S. S., DEY, P. P. Application of cluster analysis to define the level of service criteria of U-turns at median openings. *European Transport* [online]. 2021, **81**, p. 1-17. ISSN 1825-3997. Available from: https://doi.org/10.48295/ET.2021.81.3

[5] XU, P., LI, W., HU, X., WU, H., LI, J. Spatiotemporal analysis of urban road congestion during and post COVID-19 pandemic in Shanghai, China. *Transportation Research Interdisciplinary Perspectives* [online]. 2022, **13**, 100555. eISSN 2590-1982. Available from: https://doi.org/10.1016/j.trip.2022.100555

[6] MOHANTY, M., DEY, P. P. Operational effects of U-turns at median opening. *Transportation Letters* [online]. 2022, **14**(6), p. 565-577. ISSN 1942-7867, eISSN 1942-7875. Available from: https://doi.org/10.1080/19427867.2021.1908491

[7] SAMAL, S. R., MOHANTY, M., SELVARAJ, M. S. Assessment of traffic congestion under Indian environment - a case study. *Communications - Scientific Letters of the University of Zilina* [online]. 2022, **24**(4), p. D174-D182. ISSN 1335-4205, eISSN 2585-7878. Available from: https://doi.org/10.26552/com.C.2022.4.D174-D182

[8] SAMAL, S. R., MOHANTY, M., SANTHAKUMAR, S. M. Adverse effect of congestion on economy, health and environment under mixed traffic scenario. *Transportation in Developing Economies* [online]. 2021, **7**(2), 15. ISSN 2199-9287, eISSN 2199-9295. Available from: https://doi.org/10.1007/s40890-021-00125-4

[9] Morth Annual Report [online]. 2023. Available from: https://morth.nic.in/annual-report-2022-23

[10] SAMAL, S. R., MOHANTY, M., GORZELANCZYK, P. Exploring the traffic congestion and improving travel time reliability measures in heterogeneous traffic environments: a focus on developing countries. *Communications - Scientific Letters of the University of Zilina* [online]. 2023, **25**(4), p. D91-D102. ISSN 1335-4205, eISSN 2585-7878. Available from: https://doi.org/10.26552/com.C.2023.074

[11] PANDEY, A., SHARMA, M., BISWAS, S. Concept of heterogeneity index for urban mixed traffic. *International Journal of Transportation Science and Technology* [online]. 2023, **12**(2), p. 354-372. ISSN 2046-0430, eISSN 2046-0449. Available from: https://doi.org/10.1016/j.ijtst.2022.02.008

[12] MOHANTY, M., DEY, P. P., OJHA, A. K. Assessment of lane changing behaviour due to U-turns using Markov process. (No. 17-01905). 2017.

[13] BOKARE, P. S., MAURYA, A. K. Study of acceleration behaviour of motorized three-wheeler in India. *Transportation Research Procedia* [online]. 2016, **17**, p. 244-252. ISSN 2352-1457, eISSN 2352-1465. Available from: https://doi.org/10.1016/j.trpro.2016.11.088

[14] PINZKE, S., LUNDQVIST, P. Slow-moving vehicles in Swedish traffic. *Journal of Agricultural Safety and Health* [online]. 2004, **10**(2), 121. ISSN 1074-7583, eISSN 1943-7846. Available from: https://doi.org/10.13031/2013.16071

[15] SAMAL, S. R., DAS, A. K. Evaluation of traffic congestion parameters under heterogeneous traffic condition: A case study on Bhubaneswar city. In: Transportation Research: Proceedings of CTRG 2017: proceedings [online]. Springer. 2020. ISBN 978-981-32-9041-9, eISBN 978-981-32-9042-6, p. 675-684. Available from: https://doi.org/10.1007/978-981-32-9042-6_53

[16] SAMAL, S. R., KUMAR, P. G., SANTHOSH, J. C., SANTHAKUMAR, M. Analysis of traffic congestion impacts of urban road network under Indian condition. *IOP Conference Series: Materials Science and Engineering* [online]. 2020, **1006**(1), 012002. ISSN 1757-899X. Available from: https://doi.org/10.1088/1757-899X/1006/1/012002

[17] CHANDRA, S., SINHA, S. Effect of directional split and slow- moving vehicles on two lane capacity. *Road and Transport Research*. 2001, **10**(4), p. 33-41. ISSN 1037-5783.

[18] JAYASOORIYA, S. A. C. S., BANDARA, Y. M. M. S. Measuring the economic costs of traffic congestion. In: 2017 Moratuwa Engineering Research Conference MERCon: proceedings [online]. IEEE. 2017. eISBN 978-1-5090-6491-5, p. 141-146. Available from: https://doi.org/10.1109/MERCon.2017.7980471

[19] KERNER, B. S., KLENOV, S. L. A theory of traffic congestion at moving bottlenecks. *Journal of Physics A: Mathematical and Theoretical* [online]. 2010, **43**(42), 425101. ISSN 1751-8121. Available from: https://doi.org/10.1088/1751-8113/43/42/425101

[20] BOTMA, H. Effects on traffic operation of a slow moving vehicle on two lane rural roads. In: 14th Australian Road Research Board (ARRB) Conference: proceedings. 1988. Vol. 14, No. 2, p. 48-55.

[21] WICKES JR, H. G., NELSON, G. S. Collisions with slow-moving vehicles. *Professional Safety*. 2000, **45**(8), p. 39-44. ISSN 0099-0027.

[22] DEL SERRONE, G., CANTISANI, G., GRILLI, R., PELUSO, P. Effectiveness of climbing lanes for slow-moving vehicles when riding uphill: a microsimulation study. *Vehicles* [online]. 2023, **5**(3), p. 744-760. eISSN 2624-8921. Available from: https://doi.org/10.3390/vehicles5030041

[23] JAARSMA, C. F., BOTMA, H., BEUNEN, R. Passing bays for slow moving vehicles on rural two-lane roads. *Transport Reviews* [online]. 2005, **25**(4), p. 491-509. ISSN 0144-1647, eISSN 1464-5327. Available from: https://doi.org/10.1080/01441640500038805

[24] GARVEY, P. M. Motorist comprehension of the Slow-Moving Vehicle (SMV) emblem. *Journal of Agricultural Safety and Health* [online]. 2003, **9**(2), 159. ISSN 1074-7583, eISSN 1943-7846. Available from: https://doi.org/10.13031/2013.13005

[25] SYLLA, A. Influence of a slow moving vehicle on traffic: well-posedness and approximation for a mildly nonlocal model. *Networks and Heterogeneous Media* [online]. 2021, **16**, p. 221-256. ISSN 1556-1801, eISSN 1556-181X. Available from: https://doi.org/10.3934/nhm.2021005

[26] GAUR, P., SACHDEVA, S. N. Effect of shoulder and slow moving vehicles on capacity of a road. *International Journal of Engineering Applied Sciences and Technology* [online]. 2022, **4**(10), p. 377-380. ISSN 2455-2143. Available from: https://doi.org/10.33564/IJEAST.2020.v04i10.068

[27] YUSOF, N. M., KARJANTO, J., HASSAN, M. Z., SULAIMAN, S., AB RASHID, A. A., JAWI, Z. M., KASSIM, K. A. A. Effect of road darkness on young driver behaviour when approaching parked or slow-moving vehicles in Malaysia. *Automotive Experiences* [online]. 2023, **6**(2), p. 216-233. eISSN 2615-6636. Available from: https://doi.org/10.31603/ae.8206

[28] KALASOVA, A., SKRIVANEK KUBIKOVA, S., CULIK, K., PALUCH, J. Comparison of traffic flow characteristics of signal controlled intersection and turbo roundabout. *The Archives of Automotive Engineering - Archiwum Motoryzacji* [online]. 2020, **88**(2), p. 19-36. eISSN 2084-476X. Available from: https://doi.org/10.14669/AM.VOL88.ART2

[29] LIZBETIN, J., STOPKA, O. Proposal of a roundabout solution within a particular traffic operation. *Open Engineering* [online]. 2016, **6**(1), p. 441-445. eISSN 2391-5439. Available from: https://doi.org/10.1515/eng-2016-0066

[30] GORZELANCZYK, P., TYLICKI, H. Forecasting the number of road accidents in Poland depending on the day of the week using neural networks. *LOGI-Scientific Journal on Transport and Logistics* [online]. 2023, **14**(1), p. 35-42. eISSN 2336-3037. Available from: https://doi.org/10.2478/logi-2023-0004

[31] AKCELIK, R., MAHER, M. J. Route control of traffic in urban road networks: review and principles. *Transportation Research* [online]. 1977, **11**(1), p. 15-24. ISSN 0041-1647. Available from: https://doi.org/10.1016/0041-1647(77)90062-4

[32] TANIMOTO, J., NAKAMURA, K. Social dilemma structure hidden behind traffic flow with route selection. *Physica A: Statistical Mechanics and its Applications* [online]. 2016, **459**, p. 92-99. ISSN 0378-4371, eISSN 1873-2119. Available from: https://doi.org/10.1016/j.physa.2016.04.023
[33] METELSKI, A. Analysis of selected methodological problems regarding the examination of traffic events at road intersections. *The Archives of Automotive Engineering - Archiwum Motoryzacji* [online]. 2018, **82**(4), p. 75-85. eISSN 2084-476X. Available from: https://doi.org/10.14669/AM.VOL82.ART6
[34] JEREB, B., STOPKA, O., SKRUCANY, T. Methodology for estimating the effect of traffic flow management on fuel consumption and CO2 production: a case study of Celje, Slovenia. *Energies* [online]. 2021, **14**(6), 1673. eISSN 1996-1073. Available from: https://doi.org/10.3390/en14061673
[35] WITT, A. Determination of the number of required charging stations on a German motorway based on real traffic data and discrete event-based simulation. *LOGI-Scientific Journal on Transport and Logistics* [online]. 2023, **14**(1), p. 1-11. eISSN 2336-3037. Available from: https://doi.org/10.2478/logi-2023-0001
[36] AHMED S, A., ELKATATNY, S., ALI, A. Z., ABDULRAHEEM, A., MAHMOUD, M. Artificial neural network ANN approach to predict fracture pressure. In: SPE Middle East Oil and Gas Show and Conference: proceedings [online]. 2019. ISBN 978-1-61399-639-3. Available from: https://doi.org/10.2118/194852-MS
[37] SABIR, Z., BALEANU, D., SHOAIB, M., RAJA, M. A. Z. Design of stochastic numerical solver for the solution of singular three-point second-order boundary value problems. *Neural Computing and Applications* [online]. 2021, **33**(7), p. 2427-2443. ISSN 0941-0643, eISSN 1433-3058. Available from: https://doi.org/10.1007/s00521-020-05143-8
[38] ILLIAS, H. A., CHAI, X. R., ABU BAKAR, A. H., MOKHLIS, H. Transformer incipient fault prediction using combined artificial neural network and various particle swarm optimisation techniques. *PLoS One* [online]. 2015, **10**(6), e0129363. eISSN 1932-6203. Available from: https://doi.org/10.1371/journal.pone.0129363
[39] YU, B., WANG, Y. T., YAO, J. B., WANG, J. Y. A comparison of the performance of ANN and SVM for the prediction of traffic accident duration. *Neural Network World* [online]. 2016, **26**(3), p. 271-287. ISSN 1210-0522. Available from: https://doi.org/10.14311/NNW.2016.26.015
[40] Indian highway capacity manual (Indo-HCM). New Delhi: CSIR-Central Road Research Institute, 2017.
[41] National Research Council. Highway capacity manual 2000. Transportation Research Board Special Report, 209, 16-9. 2000.
[42] LEWIS, P., PEREZ, E., PIKTUS, A., PETRONI, F., KARPUKHIN, V., GOYAL, N., KUTTLER, H., LEWIS, M., YIH, W.-T., ROCKTASCHEL, T., RIEDEL, S., KIELA, D. Retrieval-augmented generation for knowledge-intensive NLP tasks. *Advances in Neural Information Processing Systems*. 2020, **33**, p. 9459-9474. ISSN 1049-5258.
[43] LIU, C., CHEN, L. C., SCHROFF, F., ADAM, H., HUA, W., YUILLE, A. L., FEI-FEI, L. Auto-deeplab: hierarchical neural architecture search for semantic image segmentation. In: IEEE/CVF Conference on Computer Vision and Pattern Recognition: proceedings [online]. IEEE. 2019. eISSN 2575-7075, eISBN 978-1-7281-3293-8, p. 82-92. Available from: https://doi.org/10.1109/CVPR.2019.00017