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MODELLING ROUNDABOUT ENTRY CAPACITY FOR MIXED TRAFFIC FLOW USING ANN: A CASE STUDY IN INDIA

Summary. Roundabouts, as an unsignalized intersection, have an effective preventative measure designed to control straight-line crashes. Efficient traffic flow in cities depends upon appropriate capacity estimation of roundabouts. This study attempts to develop models for roundabout entry capacity by applying Artificial Neural Network (ANN) analysis for mixed traffic flow conditions. Data was gathered from 27 roundabouts spread across India. The influence area for gap acceptance (INAGA) concept was used as a graphical method to identify critical gap (T_c) of entry flow at roundabouts. This study indicated that the Bayesian Regularisation Neural Network (BRNN) based model has the best R^2 and RMSE of 0.97 and 167.8. The connection weight approach and Garson algorithm evaluate the significance of each explanatory variable and identify follow-up time (T_f) as a critical parameter with values of 11.10 and 21.15%, respectively.
Keywords: INAGA, ANN entry capacity, Garson algorithm

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1. INTRODUCTION

Roundabout is an efficient traffic control measure in the form of safety and operational aspects. Circular intersections substantially mitigate head-on collisions, notably right-angle accidents, as well as facilitate the easy movement of more traffic with reduced queuing time. In comparison to signalized junctions, it has fewer conflict points. At signalized intersections, 32 potential sources of conflict are identified, but at roundabouts, the number falls to 8. As a result, roundabouts are regarded to be vital infrastructure in any country's urban traffic system. The roundabout capacity is a key statistic for evaluating operational performance, delay, and queue length.

The upholding of driver conduct, specifically lane discipline, is inadequately managed in conditions of heterogeneous traffic. In addition, the dimensions, transmission capacities of vehicles, and geometrical features of intersections in developing countries are very different from those of vehicles in affluent nations. Drivers get aggressive while attempting to manoeuvre around one another in congested areas. In such conditions, vehicle speeds vary as a result of the inherent differences between vehicles. At roundabouts, significant contributing vehicles, such as small-sized cars (SC) and two-wheelers (2W), consistently seek to merge into the mainstream flow of traffic. This results in an extremely chaotic traffic situation due to the inconsistent spacing between vehicles. HCM (2010) presents a comprehensive methodology for estimating the entrance capacity of roundabouts, however, it fails to account for people's driving behaviour under local conditions. Hence, emphasis has been given to develop the capacity models for roundabouts under constrained conditions.

Essential methodologies, such as empirical models, gap acceptance models, and microscopic simulation modelling, serve as a basis for existing roundabout capacity models. Empirical models are often solved by applying regression analysis, with capacity serving as the dependent variable and other factors, such as prevailing flow and site geometry, contributing as explanatory variables [1]. It has been identified that the entry capacity varies negatively exponentially about the opposing flow and that as the opposing flow increases, the entry capacity decreases and vice versa [2], [3]. The capacity model on the concept of gap acceptance theory reflects the decision of drivers on variables like critical gap and follow-up time. For drivers in the minor stream, the minimum acceptable duration before merging into the major stream is termed as the ‘critical gap’ while the ‘follow-up time’ refers to the time difference between vehicles in a queue during congested traffic conditions [4]. In contrast, microscopic simulation models are influenced by the interactions and motions of vehicles within a simulated network. Three primary terms can be used to describe the actions of vehicles on the route: car-following, lane-changing, and the gap acceptance concept, which includes critical gap and follow-up time. Various microscopic simulation models have been developed for parametric findings, with the flows and turns being controlled [5], [6]. Artificial neural networks (ANNs) are frequently used by professionals in academia, as they can model complicated and nonlinear data sets accurately and with the least amount of error [7]. The capacity prediction of roundabouts through ANN outperforms the gap acceptance and empirical models, further it encourages employing machine learning techniques for a proactive operational plan for roundabouts [8], [9]. Accordingly, an ANN-based entrance capacity model for Indian urban cities has been developed.

Data was obtained from 27 roundabouts in India during peak traffic hours. The graphical method of influence area, INAGA, is used to predict driver response factors such as critical gap (T_c) and follow-up time (T_f) in order to provide capacity models for roundabouts.

The effectiveness of the ANN models was evaluated using the connection weight method and Garson's approach.

The paper is structured into four sections, with section 1 providing an overview of the context of the study and a review of the relevant literature. The subsequent section discusses study sites and data-collecting procedures. The methodology and analysis of the ANN capacity models are comprehensively described in Section 3. The final section of the paper provides the conclusion of this study. It also addresses the limitations of the study and suggests avenues for future research.

2. SELECTION OF STUDY SITES AND DATA COLLECTION PROCEDURE

A total of 27 roundabouts were selected for data collection to develop capacity models. The twelve cities depicted in Fig. 1 in the four corners of India all consist of roundabouts. The roundabouts were selected following the specified criteria. Roundabouts, which have 4 approach legs, tend to be placed in commercial, industrial, and residential areas. The roundabouts tend to be at grade intersections and are unsignalized. Further, the influence of cyclists and pedestrians is modest at these roundabouts. The measured geometric specifications of roundabouts are presented in Appendix 1.

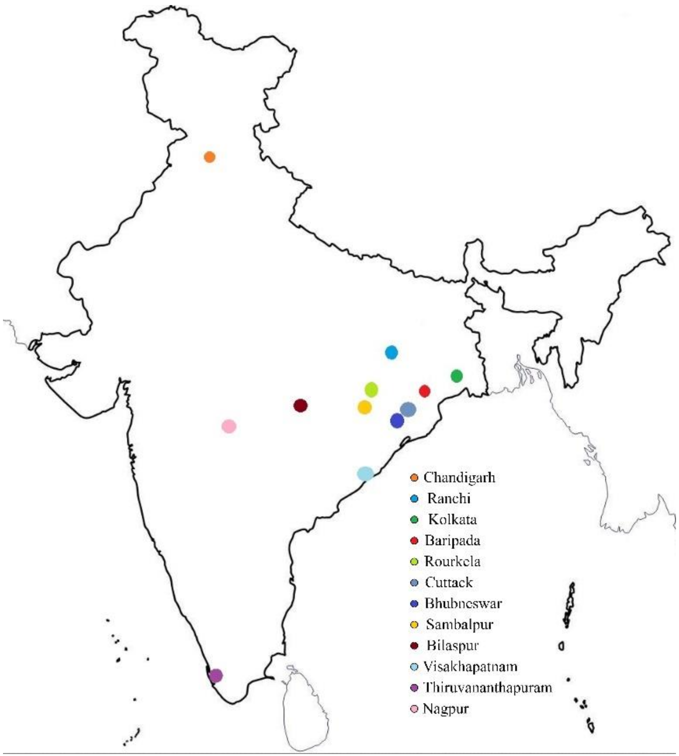


Fig. 1. Location of Cities on India Map

The collection of traffic flow data is from high-rise buildings in close proximity to the roundabouts. This approach was taken to ensure the acquisition of comprehensive and relevant data sets. The videography method utilized in this study is straightforward and economical. It is also convenient to use a post-processing method for data extraction. Videos capturing the morning and evening traffic flow peaks under clear weather conditions were utilized to account for the significant contribution of both the critical gap (T_c) and follow-up time (T_f) to the gap acceptance capacity model. Moreover, half an hour of queuing time on the approach legs was seen over the course of the two hours of observation. The gap variables were then extracted from the recorded videos. The variables that contributed to the capacity model for roundabouts, including flow, geometrics, and gap variables, were utilized in regression analysis and ANN modelling, as detailed in Tab. 1. During low-traffic volume times, a measuring tape was used to take measurements of geometric variables. The 'weaving width' refers to the road width that runs around the central island and is utilized by vehicles to navigate in a clockwise direction. Both single and multi-lane variants of the road are possible. The total distance of a segment of a rotary through which weaving takes place is referred to as the 'weaving length'. Google Earth software measurements were employed to validate the field-measured inventory data for streets. The methodologies and analysis approach are detailed in the following section.

Tab. 1

Analysis of contributing variables for this study

Variables	Units	Minimum	Maximum	Mean	Standard deviation
Observed entry capacity (Q_e)	PCU/h	251	3346	1712.5	772.75
Circulating flow (q_c)	PCU/h	220	3778	1051.28	711.42
Weaving length (W_l)	m	29.76	59.52	43.39	6.09
Weaving width (W_w)	m	9.1	19.04	16.80	5.34
Entry width (E_w)	m	6	21.22	14.17	3.87
Diameter of central island (D)	m	12.66	62.32	42.62	11.77
Critical gap (T_c)	seconds	0.68	2.66	1.73	0.58
Follow-up time (T_f)	seconds	0.88	2.34	1.78	0.52

3. METHODS AND ANALYSIS

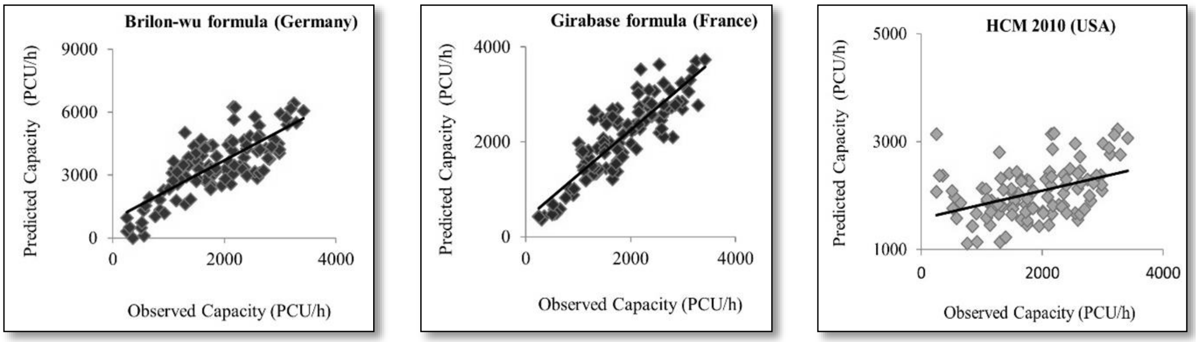
This section discusses extensively the Gap acceptance variable and the existing models' viability. Furthermore, the ANN model is being developed for the prediction of roundabout entry capacity. Additionally, the entry capacity model's suitability and the relative significance of the input variables are specified.

3.1. Gap Acceptance Variables

For capacity models of roundabouts, significant factors that are considered to describe driver conduct under real-world traffic conditions include critical gap and follow-up time. An inadequate approach for obtaining critical gap and follow-up time values results in partial capacity estimation of a roundabout. In order to determine the critical gap, both the newly accepted equilibrium probability method and the widely utilized Raff method considered homogeneous traffic flow and consistent driving conduct. Nevertheless, with a zero rejection of gap data, these approaches fail to produce reliable results. Therefore, it is presumed that this is a significant issue in mixed traffic conditions. In mixed traffic situations, zero gaps are typically rejected for congested and normal traffic flow. Subsequently, to surmount these shortcomings and variations, the INAGA method, which was recently devised, is implemented to produce dependable outcomes [10]. The INAGA technique can calculate the critical gap without having a specific distribution function as an assumption. As a result, the INAGA method is a graphical method of assumption; upon observing the mainstream where the merging of entry and circulating flows is most, a trapezoidal-shaped influencing area may be meticulously assumed.

3.2. Existing Model Evaluation

The Girabase formula (France), Brilon-Wu formula (Germany), and HCM 2010 (USA) models are used for a new set of roundabouts to evaluate their ability to anticipate traffic flow. In a study, the feasibility of using explanatory variables to establish a relationship between capacity, other geometric functions, and gap acceptance has been analysed [11]. As illustrated in Fig. 2, the aforementioned techniques generate a relation between the data obtained from field observations and the predicted capacity.



(a) (b) (c)

Fig. 2. Prediction of capacity by using international capacity models

Figures 2(b) and (c) show that, in comparison to capacities observed under field conditions, the predicted entry capacities of the Brilon-Wu formula (Germany) and the HCM 2010 approaches are, respectively, higher, and lower. This shift in capacity estimates can be attributed to a couple of factors. The first cause is the fact that metropolitan Indian streets see a wide range of vehicle types. The second issue is likely the vastly different driving conduct of Indian drivers compared to those of drivers in Western countries. In mixed traffic flow, vehicles with varied manoeuvrability coexist. The prevalence of two-wheelers over cars of all kinds predominates in Indian traffic. A breach of the principle of priority happens whenever two-wheelers (2W) in the approaching stream emphatically establish a gap in the route of the primary traffic flow. Homogeneous traffic, on the other hand, involves vehicles moving in a streamlined pattern whilst consistently maintaining some distance. When applied to data sets containing mixed traffic flows, models that were fitted under homogeneous traffic conditions overestimate entry capacity under high circulating flows, resulting in inaccurate model fitting. Measurements of driver behaviour metrics, such as critical gap and follow-up time, under actual conditions, might help reduce discrepancies in capacity projections. Furthermore, the significance of geometric variables in capacity prediction analysis is acknowledged. By integrating geometric and gap acceptance variables as explanatory variables in the context of mixed traffic flow conditions, gap acceptance capacity models are subsequently devised. However, the capacity values of the proposed Bayesian Regularisation Neural Network (BRNN) model and the Girabase formula in Fig. 2(a) are comparable.

3.3. Artificial Neural Network (ANN) Modelling

Modern data analysis techniques, such as ANN modelling, offer an alternative to the traditional statistical regression method. A linear model aims to establish a linear relationship between independent and dependent variables. However, in ANN modelling, the coefficient, and intercept variables are associated with neural network weights and biases. The hidden layers in the neural network are accomplished to evaluate the critical relationships, such as the nonlinear relationship between dependent and independent variables. For estimating roundabout capacity, the authors discovered that ANN modelling outperformed regression models [1]. In regression models, there is a probability of the occurrence of constraints between explanatory variables and capacity. However, ANN modelling can establish an appropriate relationship between explanatory variables and capacity even if there is a constraint relationship between explanatory variables and capacity.

The current study employs two distinct training algorithms, namely the Bayesian Regularisation Neural Network (BRNN) and Levenberg-Marquardt Neural Network (LMNN) to develop the ANN models. As illustrated in Fig. 3, feed-forward perceptron with back propagation training algorithm (FFBP) type of ANN with hyperbolic tangent activation functions is developed using explanatory variables like weaving length (W_l), critical gap (T_c), weaving width (W_w), entry width(E_w), circulating flow (q_c), follow up gap (T_f), and central island diameter (D) and dependent variables like entry capacity (Q_e). Nodes of feed-forward type ANN are organised in layers, with information flowing forward from input layers to output layers through hidden layers. The backpropagation algorithm is employed to train the hidden units to produce the intended output in situations where the output is unknown. In this technique, the error observed in the output layer is back propagated to the hidden layers according to the connecting weights. The weights are adjusted by the delta rule. The same approach is repeated for each training data sample. One complete cycle through the training data set is termed an epoch. The number of times that the set of training data will be entered into the network is termed as the number of epochs.

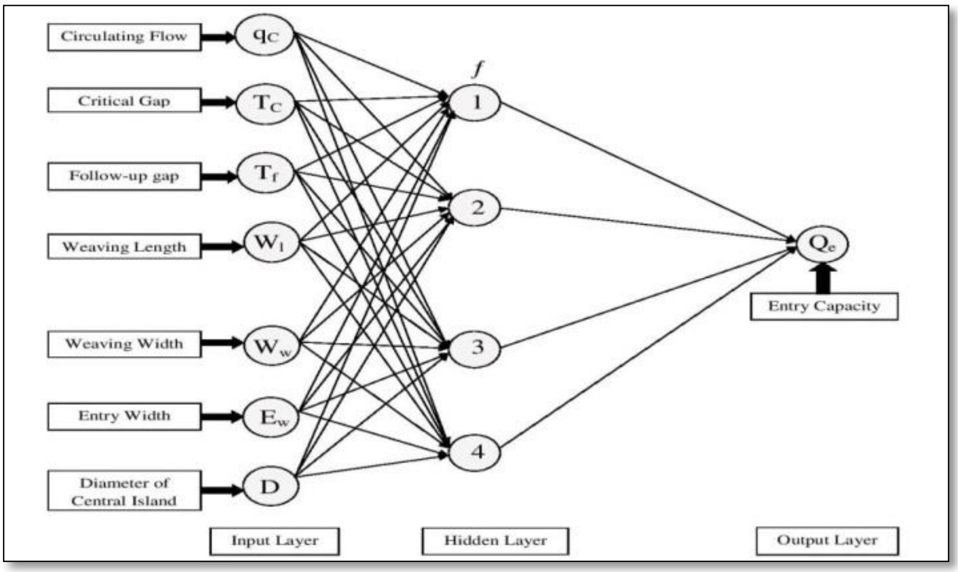


Fig. 3. Neural network diagram with 7 explanatory variables

A total of 110 data points were used to forecast the ANN capacity models. The entire dataset was split in half, with 70% being used for the training phase and 30% for the testing phase. Several iterations are performed to determine the best ANN capacity model, as detailed in Tab. 2. the best ten ANN models are selected through root-mean-square error (RMSE) and overall R^2 values. Finally, the most suitable ANN model is selected from ten ANN models. In this study, three Levenberg-Marquardt Neural Network (LMNN) and seven Bayesian Regularisation Neural Network (BRNN) based capacity models are developed. The transfer function introduces non-linearity to the neural network. It transforms the weighted sum of inputs and biases into the output of a neuron. In the present model, the hyperbolic tangent sigmoid transfer function (Tansig) squashes input values to a range between -1 and 1. It is a smooth, differentiable function, crucial for backpropagation during training. The training function Bayesian regularisation back propagation (Train BR) is responsible for adjusting the weights and biases of the network during the training phase. Its goal is to minimize the difference between the predicted outputs and the observed values. The optimisation algorithms use the gradient of the loss function concerning the parameters to update the weights and biases iteratively. The learning function involves setting hyperparameters, including the learning rate and possibly other parameters that control the training process. The learning rate determines the step size during weight updates and influences the convergence and stability of the training, and hence an adaptive learning function gradient descent with momentum (Learn GDM) is employed for the study. The performance function quantifies the difference between the predicted values and the observed values. Consequently, mean square error with regularisation (MSEREG) is a performance function that combines the Mean Square Error (MSE) with a regularisation term to prevent overfitting and control the complexity of a model during training and predicts the capacity of a developed model by using ANN. In addition to these, the number of iterations (epochs) varied from 500 to 1000 to get the best result. Based on the RMSE results and overall R^2, the most suitable model is selected. It is observed from Tab. 2 that BRNN based model having four numbers of hidden neurons is the best fitted as the RMSE and overall R^2 values of the model were found to be 167.89 and 0.97 respectively.

Tab. 2

Network details with several iterations (Trial 1-10)

Trial No.	1	**2**	3	4	5
No. of hidden layer	1	**1**	1	1	1
No. of hidden neurons	3	**4**	6	7	8
Transfer function	Tansig	**Tansig**	Tansig	Tansig	Tansig
Training function	Train LM	**Train BR**	Train BR	Train BR	Train BR
Adaptive learning function	Learn GDM	**Learn GDM**	Learn GDM	Learn GD	Learn GDM

Performance function	MSE	**MSEREG**	MSEREG	MSEREG	MSEREG
No. of epochs	500	**1000**	1000	700	1000
RMSE	267.28	**167.8**	212.21	216.63	230.30
Overall R^2	0.92	**0.97**	0.96	0.96	0.95
Trial No.	6	7	8	9	10
No. of hidden layer	1	1	1	1	1
No. of hidden neurons	3	4	7	6	8
Transfer function	Logsig	Logsig	Logsig	Logsig	Logsig
Training function	Train BR	Train BR	Train BR	Train LM	Train LM
Adaptive learning function	Learn GDM	Learn GD	Learn GDM	Learn GDM	Learn GD
Performance function	MSEREG	MSE	MSEREG	MSE	MSE
No. of epochs	500	1000	1000	1000	700
RMSE	222.14	190.3	214.00	218.2	240.9
Overall R^2	0.95	0.96	0.96	0.95	0.95

Note:
Tansig: Hyperbolic tangent sigmoid transfer function
Logsig: Log-sigmoid transfer function
Train LM: Levenberg-Marquardt backpropagation training function
Train BR: Bayesian regularization backpropagation training function
Learn GD: Gradient descent adaptive learning function
Learn GDM: Gradient descent with momentum
MSE: Mean square error
MSEREG: Mean square error with regularization

An ANN equation was formulated in the present study by utilizing 7 explanatory variables and observing through a trained network. By using the weights and biases observed in this analysis as provided in Tab. 3, the following mathematical expressions were developed for the capacity prediction of roundabouts. For this, the procedure follows three steps. In the first step, A_1 to A_4 is to be calculated using equation 1(a) to 1(d). The Input (I) and output (O) weights of four hidden neurons are represented in the Tab. 4. The values obtained from A_1 to A_4 is to be used in the equation 2(a) to 2(d) to get the desired values of B_1 to B_4. The third step belongs to C_1 which will give the final expression as per equation (3). Hence the normalized capacity equation (Q_{en}) will be written as in equation (4).

Tab. 3

Connecting weights and biases with normalized entry capacity prediction model

No. of hidden neurons	Weights								Biases	
	I1 (W_l)	I2 (T_c)	I3 (W_w)	I4 (E_w)	I5 (q_c)	I6 (T_f)	I7 (D)	O (Q_e)	I	O
1	-0.068	-0.539	0.298	0.261	-0.563	-0.537	-0.348	1.040	0.142	0.389
2	0.221	-0.329	0.003	0.545	-0.560	0.528	-0.343	0.697	-0.602	-
3	0.388	0.282	0.029	-0.262	-0.309	-0.650	0.250	0.873	-1.450	-
4	-0.061	-1.184	0.047	-0.285	-0.752	-0.497	-0.913	-0.772	-0.021	-

$$A_1 = 0.1424 - 0.0682\,W_l - 0.5399\,T_c + 0.2984\,W_w - 0.2619\,E_w - 0.5635\,q_c - 0.5374\,T_f - 0.3486\,D \quad 1(a)$$

$$A_2 = -\,0.6025 + 0.2217\,W_l - 0.329\,T_c + 0.0031\,W_w + 0.5453\,E_w - 0.5607\,q_c + 0.5281\,T_f - 0.3439\,D \quad 1(b)$$

$$A_3 = -\,1.4505 + 0.3888\,W_l + 0.2827\,T_c + 0.0295\,W_w - 0.2624\,E_w - 0.3095\,q_c - 0.6504\,T_f - 0.2506\,D \quad 1(c)$$

$$A_4 = -\,0.0210 - 0.0611\,W_l - 1.184\,T_c + 0.0474\,W_w - 0.2852\,E_w - 0.7529\,q_c - 0.4978\,T_f - 0.9136\,D \quad 1(d)$$

Tab. 4

Connecting weights of four hidden neurons

No. of hidden neurons	Weights							
	I1 (W_l)	I2 (T_c)	I3 (W_w)	I4 (E_w)	I5 (q_c)	I6 (T_f)	I7 (D)	O (Q_e)
1	-0.0682	-0.5399	0.2984	0.2619	-0.5635	-0.5374	-0.3486	1.0402
2	0.2217	-0.329	0.0031	0.5453	-0.5607	0.5281	-0.3439	0.6974
3	0.3888	0.2827	0.0295	-0.2624	-0.3095	-0.6504	0.2506	0.8736
4	-0.0611	-1.184	0.0474	-0.2852	-0.7529	-0.4978	-0.9136	-0.7726

The expression for evaluating B term is written as follows:

$$B_1 = 1.0402\,\frac{e^{A_1} - e^{-A_1}}{e^{A_1} + e^{-A_1}} \quad 2(a)$$

$$B_2 = 0.6974\,\frac{e^{A_2} - e^{-A_2}}{e^{A_2} + e^{-A_2}} \quad 2(b)$$

$$B_3 = 0.8736\,\frac{e^{A_3} - e^{-A_3}}{e^{A_3} + e^{-A_3}} \quad 2(c)$$

$$B_4 = -0.7726\,\frac{e^{A_4} - e^{-A_4}}{e^{A_4} + e^{-A_4}} \quad 2(d)$$

Then the final term C will be evaluated as

$$C_1 = 0.3898 + B_1 + B_2 + B_3 + B_4 \tag{3}$$

$$Q_{en} = \frac{e^{C_1} - e^{-C_1}}{e^{C_1} + e^{-C_1}} \tag{4}$$

The aforementioned equation (4) yields a capacity value between -1 and 1, which will be denormalized according to equation (5).

$$Q_e = 0.5\ (Q_{en} + 1)(Q_{emax} - Q_{emin}) + Q_{emin} \tag{5}$$

Where, Q_{emax} is the maximum and Q_{emin} is the minimum values of roundabouts entry capacity (Q_e) under the provided data set accordingly.

3.4. Suitability of entry capacity model

To ensure the development of a suitable entry capacity model, a number of statistical tests are performed to evaluate the reliability of the ANN model as detailed in Tab. 5. The statistical tests include best-fit calculations, error-calculating variables, mathematical calculations, cumulative probability values, and predictions with an accuracy level of less than 20%. The coefficient of determination (R^2), which executes from 0 to 1, represents the degree of goodness of fit, and higher values indicate a better fit. Nash-sutcliffe model efficiency coefficient (E) is generally used to assess the prediction ability of the developed model. The value of 'E' can range from -∞ to 1. If the value of 'E' is close to 1, then it is known to be more accurate in the developed model. The absolute value is measured by the modulus value of the difference between observed and predicted values. The average absolute error (AAE) is measured as the average of the absolute difference between observed and predicted values, whereas the maximum of the measured absolute errors is known as maximum absolute error (MAE). The Root Mean Square Error (RMSE) is intended to indicate a model's accuracy, and a smaller value is preferable. The ranges of AAE and RMSE are in between 0 to ∞. The detailed formula for evaluating the R^2, E, AAE, MAE and RMSE are given as equations 6(a) to 6(e). The O_i and P_i are the observed and predicted values of entry capacity at roundabouts, while O_{mean}, P_{mean} represents the mean values of the observed and predicted data sets, whereas 'i' and 'n' are the variable sequence and total number of data respectively. Further, the ratio of predicted capacity to observed capacity is denoted as C_P/C_O, and 'μ' and 'σ' are the mean and standard deviation of natural logarithmic values of C_P/C_O. Values for 'μ' and 'σ' are close to 1 and 0 in the present study, respectively, indicating that the proposed models can make reliable predictions. The cumulative probability density function has, 'P_{50} values' considered to be the most probable value with a probability of exceedance of about more than 50% while 'P_{90} values' are the conservative estimate having a 90% probability of exceedance. Values (P_{50} and P_{90}) are observed to be near to 1, suggesting greater effectiveness for the provided data set. The log-normal distribution function is employed, and further log-normal and histogram graphs are plotted to evaluate the accuracy percentage of a model.

$$R^2 = \frac{\sum_{i=1}^{n} [(O_i - O_{mean})(P_i - P_{mean})]^2}{\left[\sum_{i=1}^{n}(O_i - O_{mean})^2 \ \ \sum_{i=1}^{n}(P_i - P_{mean})^2\right]} \quad 6(a)$$

$$E = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - O_{mean})^2} \quad 6(b)$$

$$AAE = \frac{1}{n}\sum_{i}^{n}|O_i - P_i| \quad 6(c)$$

$$MAE = maximum(\,|O_i - P_i|) \quad 6(d)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2} \quad 6(e)$$

Tab. 5

Statistical test of developed model

Model	Data Splitting	Co-relation Analysis		Error Calculations			Mathematical Calculations of C_P/C_O		Cumulative Probability of C_P/C_O		± 20% Prediction Accuracy (%)	
									Ratio* at			
		R^2	E	AAE	MAE	RMSE	μ	σ	P_{50}	P_{90}	Log-normal	Histogram
BRNN Model	Training	0.93	0.93	149.2	455.1	184.8	1.00	0.11	0.99	1.13	92.32 %	100%
	Testing	0.95	0.94	167.9	418.7	197.9	1.05	0.22	0.95	1.22	91.01 %	94%

Note: R^2 = Coefficient of determination, E = Nash-Sutcliffe coefficient, AAE = Average Absolute Error, MAE = Maximum Absolute Error, RMSE = Root Mean Square Error, C_P = Predicted Capacity, C_O = Observed Capacity

3.5. Relative Importance of Input Variables

To assess the relative importance of input variables in ANN modelling, two methods such as Connection weight approach and Garson's algorithm are applied in this study. In connection weight approach, the product of each input and output weights (A_{ij}) are calculated in the Tab. 6. Then for each hidden neuron A_{ij} is divided by sum of all input variables to obtain B_{ij} in details given in the Tab. 7. Then for each hidden neuron, the sum of the product S_j is calculated. For example,

$$S_1 = B_{11} + B_{21} + B_{31} + B_{41} + B_{51} + B_{61} + B_{71} \quad 7(a)$$

Tab. 6

Products of each input and output weights (A_{ij})

No. of hidden neurons	I1 ($\boldsymbol{W_l}$)	I2 ($\boldsymbol{T_c}$)	I3 ($\boldsymbol{W_w}$)	I4 ($\boldsymbol{E_w}$)	I5 ($\boldsymbol{q_c}$)	I6 ($\boldsymbol{T_f}$)	I7 ($\boldsymbol{D}$)
1	-0.0709	-0.5616	0.3103	0.2724	-0.5861	-0.559	-0.3626
2	0.1546	-0.2294	0.0021	0.3802	-0.391	0.3682	-0.2398
3	0.3396	0.2469	0.0257	-0.2292	-0.2703	-0.5681	0.2189
4	0.0472	0.9147	-0.0366	0.2203	0.5816	0.3846	0.7058

Tab. 7

Ratio of (A_{ij}) with sum of all input variables (B_{ij}) and sum of product (S_j)

No. of hidden neurons	I1 ($\boldsymbol{W_l}$)	I2 ($\boldsymbol{T_c}$)	I3 ($\boldsymbol{W_w}$)	I4 ($\boldsymbol{E_w}$)	I5 ($\boldsymbol{q_c}$)	I6 ($\boldsymbol{T_f}$)	I7 ($\boldsymbol{D}$)
1	0.0455	0.3605	-0.1992	-0.1749	0.3763	0.3589	0.2328
2	3.4432	-5.1091	0.0467	8.4677	-8.7082	8.2004	-5.3407
3	-1.4359	-1.0439	-0.1086	0.9691	1.1429	2.4021	-0.9255
4	0.0167	0.3246	-0.0129	0.0781	0.2064	0.1364	0.2504
Sum	S_1= 2.069	S_2= -5.4678	S_3= -0.2741	S_4= 9.3401	S_5= -6.9825	S_6= 1.0979	S_7= -5.783

The analysis suggests that the BRNN model is best for the present study. Additionally, this study applied the Connection weight technique and Garson's algorithm for assessing the relevance of explanatory variables in ANN modelling [12]. The input variables' contributions are detailed in Tab. 8. The Connected Weights technique, as given in equation 7(a), allows greater influence on input variables with larger absolute weights on the output calculation of the hidden layer and the overall performance of the network. Garson's algorithm employs the same procedure to assess the contribution of input variables, and the ranking of each input variable is determined by equation 7(b).

$$Relative\ Importance = \frac{S_1}{S_1+S_2+S_3+S_4+S_5+S_6+S_7} \qquad 7(b)$$

Where S_1, S_2, ……S_7 is the sum of product in each hidden neuron.

Tab. 8 presents the ranking of input variables based on the absolute value of Connection weight. Follow-up time (T_f), entry width (E_w) and circulating flow (q_c), with absolute values of 11.10, 9.34, and 6.98, are specified in first, second, and third order. Tab. 5 even indicates that follow-up time (T_f), critical gap (T_c) and circulating flow (q_c) contribute around 21.15%, 19.56%, and 19.50% to model fitting, respectively. Approximately 60% of capacity modelling comes from these three variables (T_f, T_c and q_c) which characterise traffic behaviour under mixed traffic situations. The remaining contributing variables (W_w, W_w, E_w and D) that pertain to the geometric state of the roundabout collectively account for around 40% of the capacity prediction that has been formulated in the present investigation. The use of Connection weight approach and Garson algorithm revealed that weaving width (W_w) has a modest influence on the development of the model.

Tab. 8

Contribution of input variables in BRNN model

Input variables	Connection weight approach		Garson algorithm	
	Sum (Absolute Value)	Rank	Relative importance (%)	Rank
I1 (W_l)	2.07	6	7.72	6
I2 (T_c)	5.47	5	19.56	2
I3 (W_w)	0.27	7	3.53	7
I4 (E_w)	9.34	2	12.80	5
I5 (q_c)	6.98	3	19.50	3
I6 (T_f)	11.10	1	21.15	1
I7 (D)	5.78	4	15.71	4

4. CONCLUSIONS

ANN-based model has been receiving wide appreciation over regression-based models as it is capable of establishing nonlinear relationship between dependent and independent variables. In this study, ten ANN-based models were developed for roundabout entry capacity prediction purpose. It was observed that the BRNN based model has the highest R^2 value of 0.97 and lowest RMSE value of 167.89 among all ten models. Therefore, this model was selected for the capacity prediction in this study. The comparison of various existing capacity models with the ANN model is depicted in Fig. 4.

Moreover, to appraise the BRNN model, several statistical tests were performed under a given data set. Sensitivity analysis is carried out using Connection weight approach and Garson algorithm to observe the influence of input variables in the proposed BRNN model according to Garson algorithm, gap acceptance variables including follow-up time (T_f), critical gap (T_c), and circulating flow (q_c) all played significant roles in the model fitting, with corresponding contributions of 21.15, 19.56, and 19.50 percent. Based on the findings of the Connection Weight approach, the following parameters are prioritised in the model development process: follow-up time (T_f), entry width (E_w), and circulating flow (q_c). These parameters have respective absolute values of 11.10, 9.34, and 6.98 for the connection weight approach. It was also found that weaving width (W_w) has contributed just 3.53% to the overall model and that the absolute value of the connection weight was only 0.27.

Planners and designers now have a practical tool in the form of the proposed models (ANN) for predicting capacity under traffic situations analogous to those in other developing countries; however, further research is needed to determine the effect of pedestrian crossings on this estimation.

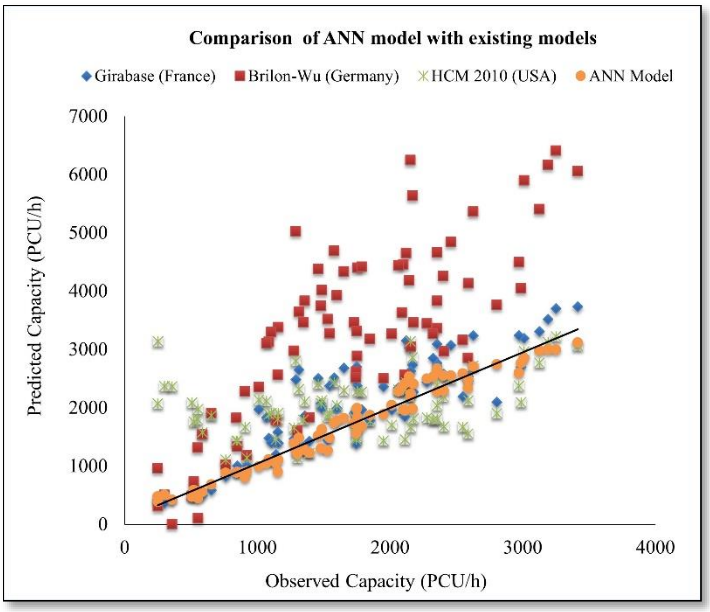


Fig. 4. Comparison of various capacity models

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Appendix 1

Geometric specifications of selected unsignalized roundabouts

Sl. No.	Site	City	Leg At	Approach width (A_w)	Entry width (E_w)	Weaving width (W_w)	Weaving length (W_l)	Diameter of central island (D)
1	Sector-2 Square	Rourkela, Odisha	E	9.58	11	12.5	34.02	23.83
			W	18.73	13.44	28.5	43.82	
			N	22.78	12	21.09	36.74	
			S	18.4	15.75	29.56	40.91	
2	SAIL Square	Rourkela, Odisha	E	6.53	19.36	32	49.31	50
			W	17.51	14.17	20.98	43.84	
			N	22	19.74	32.45	48.54	
			S	19.92	18.36	26.05	44.27	
3	Ambagan Square	Rourkela, Odisha	E	11.24	15.1	27.19	43.99	38
			W	15.14	19.81	35.01	50.22	
			N	23.4	11.59	23.43	41.59	
			S	18.91	18.23	33.72	53.77	
4	Plant Side Square	Rourkela, Odisha	E	6.2	15.43	31.12	43.31	48.87
			W	8.1	13.68	24.25	41	
			N	18.01	19.17	30.96	45	
			S	19.2	16.12	29.58	45.07	
5	Traffic Gate Square	Rourkela, Odisha	E	12.67	15.52	23.31	43.79	43.55
			W	8.63	5.41	19.63	39.87	
			N	21.27	15.74	32.25	51.7	
			S	20.13	8.5	21.58	37.92	

6	Birsa Square	Rourkela, Odisha	N	10.58	17.55	33.2	50.95	60.12
			N-E	9.63	16.61	32.72	52.33	
			E	12.06	18.9	33.91	58.72	
			W	12.77	17.22	28	47.67	
7	Panposh Square	Rourkela, Odisha	E	16.07	14.3	27.9	48.21	30.28
			S	16.95	13.76	23.75	42.87	
			W	14.02	15.08	29.56	41.86	
8	Ainthapalli Square	Sambalpur, Odisha	N-E	8.01	12.93	27.57	35.56	47.88
			N-W	14.18	13.2	19.57	43.18	
			S-E	13.12	18.97	30.95	46.97	
			S-W	11.66	13.33	24.85	37.95	
9	Master Canteen Square	Bhubaneswar, Odisha	N	25.99	17.72	26.78	48.65	45.91
			S	25.56	14.55	28.99	53.44	
			E	16.85	14.8	32.26	49.71	
			W	12.8	16.79	27.6	44.23	
10	Gopabandhu Square	Bhubaneswar, Odisha	N	10.1	18.33	32.56	49.83	51.62
			E	10.84	17.68	29.07	47.35	
			W	10.01	17.82	23.99	46.58	
11	Jobra Square	Cuttack, Odisha	N	10.2	19.68	31.25	48.71	37.21
			S	8.2	16.5	27	46.71	
			N-E	10.73	15.42	20	41.9	
			W	15.77	15.04	29.87	46.57	
12	Palbani Square	Baripada, Odisha	E	9.47	18.98	30.57	47.87	58.88
			W	9.4	17.96	31.35	52.3	
			N	9.53	16.47	27.94	50.15	
			S	10.45	12.41	21.44	40.86	
13	Dargadhi Square	Baripada, Odisha	E	10.42	14.98	23.6	45	39.38
			W	11.86	18.97	31.33	52.76	
			N	10.89	18.12	32.7	53.28	
			S	12.31	19.02	33.45	50.64	
14	Salt-lake Square	Kolkata, West Bengal	NE	8.85	15.85	30.1	46.08	33.55
			NW	8.85	11.52	21.96	42.08	
			SE	8.85	13.57	22	35.09	
			SW	8.85	11.85	28.32	36.08	
15	Albert Ekka Square	Ranchi, Jharkhand	N-E	15.45	4.72	9.48	32.08	10.76
			S	19.58	5.2	8.2	29.42	
			N-W	13.38	6.31	15.39	31.57	
16	Old Bus Stand Square	Bilaspur, Chhattisgarh	E	7	18.19	34.86	51.25	
			W	7.2	18.25	27.35	48.7	
			N	9.46	4.43	15.21	30.15	55
			S	9.81	16.9	30.15	56.2	

17	Ramnagar Square	Nagpur, Maharashtra	NE	13.93	11	23.85	40.31	36.54
			NW	11.52	13.94	23.57	36.66	
			W	11.26	11.31	25.47	37.83	
			SW	13.29	11.22	23.94	36.4	
			E	6.93	13.04	22.33	38.12	
			SE	15.33	5.9	14.8	31.2	
			S	11.45	5.12	11.02	28.96	
18	Medical Square	Nagpur, Maharashtra	N	6.74	6.14	13.39	38.96	51.22
			NE	7.32	9.5	17.45	38.52	
			SE	6.38	18.36	27.01	43.8	
			S	10.97	16.71	30.02	47.63	
			SW	9.62	16.77	28.47	49.22	
			NW	6.71	13.97	33.02	41.15	
19	Chacka Junction	Thiruvananthapuram, Kerala	NE	7.64	16.34	32.01	44.32	46.8
			NW	6.21	14.71	26.025	45.34	
			SE	8.43	16.94	26.98	39.8	
			SW	6.98	15.94	30.01	44.24	
20	Womens College, Vazhuthakadu	Thiruvananthapuram, Kerala	N	18.39	19.1	32.67	46.85	34.28
			S	17.59	16.59	20.5	40.42	
			E	6.77	13.85	28.8	43.45	
			W	13.88	16.47	25.26	40.89	
21	MVP Colony Square	Visakhapatnam, Andhra Pradesh	E	8.12	17.3	28.9	47.98	45.47
			W	8.19	18.79	29.98	50.05	
			N	8.09	14.65	27.59	43.1	
			S	7.98	20.12	29.6	52.3	
22	Diamond Park Junction	Visakhapatnam, Andhra Pradesh	E	14.51	19.8	28	53.29	54.8
			W	14.01	15.81	31.65	47.13	
			N	18.19	18.5	25.14	47.79	
			S	15.52	16.88	22.51	38	
23	BR Ambedkar Square	Visakhapatnam, Andhra Pradesh	E	11.2	18.93	30.02	45.69	40.1
			W	11.71	15.3	22.91	38.31	
			N	10.04	19.07	29.95	41.22	
			S	11.05	14.79	24.9	41.02	
24	Dornama Raju Square	Visakhapatnam, Andhra Pradesh	N	14.29	12.15	31.84	41.59	40.65
			S	20.85	14	29.84	41.22	
			E	15.86	14.58	22.9	40.26	
			W	20.47	10.12	22.86	47.86	
25	Sector 43-44 Junction	Chandigarh	NE	13.97	16.89	33.17	44.72	50
			NW	13.75	19.46	33.25	45.88	
			SE	11.68	18.48	30.04	50.89	
			SW	11.38	16.88	30.58	41.81	

26	Sector 42 Junction	Chandigarh	NE	8.28	19.79	29.55	51.59	49
			NW	9.39	19.14	29.72	45.14	
			SE	8.14	19.87	29.56	46.13	
			SW	8.38	14.98	27.9	48.62	
27	Sector 49 Junction	Chandigarh	N	10.4	16.9	34	56	57
			S	10	16.4	30.5	48.3	
			E	10.6	19.3	31	51.6	
			W	11	16.2	32.8	52.5	

Note: N = North, S = South, E = East, W = West, NE = North-East, NW = North-West, SE = South-East, SW = South- West

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